# Enhancing Stock Price Prediction: An AI/ML Approach Including Macroeconomic Indicators with a Focus on AAPL

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# 1. Abstract

This thesis explores the effect of including macroeconomic indicators, specifically Gross Domestic Product and Consumer Price Index, into stock price predictions using Support Vector Regression with an emphasis on Apple stock. This study aims to assess if these indicators can enhance the stock prediction accuracy of SVR models across different industries, including technology, retail, and consumer staples. Using historical stock data from Apple, Walmart, and PepsiCo, this thesis explores how including GDP and CPI affects the performance of SVR models in terms of mean squared error on both training and testing datasets.

The findings in this thesis reveal that the effectiveness of incorporating macroeconomic indicators varies significantly by industry. For the technology sector, including GDP and CPI data for Apple stock prediction greatly decreased the predictive accuracy. This is most likely because the technology sector is more sensitive to industry specific dynamics instead of the broader economic trends. However, for consumer focused sectors like retail and consumer staples, incorporating GDP and CPI to Walmart and PepsiCo data was much more relevant and even slightly improved PepsiCo's model performance. This thesis shows that while economic indicators do provide valuable insights for certain industries, their applicability in stock price prediction is very dependent on the industry context. Lastly, this thesis is accompanied by a Jupyter notebook on Github that contains the different functions and data preprocessing steps in Python.

## 2. Introduction

Because of the dynamic nature of the markets, accurate stock price prediction has been a challenge for companies and individuals. With advancements in artificial intelligence and machine learning, these techniques are now being integrated into stock price forecasting. This thesis focuses on the application of AI and ML to improve stock price prediction, with a specific emphasis on Apple stock, as well as an examination of Walmart and PepsiCo. The goal is to explore the complex relationship between external economic indicators and stock prices and to identify potential improvements in stock market predictions.

The objectives include evaluating the performance of SVR models and integrating major economic indicators such as the US Gross Domestic Product (GDP) and the Consumer Price Index (CPI) to understand how they effect the accuracy of stock price predictions for these companies.

## 3. Datasets and Libraries

Stock data from the last ten years will be used for Apple, Walmart, and PepsiCo predictions. All three of these datasets are sourced via the SimFin API as shown in Table 1. Additionally, to contextualize AAPL, WMT, and PEP stock trends within an economic landscape, U.S. Gross Domestic Product data will be used from the last ten years, sourced from Statistica.org. Similarly, Consumer Price Index data was sourced through the US Bureau of Labor Statistics. Different Python packages will be used to process, visualize, and model the data. For computations and data manipulation, numpy and pandas are used. For data visualization, matplotlib and seaborn are used to create different graphs and plots. Lastly, for stock predictions, scikit-learn is used because of its collection of tools for machine learning and predictive analysis.

**Apple Stock Data**

| | Date | Open | High | Low | Last | Close | Volume |
|---|---|---|---|---|---|---|---|
| **0** | 2014-05-02 | 21.16 | 21.22 | 21.06 | 21.16 | 18.64 | 191514592 |
| **1** | 2014-05-05 | 21.08 | 21.46 | 21.07 | 21.46 | 18.90 | 287067487 |
| **2** | 2014-05-06 | 21.49 | 21.59 | 21.23 | 21.23 | 18.70 | 374564775 |
| **3** | 2014-05-07 | 21.26 | 21.33 | 20.99 | 21.15 | 18.63 | 282864683 |
| **4** | 2014-05-08 | 21.01 | 21.23 | 20.94 | 21.00 | 18.60 | 230297430 |

Table 1. This table shows the first five rows of the AAPL stock price data, collected from the SimFin API. The data frame for AAPL, WMT, and PEP are all 2433 rows x 7 columns.

## 4. Support Vector Regression Overview

A Support Vector Machine (SVM) is a supervised learning algorithm that works best on smaller and more complex datasets, especially in high-dimensional spaces. SVM can be used for both regression and classification tasks, but generally work best in classification problems. The goal of an SVM is to find the optimal hyperplane that best separates the dataset into different classes (Madge, 2015). In two dimensions, the hyperplane is a line dividing a plane into two parts where each class lies on each side. The optimal hyperplane maximizes the margin, meaning the hyperplane has the largest distance between the data points of both classes (Rodríguez-Pérez, 2022).

**Main Components of an SVM**

• *Support Vectors:* Data points that are closest to the hyperplane. These influence SVM position and orientation.

• *Margin:* The gap between the two classes along the direction of the separating hyperplane.

• *Hyperplane:* The decision boundary that separates different classes in the dataset.

• *Kernel:* The functions that solve different classification cases.

There are four different kernel functions for SVM: Linear, Polynomial, RBF, and Sigmoid. The Linear Kernel is used when the data is linearly separable and is the dot product. The Polynomial Kernel is useful for non-linear data with fewer samples. The Sigmoid Kernel is useful for binary data and data that looks like a logistic function. The RBF Kernel stands for Radial Basis Function and is best used for non-linear data. In this thesis, the RBF kernel is used because of its flexibility in handling non-linear stock data.

Many factors including market sentiment and economic indicators influence stock market prices. The RBF kernel within SVM provides flexibility for input data with many features. The RBF kernel's ability to handle different types of features from the training examples is because of hyperparameters like gamma, which is set to auto in this thesis. The cost parameter C provides a trade-off between a wide margin and classification accuracy. A higher value of C places more of an emphasis on correctly classifying all training examples, potentially at the cost of a slimmer margin leading to overfitting (Madge, 2015). A lower value of C focuses on a wider margin, allowing for some misclassifications but potentially improving the model's generalization.

While SVM is used for classification problems and aims to maximize the margin between two classes, SVR is used for regression problems. The goal of SVR is to find a function that has at most $\varepsilon$ deviation from the actual target values for all the training data while minimizing the coefficients of the regression function. In SVR, the idea of the margin is applied to the regression because it tries to include as many data points as possible within the margin while penalizing those that fall outside the margin (Rodríguez-Pérez, 2022). Like SVMs, SVR uses kernel functions and hyperparameter tuning to handle non-linear relationships by transforming data into higher dimensions.

## 5. Evaluating Models with MSE, RMSE, and MAE

There are three main types of metrics that are used to evaluate model performance. The most commonly used metric for regression tasks like stock price forecasting is Mean Squared Error (MSE). MSE measures the average of the differences between the predicted and actual values. The equation for calculating MSE is given by:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

where $n$ is the number of observations $y_i$ is the actual value, and $\hat{y}_i$ is the predicted value from the model. The goal is to minimize the MSE to as low a value as possible. Lower values of MSE indicate a model with better predictive capabilities, and higher values suggest a model overfitting or underfitting. Root Mean Squared Error (RMSE) is the square root of the MSE:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

By squaring the errors before averaging, MSE gives more weight to larger errors. While MSE is measured in units that are square of the target variable, RMSE is measured in the same units as the target variable, making interpretation simpler. Like MSE, a lower RMSE value indicates a better fit for the data. Lastly, Mean Absolute Error (MAE) is the average magnitude of the errors in a set of predictions without considering direction:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}(|y_i - \hat{y}_i|)$$

Measured in the same units of the target variable, MAE is less sensitive to outliers compared to the MSE or RMSE. Regarding the direction, MAE will treat all errors equally, regardless of whether the prediction is higher or lower than the actual value because it only focuses on the absolute differences. When evaluating the SVR models, these metrics provide different perspectives on model performance and help in tuning hyperparameters like *C*.

## 6. AAPL Trading Volume

Trading volume is the total number of shares of a stock that are traded during a given time, and it is often an indicator used by investors to gauge the strength behind price movements. Higher trading volumes signal confidence among investors in the price movement, and lower volumes can indicate uncertainty or lack of interest (Twin, 2022). In this graph, there are noticeable spikes in volume at certain intervals, which could be associated with product launches, earnings reports, or changes in investor sentiment. For example, a sharp increase in volume can be the result of the release of a new iPhone model or after quarterly financial results are published.

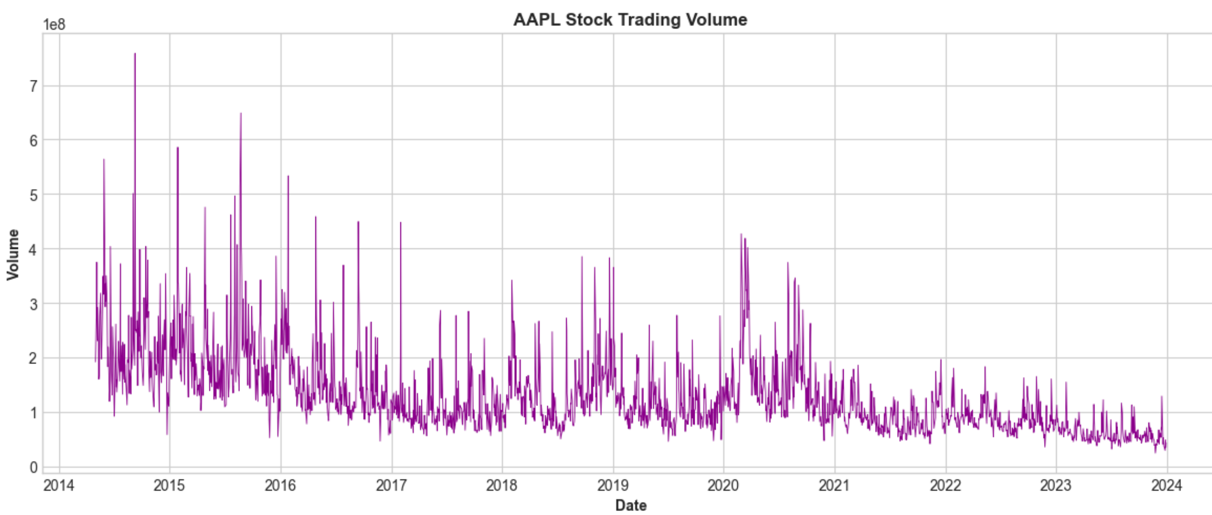


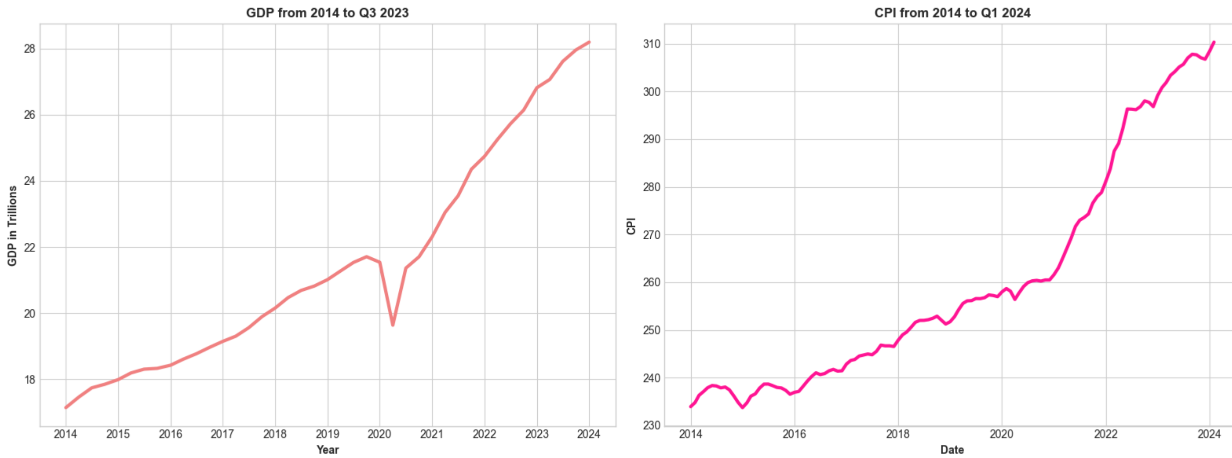
*Figure 4.* This graph shows the trading volume of Apple stock from 2014 to 2024.

Additionally, trading volume is an important aspect of liquidity, so a higher volume shows that the stock can be bought or sold quickly without a significant impact on the price

(Twin, 2022). Figure 4 shows consistently high trading volume until around early 2021, and lower trading volumes from early 2021 until the end of 2023, which could mean potential volatility in price. This thesis uses Trading Volume as a feature for the SVR.

## 7. Economic Data: Understanding and Using GDP and CPI in SVR

The US Gross Domestic Product (GDP) is the total market value of all goods and services produced within the United States, and it is a strong indicator of the US' economic health. Similarly, the US GDP growth rate is a measure of how the economy is growing or shrinking over quarters (Barnes, 2023). The Consumer Price Index (CPI) measures the level of inflation or deflation in the economy by measuring changes in prices paid by consumers for a market basket of goods and services like gas, rent, groceries, etc (U.S. Bureau of Labor Statistics, 2016). GDP and CPI are indicators that give a high-level view of the economic environment and may influence investment decisions and stock market performance. A rising GDP usually means a healthy economy, which could boost investor confidence and stock prices. Meanwhile, a high CPI might indicate rising inflation, which could reduce investors purchasing power and affect stock market returns and trading volume. By incorporating CPI and GDP as features in the SVR model, this thesis will test if these macroeconomic indicators will improve the model's accuracy by providing additional context on the economic conditions.




*Figures 1 and 2*. These figures show the US GDP and CPI for the past ten years.

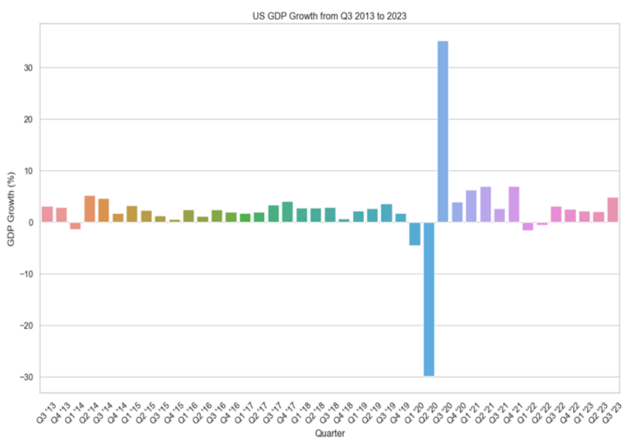



*Figure 3*. This figure shows GDP growth rate from the end of 2013 to end of 2023.

Figures 1, 2, and 3 show the trajectories of GDP, GDP growth rate, and CPI over time. Figure 1 shows a strong increase in GDP, reflecting long term economic growth. Figure 3 shows the GDP growth rate, which highlights the sharp drop in 2020 representing the Covid-19 pandemic. Meanwhile, Figure 3 shows a consistent upward trend, which means inflation has been increasing over the years. These graphs together give a holistic view of the economic landscape.

Some challenges in including macroeconomic indicators in SVR are in data preprocessing and in overfitting and noise. Macroeconomic data like GDP and CPI are released less often than daily stock market data. GDP data is released quarterly, so in data preprocessing each quarter's GDP was given a consistent weight across all days of that quarter. This meant that the ‘Weighted GDP’ column was given the exponential weighted moving average to give more weight to the more recent values in the same quarter. Additionally, CPI data is available monthly, so each day within a given month was assigned the same CPI value to maintain consistency in the dataset across the monthly period as seen in Table 2.

**Apple Stock Data**

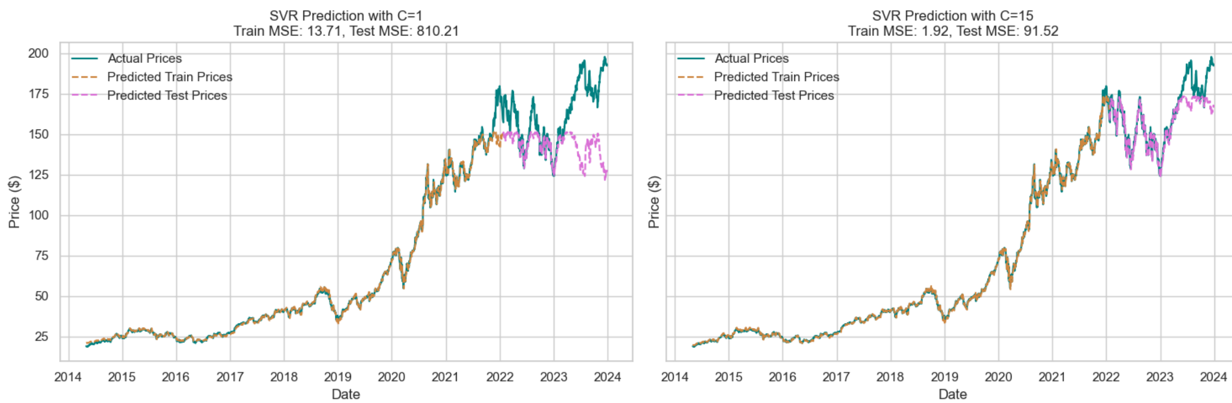
| | Date | Open | High | Low | Last | Close | Volume | GDP | Weighted GDP | CPI | Average Price |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **2363** | 2023-09-21 | 54.75 | 54.83 | 53.93 | 53.97 | 53.59 | 18787488 | 27610.128 | 27608.778442 | 307.789 | 54.214 |
| **2364** | 2023-09-22 | 54.08 | 54.41 | 53.97 | 54.12 | 53.73 | 13216917 | 27610.128 | 27608.913397 | 307.789 | 54.062 |
| **2365** | 2023-09-25 | 54.12 | 54.37 | 53.96 | 54.36 | 53.97 | 10459422 | 27610.128 | 27609.034858 | 307.789 | 54.156 |
| **2366** | 2023-09-26 | 54.31 | 54.51 | 54.12 | 54.17 | 53.78 | 14435814 | 27610.128 | 27609.144172 | 307.789 | 54.178 |
| **2367** | 2023-09-27 | 54.00 | 54.08 | 53.43 | 53.91 | 53.52 | 15711102 | 27610.128 | 27609.242555 | 307.789 | 53.788 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **2428** | 2023-12-22 | 51.82 | 52.38 | 51.72 | 52.22 | 52.04 | 19405641 | 27956.998 | 27956.303980 | 306.746 | 52.036 |
| **2429** | 2023-12-26 | 52.22 | 52.33 | 52.04 | 52.14 | 51.96 | 11679963 | 27956.998 | 27956.373382 | 306.746 | 52.138 |
| **2430** | 2023-12-27 | 52.10 | 52.65 | 52.05 | 52.63 | 52.45 | 18880389 | 27956.998 | 27956.435844 | 306.746 | 52.376 |
| **2431** | 2023-12-28 | 52.59 | 52.78 | 52.50 | 52.52 | 52.35 | 16776066 | 27956.998 | 27956.492060 | 306.746 | 52.548 |
| **2432** | 2023-12-29 | 52.51 | 52.69 | 52.39 | 52.55 | 52.37 | 21948198 | 27956.998 | 27956.542654 | 306.746 | 52.502 |

*Table 2.* This table shows the data preprocessing for AAPL stock which includes the weighted GDP and CPI.

Another larger challenge is that these indicators may not always correlate directly with stock market movements, leading to noise in the model. For instance, the new release of a product or the firing of a CEO could have a more immediate and pronounced impact on a company's stock price than macroeconomic indicators.

## 8. AAPL Support Vector Regression

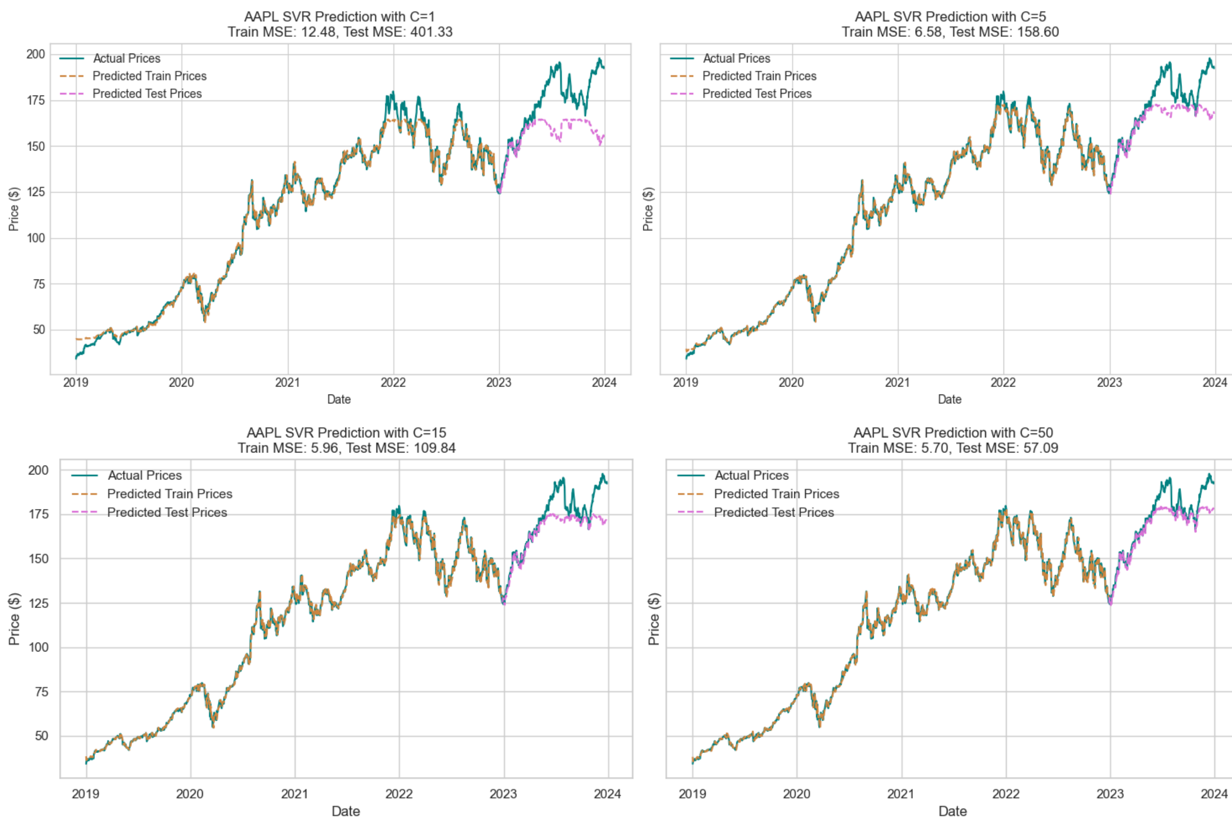
To make the base SVR model, the data needed to be preprocessed to compute the average price, future closing price, scaling of features, and splitting the data into training and testing sets. After training the SVR model on the scaled training data, the model's performance is evaluated using the training and testing MSE. In SVR, the hyperparameter represents the penalty for errors. A higher C value means that the model will try to find a solution that classifies all training examples correctly. The hyperparameter controls the trade-off between capturing the training data's trends and maintaining the ability to perform well on new, unseen data. Because hyperparameter tuning is a form of regularization, setting it too high can lead to overfitting, where the model is too tailored to the training data, and setting it too low can lead to underfitting, where the model does not capture trends well enough.




*Figures 5 and 6.* This graph shows the actual and predicted price from the SVR model with RBF.

The model in Figure 5 is trained with a hyperparameter of C=1 and the train and test MSE is displayed.  The low training MSE means that the model has learned the training data well, while the test MSE shows how well the model responds to unseen data. With C=1, the train MSE is low at 13.71, which means there’s a good fit for the training data, but the test MSE is much higher at 810.21. Figure 6 shows the model with C=15 and with a training MSE of 1.92 and a testing MSE of 91.52. Because Figure 6 presents a much tighter gap between the training and testing MSE, increasing the hyperparameter to C=15 better generalizes the model to unseen data compared to the model with C=1.

As shown in Figures 5 and 6, the SVR model is being trained on data from 2014 to the end of 2021 with predictions being made for 2022 to the end of 2023. These next four figures will focus on a shorter date range, 2019 to 2024, to improve the accuracy and relevance of the SVR model. By using more recent data for training, the model will not be skewed by older patterns that may no longer be relevant. Additionally, this shorter time frame reduces the risk of anomalies that can occur over longer periods, leading to more effective hyperparameter tuning. Figures 7-10 show that as the hyperparameter C increases, the models show a better balance between training accuracy and testing performance. This means that hyperparameter tuning is more effective when older data that might no longer be predictive of future trends is present.




*Figures 7-10.* This collection of graphs shows the different hyperparameters and their respective train and test MSE for APPL stock predictions without macroeconomic indicators.

These figures show the progression from C=1 to C=50 in how the model learns from the training data and makes predictions with unseen data. The model with C=1 shows the lowest fit to the training data with an MSE of 12.48 and a test MSE of 401.33, meaning the model is underfitting the data. Increasing C to 5 slightly improves both the training and test MSEs of 6.58 and 158.6, indicating a less restrictive penalty on the training errors, allowing the model to fit more closely to the training data without extreme overfitting. Increasing C to 15 and 50 shows a trend of decreasing MSEs for training, with C=15 having a training MSE of 5.96 and C=50 at 5.70. The test MSEs also decrease by 108.84 for C=15 and 57.09 for C=50, meaning that the model is finding more complex patterns in the data, leading to better predictions but overfitting at C=50.

## 9. AAPL Support Vector Regression with Economic Data:

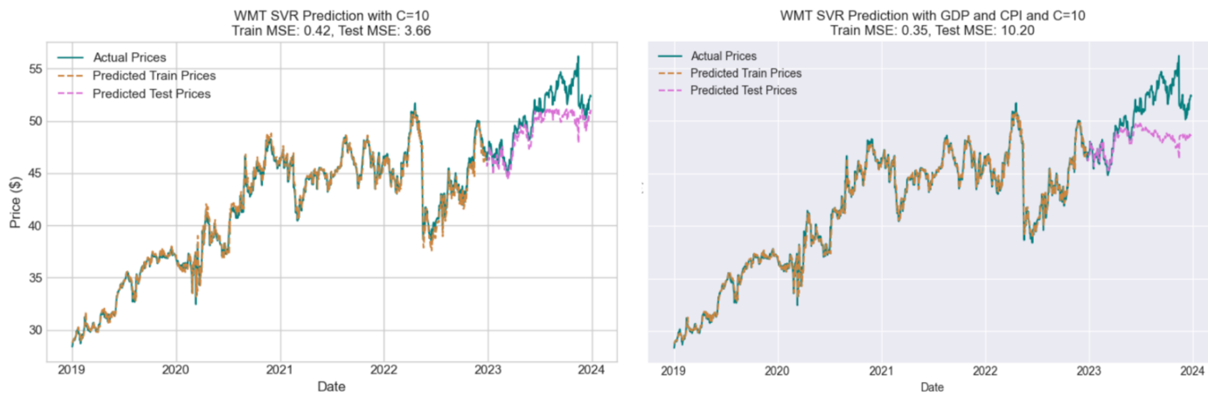

*Figure 11-14.* This collection of graphs shows the different hyperparameters and their respective train and test MSE for AAPL stock predictions with macroeconomic indicators.

The four figures above show SVR models trained with different hyperparameters of 1, 10, 20, and 60, while including GDP and CPI data in the prediction of Apple's stock price. The model with C=1 has the highest train MSE of 12.15 and test MSE of 1150.36, showing that it struggles to predict unseen data and is underfitting the data. The model with C=10 has a low train MSE of 6.33 and test MSE of 676.00 which is better than C=1 but still needs more tuning for better generalization. Next C=20 shows improvement with the train MSE further decreasing to 5.92, and the test MSE to 502.25 shows improvements in model generalization compared to 1 and 10 C values. Lastly, C=60 shows a train MSE of 5.59 and the lowest test MSE of 381.49 among the four models. Although this produces the best performance, increasing C to 60 will consequently increase the model's complexity, making it overfit the data and be sensitive to new data that does not fit the training set.

Comparing Figures 7-10 to Figures 11-14, incorporating GDP and CPI into the SVR model has worsened the model's performance, with one main reason being the industry fit. Tech stocks like AAPL are influenced by a range of factors that may not always correlate with broad economic indicators like GDP and CPI. The technology industry often moves based on innovation instead of just macroeconomic conditions, which can make its stock prices less sensitive to general economic trends compared to other industries like consumer staples or financial services. Additionally, given the higher MSE, the SVR for AAPL had difficulty interpreting the GDP and CPI data, leading to noise and undermining the SVR model's effectiveness for AAPL.

## 9. Exploring Different Industries

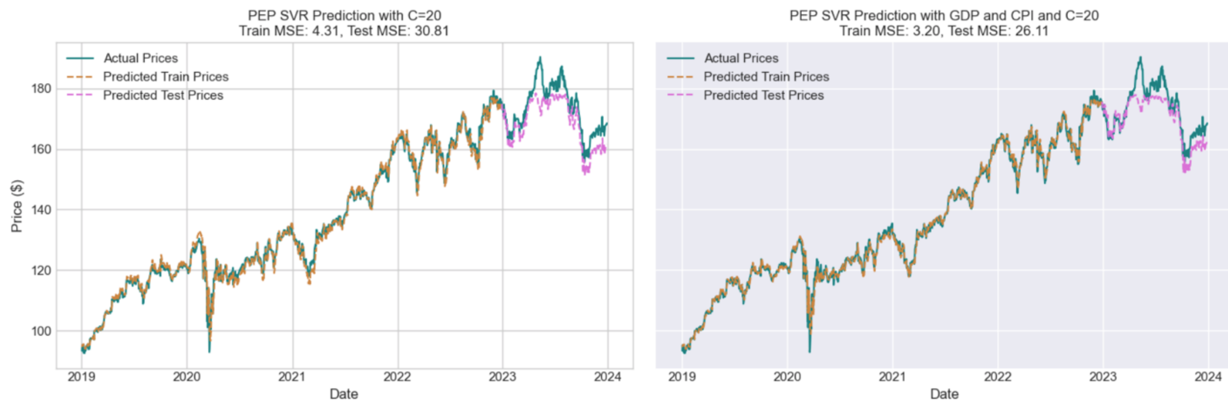
Some industries seem to have a much stronger correlation with GDP and CPI than the Tech sector. In industries like Consumer Discretionary and Retail, there is a direct relationship between economic indicators and consumer behavior (Alldredge et al., 2022). Companies in this industry, like Walmart, Amazon, and Target, do well when the economy is strong because of an increase in consumer spending power. An increase in CPI could also significantly influence these companies because high inflation leads to increased consumer prices, which most likely affects purchasing patterns. The consumer retail sector has a more sensitive correlation between their performance and macroeconomic changes than in tech industries like Apple.




*Figures 15 and 16.* These figures show SVR predictions for Walmart stock with a hyperparameter of 10. Only Figure 16 includes GDP and CPI indicators.

Because Walmart is the biggest retail player, it is modeled using the same SVR functions as the Apple predictions. Analyzing Figure 15 when GDP and CPI are not included, the model has a train MSE of 0.42 and a test MSE of 3.66. With GDP and CPI added, Figure 16 shows that the train MSE improves slightly to 0.35, but the test MSE increases to 10.20. Compared to Figure 12, Apple's prediction with C=10 and GDP and CPI, economic indicators fit Walmart's model much better, but it is still not as accurate as regular stock price data without economic indicators.

The consumer staples sector usually has a very stable stock performance because of the consistent demand for essential products regardless of economic conditions. Because PepsiCo is one of the biggest consumer staple companies, the same SVR models were performed on PepsiCo to determine if there is a correlation between GDP and CPI for stock price data.




*Figures 17 and 18.* These figures show SVR predictions for PepsiCo stock with a hyperparameter of 20. Only Figure 18 includes GDP and CPI indicators.

Figure 17 does not include GDP and CPI data, resulting in a train MSE of 4.31 and a test MSE of 30.81. However, Figure 18, which includes GDP and CPI data, shows the train MSE being reduced to 3.20 and the test MSE reduced to 26.11. This means the macroeconomic indicators suggested a better fit for PepsiCo's Stock. The company's performance is likely influenced by broader economic conditions, as changes in consumer purchasing power directly affect sales of consumer goods. The reduction in Test MSE with the inclusion of GDP and CPI data suggests that for sectors that have a direct relationship with economic cycles, such as consumer staples, integrating these macroeconomic indicators can enhance the model's accuracy on unseen data.

For a high level view of how SVR with GDP and CPI affects different industry predictions, Table 3 shows a comparison of tech, retail, and consumer staples. Even with high C values, AAPL is still very far behind WMT and PEP in accuracy, showing that GDP and CPI are not a good predictor of the tech industry stock performance. The next steps would include closely evaluating other retail and consumer staple companies like Target or Nestle.

**AAPL, WMT, and PEP SVR Predictions with GDP and CPI**

| C | AAPL Train MSE | AAPL Test MSE | WMT Test MSE | WMT Train MSE | PEP Train MSE | PEP Test MSE |
|---|---|---|---|---|---|---|
| 1 | 12.5 | 1150.36 | 0.39 | 15.75 | 5.72 | 146.11 |
| 10 | 6.33 | 676.00 | 0.35 | 10.20 | 3.33 | 36.44 |
| 15 | 6.06 | 567.81 | 0.34 | 9.79 | 3.24 | 29.09 |
| 20 | 5.92 | 502.25 | 0.34 | 9.20 | 3.20 | 26.11 |
| 50 | 5.62 | 411.00 | 0.33 | 6.55 | 3.02 | 16.76 |

Table 3. This table compares AAPL, WMT, and PEP predictions with macroeconomic indicators.

## 10. Conclusion:

In conclusion, exploring the effectiveness of incorporating GDP and CPI into stock price predictions through SVR has led to different results across different industry sectors. While macroeconomic indicators can provide useful context for the economic environment, the effectiveness of CPI and GDP varies depending on the industry of the company being evaluated. In the technology sector, including GDP and CPI did not improve the model's accuracy, instead, it made the accuracy worse. However, for consumer focused sectors like Retail and Consumer Staples, including these indicators had a better impact because these sectors are directly affected by consumer purchasing power and economic health, so GDP and CPI are relevant predictors. In the case of PepsiCo, the macroeconomic indicators helped to slightly improve the model's predictions, resulting in lower MSE for training and testing. Additionally, one key takeaway is that doing an industry analysis is important because different industries react differently to economic changes.

Using different hyperparameters for SVR shows how sensitive the models are to parameter settings. Further steps to make sure the best C value is selected is to do a grid search or a cross-validation to find the best hyperparameter with the lowest MSE, while not overfitting the data. Another step to enhance this thesis would be to use another type of prediction algorithm like Long Short Term Memory (LSTM). A more complex algorithm like LSTM would be able to make more accurate predictions and find underlying trends with other macroeconomic indicators like consumption or unemployment rate.

Overall, this thesis highlights the relationship between economic indicators and stock market behavior and provides a foundation for more research into industry specific models. While macroeconomic data can enhance stock prediction models, more research needs to be done to understand what industries are more correlated with broader economic trends.

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