

Data Collection and Preprocessing

```
In [13]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Fetch data with an extended date range
from fredapi import Fred
fred = Fred(api_key='6b6f56be8ed7dafee7f6f255d71b8f8c')

# Fetch data from FRED API
unemployment_rate = fred.get_series('UNRATE', observation_start='2000-01-01')
initial_jobless_claims = fred.get_series('ICSA', observation_start='2000-01-01')
consumer_sentiment_index = fred.get_series('UMCSENT', observation_start='2000-01-01')
housing_starts = fred.get_series('HOUST', observation_start='2000-01-01')
sp500_index = fred.get_series('SP500', observation_start='2000-01-01')
ten_year_treasury_yield = fred.get_series('GS10', observation_start='2000-01-01')

# Combine all data into a single DataFrame
combined_data = pd.DataFrame({
    'Unemployment Rate': unemployment_rate,
    'Initial Jobless Claims': initial_jobless_claims,
    'Consumer Sentiment Index': consumer_sentiment_index,
    'Housing Starts': housing_starts,
    'S&P 500 Index': sp500_index,
    '10-Year Treasury Yield': ten_year_treasury_yield
})

# Resample data to monthly, using the last observation for each month
combined_data = combined_data.resample('M').last()

# Load the Daily Treasury Par Yield Curve Rates data
yield_curve_data = pd.read_csv(r'C:\Users\salin\OneDrive\Desktop\DSC680 Applied Data Science\week
yield_curve_data['Date'] = pd.to_datetime(yield_curve_data['Date'])
yield_curve_data.set_index('Date', inplace=True)

# Load the Daily Treasury Long-Term Rates data
long_term_rates_data = pd.read_csv(r'C:\Users\salin\OneDrive\Desktop\DSC680 Applied Data Science\
long_term_rates_data['Date'] = pd.to_datetime(long_term_rates_data['Date'])
long_term_rates_data.set_index('Date', inplace=True)

# Merge yield_curve_data with combined_data
combined_data = pd.merge(combined_data, yield_curve_data, left_index=True, right_index=True, how=

# Merge long_term_rates_data with the already merged data
combined_data = pd.merge(combined_data, long_term_rates_data, left_index=True, right_index=True,

# Advanced imputation for missing values in S&P 500 Index
combined_data['S&P 500 Index'] = combined_data['S&P 500 Index'].interpolate(method='time').fillna

# Verify missing values after advanced interpolation
missing_values = combined_data.isnull().sum()
print(missing_values)

# Handle any potential NaN values (forward fill as an example)
combined_data.fillna(method='ffill', inplace=True)

# Inspect the data
print(combined_data.info())
print(combined_data.describe())

# Check for missing values
```

```
missing_values = combined_data.isnull().sum()  
print(missing_values)
```

Unemployment Rate 1
Initial Jobless Claims 0
Consumer Sentiment Index 1
Housing Starts 1
S&P 500 Index 0
10-Year Treasury Yield 1
1 Mo 102
2 Mo 248
3 Mo 89
4 Mo 282
6 Mo 89
1 Yr 89
2 Yr 89
3 Yr 89
5 Yr 89
7 Yr 89
10 Yr 89
20 Yr 89
30 Yr 122
LT COMPOSITE (>10 Yrs) 89
TREASURY 20-Yr CMT 89
Extrapolation Factor 260

dtype: int64
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 293 entries, 2000-01-31 to 2024-05-31
Freq: M

Data columns (total 22 columns):

#	Column	Non-Null Count	Dtype
0	Unemployment Rate	293 non-null	float64
1	Initial Jobless Claims	293 non-null	float64
2	Consumer Sentiment Index	293 non-null	float64
3	Housing Starts	293 non-null	float64
4	S&P 500 Index	293 non-null	float64
5	10-Year Treasury Yield	293 non-null	float64
6	1 Mo	275 non-null	float64
7	2 Mo	68 non-null	float64
8	3 Mo	293 non-null	float64
9	4 Mo	20 non-null	float64
10	6 Mo	293 non-null	float64
11	1 Yr	293 non-null	float64
12	2 Yr	293 non-null	float64
13	3 Yr	293 non-null	float64
14	5 Yr	293 non-null	float64
15	7 Yr	293 non-null	float64
16	10 Yr	293 non-null	float64
17	20 Yr	293 non-null	float64
18	30 Yr	293 non-null	float64
19	LT COMPOSITE (>10 Yrs)	293 non-null	float64
20	TREASURY 20-Yr CMT	293 non-null	float64
21	Extrapolation Factor	268 non-null	float64

dtypes: float64(22)
memory usage: 60.8 KB
None

	Unemployment Rate	Initial Jobless Claims	Consumer Sentiment Index	\
count	293.000000	2.930000e+02	293.000000	
mean	5.730717	3.862321e+05	83.205461	
std	1.970626	4.065895e+05	13.216608	
min	3.400000	1.870000e+05	50.000000	
25%	4.200000	2.610000e+05	73.500000	
50%	5.100000	3.320000e+05	84.900000	
75%	6.600000	3.990000e+05	93.500000	
max	14.800000	5.946000e+06	112.000000	

	Housing Starts	S&P 500 Index	10-Year Treasury Yield	1 Mo	\
count	293.000000	293.000000	293.000000	275.000000	
mean	1304.610922	2425.492833	3.263311	1.477273	

std	437.032543	863.068638	1.310693	1.748011
min	478.000000	1920.030000	0.620000	0.000000
25%	1002.000000	1923.570000	2.190000	0.070000
50%	1311.000000	1923.570000	3.200000	0.900000
75%	1625.000000	2673.610000	4.260000	2.175000
max	2273.000000	5304.720000	6.660000	5.560000

	2 Mo	3 Mo	4 Mo	...	2 Yr	3 Yr \
count	68.000000	293.000000	20.000000	...	293.000000	293.000000
mean	2.227353	1.777952	5.248000	...	2.145358	2.320717
std	2.123580	1.954917	0.418941	...	1.767449	1.658739
min	0.010000	0.000000	4.330000	...	0.110000	0.110000
25%	0.097500	0.100000	4.970000	...	0.580000	0.920000
50%	1.775000	1.070000	5.490000	...	1.620000	1.900000
75%	4.347500	2.990000	5.507500	...	3.600000	3.730000
max	5.570000	6.380000	5.610000	...	6.690000	6.660000

	5 Yr	7 Yr	10 Yr	20 Yr	30 Yr \
count	293.000000	293.000000	293.000000	293.000000	293.000000
mean	2.688396	2.993242	3.247065	3.761331	3.902082
std	1.498462	1.401972	1.314798	1.315270	1.254081
min	0.210000	0.390000	0.550000	0.980000	1.200000
25%	1.510000	1.920000	2.170000	2.660000	2.920000
50%	2.520000	2.900000	3.180000	3.910000	3.850000
75%	3.870000	4.090000	4.360000	4.810000	5.190000
max	6.710000	6.750000	6.680000	6.720000	6.490000

	LT COMPOSITE (>10 Yrs)	TREASURY 20-Yr CMT	Extrapolation Factor
count	293.000000	293.000000	268.000000
mean	3.729966	3.761331	-0.036045
std	1.265895	1.315270	0.047555
min	1.040000	0.980000	-0.150000
25%	2.710000	2.660000	-0.050000
50%	3.820000	3.910000	-0.050000
75%	4.730000	4.810000	-0.050000
max	6.670000	6.720000	0.180000

[8 rows x 22 columns]

```

Unemployment Rate      0
Initial Jobless Claims  0
Consumer Sentiment Index 0
Housing Starts          0
S&P 500 Index          0
10-Year Treasury Yield  0
1 Mo                    18
2 Mo                    225
3 Mo                    0
4 Mo                    273
6 Mo                    0
1 Yr                    0
2 Yr                    0
3 Yr                    0
5 Yr                    0
7 Yr                    0
10 Yr                   0
20 Yr                   0
30 Yr                   0
LT COMPOSITE (>10 Yrs)  0
TREASURY 20-Yr CMT      0
Extrapolation Factor    25
dtype: int64

```

Exploratory Data Analysis (EDA)

```
In [14]: # Inspect the data
print(combined_data.info())
print(combined_data.describe())

# Check for missing values
missing_values = combined_data.isnull().sum()
print(missing_values)

# Summary statistics
print(combined_data.describe())

# Time series plots
combined_data.plot(subplots=True, figsize=(12, 18))
plt.tight_layout()
plt.show()

# Histograms
combined_data.hist(bins=50, figsize=(20, 15))
plt.tight_layout()
plt.show()

# Calculate correlations with the Unemployment Rate
correlation_matrix = combined_data.corr()
print("Correlation Matrix with Unemployment Rate:")
print(correlation_matrix['Unemployment Rate'])
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 293 entries, 2000-01-31 to 2024-05-31
Freq: M
Data columns (total 22 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Unemployment Rate                    293 non-null    float64
1   Initial Jobless Claims              293 non-null    float64
2   Consumer Sentiment Index            293 non-null    float64
3   Housing Starts                      293 non-null    float64
4   S&P 500 Index                      293 non-null    float64
5   10-Year Treasury Yield              293 non-null    float64
6   1 Mo                               275 non-null    float64
7   2 Mo                               68 non-null     float64
8   3 Mo                               293 non-null    float64
9   4 Mo                               20 non-null     float64
10  6 Mo                               293 non-null    float64
11  1 Yr                               293 non-null    float64
12  2 Yr                               293 non-null    float64
13  3 Yr                               293 non-null    float64
14  5 Yr                               293 non-null    float64
15  7 Yr                               293 non-null    float64
16  10 Yr                              293 non-null    float64
17  20 Yr                              293 non-null    float64
18  30 Yr                              293 non-null    float64
19  LT COMPOSITE (>10 Yrs)             293 non-null    float64
20  TREASURY 20-Yr CMT                 293 non-null    float64
21  Extrapolation Factor                268 non-null    float64
dtypes: float64(22)
memory usage: 60.8 KB
None
```

	Unemployment Rate	Initial Jobless Claims	Consumer Sentiment Index	\
count	293.000000	2.930000e+02	293.000000	
mean	5.730717	3.862321e+05	83.205461	
std	1.970626	4.065895e+05	13.216608	
min	3.400000	1.870000e+05	50.000000	
25%	4.200000	2.610000e+05	73.500000	
50%	5.100000	3.320000e+05	84.900000	
75%	6.600000	3.990000e+05	93.500000	
max	14.800000	5.946000e+06	112.000000	

	Housing Starts	S&P 500 Index	10-Year Treasury Yield	1 Mo	\
count	293.000000	293.000000	293.000000	275.000000	
mean	1304.610922	2425.492833	3.263311	1.477273	
std	437.032543	863.068638	1.310693	1.748011	
min	478.000000	1920.030000	0.620000	0.000000	
25%	1002.000000	1923.570000	2.190000	0.070000	
50%	1311.000000	1923.570000	3.200000	0.900000	
75%	1625.000000	2673.610000	4.260000	2.175000	
max	2273.000000	5304.720000	6.660000	5.560000	

	2 Mo	3 Mo	4 Mo	...	2 Yr	3 Yr	\
count	68.000000	293.000000	20.000000	...	293.000000	293.000000	
mean	2.227353	1.777952	5.248000	...	2.145358	2.320717	
std	2.123580	1.954917	0.418941	...	1.767449	1.658739	
min	0.010000	0.000000	4.330000	...	0.110000	0.110000	
25%	0.097500	0.100000	4.970000	...	0.580000	0.920000	
50%	1.775000	1.070000	5.490000	...	1.620000	1.900000	
75%	4.347500	2.990000	5.507500	...	3.600000	3.730000	
max	5.570000	6.380000	5.610000	...	6.690000	6.660000	

	5 Yr	7 Yr	10 Yr	20 Yr	30 Yr	\
count	293.000000	293.000000	293.000000	293.000000	293.000000	
mean	2.688396	2.993242	3.247065	3.761331	3.902082	
std	1.498462	1.401972	1.314798	1.315270	1.254081	
min	0.210000	0.390000	0.550000	0.980000	1.200000	
25%	1.510000	1.920000	2.170000	2.660000	2.920000	

50%	2.520000	2.900000	3.180000	3.910000	3.850000
75%	3.870000	4.090000	4.360000	4.810000	5.190000
max	6.710000	6.750000	6.680000	6.720000	6.490000

	LT COMPOSITE (>10 Yrs)	TREASURY 20-Yr CMT	Extrapolation Factor
count	293.000000	293.000000	268.000000
mean	3.729966	3.761331	-0.036045
std	1.265895	1.315270	0.047555
min	1.040000	0.980000	-0.150000
25%	2.710000	2.660000	-0.050000
50%	3.820000	3.910000	-0.050000
75%	4.730000	4.810000	-0.050000
max	6.670000	6.720000	0.180000

[8 rows x 22 columns]

Unemployment Rate	0
Initial Jobless Claims	0
Consumer Sentiment Index	0
Housing Starts	0
S&P 500 Index	0
10-Year Treasury Yield	0
1 Mo	18
2 Mo	225
3 Mo	0
4 Mo	273
6 Mo	0
1 Yr	0
2 Yr	0
3 Yr	0
5 Yr	0
7 Yr	0
10 Yr	0
20 Yr	0
30 Yr	0
LT COMPOSITE (>10 Yrs)	0
TREASURY 20-Yr CMT	0
Extrapolation Factor	25
dtype: int64	

	Unemployment Rate	Initial Jobless Claims	Consumer Sentiment Index \
count	293.000000	2.930000e+02	293.000000
mean	5.730717	3.862321e+05	83.205461
std	1.970626	4.065895e+05	13.216608
min	3.400000	1.870000e+05	50.000000
25%	4.200000	2.610000e+05	73.500000
50%	5.100000	3.320000e+05	84.900000
75%	6.600000	3.990000e+05	93.500000
max	14.800000	5.946000e+06	112.000000

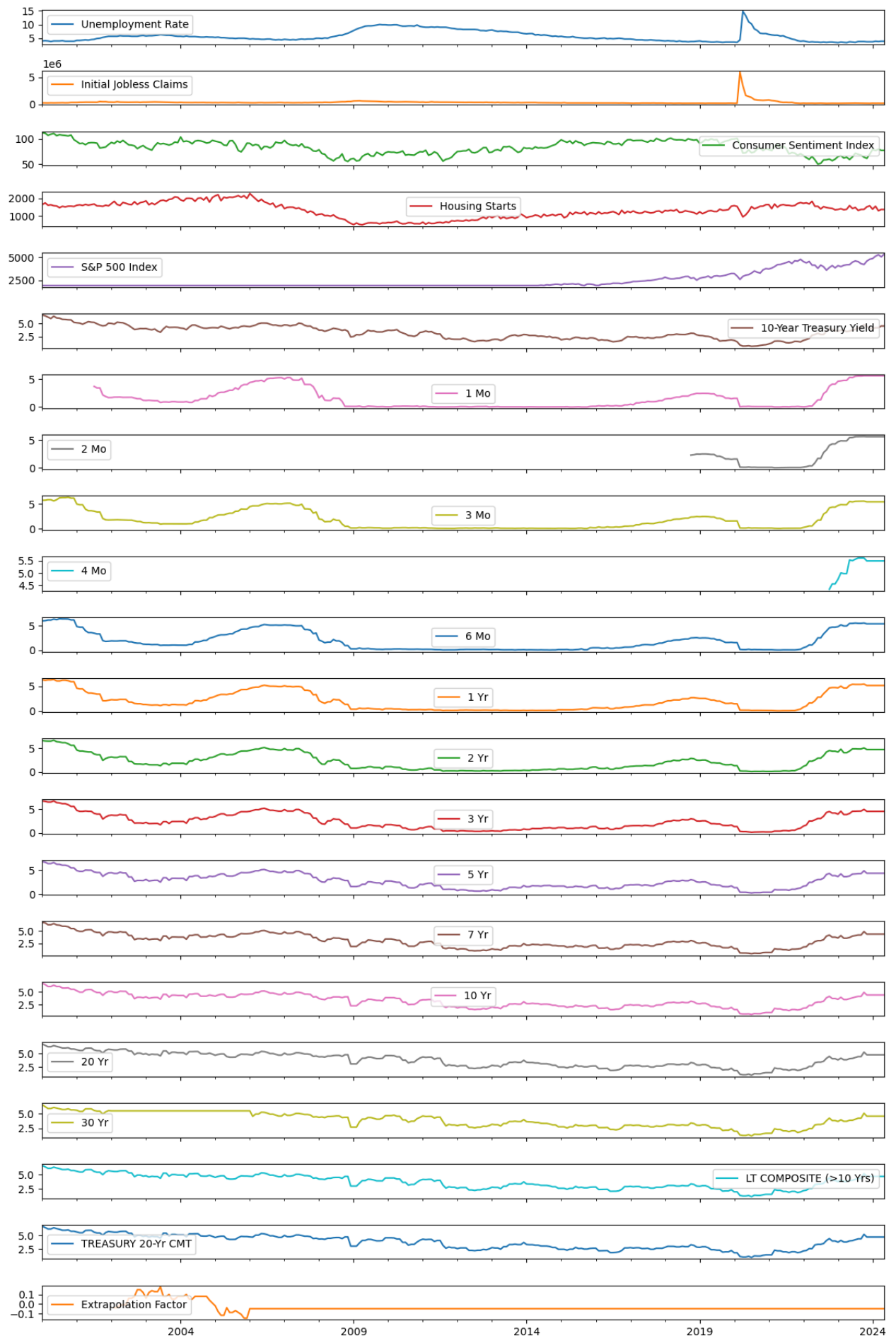
	Housing Starts	S&P 500 Index	10-Year Treasury Yield	1 Mo \
count	293.000000	293.000000	293.000000	275.000000
mean	1304.610922	2425.492833	3.263311	1.477273
std	437.032543	863.068638	1.310693	1.748011
min	478.000000	1920.030000	0.620000	0.000000
25%	1002.000000	1923.570000	2.190000	0.070000
50%	1311.000000	1923.570000	3.200000	0.900000
75%	1625.000000	2673.610000	4.260000	2.175000
max	2273.000000	5304.720000	6.660000	5.560000

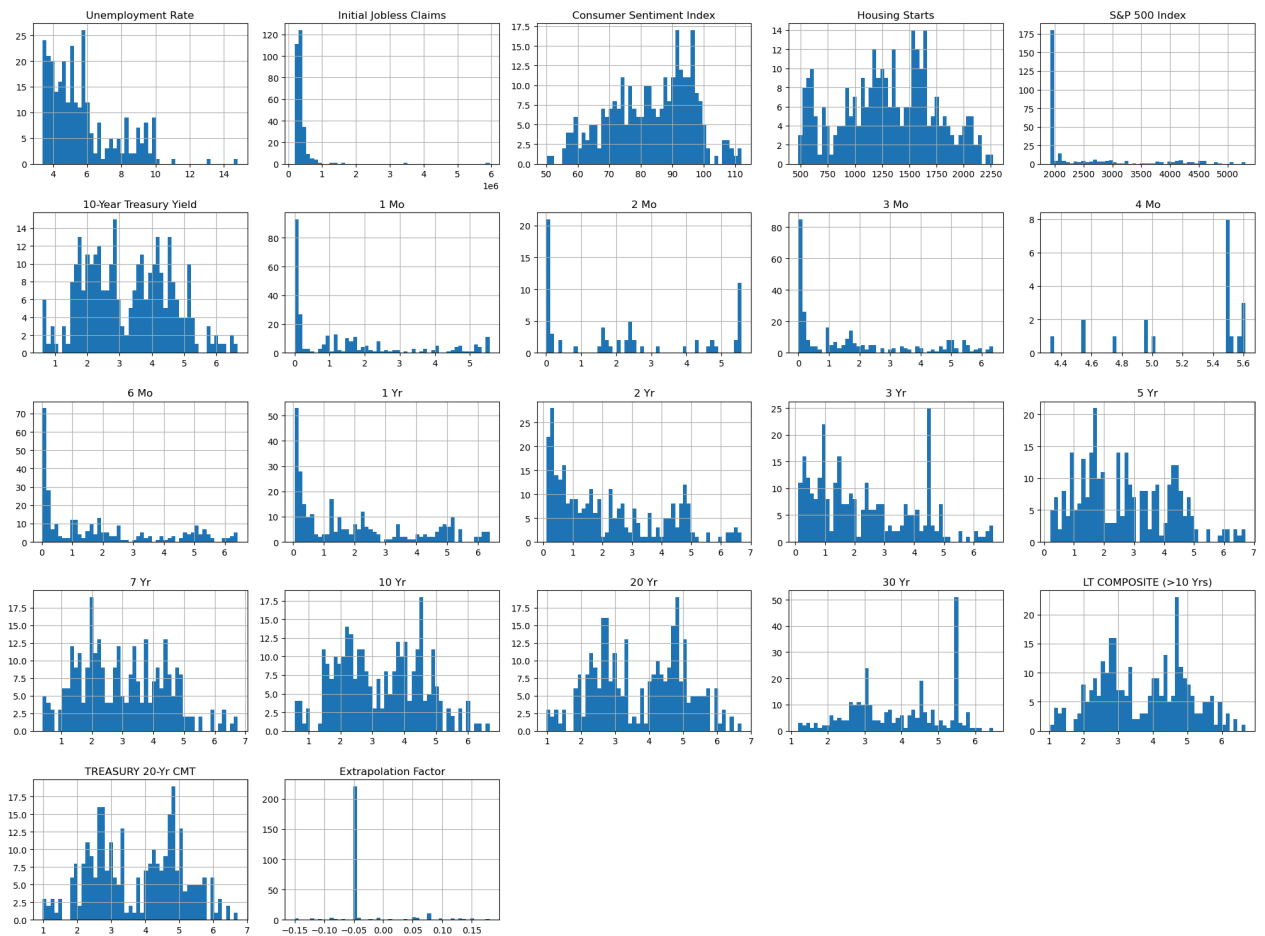
	2 Mo	3 Mo	4 Mo	...	2 Yr	3 Yr \
count	68.000000	293.000000	20.000000	...	293.000000	293.000000
mean	2.227353	1.777952	5.248000	...	2.145358	2.320717
std	2.123580	1.954917	0.418941	...	1.767449	1.658739
min	0.010000	0.000000	4.330000	...	0.110000	0.110000
25%	0.097500	0.100000	4.970000	...	0.580000	0.920000
50%	1.775000	1.070000	5.490000	...	1.620000	1.900000
75%	4.347500	2.990000	5.507500	...	3.600000	3.730000
max	5.570000	6.380000	5.610000	...	6.690000	6.660000

	5 Yr	7 Yr	10 Yr	20 Yr	30 Yr \
count	293.000000	293.000000	293.000000	293.000000	293.000000
mean	2.688396	2.993242	3.247065	3.761331	3.902082
std	1.498462	1.401972	1.314798	1.315270	1.254081
min	0.210000	0.390000	0.550000	0.980000	1.200000
25%	1.510000	1.920000	2.170000	2.660000	2.920000
50%	2.520000	2.900000	3.180000	3.910000	3.850000
75%	3.870000	4.090000	4.360000	4.810000	5.190000
max	6.710000	6.750000	6.680000	6.720000	6.490000

	LT COMPOSITE (>10 Yrs)	TREASURY 20-Yr CMT	Extrapolation Factor
count	293.000000	293.000000	268.000000
mean	3.729966	3.761331	-0.036045
std	1.265895	1.315270	0.047555
min	1.040000	0.980000	-0.150000
25%	2.710000	2.660000	-0.050000
50%	3.820000	3.910000	-0.050000
75%	4.730000	4.810000	-0.050000
max	6.670000	6.720000	0.180000

[8 rows x 22 columns]





Correlation Matrix with Unemployment Rate:

Unemployment Rate	1.000000
Initial Jobless Claims	0.350648
Consumer Sentiment Index	-0.407165
Housing Starts	-0.597250
S&P 500 Index	-0.356714
10-Year Treasury Yield	-0.299425
1 Mo	-0.564185
2 Mo	-0.486816
3 Mo	-0.596492
4 Mo	0.637163
6 Mo	-0.607067
1 Yr	-0.614367
2 Yr	-0.599557
3 Yr	-0.574485
5 Yr	-0.490350
7 Yr	-0.405321
10 Yr	-0.304152
20 Yr	-0.178577
30 Yr	-0.129028
LT COMPOSITE (>10 Yrs)	-0.207523
TREASURY 20-Yr CMT	-0.178577
Extrapolation Factor	0.009905

Name: Unemployment Rate, dtype: float64

```
In [15]: import matplotlib.pyplot as plt

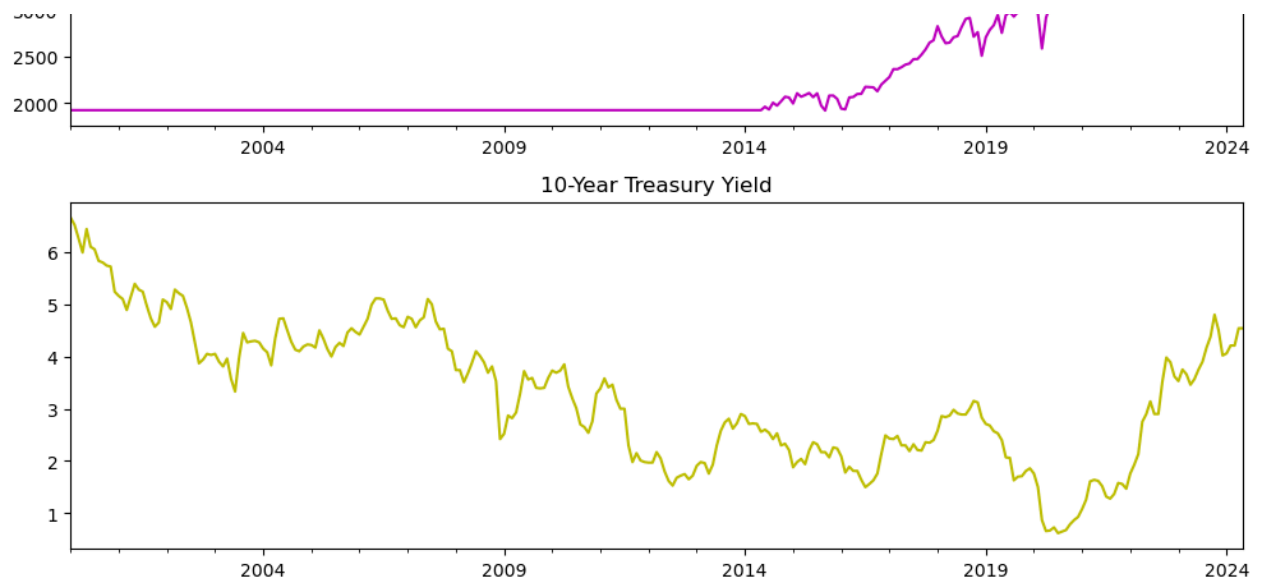
# Set figure size for Microsoft document
fig, axs = plt.subplots(6, 1, figsize=(10, 20))

# Plot each economic indicator
combined_data['Unemployment Rate'].plot(ax=axs[0], title='Unemployment Rate', color='b')
combined_data['Initial Jobless Claims'].plot(ax=axs[1], title='Initial Jobless Claims', color='g')
combined_data['Consumer Sentiment Index'].plot(ax=axs[2], title='Consumer Sentiment Index', color='r')
```

```
combined_data['Housing Starts'].plot(ax=axes[3], title='Housing Starts', color='c')
combined_data['S&P 500 Index'].plot(ax=axes[4], title='S&P 500 Index', color='m')
combined_data['10-Year Treasury Yield'].plot(ax=axes[5], title='10-Year Treasury Yield', color='y')

# Adjust Layout
plt.tight_layout()
plt.savefig('time_series_plots.png')
plt.show()
```

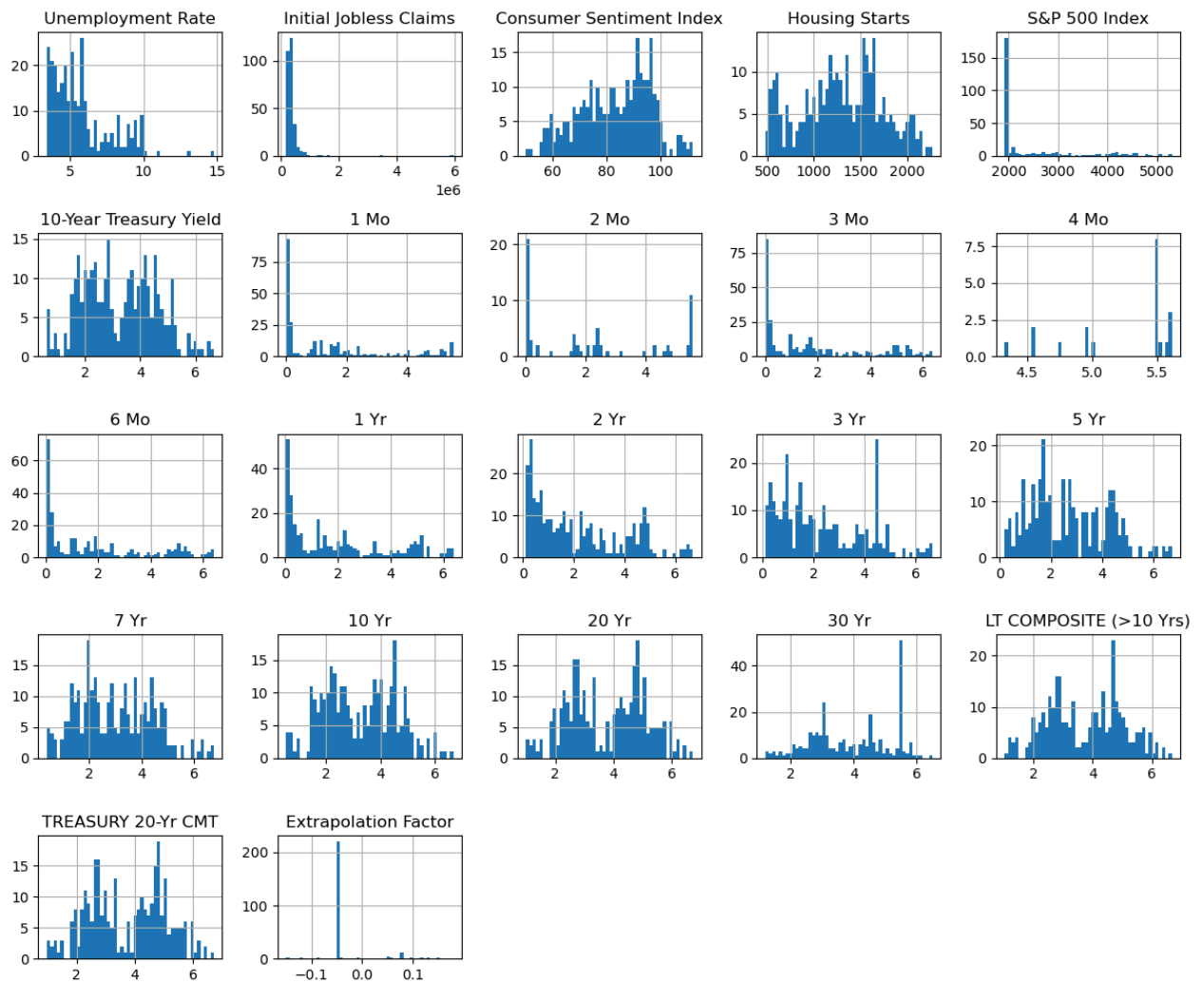




```
In [16]: import matplotlib.pyplot as plt

# Set figure size for Microsoft document
combined_data.hist(bins=50, figsize=(12, 10))

# Adjust Layout
plt.tight_layout()
plt.savefig('histograms.png')
plt.show()
```



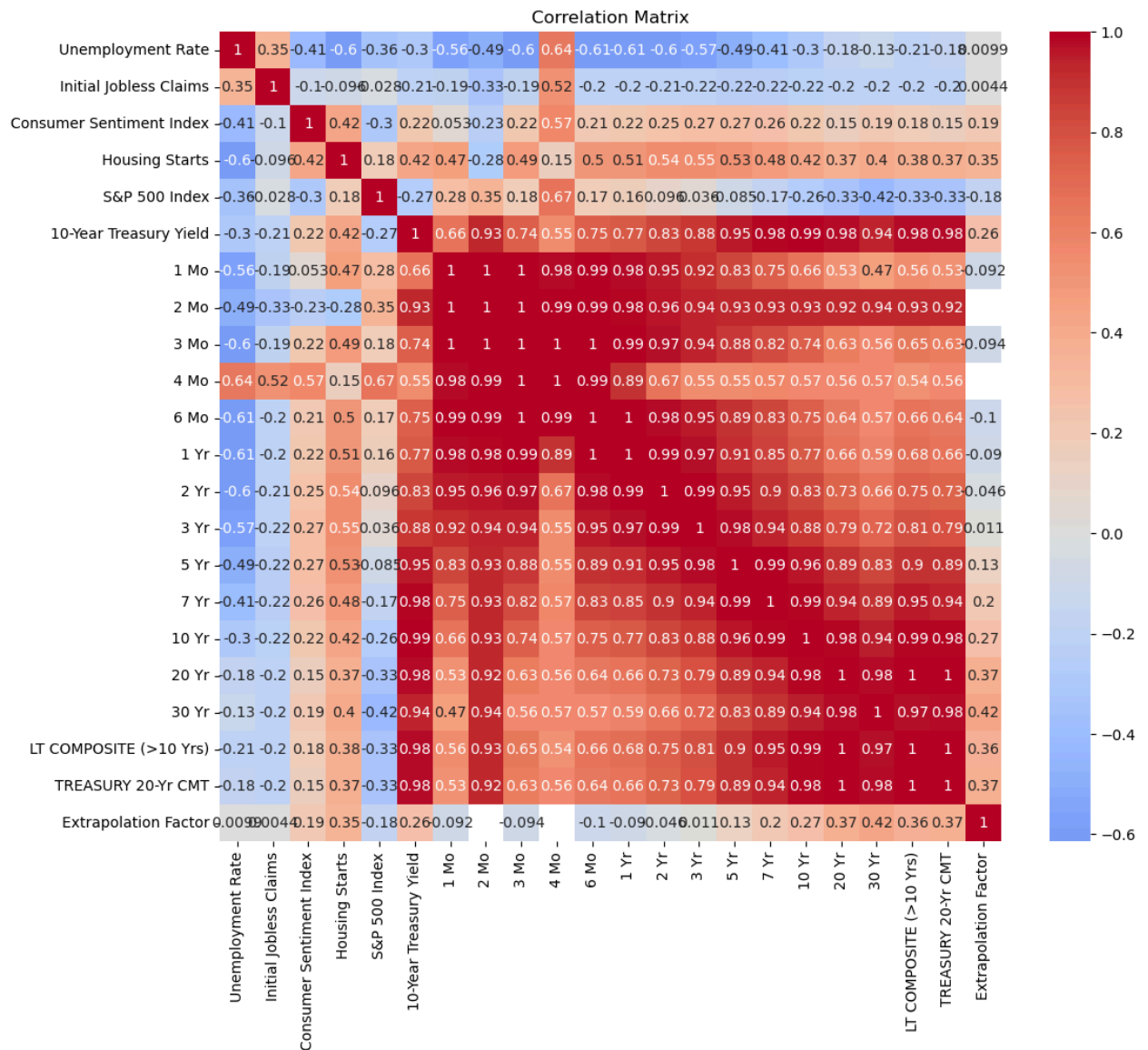
```
In [17]: import seaborn as sns
import matplotlib.pyplot as plt

# Calculate correlation matrix
correlation_matrix = combined_data.corr()

# Set figure size for Microsoft document
plt.figure(figsize=(12, 10))

# Plot heatmap
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0)

# Set title and save figure
plt.title('Correlation Matrix')
plt.savefig('correlation_heatmap.png')
plt.show()
```



```
In [18]: import matplotlib.pyplot as plt

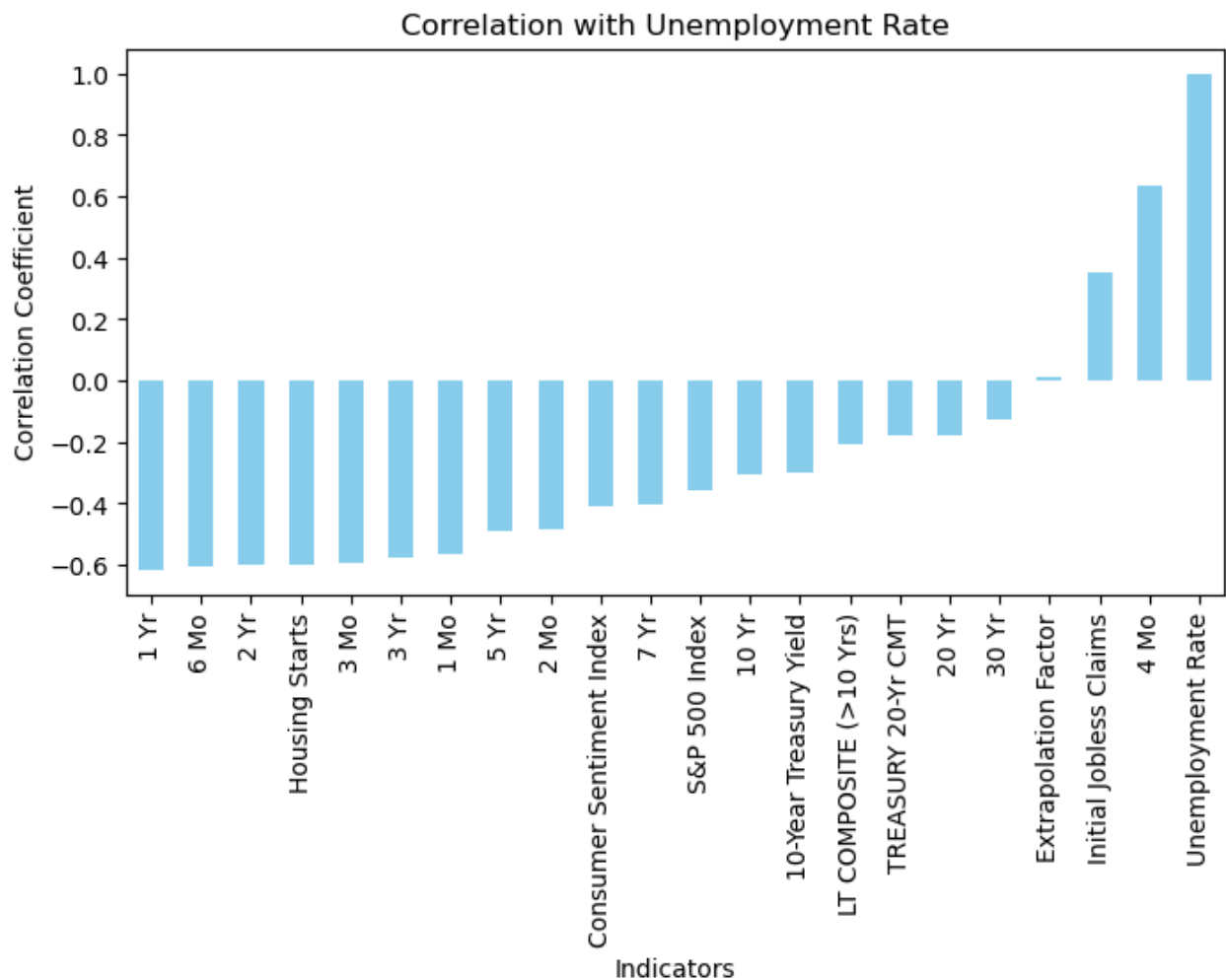
# Calculate correlations with the Unemployment Rate
correlation_with_unemployment = correlation_matrix['Unemployment Rate'].sort_values()

# Set figure size for Microsoft document
plt.figure(figsize=(8, 4))

# Plot bar chart
correlation_with_unemployment.plot(kind='bar', color='skyblue')

# Set title and labels
plt.title('Correlation with Unemployment Rate')
plt.xlabel('Indicators')
plt.ylabel('Correlation Coefficient')

# Save figure
plt.savefig('correlation_with_unemployment.png')
plt.show()
```



Feature Engineering

```
In [19]: # Create lagged variables
for lag in range(1, 13):
    combined_data[f'Unemployment Rate Lag {lag}'] = combined_data['Unemployment Rate'].shift(lag)
    combined_data[f'Initial Jobless Claims Lag {lag}'] = combined_data['Initial Jobless Claims'].shift(lag)
    combined_data[f'Consumer Sentiment Index Lag {lag}'] = combined_data['Consumer Sentiment Index'].shift(lag)
    combined_data[f'Housing Starts Lag {lag}'] = combined_data['Housing Starts'].shift(lag)
    combined_data[f'S&P 500 Index Lag {lag}'] = combined_data['S&P 500 Index'].shift(lag)
    combined_data[f'10-Year Treasury Yield Lag {lag}'] = combined_data['10-Year Treasury Yield'].shift(lag)

# Create moving averages
combined_data['Unemployment Rate MA 3'] = combined_data['Unemployment Rate'].rolling(window=3).mean()
combined_data['Unemployment Rate MA 6'] = combined_data['Unemployment Rate'].rolling(window=6).mean()
combined_data['Unemployment Rate MA 12'] = combined_data['Unemployment Rate'].rolling(window=12).mean()

combined_data.dropna(inplace=True)
```

Model Training and Evaluation

```
In [20]: from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error
from statsmodels.tsa.arima.model import ARIMA

# Prepare data for modeling
X = combined_data.drop(columns=['Unemployment Rate'])
```



```

y = combined_data['Unemployment Rate']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# ARIMA model
arima_model = ARIMA(y_train, order=(5, 1, 0))
arima_model_fit = arima_model.fit()
arima_forecast = arima_model_fit.forecast(steps=len(y_test))
arima_rmse = mean_squared_error(y_test, arima_forecast, squared=False)
arima_mae = mean_absolute_error(y_test, arima_forecast)
print(f'ARIMA RMSE: {arima_rmse}, MAE: {arima_mae}')

# Random Forest model
rf_model = RandomForestRegressor()
rf_model.fit(X_train, y_train)
rf_predictions = rf_model.predict(X_test)
rf_rmse = mean_squared_error(y_test, rf_predictions, squared=False)
rf_mae = mean_absolute_error(y_test, rf_predictions)
print(f'Random Forest RMSE: {rf_rmse}, MAE: {rf_mae}')

# Gradient Boosting model
gb_model = GradientBoostingRegressor()
gb_model.fit(X_train, y_train)
gb_predictions = gb_model.predict(X_test)
gb_rmse = mean_squared_error(y_test, gb_predictions, squared=False)
gb_mae = mean_absolute_error(y_test, gb_predictions)
print(f'Gradient Boosting RMSE: {gb_rmse}, MAE: {gb_mae}')

```

```

C:\Users\salin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A
date index has been provided, but it has no associated frequency information and so will be ignor
ed when e.g. forecasting.
    self._init_dates(dates, freq)
C:\Users\salin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A
date index has been provided, but it is not monotonic and so will be ignored when e.g. forecastin
g.
    self._init_dates(dates, freq)
C:\Users\salin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A
date index has been provided, but it has no associated frequency information and so will be ignor
ed when e.g. forecasting.
    self._init_dates(dates, freq)
C:\Users\salin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A
date index has been provided, but it is not monotonic and so will be ignored when e.g. forecastin
g.
    self._init_dates(dates, freq)
C:\Users\salin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A
date index has been provided, but it has no associated frequency information and so will be ignor
ed when e.g. forecasting.
    self._init_dates(dates, freq)
C:\Users\salin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A
date index has been provided, but it is not monotonic and so will be ignored when e.g. forecastin
g.
    self._init_dates(dates, freq)
C:\Users\salin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:834: ValueWarning: N
o supported index is available. Prediction results will be given with an integer index beginning
at `start`.
    return get_prediction_index(
ARIMA RMSE: 0.10776656125850885, MAE: 0.0770757442511163
Random Forest RMSE: 0.06452131430775292, MAE: 0.054999999999999916
Gradient Boosting RMSE: 0.12433563564472944, MAE: 0.1192440577188234

```

Deployment and Monitoring

```

In [21]: # Implementing a simple prediction function
def predict_unemployment_rate(model, new_data):
    prediction = model.predict(new_data)

```

```

    return prediction

# Continuous monitoring and updating models
# This part will be more extensive in a real-world scenario involving setting up pipelines and au
import joblib

# Save models
joblib.dump(arima_model_fit, 'arima_model.pkl')
joblib.dump(rf_model, 'random_forest_model.pkl')
joblib.dump(gb_model, 'gradient_boosting_model.pkl')

# Load models
arima_model_loaded = joblib.load('arima_model.pkl')
rf_model_loaded = joblib.load('random_forest_model.pkl')
gb_model_loaded = joblib.load('gradient_boosting_model.pkl')

# Example usage with new data
new_data = X_test.iloc[:1] # Replace with new data as needed
arima_prediction = arima_model_loaded.forecast(steps=1)
rf_prediction = predict_unemployment_rate(rf_model_loaded, new_data)
gb_prediction = predict_unemployment_rate(gb_model_loaded, new_data)

print(f'ARIMA Prediction: {arima_prediction}')
print(f'Random Forest Prediction: {rf_prediction}')
print(f'Gradient Boosting Prediction: {gb_prediction}')

ARIMA Prediction: 16      3.720503
dtype: float64
Random Forest Prediction: [3.541]
Gradient Boosting Prediction: [3.52234706]
C:\Users\salin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:834: ValueWarning: N
o supported index is available. Prediction results will be given with an integer index beginning
at `start`.
    return get_prediction_index(

```

Code to Forecast Future Economic Indicators and Predict Unemployment Rate

```

In [22]: import pandas as pd
import numpy as np
from datetime import timedelta

# Generate future dates for the next five years
future_dates = pd.date_range(start='2024-06-01', end='2029-06-01', freq='M')

# Create a DataFrame to hold future values of the indicators
future_data = pd.DataFrame(index=future_dates, columns=combined_data.columns)

# Forecast future values for the economic indicators
# Here, we will use a simple method of extending the last known value forward
# In practice, more sophisticated methods like ARIMA could be used for each indicator

for column in combined_data.columns:
    last_value = combined_data[column].iloc[-1]
    future_data[column] = last_value

# Apply some variation to simulate realistic changes over time (this is a simplified approach)
np.random.seed(42) # For reproducibility
for column in future_data.columns:
    future_data[column] = future_data[column] * (1 + 0.01 * np.random.randn(len(future_data)))

# Ensure the future data aligns with the features used in the model
feature_columns = X_train.columns
future_data = future_data[feature_columns]

```

```
# Use the trained Random Forest model to make predictions
future_predictions = rf_model.predict(future_data)

# Combine the future dates with the predicted unemployment rates
future_forecast = pd.DataFrame({'Date': future_dates, 'Predicted Unemployment Rate': future_predictions})

# Set the date as the index
future_forecast.set_index('Date', inplace=True)

# Print the predictions
print(future_forecast)
```

Date	Predicted Unemployment Rate
2024-06-30	3.817
2024-07-31	3.806
2024-08-31	3.821
2024-09-30	3.835
2024-10-31	3.797
2024-11-30	3.813
2024-12-31	3.815
2025-01-31	3.823
2025-02-28	3.820
2025-03-31	3.825
2025-04-30	3.824
2025-05-31	3.830
2025-06-30	3.823
2025-07-31	3.820
2025-08-31	3.827
2025-09-30	3.830
2025-10-31	3.825
2025-11-30	3.805
2025-12-31	3.823
2026-01-31	3.818
2026-02-28	3.838
2026-03-31	3.818
2026-04-30	3.800
2026-05-31	3.828
2026-06-30	3.824
2026-07-31	3.813
2026-08-31	3.811
2026-09-30	3.827
2026-10-31	3.812
2026-11-30	3.804
2026-12-31	3.829
2027-01-31	3.822
2027-02-28	3.802
2027-03-31	3.821
2027-04-30	3.840
2027-05-31	3.822
2027-06-30	3.818
2027-07-31	3.818
2027-08-31	3.824
2027-09-30	3.850
2027-10-31	3.806
2027-11-30	3.825
2027-12-31	3.816
2028-01-31	3.831
2028-02-29	3.789
2028-03-31	3.814
2028-04-30	3.807
2028-05-31	3.832
2028-06-30	3.848
2028-07-31	3.813
2028-08-31	3.834
2028-09-30	3.813
2028-10-31	3.827
2028-11-30	3.810
2028-12-31	3.820
2029-01-31	3.839
2029-02-28	3.811
2029-03-31	3.831
2029-04-30	3.848
2029-05-31	3.814