THE US INFLATION PHENOMENON | *It's Oil, silly*

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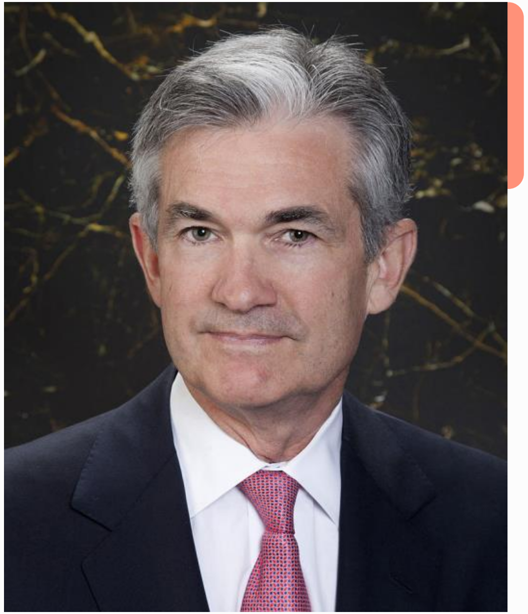
Problem Identification

Developing a model to explain & understand the phenomenon of US Inflation

Inflation is important

It's a **highly debated** phenomenon in economics. Many economists maintain that **moderate** inflation **levels** are needed to **drive consumption**, assuming that higher levels of **spending are crucial** for **economic growth**



Inflation is important

It's a highly debated phenomenon in economics. Many economists maintain that moderate inflation levels are needed to drive consumption, assuming that higher levels of spending are crucial for economic growth

& **stabilizing Inflation** is one of three objectives of the **Federal Reserve who's decisions move** the global **financials markets**

The purpose & goal of this Data Science project is to

build a model to **explain & understand** the phenomenon of **US Inflation**

02

Generated Deliverables

The power of API's

Generated Deliverables

Quandl

Quandl is a marketplace for financial, economic and alternative data

Investing.com

A financial platform & news website; one of the top 3 financial websites in the world

FRED

Federal Reserve Economic Data (FRED) a database maintained by the Research division of the Federal Reserve Bank of St. Louis

Problem Identification
(cont.)

I **shortlisted 19 variables** to determine their influence on Inflation

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

Problem Identification
(cont.)

Target Variable
Commodities
Economic Data

I **Target variable** | What we seek to understand

Items	Reported	API	API Source	Comments
Inflation	Monthly	Quandl	U.S. Bureau of Labor Statistics	The target variable

Problem Identification
(cont.)

Target Variable

Commodities

Economic Data

I Commodities | Where Inflation may show itself

Items	Reported	API	API Source	Comments
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
Corn	Daily	Investpy	Investing.com	One of many commodities
Wheat	Daily	Investpy	Investing.com	One of many commodities

Target Variable
Commodities

Economic Data

I Economic Data | Variables to determine the health of the economy

Items	Reported	API	API Source	Comments
Wages CPI	Monthly	FRED	U.S. Bureau of Labor Statistics	A component of the target variable
Capacity Utilization	Monthly	FRED	Board of Governors of the Federal Reserve	The % of resources used by corporations
M2 Velocity	Quarterly	FRED	Federal Reserve Bank of St. Louis	Movement of money; state of the economy proxy
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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

Generated Deliverables

(cont.)

Source Code

This can be found at my GitHub account referenced at the end

Research Report

Also can be found at my GitHub account referenced at the end

Presentation Report

This one...

03

Data Pre-Processing

Split it up...

Data Pre-Processing

Data Cleaning

Data Frames should talk to each other

- After pulling, the data frame was **composed of variables with different lengths**

```
<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
```

Data Pre-Processing

Data Cleaning

Data Frames should talk to each other

- After pulling, the data frame was composed of variables with different lengths
  - **Natural Gas being the constraint**
  - **Forward fill was used**

```
<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
```

Data Pre-Processing

Data Cleaning (cont.)

Data Frames should talk to each other (cont.)

- Different lengths
- **Cut the data to April 1991**

```
<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
```

Data Pre-Processing

Data Cleaning (cont.)

Data Frames should talk to each other (cont.)

- Different lengths
- Cut the Data
- **Concatenated with Inflation**
  - **Only 321 observations**

```
<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
```

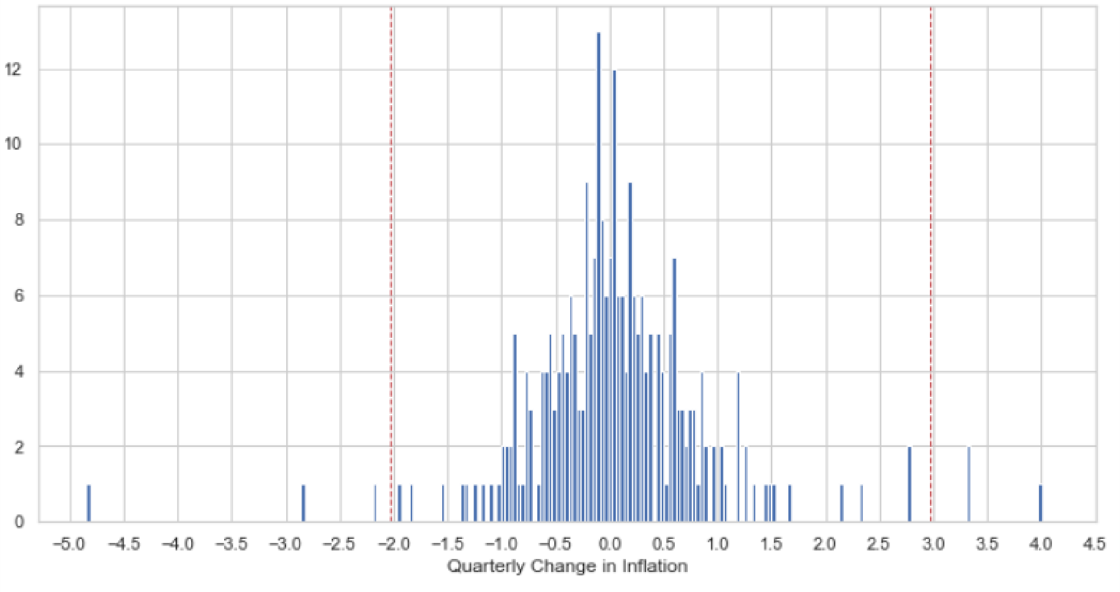
Items	Reported	API	API Source	Comments
Inflation	Monthly	Quandl	U.S. Bureau of Labor Statistics	The target variable

Data Pre-Processing

Data Cleaning (cont.)

Winsorizing

- **Winsorizing** is the transformation of statistics by limiting extreme values in data **to reduce the effect of potential spurious outliers**

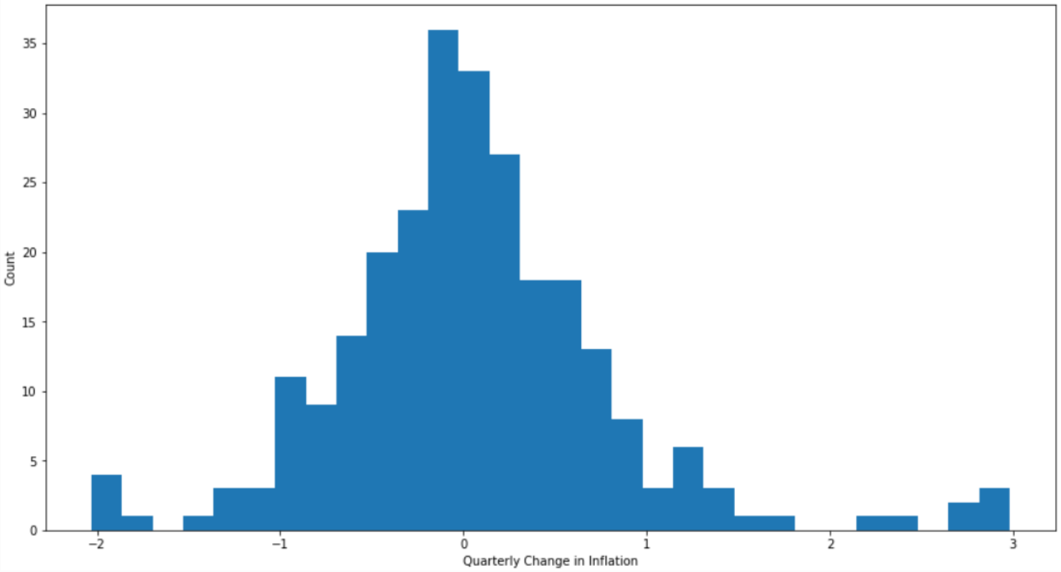


Data Pre-Processing

Data Cleaning (cont.)

Winsorizing

- Winsorizing is the transformation of statistics by limiting extreme values in data to reduce the effect of potential spurious outliers
- **Inflation was Winsorized differently on each of the approaches (described next)**

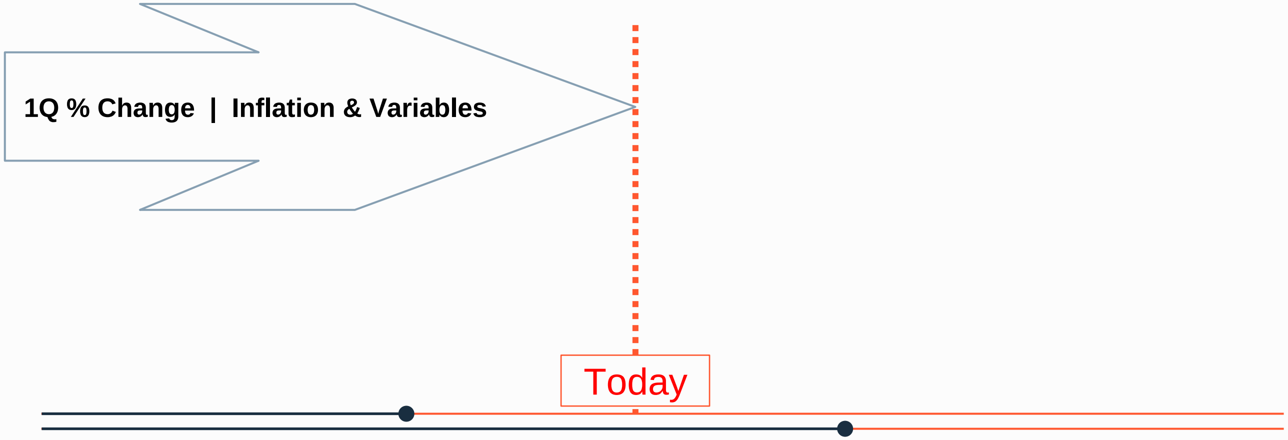


Data Pre-Processing

Exploratory Data Analysis

Investigating the Time Relationships

- **Quarter on Quarter (for all)**
  - Compared a quarterly change on Variables & Inflation
- Month on Month (for all)
- Quarter on Quarter for Variables (past) & Inflation (forwards)
- Quarter on Quarter w/ Rolling Averages

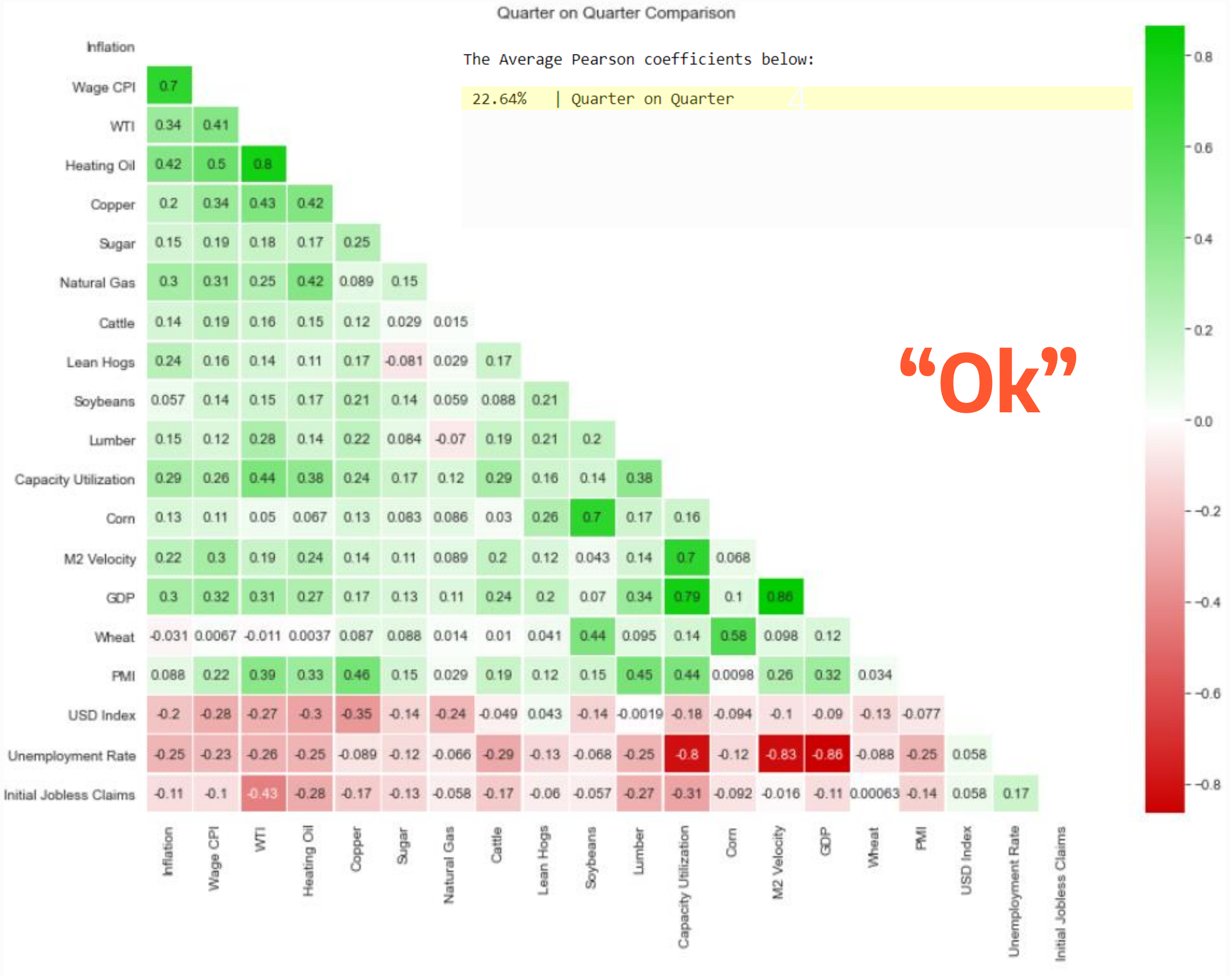


Data Pre-Processing

Exploratory Data Analysis

Quarter on Quarter (for all)

Feature Correlation Heat Maps with the Pearson correlation coefficients

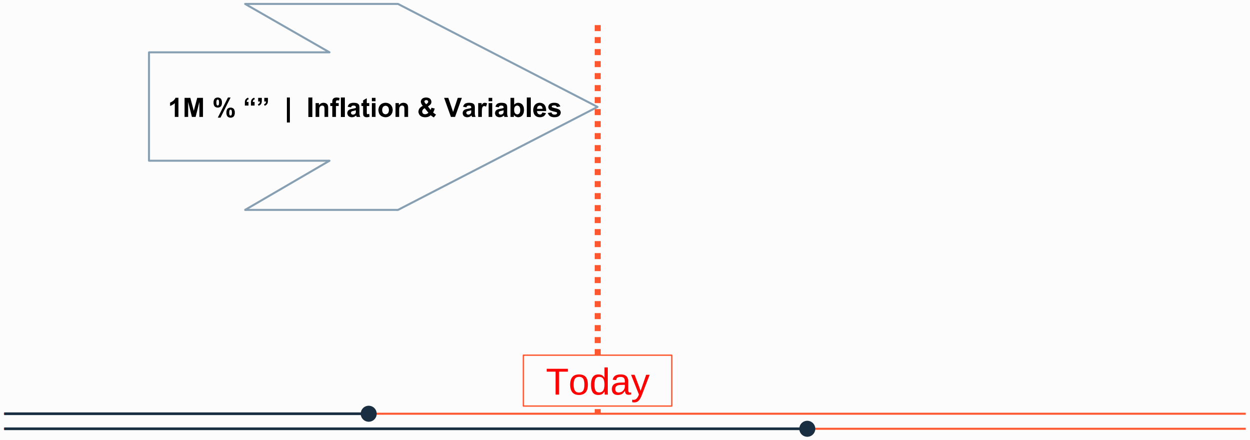


Data Pre-Processing

Exploratory Data Analysis (cont.)

Investigating the Time Relationships (cont.)

- Quarter on Quarter (for all)
- **Month on Month (for all)**
  - The same as the previous but looked at a monthly change
- Quarter on Quarter for Variables (past) & Inflation (forwards)
- Quarter on Quarter w/ Rolling Averages

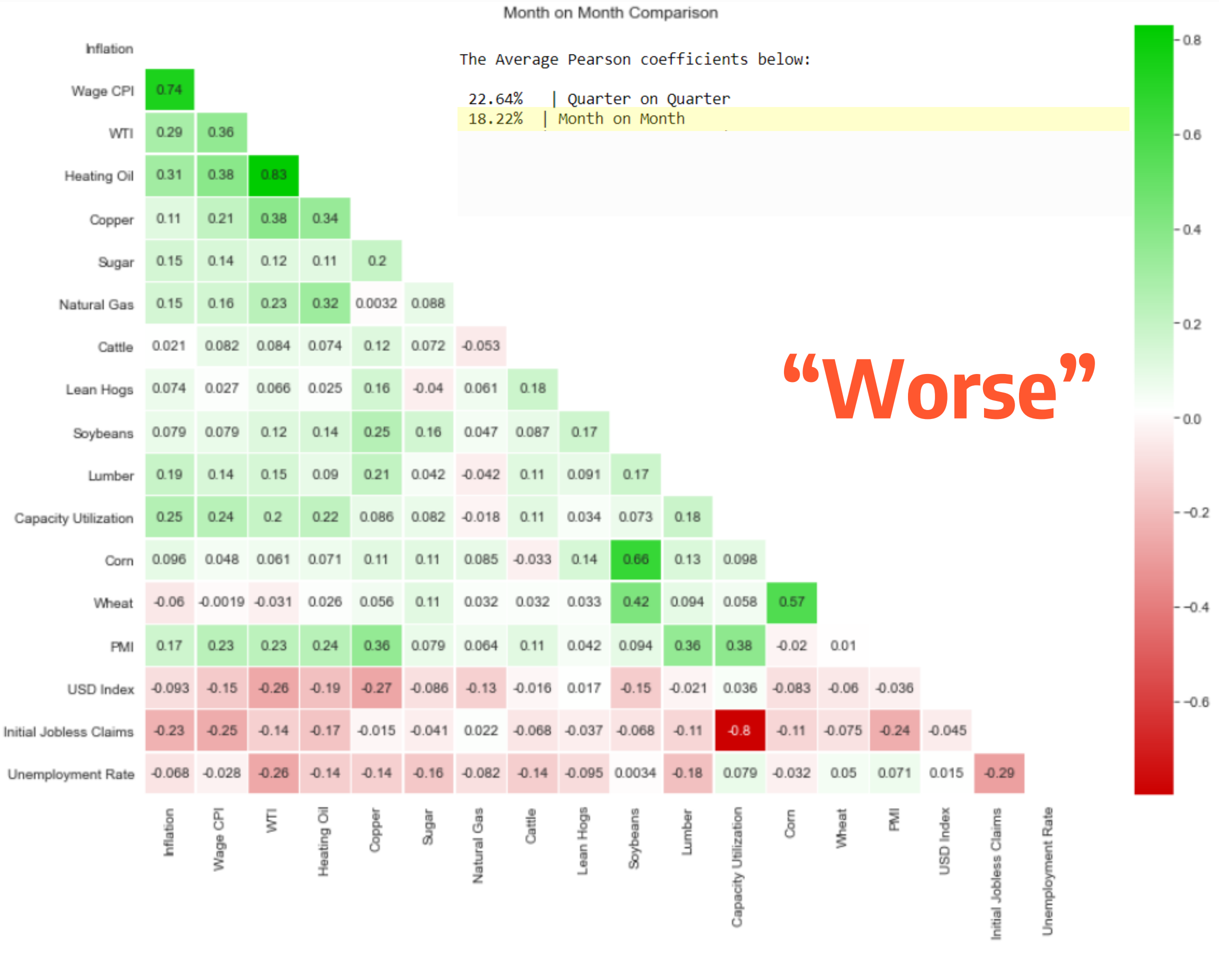


Data Pre-Processing

Exploratory Data Analysis

Month on Month (for all)

Feature Correlation Heat Maps with the Pearson correlation coefficients (cont.)

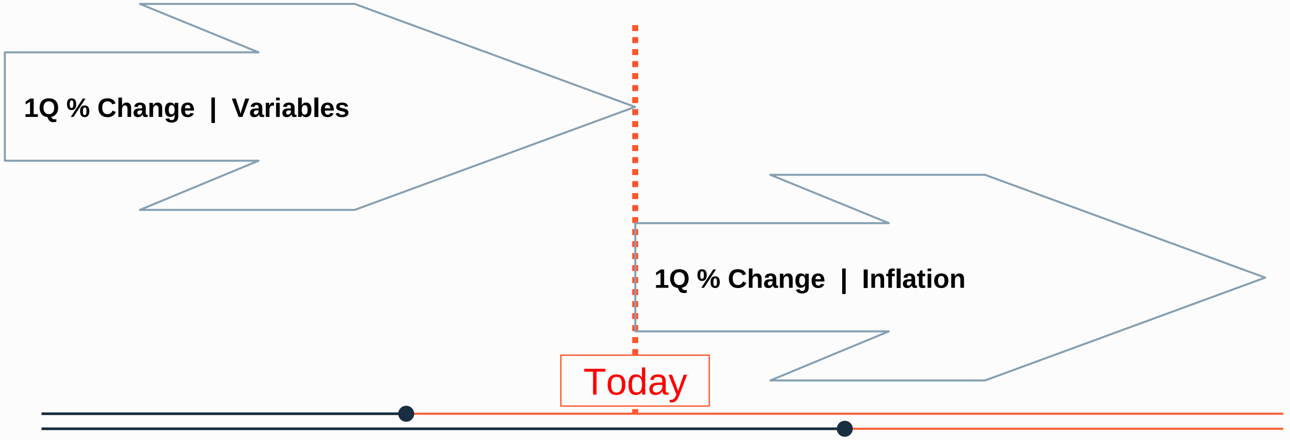


Data Pre-Processing

Exploratory Data Analysis (cont.)

Investigating the Time Relationships (cont.)

- Quarter on Quarter (for all)
- Month on Month (for all)
- **Q on Q for Variables (past) & Inflation (forwards)**
  - Looked at a previous 1 Quarter change for variables to a 1 Quarter change in Inflation in the future
- Quarter on Quarter w/ Rolling Averages



Data Pre-Processing

Exploratory Data Analysis

Q on Q for Variables (past) & Inflation (forwards)

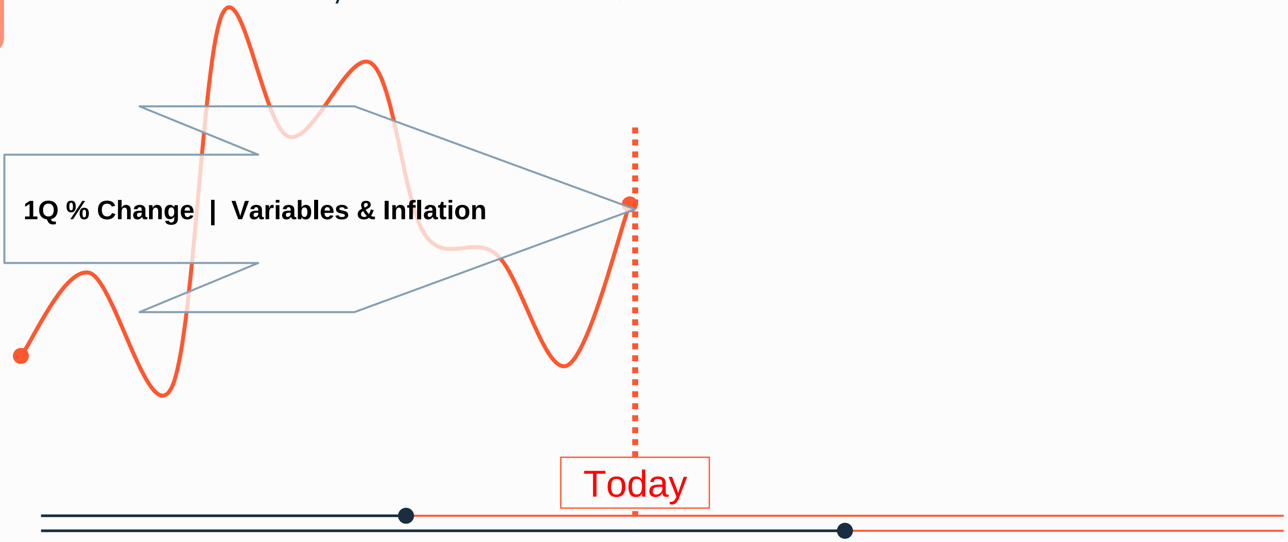
Feature Correlation Heat Maps with the Pearson correlation coefficients (cont.)

Data Pre-Processing

Exploratory Data Analysis (cont.)

Investigating the Time Relationships (cont.)

- Quarter on Quarter (for all)
- Month on Month (for all)
- Q on Q for Variables (past) & Inflation (forwards)
- **Quarter on Quarter w/ Rolling Averages**
  - Similar to # 1 albeit used a rolling average for those that were reported more often than once a Quarter as a Variable “may have had” a bad day or week when the Quarter ended



Data Pre-Processing

Exploratory Data Analysis

Quarter on Quarter w/ Rolling Averages

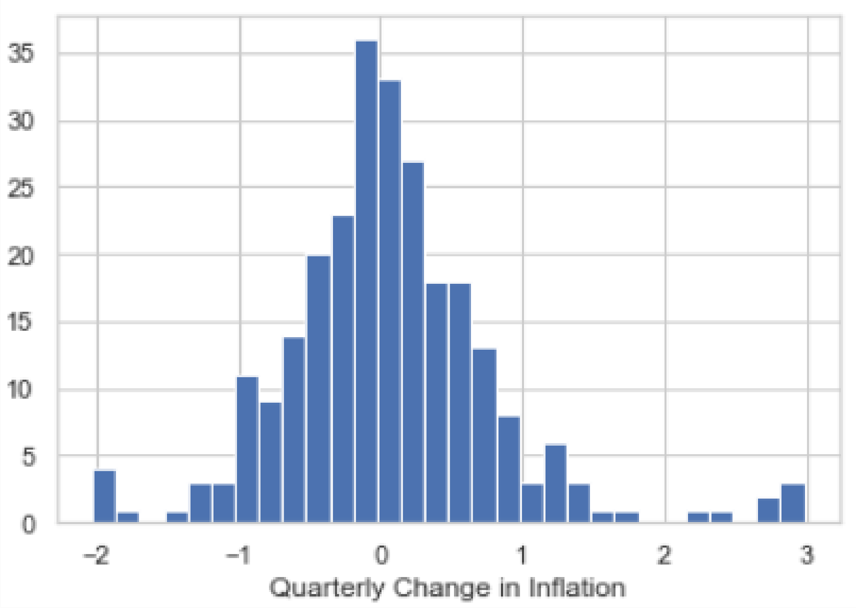
Feature Correlation Heat Maps with the Pearson correlation coefficients (cont.)

Data Pre-Processing

Exploratory Data Analysis (cont.)

Investigating the Time Relationships (cont.)

- We found the best of the 4 but **we** remembered that we **Winsorized Inflation on all; let's investigate what the variables showed without Winsorizing Inflation on our "best"**

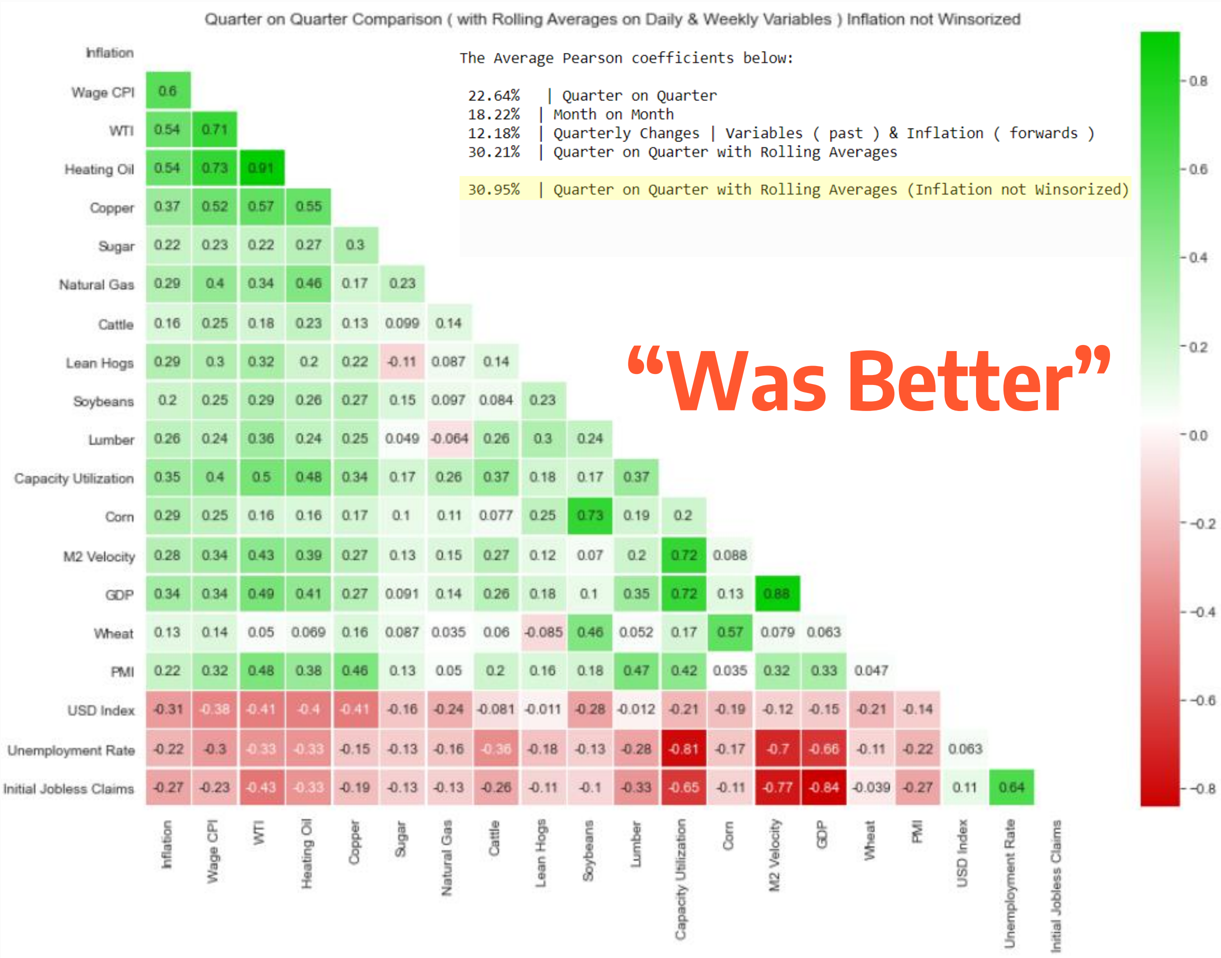


Data Pre-Processing

Exploratory Data Analysis

Quarter on Quarter w/ Rolling Averages

Feature Correlation Heat Maps with the Pearson correlation coefficients (cont.)



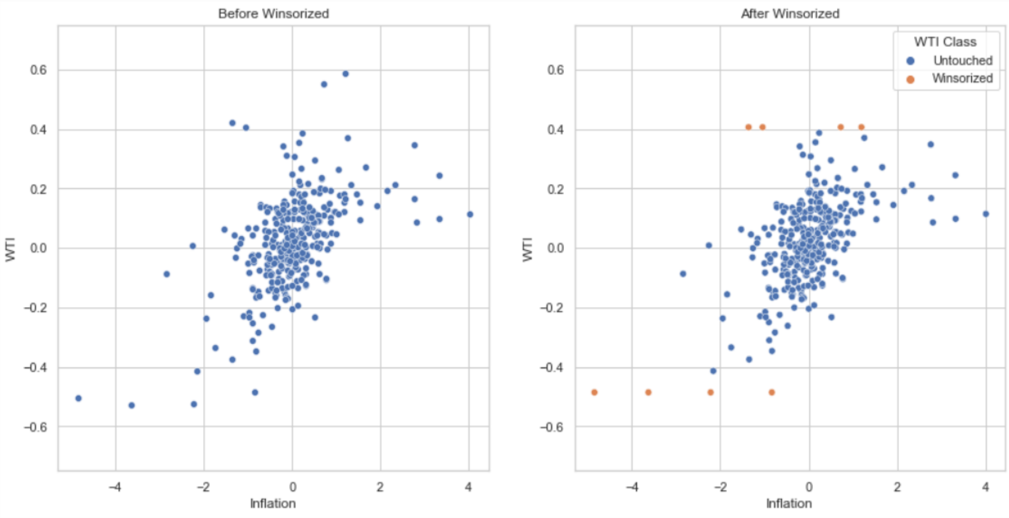
“Was Better”

Data Pre-Processing

Exploratory Data Analysis (cont.)

Investigating the Time Relationships (cont.)

- We found the best of the 4 but we remembered that we Winsorized Inflation on all; let's investigate what the variables showed without Winsorizing Inflation
- Although **Winsorizing** did not work on Inflation, it **did work on 8 variables**; this lead to an **average increase** in their Pearson correlation coefficients **of 173 bps** with one seeing a 460 bps increase



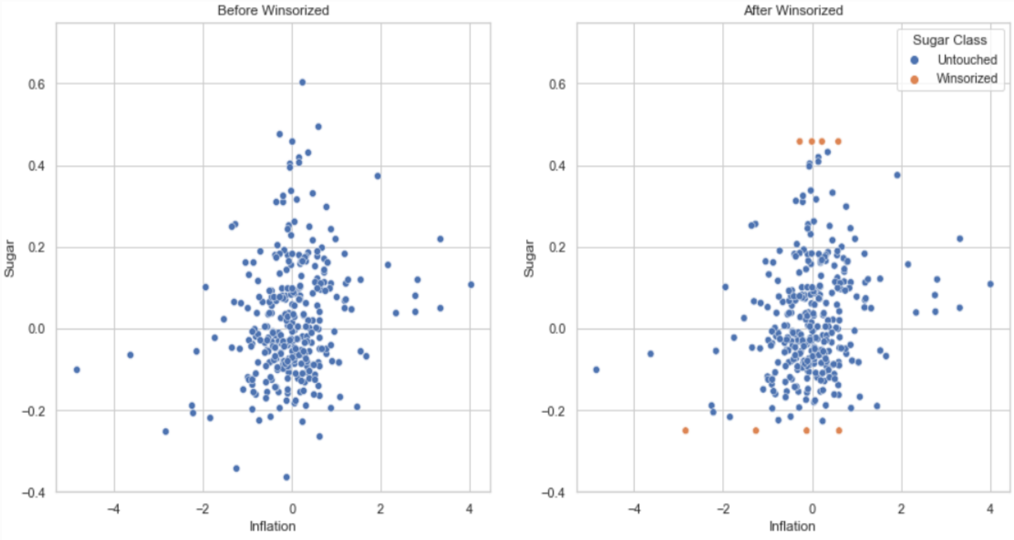
	Winsorized?
Wage CPI	n/a
WTI	Winsorized
Heating Oil	n/a
Copper	n/a
Sugar	Winsorized
Natural Gas	Winsorized
Cattle	n/a
Lean Hogs	n/a
Soybeans	n/a
Lumber	Winsorized
Capacity Utilization	Winsorized
Corn	n/a
M2 Velocity	n/a
GDP	Winsorized
Wheat	n/a
PMI	n/a
USD Index	n/a
Unemployment Rate	Winsorized
Initial Jobless Claims	Winsorized

Data Pre-Processing

Exploratory Data Analysis (cont.)

Investigating the Time Relationships (cont.)

- We found the best of the 4 but we remembered that we Winsorized Inflation on all; let's investigate what the variables showed without Winsorizing Inflation
- Although **Winsorizing** did not work on Inflation, it **did work on 8 variables**; this lead to an **average increase** in their Pearson correlation coefficients **of 173 bps** with one seeing a 460 bps increase



	Winsorized?
Wage CPI	n/a
WTI	Winsorized
Heating Oil	n/a
Copper	n/a
Sugar	Winsorized
Natural Gas	Winsorized
Cattle	n/a
Lean Hogs	n/a
Soybeans	n/a
Lumber	Winsorized
Capacity Utilization	Winsorized
Corn	n/a
M2 Velocity	n/a
GDP	Winsorized
Wheat	n/a
PMI	n/a
USD Index	n/a
Unemployment Rate	Winsorized
Initial Jobless Claims	Winsorized

Data Pre-Processing

Exploratory Data Analysis (cont.)

Investigating the Time Relationships (cont.)

- We found the best of the 4 but we remembered that we Winsorized Inflation on all; let's investigate what the variables showed without Winsorizing Inflation
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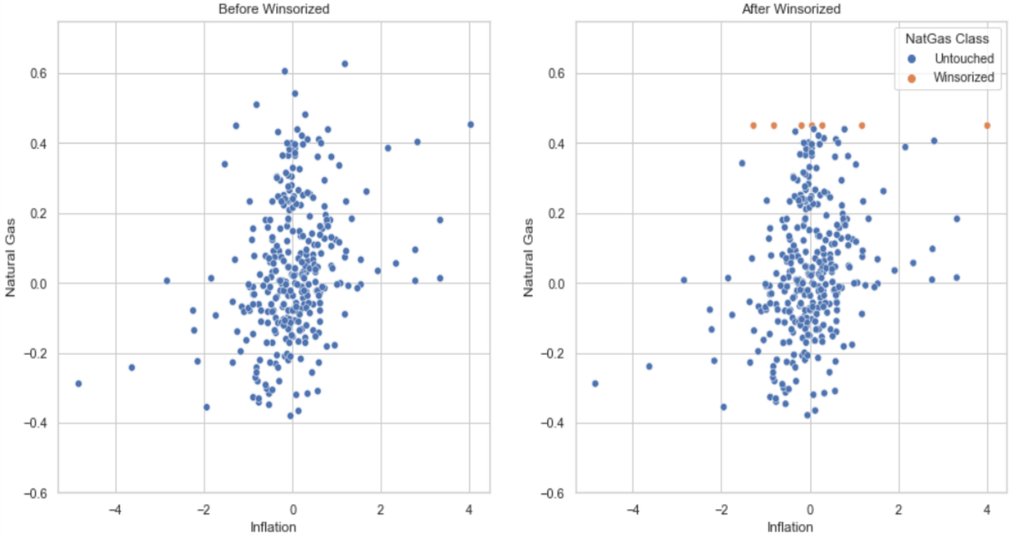

	Winsorized?
Wage CPI	n/a
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Copper	n/a
Sugar	Winsorized
Natural Gas	Winsorized
Cattle	n/a
Lean Hogs	n/a
Soybeans	n/a
Lumber	Winsorized
Capacity Utilization	Winsorized
Corn	n/a
M2 Velocity	n/a
GDP	Winsorized
Wheat	n/a
PMI	n/a
USD Index	n/a
Unemployment Rate	Winsorized
Initial Jobless Claims	Winsorized

Data Pre-Processing

Exploratory Data Analysis (cont.)

Investigating the Time Relationships (cont.)

- We found the best of the 4 but we remembered that we Winsorized Inflation on all; let's investigate what the variables showed without Winsorizing Inflation
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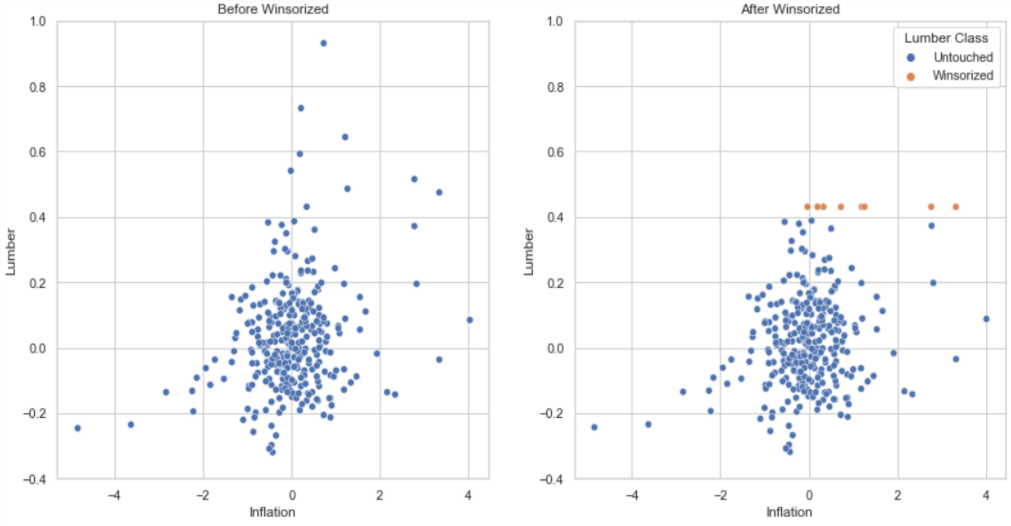

	Winsorized?
Wage CPI	n/a
WTI	Winsorized
Heating Oil	n/a
Copper	n/a
Sugar	Winsorized
Natural Gas	Winsorized
Cattle	n/a
Lean Hogs	n/a
Soybeans	n/a
Lumber	Winsorized
Capacity Utilization	Winsorized
Corn	n/a
M2 Velocity	n/a
GDP	Winsorized
Wheat	n/a
PMI	n/a
USD Index	n/a
Unemployment Rate	Winsorized
Initial Jobless Claims	Winsorized

Data Pre-Processing

Exploratory Data Analysis (cont.)

Investigating the Time Relationships (cont.)

- We found the best of the 4 but we remembered that we Winsorized Inflation on all; let's investigate what the variables showed without Winsorizing Inflation
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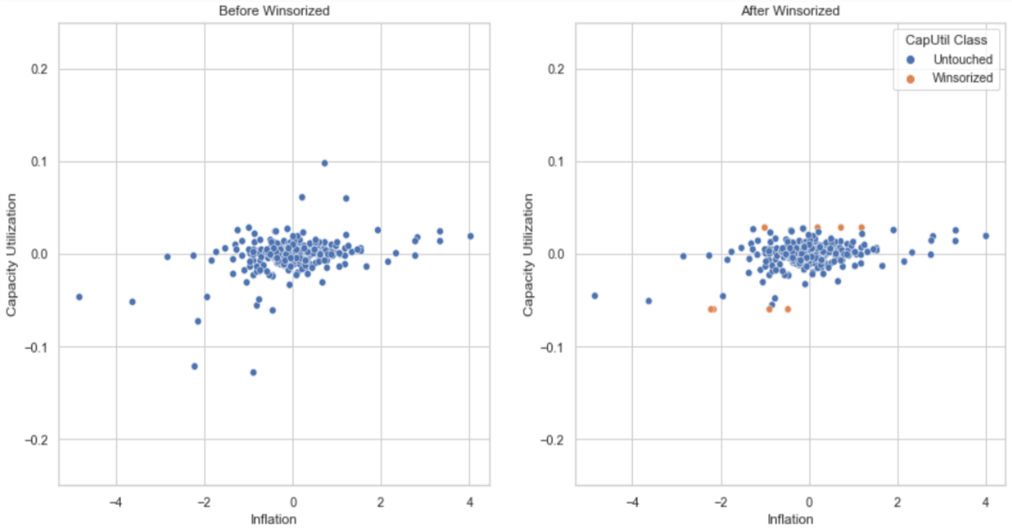

	Winsorized?
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Copper	n/a
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Natural Gas	Winsorized
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Lean Hogs	n/a
Soybeans	n/a
Lumber	Winsorized
Capacity Utilization	Winsorized
Corn	n/a
M2 Velocity	n/a
GDP	Winsorized
Wheat	n/a
PMI	n/a
USD Index	n/a
Unemployment Rate	Winsorized
Initial Jobless Claims	Winsorized

Data Pre-Processing

Exploratory Data Analysis (cont.)

Investigating the Time Relationships (cont.)

- We found the best of the 4 but we remembered that we Winsorized Inflation on all; let's investigate what the variables showed without Winsorizing Inflation
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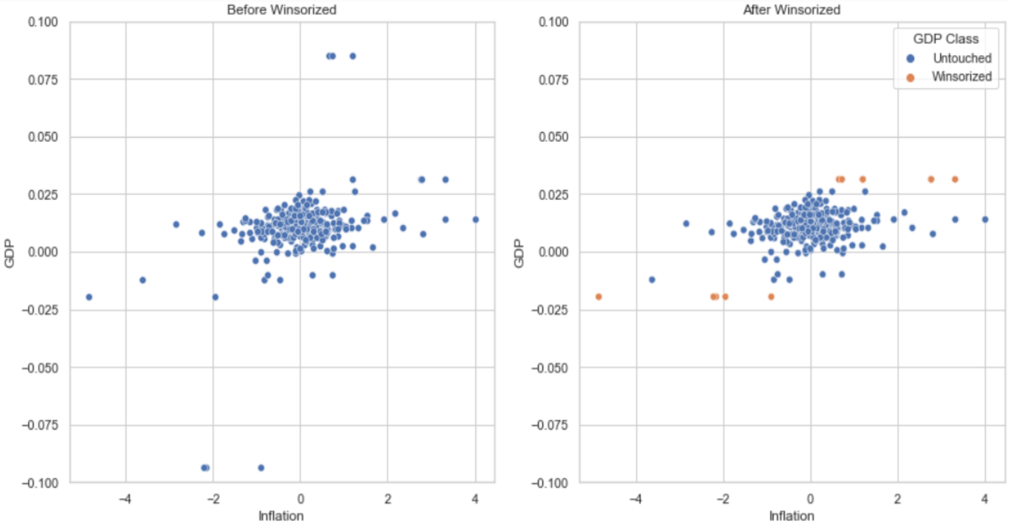

	Winsorized?
Wage CPI	n/a
WTI	Winsorized
Heating Oil	n/a
Copper	n/a
Sugar	Winsorized
Natural Gas	Winsorized
Cattle	n/a
Lean Hogs	n/a
Soybeans	n/a
Lumber	Winsorized
Capacity Utilization	Winsorized
Corn	n/a
M2 Velocity	n/a
GDP	Winsorized
Wheat	n/a
PMI	n/a
USD Index	n/a
Unemployment Rate	Winsorized
Initial Jobless Claims	Winsorized

Data Pre-Processing

Exploratory Data Analysis (cont.)

Investigating the Time Relationships (cont.)

- We found the best of the 4 but we remembered that we Winsorized Inflation on all; let's investigate what the variables showed without Winsorizing Inflation
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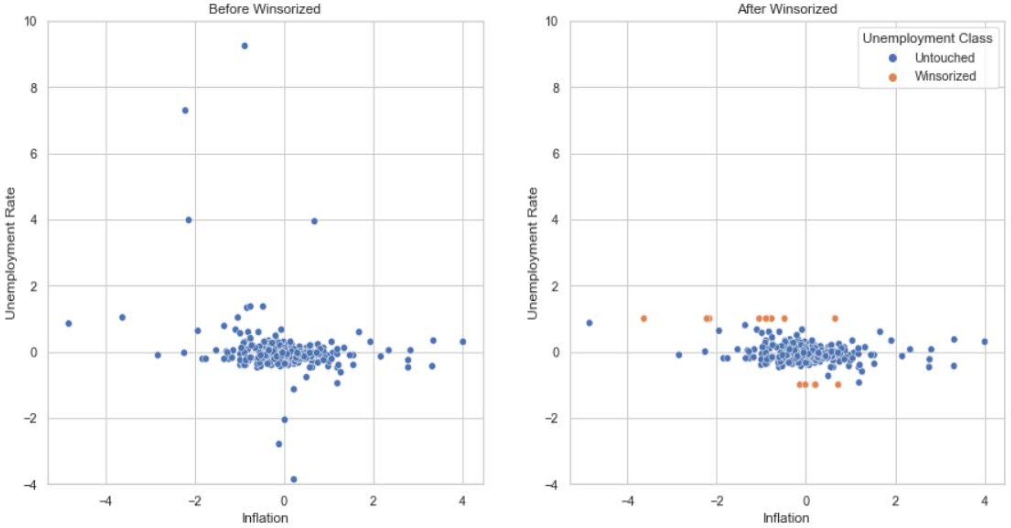

	Winsorized?
Wage CPI	n/a
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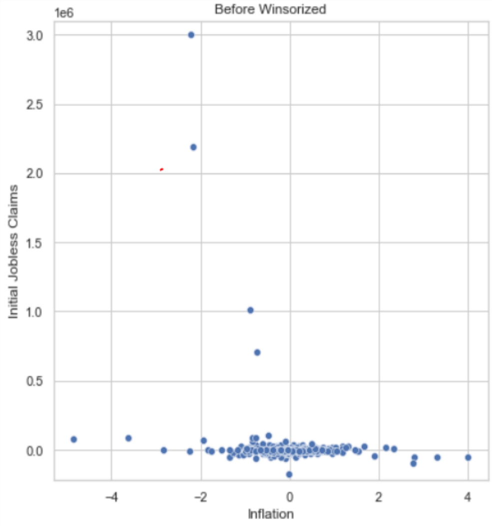
Sugar	Winsorized
Natural Gas	Winsorized
Cattle	n/a
Lean Hogs	n/a
Soybeans	n/a
Lumber	Winsorized
Capacity Utilization	Winsorized
Corn	n/a
M2 Velocity	n/a
GDP	Winsorized
Wheat	n/a
PMI	n/a
USD Index	n/a
Unemployment Rate	Winsorized
Initial Jobless Claims	Winsorized

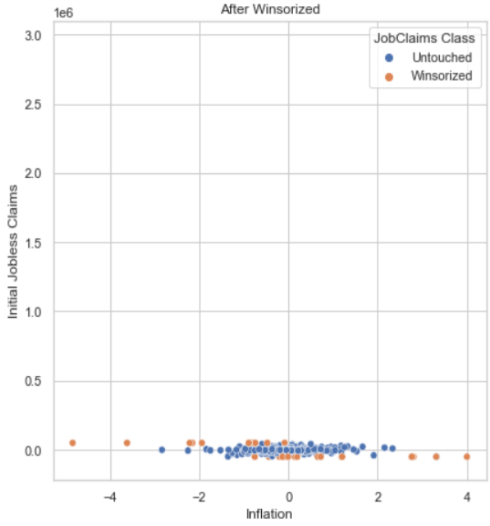
Data Pre-Processing

Exploratory Data Analysis (cont.)

Investigating the Time Relationships (cont.)

- We found the best of the 4 but we remembered that we Winsorized Inflation on all; let's investigate what the variables showed without Winsorizing Inflation
- Although **Winsorizing** did not work on Inflation, it **did work on 8 variables**; this lead to an **average increase** in their Pearson correlation coefficients **of 173 bps** with one seeing a 460 bps increase





	Winsorized?
Wage CPI	n/a
WTI	Winsorized
Heating Oil	n/a
Copper	n/a
Sugar	Winsorized
Natural Gas	Winsorized
Cattle	n/a
Lean Hogs	n/a
Soybeans	n/a
Lumber	Winsorized
Capacity Utilization	Winsorized
Corn	n/a
M2 Velocity	n/a
GDP	Winsorized
Wheat	n/a
PMI	n/a
USD Index	n/a
Unemployment Rate	Winsorized
Initial Jobless Claims	Winsorized

Data Pre-Processing

Exploratory Data Analysis

Quarter on Quarter w/ Rolling Averages

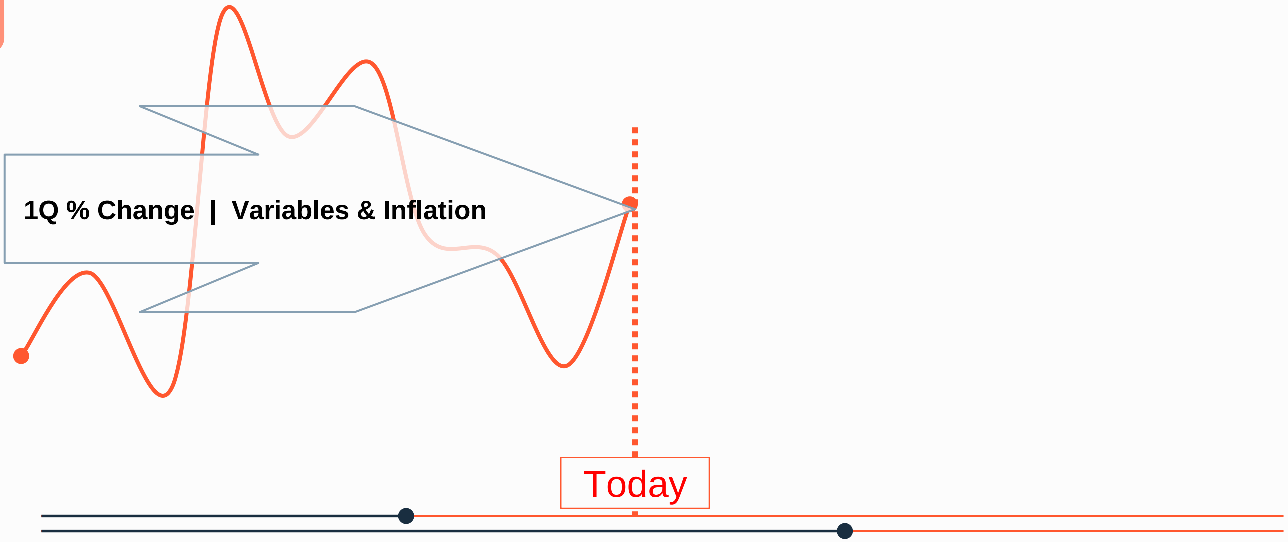
Feature Correlation Heat Maps with the Pearson correlation coefficients (cont.)

Data Pre-Processing

Pre-Processing

Splitting & Scaling

- **Chosen data frame**
  - The Quarter on Quarter w/ Rolling Averages was chosen
    - Inflation not Winsorized but 8 are
- Train, Test Split
- Scaling

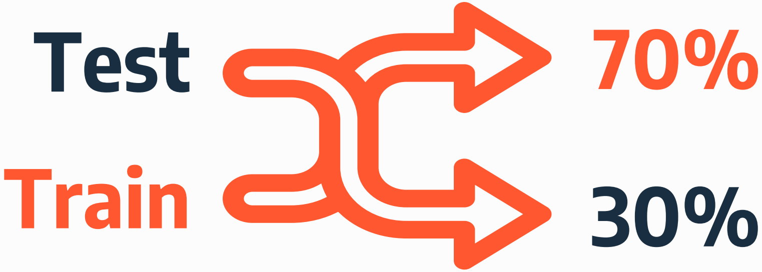


Data Pre-Processing

Pre-Processing (cont.)

Splitting & Scaling (cont.)

- Chosen data frame
- **Train, Test Split**
  - The data was then split for Training & Testing to be sent to different Scaling Approaches
- Scaling

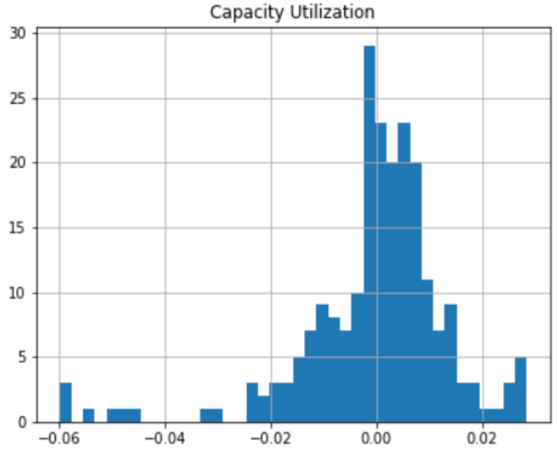


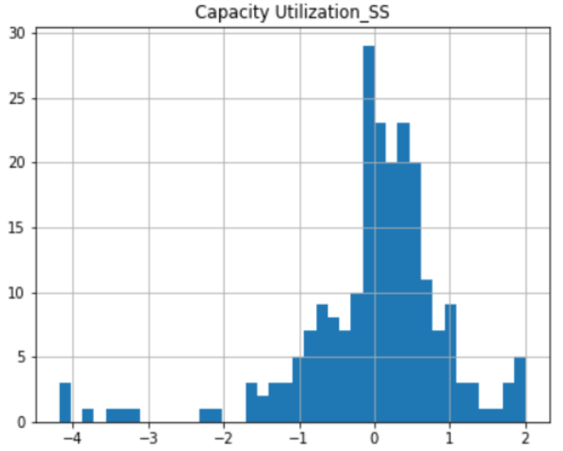
Data Pre-Processing

Pre-Processing
(cont.)

Splitting & Scaling (cont.)

- Chosen data frame
- Train, Test Split
- **Scaling**
  - 3 scaling approaches were tried to “normalize” the variables:
    - Standard Scaling (SS)
    - MinMax Scaling (MM)
    - Log Transformation (LG)



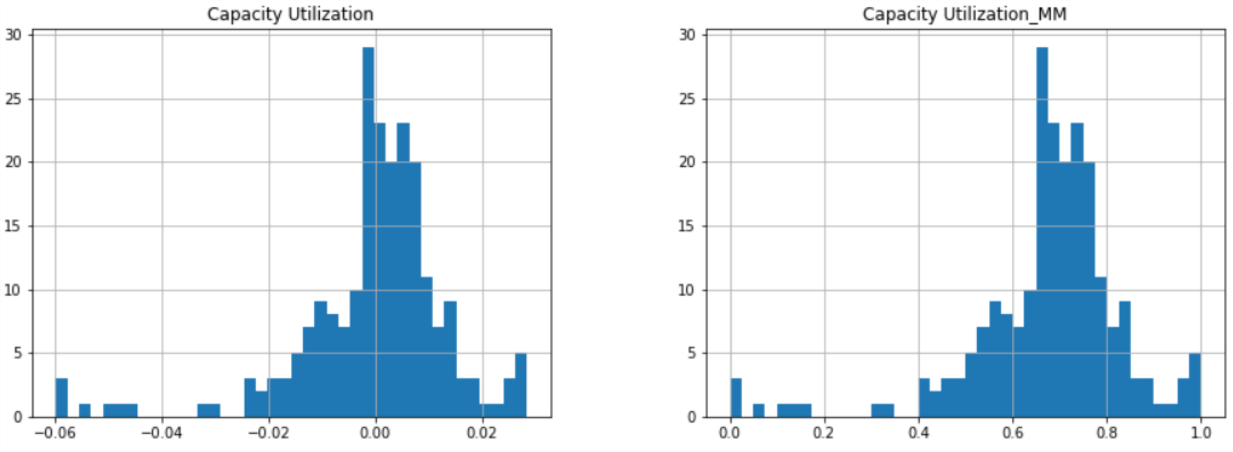


Data Pre-Processing

Pre-Processing (cont.)

Splitting & Scaling (cont.)

- Chosen data frame
- Train, Test Split
- **Scaling**
  - 3 scaling approaches were tried to "normalize" the variables:
    - Standard Scaling (SS)
    - MinMax Scaling (MM)
    - Log Transformation (LG)



Data Pre-Processing

Pre-Processing (cont.)

Splitting & Scaling (cont.)

- Chosen data frame
- Train, Test Split
- **Scaling**
  - 3 scaling approaches were tried to “normalize” the variables:
    - Standard Scaling (SS)
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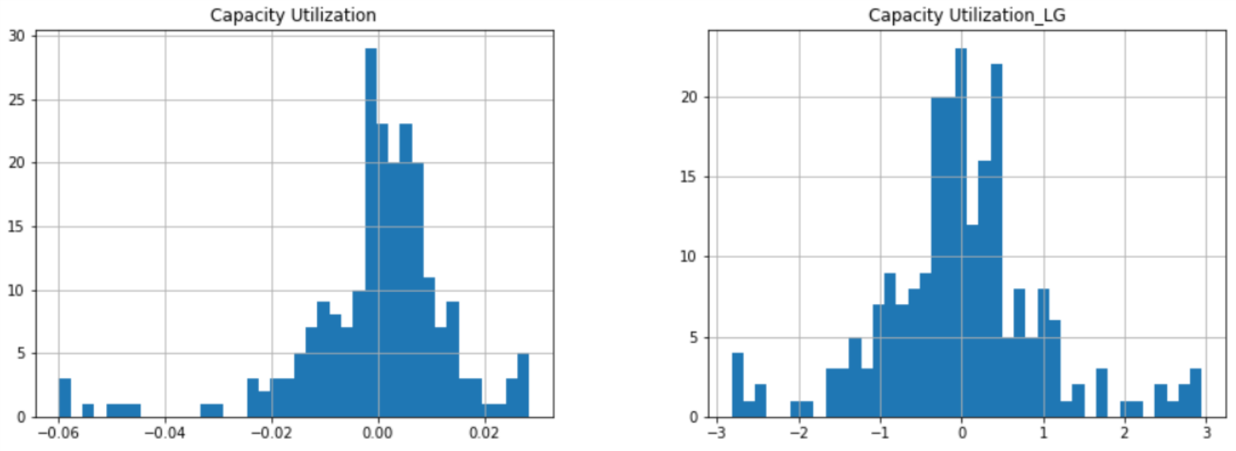
    - Log Transformation (LG)



Data Pre-Processing

Pre-Processing (cont.)

Splitting & Scaling (cont.)

- Chosen data frame
- Train, Test Split
- **Scaling**
  - 3 scaling approaches were tried to “normalize” the variables:
    - Standard Scaling (SS)
    - MinMax Scaling (MM)
    - Log Transformation (LG)

	Wages CPI_SS	WTI_SS
count	2.180000e+02	2.180000e+02
mean	-4.838128e-18	2.750094e-17
std	1.002301e+00	1.002301e+00
min	-6.977019e+00	-3.783391e+00
25%	-2.671202e-01	-5.665365e-01
50%	1.153214e-01	-3.959852e-02
75%	4.280369e-01	6.677299e-01
max	3.074376e+00	2.742497e+00

Wages CPI_MM	WTI_MM
218.000000	218.000000
0.694134	0.579751
0.099718	0.153589
0.000000	0.000000
0.667559	0.492937
0.705608	0.573683
0.736719	0.682071
1.000000	1.000000

Wages CPI_LG	WTI_LG
2.180000e+02	2.180000e+02
-2.340126e-16	-1.018553e-17
1.002301e+00	1.002301e+00
-4.203779e+00	-3.308051e+00
-3.922100e-01	-6.014282e-01
2.665979e-02	-8.488108e-02
3.947888e-01	6.501558e-01
4.675375e+00	3.071756e+00

Data Pre-Processing

Pre-Processing
(cont.)

Splitting & Scaling (cont.)

- Chosen data frame
- Train, Test Split
- **Scaling**
  - 3 scaling approaches were tried:
    - Standard Scaling (SS)
    - MinMax Scaling (MM)
    - Log Transformation (LG)
  - MM posted poor results; thus removed

```
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
```

```
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
```

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

RMSE results for X & y scaled below
SS Train | 0.7032    Test 0.8086
MM Train | 0.2694    Test 0.2685
LG Train | 0.7083    Test 0.8218

RMSE results for X only scaled below
SS Train | 0.6139    Test 0.7133
MM Train | 0.8545    Test 0.8657
LG Train | 0.6219    Test 0.723
```

Data Pre-Processing

Pre-Processing (cont.)

Splitting & Scaling (cont.)

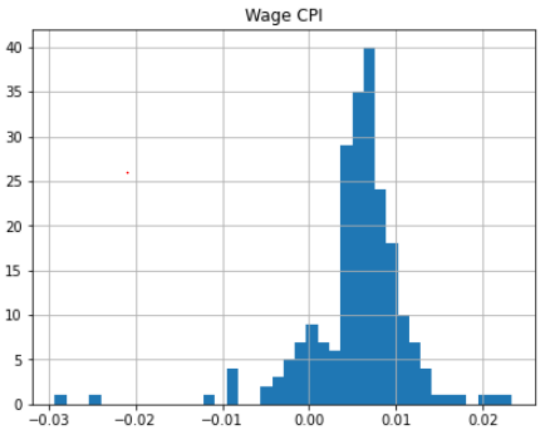
- Chosen data frame
- Train, Test Split
- **Scaling**
  - 3 scaling approaches were tried:
    - Standard Scaling (SS)
    - ~~MinMax Scaling (MM)~~
    - Log Transformation (LG)
  - MM posted poor results; thus removed
  - As SS & LG posted the best result, variables were chosen to be sent to a new data frame for either a SS or LG while keeping the y variable (Inflation) unscaled.

Data Pre-Processing

Pre-Processing (cont.)

Splitting & Scaling (cont.)

- Chosen data frame
- Train, Test Split
- **Scaling**
  - 3 scaling approaches were tried:
    - Standard Scaling (SS)
    - ~~MinMax Scaling (MM)~~
    - Log Transformation (LG)
  - MM posted poor results; thus removed
  - As SS & LG posted the best result, variables were chosen to be sent to a new data frame for either a SS or LG while keeping the y variable (Inflation) unscaled.
  - The following were sent to LG:
    - Wage CPI

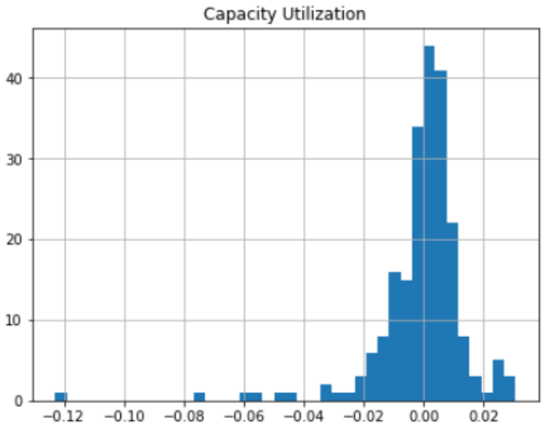


Data Pre-Processing

Pre-Processing (cont.)

Splitting & Scaling (cont.)

- Chosen data frame
- Train, Test Split
- **Scaling**
    - 3 scaling approaches were tried:
        - Standard Scaling (SS)
        - ~~MinMax Scaling (MM)~~
        - Log Transformation (LG)
    - MM posted poor results; thus removed
    - As SS & LG posted the best result, variables were chosen to be sent to a new data frame for either a SS or LG while keeping the y variable (Inflation) unscaled.
    - The following were sent to LG:
        - Wage CPI
        - Capacity Utilization

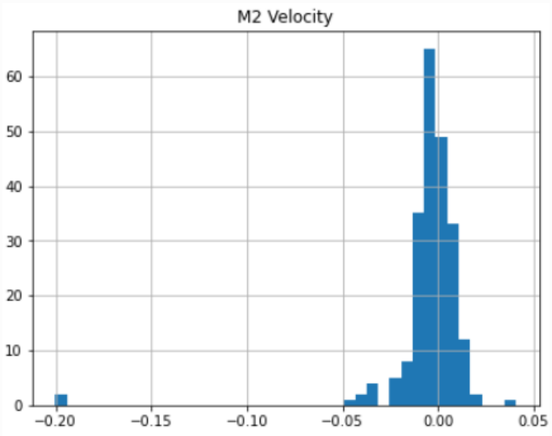


Data Pre-Processing

Pre-Processing (cont.)

Splitting & Scaling (cont.)

- Chosen data frame
- Train, Test Split
- **Scaling**
    - 3 scaling approaches were tried:
        - Standard Scaling (SS)
        - ~~MinMax Scaling (MM)~~
        - Log Transformation (LG)
    - MM posted poor results; thus removed
    - As SS & LG posted the best result, variables were chosen to be sent to a new data frame for either a SS or LG while keeping the y variable (Inflation) unscaled.
    - The following were sent to LG:
        - Wage CPI
        - Capacity Utilization
        - M2 Velocity

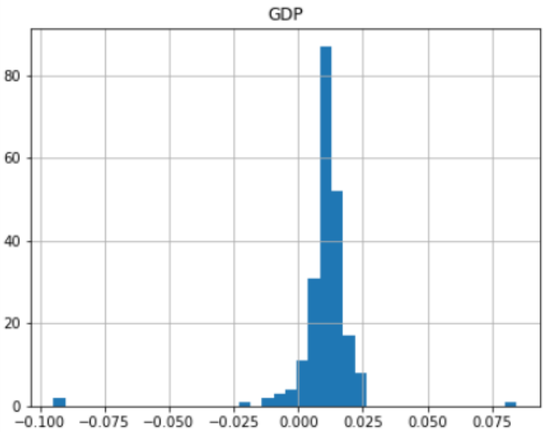


Data Pre-Processing

Pre-Processing (cont.)

Splitting & Scaling (cont.)

- Chosen data frame
- Train, Test Split
- **Scaling**
    - 3 scaling approaches were tried:
        - Standard Scaling (SS)
        - ~~MinMax Scaling (MM)~~
        - Log Transformation (LG)
    - MM posted poor results; thus removed
    - As SS & LG posted the best result, variables were chosen to be sent to a new data frame for either a SS or LG while keeping the y variable (Inflation) unscaled.
    - The following were sent to LG:
        - Wage CPI
        - Capacity Utilization
        - M2 Velocity
        - GDP

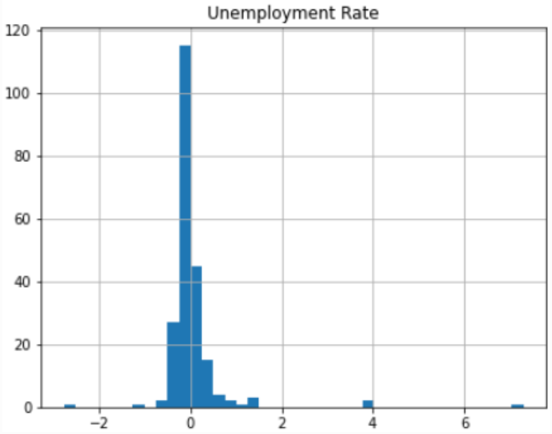


Data Pre-Processing

Pre-Processing (cont.)

Splitting & Scaling (cont.)

- Chosen data frame
- Train, Test Split
- **Scaling**
  - 3 scaling approaches were tried:
    - Standard Scaling (SS)
    - ~~MinMax Scaling (MM)~~
    - Log Transformation (LG)
  - MM posted poor results; thus removed
  - As SS & LG posted the best result, variables were chosen to be sent to a new data frame for either a SS or LG while keeping the y variable (Inflation) unscaled.
  - The following were sent to LG:
    - Wage CPI
    - Capacity Utilization
    - M2 Velocity
    - GDP
    - Unemployment Rate



Data Pre-Processing

Pre-Processing (cont.)

Splitting & Scaling (cont.)

- Chosen data frame
- Train, Test Split
- **Scaling**
  - 3 scaling approaches were tried:
    - Standard Scaling (SS)
    - ~~MinMax Scaling (MM)~~
    - Log Transformation (LG)
  - MM posted poor results; thus removed
  - As SS & LG posted the best result, variables were chosen to be sent to a new data frame for either a SS or LG while keeping the y variable (Inflation) unscaled.
  - The following were sent to LG:
    - Wage CPI
    - Capacity Utilization
    - M2 Velocity
    - GDP
    - Unemployment Rate
    - Initial Jobless Claims

Data Pre-Processing

Pre-Processing (cont.)

Splitting & Scaling (cont.)

- Chosen data frame
- Train, Test Split
- **Scaling**
    - 3 scaling approaches were tried:
        - Standard Scaling (SS)
        - ~~MinMax Scaling (MM)~~
        - Log Transformation (LG)
    - MM posted poor results; thus removed
    - As SS & LG posted the best result, “”
    - The results of these below

R^2 results for nothing scaled below
Test 0.2925 (nothing scaled)

R^2 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

R^2 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

R^2 results for the LG & SS combination below
SS Train | 0.5053 Test 0.2788

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

RMSE results for nothing scaled below
Test 0.7133 (nothing scaled)

RMSE results for X & y scaled below
SS Train | 0.7032 Test 0.8086
~~MM Train | 0.2694 Test 0.2685~~
LG Train | 0.7083 Test 0.8218

RMSE results for X only scaled below
SS Train | 0.6139 Test 0.7133
~~MM Train | 0.8545 Test 0.8657~~
LG Train | 0.6219 Test 0.723

RMSE results for the LG & SS combination below
SS Train | 0.6189 Test 0.7202

Data Pre-Processing

Pre-Processing (cont.)

Splitting & Scaling (cont.)

- Chosen data frame
- Train, Test Split
- **Scaling**
    - 3 scaling approaches were tried:
        - Standard Scaling (SS)
        - ~~MinMax Scaling (MM)~~
        - Log Transformation (LG)
    - MM posted poor results; thus removed
    - As SS & LG posted the best result, “”
    - The results of these below
    - The resulting x5 Data frames went to a Random Forest Model

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

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

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

04

Model Description

The Random Forest

The Random Forest Model was then used

with the goal of determining what variables best explain & understand Inflation

05

Model Findings

What’s moving Inflation¿

Model Findings

Where's Inflation coming from?

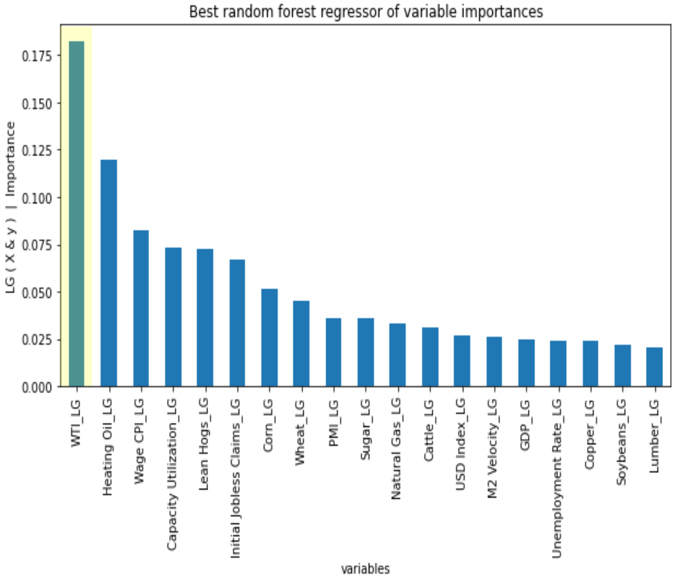
- **The standard process was taken on x5**
  - Grid Search
  - Random Forest
  - Hyperparameter search using Grid Search CV

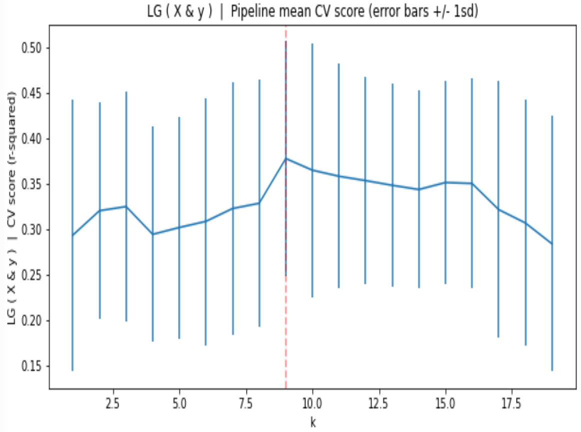
Model Findings

(cont.)

Where's Inflation coming from? (cont.)

- The standard process was taken on x5
- ## The results
  - Random Forest showed **WTI holding a ubiquitous position as being the dominate Variable** on all scaling approaches



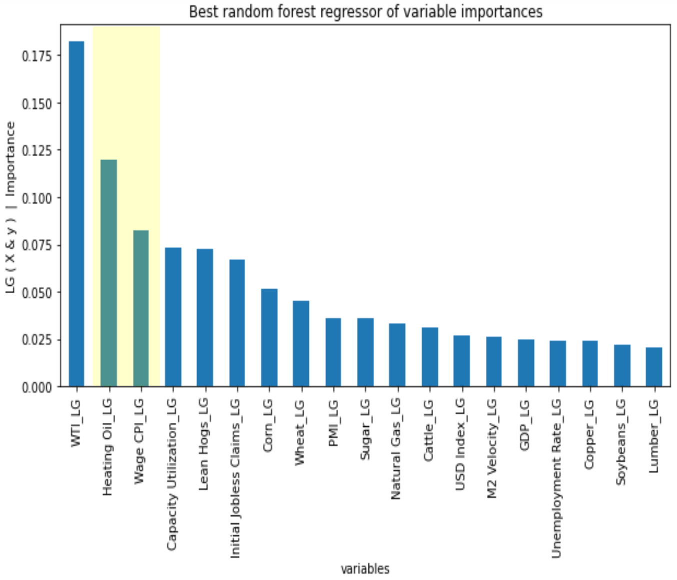


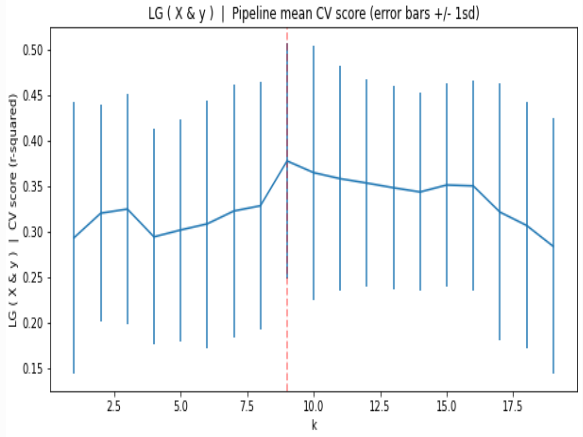
Model Findings

(cont.)

Where's Inflation coming from? (cont.)

- The standard process was taken on x5
- **The results**
  - Random Forest showed WTI holding a ubiquitous position as being the dominate Variable on all scaling approaches; **Heating Oil & Wage CPI showed up in second & third place on many**



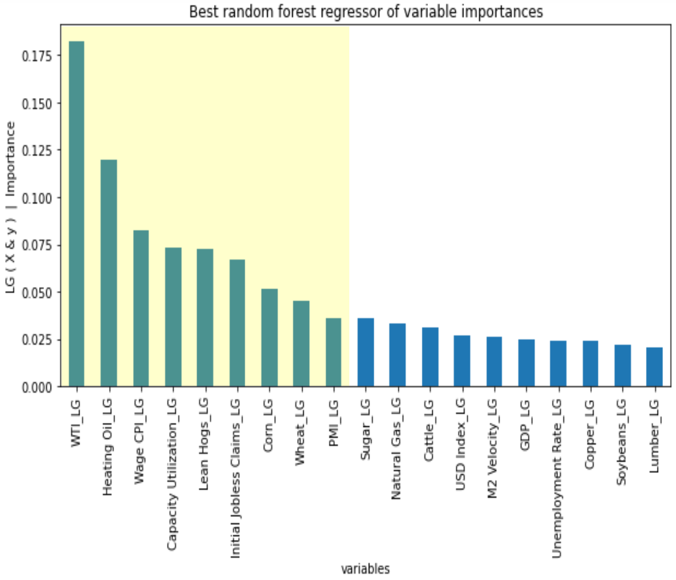


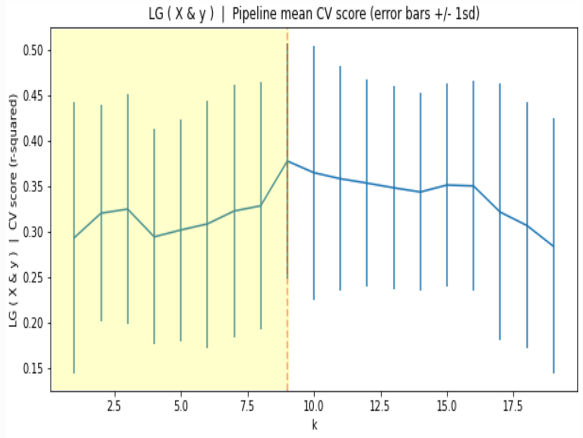
Model Findings

(cont.)

Where's Inflation coming from? (cont.)

- The standard process was taken on x5
- **The results**
  - Random Forest showed WTI holding a ubiquitous position as being the dominate Variable on all scaling approaches; Heating Oil & Wage CPI showed up in second & third place on many. **Other variables helping varied*; the below example has 9 variables**





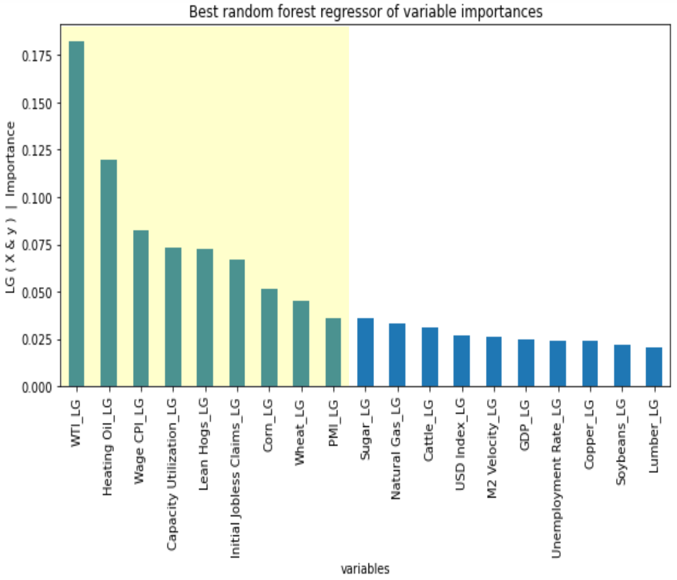
** Only one shown here; all are found in the Report*

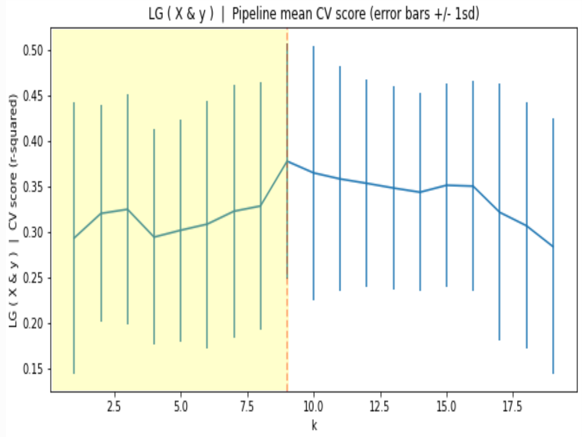
Model Findings

(cont.)

Where's Inflation coming from? (cont.)

- The standard process was taken on x5
- **The results**
    - Random Forest showed WTI holding a ubiquitous position as being the dominate Variable on all scaling approaches; Heating Oil & Wage CPI showed up in second & third place on many. Other variables helping varied*; the below example has 9 variables
    - **It was then decided to isolate each to their respective variables**





Model Findings

(cont.)

Where’s Inflation coming from? (cont.)

- The standard process was taken on x5
- **The results**
  - Random Forest showed WTI holding a ubiquitous position as being the dominate Variable on all scaling approaches; Heating Oil & Wage CPI showed up in second & third place on many. Other variables helping varied*; the below example has 9 variables
  - It was then decided to isolate each to their respective variables
  - Once completed, the **LG approach on X only presented the best results**

```
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
```

```
RMSE results for X & y scaled below
SS Train | 0.7128    Test 0.8232
LG Train | 0.7292    Test 0.8171

RMSE results for X only scaled below
SS Train | 0.6272    Test 0.8216
LG Train | 0.4343    Test 0.5702

RMSE results for the LG & SS combination below
SS Train | 0.4343    Test 0.5702
```

Model Findings

(cont.)

Where’s Inflation coming from? (cont.)

- The standard process was taken on x5
- **The results**
  - Random Forest showed WTI holding a ubiquitous position as being the dominate Variable on all scaling approaches; Heating Oil & Wage CPI showed up in second & third place on many. Other variables helping varied*; the below example has 9 variables
  - It was then decided to isolate each to their respective variables
  - Once completed, the LG approach on X only presented the best results
  - & showed that the process presented notable improvement from Pre-processing

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

 37.92 bps increase in R²

 A -23.52 bps decrease in MAE

 A -15.28 bps decrease in RMSE
```

Model Findings

(cont.)

Where's Inflation coming from? (cont.)

- The standard process was taken on x5
- **The results**
    - Random Forest showed WTI holding a ubiquitous position as being the dominate Variable on all scaling approaches; Heating Oil & Wage CPI showed up in second & third place on many. Other variables helping varied*; the below example has 9 variables
    - It was then decided to isolate each to their respective variables
    - Once completed, the LG approach on X only presented the best results
    - & showed that the process presented notable improvement from Pre-processing
    - **WTI held the dominate place on all of the different structures of scaling. To best position ourselves to understand Inflation; the verdict is...**

Model Findings

(cont.)

Where's Inflation coming from? (cont.)

- The standard process was taken on x5
- **The results**
  - Random Forest showed WTI holding a ubiquitous position as being the dominate Variable on all scaling approaches; Heating Oil & Wage CPI showed up in second & third place on many. Other variables helping varied*; the below example has 9 variables
  - It was then decided to isolate each to their respective variables
  - Once completed, the LG approach on X only presented the best results
  - & showed that the process presented notable improvement from Pre-processing
  - WTI held the dominate place on all of the different structures of scaling. To best position ourselves to understand Inflation; the verdict is…
  - **We will borrow some words to help explain**

The wise words of Bill Clintons' advisor to his 1992 political campaign

" "

- James Carville

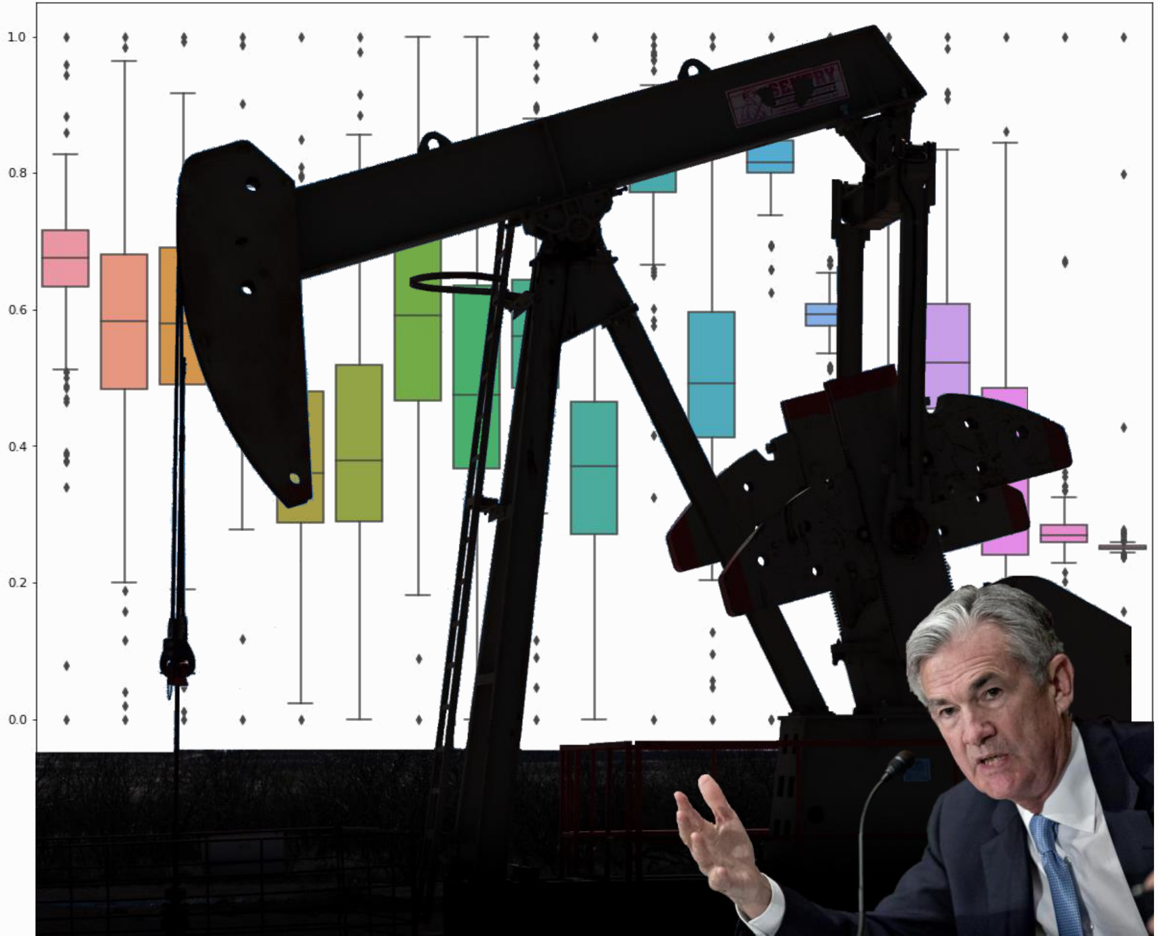
The wise words of Bill Clintons' advisor to his 1992 political campaign

"It's the economy, stupid"

- James Carville

Borrowed words...

"It's Oil, silly"



Our Conclusion

06

Next Steps

Keep going

Next Steps

Variables not included

- **Steel**
  - 2008 was the furthest I could pull

Next Steps

Variables not included

- Steel
- **Gasoline**
    - 2005 was the furthest I could pull

Next Steps

Variables not included

- Steel
- Gasoline
- **US Wages Hourly Earnings**
    - Limited Data as well

Next Steps

Variables not included

- Steel
- Gasoline
- US Wages Hourly Earnings
- **US Dollar Index: Broad, Goods & Services**
    - Only goes until 2006

Next Steps

Variables not included

- Steel
- Gasoline
- US Wages Hourly Earnings
- US Dollar Index: Broad, Goods & Services
- **Growth in M2**
  - Possible collinearity with M2 Velocity

Next Steps
(cont.)

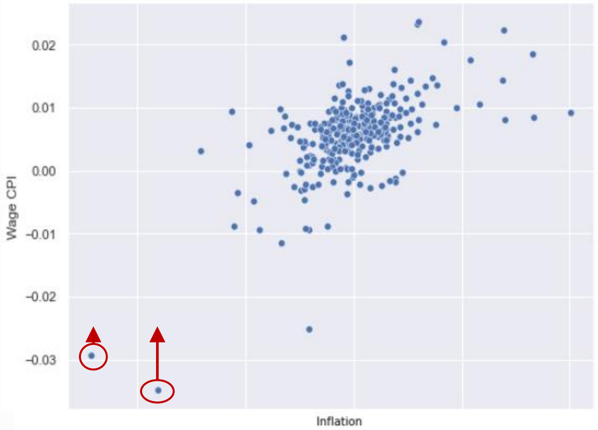
More attention may be applicable to the below:

- **Get more data**
  - The big set back would be the size of the data frame. With only 321 observations, machine learning is limited

Next Steps
(cont.)

More attention may be applicable to the below:

- Get more data
- **Winsorizing**
  - Winsorization on Inflation & other variables may be re-examined



Next Steps
(cont.)

More attention may be applicable to the below:

- Get more data
- Winsorizing
- **The SS & LG Divide**
  - Reassess the Variables which were chosen in the SS & LG divide; discussed in Pre-processing

Next Steps
(cont.)

More attention may be applicable to the below:

- Get more data
- Winsorizing
- The SS & LG Divide
- **Predict Wages CPI Itself**
    - Develop a model to remove ourselves from the US govt's reporting

Next Steps
(cont.)

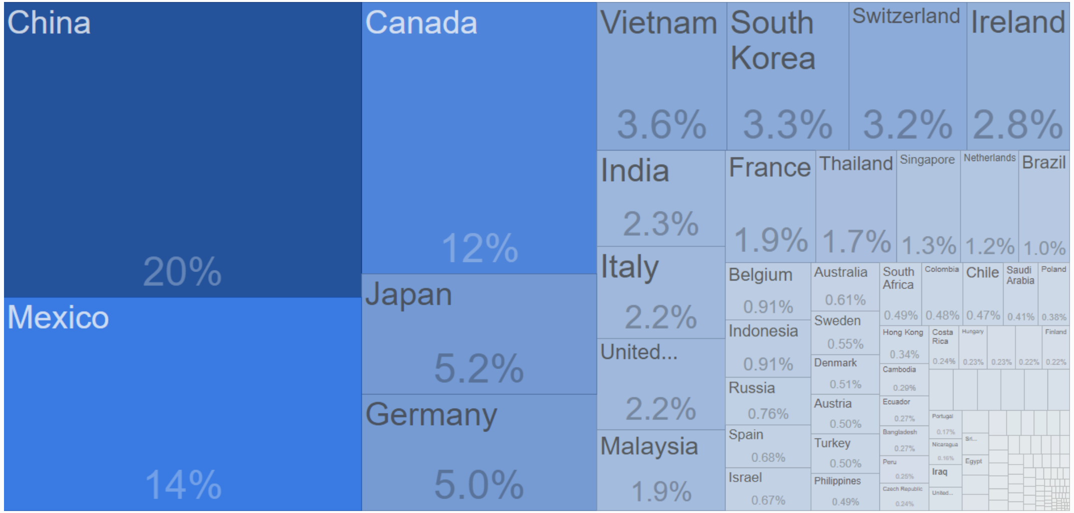
More attention may be applicable to the below:

- Get more data
- Winsorizing
- The SS & LG Divide
- Predict Wages CPI Itself
- **Build a Better Imported / Exported USD**
    - **The DXY doesn't correctly address the potential import of inflation to the US** as it's weighting is a weighted geometric mean of the:
        - Eurozone (EUR),
        - Japan (JPY),
        - United Kingdom (GBP),
        - Canada (CAD),
        - Sweden (SEK) &
        - Switzerland (CHF)

Next Steps
(cont.)

More attention may be applicable to the below:

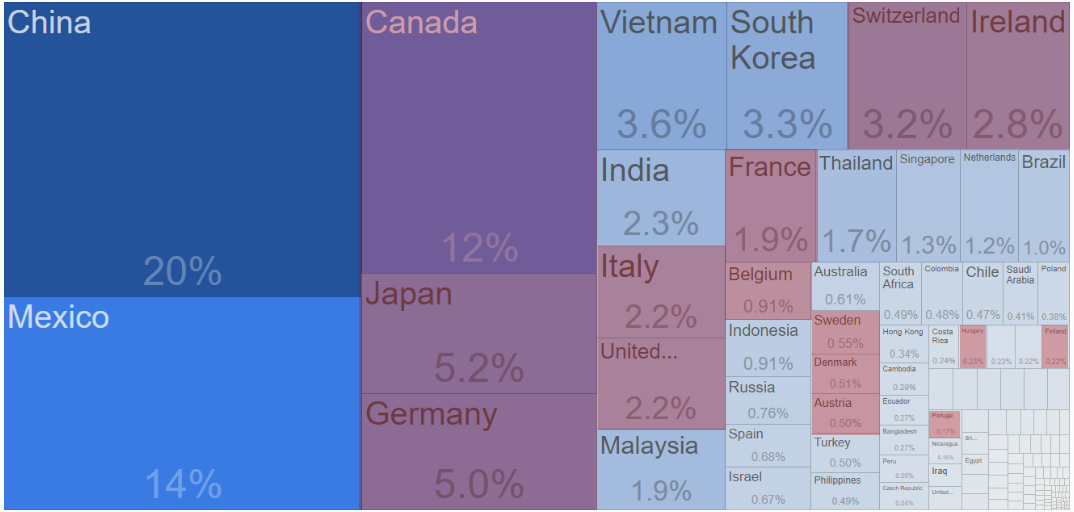
- Get more data
- Winsorizing
- The SS & LG Divide
- Predict Wages CPI Itself
- **Build a Better Imported / Exported USD**
    - The DXY doesn't correctly address the potential import of inflation to the US as it's weighting is a weighted geometric mean of various currencies
    - **This doesn't take into account the US's largest trading partner, China. Imports in 2020 shown below**



Next Steps
(cont.)

More attention may be applicable to the below:

- Get more data
- Winsorizing
- The SS & LG Divide
- Predict Wages CPI Itself
- **Build a Better Imported / Exported USD**
  - The DXY doesn't correctly address the potential import of inflation to the US as it's weighting is a weighted geometric mean of various currencies
  - This doesn't take into account the US's largest trading partner, China. Imports in 2020 shown below
  - **It takes into account less than 40% of US Import Trade**



Next Steps
(cont.)

More attention may be applicable to the below:

- Get more data
- Winsorizing
- The SS & LG Divide
- Predict Wages CPI Itself
- Build a Better Imported / Exported USD
- **Random Forest was used, while Gradient Boosting may be something to explore:**
    - **i.e. Boosting over Bagging**

Thanks

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