Predicting when the US Economy Will Recover from the Current Recession

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Abstract

While predicting the start of recession has been at the center of macroeconomic research, less studies have been done for the predictors of economic recovery from recession. Since the later half of 2022, the U.S. stock market has had several major blows with the rising interest rates, underperformance in the tech sector, and the banking crisis, which triggered an economic downturn and recession fears. However, consumer spending and the housing market rebounded early this year, followed by major indexes such as the S&P 500 starting March, 2023. In this paper, we will investigate the possible predictors for an end of the current economic downturn with historical data from previous recessions. We will examine a variety of financial market indicators that are traditionally used to predict the start of recessions to see if they are appropriate predictors for economic recovery from recession.

1. Introduction

The association between yield curve and recession has been well established through economic research. Other indexes such as real interest rates, CPI, Unemployment Rate, Housing Starts Inversions, VIX index, and price indices are also predictors for recession. These indexes are indicators of economic conditions. Yield curves, for example, follow a cyclical pattern aligned with the business cycle. For this reason, we expect that these indexes can be as strong predictors for economic recovery as for recessions.

Recent developments in machine learning, variable selection, and sentiment analysis have shown to produce accurate results modeling economic recession. In this paper, we examine the usefulness of various machine learning methods in predicting economic recovery. First, we will train the datasets with ARIMA and Holt-Winters models and obtain a prediction of the weekly feature values from 2023-2030. Then, we will first perform feature selection to get the weights of correlations with GDP for all features. We believe GDP to be the best indicator of economic health due to a recession being defined as two consecutive quarters of negative growth. Next, we will adjust the dataset with relative weights as a multiplier. Finally, we will train ARIMA and Holt-Winters models on the adjusted data to predict the final Economic Health Index, which is an aggregated index based on relative weights of all features from our best-performing feature selection.

Additionally, we will train a Yield-Curve VIX probit model on the adjusted dataset. Anne Lundgaard Hansen (2021) proposed the Yield-Curve VIX probit model which outperforms the yield curve (traditionally known as the best predictor for recession) in predicting U.S. recessions from 1950-2022. We expect indexes such as the yield curve and other predictors that are aligned with the business cycle to have similar associations, whereas indexes such as the VIX (which are driven by sudden changes in market sentiment) to have less associations with economic recovery than recession. We will augment the probit model with our indexes. Finally, we will train the model on the weight-adjusted dataset and predict the aggregated Economic Health Index for our final result.

2. Literature Review

Kihwan Kim et al. (2022) explore machine learning, shrinkage, and variable selection methods for predicting the Great Recession of 2008. They propose a simple “hybrid” model that switches between benchmark linear models and more complex index-driven models depending on GDP growth condition and found that the proposed model performs better for all forecast horizons than the nonhybrid models. For our paper to predict the next business cycle, we will apply a similar “hybrid” model that switches between linear regressors and a more complex diffusion index model depending on the level of GDP growth.

Ercolani and Natoli (2020) find that macroeconomic uncertainty (macroeconomic and financial uncertainty indexes) is the second best predictor after yield curve slope for predicting recession. They estimate the probability of recession with both yield-curve slope models and the augmented slope model with macroeconomic and financial uncertainty indexes. They find that incorporating uncertainty indexes significantly improves the performance of the standard yield-curve slope model and conclude that uncertainty indexes are also strong predictors for recessions. For our paper, we want to look at if uncertainty indexes as predictors for economic recovery - hence the business cycle - and if reversal in trends for economic uncertainty signal economic recovery. Since macroeconomic uncertainty is correlated with market sentiment, we will also analyze macroeconomic uncertainty in conjunction with sentiment analysis.

Anne Lundgaard Hansen (2021) predicts U.S. recession using an indicator of the economy’s location on the VIX-yield curve cycle. The paper finds that the VIX index (volatility index) and the spread between long- and short-term Treasury bond yields co-move in counterclockwise cycles that align with the business cycle. The proposed indicator outperforms the yield curve (traditionally known as the best predictor for recession) in predicting U.S. recessions from 1950-2022. For our paper, we will apply the proposed indicator for predicting the business cycle and augment the model with diffusion indexes to observe any improvement in performance.

3. Dataset Description

The primary dataset used for this research paper is from Kaggle and is titled "Financial Indicators of US Recession." This dataset offers an extensive collection of historical US financial data, which we use to build our Economic Health Index (EHI). The dataset comprises 26 distinct CSV files, with each focusing on a specific economic indicator or market trend. Here is a detailed overview of the datasets:

1. 10-Year Real Interest Rate: Reflects the interest rate after adjusting for inflation, providing insights into long-term borrowing costs.
2. Bank Credit All Commercial Banks: Indicates the total credit extended by commercial banks, a measure of lending activity.
3. Commercial Real Estate Prices for US: Tracks the price trends of commercial properties.
4. Consumer Loans - Credit Cards & Other Revolving Plans All Commercial Banks: Offers a view into consumer borrowing habits.
5. CPI for All Urban Consumers: Measures the average change in prices paid by urban consumers for goods and services.
6. CPI for All Items: A broader measure of consumer price changes.
7. Continued Claims: Represents the number of individuals claiming unemployment benefits.
8. Delinquency Rate on Credit Card Loans: Highlights the percentage of loans with overdue payments.
9. Federal Funds Rate: The interest rate at which banks lend to each other overnight.
10. GDP: The total value of goods and services produced, a primary indicator of economic health.
11. Households Owners Equity in Real Estate: Represents the value of real estate owned by households minus their mortgage debt.
12. Inflation Consumer Prices: Tracks the rate at which the general level of prices for goods and services rises.
13. M1: A measure of the money supply that includes physical currency and demand deposits.
14. M2: A broader measure of the money supply, encompassing M1 plus short-term time deposits.
15. Median CPI: A measure of core inflation that captures the median change in consumer prices.
16. NASDAQ: An index tracking the performance of more than 3,000 tech and non-tech companies.
17. Personal Savings Rate: Indicates the percentage of disposable income that households are saving.
18. Real Estate Loans Commercial Real Estate: Highlights the lending activity in the commercial real estate sector.
19. Real Estate Loans Residential Real Estate: Provides insights into lending trends in the residential real estate market.

20. Real GDP: GDP adjusted for inflation, offering a clearer picture of economic growth.
21. SPX500: An index reflecting the stock performance of 500 large companies listed on US stock exchanges.
22. Sticky CPI less Food and Energy: A measure of core inflation that excludes volatile food and energy prices.
23. Sticky CPI: Captures the rate of price change for items that are less frequently adjusted.
24. Total Unemployed + All Persons Marginally Attached: A comprehensive measure of unemployment that includes those marginally attached to the labor force.
25. Unemployment Level: The total number of individuals actively seeking employment.
26. Unemployment Rate: The percentage of the labor force that is unemployed and actively seeking employment.

By integrating and aggregating these datasets into a single large dataset, organized by date, we can construct a multifaceted view of the US economy's current state and build our Economic Health Indicator. The historical trends embedded within this data allows us to extrapolate and predict the trajectory of the economy's future health, therefore allowing us to predict the end of the current recession.

4. Methodology

The goal of our project is to build our own Economic Health Index, and use its historical values to predict its current and future values to identify trends that will provide insight into when the current economy will begin to recover.

I: Data Preprocessing

With 26 unique economic and market features, we first conducted a preliminary step of data preprocessing to reduce the size of our data. Since historical data is vital to our research, we eliminated all features that have a start date after 1/1/1991. The reason for the strict date cutoff is to ensure that our models have ample training data that encompasses the 1990's recession, early 2000's recession, the Great Recession, and the COVID-19 recession. By ensuring these recessions are accounted for in our data, we can look for similar trends in the current economy to predict when the recession will end. Additionally, we removed the Unemployment Level dataset, because the Unemployment Rate dataset contains the same data and is also standardized.

With the remaining 20 unique economic and market features, we decided to impose a second cutoff date of 1/1/1983. This is because four of the remaining 20 features have a start date in the 1990s, and we want to test if these four features provide additional, important information regarding the economy's health. Thus, we have two current datasets: a dataset from 1/1/1983 - 4/1/2023 with 16 features and a dataset from 1/1/1991 - 4/1/2023 with 20 features.

Next, we iterated through each feature and replaced all missing values. Since the data of these features are reported differently (e.g. data is daily, weekly, monthly, or quarterly), we created a Python program to make every feature have a daily value, and we filled in all missing values with the feature's most recent value. For example, if a feature is reported monthly (e.g. 1/1, 2/1, 3/1 etc.), every day of the month will assume the value reported on the first day of the month.

Now, our two datasets are complete, with every feature having a daily value from the start to end dates. However, shortly into a few preliminary feature selection and regression models, we realized that the daily data is too memory intensive. With over 14000 rows of data, the models we ran either took too long, or crashed in the process. Therefore, we decided to reduce our datasets by converting them from daily data to weekly data.

Thus, our finalized two datasets are:

- 16 features from 1/1/1983 - 4/1/2023, reported weekly
- 20 features from 1/1/1991 - 4/1/2023, reported weekly

However, since the performance of both datasets are similar, we will only be evaluating the results learned from the 1/1/1983 - 4/1/2023 dataset. The results of the dataset from 1/1/1991 - 4/1/2023 will be included in the Excluded Models section below.

II. Feature Selection

Although our dataset consists of multiple features, not all features have the same predictive capabilities. To select the most predictive features, we implemented a variety of feature selection algorithms. Specifically, we used the following: Weight by Information Gain, Weight by Relief, Weight by Correlation, and a custom ensemble program.

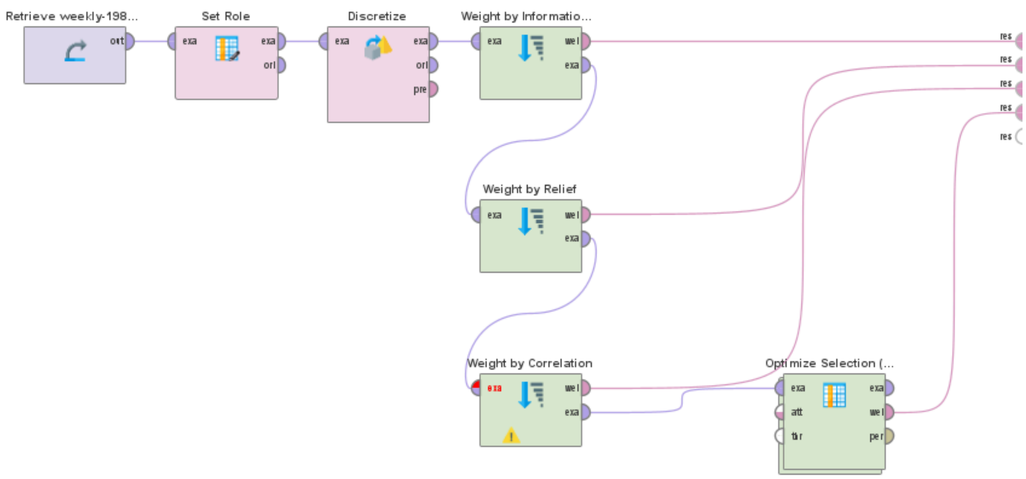

Figure 1. Feature Selection Algorithm Design

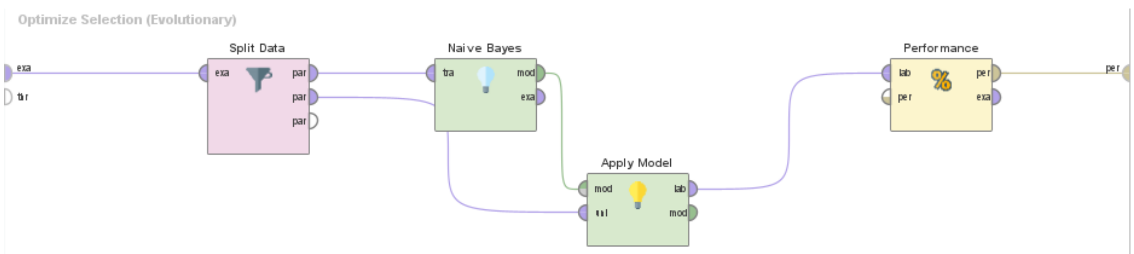

Figure 2. Optimize Selection (Evolutionary) Algorithm Design

attribute	wei... ↓
Bank Credit All Commercial Banks	1
CPI All Urban Consumers	1.000
Real GDP	0.994
M2	0.970
S&P 500 Price	0.940
Households Owners Equity in Real Estate Level	0.927
NASDAQ Price	0.875
10-Year Real Interest Rate	0.873
Federal Funds Rate	0.772
M1	0.677
Sticky Price Consumer Price Index less Food and Energy	0.441
Sticky Price Consumer Price Index	0.248
Unemployment Rate	0.220
Continued Claims (Insured Unemployment)	0.074
Median CPI	0.065
Personal Savings Rate	0.042
CPI All Items	0

Figure 3. Weight by Correlation

attribute	wei... ↓
Real GDP	1
Bank Credit All Commercial Banks	0.906
CPI All Urban Consumers	0.887
Federal Funds Rate	0.827
M2	0.797
Households Owners Equity in Real Estate Level	0.683
10-Year Real Interest Rate	0.670
S&P 500 Price	0.651
Sticky Price Consumer Price Index less Food and Energy	0.580
NASDAQ Price	0.535
Unemployment Rate	0.390
M1	0.374
Median CPI	0.188
Sticky Price Consumer Price Index	0.172
Personal Savings Rate	0.099
CPI All Items	0.030
Continued Claims (Insured Unemployment)	0

Figure 4. Weight by Relief

attribute	wei... ↓
Households Owners Equity in Real Estate Level	1
Bank Credit All Commercial Banks	1.000
CPI All Urban Consumers	1.000
Real GDP	1.000
M2	0.991
M1	0.966
Federal Funds Rate	0.953
10-Year Real Interest Rate	0.927
Sticky Price Consumer Price Index less Food and Energy	0.918
S&P 500 Price	0.890
Unemployment Rate	0.887
NASDAQ Price	0.872
Continued Claims (Insured Unemployment)	0.775
Personal Savings Rate	0.770
Sticky Price Consumer Price Index	0.268
Median CPI	0.083
CPI All Items	0

Figure 5. Weight by Information Gain

attribute	wei... ↓
CPI All Items	1
Continued Claims (Insured Unemployment)	1
Federal Funds Rate	1
Households Owners Equity in Real Estate Level	1
Personal Savings Rate	1
Sticky Price Consumer Price Index less Food and Energy	1
Sticky Price Consumer Price Index	1
Unemployment Rate	1
NASDAQ Price	1
S&P 500 Price	1
10-Year Real Interest Rate	0
Bank Credit All Commercial Banks	0
CPI All Urban Consumers	0
M1	0
M2	0
Median CPI	0
Real GDP	0

Figure 6. Ensemble Feature Selection Results

It is important to note that the Weight by Information Gain, Weight by Relief, and Weight by Correlation results are similar since all features have an assigned weight *W* such that 0 <= *W* <= 1. On the other hand, the Ensemble Feature Selection result only assigned the most important features with a value of 1. Therefore, we decided to combine the results of the Weight by Information Gain, Weight by Relief, and Weight by Correlation algorithms to create a new weight such that the new weight is the mean of the three algorithms' results.

The final step in our feature selection process is to transform these individual weights into relative weights. To do this, we did the following: *For every attribute a, let W(a) be the assigned weight of the feature. Let Sum(a) be the sum of all the attributes' weights. For every attribute a, let R(a) be the relative weight of a, and let R(a) = W(a) / Sum(a).*

Thus, now we have two different feature selection results, with relative feature weights, that we will test in our models.

5. Modeling

Now that we have each feature's relative weight, we can create our weekly Economic Health Index using this equation: *Weekly EHI = SUM(V(a) * R(a)) for 'a' in Attribute list, such that V(a) is the attribute's* *weekly value, and R(a) is the attribute's relative weight.* Consequently, we now have an additional column of data in our original dataset called "Economic Health Index" for the dates ranging from 1/1/1983 - 4/1/2023. However, to predict when the recession will end, we need to predict the future values of the Economic Health Index.

We decided to predict the Economic Health Index up until 2030, because 7 years is sufficient time to view an economic recovery while also being recent enough to ensure the accuracy of each feature's predicted values. We accomplished this by using two models: ARIMA model and Holt-Winters model. We decided on these two models, because our dataset contains time-series data, so the chronological order of each feature's values are crucial. Our training data was from 1/1/1983 to 1/1/2015, and our test data was from 1/1/2015 to 4/1/2023. Through trial and error, we realized that this split was ideal for minimizing the MSE scores of each feature.

After evaluating the performance of both models using this train test split, we opted for the ARIMA model. Although the Holt-Winters model can inherently account for seasonality, which is important because the economy is cyclical, it smooths out too much noise, which is not realistic in the real economy where volatility is constant. Below are a few examples of the ARIMA predictions vs the actual data for some of the dataset's features.

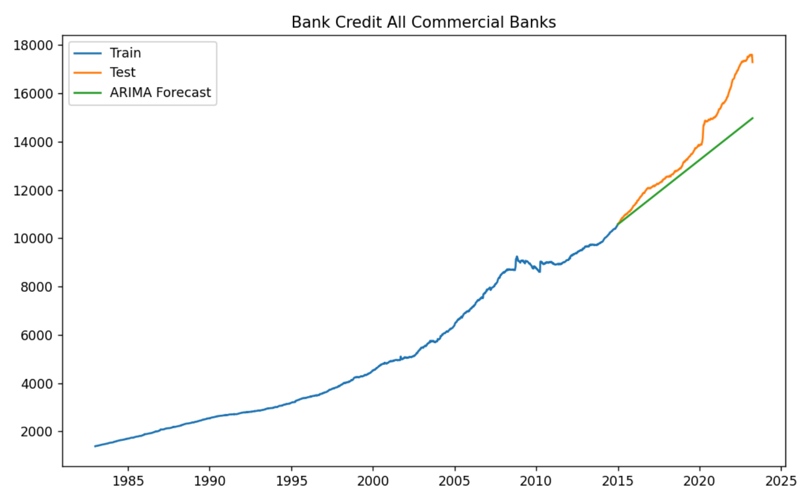

Figure 7. ARIMA Prediction of Bank Credit All Commercial Banks

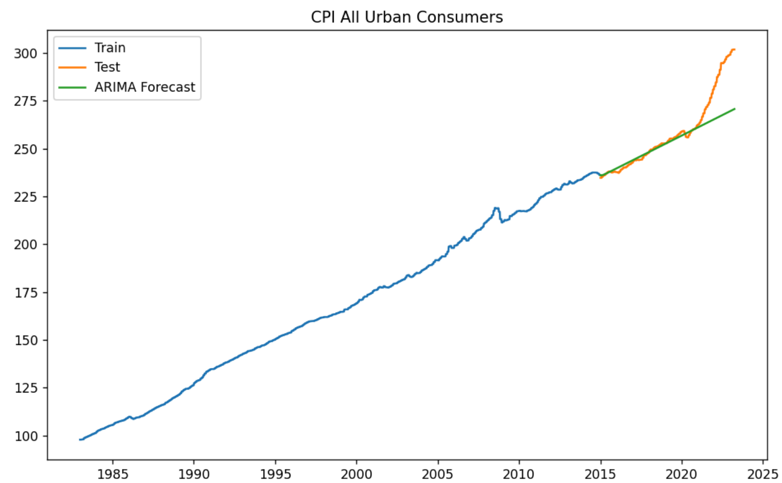

Figure 8. ARIMA Prediction of CPI All Urban Consumers

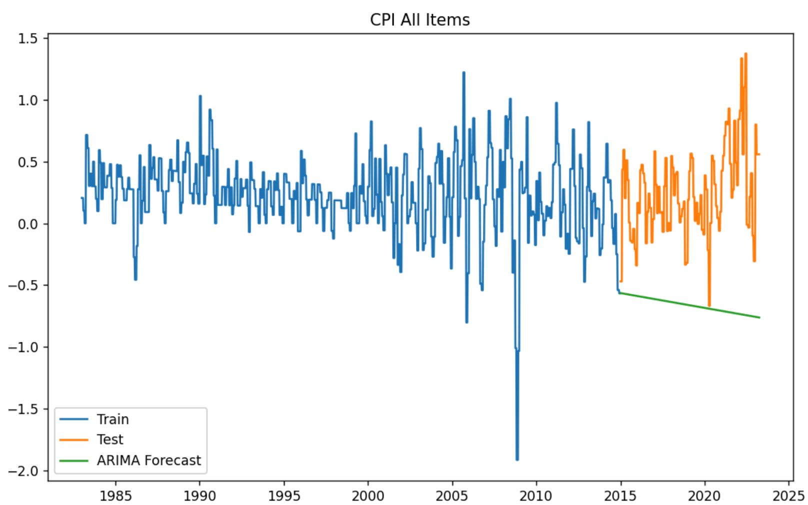

Figure 9. ARIMA Prediction of CPI All Items

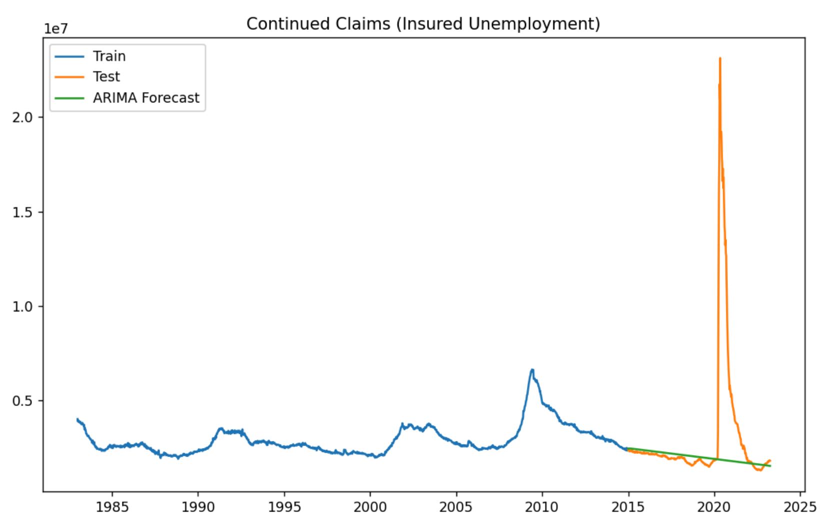

Figure 10. ARIMA Prediction of Continued Claims (Insured Unemployment)

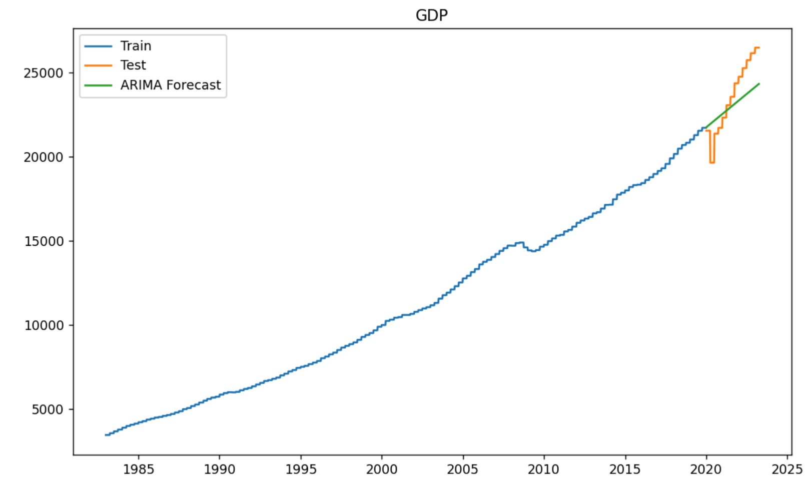

Figure 11. ARIMA Prediction of GDP

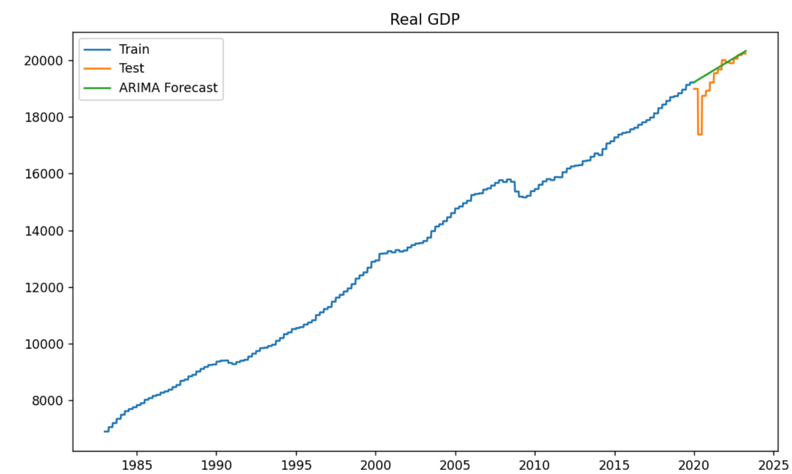

Figure 12. ARIMA Prediction of Real GDP

It is important to note that while the ARIMA model was able to accurately predict the test data for some features, it was inaccurate when predicting features that have lots of volatility (e.g. CPI All Items). With all of the features' predicted values until 2030 now, we simply apply the *Weekly EHI* equation from above to get our predicted EHI values from 2023 to 2030.

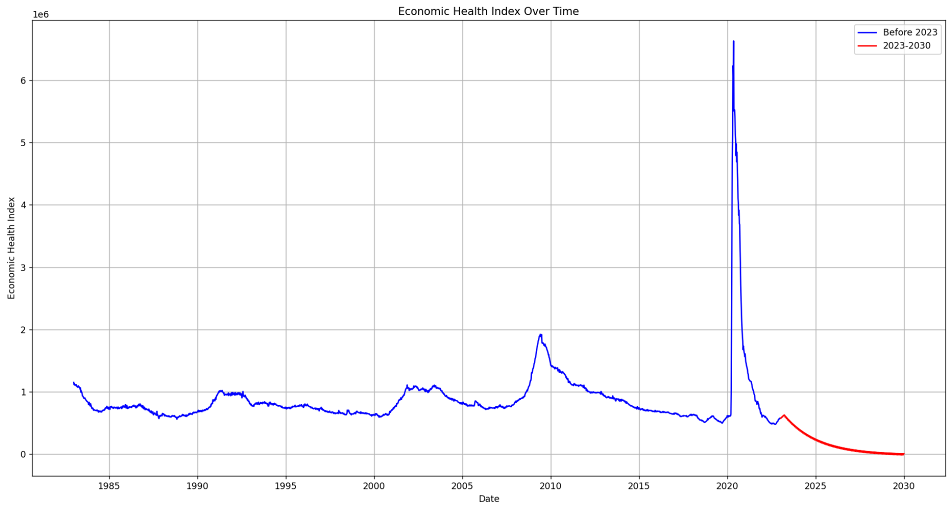

Figure 13. ARIMA Prediction of Economic Health Index

6. Conclusion

<u>I. Interpreting the Graph</u>

Upon examining our model's outcomes, we can pinpoint historical recessions by observing distinct spikes. For instance, a subtle surge in the early 1990s signifies the recession of that decade. Similarly, a minor peak in the early 2000s denotes the 2000s recession. A pronounced spike between 2007 and 2009 corresponds to the Great Recession. Lastly, a significant surge in 2020 is indicative of the COVID-19 recession. The recession that there is a spike instead of a dip is because the Economic Health Indicator

<u>II. Interpreting the ARIMA Results</u>

Looking specifically at the index values from 2023 onwards (red line), there is a small uptick right after 2023, suggesting that the economy will be on a decline. However, since the magnitude of the uptick is small, and the index starts decreasing shortly after, the model suggests that economic recovery is imminent and perhaps achievable within 6 to 12 months.

7. Excluded Models

Talk about multivariate regression and past the output in the appendix (multivariate regression did not work out: had a very high MSE score, and an extremely negative R^2 value). Do not include.

<u>1. Dataset 1/1/1991 - 4/1/2023 Feature Selection</u>

attribute	wei...
CPI All Urban Consumers	1
Bank Credit All Commercial Banks	0.998
Real GDP	0.990
M2	0.973
S&P 500 Price	0.917
Households Owners Equity in Real Estate Level	0.905
NASDAQ Price	0.865
10-Year Real Interest Rate	0.825
Delinquency Rate on Credit Card Loans	0.723
M1	0.693
Federal Funds Rate	0.620
Commercial Real Estate Loans	0.561
Median CPI	0.195
Personal Savings Rate	0.120
Unemployment Rate	0.097
Sticky Price Consumer Price Index less Food and Energy	0.076
Sticky Price Consumer Price Index	0.037
CPI All Items	0.017
Continued Claims (Insured Unemployment)	0

Figure 1. Weight by Correlation

attribute	wei...
Commercial Real Estate Loans	1
Real GDP	0.845
Federal Funds Rate	0.805
Bank Credit All Commercial Banks	0.803
M2	0.745
CPI All Urban Consumers	0.739
10-Year Real Interest Rate	0.694
Delinquency Rate on Credit Card Loans	0.659
Households Owners Equity in Real Estate Level	0.624
S&P 500 Price	0.537
NASDAQ Price	0.479
M1	0.382
Unemployment Rate	0.319
Sticky Price Consumer Price Index less Food and Energy	0.315
Median CPI	0.104
Sticky Price Consumer Price Index	0.061
Personal Savings Rate	0.055
CPI All Items	0.016
Continued Claims (Insured Unemployment)	0

Figure 2. Weight by Relief

attribute	wei...
Households Owners Equity in Real Estate Level	1
Delinquency Rate on Credit Card Loans	1
CPI All Urban Consumers	1.000
Real GDP	1.000
Bank Credit All Commercial Banks	0.999
M2	0.993
Commercial Real Estate Loans	0.989
M1	0.959
Federal Funds Rate	0.931
Unemployment Rate	0.886
NASDAQ Price	0.876
S&P 500 Price	0.869
10-Year Real Interest Rate	0.854
Sticky Price Consumer Price Index less Food and Energy	0.851
Continued Claims (Insured Unemployment)	0.829
Personal Savings Rate	0.737
CPI All Items	0.075
Median CPI	0.066
Sticky Price Consumer Price Index	0

Figure 3. Weight by Information Gain

attribute	wei...
10-Year Real Interest Rate	1
Bank Credit All Commercial Banks	1
CPI All Items	1
Federal Funds Rate	1
Households Owners Equity in Real Estate Level	1
M1	1
M2	1
Real GDP	1
Sticky Price Consumer Price Index less Food and Energy	1
Unemployment Rate	1
NASDAQ Price	1
S&P 500 Price	1
Delinquency Rate on Credit Card Loans	1
CPI All Urban Consumers	0
Continued Claims (Insured Unemployment)	0
Median CPI	0
Personal Savings Rate	0
Sticky Price Consumer Price Index	0
Commercial Real Estate Loans	0

Figure 4. Ensemble Feature Selection Results

2. Random Forest Feature Selection

attribute	weight
Unemployment Rate	0.038
M1	0.017
M2	0.045
Sticky Price Consumer Price Index	0.012
Personal Savings Rate	0.036
Real GDP	0.098
Federal Funds Rate	0.036
CPI All Items	0.042
NASDAQ Price	0.025
Households Owners Equity in Real Estate Level	0.130
Median CPI	0.020
Sticky Price Consumer Price Index less Food and Energy	0.053
CPI All Urban Consumers	0.154
Continued Claims (Insured Unemployment)	0.052
Bank Credit All Commercial Banks	0.158
10-Year Real Interest Rate	0.064
S&P 500 Price	0.021

Figure 5. Weight by Random Forest

The normalized values of the random forest weights are: [0.12360289, 0.05529603, 0.14637185, 0.03903249, 0.11709748, 0.31876535, 0.11709748, 0.13661372, 0.08131769, 0.422852, 0.06505415, 0.17239351, 0.50091698, 0.1691408, 0.51392781, 0.20817329, 0.06830686]. Ultimately, we decided against using the random forest weights, because both the actual weights and the normalized weights differ too much from all the other feature selection algorithms employed.

Note: We also tried to implement Sequential Forward Selection and Sequential Backward Selection, but RapidMiner would only select 1 feature every time instead of assigning weights.

3. Multivariate Regression

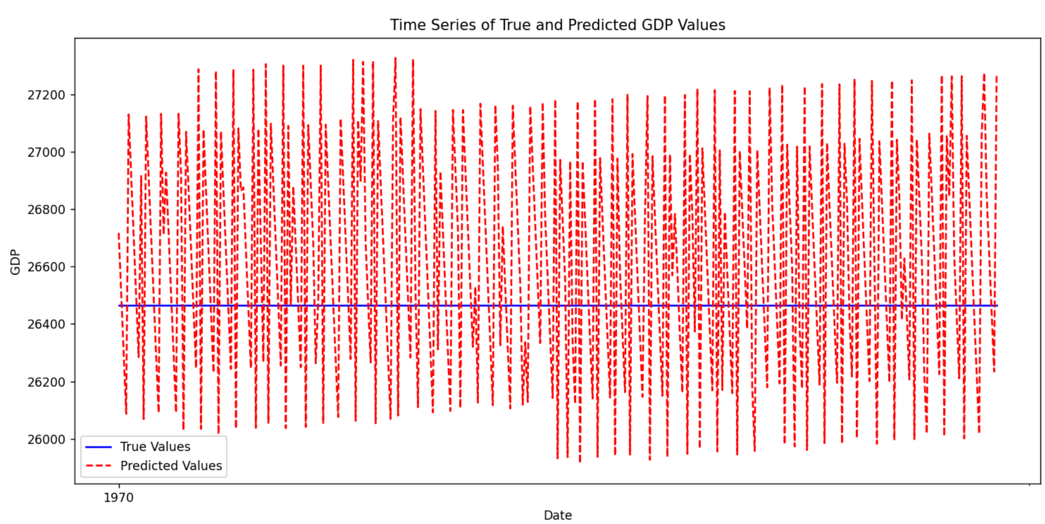

Figure 6. Time Series of True and Predicted GDP Values using Multivariate Regression Analysis

We couldn't really understand this model, and the model was very inaccurate, as it had Mean Squared Error: 191932.28096097067 and R^2 Value: -14501993129452922457649315840.00

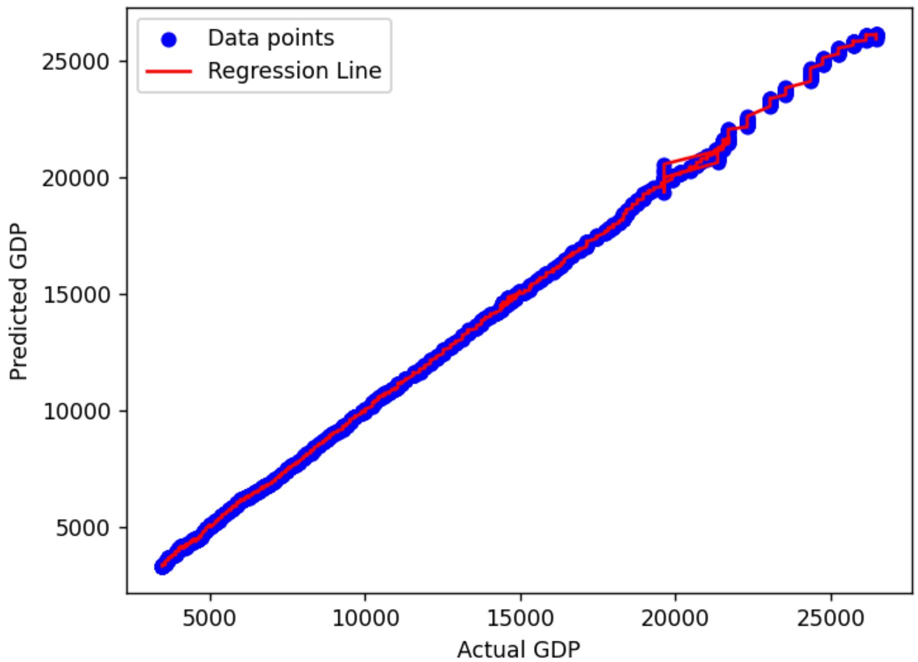

Figure 7. Multivariate Regression Analysis

We also ran a regular multivariate regression model. However, with an R^2 value of 0.999, we decided against this model, because the data is clearly overfitted. Additionally, in hindsight, our dataset has time series data, so a regression model is not optimal.

References

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