Forecasting Crude Oil Returns using News Sentiment and Machine Learning *

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This can help me in chapter seven!

In order to identify the predictive power of sentiment data on crude oil returns, this study involves three major datasets, a the daily spot price of crude oil at the West Texas Intermediate (WTI) from which returns are computed, ii) a news sentiment dataset from Ravenpack News Analytics (RPNA), and iii) other macroeconomic indicators proxying the overall economic background.

2.1 The West Texas Intermediate (WTI) Crude Oil Dataset

West Texas Intermediate (WTI) is a class of light and sweet crude oil that serves as a benchmark for crude oil prices in the past few decades. Cushing, Oklahoma, where the Cushing oil field locates, has been the delivery point for commodities behind crude oil contracts traded at New York Mercantile Exchange (NYMEX). U.S. Energy Information Administration (EIA) provides a daily time series of spot prices of WTI crude oil delivered from Cushing. This time series can serve as a benchmark of measuring activities in the global crude oil market.

Because of the limited availability of the RavenPack dataset, this paper focuses only on crude oil prices after January 1, 2000. Analysis of the crude oil market (Baumeister & Kilian, 2016). shows the spot price is highly responsive to news and other macroeconomic shocks, which is exactly the tricky part of forecasting financial time series. If the proposed forecasting algorithm performs well on the crude oil dataset, such an algorithm is conceivably promising on other datasets as well.

2.2 Crude Oil Returns

One side goal of this paper is to identify to what extend machine learning techniques improves existing time series models. Moreover, this paper aims to examine whether machine learning techniques can better extract information from sentiment dataset.

The augmented Dickey-Fuller test on the raw price series gives a p-value of 0.26, which suggests the movement of crude oil prices exhibits significant non-stationarity. This non-stationarity confines classical time series models on this dataset, and makes the above-mentioned comparison between new and classical techniques infeasible. Besides, an accurate prediction of returns is more related to profitability in practice. Therefore, this paper focuses on forecasting returns of crude oil instead of raw prices.

The closing spot prices of crude oils are available at a daily frequency for weekdays only. Besides weekends, observations are missing on certain weekdays when the exchange market is closed. In subsequent sections, this article refers to these days with valid price data as *trading days*.

The table below reports dates that are most frequently associated with a missing data over the span of 20 years. The set of days with missing data is consistent over these years: the market is always closed on January 1, July 4 (Independence Day) and December 25 (Christmas). Because the entire dataset ranges from January 3, 2000 to October 31, 2019, missing data problems on December 25 are only reported 19 times in the table. The Thanksgiving holiday varies year by year. In particular, the group of dates in late November are responsible for missing data on Thanksgiving holidays.

Table 1: Top Days with Missing Data

Date	Counts (all)	Counts (excl. weekends)
July 4	20	16
January 1	20	14
December 25	19	14
July 3	10	5
November 23	10	5
November 24	10	4
November 25	10	3
November 22	9	4
November 26	9	3

There are only ten weekdays with missing data problem each year on average (3.77% of the entire dataset). The insignificant percentage of missing data allows us to drop those dates without hurting the generalizability of models and experiments in subsequent sections.

On one particular trading day t, let Δ denotes the gap between date t and the previous trading day, so that $t-\Delta$ is the last trading day before day t. Within a short time period such as the gap between two trading days, this paper assumes crude oil prices exhibits an exponential growth with constant daily growth rate of r_t. So that the following relationship quantifies the relationship between $p_{t-\Delta}$ and p_t:

$$p_t = e^{r_t \Delta} p_{t-\Delta} \tag{2.1}$$

This paper calculates crude oil returns on one particular day t by taking the difference in logged prices at t and the previous trading day and dividing it by the length of duration, Δ:

$$r_t = \frac{\ln(p_t) - \ln(p_{t-\Delta})}{\Delta} \tag{2.2}$$

Equivalently, r_t measures the daily return over the Δ day period. Because returns are closed to zero in most time, in order to avoid decimal issues, this paper converts all r_t's into percentage points.

As mentioned before, the time gap between two observed prices are not uniform. For instance, the return on a Monday can be computed by taking difference between the log close price on Monday and the previous Friday, if available. In this case, $\Delta = 3$. If the previous Friday was a holiday without valid price data, r_t will be $\ln(p_{\text{Mon}}) - \ln(p_{\text{Prev Thu}})$, and $\Delta = 4$.

Table 2: Distribution of Δ by Weekdays

Day of the week	Num. Days.	Num. Trading Days	Δ=1	2	3	4	5
Monday	1,034	931	0	0	887	33	11
Tuesday	1,035	1,023	926	0	0	97	0
Wednesday	1,035	1,027	1,016	5	0	0	6
Thursday	1,035	1,007	999	8	0	0	0
Friday	1,034	990	973	17	0	0	0
Saturday	1,035	0	0	0	0	0	0
Sunday	1,035	0	0	0	0	0	0
Total	7,243	4,978	3,914	30	887	130	17

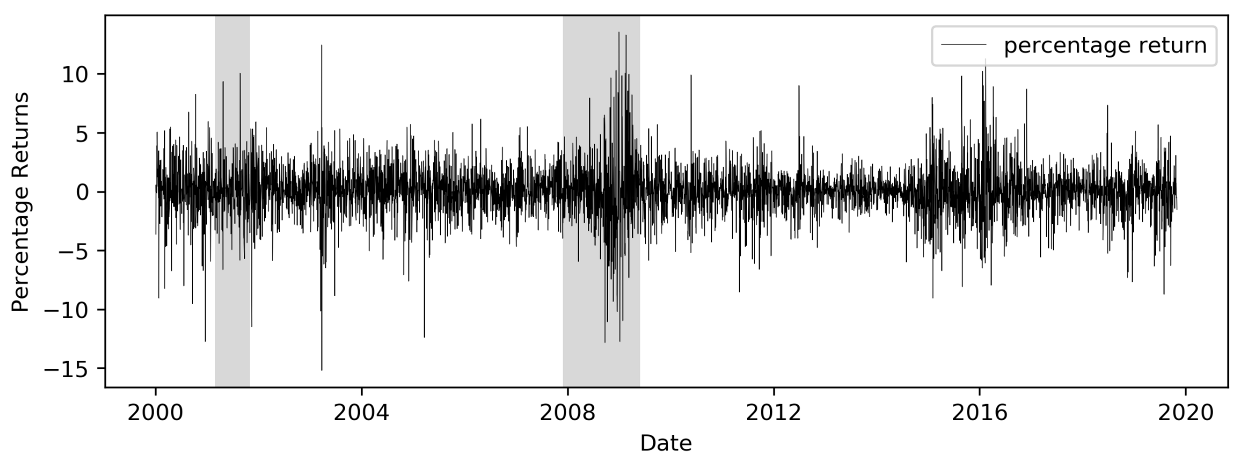
The table above summaries the distribution of Δ values. The Δ values for Mondays are at least 3 because weekend data are always unavailable. One extreme coincident case is that data are missing on both Monday and Tuesday, so that the Δ value for the coming Wednesday would be 5. This happened in 6 weeks in total. The previous assumption of constant return are only likely to be true within a short time window, and in this kind of rare scenarios, the assumption becomes less convincing.

The movement of crude oil returns in the past two decades has exhibited volatile patterns. **The figure below** plots the pattern of returns, in which shaded areas indicate U.S. recessions (March 2001 to November 2001 and December 2007 to June 2009).

cite data

Add more descriptions on the chronology.

Figure 1: Crude Oil Returns

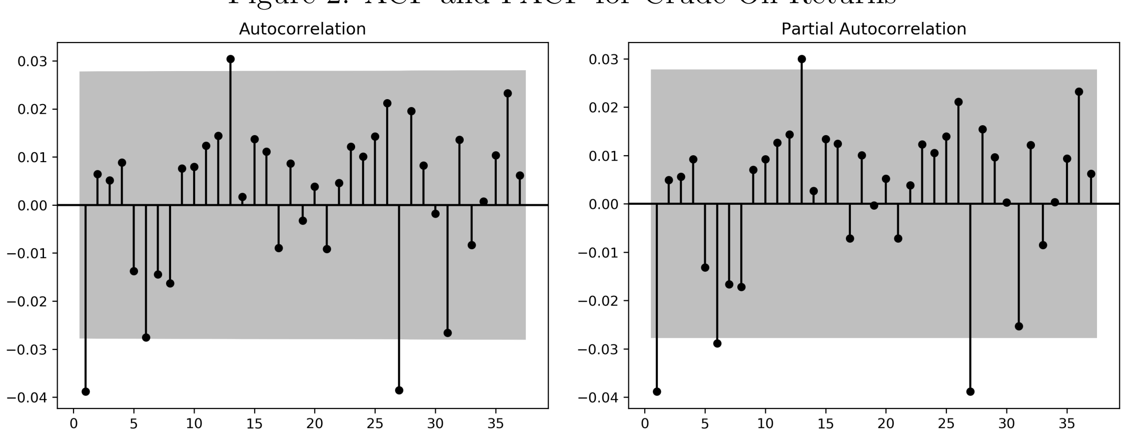


The table of summary statistics below suggests the mean return within each year are nearly zero. During periods of recessions, the average returns are below -2%, the series becomes significantly more volatile as well. Given the high kurtosis between 2008 and 2009, one are more likely to encounter extreme returns, both positive and negative, during recession periods.

Table 3: Summary Statistics for Crude Oil Returns (Percentages)

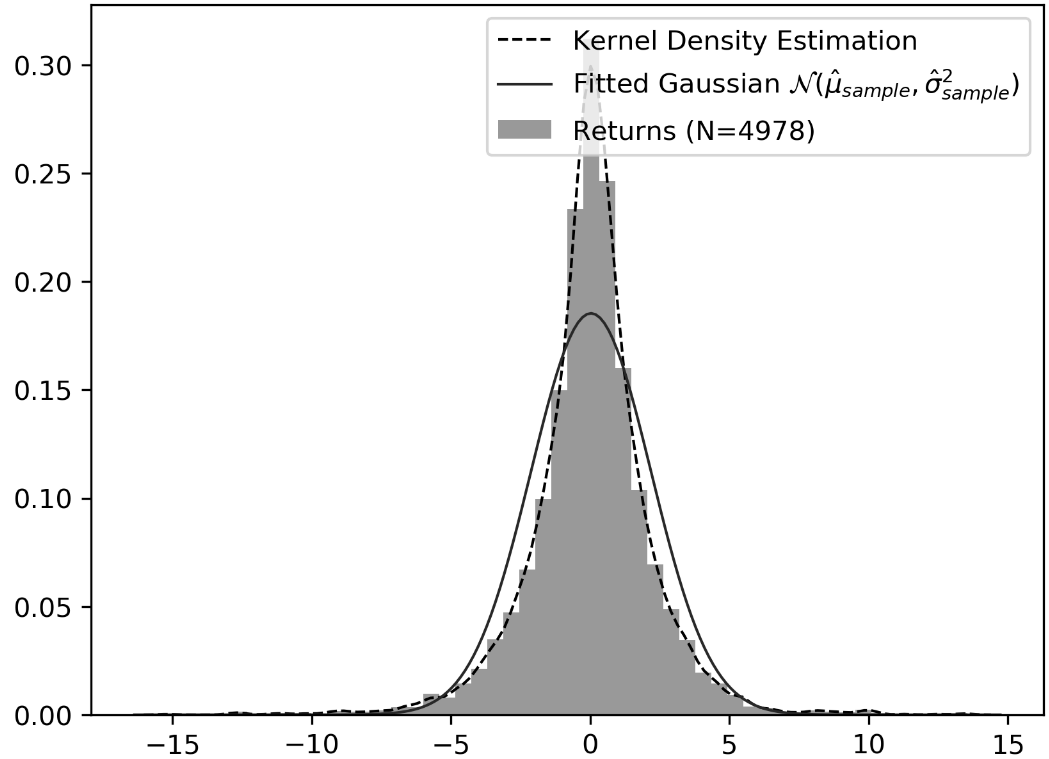
Year	Obs.	Mean	Median	Std.	Min	Max	Normalized Skewness	Excess Kurtosis
2000	249	0.03433	0.20148	2.61996	-12.74152	8.26343	-0.92174	3.45580
2001	250	-0.02409	-0.04434	2.54058	-11.48581	10.05107	-0.06444	3.15304
2002	250	0.15535	0.15221	1.70283	-5.86460	5.43272	-0.22297	0.62431
2003	250	0.07861	0.13203	2.57315	-15.19090	12.44253	-0.89439	7.30189
2004	249	0.08918	0.11605	2.08792	-7.60501	5.70121	-0.38117	1.01395
2005	251	0.05257	0.11019	1.96717	-12.39009	5.02715	-1.04498	5.84007
2006	249	-0.00539	0.12995	1.58949	-4.45214	6.15402	0.13487	1.03258
2007	252	0.23400	0.09798	1.69800	-4.66915	5.51381	0.13705	0.65946
2008	253	-0.29945	-0.07920	3.34992	-12.82672	13.54551	-0.01650	2.60308
2009	252	0.26537	0.19157	2.92040	-12.74310	13.29544	0.29333	4.25972
2010	252	-0.02077	0.03198	1.74554	-5.18874	9.89802	0.39313	3.82001
2011	252	0.00583	0.10994	1.94170	-8.53498	5.18170	-0.69170	2.27400
2012	252	-0.04164	0.03600	1.51078	-4.76060	9.00091	0.54820	5.53225
2013	252	0.01455	0.04489	1.06690	-3.46951	3.20999	0.05495	0.67398
2014	252	-0.16510	-0.05343	1.36052	-5.98638	4.91592	-0.76983	3.16348
2015	252	-0.03610	-0.25616	2.63361	-9.05140	9.81397	0.24129	1.25225
2016	252	0.20931	0.00000	2.79698	-7.95603	11.28922	0.70466	2.11826
2017	250	0.06564	0.17286	1.40987	-5.56187	3.32016	-0.87368	2.07271
2018	249	-0.10076	0.07393	1.81925	-7.67683	7.33414	-0.64252	3.38603
2019	210	0.04359	0.10073	1.93931	-8.72444	5.67862	-0.66251	2.87153
Total	4978	0.02754	0.06307	2.15250	-15.19090	13.54551	-0.16152	5.12757

Figure 2: ACF and PACF for Crude Oil Returns



For both autocorrelation function (ACF) and partial autocorrelation function (PACF), only a few lags are statistically significant, which suggests the impotency of linear models on this problem. Stopped here

Figure 3: Distribution of Crude Oil Returns



2.3 Day of the Week Effect in Crude Oil Dataset

2.3.1 Difference in Returns across the Week

Gibbons and Hess' work examined returns on stocks from S&P 500, Dow Jones 30, and Treasury Bills. They found strong negative mean returns on Monday compared with other weekdays. The seasonality persisted even after taking market adjustment measures, such as using mean-adjusted returns instead (Gibbons & Hess, 1981). Analysis in my paper unveils a similar daily seasonality presents in crude oil returns as well. **Panels in the figure below** demonstrate the empirical distributions of returns on each day of the week. We can see that Mondays and Wednesdays have relatively larger variances, which again matches Gibbons and Hess' observations.

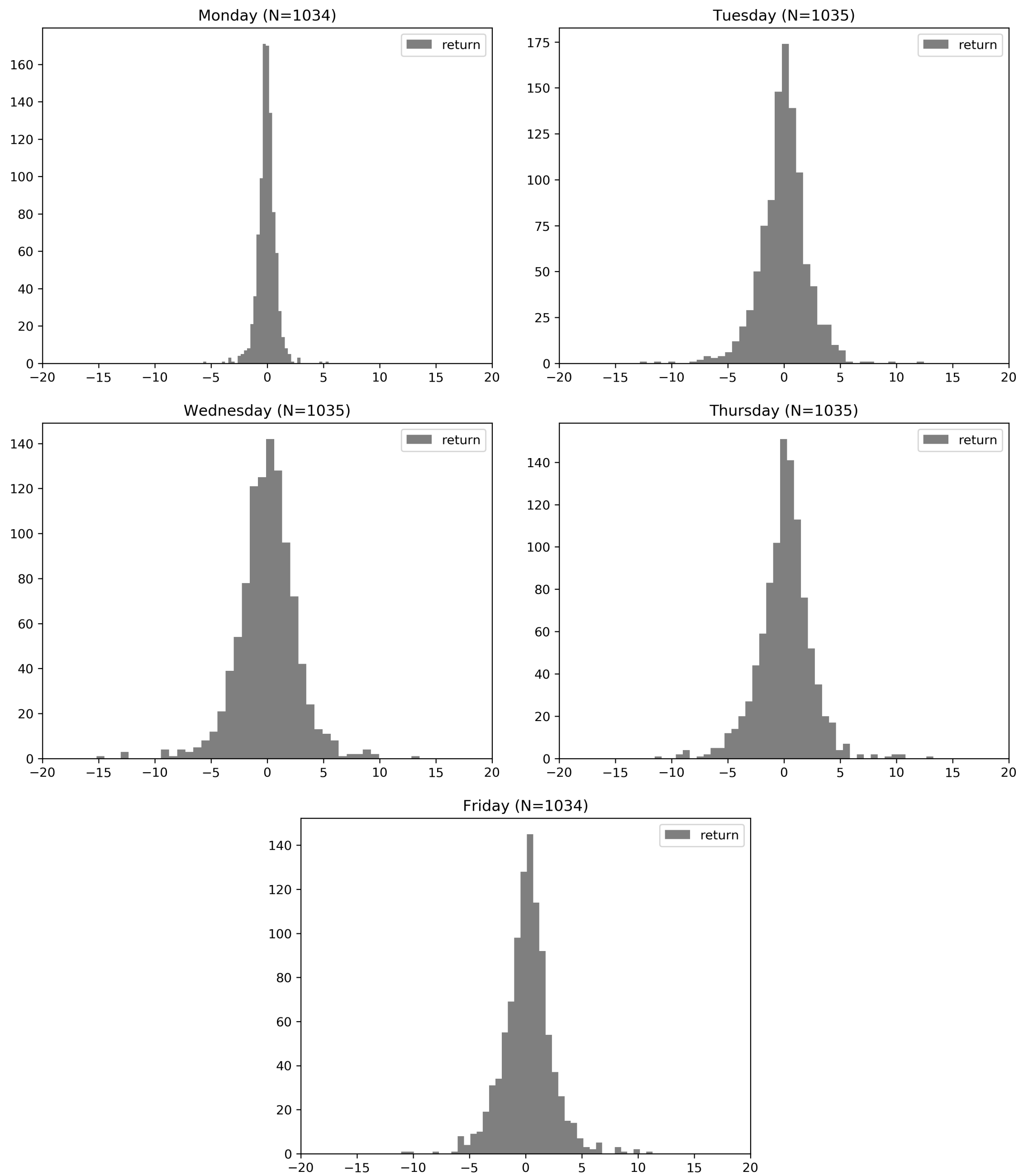


Figure 4: Crude oil returns on each weekday. Weekend data are not available in the daily dataset provided by U.S. Energy Information Administration (EIA). Ns within parentheses in figure titles denote the number of observations. See appendix for distributions of crude oil prices.

The **two tables** below provide summary statistics for prices and returns on each day. It turns out that Monday is the only weekday with a mean return significantly less than zero.

Day of the week	Num. Obs.	Mean (P-Value)	Std.	3^{rd} Moment
Monday	927	**-0.002 (0.049)**	0.025	-0.0000019
Tuesday	1018	-0.000 (0.900)	0.023	-0.0000031
Wednesday	1022	0.000 (0.884)	0.027	-0.0000054
Thursday	1002	0.001 (0.361)	0.024	-0.0000006
Friday	986	**0.002 (0.0311)**	0.023	0.0000021
Total	4955			

Table 4: Summary statistics of crude oil returns on each day of week. The first day (January 1, 2000) of the oil price dataset was Saturday, and the observation on the following Monday (January 3) was missing. Hence, the return on Tuesday (January 4) could not be computed because it was the first trading day in this dataset, and there are only 1018 Tuesdays in the dataset of returns. A value of -0.000 indicates a negative value with magnitude less than 0.0005. P-values are calculated in a two-tailed t-test with $\mu_0 = 0$. Bold fonts indicate statistically significance at level $\alpha = 0.05$.

2.3.2 Kolmogorov-Smirnov test for Distributional Similarities

Smirnov developed a non-parametric method of testing the equality between two continuous distributions, with CDFs $F(x)$ and $G(x)$ respectively, (Smirnov, 1939). Refer to Hodges' work for a detailed review on the Kolmogorov-Smirnov test (Hodges, 1958). I am using the two-tailed version of Kolmogorov-Smirnov test to check whether distributions of two different days are similar. Given two datasets, take returns on Mondays and Tuesdays for example, the null hypothesis says those two datasets are drawn from the same distribution, and the alternative says they are from different distributions [1]. Firstly, the Kolmogorov–Smirnov test constructs the empirical CDFs $F_{Mon,927}(x)$ and $F_{Tue,1018}(x)$ from the dataset. Then, the Kolmogorov–Smirnov statistic measures the maximum discrepancy between two distribution functions, which is

$$D := \sup_x |F_{Mon,927}(x) - F_{Tue,1018}(x)| \in [0, 1] \tag{2.3}$$

A smaller D-statistic implies stronger distributional similarity between two distributions. For instance, when $F_{Mon,927}(x)$ and $F_{Tue,1018}(x)$ are exactly the same, the D-statistic is zero.

[1] Different alternative hypotheses can be used in Kolmogorov–Smirnov test: i) $H_1 : F(x) \geq G(x)$, ii) $H_1 : F(x) \leq G(x)$, and iii) $H_1 : F(x) \neq G(x)$. This paper is using the third (two-tailed) alternative hypothesis.

In contrast, let $X = 0$ and $Y = 1$ be two deterministic random variables, in this case, $D_{X,Y} = 1$.

The test rejects H_0 at a significance level of α if

$$D > \sqrt{-\frac{1}{2}\ln\frac{\alpha}{2}}\sqrt{\frac{n+m}{nm}} \tag{2.4}$$

where m and n denote sizes of two datasets.

D-Statistic (P-Value)	Monday	Tuesday	Wednesday	Thursday	Friday
Monday	0.000(1.000)	**0.193(0.000)**	**0.243(0.000)**	**0.189(0.000)**	**0.180(0.000)**
Tuesday		0.000(1.000)	0.064(0.030)	0.064(0.030)	0.071(0.010)
Wednesday			0.000(1.000)	0.058(0.062)	0.084(0.001)
Thursday				0.000(1.000)	0.030(0.729)
Friday					0.000(1.000)

Table 5: The Kolmogorov-Smirnov D-Statistic for all pairs of distributions. Bold font indicates the null hypothesis is rejected at a significance level of 0.01, which implies discrepancy in distributions.

The table above presents the Kolmogorov-Smirnov D-Statistic for distributions of every pairs of days. At a significance level of 0.05, we can see that Mondays follow a distribution significantly different from distributions of other weekdays follow. Because the dataset does not contain weekend data, returns on Mondays is always computed using the difference between log prices on Monday and the previous Friday (Thursday if Friday is not a trading day and so on). Therefore, returns associated with Mondays pick the weekend effect. In fact, the distribution of returns on Mondays (over weekends) is the only one with negative mean among distributions of all five days.

2.4 News and Sentiment Datasets

The event sentiment dataset from RavenPack News Analytics (RPNA) tracks and analyzes all information of companies, organizations, countries, commodities, and currencies from four major sources: Dow Jones Newswires, Wall Street Journal, Barron's and MarketWatch.

The dataset covers events from January 1, 2000, to September 30, 2019. RavenPack records the exact date and coordinated universal time (UTC) when each news is published.s

For each piece of news, the dataset links it to a unique entity name attribute. To filter out noise data less relevant to crude oil returns, this paper selects the subset of news with crude oil topic. There are 106, 960 entries from the original dataset left, lead to 15 events per day on average. In the figure below, panel A presents a distribution of ESS for all news related to crude oil in the time span of 20 years and panel B shows all distributions of events within each year.

Moreover, the dataset categorizes each event following the RavenPack taxonomy.

(i) topic;

(ii) group;

(iii) type;

(iv) sub-type;

(v) property;

(vi) category: fine details.

Figure 5: Ravenpack taxonomy

Add examples of each level.

Add definitions of each level.

To proxy the potential economic impact upon news arrival and afterwards, Ravenpack assigns each piece of news an Event Sentiment Score (ESS) between 0 and 100 using an algorithm combines results from surveying financial experts and pattern matching. An ESS of 100 indicates extreme positive short-term positive financial or economic impact. In contrast, a 0 ESS score indicates extreme negative impact. And a ESS of 50 indicates exact neutral news. From this point, scores are normalized by subtracting 50, so that the sign of normalized ESS matches the nature of news, and a zero score represents a neutral news. **The histogram below** plots the distribution of normalized ESS for all news about crude oil. It turns out that only a small portion of news is purely neutral (i.e., with zero ESS)

(Probably move this part to the 'classification' section.)

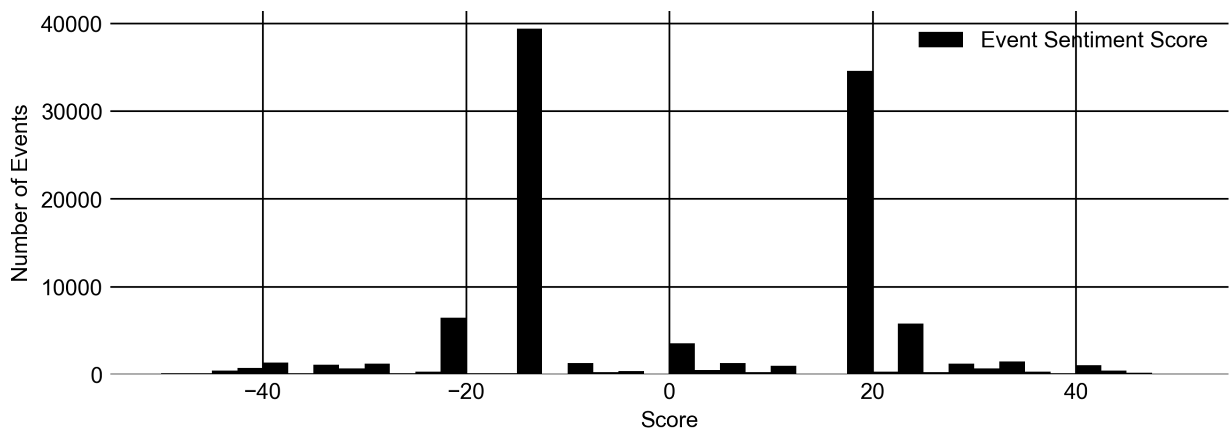


Figure 6: Distribution of Event Sentiment Scores of all 106,960 news items.

It is worth mentioning that ESS measures the potential impact on the topic of this news. For example, a civil unrest in a middle east country is often considered as news forerun negative economic impact, especially for the country itself. However, such news is in general associated with positive ESS scores because the expected negative supply shocks carried by these news are typically positively correlated crude oil prices and returns. **Tables below** present a list of categories frequently associated with positive and negatives news. From these two table we can see that the majority of themes of positive news would impact crude oil prices and returns positively.

Category	Number of positive news
commodity-price-gain	22,893
commodity-futures-gain	11,648
supply-decrease-commodity	5,845
imports-up	2,705
commodity-buy-target	1,171
demand-increase-commodity	1,070
exports-down	1,020
other 28 categories	3,014
all positive news	49,366

Table 6: Most frequent categories of positive news. Only categories with frequency greater than 1,000 are shown in this table.

Category	Number of negative news
commodity-price-loss	26,475
commodity-futures-loss	12,818
supply-increase-commodity	6,629
imports-down	2,017
exports-up	1308
resource-discovery-commodity	1,179
technical-view-bearish	1,172
other 24 categories	2,517
all negative news	54,115

Table 7: Most frequent categories of positive news. Only categories with frequency greater than 1,000 are shown in this table.

Table 8: Summary Statistics for Daily News Arrival by Years

Year	Mean	Median	Std.	Min	Max	3^{rd} Moment	4^{th} Moment
2000	10.990	10.000	7.883	1.000	48.000	624.140	20580.847
2001	14.929	14.000	9.225	1.000	51.000	489.795	25704.202
2002	4.807	4.000	3.452	1.000	19.000	60.569	801.811
2003	6.519	4.000	6.241	1.000	39.000	478.654	12369.937
2004	24.608	23.000	16.612	1.000	84.000	3190.837	261755.365
2005	20.921	21.000	12.480	1.000	57.000	668.782	71292.410
2006	21.375	21.000	13.224	1.000	58.000	311.175	72550.280
2007	19.695	18.000	12.724	1.000	66.000	1080.233	80582.446
2008	22.264	23.000	14.481	1.000	66.000	773.619	114575.879
2009	16.642	16.000	10.145	1.000	48.000	229.465	26102.072
2010	17.373	18.000	10.704	1.000	52.000	223.408	32208.647
2011	22.252	23.000	12.838	1.000	65.000	346.488	76634.229
2012	22.679	23.000	13.582	1.000	65.000	327.492	89356.087
2013	17.048	17.000	10.419	1.000	57.000	405.999	35381.337
2014	16.193	13.000	13.162	1.000	69.000	3434.647	167509.547
2015	22.334	20.000	14.945	1.000	80.000	2368.778	171467.903
2016	24.361	22.000	16.265	1.000	101.000	3602.310	285093.246
2017	15.428	14.000	10.105	1.000	58.000	815.307	43032.009
2018	15.692	15.000	10.870	1.000	93.000	1976.611	145822.537
2019	15.157	14.000	9.584	1.000	65.000	968.021	47684.600

Table 9: Average Numbers of News on Each Day

Year	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
2000	11.157	14.135	13.077	11.885	9.769	1.643	1.500
2001	12.547	17.569	21.327	15.058	14.078	1.000	1.200
2002	5.771	5.019	5.224	3.980	5.469	1.200	1.600
2003	7.080	6.529	9.942	6.863	5.490	1.200	1.136
2004	24.058	28.981	39.250	28.660	22.302	2.182	2.240
2005	21.462	21.846	33.596	24.654	19.000	1.765	2.259
2006	22.981	24.885	35.904	24.846	19.731	1.346	2.161
2007	19.792	21.385	33.577	23.846	16.769	1.941	2.212
2008	24.788	26.415	36.415	26.269	25.250	2.207	3.065
2009	16.058	21.346	29.192	16.925	15.538	1.688	2.366
2010	16.327	23.058	28.654	20.596	17.135	2.261	2.932
2011	23.769	28.577	32.904	25.750	19.942	2.053	3.441
2012	22.340	26.654	36.423	26.981	25.118	3.783	2.756
2013	16.673	19.642	28.588	19.038	15.846	2.500	2.366
2014	15.510	18.846	25.113	16.923	15.529	2.167	2.467
2015	23.019	27.135	35.558	23.189	19.843	2.091	2.957
2016	23.333	29.192	38.462	24.808	23.077	2.190	2.105
2017	14.220	16.788	25.192	16.077	14.039	1.696	1.667
2018	13.654	19.059	24.712	18.635	15.235	2.586	2.143
2019	11.263	15.872	24.600	15.026	13.795	1.923	1.500

2.5 Classifying News Type

2.6 Case Studies of Events

2.6.1 Positive Spike on November 30, 2016

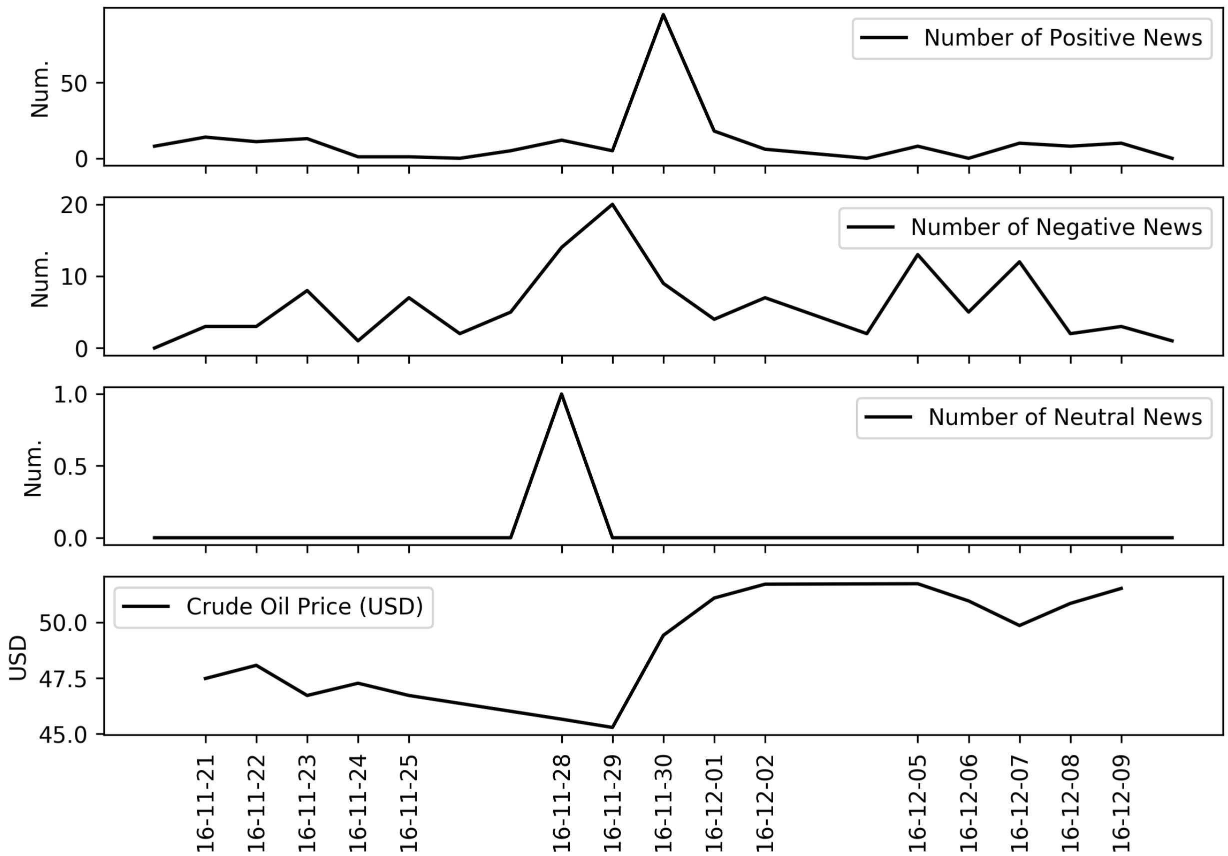


Figure 7:

2.6.2 Negative Spike on December 6, 2018

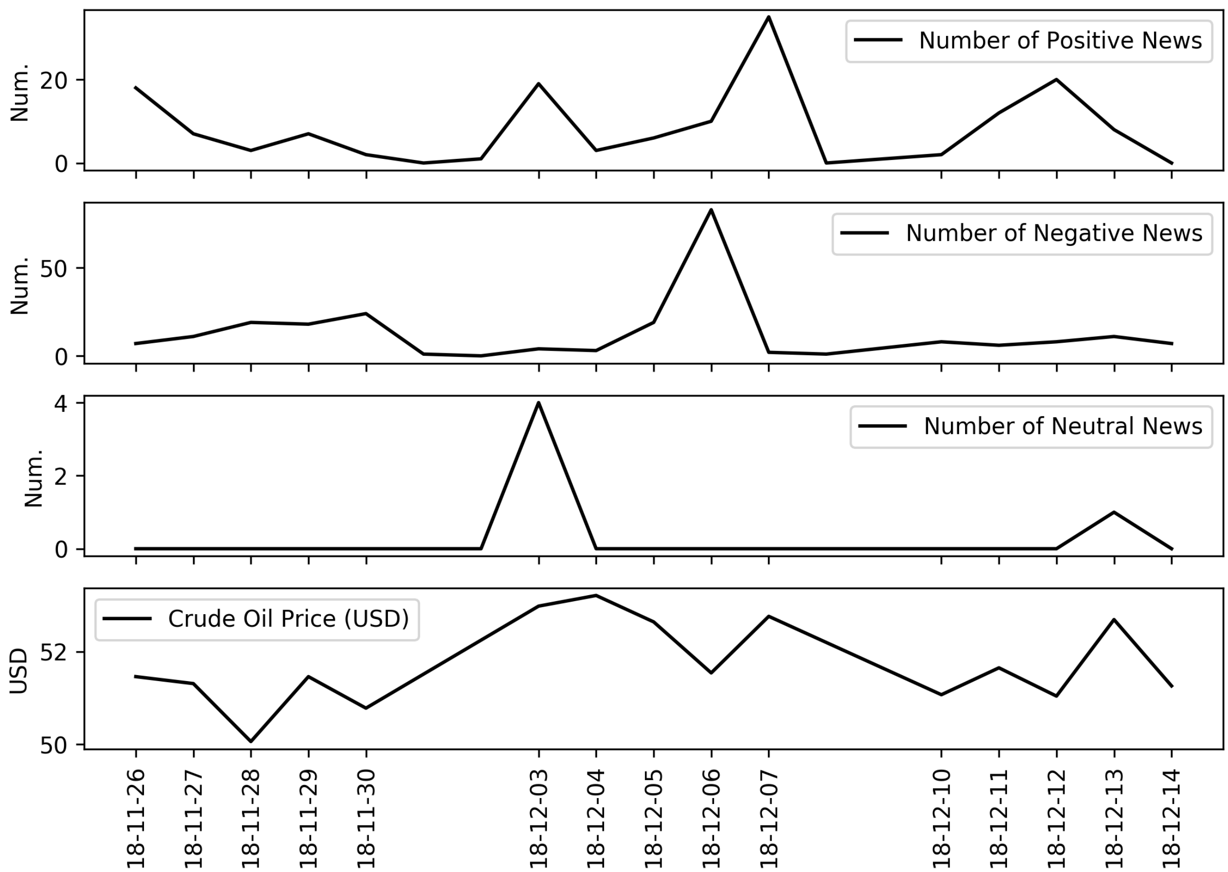


Figure 8:

2.6.3 Positive Spike on June. 12 - 13, 2019

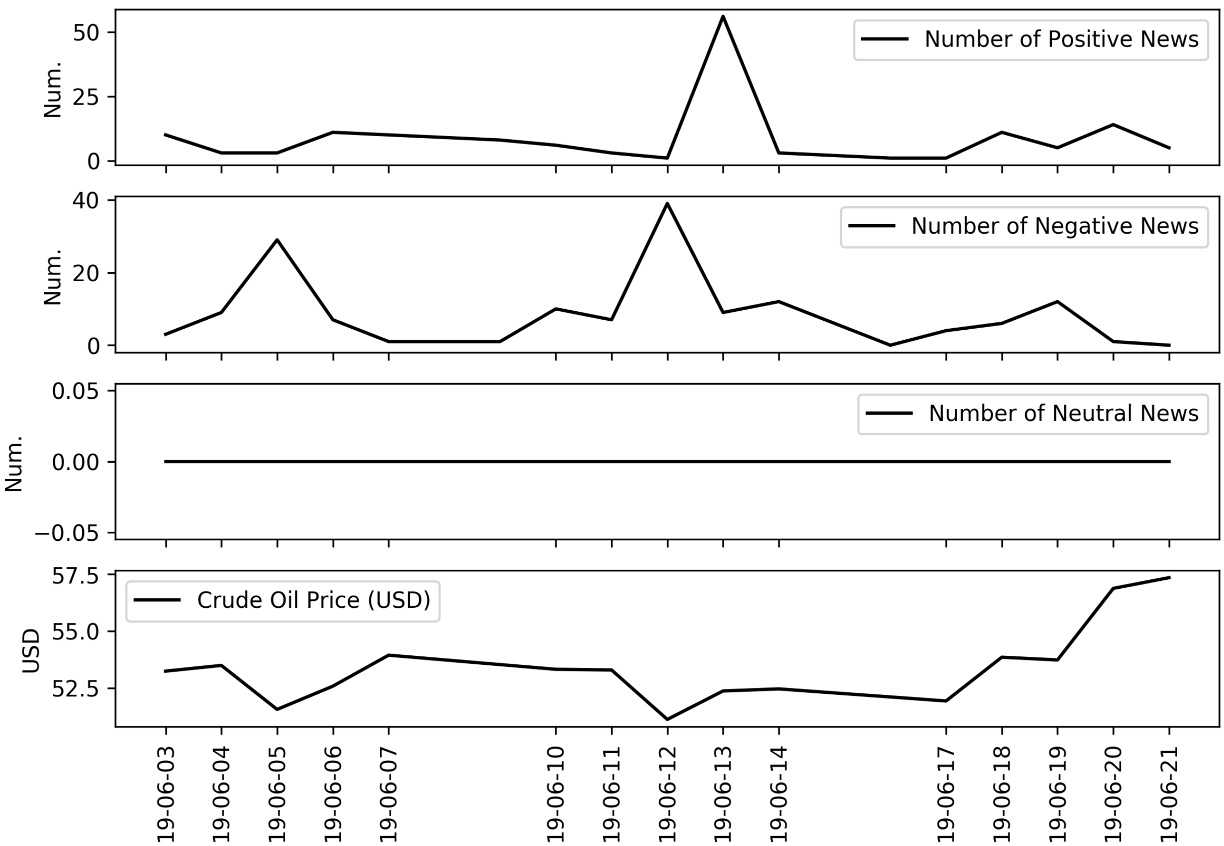


Figure 9:

3 Models

4 Experiments

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