TECHNISCHE UNIVERSITÄT CHEMNITZ

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Chemnitz Economic Papers, No. 027, Dezember 2018

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January 4, 2019

Abstract

This paper examines the effect of different dimensions of uncertainty on expectations of WTI crude oil futures momentum traders at a daily level. We consider two concepts of uncertainty and two momentum trading indicators based on technical analysis. In addition, we also use wavelet techniques to decompose crude oil futures prices into different frequencies accounting for investors' sentiment at various horizons. To allow for different effects on the propagation mechanism of uncertainty shocks, we apply a time-varying Bayesian VAR approach. Our findings indicate that both measures of uncertainty affect momentum trading on the crude oil futures market in several periods, especially during the great recession between 2007 and 2009. For the decomposed futures prices our results also show that the reaction to uncertainty differs substantially across frequencies. High frequencies exhibit a very short-lived reaction to uncertainty while low frequencies show a persistent reaction to uncertainty shocks.

Keywords: Crude oil futures, technical analysis, time-varying Bayesian VAR, uncertainty, wavelets
JEL classification: C32, G13, Q47

*Thanks for valuable comments are due to the participants of the International Conference on Energy, Finance and the Macroeconomy in Montpellier, the Workshop on Financial Econometrics and Empirical Modeling of Financial Markets at the Kiel Institute for the World Economy, the 22th Annual International Conference on Macroeconomic Analysis and International Finance in Crete, the INFINITI Conference on International Finance in Poznań and seminar participates at the University of Erlangen-Nürnberg and the ESCP Europe Business School Berlin.

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1 Introduction

The main contribution of this study is to examine the effect of uncertainty on expectations of West Texas Intermediate (WTI) crude oil futures momentum traders. Such an effect is plausible referring to rational expectations models and the presence of information rigidities, which are more pronounced due to uncertainty shocks (Coibion and Gorodnichenko, 2012, 2015). Considering the growing importance and success of technical indicators in predicting the behavior on financial markets (Neely *et al.*, 2014; Yin and Yang, 2016; Yin *et al.*, 2017), expectations of momentum traders at a daily level are proxied by two conventional technical analysis indicators – the moving average convergence divergence (MACD) and the relative strength index (RSI). As uncertainty is not directly observable and can have several different sources, we consider different concepts of uncertainty and analyze their impact on crude oil futures trading. As two most obvious choices we use an uncertainty measure relying on the risk on stock markets given by the CBOE volatility index of the S&P500 (VIX) and another measure based on daily news about the stance of economic policy provided by Baker *et al.* (2016).[1] Especially, the latter measure constitutes a plausible choice considering the role of media news for financial markets (Gentzkow and Shapiro, 2006; Tetlock, 2007) and also the recently observed effects on crude oil markets associated with the unilateral termination of the Iran nuclear deal agreement by the US government. Although spillovers between economic policy uncertainty and oil demand and supply shocks have already been tackled in the previous literature (Kang and Ratti, 2013; Antonakakis *et al.*, 2014; Kang *et al.*, 2017), to the best of our knowledge this is the first study that focuses on the propagation of uncertainty shocks on expectations of crude oil futures investors proxied by technical analysis indicators. If investors' expectations are affected by uncertainty, the latter is able to push futures prices upwards and downwards and to result in an increased price volatility that has been observed in the recent decade. Therefore, the present study is able to provide new insights on the surge and burst in crude oil prices discussed since 2007.

In this context, we also use wavelet techniques to decompose crude oil futures prices into its short-run, medium-run and long-run trends. In doing so, we are able to analyze the effect of uncertainty

[1] Alternative uncertainty measures recently suggested in the literature include macroeconomic and financial uncertainty based on cross-sectional unpredictable components of macroeconomic and financial variables (Jurado *et al.*, 2015), survey data forecasters' disagreement measures (Bachmann *et al.*, 2013) and the text-based measure of news implied volatility (Manela and Moreira, 2017). However, these measures are only available at a monthly frequency and do not enable us to analyze the impact of uncertainty on investors' expectations at a daily level. In addition, it is worth noting that although the VIX is clearly a measure of risk and the economic policy uncertainty index is a proxy for uncertainty, we do not explicitly distinguish between the definition of risk and uncertainty in the sense of Knight (1921) in this study.

on momentum trading with respect to different frequencies which enables us to examine investors' sentiment at various horizons. This decomposition mimics the heterogeneity of agents with regard to different consumption requirements, risk tolerance levels, assimilation of information, institutional constraints and heterogeneous beliefs (Chakrabarty *et al.*, 2015) and is also able to improve return forecasts in financial markets (Berger, 2016; Faria and Verona, 2018; Risse, 2019). For instance, negative news may be seen as a selling signal for short-term investors, while long-term investors may interpret the same news as buying opportunity. The benefit of the wavelet decomposition is that it enables us to distinguish between different horizons and this is important since e.g. short-run components might be related to speculative trading or traders' position changes while long-run components might be related to long-term supply and demand of crude oil. It is reasonable that uncertainty has a different impact across different horizons.

In the recent years not only the press but also the academic literature has focused on different dimensions of uncertainty and their effect on financial and economic indicators (Bachmann *et al.*, 2013; Jurado *et al.*, 2015; Baker *et al.*, 2016; Scotti, 2016; Manela and Moreira, 2017). Previous studies have analyzed the impact of uncertainty shocks on output and employment (Born *et al.*, 2018) lending support to the hypothesis that a heightening in uncertainty reflects an exogenous impulse that causes recessions (Ludvigson *et al.*, 2015) and showing the ability of uncertainty to predict future US recessions (Karnizova and Li, 2014) since higher uncertainty causes firms to temporarily pause their investments (Bloom, 2009). Due to the fact that the oil market is connected to the global business cycle and international political stability (Hamilton, 1983), several studies also focused on its relationship to uncertainty. In this vein, Kellogg (2014) finds that oil-drilling firms' investment decisions are significantly affected by uncertainty. In addition, Kang and Ratti (2013) and Antonakakis *et al.* (2014) have identified spillovers between economic policy uncertainty and oil demand and supply shocks applying the framework proposed by Kilian (2009) and Kilian and Park (2009). They also show that total spillovers increased considerably during the great recession period around 2007 to 2009. Van Robays (2016) shows that higher macroeconomic uncertainty measured by global industrial production volatility increases the sensitivity of oil prices to oil demand and supply shocks. The predictability of economic policy uncertainty for oil returns and its volatility has also been reported in the most recent literature (Balcilar *et al.*, 2017; Shahzad *et al.*, 2017; Ma *et al.*, 2018). However, most of the studies focus on crude oil spot markets. But in times characterized by a high degree of uncertainty, futures markets are of particular relevance for producers to hedge the risk associated with unforeseeable developments of the spot price and this makes this period also very attractive for speculators providing liquidity by taking the other side of trades and gaining a risk premium (Szymanowska *et al.*, 2014). According to Ready (2018) an increase in the slope of the term structure of futures prices suggests that expected returns to a long position in oil futures markets have fallen substantially in the period between 2005 and 2012, which coincides with a strong increase in uncertainty related to several financial and economic events.

When analyzing global crude oil prices, an important stylized fact is the substantially increased volatility after the turn of the Millennium, especially around 2007 and 2009. Besides several factors such as increased demand from emerging economies like China and India and the weak US dollar (Beckmann and Czudaj, 2013), previous literature also focuses on financialization of crude oil (Hamilton and Wu, 2014, 2015) and speculation on its markets as potential reasons for the huge swings in crude oil prices (Lammerding *et al.*, 2013; Joëts, 2015; Gogolin and Kearney, 2016). In general, the financialization of commodities has increased over the last decade since the group of futures speculators including hedge funds and commodity index traders has entered the market, who are not interested in the commodities itself but solely see them as financial assets for portfolio diversification and risk management (Cheng *et al.*, 2015; Henderson *et al.*, 2015; Basak and Pavlova, 2016). The large spikes in commodity prices have stimulated an intense debate on the financialization of commodity markets and whether it has created a commodity bubble (Masters, 2008; Lombardi and Van Robays, 2011; Lammerding *et al.*, 2013; Juvenal and Petrella, 2015).

Moreover, the financialization of crude oil has also entailed an increased popularity of the so-called technical analysis for professional crude oil futures trading.[2] Technical analysis offers better tools for predicting trends and momentum in financial markets compared to traditional ARIMA models and has shown its profitability in several foreign exchange, equity and futures markets (Park and Irwin, 2007; Neely *et al.*, 2014). In contrast to fundamental analysts, technical analysts do not attempt to measure the intrinsic value of an asset, but rather, rely on charts and indicators to identify trends and patterns that provide guidance for investment decisions.[3] Recently, the literature has also provided evidence that technical indicators exhibit statistically and economically significant forecasting power for the crude oil spot price, clearly outperforming macroeconomic

[2]See, for instance, `https://www.investing.com/commodities/crude-oil-technical` or `https://www.xm.com/technical-analysis-wti-oil-futures-risk-seeing-more-downside-58702`.

[3]The relevance of technical analysis can also be theoretically founded within heterogeneous agents models, in which fundamentalists and chartists coexist. In this vein, Joëts (2015) shows that the surge in energy prices especially observed around 2007 and 2009 can be attributed to chartists' behavior.

variables, especially in recession and expansion periods (Yin and Yang, 2016). Therefore, we rely on technical indicators to approximate crude oil futures investors' expectations over a daily horizon.[4]

To analyze the transmission of uncertainty on momentum trading in the crude oil futures market, we estimate a Bayesian time-varying structural vector autoregression (VAR) following Primiceri (2005), where the variation over time stems from both the coefficients and the variance-covariance structure of the error terms. The latter is achieved by using a multivariate stochastic volatility modeling strategy as the law of motion of the variance-covariance matrix and captures potential heteroscedasticity of the model's disturbances. This is important since uncertainty varies substantial over time and this may have direct effects on the transmission mechanism of shocks. Rational and forward looking investors would adjust their expectations to shifts in the level of uncertainty and this potentially implies day-by-day changes in the propagation mechanism of uncertainty shocks. Allowing both the coefficients and the variance-covariance structure of the error terms to change over time, enables the approach to distinguish between changes in the typical size of the exogenous innovations and changes in the propagation mechanism (Primiceri, 2005). Therefore we apply a framework which accounts for time-varying parameters in order to measure changes in the corresponding relationship and implied shifts in investors' expectations proxied by momentum trading strategies. Applying a time-varying coefficient model is much more appropriate in our context compared to a framework modeling discrete shifts between regimes since changes on financial markets are often smooth rather than discrete due to the role of aggregation over a large number of investors with different expectations and risk aversion. In addition, according to the so-called Swamy and Mehta (1975) theorem, which shows that any nonlinear functional form can be represented by a time-varying coefficient model, our model is also able to capture potential nonlinearity that has already been identified for energy futures markets in the literature (Beckmann *et al.*, 2014).

As will be shown our findings indicate that both measures of uncertainty affect momentum trading on the crude oil futures market in several periods, especially during the great recession between 2007 and 2009. This indicates that besides other factors trading activity has contributed to the destabilization of crude oil prices during this period. For the decomposed futures prices our results also show that the reaction to uncertainty differs substantially across frequencies. High frequencies exhibit a very short-lived reaction to uncertainty while low frequencies show a persistent reaction to uncertainty shocks. This finding might also have implications for forecasting momentum trading

[4]Alternatively, Reitz *et al.* (2012) make use of survey data provided by the ECB at quarterly basis to approximate oil price expectations. However, survey based measures are of course not available at daily frequency.

indicators in order to react forward looking on changing trends and momentum. Therefore, this study is relevant for crude oil futures investors pursuing forward looking trading decisions and also for policy makers concerned about financialization and speculation.

The remainder of the paper is structured as follows. Section 2 describes our data set and our empirical framework while Section 3 discusses our empirical results. Section 4 concludes.

2 Data and empirical methodology

2.1 Data

We use daily data on West Texas Intermediate (WTI) light sweet crude oil futures closing prices of first nearby contracts traded at the New York Mercantile Exchange (NYMEX).[5] Data for continuous nearby futures prices (Light-Sweet, Cushing, Oklahoma Crude Oil Future Contract 1)[6] denominated in US dollar per barrel are provided by the US Energy Information Administration (EIA) for a sample period running from January 1990 to August 2018.[7] As will be mentioned in Section 3.1, we have also considered futures contracts with later expiration (i.e. Contracts 2, 3 and 4) to check for robustness of our results. Figure A.1 reported in Appendix A.2 shows the time series pattern of crude oil futures prices for the different contracts and already indicates that the choice of the contract does not affect our findings. The upper panel of Figure 1 gives the price of WTI crude oil futures (in green) and clearly shows the huge price increase that started in the beginning of 2007, reached its peak in July 2008 and was followed by an even larger downturn. We also see another substantial downturn that started in the end of 2014.

*** Insert Figure 1 about here ***

[5] WTI crude oil futures are also traded at the Intercontinental Exchange (ICE). However, ICE data on WTI crude oil futures prices is only available starting from 2006. Therefore, we have decided to rely on NYMEX data but we have also used ICE data for the shorter sample period as a robustness check. The results generally confirm our findings.

[6] Contract 1 expires on the third business day prior to the 25th calendar day of the month preceding the delivery month. If the 25th calendar day of the month is a non-business day, trading ceases on the third business day prior to the business day preceding the 25th calendar day. See `https://www.eia.gov/dnav/pet/TblDefs/pet_pri_fut_tbldef2.asp` for details.

[7] More precisely, data for crude oil futures prices provided by the EIA already start in 1983 but the availability for uncertainty measures, especially the VIX which is available since 1990, restricts the sample period to start in January 1990.

To analyze the role of uncertainty on momentum trading in the crude oil futures market, we take into account two distinct measures of uncertainty available at daily frequency. As a first choice, we use the CBOE volatility index of the Standard & Poor's 500 known as VIX.[8] The latter is a measure of US stock market volatility but is also highly correlated to the uncertainty on several other stock markets around the globe and reflects a conventional measure of risk or uncertainty on stock markets. As an alternative measure, we also consider daily news about the stance of economic policy in the US which is compressed in the economic policy uncertainty (EPU) index suggested by Baker *et al.* (2016). This measure is based on day-by-day searches in archives of thousands of articles published in US newspapers and other news sources provided in the NewsBank Access World News database.[9] The index measures the number of articles containing the triple of the following terms: (1) 'economic' or 'economy', (2) 'uncertainty' or 'uncertain' and (3) at least one policy expression such as: 'Congress', 'deficit', 'Federal Reserve', 'legislation', 'regulation' or 'White House' (Baker *et al.*, 2016).[10] Hence, the index aggregates different aspects of uncertainty which are directly related to the political situation in the US. This may also affect momentum trading in the crude oil futures market since political uncertainty is related to firms' investment decisions and therefore also to the price of crude oil due to the fact that the latter is important in several production processes and that the beliefs of investors about the future development of the economy in general are reflected in asset prices.

The time series of both uncertainty measures, namely the VIX and the EPU index, are shown in Figure 2. Both exhibit large peaks during (and shortly after) the three US recession periods included

[8] A sensible alternative would either be the CBOE Energy Sector ETF Volatility Index or even more specific the CBOE Crude Oil ETF Volatility Index. Both are constructed based on the same methodology as the VIX but specifically refer to the volatility in the energy sector and the crude oil market, respectively. Unfortunately, these indexes are only available starting from March 16, 2011 and May 10, 2007, respectively, and would therefore imply the omission of most of our data starting from January 1990. However, for the available sample periods their time series patterns are very similar to the VIX and the correlation between both is 0.89 and 0.75, respectively. Therefore, we would not expect our results to vary substantially depending on this choice.

[9] Ready (2018) also relies on article searches in major news sources to construct an uncertainty measure for oil supply on a yearly basis.

[10] The data have been downloaded from Baker *et al.* (2016)'s companion website (`http://www.policyuncertainty.com/`). In addition, it should be noted that although policy uncertainty indexes are also available for several other economies that would provide interesting news in our context such as China or India, the only indexes available at daily frequency are the US and the UK indexes. To save space we solely rely on US economic policy uncertainty since WTI crude oil is produced in the US. The corresponding results for the UK index can be provided upon request. Moreover, we have also taken the macroeconomic and financial uncertainty measures provided by Jurado *et al.* (2015) under consideration which are based on cross-sectional unpredictable components of macroeconomic and financial variables. However, as already mentioned in the Introduction these indexes are solely provided on a monthly basis and are also strongly correlated with the VIX. For the available sample period (January 1990 to December 2017) the correlation between the monthly averages of the VIX and the macroeconomic and the financial uncertainty index provided by Jurado *et al.* (2015) is 0.6 and 0.85, respectively. Therefore, we generally do not expect our results to vary by focusing on this measure of uncertainty.

in the sample period (July 1990 to March 1991, March 2001 to November 2001 and December 2007 to June 2009), especially for the latest – the so-called great recession period. However, the main difference between both is that the EPU index is much more volatile compared to the VIX. This is also confirmed by the much larger standard deviation (SD) for the EPU. According to the descriptive statistics presented in Table 1 for both measures, the SD is more than eight times higher for the EPU compared to the VIX. The coefficient of variation is also larger for the EPU, which is a standardized measure of SD that takes into account that the two uncertainty proxies are measured at different scales. The correlation between both measures is nearly 0.33 for the period between January 1990 and August 2018. Therefore, we expect to see some differences in the effects of uncertainty on momentum trading in the crude oil futures market with respect to the uncertainty measure and it makes sense to consider both to get a broader picture.

*** Insert Figure 2 and Table 1 about here ***

2.2 Wavelet decomposition

We also examine the role of uncertainty on momentum trading in the crude oil futures market at different frequency scales which could be interpreted as investors' sentiment at various horizons. Therefore, our aim is to decompose the signal time series y_t, i.e. WTI crude oil futures prices, into different frequencies on a scale-by-scale basis using the maximal overlap discrete wavelet transform (MODWT) following Percival and Walden (2000).[11] This means that we decompose the original series into a set of $j = 1, 2, \ldots, J$ components which can be interpreted as short- and medium-run noise, long-run trends and a smoothed version of the original series at scale J as follows

$$y = y(\widetilde{D}_1) + y(\widetilde{D}_2) + \ldots + y(\widetilde{D}_J) + y(\widetilde{S}_J), \quad (1)$$

where $y(\widetilde{D}_j)$ denotes local details of the time series at decomposition level j and $y(\tilde{S}_J)$ is the smoothed version of the original time series. More precisely, $y(\widetilde{D}_1)$ describes high frequency components which might be related to speculative trading or traders' position changes while $y(\widetilde{D}_8)$

[11]Wavelet techniques have originally been applied for picture and audio data compression but have already been established in the economics and finance literature over the recent years (see e.g. Rua and Nunes, 2009; Rua, 2012; Berger and Uddin, 2016). We rely on MODWT since it has basically two main advantages compared to the classic DWT: it does not require dyadic length and it is shift invariant (Crowley, 2007).

contains low frequency components which might be related to long-term supply and demand of crude oil. Intuitively, $y(\widetilde{D}_j)$ exhibits oil futures price changes between 2^j succeeding days. Table 2 provides an economic interpretation of the individual wavelet components according to Crowley (2007) and Berger and Gençay (2018) together with the average contribution of each component to the unconditional variance of the original futures price series.

*** Insert Table 2 about here ***

We have applied the least asymmetric (LA) wavelet transform filter with length 8 to capture the entire variation of the signal time series at different frequency scales.[12] Figure 3 shows all eight individual wavelet components together with the original time series of WTI crude oil prices. It becomes evident that $y(\widetilde{D}_1)$ includes high frequency short-run variation while $y(\widetilde{D}_8)$ contains low frequency long-run variation of oil futures prices. The high frequency components of the time series are usually very volatile while low frequency components are very smooth. As can be seen in Figure 3 the largest price swings in the period between 2008 and 2009 are captured by the high frequency components. Table 3 also provides the unconditional correlations between the individual components and shows that these are close to zero. This shows that the individual wavelet components convey different information. In the following we predict trends and momentum based on the original time series of crude oil futures prices and its eight frequency scales by applying technical analysis and check whether investors can benefit from the wavelet decomposition.

*** Insert Figure 3 and Table 3 about here ***

2.3 Technical analysis

The so-called technical analysis, which has been established by professional traders over the last decades, has shown its ability to predict most recent trends and momentum in financial markets

[12]The choice of the length is motivated by the aim to dissect the variation of the signal time series into as much components as offer some variation and follows the empirical wavelet literature (Berger and Uddin, 2016). We have also considered other filter techniques such as the Daubechies filter and the Haar filter but received wavelet components with very similar time series patterns across the different filters. Therefore, we believe that our results are not sensitive to this choice.

(Appel, 2009; Gerritsen, 2016; Fan and Yao, 2017). Two popular technical indicators introduced in the following are applied as proxy for investors' expectations: the moving average convergence divergence (MACD) and the relative strength index (RSI).

2.3.1 Moving average convergence divergence

The MACD indicator is based on the exponential moving average (EMA) for a given parameter k

$$\text{EMA}_{k,t} = \frac{2}{k+1} P_t + \frac{k-1}{k+1} \text{EMA}_{k,t-1}, \tag{2}$$

where P_t represents an asset's price. MACD is then defined as the difference between a short-run and a long-run EMA

$$\text{MACD}_{s,l,t} = \text{EMA}_{s,t} - \text{EMA}_{l,t} \quad \text{with} \quad l > s \geq 1. \tag{3}$$

$\text{MACD}_{s,l,t}$ oscillates around the zero line which marks the trading rule based on MACD: Buy if $\text{MACD}_{s,l,t} > 0$ and sell if $\text{MACD}_{s,l,t} < 0$. The rational behind this proceeding is that in case of $\text{MACD}_{s,l,t} > 0$ ($\text{MACD}_{s,l,t} < 0$) the short-run (long-run) moving average is above the long-run (short-run) moving average and this indicates a *bullish* (*bearish*) trend. Conventional choices for s and l are 12 and 26 days, respectively (Murphy, 1999). Therefore we apply $\text{MACD}_{12,26,t}$ in the following.

However, the corresponding trading rule sometimes over-weights the most recent information on the asset price. An alternative trading rule is based on an EMA of $\text{MACD}_{s,l,t}$, the so-called signal line:

$$\text{Signal}_{k,t} = \frac{2}{k+1} \text{MACD}_{s,l,t} + \frac{k-1}{k+1} \text{Signal}_{k,t-1}. \tag{4}$$

A conventional choice for k is 9 days. Since a signal line crossover gives no information about the length and magnitude of a trend, the trading rule can be based on the so-called MACD histogram. The latter is defined as the difference between Eq. (3) and Eq. (4):

$$\text{Hist}_{s,l,k,t} = \text{MACD}_{s,l,t} - \text{Signal}_{k,t}. \tag{5}$$

Large positive (negative) values for $\text{Hist}_{s,l,k,t}$ indicate a strong bullish (bearish) momentum and prompt the trader to buy (sell). The middle panel of Figure 1 displays the corresponding time series obtained by Eqs. (3), (4) and (5) for $s = 12$, $l = 26$ and $k = 9$. Price increases (decreases) are signaled by $\text{Hist}_{s,l,k,t} > 0$ ($\text{Hist}_{s,l,k,t} < 0$) which is displayed by light gray (dark gray) areas. The gray line represents $\text{Signal}_{9,t}$ while the red dotted line is $\text{MACD}_{12,26,t}$. The aim of this study is to examine how momentum trading on crude oil futures markets is affected by different forms of uncertainty and therefore we use $\text{Hist}_{12,26,9,t}$ as one proxy for investors' expectation about the momentum. In addition, we have also computed $\text{Hist}_{12,26,9,t}$ for all eight frequency scales achieved by the wavelet decomposition. Descriptive statistics for this trading indicator for the original time series and its components are reported in Table 1 and show that the standard deviation of $\text{Hist}_{12,26,9,t}$ (denoted by MACD in the table) is much higher for the individual components, especially for the fifth scale, than for the original series.

2.3.2 Relative strength index

The presented indicators based on MACD have two major drawbacks: first, they are boundless and therefore it is difficult to identify extremes in trends and momentum. Second, MACD indicators sometimes identify trends and momentum with a delay. To address these issues we also use the relative strength index (RSI) as a bounded counter-trend indicator defined as follows

$$\text{RSI}_{k,t} = 100 \cdot \frac{\overline{\text{G}}_{k,t}}{\overline{\text{G}}_{k,t} + \overline{\text{L}}_{k,t}}, \tag{6}$$

where $\overline{\text{G}}_{k,t}$ and $\overline{\text{L}}_{k,t}$ denote the average gain and loss at time t for a period of k days. These are calculated by exponential smoothing over the last $k = 14$ days (Murphy, 1999):

$$\overline{\text{G}}_{k,t} = \frac{1}{k}(P_t - P_{t-1})I(P_t > P_{t-1}) + \frac{k-1}{k}\overline{\text{G}}_{k,t-1} \tag{7}$$

and

$$\overline{\text{L}}_{k,t} = \frac{1}{k}(P_t - P_{t-1})I(P_t < P_{t-1}) + \frac{k-1}{k}\overline{\text{L}}_{k,t-1}, \tag{8}$$

where $I(.)$ denotes an indicator function and $(P_t - P_{t-1})I(P_t > P_{t-1})$ and $(P_t - P_{t-1})I(P_t < P_{t-1})$ represent gains and losses, respectively. $\text{RSI}_{k,t}$ is bounded to oscillate between 0 and 100 and therefore the extremes indicate whether the market is *overbought* or *oversold*. If $\text{RSI}_{k,t} > 70$ ($\text{RSI}_{k,t} < 30$) the asset is usually considered to be overvalued (undervalued) and therefore provides the trader a selling (buying) signal. The bottom panel of Figure 1 reports $\text{RSI}_{14,t}$ for the crude oil futures market as a blue line. Sharp price increases that are followed by sharp decreases are often associated with overbought signals (i.e $RSI_{14,t} > 70$) without any delay. $RSI_{14,t}$ has also been calculated for all individual components according to the wavelet decomposition and their descriptive statistics are provided in Table 1. The standard deviation is an increasing function of the frequency scale. We will use $RSI_{14,t}$ together with $Hist_{12,26,9,t}$ as a proxy for expectations of momentum traders in the crude oil futures market.

2.3.3 Trading exercise

To illustrate the usefulness of the technical analysis indicators and to confirm their role as proxies for investors' expectations, we have run a simple trading exercise abstracting from transaction costs.[13] In our exercise the technical trader uses the MACD, the MACD histogram (Hist henceforth) and the RSI as potential indicators and buys (long position) or sells (short position) in each period he receives a buying or selling signal.[14] After the signal he holds his long or short position over a horizon of 1, 2, 3, 4, 5, 30, 90, or 260 days, respectively. We have computed the difference of the mean return of the buying and selling signals and therefore the overall return of a given trading strategy and compare it with the mean return resulting from a simple unconditional buy and hold strategy (B&H henceforth).[15] Table 4 reports the corresponding mean returns together with t-statistics for testing the null of zero return using trading signals based on the original WTI crude oil futures price series and its individual wavelet components at the first (W1), the fifth (W5) and the eighth scale (W8) representing the decomposed series.

*** Insert Table 4 about here ***

The main findings are as follows. First, comparing the performance of the technical analysis indicators with the simple unconditional buy and hold strategy (B&H) indicates that the latter is

[13]For short-run trading horizons (i.e. a few days) transaction costs effect the absolute trading performance of the technical analysis indicators but not its relative performance compared to the unconditional buy and hold strategy considered in the following. This is due to the fact that all trading rules are compared for the same holding period (i.e. number of days) as indicated in Table 4. This is especially true for the trades based on the RSI. In the latter case we clearly have substantially less trades compared to the MACD, the MACD histogram and also the buy and hold strategy (see the first two rows in Table 4) and therefore also less transaction costs. For longer horizons the inclusion of transaction costs would of course be beneficial for the performance of the buy and hold strategy.

[14]It is worth noting that a signal can appear in subsequent periods. Therefore, the individual trades are allowed to overlap.

[15]For horizon 1 the B&H corresponds to a strategy following the simple random walk.

outperformed by at least one indicator for each horizon, expect for the long-run horizon of one year (i.e. 260 trading days). Especially the MACD performs much better compared to the B&H (except for the 90 and 260 days horizon) and is able to generate significantly positive returns. The result that MACD performs better than Hist over short horizons and worse than Hist over longer horizons confirms the fact that MACD puts more weight on the most recent information compared to Hist as mentioned earlier. Second, applying the same exercise for each individual wavelet component shows that investors can also benefit from the wavelet decomposition by relying on signals at different scales. For instance, relying on signals at the eighth scale (W8) outperforms the returns realized for the original series. The RSI shows its usefulness over a longer horizon (260 days) and also outperforms the B&H strategy.[16] Although a comprehensive study on the performance of technical analysis indicators is not the main focus of this study, the results provided in Table 4 confirm the practical usefulness of (1) technical analysis indicators supporting their role as proxies for investors' expectations and (2) the wavelet decomposition for trading in the WTI crude oil futures market.

As a next step, we examine the performance of the technical analysis indicators depending on the level of previous periods' uncertainty proxied by VIX and EPU. In doing so, we re-run our trading exercise for the one day horizon by distinguishing between three different scenarios related to the level of previous days' uncertainty proxied by VIX and EPU: (1) low uncertainty regime, (2) normal uncertainty regime and (3) high uncertainty regime. The three regimes are classified as follows: (1) $\leq$5% quantile, (2) $>$5% quantile and $<$95% quantile and (3) $\geq$95% quantile, where the quantiles refer to the empirical distributions of VIX or EPU for the entire sample period. Table 5 reports the results and shows that the trading performance of the technical analysis indicators differs for the different levels of previous days' uncertainty. This indicates an impact of uncertainty on trading in the crude oil futures market. Especially, the high uncertainty regime for VIX and EPU offers the potential to gain excess returns according to our findings, which show statistical significance for the RSI applied on the raw data and for the MACD and the MACD histogram applied to low frequency components represented by W5 and W8 in Table 5.

*** Insert Table 5 about here ***

[16] The returns for the remaining scales (W2, W3, W4, W6, and W7) support these findings but are not reported to save space. These are available upon request. We have also re-run this trading exercise for the sample period starting after the financialization of crude oil in the early 2000s (more precisely in 2004) and these findings highlight the superior trading performance of technical analysis indicators even more clear.

2.4 Time-varying Bayesian VAR approach

Finally, we conduct the time-varying Bayesian vector autoregression (VAR) approach proposed by Primiceri (2005) to account for time-variation in the reaction of momentum traders on the crude oil futures market to uncertainty shocks by allowing both the coefficients and the variance-covariance matrix to change over time.[17] A major advantage of this approach is that it lets the data determine whether the time-variation is attributable to changes in the size of the shock – the *impulse* – or to changes in the transmission mechanism – the *response*. The VAR model is specified as

$$Y_t = B_{0,t} + B_{1,t} Y_{t-1} + \ldots + B_{p,t} Y_{t-p} + A_t^{-1} \Sigma_t \epsilon_t, \tag{9}$$

where Y_t is a bivariate vector including one uncertainty measure (either VIX or EPU) and one trading indicator (either $\text{Hist}_{12,26,9,t}$ or $\text{RSI}_{14,t}$) in this ordering.[18] A_t represents a lower triangular matrix with ones on the main diagonal, Σ_t is a diagonal matrix with positive elements $\varsigma_t = \text{diag}(\Sigma_t)$, ϵ_t is a bivariate error term distributed as $N(0, I_2)$ and $\{B_{j,t}\}_{j=0}^{p}$ are time-varying coefficient matrices.[19] A crucial issue in this framework is to allow A_t to change over time. Constancy of A_t would imply that a shock to one variable has a time-invariant effect on the other variable. Furthermore, allowing Σ_t to vary over time accounts for the possibility of heteroscedasticity. This is also important, especially in our context, since ignoring heteroscedasticity could generate fictitious dynamics (Cogley and Sargent, 2005).

To complete the model given by Eq. (9), it can be rewritten in compact form by stacking all $\{B_{j,t}\}_{j=0}^{p}$ into one vector B_t as follows

$$Y_t = X_t' B_t + A_t^{-1} \Sigma_t \epsilon_t \quad \text{with} \quad X_t' = I_2 \otimes [1, Y_{t-1}, \ldots, Y_{t-p}], \tag{10}$$

$$B_t = B_{t-1} + v_t, \quad a_t = a_{t-1} + \xi_t, \quad \text{and} \quad \log \varsigma_t = \log \varsigma_{t-1} + \eta_t, \tag{11}$$

where a_t is a vector stacking all free elements of A_t row-wise. B_t and a_t are modeled as random

[17] The implementation of a time-varying VAR model with stochastic volatility is also in line with previous literature on crude oil market modeling (Baumeister and Peersman, 2013; Jo, 2014; Riggi and Venditti, 2015).

[18] To identify the shocks, we rely on a recursive structure assuming the trading indicator (used here as proxy for investors' expectations) being contemporaneously affected by uncertainty shocks while uncertainty is affected by the trading indicator shock with a delay of one day. The latter seems plausible especially for the EPU index, which is constructed by newspaper coverage of specific word combinations, since daily newspaper articles mostly cover the news from the previous day. To check for sensitivity of our results due to this assumption, we have also considered the other way of variable ordering without noticing any difference in the results.

[19] p denotes the lag length of the VAR model, which has been selected by minimization of the AIC and has been set to $p = 2$.

walks while ς_t follows a geometric random walk which belongs to the class of stochastic volatility models. Finally, we assume the disturbances of the full model $\{\epsilon_t, v_t, \xi_t, \eta_t\}$ to be jointly normally distributed with the variance-covariance matrix represented by V:

$$V = \text{var}\begin{pmatrix} \epsilon_t \\ v_t \\ \xi_t \\ \eta_t \end{pmatrix} = \begin{pmatrix} I_2 & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{pmatrix}, \tag{12}$$

where Q, S and W are positive definite matrices (Primiceri, 2005).

We estimate the model described by Eqs. (10) and (11) by means of a Bayesian Markov Chain Monte Carlo (MCMC) algorithm. An important benefit of the Bayesian approach compared to classical maximum likelihood is the possibility to use uninformative priors on reasonable regions of the parameter space which rules out possible misbehavior. Such a huge model will potentially have multiple peaks in the likelihood, some of which are in implausible regions of the parameter space and this can lead to senseless results when relying on maximum likelihood instead of Bayesian techniques. Therefore, we apply the Gibbs sampler proposed by Del Negro and Primiceri (2015) to generate a sample from the joint posterior distribution of $\{B^T, A^T, \Sigma^T, V\}$, where B^T denotes the entire path of the coefficients $\{B_t\}_{t=1}^T$ while Σ^T and A^T accordingly give the entire path of the variance-covariance matrices and their lower triangular matrices. See Appendix A.1 for details of the Gibbs sampling algorithm.

3 Empirical findings

3.1 Impulse response analysis

This subsection provides an impulse response analysis of a one-unit shock of uncertainty proxied by VIX or EPU on both momentum trading indicators (the MACD histogram $\text{Hist}_{12,26,9,t}$ and the relative strength index $\text{RSI}_{14,t}$) over a horizon of 60 days. Since these responses depend on the estimated parameters for B_t, A_t and Σ_t on a given day t, we have calculated these for each day t of our data set (excluding the first 80 days which have been used as a training sample to initialize our priors) resulting in time-varying impulse responses depending on t. Figures 4 and 5 report these time-varying impulse response functions in a three-dimensional space showing the response of both trading indicators for the crude oil futures market to a shock either on the VIX or on the EPU index. The reactions are represented by the median of the posterior distribution at a specific day and a specific horizon but do not include confidence bands conventionally reported in impulse response analyses due to clarity of visualization. However, to be able to make statements about the significance of the responses visualized in Figures 4 and 5, we have also plotted the corresponding reactions for a fixed horizon with $h = 1$ and $h = 10$ in Figures 6 and 7 together with their 68% and 95% confidence intervals and the time-varying forecast error variance decomposition (FEVD) of both momentum trading indicators. All graphs unambiguously show that the impact of uncertainty on momentum trading in the crude oil futures market is time-varying and this emphasizes the importance to account for this feature when modeling the behavior of this market. This implies that investors incorporate changes in uncertainty when forming their expectations, inducing day-by-day modifications in the propagation mechanism of uncertainty shocks.

*** Insert Figures 4 and 5 about here ***

First of all, we discuss the effect of both momentum trading indicators to a shock on US stock market volatility (VIX) and refer to Figure 4. A positive (negative) reaction of the MACD histogram to an uncertainty shock implies that the technical momentum trader revises his expectations towards a bullish (bearish) momentum period in the near future and is therefore in favor of a buying (selling) signal. For the RSI a strong positive (negative) reaction indicates that the market is overbought (oversold). The main findings are fourfold. First, for the MACD histogram we find sharp and significant decreases in the very-short run, which are most pronounced for some periods such as the three recession periods in our sample (July 1990 to March 1991, March 2001 to November 2001 and December 2007 to June 2009). This finding is in line with the often observed negative uncertainty effect on industrial production and it could be argued accordingly that an increase in uncertainty lets firms temporarily pause their investments (Bloom, 2009). Since crude oil is an important input factor in many production processes, it is reasonable that expectations regarding its futures price are also affected by uncertainty due to this channel. Especially, for the great recession period between 2007 and 2009, we find a strong negative short-run reaction which changes in the following period to a pronounced positive reaction when referring to the MACD histogram.

The former is also in line with the statement by Ready (2018) mentioned in the Introduction that expected returns to a long position in oil futures markets have fallen substantially in this period. The latter finding implies a buying signal and could result from an investors' belief that crude oil futures can be regarded as an alternative asset class compared to stocks providing a safe haven function in times of high uncertainty according to the definition by Baur and McDermott (2010). However, this potential safe haven property could also result in an overreaction by investors in times of crisis which could destabilize the crude oil futures market in periods characterized by a high stock market uncertainty (Lombardi and Van Robays, 2011; Juvenal and Petrella, 2015). The finding of a significantly negative short-run uncertainty effect with a reversal to a positive reaction during and shortly after the great recession period becomes also evident in Panel (a) in Figure 6 when comparing the reaction for a horizon of one day (left plot) with the reaction after ten days (right plot).

Second, we also find a sharp increase of the MACD histogram reaction at the very end of 2015 and therefore immediately after the strong drop in crude oil prices in the year 2015 observed in Figure 1. This positive effect associated with a buying signal conveys the positive expectations of technical crude oil futures traders, which expected futures price increases in this period. Third, at the end of our sample period beginning in 2018, we again find strong negative effects of stock market uncertainty on futures trading for crude oil, which might be associated with the policy of US president Donald Trump to abandon the so-called Iran deal. The latter event caused a heightening of uncertainty and an increase of crude oil futures prices. Finally, the impact on the RSI is more pronounced in magnitude but shows roughly the same pattern as the response of the MACD histogram. However, the RSI identifies periods in which the market is overbought and thus provides an earlier selling signal compared to the MACD histogram. This is due to the fact that in contrast to the MACD the RSI is a counter-trend indicator which tracks down changes in the market earlier and therefore provides faster and stronger reactions to uncertainty. The time-varying FEVD graphs presented in Panels (c) and (d) in Figure 6 support the above-mentioned findings. Generally, the fraction of the forecast error variance explained by VIX shocks is unsurprisingly low but gets much higher in high uncertainty periods, especially during the great recession. For the RSI the share of the forecast error variance stemming from VIX shocks goes up to around 40% during the great recession period for the horizon of one day and even to above 50% after ten days (see Panel (d) in Figure 6).

*** Insert Figures 6 and 7 about here ***

As a next step, we focus on the findings for economic policy uncertainty shocks reported in Figures 5 and 7. Although both uncertainty measures refer to different concepts of uncertainty and only show a low correlation of nearly 0.33, the general patterns of the reactions of both trading indicators are remarkably similar compared to the impact of the VIX. In contrast, the response to EPU shocks is substantially more volatile compared to the response to VIX shocks. This is simply due to the fact that the variance of EPU is much higher compared to the VIX. Interestingly, the reaction to EPU shocks can be roughly subdivided into two different periods with a change point marked by the bankruptcy of Lehman Brothers at September 15, 2008 that caused a high degree of uncertainty. Prior to the Lehman collapse, we only see the two strong negative effects around the two recession periods in the beginning of the 1990s and in 2001. In all other periods we observe either very mild effects or no effects at all. However, after the bankruptcy of Lehman Brothers we find pronounced, very volatile and mostly positive effects of both trading indicators due to an EPU shock and therefore buying (selling) signals according to the MACD histogram (RSI) which support the potential role of crude oil futures as a safe haven asset in a more general sense. This emphasizes the need to consider several sources when analyzing the effects of uncertainty, especially when referring to the events in the latest period such as the election of Donald Trump as US president resulting in a strong increase in policy uncertainty (Bloomberg, 2017). In addition, the effects of the VIX are generally more persistent compared to EPU effects. EPU shocks decay much faster than VIX shocks and also faster for the MACD histogram compared to the RSI.[20]

3.2 Disaggregated perspective

To gain further insights on the reaction of crude oil futures momentum trading to uncertainty and especially to analyze if trading signals due to uncertainty shocks differ for short-term and for long-term investors, we have provided the same analysis at a disaggregated level that means for each individual component based on the wavelet decomposition. Figure 8 provides the results but to save space solely includes the $RSI_{14,t}$ as the momentum trading indicator which reacts faster,

[20]To check for robustness of our findings, we have considered futures contracts with different expiration dates (as shown in Figure A.1 in Appendix A.2), a different crude oil futures prices data set from the Intercontinental Exchange (ICE), which offers a shorter sample period starting in 2006, and different orderings of variables in the VAR model. The results are remarkable robust to all these variation. To save space the corresponding findings are not shown but are available upon request.

stronger and more persistent due to the results of the previous subsection.[21] As can be seen in Panel (a) of Figure 8 for the first frequency scale denoted by W1 (and similar to W2), uncertainty effects are very short-lived and especially show up in the high uncertainty period around 2007 and 2009. For scales three and four the reaction of the RSI exhibits more pronounced patterns as for the high-frequency components with peaks during all three US recession periods, which are much stronger in magnitude and much more persistent as displayed in Panel (b) of Figure 8. For the fifth frequency scale shown in Panel (c) of Figure 8 the reaction gets even stronger in magnitude and also more persistent. For the low frequency components (i.e. scales seven and eight) shown in Panel (d) of Figure 8, the reaction gets lower in magnitude compared to the fifth and sixth scale but it also gets much more persistent. Overall, the results for each individual component show that the reaction to uncertainty differs substantially between the different frequencies. High frequencies exhibit short-run variation in oil futures prices and therefore show a very short-lived reaction to uncertainty while low frequencies display a very smoothed long-run variation and show a persistent reaction to uncertainty shocks. The latter finding indicates that uncertainty shocks are not just short-run noise but also have an impact on long-term oil supply and demand shocks. Interestingly, the medium frequencies at scales five and six show the strongest reactions to uncertainty shocks. These findings can be important for investors when building their expectations about future oil prices over several horizons based on the current level of uncertainty. This is also in line with findings of previous studies that already showed the relevance of wavelet decomposition for forecasting returns on financial markets (Berger, 2016; Faria and Verona, 2018; Risse, 2019).

*** Insert Figure 8 about here ***

4 Conclusion

This paper contributes to the literature by analyzing the impact of different dimensions of uncertainty on expectations of momentum traders in the WTI crude oil futures market while allowing for time-variation due to potential changes in the transmission of uncertainty shocks. In doing so, we make use of a flexible Bayesian VAR framework which accounts for daily shifts in both the

[21]In Figure 8 we only show the reaction for the first, third, fifth, and eighth scale denoted by W1, W3, W5, and W8, respectively. The results for the remaining scales are provided in Figure A.2 in Appendix A.3.

coefficients and the variance-covariance matrix of the model's disturbances. To approximate the expectations of momentum traders we consider two technical analysis indicators (namely the moving average convergence divergence and the relative strength index) and to allow for different dimensions of uncertainty we use two different concepts of uncertainty (namely the VIX and daily news about the stance of economic policy in the US). Our findings indicate that both measures of uncertainty affect momentum trading on the crude oil futures market in a time-varying fashion. This implies that investors take into account changes in uncertainty when forming their expectations, inducing day-by-day modifications in the propagation mechanism of uncertainty shocks.

The strongest impacts are observed during recession periods, especially for the great recession period between 2007 and 2009. For this period we find evidence for a negative short-run effect on both trading indicators and an even more pronounced positive effect indicating substantial buying signals in case of the MACD in the subsequent periods. These effects are even stronger and also selling signals appear earlier for the RSI compared to the MACD. This indicates that the RSI is a counter-trend indicator which signals when the market is overbought or oversold and therefore reacts stronger and faster to uncertainty. Generally, the fact that we find a substantial effect of uncertainty on momentum trading in high uncertainty periods, which is negligible in several periods with relatively low uncertainty, shows that (1) crude oil futures prices are attached to the business cycle and therefore also show negative uncertainty effects in the short-run but (2) crude oil futures are also a financial asset, which might be used as safe haven to shield (equity market) investors from suffer large losses in crises periods. However, the other side of the coin is that the corresponding buying signals could favor the occurrence of bubble behavior and destabilize crude oil futures markets in periods characterized by a high stock market uncertainty. This could also be seen as confirmation that the crude oil market has become more financialized over the recent years and is therefore not solely driven by fundamentals.

Moreover, the findings for each individual futures price component show that the reaction to uncertainty differs substantially across different frequencies. High frequencies governed by short-run variation in oil futures prices show a very short-lived reaction to uncertainty while low frequencies mimic a smoothed long-run trend of prices and react much more persistent to uncertainty shocks. This could also have implications for forecasting momentum trading indicators in order to react forward looking on changing trends and momentum.

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Tables

TABLE 1 **Descriptive statistics of uncertainty measures and trading indicators**

		Mean	SD	CV	Median	Min	Max	Skewness	Kurtosis
	VIX	19.3032	7.8465	0.4065	17.4000	9.1400	80.8600	2.0943	7.6640
Uncertainty	**EPU**	97.0145	66.8942	0.6895	79.9800	3.3200	719.0700	2.0787	7.8415
	Crude oil	-0.0003	0.7114	-2371.3333	-0.0051	-4.0587	4.2108	0.0136	1.6592
	W1	0.1113	823.4193	7398.1968	-0.3731	-48976.6130	11442.3162	-36.2531	1974.9571
	W2	-0.2084	1116.8119	-5358.9822	-4.6755	-28874.8797	45327.4398	19.0414	842.8534
	W3	0.0548	2517.0184	45930.9927	-20.2158	-92227.7883	103699.0882	5.0645	831.2836
MACD	**W4**	0.0998	1877.2321	18809.9409	-27.1765	-58544.5243	46038.5769	-8.1170	474.3172
	W5	0.0893	263371.7147	2949291.3180	-27.8838	-4232568.3052	21164405.4212	71.1100	5822.3150
	W6	-0.4417	2395.5465	-5423.4695	-14.6651	-76277.8831	162966.5396	39.5425	3141.1674
	W7	-0.1379	8385.9323	-60811.6918	-5.0793	-607980.1242	267133.6901	-47.8615	4001.6209
	W8	0.0034	743.2113	218591.5588	-1.3747	-19117.9168	46144.4614	30.9141	2208.1529
	Crude oil	50.9568	11.8561	0.2327	51.4967	16.3037	91.0236	-0.1417	-0.4354
	W1	50.0012	2.7523	0.0550	50.0239	37.1128	63.9067	-0.0253	0.4836
	W2	50.0099	4.5317	0.0906	50.0458	33.4522	70.9358	-0.0127	0.1315
	W3	50.0463	8.3716	0.1673	50.1261	21.6923	79.2095	-0.0036	-0.4133
RSI	**W4**	50.3247	14.9677	0.2974	50.6151	13.1793	87.4254	-0.0332	-0.8556
	W5	50.4191	26.0538	0.5167	50.8338	3.0439	97.5791	-0.0272	-1.3444
	W6	51.8811	35.6410	0.6870	54.6247	0.4182	99.7044	-0.0752	-1.6037
	W7	52.0144	43.1719	0.8300	58.4628	0.0029	99.9983	-0.0771	-1.8115
	W8	49.5877	46.5097	0.9379	45.0200	0.0000	100.0000	0.0209	-1.9057

Note: The table reports descriptive statistics for the CBOE volatility index of the S&P500 (VIX) and the US economic policy uncertainty (EPU) index following Baker *et al.* (2016) as well as both trading indicators, namely the moving average convergence divergence histogram (MACD) and the relative strength index (RSI), for daily crude oil futures prices and their components according to the wavelet decomposition described in Section 2.2 (e.g. W1 stands for $y(\widetilde{D}_1)$ etc.). SD denotes standard deviation and CV stands for the coefficient of variation defined as the ratio of the standard deviation to the mean.

Table 2 **Economic interpretation of wavelet components**

Abbreviation	Information horizon	Horizon in days	% of variance
W1	Short-run	2-4	0.4771
W2	Short-run	4-8	0.6164
W3	Mid-run	8-16	1.0959
W4	Mid-run	16-32	1.9427
W5	Mid-run	32-64	3.6463
W6	Long-run	64-128	7.1943
W7	Long-run	128-256	25.8469
W8	Trend	256-512	59.1804

Note: The table reports the economic interpretation of the individual components of the daily crude oil futures prices according to the wavelet decomposition described in Section 2.2 (e.g. W1 stands for $y(\widetilde{D}_1)$ etc.) and the average contribution to the variance of the original futures price series.

Table 3 **Correlation between wavelet components**

	W1	W2	W3	W4	W5	W6	W7	W8
W1	1.0000	0.0185	-0.0015	-0.0007	-0.0001	-0.0000	0.0000	-0.0000
W2		1.0000	0.0197	0.0033	-0.0011	0.0000	0.0000	-0.0000
W3			1.0000	-0.0335	0.0056	-0.0013	-0.0001	-0.0000
W4				1.0000	-0.0063	0.0073	0.0000	-0.0003
W5					1.0000	0.0230	-0.0057	-0.0027
W6						1.0000	0.1214	0.0245
W7							1.0000	0.0571
W8								1.0000

Note: The table reports the unconditional correlation coefficients between the individual components of the daily crude oil futures prices according to the wavelet decomposition described in Section 2.2 (e.g. W1 stands for $y(\widetilde{D}_1)$ etc.).

TABLE 4 **Performance of technical analysis indicators**

		Original series				W1			W5			W8		
	Days	MACD	Hist	RSI	B&H	MACD	Hist	RSI	MACD	Hist	RSI	MACD	Hist	RSI
N_{Buy}		4660	4194	368		8182	4127	0	5704	2202	2474	4487	955	4028
N_{Sell}		3748	4206	385		226	4273	0	2704	6198	2590	3921	7445	3921
$\mu_{\text{Buy}} - \mu_{\text{Sell}}$	1	0.0004	-0.0001	0.0007	0.0001	-0.0010	-0.0005		0.0002	-0.0001	0.0002	0.0007	0.0003	-0.0003
t-Stat.		0.9018	-0.1208	0.4927	0.5447	-0.7968	-1.2490		0.3808	-0.1563	0.4170	1.7314	0.4483	-0.6247
$\mu_{\text{Buy}} - \mu_{\text{Sell}}$	2	0.0009	0.0001	-0.0004	0.0002	-0.0002	-0.0006		0.0000	-0.0003	0.0006	0.0014	0.0006	-0.0006
t-Stat.		1.4802	0.2467	-0.1847	0.7768	-0.1258	-0.9918		0.0164	-0.4812	0.7375	2.3388	0.5980	-0.9065
$\mu_{\text{Buy}} - \mu_{\text{Sell}}$	3	0.0014	0.0000	-0.0004	0.0003	-0.0002	0.0002		-0.0001	0.0000	0.0006	0.0021	0.0009	-0.0008
t-Stat.		1.9121	0.0358	-0.1654	0.9616	-0.0703	0.2342		-0.1313	0.0098	0.6708	2.9302	0.7638	-1.0755
$\mu_{\text{Buy}} - \mu_{\text{Sell}}$	4	0.0018	0.0001	-0.0012	0.0005	0.0006	-0.0000		-0.0004	0.0003	0.0005	0.0028	0.0009	-0.0011
t-Stat.		2.1205	0.0948	-0.4261	1.1189	0.2525	-0.0251		-0.4095	0.2848	0.4870	3.3944	0.7039	-1.2871
$\mu_{\text{Buy}} - \mu_{\text{Sell}}$	5	0.0020	-0.0000	-0.0017	0.0006	0.0028	0.0004		-0.0002	0.0008	0.0006	0.0035	0.0010	-0.0014
t-Stat.		2.1225	-0.0146	-0.5705	1.2487	1.0033	0.3880		-0.1664	0.8096	0.4951	3.7599	0.7173	-1.4578
$\mu_{\text{Buy}} - \mu_{\text{Sell}}$	30	0.0096	0.0067	-0.0385	0.0035	-0.0073	0.0044		-0.0071	-0.0053	0.0039	0.0083	-0.0128	-0.0040
t-Stat.		4.1772	2.9559	-5.0686	3.0467	-1.0383	1.9320		-2.8993	-2.0313	1.3182	3.6341	-3.5716	-1.6867
$\mu_{\text{Buy}} - \mu_{\text{Sell}}$	90	-0.0152	0.0187	-0.0169	0.0100	-0.0157	0.0091		-0.0063	-0.0150	0.0008	0.0161	-0.0109	-0.0200
t-Stat.		-3.5277	4.3654	-1.1845	4.6849	-1.1787	2.1146		-1.3803	-3.0829	0.1521	3.7603	-1.6137	-4.5362
$\mu_{\text{Buy}} - \mu_{\text{Sell}}$	260	-0.0083	0.0180	0.0048	0.0261	0.0241	0.0194		-0.0061	-0.0116	-0.0007	-0.0093	0.0442	0.0427
t-Stat.		-1.2321	2.6845	0.2117	7.7722	1.1582	2.8845		-0.8455	-1.5144	-0.0794	-1.3813	4.2019	6.1788

Note: The table reports mean returns and their corresponding t-statistics for several different trading strategies applied on the original WTI crude oil futures price series and on its individual wavelet components at the first (i.e. W1), the fifth (i.e. W5) and the eighth scale (i.e. W8). The trading strategies follow buying and selling signals according to the moving average convergence divergence (MACD) given in Eq. (3), the MACD histogram (Hist) displayed in Eq. (5) and the relative strength index (RSI) given in (6). B&H stands for an unconditional buy and hold strategy. N_{Buy} and N_{Sell} denote the number of buying and selling signals of the corresponding strategy, $\mu_{\text{Buy}} - \mu_{\text{Sell}}$ gives the difference of the mean return of the buying and selling signals and therefore the overall return of a given trading strategy. t-stat. reports its t-statistics for testing the null of zero return calculated as follows: $t\text{-stat} = \frac{\mu_{\text{Buy}} - \mu_{\text{Sell}}}{\sqrt{\sigma^2/N_{\text{Buy}} + \sigma^2/N_{\text{Sell}}}}$ for MACD, Hist and RSI as well as $t\text{-stat} = \frac{\mu}{\sqrt{\sigma^2/N}}$ for B&H, where σ^2 denotes the variance of the entire crude oil futures return series. The column Days reports the horizon of the investment after a buying or selling signal. The separate returns of the buying and selling signals and the returns for the remaining scales (i.e. W2, W3, W4, W6, and W7) are available upon request.

Table 5 **Performance of technical analysis indicators depending on the level of uncertainty**

		Original series			W1			W5			W8		
		MACD	**Hist**	**RSI**	**MACD**	**Hist**	**RSI**	**MACD**	**Hist**	**RSI**	**MACD**	**Hist**	**RSI**
	N_{Buy}	219	211	12	353	166	0	257	55	119	243	40	146
	N_{Sell}	142	150	15	8	195	0	104	306	113	118	321	197
VIX Low	$\mu_{\text{Buy}} - \mu_{\text{Sell}}$	0.0013	-0.0014	-0.0029	0.0034	-0.0033		-0.0001	0.0034	-0.0022	0.0003	-0.0037	-0.0038
	t-Stat.	0.5029	-0.5436	-0.3092	0.3970	-1.2918		-0.0431	0.9582	-0.7042	0.1133	-0.9092	-1.4342
	N_{Buy}	3616	3165	277	6280	3194	0	4407	1713	1945	3383	772	3182
	N_{Sell}	2831	3282	308	167	3253	0	2040	4734	1997	3064	5675	2898
VIX Normal	$\mu_{\text{Buy}} - \mu_{\text{Sell}}$	-0.0006	-0.0004	0.0010	-0.0021	-0.0004		0.0001	0.0001	0.0002	0.0006	-0.0002	-0.0007
	t-Stat.	-1.0033	-0.7165	0.5097	-1.1399	-0.6169		0.2179	0.1004	0.2538	1.0146	-0.2303	-1.1988
	N_{Buy}	164	173	23	351	168	0	220	82	72	211	41	92
	N_{Sell}	195	186	5	8	191	0	139	277	104	148	318	253
VIX High	$\mu_{\text{Buy}} - \mu_{\text{Sell}}$	0.0040	-0.0056	0.0619	0.0104	-0.0037		-0.0042	0.0002	0.0017	0.0128	0.0102	0.0030
	t-Stat.	1.5734	-2.2074	5.2194	1.2143	-1.4573		-1.5940	0.0688	0.4697	4.9790	2.5615	1.0411
	N_{Buy}	211	212	12	352	191	0	225	95	101	171	44	184
	N_{Sell}	148	147	27	7	168	0	134	264	126	188	315	157
EPU Low	$\mu_{\text{Buy}} - \mu_{\text{Sell}}$	0.0022	-0.0040	0.0030	0.0104	-0.0043		-0.0021	0.0008	0.0045	0.0017	-0.0021	-0.0025
	t-Stat.	0.8536	-1.5436	0.3581	1.1299	-1.6770		-0.8049	0.2882	1.3977	0.6878	-0.5530	-0.9444
	N_{Buy}	3639	3173	280	6293	3161	0	4422	1653	1952	3450	758	3117
	N_{Sell}	2821	3287	293	167	3299	0	2038	4807	1961	3010	5702	2982
EPU Normal	$\mu_{\text{Buy}} - \mu_{\text{Sell}}$	-0.0005	-0.0004	0.0023	-0.0022	-0.0001		-0.0003	0.0002	-0.0002	0.0012	-0.0002	-0.0007
	t-Stat.	-0.7977	-0.6766	1.1263	-1.1709	-0.2260		-0.4313	0.3002	-0.2812	1.9428	-0.1932	-1.0911
	N_{Buy}	154	168	20	349	182	0	244	104	85	220	51	125
	N_{Sell}	205	191	9	10	177	0	115	255	129	139	308	214
EPU High	$\mu_{\text{Buy}} - \mu_{\text{Sell}}$	0.0018	-0.0022	0.0209	0.0030	-0.0064		0.0057	-0.0007	-0.0002	0.0018	0.0073	0.0011
	t-Stat.	0.6964	-0.8732	2.1661	0.3858	-2.5278		2.0864	-0.2441	-0.0454	0.6805	2.0083	0.4233

Note: The table reports mean returns and their corresponding *t*-statistics for several different trading strategies applied on the original WTI crude oil futures price series and on its individual wavelet components at the first (i.e. W1), the fifth (i.e. W5) and the eighth scale (i.e. W8). The trading strategies follow buying and selling signals according to the moving average convergence divergence (MACD) given in Eq. (3), the MACD histogram (Hist) displayed in Eq. (5) and the relative strength index (RSI) given in (6). N_{Buy} and N_{Sell} denote the number of buying and selling signals of the corresponding strategy, $\mu_{\text{Buy}} - \mu_{\text{Sell}}$ gives the difference of the mean return of the buying and selling signals and therefore the overall return of a given trading strategy. *t*-stat. reports its *t*-statistics for testing the null of zero return calculated as follows: $t\text{-stat} = \frac{\mu_{\text{Buy}} - \mu_{\text{Sell}}}{\sqrt{\sigma^2/N_{\text{Buy}} + \sigma^2/N_{\text{Sell}}}}$, where σ^2 denotes the variance of the entire crude oil futures return series. The investment horizon is one day in all cases and the trading performance has been analyzed depending on the level of previous periods' uncertainty. We distinguish between three different uncertainty regimes: low ($\leq$5% quantile), normal ($>$5% quantile and $<$95% quantile) and high ($\geq$95% quantile), where the quantiles refer to the level of VIX or EPU for the entire sample period. The separate returns of the buying and selling signals and the returns for the remaining scales (i.e. W2, W3, W4, W6, and W7) are available upon request.

Figures

Figure 1 **WTI crude oil futures prices and trading indicators**

The plots show the futures prices (in green) for WTI crude oil and their corresponding technical trading indicators for a sample period running from January 1990 to August 2018 on a daily basis. The gray line below gives the moving average convergence divergence $MACD_{12,26,t}$ according to Eq. (3), the red dotted line the corresponding signal line $Signal_{9,t}$ according to Eq. (4) and the gray areas indicate $Hist_{12,26,9,t}$ defined in Eq. (5). The blue line below displays the relative strength index $RSI_{14,t}$ defined in Eq. (6).

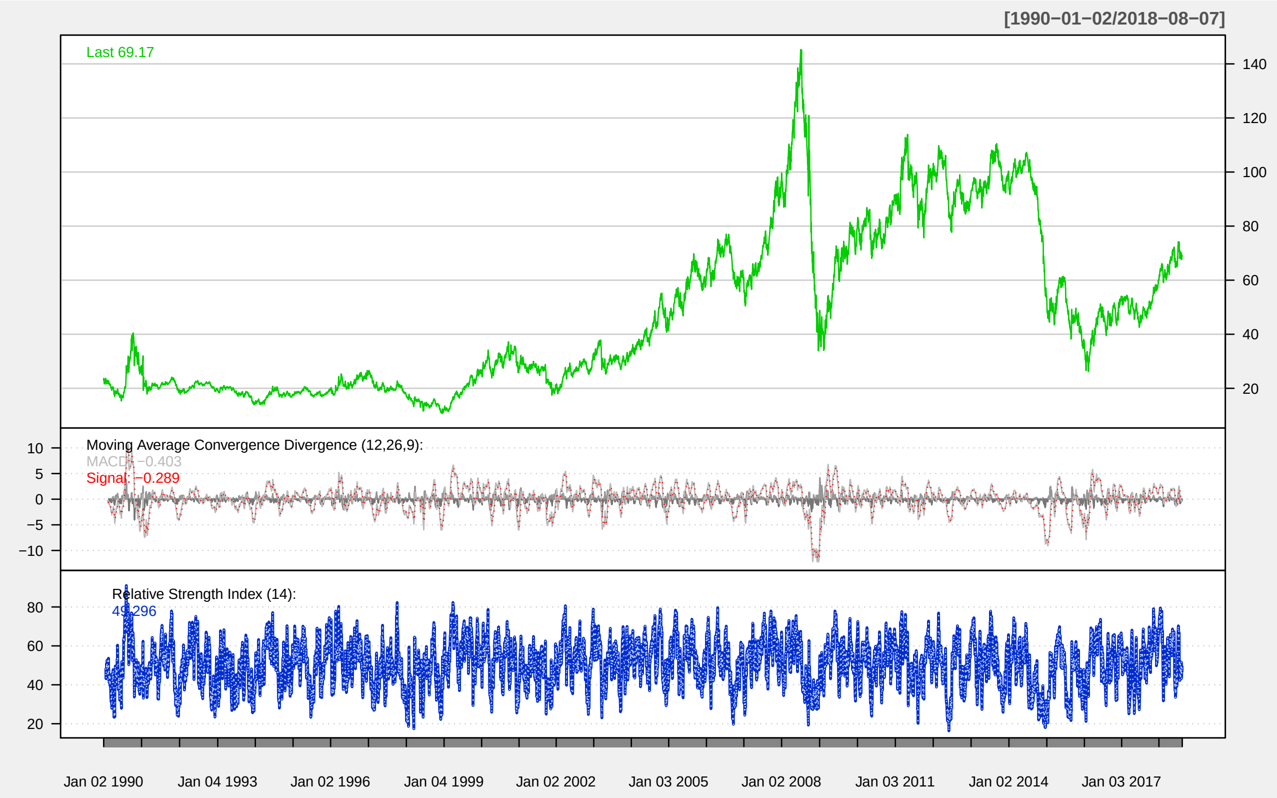
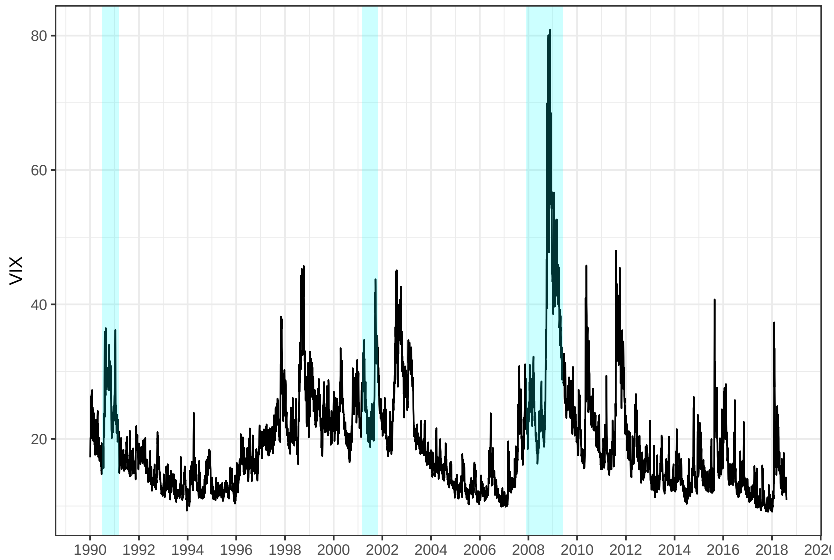


FIGURE 2 **Uncertainty measures**

The plots show the CBOE volatility index of the S&P500 (VIX) in Panel (a) and the US economic policy uncertainty (EPU) index following Baker *et al.* (2016) in Panel (b) for a sample period running from January 1990 to August 2018. The cyan area highlights the US recession periods running from July 1990 to March 1991, March 2001 to November 2001 and December 2007 to June 2009 according to the classification of the National Bureau of Economic Research.

Panel (a)



Panel (b)

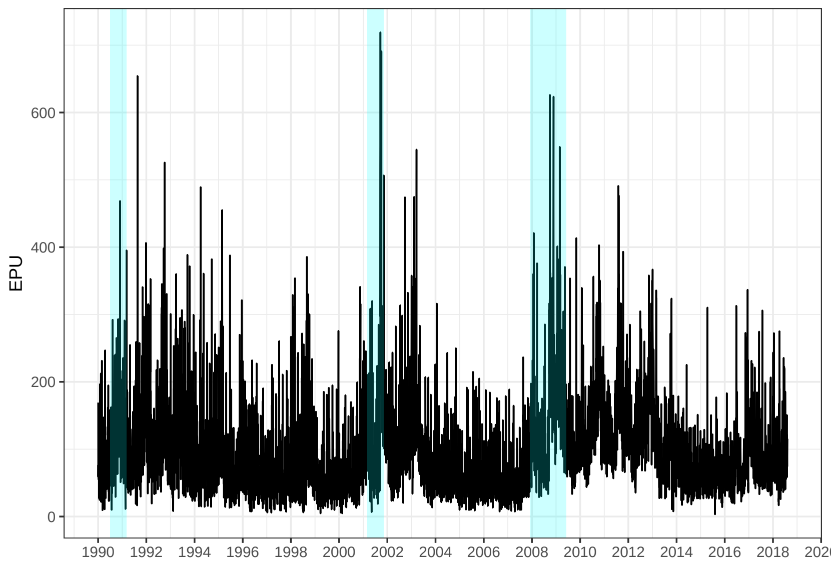


Figure 3 **Wavelets**

The plots show the original time series for WTI crude oil futures prices (at the bottom) and the components of its decomposition into eight wavelets denoted by W1, W2, etc. for a sample period running from January 1990 to August 2018.

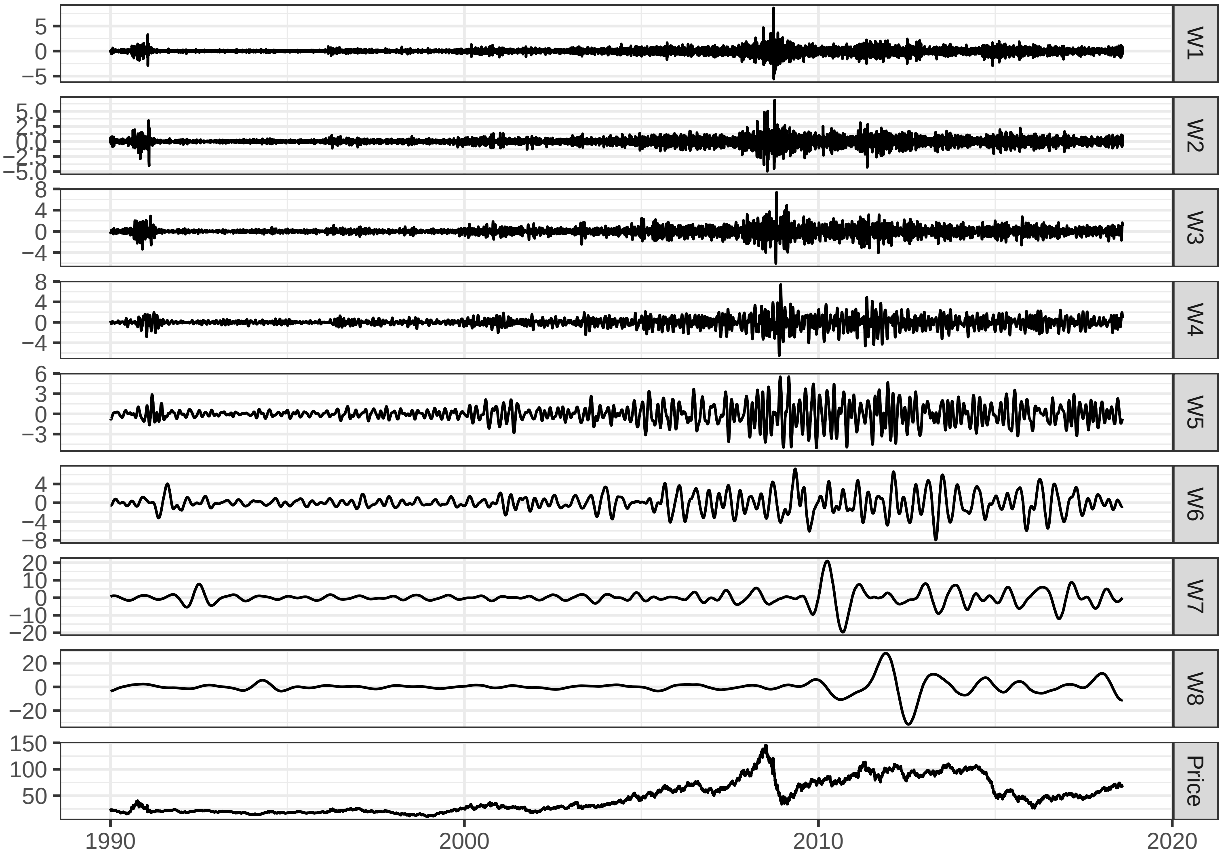
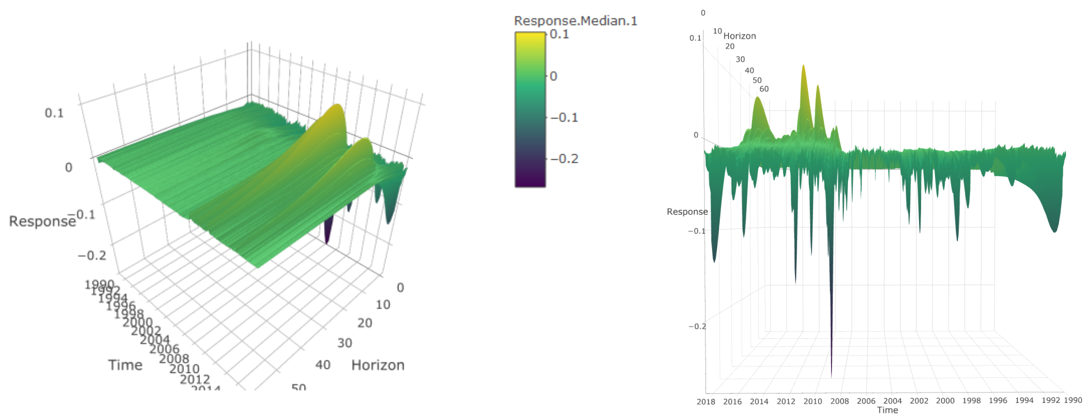


FIGURE 4 **Time-varying impulse responses of technical indicators to a shock on VIX**

The plots show the time-varying reaction of two technical trading indicators (namely MACD Hist and RSI) of crude oil futures to a one unit shock of the CBOE volatility index of the S&P500 (VIX). The corresponding reactions have been calculated for a sample period running from January 1990 to August 2018 on a daily basis while data for the first 80 days have been used as a training sample to initialize the coefficient priors. Panel (a) shows the reaction of the MACD Hist while Panel (b) gives the response of the RSI. The graphs on the right are rotations of the same graph on the left.

Panel (a): Response of MACD to a shock on VIX



Panel (b): Response of RSI to a shock on VIX

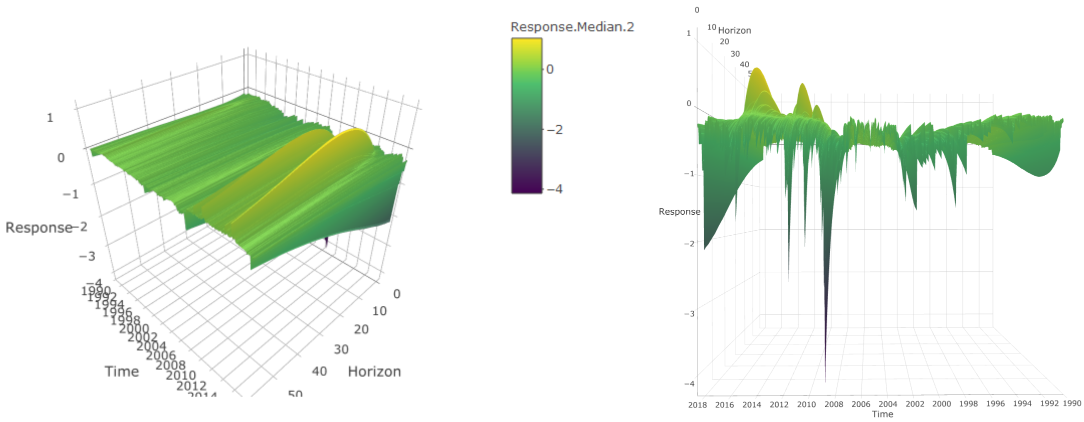
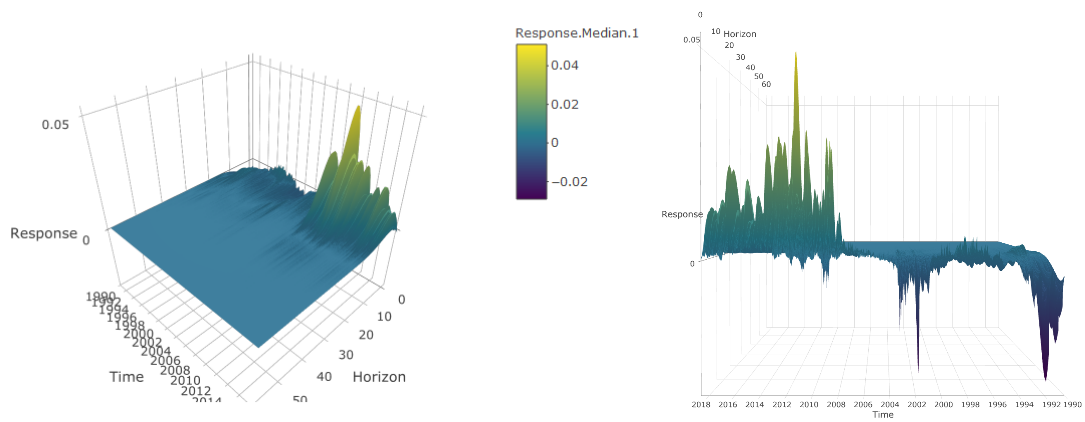


FIGURE 5 **Time-varying impulse responses of technical indicators to a shock on EPU**

The plots show the time-varying reaction of two technical trading indicators (namely MACD Hist and RSI) of crude oil futures to a one unit shock of the US economic policy uncertainty (EPU) index following Baker *et al*. (2016). The corresponding reactions have been calculated for a sample period running from January 1990 to August 2018 on a daily basis while data for the first 80 days have been used as a training sample to initialize the coefficient priors. Panel (a) shows the reaction of the MACD Hist while Panel (b) gives the response of the RSI. The graphs on the right are rotations of the same graph on the left.

Panel (a): Response of MACD to a shock on EPU



Panel (b): Response of RSI to a shock on EPU

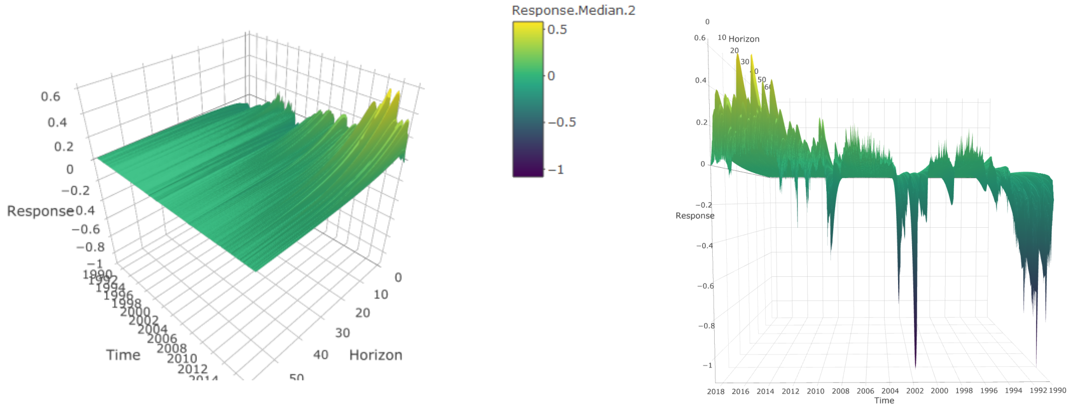
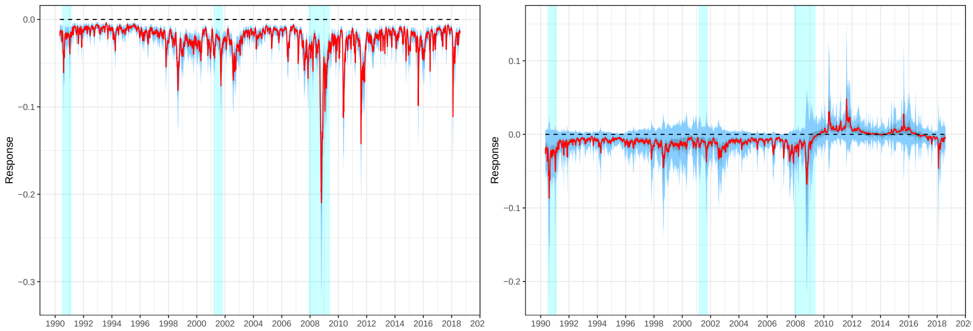


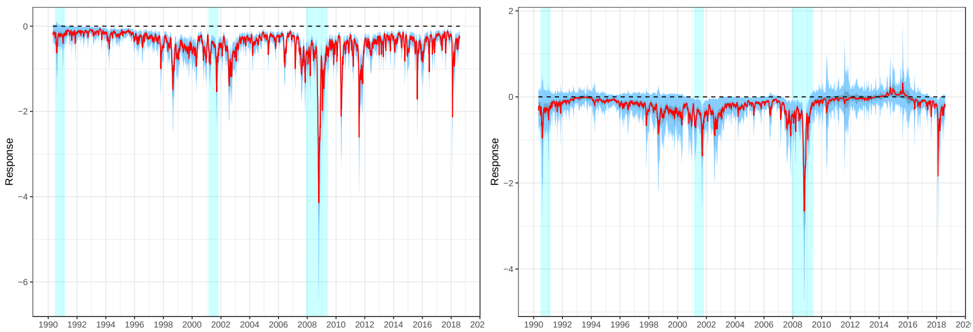
FIGURE 6 **Time-varying impulse responses and FEVD to a shock on VIX with a fixed horizon**

The plots show the time-varying reaction and forecast error variance decomposition (FEVD) of two technical trading indicators (namely MACD histogram and RSI) of crude oil futures to a one unit shock of the CBOE volatility index of the S&P500 (VIX) with a fixed horizon ($h = 1$ and $h = 10$). The corresponding reactions have been calculated for a sample period running from January 1990 to August 2018 on a daily basis while data for the first 80 days have been used as a training sample to initialize the coefficient priors. Panel (a) shows the reaction of the MACD histogram while Panel (b) gives the response of the RSI. The reaction is represented by the solid red line and the corresponding confidence bands by blue shadings (the 95% level in light blue and the 68% in dark blue). The dashed black line displays the zero line. The cyan area highlights the US recession periods running from July 1990 to March 1991, March 2001 to November 2001 and December 2007 to June 2009 according to the classification of the National Bureau of Economic Research. Panel (c) and Panel (d) display the FEVD of the MACD histogram and the RSI, respectively, while the share of VIX shocks on the forecast error variance is given in orange and the share of own shocks in turquoise. For the graphs on the left (right) the horizon has been fixed to $h = 1$ ($h = 10$).

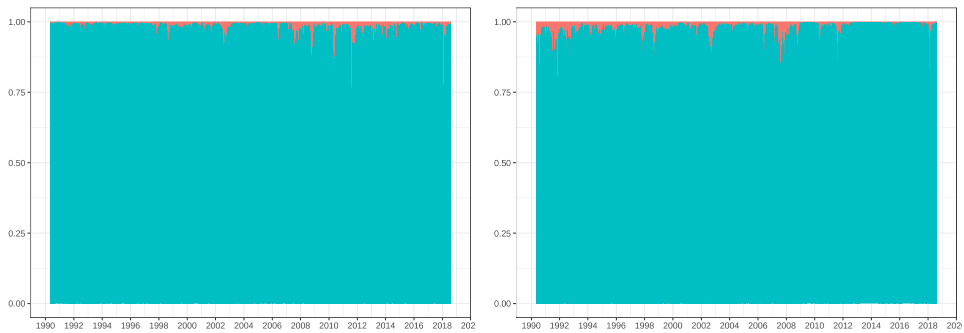
Panel (a): Response of MACD to a shock on VIX



Panel (b): Response of RSI to a shock on VIX



Panel (c): Forecast error variance decomposition of MACD



Panel (d): Forecast error variance decomposition of RSI

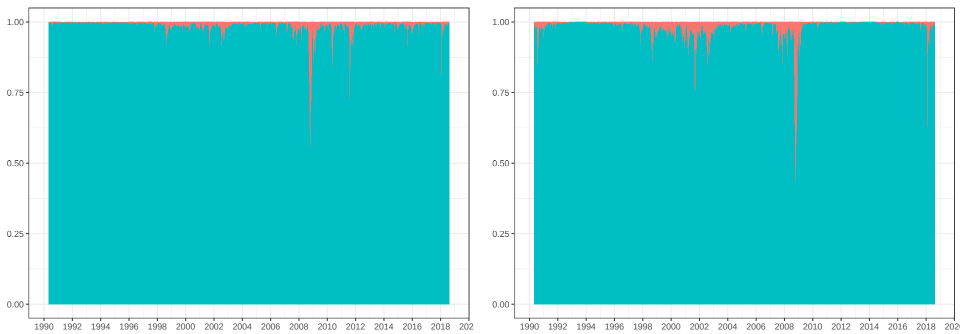
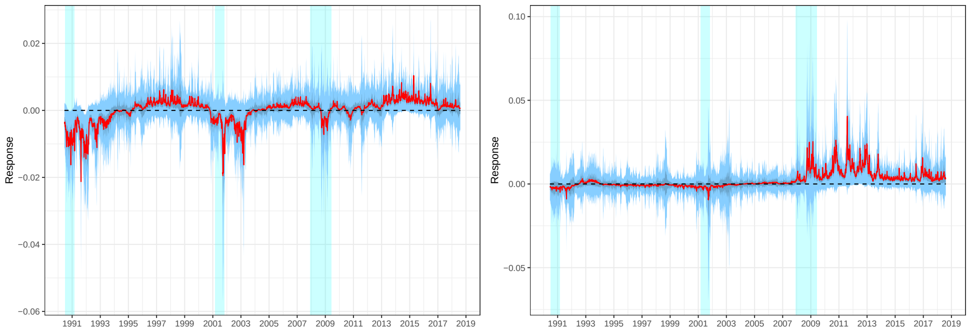


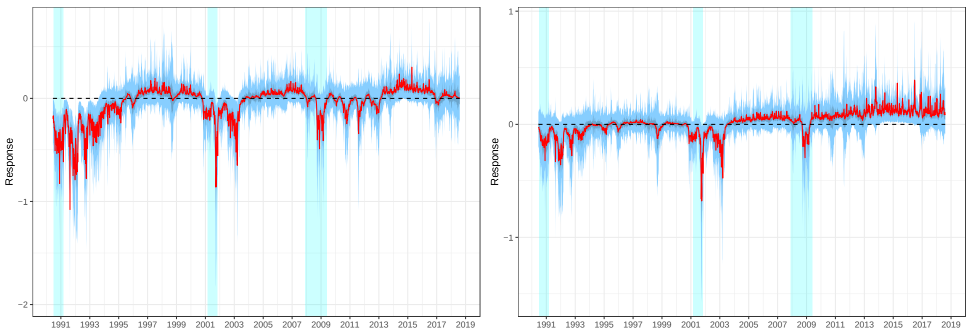
FIGURE 7 **Time-varying impulse responses and FEVD to a shock on EPU with a fixed horizon**

The plots show the time-varying reaction and forecast error variance decomposition (FEVD) of two technical trading indicators (namely MACD histogram and RSI) of crude oil futures to a one unit shock of the US economic policy uncertainty (EPU) index following Baker *et al.* (2016) with a fixed horizon ($h = 1$ and $h = 10$). The corresponding reactions have been calculated for a sample period running from January 1990 to August 2018 on a daily basis while data for the first 80 days have been used as a training sample to initialize the coefficient priors. Panel (a) shows the reaction of the MACD histogram while Panel (b) gives the response of the RSI. The reaction is represented by the solid red line and the corresponding confidence bands by blue shadings (the 95% level in light blue and the 68% in dark blue). The dashed black line displays the zero line. The cyan area highlights the US recession periods running from July 1990 to March 1991, March 2001 to November 2001 and December 2007 to June 2009 according to the classification of the National Bureau of Economic Research. Panel (c) and Panel (d) display the FEVD of the MACD histogram and the RSI, respectively, while the share of EPU shocks on the forecast error variance is given in orange and the share of own shocks in turquoise. For the graphs on the left (right) the horizon has been fixed to $h = 1$ ($h = 10$).

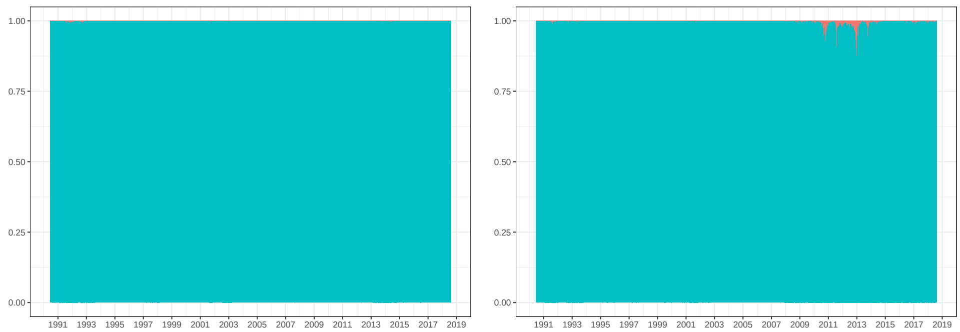
Panel (a): Response of MACD to a shock on EPU



Panel (b): Response of RSI to a shock on EPU



Panel (c): Forecast error variance decomposition of MACD



Panel (d): Forecast error variance decomposition of RSI

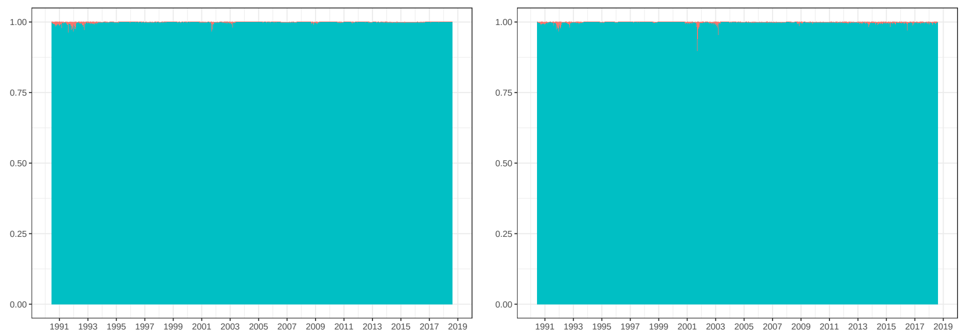
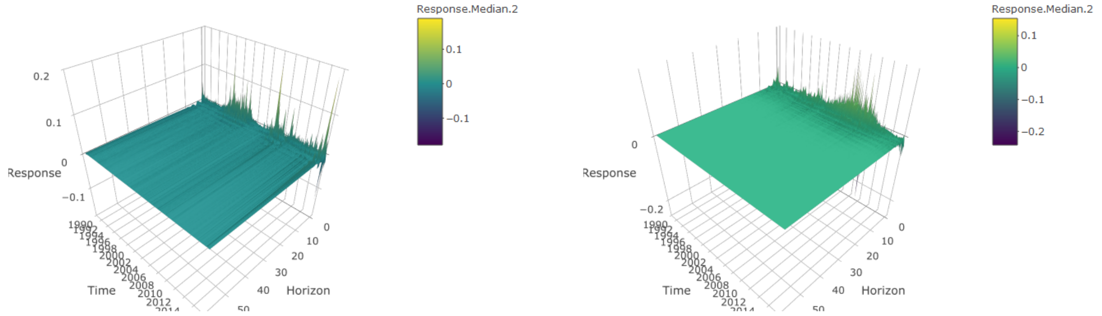


FIGURE 8 **Disaggregated time-varying impulse responses**

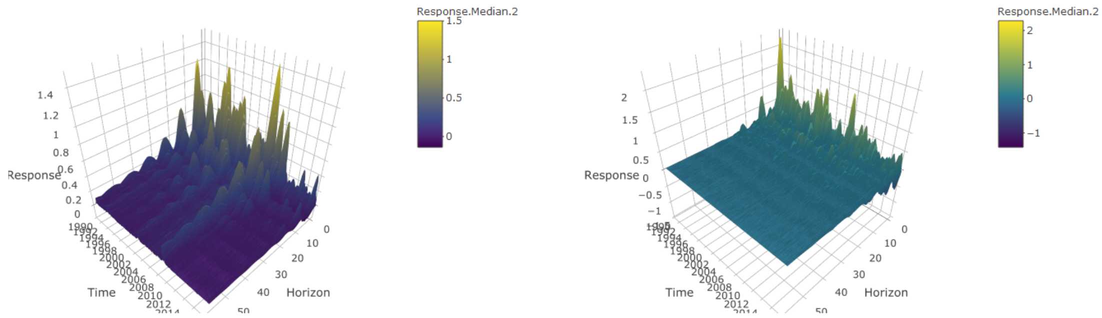
The plots show the time-varying reaction of the RSI for disaggregated crude oil futures provided for the wavelet scales W1, W3, W5 and W8 (i.e. $y(\widetilde{D}_1)$, $y(\widetilde{D}_3)$, $y(\widetilde{D}_5)$, and $y(\widetilde{D}_8)$) to a one unit shock of uncertainty. As measure of uncertainty we consider the CBOE volatility index of the S&P500 (VIX) and the US economic policy uncertainty (EPU) index following Baker *et al.* (2016). The corresponding reactions have been calculated for a sample period running from January 1990 to August 2018 on a daily basis while data for the first 80 days have been used as a training sample to initialize the coefficient priors.

Response of RSI to a shock on VIX | Response of RSI to a shock on EPU

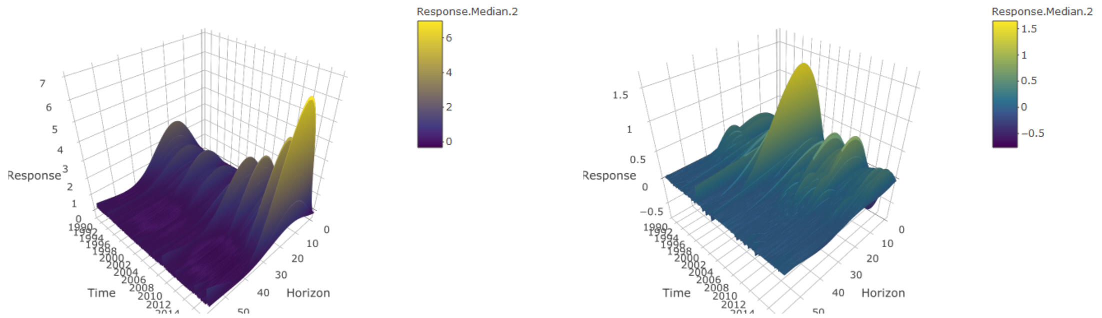
(a) W1



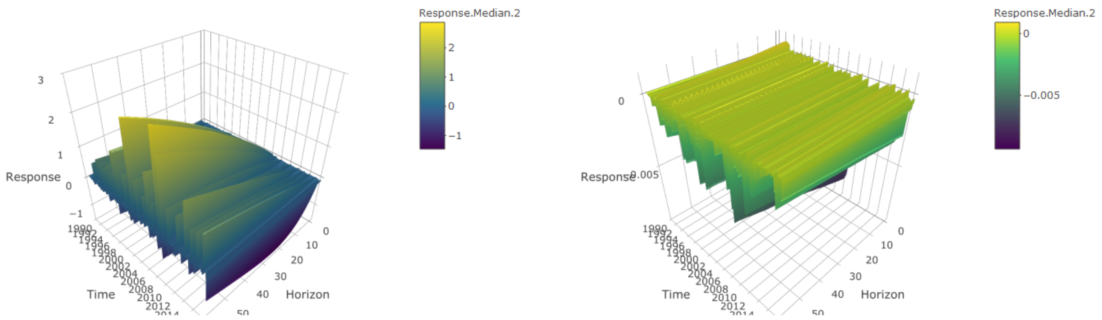
(b) W3



(c) W5



(d) W8



A. Appendix

A.1 MCMC algorithm

In the following we illustrate the Bayesian MCMC algorithm used to estimate the model described by Eqs. (10) and (11). The uninformative priors are given as follows

$$p(B_0) = N(\hat{B}_{OLS}, k_B \cdot \hat{V}(\hat{B}_{OLS})) \quad \text{with} \quad k_B = 4, \tag{13}$$

$$p(A_0) = N(\hat{A}_{OLS}, k_A \cdot \hat{V}(\hat{A}_{OLS})) \quad \text{with} \quad k_A = 4, \tag{14}$$

$$p(\log \varsigma_0) = N(\log \hat{\varsigma}_{OLS}, k_\varsigma \cdot I_2) \quad \text{with} \quad k_\varsigma = 1, \tag{15}$$

$$p(Q) = IW(k_Q^2 \cdot pQ \cdot \hat{V}(\hat{B}_{OLS}), pQ) \quad \text{with} \quad k_Q = 0.01, pQ = 80, \tag{16}$$

$$p(W) = IW(k_W^2 \cdot pW \cdot I_2, pW) \quad \text{with} \quad k_W = 0.01, pW = 3, \tag{17}$$

$$p(S) = IW(k_S^2 \cdot pS \cdot \hat{V}(\hat{A}_{OLS}), pS) \quad \text{with} \quad k_S = 0.01, pS = 2, \tag{18}$$

where $N(.)$ denotes the normal and $IW(.)$ the inverse Wishart distribution. To initialize the priors, $\hat{B}_{OLS}$, $\hat{V}(\hat{B}_{OLS})$, $\hat{A}_{OLS}$, $\hat{V}(\hat{A}_{OLS})$ have been estimated by OLS within a training sample period using the first 80 days.

We apply the Gibbs sampling algorithm by Del Negro and Primiceri (2015) with 50,000 draws excluding a burn-in sample of 5,000 as follows:

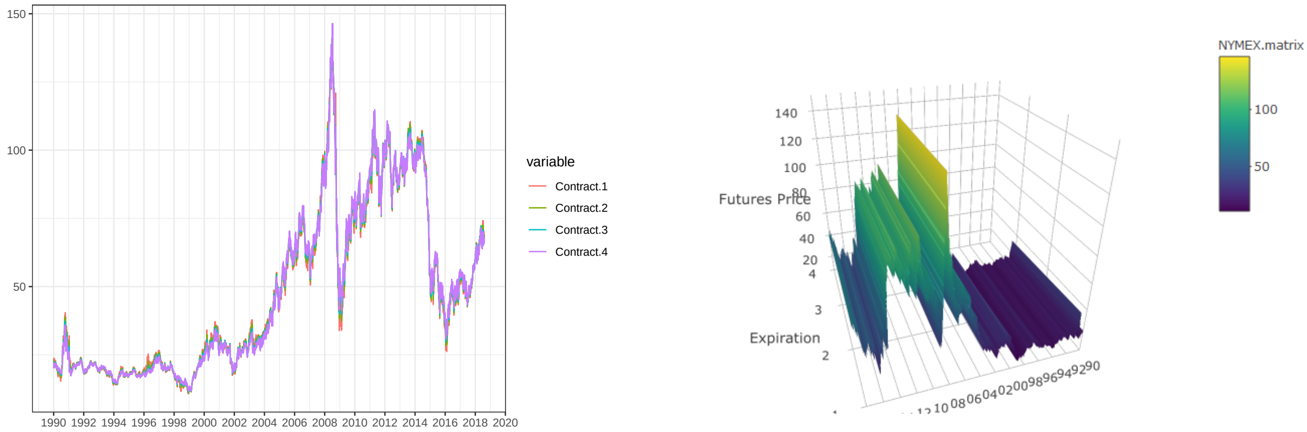
1. Initialize A^T, Σ^T, s^T and V^T,
2. Sample B^T from $p(B^T|\vartheta^{-B^T}, \Sigma^T)$ by applying the Carter and Kohn (1994) algorithm,
3. Sample Q from the inverse Wishart posterior $p(Q|B^T)$,
4. Sample A^T from $p(A^T|\vartheta^{-A^T}, \Sigma^T)$ by applying the Carter and Kohn (1994) algorithm,
5. Sample S from the inverse Wishart posterior $p(S|\vartheta^{-S}, \Sigma^T)$,
6. Sample s^T from $p(s^T|\Sigma^T, \vartheta)$ by applying the Kim *et al.* (1998) algorithm,
7. Sample Σ^T from $p(\Sigma^T|\vartheta, s^T)$ by applying the Carter and Kohn (1994) algorithm,
8. Sample W from the inverse Wishart posterior $p(W|\Sigma^T)$,
9. Go back to step 2,

where s^T denotes the entire path of auxiliary discrete variables necessary to conduct inference on the volatilities given in Σ^T (Del Negro and Primiceri, 2015). ϑ is defined as $\vartheta = [B^T, A^T, V]$ and ϑ^{-B^T} means $\vartheta \setminus B^T$.

A.2 WTI crude oil futures prices

FIGURE A.1 **WTI crude oil futures prices with different maturities**

The plots show the futures prices for WTI crude oil for four different contracts for a sample period running from January 1990 to August 2018 on a daily basis in a simple time series diagram (left panel) and within the three-dimensional space (right panel).



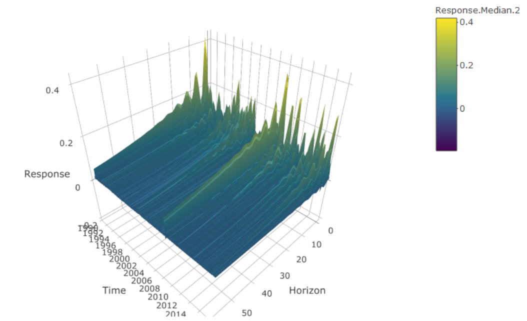
A.3 Time-varying impulse response functions

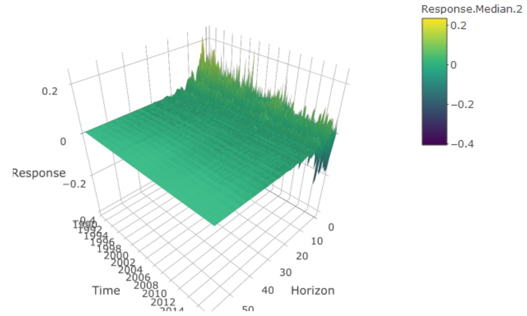
Figure A.2 **Disaggregated time-varying impulse responses**

The plots show the time-varying reaction of the RSI for disaggregated crude oil futures provided for the wavelet scales W2, W4, W6 and W7 (i.e. $y(\widetilde{D}_2)$, $y(\widetilde{D}_4)$, $y(\widetilde{D}_6)$, and $y(\widetilde{D}_7)$) to a one unit shock of uncertainty. As measure of uncertainty we consider the CBOE volatility index of the S&P500 (VIX) and the US economic policy uncertainty (EPU) index following Baker *et al.* (2016). The corresponding reactions have been calculated for a sample period running from January 1990 to August 2018 on a daily basis while data for the first 80 days have been used as a training sample to initialize the coefficient priors.

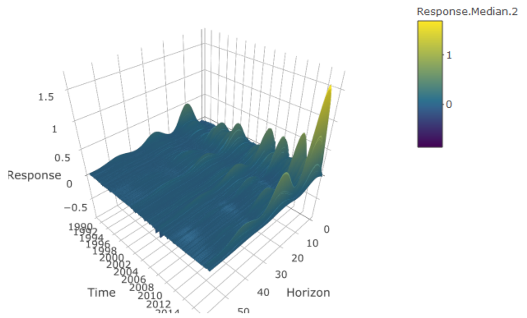
Response of RSI to a shock on VIX　　　Response of RSI to a shock on EPU

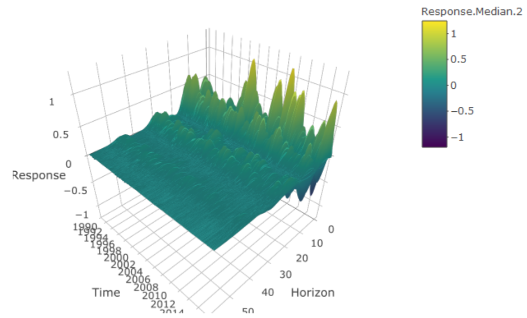
(a) W2



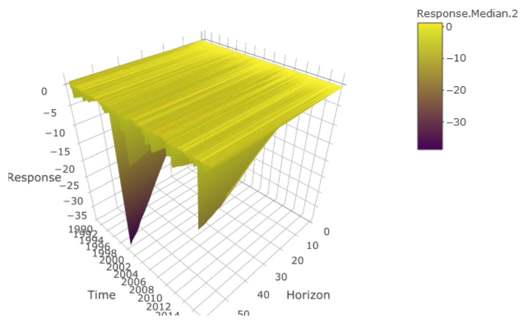


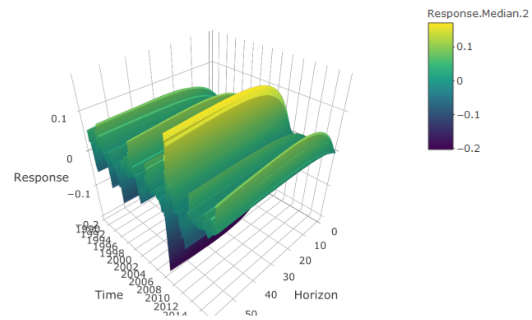
(b) W4





(c) W6





(d) W7