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Relevance of uncertainty on the volatility and trading volume in the US Treasury bond futures market

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February 23, 2015

Abstract

This paper studies the impact of uncertainty on the investors' reactions to news on macroeconomic statistics. With daily data on realized volatility and trading volume, we show that the investors in the US Treasury bond futures market react significantly stronger to US macroeconomic news in times of low macroeconomic, financial and political uncertainty. We also find that investors are more sensitive to the uncertainty in the financial market compared to the macroeconomic and political uncertainties. Our results might partly explain the sudden freeze and low liquidity in some financial markets during the latest financial crisis.

*email: helina.laakkonen@bof.fi, address: Bank of Finland, Department of Financial Markets and Statistics, P.o. Box 160, 00101 Helsinki. This work was started and mainly done when I was working as a post doc researcher at University of Helsinki, financed by the Finnish Foundation for Advancement of Securities Markets, the Okobank research foundation, Emil Aaltonen Foundation and Nordea Bank Foundation. The views presented in the article are those of the author and do not necessary reflect the views of the Bank of Finland.

1 Introduction

Investment choices are always made under uncertainty about the future value of an asset. Uncertainty comes from various sources, such as changes in asset's fundamentals, macroeconomic conditions, political decisions or unexpected events like financial crisis (Bloom, 2009; Kose and Terrones, 2012). In the traditional financial literature, uncertainty is typically modelled by assuming that investors act as if they knew the probability distribution of the possible future outcomes of the value of an asset. This kind of randomness with known odds, similar to one e.g. in the game of roulette, is called risk. However, often the randomness faced by investors is more likely to be such that the probability distribution is unknown. In this case the randomness refers to uncertainty about the data-generating process itself. In the literature, this type of randomness is called ambiguity or Knightian uncertainty after Knight (1921), who was the first to make a distinction between risk and uncertainty.

It is well known that investors dislike risk, but less acknowledged that they are also aversive to ambiguity. In his famous experimental study, Ellsberg (1961) demonstrated that people dislike situations in which they have to make decisions under ambiguity, and that their behavior may hence contradict the axioms of the expected utility theory (Ellsberg's paradox)[1]. Even though ambiguity aversion is not a new concept in finance, it has gained wider interest only recently, especially after the latest financial crisis. Now there exists various theoretical models that study the implications, such as nonparticipation, of ambiguity aversion on capital markets. See Guidolin and Rinaldi (2010) for a survey on the literature.

In traditional finance, trader is always either buyer or seller. Given his expectations on the value of on asset, if the market price is less than the value of an asset, he buys, and otherwise he (short) sells. For ambiguity aversive investor, however, the optimal decision with a given price might be not to trade at all. In the recent model of Easley and O'hara (2010), investors have incomplete preferences over portfolios due to high uncertainty caused by e.g. financial crisis. The lack of ability to rank all the portfolios leads to absence of trading - the investor changes his portfolio only if the trade improves his expected utility for every belief in the set of beliefs

[1] More recent portfolio choice experiments by Ahn (2008) and Bossaerts et al. (2010) also support the existence of ambiguity aversion in the behaviour of the investors.

representing his preferences[2]. Easley and O'hara (2010) propose that their model might explain the complete freeze observed in some markets during the financial crisis, such as the collateralized debt obligation (CDO) market and some stressed European sovereign debt markets (e.g. Greece).

While the theoretical literature on ambiguity aversion is voluminous, the growing literature on uncertainty and its impact on asset pricing has not generated much empirical research. In this paper, we study the link between uncertainty and trading volume empirically. In particular, we study the relevance of uncertainty on the effect of news announcements concerning 21 macroeconomic indicators on the volatility and trading volume of the 10Y US treasury note futures. We study whether the news announcements associated with higher uncertainty have different kind of effects on the trading volume than those with lower uncertainty. If the investors' aversion to ambiguity is causing non-trading as proposed by the model of Easley and O'hara (2010), macroeconomic announcements associated with higher uncertainty should cause less trading than those with lower uncertainty.

As discussed in the beginning of the paper, the sources of uncertainty vary greatly. In order to capture the different sources of uncertainty, we consider three different uncertainty measures that reflect macroeconomic, financial market and political uncertainties. Our measure of macroeconomic uncertainty is based on the degree of disagreement of professional forecasters of the macroeconomic figures. We assume that dispersed forecasts indicate higher level of uncertainty about the state of the economy and define the news announcement to be associated with low (high) macroeconomic uncertainty if the standard deviation of the individual forecasts is below (above) the sample average.

We measure financial market uncertainty by using the Chicago Board Options Exchange Volatility Index, i.e. VIX-index, which is constructed by using the implied

[2] Another, very common approach to model investors choice under ambiguity is to use maxmix expected utility, as proposed by Gilboa and Schmeidler (1989). In this case, investor has many prior probability distributions on different future outcomes of an asset value, instead of only one. Because of his dislike to ambiguity, he chooses to act according to a worst case scenario, i.e. he maximizes the minimum expected utility across different possible outcomes. Nonparticipation arises when the investor ends up selecting the safe asset over the asset with ambiguous future value. This approach has been used e.g. Dow and Werland (1992) and Easley and O'Hara (2009) and it has been suggested to explain e.g. why large fraction of people select not to participate the stock market in general (Easley and O'Hara, 2009), as well as flight-to-safety phenomenon during the financial crisis (Caballero and Krishnamurthy, 2008).

volatility of the S&P 500 index options with different strikes. VIX-index reflects the expected movement in the S&P 500 index over the next 30-day period and is widely used in the financial market as an index of market sentiment or fear. Higher values of the index reflect higher uncertainty in the financial market. Hence, we define the macroeconomic news announcement to be associated with low (high) financial market uncertainty if they are announced on the day when the level of VIX index is lower (higher) than its sample average.

Our third measure of uncertainty captures the economic uncertainty caused by political decision making, such that could arise as a consequence e.g. from the political debates over the US debt ceiling. As a measure of political uncertainty, we use a daily index on US policy-rated economic uncertainty provided by Baker, Bloom and Davis (2013). As the same as with the VIX index, we define the macroeconomic news announcement to be associated with low (high) political uncertainty if they are announced on the day when the level of political uncertainty index is lower (higher) than its average over the entire sample period.

Our results show that investors react statistically significantly stronger to the news announcements that are associated with lower uncertainty, regardless of the used measure of uncertainty. With all three uncertainty measures, the news announcements that are associated with lower uncertainty increase the volatility and volume of trade of the 10Y US treasury note futures statistically significantly more than announcements with higher uncertainty. Hence, our results support the theoretical model of Easley and O'hara (2010), which suggest that ambiguity aversive investors might find it optimal not to trade at situations when uncertainty prevents them to make a decision between different portfolios.

The plan of the paper is as follows. Section 2 describes the data and the Fractionally Integrated AR model, which is used for estimating the long memory properties of the realized volatility and volume series. Section 3 presents the different measures of uncertainty and the estimation results. Section 4 concludes.

2 Data and the ARFIMA model

In this section we first describe the treasure bond future data and the fractionally integrated autoregressive model that is used to model the daily realized volatility and volume of the bond data. We then describe the data on macroeconomic announcements and present the measures that are used to define the level of macroeconomic and financial uncertainty.

2.1 Treasury note futures data

We chose to study the relevance of uncertainty in the effect of macroeconomics announcements in the US Treasury bond market, because it is one of the largest and most active financial markets in the world. Also, during the last two decades, the empirical literature examining the impact of macroeconomic news on financial market dynamics has discovered that the releases of news concerning macroeconomic fundamentals like gross domestic product and unemployment cause a jump in the returns and significantly increases the volatility of returns and that the reactions to macroeconomic announcements are strongest in the treasury bond market (Andersen et al. 2007). According to Bollerslev et al. (2000), Treasury bond market is not affected by any asset-specific information like the assets in other financial markets, and hence the treasury bond markets are more strongly linked to the state of the economy.

Our original data set[3] contains the transaction prices and the number of trades of the 10Y US Treasury bond futures traded in the Chicago Board of Trade stamped at five minute frequency from January 2004 to December 2009. We select to use only the regular trading hours of CBOT, namely 08:20 to 15:00 EST, and hence have a total of 81 5-minute transaction prices for each trading. We use the daily transaction prices to compute 5-minute intraday returns as the differences of logarithmic prices, resulting a total of 80 5-minute returns[4] for each trading days and use the 5-minute intraday returns to compute the daily realized variance RV_t (Andersen and Bollerslev, 1997) by summing up the squared intraday returns as

[3] The data was obtained from Olsen data.

[4] According to many studies, five-minute returns strike the best balance between the disadvantages of microstructure noise (when sampling too frequently) and the loss of important information (when sampling too infrequently). For a discussion, see Andersen et al. (2007).

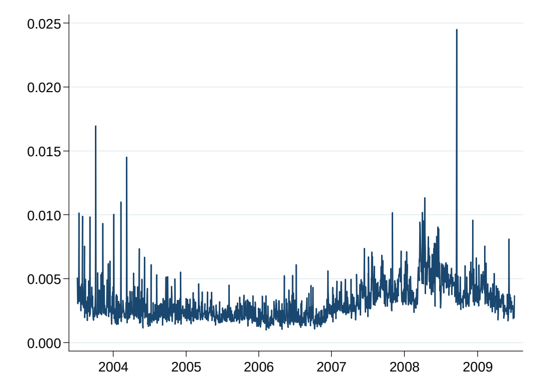
$$RV_t = \sum_{i=1}^{m} r_{t,i}^2$$

where $r_{t,i}$ are 5-minute intraday i returns within a day t. Finally, we define the realized volatility as the square root of realized variance $RV_t^{1/2}$.

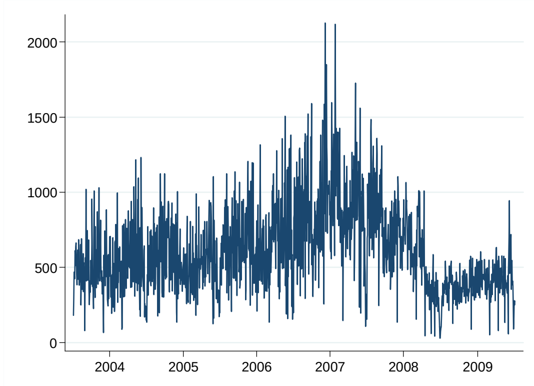
As we now have a daily time series of realized volatility, we also need to transform the intraday volume of trade data to daily frequency. This we do simply by summing up the intraday number of trades to obtain the daily number of trades as $VOL_t = \sum_{i=1}^{m} VOL_{t,i}$. Figure 1 presents the time series of the daily realized volatility and volume with the total of 1501 observations. It can be seen that the level of volatility has increased after the financial crisis started in 2007, although large spikes in volatility can be observed also in the early phase of the data. The largest spike in volatility was observed in 18 March 2009, when the Federal Open Market Committee (FOMC) announced the decision to purchase an additional $750 billion of agency mortgage-backed securities (as well as some other asset purchases) in order to improve the conditions in the financial market, where the crisis had started to escalate after the bankruptcy of Lehman Brothers in September 2008. It is also clear that the financial crisis affected strongly to the trading volumes of US treasury note futures. It can be seen from the figure, that the trading volumes started to decline in 2007 and stayed exceptionally low during the rest of the data set until the end of 2009.

Figure 1 10Y US Treasury note future data

realized volatility



volume (1000s)



The figures present the daily realized volatility (left figure) and the number of trades (right figure) of the 10Y US Treasury note futures from January 2004 to December 2009.

Table 1 presents the key statistics for the daily realized volatility as well as volume series. As can be seen, both of the series are highly non-normal with leptokurtic and skewed distribution. The logarithmic realized volatility is a lot closer to normal distribution, as was also pointed out by Andersen et al. (2001) in the case of the realized volatility of foreign exchange returns.

Table 1 Key statistical figures

Table presents the key statistical figures for the daily realized volatility RV_t, logarithmic realized volatility $ln(RV_t)$, volume of trade (number of transactions) VOL_t and the logarithmic volume of trade $ln(VOL_t)$ of the 10Y US Treasury note futures from 2004 to 2009.

	RV_t	$ln(RV_t)$	VOL_t	$ln(VOL_t)$
Mean	0.003	−5.85	611.2	6.30
Standard deviation	0.002	0.43	287.5	0.52
Skewness	3.23	0.49	0.98	−0.97
Kurtosis	28.46	3.34	4.51	5.99
Minimum	0.001	−6.92	29	3.37
Maximum	0.025	−3.71	2125	7.67

Figure 2 presents the autocorrelograms for the logarithmic realized volatility and volume series. It can be seen that the autocorrelations are decreasing very slowly, a lot more slowly as would be expected in the case of standard ARMA models. Hence, we follow Andersen et al (2003) and use a fractionally integrated autoregressive model in order to account for the long memory properties of realized volatility.

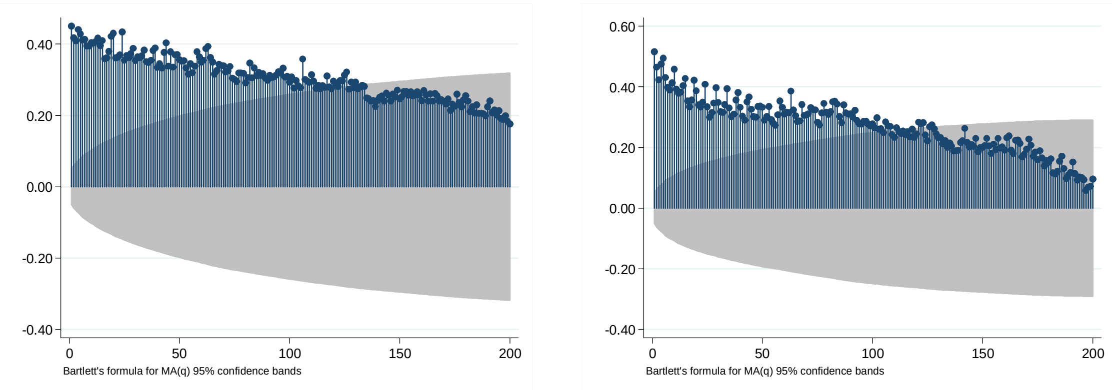
The fractionally integrated ARMA model (ARFIMA) is given by

$$\begin{aligned}
(1-L)^d y_t &= \alpha + \gamma X_t + u_t \qquad (1)\\
u_t &= \frac{\Theta(L)}{\Phi(L)}\epsilon_t \\
\Theta(L) &= 1 + \theta_1 L + ... + \theta_q L^q \\
\Phi(L) &= 1 - \phi_1 L - ... - \phi_p L^p \\
\epsilon_t &\sim N(0, \sigma^2)
\end{aligned}$$

where $y_t = \ln(RV_t^{1/2})$ in the case of the volatility model and $\ln(VOL_t)$ in the case of the trading volume model, d is a long memory fractional integration parameter, α is constant, γ is a vector of regression parameters for explanatory variables X_t, σ^2 is variance (showing variation in realized volatility), $\Theta(L)$ and $\Phi(L)$ are p-th order and q-th order polynomials in the backward shift (lag) operator L, respectively. Brockwell and Davis (1987) state that, when $p = q = 0$, $\{y_t\}$ is a covariance stationary process if $-0.5 < d < 0.5$. If $0 < d < 1$ the ARFIMA model is called a long memory process.

Figure 2 Autocorrelation coefficients

realized volatility volume



The figure presents the autocorrelation coefficients (200 lags) of daily realized volatility (left figure) and volume (right figure) of the 10Y US Treasury note futures.

2.2 Macroeconomic Announcement Data

The macroeconomic news data set includes the scheduled releases of 21 US macroeconomic indicators from the years 2004-2009 published in the Bloomberg World Economic Calendar (WECO). Table 2 presents the number of the releases of different macro indicators in our data set. Most of the indicators are released once a month, but some of them more rarely than monthly (such as gross domestic product or FOMC rate decision), and one of them weekly (initial jobless claims). The data comprise the announcement date and time to an accuracy of one minute, the released estimate of the present month's figure of a macro indicator k $(k = 1, 2, ..., 21)$, denoted as $A_{t,k}$, and the market forecast for each released figure, denoted as $F_{t,k}$. The market forecast is the median of the all individual survey forecasts that Bloomberg collects from the market agents. Besides the median forecast, our data includes all the individual forecasts from different market agents for each figure, denoted as $F_{t,k,i}$. These individual forecasts are used in determining the level of macroeconomic uncertainty in the economy. The different ways of defining uncertainty are described more carefully in the next subsection.

Table 2 Number of announcements

Indicator	Announcements
Advance Retail Sales	72
Change in Nonfarm Payrolls	72
Consumer Confidence Index	72
Consumer Price Index	72
Durable Goods Orders	72
Existing Home Sales	60
Factory Orders	72
FOMC Rate Decision	51
Gross Domestic Product	24
Housing Starts	72
Industrial production	72
Initial Jobless Claims	313
ISM Manufacturing Index	72
Leading Indicators Index	72
New Home Sales	72
Personal Income	72
Personal Spending	72
Producer Price Index	72
Trade Balance	72
University of Michigan Consumer Confidence Index	72
Unemployment rate	72

2.3 Measuring uncertainty

One of the most challenging parts in the empirical studies on ambiguity aversion is to measure uncertainty. As discussed in the Introduction, the sources of uncertainty vary greatly. Hence, we consider three different types of uncertainty: uncertainty related to future state of the economy, uncertainty in the financial markets and political uncertainty.

One of the most often used uncertainty measures is the dispersion of the market participants' forecasts or opinions on the statistics of a firm or country. As an example, the more the market participants disagree on the next GDP growth figure, the higher is the uncertainty related to the economic growth. This kind of measure of uncertainty has been used e.g. in Zhang (2006), Barron et al. (2009) and Anderson et al. (2009). Huisman et al. (2011) also consider the dispersion in expectations as a measure of uncertainty. But different from the others, they set up a unique survey measuring investors' expected returns and volatilities. While the average of the individual's expected variance represents risk, the dispersion in individuals' expected return is used as a measure of uncertainty.

As Huisman et al. (2011), we also assume that the increased uncertainty about the future state of the economy will show in increased degree of disagreement among the professional forecasters of the macroeconomic figures and hence high standard deviation of the individual forecasts of a macroeconomic release indicates high uncertainty. Hence, we create two dummy variables $D_t^{low\_m}$ and $D_t^{high\_m}$, which take on value 1 if the standard deviation of the individual forecasts $F_{t,k,i}$ for a macroeconomic release $A_{t,k}$, denoted as $\hat{\sigma}_{t,k}$, is lower or higher than the sample mean of the standard deviations $\bar{\sigma}_k$ over the entire sample period, respectively, and 0 otherwise.

We use these two dummy variables to categorize the macroeconomic news releases $A_{t,k}$ to those released in the times of high and low macroeconomic uncertainty. First, we create a news variable $N_{t,k}$ that gets a value of 1 if there is a macroeconomic statistics of indicator k released at day t, and 0 otherwise. We then multiply the news variables with the dummy variables as $N_{t,k} \times D_t^{low\_m}$ and $N_{t,k} \times D_t^{high\_m}$, respectively. Finally we combine the releases of different macroeconomic indicators k to two news variables $N_t^{low\_m}$ and $N_t^{high\_m}$, that get a value of 1 if $N_{t,k} \times D_t^{low\_m}$ or $N_{t,k} \times D_t^{high\_m}$ get value of one, respectively, and zero otherwise. It is possible that at some days there might be more than one news release, and therefore it is possible that both $N_t^{low\_m}$ and $N_t^{high\_m}$ get value of 1 at the same day. It is also possible that on some days there are more than one news announcements that are classified either high or low uncertainty. In these cases the news announcements are treated as one. Altogether there are news releases classified as 'low macroeconomic uncertainty' in 728 days and 536 days when news announcements are classified as high macroeconomic uncertainty.

While our first uncertainty measure is linked to the uncertainty about the macroeconomic growth, our second definition of uncertainty is rather linked to the uncertainty among investors in the global financial market. For defining the level of uncertainty in the financial market, we use the Chicago Board Options Exchange Volatility Index, also know has the VIX index, which is probably the most common used measure of uncertainty, risk sentiment or fear in the financial market[5] (see Bird and Yeung, 2000; Bloom, 2009; Carr and Wu, 2009; Drechsler and Yaron, 201; Eraker, 2004 and Williams, 2009). The VIX index is constructed using the implied volatility of the S&P 500 index options and it measures the expected future stock market volatility for the next 30 days. It is expected that a high expected volatility corresponds to a high level of uncertainty in the market.

VIX index has also been used as a measure of uncertainty in the studies that are very similar to ours. Williams (2009) and Bird and Yeung (2012) both examine the asymmetries in news effects caused by ambiguous information. They study the role of uncertainty in responses of stock market participants to firm-specific information releases. They both use changes in VIX-index to capture changes in uncertainty and document that following increases (decreases) in VIX, investors respond asymmetrically (symmetrically), weighting bad earnings news more than (the same as) good earning news.

Our third measure of uncertainty captures the economic uncertainty caused by political decision making, such that could arise as a consequence e.g. from the recent political debates over the US debt ceiling. As a measure of political uncertainty, we use an index on economic political uncertainty, denoted as PU_t provided by Baker,

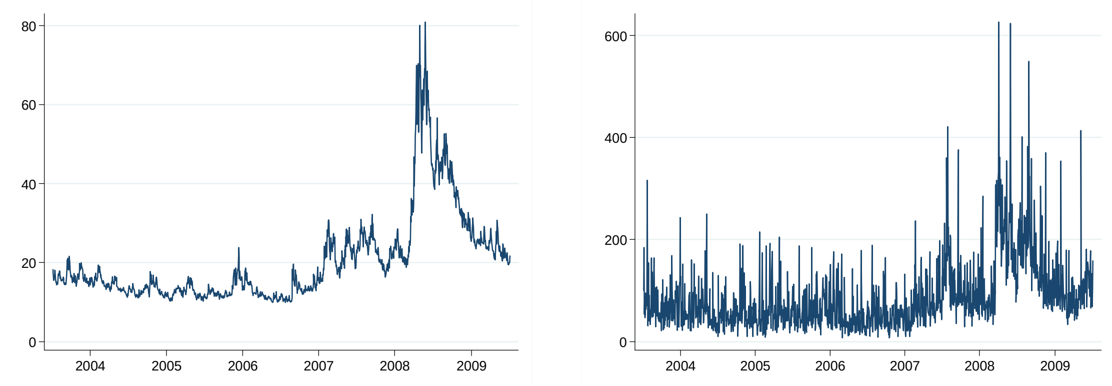
[5] Drechsler (2013) shows that the level of the VIX index and the dispersion of the individual macroeconomic forecasts are highly correlated. This also supports the interpretation of the VIX index as an uncertainty measure.

Bloom and Davis (2013). Their index is constructed daily for several countries as a combination of three components: the newspaper coverage of policy uncertainty related news, the number of federal tax code provisions that are set to expire in future years, and the disagreement among economic forecasters about policy-related macroeconomic variables.

Figure 3 presents the VIX and the political uncertainty indices for our sample period 2004-2009. It can be seen that the VIX index reacts very strongly to the financial crises. The level of the index increases already in 2007 and jumps very significantly after the collapse of the Lehman Brothers in autumn 2008. The political uncertainty index shows a very similar pattern to that of VIX index. Their correlation is quite high, 0.6537, which means that they are likely to reflect partly the uncertainties from the same sources.

Figure 3 Financial market and political uncertainty

VIX index | Political uncertainty index



The figure presents the Chicago Board Options Exchange Volatility Index (VIX) (left figure) and the policy uncertainty index by Baker etl al. (2013) (right figure).

We use the VIX index for creating two dummy variables $D_t^{low\_f}$ and $D_t^{high\_f}$, which take on value 1 if the level of the VIX index, denoted as VIX_t, is lower or higher than its sample mean over the entire sample period $\overline{VIX}$, respectively, and 0 otherwise. We then create a news variable N_t that gets a value of 1 if there is a macroeconomic statistics (of any indicator k) released at day t, and 0 otherwise and finally divide the news releases to those announced at the times of low ($N_t^{low\_f}$) and high ($N_t^{high\_f}$) financial market uncertainty by multiplying the news variable N_t with the dummy variables as $N_t \times D_t^{low\_f}$ and $N_t \times D_t^{high\_f}$, respectively. Altogether there are 628 days when news are announced at times of low financial market uncertainty and 276 macroeconomic news announcements released at time of high uncertainty in the financial markets. The same procedure as for VIX index is done for the policy uncertainty index to divide the macroeconomic news N_t to those announced at times of low ($N_t^{low\_p}$) and high ($N_t^{high\_p}$) political uncertainty. The number of days in these two categories are 653 and 531, respectively.

3 Empirical results

In this section, we present the empirical results on the relevance of uncertainty in the impact of macroeconomic news on 10Y US treasury note future volatility and trading volume. As discussed in the previous section, we consider three types of uncertainty: the macroeconomic uncertainty measured by the dispersion of the individual forecasts of the macroeconomic statistics, financial market uncertainty which level is based on the level of the VIX index and the policy uncertainty measured by the policy uncertainty index by Baker et al. (2013). We begin by finding a proper ARFIMA model to capture the time series properties of the realized volatility and volume series, and then proceed to study the relevance of uncertainty on the macroeconomic news effects.

3.1 ARFIMA model

We start by finding a proper $ARFIMA(p, d, q)$ model for the $ln(RV_t^{1/2})$ and the $ln(VOL_t)$ series. We estimate the model (1) for both of these series separately. At this point we do not divide the macroeconomic news to different categories based on uncertainty, but instead have only one news variable to control for the effect of the macroeconomic news N_t. We consider all possible combinations between the $ARFIMA(0, d, 0)$ model with no autocorrelation and moving average components and $ARFIMA(1, d, 1)$ model with one lag for both autoregressive and moving average parts[6].

We find that for both of the series $ARFIMA(1, d, 0)$ seems to be appropriate in

[6] We also control for the weekday effects, because if some of the weekdays are more active than others (e.g. Monday and Friday) in terms of trading activity, it might cause some periodicity and hence autocorrelation in the volatility and volume dynamics.

terms of being the most parsimonious specification after which there are no systematic autocorrelation left in the residuals. However, the residuals are not normally distributed and the white noise test is rejecting for the squared residuals when more than 20 lags are included in the test. Hence, there seems to be some heteroskedasticity left in the residuals. Therefore, we use the White's robust standard errors in all the model specifications.

The estimated parameter values for the model (1) are presented in the third column of Tables 4 and 5 for volatility and volume, respectively. For both volatility and volume, the first order autocorrelation coefficient ϕ_1 is negative and statistically significant. The autocorrelation is stronger in the case of volatility compared to volume. The estimated fractional integration parameter d is 0.411 for $ln(RV_t^{1/2})$ and a little bit less, 0.381, for $ln(VOL_t)$ The lower degree of persistence in the $ln(VOL_t)$ is quite expected, because the faster degree of decline of autocorrelation functions could also be depicted in Figure 2. Macroeconomic news announcements increase volatility and volume significantly: the news variable coefficient γ is positive and significant for both volatility and volume, as expected.

3.2 The effect of uncertainty

Next, we study whether investors react differently to announced macroeconomic news depending on the level of macroeconomic, financial and political uncertainty. We begin with the macroeconomic uncertainty. To examine the relevance of macroeconomic uncertainty on the announcement effects, we consider the following $ARFIMA(1, d, 0)$ model that now includes two macroeconomic news variables: macroeconomic news associated with low $N_t^{low\_m}$ and and $N_t^{high\_m}$ macroeconomic uncertainty:

$$(1 - \phi_1 L)(1 - L)^d \left(y_t - \alpha - \gamma^{low\_m} N_t^{low\_m} - \gamma^{high\_m} N_t^{high\_m} \right) = \varepsilon_t \qquad (2)$$

where $y_{t,n} = ln(RV_t^{1/2})$ when we examine the news effects on volatility and $ln(VOL_t)$ when we study the impact of news on volume. The results of the model (2) are presented in the fourth column of Table 4 and 5 for volatility and volume, respectively. The macroeconomic statistics for which the forecast dispersion was lower than average, and which are hence associated with the low macroeconomic uncertainty increase both volatility and volume of the US treasury note futures significantly more than those which are associated with high macroeconomic uncertainty (p-values of the Wald tests for the equality of the coefficients are 0.011 and 0.049 for volatility and volume, respectively).

We continue by studying the effect of financial market uncertainty on the investors' reactions to macroeconomic news. For doing this we estimate the following $ARFIMA(1, d, 0)$ model that now includes two news variables that divide all the released macroeconomic announcement to those released at times of low or high financial market uncertainty:

$$(1 - \phi_1 L)(1 - L)^d \left(y_t - \alpha - \gamma^{low\_f} N_t^{low\_f} - \gamma^{high\_f} N_t^{high\_f} \right) = \varepsilon_t \qquad (3)$$

The fifth column in Table 4 and 5 present the results of the model (3) for volatility and volume, respectively. The results are very similar to those of model (2). The macroeconomic news that are released at times of low financial market uncertainty increase both volatility and volume significantly more than those released at times of high financial market uncertainty. (p-value of the Wald tests equal 0.001 and 0.039 for the volatility and volume, respectively).

Finally, we study the relevance of the political uncertainty on the macroeconomic news reactions. Similarly as in the two previous models, we estimate the following ARFIMA(1,d,0) model that contains the macroeconomic news announcements, which have been divided to those released on the days when political uncertainty was low or high:

$$(1 - \phi_1 L)(1 - L)^d \left(y_t - \alpha - \gamma^{low\_p} N_t^{low\_p} - \gamma^{high\_p} N_t^{high\_p} \right) = \varepsilon_t \qquad (4)$$

The results of the model (4) are reported in the final column of Table 4 and 5 for volatility and volume, respectively. Again the macroeconomic news released on the times of low political uncertainty cause a significantly greater effect on the volatility and volume of the Treasury bond futures (p-value of the Wald tests equal 0.007 and 0.0001 for the volatility and volume, respectively).

Thus, our results strongly suggest that treasury bond market investors' reaction

Table 4 Estimation results for the realized volatility

Table presents the parameter estimates of the models (1−4) for a daily realized volatility of the US Treasury note future with a ARFIMA(1,d,0) specification. See the details on different N_t macroeconomic news variables in section 2.3. Robust standard errors were used. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Variable	Parameter	(1)	(2)	(3)	(4)
N_t	γ	0.182***	–	–	–
$N_t^{low\_m}$	γ^{low_m}	–	0.153***	–	–
$N_t^{high\_m}$	γ^{high_m}	–	0.105***	–	–
$N_t^{low\_f}$	γ^{low_f}	–	–	0.215***	–
$N_t^{high\_f}$	γ^{high_f}	–	–	0.130***	–
$N_t^{low\_p}$	γ^{low_p}	–	–	–	0.198***
$N_t^{high\_p}$	γ^{high_p}	–	–	–	0.145***
$AR(1)$	ϕ_1	−0.223***	−0.227***	−0.226***	−0.212***
Fract. integr.	d	0.411***	0.415***	0.422***	0.405***
Wald test, p-value					
$\gamma^{low\_m} = \gamma^{high\_m}$		–	0.011	–	–
$\gamma^{low\_f} = \gamma^{high\_f}$		–	–	0.001	–
$\gamma^{low\_p} = \gamma^{high\_p}$		–	–	–	0.007

to macroeconomic news announcements is significantly stronger at times of low uncertainty compared to high uncertainty. The results are the same whether we consider macroeconomic, financial or political uncertainty and it can be seen in both in the return volatility of the treasury note futures as well as in the number of trades following the news announcements.

Our model is purely empirical and is not trying to test any particular asset pricing theory. But one possible interesting interpretation is provided by the theoretical model by Easley and O'Hara (2010), which suggests that at times of high uncertainty, it might be too difficult for the investors to evaluate different investment choices and hence it might be optimal for them to not change their positions. At times of extreme uncertainty, this kind of behavior might lead to market freeze, such as those witnessed in some markets during the latest financial crisis.

In the previous three models, we studied the effect of the three different uncertainty measures separately. Next, we study if any of three uncertainty measures is

Table 5 Estimation results for the trading volume

Table presents the parameter estimates of the models $(1-4)$ for trading volume of the US Treasury note with a ARFIMA(1,d,0) specification. See the details on different N_t macroeconomic news variables in section 2.3. Robust standard errors were used. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

Variable	Parameter	(1)	(2)	(3)	(4)
N_t	γ	0.199***	–	–	–
$N_t^{low\_m}$	γ^{low_m}	–	0.151***	–	–
$N_t^{high\_m}$	γ^{high_m}	–	0.100***	–	–
$N_t^{low\_f}$	γ^{low_f}	–	–	0.230***	–
$N_t^{high\_f}$	γ^{high_f}	–	–	0.150***	–
$N_t^{low\_p}$	γ^{low_p}	–	–	–	0.209***
$N_t^{high\_p}$	γ^{high_p}	–	–	–	0.111***
$AR(1)$	ϕ_1	−0.096*	−0.085**	−0.090**	−0.099**
Fract. integr.	d	0.381***	0.375***	0.379***	0.380***
Wald test, p-value					
$\gamma^{low\_m} = \gamma^{high\_m}$		–	0.049	–	–
$\gamma^{low\_f} = \gamma^{high\_f}$		–	–	0.039	–
$\gamma^{low\_p} = \gamma^{high\_p}$		–	–	–	0.0001

dominating the behavior of the investors, i.e. whether they dislike more one type of uncertainty compared to another. To allow for all uncertainty measures to have an effect simultaneously, we let the news variables to interact as follows,

$$
\begin{aligned}
(1-\phi_1 L)(1-L)^d y_t \;=\; & \alpha + \gamma^{l\_m,l\_f,l\_p}[N_t^{low\_m} \times N_t^{low\_f} \times N_t^{low\_p}] \\
& + \gamma^{l\_m,l\_f,h\_p}[N_t^{low\_m} \times N_t^{low\_f} \times N_t^{high\_p}] \\
& + \gamma^{l\_m,h\_f,l\_p}[N_t^{low\_m} \times N_t^{high\_f} \times N_t^{low\_p}] \\
& + \gamma^{h\_m,l\_f,l\_p}[N_t^{high\_m} \times N_t^{low\_f} \times N_t^{low\_p}] \\
& + \gamma^{h\_m,h\_f,l\_p}[N_t^{high\_m} \times N_t^{high\_f} \times N_t^{low\_p}] \\
& + \gamma^{h\_m,l\_f,h\_p}[N_t^{high\_m} \times N_t^{low\_f} \times N_t^{high\_p}] \\
& + \gamma^{l\_m,h\_f,h\_p}[N_t^{low\_m} \times N_t^{high\_f} \times N_t^{high\_p}] \\
& \gamma^{h\_m,h\_f,h\_p}[N_t^{high\_m} \times N_t^{high\_f} \times N_t^{high\_p}] + \varepsilon_t
\end{aligned} \tag{5}
$$

Here, for instance, γ^{l_m,l_f,l_p} gives the effect of macroeconomic news when three kinds of uncertainties are considered to be low, and γ^{l_m,h_f,h_p} gives the news effect when the financial market and political uncertainty are high but macroeconomic uncertainty is low. The model (5) allows us to study the effect of uncertainty on investors reactions in various ways and shows us if one type of uncertainty is dominating the other. The estimation results of model (5) for both volatility and volume, as well as the p-values of Wald tests of some hypotheses of interest are presented in Table 6.

The results complement the findings from the models where the effects of different kinds of uncertainties were examined separately. The macroeconomic news effects have significantly greater impact on US Treasury note futures, both in terms of volatility and trading volume, when uncertainty is low, compared to when it is high. The p-values of the Wald tests for the equality of the coefficients of γ^{l_m,l_f,l_p} and γ^{h_m,h_f,h_p} equal 0.0002 and 0.007 for the volatility and volume, respectively). Interestingly, when the uncertainty is regarded to be in a high level in terms of all uncertainty measures, the release of the macroeconomic news does not lead to increased trading volume, as the parameter estimate for γ^{h_m,h_f,h_p} is statistically not different from zero.

The results also suggest that the effect of the financial uncertainty on investors reactions to macroeconomic news is somewhat stronger compared to other kinds of uncertainty. The Wald test results for the equality of the coefficients γ^{l_m,l_f,l_p} and γ^{l_m,h_f,l_p} suggests that even if the economic and political uncertainty levels are considered to be low, the high financial market uncertainty is enough to cause reduced investor reaction to macroeconomic news. However, the effect is only statistically significant in the impact of macroeconomic news on realized volatility.

4 Conclusion

This is an empirical study that tries to shed light on the impact of uncertainty on the investors' reactions to news on macroeconomic statistics. We consider three types of uncertainties related to state of the economy, financial markets and political decision making and examine whether the investors in the US Treasury bond futures market react differently to US macroeconomic news in times of low and high uncertainty.

Our results suggest that investors react to news significantly stronger when uncertainty is low than high. In particular, macroeconomic news cause stronger volatility and increase trading volume statistically significantly more at times of low uncertainty. The results are the same regardless of the source of the uncertainty. Also, we find that investors are more sensitive to the uncertainty in the financial market compared to the macroeconomic and political uncertainties.

Our results might give a partial explanation on why some markets, such as CDO market and some European sovereign bond market, have suffered from a very low liquidity or a total freeze during the latest financial and European debt crisis. Easley and O'Hara (2010) proposed in their theoretical model that for ambiguity aversive investors it might sometimes be optimal not to trade, if they are not able to evaluate the value of different portfolios due to high uncertainty. Our empirical model is not directly testing for the model of Easley and O'Hara (2010), but it does support the view that higher uncertainty may cause less trading.

Table 6 Estimation results

Table presents the parameter estimates for the news variables in model (5). Robust standard errors were used. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

		(5)	
Variable	Parameter	$ln(RV_t^{1/2})$	$ln(VOL_t)$
$N_t^{low\_m} \times N_t^{low\_f} \times N_t^{low\_p}$	γ^{l_m,l_f,l_p}	0.182***	0.178***
$N_t^{high\_m} \times N_t^{low\_f} \times N_t^{low\_p}$	γ^{h_m,l_f,l_p}	0.125***	0.131***
$N_t^{low\_m} \times N_t^{high\_f} \times N_t^{low\_p}$	γ^{l_m,h_f,l_p}	0.091***	0.103***
$N_t^{low\_m} \times N_t^{low\_f} \times N_t^{high\_p}$	γ^{l_m,l_f,h_p}	0.182***	0.180***
$N_t^{low\_m} \times N_t^{high\_f} \times N_t^{high\_p}$	γ^{l_m,h_f,h_p}	0.105***	0.094**
$N_t^{high\_m} \times N_t^{low\_f} \times N_t^{high\_p}$	γ^{h_m,l_f,h_p}	0.138***	0.082
$N_t^{high\_m} \times N_t^{high\_f} \times N_t^{low\_p}$	γ^{h_m,h_f,l_p}	0.066**	0.088*
$N_t^{high\_m} \times N_t^{high\_f} \times N_t^{high\_p}$	γ^{h_m,h_f,h_p}	0.070***	0.059
$AR(1)$	ϕ_1	−0.228***	−0.083**
Fractional integration	d	0.426***	0.374***
Wald test, p-value			
$\gamma^{l\_m,l\_f,l\_p} = \gamma^{h\_m,h\_f,h\_p}$		0.0002	0.007
$\gamma^{l\_m,l\_f,l\_p} = \gamma^{h\_m,l\_f,l\_p}$		0.528	0.251
$\gamma^{l\_m,l\_f,l\_p} = \gamma^{l\_m,h\_f,l\_p}$		0.005	0.104
$\gamma^{l\_m,l\_f,l\_p} = \gamma^{l\_m,l\_f,h\_p}$		0.994	0.962
$\gamma^{h\_m,h\_f,h\_p} = \gamma^{l\_m,h\_f,h\_p}$		0.335	0.446
$\gamma^{h\_m,h\_f,h\_p} = \gamma^{h\_m,l\_f,h\_p}$		0.154	0.728
$\gamma^{h\_m,h\_f,h\_p} = \gamma^{h\_m,h\_f,l\_p}$		0.906	0.600

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