# PREDICTING CPI MONTH OVER MONTH INFLATION RATE

In [26]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import requests
from datetime import datetime
import os
import pickle

import plotly.express as px
```

In [27]:

```
import matplotlib.pyplot as plt
import seaborn as sns  # Import seaborn for a nicer color palette

# Set a seaborn style
sns.set(style="whitegrid")

# Deep, muted, and bright are good choices for a color palette
colors = sns.color_palette("deep")
```

In [28]:

```
with open("fred_key.txt", 'r') as f: FRED_KEY = f.read()
```

## Query Data

**the following downloads and adjusts macro Indicators that might be able to predict CPI for FRED and varous other websites.**

**In addition the data gets converted to monthly features and and laged to eliminate data leakage.**

**CPI data gets released every 2nd Wednesday of the month, so we had to make sure that i cpi (or target variable) was released on the 13.03.21 all the input features (independent varables X) where already available on the 12.03.21**

**To achive that we need to lag almost all of the variables. Lag values varies between 1 to 5 month.**

In [29]:

```
start_date = '1970'
```

In [30]:

```
from fredapi import Fred
fred = Fred(api_key=FRED_KEY)
```

In [31]:

```
def change_fred_dtypes(fred_df):

    fred_df.dropna(subset=['value'], inplace=True)

    fred_df.date = pd.to_datetime(fred_df.date)
    fred_df.realtime_start = pd.to_datetime(fred_df.realtime_start)

    fred_df = fred_df.sort_values(['date', 'realtime_start'])
    fred_df = fred_df.drop_duplicates(subset='date', keep='first')
```

```
    fred_df = fred_df[fred_df.date >= pd.to_datetime('1985')].reset_index(drop=True)
    fred_df.value = fred_df.value.astype(float)

    return fred_df
```

In [32]:

```
def get_fred_df(fred_id):
    fred_s = fred.get_series(fred_id)
    fred_s.dropna(inplace=True)
    fred_df = pd.DataFrame(fred_s, columns=['value'])
    fred_df.index = pd.to_datetime(fred_df.index)
    fred_df['value'] = fred_df['value'].astype(float)


    return fred_df



def get_fred_resample_daily_to_monthly(fred_df):
    """
    get the value for every start of the month and the pct change (log) of the prev start
of month to this start of month
    data can then just be merged on index with cpi (release_month) without risk of datale
akage

    """

    fred_df['date'] = fred_df.index


    fred_df = fred_df.resample('M').first()
    fred_df.date = fred_df.date.apply(lambda x: x.replace(day=1))
    fred_df.index = fred_df.date

    fred_df['pct_change'] = np.log(fred_df.value).diff()

    fred_df.drop('date', axis=1, inplace=True)

    return fred_df


def get_yf_df(yf_id):
    import yfinance as yf

    # Set the start and end dates for the historical data
    start_date = "1950-01-01"

    # Download historical data
    df = yf.download(yf_id, start=start_date)

    # Display the first few rows of the data
    df = df[['Adj Close']].rename({'Adj Close': 'value'}, axis=1)
    return df



def get_fred_montly(fred_id, offset=2):

    df = fred.get_series_all_releases(fred_id)
    df = df.dropna(subset='value')
    df.value = df.value.astype(float)
    df = df.drop_duplicates(subset='date', keep='first')
    df.index = pd.to_datetime(df.date)
    df.index += pd.DateOffset(months=offset)

    return df
```

In [33]:

```
def download_excel(excel_url):
```

```python
    response = requests.get(excel_url)


    if response.status_code == 200:
        # Specify the local path to save the Excel file
        local_path = "temp.xlsx"
        # Write the content to a local Excel file
        with open(local_path, 'wb') as file:
            file.write(response.content)

        # Read the Excel file into a Pandas DataFrame
        df = pd.read_excel(local_path)
        print('excel downloaded')

        os.remove(local_path)
    else:
        print(f"Failed to retrieve the file. Status code: {response.status_code}")

    return df
```

In [34]:

```python
def get_manheim_dataset():
    from datetime import datetime, timedelta

    # Get the current date
    current_date = datetime.now() - timedelta(days=10)

    # Calculate the date one month ago
    one_month_ago = current_date - timedelta(days=30)

    # Extract month and year components
    month = current_date.month
    year = current_date.year
    month_prev_str = one_month_ago.strftime("%b")
    year_prev = one_month_ago.year

    print(f'{year}/{month}/{month_prev_str}-{year_prev}')

    excel_url = f"https://site.manheim.com/wp-content/uploads/sites/2/{year}/{month}/{mon
th_prev_str}-{year_prev}-ManheimUsedVehicleValueIndex-web-table-data.xlsx"


    df = download_excel(excel_url)


    df = df.rename({'Unnamed: 0': 'date', 'Index (1/97 = 100)': 'value'}, axis=1)


    df.date = df.date.apply(lambda x: x.replace(day=1))

    df.index = df.date

    df.index += pd.DateOffset(months=1)

    return df
```

In [35]:

```python
def dowload_china_balence():

    excel_url = 'https://www.census.gov/foreign-trade/balance/country.xlsx'

    df = download_excel(excel_url)

    df = df[df['CTYNAME'] == 'China']
    df = df.drop(['CTYNAME', 'CTY_CODE', 'IYR', 'EYR'], axis=1)

    df = pd.melt(df, id_vars=['year'], var_name='month', value_name='value')

    df['type'] = df.month.str[0]
```

```
    df['month'] = df.month.str[1:]

    df['date'] = df['year'].astype(str) + '-' + df['month'].str.lower()

    df['date'] = pd.to_datetime(df.date, format='%Y-%b')

    df = df.pivot(columns='type', values='value', index='date')

    df.columns = ['exports', 'imports']

    df['value'] = df['exports'] - df['imports']


    return df.replace(0, np.NaN)
```

In [36]:

```
def dow_jones_industial_average():
    dji_new = get_yf_df('^DJI')

    dji_hist = get_yf_df('DJI')

    df = pd.concat([dji_hist[dji_hist.index < dji_new.index[0]], dji_new])

    df_no_duplicates = df[~df.index.duplicated(keep='first')]

    return df_no_duplicates.sort_index()
```

In [37]:

```
def quater_to_month(fred_df):
    index = pd.date_range('1960-01-01', '2030-01-01', freq='MS')
    df = pd.DataFrame(None, index=index, columns=['to_drop'])

    return pd.concat([fred_df, df], axis=1).drop('to_drop', axis=1).ffill()
```

In [38]:

```
cpi = pd.DataFrame(fred.get_series('CPIAUCSL'), columns=['value'])
cpi = cpi.dropna()
cpi.index = pd.to_datetime(cpi.index)
cpi['cpi_month'] = cpi.index
cpi.index += pd.DateOffset(months=1)
```

In [39]:

```
# feature engeneering from cpi data

cpi['cpi_pct'] = np.log(cpi.value).diff()

cpi['month'] = cpi.cpi_month.dt.month
cpi['jan-sep'] = (cpi['month'] <= 9).astype(int)
cpi['oct-dec'] = (cpi['month'] > 9).astype(int)



cpi['cpi_lag1'] = cpi['cpi_pct'].shift(1)
cpi['cpi_3ema'] = cpi['cpi_lag1'] - cpi['cpi_lag1'].ewm(3, min_periods=1).mean()
cpi['cpi_9ema'] = cpi['cpi_lag1'] - cpi['cpi_lag1'].ewm(9, min_periods=1).mean()
cpi['cpi_50ema'] = cpi['cpi_lag1'] - cpi['cpi_lag1'].ewm(50, min_periods=1).mean()

cpi
```

Out[39]:

| | value | cpi_month | cpi_pct | month | jan-sep | oct-dec | cpi_lag1 | cpi_3ema | cpi_9ema | cpi_50ema |
|---|---|---|---|---|---|---|---|---|---|---|
| **1947-02-01** | 21.480 | 1947-01-01 | NaN | 1 | 1 | 0 | NaN | NaN | NaN | NaN |
| **1947-03-01** | 21.620 | 1947-02-01 | 0.006497 | 2 | 1 | 0 | NaN | NaN | NaN | NaN |
| **1947-04-01** | 22.000 | 1947-03-01 | 0.017424 | 3 | 1 | 0 | 0.006497 | 0.000000 | 0.000000 | 0.000000 |

| | value | cpi_month | cpi_pct | month | jan-sep | oct-dec | cpi_lag1 | cpi_3ema | cpi_9ema | cpi_50ema |
|---|---|---|---|---|---|---|---|---|---|---|
| **1947-05-01** | 22.000 | 1947-04-01 | 0.000000 | 4 | 1 | 0 | 0.017424 | 0.004683 | 0.005176 | -0.005409 |
| **1947-06-01** | 21.950 | 1947-05-01 | -0.002275 | 5 | 1 | 0 | 0.000000 | -0.007231 | -0.007728 | -0.007930 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **2023-08-01** | 304.348 | 2023-07-01 | 0.001667 | 7 | 1 | 0 | 0.001802 | -0.000673 | -0.001823 | -0.001144 |
| **2023-09-01** | 306.269 | 2023-08-01 | 0.006292 | 8 | 1 | 0 | 0.001667 | -0.000606 | -0.001762 | -0.001253 |
| **2023-10-01** | 307.481 | 2023-09-01 | 0.003949 | 9 | 1 | 0 | 0.006292 | 0.003014 | 0.002577 | 0.003306 |
| **2023-11-01** | 307.619 | 2023-10-01 | 0.000449 | 10 | 0 | 1 | 0.003949 | 0.000504 | 0.000211 | 0.000944 |
| **2023-12-01** | 307.917 | 2023-11-01 | 0.000968 | 11 | 0 | 1 | 0.000449 | -0.002248 | -0.002961 | -0.002507 |

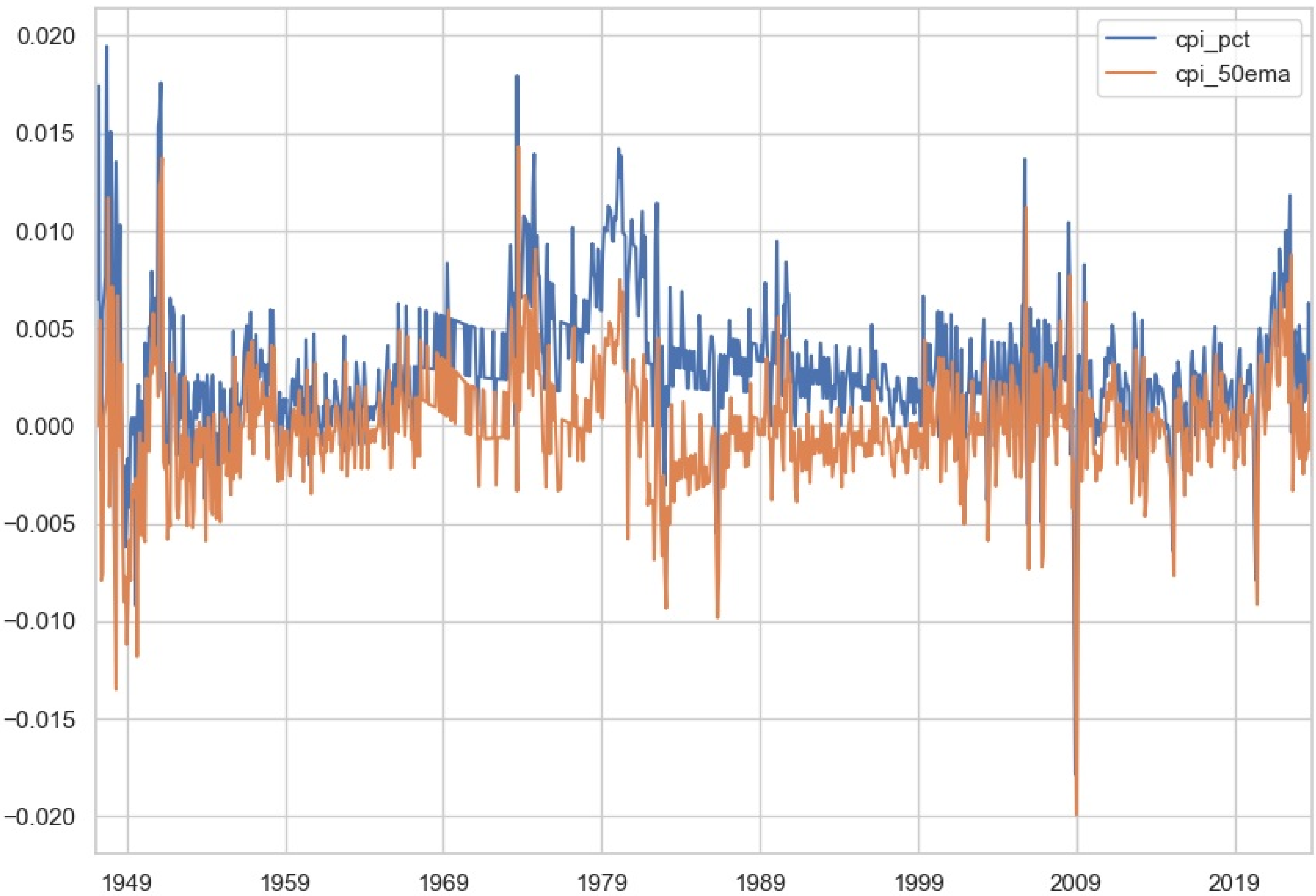
923 rows × 10 columns

In [40]:

```
cpi[['cpi_pct', 'cpi_50ema']].plot(figsize=(10, 7))
```

Out[40]:

<Axes: >




In [41]:

```
cpi.corr()
```

Out[41]:

| | value | cpi_month | cpi_pct | month | jan-sep | oct-dec | cpi_lag1 | cpi_3ema | cpi_9ema | cpi_50ema |
|---|---|---|---|---|---|---|---|---|---|---|
| **value** | 1.000000 | 0.975454 | -0.109800 | 0.009020 | -0.005303 | 0.005303 | -0.106551 | 0.003167 | 0.011904 | 0.008478 |
| **cpi_month** | 0.975454 | 1.000000 | -0.057241 | 0.009985 | -0.006532 | 0.006532 | -0.056292 | 0.011677 | 0.027361 | 0.040371 |
| **cpi_pct** | -0.109800 | -0.057241 | 1.000000 | -0.029611 | 0.053677 | -0.053677 | 0.575376 | 0.257891 | 0.320634 | 0.436924 |
| **month** | 0.009020 | 0.009985 | -0.029611 | 1.000000 | -0.751884 | 0.751884 | -0.012305 | -0.032748 | -0.019700 | -0.012253 |
| **jan-sep** | -0.005303 | -0.006532 | 0.053677 | -0.751884 | 1.000000 | -1.000000 | 0.015794 | 0.034995 | 0.024408 | 0.016919 |

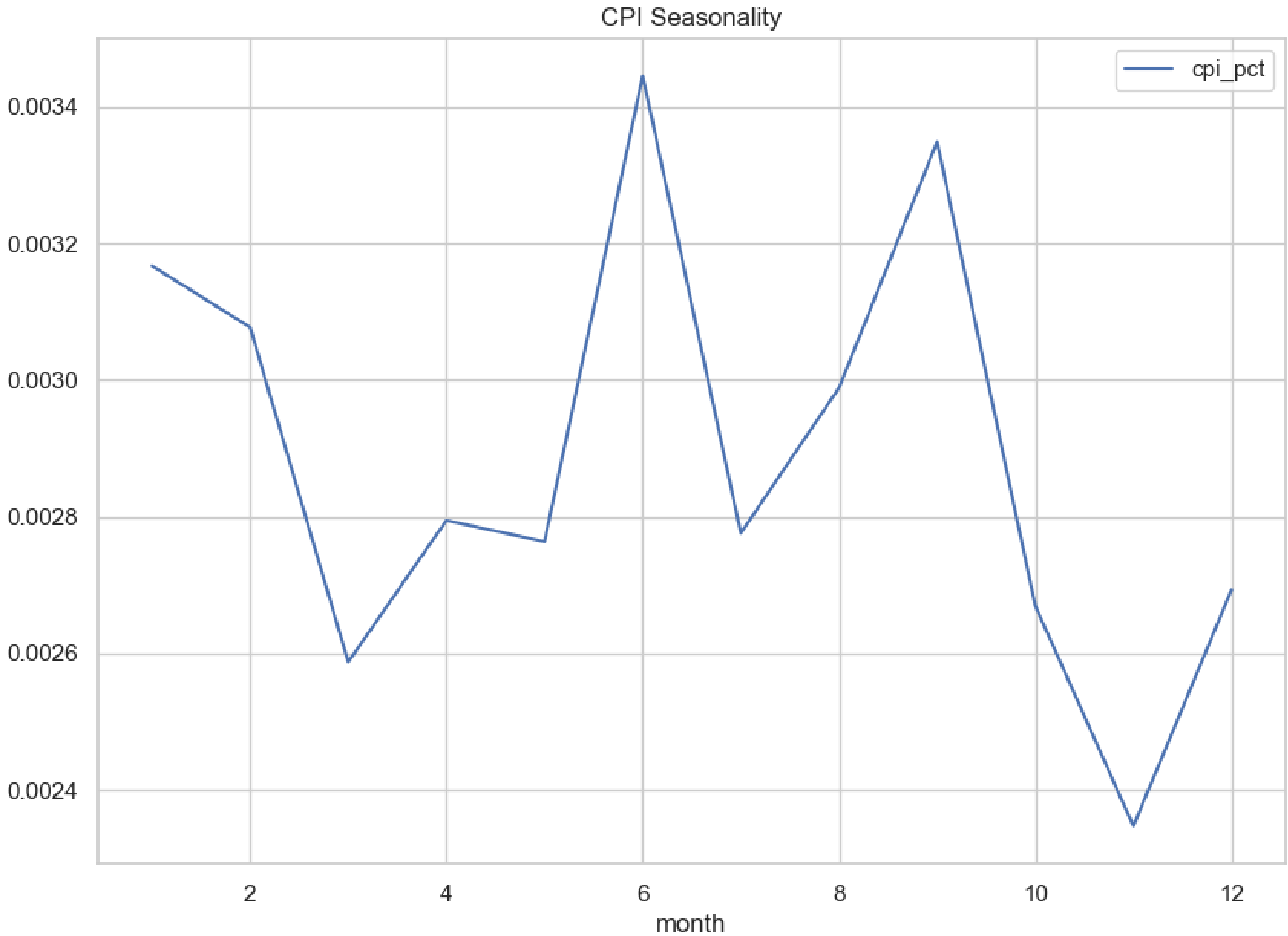
| | value | cpi_month | cpi_pct | month | jan-sep | oct-dec | cpi_lag1 | cpi_3ema | cpi_9ema | cpi_50ema |
|---|---|---|---|---|---|---|---|---|---|---|
| **oct-dec** | 0.005503 | -0.006532 | -0.053677 | 0.751884 | -1.000000 | 1.000000 | -0.015794 | -0.034995 | -0.024408 | -0.016919 |
| **cpi_lag1** | -0.106551 | -0.056292 | 0.575376 | -0.012305 | 0.015794 | -0.015794 | 1.000000 | 0.705925 | 0.783564 | 0.879882 |
| **cpi_3ema** | 0.003167 | 0.011677 | 0.257891 | -0.032748 | 0.034995 | -0.034995 | 0.705925 | 1.000000 | 0.956023 | 0.829419 |
| **cpi_9ema** | 0.011904 | 0.027361 | 0.320634 | -0.019700 | 0.024408 | -0.024408 | 0.783564 | 0.956023 | 1.000000 | 0.927964 |
| **cpi_50ema** | 0.008478 | 0.040371 | 0.436924 | -0.012253 | 0.016919 | -0.016919 | 0.879882 | 0.829419 | 0.927964 | 1.000000 |

In [42]:

```
cpi.groupby('month').agg({'cpi_pct': 'mean'}).plot(title='CPI Seasonality', figsize=(10, 7))
```

Out[42]:

```
<Axes: title={'center': 'CPI Seasonality'}, xlabel='month'>
```




In [43]:

```
data_dict = {}
```

In [44]:

```
usd = get_yf_df('DX-Y.NYB')
usd = get_fred_resample_daily_to_monthly(usd)
data_dict['usd'] = usd
```

```
[*********************100%%***********************]  1 of 1 completed
```

In [45]:

```
wti_raw = get_fred_df('DCOILWTICO')
wti = get_fred_resample_daily_to_monthly(wti_raw)
data_dict['wti'] = wti
```

In [46]:

In [46]:

```
gas_raw = get_fred_df('DHHNGSP')
gas = get_fred_resample_daily_to_monthly(gas_raw)
data_dict['gas'] = gas
```

In [47]:

```
dji = dow_jones_industial_average()
dji = get_fred_resample_daily_to_monthly(dji)
data_dict['dji'] = dji
```

```
[*********************100%%**********************]  1 of 1 completed
[*********************100%%**********************]  1 of 1 completed
```

In [48]:

```
ffr_raw = get_fred_df('FEDFUNDS')
ffr = get_fred_resample_daily_to_monthly(ffr_raw)
ffr.index += pd.DateOffset(months=1)
data_dict['ffr'] = ffr
```

In [49]:

```
vehic = get_manheim_dataset()
data_dict['vehic'] = vehic
```

```
2023/12/Nov-2023
excel downloaded
```

In [50]:

```
m2 = get_fred_montly('M2SL', 2)
data_dict['m2'] = m2
```

In [51]:

```
m2v = get_fred_montly('M2V', 4)
m2v = quater_to_month(m2v)
data_dict['m2v'] = m2v
```

In [52]:

```
chn_trd = dowload_china_balence()
chn_trd.index += pd.DateOffset(months=2)
data_dict['chn_trd'] = chn_trd
```

```
excel downloaded
```

In [53]:

```
wages = get_fred_montly('LES1252881600Q', 4)
wages = quater_to_month(wages)
data_dict['wages'] = wages
```

In [54]:

```
saving = get_fred_montly('PSAVERT', 2)
data_dict['saving'] = saving
```

In [55]:

```
pce = get_fred_montly('PCE', 2)
data_dict['pce'] = pce
```

In [56]:

```
unemp = get_fred_montly('UNRATE', 1)
data_dict['unemp'] = unemp
```

In [57]:

```
i_claims = fred.get_series_all_releases('ICSA')
i_claims.date = pd.to_datetime(i_claims.date)

i_claims.date = i_claims.date.apply(lambda x: x.replace(day=1))
i_claims.drop_duplicates(subset='date', keep='first', inplace=True)
i_claims.index = i_claims.date
i_claims.value = i_claims.value.astype(float)
data_dict['i_claims'] = i_claims
```

In [58]:

```
c_claims = fred.get_series_all_releases('CCSA')
c_claims.date = pd.to_datetime(c_claims.date)

c_claims.date = c_claims.date.apply(lambda x: x.replace(day=1))
c_claims.drop_duplicates(subset='date', keep='first', inplace=True)
c_claims.index = c_claims.date
c_claims.index += pd.DateOffset(months=1)
c_claims.value = c_claims.value.astype(float)
data_dict['c_claims'] = c_claims
```

In [35]:

```
job_open = get_fred_montly('JTSJOL', 2)
data_dict['job_open'] = job_open
```

In [36]:

```
sticky = get_fred_montly('CORESTICKM159SFRBATL', 2)
data_dict['sticky'] = sticky
```

In [37]:

```
ppi = get_fred_montly('PPIACO', 2)
data_dict['ppi'] = ppi
```

In [38]:

```
copper = get_fred_montly('PCOPPUSDM', 2)
data_dict['copper'] = copper
```

In [39]:

```
wheat = get_fred_montly('PWHEAMTUSDM', 2)
data_dict['wheat'] = wheat
```

In [40]:

```
housing = get_fred_montly('USSTHPI', 5)
housing = quater_to_month(housing)

data_dict['housing'] = housing
```

In [41]:

```
fuel = get_fred_montly('WPU057303', 2)
data_dict['fuel'] = fuel
```

In [42]:

```
gov_spending = get_fred_montly('FGEXPND', 4)
gov_spending = quater_to_month(gov_spending)
data_dict['gov_s'] = gov_spending
```

In [43]:

```
cur_acc = get_fred_montly('NETFI', 5)
cur_acc = quater_to_month(cur_acc)
data_dict['cur_acc'] = cur_acc
```

In [44]:

```
trades = get_fred_montly('BOPGSTB', 2)
data_dict['trades'] = trades
```

In [45]:

```
taxes = get_fred_montly('W006RC1Q027SBEA', 5)
taxes = quater_to_month(taxes)
data_dict['taxes'] = taxes
```

In [46]:

```
gdp = get_fred_montly('GDP', 4)
gdp = quater_to_month(gdp)
data_dict['gdp'] = gdp
```

In [47]:

```
new_dict = {}
for name, df in data_dict.items():
    new_dict[name] = df['value']
    print(name, len(df))
    if df.index.duplicated().any():
        print(name, 'has duplicated idxs')
```

```
usd 636
wti 456
gas 324
dji 648
ffr 833
vehic 323
m2 778
m2v 844
chn_trd 468
wages 841
saving 778
pce 778
unemp 911
i_claims 684
c_claims 684
job_open 275
sticky 672
ppi 1331
copper 527
wheat 527
housing 841
fuel 610
gov_s 896
cur_acc 892
trades 382
taxes 892
gdp 896
```

In [48]:

```
features = pd.concat(new_dict, axis=1)
```

In [49]:

```
full_dataset = pd.concat([cpi, features], axis=1)
```

In [50]:

```
full_dataset = full_dataset[(full_dataset.index > pd.to_datetime(start_date)) & (full_da
taset.index < pd.to_datetime('2024'))]
```

In [51]:

```
full_dataset.to_csv(f'datasets/raw_data{datetime.now().strftime("%Y-%m-%d")}.csv')
```

## Plot NaN values Chart

In [52]:

```
import pandas as pd
import numpy as np
import plotly.express as px


df = full_dataset.copy()

# Create a mask where NaN values are True, and non-NaN values are False
mask = ~df.isna()

# Create a heatmap using Plotly
fig = px.imshow(mask, color_continuous_scale='gray', labels=dict(x='Columns', y='Rows'),
                title='NaN Values (Black) and Non-NaN Values (White)')

fig.update_layout(coloraxis_showscale=False)
fig.update_layout(width=800, height=2000)

# Show the plot
fig.show()
```

## Missing Value Interpolation

**Explanation: The function takes a time series as input and performs backward interpolation from the first valid data point up to the earliest available data point in the year 2013.**

1. **Extract a sub-series from the input series for the years 2013 to 2019.**
2. **Calculate the mean of the values in this sub-series (vector_2013_2019).**
3. **Find the first valid index and its corresponding value in the input series.**
4. **Calculate the time frame between the first valid index and the year 2016.**
5. **Compute the gradient (rate of change) using the mean value and the first valid value over the time frame.**
6. **Determine the length of the portion of the series up to the first valid index.**
7. **Generate interpolated values using the gradient for the determined length.**
8. **Update the series up to the first valid index with the interpolated values**

In [53]:

```
def interpolate_backward(_series):

    series = _series.copy()

    # Extract sub-series for the years 2013 to 2019
    vector_2013_2019 = series[(series.index > pd.to_datetime('2013')) & (series.index <
pd.to_datetime('2019'))]

    # Calculate mean of the sub-series
    mean_2013_2019 = vector_2013_2019.mean()

    # Find the first valid index and its corresponding value
    first_valid_index = series.first_valid_index()
    first_valid_value = series.loc[first_valid_index]

    # Calculate the time frame between the first valid index and the year 2016 in months
    time_frame = pd.to_datetime('2016') - first_valid_index
    time_frame = time_frame.days / 30.44

    # Calculate the gradient (rate of change)
    gradient = (mean_2013_2019 - first_valid_value) / time_frame

    # Determine the length of the portion of the series up to the first valid index
    n = len(series.loc[:first_valid_index])
```

```
    # Generate interpolated values using the gradient
    interpolated = np.arange(1, n + 1) * gradient
    interpolated -= interpolated[-1]
    interpolated += first_valid_value

    # Update the series up to the first valid index with the interpolated values
    series.loc[:first_valid_index] = interpolated

    return series
```

In [54]:

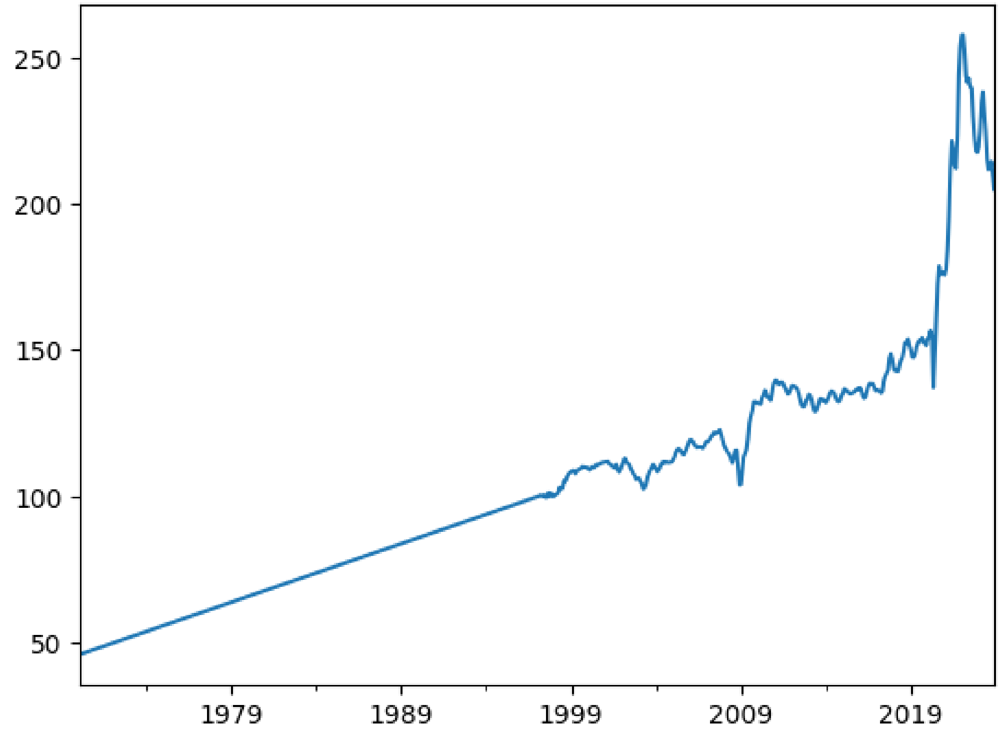
```
for nan_col in df.columns[df.isna().any()].tolist():
    df[nan_col] = interpolate_backward(df[nan_col])
```

In [55]:

```
interpolate_backward(full_dataset['vehic']).plot()
```

Out[55]:

<Axes: >




# Feature Engineering

To ensure that our model can derive meaningful insights from our input data, we must ensure that our input features make sense. We can't simply input the stationary values of the Dow Jones Industrial Index, for example, and expect our model to predict anything. Therefore, we need to perform some feature engineering on the data to make it stationary and preferably linearly correlated with the CPI month-over-month change, which is our target variable.

However, we also need to be careful not to overdo it with our feature engineering. We don't have a very high sample size (n) with between 400 to 600 samples based on where we choose our cutoff date (somewhere between 1970-2000). If we engineer too many new features, it could be that some just correlate with our target variable by chance. No model can filter out these random correlations, not even with Bayesian statistics unless we set an uninformative prior by hand, which we can't do because it is impossible to know if the correlation is just by chance or not.

That's why the best solution is to be cautious with your feature engineering.

## Feature Engineering Methods:

- 1-month, 3-month, and 9-month log differences
- 3-month and 9-month log differences lagged by 6 and 9 months, respectively
- _24ma = cpi_pctt1 - 24m_rolling_pct_change

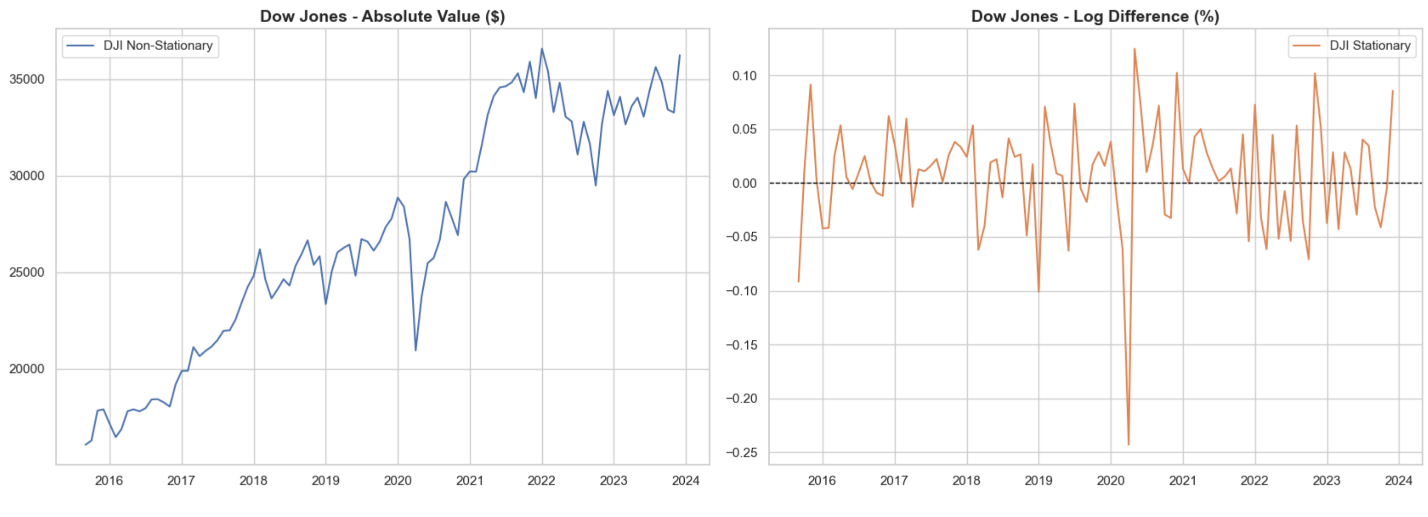
## Making Data Stationary

In [59]:

```
import matplotlib.pyplot as plt
import seaborn as sns  # Import seaborn for a nicer color palette

# Set a seaborn style
sns.set(style="whitegrid")

# Deep, muted, and bright are good choices for a color palette
colors = sns.color_palette("deep")
```

In [64]:

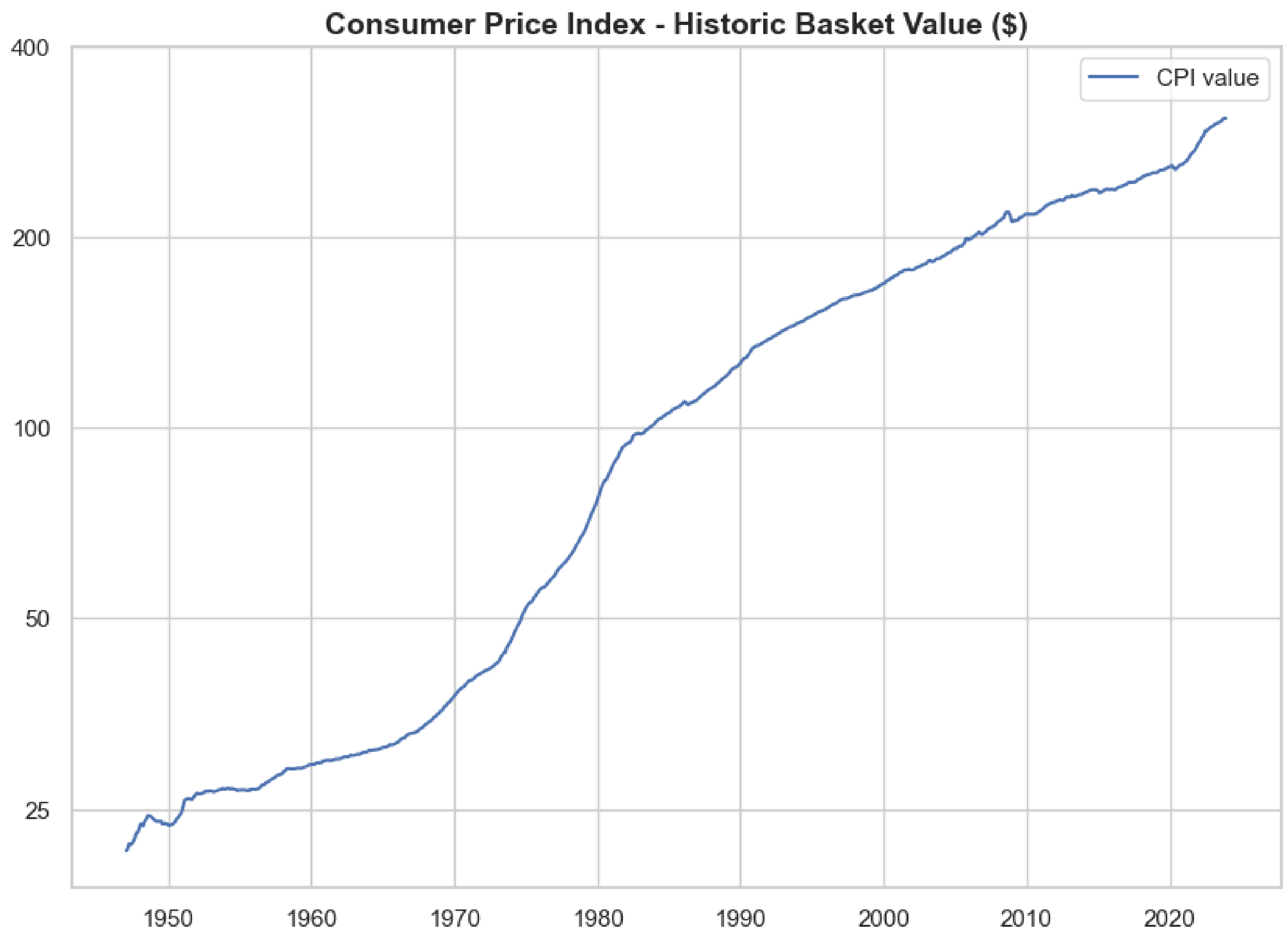
```
plot_data = dji.iloc[-100:].copy()

# Create subplots with 1 row and 2 columns
fig, axs = plt.subplots(1, 2, figsize=(17, 6))

# Plot the first graph on the left
axs[0].plot(plot_data.index, plot_data['value'], color=colors[0], label='DJI Non-Station
ary')
axs[0].set_title('Dow Jones - Absolute Value ($)', fontsize=14, fontweight='bold')
axs[0].legend()
axs[0].grid(True)

# Plot the second graph on the right
axs[1].plot(plot_data.index, plot_data['pct_change'], color=colors[1], label='DJI Statio
nary')
axs[1].set_title('Dow Jones - Log Difference (%)', fontsize=14, fontweight='bold')
axs[1].legend()
axs[1].grid(True)

# Add a dashed horizontal line at 0 in the second plot
axs[1].axhline(y=0, color='black', linestyle='--', linewidth=1)

# Adjust layout to prevent clipping of titles
plt.tight_layout()

# Show the plots
plt.savefig('plots/stationary_data_dji.png', dpi=300)
plt.show()
```




In [101]:

```
from matplotlib.ticker import ScalarFormatter
```

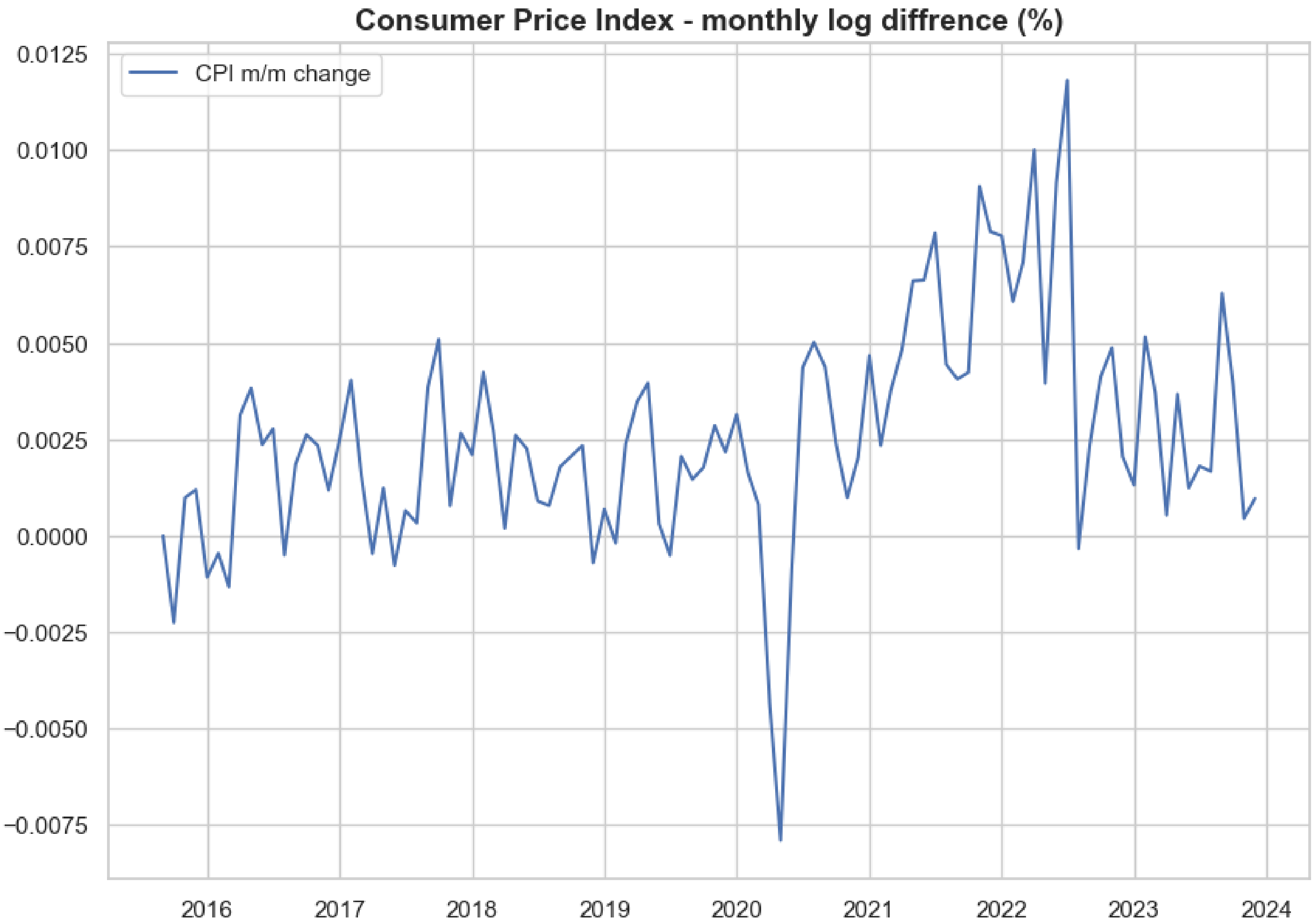
```
# Assuming 'cpi' is a DataFrame with a 'value' column
plot_data = cpi[['value']]

# Create subplots with 1 row and 2 columns
fig, axs = plt.subplots(1, 1, figsize=(10, 7))

# Plot the first graph on the left with log scale on y-axis
axs.plot(plot_data.index, plot_data['value'], color=colors[0], label='CPI value')
axs.set_yscale('log')  # Set y-axis to log scale
custom_y_labels = [25, 50, 100, 200, 400]
axs.set_yticks(custom_y_labels)
axs.get_yaxis().set_major_formatter(ScalarFormatter())

# Customize y-axis labels to display actual values
axs.yaxis.set_major_formatter(ScalarFormatter())

axs.set_title('Consumer Price Index - Historic Basket Value ($)', fontsize=14, fontweight
='bold')
axs.legend()
axs.grid(True)


plt.savefig('plots/cpi_history.png', dpi=300)
```




In [103]:

```
from matplotlib.ticker import ScalarFormatter

# Assuming 'cpi' is a DataFrame with a 'value' column
plot_data = cpi[['cpi_pct']].iloc[-100:]

# Create subplots with 1 row and 2 columns
fig, axs = plt.subplots(1, 1, figsize=(10, 7))

# Plot the first graph on the left with log scale on y-axis
axs.plot(plot_data.index, plot_data['cpi_pct'], color=colors[0], label='CPI m/m change')
```

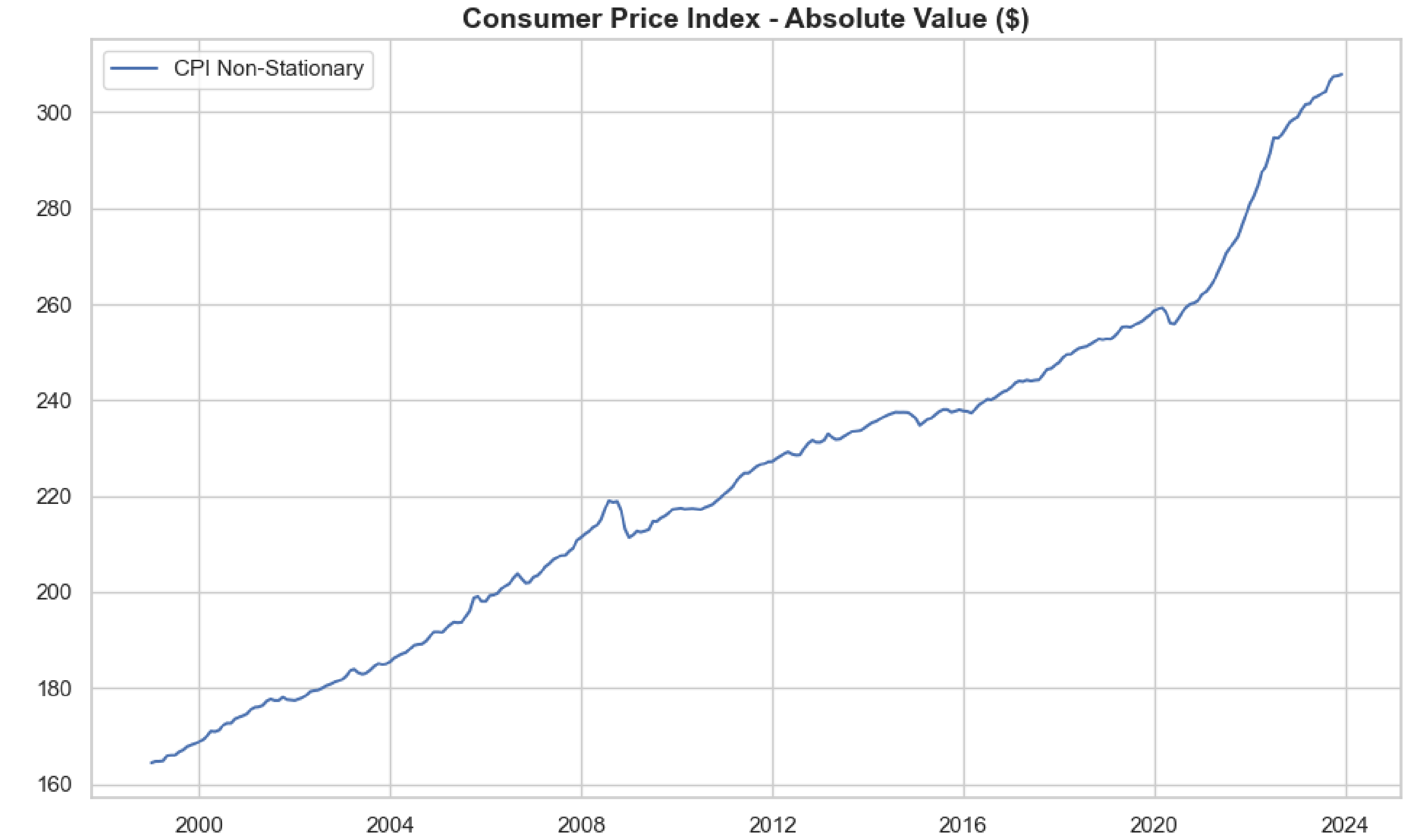
```
axs.set_title('Consumer Price Index - monthly log diffrence (%)', fontsize=14, fontweight
='bold')
axs.legend()
axs.grid(True)


plt.savefig('plots/cpi_pct_change.png', dpi=300)
```

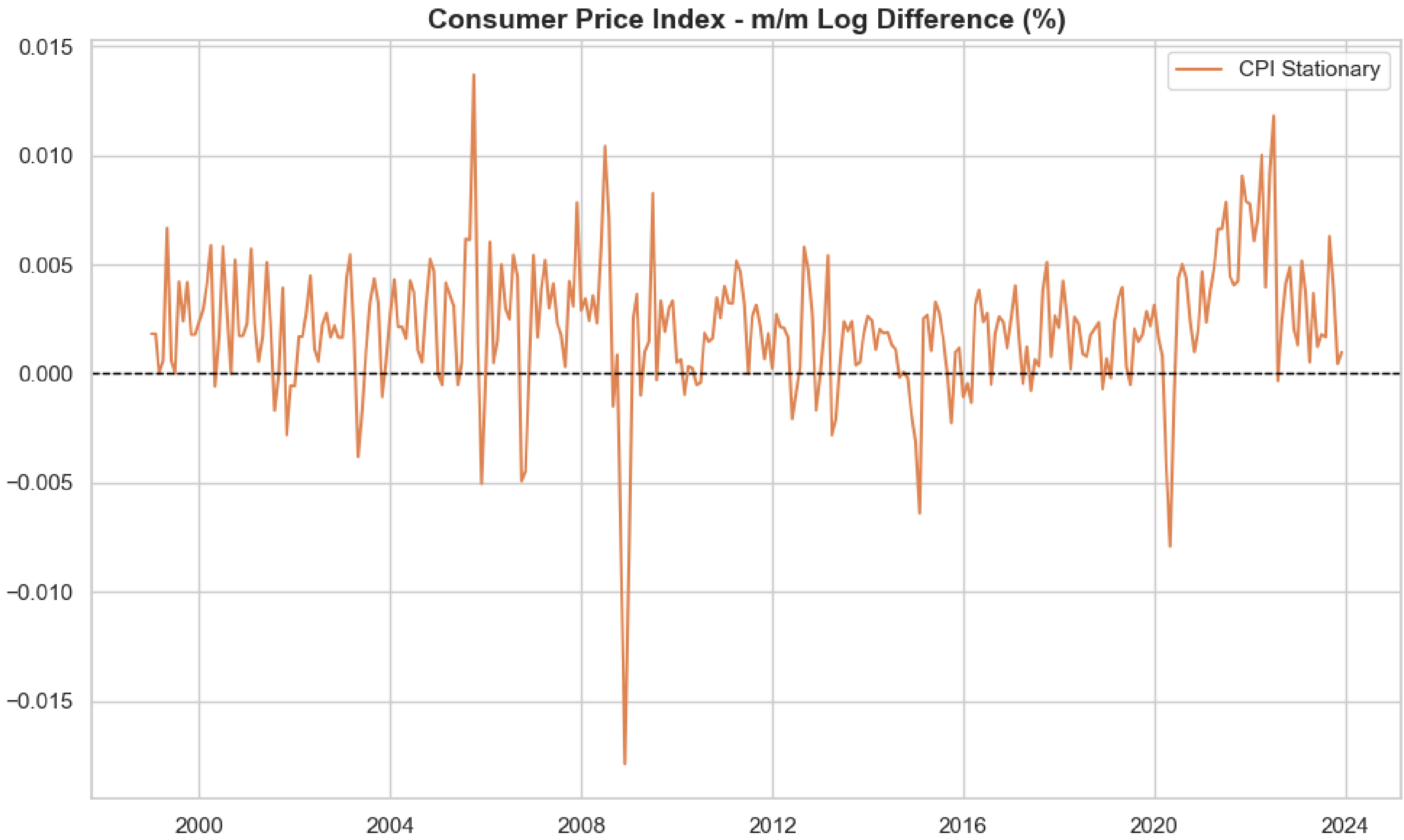



In [85]:

```
plot_data = cpi[['value', 'cpi_pct']].iloc[-300:].copy()


# Create subplots with 1 row and 2 columns
fig, axs = plt.subplots(2, 1, figsize=(10, 12))

# Plot the first graph on the left
axs[0].plot(plot_data.index, plot_data['value'], color=colors[0], label='CPI Non-Station
ary')
axs[0].set_title('Consumer Price Index - Absolute Value ($)', fontsize=14, fontweight='bo
ld')
axs[0].legend()
axs[0].grid(True)

# Plot the second graph on the right
axs[1].plot(plot_data.index, plot_data['cpi_pct'], color=colors[1], label='CPI Stationar
y')
axs[1].set_title('Consumer Price Index - m/m Log Difference (%)', fontsize=14, fontweight
='bold')
axs[1].legend()
axs[1].grid(True)

# Add a dashed horizontal line at 0 in the second plot
axs[1].axhline(y=0, color='black', linestyle='--', linewidth=1)

# Adjust layout to prevent clipping of titles
plt.tight_layout()
```

```python
# Show the plots
plt.savefig('plots/stationary_data_cpi.png', dpi=300)
```




In [58]:

```python
dji['pct_change']
```

Out[58]:

```
date
1970-01-01          NaN
1970-02-01    -0.080731
1970-03-01     0.044273
1970-04-01     0.015023
1970-05-01    -0.076607
                  ...
```

```
2023-08-01    0.034614
2023-09-01   -0.022507
2023-10-01   -0.041146
2023-11-01   -0.004760
2023-12-01    0.085522
Name: pct_change, Length: 648, dtype: float64
```

In [535]:

```
make_stationary = ['usd', 'wti', 'gas', 'dji', 'ffr', 'vehic', 'm2', 'm2v', 'wages', 'saving', 'pce', 'unemp',
                   'i_claims', 'c_claims', 'job_open', 'sticky', 'ppi', 'copper', 'wheat', 'housing',
                   'fuel', 'gov_s', 'cur_acc', 'trades', 'taxes', 'gdp', 'chn_trd']

keep_non_stationary = ['ffr', 'usd', 'm2v', 'saving', 'unemp', 'i_claims', 'c_claims', 'chn_trd']
```

In [536]:

```
# 'chn_trades' needs to be featureengeneered seperatly and the seasonality needs to be taken out take it relative to US gdp
df['chn_trd'] = -df['chn_trd'].rolling(12, min_periods=1).mean() / df['gdp']
```

In [537]:

```
make_stationary = ['usd', 'wti', 'gas', 'dji', 'ffr', 'vehic', 'm2', 'm2v', 'wages', 'saving', 'pce', 'unemp',
                   'i_claims', 'c_claims', 'job_open', 'sticky', 'ppi', 'copper', 'wheat', 'housing',
                   'fuel', 'gov_s', 'cur_acc', 'trades', 'taxes', 'gdp', 'chn_trd']

keep_non_stationary = ['ffr', 'usd', 'm2v', 'saving', 'unemp', 'i_claims', 'c_claims', 'chn_trd']


for raw_feature in df.loc[:, 'usd':].columns:
    raw_series = df[raw_feature].copy()

    if raw_feature in make_stationary:
        if (raw_series <= 0).any():
            pct_chg = (raw_series - raw_series.shift(1)).copy()
        else:
            pct_chg = np.log(raw_series).diff().copy()

        new_columns = {
            f'{raw_feature}_1m_pct': pct_chg,
            f'{raw_feature}_3m_pct': pct_chg.rolling(3, min_periods=1).sum(),
            f'{raw_feature}_9m_pct': pct_chg.rolling(9, min_periods=1).sum(),
            f'{raw_feature}_3m_pct_6m_lag': pct_chg.rolling(3, min_periods=1).sum().shift(6),
            f'{raw_feature}_9m_pct_9m_lag': pct_chg.rolling(9, min_periods=1).sum().shift(9),
            f'{raw_feature}_24ma': pct_chg - pct_chg.ewm(24, min_periods=1).mean()
        }

    df.drop(raw_feature, axis=1, inplace=True)

    df = pd.concat([df, pd.DataFrame(new_columns)], axis=1)

    if keep_non_stationary:
        df[f'{raw_feature}_raw'] = raw_series
```

In [538]:

```
df = df.dropna()
```

In [539]:

```
df.to_pickle(f'datasets/final_dataset_{datetime.now().strftime("%Y-%m-%d")}.pkl')
```

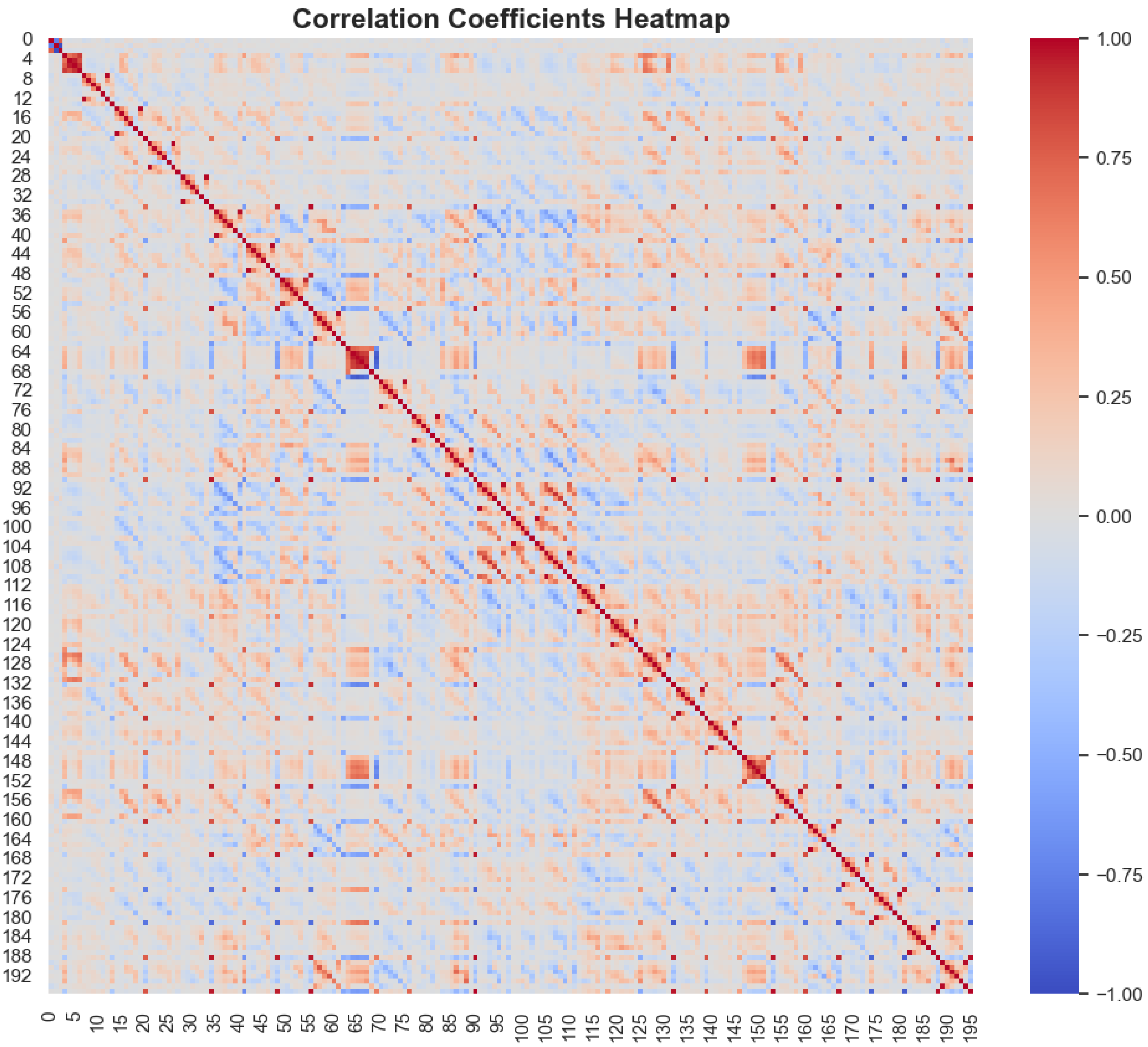
In [4]:

```
df = pd.read_pickle(f'datasets/final_dataset_2023-12-18.pkl')
```

## Plotting Correlation Matrix

In [22]:

```
corr_matrix = df.loc[:, 'month':].corr().values

# Create a heatmap using Seaborn
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, cmap="coolwarm")

# Show the plot
plt.title('Correlation Matrix')

# Customize the title
title_fontdict = {'fontsize': 16, 'fontweight': 'bold'}
plt.title('Correlation Coefficients Heatmap', fontdict=title_fontdict)

plt.savefig('plots/covariate_correlation.png', dpi=300)
```




## Train Test Split

In [5]:

```
split_pct = 0.25
slice_len = 4

np.random.seed(69)

dflen = len(df)

n_slices = round((dflen * split_pct) / slice_len)

test_index = []
for idx in np.random.choice(np.arange(dflen), size=n_slices):
    idx += 1
    test_index += list(range(idx, min(idx+slice_len, dflen-1)))

test_index = list(set(test_index))

test_index = df.iloc[test_index].index.tolist()
train_index = df.index.difference(test_index).tolist()

train_df = df.loc[train_index]
test_df = df.loc[test_index]
```

In [6]:

```
train_df.shape, test_df.shape
```

Out[6]:

```
((497, 199), (140, 199))
```

In [7]:

```
train_df
```

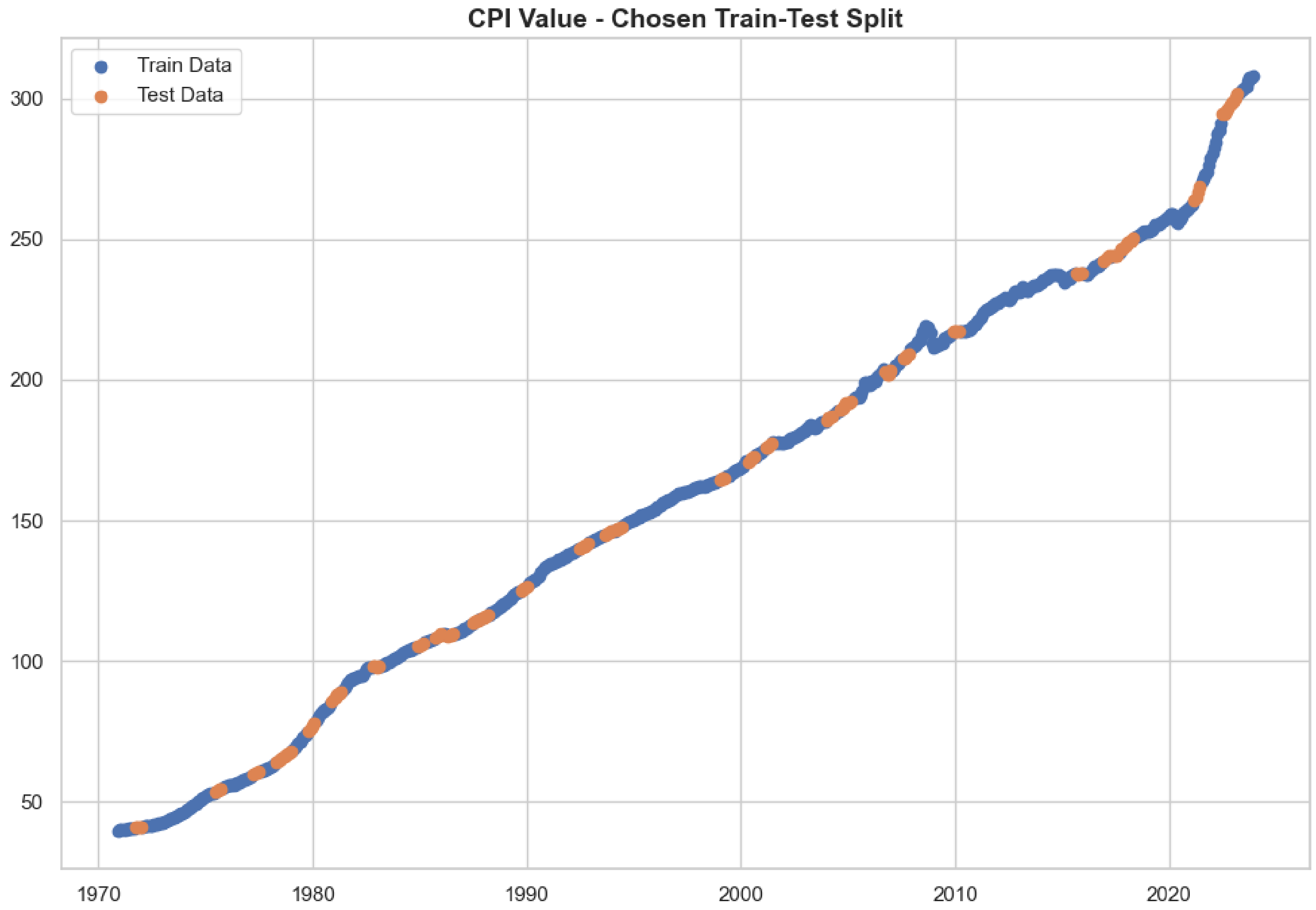
Out[7]:

| | value | cpi_month | cpi_pct | month | jan-sep | oct-dec | cpi_lag1 | cpi_3ema | cpi_9ema | cpi_50ema | ... | taxes_9m_pct_9m_lag |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1970-12-01** | 39.600 | 1970-11-01 | 0.005063 | 11.0 | 0.0 | 1.0 | 0.005089 | 0.000742 | 0.000685 | 0.001993 | ... | 0.004826 |
| **1971-01-01** | 39.800 | 1970-12-01 | 0.005038 | 12.0 | 0.0 | 1.0 | 0.005063 | 0.000537 | 0.000593 | 0.001928 | ... | 0.004826 |
| **1971-02-01** | 39.900 | 1971-01-01 | 0.002509 | 1.0 | 1.0 | 0.0 | 0.005038 | 0.000384 | 0.000511 | 0.001865 | ... | 0.004826 |
| **1971-03-01** | 39.900 | 1971-02-01 | 0.000000 | 2.0 | 1.0 | 0.0 | 0.002509 | -0.001609 | -0.001816 | -0.000650 | ... | -0.039470 |
| **1971-04-01** | 40.000 | 1971-03-01 | 0.002503 | 3.0 | 1.0 | 0.0 | 0.000000 | -0.003089 | -0.003893 | -0.003097 | ... | -0.039470 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **2023-08-01** | 304.348 | 2023-07-01 | 0.001667 | 7.0 | 1.0 | 0.0 | 0.001802 | -0.000673 | -0.001823 | -0.001144 | ... | 0.168140 |
| **2023-09-01** | 306.269 | 2023-08-01 | 0.006292 | 8.0 | 1.0 | 0.0 | 0.001667 | -0.000606 | -0.001762 | -0.001253 | ... | 0.207802 |
| **2023-10-01** | 307.481 | 2023-09-01 | 0.003949 | 9.0 | 1.0 | 0.0 | 0.006292 | 0.003014 | 0.002577 | 0.003306 | ... | 0.207802 |
| **2023-11-01** | 307.619 | 2023-10-01 | 0.000449 | 10.0 | 0.0 | 1.0 | 0.003949 | 0.000504 | 0.000211 | 0.000944 | ... | 0.207802 |
| **2023-12-01** | 307.917 | 2023-11-01 | 0.000968 | 11.0 | 0.0 | 1.0 | 0.000449 | -0.002248 | -0.002961 | -0.002507 | ... | 0.119193 |

**497 rows × 199 columns**

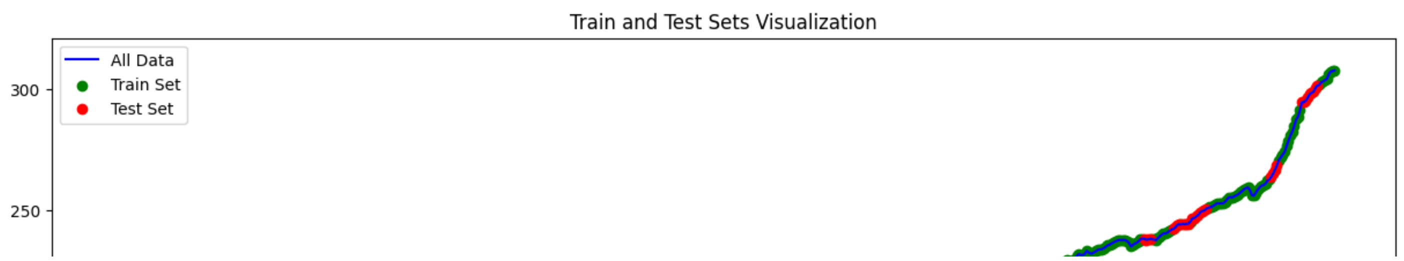
In [19]:

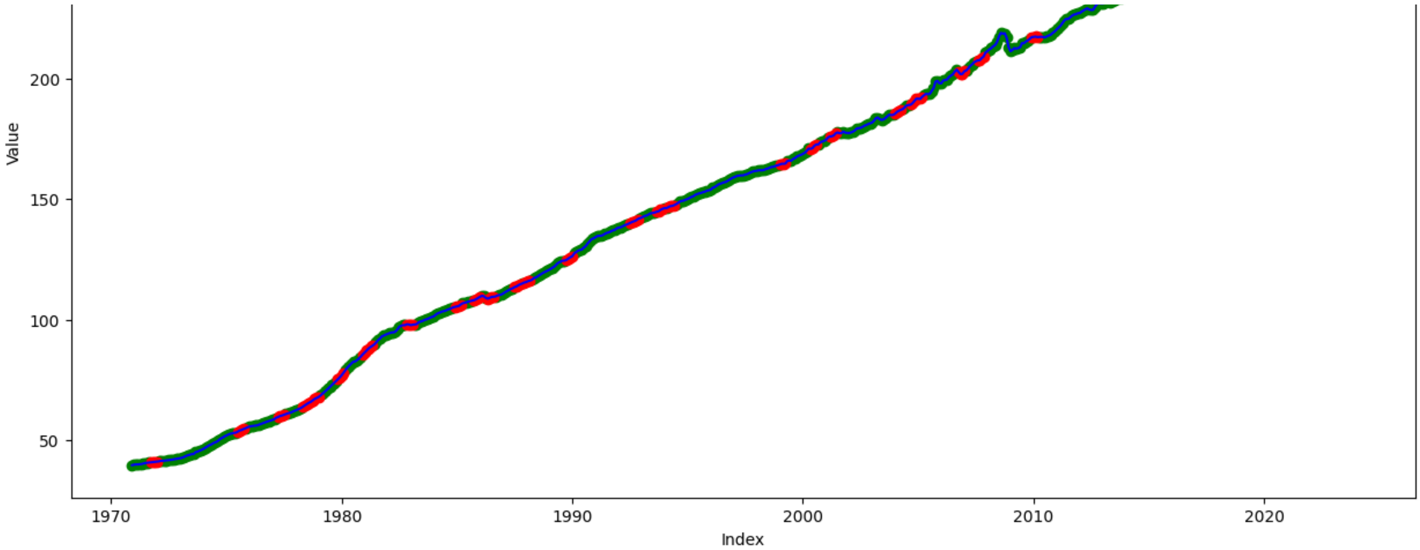
```
# Create subplots with 1 row and 2 columns
fig, axs = plt.subplots(1, 1, figsize=(10, 7))

# Plot the first graph on the left
axs.scatter(train_df.index, train_df['value'], color=colors[0], label='Train Data')
axs.scatter(test_df.index, test_df['value'], color=colors[1], label='Test Data')
axs.set_title('CPI Value - Chosen Train-Test Split', fontsize=14, fontweight='bold')
axs.legend()
axs.grid(True)

# Adjust layout to prevent clipping of titles
plt.tight_layout()

# Show the plots
plt.savefig('plots/train_test_split.png', dpi=300)
```




In [543]:

```
# Plotting
plt.figure(figsize=(15, 8))
plt.plot(df['value'], label='All Data', color='blue')
plt.scatter(train_index, df.loc[train_index, 'value'], label='Train Set', color='green')
plt.scatter(test_index, df.loc[test_index, 'value'], label='Test Set', color='red')
plt.title('Train and Test Sets Visualization')
plt.xlabel('Index')
plt.ylabel('Value')
plt.legend()
plt.show()
```






In [544]:

```
# We save the previous month cpi raw, so we can use is it as benchmark Predictions for ou
r target
test_df[['cpi_lag1']].rename({'cpi_lag1': 'pred'}, axis=1).reset_index(drop=True).to_csv
('predictions/benchmark2_prev.csv')
```

In [545]:

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

train_df.loc[:, 'month':] = scaler.fit_transform(train_df.loc[:, 'month':])
test_df.loc[:, 'month':] = scaler.transform(test_df.loc[:, 'month':])
```

In [546]:

```
dir_ = 'models/raw_scaler.pkl'
with open(dir_, 'wb') as file:
    pickle.dump(scaler, file)

train_df.to_csv(f'datasets/train_set.csv', index=False)
test_df.to_csv(f'datasets/test_set.csv', index=False)
```

In [547]:

```
train_df.describe().round(5)
```

Out[547]:

| | value | cpi_month | cpi_pct | month | jan-sep | oct-dec | cpi_lag1 | cpi_3ema | cpi_9ema | cpi_50em |
|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 497.00000 | 497 | 497.00000 | 497.00000 | 497.00000 | 497.00000 | 497.00000 | 497.00000 | 497.00000 | 497.0000 |
| **mean** | 159.05416 | 1997-04-28 16:45:23.541247488 | 0.00318 | 0.00000 | 0.00000 | -0.00000 | -0.00000 | -0.00000 | -0.00000 | 0.0000 |
| **min** | 39.60000 | 1970-11-01 00:00:00 | -0.01786 | -1.58859 | -1.85405 | -0.53936 | -6.40457 | -6.95822 | -7.52447 | -6.9494 |
| **25%** | 102.60000 | 1984-02-01 00:00:00 | 0.00155 | -0.99496 | 0.53936 | -0.53936 | -0.48199 | -0.44392 | -0.42915 | -0.5476 |
| **50%** | 160.40000 | 1997-07-01 00:00:00 | 0.00266 | -0.10451 | 0.53936 | -0.53936 | -0.13828 | -0.01748 | -0.01555 | -0.0614 |
| **75%** | 219.03500 | 2010-10-01 00:00:00 | 0.00461 | 0.78593 | 0.53936 | -0.53936 | 0.44466 | 0.47084 | 0.47652 | 0.4627 |
| **max** | 307.91700 | 2023-11-01 00:00:00 | 0.01794 | 1.67638 | 0.53936 | 1.85405 | 4.47105 | 5.14250 | 5.11477 | 4.9710 |
| **std** | 71.18925 | NaN | 0.00333 | 1.00101 | 1.00101 | 1.00101 | 1.00101 | 1.00101 | 1.00101 | 1.0010 |

8 rows × 199 columns

# PCA Transform

In [548]:

```
train_df = pd.read_csv(f'datasets/train_set.csv')
test_df = pd.read_csv(f'datasets/test_set.csv')
```

In [549]:

```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
```

In [550]:

```
pca = PCA()
```

In [551]:

```
train_df.loc[:, 'month':].shape, test_df.loc[:, 'month':].shape,
```

Out[551]:

```
((497, 196), (140, 196))
```

In [552]:

```
train_pca = pca.fit_transform(train_df.loc[:, 'month':])
test_pca = pca.transform(test_df.loc[:, 'month':])


dir_ = 'models/pca_model.pkl'
with open(dir_, 'wb') as file:
    pickle.dump(pca, file)
```

In [553]:

```
pca_train_df = pd.DataFrame(train_pca, columns = [f'pca_{i}' for i in range(train_pca.sh
ape[1])])
pca_test_df = pd.DataFrame(test_pca, columns = [f'pca_{i}' for i in range(test_pca.shape
[1])])
```

In [554]:

```
pca_train_df = pd.concat([train_df.loc[:, :'cpi_pct'], pca_train_df], axis=1)
pca_test_df = pd.concat([test_df.loc[:, :'cpi_pct'], pca_test_df], axis=1)
```

In [555]:

```
pca_train_df.loc[:, 'cpi_pct':].corr().round(5).sort_values('cpi_pct')
```

Out[555]:

| | cpi_pct | pca_0 | pca_1 | pca_2 | pca_3 | pca_4 | pca_5 | pca_6 | pca_7 | pca_8 | ... | pca_186 | pca_187 | pca_1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **pca_0** | -0.51772 | 1.00000 | 0.00 | -0.00000 | 0.00000 | 0.00000 | -0.00000 | -0.00000 | 0.00000 | -0.00000 | ... | 0.00000 | 0.00000 | 0.000 |
| **pca_5** | -0.16732 | -0.00000 | -0.00 | -0.00000 | -0.00000 | 0.00000 | 1.00000 | -0.00000 | 0.00000 | 0.00000 | ... | -0.00000 | -0.00000 | 0.000 |
| **pca_1** | -0.15000 | 0.00000 | 1.00 | -0.00000 | 0.00000 | -0.00000 | -0.00000 | -0.00000 | 0.00000 | 0.00000 | ... | -0.00000 | 0.00000 | 0.000 |
| **pca_13** | -0.13496 | 0.00000 | 0.00 | -0.00000 | 0.00000 | 0.00000 | 0.00000 | -0.00000 | 0.00000 | 0.00000 | ... | -0.00000 | -0.00000 | 0.000 |
| **pca_18** | -0.12783 | -0.00000 | -0.00 | 0.00000 | 0.00000 | -0.00000 | -0.00000 | 0.00000 | 0.00000 | -0.00000 | ... | -0.00000 | 0.00000 | 0.000 |

| ... | cpi_pct | pca_0 | pca_1 | pca_2 | pca_3 | pca_4 | pca_5 | pca_6 | pca_7 | pca_8 | ... | pca_186 | pca_187 | pca_1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **pca_19** | 0.10865 | -0.00000 | -0.00 | -0.00000 | -0.00000 | 0.00000 | 0.00000 | -0.00000 | 0.00000 | 0.00000 | ... | 0.00000 | -0.00000 | 0.000 |
| **pca_2** | 0.16177 | -0.00000 | -0.00 | 1.00000 | -0.00000 | 0.00000 | -0.00000 | -0.00000 | -0.00000 | 0.00000 | ... | -0.00000 | 0.00000 | 0.000 |
| **pca_151** | 0.18350 | -0.00000 | 0.00 | -0.00000 | 0.00000 | -0.00000 | -0.00000 | -0.00000 | -0.00000 | 0.00000 | ... | 0.00000 | -0.00000 | 0.000 |
| **pca_3** | 0.30103 | 0.00000 | 0.00 | -0.00000 | 1.00000 | -0.00000 | -0.00000 | 0.00000 | 0.00000 | 0.00000 | ... | -0.00000 | 0.00000 | 0.000 |
| **cpi_pct** | 1.00000 | -0.51772 | -0.15 | 0.16177 | 0.30103 | -0.00765 | -0.16732 | 0.08012 | 0.10071 | -0.09268 | ... | 0.01508 | 0.02404 | 0.039 |

197 rows × 197 columns

In [556]:

```
explained_variance = pca.explained_variance_ratio_
```

In [557]:

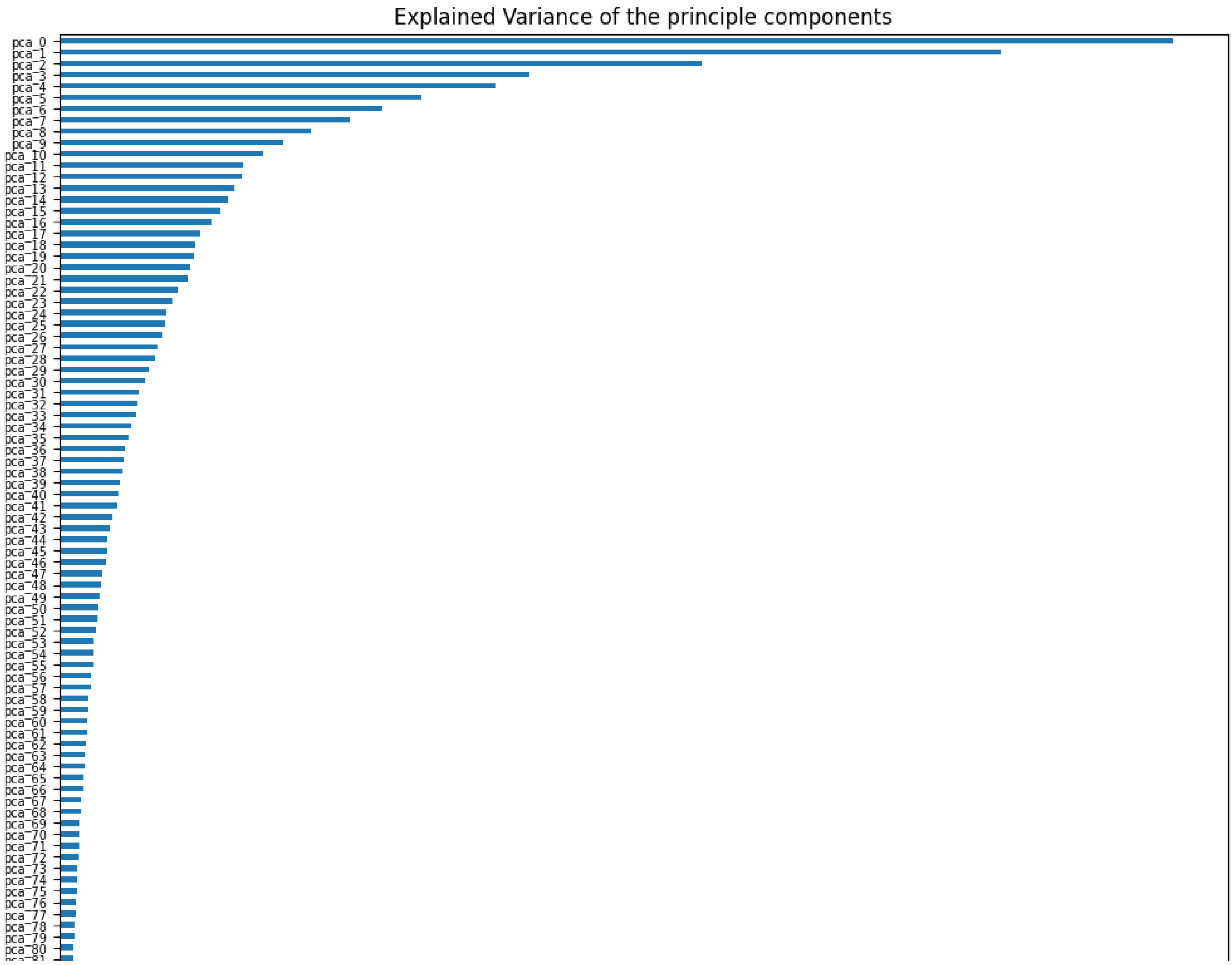
```
exp_var = pd.DataFrame(explained_variance, index=[f'pca_{i}' for i in range(test_pca.sha
pe[1])], columns=['explained_variance'])
```

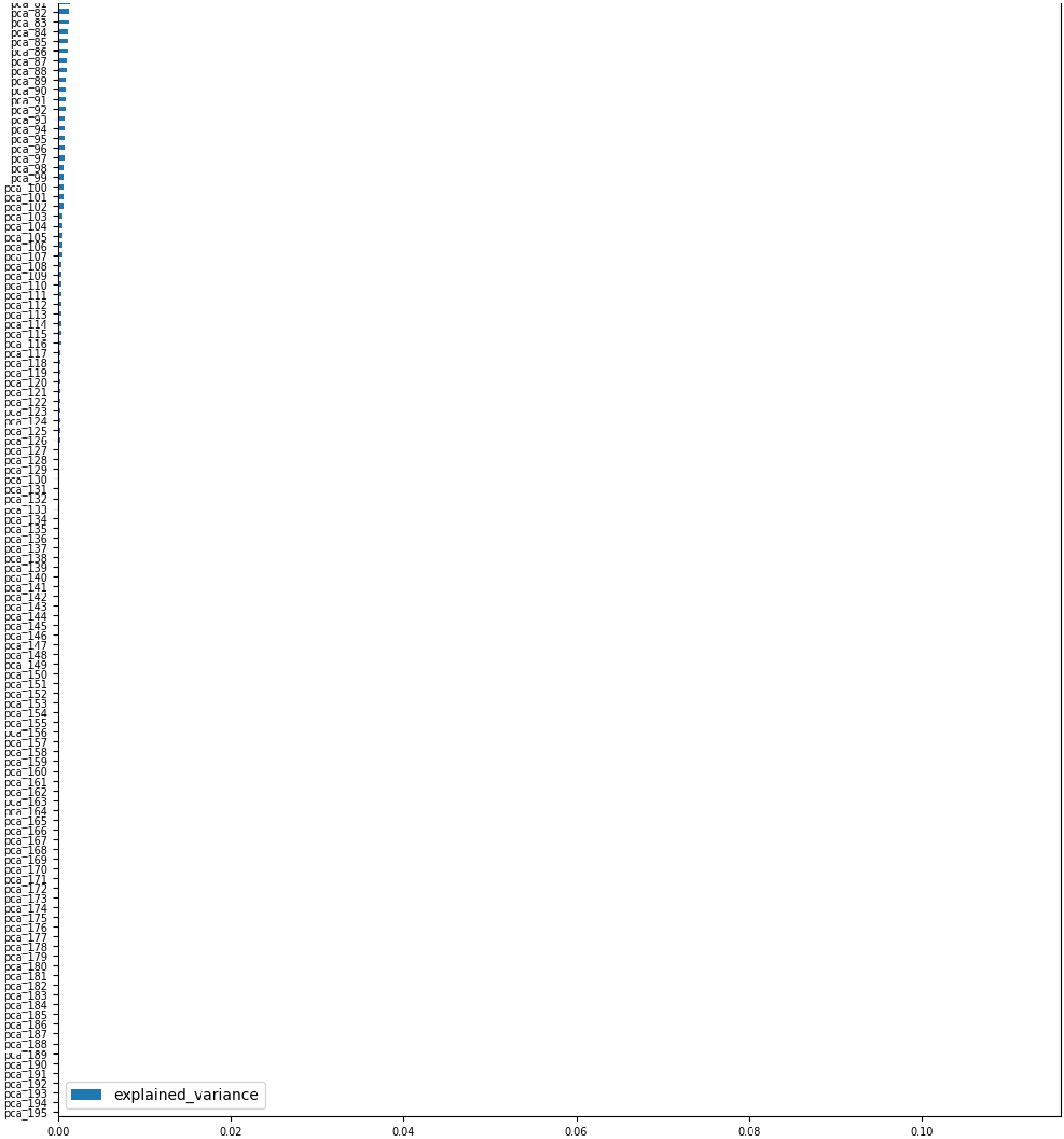
In [558]:

```
exp_var[::-1].plot(kind='barh', figsize=(12, 23), fontsize=7, title='Explained Variance
of the principle components')
```

Out[558]:

```
<Axes: title={'center': 'Explained Variance of the principle components'}>
```






# Scaling the Dataset After The PCA transformation

In [559]:

```
pca_scaler = StandardScaler()
```

In [560]:

```
pca_train_df.loc[:, 'pca_0':] = pca_scaler.fit_transform(pca_train_df.loc[:, 'pca_0':])
pca_test_df.loc[:, 'pca_0':] = pca_scaler.transform(pca_test_df.loc[:, 'pca_0':])

dir_ = 'models/pca_scaler.pkl'
with open(dir_, 'wb') as file:
    pickle.dump(pca_scaler, file)
```

In [561]:

```
pca_train_df.to_csv(f'datasets/train_set_pca.csv')
pca_test_df.to_csv(f'datasets/test_set_pca.csv')
```

In [562]:

```
pca_train_df.describe().round(5)
```

Out[562]:

| | value | cpi_pct | pca_0 | pca_1 | pca_2 | pca_3 | pca_4 | pca_5 | pca_6 | pca_7 | ... | pc |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 497.00000 | 497.00000 | 497.00000 | 497.00000 | 497.00000 | 497.00000 | 497.00000 | 497.00000 | 497.00000 | 497.00000 | ... | 497. |
| **mean** | 159.05416 | 0.00318 | 0.00000 | 0.00000 | -0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | -0.00000 | ... | -0 |
| **std** | 71.18925 | 0.00333 | 1.00101 | 1.00101 | 1.00101 | 1.00101 | 1.00101 | 1.00101 | 1.00101 | 1.00101 | ... | 1. |
| **min** | 39.60000 | -0.01786 | -2.23113 | -4.58016 | -5.69774 | -4.37224 | -3.40061 | -7.04036 | -4.71155 | -10.14257 | ... | -3 |
| **25%** | 102.60000 | 0.00155 | -0.54973 | -0.43762 | -0.39999 | -0.54432 | -0.50946 | -0.37036 | -0.46537 | -0.31478 | ... | -0 |
| **50%** | 160.40000 | 0.00266 | -0.03488 | 0.10455 | -0.11471 | -0.06618 | -0.08679 | 0.07341 | 0.01316 | 0.05726 | ... | -0 |
| **75%** | 219.03500 | 0.00461 | 0.74023 | 0.43058 | 0.30893 | 0.43021 | 0.38208 | 0.49974 | 0.54475 | 0.37001 | ... | 0. |
| **max** | 307.91700 | 0.01794 | 4.28283 | 6.33547 | 7.19177 | 10.35691 | 8.86237 | 8.57933 | 6.82601 | 10.24010 | ... | 3. |

8 rows × 198 columns

In [563]:

```
# dont look at test data! its cheating
# pca_test_df.describe()
```

In [564]:

```
pca_components = pd.DataFrame(pca.components_, index=pca.feature_names_in_, columns=[f'p
ca_{i}' for i in range(pca.components_.shape[1])])
pca_components.to_csv('pca_components.csv', index=False)
```

In [565]:

```
pca_components.iloc[:, :5]
```

Out[565]:

| | pca_0 | pca_1 | pca_2 | pca_3 | pca_4 |
|---|---|---|---|---|---|
| **month** | 7.400279e-03 | -0.002813 | 0.002813 | -1.233000e-01 | -2.307301e-02 |
| **jan-sep** | -8.841350e-03 | 0.006560 | -0.006560 | -5.353674e-02 | -6.266447e-02 |
| **oct-dec** | 1.015460e-02 | 0.005552 | -0.005552 | 5.223964e-02 | 1.079565e-01 |
| **cpi_lag1** | -2.590817e-02 | 0.039726 | -0.039726 | 1.005350e-01 | 7.094441e-02 |
| **cpi_3ema** | 2.296947e-02 | -0.030689 | 0.030689 | -1.143760e-02 | -6.420835e-02 |
| **...** | ... | ... | ... | ... | ... |
| **gdp_9m_pct** | -2.124664e-04 | 0.000059 | -0.000059 | -1.991705e-02 | 4.343115e-04 |
| **gdp_3m_pct_6m_lag** | 1.520238e-04 | 0.000152 | -0.000152 | -1.624799e-02 | 8.874425e-03 |
| **gdp_9m_pct_9m_lag** | -2.944374e-04 | -0.000283 | 0.000283 | 8.630484e-02 | -8.427119e-03 |
| **gdp_24ma** | -6.043687e-05 | 0.000033 | -0.000033 | 3.336930e-02 | -4.450654e-03 |
| **gdp_raw** | 2.940521e-15 | 0.707107 | 0.707107 | -4.725803e-15 | 3.595591e-16 |

196 rows × 5 columns

In [168]:

```
train_data = pd.read_csv('datasets/train_set.csv')
train_data['cpi_month'] = pd.to_datetime(train_data['cpi_month'])
train_data['test'] = False
```

```
test_data = pd.read_csv('datasets/test_set.csv')
test_data['cpi_month'] = pd.to_datetime(test_data['cpi_month'])
test_data['test'] = True

data_joined = pd.concat([train_data, test_data]).reset_index(drop=True)


whole_set = pd.read_pickle('datasets/final_dataset_2023-12-18.pkl').loc[:, :'cpi_pct']


whole_set['pred_month'] = whole_set.index
whole_set.reset_index(drop=True, inplace=True)
```

In [169]:

```
whole_set = whole_set.merge(data_joined.drop(['value', 'cpi_pct'], axis=1), how='left',
left_on='cpi_month', right_on='cpi_month').set_index('pred_month')
```

In [170]:

```
last_column_name = whole_set.columns[-1]
whole_set = pd.concat([whole_set[last_column_name], whole_set.drop(last_column_name, axi
s=1)], axis=1)
```

In [171]:

```
whole_set.to_pickle('datasets/whole_dataset.pkl')
```