Crude oil futures trading and uncertainty

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Abstract

This paper examines the effect of different dimensions of uncertainty on momentum trading in the WTI crude oil futures market. We consider two concepts of uncertainty, i.e. US stock market volatility proxied by the VIX and daily news about the stance of economic policy in the US, and two momentum trading indicators based on technical analysis, i.e. the moving average convergence divergence and the relative strength index. In addition, we also use wavelet techniques to decompose crude oil futures prices into different frequencies accounting for investor's 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. Finally, based on an out-of-sample forecasting analysis, we also find that an investor can benefit from decomposing crude oil futures prices into its individual components and forecasting each of them separately.

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

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1 Introduction

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 conditions (Jurado *et al.*, 2015; Baker *et al.*, 2016; Scotti, 2016). Previous studies have analyzed the impact of uncertainty shocks on output and employment and show 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). Referring to oil markets, Kellogg (2014) finds that oil-drilling firm's 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. They also show that total spillovers increased considerably during the great recession period around 2007 to 2009.

At the same time the volatility of global crude oil prices has substantially increased in recent years, 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 and speculation on its markets as potential reasons for the huge swings in crude oil prices (Lammerding *et al.*, 2013). In general, the financialization of commodities has increased over the last decade since the group of futures speculators has entered the market, who are not interested in the commodities itself but solely see them as financial assets. The instrument of futures market trading, which allows shifting the risk from producers (hedgers) to speculators, is now part of a complex risk management process (Pennings and Garcia, 2010) and 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; Lammerding *et al.*, 2013).

Moreover, the financialization of crude oil has also entailed the so-called technical analysis for trading on financial markets that has been established by professional traders over the last decades. Technical analysis offers better tools for predicting trends and momentum on financial markets compared to traditional ARIMA models or their extensions and is used to trade on crude oil futures markets by professional traders.[1] In times characterized by a high degree of uncertainty, futures markets are of particular relevance for producers to hedge the risk associated with unforeseeable

[1]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`.

developments of the spot price and this makes this period also very attractive for speculators.

Thus the main aim of this study is to examine the effect of uncertainty on momentum trading on the West Texas Intermediate (WTI) crude oil futures market. Momentum trading is 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). 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), to the best of our knowledge this is the first study that focuses on the transmission of uncertainty shocks from different sources on expectations of crude oil futures investors proxied by momentum trading strategies. If investor's expectations are affected by uncertainty, the latter is able to push futures prices upwards and downwards and result in an increased price volatility. In addition, 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 on momentum trading with respect to different frequencies which could be interpreted as investor's sentiment at various horizons.

To analyze the transmission of uncertainty on momentum trading on the crude oil futures market, we estimate a Bayesian time-varying structural vector autoregression (VAR) in the spirit of Primiceri (2005), where the time-variation derives from both the coefficients and the variance-covariance structure of the model's innovations. 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. If investors are rational and forward looking, changes in uncertainty will be incorporated in their expectations, inducing day-by-day modifications in the transmission 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 investor's 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 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, our time-varying coefficient model is also able to capture potential nonlinearity which has already been identified for energy futures markets in the literature (Beckmann *et al.*, 2014).

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) crude oil futures closing prices of first nearby contracts traded at the Intercontinental Exchange. Data for a sample period running from February 2006 to December 2014 has been provided by Stevens Analytics via Quandl. Continuous nearby futures prices are constructed by rolling over on the last trading day of the expiring or front contract. Hence, the continuous contract series is a non-overlapping end-to-end concatenation of the underlying individual contracts, spliced on successive expiry dates. Oil futures prices can be regarded as a proxy for expectations about future spot prices since futures price changes have predictive power for price changes on spot markets and are also used by many producers to make their price projections (Kellogg, 2014). 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 at the end of our sample period.

*** Insert Figure 1 about here ***

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. 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. 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). Hence, the index aggregates different aspects of uncertainty which are directly related to the political situation in the US.[2]

The time series of both uncertainty measures, i.e. the VIX and the EPU, are shown in Figure 2. Both have their largest peak at the end of 2008. 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 that seven times higher for EPU compared to the VIX. The correlation between both measures is 0.4657 for the period between February 2006 and December 2014. Therefore we expect to see some differences in the effects of uncertainty on momentum trading on crude oil futures markets with respect to the uncertainty measure.

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

[2]The data has been downloaded from Baker *et al.* (2016)'s companion website (`http://www.policyuncertainty.com/`). It should be noted that policy uncertainty indexes for several other economies are also available, however 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. In addition, 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, these are only available at monthly frequency and are also highly correlated with the VIX. For our the sample period (i.e. February 2006 to December 2014) the correlation between the monthly averages of the VIX and the macroeconomic and the financial uncertainty index provided by Jurado *et al.* (2015) is 0.75 and 0.88, respectively. Therefore, we do not expect to gain further insights by focusing on the Jurado *et al.* (2015) measure of uncertainty.

2.2 Wavelet decomposition

We also examine the role of uncertainty on momentum in the crude oil futures market at different frequency scales which could be interpreted as investor's 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) and Berger and Uddin (2016). 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

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

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 while $y(\widetilde{D}_8)$ contains low frequency components.

MODWT is an extension of the discrete wavelet transform (DWT), which uses a linear time invariant filter $h_{j,l}$ such that

$$\sum_{l=0}^{L-1} h_{j,l} = 0, \quad \sum_{l=0}^{L-1} h_{j,l}^2 = 1, \quad \text{and} \quad \sum_{l=-\infty}^{+\infty} h_{j,l} h_{j,l+2n} = 0, \tag{2}$$

where $h_{j,l}$ is the so-called DWT mother wavelet filter with length $l = 0, \ldots, L-1$ and decomposition level $j = 1, \ldots, J$. $g_{j,l}$ represents the so-called scaling filter determined by the quadrature mirror relationship. The MODWT wavelet and scaling filters are obtained directly from the DWT filters by the following transformation

$$\tilde{h}_{j,l} = h_{j,l}/2^{j/2} \quad \text{and} \quad \tilde{g}_{j,l} = g_{j,l}/2^{j/2}. \tag{3}$$

To decompose the time series of daily crude oil futures prices $y = \{y_t, t = 1, 2, \ldots, T\}$ into $J = 8$ frequencies, the wavelet coefficients of level j are achieved by the convolution of y and the MODWT filters

$$\widetilde{W}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{h}_{j,l} y_{t-l \bmod N} \quad \text{and} \quad \widetilde{V}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{g}_{j,l} y_{t-l \bmod N} \tag{4}$$

with $L_j = (2^j - 1)(L-1) + 1$. The index $t - l \bmod N$ stands for $t - l$ modulo N which means that if j is an integer such that $0 \leq j \leq N-1$, then j modulo $N \equiv j$ (see Percival and Walden, 2000, p. 30

for details). We have applied the least asymmetric (LA) wavelet transform filter with length $L = 8$. 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. In the following we estimate trends and momentum of the original time series of crude oil futures prices and its eight frequency scales by applying technical analysis.

*** Insert Figure 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 (Appel, 2009; Gerritsen, 2016; Fan and Yao, 2017). In this context, we distinguish between an upward (i.e. *bullish*) and a downward (i.e. *bearish*) trend and refer to upward and downward moving asset prices. An upward and a downward momentum describes a situation where rising prices proceed rising even further or falling prices keep falling even further. To predict recent trends and momentum in financial markets, two popular technical indicators are introduced and applied in the following: 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

$$\text{EMA}_{k,t} = \frac{2}{k+1} P_t + \frac{k-1}{k+1} \text{EMA}_{k,t-1}, \tag{5}$$

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

$$\text{MACD}_{s,l,t} = \text{EMA}_{s,t} - \text{EMA}_{l,t} \quad \text{with} \quad l > s \geq 1. \tag{6}$$

$\mathrm{MACD}_{s,l,t}$ oscillates around the zero line which marks the trading rule based on MACD: Buy if $\mathrm{MACD}_{s,l,t} > 0$ and sell if $\mathrm{MACD}_{s,l,t} < 0$. The rational behind this proceeding is that in case of $\mathrm{MACD}_{s,l,t} > 0$ ($\mathrm{MACD}_{s,l,t} < 0$) 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 $\mathrm{MACD}_{12,26,t}$ 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 $\mathrm{MACD}_{s,l,t}$, the so-called signal line:

$$\mathrm{Signal}_{k,t} = \frac{2}{k+1}\mathrm{MACD}_{s,l,t} + \frac{k-1}{k+1}\mathrm{MACD}_{s,l,t-1}. \tag{7}$$

In this case the trading rule is: Buy if $\mathrm{MACD}_{s,l,t}$ increases and crosses the signal line from below and sell if $\mathrm{MACD}_{s,l,t}$ decreases and crosses the signal line from above. 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 should be based on the so-called MACD histogram. The latter is defined as the difference between Eq. (6) and Eq. (7):

$$\mathrm{Hist}_{s,l,k,t} = \mathrm{MACD}_{s,l,t} - \mathrm{Signal}_{k,t}. \tag{8}$$

Large positive (negative) values for $\mathrm{Hist}_{s,l,k,t}$ 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. (6), (7) and (8) for $s = 12$, $l = 26$ and $k = 9$. Price increases (decreases) are signaled by $\mathrm{Hist}_{s,l,k,t} > 0$ ($\mathrm{Hist}_{s,l,k,t} < 0$) which is displayed by light gray (dark gray) areas. The gray line represented the signal line $\mathrm{Signal}_{9,t}$ while the red dotted line is the $\mathrm{MACD}_{12,26,t}$. 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 the $\mathrm{Hist}_{12,26,9,t}$ as one proxy for the momentum or more precisely the investor's expectation about the momentum. In addition, we have also computed $\mathrm{Hist}_{12,26,9,t}$ for all eight frequency scales achieved by the wavelet decomposition. The descriptive statistics for our trading indicator for the original time series and its components are reported in Table 1 and show that the standard deviation of $\mathrm{Hist}_{12,26,9,t}$ (denoted by MACD in the table) is much higher for the individual components than for the original series and tends to be higher for lower compared to higher frequencies.

2.3.2 Relative strength index

The presented indicators based on MACD have two major drawbacks: first, they are boundless and therefore it difficult to identify extremes in trends and momentum. Second, MACD indicators sometime 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

$$\mathrm{RSI}_{k,t} = 100 \cdot \frac{\overline{\mathrm{G}}_{k,t}}{\overline{\mathrm{G}}_{k,t} + \overline{\mathrm{L}}_{k,t}}, \tag{9}$$

where $\overline{\mathrm{G}}_{k,t}$ and $\overline{\mathrm{L}}_{k,t}$ 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):

$$\overline{\mathrm{G}}_{k,t} = \frac{1}{k}(P_t - P_{t-1})I(P_t > P_{t-1}) + \frac{k-1}{k}\overline{\mathrm{G}}_{k,t-1} \tag{10}$$

and

$$\overline{\mathrm{L}}_{k,t} = \frac{1}{k}(P_t - P_{t-1})I(P_t < P_{t-1}) + \frac{k-1}{k}\overline{\mathrm{L}}_{k,t-1}, \tag{11}$$

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. $\mathrm{RSI}_{k,t}$ is bounded to oscillate between 0 and 100 and therefore the extremes indicate whether the market is *overbought* or *oversold*. If $\mathrm{RSI}_{k,t} > 70$ ($\mathrm{RSI}_{k,t} <$ 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 $\mathrm{RSI}_{14,t}$ 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 $\mathrm{RSI}_{14,t} > 70$) without any delay. $\mathrm{RSI}_{14,t}$ 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 $\mathrm{RSI}_{14,t}$ together with $\mathrm{Hist}_{12,26,9,t}$ to analyze the impact of uncertainty on momentum trading in the crude oil futures market.

2.4 Time-varying Bayesian VAR approach

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

$$Y_t = B_{0,t} + B_{1,t}Y_{t-1} + \ldots + B_{p,t}Y_{t-p} + A_t^{-1}\Sigma_t\epsilon_t, \tag{12}$$

where Y_t is a bivariate vector including one trading indicator (i.e. $\text{Hist}_{12,26,9,t}$ or $\text{RSI}_{14,t}$) and one uncertainty measure (i.e. VIX or EPU). 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.[3] 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. (12), it can be written in compact form by stacking all $\{B_{j,t}\}_{j=0}^{p}$ into one vector B_t as follows

$$Y_t = X_t'B_t + A_t^{-1}\Sigma_t\epsilon_t \quad \text{with} \quad X_t' = I_2 \otimes [1, Y_{t-1}, \ldots, Y_{t-p}], \tag{13}$$

$$B_t = B_{t-1} + v_t, \tag{14}$$

$$a_t = a_{t-1} + \xi_t, \tag{15}$$

and

$$\log \varsigma_t = \log \varsigma_{t-1} + \eta_t, \tag{16}$$

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

[3] p denotes the lag length of the VAR model which has been selected by minimization of the AIC.

walks while ς_t follows a geometric random walk which belongs to the class of stochastic volatility models. The disturbances of the full model $\{\epsilon_t, \upsilon_t, \xi_t, \eta_t\}$ are assumed to be jointly normally distributed using the following assumptions on the variance covariance matrix represented by V:

$$V = \text{var}\begin{pmatrix} \epsilon_t \\ \upsilon_t \\ \xi_t \\ \eta_t \end{pmatrix} = \begin{pmatrix} I_2 & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{pmatrix}, \tag{17}$$

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

We estimate the model described by Eqs. (13) to (16) 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 large and complicated model will potentially have a likelihood with multiple peaks, 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 Gibbs sampling 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 individual impulse response analysis of a one-unit shock of uncertainty proxied by VIX or EPU on both momentum trading indicators (i.e. 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. Figure 4 reports 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 Figure 4, we have also plotted the corresponding reactions for four different trading days (i.e. 2008-01-02, 2010-01-04, 2012-01-03 and 2014-12-31) together with their 68% and 95% confidence intervals (see Figure A.2.1 in Appendix A.2).[4] All four graphs displayed in Panels (a) and (b) in Figure 4 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 Figure 4 about here ***

First of all, we discuss the effect of both momentum trading indicators to a shock on US stock market volatility (i.e. VIX) and refer to Panel (a) in Figure 4. A positive (negative) reaction of these indicators 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. The main findings are threefold. First, for the great recession period between 2007 and 2009, we find a negative short-run reaction on both trading indicators which changes after a few days to an even more pronounced positive reaction. The latter implies a buying signal and therefore indicates that the crude oil futures market is regarded as an alternative asset class compared to stock markets and provides a safe haven function in times of high uncertainty according to the definition provided by Baur and McDermott (2010). However, this potential safe haven property could also result in an overreaction in times of crisis which could promote the creation of speculative bubbles on the crude oil futures market in periods characterized by a high stock market uncertainty. Second, the impact on the RSI is more pronounced in magnitude and also the mentioned turn around in favor of buying signals after a negative short-run effect appears faster compared to the MACD histogram. This is due to the fact that in contrast to the MACD the RSI is

[4]The four periods including the first trading day in the years 2008, 2010 and 2012 as well as the last trading day in the sample period have been arbitrarily chosen to represent different points in time.

a counter-trend indicator which indicates when the market is overbought or oversold and seems to react stronger and faster to uncertainty. Finally, at the very end of our sample period around 2014, we again find negative short-run effects of stock market uncertainty on futures trading for crude oil which turn around to large positive effects in a few days. This corresponds with an increase of the VIX at the very end of the sample period (see Panel (a) in Figure 2) associated with decreasing futures prices for crude oil observed in Figure 1.

As a next step, we focus on the findings for economic policy uncertainty shocks reported in Panel (b) in Figure 4. Unsurprisingly, the effects differ between the EPU and the VIX. This is due to the fact that both uncertainty measures refer to different concepts of uncertainty and only show a mild correlation of nearly 0.5 as already mentioned. 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. Although this period is outside our sample, it is associated with an increased policy uncertainty (Bloomberg, 2017) and therefore the impact of EPU shocks on financial markets might be even stronger. Overall, 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 VIX. Interestingly, we find negative effects and therefore selling signals for the first part of the sample period which is marked by the bankruptcy of Lehman brothers at September 15, 2008 that caused a high degree of uncertainty. For the post crisis period we find strong positive effects and therefore buying signals which support the role of crude oil futures as a safe haven asset. Again effects of the RSI are stronger compared to the MACD histogram. In addition, the effects of the VIX are generally more persistent compared to EPU effects. EPU shocks die out much faster than VIX shocks – after around 20 days for the MACD histogram and after around 30 days for the RSI.

Due to the finding of predictive power of commodity prices for economic policy uncertainty provided by Wang *et al.* (2015), we have also examined the impact of both momentum trading indicators on the two uncertainty measures. However, we do not find any reactions of momentum trading shocks on uncertainty indexes indicating that a trading shock in a specific market is neither able to significantly affect stock market uncertainty nor economic policy uncertainty. The corresponding results are not reported but available upon request.

3.2 Disaggregated perspective

To gain further insights on the reaction of crude oil futures momentum trading on uncertainty, we have provided the same analysis at a disaggregated level that means for each individual component based on the wavelet decomposition. Figures 5 to 12 provide the results but to save space solely include the $\mathrm{RSI}_{14,t}$ as the momentum trading indicator which reacts faster, stronger and more persistent due to the results of the previous subsection. As can be seen in Figures 5 and 6 for the first two frequency scales denoted by W1 and 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 basically the same pattern as for the high-frequency components but is much stronger in magnitude and much more persistent as displayed in Figures 7 and 8. For the lower frequency components (i.e. scales from five to eight) shown in Figures 9 to 12, the reaction gets lower in magnitude compared to the third and fourth scale but it also gets much more persistent and more time-varying. 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. Interestingly, the medium frequencies at scales three and four 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. To examine the implications of the different reactions to uncertainty across frequencies for forecasting, we analyze the predictive densities of all frequency scales in the next subsection.

*** Insert Figures 5 to 12 about here ***

3.3 Out-of-sample forecasting

Finally, we have conducted a simple out-of-sample forecast of the last trading day in the sample period (i.e. December 31, 2014) for both trading indicators based on the VAR models including the two uncertainty measures which have been re-estimated excluding the last observation.[5] Figure 13 provides the resulting predictive densities for all four models together with the point forecasts as medians of the predictive densities (solid black line) and the actual observations (dashed orange line). In addition, to compare the forecasts based on the predictive density, the plots include the corresponding log score as a performance measure for distribution forecasts.

Figure 13 shows that the MACD histogram indicator can be forecasted pretty good based on previous stock market volatility (i.e. VIX). The actual observation is very close to the point forecast and the predictive density is much more concentrated compared to the MACD histogram forecast distribution based on previous uncertainty about the stance of economic policy (i.e. EPU) and also compared to both RSI forecast distributions. This is also confirmed by the relatively larger log score (i.e. 0.8623). When considering RSI forecasts the VIX has also a better forecast performance compared to the EPU, however the forecast has a log score of -2.5366 and is therefore worse than the MACD histogram forecast. Thus we want to examine in the following (1) whether the RSI forecasting ability can be enhanced by a decomposition of the crude oil futures price into its individual wavelet components and (2) whether the VIX is a superior predictor compared to the EPU over all frequencies or whether the EPU is also able to provide gains for RSI forecasts at some scales.

*** Insert Figure 13 about here ***

Figure 14 provides the predictive densities for RSI based on the wavelet decomposition. The plots in the first row show that RSI forecasts are very accurate at the highest frequency (i.e. W1). The point forecasts hit the actual observation almost exactly, the log scores are higher compared to the aggregated level mentioned above and both the VIX and the EPU provide nearly the same forecast performance while the log score of the EPU is slightly higher. On the second frequency scale the forecasting performance gets weaker but is still superior compared to the aggregated level according to the log score. Generally, the superiority of the individual forecast holds for all frequencies expect of the third and sixth scale which show lower log scores. Especially, the lowest scales (i.e. seven and eight) provide very accurate forecasts. Their forecast distributions are very much concentrated around the actual observations and they also exhibit very high log scores slightly below 2.5. In addition, for four out of eight scales EPU shows a better forecasting

[5] The findings provided in the following are not sensitive to variations of the trading day being forecasted and also continue to hold qualitatively for higher forecast horizons. The corresponding results are available upon request.

performance compared to the VIX. Especially, at the fifth scale EPU is superior.

*** Insert Figure 14 about here ***

Overall, the results show that an investor pursuing forward looking trading decisions can benefit from decomposing crude oil futures prices into its individual components and forecasting each of them separately. In addition, it is also reasonable for the investor to consider both sources of uncertainty when focusing on forecasts at the disaggregated level since both measures offer important information.

4 Conclusion

This paper contributes to the literature by analyzing the impact of different dimensions of uncertainty on momentum trading 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 coefficients and the variance-covariance matrix of the model's disturbances. To approximate the expectations of momentum traders we consider two technical analysis indicators (i.e. 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 (i.e. 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 impact has been observed during 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 with a delay of less than a week. These effects are even stronger and also the delay of the buying signal is shorter 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 crude oil futures also provide a safe haven function 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 speculative bubbles on crude oil futures markets in periods characterized by a high stock market uncertainty.

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 has direct implications for forecasting momentum trading indicators in order to react forward looking on changing trends and momentum. Based on an out-of-sample forecast exercise, we have shown that investors pursuing forward looking trading decisions can benefit from decomposing crude oil futures prices into its individual components and forecasting each of them separately. In addition, it is also reasonable for the investor to consider both sources of uncertainty when focusing on forecasts at the disaggregated level since both measures offer important information.

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Tables

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

		Mean	SD	Median	Min	Max	Skewness	Kurtosis
	VIX	21.0552	10.2316	18.0500	9.8900	80.8600	2.1807	6.1046
Uncertainty	**EPU**	114.1496	72.2998	98.6700	3.3800	626.0300	1.6504	4.9116
	Crude oil	-0.0135	0.6557	-0.0102	-2.4137	3.8726	0.2088	1.8557
	W1	-0.3861	398.4406	-0.9095	-5446.2714	11469.5477	15.0945	449.2930
	W2	-0.3037	1092.9661	-8.5694	-28324.2379	25071.4050	-2.0114	391.9121
	W3	-2.0201	889.4490	-16.9395	-26641.0181	20525.7129	-6.3724	499.5453
MACD	**W4**	-0.5760	14699.6476	-41.1214	-136065.7813	662212.5404	39.5600	1815.9588
	W5	-2.5079	1095.5973	-30.6469	-11528.4224	24821.1921	10.5508	228.3090
	W6	0.6622	773.0459	-13.3684	-7320.6853	25045.2289	17.4130	550.5627
	W7	0.1201	21338.6610	-3.9713	-931683.2329	208548.9774	-35.7468	1606.3465
	W8	0.0923	1374.7072	-1.5985	-58523.3104	12458.9259	-33.3286	1453.1348
	Crude oil	50.9498	12.4058	52.0677	16.7916	78.9741	-0.2499	-0.5831
	W1	49.9981	2.7314	50.0861	37.8037	59.6358	-0.1393	0.2747
	W2	50.0010	4.5299	50.0116	31.3739	65.5401	-0.0992	0.2419
	W3	50.0480	8.2508	50.1411	23.0205	75.0385	-0.0386	-0.3956
RSI	**W4**	50.3417	15.2219	51.0437	13.7717	87.4473	-0.1045	-0.9058
	W5	50.7596	25.1199	51.9313	3.7928	97.9080	-0.0484	-1.3269
	W6	50.5636	36.1351	50.9587	0.0000	99.4639	-0.0220	-1.6312
	W7	54.0333	43.5273	68.9070	0.0044	99.9975	-0.1640	-1.8021
	W8	54.7853	46.5692	82.7896	0.0000	100.0000	-0.1914	-1.8766

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, i.e. 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 (i.e. W1 stands for $y(\widetilde{D}_1)$ etc.). SD denotes standard deviation.

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 February 2006 to December 2014 on a daily basis. The gray line below gives the moving average convergence divergence $MACD_{12,26,t}$ according to Eq. (6), the red dotted line the corresponding signal line $Signal_{9,t}$ according to Eq. (7) and the gray areas indicate $Hist_{12,26,9,t}$ defined in Eq. (8). The blue line below displays the relative strength index $RSI_{14,t}$ defined in Eq. (9).

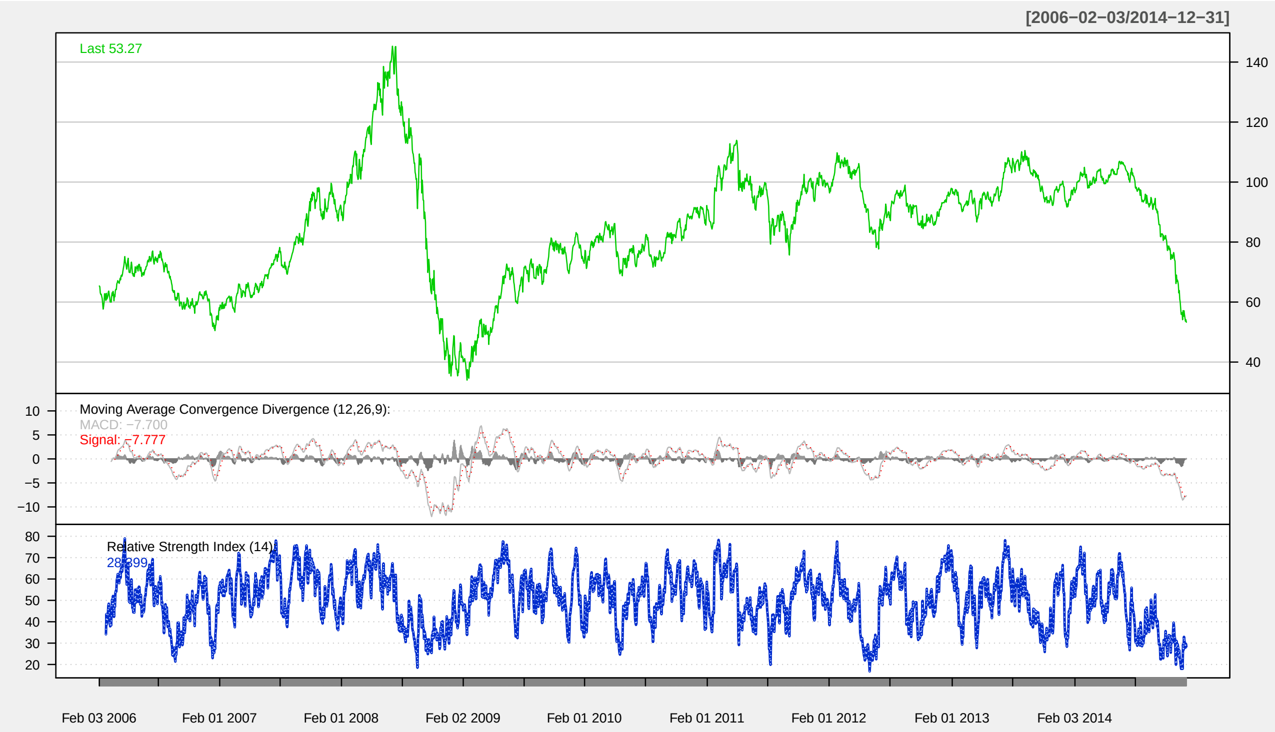
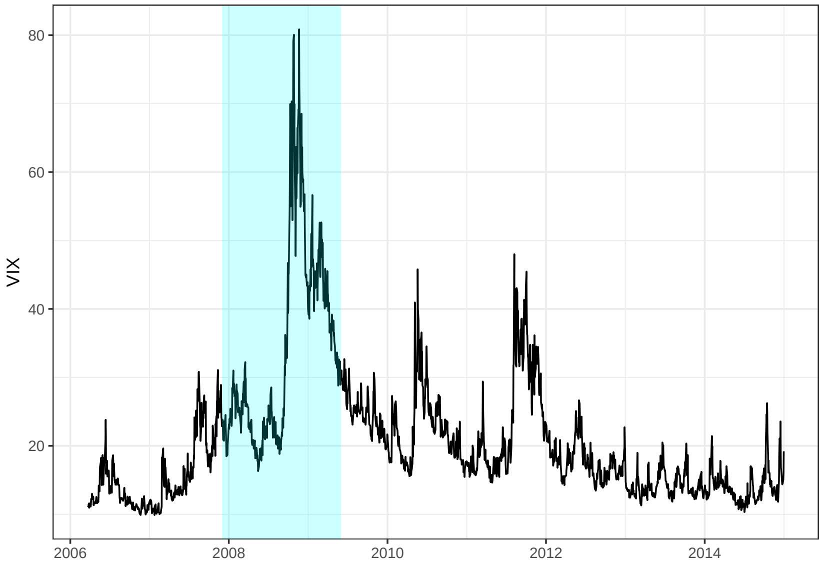


FIGURE 2 **Uncertainty measures**

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 February 2006 to December 2014. The cyan area highlights the US recession period running from December 2007 to June 2009 according to the classification of the National Bureau of Economic Research.

Panel (a)



Panel (b)

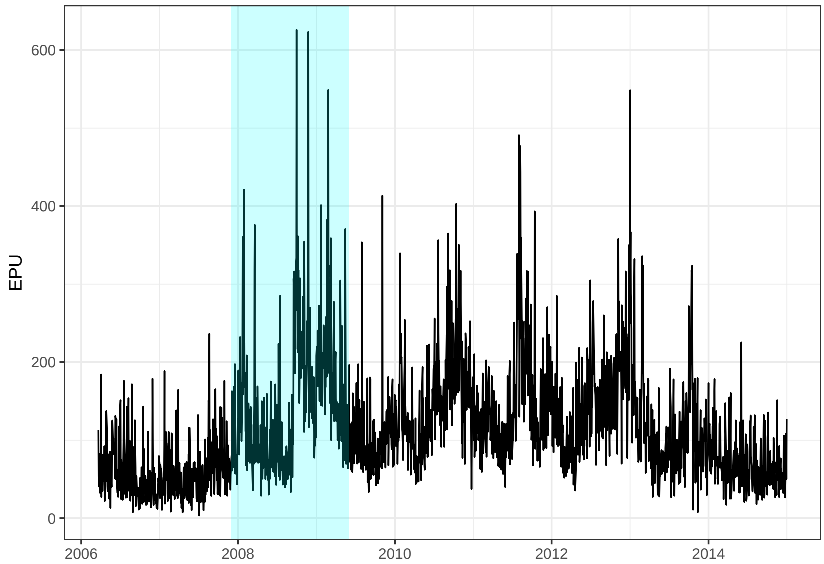


Figure 3 **Wavelets**

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 February 2006 to December 2014.

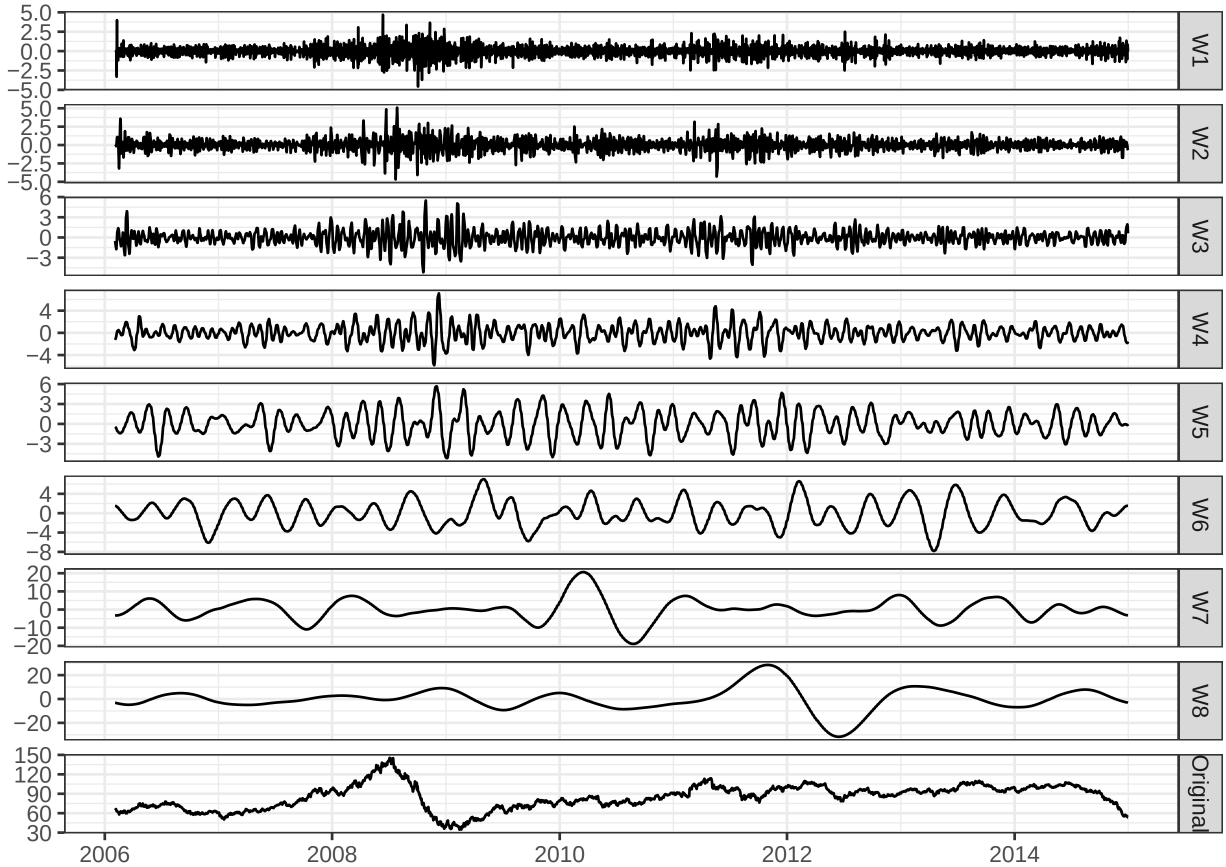
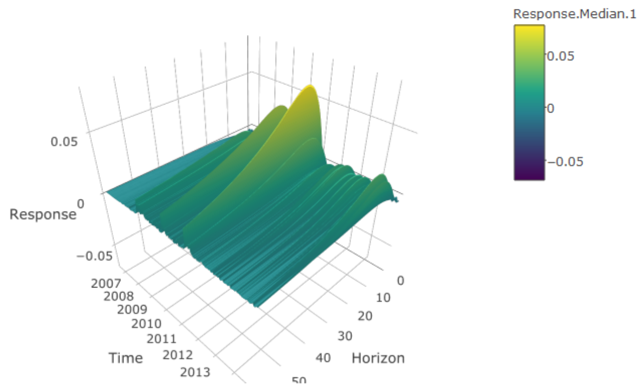


Figure 4 **Time-varying impulse responses for crude oil**

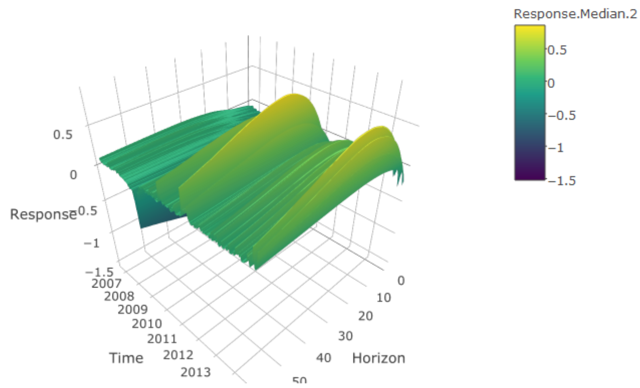
The plots show the time-varying reaction of two technical trading indicators (i.e. MACD Hist and RSI) of crude oil futures to a one unit shock of uncertainty. As measure of uncertainty we consider the CBOE volatility index of the S&P500 (VIX) and the US economic policy uncertainty (EPU) index following Baker *et al.* (2016). The corresponding reactions have been calculated for a sample period running from February 2006 to December 2014 on a daily basis while data for the first 80 days has been used as a training sample to initialize the coefficient priors.

Panel (a):

Response of MACD to a shock on VIX

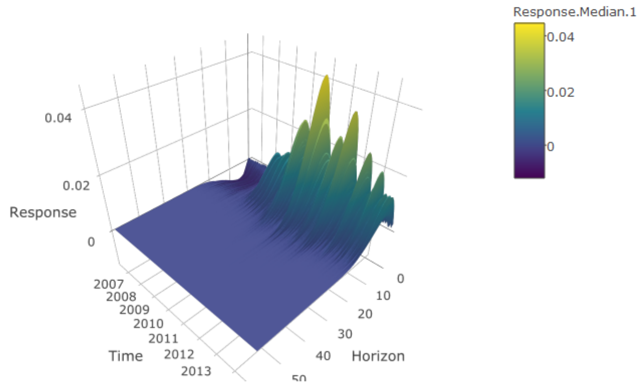


Response of RSI to a shock on VIX



Panel (b):

Response of MACD to a shock on EPU



Response of RSI to a shock on EPU

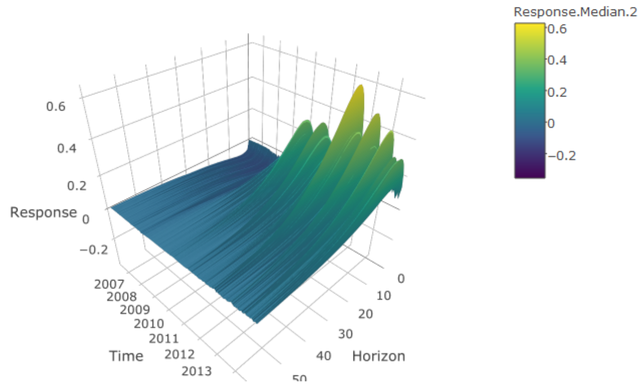


Figure 5 **Time-varying impulse responses for W1**

The plots show the time-varying reaction of the RSI for the first wavelet scale (W1) of crude oil futures (i.e. $y(\widetilde{D}_1)$) 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 February 2006 to December 2014 on a daily basis while data for the first 80 days has been used as a training sample to initialize the coefficient priors.

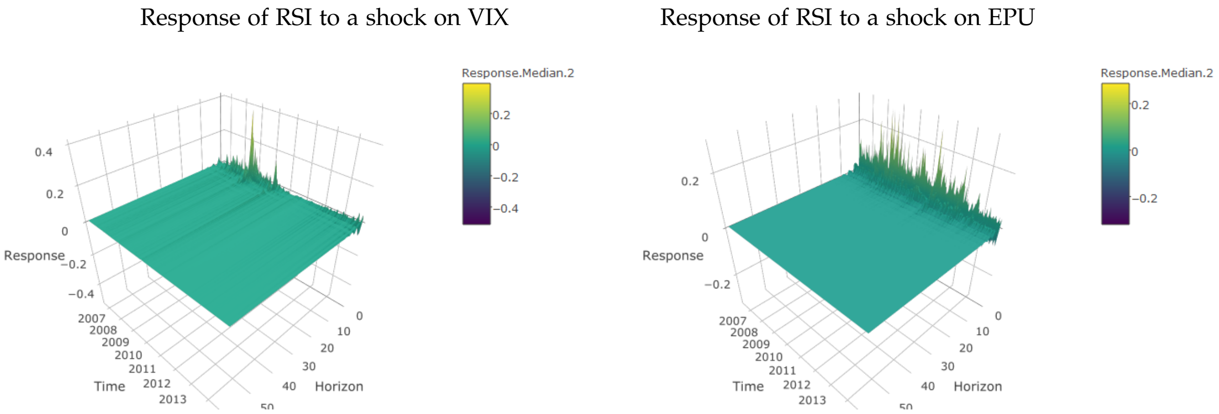


Figure 6 **Time-varying impulse responses for W2**

The plots show the time-varying reaction of the RSI for the second wavelet scale (W2) of crude oil futures (i.e. $y(\widetilde{D}_2)$) 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 February 2006 to December 2014 on a daily basis while data for the first 80 days has been used as a training sample to initialize the coefficient priors.

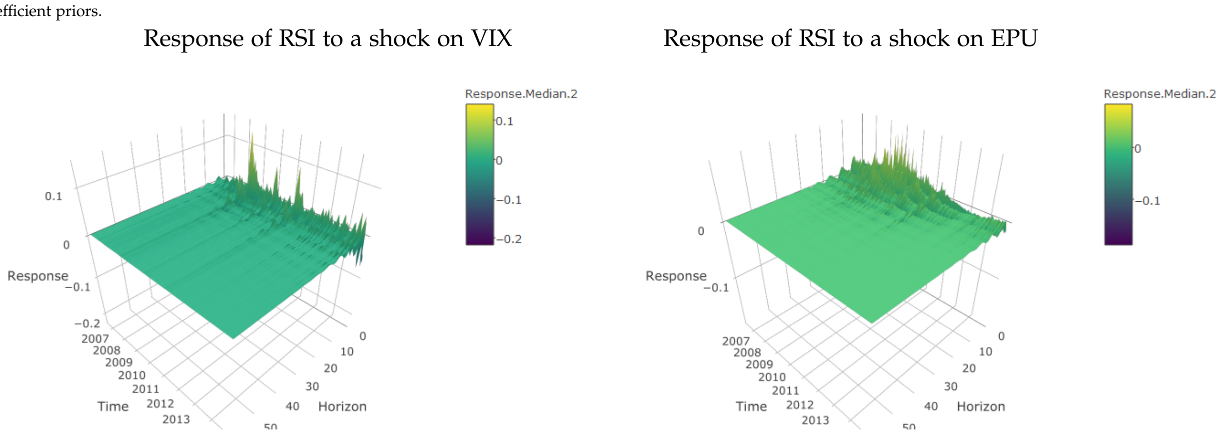


Figure 7 **Time-varying impulse responses for W3**

The plots show the time-varying reaction of the RSI for the third wavelet scale (W3) of crude oil futures (i.e. $y(\widetilde{D}_3)$) 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 February 2006 to December 2014 on a daily basis while data for the first 80 days has 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

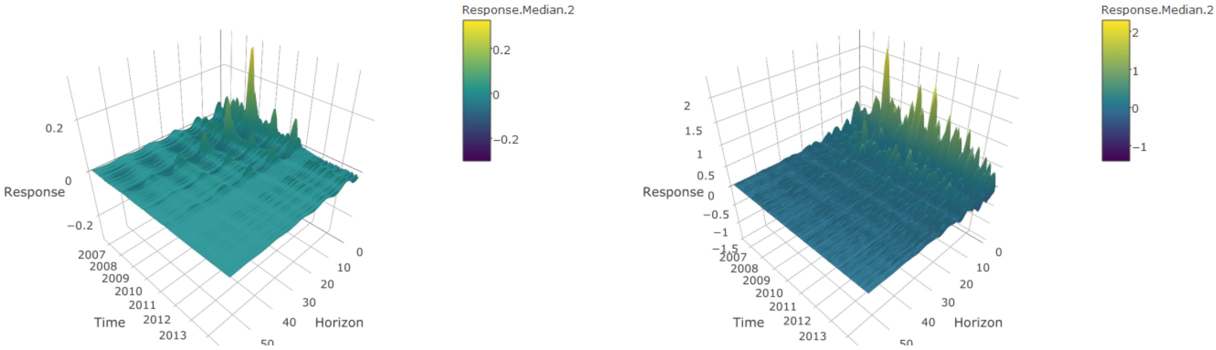


Figure 8 **Time-varying impulse responses for W4**

The plots show the time-varying reaction of the RSI for the fourth wavelet scale (W4) of crude oil futures (i.e. $y(\widetilde{D}_4)$) 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 February 2006 to December 2014 on a daily basis while data for the first 80 days has 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

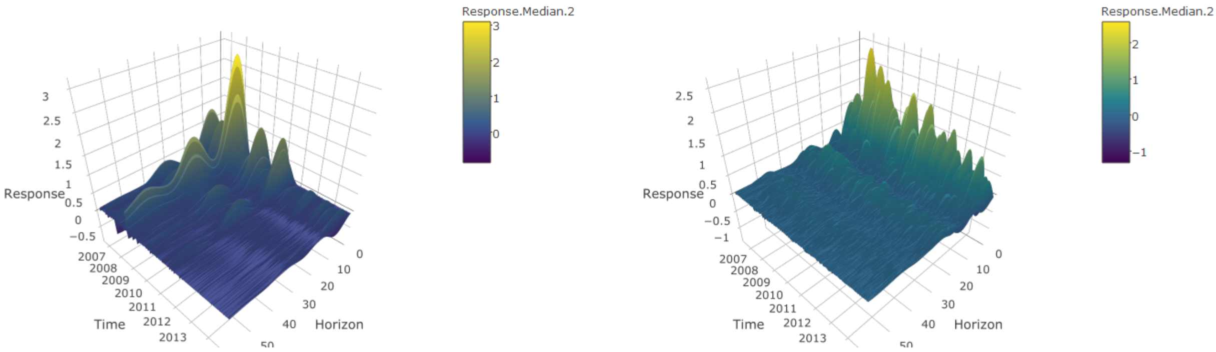


Figure 9 **Time-varying impulse responses for W5**

The plots show the time-varying reaction of the RSI for the fifth wavelet scale (W5) of crude oil futures (i.e. $y(\widetilde{D}_5)$) 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 February 2006 to December 2014 on a daily basis while data for the first 80 days has been used as a training sample to initialize the coefficient priors.

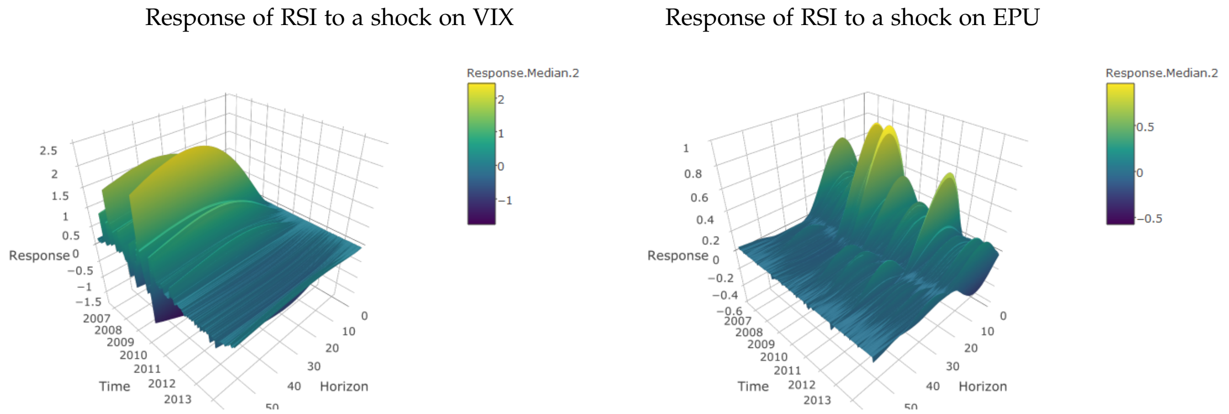


Figure 10 **Time-varying impulse responses for W6**

The plots show the time-varying reaction of the RSI for the sixth wavelet scale (W6) of crude oil futures (i.e. $y(\widetilde{D}_6)$) 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 February 2006 to December 2014 on a daily basis while data for the first 80 days has been used as a training sample to initialize the coefficient priors.

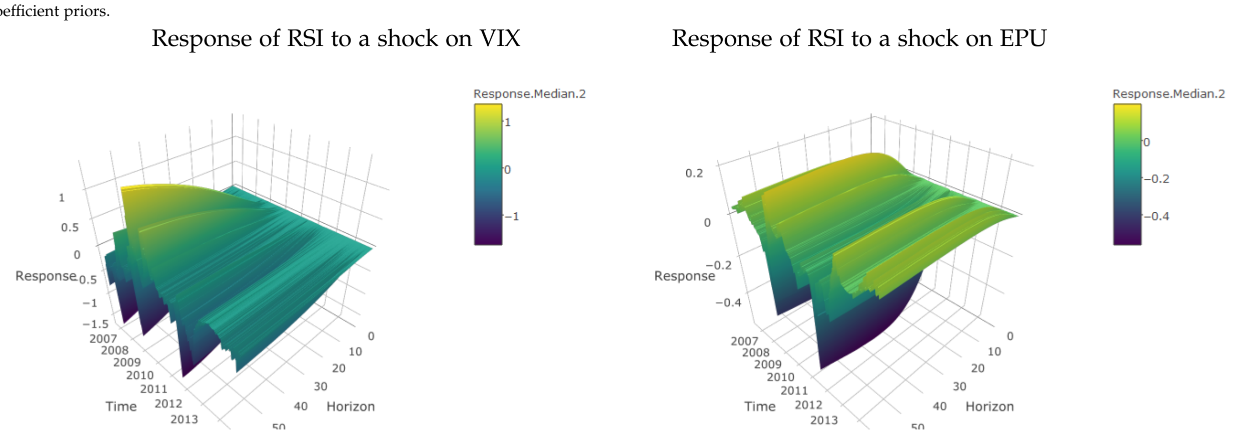


Figure 11 **Time-varying impulse responses for W7**

The plots show the time-varying reaction of the RSI for the seventh wavelet scale (W7) of crude oil futures (i.e. $y(\widetilde{D}_7)$) 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 February 2006 to December 2014 on a daily basis while data for the first 80 days has 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

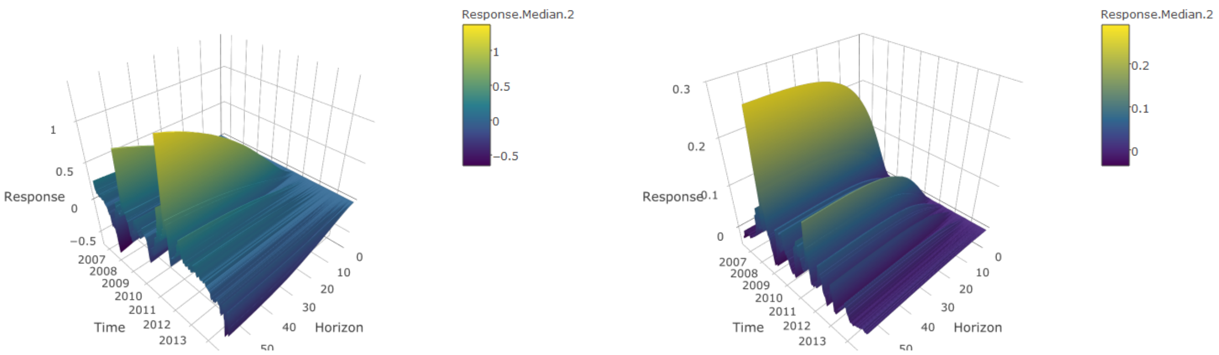


Figure 12 **Time-varying impulse responses for W8**

The plots show the time-varying reaction of the RSI for the eighth wavelet scale (W8) of crude oil futures (i.e. $y(\widetilde{D}_8)$) 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 February 2006 to December 2014 on a daily basis while data for the first 80 days has 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

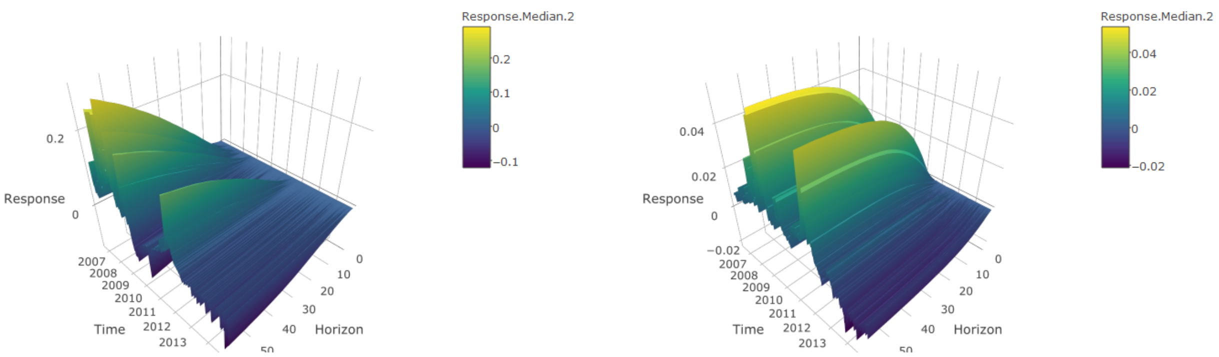


FIGURE 13 **Predictive density for trading indicators**

The plots show the predictive densities for out-of-sample forecasts of the last trading day in the sample period (i.e. December 31, 2014) for both trading indicators (i.e. MACD histogram and RSI) based on the VAR models including uncertainty measures. 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 solid black line represents the actual observation for the corresponding trading indicator and the dashed orange line its point forecast as the median of the predictive density.

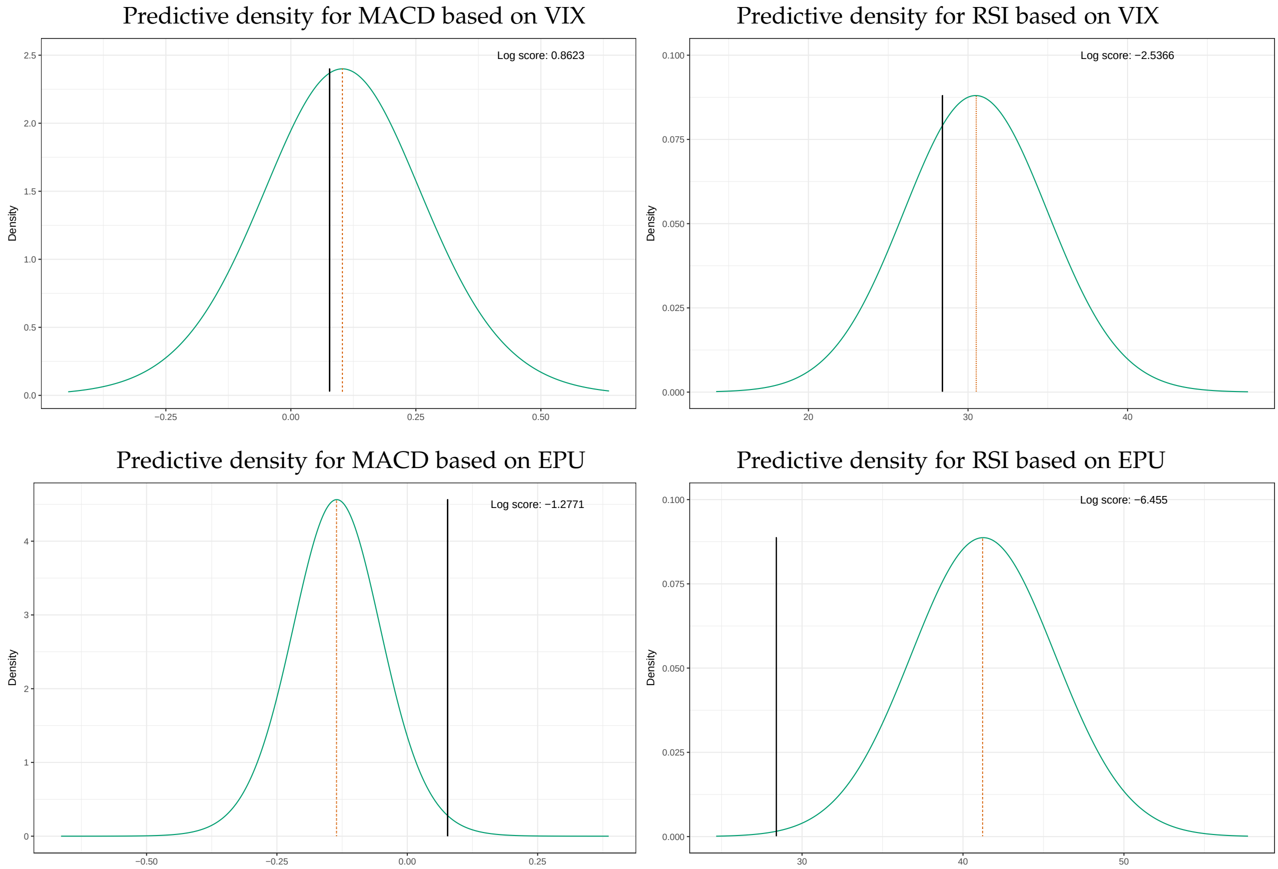
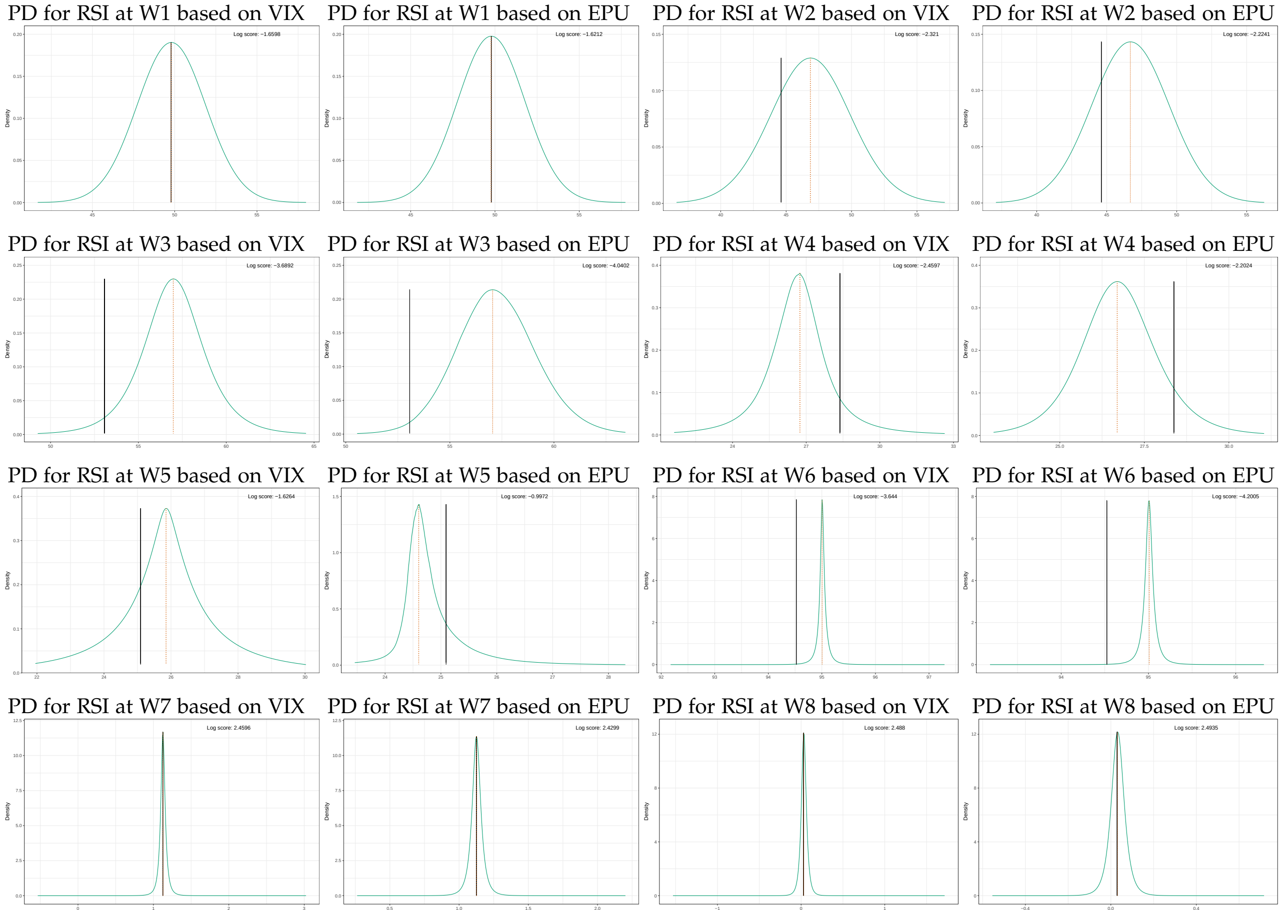


FIGURE 14 **Predictive density for individual wavelets**

The plots show the predictive densities (PD) for out-of-sample forecasts of the last trading day in the sample period (i.e. December 31, 2014) for the relative strength index (RSI) for each individual wavelet scale (i.e. W1, W2 etc.) based on the VAR models including uncertainty measures. 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 solid black line represents the actual observation for the corresponding trading indicator and the dashed orange line its point forecast as the median of the predictive density.



A. Appendix

A.1 MCMC algorithm

In the following we illustrate the Bayesian MCMC algorithm used to estimate the model described by Eqs. (13) to (16). The uninformative priors are given as follows

$$p(B_0) = N(\hat{B}_{OLS}, k_B \cdot \hat{V}(\hat{B}_{OLS})) \quad \text{with} \quad k_B = 4, \tag{18}$$

$$p(A_0) = N(\hat{A}_{OLS}, k_A \cdot \hat{V}(\hat{A}_{OLS})) \quad \text{with} \quad k_A = 4, \tag{19}$$

$$p(\log \varsigma_0) = N(\log \hat{\varsigma}_{OLS}, k_\varsigma \cdot I_2) \quad \text{with} \quad k_\varsigma = 1, \tag{20}$$

$$p(Q) = IW(k_Q^2 \cdot pQ \cdot \hat{V}(\hat{B}_{OLS}), pQ) \quad \text{with} \quad k_Q = 0.01, pQ = 80, \tag{21}$$

$$p(W) = IW(k_W^2 \cdot pW \cdot I_2, pW) \quad \text{with} \quad k_W = 0.01, pW = 3, \tag{22}$$

$$p(S) = IW(k_S^2 \cdot pS \cdot \hat{V}(\hat{A}_{OLS}), pS) \quad \text{with} \quad k_S = 0.01, pS = 2, \tag{23}$$

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,

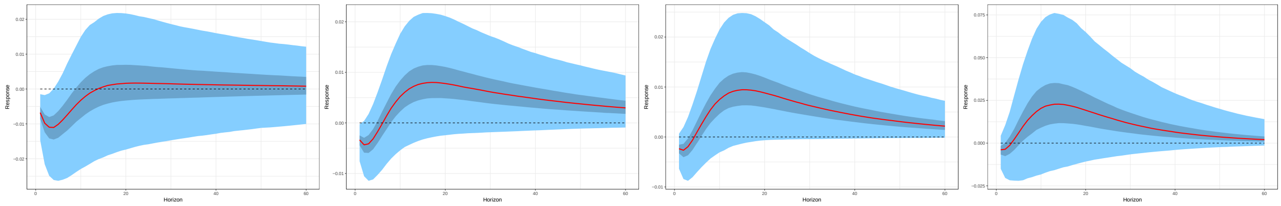
where s^T denotes the entire path of auxiliary discrete variables necessary to conduct inference on the volatilities given in Σ^T (Del Negro and Primiceri, 2015). ϑ is defined as $\vartheta = [B^T, A^T, V]$ and ϑ^{-B^T} means $\vartheta \setminus B^T$.

A.2 Time-varying impulse response functions

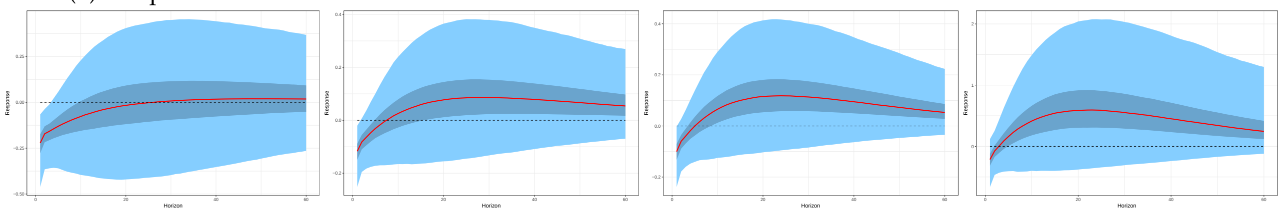
Figure A.2.1 **Impulse responses for the original series**

The plots show the time-varying reaction of the moving average convergence divergence histogram (MACD) and the relative strength index (RSI) to a one unit shock of uncertainty. As measure of uncertainty we consider the VIX and EPU index. The corresponding reactions are shown for four different points in time: 2008-01-02, 2010-01-04, 2012-01-03 and 2014-12-31. 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.

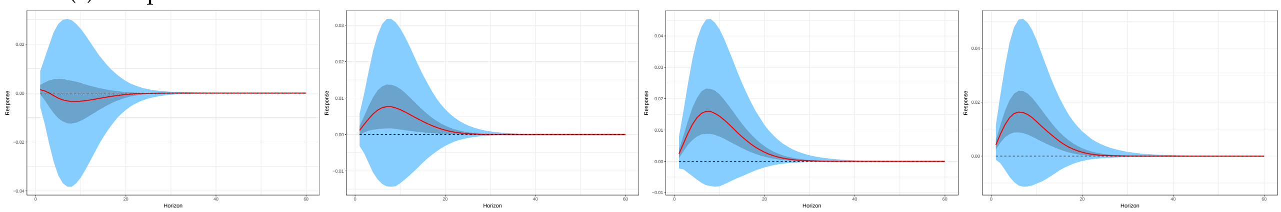
Panel (a): Response of MACD to a shock on VIX



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



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



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

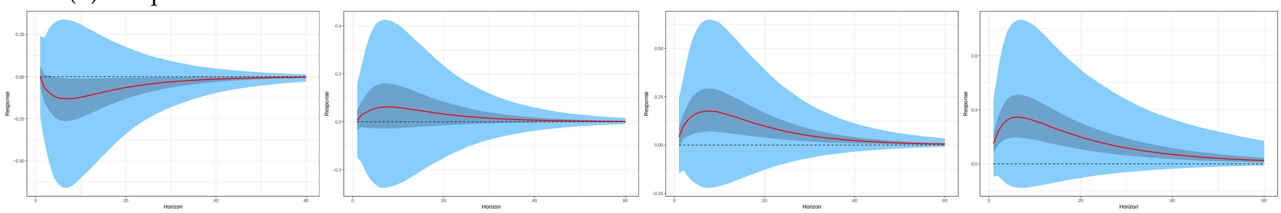
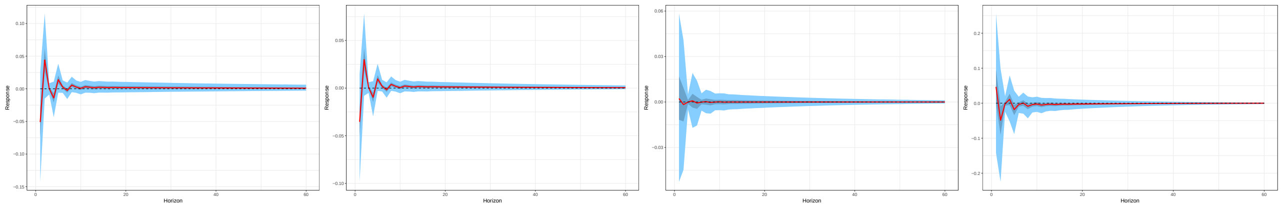


Figure A.2.2 **Impulse responses for W1**

The plots show the time-varying reaction of the relative strength index (RSI) to a one unit shock of uncertainty. As measure of uncertainty we consider the VIX and EPU index. The corresponding reactions are shown for four different points in time: 2008-01-02, 2010-01-04, 2012-01-03 and 2014-12-31. 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.

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



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

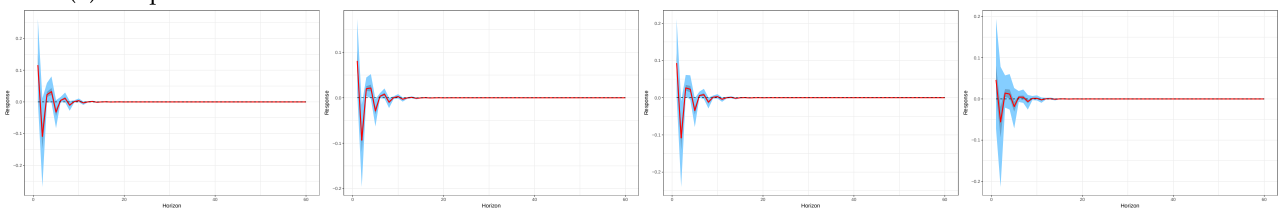
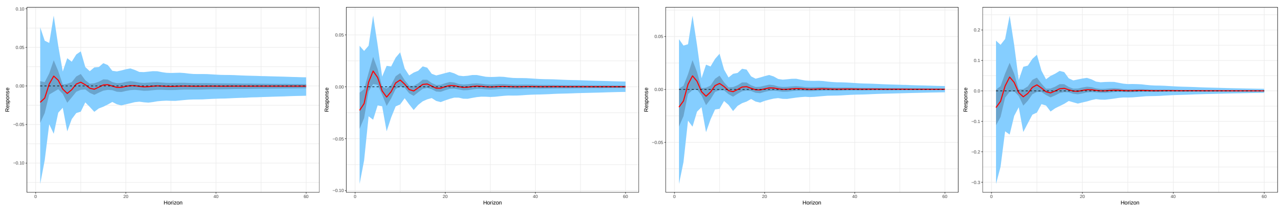


Figure A.2.3 **Impulse responses for W2**

The plots show the time-varying reaction of the relative strength index (RSI) to a one unit shock of uncertainty. As measure of uncertainty we consider the VIX and EPU index. The corresponding reactions are shown for four different points in time: 2008-01-02, 2010-01-04, 2012-01-03 and 2014-12-31. 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.

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



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

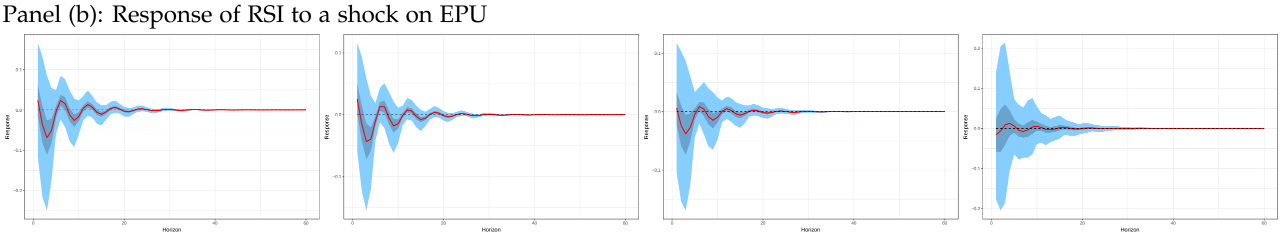
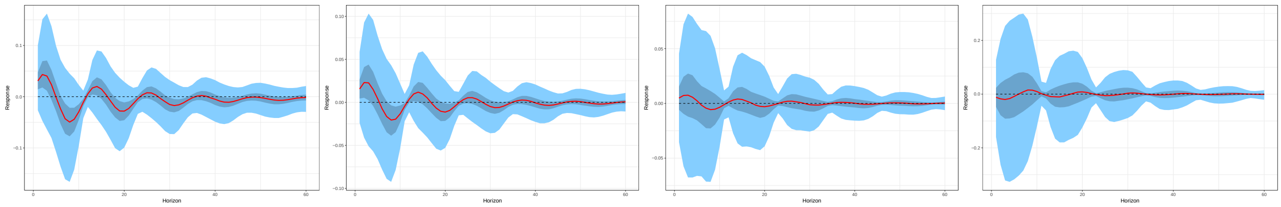


Figure A.2.4 **Impulse responses for W3**

The plots show the time-varying reaction of the relative strength index (RSI) to a one unit shock of uncertainty. As measure of uncertainty we consider the VIX and EPU index. The corresponding reactions are shown for four different points in time: 2008-01-02, 2010-01-04, 2012-01-03 and 2014-12-31. 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.

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



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

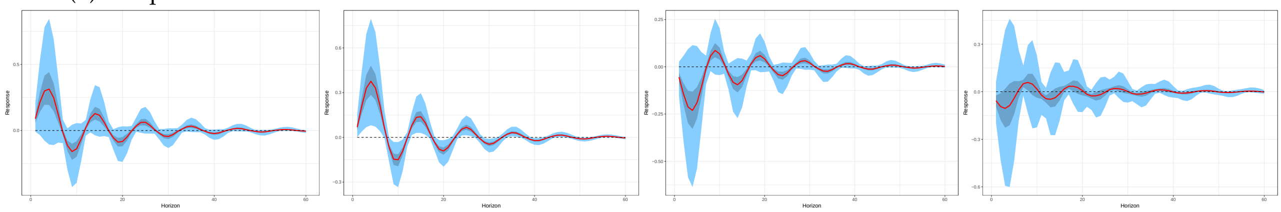
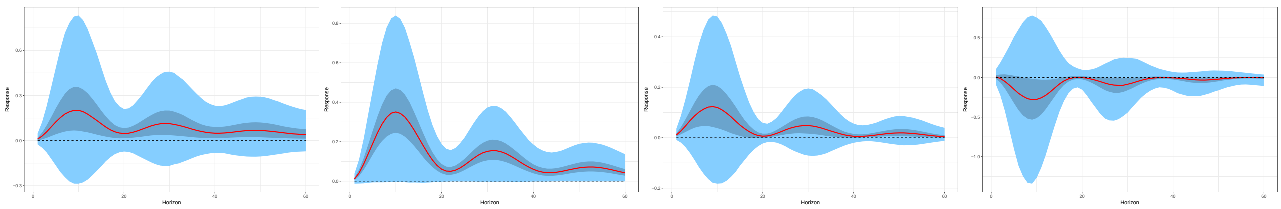


Figure A.2.5 **Impulse responses for W4**

The plots show the time-varying reaction of the relative strength index (RSI) to a one unit shock of uncertainty. As measure of uncertainty we consider the VIX and EPU index. The corresponding reactions are shown for four different points in time: 2008-01-02, 2010-01-04, 2012-01-03 and 2014-12-31. 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.

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



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

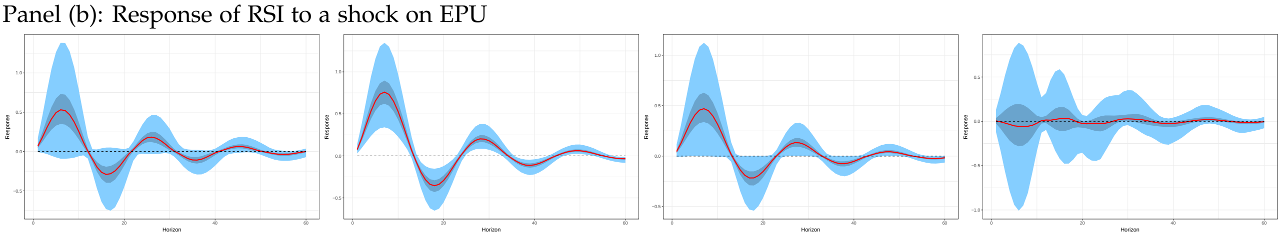
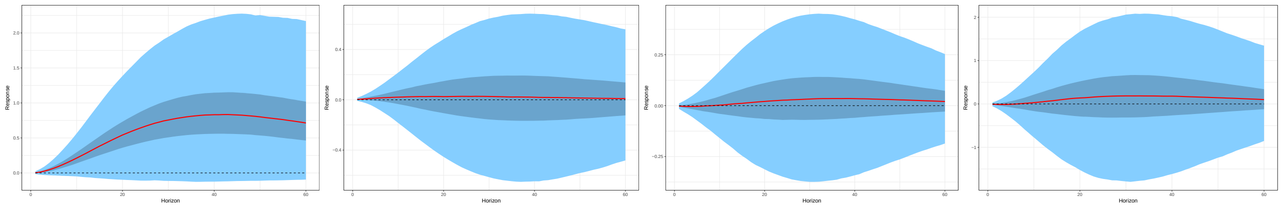


Figure A.2.6 **Impulse responses for W5**

The plots show the time-varying reaction of the relative strength index (RSI) to a one unit shock of uncertainty. As measure of uncertainty we consider the VIX and EPU index. The corresponding reactions are shown for four different points in time: 2008-01-02, 2010-01-04, 2012-01-03 and 2014-12-31. 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.

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



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

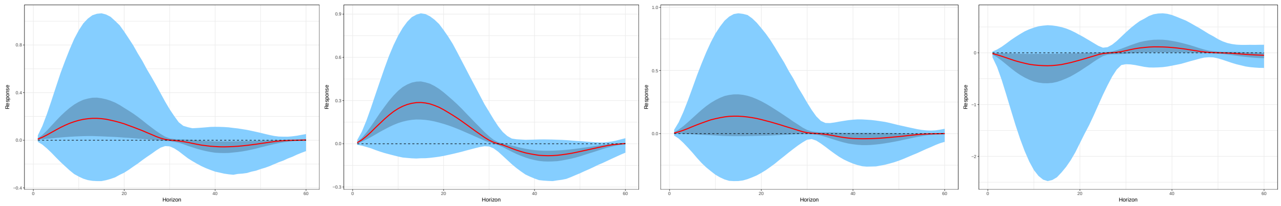
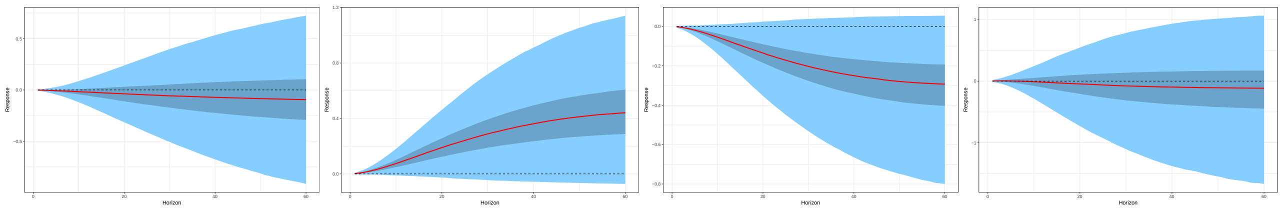


Figure A.2.7 **Impulse responses for W6**

The plots show the time-varying reaction of the relative strength index (RSI) to a one unit shock of uncertainty. As measure of uncertainty we consider the VIX and EPU index. The corresponding reactions are shown for four different points in time: 2008-01-02, 2010-01-04, 2012-01-03 and 2014-12-31. 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.

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



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

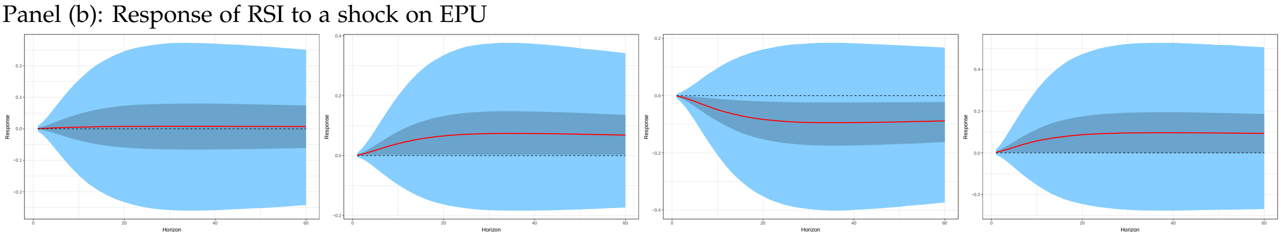
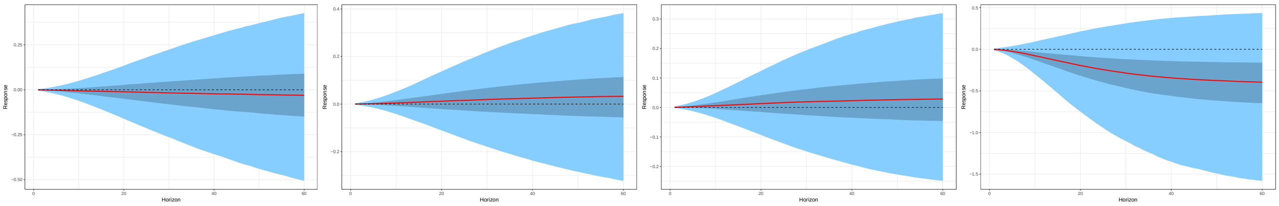


Figure A.2.8 **Impulse responses for W7**

The plots show the time-varying reaction of the relative strength index (RSI) to a one unit shock of uncertainty. As measure of uncertainty we consider the VIX and EPU index. The corresponding reactions are shown for four different points in time: 2008-01-02, 2010-01-04, 2012-01-03 and 2014-12-31. 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.

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



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

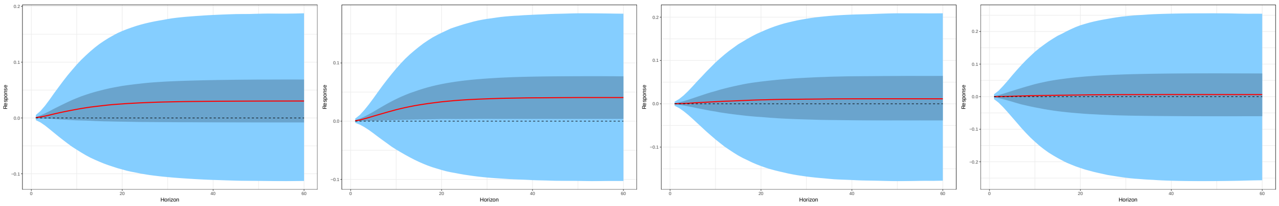
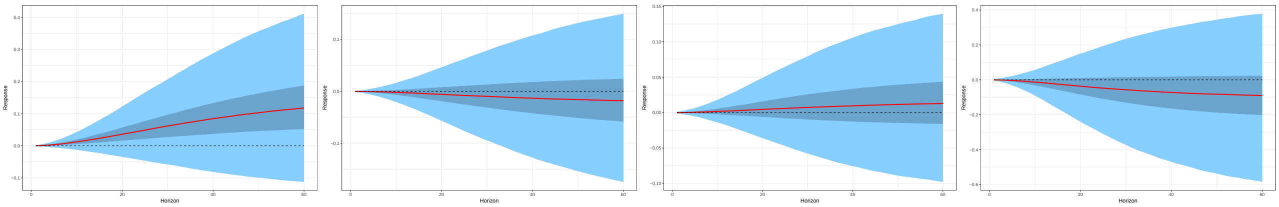


Figure A.2.9 **Impulse responses for W8**

The plots show the time-varying reaction of the relative strength index (RSI) to a one unit shock of uncertainty. As measure of uncertainty we consider the VIX and EPU index. The corresponding reactions are shown for four different points in time: 2008-01-02, 2010-01-04, 2012-01-03 and 2014-12-31. 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.

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



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