Macroeconomic Uncertainty and Its Impact on Economic Activity: Investigating Two Different Measures

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Abstract

This paper investigates *ex-post* uncertainty and its impact on real economy, employing two measures of uncertainty, Economic Policy Uncertainty (EPU) by Baker et al. (2013) and Relative Sentiment Shift (RSS) by Tuckett et al. (2014) [1]. Although EPU has recently gained popularity for the analysis of policy-related disturbances, it fails to provide a rationale for decision-making process. RSS rather focuses on assessing the changes in economic agents' confidence about the future, where two domains of emotion, excitement and anxiety, play an important role for either promoting or inhibiting decisions in real activity. In addition, RSS covers text source more centred to financial market and subjective assessment by brokers and policymakers, allowing the measure to reflect rich information of investors' behaviour. The two measures show similar trend and high correlation even though there are some exceptions as EPU reacted sensitive to political events, such as elections and war, whereas RSS responded more for financial events, for instance, stock market burst after dotcom bubble.

Empirical analysis covers structural VAR with 5 variables, uncertainty, stock market index, interest rate, employment, and industrial production, and Bayesian VAR with same specification and the specification incorporating inflation expectation, using the US data from 1996 to 2013. For RSS shock, the magnitude of the effect on both production and employment is larger and the responses persist longer than the EPU shock. The rebound and overshoot after the downturn of the real activity is more noticeable in RSS shocks than EPU. In response of uncertainty shock for both measures, expansionary monetary policy was implemented by reducing policy rate within a year. To account for whether the effect evolves from mean preserving variance, not from bad news itself, VAR with Michigan Consumer Sentiment Index is estimated, showing that the effect is smaller than the benchmark model but still significant.

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[1] The RSS data obtained in collaboration with UCL Centre for Study of Decision-Making Uncertainty.

1 Introduction

Uncertainty has been increasingly recognised as one of the significant causes of prolonged recession after the Great Financial Crisis of 2008. The US economy experienced persistent stagnation with low growth and high unemployment rate as the zero lower bound on interest rate discouraged demand. Many argue that the structural shift might have taken place due to high uncertainty in economy, changing economic agents' behaviour towards reduced propensity to spend and invest. In order to resolve the unprecedented economic crisis, in many advanced countries, nontraditional monetary and fiscal policies were implemented to affect the real interest rate and boost economy. As Summers (2014) pointed out, unconventional monetary policy measures might create economic uncertainty around policy as markets get confused about when and how these measures put into practice and eventually affect investors' beliefs.

In general, heightened perceived uncertainty level in economy, whether it is provoked by policy or not, might discourage individuals to make economic decisions. They will wait until the situation gets better. The real option theory explains this counter-cyclicality of uncertainty as wait-and-see effect. (Bernake, 1983; Dixit and Pindyck, 1994) Dixit and Pindyck (1994) argue that if investment is irreversible, uncertainty raises the value of hoarding cash and waiting to see what happens, making an analogy between an investment opportunity and a stock option in financial market. After the seminal works of real option theory, the potential channels of uncertainty on real economy have been widely examined by many, taking demand, supply and financial sectors into account. (Carroll, 1996; Romer, 1990; Lazear and Spletzer, 2011; Gilchrist, Sim and Zakrajsek, 2010)

Despite the endeavour of existing research which is heavily dependent on macroeconomic effect of uncertainty proxied by market volatility, one of the remaining obstacles in empirical field is how we measure macroeconomic uncertainty upon reasonable microfoundation. Most of the previous studies use implied stock market volatility (VIX or VXO) as an appropriate proxy for uncertainty for practical reasons. However, there are doubts whether market volatility could measure uncertainty *per se* since it is more closely related to risk-aversion in financial markets (Jurado et al., 2013).

Thanks to the influential study by Frank Knight (1921), recent literature explores wide range of approaches to estimate "true" uncertainty, borrowing theoretical background from decision theory in microeconomics. The von-Neumann Morgenstern expected utility theory considers only alternatives with uncertain outcomes by means of objectively known probabilities, which is called "Risk" by Knight (1921). In real life, however, the assumption that uncertain prospects are given to us with known probability rarely holds as Knight pointed out. This is the world where Knightian uncertainty lies. With probabilities of certain events unknown, individuals make decision *as if* they held probabilistic beliefs (Savage, 1954). Under this subjective probability assumption, the well-defined probabilistic beliefs can be uniquely revealed by the choice behaviour of individuals. As Mas-Colell et al. (1995) wrote, subjective probabilities dissolves the distinction between 'risk' and '(Knightian) uncertainty' by using beliefs expressible as probabilities. [2]

Literature on measuring macroeconomic uncertainty based on micro-foundation is a fast growing area in applied research. (Bloom; 2009, Baker et al.; 2013, Jurado et al.; 2013, Bachmann et al.; 2012, Charemza et al.; 2013, Tucket et al.; 2014, ILO; 2013, 2014) However, there has been little agreement on the definitions and best strategies to capture the "true" uncertainty. One popular approach is to search for the underlying components of uncertainty, either from news quotes (Baker et al.; 2013, Tucket et al.; 2014) or from macro data (Jurado et al.; 2013, BOE; 2013, ILO; 2013, 2014). On the other hand, some rely on non-Knightian uncertainty ('risk') by evaluating forecast errors (Charemza et al.; 2013) or measuring disagreement among forecasters (Wallis; 2004, 2005). It can be interpreted as non-Knightian approach since it assumes a certain probability density function to calculate uncertainty.

In terms of estimating the impact of macroeconomic uncertainty given a certain uncertainty measure, there is increasing concern on how we recover causal effect using appropriate identification strategy. Existing empirical papers use different VAR specification to gauge the effects of uncertainty (Baker et al.; 2013, Jurado et al.; 2013, Bachmann et al.; 2012), sometimes with Bayesian inference technique (Aastveit et al., 2013). However, there is no guarantee that VAR models could estimate true causal effect, free of any potential bias. One remaining key issue regarding the estimation is whether we could separate out the mean preserving spread effect (second moment shock) from the first moment effect, so-called bad news effect. In this regard, Baker and Bloom (2013) constructed cross country panel and used natural disasters, terrorist attacks and unexpected political shocks as instruments for stock market proxies of first and second moment shocks. They found that second moment shocks, uncertainty, appear to explain the variation in growth as well as the first moments. Obviously, the identification strategy is the field in which the future research will focus more on the development of

This paper attempt to give an account of those two main challenges: the measurement of macro uncertainty and the estimation of the impact of uncertainty on real economy. The first section of this paper will examine the measurement issue of macroeconomic uncertainty. Among many different concepts and applications, I will focus on two recently developed measures based on text resources: Economic Policy Uncertainty (EPU) by Baker et al. (2013) and Relative Sentiment Shift (RSS) by (2014). [3] In this section, pairwise correlation and Granger causality will be analysed to examine the relationship among different measures of uncertainty. In terms of measuring the impact

[2] This naturally leads us to a basis of applying Bayesian approach in estimation stage in section 4.

[3] Non-Knightian uncertainty, such as disagreement among forecasters is not considered here, leaving it as a future research.

of macroeconomic uncertainty, I will review the theoretical background of real option theory and develop empirical models for estimation of the impact of macroeconomic uncertainty on real economy, including classical VAR model and Bayesian VAR model. In the following sections of each model, I will examine the Impuse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD) to investigate results.

2 Measurement of Macroeconomic Uncertainty

2.1 Various Measures of Macroeconomic Uncertainty

The implied volatility in stock market (often referred as VIX or VXO, VXO onwards for the notation in econometric analyses) from Chicago Board Options Exchange is used as the canonical proxy for uncertainty in most existing finance and economic literature. It is often used as a proxy for uncertainty at the firm level. (e.g. Leahy and Whited, 1995; Bloom, Bond, and Van Reenen, 2007) However, the volatility measures lack theoretical background as it captures the consequence of collective decisions of stock market participants. Jurado et al. (2013) pointed out that stock market volatility is more correlated with time-varying risk aversion, rather with economic uncertainty *per se*. Baker et al. (2013) showed that stock market volatility is a measure based on explicit time frame, generally 30 days, so that it does not capture the perception of uncertainty in longer period of time.

The most recent and popular macroeconomic uncertainty index is the Economic Policy Uncertainty (EPU) by Nick Bloom and Scott Baker of Stanford University and Steve Davis of the University of Chicago. (Baker et al., 2013). EPU counts how often uncertainty related to policy is mentioned in newspapers, the number of temporary provisions in the tax code and the degree to which forecasts of inflation and federal spending differ from each other. They report both EPU and news-based EPU (EPUN is the notation for news-based index hereafter) for advanced countries - such as US, Japan, Germany, UK, France, Italy, and Spain - and for emerging economies - China, India, and Russia.

Another perspective of measuring macro uncertainty emphasizes emotions as key drivers of economic and financial activity. (Akerlof & Shiller; 2009, Tucket; 2011) In the states of high uncertainty in economy, market participants make their decision by securing conviction through narratives. Such conviction narratives (Chong & Tuckett, 2014) can be persistent for a certain period of time, supporting human decision-making to be easy and quick despite the presence of incomplete information and uncertainty. It is important to note that social interactions enable such narratives to spread 'systemically' as we have witnessed in historical examples, such as dotcom bubbles and house price bubble supported by structured finance during late 2000s. Aikman et al. (2013) pointed out that financial markets can be systematically linked because of the search for yield with top performers as a reference, namely "keeping up with the Goldmans".

Based on the theory of conviction narrative, Tuckett et al. (2014) developed a Relative Sentiment Shift (RSS) measure, using the Directed Algorithmic Text Analysis (DATA) to assess the change in economic confidence about the future. They focus on the two emotion groups, excitement and anxiety, which either promotes or inhibit decision-making. They point out that shifting between two emotional groups is likely to be determined by the degree of confidence (or doubt) and suggest that the relative degree of sentiment movement could reflect the conditions of uncertainty perceived by agents in economy. This approach is in line with the concept of Knightian uncertainty. Knight (1921) emphasizes the degree of confidence in the evaluation of probability can be determined not only by whether the estimate is the best guess from model (a priori probability) but by how much the forecaster (or a decision maker) is confident of it. [4] RSS offers a complete account for the degree of confidence as it is based on the individual's behavioural aspect where excitement explains attraction process in gain domain and anxiety, defined in loss domain, signals inhibition process.

On the other hand, it seems that EPU fails to provide a rationale for uncertainty measure based on decision theory. News-based EPU directly measures the number of word counts which include "uncertainty", "economy" and "policy terms" from some selective popular newspapers. Therefore, it is fairly straightforward measure for policy-related uncertainty and contains relatively objective and neutral information about economic uncertainty. However, because of that feature, it might not sufficiently represent the notion of confidence in economy from the perspective of individual's decision-making process. In addition, EPU may incorporate mixed signal of Knightian and non-Knightian uncertainty as one of the components in EPU, forecast disagreement, indeed portrays non-Knightian uncertainty.

Finally, news-based EPU and RSS have distinctive features in terms of text sources. EPU refers to leading newspapers in a country, for example, the US news-based EPU uses the archive of 10 major newspapers.[5] Therefore, EPU has relatively easier accessibility of data source. RSS, however, covers targeted text resources, which comprises Reuters News Archive, Broker reports of 14 brokers' commentaries, and Bank of England internal market commentaries.[6] Since the coverage of RSS text source is quite specific to financial market and contains assessments of brokers and policy makers, RSS might include rich information about investors' behaviour and their qualitative evaluation on uncertainty level in the market. Taking all things into consideration, it seems that RSS focuses more on micro-foundation of individual investor's decision whereas EPU is designed for measuring policy-related uncertainty with an advantage of easy accessibility of source text.

[4] Knight (1921) explains that "The action which follows upon an opinion depends as much upon the amount of confidence in that opinion as it does upon the favorableness of the opinion itself."

[5] USA Today, Miami Herald, Chicago Tribune, Washington Post, Los Angeles Times, Boston Globe, San Francisco Chronicle, Dallas Morning News, New York Times, and the Wall Street Journal

[6] The brokers' report and Bank of England's market commentaries were obtained by the collaboration of Bank of England.

2.2 Comparing Measures of Uncertainty

This section will examine the descriptive statistics to compare the various uncertainty measures previously concerned, VXO, EPU, news-based EPU (EPUN), and RSS. In addition, Michigan Consumer sentiment index (MCI) is considered as a reference to capture consumer confidence level. [7] In addition, it will move on to Granger causality estimation to investigate the dynamic relationship among the uncertainty indices.

2.2.1 Time Series Plot and Correlation Matrix

Figure 1 shows the trend of stock market volatility and three types of macro uncertainty measures, RSS, EPU, and EPUN. In order to make comparison easier, RSS is multiplied by -1 so that positive (negative) values of RSS indicate the increase (decrease) of uncertainty level. [8] Although the main interest lies in VXO and three uncertainty measures, MCI is included in the figure and the basic summary statistics. [9]

The most distinctive difference between stock volatility index and other uncertainty indices can be found in the recent trend. Uncertainty indices, EPU and RSS, showed prolonged high level after the Great Recession while stock volatility returned quickly to the normal level after 2012. Comparing the volatility after the Great Depression, Schwert (2011) found that the volatility seen after 2008 crisis was relatively short-lived in many advanced countries, suggesting that a link between stock volatility and real activity might be misleading. The potential structural break after the Great Recession advise that VXO might fail to exhibit true uncertainty in economy, even without mentioning a view that volatility lacks theoretical background for measuring Knightian uncertainty.

On the other hand, RSS and EPU show similar trend with some exceptions. One of the examples of their split is the stock market downturn in September 2002. RSS increased sharply due to bursting dotcom bubble, while EPU level did not rise that much during that period. Similarly, there was only RSS hike in August 2007 when BNP Paribas froze redemption for three investment funds and announced that they could not value the underlying assets of their funds fairly due to their exposure to subprime mortgage loans. This event did not cause EPU measure to increase but RSS increased substantially. In fact, this event is considered as the first acknowledgment of the risk of major banks' high exposure to subprime mortgages. Brunnermeier (2008) dubbed this

[7] Michigan Consumer sentiment index (MCI) is a monthly survey data, based on the responses to five questions; two questions on personal finances, two on the outlook for the economy, and one question on buying conditions for durables. It is considered as a leading indicator of future perspective of macroeconomic conditions as it represents consumer expectations in general. Several studies (Estrella and Mishkin; 1998, Golinelli and Parigil; 2004) indicated that MCI measures could predict and be predicted by a wide range of economic variables.

[8] For correlation coefficients and VAR models, variables are standardized using sample mean and standard deviations except RSS, which is designed to be standardized. Plotted graphs are variables with pre-transformed level.

[9] MCI is standardized and converted to have opposite sign of original series for fair comparison.

episode "illiquidity wave", arguing that interbank market was frozen up as the perceived default and liquidity risks of banks rose significantly and the LIBOR increased sharply.

Other exceptions are found during Russian financial crisis/LTCM and 9/11 episode, where RSS increases sharply but not for EPU. During the episodes of Gulf war, the interest cuts and stimulus in January 2008, and the US Midterm election in September 2010, there were steeper increase in EPU than in RSS. However, there were also episodes where both EPU and RSS react similarly, for instance, in early 2003 when second Gulf war started. The past events that had affected uncertainty measures to move different direction partly explains the potential divergence of two measures: EPU seems to react relatively sensitive to political events, such as elections and war, whereas RSS has been affected largely by financial events. [10]

Table 1: Pairwise Correlation Marix

	RSS	EPU	EPUN	VXO	MCI
EPU	0.8042	1.0000			
EPUN	0.7714	0.9040	1.0000		
VXO	0.4274	0.3785	0.4933	1.0000	
MCI	0.6505	0.7135	0.5353	0.1729*	1.0000

1) all coefficients are statistically significant in 99% level,
except *(p-value=0.0113).

Pairwise correlation matrix in Table 1 indicates that correlation coefficient is largest between EPU and EPUN, simply because EPUN is one of the component consisting EPU. The second largest correlation is shown in the pair of RSS and EPU. MCI has higher correlation coefficients when pairing with other uncertainty measures rather than paring with VXO. This suggests the possibility of stronger predictability in MCI on macroeconomic variables than in VXO index. It is noticeable fact is that stock volatility shows low correlation with other uncertainty measures, ranging from 0.38 to 0.49. Indeed, the lowest correlation exhibits between VXO and MCI, suggesting that the stock market volatility and the consumer sentiment moves quite independently.

[10]I. Major events that is associated with substantial increase in EPU: Russian Crisis/LTCM (August 1998), Bush election controversy(November 2000), 9/11 (August to September 2001), Second Gulf War (March 2003), Large interest cuts and stimulus (January 2008), Lehman and TARP (September 2008), Obama election (November 2008), Banking crisis (February 2009), Midterm elections (September 2010), Debt ceiling dispute (July 2011), Government shut down and debt ceiling (September 2013).
II. Major events that is associated with substantial increase in RSS but not in EPU: Dotcom bubble stock market burst (September 2002), Interbank illiquidity wave (August 2007)

2.2.2 Granger Causality Test

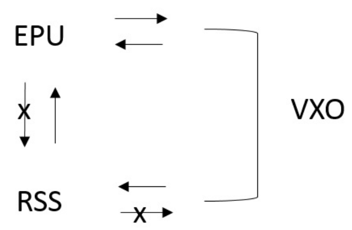
The next step to investigate the dynamic relationship among uncertainty variables is to test Granger causality. The motivation of Granger causality test is to question whether the past values of X_t help predict Y_t in bivariate model. Granger Causality is tested by estimating the following specification:

$$\begin{aligned} \begin{pmatrix} Y_t \\ X_t \end{pmatrix} &= A_1 \begin{pmatrix} Y_{t-1} \\ X_{t-1} \end{pmatrix} + \cdots + A_p \begin{pmatrix} Y_{t-p} \\ X_{t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{yt} \\ \varepsilon_{xt} \end{pmatrix} \\ &= \begin{pmatrix} a_1 & b_1 \\ c_1 & d_1 \end{pmatrix} \begin{pmatrix} Y_{t-1} \\ X_{t-1} \end{pmatrix} + \cdots + \begin{pmatrix} a_p & b_p \\ c_p & d_p \end{pmatrix} \begin{pmatrix} Y_{t-p} \\ X_{t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{yt} \\ \varepsilon_{xt} \end{pmatrix} \end{aligned} \tag{1}$$

Definition 1: X_t does not Granger causes Y_t if $A_1, \cdots, A_p$ are lower triangular, i.e. $b_1 = \cdots = b_p = 0$. Therefore, if we reject the null hypothesis, this means that X_t Granger causes Y_t.

In order to analyze the dynamic relationships in variables, all possible cases of pair are considered. The frequency of data is monthly and the sample period is from January 1996 to November 2013, where data is available. [11] All variables are standardized with mean equals 0 and standard deviation equals 1. [12] To determine the stationarity, Augmented Dickey Fuller test is conducted and the results shows that for all of the series, the null hypothesis of unit root can be rejected at a 5% confidence level. Then, since the Granger causality test is very sensitive to the number of lags included in the model, the appropriate lag length is selected by checking the serial correlation in residuals. If the number of lags included in the model is sufficient, then we could find the corresponding residuals are not serially correlated. The Table 2 and corresponding Figure 1 show the models' VAR specifications and F-statistics (p-value) for Granger causality test.

Figure 1: Visualisation of Granger Causality Results



The first six rows of Table 2 lead us to a set of comprehensive interpretation of dynamic relationship among three main uncertainty variables even though Granger causal-

[11] Monthly data for RSS is only available from January 1996 while EPU, EPUN is available from January 1985; VXO from January 1986.

[12] Notice that RSS is standardized by its construction.

Table 2: Granger causality test

Y_t	X_t	lag length (p)	F-stat	p-value
EPU	RSS	3	5.96	0.0006***
RSS	EPU	3	1.34	0.2612
VXO	RSS	2	0.07	0.9342
RSS	VXO	3	2.88	0.0369**
VXO	EPU	2	6.75	0.0014***
EPU	VXO	4	2.60	0.0374**
RSS	EPUN	3	4.18	0.0067***
EPUN	RSS	2	18.45	0.0000***
VXO	EPUN	2	5.89	0.0032***
EPUN	VXO	4	2.90	0.0232**
EPU	EPUN	3	5.54	0.0011***
EPUN	EPU	3	3.23	0.0236**

ity has little to do with underlying true causal relationship between variables. [13] VXO Granger cause RSS but RSS does not Granger cause VXO directly. RSS affects VXO only through EPU. Similarly, RSS Granger cause EPU but not vice versa. EPU has impact on RSS only through VXO. EPU has shown bi-directional Granger causality with VXO. [14]

If we assume stock market volatility is endogenous variable as the result of collective decisions made in the market, VXO cannot be a initial trigger but rather a channel that delivers exogenous shocks and magnifies (or possibly reduces) the effects of shocks. Therefore, under this assumption, we could think of two possible channels of prediction. First, the initial EPU innovation Granger causes stock market volatility and then relative sentiment shifts occur. Another channel is that relative sentiment shift might act as an appropriate predictor for economic policy uncertainty and then stock market volatility. The different channels are, of course, dependent upon the different features of two measures. EPU measures directly the number of words counts including "uncertainty" and "economy" and "policy terms" in the selective popular newspapers. Therefore, the information that EPU contains is more objective and neutral than the emotional words that RSS counts.

[13]The general notion of causality in econometrics is defined in terms of randomised controlled experiments or at least quasi-random assignment. In contrast, Granger causality means "predictability" rather than "causality" precisely.

[14]News-based EPU and its relationship is also estimated. While EPU has bi-directional Granger causality only with VXO, news-based EPU (EPUN) has bi-directional Granger causality with each of the variables, RSS and VXO, respectively. EPU and EPUN affect each other in both direction as expected.

The result that RSS can be affected by VXO, but not vice versa, could also be partly explained by the feature of RSS and the methods how RSS is measured. Once stock market swings, it might take some time to process those fuzzy information in the market to take a certain direction of sentiment which RSS depicts. Moreover, the text source of RSS is analytical commentaries, containing processed and collective information on market sentiment. On the hand, RSS cannot be directly predicted by past EPU changes but RSS Granger causes EPU. The latter part of Granger causality can be interpreted as policy responses to relative sentiment shift. However, it should be noted that it is very difficult to conclude which channel is more reasonable or convincing without any theoretical background and/or statistically significant results from well-specified dynamic time series models.

3 The Impact of Macroeconomic Uncertainty on the Real Activity

3.1 Theoretical background

One of the earliest attempt of analysis on the impact of macro uncertainty was Bloom (2009). He applied real option theory to investigate "wait-and-see" effect of uncertainty innovation by setting RBC model with frictions in capital and labour. Prior to this empirical study, there exist rich previous literature on channels of uncertainty. Demand side of uncertainty channel was investigated by both firm- and household-level approach. Real options theory tells us that uncertainty reduces the level of investment of firms (Bernanke, 1983; Dixit and Pindyck, 1994). Households might build up a buffer stock of savings to draw on in periods of temporarily low income when they faced with uncertainty about their future labour income. (Carroll, 1996; Romer, 1990)

For the supply side channel, Bentolila and Bertola (1990) argue that hiring plans are negatively affected by uncertainty due to high adjustment costs and Bloom(2009) suggests the uncertainty may have effects of postponing hiring and firing decisions. More recently, Lazear and Spletzer (2011) point out that uncertainty reduces productivity growth through less efficient matching of skills to jobs. In terms of productivity, Disney, Haskell and Heden (2003) argue that in times of high uncertainty, companies may be more reluctant to enter new export markets in times of high uncertainty so that this behaviour may prevent the most productive use of resources and consequently reduce supply.

Uncertainty about the macroeconomic outlook is likely to have a negative effect on asset prices because investors require compensation that captures the risk of holding the asset. (Gilchrist, Sim and Zakrajsek, 2010) High uncertainty with financial market imperfection leads to reduction in banks' incentives to provide loans for households and companies, tightening in credit conditions.

Some of previous literature explores heterogeneous responses upon high uncertainty.

Carrière-Swallow and Céspedes (2011) investigate the effect of uncertainty differs across countries. In comparison to developed countries, emerging economies suffer much more severe falls in investment and private consumption following an exogenous uncertainty shock, take significantly longer to recover, and do not experience a subsequent overshoot in activity. They argue that the dynamics of investment and consumption are correlated with the depth of financial markets and monetary and fiscal policy actions that alleviate the impact of credit constraints facing firms and households may reduce the impact of uncertainty shocks in these economies.

There exists an interesting research closely examined the uncertainty in international economics. Fernandez-Villaverde et al (2009) found that a domestic uncertainty shock enables agents to increase their savings abroad, often called *capital flight*. They estimated a stochastic volatility process for real interest rate using T-bill rates and country spreads with Particle filter and Bayesian methods.

3.2 Data and structural VAR specification

The first model specification is similar to the one in Baker et al. (2013). A common representation of the VAR(p) is as following:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \mathcal{E}_t \tag{2}$$

where $\mathcal{E}_t \sim$ iid N(0, Ω). The vector Y_t includes all the endogenous variables.

$$Y_t = \begin{pmatrix} \text{Uncertainty} \\ \text{Stock Market Index} \\ \text{Interest Rate} \\ \text{Employment} \\ \text{Production} \end{pmatrix} \tag{3}$$

To take account for the different notions of uncertainty into the model, two uncertainty measures previously investigated are employed in each specification: EPU (Baker et al., 2013) and RSS (David et al. 2014). The model includes S&P500 index as a measure of stock market index (*Stock*); the Federal Funds Rate as a proxy for short-run interest rate (i); the number of people employed in manufacturing sector as a proxy for labour market conditions (EMP); manufacturing industrial production as a proxy for business cycle (IP); and a linear time trend. Stock index, employment and industrial production are in log level, divided by CPI and detrended using HP filter in order to transform the variables as a deviation from the steady states. The Federal Funds Rate is in percent level and also detrended by HP filter. RSS is, by construction, standardised with standard deviation of 1. For the easier comparison, EPU index is standardised by dividing the series by its standard deviation.

The order of variables is selected as in equation (3), taking into account the transmission channel of uncertainty, which seems very alike with variation in included number of variables. (Baker et al. (2013), Bachmann et al. (2013), JLN (2013)). [15] Macroeconomic data is collected from FRED economic database by St. Louise Federal Reserve, monthly from Jan 1985 to Dec 2013. (`http://research.stlouisfed.org/fred2/`) EPU index is retrieved from the website constructed by D. Baker, N. Bloom and S. Davis. (`http://www.policyuncertainty.com/`) The choice of lag length ($p = 6$) is decided by checking the absence of autocorrelation in residuals and cross-autocorrelation among the residuals for all the equations in VAR system. [16]

3.3 Results

3.3.1 Impulse Response Function

As in most of existing empirical research, the result suggests that an increase in uncertainty shock leads to real activity collapse followed by rebound. Figure 3 and Figure 5 describe the impulse response functions to a one-standards deviation shock to the EPU or RSS uncertainty in the US. Shocks to EPU uncertainty sharply reduce production and employment with the effects of statistical significance persisting 16 months and 21 months horizon respectively. The magnitude of the effects of uncertainty innovation on industrial production reaches its minimum level around -0.45% 9 months after the initial innovation. Hitting the minimum level for the employment takes longer, 13 months, and has smaller effect around -0.32%.

For the shock in RSS uncertainty, both the magnitude and the persistence of the responses of macro variables are larger than in EPU. The impulse response of industrial production hits the minimum level of -0.53% after 13 months and the statistically significant effects lasted for 18 months. The impulse response of employment reaches its minimum of -0.44% after 17 months. The effect of RSS innovation on employment remains negative significantly after two years. The rebound and overshoot after the downturn of the real activity is more noticeable in RSS shocks than in EPU. The impulse response function of manufacturing production to RSS shocks exhibits the maximum level of 0.10% at 3 years and 10 months horizon while the impulse response of employment hits the maximum 0.09% 4 years and 3 months ahead. The magnitude of overshoot is approximately 18-20% of the minimum in absolute value. [17]

The responses of interest rate to two different macroeconomic uncertainty shocks are similar to the previous results. The responses of interest rate are more protracted and larger in magnitude for RSS uncertainty measure than EPU. The EPU shock leads to -0.14% minimum level of interest rate at $h = 10$ while the RSS shock is associated with

[15] The question for appropriate identification for the uncertainty in economy has been stayed much unsolved. For example of recent development in the area, Merten and Ravn (2013) investigated the impact of an unanticipated change in taxes on the economy using proxy structural VAR.

[16] The likelihood-ratio tests selected a model with 10 lags. AIC has chosen a model with 4 lags while BIC suggests a model with lag 2.

[17] The EPU impulse response shows the overshoot around 0.03% for production and 0.02% for employment, which amounts to approximately 6% of the minimum level in each variable.

-0.19% at $h = 13$. The rebound effect in impulse response function of interest rate is also stronger for RSS uncertainty, approximately 27% of the minimum level in absolute value for RSS than that of EPU (10%). This results shed light on the monetary policy reactions upon uncertainty shock. In response of positive uncertainty shock, the central bank runs expansionary monetary policy by reducing the policy rate within a year.

For the robustness check, several different specifications have been estimated: benchmark model with lag length variation ($p = 3$, $p = 9$), bivariate model (uncertainty and industrial production), and additional volatility variable (VXO) in the benchmark model. Figure 4 and Figure 6 shows the results of impulse response functions in various specifications. The magnitude of uncertainty effect on real activity are very similar in alternative specifications except that the model with VXO index shows the smallest effect around -0.26%, half of the effect in the benchmark model. In the model with VXO, volatility measure is placed in the first of Cholesky ordering to capture the overall uncertainty while economic policy uncertainty index focuses more on uncertainty induced by policy changes.

One important issue for the empirical analysis is whether we estimate the impact from the mean preserving variance or that of bad news itself. The periods with high uncertainty often coincide with the periods with bad news. To separate out the effect of changes in future expectation of business cycle, the model include S&P stock market index, given that stock market is forward-looking. In addition, the specification adding consumer sentiment index is performed as confidence often implies both mean and variance effects. The VAR specification with consumer sentiment as a first variable shows the insignificant effects of EPU on both production and employment. However, the model with additional CSI placed in the second variable after EPU shows significant negative impact on real economy. The effect is smaller than the benchmark model, implying that CSI has predictive power of the EPU index.

3.3.2 Forecast Error Variance Decomposition

Table 3 shows the fraction of the uncertainty shocks in explaining the fluctuations in macroeconomic variables. The upper panel reports the forecasting error variance decomposition (FEVD) for industrial production and employment in the VAR model with EPU uncertainty measure. The lower panel compares the FEVD for the same macro variables in the VAR model with RSS specification. The results of the contribution of the monetary policy shocks, represented by shocks in Federal Funds Rate, is also reported in each table denoted as FFR. h is the forecasting horizon. The table includes the decomposition for several horizons from 3 months up to 2 year. The 'max h' denotes the horizon h for which the fraction of each shock that attributes to the variations in macro variables by the largest.

The uncertainty shocks explain much larger proportion of the short-term fluctuations in macro variables than the monetary policy (FFR) shocks do. The relative importance of EPU uncertainty shocks for production fluctuations is around 19% for one-year forecast horizon and 23% at maximum for $h = 27$. EPU uncertainty shocks are associated with the employment variations by 20% for one-year horizon and 26% at maximum for $h = 35$. However, shocks to the federal funds rate explains the variations in production and employment by approximately 6% and 10%, respectively for $h = 12$. Thus, the magnitude of relative importance of EPU uncertainty shocks in explaining short-term production fluctuation is three times larger than that of monetary policy shocks at 1-year horizon and twice larger in explaining employment fluctuations.

Table 3: Forecast Error Variance Decomposition

1. Uncertainty Measure: Economic Policy Uncertainty (EPU)

	Production		Employment	
	EPU	FFR	EPU	FFR
h=3	3.45	2.89	2.62	2.49
h=6	12.55	3.55	13.43	5.28
h=12	19.26	6.48	20.91	9.96
h=18	22.11	8.37	23.85	12.76
h=24	22.96	9.04	25.30	14.17
max h	27	53	35	63
h=max	23.02	9.26	26.05	14.83

2. Uncertainty Measure: Relative Sentiment Shift (RSS)

horizon	Production		Employment	
	RSS	FFR	RSS	FFR
h=3	2.68	0.61	0.64	0.24
h=6	9.50	2.20	7.08	2.16
h=12	17.28	9.75	19.96	8.01
h=18	22.80	16.10	28.35	13.36
h=24	25.87	17.68	33.58	15.64
max h	29	48	34	55
h=max	26.47	20.08	36.64	17.76

1) 'max h' indicates the horizon h for which the fraction of each shock that attributes to the variations in macro variables by the largest.

The lower panel reports the results of the model with RSS uncertainty. Similarly, the RSS uncertainty shocks explains the larger share of the variation in macro variables than FFR shocks do. For one-year horizon, RSS innovations attributes the short-term fluctuations in production by 17% while FFR explains 10% of the variation. Comparing this with the upper panel results, the difference in the magnitude of decomposition between uncertainty and monetary policy shocks is smaller for RSS than EPU. The relative importance of shocks in the variations in employment is more than twice larger for RSS shocks (20%) than for the federal funds rate shocks (8%).

Comparing the two different measures of uncertainty, the dynamic correlation of RSS uncertainty with the employment exhibit greater importance than the EPU uncertainty at the maximum value of FEVD. Shocks to RSS uncertainty are associated with a maximum of 26% of the forecast error variance in production, and 37% of the forecast error variance in employment while shocks to EPU uncertainty are associated with a maximum value at 23% and 26%, respectively.

3.4 Bayesian VAR Models

Begin with simple VAR model:

$$Y_t = \Phi X_t + \mathcal{E}_t \tag{4}$$

where $\mathcal{E}_t \sim iid\, \mathrm{N}(0, \Omega_\varepsilon)$. X_t could be a matrix with constant, lagged Y_t and other exogenous variables. In this simplified model specification, the parameter to be estimated can be defined as $\theta = (\Phi, \Omega_\varepsilon)$. For macroeconomic empirical analysis, the data availability is often a very important issue since most of macro time series are quarterly or annual unlike financial data which could be obtained monthly up to daily bases. On the other hand, macro models often involves a quite large number of variables to be estimated. Thus, the curse of dimensionality arises in many situations when the estimation follows ordinary frequentist approach, such as MLE. Using the standard frequentist technique, the estimates suffers large estimation errors. Therefore, Bayesian techniques have been widely implemented recently as they could address the problem of low-frequency data with large number of parameters to be estimated. The issue of high dimensionality could be improved applying Bayesian methods for the analysis of uncertainty impact as the previous structural VAR estimation is dealing with 8 years of monthly data points, although the EPU data for the US has been established from 1800s.

In addition, Bayesian methods impose priors to the model which is an econometrician's *a priori* beliefs about the parameter values. By setting priors as a type of regularization, the Bayesian estimation leads econometricians to strong conclusions, providing reasonable confidence intervals. This feature could help us to interpret the effects of uncertainty from Bayesian VAR estimation in the manner of updating and adjusting in the decision-making process.

3.4.1 Motivating Bayesian Inference

In general, Bayesian estimation requires fully specified model, including the error distribution, so that the likelihood function of observed data $Y_{0:T}$ conditional on parameters $\theta = (\Phi, \Omega_\varepsilon)$ can be defined as follows:

$$p(Y_{0:T}|\theta) = \prod_{t=1}^{T} p(Y_t|X_t;\theta) \times p(Y_0|\theta) \tag{5}$$

The standard MLE estimation requires errors to follow Normal distribution, which leads to the likelihood function of data conditional on parameters, $\theta = (\Pi, \Omega_\varepsilon)$, can be expressed as follows.

$$P(Y_t|X_t;\theta) = \frac{1}{\sqrt{(2\Phi)^k|\Omega_\varepsilon|}} exp\left[-\frac{1}{2}(Y_t - \Phi X_t)'\Omega_\varepsilon^{-1}(Y_t - \Phi X_t)\right] \tag{6}$$

We then compute MLE treating θ known.

$$\hat{\theta}_{MLE} = arg \max_{\theta\in\Theta} p(Y_{0:T}|\theta) \tag{7}$$

Solving the first-order condition for the maximization problem, which gives us the MLE identical to OLS estimator.

$$\hat{\Phi}_{MLE} = \left[\sum_{t=1}^{T} X_t X_t'\right]^{-1} \sum_{t=1}^{T} X_t Y_t' \tag{8}$$

$$\hat{\Omega}_{MLE} = \sum_{t=1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_t{}' \tag{9}$$

where However, Bayesian approach assumes θ is a random variable, with a prior distribution which has been chosen in advance. Let $\pi(\theta)$ a prior distribution, then the joint distribution of $Y_{0:T}$ and θ can be written as follows:

$$p(Y_{0:T}, \theta) = p(Y_{0:T}|\theta)\pi(\theta) \tag{10}$$

Applying Bayes Rule yields posterior distribution,

$$p(\theta|Y_{0:T}) = \frac{p(Y_{0:T}|\theta)\pi(\theta)}{p(Y_{0:T})} \tag{11}$$

where

$$p(Y_{0:T}) = \int p(Y_{0:T}|\theta)\pi(\theta)d\theta \tag{12}$$

I choose prior distribution of Uhlig's (2005) independent Normal-Wishart as follows:

$$vec(\Phi)|\Omega_\varepsilon \sim N(vec(\Phi_0)), \Omega_\varepsilon \otimes \Sigma_0^{-1}) \tag{13}$$

$$\Omega_\varepsilon \sim IW(\nu_0 S_0, \nu_0) \tag{14}$$

where Σ_0, S_0 are $k \times k$ positive definite matrices and $\nu_0 > 0$ are normally referred to as hyper parameters. The choice of hyper parameters reflects the prior beliefs and uncertainty about individual parameters. For instance, Φ_0 can be interpreted as a priori expected value of parameters in VAR specification and Σ_0 as a dispersion of prior distributions.
The posterior can be computed as follows:

$$vec(\Phi)|\Omega_\varepsilon \sim N(vec(\Phi_T)), \Omega_\varepsilon \otimes \Sigma_T^{-1}), \tag{15}$$

$$\Omega_\varepsilon \sim IW(\nu_T S_T, \nu_T) \tag{16}$$

where

$$\nu_T = T + \nu \tag{17}$$

$$\Sigma_T = \Sigma_0 + \Sigma_{t=1}^T X_t X_t' \tag{18}$$

$$\Phi_T = \Sigma_T^{-1}(\Sigma_0 \Phi_0 + \Sigma_{t=1}^T X_t X_t' \hat{\Phi}_{MLE}) \tag{19}$$

$$S_T = \frac{\nu_0}{\nu_T} S_0 + \frac{T}{\nu_T} \hat{\Omega}_{\varepsilon,MLE} + \frac{1}{\nu_T} (\hat{\Phi}_{MLE} - \Phi_0)' \Sigma_T^{-1} \Sigma_0 (\hat{\Phi}_{MLE} - \Phi_0) \tag{20}$$

where $\hat{\Phi}_{MLE}$ and $\hat{\Omega}_{\varepsilon,MLE}$ are Gaussian MLE. [18] Bayesian approach could improve the drawbacks in classical maximum likelihood estimation in case of high dimensionality and nonlinearity, such as broad confidence band and large errors. Also it is because of practical reason: even though it is theoretically possible to solve for closed form maximizer of likelihood function, it is too cumbersome or hard when involving in high dimensional problems. However, Bayesian methods enable us to deal with high dimension of the parameter space and the nonlinearities in the model, using numerical evaluation methods. This paper uses Gibbs sampler.

3.4.2 Specification for Estimating the Effects of Uncertainty

First, as a counterpart model for the structural VAR, same 5-variable model is estimated, using demeaned variables. Data is monthly data from January 1996 to November 2013.

model I

$$Y_t = \begin{pmatrix} \text{Uncertainty} \\ \text{Stock Market Index} \\ \text{Interest rate} \\ \text{Employment} \\ \text{Production} \end{pmatrix} \tag{21}$$

For uncertainty measure, either EPU or RSS is entered into the model. Included lag length is 6. In the IRF results (Figure 7, 8), the response of four macro variables are

[18] As $T \to \infty$,
$\Phi_T \simeq \hat{\Phi}_{MLE}$, $\nu_T S_T \simeq \hat{\Omega}_{\varepsilon,MLE}$. In large samples, posterior means are equivalent to the Gaussian Maximum Likelihood means.

examined: stock market index *(Stock)*, interest rate *(FFR, Federal Funds Rate)*, Employment *(EMP)*, and industrial production *(IP)*. [19]

Then the second model explicitly considers the survey based inflation expectations. Inflation expectation data is retrieved from Federal Reserve of Philadelphia Survey of Professional Forecasters (`http://www.philadelphiafed.org/`). Macroeconomic data is collected from FRED economic database by St. Louise Federal Reserve, quarterly from 1Q 1992 to 1Q 2014. (`http://research.stlouisfed.org/fred2/`). All series are demeaned.

model II

$$Y_t = \begin{pmatrix} \text{Uncertainty} \\ \text{Real GDP} \\ \text{Long-term inflation expectation} \\ \text{Short-term inflation expectation} \\ \text{Short-term market interest rate} \end{pmatrix} \tag{22}$$

For uncertainty measure, either EPU or RSS is entered into the model. [20] Included lag length is 2 quarters. In the IRF results (Figure 9, 10), the response of four variables are examined: real GDP *(GDP)*, long-term inflation expectation *(LT)*, short-term inflation expectation *(ST)*, and 3-month money market interest rate *(MMR)*. Inflation expectation is based on Consumer Price Index and median of the individual forecasts. Long-term inflation expectation refers to annual average inflation over the current and next nine years. Short-term inflation expectation refers to annualized percentage points, seasonally adjusted, and based on quarterly average index level.

3.4.3 Results

The responses to RSS uncertainty are more protracted and larger than those to the EPU uncertainty, which underscores the greater persistence of RSS measures as compared to policy related EPU measures. The response of industrial production to EPU shock reaches its minimum level at $h = 10$, showing the magnitude of -0.037 standard deviation of demeaned data. [21] Monthly production rebound to nearly zero after 2 years and 4 months. Employment exhibits the same results: minimum at $h = 13$ with magnitude of -0.035 standard deviation in employment, rebounding to zero after 3 years and 3 months. The results for EPU effect suggest more detrimental impact on employment. The negative response to RSS uncertainty to production peaks at $h = 12$ to $h = 14$ with the magnitude around -0.055 standard deviation, bouncing back to zero after nearly three years. The magnitude of employment effect is similar to the effect of production with more protracted length ($h = 19$). It takes nearly 4 years to rebound to zero. The

[19] Employment and industrial production is for manufacturing sector.
[20] RSS is available from 1Q 1996.
[21] Notice that the time series for SVAR is HP filtered.

monetary policy reducing its policy rate at the minimum level, around 0.13 standard deviation lower than average interest rate, one year after initial uncertainty shock (EPU: $h = 14$, RSS: $h = 16$).

The second specification shows immediate response of real GDP. The response of long-term inflation expectation to both of uncertainty disturbances is outright statistically insignificant for all of the horizons whereas short-term inflation expectation decreases significantly. The money market interest rate reaches its minimum level after 3 quarters and bounce back at $h = 7$.

4 Conclusion

This paper investigates *ex-post* uncertainty and its impact on real economy, employing two measures of uncertainty, Economic Policy Uncertainty (EPU) by Baker et al. (2013) and Relative Sentiment Shift (RSS) by Tuckett et al. (2014) Although EPU has recently gained popularity for the analysis of policy-related disturbances, it fails to provide a rationale for decision-making process. RSS rather focuses on assessing the changes in economic agents' confidence about the future, where two domains of emotion, excitement and anxiety, play an important role for either promoting or inhibiting decisions in real activity. In addition, RSS covers text source more centred to financial market and subjective assessment by brokers and policymakers, allowing the measure to reflect rich information of investors' behaviour. The two measures show similar trend and high correlation even though there are some exceptions as EPU reacted sensitive to political events, such as elections and war, whereas RSS responded more for financial events, for instance, stock market burst after dotcom bubble.

Empirical analysis covers structural VAR with 5 variables, uncertainty, stock market index, interest rate, employment, and industrial production, and Bayesian VAR with same specification and the specification incorporating inflation expectation. For RSS shock, the magnitude of the effect on both production and employment is larger and the responses persist longer than the EPU shock. The rebound and overshoot after the downturn of the real activity is more noticeable in RSS shocks than EPU. In response of uncertainty shock for both measures, expansionary monetary policy was implemented by reducing policy rate within a year. To account for whether the effect evolves from mean preserving variance, not from bad news itself, VAR with Michigan Consumer Sentiment Index is estimated, showing that the effect is smaller than the benchmark model but still significant.

A Appendix I: Relative Sentiment Shift (RSS) Data Construction

A Relative Sentiment Shift measure developed in Tuckett et al (2014) uses Directed Algorithmic Text Analysis (DATA), which assesses shifting economic confidence about the future by assessing the shifts in the relative quantities of excitement and anxiety in relevant texts. This approach selects text variables, directed by the conviction narrative theory of decision making without making any distributional assumptions. Unlike other text analysis methods, the selection of relevant words is drawn from the context-independent algorithm directed by the underlying theory and validated in laboratory settings. Emotionally-charged words used to construct RSS are grounded upon the social psychological theory of action under uncertainty.

Table 4: Examples of emotional words for extracting RSS

Positive Domain	Negative Domain
Amaze	Anxiety
Amazed	Anxious
Attract	Avoid
Attracted	Avoids
Beneficial	Bother
Boost	Bothers
Confident	Distress
Confidently	Doubt

The laboratory experiment done by Strauss (2013) back up the idea of word choice. Random samples of words from the two domains were shown in the general context to financially-literate individuals so that they could give rates on whether the words match the anxiety about the loss or excitement about gain. The findings strongly suggests that the two lists well represent the two distinctive emotional domains.

The summary statistic of a collection of texts, 'T' is calculated by counting the number of words for each domain and scaling these numbers by the total text size in number of characters.

$$Sentiment[T] = \frac{|Excitement| - |Anxiety|}{size[T]} \tag{23}$$

B Appendix II: Figures

Figure 2: Stock Volatility, Uncertainty and Consumer Sentiment

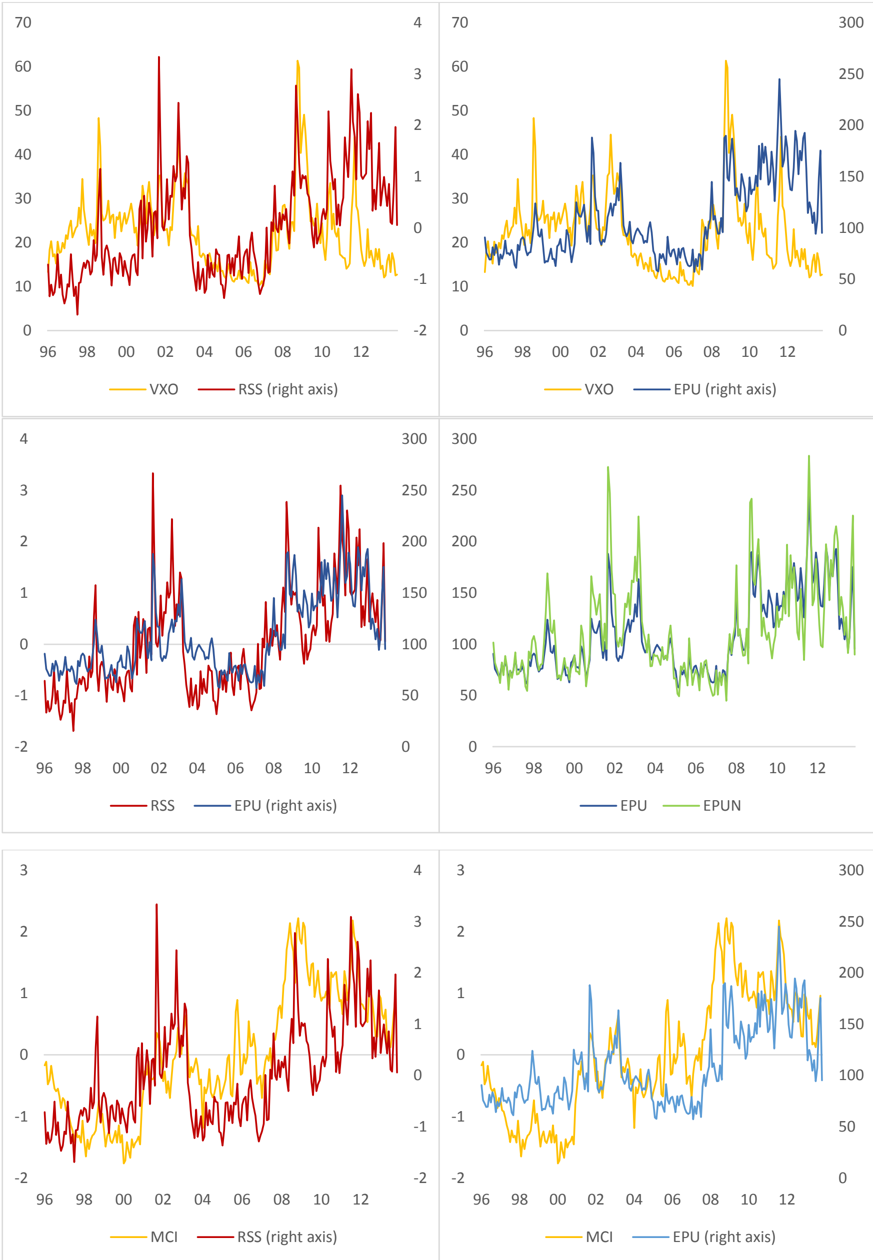


Figure 3: Impulse Response Function: EPU

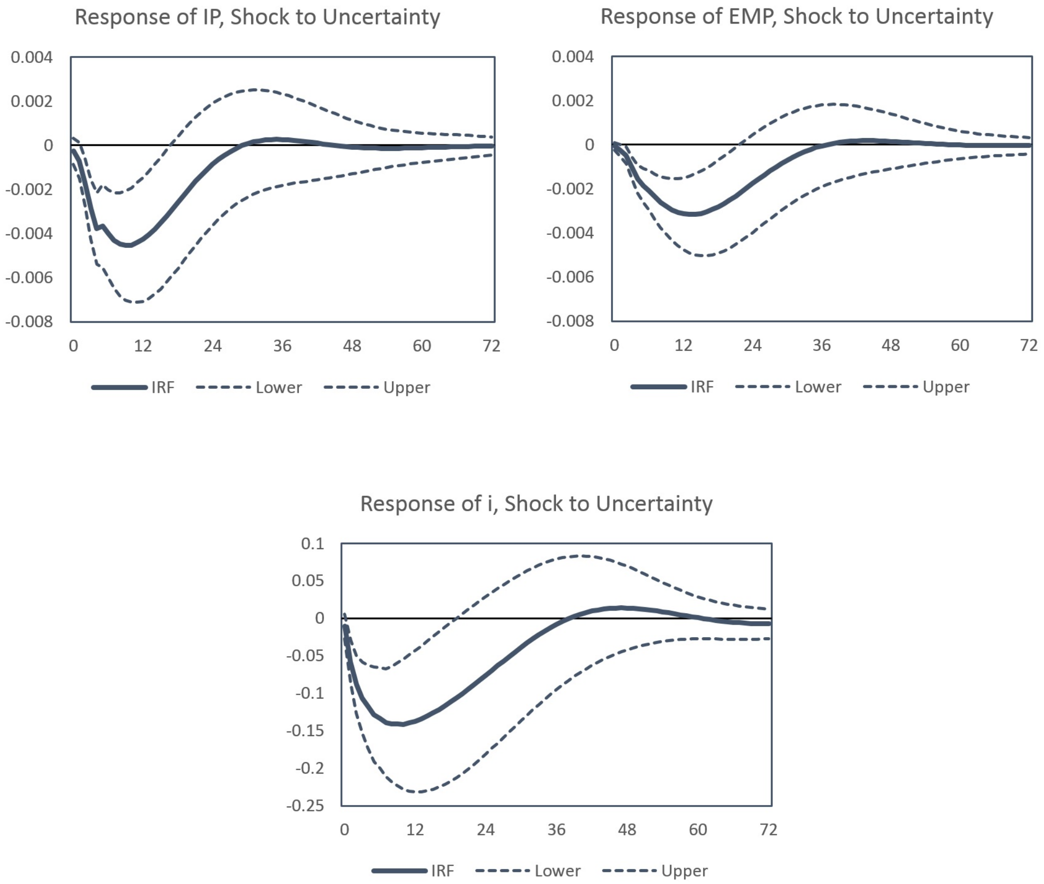


Figure 4: Impulse Response Function Robustness: EPU

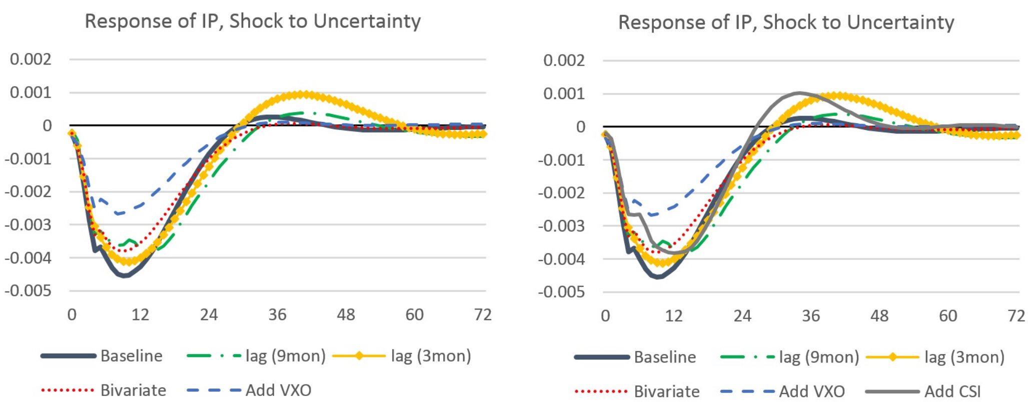


Figure 5: Impulse Response Function: RSS

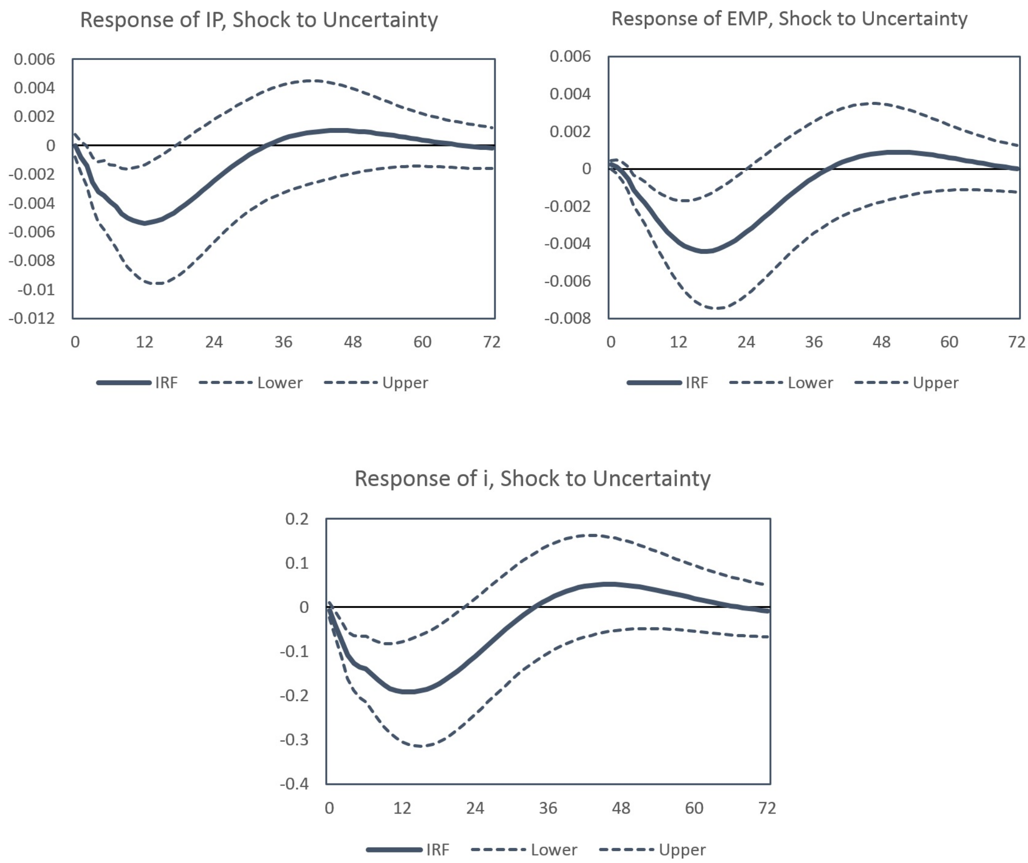


Figure 6: Impulse Response Function Robustness: RSS

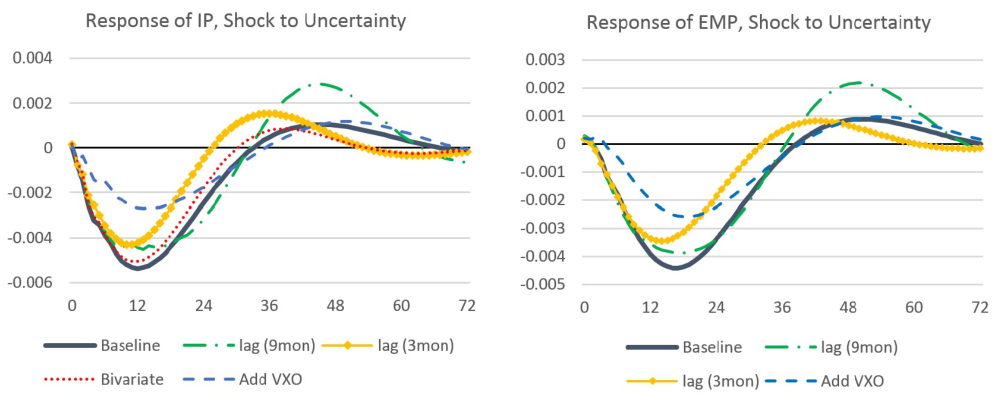


Figure 7: Impulse Response Function: Bayesian VAR (EPU)

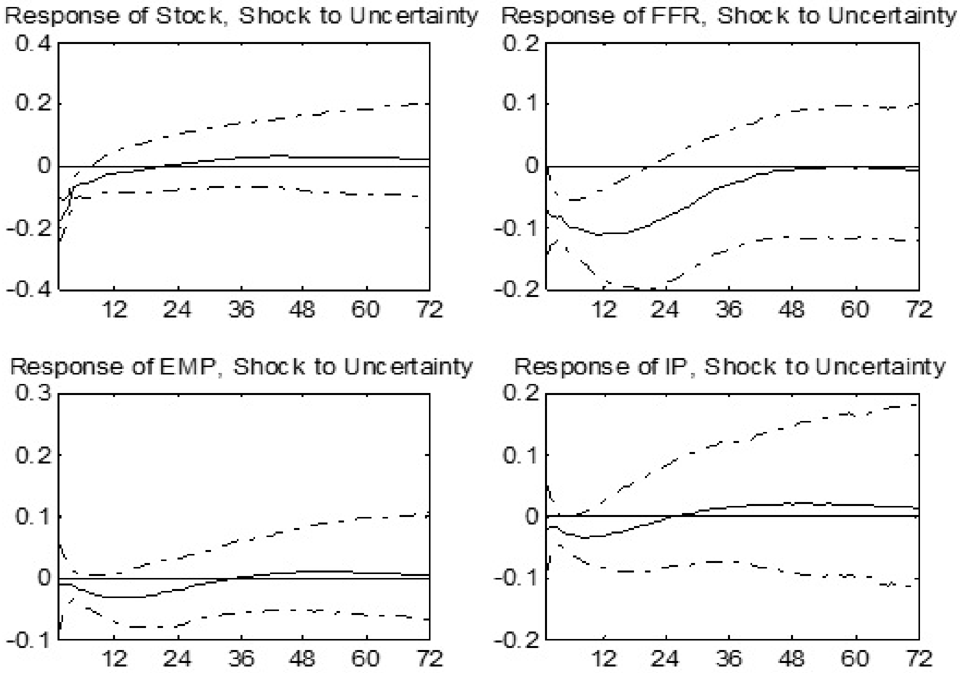


Figure 8: Impulse Response Function: Bayesian VAR (RSS)

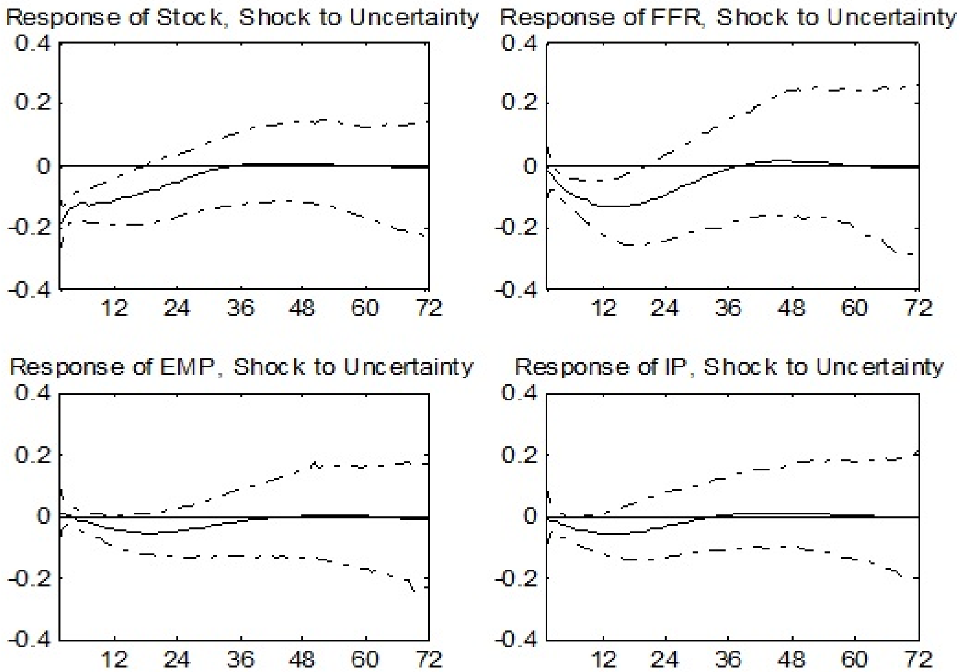


Figure 9: Impulse Response Function: Bayesian VAR (EPU)

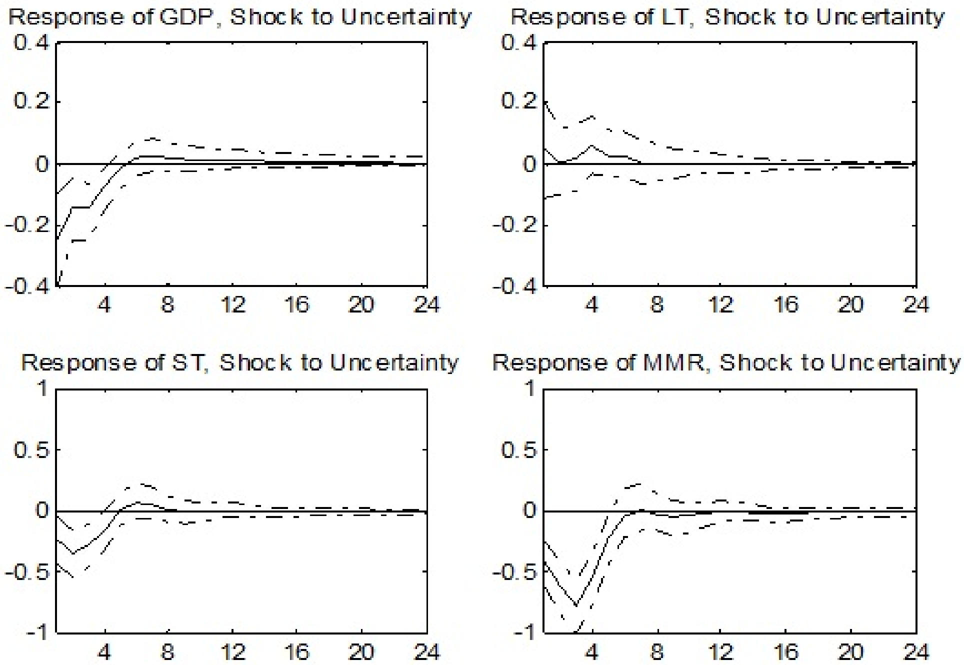
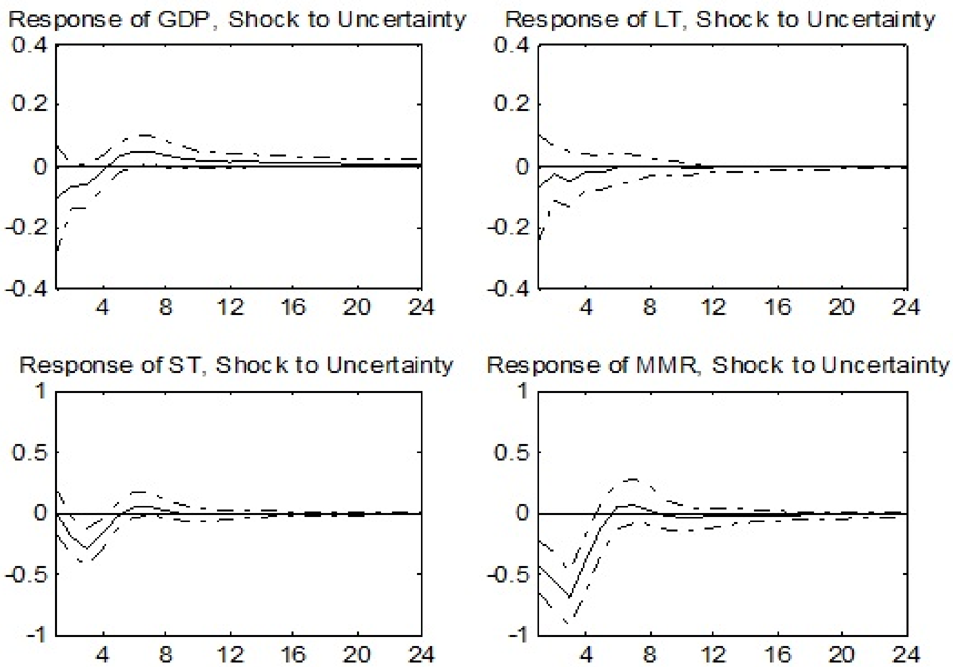


Figure 10: Impulse Response Function: Bayesian VAR (RSS)



References

[1] Aastveit, Knut Are, Gisle James Natvik, and Sergio Sola. (2013), *Economic uncertainty and the effectiveness of monetary policy.* No. 2013/17. Norges Bank.

[2] Aikman, D., Haldane, A. G., & Nelson, B. D. (2013), *Curbing the credit cycle*, The Economic Journal.

[3] Akerlof, G. A. & Shiller, R. J. (2009), *Animal Spirits: How Human Psychology Drives the Economy, and Why It Matters for Global Capitalism*, Princeton: Princeton University Press.

[4] Bank of England, (2013) *Macroeconomic uncertainty: what is it, how can we measure it and why does it matter?*, Quarterly Bulletin 2013 Q2, pp.100-109.

[5] Baker, S. R., N. Bloom, and S. J. Davis (2013), *Measuring Economic Policy Uncertainty*, Stanford University and University of Chicago Booth School of Business.

[6] Baker, Scott R., and Nicholas Bloom. (2013) *Does uncertainty reduce growth? Using disasters as natural experiments.* No. w19475. National Bureau of Economic Research.

[7] Bentolila, S., & Bertola, G. (1990), *Firing costs and labour demand: how bad is eurosclerosis?*, The Review of Economic Studies, 57(3), 381-402.

[8] Bernanke, B. S. (1983), *Irreversibility, uncertainty, and cyclical investment*, The Quarterly Journal of Economics, 98(1), 85-106.

[9] Bloom, N (2009), *The impact of uncertainty shocks*, Econometrica, Vol. 77, pages 623–85.

[10] Bloom, N., Bond, S., & Van Reenen, J. (2007), *Uncertainty and investment dynamics*, The review of economic studies, 74(2), 391-415.

[11] Brunnermeier, Markus K. (2008), *Deciphering the liquidity and credit crunch 2007-08*, No. w14612. National Bureau of Economic Research.

[12] Carriere-Swallow, Y., & Cespedes, L. F. (2013). *The impact of uncertainty shocks in emerging economies*, Journal of International Economics, 90(2), 316-325.

[13] Carroll, C (1996), *Buffer-stock saving and the life cycle/permanent income hypothesis*, NBER Working Paper No. 5788.

[14] Charemza W., C. Diaz, and S. Makarova, (2013), *Term structure of inflation forecast uncertainties and skew normal distributions*, Working Paper No. 14/01, Economics Department, University of Leicester.

[15] Denis, S and Kannan, P (2013), *The impact of uncertainty shocks on the UK economy*, IMF Working Paper No. 13/66.

[16] Disney, R, Haskell, J & Heden, Y (2003), *Restructuring and productivity growth in UK manufacturig*, Economic Journal, Vol. 113, Issue 489, pp. 666-94.

[17] Dixit, A and Pindyck, R (1994), *Investment under uncertainty*, Princeton University Press, Princeton.

[18] Estrella, Arturo, and Frederic S. Mishkin, (1998), *Predicting US recessions: financial variables as leading indicators*, Review of Economics and Statistics 80.1: 45-61.

[19] Fernandez-Villaverde, J., Guerron-Quintana, P. A., Rubio-Ramirez, J., & Uribe, M. (2009). *Risk matters: The real effects of volatility shocks*, NBER Working Paper No. w14875.

[20] Gilchrist, S, Sim, J and Zakrajsek, E (2010), *Uncertainty, financial frictions, and investment dynamics*, 2010 Meeting Papers No. 1285, Society for Economic Dynamics.

[21] Golinelli, Roberto, and Giuseppi Parigi. *Consumer sentiment and economic activity: a cross country comparison*, Journal of Business Cycle Measurement and Analysis 1.2 (2004): 147-172.

[22] Hansen, L. P. (2012). *Challenges in identifying and measuring systemic risk*, NBER Working Paper No. w18505.

[23] ILO, (2013), *Global Employment Trends. Recovering from a second jobs dip*, (Geneva).

[24] ILO, (2014), *Global Employment Trends. Risk of a jobless recovery?*, (Geneva).

[25] Jurado, K., Ludvigson, S. C., and Ng, S. (2013), *Measuring Uncertainty*, NBER Working Paper 19456.

[26] Kahneman, Daniel and Amos Tversky (1979), *Prospect Theory: An Analysis of Decision under Risk*, Econometrica, 47, 263-291.

[27] Knight, F (1921), *Risk, uncertainty and profit*, Signalman Publishing, Kissimmee, Florida.

[28] Lazear, E & Spletzer, R (2011), *Hiring, churn and the business cycle*, NBER Working Paper No. 17910.

[29] Leahy, J. V. & Whited, T. M. (1995), *The effect of uncertainty on investment: some stylized facts*, NBER Working Paper No. w4986.

[30] Mas-Colell, Andreu, Michael Dennis Whinston, and Jerry R. Green. (1995), *Microeconomic theory.* Vol. 1. New York: Oxford university press.

[31] McDonald, R., & Siegel, D. (1986). *The value of waiting to invest*, The Quarterly Journal of Economics, 101(4), 707-727.

[32] Mertens, K., & Ravn, M. O. (2013), *The dynamic effects of personal and corporate income tax changes in the United States*, The American Economic Review, 103(4), 1212-1247.

[33] Nyman R., Gregory D., Kapadia S., Smith R., & Tuckett D. (forthcoming), *News and narratives in financial systems*, ECB conference slides on 4 April 2014.

[34] Romer, C (1990), *The Great Crash and the onset of the Great Depression*, Quarterly Journal of Economics, Vol. 105(3), pp. 597–624.

[35] Schwert, G. W. (2011), *Stock Volatility during the Recent Financial Crisis*, European Financial Management, 17: 789–805.

[36] Strauss, V. M. (2013), *Emotional Values of Words in Finance: Anxiety about Losses and Excitement about Gains*, M.Sc. thesis in Social Cognition, University College London.

[37] Tuckett, D., (2011), *Minding the Markets: An Emotional Finance View of Financial Instability*, Palgrave MacMillan, London and New York.

[38] Tuckett, D., P. Ormerod, R. Nyman and R. E. Smith (2014), *Conviction Narrative Theory and Directed Algorithmic Text Analysis: Predicting the Evolution of the US and UK Economies*, University College London Centre for the Study of Decision-Making Uncertainty. (Mimeo)