

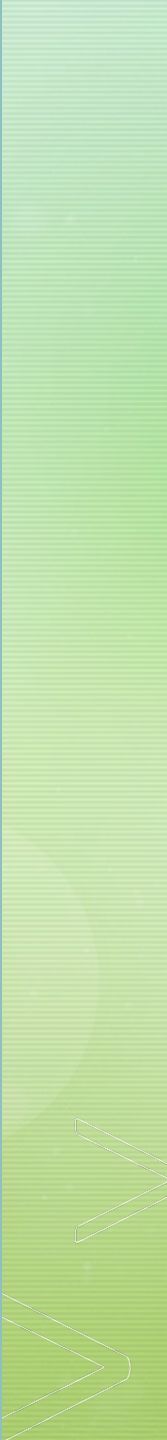
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# Defensive Stock Analysis



# Business Problem

- During times of uncertainty investors want to protect their assets from loss.
  - This project analyzes 3 consumer defensive stocks by performing time series analysis (SARIMA models) and linear regression.
  - We will choose the 3 stocks based on highest market caps.
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# Data

- The data acquired for this project represents broad market data including, S&P 500, stocks within the S&P500, Ethereum, PPI (producer price index), Dollar index, and gold rates.
- Columns:
  - Date: Date of close
  - Symbol: Symbol of defensive stock
  - Close: Close price of defensive stock
  - SPClose: Close Price of S&P 500
  - Gold: Gold Price
  - Ether: Ethereum Price
  - USD: US dollar index
  - PPI: Producer Price Index

# Methods SARIMA models

- Begin analysis by defining P, D, and Q
- Modeling steps:
  1. Dropped all columns but date and close price.
  2. Used bfill to fill all missing dates, weekends and holidays.
  3. We then ran a grid pdq and seasonal pdq parameters calculated above and get the best AIC value.
  4. Plug the optimal parameter values into a new SARIMAX model and fit the results.
  5. Call plot\_diagnostics() on the results calculated.
  6. Get predictions starting from 01-01-1998 and calculate confidence intervals and Plot real vs predicted values along with confidence interval.
  7. Get the real and predicted values and get the mean squared error.
  8. Plot the dynamic forecast with confidence intervals.

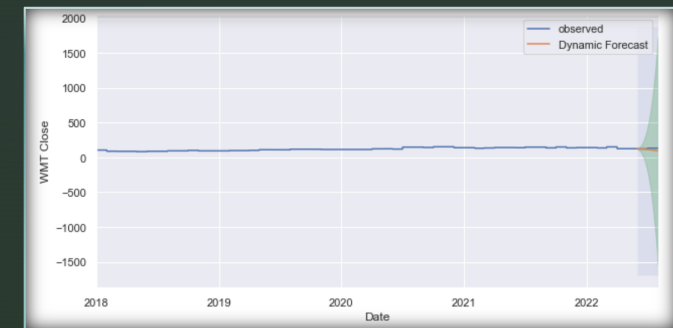
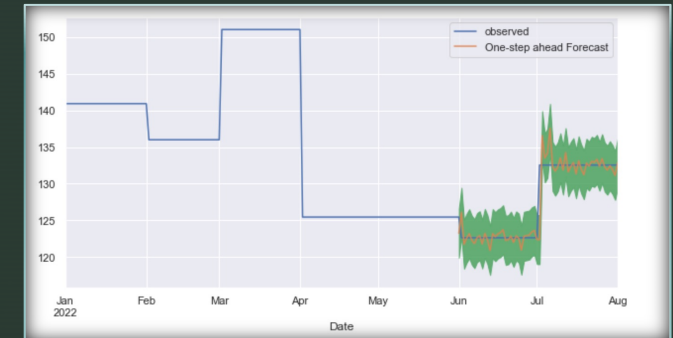
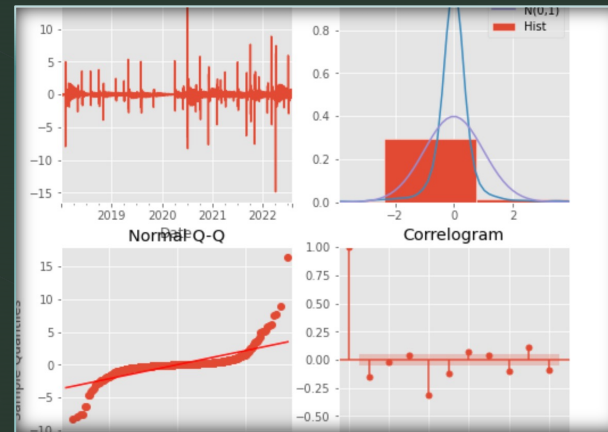
# Methods for Linear Regression

- Steps:
  1. Create initial model and visualize the terms.
  2. Log transform close price and most correlated feature.
  3. Create final model.
  4. Plot final model on Q-Q plot.
  5. Plot residuals.



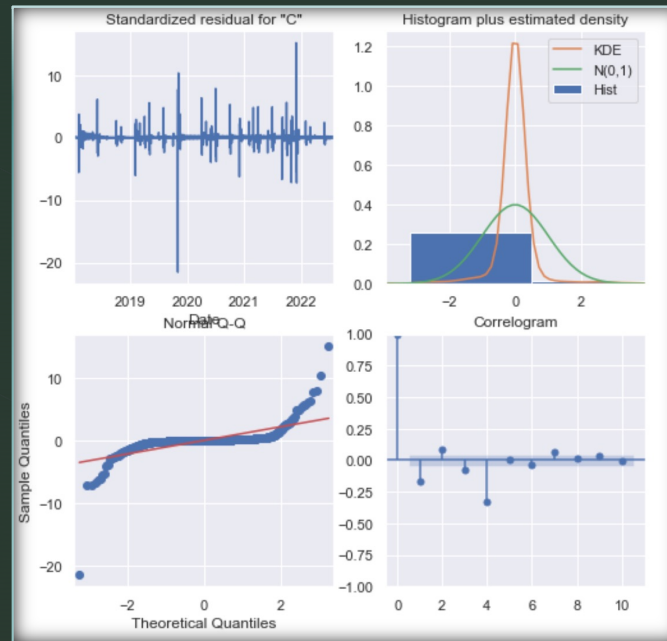
# SARIMA model WMT

- Mean squared error:  
3.12



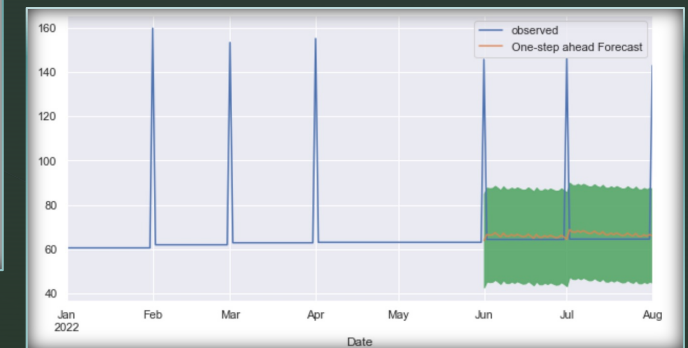
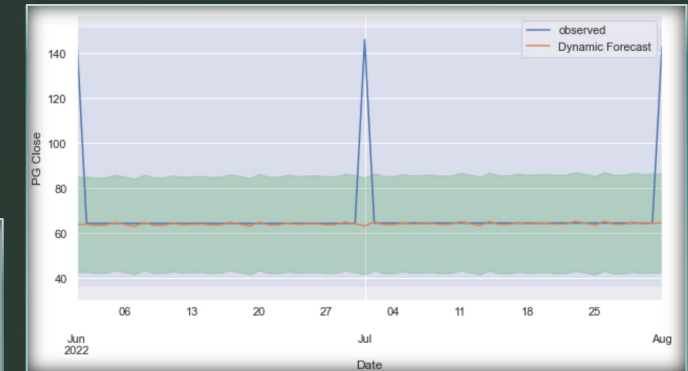
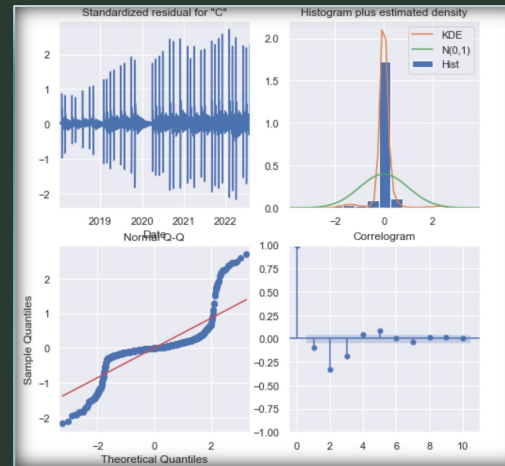
# SARIMA model KO

- Mean squared error:  
.03



# SARIMA model PG

- Mean squared error:  
315.37

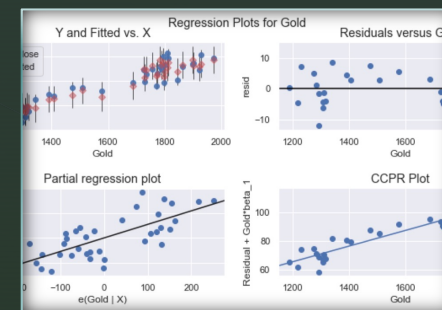
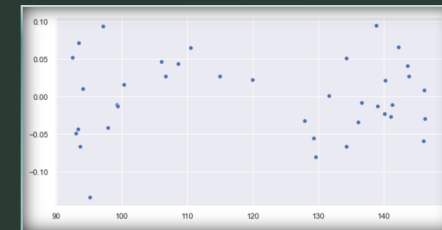




# Linear Regression WMT

- 'Test Statistic':  
17.454007239058875
- 'Test Statistic p-value':  
0.6233267123820959
- 'F-Statistic':  
0.7220827110094082
- 'F-Test p-value':  
0.7589067655725635

Dep. Variable:	log_Close	R-squared:	0.920			
Model:	OLS	Adj. R-squared:	0.908			
Method:	Least Squares	F-statistic:	73.94			
Date:	Tue, 13 Dec 2022	Prob (F-statistic):	1.26e-16			
Time:	14:22:05	Log-Likelihood:	59.517			
No. Observations:	38	AIC:	-107.0			
Df Residuals:	32	BIC:	-97.21			
Df Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
Intercept	-1.0670	0.650	-1.642	0.110	-2.391	0.257
log_Gold	0.7166	0.113	6.331	0.000	0.486	0.947
Ether	-3.057e-05	1.74e-05	-1.754	0.089	-6.61e-05	4.94e-06
USD	0.0028	0.003	0.912	0.368	-0.003	0.009
PPI	-0.0015	0.000	-3.168	0.003	-0.002	-0.001
SPClose	0.0002	4.75e-05	3.553	0.001	7.21e-05	0.000
Omnibus:	0.350	Durbin-Watson:	1.528			
Prob(Omnibus):	0.839	Jarque-Bera (JB):	0.335			
Skew:	-0.203	Prob(JB):	0.846			
Kurtosis:	2.783	Cond. No.	2.83e+05			



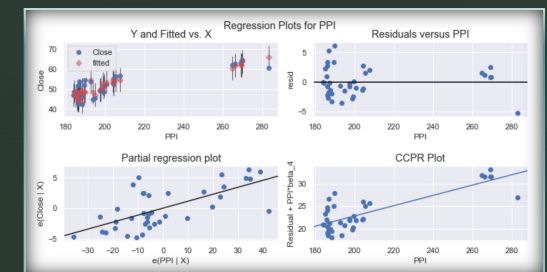
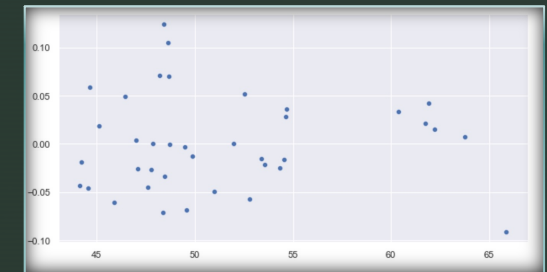
# Linear Regression KO

- 'Test Statistic':  
23.545451639264005
- 'Test Statistic p-value':  
0.2628115007420615  
5
- 'F-Statistic':  
1.384590745687979
- 'F-Test p-value':  
0.2511204642696958  
6

Dep. Variable:	log_Close	R-squared:	0.834
Model:	OLS	Adj. R-squared:	0.808
Method:	Least Squares	F-statistic:	32.07
Date:	Tue, 13 Dec 2022	Prob (F-statistic):	1.44e-11
Time:	14:22:07	Log-Likelihood:	61.071
No. Observations:	38	AIC:	-110.1
Df Residuals:	32	BIC:	-100.3
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.9004	0.462	1.949	0.060	-0.041	1.841
Gold	-0.0002	6.99e-05	-2.317	0.027	-0.000	-1.96e-05
Ether	-4.099e-05	1.68e-05	-2.443	0.020	-7.52e-05	-6.82e-06
USD	0.0027	0.003	0.945	0.352	-0.003	0.009
log_PPI	0.4454	0.103	4.340	0.000	0.236	0.654
SPClose	0.0002	4.58e-05	4.180	0.000	9.82e-05	0.000

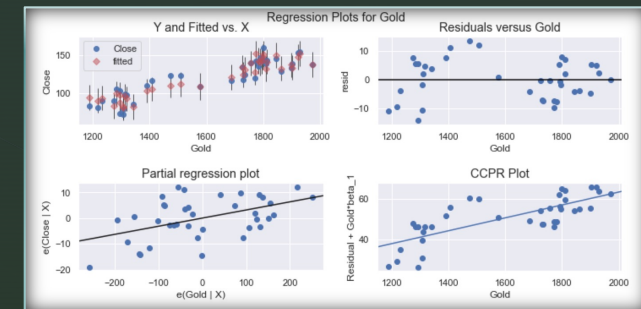
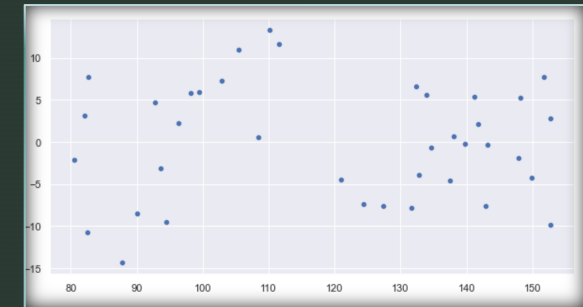
Omnibus:	1.841	Durbin-Watson:	1.323
Prob(Omnibus):	0.398	Jarque-Bera (JB):	1.455
Skew:	0.476	Prob(JB):	0.483
Kurtosis:	2.884	Cond. No.	2.27e+05



# Linear Regression PG

- 'Test Statistic':  
23.545451639264005
- 'Test Statistic p-value':  
0.26281150074206155
- 'F-Statistic':  
1.384590745687979
- 'F-Test p-value':  
0.25112046426969586

Dep. Variable:	Close	R-squared:	0.925			
Model:	OLS	Adj. R-squared:	0.913			
Method:	Least Squares	F-statistic:	78.62			
Date:	Tue, 13 Dec 2022	Prob (F-statistic):	5.13e-17			
Time:	14:22:08	Log-Likelihood:	-126.86			
No. Observations:	38	AIC:	265.7			
Df Residuals:	32	BIC:	275.5			
Df Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
Intercept	-508.2905	87.705	-5.795	0.000	-686.939	-329.642
log_Gold	51.1521	15.273	3.349	0.002	20.042	82.262
Ether	-0.0048	0.002	-2.058	0.048	-0.010	-4.99e-05
USD	1.3498	0.412	3.276	0.003	0.511	2.189
PPI	0.0227	0.062	0.366	0.717	-0.104	0.149
SPClose	0.0282	0.006	4.400	0.000	0.015	0.041
Omnibus:	1.909	Durbin-Watson:	0.588			
Prob(Omnibus):	0.385	Jarque-Bera (JB):	1.187			
Skew:	-0.072	Prob(JB):	0.552			
Kurtosis:	2.146	Cond. No.	2.83e+05			

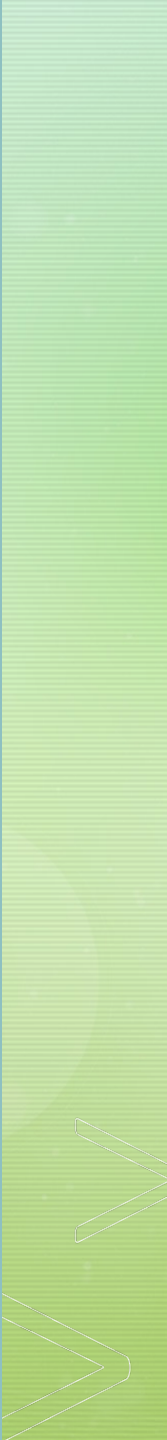


# Conclusions

- Defensive stocks do provide protection against market volatility.
- Recommendations:
  1. 1) Walmart showed to have an downward trend, hold or sell WMT.
  2. KO showed to have an upward trend, buy KO.
  3. PG showed a upward trend, buy PG.



## Next Steps

- This project focused mainly on recent market data, beginning in 2017. This created issues when trying to identify an accurate trend. For more accurate results we will gather information about the markets at an earlier date, starting preferably at 2010.
  - We will include other indices such as the VIX, NASDAQ, and Dow Jones to provide a wider market perspective to see how defensive stocks hedge against moves in the broader market.
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# Thank You

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