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Ranking of US macroeconomic news impacting WTI crude oil volatility risk

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ABSTRACT

This study had the purpose to investigate the impact of 38 scheduled major United States (US) macroeconomic news on WTI crude oil intraday volatility for the period 2012-2018. It was the aim to provide a news ranking that indicates upcoming high volatility episodes at a specific point in time. The West Texas Intermediate (WTI) light crude oil represents a benchmark, since it has a signal effect on market players. High crude oil price volatility is a measure of risk and known to increase inflation, to affect producers, consumers and investors and to destabilize economic growth. In this research approach one-minute high-frequency bid close prices provided the basis for a 1h window rolling standard deviation. Data modeling was performed using simple and multiple robust ordinary least squares (OLS) regression performed with programming language Python. The model successfully identified 21 significant news announcements in both, the simple and multiple regression model, however, simple OLS-regression appears to be more sensitive. It also provided a ranking of US news impacting WTI volatility risk. The results support the prediction of approaching high price volatility and thus, display an opportunity for market participants and decision-makers to minimize risk.

Introduction

Energy price developments have fundamental impacts on economy. As a basic characteristic of financial markets volatility represents an important measure of risk (Xiao & Aydemir, 2007). Among any other assets and commodities crude oil price is known to display the most volatile structure worldwide (Lipsky, 2009). The inelasticity of the oil supply and demand side (Kilian, 2009; Cooper, 2003), speculations on oil derivatives (Kilian, 2010) and the lack of exact global data of current oil market conditions, e.g. unavailable global inventory data (Lipsky, 2009; JODI, 2012), were identified as main drivers of current price fluctuations. High oil price volatility levels are also described as a *"fundamental barrier to economic growth, due to its damaging and destabilizing effects on the macroeconomy"* (Ebrahim, et al. 2014) and they are equivalent to high risk and unpredictability in energy markets. Crude oil prices are influenced by a wide range of factors (Libo Wu, et al. 2011; EIA, 2015) and different geopolitical and global events are supposed to affect energy prices significantly (Kilian, 2010; Namboodiri, 1983; Triki & Affes, 2011). However, not all of them occur spontaneously, many of them are scheduled and released on a regular basis: macroeconomic news announcements.

This research is based on the assumption that the release of major macroeconomic news from the United States impacts WTI light crude oil price volatility. WTI represents a benchmark, since it has a signal effect on market players. It is the aim of this project to reveal those news having a significant impact on crude oil price volatility risk and to provide a news ranking that indicates upcoming high volatility episodes at a specific point in time. The availability of a ranking list is an opportunity for market players to minimize risk. Close attention can be paid right in time to a defined pool of approaching events, knowing which one is most important. Reliable forecasts support decision makers in economy and other fields of life in their everyday work. Thus, forecasting oil price volatility can contribute to economic stability (Henriques & Sadorsky, 2011).

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In this approach the supposed impact of a total of 38 scheduled macroeconomic news announcements from the United States on the light sweet crude oil benchmark WTI is analyzed. Light and sweet crudes can be easily processed and are highly eligible for gasoline production (Klimisch, et al. 1997). A one hour window rolling standard deviation was used as a measure of volatility. High frequency time series data are required to capture intraday effects. The 1h interval used in this research is assumed to be long enough to minimize disturbing market microstructure effects (Andersen, et al. 2001), but short enough to capture the assumed interaction between news releases and oil price fluctuations.

Literature Review

A wide range of research on crude oil and news announcements was predominantly performed with daily and weekly price intervals. Investigations on OPEC news announcements (Schmidbauer & Rösch, 2012), on inventory announcements (Hui, 2014) and analyzing volatility spillovers (Belgacem, et al. 2014) were each using daily returns. It was shown that oil price shocks are capable to increase inflation (Libo Wu, et al. 2011) and has negative effects on oil importing as well as oil exporting countries (Zhang, et al. 2017; Kilian & Vega, 2011).

Monthly returns were used to analyze economic news on the oil and gas industry stock index (Liu & Kemp, 2019). It was demonstrated that high volatility increases macroeconomic uncertainty in commodity markets (Bakas &Triantafyllou, 2018; 2019;) and the role of uncertainty shocks on volatility was investigated (Su, et al. 2019). Additional research on crude oil market uncertainty was performed (Jo, 2012; Bredin, et al. 2010; Elder & Serletis, 2010; Bernanke, 1983; Pindyck, 1991; Park & Ratti, 2008). The relationship between macroeconomic variables and forecasting in commodity markets was issued (Nguyen & Walther, 2018), and FOMC announcement effects on the market were studied (Fernandez-Perez, et al. 2017). Scheduled macroeconomic news was also investigated using crude oil volatility index (Lopez, 2018) and using oil futures options (Horan, et al. 2004). Currently, increasing attention is focused on intraday data, which becomes more relevant for further research activity. The impact of US inventory changes on WTI was investigated using 30min intervals and a GARCH (1,1) model (Faseli & Zamani, 2016) and the effects of transatlantic macroeconomic indicators on WTI and Brent Oil was analyzed using 1h intervals (Faseli, 2019) in a data mining process. The economic response of transitory or persistent oil price volatility on producers, investors and consumers was issued from different points of view (Elder, 2018; Plante & Traum, 2012; Guo & Kliesen, 2005). Direct and indirect effects of volatility on economy were reported (Ebrahim, et al. 2014; Sadorsky, 1999) and it was shown that the negative effects of increased oil prices on economy are even stronger than the positive effects of decreasing prices are (Mork, 1989). For investors the most recent information is most valuable and thus, plays a more significant role (Baumohl, 2013).

Research and Methodology

The implemented *data science procedure* is outlined in Table 1. The data mining workflow comprises an extract, transform and load (ETL)-process and subsequent data modeling performed with programming language Python, which is world-wide predominantly used and found to be at the leading edge of today's programming languages (Diakopoulous, 2019; Piatetsky-Shapiro, 2018). The ETL-process stands for the retrieval (extract), preprocessing and synchronization/merging of price and news data and is crucial for subsequent data modeling. Usually these three steps are performed in parallel. Depending on different authors (Han, et al. 2012; Chen, et al. 2007) the data mining workflow is described slightly different. Data mining clearly shows interdisciplinary features, reflecting the intention and character of this entire research: "*Data mining can be viewed as a result of the natural evolution of information technology*." (Han, et al. 2012)

Macroeconomic News Data

In this investigation the data mining process requires the exact release time of macroeconomic news announcements, which indicate changes in the macroeconomic indicator content and are used as a dummy variable. The presence or absence of news announcements D at the exact time t is indicated by 1 (presence) or 0 (absence). The observation period runs from January, 2012 to December, 2018 comprising a total of 7069 observations. News release usually follows a precise weekly, monthly or quarterly schedule, which is publicly announced from governmental or financial institutions and following a strictly standardized time table. However, despite this standard, deviations from the scheduled weekdays occur frequently over the years. It needs to be outlined that all regressor variables, i.e. the news announcements, are introduced and positioned in the data synchronization dynamically, following their exact and realized publishing date and time and not according to the a priori announced schedule.

Data Preprocessing

The exact time of release was directly *retrieved* from the websites of the publishing source institutions. Subsequently, the data was stored as csv-formats in a repository together with the price data. News data preprocessing is required due to variations in the date and release time formats and results in the *transformation* into dummy variables. Data of different economic news show variations in the notation and chronological order of the formats, e.g. the month-day-year order versus the day-month-year order. Additionally, the release time may be provided as a 12-hour time frame or as a 24-hour time frame. In this research project the 24-hour time-frame was used. For subsequent synchronization and merging of price and news data, all news release dates were transformed into identical formats.

Table 1: Overview of the implemented data science process using data mining techniques.

<table>
<tr><td colspan="4">The Data Mining Workflow
in the Data Science Process</td></tr>
<tr><td rowspan="5">ETL-Process</td><td colspan="2">Retrieval and collection of raw data</td><td rowspan="5">ETL-Process</td></tr>
<tr><td>PRICE DATA
WTI Light Crude Oil</td><td>MACROECONOMIC NEWS
Governmental & Financial Institutions</td></tr>
<tr><td colspan="2">Preprocessing of raw data</td></tr>
<tr><td>Cleaning
Integration
Reduction
Transformation
(Derived Measure >Volatility Estimation)</td><td>Cleaning
Integration
Transformation
(Creating Dummy Variables = Regressor)</td></tr>
<tr><td colspan="2">Synchronization and combining (merging) of
preprocessed price and news data</td></tr>
<tr><td colspan="4">Data modeling, diagnostic and analysis via Python
prediction analysis / OLS- regression</td></tr>
</table>

WTI Crude Oil Price Data

One minute high frequency WTI price time series data (dependent variable) were *retrieved* from the financial data provider ForeX Capital Markets (FXCM). The company granted access to historical price data over a period of seven years from January, 2012 to December, 2018. Market close times from Friday 10 p.m. GMT to Sunday 11 p.m. GMT were excluded. During *data cleaning* time intervals are checked for completeness. Some positions in the time series may be incomplete by showing either no values (blank fields) or incorrect values (letter or special signs). These positions were deleted. Subsequently, data of different sources or files became *integrated* into a single data set. Data *reduction* was performed by resampling 1min price data to 15min mean, providing the basis for data *transformation* into the one hour window rolling standard deviation as a measure of WTI volatility (V_t). The time series was statistically described (see Table 2) and tested for autocorrelation using ACF/PACF plot (see Figure 1). Normality test was performed using Histogram-plot, Kolmogorov Smirnov and D'Agostino Pearson test (see Figure 1 and Table 2).

Table 2: Data statistics of a one hour window rolling standard deviation.

Statistical Description of WTI 1h Rolling Standard Deviation	
Count Non-Zero	1.60E+05
Variance / Median / Mean	5.48E-03 / 4.78E-02 / 7.02E-02
Skew / Kurtosis	3.95E+00 / 3.40E+01
Kolmogorov Smirnov t-statistic /p-value	1.80E-01 / 0.00E+00
D'Agostino Pearson t-statistic / p-value	1.39E-05 / 0.00E+00

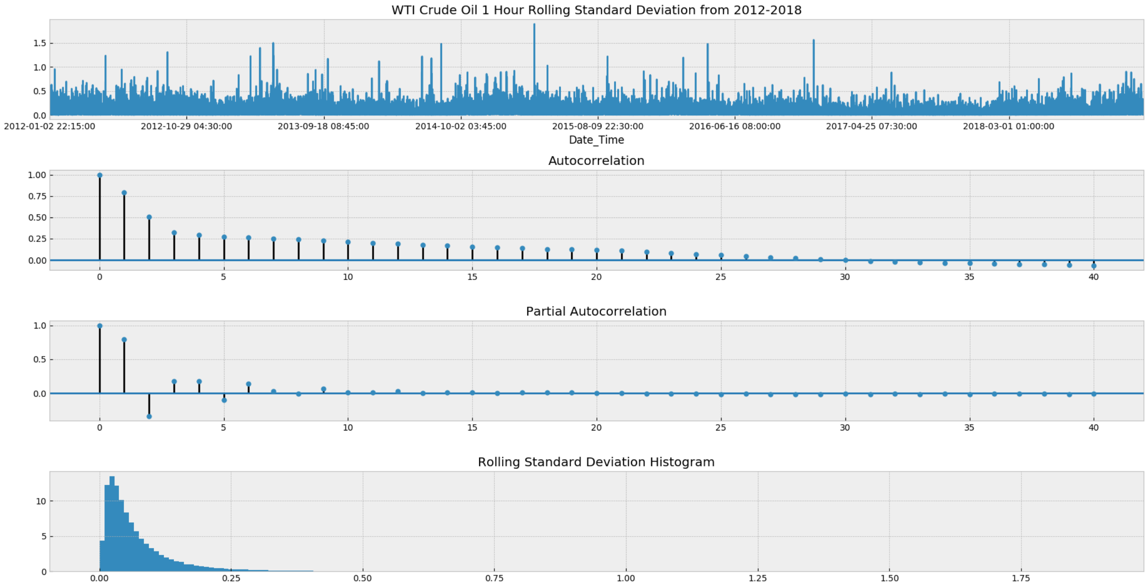

Figure 1: ACF/PACF-plot and Histogram-plot of WTI Light Crude Oil 1 hour window rolling standard deviation from (Jan. 2012 - Dec. 2018), original raw price data

Autoregressive OLS-Regression Model

The model uses simple and multiple robust Ordinary Least Squares (OLS) regression analysis to identify news announcements that significantly impact WTI price volatility. Heteroscedasticity and Autocorrelation Consistent (HAC) robust standard errors were applied (Newey & West, 1987). Macroeconomic news announcements are introduced as dummy variable *D* at the precise time *t* into the regression equations according to their presence (1) or absence (0). The basic equations for the derivation of the regression model follow (Auer & Rottman, 2015; Geyer, 2008):
Simple linear regression model is defined in Equation (1):

$$V_t = \beta_0 + \beta_1 D + \epsilon_t \tag{1}$$

Multiple linear regression model is defined in Equation (2):

$$V_t = \beta_0 + \beta_1 D_1 + \beta_2 D_2 + \ldots + \beta_k D_{k,t} + \epsilon_t \tag{2}$$

summarized in Equation (3):

$$V_t = \beta_0 + \sum_{k=1}^{q} \beta_k \, D_{k,t} + \epsilon_t \tag{3}$$

Simple autoregressive method is described in Equation (4):

$$V_t = \beta_0 + \sum_{j=1}^{p} \beta_j \, V_{t-j} + \beta_k D_{k,t} + \epsilon_t \tag{4}$$

Multiple autoregressive method is described in Equation (5):

$$V_t = \beta_0 + \sum_{j=1}^{p} \beta_j \, V_{t-j} + \sum_{k=1}^{q} \beta_k \, D_{k,t} + \epsilon_t \tag{5}$$

Equation (1-5): The autoregressive process is defined for the correction of measured serial correlation. As a consequence lags of the volatility measure are introduced into the total formula, indicated by V_{t-j}. β_j is the coefficient of lag *j* in the autoregressive process for the variable V_t. $D_{k,t}$ denotes the binary categorical variable (dummy) for macroeconomic announcements k (1, 2, 3…, 38) at the exact time t, β_k denotes the regression coefficient. V_t denotes volatility, indicated by the WTI one-hour window rolling standard deviation, β_0 indicates the intercept and ϵ_t is the error term at time t. All t-stat values are based on HAC standard errors. Asymptotic normality of large data sets is assumed following (Auer & Rottman, 2015; Geyer, 2008).

A total of 38 US news announcements was introduced to the model. Evaluation and interpretation of the regression coefficients β_k was performed with significance tests applying test statistics t-value, p-value and R-squared. The coefficients indicate, if the relationship is positive or negative and describe the strength of the correlation. Large coefficients stand for strong and those near zero describe weak relationships. Two-tailed t-test was used for testing the null hypothesis (H0) with restriction to a single coefficient. The p-value indicates the probability of a certain test result, when the H0 is true. Significance levels <1% (***p<.01), <5% (**p<.05) and <10% (*p<.10) indicate the rejection of the null hypothesis.

Results and Discussion

Simple OLS-Regression Results

In simple autoregressive OLS-regression 27 out of 38 US macroeconomic indicators significantly impact WTI oil price volatility. ACF/PACF-plot and Histogram-plot of the model residuals indicate the EIA Weekly Distillates Stocks effect on WTI, provided in Figure 2, the significant news items are listed in Table 3.

The eleven non-responsive US news used in simple regression are: ADP Nonfarm Employment Change, Baker Hughes Oil Rig Count, Building Permits, Current Account, FOMC Meeting Minutes, Housing Starts (MoM), MBA 30 Year Mortgage Rate, MBA Mortgage Applications (WoW), MBA Purchase Index, Mortgage Refinance Index, Philadelphia Fed Manufacturing Index.

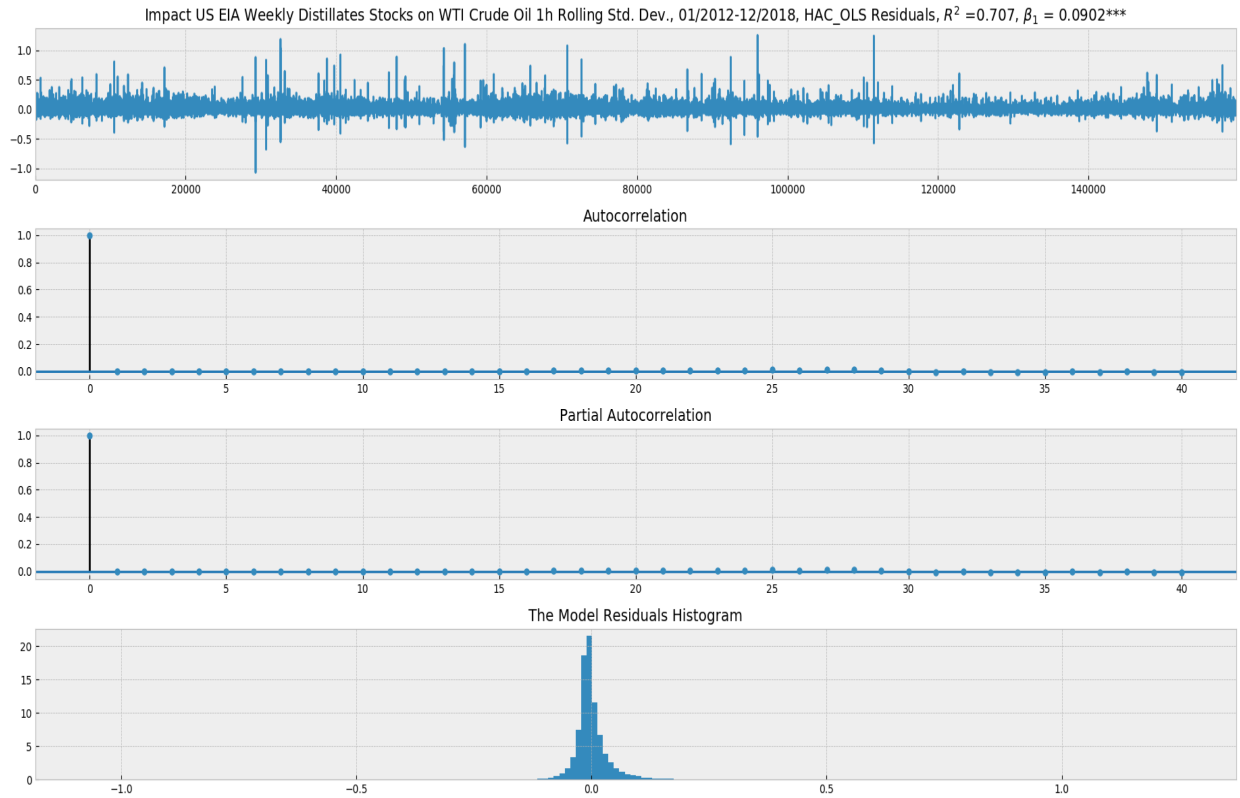

Figure 2: Model Residuals: ACF/PACF-plot and Histogram-plot of EIA Weekly Distillates Stocks on WTI Crude Oil. 1-hour window rolling standard deviation from (Jan. 2012 - Dec. 2018)

Table 3: Ranking of Significant US News Announcements on WTI Crude Oil, Simple Autoregressive OLS-Model, Significance Level: 1% (***p<.01),5% (**p<.05), 10% (*p<.10).

	Regressor	Coeff. β_1		t-value	R^2
1	EIA Weekly Distillates Stocks	0.0902	***	13.204	0.7067
2	Crude Oil Inventories	0.0861	***	14.132	0.7073
3	Gasoline Inventories	0.0861	***	14.132	0.7073
4	API Weekly Crude Oil Stock	0.0439	***	9.220	0.7033
5	Unemployment Rate	0.0373	***	3.929	0.7033
6	Factory Orders (MoM)	0.0233	***	2.630	0.7031
7	Durable Goods Oders (MoM)	0.0202	***	2.864	0.7031
8	Existing Home Sales	0.0188	***	3.028	0.7030
9	Redbook (MoM)	0.0185	***	55.554	0.7029
10	House Price Index (MoM)	0.0180	***	2.836	0.7030
11	Pending Home Sales (MoM)	0.0171	***	3.375	0.7031
12	Existing Home Sales (MoM)	0.0171	***	3.112	0.7030
13	GDP (QoQ)	0.0168	***	3.390	0.7031
14	New Home Sales	0.0166	**	2.561	0.7033
15	New Home Sales (MoM)	0.0163	***	2.891	0.7032
17	Natural Gas Storage	0.0154	***	5.180	0.7035
18	Personal Spending (MoM)	0.0154	**	2.348	0.7030
16	NAHB Housing Market Index	0.0150	***	2.680	0.7031
19	CB Consumer Confidence	0.0148	***	2.702	0.7030
20	Core Retail Sales (MoM)	0.0134	**	2.559	0.7031
21	Import Price Index (MoM)	0.0131	***	3.107	0.7030
22	Continuing Jobless Claims	0.0081	***	3.555	0.7036
23	Initial Jobless Claims	0.0076	***	3.308	0.7029
24	Four Week Bill Auction	0.0075	**	2.363	0.7031
25	Building Permits (MoM)	0.0065	*	1.720	0.7025
26	Housing Starts	0.0061	***	1.634	0.7025
27	CFTC Crude Oil speculative net pos.	-0.0086	***	-6.597	0.703

Multiple OLS-Regression Results

In multiple autoregressive OLS-regression analysis 21 out of 38 US indicators showed significant coefficients. Model specifications are provided in Table 4 and regression results in Table 5. All relevant news were also identified in the simple regression model. The seventeen non-responsive US news used in multiple regression are: ADP Nonfarm Employment Change, Baker Hughes Oil Rig Count, Building Permits, Building Permits (MoM), Current Account, Existing Home Sales, Existing Home Sales (MoM), FOMC Meeting Minutes, Housing Starts (MoM), MBA 30 Year Mortgage Rate, MBA Mortgage Applications (WoW), MBA Purchase Index, Mortgage Refinance Index, New Home Sales, New Home Sales (MoM), Philadelphia Fed Manufacturing Index and Redbook (MoM).

Table 4: Specifications of multiple autoregressive robust OLS-Regression Model

Multiple OLS-Regression Model Specifications	
Dependent Variable:	WTI 1h Window Rolling Standard Deviation based on
	15min mean resampled from 1min bid close prices
Obs. Period:	01/2012-12/2018
Model:	OLS
Method:	Least Squares
Covariance Type:	HAC
No. of Observations	159631
R-Squared:	0.707
Adj. R-Squared	0.707

Table 5: Ranking of Significant US News Announcements on WTI Crude Oil; Multiple Auto- regressive OLS-Model (robust), Significance Level: 1% (***p<.01),5% (**p<.05), 10% (*p<.10).

	Regressor	Coeff β_k		t-value
1	Initial Jobless Claims	0.0913	***	161.298
2	API Weekly Crude Oil Stock	0.0438	***	9.189
3	EIA Weekly Distillates Stocks	0.0343	***	2.728
4	Crude Oil Inventories	0.0293	***	5.486
5	Gasoline Inventories	0.0293	***	5.486
6	Factory Orders (MoM)	0.0235	***	2.729
7	Pending Home Sales (MoM)	0.0172	***	3.401
8	Durable Goods Orders (MoM)	0.0167	**	2.406
9	House Price Index (MoM)	0.0164	**	2.563
10	GDP (QoQ)	0.0154	***	3.059
11	Natural Gas Storage	0.0154	***	5.165
12	NAHB Housing Market Index	0.0152	***	2.745
13	Personal Spending (MoM)	0.0127	**	2.089
14	CB Consumer Confidence	0.0126	**	2.225
15	Unemployment Rate	0.0124	***	3.986
16	Core Retail Sale (MoM)	0.0105	*	1.876
17	Import Price Index (MoM)	0.0093	**	2.011
18	Housing Starts	0.0085	*	1.746
19	Four Week Bill Auction	0.0079	**	2.508
20	CFTC Crude Oil spec. net pos.	-0.0095	***	-4.658
21	Continuing Jobless Claims	-0.0903	***	-32.886

Conclusions

This research is based on the assumption that certain US macroeconomic news announcements show a significant impact on intraday WTI crude oil price volatility. The model compares the efficiency of simple and multiple robust OLS-regression analysis to identify volatility triggering news releases. Both models were capable to identify a pool of 21 significant news out of a sample of 38, however, simple OLS-regression appears to be more sensitive. The implementation of high frequency intraday data is crucial to detect abnormal volatility episodes during the market open times. For investors and decision-makers in economy and finance it is essential to know about upcoming volatility peaks right in time. They need to gain information about which news announcements could bring their investments at risk and thus, need reliable prediction tools.

The implemented data science process provides several benefits as well as a novel and comprehensive approach: firstly, a ranking of a series of United States news releases significantly impacting the benchmark WTI, secondly a comparison of the efficiency of two different regression models, thirdly an extended observation period over seven years using high frequency intraday data and the state of the art programming language Python used for data modeling,

Providing an improved prediction model for the detection of approaching crude oil price volatility fluctuations contributes to economic stability - the destabilizing and damaging effects of increased oil price volatility were described. It must also be outlined that the macroeconomic news variables in this research project were not positioned in the regression according only to the scheduled date and time of release. Instead, they were implemented dynamically following their realized exact publishing date and time. The available results encourage to apply the methodology for additional research on time-series in the field of economy. Revealing further interactions among different commodities and macroeconomic indicators will provide a deeper understanding in the dynamic field of global economic relationships.

Annotation

The results, tables and figures provided in this article are part of my dissertation (Faseli, 2019).

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