Does Crude Oil Markets Obtain Unrealized Predictive Capabilities?

——from Gasoline to CO_2 Concentration

Executive Summary

In 1984, Richard Roll published the paper *"Orange Juice and Weather,"* where he determined that there is a "statistically significant relation between OJ returns and subsequent errors in temperature forecasts." This insight led to the conclusion that commodity markets contain valuable information in addition to the information contained in the weather forecast, which shows that financial instruments are beneficial in aiding the prediction of prices of everyday goods that the general public is typically invested in.[1]

This paper investigates three powerful insights buried within the pricing of crude oil instruments.This paper explored the statistical relationships that crude oil spot and futures prices had with gasoline, something that the general public really cares about. Building off these relationships, this paper further explores crude oil prices to see if they're capable of providing the three buried insights for something the general public should care about - Carbon Dioxide Concentrations (CO_2).[2]

This paper establishes meaningful connections between crude oil and these two important elements. In addition, this paper also tested their statistical significance and used these relationships to predict their future values through various time series models and machine learning techniques. In doing so, the three hidden insights became more evident. The first is that futures can provide evidence of statistically significant relationships between the listed prices and some other thing that impacts the general public. Second, the time frame in which these relationships are realized at the spot prices becomes evident, allowing people to grasp when these expected changes occur. Lastly, investors can take advantage of this hidden knowledge to construct portfolios that profit from these unrealized expectations.

1. Data Description

Table 1: Data Description

Variables	Frequency	Source	Period
Oil WTI	W	US EIA	Jan-1986 — Jan-2021
Oil Brent	W	US EIA	June-1988 — Jan-2021
Oil Futures	W	US EIA	Jan-1986 — Jan-2021
Gasoline Price	W	US EIA	Jan-1991 — Jan-2021
CO_2 Concentration	W	NOAA	May-1974 — Jan-2021
	M	NOAA	May-1974 — Jan-2021
	Q	NOAA	May-1974 — Jan-2021
GDP-USA	Q	OECD	Jan-1987 — Jan-2021
GDP-Europe	Q	OECD	Jan-1987 — Jan-2021
GDP-China	Q	OECD	Jan-1987 — Jan-2021
Global Temperature	M	NOAA	Jan-1958 — Dec-2020
Sugar Price	W	Macrotrends	Nov-1962 — Jan-2021
Ethanol Price	W	Investing.com	Apr-2005 — Jan-2021

([Source][3, 4] US EIA: US Energy Information Administration ; NOAA: National Oceanic and Atmospheric Administration ; OECD: Oceanic and Atmospheric Administration web-site, based on the Mauna Loa Observatory Station; MT: Macro trends; [Frequency]W: Weekly; M: Monthly; Q: Quarterly)*

2. Exploratory analysis

Generating different scenarios for each of the research questions, it becomes easier to find which time frame is the best for statistical modeling. As mentioned before, the research will be conducted on three different time frames, corresponding to 3 different investment behaviors:

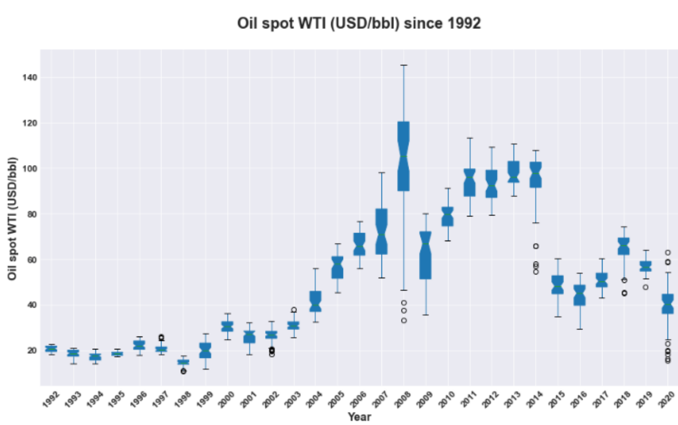
- Weekly Time Frame (Swing Investment)
- Monthly Time Frame (Value Investment)
- Quarterly Time Frame (Economic Investment)

2.1 Historical Performance of Crude Oil, Oil Futures, and CO_2 Concentration

The expectation that crude oil prices directly affects gasoline prices stems from the fact that crude oil costs are the main component of retail gasoline prices. From 2010-2020, approximately 59% of the average gasoline price was associated with the cost of crude oil. The remaining components of gasoline's retail prices were refining fees, distribution, marketing, and federal/state taxes. From a composition perspective, crude oil price fluctuations will have the most considerable impact on gasoline prices.

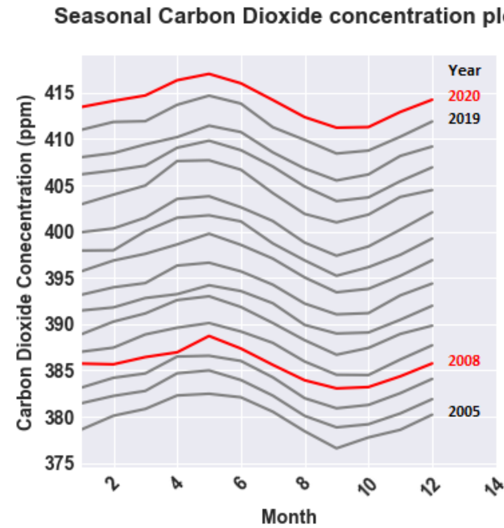
It is crucial to understand the crude oil supply and demand chain's primary disputers in the United States. The price of crude oil is driven by the amount of supply and demand present in the economy. This supply and demand chain has been and, for the foreseeable future, always exposed under the threat of disruption. Events, such as geopolitical and weather-related developments, play a significant role in physical turmoil and the uncertainty of possible trouble. Increases in uncertainty can lead to higher volatility in prices. Future contracts help mitigate this uncertainty for market players by locking in the price that a buyer and seller agree upon at a future delivery date. This agreed transaction provides direct information about the market's expectation of oil futures' price and potential expectations of oil-based products such as gasoline.[5, 6]

Figure 1: Oil Spot WTI (USD/bbl) since 1992



Demand-supply and extreme market events drive WTI. Its price levels reach the highest yearly variance levels during crises, from a high correlation with financial markets. A structural break in 2008 is included in the analysis due to the high volatility of crude oil prices. Hence, the research focuses on Crude oil price derived from WTI (Figure 1) the dummy variable for the financial crisis included as additional variable.

Figure 2: Seasonal Carbon Dioxide Concentration Plot



CO_2 Concentration shows seasonal trends, with a peak in Spring and bottom in Autumn every year (Figure 2). CO_2 Concentration has increased every year. Different time frames: weekly, quarterly, and monthly can explain lags in time series differently. The wider the time frame, the more seasonal lag effect is aggregated, resulting in a less seasonal effect in the time series. [7]

Figure 3: Augmented Dickey Fuller Test(Test statistics)

Augmented Dickey Fuller Test (t-score)

	Weekly		*Monthly*			*Quarterly*		
Variables	*Level*	*First diff*	*Level*	*First dif*	*Seasonal dif*	*Level*	*First dif*	*Seasonal dif*
Gasoline price	-1.94	-9.66***	-1.43	-6.09***	-9.00***	-1.42	-11.05***	-4.71***
CO2%	0.24	-0.15***	3.09	-4.97***	-9.58***	2.83	-2.71*	-6.45***
WTI spot	-2.37	-12.10***	-1.70	-14.06***	-6.9***	-1.79	-9.79***	-5.23***
BRENT spot	-2.12	-25.29***	-2.14	-17.79***	-8.27***	-2.21	-9.52***	-4.84***
Oil futures	-2.36	-10.91***	-1.69	-17.27***	-6.94***	-1.76	-9.53***	-5.25***
Sugar price	-2.57	-21.91***	-2.00	-15.96***	-9.57***	-2.06	-10.58***	-6.87***
Ethanol price	-3.26**	-27.80***	-3.13	-13.96***	-6.45***	-3.64	-7.48***	-4.27***
Global temp	-2.57*	-5.87***	-1.45	-9.90***	-11.4***	-1.45	-6.82***	-11.4***
USA GDP	1.46	-5.57***	0.99	-3.39**	-6.18***	1.50	-4.06***	-2.87**
China GDP	1.73	-14.62***	2.07	-2.89**	-6.36***	1.00	-2.96**	-5.22***
Europe GDP	-0.36	-5.52***	-0.37	-3.65***	-7.06***	-0.37	-5.71***	-5.05***

*Statistical significance at the 10% level **Statistical significance at the 5% level***Statistical significance at the 1% level

2.2 Stationarity

The stationarity study of variables was performed using the traditional unit root test, Augmented Dickey-Fuller. Weekly, monthly, and quarterly time frames were tested, and the results are summarized in Figure 3. These results show that at any time frame, crude Oil (WTI) and gasoline are non-stationary *(based on the level basis t-statistic and confidence level)* and stationary in the first logarithmic difference. After taking the first logarithmic difference

Figure 4: Two-way Granger Causality Test- 10 lags showing p-values

Quarterly time frame — Second way effect (Y to X)

Two way Granger Causality	1	2	3	4	5	6	7	8	9	10	11
1. Gasoline Price return	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	
2. Change in CO2 Concentration	0.00	1.00	0.00	0.00	0.00	0.00	0.00				0.00
3. Oil spot WTI return		0.00	1.00			0.03	0.00	0.00	0.00		
4. Oil spot Brent return	0.00	0.00		1.00		0.00	0.00	0.00	0.00		
5. Oil futures return	0.05	0.00			1.00	0.03	0.00	0.00	0.00		
6. Sugar price return	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.04	0.00	0.01
7. Ethanol price return				0.01			1.00		0.00		0.00
8. Change in China GDP	0.00	0.00	0.05	0.05	0.04		0.00	1.00	0.00	0.01	
9. Change in USA GDP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.01
10. Change in Europe GDP	0.01	0.00						0.00	0.02	1.00	
11. Change in Global temperature	0.00	0.01	0.00	0.00	0.00	0.01	0.00		0.00	0.04	1.00

Monthly time frame — Second way effect (Y to X)

Two way Granger Causality	1	2	3	4	5	6	7	8	9	10	11
1. Gasoline Price return	1.00	0.03	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.01	0.00
2. Change in CO2 Concentration		1.00	0.02		0.03	0.05					
3. Oil spot WTI return	0.04		1.00	0.01	0.01			0.00	0.02	0.00	0.00
4. Oil spot Brent return				1.00			0.02	0.00	0.01		0.01
5. Oil futures return				0.02	1.00			0.00	0.02	0.01	0.00
6. Sugar price return						1.00		0.00	0.00	0.00	
7. Ethanol price return							1.00				0.00
8. Change in China GDP								1.00		0.00	0.00
9. Change in USA GDP	0.00					0.00		0.00	1.00	0.00	0.02
10. Change in Europe GDP	0.02							0.00		1.00	0.02
11. Change in Global temperature								0.01	0.01		1.00

Weekly time frame — Second way effect (Y to X)

Two way Granger Causality	1	2	3	4	5	6	7	8	9	10	11
1. Gasoline Price return	1.00	0.01	0.00	0.00	0.00		0.00		0.03		
2. Change in CO2 Concentration	0.00	1.00							0.03		0.01
3. Oil spot WTI return	0.00		1.00	0.00	0.00	0.02					
4. Oil spot Brent return	0.00		0.00	1.00	0.00						
5. Oil futures return	0.00		0.00	0.00	1.00	0.03			0.05		
6. Sugar price return						1.00				0.05	0.00
7. Ethanol price return							1.00	0.01		0.01	
8. Change in China GDP							0.05	1.00			
9. Change in USA GDP	0.02	0.01				0.00			1.00		
10. Change in Europe GDP	0.04		0.03		0.02	0.01				1.00	
11. Change in Global temperature	0.02						0.05				1.00

p-value of confidence level at: 99% 95% *Red box empasizes the impact of oil return and change in GDP to Gasoline return and change in Carbon Dioxide in a different time frame

in the monthly and quarterly time frame for CO_2, a residual seasonal effect was found. The project remedies the seasonal effect of CO_2 by taking 12-month-difference for monthly time frame and 4-quarter-difference for quarterly time frame and logarithmic difference is applied in the rest of the analysis.[8]

2.3 Granger Causality

A two-way Granger Causality test helps understand how significantly two variables explain cause and effect on each other, especially when one comes before the other in the time series *(under lagged conditions)*. The null hypothesis states that the lagged independent variable does not explain the dependent variable's variation *(does not Granger-Cause)*.

Gasoline: From Figure 4, Oil spot WTI, Oil spot Brent and Oil futures returns impact gasoline price returns in all of the time-frames indicated by small p-values. The bi-directional relationship of gasoline returns and crude oil returns (Spot and Future) exists, so the Vector autoregression oil as endogenous variable) and Vector error correction mechanism oil as endogenous variable) are appropriate. In addition , the bi-directional relationship also exist among the gasoline, ethanol and sugar returns, suggesting that these variables should be treated as endogenous variable in Vector Autoregression/Vector Error correction Mechanism model (Treating oil as exogenous variable).

CO_2 Concentration: From Figure 4, along with Oil spot WTI, Oil spot Brent and Oil futures returns, change in GDP also impacts the change in CO_2 Concentration in the quarterly time frame. Hence, along with the above variables, one should consider the impact of global temperature on the change in CO_2 Concentration because of its Granger causal significance suggesting Vector based model (VAR, VECM) are appropriate.

2.4 Asymmetry of Returns and Lags

Ten lags have been picked to explore crude oil and oil futures' effect to explain gasoline price fluctuation and CO_2 Concentration. Asymmetry in price returns of crude oil was observed, with negative returns dominating over positive returns and significantly impacting gasoline returns *(with a positive correlation)*.

Gasoline and Future Gasoline: With 99% confidence, one can see that crude oil predicts gasoline's price return, up to **two lags** with a positive relationships in the weekly time frame (For example, from Figure 5, t-scores of 4.2 and 3.3 in lag 1 and lag 2, respectively)

Similarly, oil futures impact Future gasoline's price return, up to **two lags** with a positive correlation in the weekly time frame.

When aggregate the time frames to monthly and quarterly levels, the prediction is significant only up to the first lag (for gasoline), further diminishing to zero lag in the quarterly time frame (for future gasoline).

CO_2 Concentration: Contrasting to gasoline's observations, crude oil predicts CO_2 Concentration significantly only with data encompassing negative returns *(asymmetry explained already)*, and the lags also expand with the time frames **(Lag 6 for Monthly and Lag 2 for Quarterly time frame)**.

2.5 Correlation

Gasoline: From the correlation plot, Figure 6, one can deduce that crude oil WTI returns, oil futures returns, and gasoline price returns are strongly correlated. Oil futures and oil spot WTI show multicollinearity and should not be considered as indepen-

Figure 5: T-scores for asymmetric multiple linear regressions, 10 lags at different time frames.

	Timeframe	Adj R-squred	Positive return: delta P+	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9	Lag 10	Negative return: delta P-	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9	Lag 10
Gasoline	*Weekly*	0.19	0.17	4.22	3.32	0.96	2.16	0.63	1.50	-0.20	1.47	1.03	0.37	3.93	5.25	5.76	2.13	0.11	-1.00	-2.02	-1.54	-0.13	0.32	0.62
	Monthly	0.39	6.11	4.41	0.48	0.18	0.02	-1.22	-2.84	0.50	1.22	-0.70	0.42	6.92	5.16	1.87	0.95	-1.00	-0.27	0.72	-0.37	-2.03	0.32	-0.24
	Quarterly	0.50	3.35	0.01	-0.91	-0.10	2.59	-0.42	-1.16	0.32	-0.18	1.19	-1.05	7.81	1.23	-0.69	-0.36	0.54	-1.28	1.33	-0.27	-0.35	0.04	-1.20
Future Gasoline	*Weekly*	0.19	4.08	4.00	1.26	0.86	0.74	0.89	-0.55	0.77	-0.07	-0.64	1.48	6.76	5.99	2.33	0.56	-0.31	-1.76	-1.22	-0.43	0.48	1.15	-2.79
	Monthly	0.20	3.08	1.27	0.00	-0.26	-0.34	-2.01	-0.20	0.61	-1.20	-0.19	2.96	5.86	-0.90	0.27	-0.48	-1.43	0.67	0.56	-2.03	0.21	-0.35	1.32
	Quarterly	-0.10	-0.09	-0.35	0.61	0.24	-1.26	-0.76	0.49	0.47	0.24	-1.39	0.06	-0.18	-1.43	-0.32	0.65	0.06	-0.59	-0.32	-1.26	0.11	-0.33	-0.30
CO2 Concentr ation	*Weekly*	0.01	0.12	0.03	0.97	0.12	-1.16	0.25	-0.17	-0.13	0.55	-0.59	1.93	2.11	1.03	1.52	0.50	0.30	-0.07	0.36	0.10	0.00	0.04	-0.79
	Monthly	0.04	0.49	0.08	-0.64	0.96	-1.55	-0.62	2.12	-0.38	-0.30	-0.52	0.70	-1.20	0.50	-0.78	1.75	-1.86	1.96	-2.66	0.95	0.37	0.34	0.73
	Quarterly	0.09	-0.58	-1.01	-0.83	1.28	0.59	0.69	0.45	-1.15	0.40	-0.62	0.54	-0.10	1.88	-2.84	0.51	-1.10	-0.57	0.12	0.89	0.68	-0.20	-0.13

99% confidence level 95% confidence level

Crude oil spot return (Δ P) as a predictor of gasoline return and CO_2 Concentration. Oil futures return (ΔP) as a predictor of future gasoline.

Figure 6: Correlation plots of each feature with respect to Gasoline

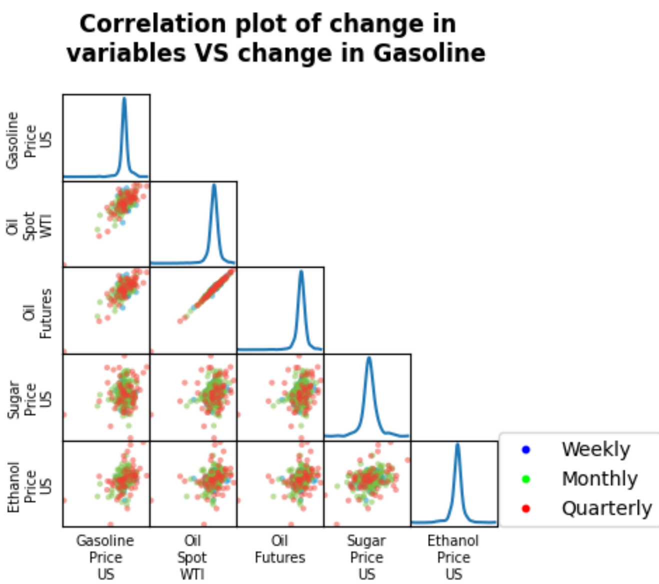
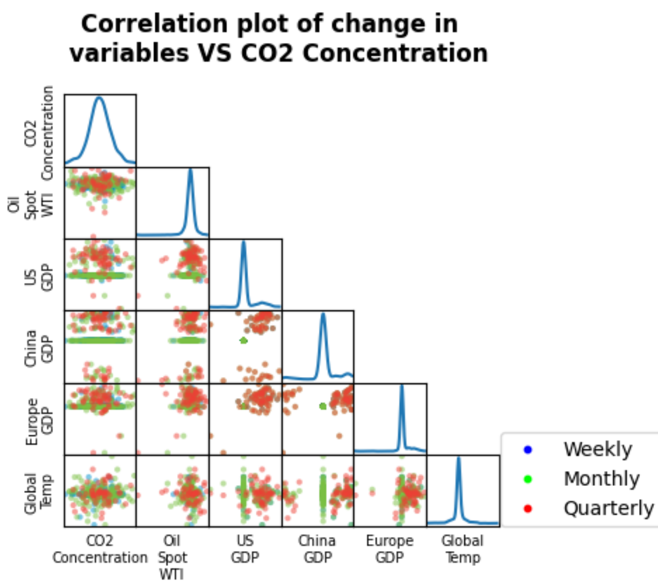


Figure 7: Correlation plots of each feature with respect to CO_2 Concentration



dent variables together. The other variables' returns (Sugar and Ethanol) are not strongly correlated with gasoline price returns.

CO_2 Concentration: From the correlation plot, Figure 7, one can see that Oil Spot WTI price returns are correlated with change in CO_2 Concentration. Global Temperature and GDP show a strong correlation with the change in CO_2 Concentration in the quarterly time frame *(thus conforming to Granger-Causal results)*. Further statistical analysis is required in the quarterly time frame. The results do show a moderate relationship in the all of the time frame.

3. Methodologies

This paper focuses on two major methods to address the research objectives: the inference method and the prediction method. The Inference method is used to find the statistical causation according to the econometric and time series modeling by investigating the sign, relationship, and magnitude of the coefficients of oil variables within models, to determine whether the Oil variable has a statistical influence on the objective variable or not.

The prediction method is used to find the prediction performance on out of sample data using time series and machine learning models. To see the performance of models with oil as a feature, models with oil features are compared with models without oil.

To strengthen the final conclusion, this research will not be based solely on one model. Instead, three models for inference and five models for prediction analysis will be studied. The inference part is based on three different econometric and time series modeling: Autoregressive Mean with GARCH Volatility, Vector Autoregression(VAR), and Vector Error Correction Mechanism(VECM). The prediction part is based on five different time series and machine learning models: Linear Regression, Autoregressive Mean with GARCH Volatility, Vector Autoregression(VAR), Decision tree regression, and Random Forest Regression.

3.1 Inferential Analysis Models

The inferential analysis construct by exploring the beta coefficient in direction, lag, and significant of oil related variable (oil spot and oil futures returns) across all of the model at different time frame. Those model are following:

3.1.1 Auto-regressive Time Series with GARCH Volatility (ARX-GARCH)

The Uni-variate time series is a simple model for the mean modeling. Adding Auto-regressive terms provide better-fitted results. The variance modeling is represented by the GARCH effect, which helps capture the volatility clustering.

The Mean Equation is defined as:

$$\begin{aligned} Y_t = & a + a_i \sum_{i=1}^{p} y_{t-i} + b_+ \sum_{i=0}^{nx} (X_{t-i}^+) + \\ & b_- \sum_{i=0}^{nx} (X_{t-i}^-) + c_i \sum_{i=1}^{n} z_{i,t} + \varepsilon t \end{aligned} \tag{1}$$

where Y_t is the percentage change in objective variable, such as ΔGasoline Price, ΔFuture Gasoline Price (at period $t+1$), and ΔCO_2 Concentration at time t. X_{t-i}^+ is the percentage change in oil variable when the percentage change is positive, such as ΔOil Spot Price or ΔOil Future Price at time t. X_{t-i}^- is the percentage change in oil variable when the percentage change is negative, such as ΔOil Spot Price, and ΔOil Future Price at time t. $\sum_{i=1}^{n} z_{i,t}$ represents other features that will be included into the model, which includes financial crisis, other future prices, global temperature, and GDP by countries.

The Variance Equation is defined as:

$$\begin{aligned} \sigma^2 t = & \omega + \alpha \sum_{i=1}^{q} \varepsilon_{t-q}^2 + \\ & \beta \sum_{i=1}^{p} \sigma_{t-p}^2 + \zeta t \end{aligned} \tag{2}$$

where σ is the standard deviation of the percentage change in objective variable, such as ΔGasoline Price, ΔFuture Gasoline Price (at period $t+1$), and ΔCO_2 Concentration at time t. $\sum_{i=1}^{q} \varepsilon_{t-q}^2$ represents the lag of error terms ε^2 from time t to time t-q. $\sum_{i=1}^{p} \sigma_{t-p}^2$ are terms represent the σ^2 from time t to time t-p.

3.1.2 Vector Auto Regression (VAR-EN,VAR-EX)

The research has shown from Granger causality that the bi-causation relationship between objective variables and oil variables exists with the variable dynamics. The model that best suits the current situation is Vector auto-regression treating oil as the endogenous variable (VAR-EN). However, the paper from Lucio Carpio [9] provided that the variable, oil price percentage change, suits as the exogenous. In this case, the endogenous variable contains other features, such as the ethanol and sugar price change, representing substitution and cost-effectiveness. Therefore developing vector auto-regression and treated the oil variable as the exogenous variable (VAR-EX).

The vector equation for the VAR model is defined as:

$$Y_t = A \sum_{i=i}^{p} Y_{t-i} + B \sum_{i=i}^{n} Z_{t,i} + Et \tag{3}$$

Where Y_t represent vector of endogenous variable. $\sum_{i=i}^{p} Y_{t-i}$ are the lag of vector of endogenous variables from time t-1 to time t-p. $\sum_{i=i}^{n} Z_{t,i}$ are the vector of exogenous variables. E_t is the vector of error terms.

3.1.3 Vector Error Correction Mechanism (VECM-EN)

In addition to the multivariate causation of variables, the relationship of oil and objective variables might have co-integrating relationships. The best-suited model for this situation is the vector error correction mechanism. The error correction mechanism equation indicates the short-term effects.[10]

The VECM equation is defined as:

$$\Delta y_t = \beta_0 + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + \sum_{i=0}^{n} \delta_i X_{t-i} + \phi z_{t-1} + \mu_t \tag{4}$$

Where Y_t is the vector of endogenous variable. $\sum_{i=1}^{p} \Delta y_{t-i}$ are the lag of vector of endogenous variables from time $t-1$ to time $t-p$. $\sum_{i=0}^{n} X_{t-i}$ are the vector of exogenous variables.

3.2 Prediction Models

The main objective is to compare the prediction performance of models with and without oil variable as predictors. The research construct 5 different model to predict the objective variable in unseen data. There are linear regression (LR), Auto-regressive Mean with Garch volatility (ARXGARCH), Vector Auto-regression (VAR), Decision Tree regression (DT) and Random Forest regression (RF). Most of the model will construct based on 4 different scenarios (More explanation in section 4). The model use training data set for training the model 5 and evaluate those model on 2 different testing data set by RMSE metric (see equations 6 , 7).

$$F(x) = f(x_{train}) \tag{5}$$

$$RMSE_1 = \sqrt{\sum_{i=1}^{n} \frac{\left(F(x_{test1,i}) - y_{test1,i}\right)^2}{n}} \tag{6}$$

$$RMSE_2 = \sqrt{\sum_{i=1}^{n} \frac{\left(F(x_{test2,i}) - y_{test2,i}\right)^2}{n}} \tag{7}$$

4. Statistical Analysis

4.1 Inference Analysis

For statistical inference modeling, the ARX-GARCH, VAR (Both VAR model), and VECM (oil as endogenous) were used to develop the statistical significance for the relationships between crude oil spot and gasoline, future crude oil to future gasoline,

Table 2: Weekly Inference Analysis Result

Objective-Y / Explanatory-X		Gasoline / Oil Spot		Future Gasoline / Oil Futures		CO_2 / Oil Spot	
Weekly	Lag	$\beta+$	$\beta-$	$\beta+$	$\beta-$	$\beta+$	$\beta-$
ARX-GARCH	0	-0.050*	0.064*	0.269***	0.142***	-0.92**	
	1	0.253***	0.138***	0.088**	0.124***	0.03	
	2	0.066**	0.110***	0.050	0.040	-0.55*	
VAR-EN	1	0.179***		0.181***		-0.35	
	2	0.135***		0.138***		-0.03	
VAR-EX	0	0.0004	0.0114	0.237***	0.144***	-0.32	-0.05*
	1	0.217***	0.118***	0.141***	0.158***	-0.60	-0.35
	2	0.123***	0.151***	0.040**	0.052*	-0.19	-0.12
	3	0.028	0.058**	0.066	0.017	0.58	-0.48
	4	0.050*	0.019	0.004	0.004	0.34	-0.62
VECM-EN	1	0.161***		0.154***		No Cointegration	
	2	0.113***		0.120***			

*Statistical significance at the 10% level **Statistical significance at the 5% level***Statistical significance at the 1% level

Table 3: Monthly Inference Analysis Result

Objective-Y / Explanatory-X		Gasoline / Oil Spot		Future Gasoline / Oil Futures		CO_2 / Oil Spot	
Monthly	Lag	$\beta+$	$\beta-$	$\beta+$	$\beta-$	$\beta+$	$\beta-$
ARX-GARCH	0	0.469***	0.431***	0.574***	0.584***	-0.00	
	1	0.301***	0.144	0.056	0.043	0.00	
	2	0.058	0.186*	0.202*	0.166*	-0.00	
	3					0.00	
	12					-0.00***	
VAR-EN	1	0.220***		0.257***		0.00	
VAR-EX	0	0.395***	0.547***	0.513***	0.684***	0.00	-0.00
	1	0.262**	0.157*	0.144	0.053	0.00	0.00
	2	0.108	-0.073	0.139	-0.132*	0.00	0.00
	3					0.05	-0.00
VECM-EN	1	0.104		0.140*		No Cointegration	

*Statistical significance at the 10% level **Statistical significance at the 5% level***Statistical significance at the 1% level

crude oil spot and CO_2 Concentrations, all of these variable are transformed into returns. These models were conducted at the predefined time frames of weekly, monthly, and quarterly intervals to develop insight into those variables' underlying relationships and analyze which lags produced significant relationships. ARX-GARCH and VAR (oil as exogenous) are also created to reflect how the relationships behave where retrns are increasing and when returns are decreasing (*(indicated through the columns* $\beta+$ *and* $beta-$*)*. The results of these models are summarized in Table 2, Table 3, and Table 4 for each time frame. The standard deviation of each time frame is included in the Appendix (Table **??**, Table **??**, and Table **??**).

The models showed that highly significant coeffi-

Table 4: Quarterly Inference Analysis Result

Objective-Y Explanatory-X		Gasoline Oil Spot		Future Gasoline Oil Futures		CO_2 Oil Spot	
Quarterly	Lag	$\beta+$	$\beta-$	$\beta+$	$\beta-$	$\beta+$	$\beta-$
ARX-GARCH	0	0.546***	0.549***	0.611***	0.623***	0.00	
	1	0.130	0.180*	0.161	-0.008	0.00	
	8					0.00***	
	11					-0.00*	
VAR-En	1	0.409**		0.354		0.00	
VAR-EX	0	0.487***	0.790***	0.477***	0.833***		
	1	0.133	-0.099	0.090	-0.119		
	2	0.055	-0.016	0.209	-0.032		
	4	0.054	0.100	0.079	0.112	-0.00	-0.00*
	6					0.00	-0.00**
VECM-EN	1	0.365		0.385		No	
	2	-0.268		-0.097		Cointegration	

*Statistical significance at the 10% level **Statistical significance at the 5% level***Statistical significance at the 1% level

cients *(with 99% confidence levels)* are present in the first and second lag relationship for the weekly time frame of the relationship between crude oil and gasoline returns. For lag of 1 and lag of 2, the significant and positive coefficients indicate that the change in crude oil spot prices will result in the same direction move in gas prices realizing approximately 1-2 weeks later. The magnitude of these coefficients is also different for each asymmetric profile of the changes in prices. At lag 1, for the ARXGARCH and VAR *(oil as exogenous)* models, it can be noted that the costs of gasoline increase at a higher rate and fall at a slower pace in response to the movements of crude spot oil, which follows the expectation of the general public and last journals.[11, 12]

For the weekly time frame of the relationship between crude oil future returns and future gasoline returns, the models showed highly significant coefficients *(with 99% confidence)* from the lag of 0 to lag of 2. As the relationship between spot and gasoline returns, these coefficients are positive and have asymmetric profiles. Additionally, the models suggest that the relationship can be realized immediately. In summary, both oil spots and futures' returns present a quick transition of 0 to 2 weeks into gasoline returns.[13]

For the weekly time frame of the relationship of oil future returns and carbon dioxide returns, the models showed no significant coefficients except for the ARXGARCH at lag 0. However, this coefficient is negative and indicates that when oil future returns increase, the CO_2 Concentration will decrease, contributing to the instant increase in production costs resulting in CO_2 emissions. The monthly and quarterly time frames were explored to retrieve more meaningful results for this relationship.

For the monthly time frame of the relationships between crude oil returns *(spot and futures)* and gasoline prices *(current and future)*, every models showed significance coefficients at lag 0, but only few showing statistically significant coefficients in lag 1 (Table 3). The finding above also aligns with the analysis that was done at the weekly time frame that the transmission usually take place around 0-2 weeks.

For the monthly CO_2 Concentrations, only the ARXGARCH model showed a significant coefficient at a lag of 12. This coefficient was small and negative but indicates that the oil futures returns may have realized CO_2 Concentrations at a longer time frame. Therefore, the analysis of quarterly time frame are necessary.

As shown in Table4, the relationship between crude oil*(spot and futures)* and gasoline prices at a quarterly time frame aligns with the previous analysis. The models show significant coefficients in lag 0 once again, further indicating the relationships have instant reactions.

For the CO_2 coefficients at the quarterly time frame, the models begin to depict significant coefficients at lags 4, 6, 8, and 11. However, these lags are almost all negative and small in magnitude, suggesting that the optimal lag predict CO_2 is indicated in the more oversized time frame. Therefore, among all of the three time frame, the longer horizon "quarterly" is the time frame in explaining the relationship between crude oil and CO_2 Concentration indicate the very slow transmission mechanism.

In conclusion, one can confidently confirm that **crude oil spot and futures' expectation affect gasoline prices in a zero to two-week time frame.** This is the short-term effect which explain why people generally expected this to happens. The relationship almost all positive for the significant coefficient across three time frame and both asymmetric profile (with different magnitude).

On the other hand, the relationship between crude oil and CO_2 Concentrations accounting as negative relationships.**(as oil return increase the CO_2 Concentration returns will move to the opposite direction)**. They takes a much longer time for their relationship to exist which explain why people are not generally expected this relationships to happen.

4.2 Prediction Analysis

Table 5: Weekly Prediction Analysis Result

		Gasoline + Oil		Gasoline + Oil(Future)		Oil and CO_2	
Weekly	Variables	RMSE 1	RMSE 2	RMSE 1	RMSE 2	RMSE 1	RMSE 2
Linear Regression	Only Y	0.0119	0.0167	0.0124	0.0163	0.647	0.581
	Y and Oil	0.0100	0.0127	0.0103	0.0177	0.645	0.582
	All Features w/o Oil	0.0121	0.0207	0.0129	0.0196	0.643	0578
	All Features	0.0101	0.0126	0.0104	0.0219	0.641	0.579
SARIMA with GARCH Volatility	Only Y	0.0117	0.0202	0.0117	0.0202	0.694	0.651
	Y and Oil	0.0103	0.0234	0.0098	0.0188	0.696	0.653
	All Features w/o Oil	0.0133	0.0182	0.0143	0.0172	0.689	0.645
	All Features	0.0105	0.0246	0.0094	0.0185	0.691	0.647
VAR	Oil as Endogenous	0.0103	0.0239	0.0101	0.0192	0.686	0.635
	Oil as Exogenous	0.0098	0.0170	0.0105	0.0166	0.698	0.641
	No Oil	0.0125	0.0273	0.0125	0.0170	0.701	0.640
Decision Tree	Only Y	0.0134	0.0151	0.0165	0.0139	0.727	0.661
	Y and Oil	0.0132	0.0214	0.0181	0.0212	0.853	0.763
	All Features w/o Oil	0.0133	0.0104	0.0144	0.0231	0.731	0.721
	All Features	0.0147	0.0147	0.0145	0.0188	0.852	0.718
Random Forest	Only Y	0.0126	0.0147	0.0134	0.0151	0.639	0.573
	Y and Oil	0.0115	0.0153	0.0147	0.0241	0.653	0.586
	All Features w/o Oil	0.0123	0.0152	0.0145	0.0188	0.644	0.586
	All Features	0.0153	N/A	0.0149	0.0216	0.652	0.589
Summary		Best	Worst	Best	Worst	Best	Worst
	With Oil	7	4	6	5	4	7
	No Oil	3	6	4	5	6	3
	Scaling Ratio	2.33	0.67	1.50	1.00	0.67	2.33

This research used the five models described in the methodologies section. The models were run at the three different time frames (weekly, monthly, and quarterly) and used three to four different sets of features as agents to predict the future gasoline price returns and CO_2 Concentration returns. These data sets were split into three sets (Training, Testing set1, Testing set2). Two of the test sets were used for the generalized result, but only one test set was used for the quarterly time frame due to limitation of data horizon. The prediction performance was evaluated as RMSE (Root mean square error). The Lower RMSE in test sets the better model should be. Four of the five models were conducted using four different feature sets:

- "Only Y" the lag of objective variable
- "Y and Oil" the lag of objective variable + the oil variable lag of them
- "Every Feature no Oil" the additional explanatory variable for each objective
- "Every feature" all of the variables will be included as the features

Table 6: Monthly Prediction Analysis Result

		Gasoline + Oil		Gasoline + Oil(Future)		Oil and CO_2	
Monthly	Variables	RMSE 1	RMSE 2	RMSE 1	RMSE 2	RMSE 1	RMSE 2
Linear Regression	Only Y	0.052	0.070	0.015	0.023	0.00181	0.00185
	Y and Oil	0.045	0.111	0.018	0.046	0.00197	0.00182
	All Features w/o Oil	0.054	0.056	0.016	0.022	0.00189	0.00177
	All Features	0.043	0.107	0.048	0.111	0.00205	0.00176
SARIMA with GARCH Volatility	Only Y	0.067	0.079	0.067	0.079	0.00455	0.00379
	Y and Oil	0.043	0.111	0.056	0.111	0.00441	0.00365
	All Features w/o Oil	0.067	0.068	0.067	0.062	0.00397	0.00368
	All Features	0.041	0.109	0.054	0.108	0.00433	0.00366
VAR	Oil as Endogenous	0.041	0.082	0.047	0.051	0.00252	0.00213
	Oil as Exogenous	0.040	0.121	0.053	0.114	0.00257	0.00211
	No Oil	0.057	0.076	0.057	0.076	0.00249	0.00212
Decision Tree	Only Y	0.052	0.091	0.034	0.044	0.00302	0.00297
	Y and Oil	0.061	0.078	0.039	0.024	0.00309	0.00288
	All Features w/o Oil	0.109	0.075	0.042	0.042	0.00304	0.00288
	All Features	0.057	0.083	0.071	0.068	0.00352	0.00302
Random Forest	Only Y	0.052	0.072	0.027	0.028	0.00226	0.00203
	Y and Oil	0.045	0.057	0.025	0.022	0.00232	0.00215
	All Features w/o Oil	0.050	0.067	0.027	0.028	0.00219	0.00202
	All Features	0.047	0.055	0.046	0.038	0.00227	0.00202
Summary		Best	Worst	Best	Worst	Best	Worst
	With Oil	5	3	6	8	5	7
	No Oil	5	7	4	2	5	3
	Scaling Ratio	1.00	0.43	1.50	4.00	1	2.33

The VAR (Vector Auto regression) model used three different feature sets, "Oil as Endogenous," "Oil as Exogenous," and "No Oil," which the titles are self-explanatory for the feature sets.

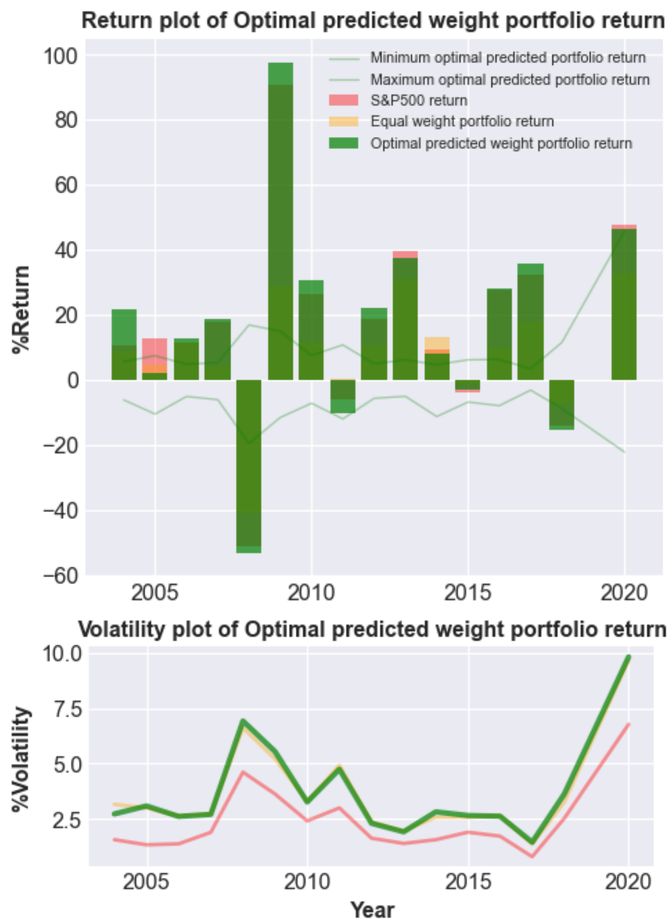
The results from running the models at the weekly, monthly, and quarterly time frame are summarized in Table 5, Table 6, and Table 7. These results were then further consolidated into performance ratios at the bottom of each table. These performance ratios were created by counting the models that performed the best when using features with oil versus models that performed the best without oil features. The same was done for the models that performed the worst with and without features that included oil. A performance ratio of more than one under the "Best" column indicates that more models with the oil features performed better than those without oil features. A performance ratio less than 1 in the "Worst" column means that more models without oil features performed the worst, compared to the ones with oil features. To conclude, oil and oil futures are capable of predicting gasoline prices and CO_2 Concentrations. The "Best" column ratios should be greater than 1, and the ratios for the "Worst" column should be less than 1.

This being said, it can be seen that the weekly time frame for predicting gasoline prices with crude oil spot prices is as expected by its performance ratios of 2.33 for the "Best" and 0.66 for the "Worst". Oil futures seem to contain information to predict future

Table 7: Quarterly Prediction Analysis Result

Quarterly	Variables	Gasoline + Oil	Gasoline + Oil(Future)	Oil and CO_2
		RMSE	RMSE	RMSE
Linear Regression	Only Y	0.100	0.037	0.0008
	Y and Oil	0.184	0.049	0.0017
	All Features w/o Oil	0.092	0.038	0.0033
	All Features	0.188	0.205	0.0031
SARIMA with GARCH Volatility	Only Y	0.090	0.090	1.1165
	Y and Oil	0.258	0.209	0.0023
	All Features w/o Oil	0.068	0.100	0.0032
	All Features	0.272	0.183	0.0039
VAR	Oil as Endogenous	0.242	0.115	0.00141
	Oil as Exogenous	0.398	0.300	0.00148
	No Oil	0.033	0.033	0.00154
Decision Tree	Only Y	0.146	0.058	0.0019
	Y and Oil	0.121	0.060	0.0017
	All Features w/o Oil	0.177	0.062	0.0030
	All Features	0.086	0.188	0.0028
Random Forest	Only Y	0.129	0.055	0.00150
	Y and Oil	0.056	0.030	0.00152
	All Features w/o Oil	0.094	0.050	0.00154
	All Features	0.048	0.064	0.00147
Summary		Best/Worst	Best/Worst	Best/Worst
	With Oil	2/3	1/4	4/1
	No Oil	3/2	4/1	1/4
	Scaling Ratio	0.67/1.50	0.25/4	4/0.25

Figure 8: Return and Volatility Plot of Optimal Predicted Weight Portfolio



gasoline prices at a weekly time frame, but because of the uncertainty of the future gasoline variable and the volatility of the futures price, the predictor contains noise which can eventually lead to over-fitting the models. Regarding CO_2 Concentrations, it can be seen that oil futures do not include additional information for predicting at the weekly time frame. The prediction performance is overwhelmed with statistical noise and inconclusive.

As the time frames increase to monthly and quarterly, the performance metrics for predicting gasoline from crude oil spot and futures prices begin to decrease. The Best and Worst ratios decrease and increase, respectively. However, the larger time frames benefit the performance metrics of oil spot predicting CO_2 Concentrations. **This leads to the conclusion that for oil and oil future returns to be good predictors of gasoline prices and future gasoline prices returns at weekly basis. The crude oil returns has the potential to be the great predictor of and CO_2 Concentrations returns in the quarterly time frame or even longer horizon.**

5. Investment Strategy

The oil price/CO_2 Concentration change has a long-term impact which the general person does not expect. Therefore, the research might leverage this effect to an environmentally friendly investment strategy in a more significant time frame. The information can construct the portfolio reallocated assets quarterly (to match the analysis time frame). The portfolio will consist of 4 stocks (1. Trane Technologies (TT) offering energy-efficient climate-control systems, 2. Rockwell Automation (ROK) owns division that helps companies monitor energy usage and waste, 3. Hubbell (HUBB) does business in energy-efficient lighting and Schneider Electric, 4. ON Semiconductor (ON) sells power-management chips used in the electric-vehicle space) and an SP 500 index.

First, to create the optimal portfolio, the max shape ratios portfolio will be selected from 1,000 simulated portfolios as the ideal portfolio per quarter. Second, the features consisted oil features, CO_2 Concentration, and additional features for CO_2 analysis were included as well. Third, create machine learning using described features to predict the optimal weight of the portfolio. Forth, evaluate the optimal predicted portfolio by comparing it to the equal-weighted portfolio and the SP 500 market index.

The performance presents a **significant margin** over other strategies by comparing their compounded annually returns from Figure 8. It wins 8 out of 16 years as the annual best portfolio and 5 out of 16 years as the worst portfolio. With this attractive return, the portfolio's risk is not the worst—the maximum standard deviation of 8 weeks out of 16 equal to the equally weighted portfolio. In extreme case, the weekly maximum returns draw down is the worst six years out of 16 compared to the similarly weighted ten years out of 16. However, the optimal predicted portfolio's weekly maximum upside is 12 years out of 16 in total, while the equaled weight portfolio has only get 4 out of 16.

The predicted portfolio greatly outperforms both portfolios because its the expected weight contains the future CO_2 *(which the public does not generally care about but they should)*. In conclusion, the investor can successfully leverage this "Optimal Predicted Environmental Portfolio" strategy even before the information becomes something that "people generally expect."

6. Conclusion

The analysis shows three reasons why the futures market is an extremely powerful tool. First, futures are capable of providing evidence of statistically significant relationships between the listed futures prices and some other thing that impacts the general public. This paper proved through the relationship of crude oil prices and gasoline, then apply this methodology to CO_2 Concentrations. Second, the time frame in which these relationships are realized at the spot prices becomes evident, allowing for people to grasp when these expected changes are going to occur. Lastly, investors can take advantage of this hidden knowledge to construct portfolios that profit from these unrealized expectations. Overall, the futures market contains powerful predictive information that can not only be used to obtain profits but leads the general public to become more conscious of increasingly concerning topics such as climate change.

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