1. Introduction

In line with recent global uncertainty and structural changes, recessions have become a looming threat to various economies, including the US. As the US is Singapore's largest foreign investor, it is prudent that Singapore is updated on changes in the US economy for policy decisions. (Medina, 2021) This paper aims to generate high-level US economic forecasts, focusing on the probability of downturns.

2. Data

2.1. Data Exploration and Cleaning

From the quarterly data, 31 features (excluding dates) were manually selected for analysis based on their relevance to measuring general economic outlooks. General key macroeconomic indicators were chosen, including CPI, unemployment rate and trade activities. Auxiliary variables such as stock prices were also kept for data visualisations. Data cleaning through removal of observations with NA values and checking for duplicates results in a dataset containing information from Q1 2006 to Q3 2024.

2.2. Visualising our Data

Keeping the data mostly unchanged, various time series visualisations were done to observe trends and their incidence with recessive periods. One such visualisation done was on exports and imports, as shown in Figure 1.

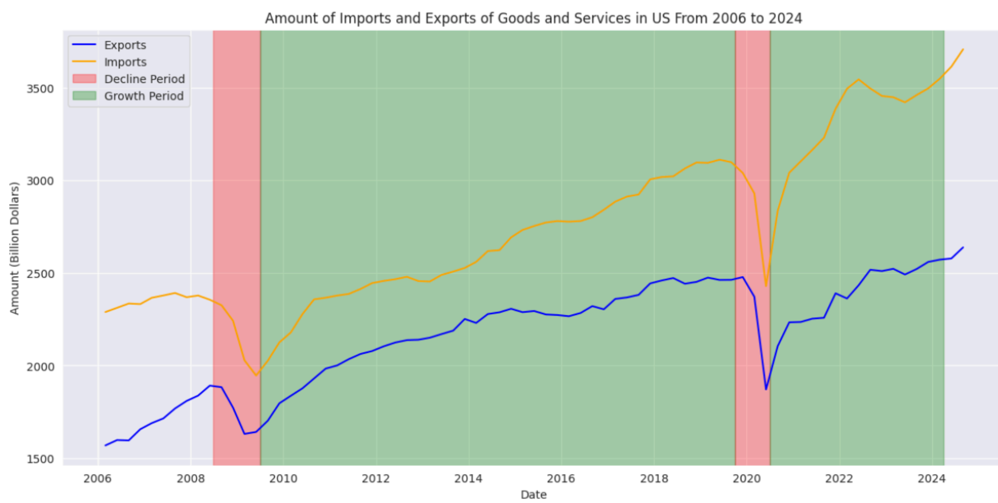

Figure 1. Trade Activities across time with decline & growth periods

Exports and imports coincide with trends in economic growth with a consistent trade deficit. Notable declines in both imports and exports were observed during the 2008-2009 financial crisis and the 2020 COVID-19 pandemic due to the disruption of global supply chains. We also observe that the gap between imports and exports widened over time beginning in 2008, indicating that imports grew faster than exports. This trend can be attributed to several factors, including a strengthening of the US dollar and growing disposable income leading to changes in spending habits (*How Importing and Exporting Impacts the Economy*, n.d.).

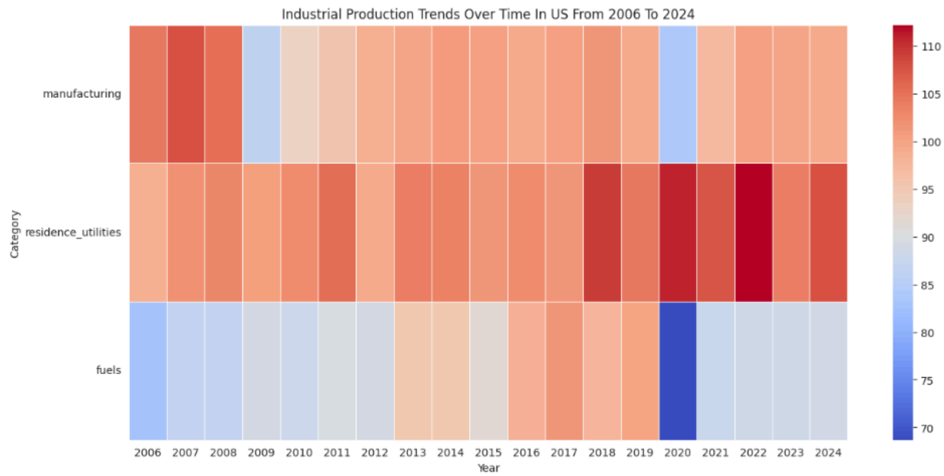

Figure 2. Industrial Production in US by type over time

Similar to trade activities, manufacturing production was likely affected by the 2008 global financial crisis and COVID-19. Residential utilities also spiked during COVID-19 with increased home occupancy leading to higher electricity, water, and gas consumption. Fuel production grew steadily from 2006 to 2014, peaking between 2014 and 2017, likely due to the US shale boom. However, it plunged in 2020 as pandemic-related travel restrictions drastically reduced demand. While a slow recovery began post-2021, production remains below pre-pandemic levels.

3. ARDL Model Implementation

3.1. Methodology

The Autoregressive Distributed Lag (ARDL) model extends the Autoregressive (AR) model, and focuses on the prediction of economic downturns through capturing dynamic interactions with real GDP, our indicator for economic growth and decline. However since most macroeconomic variables exhibit trends, seasonality or volatility, differencing is first applied to ensure stationarity.

To optimize model selection, the Akaike Information Criterion (AIC) helps balance fit and complexity, preventing overfitting. The analysis involves selecting the best lag structure for GDP and other variables to enhance forecasting accuracy.

3.2. Model Evaluation & Optimisation

To evaluate our model's performance, we assess both its predictive ability and the statistical properties of its residuals. Using the optimal lags generated by our model, the Durbin-Watson statistic indicates no significant autocorrelation, suggesting independence. However, the Omnibus and Jarque-Bera tests reveal significant deviations from normality. The negative skew test (-1.804) suggests extreme negative residuals, while high kurtosis (11.714) indicates a heavy-tailed distribution, likely due to outliers. These results are as shown in figure 3.

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==============================================================================
Omnibus:                       47.039   Durbin-Watson:                   1.932
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              259.428
Skew:                          -1.804   Prob(JB):                     4.63e-57
Kurtosis:                      11.714   Cond. No.                     4.99e+05
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Figure 3: Results of statistical tests to determine properties of residuals

To enhance model reliability, we identified and identified outliers in the residuals of our ARDL model using 3 main statistical tests: Standardized Residuals, Cook's distance, and Leverage. Once all outliers were removed and ARDL model was refitted, the Omnibus and Jarque-Bera tests now suggest approximate normality, with only slight left skew (-0.550) and mildly heavy tails (kurtosis = 3.506), supporting the model's validity.

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==============================================================================
Omnibus:                        4.738   Durbin-Watson:                   1.721
Prob(Omnibus):                  0.094   Jarque-Bera (JB):                3.782
Skew:                          -0.550   Prob(JB):                        0.151
Kurtosis:                       3.506   Cond. No.                     5.43e+05
==============================================================================
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Figure 4: Results of statistical tests after outliers were removed from our model

4. Random Forest Model Implementation

4.1. Methodology & Feature Selection

Random Forest (RF) is an alternative model that is commonly used to forecast future macroeconomic indicators and trends (Nyman & Ormerod, 2017).

Using the same quarterly data, similar macroeconomic indicators were selected. In addition however, variables from financial markets (e.g., bond yield) as well as consumer sentiment were also selected due to their leading nature, hence giving greater insight to future outlooks. Data cleaning gives a time range from Q2 1985 to Q3 2024, a larger range giving more data points to train the model with.

The dataset was split into train (1985 to 2012) and test sets (2013 to 2024) for model validation. After creating a basic RF model with untransformed training data, feature selection was conducted by their importance (level of contribution of feature towards the model). The top 9 variables were selected and a new RF model was fitted.

4.2. Model Evaluation & Optimisation

The model provided a reasonable R^2 value of 0.772, and similar promising results with MAPE, RMSE and MAE for training predictions. However, the RF model became highly inaccurate when predicting test values, likely due to the drastic (within 1-2 quarters) and severe change (up to 8% spikes) in GDP growth during the height of COVID-19 in 2020.

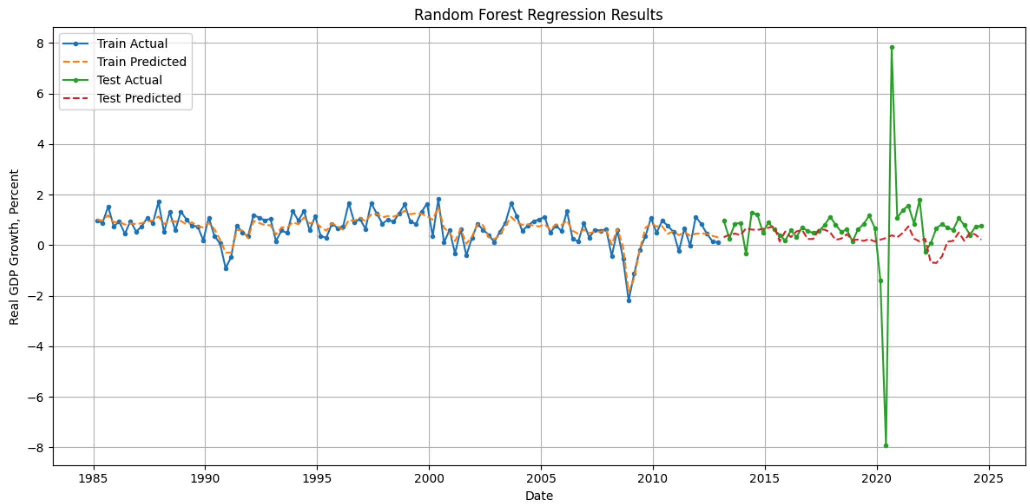

Figure 5. RF Regression Predictions against Actual Values

To test this theory, a second subset of test data was taken up until the end of 2019 instead. With this dataset, the model proved far more accurate, giving a R^2 value of -0.717. Its negative sign however suggests negative correlation between GDP growth and one or more of the exogenous variables. Overall, disregarding the anomalous values generated during COVID-19, the model has considerable accuracy.

4.3. Forecast Results with RF and ARIMA

Date	GDP Growth Forecast
2024-12-01	-0.552358
2025-03-01	-0.552358
2025-06-01	-0.552358
2025-09-01	-0.543941
2025-12-01	-0.543941

As the RF model required future data from our selected variables, we employed Autoregressive Integrated Moving Average (ARIMA) to first predict values of each exogenous variable for the next 5 quarters. Variables were first checked for stationarity and differencing was conducted for those non-stationary.

Once this forecasted dataset was created, the RF model was fitted and GDP growth values were generated for 2025. The values were generally consistent at roughly -0.54, indicating an economic contraction for all quarters.

Overall, the trend shows possible economic recession occurring throughout 2025, though the magnitude is relatively small. Given that consumer sentiment was the top contributor towards our model, this suggests that there is expectation of a worsening economy, or greater uncertainty.

While consumer sentiment does not directly affect GDP growth, the expectations may lead to the slowing of productivity (e.g., through lower consumer spending), thereby lowering GDP growth. Considering that our other contributors included bond yields, inventory to sales ratios, unemployment rates and new private housing permits – all of which deal with consumer demand, it may allude to the above explanation for a negative GDP growth.

5. Overall Evaluation & Concluding Remarks

Comparing the ARDL model with the RF model, both have similar levels of accuracy, with the RF model being marginally better due to a higher R^2 with its training data (RF: 0.727, ARDL: 0.727). This could be due to RF's ability to fit non-linear regressions, while ARDL only captures linear relationships. However, even the RF model may still struggle with sudden shocks to the economy, such as the pandemic.

Moreover, greater refining of our models could have been done through an ensemble, where we consider both models to a specified ratio and generate a more accurate prediction using the train and test data, before forecasting the final results with greater precision. Other validation techniques such as rolling window can also help smooth out the models.

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