The US Inflation Phenomenon | It’s Oil, silly

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1.0 Problem Identification Overview

The United States Consumer Price Index (**"Inflation"**) is calculated by the U.S. Bureau of Labor Statistics. It has gone through various periods of prominent increases; notably in the 1920's, 1940's, & 1970's. Otherwise, it has remained relatively constant or declining.

Inflation is important in all facets of life but the financial world pays special attention to it as the key objectives of the Federal Reserve are maximizing employment, stabilizing prices & moderating long-term interest rates; the second of which is Inflation & the third of which is generally decided by the condition of the other two (2). Their decisions can move financial markets around the world; we won't go into that here. In short, **Inflation is an important component of developing investment strategies for portfolios across the world**. **The view on inflation becoming positive or negative is not agreed upon nor are the variables which influence it**.

The purpose of this Data Science project is to develop a model to understand the phenomenon of Inflation. **Nineteen (19) variables ("Variables") were shortlisted to determine their influence on Inflation**; Appendix I.

2.0 Generated Deliverables

The following Application Programming Interface's ("API") were used to pull the relevant data:

1. Quandl
2. Investing.com ("Investpy")
3. Federal Reserve Economic Data ("FRED")

The data retrieved by the API's & respective websites **are from sources highlighted in Appendix I**.

With this, **three (3) deliverables were generated**:

1. The source code for the modeling developed to analyze the aforementioned problem (link)
2. This document outlining the process
3. A PDF presentation with our findings (link)

3.0 Data Pre-Processing Steps

Data Cleaning:

1. The data for the Variables & Inflation were first pulled using the API's
2. The result, however, produced a data frame with non-congruent lengths in time (Appendix II)
3. It was required to draw the line at the 18 April 1990 to ensure they aligned appropriately (Appendix II)
4. The resulting data frame was fully comprised of 9,752 non-null float values
5. The Variables were concatenated with Inflation using a Forward Fill technique as their reporting schedules did not align. This resulted in a Daily (Mon-Fri (excluding holidays)) data frame with 321 observations (Appendix II)
6. This data frame was used to cross reference the accuracy of the next steps in Exploratory Data Analysis

Exploratory Data Analysis:

Which time periods for percent changes to use wasn't confirmed for the Variables & Inflation. The first step was to **run through the process on multiple configurations with Winsorization on Inflation** as per below:

1. **Quarter-on-Quarter**
   a. **Description** | Looking at Quarterly percent change in both Variables & Inflation
   b. **Inflation Winsorization** | +3% & -2%
   c. **Average Pearson Coefficient** | 22.64%
2. **Month-on-Month**
   a. **Description** | Looking at Monthly percent change in both Variables & Inflation
   b. **Inflation Winsorization** | ±1%
   c. **Average Pearson Coefficient** | 18.22%
3. **Quarter-on-Quarter for Variables (past) & Inflation (forwards)**
   a. **Description** | Looking at Quarterly percent change on Variables looking backwards while a forward looking Quarterly change on Inflation to ascertain if changes in the Variables took time to reach Inflation
   b. **Inflation Winsorization** | +2.51% & -2.84%
   c. **Average Pearson Coefficient** | 12.18%
4. **Quarter-on-Quarter w/ Rolling Averages on Daily, Weekly & Monthly Variables**
   a. **Description** | This approach is similar to # 1 (looking at the Quarterly percent change on both Variables & Inflation) albeit used a rolling average for those that reported more often than once a Quarter. The rational was that a Variable may have had a bad week or day when the Quarter ended; as such, the entire changes throughout the Quarter may need to be accounted for evenly
   b. **Inflation Winsorization** | ±3%
   c. **Average Pearson Coefficient** | 30.21%

It was also observed that Winsorization on Inflation in #4 above (Best) reduced the average Pearson Coefficient score. The results before Winsorization are below:

5. **Quarter-on-Quarter w/ Rolling Averages (without Inflation Winsorized)**
   a. **Description** | Same as #4 above less Winsorization on Inflation
   b. **Inflation Winsorization** | n/a
   c. **Average Pearson Coefficient** | 30.95%

It was decided that Winsorization did not work on the Inflation data herein; thus, Inflation was not Winsorized & this data frame was chosen to move on.

While Winsorization may not work on Inflation, that does not mean it doesn't work on the Variables. Eight (8) variables were chosen to be Winsorized. These saw an average increase in their Pearson correlation coefficients of 173 bps with one seeing a 460 bps increase. Our final round presented the following:

6. **Quarter-on-Quarter w/ Rolling Averages (without Inflation Winsorized & 8 Variables Winsorized)**
   a. **Description** | Same as #5 above but 8 variables Winsorized
   b. **Inflation Winsorization** | n/a
   c. **Average Pearson Coefficient** | 31.67%

	NoWinzor_p	Win_p	Win_plus	Winsorized?
Wage CPI	0.595358	0.595358	0.000000	n/a
WTI	0.540347	0.541041	0.000694	Winsorized
Heating Oil	0.542445	0.542445	0.000000	n/a
Copper	0.372813	0.372813	0.000000	n/a
Sugar	0.219235	0.220639	0.001405	Winsorized
Natural Gas	0.289579	0.292725	0.003146	Winsorized
Cattle	0.162077	0.162077	0.000000	n/a
Lean Hogs	0.291943	0.291943	0.000000	n/a
Soybeans	0.199634	0.199634	0.000000	n/a
Lumber	0.255493	0.255685	0.000191	Winsorized
Capacity Utilization	0.349075	0.367072	0.017997	Winsorized
Corn	0.293481	0.293481	0.000000	n/a
M2 Velocity	0.281344	0.281344	0.000000	n/a
GDP	0.343129	0.387090	0.043961	Winsorized
Wheat	0.125293	0.125293	0.000000	n/a
PMI	0.223222	0.223222	0.000000	n/a
USD Index	0.307158	0.307158	0.000000	n/a
Unemployment Rate	0.215974	0.261978	0.046005	Winsorized
Initial Jobless Claims	0.272464	0.297205	0.024741	Winsorized

The "Win_plus" column in the chart on the right, shows each of the variables improvement with Winsorization. If it's a Zero, the Variable wasn't chosen.

The **Feature Correlation Heat Maps with the Pearson correlation coefficients of each variable against Inflation are found in Appendix III;** these go into greater detail on the Average Pearson Coefficient (c) above. Scatter Plots for those Winsorized are in Appendix IV; all others are in the source code.

In summary, **the Best Configuration** (**#6**) **was chosen as it presented the most optimal Pearson correlation coefficients to achieve our goal of developing a model to understand the phenomenon of Inflation.**

Pre-processing:

1. The first step in pre-processing, per the Machine Learning process, was to create a "Best Guess" number. The standard mean & DummyRegressor functions were used. The data frame has no categorical data so **this step** was purely to "go through the process" but **is irrelevant**; **please disregard when reading the source code**
2. The next step was to **split the data into training & testing data frames, 70% & 30% respectively**
3. Next was to **scale the data**. **There is no certainty to which scaling technique to use** & thus, **the following were all applied on both the X & y variables & X only** (x6 in total):
    a. Standard Scaling (SS)
    b. MinMax Scaling (MM)
    c. Log Transformation (LG)
4. **The Variables were divided into selected groups to apply SS, MM & LG separately to where SS, MM & LG may be better suited**; they were merged with Inflation
5. The **initial results** (Appendix V) showed that MM presented negative results for R^2 on the test set. The Mean Absolute Error (MAE) & the Mean Squared Error (MSE) presented a mix bag for the MM structure. It was decided that due to this relative uncertainty & negative R^2, the MM structure was taken out of consideration.
6. Five (5) scaling approaches were used & it was determined that all showed results that should be put to the process of the Random Forest Generator to identify the best Variables presented below & in Appendix VI.

```
R² results for X & y scaled below
SS Train | 0.5055   Test 0.2962
LG Train | 0.4983   Test 0.2781

R² results for X only scaled below
SS Train | 0.5133   Test 0.2925
LG Train | 0.5005   Test 0.2732

R² results for the LG & SS combination below
SS Train | 0.5053   Test 0.2788
```

4.0 Model Description

Although Dummy Regressor & Linear Regression analysis was undertaken, they were discounted due to the data frame being entirely float based & displayed comparatively worse performance respectively. Therefore, **the Random Forest Model was used with the goal of determining what variables best explain Inflation**.

5.0 Model Findings

As the purpose of this Data Science project is to develop a model to explain & understand the phenomenon of Inflation, **the following process was undertaken on the five (5) shortlisted scaling approaches**:

1. Grid Search
2. Random Forest
3. Hyperparameter search using Grid Search CV

The final outcomes can be seen in [Appendix VII].

WTI held a ubiquitous position as being the dominate Variable on all scaling approaches. **This may be justified due to its connection with just about all activity in the United States**; whether it be plowing a field for grains, transporting the grains to a factory to make bread & then transporting the bread to a shopping center for example. Heating Oil, a byproduct using WTI, & Wages CPI stayed in second & third place on many respectively.

Nevertheless, they weren't the only ones helping improve the k-value. The total number of variables ranged from 9 to 11 & the breakdown is in [Appendix VII] for review.

The variables that were not helping were then removed & the process was run the last time. The results are below:

```
R² results for X & y scaled below
SS Train | 0.492    Test 0.2706
LG Train | 0.4682   Test 0.2862

R² results for X only scaled below
SS Train | 0.492    Test 0.2734
LG Train | 0.7563   Test 0.6524

R² results for the LG & SS combination below
SS Train | 0.4776   Test 0.2918
```

```
MAE results for X & y scaled below
SS Train | 0.5143   Test 0.6133
LG Train | 0.5261   Test 0.5955

MAE results for X only scaled below
SS Train | 0.4526   Test 0.6034
LG Train | 0.2229   Test 0.294

MAE results for the LG & SS combination below
SS Train | 0.2229   Test 0.294
```

```
MSE results for X & y scaled below
SS Train | 0.508    Test 0.6776
LG Train | 0.5318   Test 0.6676

MSE results for X only scaled below
SS Train | 0.3933   Test 0.675
LG Train | 0.1886   Test 0.3251

MSE results for the LG & SS combination below
SS Train | 0.1886   Test 0.3251
```

After review of the **Test set results** (**the arbiter**), the **LG on X only was chosen** amongst the other scaling approaches **given it had the highest R² & lowest MAE & MSE**.

So **how do these test results compare to those presented in the Pre-processing step?**

```
Comparing final to the averages in the Pre-processing Step

 37.92 bps increase in R²

 A -23.52 bps decrease in MAE

 A -19.76 bps decrease in MSE
```

Our conclusion on how to explain & understand the phenomenon of Inflation is a reconfiguration of words used by James Carville ([link]) | **It's Oil, silly**.

6.0 Next Steps

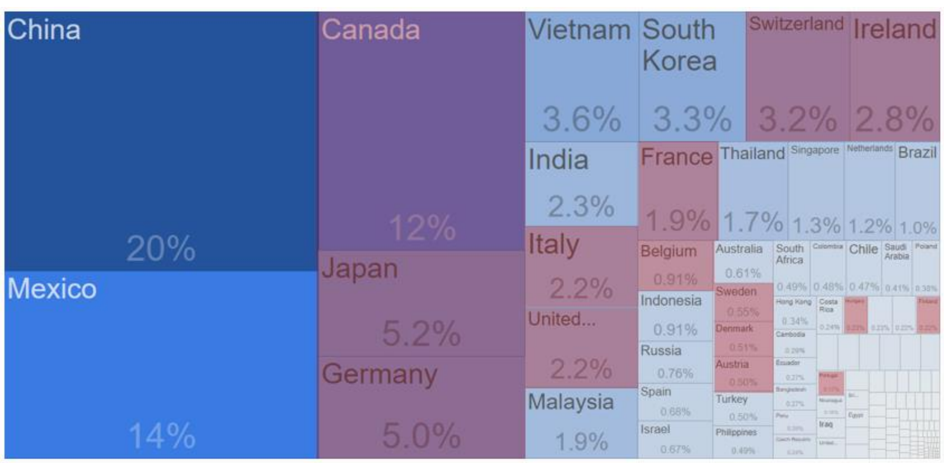
Inflation is a difficult & highly disputed financial beast but the closer you get to taming it, your eyes will open wider.

Throughout the process there were a number of actions & variables that may have been done or included. **Highlighted below are some Variables which were not included** due to financial & time constraints:

1. Steel
   - Could only identify data back to 2008
2. Gasoline
   - Could only identify data back to 2005
3. Growth of M2
   - Put it aside to mitigate any collinearity with M2 Velocity
4. US Wages Hourly Earnings
   - Limited data as well
5. US Dollar Index: Broad, Goods and Services
   - This only goes back to 2006

Further to these, **further consideration may be applicable to the below**:

1. The big set back would be the size of the data frame. With only 321 observations, machine learning is limited
2. Winsorization on Inflation & other variables may be re-examined
3. Reassess the Variables chosen in the SS & LG divide; discussed in Pre-processing above
4. Develop a model to predict Wages CPI itself in order to minimize reliance on US gov't reporting
5. It is believed that the US Dollar Index Variable (DXY) does not correctly address the relationship of US Imports on Inflation. This may be because the DXY's weighting does not correctly align to US trade. In short, it's a weighted geometric mean of the currencies in the Eurozone (EUR), Japan (JPY), the United Kingdom (GBP), Canada (CAD), Sweden (SEK) & Switzerland (CHF) but that does not correctly align with US trade with the world
   - Highlighted below is the US Import Trade in 2020 by country; in red are those in the DXY
   - It only accounts for under ~40%



There are a number of Variables to take into consideration. **For now the machine recommends keeping an eye on Oil.**

Appendix I

Items	Reported	API	API Source	Comments
Inflation	Monthly	Quandl	U.S. Bureau of Labor Statistics	The target variable
Wages CPI	Monthly	FRED	U.S. Bureau of Labor Statistics	A component of the target variable
WTI	Daily	Quandl	CME	West Texas Intermediate - One of many commodities
Heating Oil	Daily	Investpy	Investing.com	One of many commodities
Copper	Daily	Investpy	Investing.com	One of many commodities
Sugar	Daily	Investpy	Investing.com	One of many commodities
Natural Gas	Daily	Investpy	Investing.com	One of many commodities
Cattle	Daily	Investpy	Investing.com	One of many commodities
Lean Hogs	Daily	Investpy	Investing.com	One of many commodities
Soybeans	Daily	Investpy	Investing.com	One of many commodities
Lumber	Daily	Investpy	Investing.com	One of many commodities
Capacity Utilization	Monthly	FRED	Board of Governors of the Federal Reserve	The % of resources used by corporations
Corn	Daily	Investpy	Investing.com	One of many commodities
M2 Velocity	Quarterly	FRED	Federal Reserve Bank of St. Louis	Movement of money; state of the economy proxy
GDP	Quarterly	FRED	U.S. Bureau of Economic Analysis	A proxy for the state of the economy
Wheat	Daily	Investpy	Investing.com	One of many commodities
PMI	Monthly	Quandl	Institute of Supply Management	Manufacturing PMI - A proxy for the economy
USD Index	Daily	Quandl	Intercontinental Exchange Inc	(DXY) Proxy for potentially importing inflation
Unemployment Rate	Monthly	Quandl	U.S. Bureau of Labor Statistics	A proxy for the state of the economy
Initial Jobless Claims	Weekly	Quandl	U.S. Employment and Training Administration	A proxy for the state of the economy

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Appendix II

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 14302 entries, 1946-01-01 to 2021-09-03
Data columns (total 19 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Wage CPI                 14293 non-null  float64
 1   WTI                      12088 non-null  float64
 2   Heating Oil              13087 non-null  float64
 3   Copper                   10440 non-null  float64
 4   Sugar                    13087 non-null  float64
 5   Natural Gas              9915 non-null   float64
 6   Cattle                   13084 non-null  float64
 7   Lean Hogs                13089 non-null  float64
 8   Soybeans                 9999 non-null   float64
 9   Lumber                   13089 non-null  float64
 10  Capacity Utilization     14033 non-null  float64
 11  Corn                     13086 non-null  float64
 12  M2 Velocity              14151 non-null  float64
 13  GDP                      14295 non-null  float64
 14  Wheat                    10001 non-null  float64
 15  PMI                      14281 non-null  float64
 16  USD Index                11273 non-null  float64
 17  Unemployment Rate        14281 non-null  float64
 18  Initial Jobless Claims   14030 non-null  float64
dtypes: float64(19)
memory usage: 2.2 MB
```

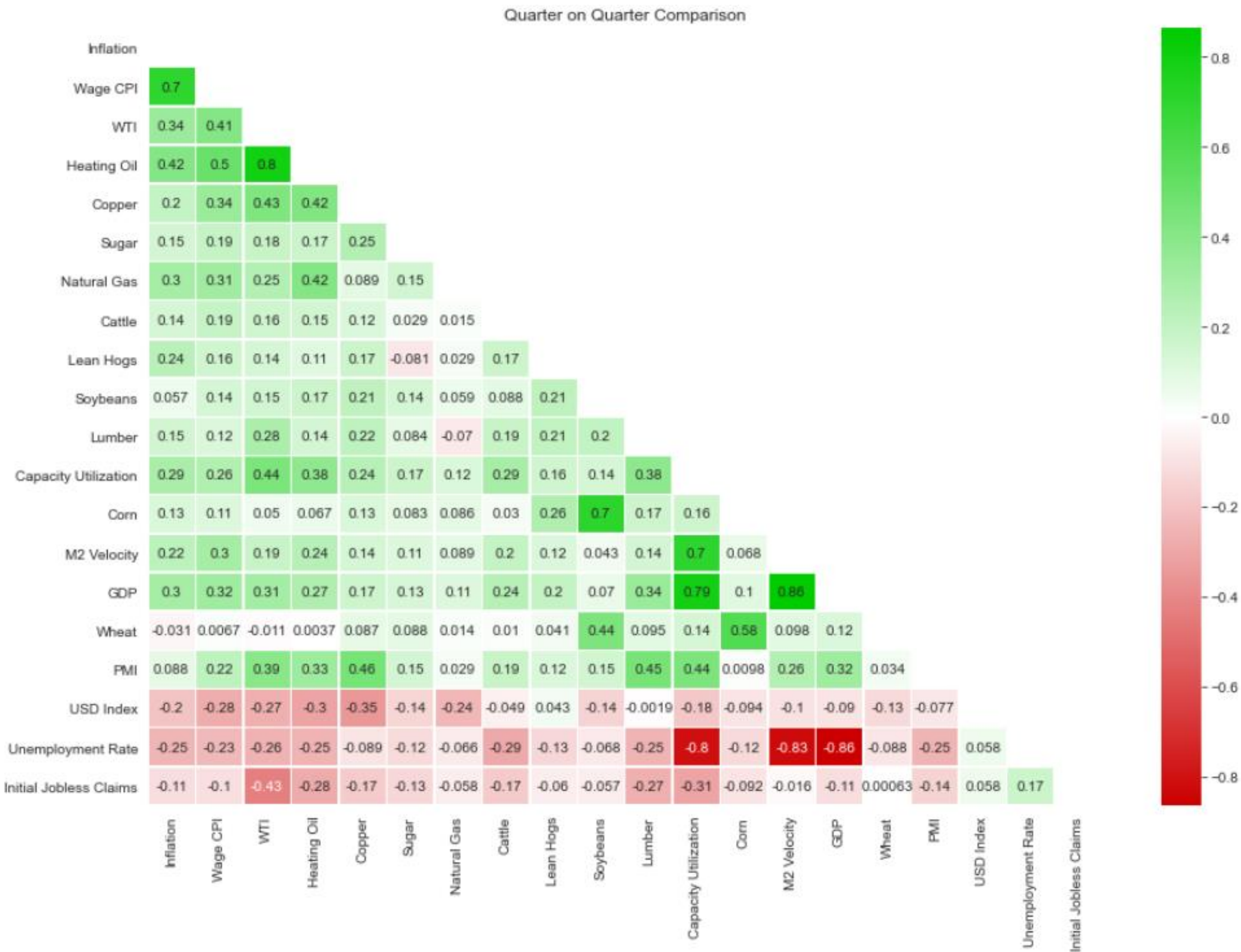
```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 9752 entries, 1991-04-18 to 2021-09-03
Data columns (total 19 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Wage CPI                 9752 non-null   float64
 1   WTI                      9752 non-null   float64
 2   Heating Oil              9752 non-null   float64
 3   Copper                   9752 non-null   float64
 4   Sugar                    9752 non-null   float64
 5   Natural Gas              9752 non-null   float64
 6   Cattle                   9752 non-null   float64
 7   Lean Hogs                9752 non-null   float64
 8   Soybeans                 9752 non-null   float64
 9   Lumber                   9752 non-null   float64
 10  Capacity Utilization     9752 non-null   float64
 11  Corn                     9752 non-null   float64
 12  M2 Velocity              9752 non-null   float64
 13  GDP                      9752 non-null   float64
 14  Wheat                    9752 non-null   float64
 15  PMI                      9752 non-null   float64
 16  USD Index                9752 non-null   float64
 17  Unemployment Rate        9752 non-null   float64
 18  Initial Jobless Claims   9752 non-null   float64
dtypes: float64(19)
memory usage: 1.5 MB
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 321 entries, 1991-04-30 to 2021-07-31
Data columns (total 20 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Inflation                321 non-null    float64
 1   Wage CPI                 321 non-null    float64
 2   WTI                      321 non-null    float64
 3   Heating Oil              321 non-null    float64
 4   Copper                   321 non-null    float64
 5   Sugar                    321 non-null    float64
 6   Natural Gas              321 non-null    float64
 7   Cattle                   321 non-null    float64
 8   Lean Hogs                321 non-null    float64
 9   Soybeans                 321 non-null    float64
 10  Lumber                   321 non-null    float64
 11  Capacity Utilization     321 non-null    float64
 12  Corn                     321 non-null    float64
 13  M2 Velocity              321 non-null    float64
 14  GDP                      321 non-null    float64
 15  Wheat                    321 non-null    float64
 16  PMI                      321 non-null    float64
 17  USD Index                321 non-null    float64
 18  Unemployment Rate        321 non-null    float64
 19  Initial Jobless Claims   321 non-null    float64
dtypes: float64(20)
memory usage: 52.7 KB
```

(back)

Appendix III (Feature Correlation Heatmap)

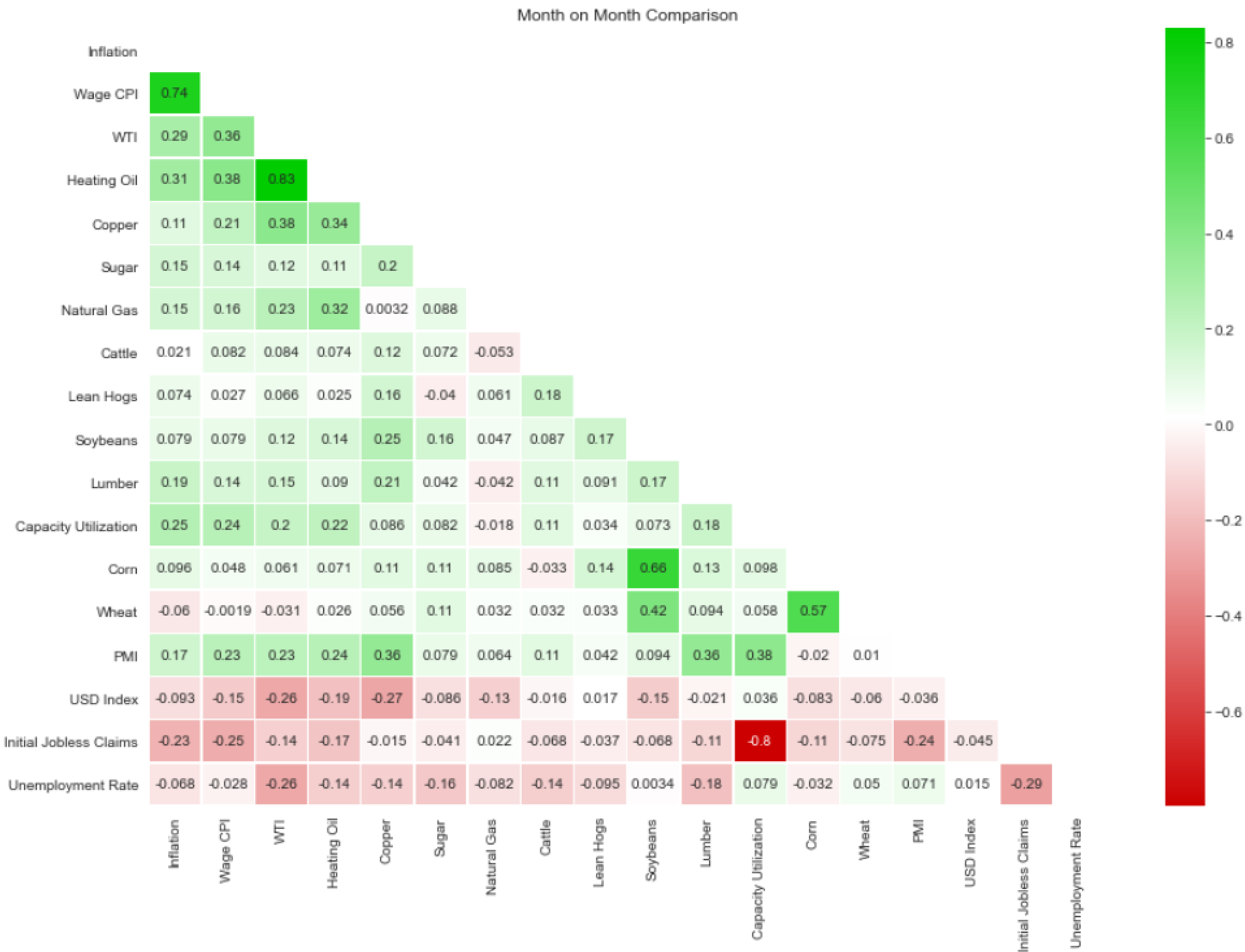
#1



(*back*)

Appendix III (Feature Correlation Heatmap)

#2



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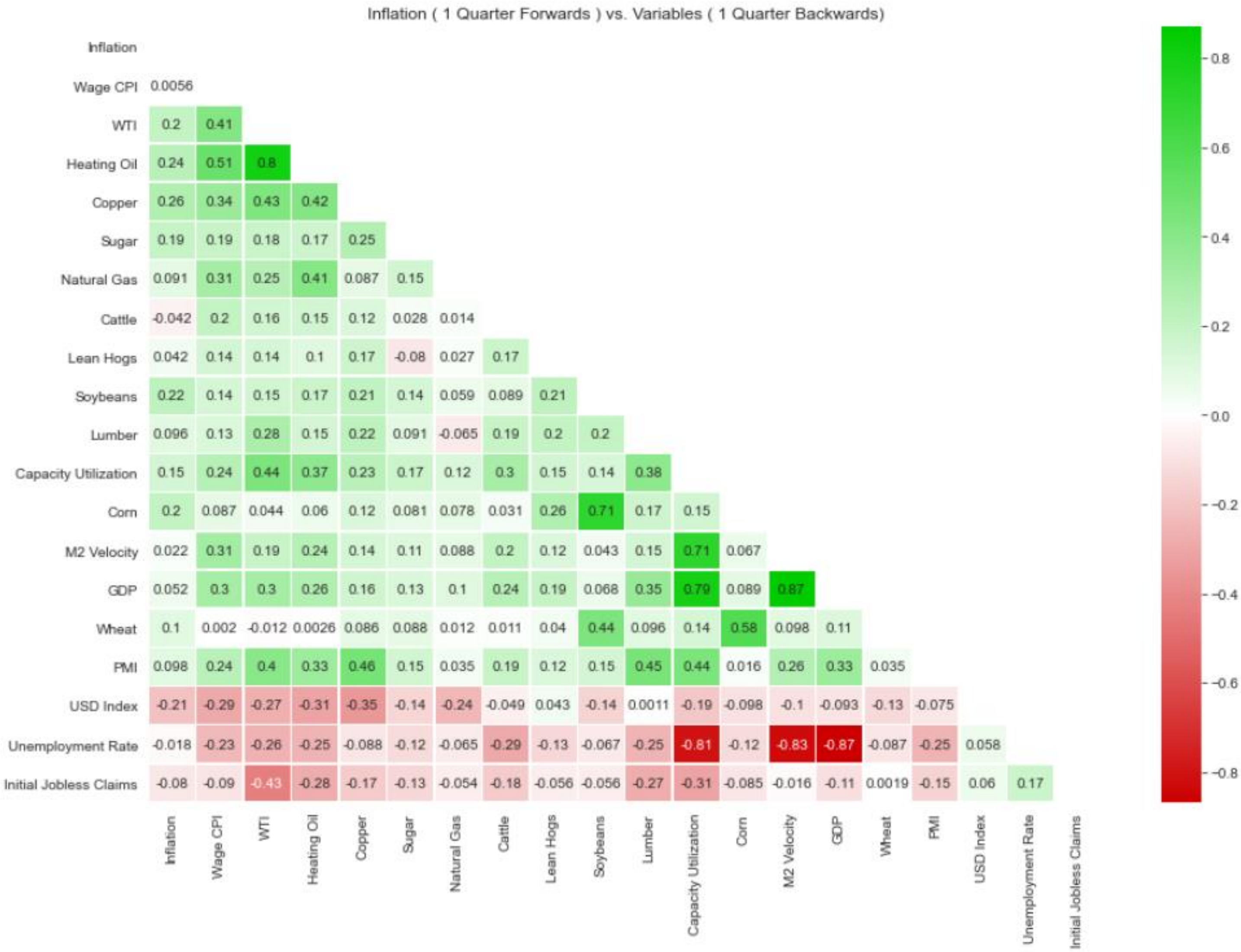
Appendix III (Feature Correlation Heatmap)

#3



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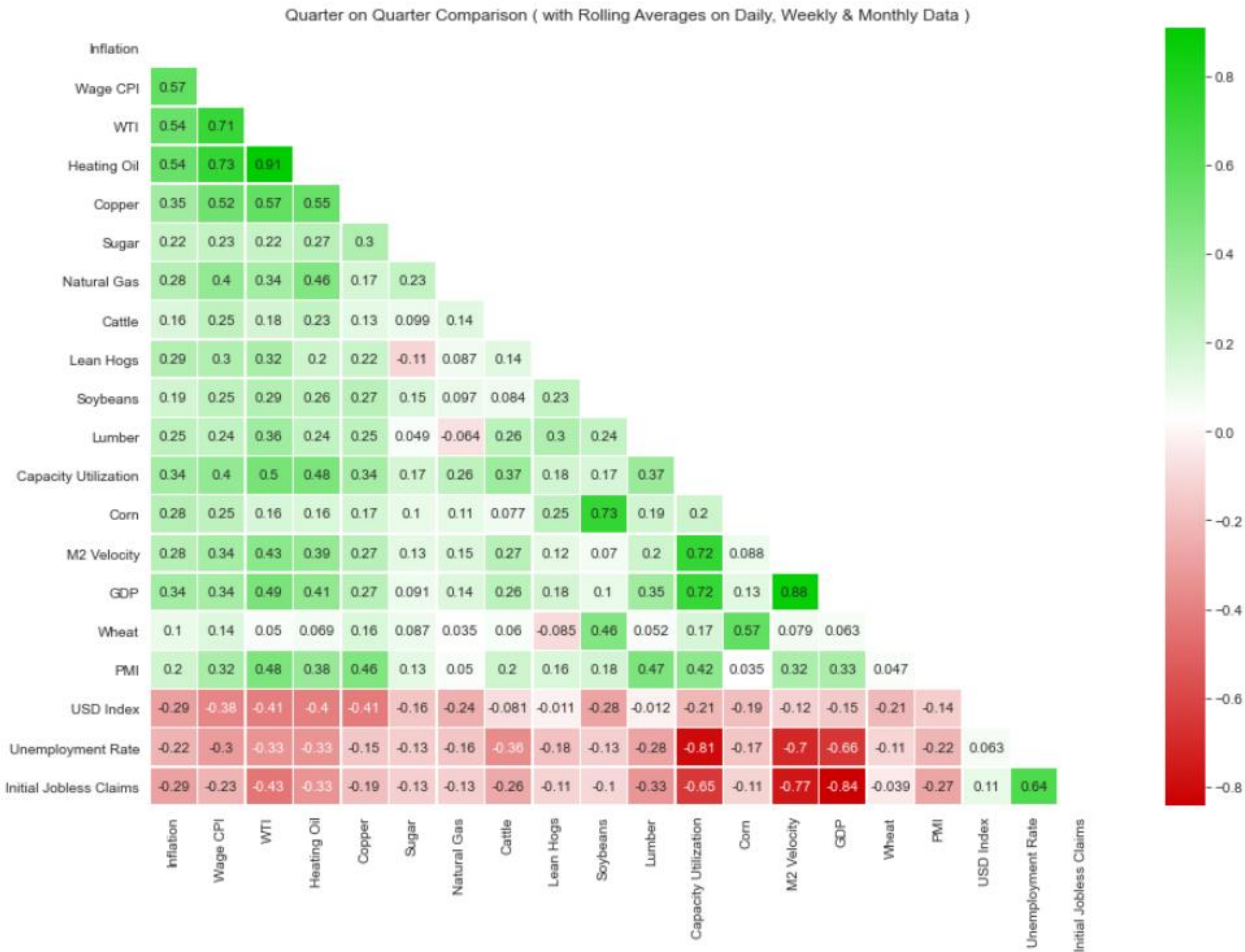
Appendix III (Feature Correlation Heatmap)

#4



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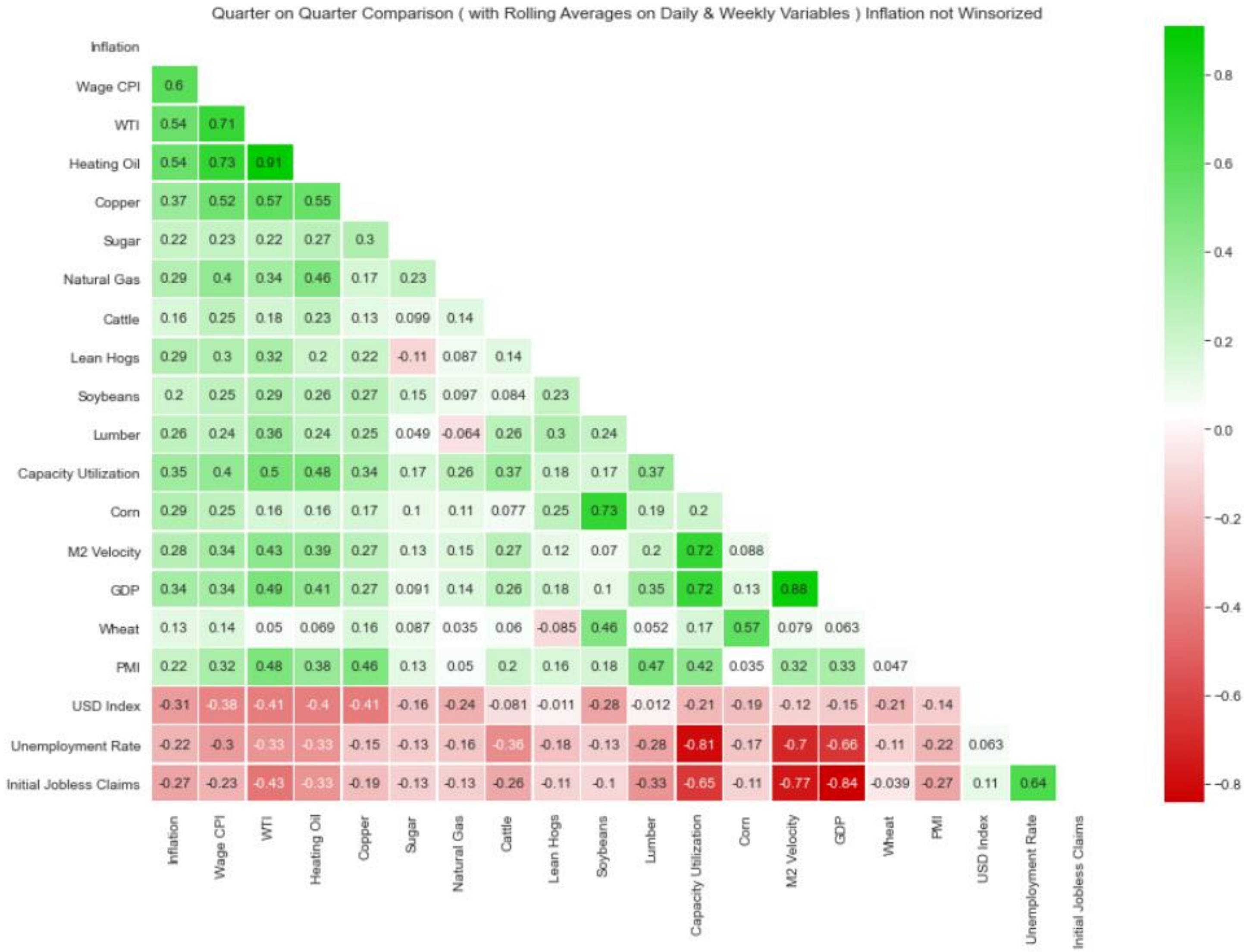
Appendix III (Feature Correlation Heatmap)

#5



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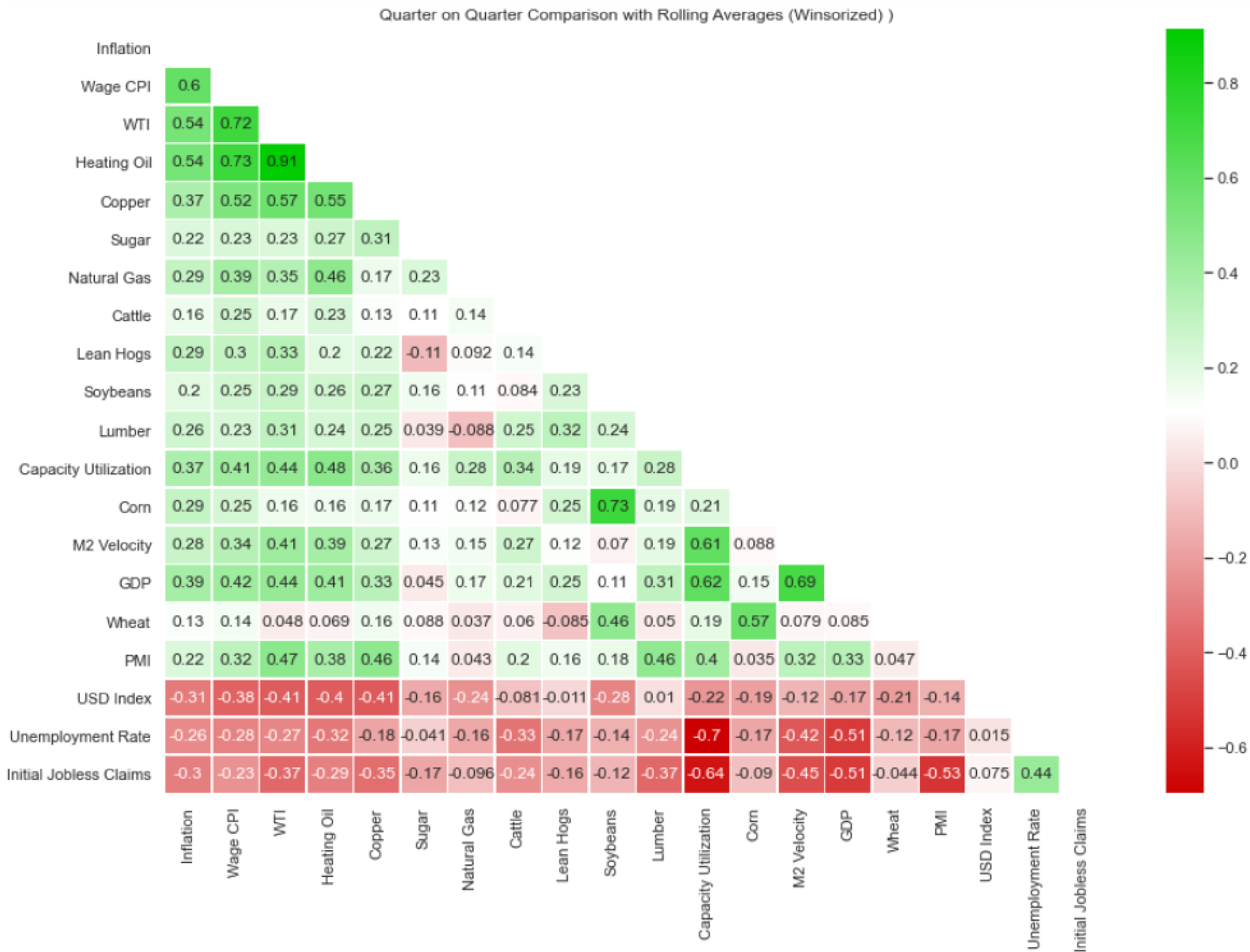
Appendix III (Feature Correlation Heatmap)

#6



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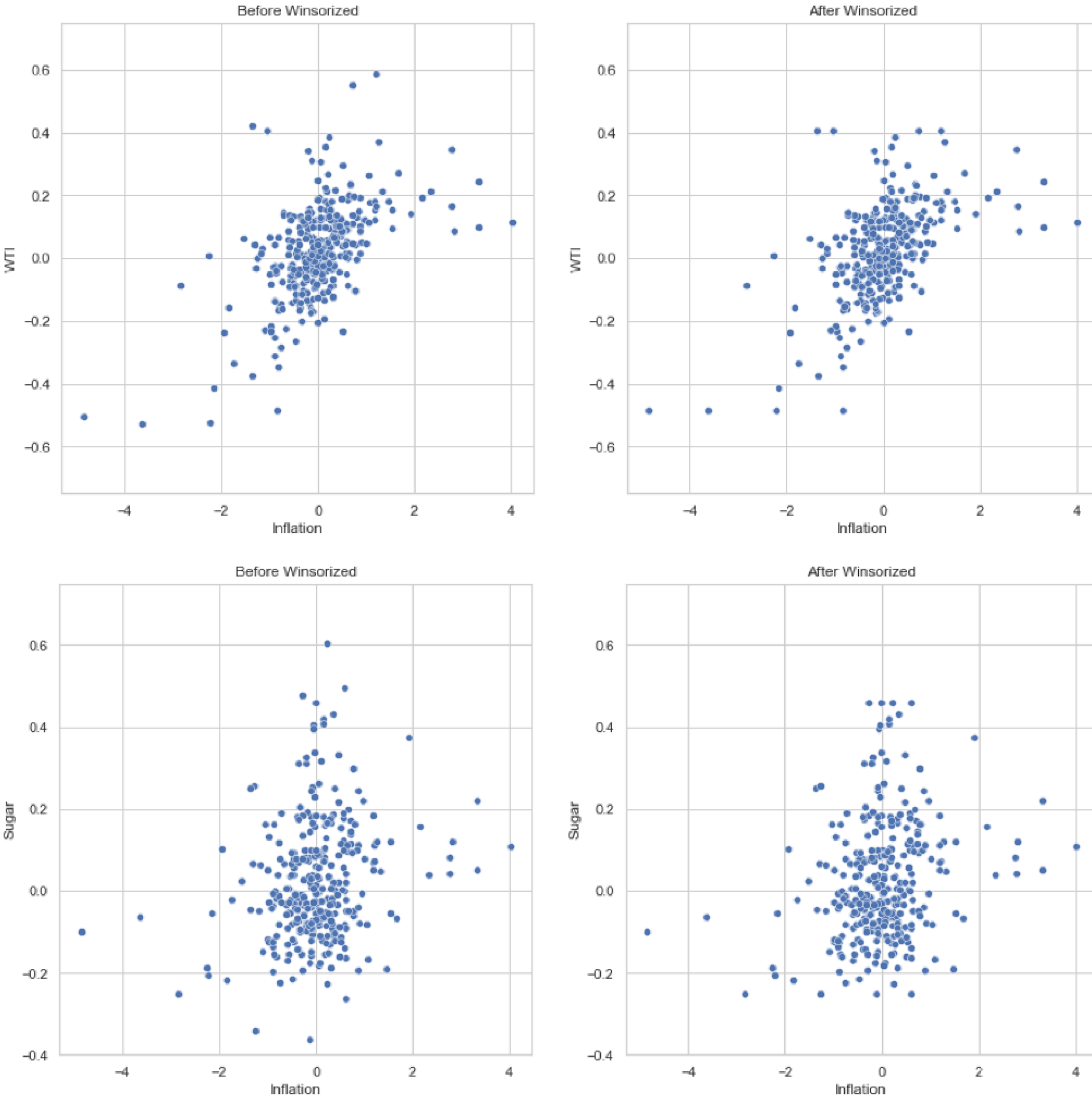
Appendix IV (Scatter Plots)



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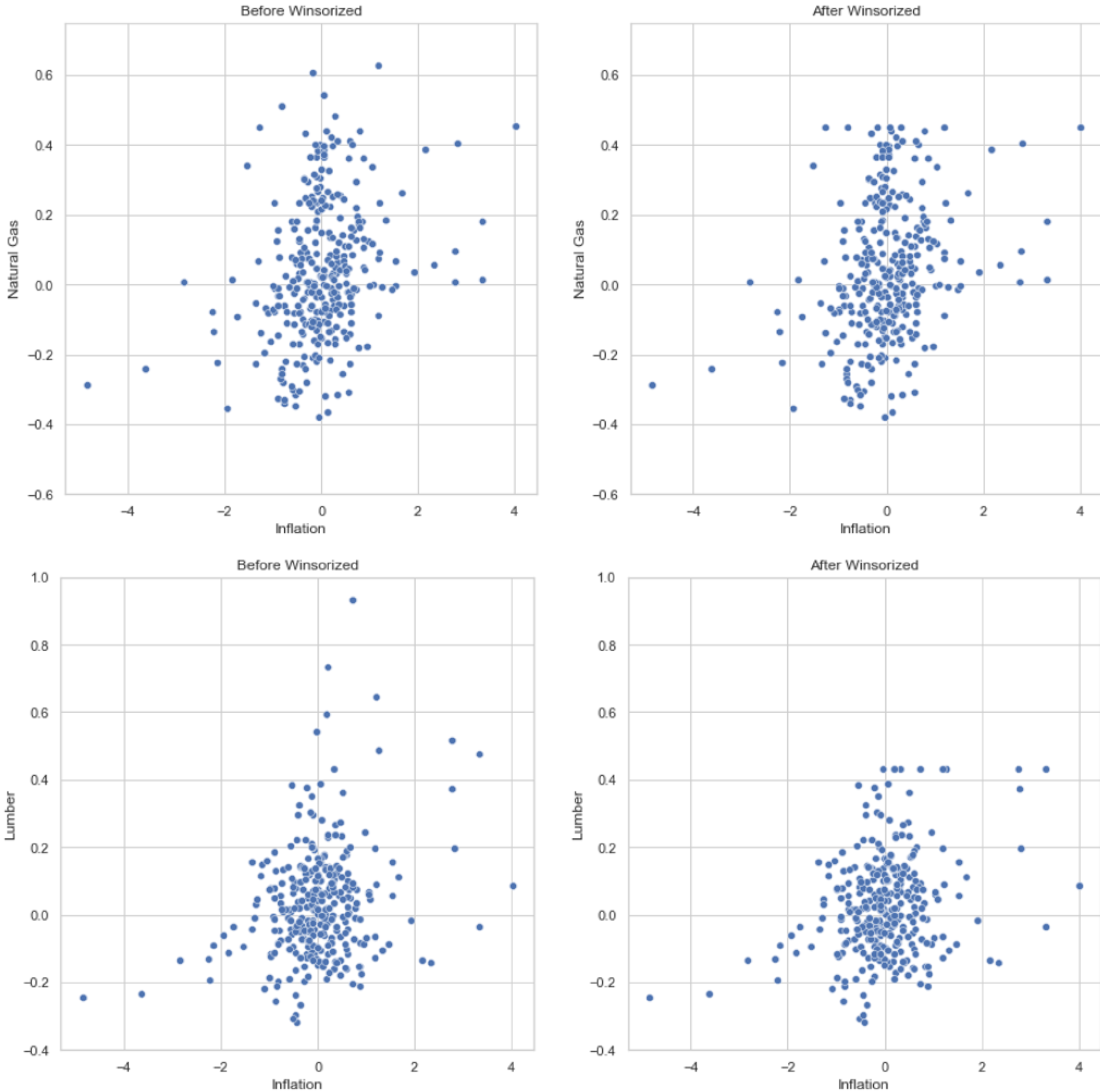
Appendix IV (Scatter Plots)



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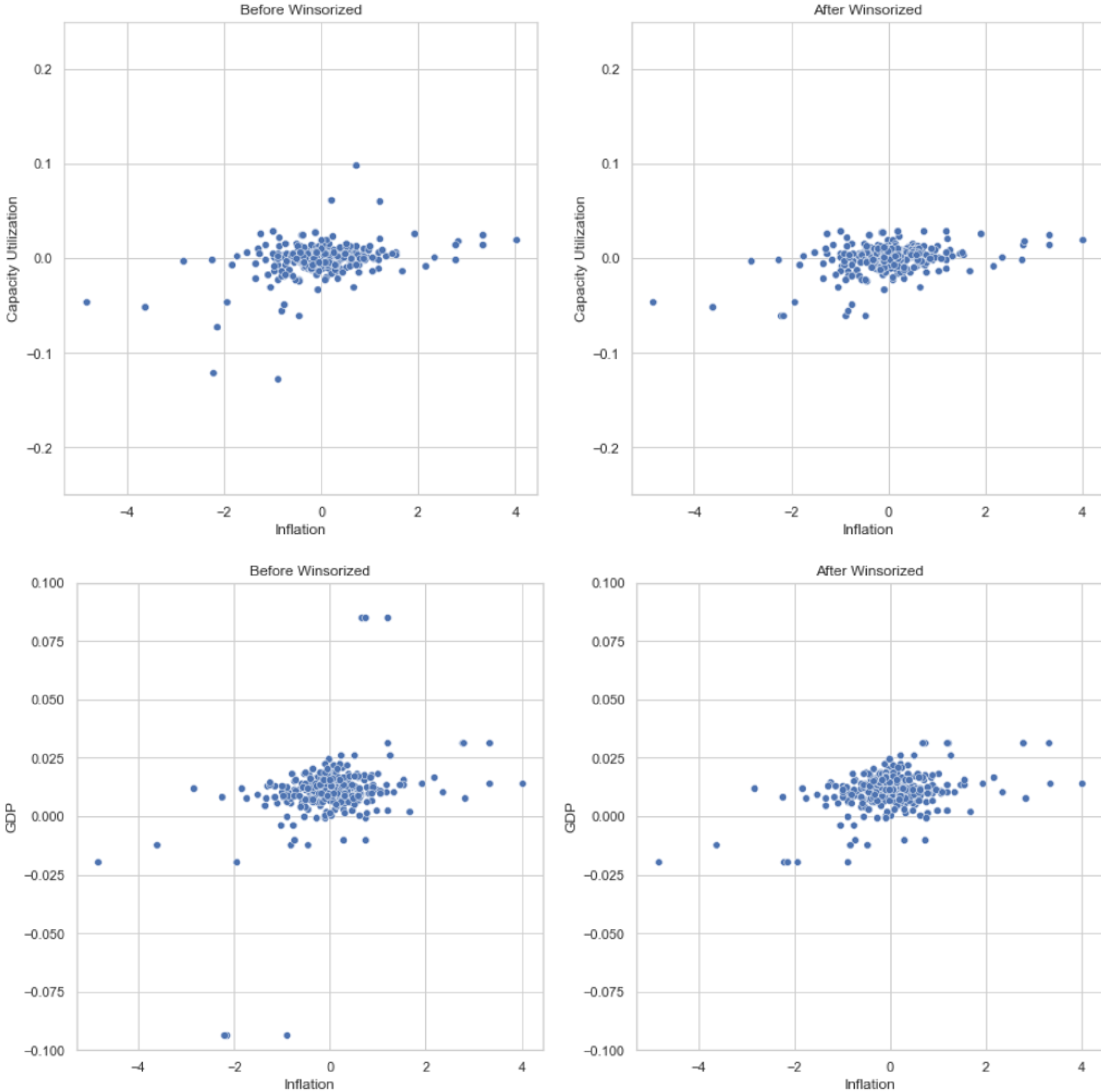
Appendix IV (Scatter Plots)



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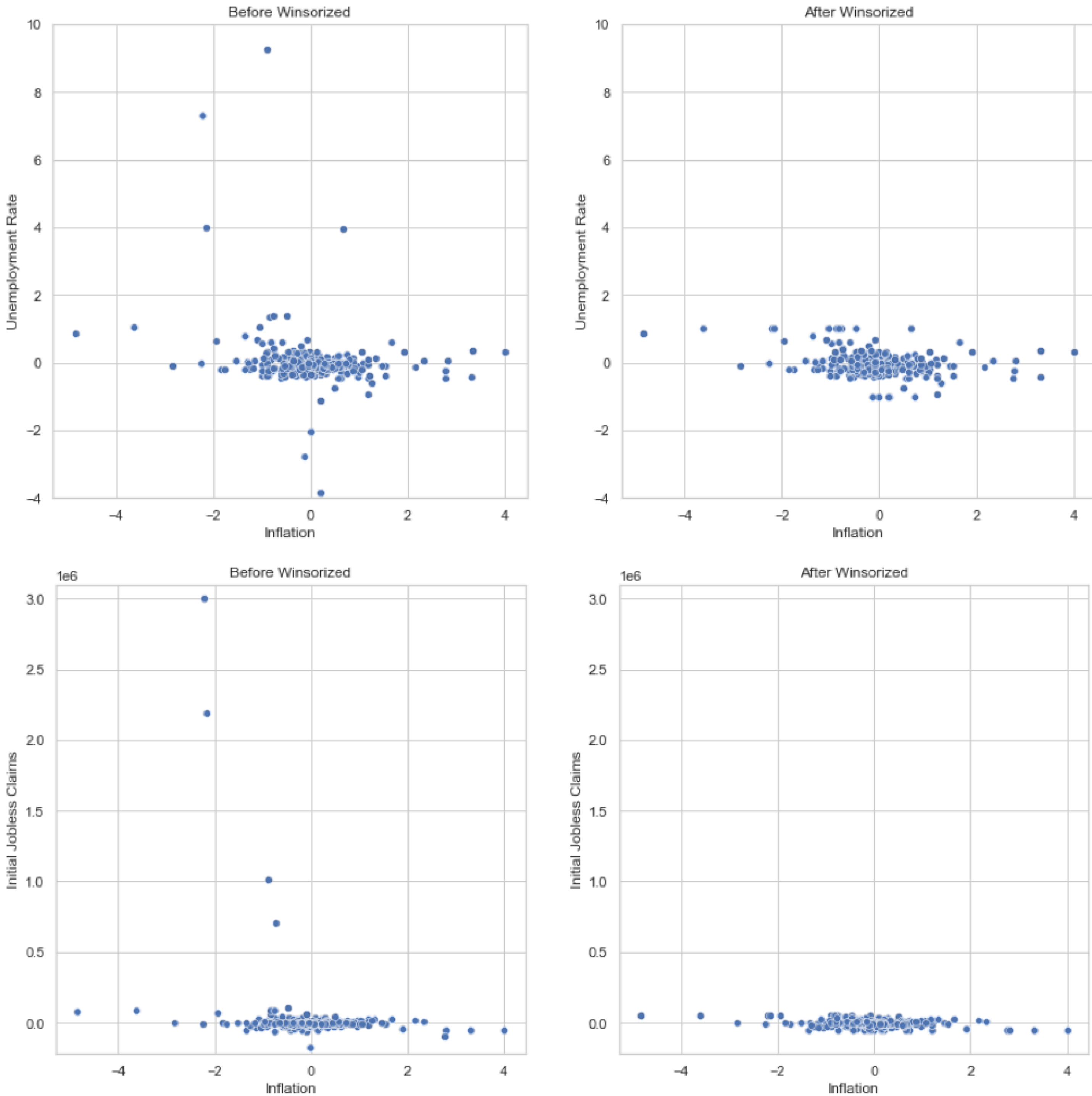
Appendix IV (Scatter Plots)



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Appendix V

```
R² results for nothing scaled below
                    Test 0.2925 ( nothing scaled )

R² results for X & y scaled below
SS Train | 0.5055   Test 0.2962
MM Train | -6.3454   Test -6.8587
LG Train | 0.4983   Test 0.2781

R² results for X only scaled below
SS Train | 0.5133   Test 0.2925
MM Train | 0.057  Test -0.042
LG Train | 0.5005   Test 0.2732


R² results for the LG & SS combination below
SS Train | 0.5053   Test 0.2788

R² averages of LG & SS X only scaled below
Av. Train | 0.5069   Test 0.2828
```

~~~~~~

```
MAE results for nothing scaled below
                    Test 0.5214 ( nothing scaled )

MAE results for X & y scaled below
SS Train | 0.5085   Test 0.5859
MM Train | 0.2581   Test 0.2538
LG Train | 0.5172   Test 0.603

MAE results for X only scaled below
SS Train | 0.4461   Test 0.5214
MM Train | 0.5971   Test 0.6354
LG Train | 0.4545   Test 0.5291


MAE results for the LG & SS combination below
SS Train | 0.4488   Test 0.5229

MAE averages of LG & SS X only scaled below
Av. Train | 0.4503  Test 0.5253
```

~~~~~~

```
MSE results for nothing scaled below
                    Test 0.7133 ( nothing scaled )

MSE results for X & y scaled below
SS Train | 0.4945   Test 0.6538
MM Train | 0.0726   Test 0.0721
LG Train | 0.5017   Test 0.6753

MSE results for X only scaled below
SS Train | 0.3768   Test 0.5089
MM Train | 0.7301   Test 0.7494
LG Train | 0.3867   Test 0.5227


MSE results for the LG & SS combination below
SS Train | 0.383   Test 0.5187

MSE averages of LG & SS X only scaled below
Av. Train | 0.3818  Test 0.5158
```

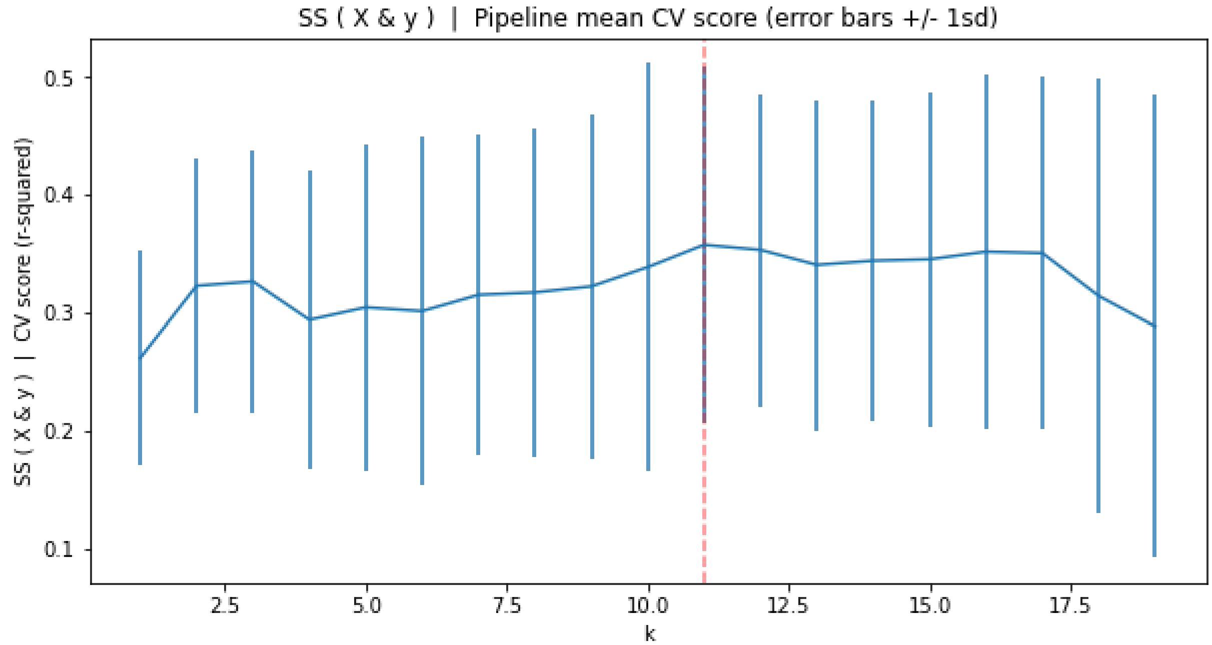
(back)

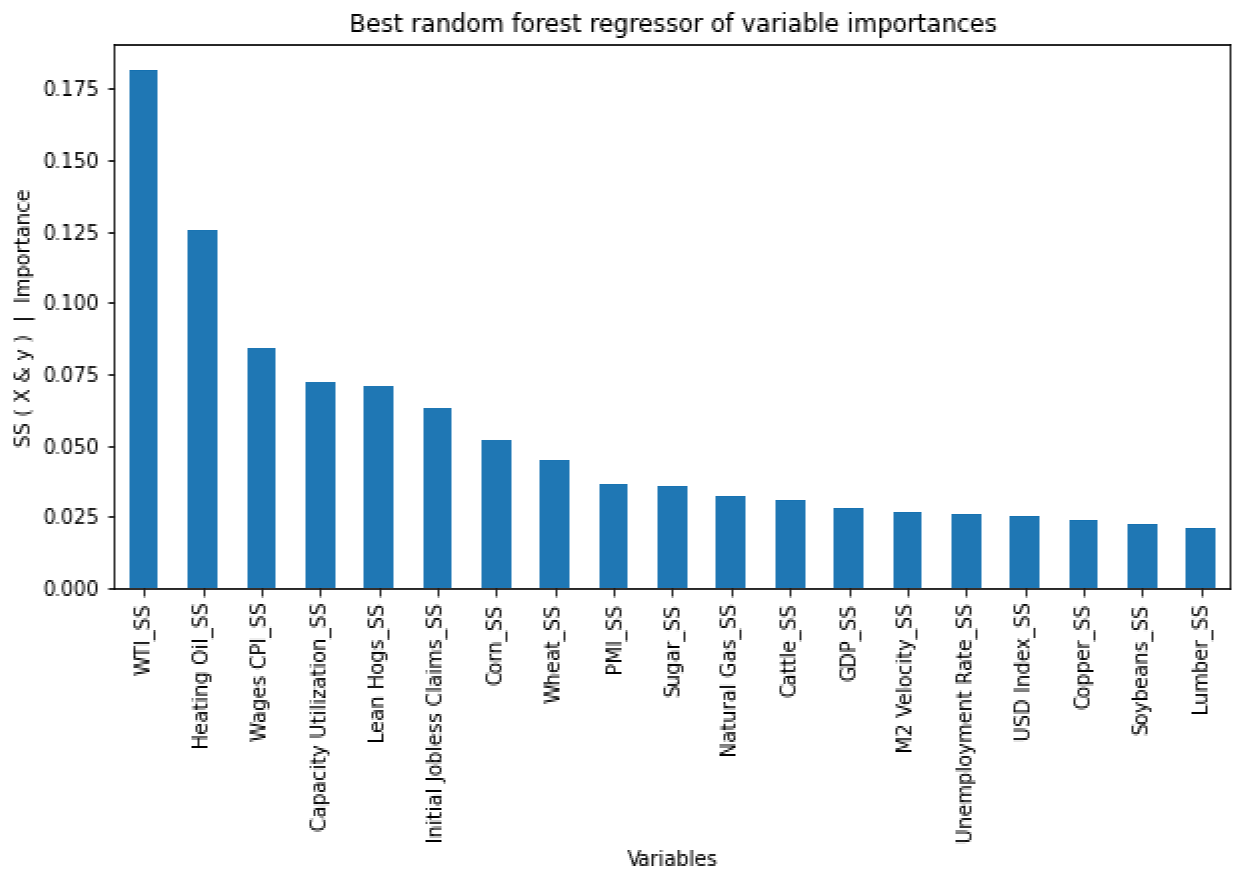
Appendix VI

```
R² results for X & y scaled below
SS Train | 0.5055   Test 0.2962
LG Train | 0.4983   Test 0.2781

R² results for X only scaled below
SS Train | 0.5133   Test 0.2925
LG Train | 0.5005   Test 0.2732

R² results for the LG & SS combination below
SS Train | 0.5053   Test 0.2788
```

(*back*)

Appendix VII





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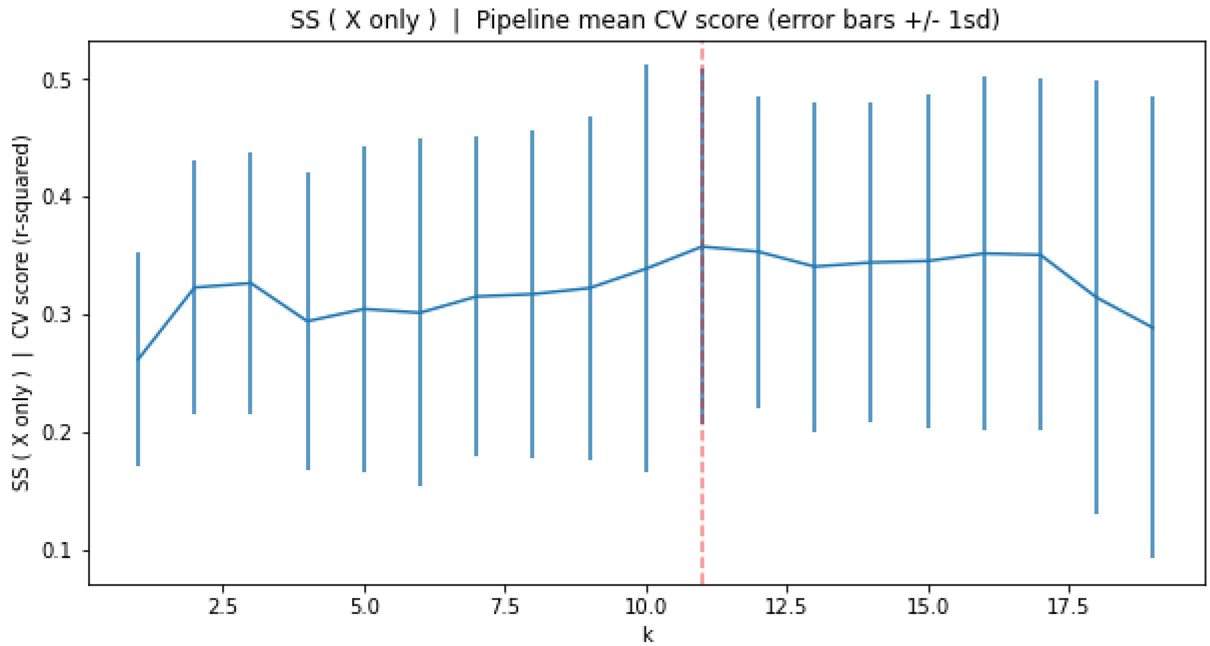
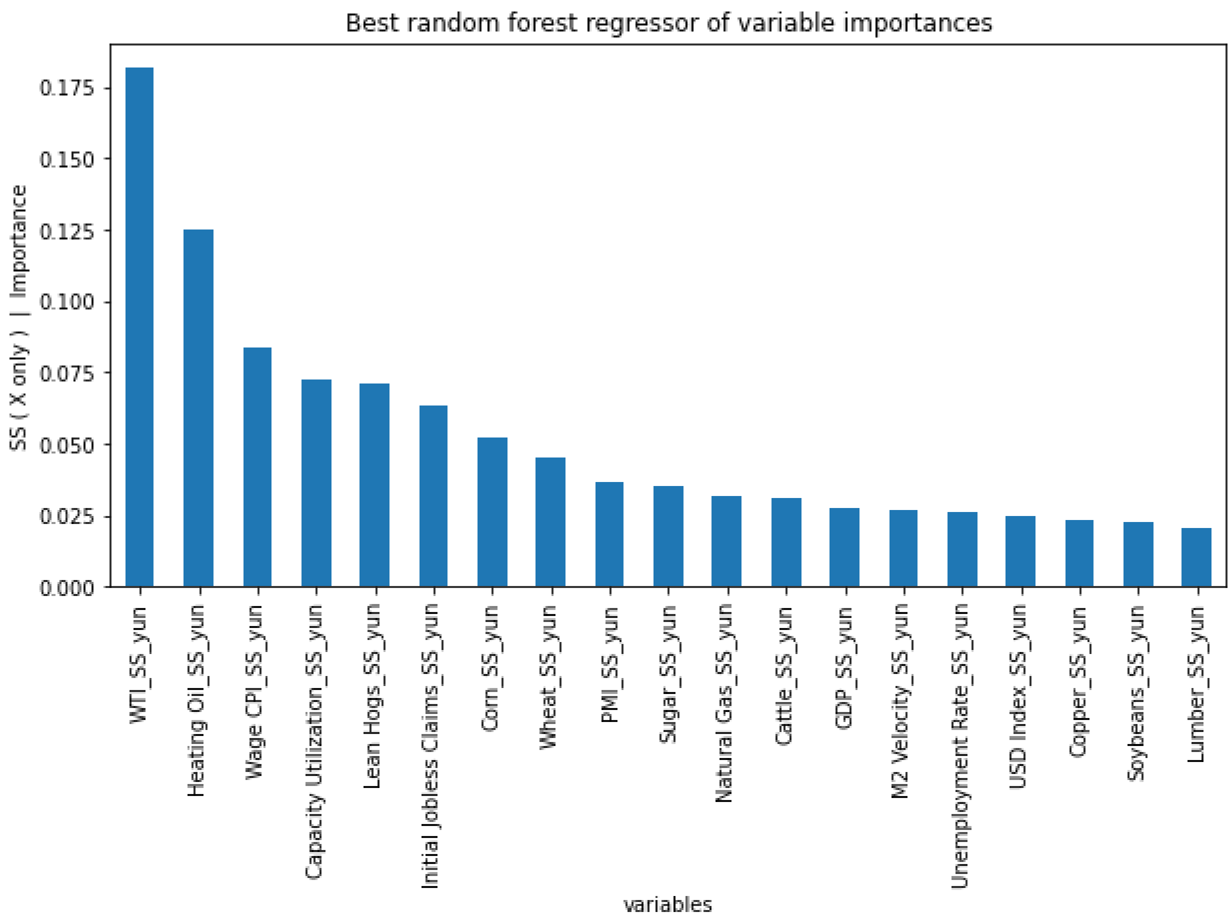
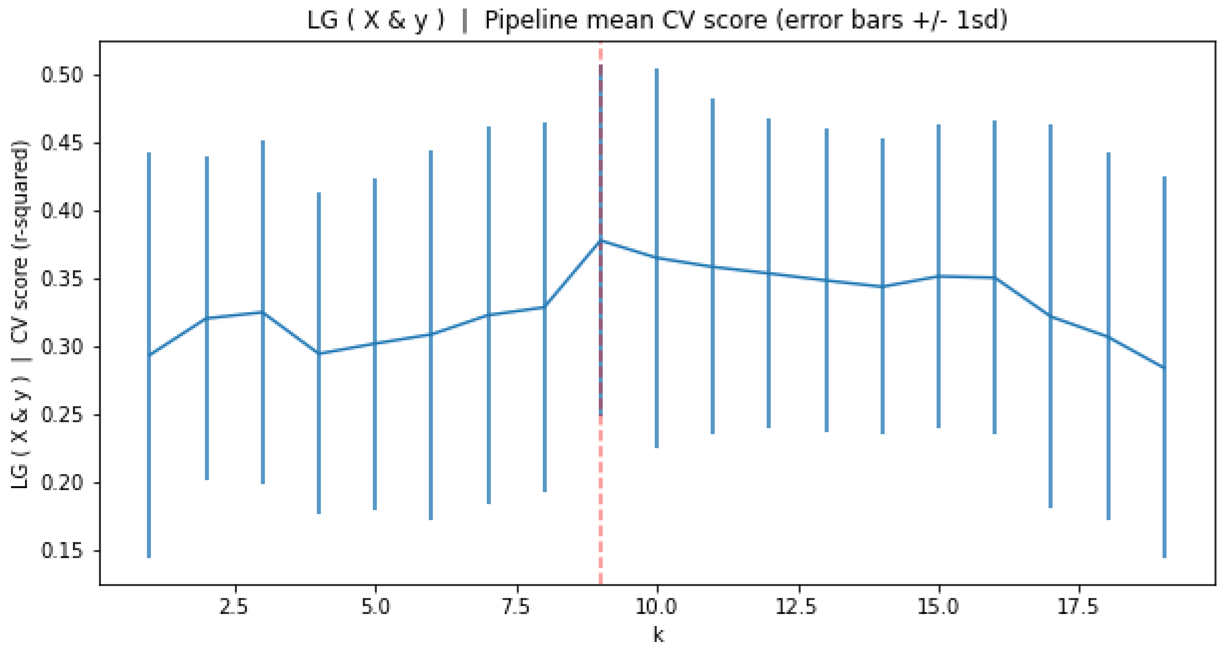
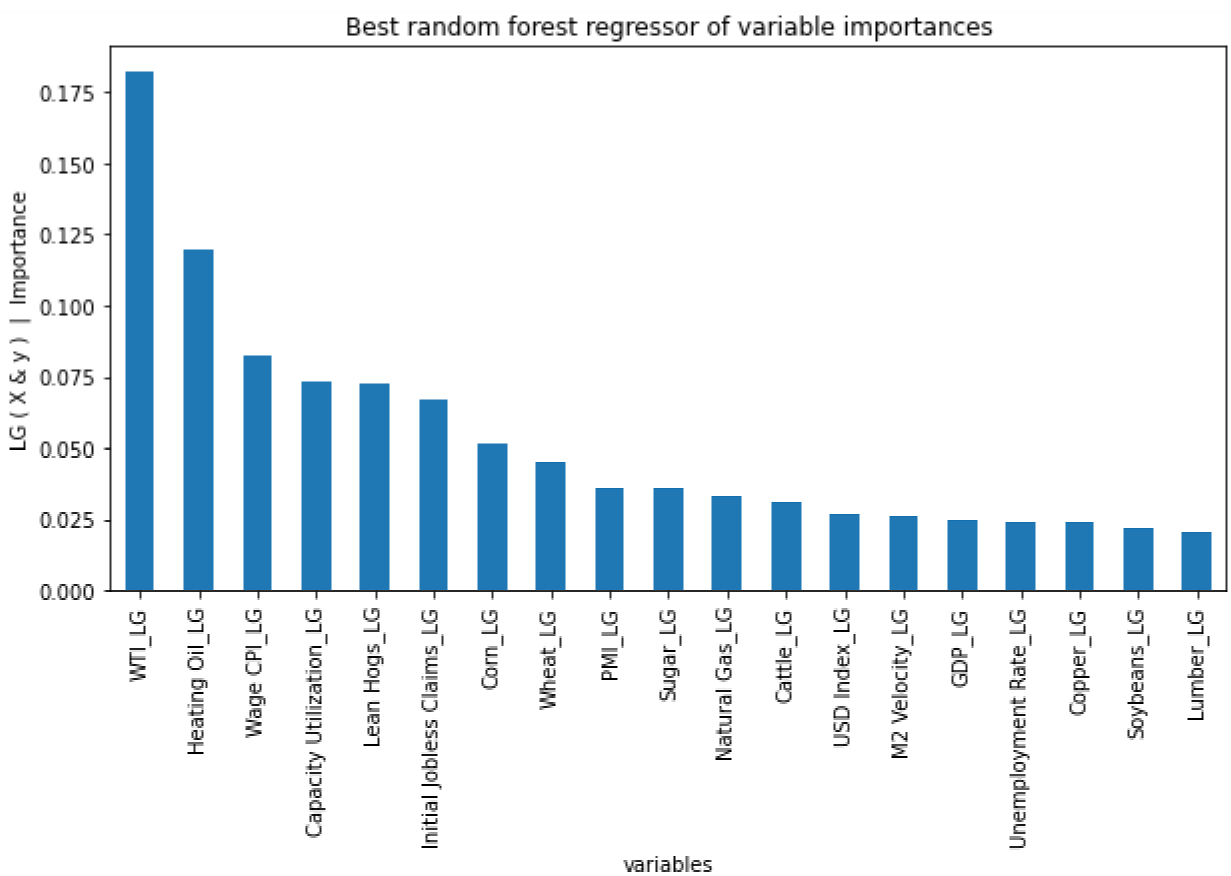

SS (X only) | Pipeline mean CV score (error bars +/- 1sd)
SS (X only) | CV score (r-squared)
0.5
0.4
0.3
0.2
0.1
2.5
5.0
7.5
10.0
12.5
15.0
17.5
k

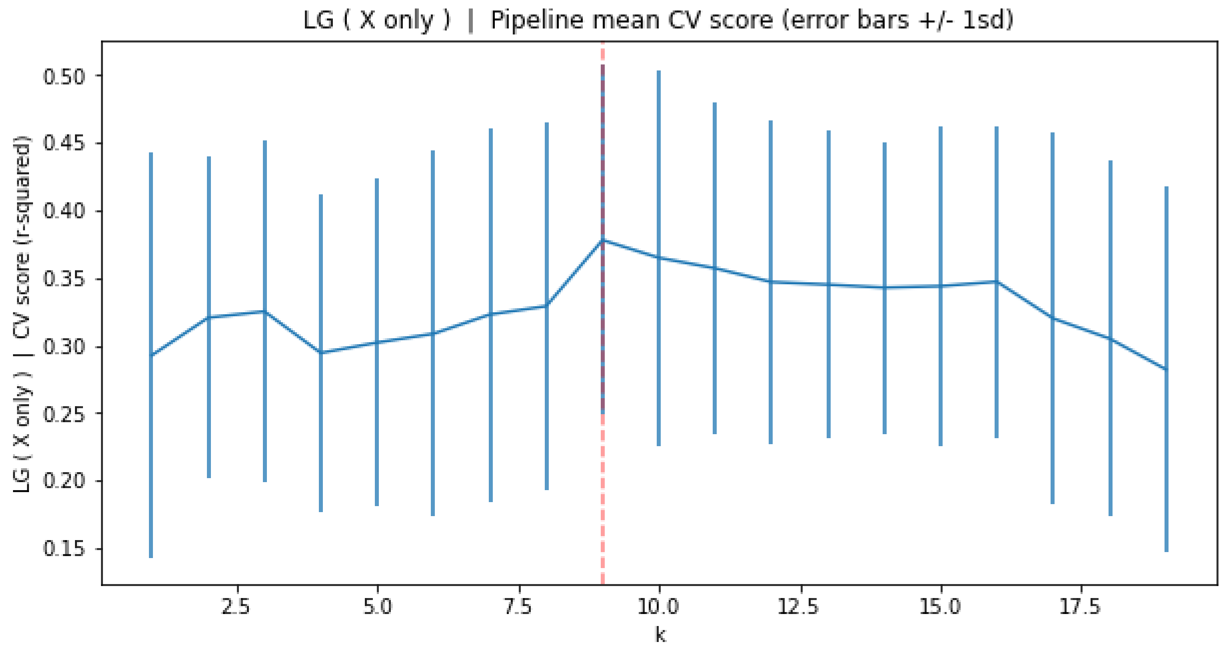

Best random forest regressor of variable importances
SS (X only) | Importance
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
WTI_SS_yun
Heating Oil_SS_yun
Wage CPI_SS_yun
Capacity Utilization_SS_yun
Lean Hogs_SS_yun
Initial Jobless Claims_SS_yun
Corn_SS_yun
Wheat_SS_yun
PMI_SS_yun
Sugar_SS_yun
Natural Gas_SS_yun
Cattle_SS_yun
GDP_SS_yun
M2 Velocity_SS_yun
Unemployment Rate_SS_yun
USD Index_SS_yun
Copper_SS_yun
Soybeans_SS_yun
Lumber_SS_yun
variables

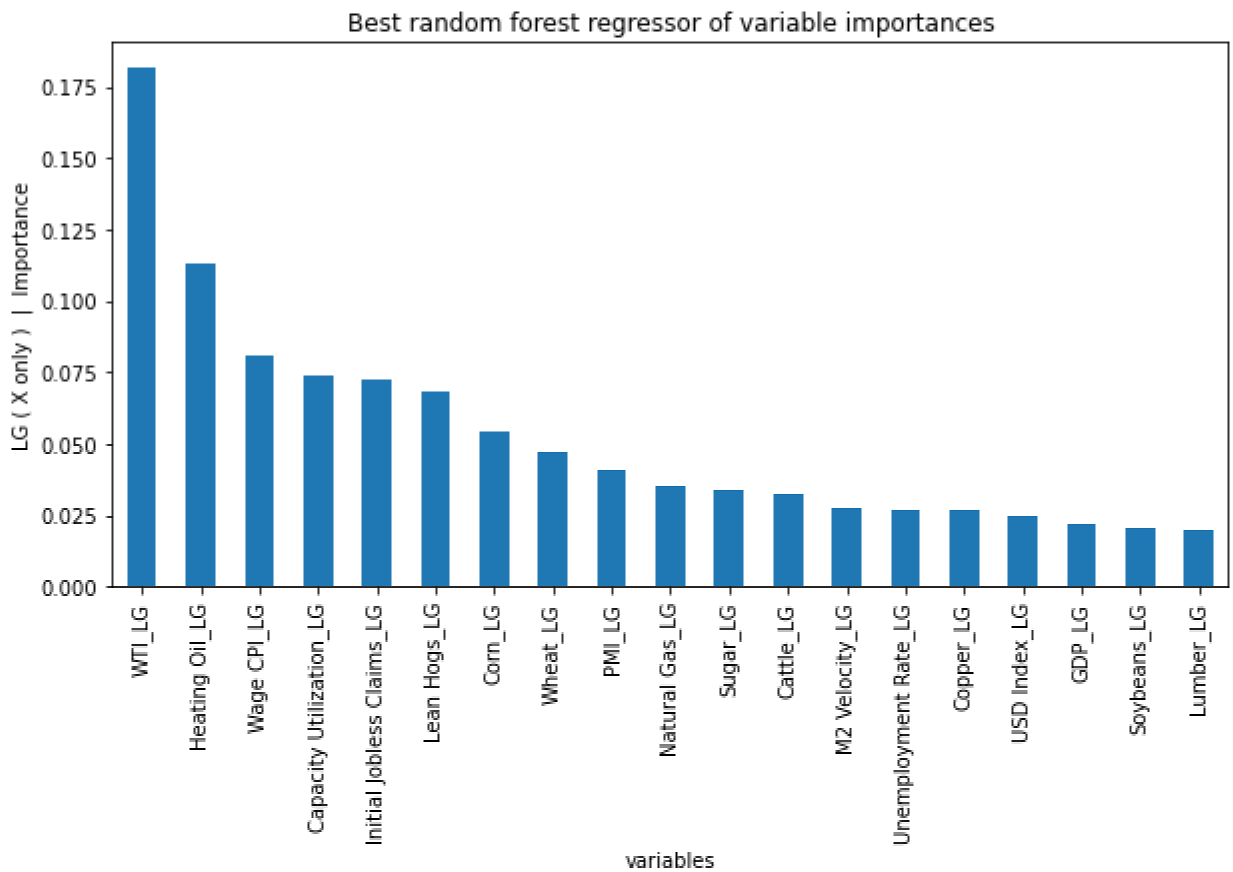
(back)


LG (X & y) | Pipeline mean CV score (error bars +/- 1sd)
LG (X & y) | CV score (r-squared)
k

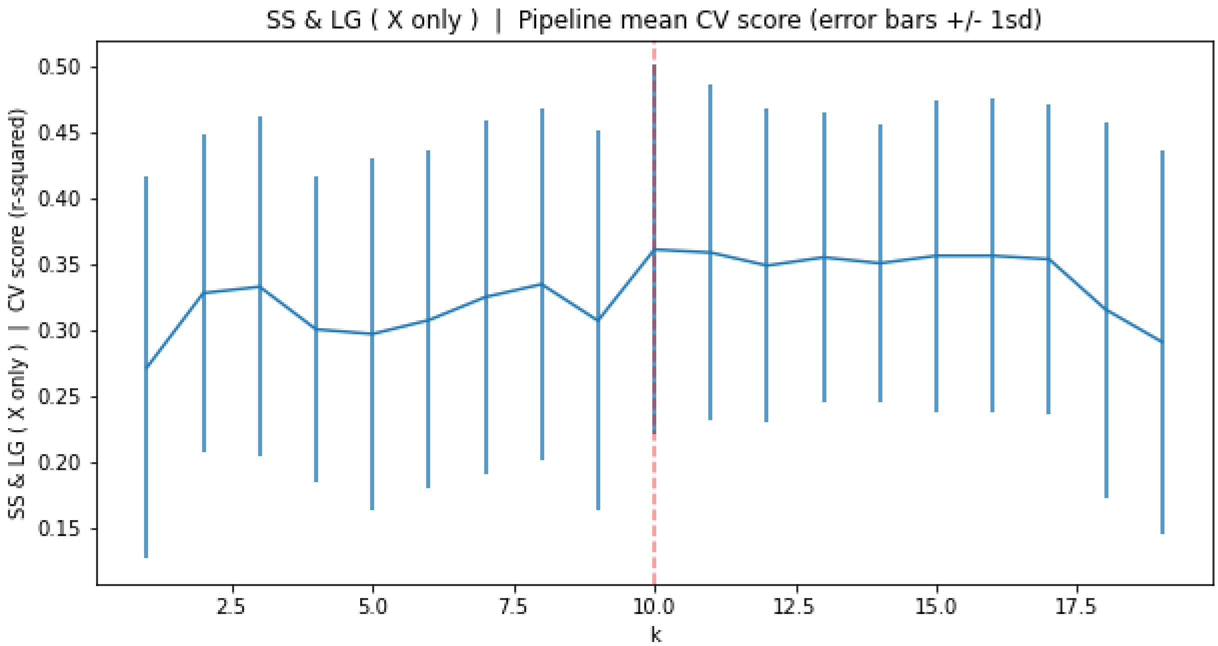

Best random forest regressor of variable importances
LG (X & y) | Importance
variables
WTI_LG
Heating Oil_LG
Wage CPI_LG
Capacity Utilization_LG
Lean Hogs_LG
Initial Jobless Claims_LG
Corn_LG
Wheat_LG
PMI_LG
Sugar_LG
Natural Gas_LG
Cattle_LG
USD Index_LG
M2 Velocity_LG
GDP_LG
Unemployment Rate_LG
Copper_LG
Soybeans_LG
Lumber_LG

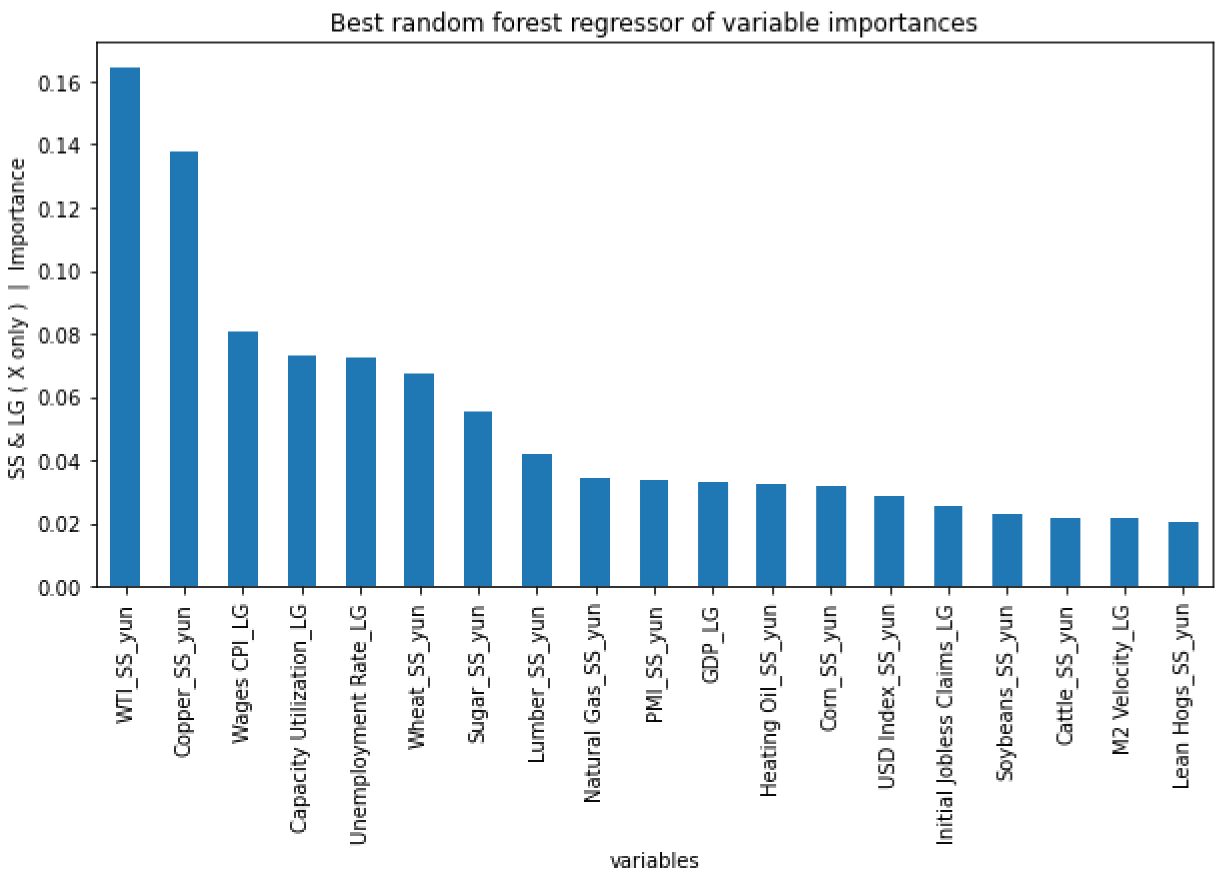
(*back*)


LG (X only) | Pipeline mean CV score (error bars +/- 1sd)
LG (X only) | CV score (r-squared)
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
2.5
5.0
7.5
10.0
12.5
15.0
17.5
k


Best random forest regressor of variable importances
LG (X only) | Importance
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
WTI_LG
Heating Oil_LG
Wage CPI_LG
Capacity Utilization_LG
Initial Jobless Claims_LG
Lean Hogs_LG
Corn_LG
Wheat_LG
PMI_LG
Natural Gas_LG
Sugar_LG
Cattle_LG
M2 Velocity_LG
Unemployment Rate_LG
Copper_LG
USD Index_LG
GDP_LG
Soybeans_LG
Lumber_LG
variables

(back)


SS & LG (X only) | Pipeline mean CV score (error bars +/- 1sd)
SS & LG (X only) | CV score (r-squared)
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
2.5
5.0
7.5
10.0
12.5
15.0
17.5
k


Best random forest regressor of variable importances
SS & LG (X only) | Importance
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
WTI_SS_yun
Copper_SS_yun
Wages CPI_LG
Capacity Utilization_LG
Unemployment Rate_LG
Wheat_SS_yun
Sugar_SS_yun
Lumber_SS_yun
Natural Gas_SS_yun
PMI_SS_yun
GDP_LG
Heating Oil_SS_yun
Corn_SS_yun
USD Index_SS_yun
Initial Jobless Claims_LG
Soybeans_SS_yun
Cattle_SS_yun
M2 Velocity_LG
Lean Hogs_SS_yun
variables

(*back*)