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The relationship between European Brent crude oil price development and the US macro economy

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ABSTRACT

Abnormal volatility has a damaging effect on the macroeconomy and is seen as a measure of risk in asset and commodity markets. This investigation had the aim to analyze the supposed transatlantic volatility inducing effect of the most prominent scheduled macroeconomic news announcements from the United States (US) on Brent Blend crude oil price intraday volatility over a period of seven years from 2012 to 2018. The objective was to generate a ranking list of scheduled US macroeconomic news that forecast high intraday volatility episodes at precise points in time. A total of 38 US news was analyzed using a data mining workflow. Data modeling was conducted using a simple ordinary least squares regression model and performed with programming language Python. A one hour window of rolling standard deviation based on one minute high frequency closing prices was applied. As a result, 20 scheduled US macroeconomic news were successfully identified to significantly impact Brent crude oil price volatility. The model strongly supports the forecast of high price fluctuations and provides an opportunity for market players to adjust their risk management strategies right in time.

Introduction

The economy is fundamentally impacted by energy price developments. Price volatility is a basic market behavior and represents an important key measure of risk (Xiao & Aydemir, 2007). Crude oil price shows the most volatile development among any other global assets and commodities (Lipsky, 2009). Current oil price variability was found to be mainly powered by a lack of precise worldwide data of current market conditions, e.g. exact crude oil inventory data on a global scale (Lipsky, 2009; JODI, 2012). Oil prices may also be impacted by numerous geopolitical and economic factors (Libo Wu et al., 2011; EIA, 2014) and global fluctuations in business cycles were also found to significantly affect energy prices as well (Kilian, 2010; Triki & Affes, 2011). Speculative positions on oil derivatives (Kilian, 2010) and the inelastic character of crude oil supply and demand (Cooper, 2003; Kilian, 2009) play an important role for oil price fluctuations. Increased price volatility represents uncertainty and high risk in energy markets and it was found to inhibit economic growth *"..., due to its damaging and destabilizing effects on the macroeconomy"* (Ebrahim et al., 2014).
Certain US news were found to impact US WTI light crude oil (Faseli, 2019, 2020; Faseli & Zamani, 2016) and it would be important to reveal a transatlantic spillover effect to another light crude oil. Both, Brent Blend and WTI are highly eligible for gasoline production (Klimisch et al., 1997) and seen as a benchmark, since they show a signal effect on market participants. The availability of an extended news ranking indicating approaching high price volatility events at precise points in time could strongly support investors and decision-makers in minimizing risk and optimizing risk management strategies. Close attention could be paid to a

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specific selection of upcoming news releases, knowing which one usually shows highest impact. Economic stability can be supported by improved prediction of oil price volatility. (Henriques & Sadorsky, 2011)
In this study I investigate the effect of 38 scheduled US macroeconomic news announcements on Brent Blend crude oil. One minute high frequency price data are required to reveal abnormal intraday volatility episodes. The volatility measure V_t is represented by a 1 hour window of rolling standard deviation. The frequency of the measure is supposed to be long enough to keep disturbing market microstructure effects at a minimum level (Andersen et al., 2001). Simultaneously, the price interval should be short enough to capture the assumed news impact.
This study has the aim to resolve the research question, if there is a significant effect of certain scheduled US macroeconomic news announcements on the intraday price volatility of the European light crude oil Brent Blend. A transatlantic spillover effect of major US macroeconomic news is assumed. Although, Brent crude is a European benchmark, the hypothesis is that due to the internationally leading role of US economy, there might be a transatlantic spillover effect to Brent Blend. The objective of this research is to capture the assumed effect and to provide a ranking of US news announcements that may significantly impact the intraday price development of Brent Blend.
Subsequent to this introduction, the literature review is provided issuing basic and current related work on the topic. The implemented data mining workflow as well as the retrieval, preprocessing and statistics of applied data are described in the section Research and Methodology. A characterization of the utilized ordinary least squares (OLS) regression model is included. In the section Result and Discussion the news ranking list and the statistics of model residuals are shown. Finally, the conclusion of the research outcome is presented.

Literature Review

In the past, studies referring to the impact of macroeconomic news on crude oil were primarily performed with weekly and daily price intervals. Daily returns were used to study the effect of OPEC news releases (Schmidbauer & Rösch, 2012), inventory announcements (Hui, 2014) and volatility spillovers (Belgacem et al., 2014) in the crude oil market. Libo Wu et al. (2011) analyzed increasing inflation after oil price shocks, which were found to negatively impact oil exporting as well as oil importing countries (Kilian & Vega 2011; Zhang Xun et al., 2017). The effect of news announcements on the oil and gas industry stock index was issued using monthly returns (Liu & Kemp, 2019). High volatility shows increased uncertainty effects on macroeconomy in commodity markets (Bakas & Triantafyllou, 2018, 2019) and the role of uncertainty shocks was analyzed from Su et al. (2018). Uncertainty effects in the crude oil market were issued for more than three decades (Bernanke 1983; Pindyck, 1991; Park & Ratti, 2008; Elder & Serletis, 2010; Bredin, 2010; Jo, 2012, Su, 2018). Prediction in the commodity markets using macroeconomic variables was issued from Nguyen & Walther (2018) and Fernandez-Perez et al. (2017), the latter using FOMC announcement effects. The impact of scheduled macroeconomic news on the crude oil market was investigated using oil futures options (Horan et al, 2004) and crude oil volatility index (Lopez, 2018). It was shown that the most valuable information for investors is the most recent one (Baumohl, 2013), which may be one reason that increased attention is currently paid to intraday price data. Changes in US crude oil inventory data on WTI light crude oil was investigated with a GARCH (1,1) model (Faseli & Zamani, 2016) using 30min price intervals. The impact of US macroeconomic news on WTI was tested using a one hour rolling standard deviation based on a 15min mean in a data mining workflow (Faseli, 2019; 2020). It was also demonstrated that the negative impact of increased crude oil prices is stronger then the positive effect of decreasing prices (Mork, 1989). Direct and indirect volatility effects on economy were reported (Sadorsky, 1999; Ebrahim et al., 2014;), and the economic response of persistent or transitory oil price volatility on investors, producers and consumers was investigated from Guo & Kliesen (2005), Plante & Traum (2012), and Elder (2018).

Research and Methodology

Data Mining Workflow

The data science process in this study uses the programming language Python, which is currently state of the art and globally predominantly used (Piatetsky, 2018; Diakopoulous, 2019). The study uses a data mining workflow consisting of tools and techniques that perform a series of usually sequentially conducted operations (see Figure 1). Several names and varying definitions exist and describe the data mining procedure, such as knowledge mining from data, knowledge extraction, data/pattern analysis and knowledge discovery from data (KDD). However, all of them reveal analogous meaning described with varying specifications depending on the authors (Chen et al., 2007; Han et al., 2012) Data mining clearly presents interdisciplinary features, which reflects the character of this entire research approach. The data mining workflow started with the retrieval of relevant news and crude oil price data as a first step. Subsequently, data pre-processing including data cleaning, transformation and consolidation was performed, which will be described in more detail below in the sections *Macroeconomic News Announcements* and *Brent Crude Price Data*. During ordinary least squares (OLS) regression analysis those US news announcements showing the highest impact on Brent crude oil were revealed. The analysis process was supported by the visual analysis tools ACF/PACF and Histogram plot.

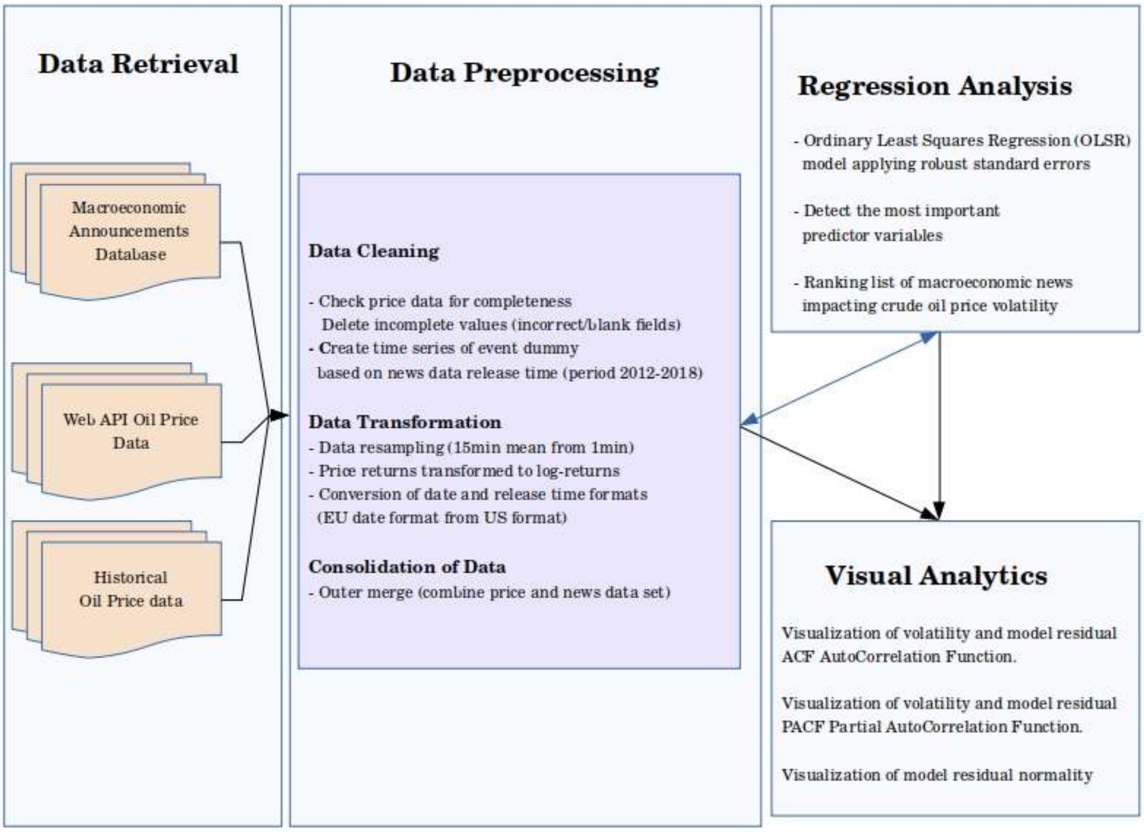

Figure 1: Overview of the implemented data mining techniques showing the summarized principles of the data science workflow.Source: Faseli, 2020.

Data Retrieval

The observation period is determined from January, 2012 to December, 2018 and the required variables comprise 38 US macroeconomic news releases and Brent crude oil price time-series data.

The *news announcements* display changes in the macroeconomic indicator content and are used as a dummy variable D_t, representing the regressor variable. The presence or absence of regressor D at the exact time t is indicated by 1 (presence) or 0 (absence). Precise release times are required to capture the assumed volatility inducing effect on an intraday basis. The news are released from financial or governmental institutions and the announcement pattern follows a strictly standardized weekly, monthly or quarterly schedule. However, over the years deviations from the scheduled weekdays occur frequently, despite the strictly performed time-table. It needs to be outlined that all news observations were introduced and positioned dynamically according to the realized exact publishing day and time and not according to the a priori announced schedule.

The required *Brent crude price time series data* (dependent variable) were retrieved in one minute high frequency time intervals over the period January, 2012 to December, 2018 and acquired from the financial data provider ForeX Capital Markets (FXCM), market closing times were excluded (Friday 10 p.m. GMT to Sunday 11 p.m. GMT).

Date Pre-processing and Statistics

Macroeconomic News Announcements

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 pre-processing is required due to variations in the date and release time formats and results in data 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 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 needed were transformed into identical formats.

Brent Crude Price Data

During data cleaning time intervals are checked for completeness. Some positions in the time series may be incomplete by showing either no (blank fields) or incorrect values (letters or special signs) instead of numerical values. 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 of rolling standard deviation as a measure of Brent volatility (V_t). The time series was statistically described and tested for autocorrelation using ACF/PACF plot (see Figure 2). Normality test was performed using Histogram-plot (see Figure 2), Kolmogorov Smirnov and D'Agostino Pearson test, skewness and kurtosis were defined (see Table 1),

Table 1: Data statistics of a one hour window rolling standard deviation

Statistical Description of Brent 1h Rolling Standard Deviation	
Count Non-Zero	1.42E+05
Variance / Median / Mean	6.99E-03 / 5.55E-02 / 7.73E-02
Skew / Kurtosis	9.86E+00 / 3.01E+02
Kolmogorov Smirnov t-statistic /p-value	1.84E-01 / 0.00E+00
D'Agostino Pearson t-statistic / p-value	2.27E+05 / 0.00E+00

Source: Faseli, 2020

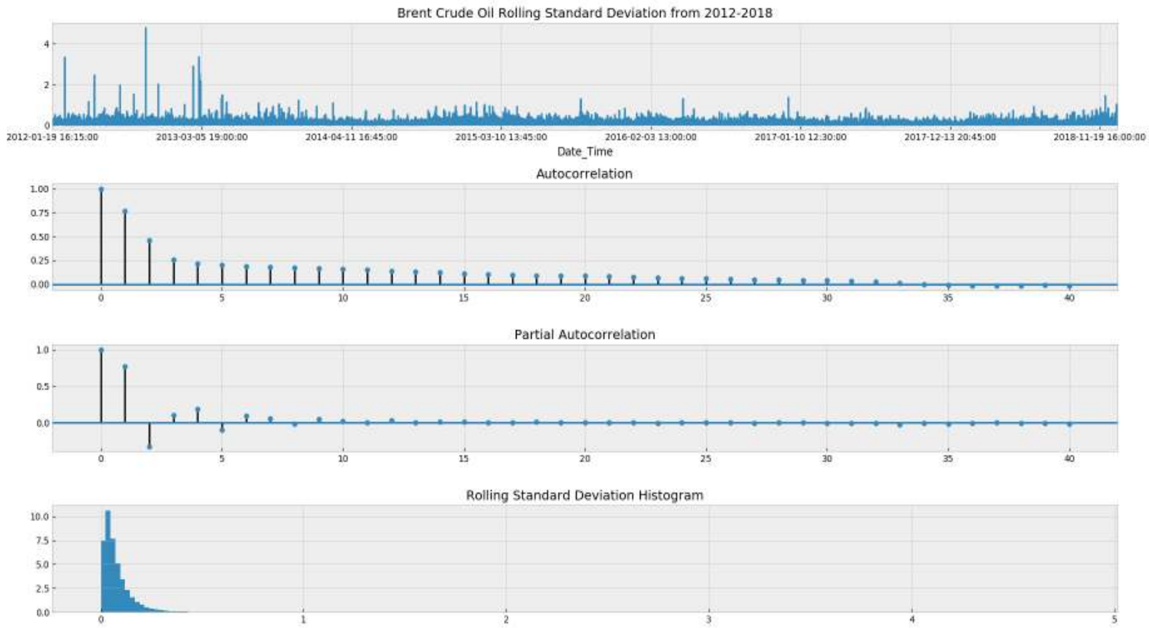

Figure 2: Brent Crude Oil 1 hour window of rolling standard deviation (Jan. 2012 - Dec. 2018), original raw price data; ACF/PACF- and Histogram-plot; *Source*: Faseli, 2020.

Simple Autoregressive OLS-Regression Model

Data modeling was conducted with simple ordinary least squares (OLS) regression analysis considering an autoregressive process to reveal macroeconomic news announcements that significantly impact Brent crude volatility. Heteroscedasticity and Autocorrelation Consistent (HAC) robust standard errors were applied (Newey & West, 1987). Macroeconomic indicators are introduced as dummy variable D into the regression equations according to their presence (1) or absence (0) at the exact time t. For the derivation of the regression model the basic equations follow (Auer & Rottman, 2015; Geyer, 2019):

Simple linear regression model is defined in Equation (1):

$$V_t = \beta_0 + \beta_1 D + \epsilon_t \quad (1)$$

Equation (1): V_t denotes the volatility measure of a 1 hour window rolling standard deviation of Brent oil (dependent variable) in the simple linear regression model. β_0 stands for the intercept of the equation, β_1 for the regression coefficient and ϵ_t denotes the error term at time *t*. The value of the coefficient denotes the strength of the relationship and indicates positive or negative correlation. Variable *D* (regressor or binary categorical variable) indicates the presence (1) or absence (0) of US news releases and stands synonymous for the dummy variable. ϵ_t describes the residual at time *t*.

Simple autoregressive method is described in Equation (2):

$$V_t = \beta_0 + \sum_{j=1}^{p} \beta_j V_{t-j} + \beta_k D_{k,t} + \epsilon_t \quad (2)$$

Equation (2): For the correction of detected autocorrelation the autoregressive process is introduced into the equation indicated by V_{t-j}. β_j denotes the coefficient of lag *j* for the variable V_t. $D_{k,t}$ indicates the binary categorical variable (dummy variable) for macroeconomic news releases *k (1, 2, 3, ..., 38)* at the exact point in time *t* and β_k. is the regression coefficient. All *t*-statistics are based on robust HAC standard errors, asymptotic normality of large data sets following the central limit theorem is assumed (Auer & Rottman, 2015; Geyer, 2019).

Thirty-eight (38) US macroeconomic news were introduced to the simple autoregressive OLS regression model. Significance tests were performed applying test statistics t-value (two-tailed t-test), p-value and R^2 on the regression coefficients β_k. The p-value denotes the significance level of the interaction and indicates the probability of a specific test result, when the Null-Hypothesis is true. Significance levels indicate the rejection of the H_0 at <1% (***p<.01), <5% (**p<.05) and <10% (*p<.10)

Results and Discussion

OLS-Regression Results

In simple OLS regression 20 out of 38 US macroeconomic news significantly impacted Brent crude price volatility. ACF/PACF-plot and Histogram-plot of the model residuals show the EIA Weekly Distillates Stocks effect on Brent, provided in Figure 3.

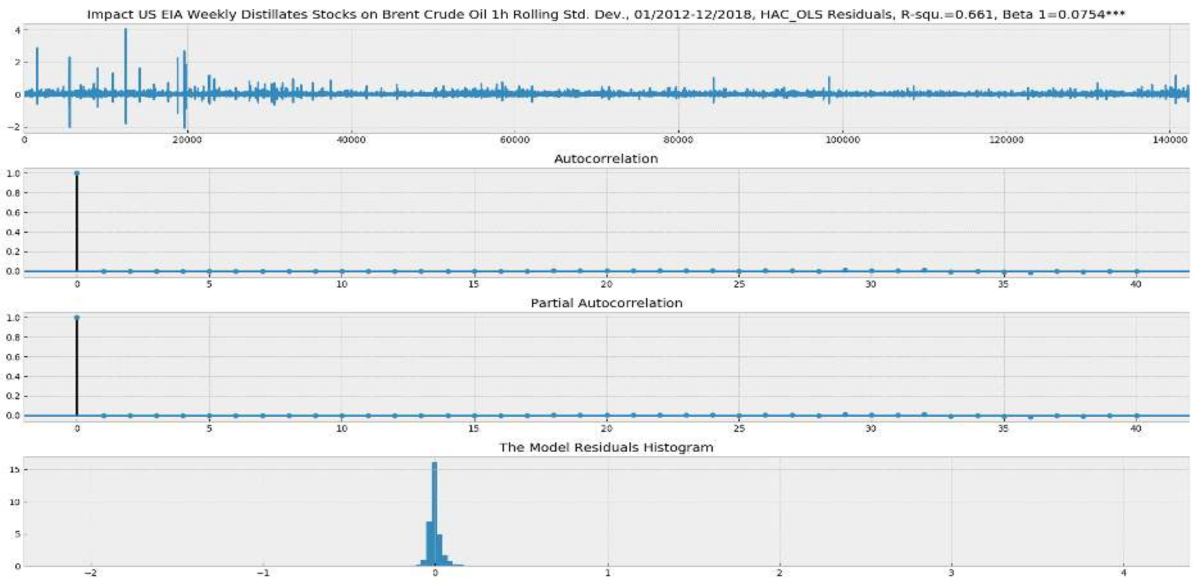

Figure 3: Model Residuals. ACF/PACF-plot and Histogram-plot of EIA Weekly Distillates Stocks on Brent Crude Oil 1hour window rolling standard deviation from (Jan. 2012 - Dec. 2018); *Source:* Faseli, 2020.

The ranking of the 20 news significantly impacting Brent Blend is provided in Table 2. The eighteen non-responsive news announcements include ADP Nonfarm Employment Change, Baker Hughes Oil Rig Count, Building Permits, Building Permits

(MoM), Current Account, Durable Goods Orders (MoM), FOMC Meeting Minutes, GDP (QoQ), House Price Index (MoM), Housing Starts, Housing Starts (MoM), Import Price Index (MoM), MBA 30 Year Mortgage Rate, MBA Purchase Index, New Home Sales, New Home Sales (MoM), Pending Home Sales (MoM) and Personal Spending.

Table 2: Ranking of Significant US News Announcements on Brent Crude Oil, Simple Autoregressive OLS Model, Significance Level: 1% (***p<.01),5% (**p<.05), 10% (*p<.10)

	Regressor	Coeff. β1	t-value	R2
1	EIA Weekly Distillates Stocks	0.0754 ***	12.142	0.658
2	Crude Oil Inventories	0.0712 ***	12.563	0.658
3	Gasoline Inventories	0.0712 ***	12.563	0.661
4	Private Nonfarm Payrolls	0.0300 ***	3.781	0.658
5	Unemployment Rate	0.0296 ***	3.742	0.658
6	Redbook (MoM)	0.0285 ***	27.225	0.658
7	Philadelphia FED Manufacturing Index	0.0222 **	2.154	0.658
8	API Weekly Crude Oil Stock	0.0218 ***	5.702	0.658
9	Existing Home Sales	0.0204 ***	2.711	0.658
10	Factory Orders (MoM)	0.0203 ***	3.064	0.658
11	NAHB Housing Market Index	0.0185 ***	2.971	0.658
12	CB Consumer Confidence	0.0183 ***	3.361	0.658
13	Natural Gas Storage	0.0177 ***	4.520	0.658
14	Four Week Bill Auction	0.0142 ***	4.444	0.658
15	Existing Home Sales (MoM)	0.0113 **	2.091	0.658
16	Continuing Jobless Claims	0.0041 *	1.890	0.658
17	Initial Jobless Claims	0.0040 *	1.839	0.658
18	MBA Mortgage Applications (WoW)	-0.0046 ***	-3.042	0.658
19	CFTC Crude Oil speculative net positions	-0.0084 ***	-2.998	0.658
20	Core Retail Sale (MoM)	-0.0097 **	-2.511	0.659

Source: Faseli, 2020.

The OLS regression model successfully revealed 20 US news impacts on Brent crude oil and a ranking of significant US news was provided. Abnormal price volatility is indicated at the news release and starting at a precise time. It is an interesting fact that the top three news that impacted Brent crude oil (EIA Weekly Distillates Stocks, Crude Oil Inventories and Gasoline inventories) are congruent with the top three news that affected the US light crude oil WTI (Faseli, 2019; 2020). Furthermore, all but three significant news from Table 2 (Private Nonfarm Payrolls, Philadelphia FED Manufacturing Index and MBA Mortgage Applications) impacted both, Brent Blend and WTI (Faseli, 2019).

Conclusions

This research study was based on the assumption that a defined range of 38 scheduled macroeconomic news announcements from the United States may have the potential to significantly impact the intraday price volatility of the European light crude oil benchmark Brent Blend during the period 2012-2018. The analysis had the objective to capture an assumed spillover effect from the US to the European economy by means of economic indicator announcements. An additional aim was to provide a transatlantic news ranking list indicating upcoming abnormal crude oil price volatility at a specific point in time. In order to reveal the expected intraday effect, high frequency intraday data were applied. The study captured the supposed effect from the US to the European economy, which is displayed in a novel transatlantic news ranking list. Three macroeconomic news including EIA Weekly Distillates Stocks, Crude Oil Inventories and Gasoline Inventories were found to highly affect Brent Blend. The results support the prediction of Brent crude price volatility and provide an opportunity for investors, producers and decision-makers in different economic fields to act right in time and by this to minimize risk on their investments and to optimize their risk management strategies. The importance of the results is emphasized and reflected by the challenging effects that high oil price volatility has displayed on the global economy for more than forty years. Using intraday time frequencies was essential to capture imminent abnormal oil price volatility peaks during a trading day. High frequency data, an extended observation period of seven years and the state of the art programming language Python for data modeling provide an improved prediction model to detect approaching crude oil price volatility. This may contribute to make better economic decisions in the future - the destabilizing and damaging effects of increased oil price volatility have been described.

The results motivate to use the methodology for further price-time series analyses to search for more correlations between macroeconomic news and commodities to better understand the dynamic interrelationships of today's globalized economy.

Annotation: All results, tables and figures provided in this article were extracted from my dissertation.

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