Three essays on uncertainty: real and financial effects of uncertainty shocks

Lee, Seohyun

UCL

July 2017

Three Essays on Uncertainty: Real and Financial Effects of Uncertainty Shocks

Seohyun Lee

Thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

University College London

2017

Declaration

I, Seohyun Lee, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Abstract

The thesis consists of three essays on real and financial effects of uncertainty shocks.The first chapter investigates two different news-based uncertainty indices, Economic Policy Uncertainty Index (EPU) and Relative Sentiment Shift Index (RSS). I employ reduced form VAR and local projections (Jordá, 2005) to explore the differences in wait-and-see effect of uncertainty on the real economy. Surprises in either index lead to significant declines in production and employment and the effect is larger and persistent in the case of RSS shocks than EPU. In the second chapter, the probabilistic approach is applied to uncover the dependence structure in inflation uncertainty for the countries bordering a major currency area, the UK and the euro area. Inflation uncertainty is measured by the conditional volatility removing entire forecastable variations by bivariate VAR GARCH model and joint distribution of uncertainties of two regions is estimated by using copula to account for non-linear association. The results show that the left tail events of inflation are positively correlated between the two regions. This implies that the appropriate monetary policy can be drawn if policymakers consider the interconnectedness of the deflationary pressures. Finally, the third chapter examines the long run relationship between gross capital flow and its determinants, focusing on the impact of uncertainty as global and contagion factors. I apply bounds testing approach by Pesaran, Shin, and Smith (2001) allowing for the underlying regressors being either I(0), I(1) or mutually cointegrated. Both gross capital inflows and outflows exhibit significant level relationship with global, contagion and domestic factors and uncertainty spillovers through financial linkages between the UK and the euro area play crucial role in predicting capital flows of the UK.

Contents

List of Figures

List of Tables

Chapter 1

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

Abstract

This chapter investigates various measures of macroeconomic uncertainty and the impact of uncertainty on real economy, focusing mainly two measures, Economic Policy Uncertainty Index (EPU) by Baker, Bloom and Davis (2015) and Relative Sentiment Shift Index (RSS) by Tuckett et al. (2014), Tuckett, Smith, and Nyman (2014). Although the two measures show similar trend and high correlation, there exist distinctive features among measures due to the differences in the methodology to construct the indices: EPU is sensitive to political events or natural disasters whereas RSS responds more to financial events. The impulse responses from reduced form VAR and local projections (Jordá, 2005) show significant differences in the impact of two different uncertainty measures on the real economy. The magnitude of the RSS shocks on both production and employment is larger and the responses persist longer than EPU. Wait-and-see effect, the rebound and overshoot after the downturn of the real activity, is more noticeable in EPU than in RSS. RSS may capture contemporaneous structures among variables in VAR model and consequently explains alternative channels other than wait-and-see effect. To account for whether the effect evolves from mean preserving variance, not from bad economic situation itself, the baseline specification includes stock market index to separate out the effect of changes in future expectation of business cycle, assuming stock market returns are forward-looking. The robustness check confirms that the result is consistent with the theoretical predictions. The volatility is more relevant for the short run negative effect while the expectation of the state of economy mainly explains the persistent negative effects.

Acknowledgment
I hereby declare that the permission of using the Relative Sentiment Shift Index is granted by UCL Centre for Study of Decision-Making Uncertainty. I am solely responsible for all remaining deficiencies.

1.1 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 because of the limited monetary policy effectiveness under the zero lower bound on interest rate. Jurado, Ludvigson and Ng (2015) argues 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. Stock and Watson (2010) also found that uncertainty was one of the main contributors to the recent Great Recession. 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. Besides the crisis-led structural changes, the implementation of new policies is largely recognised as another important source of uncertainty since 2008. Among many studies, Summers (2014) pointed out that 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 countercyclicality 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 (see Romer, 1990; Carroll, 1996; Gilchrist, Sim, and Zakrajšek, 2014; Lazear and Spletzer, 2011, among others).

There are mainly two challenges in the empirical analysis of the uncertainty and its economic consequences: the measurement and the identification of uncertainty in estimation. Regarding the former issues, it is important to examine the related concepts and proxies of uncertainty in the pre-existing studies. One popular uncertainty proxy is volatility measures. Most of empirical papers use implied stock market volatility index (VIX or VXO) by Chicago Board Options Exchange Market as a proxy for uncertainty for practical reasons, not resting on a profound theoretical background. The doubts and critiques whether market volatility could measure uncertainty *per se* have been emerged recently. For example, Jurado, Ludvigson and Ng (2015) claimed that it is more closely related to risk-aversion in financial markets (see Bekaert, Hoerova, and Duca, 2013 for a comprehensive critique).

Other related concept is sentiment. Sentiment indices reflect broader market expectation (including perceived uncertainty by economic agents) and may explain real economic fluctuations. Among numerous studies, Estrella and Mishkin (1998) and Golinelli and Parigi (2004) found that Michigan Consumer Sentiment Index (MCI) could predict and be predicted by a wide range of economic variables in the US. Although MCI seems to be loosely linked to uncertainty *per se*, it captures the changes in confidence and beliefs about the economic situation that can be interpreted as the changes in perceived uncertainty.

Risk is also conceptually related to uncertainty. In fact, it is often misunderstood. Frank Knight's seminal paper (1921) provides useful insights to refine the concepts of uncertainty and risk. Knight laid out two concepts of uncertainty: one is often called Knightian uncertainty and another is non-Knightian uncertainty. The key distinction between the two concepts is whether it is measurable and observable. Knightian uncertainty is not directly measurable and unobservable, whereas non-Knightian uncertainty refers to measurable and observable uncertainty. In addition, the concept of risk and non-Knightian uncertainty are confusing and requires clarification. Makarova (2014) clearly explained that the non-Knightian uncertainty 'becomes a risk after such marks are explicitly known and addressed'.[1]

In clarifying the definition of different related concepts of uncertainty, we found it interesting to relate decision theory to Knight's concepts of uncertainty. In the von-Neumann Morgenstern expected utility theory, agent considers alternatives with uncertain outcomes by means of objectively known probabilities. That is, the probability density of *ex ante* realisations is defined (non-Knightian uncertainty). However, the assumption that the probability densities are defined with known probability rarely holds. This is the world where Knightian uncertainty lies. In the subjective probability theory, initially proposed by Savage (1972), with probability density unknown, individuals make decision *as if* they held probabilistic beliefs. The well-defined probabilistic beliefs can be uniquely revealed by the choice behaviour of individuals. The subjective probability theory dissolves the distinction between 'risk' and 'uncertainty' by using beliefs expressible as probabilities (Mas-Colell, Whinston, and Green, 1995). For empirical technique, this naturally leads to a basis of Bayesian approach as beliefs

[1] Makarova (2014) defined the non-Knightian uncertainty as 'the uncertainty of a phenomenon which is potentially measurable in the sense that a probability distribution of *ex ante* realisations can be defined, but the marks (values of interest) are not defined'.

are the important key for defining subjective probabilities.

To analyse the macroeconomic effects of uncertainty, it is also important to discuss the implication of measuring uncertainty in the macro level. Decision theory in microeconomics provides insights how uncertainty affect the choice of individual economic agent. Based on this micro-foundation, the appropriate macroeconomic uncertainty measure needs to offer time-varying data that can be used in the estimation of macro time-series models. Literature on measuring macroeconomic uncertainty based on micro-foundation is a fast growing area in applied research (see, *inter alia* Bloom, 2009; Bachmann, Elstner, and Sims, 2013; Charemza, Diaz, and Makarova, 2013; ILO, 2013, 2014; Tuckett et al., 2014; Tuckett, Smith, and Nyman, 2014; Baker, Bloom and Davis, 2015; Jurado, Ludvigson, and Ng, 2015). However, there has been little agreement on the definitions and best strategies to capture the *true* uncertainty. In addition, the classification of the methods of measurements has not reached to any conventions in the field.[2] One popular approach is to search for the *(unobservable)* underlying components of uncertainty, either from news quotes (Baker, Bloom and Davis, 2015; Tuckett et al., 2014; Tuckett, Smith, and Nyman, 2014) or from a huge set of macro variables (Bank of England, 2013; ILO; 2013, 2014; Jurado, Ludvigson and Ng, 2015). On the other hand, some rely on non-Knightian uncertainty by evaluating forecast errors of a certain economic variable (Charemza, Diaz, and Makarova, 2013) or measuring disagreement among the forecasters (Wallis, 2005; Clements, 2014). These methods can be interpreted as non-Knightian approach since it assumes a certain probability density function to measure 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 implemented different strategies of VAR (Vector Autoregression) specification to estimate the effects of uncertainty (Bachmann, Elstner, and Sims, 2013; Colombo, 2013; Baker, Bloom and Davis, 2015; Jurado, Ludvigson and Ng, 2015). Some of them employ Bayesian inference technique (for example, Aastveit, Natvik and Sola, 2013). However, the specification issue still arises as simple VAR models may not guarantee whether they estimate true causal effect, free of any potential bias. Based on these potential shortcomings of VAR models, the discussion has been extended to the distinction between endogenous and exogenous uncertainty (See Ludvigson, Ma, and Ng, 2015; Segal, Shaliastovich, and Yaron, 2015; Berger, Dew-Becker and Giglio, 2016). Another remaining issue 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)

[2]One interesting work on the classification of the methods in assessing uncertainty is Makarova (2014). The methods of assessing uncertainty can be categorised into three groups: (i) assessing the disagreement among the forecasters, (ii) uncertainty by model, and (iii) mixed approach and other aggregate measures.

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 potential field of the future research to focus.

This chapter attempts to give an account of those two main challenges: the measurement of macroeconomic uncertainty and the estimation of the impact of uncertainty on real economy. Among many different concepts of uncertainty, it mainly focuses on two recently developed measures based on text resources: Economic Policy Uncertainty Index (EPU) by Baker, Bloom and Davis (2015) and Relative Sentiment Shift Index (RSS) by Tuckett et al. (2014) and Tuckett, Smith, and Nyman (2014). This study also contributes to the development of empirical models to estimate the real impact of uncertainty. In particular, it builds reduced form VAR model with Impulse Response Functions (IRFs) robust to the misspecification due to serial correlation across different forecast horizons. The real economic variables that are considered to estimate impact of two different uncertainty shocks are industrial production and employment. In order to deal with the misspecification problem, the local projections by Jordá (2005) and simultaneous confidence regions by Jordá (2009) are considered. This estimation strategy would help interpret the impulse responses at time h, orthogonal to the variability up to $h-1$ periods.

The plan for the remaining sections is as follows. Section 1.2 broadly examines the measurement issue of macroeconomic uncertainty. It covers six different measures and proxies for macroeconomic uncertainty including stock market volatility measure, consumer sentiment measure, and other macroeconomic uncertainty measures which have been developed recently. The institutional backgrounds, trend and cyclical behaviour of these indices are also investigated and compared. Section 1.3 is dedicated to the analysis of the impact of macroeconomic uncertainty. Beginning with reviewing the theoretical backgrounds, this section examines the empirical model for estimation. In particular, the classical reduced form VAR model and local projections (Jordá, 2005) for estimating impulse responses will be outlined. Then I will investigate the empirical strategy for constructing the conditional bands of the impulse responses introduced by Jordá (2009) and explain data. Section 1.4 reviews the results from the empirical models, including Impulse Response Functions (IRFs) and Forecast Error Variance Decomposition (FEVD). Finally, Section 1.5 concludes.

1.2 Different Measures of Macroeconomic Uncertainty and Proxies

1.2.1 Descriptive analysis of uncertainty measures

Six different proxies related to macroeconomic uncertainty are considered in this study: financial market volatility index (often referred as VIX or VXO, VXO onwards), Michigan Consumer Sentiment Index (MCI), Economic Policy Uncertainty Index (EPU), Relative Sentiment Shift Index (RSS), macroeconomic uncertainty measure by Jurado, Ludvigson and Ng (2015, denoted as JLN), and the measure of inflation uncertainty by Charemza, Díaz, and Makarova (2015, referred as CDM).

The implied volatility index for stock market by Chicago Board Options Exchange is used as the canonical proxy for uncertainty in most existing finance and economic literature, in particular, 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 simply captures the consequence of collective decisions of stock market participants. Stock market volatility may fluctuate for many reasons other than changes in uncertainty, for example, leverage, risk-aversion, sentiment. Bekaert, Hoerova, and Duca (2013) argued that VIX consists of components driven by factors associated with time-varying risk aversion. Moreover, Jurado, Ludvigson and Ng (2015) pointed out that stock market volatility is more correlated with time-varying risk aversion rather with economic uncertainty *per se*. From the empirical point of view, Baker, Bloom and Davis (2015) 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.

Another popular proxy for uncertainty is Michigan Consumer Sentiment Index (MCI). MCI is a monthly survey data published by University of Michigan. The index is based on the survey responses to five questions; two questions on personal finances, two on the outlook for the economy, and one question on buying conditions for durables. MCI is often considered as consumer confidence level in the literature. In a broad sense, there are two contrasting views on the impact of sentiment on business cycle fluctuations (see Barsky and Sims, 2012). One is the "animal spirit" view, which postulates that the exogenous fluctuations in beliefs cause business cycle. For example, Blanchard (1993) suggested that the cause of the 1990-1991 recession was the prolonged negative consumption shock associated with an exogenous shift in sentiment. Another view is the "information" or "news" view, which suggests that the sentiment or confidence indicies contain the the fundamental information about the current and future economic developments. Beaudry and Portier (2006) proposed a VAR model specification where the anticipated changes in expectation may drive the business cycle fluctuations.

Grounded on the model by Beaudry and Portier (2006), Barsky and Sims (2012) found that the confidence does not play an important role in macroeconomic fluctuations. The conclusions from two contrasting views on the impact of sentiment still remain ambiguous both theoretically and empirically.

The most recent and popular macroeconomic uncertainty index is the Economic Policy Uncertainty Index (EPU) by Baker, Bloom and Davis (2015). EPU for the US consists of three components: the counts how often uncertainty related to policy is mentioned in newspapers (news-based EPU, denoted as EPUN hereafter), 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 EPUN for the US. The index is available for other advanced countries or region - such as Japan, Canada, some European countries - including Germany, UK, France, Italy, Spain, Ireland, Netherlands, and Sweden - and emerging economies - Australia, Brazil, Chile, China, India, Korea, Russia, and Singapore. For Canada, Europe and India, they report composite index of news-based index, budget disagreement index, and CPI disagreement index from Consensus Economics throughout March 2014 but as of April 2014 they are no longer using Consensus Economics forecaster dispersion data and solely constructing indices based on newspaper articles. For other remaining countries, EPU indices are solely news-based EPU.

Figure 1.1 plots the the historical movements in EPUN for the US. EPUN directly measures the number of word counts which include “uncertainty”, “economy” and “policy terms” from the selective choice of popular newspapers. It is straightforward measure for policy-related uncertainty and contains relatively objective and neutral information about economic uncertainty reflected in the newspaper articles. As EPUN measures unobservable component of policy-driven uncertainty, it can be interpreted as Knightian uncertainty. However, as Makarova (2014) pointed out, EPU may incorporate mixed signal of Knightian and non-Knightian uncertainty because one of the components in EPU, forecast disagreement, indeed portrays non-Knightian uncertainty.

Another perspective in measuring macroeconomic uncertainty emphasizes emotions as key drivers of economic and financial activity (Akerlof and Shiller, 2009; Tuckett, 2011). In the states of economy with high uncertainty, market participants make their decision by securing conviction through narratives (Chong and Tuckett, 2015). Such conviction narratives 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 backed by structured finance during late 2000s. Aikman, Haldane, and Nelson (2013) pointed out that financial markets can be

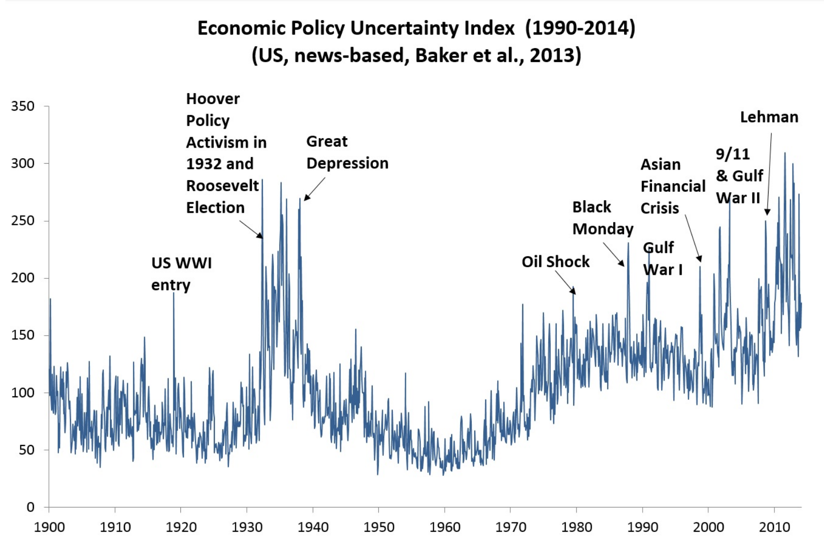

Figure 1.1: The US news-based Economic Policy Uncertainty Index

Source: Economic Policy Uncertainty website, `http://www.policyuncertainty.com/`.

systematically linked because of the search for yield with top performers as a reference, namely "keeping up with the Goldmans" (Nyman et al, 2014).

Based on the theory of conviction narrative, Tuckett et al. (2014), Tuckett, Smith and Nyman (2014) developed a Relative Sentiment Shift Index (RSS), using the Directed Algorithmic Text Analysis (DATA) to assess the change in economic confidence about the future. They focused on the two emotion groups, excitement and anxiety, which either promotes or inhibit decision-making. They pointed 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 that 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. 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 signals inhibition process in loss domain.

The wider availability in digital form of texts sources opens the opportunities for investigating the sentiment efficiently. For example, Sinha (2014) proposed a machine-learning algorithm for classifying news by three dimensions, positive, negative, and neutral to construct a sentiment index. The critical feature for these type of algorithms to effectively capture sentiment is the selection of relevant words list. Unlike other text analysis methods, the selection of word lists for RSS is drawn from the context-independent algorithm directed by the underlying theory and validated in laboratory settings (Tuckett, Smith and Nyman, 2014). They create very focused word lists with around 150 words that are psychologically justified to depict conviction narratives. Comparing to common word lists which often include over one thousand words, e.g. Harvard-IV word list published in 2014 contains 1,915 positive words and 2,291 negative words, RSS is very parsimonious. For more detailed explanation how RSS is constructed and sample word list, see Appendix 1.6.1.

Comparing EPU and RSS, there are distinctive features in terms of text sources. News components of EPU refers to leading newspapers in a country. For example, the US news-based EPU uses the archive of 10 major newspapers.[3] Therefore, EPU has relatively broader data sources overarching worldwide and regional topics. RSS, however, covers targeted text resource, Reuters News Archive, comprising over 20 million news articles in English from 1996 to 2013.[4] Since the coverage of RSS text source is quite specific to financial market and contains assessments of market participants and journalists, RSS might include rich information about investors' behaviour and their qualitative evaluation on uncertainty level in the market. On the other hand, it can be viewed as narrow information neglecting the sentiment of general public since Reuters News Archive could only provide professional views focusing on financial markets. By and large, it seems that RSS reflects the individual investor's decision making process by directly selecting words from the theory of conviction narratives whereas EPU is designed for measuring policy-related uncertainty with an advantage of broader accessibility of source texts.

Jurado, Ludvigson and Ng (2015) constructed the macroeconomic uncertainty in terms of forecasting errors estimated using the huge set of macro variables. They define root mean squared forecast errors as h-period ahead uncertainty in variable y_{jt} for $j = 1, \cdots, N_y$ as

$$U_{jt}(h) = \sqrt{E\Big[[y_{j,t+h} - E[y_{j,t+h}|I_t]]^2|I_t\Big]}$$

where I_t denotes the information set available at time t. Then they aggregate across the macro variables, j, to obtain a measure of macroeconomic uncertainty using common latent factor.

$$U_t(h) \equiv \text{plim}_{N_y \to \infty} \sum_{j=1}^{N_y} w_j U_{jt}(h) \equiv E_w[U_{jt}(h)]$$

[3] 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.

[4] Tuckett, Smith and Nyman (2014) developed similar index which comprises Reuters News Archive, Broker reports of 14 brokers' commentaries, and Bank of England internal market commentaries using the same DATA algorithm. Bank of England commentaries were obtained by the collaboration of Bank of England.

JLN macroeconomic uncertainty index is available for 1-month, 3-month, and 12-month ahead forecasts from June 1960 until December 2014 (`http://www.econ.nyu.edu/user/ludvigsons/`) for the US macro variables.

Charemza, Díaz, and Makarova (2015) constructed a measure of inflation uncertainty by computing the squares of forecast errors evaluated from a univariate ARMA-GARCH model. CDM is a non-Knightian measure of inflation uncertainty since it assumes that inflation uncertainty can be backed out from *ex post* observable density. Depending on the forecasting horizon, h, inflation uncertainty can be interpreted as unexpected components in inflation fluctuations unpredictable at the time of forecast. Comparing to other uncertainty measures that uses big data from newspaper quotes (EPU, RSS) or huge dataset of macro variables (JLN), CDM is much more parsimonious as it can be constructed by univariate model. Therefore, if there exist significant correlations in the movements of CDM and other measures, CDM can be useful as a compact measure for uncertainty of individual variable of interest.

Figure 1.2 illustrates time series trajectories of stock market volatility (VXO), consumer sentiment index (MCI) and other types of uncertainty measures, RSS, EPU, EPUN, JLN and CDM. The sample period is from January 1996 to December 2014, except RSS (since it is only available from January 1996 to November 2013). The original RSS and MCI series is multiplied by -1 so that positive (negative) values of RSS and MCI indicate the increase (decrease) of uncertainty level. CDM is illustrated using 6-month moving average to smooth out large fluctuations in the figure.

The most distinctive difference between stock volatility index and RSS, EPU, CDM is found after September 2011 when VXO hiked for the second time due to European debt crisis. EPU, RSS, and CDM uncertainty indices showed prolonged high level at least for a year until the end of 2012 while stock volatility dropped sharply during the consecutive 6 months, returning quickly to the normal level. Schwert (2011) found that the volatility seen after 2008 crisis was relatively short-lived in many advanced countries comparing to the volatility after the Great Depression. Due to the potential structural break after the Great Recession, VXO might fail to have higher correlation with perceived uncertainty in economy. Therefore, the premise of stable relationship between stock volatility and real activity might also have been changed since the recent crisis.

The trajectories of uncertainty measures in mid-2000s show similar trend. During the period between 2004-06, VXO, EPU and RSS remained very low, in line with the reasoning of the Great Moderation. During the Great Moderation, macro volatility and the cost of risk in most advanced countries had dropped remarkably.[5] During 2000s,

[5]Bernanke mentioned such trend in the FRB Governer's Speech in 2004. Retrieved online from `http://www.federalreserve.gov/BOARDDOCS/speechES/2004/20040220/default.htm`.

there was an episode of natural disaster and the effect of disaster on uncertainty varies across different measures. MCI and JLN uncertainty increased sharply in October 2005 when Hurricane Katrina hit the US while RSS, EPU uncertainty increased modestly and VXO remained intact.

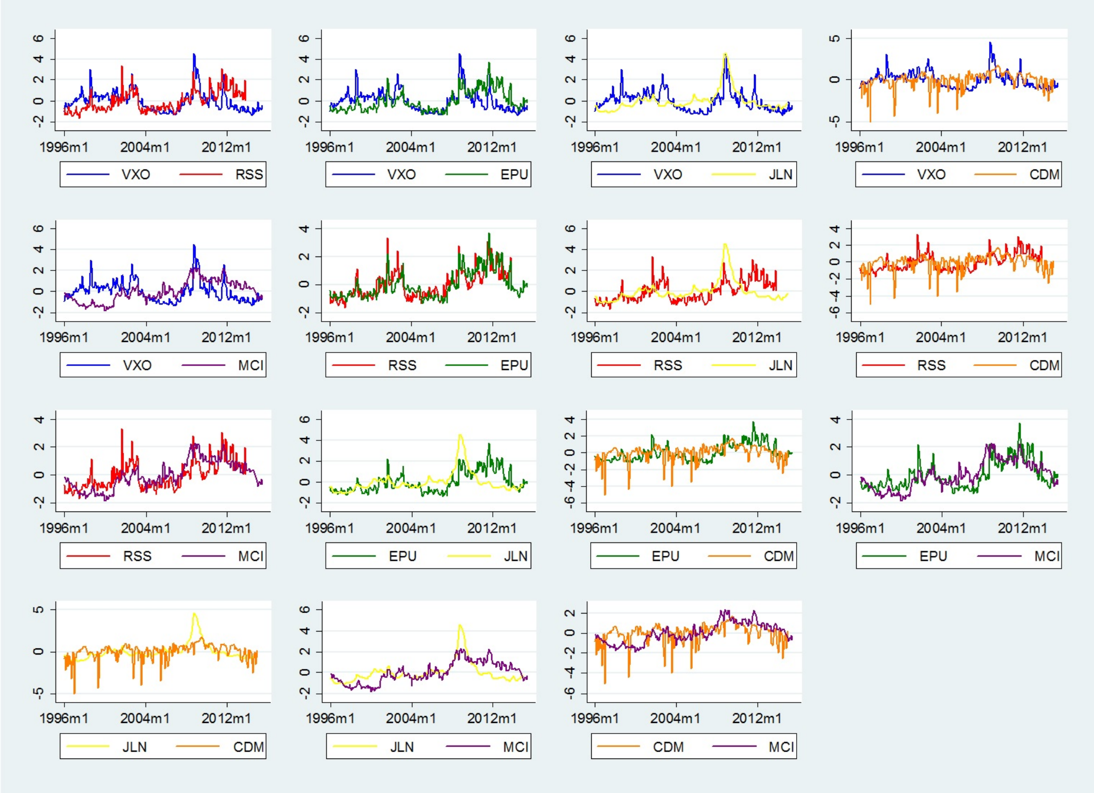

Figure 1.2: Uncertainty indices and proxies

Source: Thomson Reuters Datastream (VXO, MCI), Economic Policy Uncertainty website, `http://www.policyuncertainty.com/` (EPU), UCL Centre for Study of Decision-Making Uncertainty (RSS), Charemza, Díaz, and Makarova (2015, CDM).

Focusing RSS and EPU only (see Figure 1.3), they show similar trend with some episodes of divergence. Three cases of divergence are examined: (i) RSS increases without any significant changes in EPU, (ii) both measures increase but RSS increases more, and (iii) both increases but EPU increase more.

As for the first case, there are four episodes where RSS increased sharply without any significant signal of EPU increase.[6] These events of dramatic increase in RSS relative to EPU occurred when RSS was influenced by global financial events. In particular, RSS acted as an early warning for the subsequent financial crisis in some cases. The first episode of the split between two measures 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

[6]These episodes occurred in September 2002, August 2007, July 2008, and May 2010.

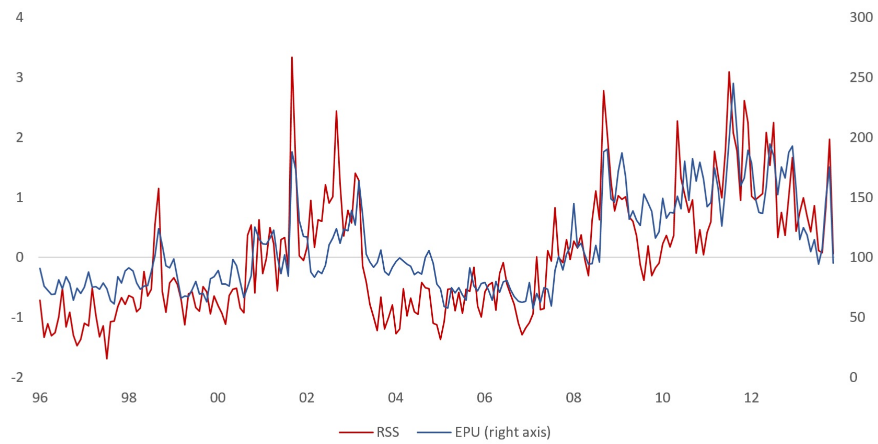

Figure 1.3: Economic Policy Uncertainty and Relative Sentiment Shift

Source: Economic Policy Uncertainty website, `http://www.policyuncertainty.com/` (EPU), UCL Centre for Study of Decision-Making Uncertainty (RSS)

they could not value the underlying assets of their funds fairly due to their exposure to subprime mortgage loans. 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 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. The next example is the failure of IndyMac Bank in the US in July 2008. IndyMac, one of the largest US mortgage lender then, was closed by the Office of Thrift Supervision and the Federal Deposit Insurance Corporation (FDIC) established IndyMac Federal Bank, FSB, as successor to the Bank.[7] In May 2010, RSS rose sharply while EPU remained relatively stable level due to global financial market turbulence upon the Greek government's announcement of austerity measures.

By examining the remaining two cases where both measures increase but either one of the measure increases more, it seems that EPU tends to react relatively sensitive to political events, such as elections and war, whereas RSS has been affected largely by financial events. For example, there were steeper increases in EPU than in RSS during the US interest cuts and stimulus in January 2008, banking crisis in February 2009, and the US midterm election in September 2010. On the contrary, the episodes when RSS increased more than EPU can be found mostly during the financial turbulences: Russian financial crisis/LTCM in September 1998, 9/11 in 2001, the bankruptcy of Lehman in September 2008, the European debt crisis in November 2011, and the US debt ceiling debate in October 2013.[8]

[7] See FDIC Press release, July 11 2008, `https://www.fdic.gov/news/news/press/2008/pr08056.html` for more details.

[8] (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

It is also worthwhile to pay attention to the period of low uncertainty state and compare the patterns before and after the Great Recession in 2008. Before the recent crisis, RSS was persistently lower than EPU and the state continued for longer period when uncertainty remained below average level: January 1996–March 1998 (27 months' duration), December 1999–August 2000 (9 months' duration), August 2003–April 2005 (21 months' duration). Assuming that RSS reacts more to financial factors than policy factors while EPU reacts mainly to policy factors, it demonstrates that financial stability effect constantly dominates the effect of politics and policy related uncertainty in low uncertainty era before recent crisis. However, the durations of diversion between EPU and RSS after the crisis have been shortened: July 2009–May 2010 (10 months' duration) and August 2010–January 2011 (6 months' duration). It suggests that the financial stability effects are short-lived and macro uncertainty is mainly governed by political or policy factors after the Great Recession.

To analyse the dependence structure among various uncertainty measures, pairwise Pearson's correlation and Spearman's rank correlation are computed. Correlation coefficient is the most widely used linear dependence measure between two variables, X and Y:

$$\rho_{XY} = \frac{\mathrm{COV}(X,Y)}{\sigma_X \sigma_Y}$$

Where σ_X and σ_Y denote the standard deviation of random variables, X and Y. Correlation coefficient satisfies desirable properties of dependence measures as it is (1) symmetric, (2) satisfies normalization, $-1 \leq \rho_{XY} \leq 1$, (3) measures perfect positive and negative dependence, and (4) invariant to linear transformation. Furthermore, if (X, Y) follows bivariate Gaussian, then the correlation coefficient fully determines its dependence structure and $\rho_{XY} = 0$, if they are independent. In case of multivariate distributions, the dependence structure of elliptical families can be fully characterized by correlation matrix.

However, the correlation coefficient cannot measure non-linear dependence.[9] In addition, the correlation coefficient is not a sufficient measure for dependence in cases where there is heavy tail or asymmetric dependences (see, for example, Cont, 2001). Another crucial limitation of Pearson's correlation coefficient is that it is invariant only for linear transformation. That is, for strictly increasing nonlinear transformation, T : $R \to R$, $\rho[T(X), T(Y)] \neq \rho_{XY}$.

(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 debate (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).

[9] For example, if $X \sim N(0,1)$ and $Y = X^2$, then $\mathrm{cov}[X,Y] = 0$ but the pair is obviously dependent.

Unlike Pearson's correlation coefficient, Spearman's rank correlation measures the degree of monotonic dependence even in non-linear fashion. For sample of size n, Spearman's ρ_S is computed as follows:

$$\rho_S(X, Y) = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

where $d_i = x_i - y_i$, and x_i, y_i are the converted rank of the raw random variables X_i, Y_i. In order to assess the degree of dependence of time series data potentially from non-Gaussian data generating process, rank correlation seems to be more reliable measure.

Table 1.1-1.2 illustrate the results of Pearson's correlation coefficients and Spearman's rank correlation coefficients among uncertainty measures. CDM is calculated from 12-months-ahead forecast errors which has the largest and significant correlation with most of uncertainty measures.[10]

Pairwise Pearson's correlation coefficients between EPU and all other measures of uncertainty are statistically significant at 1%. EPU and EPUN has the largest coefficients for both Pearson's correlation (0.90) and rank correlation (0.93), simply because EPUN is one of the component consisting EPU. RSS has the second largest correlation coefficient with EPU (0.78-0.80). VXO and CDM exhibit similar magnitude of correlation with EPU although CDM has slightly larger rank correlation than VXO. Among different horizons of JLN measures, JLN based on 1-month-ahead forecast error has the largest correlation with EPU (0.29-0.35).

Pairwise Pearson's correlations between RSS and VXO (0.43) and MCI (0.65) are the evidence of representativeness of RSS as an uncertainty proxy. The rank correlation between RSS and VXO (0.35) and MCI (0.67) also exhibit similar results. Among different horizons of JLN measures, 1-month-ahead JLN index shows the largest correlation with RSS as in the case of EPU.

As seen in the graphical analysis, volatility index (VXO) exhibits relatively low correlation with other measures of uncertainty. Rank correlation is the largest when paring with EPUN but the magnitude is rather moderate (0.43). Rank correlation between VXO and MCI is negative and insignificant. On the contrary, MCI shows relatively higher correlation with other measures except VXO. Among them, the rank correlation with EPU and with RSS are the largest, approximately 0.68.

[10] In particular, $\text{CDM}_{t,h} = \log(\sqrt{(\text{forecast error}_{t|t-h} \times 100)^2})$, where $h = 12$. See Appendix 1.6.2. for the correlation coefficients between CDM and other measures based on different forecasting horizons.

Table 1.1: Pearson's correlation coefficients

	EPU	EPUN	VXO	MCI	RSS	JLN1	JLN3	JLN12	CDM
EPU	1								
EPUN	0.9042*	1							
	0.0000								
VXO	0.3955*	0.4974*	1						
	0.0000	0.0000							
MCI	0.6956*	0.5227*	0.1493	1					
	0.0000	0.0000	0.0242						
RSS	0.8035*	0.7714*	0.4274*	0.6497*	1				
	0.0000	0.0000	0.0000	0.0000					
JLN1	0.3544*	0.3028*	0.5154*	0.5786*	0.3370*	1			
	0.0000	0.0000	0.0000	0.0000	0.0000				
JLN3	0.3374*	0.2944*	0.5283*	0.5540*	0.3230*	0.9981*	1		
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000			
JLN12	0.2637*	0.2454*	0.5468*	0.4509*	0.2576*	0.9723*	0.9832*	1	
	0.0001	0.0002	0.0000	0.0000	0.0001	0.0000	0.0000		
CDM	0.3362*	0.2552*	0.2065*	0.3207*	0.3192*	0.3724*	0.3653*	0.3379*	1
	0.0000	0.0001	0.0017	0.0000	0.0000	0.0000	0.0000	0.0000	

Notes: Sample period is 1996m1-2014m12, except RSS (1996m1-2013m11). JLN1 denotes JLN macroeconomic uncertainty measured based on 1-month-ahead forecast errors. Similarly, JLN3 and JLN12 denotes the measure based on 3-months- and 12-months-ahead forecast errors. The values in the first row of each variable is the correlation coefficients and the values in the second row are significance level. * denotes the correlation coefficients are significant at 1%.

Table 1.2: Spearman's rank correlation coefficients

	EPU	EPUN	VXO	MCI	RSS	JLN1	JLN3	JLN12	CDM
EPU	1								
EPUN	0.9339*	1							
	0.0000								
VXO	0.3557*	0.4306*	1						
	0.0000	0.0000							
MCI	0.6776*	0.5364*	-0.0111	1					
	0.0000	0.0000	0.8681						
RSS	0.7800*	0.7621*	0.3465*	0.6748*	1				
	0.0000	0.0000	0.0000	0.0000					
JLN1	0.2887*	0.2222*	0.2327*	0.4453*	0.3144*	1			
	0.0000	0.0007	0.0004	0.0000	0.0000				
JLN3	0.2562*	0.2047*	0.2706*	0.3946*	0.2964*	0.9907*	1		
	0.0001	0.0019	0.0000	0.0000	0.0000	0.0000			
JLN12	0.1453	0.1206	0.3314*	0.2321*	0.1888*	0.9209*	0.9552*	1	
	0.0282	0.0692	0.0000	0.0004	0.0055	0.0000	0.0000		
CDM	0.3853*	0.3114*	0.2449*	0.3892*	0.3972*	0.4474*	0.4260*	0.3481*	1
	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	

Notes: Sample period is 1996m1-2014m12, except RSS (1996m1-2013m11). JLN1 denotes JLN macroeconomic uncertainty measured based on 1-month-ahead forecast errors. Similarly, JLN3 and JLN12 denotes the measure based on 3-months- and 12-months-ahead forecast errors. The values in the first row of each variable is the correlation coefficients and the values in the second row are significance level. * denotes the correlation coefficients are significant at 1%.

1.2.2 Trend and cyclical behaviours of uncertainty measures

Followed by the descriptive analysis, the uncertainty measures can be further investigated considering trend and cycle.[11] The common principle of the data preparation for time series estimation is the symmetric treatment of the actual data and the theoretical model (DeJong and Dave, 2011). In the conventional theoretical models, covariance-stationarity of data is often required because most macroeconometric models, such as VAR, aim to estimate the impact of a shock as deviations from steady states. To obtain covariance-stationary series, trend removal and isolation of cycles in log level original variables are involved.[12] Therefore, investigating the patterns of trend and fluctuations around the trend is critical step ahead of the estimation.

There are three types of transformation techniques depending on the assumptions of trend and cyclical behaviour: (i) linear detrending, (ii) differencing, and (iii) filtering. If a series is characterised by deterministic time trend, detrending by fitting a linear trend to logged variable with OLS regression is suffice to yield stationarity. In this case, the series is said to be trend stationary. For unit root processes, differencing the series will induce stationarity. The choice between two treatment hinges on the assumptions regarding which process, either deterministic trend or unit root, provides more reasonable representation for logged variables. As Hamilton (1994) noted, if a series y_t follows unit root process, subtracting linear time trend from y_t would fail to remove the time trend in variance although the time dependence in the mean can be removed by the treatment. In addition, if a trend stationary series are to be differenced, the differenced series becomes stationary, but there will be a unit root process in the moving average representation, resulting non-invertibility. A widely accepted remedy for this problem is to try both specifications and evaluate the relative sensitivity (see DeJong and Dave, 2011).

Other potential problem of trend removal lies when there are structural breaks in trend. If this is the case, the detrended series would show spurious persistence, causing the inferences based on transformed data become invalid (see Perron, 1989). To account for this problem, filtering techniques can be used for removal of such trend behaviour. The most widely used technique is Hodrick-Prescott (H-P) filter, which is designed to remove trend from cycle, given slowly evolving trend. In particular, decomposing $\log y_t$ as

$$\log y_t = g_t + c_t$$

where g_t is the growth component and c_t is cyclical components. The H-P filter esti-

[11]The theoretical background for the analysis of trend and cycle is heavily drawn from the textbooks, such as Hamilton (1994), DeJong and Dave (2011).

[12]In general practice, take logarithm of the original variables first. Taking logarithm before trend removal has two implications in general: log-linear approximation to represent the growth rate of the variables and the reduction in cascade effects in raw data.

mates g_t and c_t by minimising the following objective function:

$$\sum_{t=1}^{T} {c_t}^2 + \lambda \sum_{t=3}^{T} [(1-L)^2 g_t]^2$$

The parameter λ determines the smoothness of evolving trend. If $\lambda = 0$, all fluctuations in $\log y_t$ will be assigned to the growth component. On the other hand, if $\lambda = \infty$, the weight on the trend component in the objective function becomes maximal so that all variations in $\log y_t$ will be assigned to the cyclical component. In general, λ is set to 1,600 for quarterly data and 129,600 for monthly data.

These three different versions of transformed uncertainty measures are illustrated in Figure 1.4. By examining the persistence of linearly detrended series, one may find potential structural breaks. Most of uncertainty measures except CDM, the linearly detrended series exhibit persistent positive values during 2001-04 and the subsequent reversal to negative values during 2005-07. After recent crisis, the pattern of the persistent large departure above zero followed by negative values was repeated. Broadly speaking, these patterns provide the evidence of structural breaks in 2005, 2008 and 2014.[13] The linearly detrended series of RSS and VXO show similar movements as EPU except the absence of extended period of below linear trend after 2014. The detrended CDM seems more random, showing quite a few negative spikes before the recent crisis in 2008.

In addition, spectral analysis can be implemented (DeJong and Dave, 2011).[14] First, B-P filtered series are generated to look at business cycle fluctuations. Then, the autocorrelation functions and spectra of four types of transformed series are examined.

The left panels of Figure 1.14 and 1.15 in Appendix 1.6.4 demonstrate the autocorrelation functions against the time horizons. The autocorrelation function indicates the persistence of innovations and cyclical patterns of uncertainty measures. As discussed, linearly detrended series show high degree of persistence due to several structural breaks. Slowly decaying autocorrelation suggests that the dynamics of linearly detrended series have MA components as well as AR components. The duration of having positive correlation is longer in MCI (33 months) and EPU (24 months) than RSS (18 months) and VXO (22 months). The two types of filtered data reveal some hints of cyclical behaviour. In particular, B-P filtered data exhibit repeated rotation of positive and negative autocorrelation. For instance, B-P filtered EPU index shows positive autocorrelation over the first six months and then negative autocorrelation

[13] The possibility of breaks in uncertainty and volatility measures as well as other macro variables are widely acknowledged and crucial in estimating uncertainty effects on macroeconomics. To my knowledge, however, the recent literature on uncertainty rarely consider structural breaks explicitly yet, except Göktaş and Dişbudak (2014). Therefore, as a starting point, Chow's breakpoint test for detecting structural breaks is conducted for each equations in plain vanilla VAR estimation (described in Section 1.3-1.4.) in Appendix 1.6.3.

[14] See Appendix 1.6.4 for details.

Figure 1.4: Detrended output of uncertainty measures

Notes: Detrended output is computed by author.

Source: Thomson Reuters Datastream (VXO, MCI), Economic Policy Uncertainty website, `http://www.policyuncertainty.com/` (EPU), UCL Centre for Study of Decision-Making Uncertainty (RSS), Charemza, Díaz, and Makarova (2015, CDM)

for 10 months. The phase of positive autocorrelations followed by negative phase is repeated afterwards. The H-P filtered data of EPU shows long term cycle compared to the H-P filtered RSS. The autocorrelation of differenced series are very small and insignificant.

The estimated spectrum densities are illustrated in the right panels of Figure 1.14 and 1.15. The x-axis of the spectrum density is frequency, denoted as cycles per unit period (month). The linearly detrended series peak at zero frequency, reflecting persistence. The period of a cycle for linearly detrended series approaches infinity, meaning that the cycle is never repeated. Likewise, the spectra spike at zero for H-P filtered series. This also indicate evident persistence in the H-P filtered series. The comparison of the height of spectrum provides relative importance of variations at the chosen frequency. For H-P filtered VXO and EPU, the level of spectrum at zero frequency is relatively large among other uncertainty indices. That is, the variations at low frequency are important in explaining total variations in VXO and EPU. For RSS, the height at zero is the smallest, meaning that the variations at low frequency are less important. For B-P filtered series, the peaks in the spectra lie in $[1/96, 1/18] \simeq [0.010, 0.056]$ by construction.[15] Comparing the level of spectra at the peak, two sentiment indices, RSS and MCI, are higher than EPU and VXO. This may confirm the findings of existing literature that the variations in sentiment indices are highly associated with business cycle fluctuations.

To sum up, the institutional aspects and the dynamics of different uncertainty measures are important for the application of data transformation. It is more desirable if the high frequency fluctuations in the original series in uncertainty measures are retained after the transformation because the influence of high frequency fluctuations on the overall dynamics is important. In addition, it is preferable to avoid spuriousness in persistence of detrended data. Overall, H-P filtered uncertainty measures seem to comply with the criteria for empirical analysis.[16]

[15]The frequencies at peaks are 0.045 (EPU), 0.043 (RSS), 0.047 (VXO), 0.036 (MCI), respectively.

[16]Notice that there are some critiques on H-P filtering. For example, Cogley and Nason (1995) argued that H-P filter can generate spurious business cycle even if the underlying raw data of a model do not exhibit cyclicality. Moreover, Phillips and Jin (2015) showed that H-P filter can capture long run behaviour, which includes stochastic trend and combination of deterministic and stochastic trend that allows breaks by choosing an appropriate smoothing parameter (λ).

1.3 The Impact of Macroeconomic Uncertainty on Economic Activity

1.3.1 Theoretical backgrounds

Numerous studies have investigated the channels of uncertainty impact on real economy. Demand side of uncertainty channel was investigated by both firm- and household-level approach. Real options theory borrowed the concept of financial derivative, option, to explain the countercyclicality of uncertainty due to the irreversibility of firms' investment (Bernanke, 1983; Dixit and Pindyck, 1994). Others (Carroll, 1996; Romer, 1990) focused on the household-level explanation. They noted that households might build up a buffer stock of savings to draw on in periods of temporarily low income when they face with uncertainty about their future labour income. One of the seminal paper to analyse the impact of macroeconomic uncertainty is Bloom (2009). He adopted real option theory to evaluate *wait-and-see* effect of uncertainty by setting Real Business Cycle (RBC) model with frictions in capital and labour.

Other studies have examined the supply side channel of uncertainty. Bentolila and Bertola (1990) argued that hiring plans are negatively affected by uncertainty due to high adjustment costs in labour market. Bloom (2009) also mentioned that the uncertainty may affect hiring and firing decisions to be postponed. More recently, Lazear and Spletzer (2011) pointed out that uncertainty reduces productivity growth through less efficient matching of skills to jobs. In terms of the link between uncertainty and productivity shocks, Disney, Haskell and Heden (2003) suggested that in times of high uncertainty, companies may be more reluctant to enter new export markets, which may prevent the most productive use of resources and consequently reduce supply. Bachmann, Elstner and Sims (2013) hypothesized the *wait-and-see* effect incorporated with the endogenous growth mechanism and argued that this mechanism may induce the persistent and prolonged negative responses of real macro variables. They suggested that the determinants of endogenous growth, such as R&D investment, human capital investment and technological progress, can be affected by the initial innovations in uncertainty and strengthen the demand channel that has persistent but not permanent impact on the real economy.

Others have built the theoretical models for alternative channels of uncertainty, mainly focusing on financial frictions. Gilchrist, Sim, and Zakrajšek (2014) demonstrated that uncertainty about the macroeconomic outlook is likely to have a negative effect on asset prices because investors require compensation for the risk of holding the asset. They explained that high uncertainty with financial market imperfection leads to reductions in banks' incentives to provide loans for households and companies, tightening in credit conditions. Arellano, Bai and Kehoe (2012) similarly emphasised the role of endogenous credit tightening for the channel of uncertainty in the imperfect financial market setting. Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016) also found that financial and uncertainty shocks are often hard to distinguish and the interactions between these two shocks are important in explaining the Great Recession.

Some of the theoretical and empirical papers have demonstrated the uncertainty channels can be explained under the context of international economics. Fernandez-Villaverde et al. (2009) indicated that domestic uncertainty shocks may lead agents to increase their savings abroad, which is often called *capital flight*. They estimated a stochastic volatility process for real interest rate using T-bill rates and country spreads. They employed Particle filter and Bayesian methods in order to evaluate the impact of uncertainty via capital flows in international dimensions. Carriére-Swallow and Céspedes (2011) explored heterogeneous responses of different countries when facing high uncertainty. In comparison to advanced countries, emerging economies suffer severe falls in investment and private consumption following an exogenous uncertainty shock. It takes significantly longer to recover, and they do not experience a subsequent overshoot in real activity. They argue that the dynamics of investment and consumption are correlated with the depth of financial markets and monetary and fiscal policy because the development of financial markets and effective policy reactions could alleviate the impact of credit constraints for firms and households.

Another transmission channel proposed by Hansen, Sargent and Tallarini (1999) is the risk premia mechanism through confidence. Their model consists of consumers with pessimistic beliefs, i.e. 'consumers who fears model misspecification'. Due to the representative agents inability to acknowledge a probabilistic distribution, the model predicts the agents act based on the worst-case scenario, following Gilboa and Schmeidler (1989). As uncertainty increases, consumers expect that the worst outcome gets worse so that they reduce investment and hiring.

Lastly but most importantly, there have been constant discussions about the distinction between endogenous and exogenous uncertainty effect. Some argues that the *wait-and-see* effect is indeed the causal channel from macroeconomic uncertainty to real activity and business cycle. For the empirical analysis, reduced form VAR or other types of SVAR are implemented (see, for example, Bloom, 2009; Colombo; 2013; Baker, Bloom and Davis, 2015; and Jurado, Ludvigson and Ng, 2015). Others claims the *by-product* hypothesis, suggesting that countercyclicality of macroeconomic uncertainty reflects endogeneity.[17] They argue that the bad economic situation itself (first moment shock) may cause increases in uncertainty (second moment shock). One of the earliest attempt is Van Nieuwerburgh and Veldkamp (2006). They proposed the theoretical

[17] Refer to Bachmann, Elstner, and Sims (2013) for the list of the literature on *by-product* hypothesis. For recent development, see Ludvigson, Ma, and Ng (2015), Segal, Shaliastovich, and Yaron (2015), Berger, Dew-Becker and Giglio (2016).

model to illustrate the causal relationship from first moment shocks to higher volatility. They highlighted the role of the learning process of economic agents on real business cycle and constructed a model where information imprecision (or uncertainty) leads to endogenously driven recession.

1.3.2 Empirical models

Most of previous attempts to build models for estimating the influence of uncertainty on the macro variables focus on the VAR specification. For the US data, Bloom (2009) identified uncertainty effects on the US economy with 5-variable VAR specification with Cholesky ordering. Later research, such as Baker, Bloom and Davis (2015) and Juardo, Ludvigson and Ng (2015), replicated the specification in Bloom (2009) with their own uncertainty index with variations of the ordering of the variables in the system. For the UK, Denis and Kannan (2013) built a low-dimensional VAR model to quantify the effect of uncertainty shocks on monthly UK industrial production data while Bank of England (2013) applied reduced form six-variable VAR with quarterly data to estimate the impact of uncertainty on UK GDP. Colombo (2013) constructed structural VAR to investigate the effects of a US economic policy uncertainty shock on euro area macroeconomic variables.

The key issue in the estimation of uncertainty impact is the endogeneity among macro variables in the VAR model. VAR requires restrictions for the identification to trace out structural shocks and their dynamic effects. The literature varies across different identification restrictions imposed in VAR systems. Bekaert, Hoerova, and Duca (2013), for example, first uses standard Cholesky decomposition of the estimation of covariance matrix. Then, they impose five contemporaneous restrictions with long run restriction. It assumes that the effect of monetary policy on industrial production is shut down in the long run. This assumption relies on theory of long-run money neutrality. Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016) further develop empirical methodology by using penalty function approach within SVAR framework to trace out the interaction between economic uncertainty and financial conditions.

The existing studies hinged on the conventional approach to construct the standard errors for Impulse Response Function (IRF), which could be problematic if the model is misspecified. Traditional VAR estimation represents a linear global approximation of the true Data Generating Process (DGP). However, problem arises for the estimation of IRFs based on the misspecified VAR. As IRFs are the functions of forecast horizon, the estimation of IRFs naturally accumulates the errors in the coefficients and the inference of impulse responses could suffer from low precision.

There are several approaches to detour the issues in estimating impulse responses. In general, restricted VAR models or Bayesian technique are largely implemented to cope with large standard errors in the IRFs. In addition, local projection approach suggested by Jordá (2005) can be employed. He proposed the estimation of IRF being local projections to each forecast horizon instead of extrapolating the distant horizon estimates from a globally estimated model. This approach essentially estimates the impulse responses by sequential regressions with overlapping points in each adjacent regression. Jordá (2005) also showed the Monte Carlo evidence of consistency and efficiency in the local projections for the model under the true DGP and for the misspecification cases.

In addition to the large standard error in the impulse responses, the potential serial correlation in the impulse response functions could be another issue for inferences about the estimated IRFs in practice (see, for example, Sims and Zha, 1999; Lütkepohl, 2007). Jordá (2009) focused on simultaneous confidence regions and proposed two methods for presenting the insights. Using Scheffé's S-method, Scheffé bands represent uncertainty around the *shape* of the impulse responses. On the other hand, conditional bands can be constructed to analyse the significance of individual coefficient conditional on the past trajectory.

The two aforementioned issues on the estimation of impulse responses in VARs are particularly significant when illustrating the impact of uncertainty on macroeconomic variables. The DGPs for different uncertainty measures are unknown and potentially non-Gaussian. Moreover, misspecification of underlying data generating processes could aggravate the robustness of estimated errors in impulse responses which is non-linear function of forecasts at distant horizons. Therefore, sequential local projections and conditional confidence bands could provide crucial implications for impulse responses to uncertainty disturbances. The estimated conditional confidence intervals for responses to uncertainty shocks can be interpreted as the variability in impulse responses at h, unaffected by the variability from history up to $h-1$ periods. Overall, this approach can equip us with a pertinent tool for assessing the significance of the shape of the dynamic transmission mechanisms of uncertainty shocks to real economy.

Throughout this section, Jordá's approach (2005) of local projection is outlined. In addition, the construction of the simultaneous confidence intervals (Jordá, 2009) is demonstrated. Based on the conventional reduced form VAR structure,[18] the generic notation for the impulse response function is as follows.

$$\mathrm{IR}(t,s,d_i) = E(y_{t+s}|v_t = d_t; X_t) – E(y_{t+s}|v_t = \mathbf{0}; X_t) \tag{1.1}$$

where the operator $E(.|.)$ denotes the best mean squared error predictor; y_t is an n×1 random vector; $X_t \equiv (y_{t-1}, y_{t-2}, \dots)'$; $\mathbf{0}$ is a zero vector with dimension n×1; v_t is the n×1 vector of reduced form disturbances; and $\boldsymbol{D}$ is the matrix that contains shocks, such that the i^{th} column, d_i, represents the disturbances to the i^{th} element in y_t.

[18]See Appendix 1.6.5 for the sketch of the general VAR model. Its orthogonalised Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD) for the baseline VAR model estimation are also derived.

In order to identify the contemporaneous causal structure in the variance-covariance matrix, the traditional approach suggests the Wold decomposition after estimating VAR system. The triangular factorisation in Cholesky decomposition ($\Omega = AD^{1/2}D^{1/2}A' = PP'$) is equivalent to setting $\boldsymbol{D} = P^{-1}$, so that the i^{th} column of the disturbance matrix represents the structural shocks to the i^{th} element in y_t. The estimation in conventional VAR model is meaningful only if the original DGP is well-represented by the VAR model specification. Without making any assumptions on the DGP, the natural alternative to the Wold decomposition is to project y_{t+s} locally to the linear space of past values of y_t up to p lags, $(y_{t-1}, y_{t-2}, \ldots, y_{t-p})'$.

$$y_{t+s} = \alpha^s + B_1^{s+1} y_{t-1} + B_2^{s+1} y_{t-2} + \cdots + +B_p^{s+1} y_{t-p} + u_{t+s}^s \tag{1.2}$$

for $s = 0, 1, 2, \ldots, h$. α^s is an n×1 vector of constants; B_i^{s+1}'s are the matrices of coefficients for lag i and forecast horizon $s+1$; and u_{t+s}^s is the residual.

The impulse responses from the local projection in equation (1.2) can be demonstrated using the generic function of equation (1.1).

$$\mathrm{IR}(t, s, d_i) = B_1^s d_i \tag{1.3}$$

The representation for the estimated impulse response function is

$$\widehat{\mathrm{IR}}(t, s, d_i) = \hat{B}_1^s d_i \tag{1.4}$$

for $s = 0, 1, 2, \ldots, h$, with normalinsation of $\hat{B}_1^0 = I$. It can be undoubtedly established that the estimates $\hat{B}_1^s$ are consistent because the residuals, u_{t+s}^s, are the moving average of the forecast errors from t to $t+h$ uncorrelated with the regressors, $(y_{t-1}, y_{t-2}, \ldots, y_{t-p})'$.

Local projections can provide the expression for the forecast error variance decomposition, straight from the definition of forecast errors in equation (1.2).

$$y_{t+s} - E(y_{t+s}|X_t) = u_{t+s}^s \tag{1.5}$$

for $s = 0, 1, 2, \ldots, h$. Normalisation for mean squared error (MSE) with the disturbance matrix, $\boldsymbol{D}$, yields

$$\mathrm{MSE}(E(y_{t+s}|X_t)) = \boldsymbol{D}^{-1} E(u_{t+s}^s u_{t+s}^{s'}) \boldsymbol{D}'^{-1} \tag{1.6}$$

for $s = 0, 1, 2, \ldots, h$.

It might be interesting to examine the relationship between the local projections and conventional VARs. In conventional VAR specification in Appendix 1.6.5, equation (1.38) can be written as follows, unfolding the matrix notations into vector notations.

$$\xi_{t+s} = \nu_{t+s} + F\nu_{t+s-1} + F^2\nu_{t+s-2} + \cdots + F^{s-1}\nu_{t+1} + F^s\xi_t + F^{s+1}\xi_{t-1}$$

$\Rightarrow$

$$\begin{aligned} y_{t+s} - \mu =& \varepsilon_{t+s} + F_1^1\varepsilon_{t+s-1} + F_1^2\varepsilon_{t+s-2} + \cdots + F_1^s\varepsilon_t \\ &+ F_1^{s+1}(y_{t-1} - \mu) + \cdots + F_p^{s+1}(y_{t-p} - \mu) \end{aligned} \tag{1.7}$$

where F_i^s is the i^{th} upper (n×n) block of the matrix F^s in equation (1.34) of reduced form VAR.

Assuming the covariance stationarity of y_t, the original VAR system has the representation of infinite sum of moving averages.

$$y_t = \gamma + \varepsilon_t + F_1^1\varepsilon_{t-1} + F_1^2\varepsilon_{t-2} + \cdots + F_1^s\varepsilon_{t-s} + \cdots \tag{1.8}$$

This is equivalent to equation (1.45) in conventional reduced form VAR with different notations for the coefficient matrices and error. Accordingly, the impulse response function is given by

$$\mathrm{IR}(t, s, d_i) = F_1^s d_i \tag{1.9}$$

Suppressing the constant terms and rearranging equation (42) gives the expression that can be directly comparable with the local projections in equation (38).

$$\begin{aligned} y_{t+s} =& \alpha^s + F_1^{s+1}y_{t-1} + \cdots + F_p^{s+1}y_{t-p} \\ &+ \varepsilon_{t+s} + F_1^1\varepsilon_{t+s-1} + \cdots + F_1^s\varepsilon_t \end{aligned} \tag{1.10}$$

where $B_i^{s+1} = F_i^{s+1}$ for $i = 1, \ldots, p$; and $u_{t+s}^s = \varepsilon_{t+s} + F_1^1\varepsilon_{t+s-1} + \cdots + F_1^s\varepsilon_t$. The equivalence is established by the assumption that the original VAR system with *iid* disturbances, ε_t, is indeed the data generating process of the time series y_t.

Considering the $h-$period ahead joint estimation with local projections by stacking the forecasts in the following way.

$$Y_t = X_t G + V_t H \tag{1.11}$$

where $Y_t \equiv (y_{t+1}, \cdots, y_{t+h})$; $X_t \equiv (y_{t-1}, \cdots, y_{t-p})$; and $V_t \equiv (\varepsilon_{t+1}, \cdots, \varepsilon_{t+h})$. The restrictions on the matrices, G and H implied by reduced form VAR, are as follows.

$$G \equiv \begin{bmatrix} F_1^1 & F_1^2 & \cdots & F_1^h \\ F_2^1 & F_2^2 & \cdots & F_2^h \\ \vdots & \vdots & \cdots & \vdots \\ F_p^1 & F_p^2 & \cdots & F_p^h \end{bmatrix}$$

$$H \equiv \begin{bmatrix} I_n & F_1^1 & \cdots & F_1^h \\ \mathbf{0} & I_n & \cdots & F_1^{h-1} \\ \vdots & \vdots & \cdots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & I_n \end{bmatrix}$$

Defining $E(\varepsilon_t \varepsilon_t') = \Omega_\varepsilon$, $E(V_t V_t') = H(I_h \otimes \Omega_\varepsilon)H' \equiv \Sigma$. The maximum likelihood estimation associated with GLS is given by

$$\text{vec}(\hat{G}) = [(I \otimes X)'\Sigma^{-1}(I \otimes X)]^{-1} \times (I \otimes X)'\Sigma^{-1}\text{vec}(Y) \tag{1.12}$$

Then the impulse responses and standard errors can be obtained from the estimates of $\hat{G}$ directly and the ML estimation would achieve exact asymptotic formulas for single and joint inference on the impulse response coefficients provided the DGP being the implied VAR. In more general cases where the DGP and the specific structure of G are unknown, the impulse responses can still be computed by univariate regressions with a heteroskedasticity and autocorrelation (HAC) robust errors, $\hat{\Sigma}_L$. The confidence intervals for 95 percent significance level would then be constructed as $1.96 \pm (d_i'\hat{\Sigma}_L d_i)$. This is possible because the structure of the error terms of the local projections, u_{t+s}^s, is a moving average of forecast errors whose order is dependent on the forecast horizon, s. In practice, the recursive regressions would help improving the efficiency.

Although having constructed the local projections for the coefficients of VAR specification and the associated impulse responses, the inference of the impulse responses can be contested on different dimensions. The inference about the impulse responses is associated with the multiple testing of the shape of the impulse response functions, which often accompanied by the serial correlation. To take account for the serial correlation in the estimated coefficients, Jordá (2009) proposed the simultaneous inferences for the impulse responses, namely, Scheffé bands and conditional error bands, which I will describe below.[19]

For constructing the simultaneous confidence regions, suppose the system of impulse responses over $h = 1, 2, \ldots, H$, where y_t, the $n \times 1$ vector, is the original time series considered in VAR.

$$\Theta(1, H) = \begin{bmatrix} \Theta_1 \\ \vdots \\ \Theta_H \end{bmatrix} \tag{1.13}$$

Θ_h is $n \times n$ matrix of the coefficients in impulse response functions and the (i, j) element in Θ_h indicates the impulse response of i^{th} variable to a shock in j^{th} variable at horizon h. By stacking the Θ_h from $h = 1$ to $h = H$, $\Theta(1, H)$ becomes $nH \times n$ matrix. Obviously, in reduced form VAR, the initial non-stochastic shocks for the impulse responses are set as $\Theta_0 = I_n$, because there is no contemporaneous correlation.

Suppose the estimates of $\Theta(1, H)$ based on the sample of T observations of y_t are $n^2H \times 1$ matrix, $\hat{\Theta}_T = \text{vec}(\hat{\Theta}(1, H))$ and assume the asymptotic distribution of the

[19] In addition, there are interesting studies which address the serial correlation issues, for example, Sims and Zha (1999) and Lütkepohl (2007).

estimates as follows.

$$\sqrt{T}(\hat{\Theta}_T - \Theta_0) \xrightarrow{d} N(0, \Omega_\theta) \tag{1.14}$$

Traditionally, the significance of the impulse response estimates is reported by displaying 2 standard error bands, rectangular interval around each coefficient estimate.

$$P\left[\left|\frac{\hat{\theta}_h(i,j)}{\hat{\sigma}_h(i,j)}\right| \leq z_{\alpha/2}\right] = 1 - \alpha \tag{1.15}$$

where $\hat{\theta}_h(i,j)$ denotes the estimates of (i,j) element in Θ_h; $\hat{\sigma}_h(i,j)$ denotes the estimate of the standard error of $\hat{\theta}_h(i,j)$, which is the square root of the diagonal entry of the variance-covariance matrix, $\hat{\Omega}_h$. The associated t-ratio is

$$\hat{t}_h(i,j) = \frac{\hat{\theta}_h(i,j) - \theta_h(i,j)}{\hat{\sigma}_h(i,j)} \rightarrow N(0,1) \tag{1.16}$$

Suppose the shape of the path of impulse responses being our interest, not the particular value of coefficients. Then the Wald principle and the delta method can be applied with $g(\cdot) : R^H \rightarrow R^k$, for $k \leq H$, a first-order differentiable function with invertible Jacobian, $G(\cdot)$.

$$\hat{W}(i,j) = (g(\hat{\theta}(i,j)) - g_0)'(\hat{G}'\hat{\Omega}(i,j)\hat{G})^{-1}(g(\hat{\theta}(i,j)) - g_0) \xrightarrow{d} \chi^2_k \tag{1.17}$$

where $\hat{G}$ denotes the Jacobian evaluated at $\hat{\theta}(i,j)$. The resulting confidence region is multidimensional ellipsoid, which cannot be easily depicted in two-dimensional spaces.

$$P\left[\hat{W}(i,j) \leq c^2_\alpha\right] = 1 - \alpha \tag{1.18}$$

where c^2_α is the critical value of a χ^2_k distributed random variable.

Scheffé's S-Method of simultaneous inference exploits the Cauchy-Schwarz inequality to transform Wald statistic to be demonstrated easily in two-dimensional spaces (Scheffé, 1953, cited in Jordá, 2009, p.629) . Consider less general case first where the elements of $\hat{\theta}(i,j)$ are uncorrelated, so that $\Omega(i,j)$ is diagonal. The null hypothesis of joint significance $H_0 : \theta(i,j) = 0$ for any $i, j = 0, \cdots, n$. The Wald statistic is the sum of the squared t statistics because of the assumption of uncorrelated $\hat{\theta}(i,j)$.

$$\begin{aligned} \hat{W}(i,j) &= \hat{\theta}(i,j)'\hat{\Omega}(i,j)^{-1}\hat{\theta}(i,j) \xrightarrow{d} \chi^2_H \\ &= \sum_{h=1}^{H} \hat{t}^2_h(i,j) \end{aligned} \tag{1.19}$$

Therefore, the confidence region is given by

$$P\left[\hat{W}(i,j) \leq c^2_\alpha\right] = P\left[\sum_{h=1}^{H} \hat{t}^2_h(i,j) \leq c^2_\alpha\right] \tag{1.20}$$

The Bowden's (1970, cited in Jordá, 2009, p.631) lemma implied by the Scheffé's S-method yields

$$\max\left[\frac{|\sum_{h=1}^{H} \frac{\hat{t}_h(i,j)}{h}|}{\sqrt{\sum_{h=1}^{H} \frac{1}{h}}}; |h| < \infty\right] = \sqrt{\sum_{h=1}^{H} \hat{t}^2_h(i,j)} \tag{1.21}$$

By applying the previous lemma directly, the resulting confidence bands for uncorrelated impulse responses are as follows.

$$P\Bigg[\Bigg|\sum_{h=1}^{H}\frac{\hat{t}_h(i,j)}{h}\Bigg| \leq \sqrt{\frac{c_\alpha^2}{H}}\Bigg] \simeq P\Bigg[\sum_{h=1}^{H}\hat{t}_h^2(i,j) \leq c_\alpha^2\Bigg] = 1-\alpha \tag{1.22}$$

The $100(1-\alpha)\%$ confidence bands are guided by the critical values computed from χ_H^2.

In more general cases where there might be possible serial correlations in impulse responses, local projection can be utilised to address the problem. Orthogonalising the impulse response by projecting h-th impulse response conditional on its past path from 1 to $h-1$, which gives additional interpretation to resulting IRFs. The Wald principle and the Cholesky decomposition of the variance-covariance matrix, Ω, for the (i,j) elements are as follows.

$$\hat{\Omega}(i,j) = \hat{A}_{ij}\hat{D}_{ij}\hat{A}_{ij}' \tag{1.23}$$

for $i,j = 1,\ldots,n$. $\hat{A}_{ij}$ is a lower triangular matrix with 1s in the diagonal entries and $\hat{D}_{ij}$ is a diagonal matrix whose elements in the diagonal are the variances of the local projections. More specifically, define

$$\begin{aligned} &\hat{\psi}_h(i,j) = E[\hat{\theta}_h(i,j)|\hat{\theta}_{h-1}(i,j),\cdots,\hat{\theta}_0(i,j)] \\ &i,j = 1,\ldots,n; h = 1,\ldots,H. \end{aligned} \tag{1.24}$$

where $E(.|.)$ is the linear projection operator. Denote the variances of $\hat{\psi}_h(i,j)$ as $\tilde{\sigma}_h(i,j)$, being the diagonal elements in $\hat{D}_{ij}$. Here, the Cholesky ordering is neither arbitrary nor ambiguous. The reasoning behind the ordering involves the time frame of the transmission of shocks; the impulse responses evolve from the earlier time horizon to the future. This throws contrasts to the Cholesky ordering for the reduced form VAR or structural VAR which often requires debatable theoretical backgrounds.

The Wald statistic for testing the hypothesis of joint significance in the impulse responses coefficients, $H_0 : \hat{\theta}(i,j) = \mathbf{0}_{H\times 1}$, can be constructed as

$$\hat{W}(i,j) = \hat{\theta}(i,j)'\hat{\Omega}(i,j)^{-1}\hat{\theta}(i,j) \xrightarrow{d} \chi_H^2 \tag{1.25}$$

with $\hat{\Omega}(i,j) \xrightarrow{p} \Omega(i,j)$.

The Cholesky decomposition of $\hat{\Omega}(i,j)$ yields,

$$\begin{aligned} \hat{W}(i,j) &= \hat{\theta}(i,j)'(\hat{A}_{ij}\hat{D}_{ij}\hat{A}_{ij}')^{-1}\hat{\theta}(i,j) \\ &= (\hat{A}_{ij}^{-1}\hat{\theta}(i,j))'\hat{D}_{ij}^{-1}(\hat{A}_{ij}^{-1}\hat{\theta}(i,j)) \\ &= \sum_{h=1}^{H}\left(\frac{\hat{\psi}_h(i,j)}{\tilde{\sigma}_h(i,j)}\right)^2 \end{aligned} \tag{1.26}$$

Notice that the decision problem of testing the joint null of significance of correlated impulse response coefficients into the sum of the t-statistics of the individual nulls of significance of the conditional impulse response function.

$$\hat{W}(i,j) = \sum_{h=1}^{H} \left(\frac{\hat{\psi}_h(i,j)}{\tilde{\sigma}_h(i,j)} \right)^2 = \sum_{h=1}^{H} \hat{t}^2_{h|h-1,\ldots,0}(i,j) \xrightarrow{d} \chi^2_H \tag{1.27}$$

$$\hat{t}_{h|h-1,\ldots,0}(i,j) \xrightarrow{d} N(0,1)$$

where $\psi_h(i,j)$ is the linear projection of $\hat{\theta}_h(i,j)$ conditional on its past, and $\tilde{\sigma}_h(i,j)$ denotes the corresponding variances. By asymptotic normal distribution, the confidence region for the conditional impulse response coefficients is given as

$$P[|t_{h|h-1,\ldots,0}(i,j)| \leq z_{\alpha/2}] = 1 - \alpha \tag{1.28}$$

The corresponding error bands for impulse responses can be established in two ways: Sheffé bands derived from equation (1.21) and the conditional bands derived from equation (1.27). First, Sheffé bands are simply

$$\hat{\theta}(i,j) \pm \hat{A}_{ij}\hat{D}^{1/2}_{ij}\sqrt{\frac{c^2_\alpha}{H}}\boldsymbol{i}_H \tag{1.29}$$

where $\boldsymbol{i}_H$ is a $H \times 1$ vector of ones. The computation requires the Cholesky decomposition of $\hat{\Omega}$, which is not restricted to the local projection described earlier. Hence, the Scheffé bands could be tainted by the serial correlations in the impulse responses. To address the inaccuracy of the $100(1-\alpha)\%$ confidence regions due to serial correlation, fan chart is considered where the different values of α can be illustrated.

The conditional bands from the orthogonalisation using local projections are calculated as

$$\hat{\theta}(i,j) \pm z_{\alpha/2} diag(\hat{D}^{1/2}_{ij}) \tag{1.30}$$

Notice that the variability in the conditional bands represents the variability in the estimated coefficients of impulse responses sterilised from serial correlation. The diagonal terms in $\hat{D}_{ij}$ are obtained by linear projections of the h-period horizon forecasts of impulse response coefficients on to the past values of the estimated coefficients.

1.3.3 Data

For estimating the orthogonalised Impulse Response Function (IRF), the order of variables in the VAR system bears important implication as well as the choice of variables. The selection of variables in the VAR systems is overlapping among the existing studies. Bachmann, Elstner and Sims (2013) mainly compared the several bivariate VAR models with a certain selection of an uncertainty measure and a macro variable. Baker, Bloom and Davis (2015) included their measure of uncertainty (EPU), S&P 500 index, the federal funds rate, employment, real industrial production and place them in this order. Jurado, Ludvigson and Ng (2015) investigated the VAR with 8 variables, ordering from S&P 500 index, uncertainty measure, the federal funds rate, wages, CPI, hours or work, employment, to industrial production.

As for the ordering of variables in a chosen reduced form VAR model, discussions are based on the contrasting views on exogeneity (or endogeneity) of uncertainty innovations. The *wait-and-see* effect hypothesis supports the ordering that starts from uncertainty followed by other financial and real macro variables. On the other hand, the *by-product* hypothesis would argue that such ordering is invalid and exaggerate the impact of uncertainty. Bachmann, Elstner and Sims (2013) claimed that the relative importance of the two channels can be further investigated by comparing different countries with different institutional aspects, such as the frictions in the labour market. One of the recent example of the development in the area to uncover the endogeneity problem in VAR for policy uncertainty shocks is the paper by Mertens and Ravn (2013). They investigated the impact of an unanticipated change in taxes on the economy using proxy structural VAR.

Acknowledging the potential endogeneity of both EPU and RSS uncertainty measures, a 5-variable VAR model with the following ordering is suggested to estimate the impact of uncertainty on the US economy.

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

This benchmark model implicitly assumes that the *wait-and-see* effect is predominant in the US economy because uncertainty shocks contemporaneously affect other macro variables but not vice versa in the VAR system. It is relatively simple and straightforward to compare the effects of different uncertainty measures but the endogeneity cannot be fully overlooked. Obviously, there must be large potential for further studies regarding the choice of appropriate model, not restricted to reduced VARs, to investigate the causal effect of macroeconomic uncertainty. However, as the first step of such efforts, this study looks at reduced form VAR with different specification to check robustness of the estimation.

The uncertainty measures and proxies for the estimation are EPU, EPUN, RSS, VXO, MCI and CDM. RSS is, by construction, standardised with mean 0 and standard deviation of 1. CDM is defined as CDM $= \log(\sqrt{(\text{forecast error} \times 100)^2})$. Other uncertainty measures are H-P filtered series of the logarithm of raw data. EPU index is retrieved from the website, `http://www.policyuncertainty.com/`. RSS is obtained from the UCL Centre for Study of Decision-Making Uncertainty with permission and CDM from Charemza, Díaz, and Makarova (2015).

The macroeconomic variables are stock returns from S&P500 index to account for short-term dynamics in stock market; the federal funds rate as a proxy for short-run interest rate (i); manufacturing industrial production as a proxy for business cycle (IP); the number of people employed in manufacturing sector as a proxy for labour market conditions (EMP). Stock return is the first difference of logged stock market index, employment and industrial production are in log level and detrended using H-P 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 H-P filter. All macroeconomic variables (monthly data from January 1996 to June 2015) are collected from FRED economic database and Thomson Reuters Datastream.

As for the initial step for VAR estimation, the detrended-GLS test and feasible point optimal test (Ng and Perron, 2001; Perron and Qu, 2007) are implemented for different uncertainty indicies and macroeconomic variables.[20] Table 1.9-1.10 in Appendix 1.6.6 illustrate the results of the stationarity test for uncertainty measures and macroeconomic variables allowing for the potential structural breaks or linear time trend. The results show the prevalence of the stationarity hypothesis, depending on the different assumptions of trend and structural breaks. The result is consistent with the Augmented Dickey Fuller (ADF) test results.

Finally, the lag length is chosen based on the information criteria (AIC C) suggested by Hurvich and Tsai (1993).

1.4 Estimation Results and Robustness Checks

The plan for this section is as follows. First, the impulse responses and the 2 standard error bands from traditional reduced form VAR are illustrated in parallel with the estimates of impulse responses with local projections (Jordá, 2005). Next, the results of the impulse responses estimated from local projections with marginal and conditional bands proposed by Jordá (2009) are analysed. For the robustness check, several different specifications are estimated: a 3-variable model (uncertainty, industrial production, and employment), and a 5-variable model replacing the stock return with the VXO stock market volatility index. In addition, Scheffé fan charts for various uncertainty shocks are demonstrated. Finally, it concludes with the analysis of Forecast Error Variance Decomposition (FEVD) for the conventional VAR model.

Figure 1.5 illustrates the impulse responses obtained by local projections (red lines)

[20] In Appendix 1.6.6, the various stationary tests statistics are summarised. The test statistics considered are $ADF^{GLS}, Z_\alpha, MZ_\alpha^{GLS}, MSB^{GLS}, MZ_t^{GLS}, P_T, MP_T$, respectively. The Gauss code by Carrion-i-Silvestre et al., 2009, (`http://www.eco.ub.edu/~carrion/Welcome.html`) is used for computation.

and by reduced form VAR (blue lines) with 2 standard error bands.[21] It shows that the impulse responses of two different uncertainty shocks, EPU and RSS, on industrial production (IP) and employment (EMP) exhibit the negative effects as anticipated in the literature. The impulse responses of local projections provide similar trajectories as those of conventional reduced form VAR estimations. All of the impulse responses estimated by local projections are inside the 2 standard error bands of the IRFs from reduced form VAR, indicating the robustness of the estimation. The IRFs from local projections are considerably similar to the IRFs from orthogonalised VAR for the RSS shocks. However, for the EPU shocks, the estimated IRFs from local projections show some deviations from the classical IRFs. The local projections and the Cholesky decomposition of reduced form VAR would produce identical impulse responses only if the actual data generating process (DGP) of y_t follows the multivariate process as assumed. Therefore, the wider gap for the EPU surprises suggests potential misspecification of the reduced form VAR model, in particular the assumption about the contemporaneous dynamics among the variables.

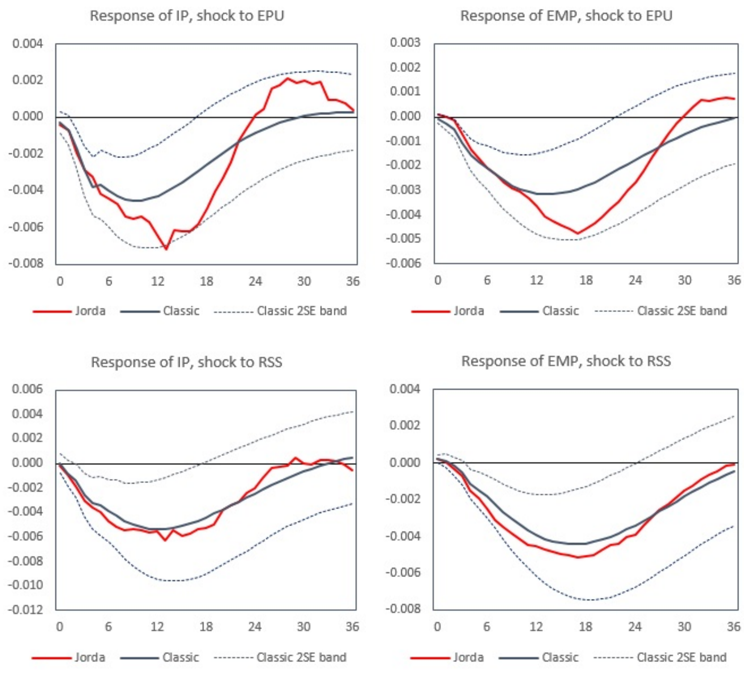

Figure 1.5: IRFs of the reduced form VAR vs. local projections

Notes: The estimates of reduced form VAR by author using STATA. The local projection is estimated using Gauss (codes retrieved from Jordá's personal webpage, `http://www.econ.ucdavis.edu/faculty/jorda/pubs.html`).
Source: Thomson Reuters Datastream (employment, industrial production, S&P stock market index), FRED economic database (federal funds rate), Economic Policy Uncertainty website, `http://www.policyuncertainty.com/` (EPU), UCL Centre for Study of Decision-Making Uncertainty (RSS).

[21] See Appendix 1.6.7 for the estimation results of the canonical reduced form VAR coefficients. Appendix 1.6.8. presents the IRFs of the all 5 variables in the VAR system, using Jordá's (2005, 2009) approach.

In addition, the *wait-and-see* effect for EPU surprises, which can be depicted as the short lived negative effect accompanied by quick bouncing back afterwards, is more salient in the local projections than the reduced form VAR estimation. In general, the longer horizon impulse responses from the VAR coefficient estimates would produce compounded errors as it is optimal for one-period ahead forecasts. Assuming that the local projection results boil down to more precise impulse responses, the overshooting effect in longer term horizon for both industrial production and employment to EPU shocks would be meaningful. EPU shocks are sensitive to political events and sometimes characterisd by natural disasters because economic policies would response to those exogenous factors. The political events and natural calamities would have short lived negative effects on economy as they are identified as exogenous, one-off events, unlike financial events. Nevertheless, it is not sufficient to affirm that EPU is strictly exogenous to other economic situations. Economic policy can be largely unpredictable when facing adverse economic conditions, which may introduce potential endogeneity. Therefore, the causal interpretation of the estimated responses to EPU shocks needs to be carefully treated.

What stands out from the estimation results is the persistent and protracted effects of RSS surprises on the real economy. RSS tends to capture financial events as shown in Section 1.2. Theoretically, it is also closely related to economic agents' decision making process since it is drawn from the emotional words. RSS might interact contemporaneously with other macroeconomic variables, which suggests that there might be more chances of being affected by alternative channels other than *wait-and-see* effect. The channel of financial frictions, endogenous growth mechanism and *by-product* hypothesis would be easily interpreted within RSS uncertainty measure.

Figure 1.6 displays the estimated impulse response functions by Jordá's (2005) local projections along with marginal 2 standard error bands and the conditional 2 standard error bands (Jordá, 2009) for EPU shock on industrial production and employment. While the marginal bands show that the impact of uncertainty shocks is insignificant after approximately 17 months, the narrower conditional bands suggest that the effect of uncertainty remains significantly negative for approximately over than 2 years after the shock. Employment impulse response functions and their bands show the similar results with the conditional bands being narrower in employment than in production. The effects on employment is more protracted then those of production, suggesting the frictions in the labour market require larger adjustment costs than in the capital market. The conditional bands provide another interesting implication. As the past realisations are entirely considered in estimating the confidence region in the next horizon, the conditional bands offer the joint significance of the impulse responses given the past values.

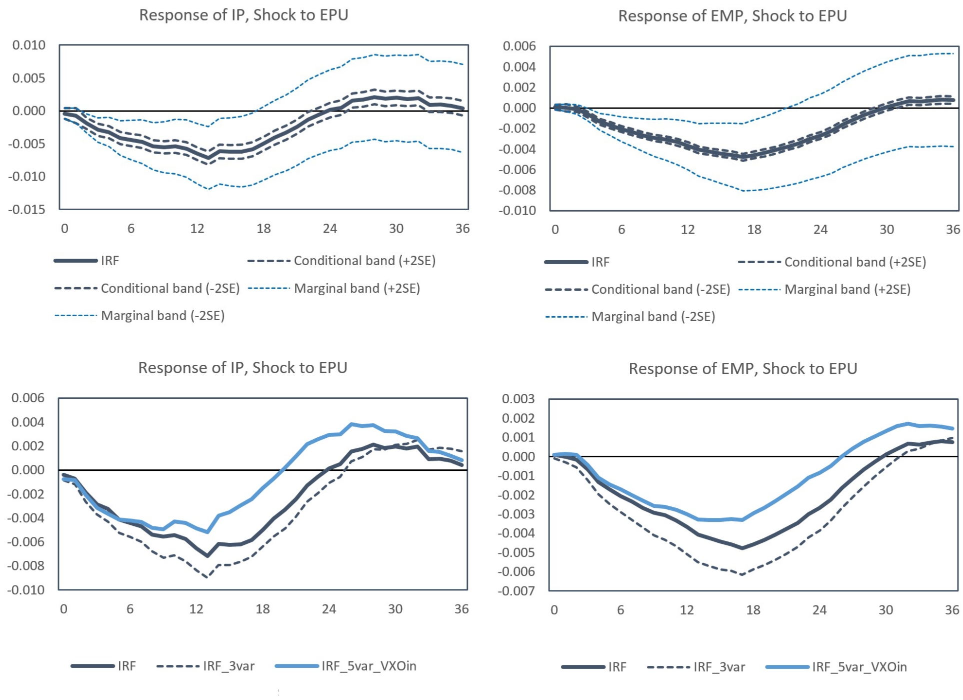

Figure 1.6: IRFs of local projections and conditional bands: EPU

Notes: The IRFs are estimated by author using Gauss (codes retrieved from Jordá's personal webpage, `http://www.econ.ucdavis.edu/faculty/jorda/pubs.html`).
Source: Thomson Reuters Datastream (employment, industrial production, S&P stock market index and VXO), FRED economic database (federal funds rate), Economic Policy Uncertainty website, `http://www.policyuncertainty.com/` (EPU).

Figure 1.7 illustrates the impulse responses for RSS disturbances. Interestingly, the shock in RSS uncertainty affects both production and employment negatively for longer period than EPU shock. For example, RSS shock leads employment to decline almost for 3 years. As mentioned, the difference comes from the institutional aspects of two different measures. Combining with the findings from the analysis of different measures, the persistent negative impact of RSS is related to the methodology that is used to construct the index. The perceived sentiment measured by the relative shift from excitement to anxiety could directly influence alternative channels, such as endogenous growth mechanism, financial frictions, and *by-product* hypothesis, as well as the main channel from real options theory. RSS represents the collective information about the agents' sentiments towards uncertainty and determines the crucial factors for the endogenous growth mechanism. For example, the level of human capital investment and/or R&D investment can be adjusted according to the collective sentiments regarding the decision-making under uncertainty. Financial frictions exacerbate the initial negative effect of uncertainty and RSS captures the financial factors better which had not been successfully picked up with EPU index. Moreover, RSS is constructed by analysing the emotional words in the news article that would have contemporaneous interactions with other macroeconomic variables. The endogeneity of RSS suggests that the *by-product* hypothesis plays more significant role in the model with RSS.

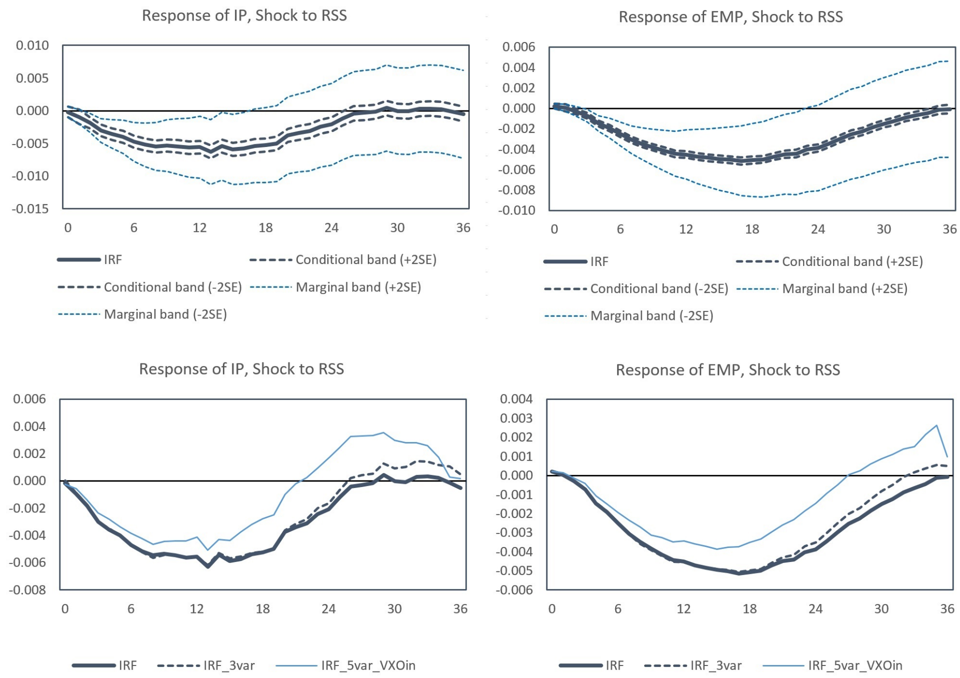

Figure 1.7: IRFs of local projections and conditional bands: RSS

Notes: The IRFs and conditional bands are estimated by author using Gauss (codes retrieved from Jordá's personal webpage, `http://www.econ.ucdavis.edu/faculty/jorda/pubs.html`).
Source: Thomson Reuters Datastream (employment, industrial production, S&P stock market index and VXO), FRED economic database (federal funds rate), UCL Centre for Study of Decision-Making Uncertainty (RSS).

In order to check the robustness of the impulse responses by local projection, two additional specifications are estimated (see the bottom panels of Figure 1.6 and 1.7). First, the dotted line is estimated with more parsimonious model, 3-variables VAR of uncertainty, production and employment. The negative effect of EPU uncertainty in this specification is slightly exaggerated for both production and employment but the shape of the trajectory is similar to the baseline model. For RSS shocks, the difference between the 5-variable VAR and 3-variable VAR is not sizeable. The impulse responses of the shock in RSS uncertainty in low-dimension model tend to move similar to the baseline model in the short run but exhibit slightly stronger bounce-back effects after approximately $1\frac{1}{2}$ years. Second, the 5-variable VAR specification that replaces the stock market index with VXO is estimated. For both production and employment, the negative effects of uncertainty are alleviated and the IRFs show stronger *wait-and-see* aspects.

The interpretation of the second specification requires additional reasoning about the underlying notions of different uncertainty measures and endogeneity. When interpreting the impact of uncertainty, it is important whether we estimate the impact of the mean preserving variance or that of bad economic situation. The narrative uncertainty measures, EPU and RSS, may be affected by both *pure* second moment shocks and first moment shocks by construction. These measures are the variables that gauge the level of unobservable *(Knightian)* uncertainty in the economy. The blurriness is getting even worse because the periods with high volatility often coincide with the periods with bad economic situation. Indeed, it is hard to trace out whether the estimated effect of uncertainty is solely due to mean preserving variance. The baseline specification include S&P stock market index to separate out the effect of changes in future expectation of business cycle, assuming stock market returns are forward-looking. The VAR model with VXO instead of stock market returns is designed to capture the effect of *pure* second moment shocks in general. Controlling for volatility instead of stock returns, the magnitude of the estimated coefficients in impulse responses mitigated and the *wait-and-see* effects becomes stronger. In other words, the benchmark model may overstate the prolonged negative effects of uncertainty shocks on real economy. The result is consistent with the theoretical predictions as the volatility is more relevant for the short run negative effect and quick overshooting while the expectation of the adverse state of economy in the stock market is associated with the persistent downside phase in real activities.

Figure 1.8-1.9 illustrate the impulse responses and their confidence regions for the shock in the different uncertainty measures and proxies, EPUN, VXO, MCI and CDM, respectively. The shape of IRFs and the conditional confidence bands for EPUN show similar trajectories as EPU does simply because EPUN is one of the components in EPU. VXO shocks create negative influences on real macro variables, for nearly up to 3 years based on the conditional bands. The relatively persistent negative impact is inconsistent with the theory that anticipated *wait-and-see* effect for one-shot volatility innovations. Although it is difficult to uncover the reason, the preliminary explanation would also be drawn from the feature of VXO index. Implied stock market volatility is not a measure for uncertainty itself and merely captures the narrow perception of uncertainty at most. In addition, the model specification containing both first and second moments which are formed in the stock market would have contemporaneous influences among variables, which may result in the prolonged impulse responses.

The negative shock in Michigan consumer sentiment (MCI) leads production to decline for nearly 2 years but comparing to other uncertainty shock, it is less persistent with a notable rebound. For CDM uncertainty shock, the impulse response of production increases up to approximately 7-8 months. Then the impulse response decreases until it rebounds approximately at $h = 30$. The distinctive trajectory for the impulse response for CDM shock can be partially explained by the lowest correlation (both linear and rank correlation) with other uncertainty measures.

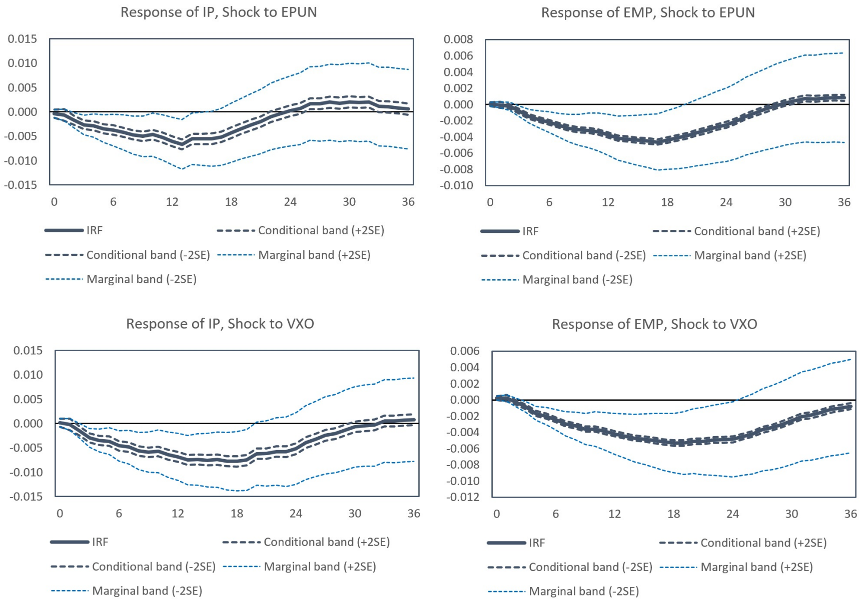

Figure 1.8: IRFs of local projections and conditional bands: EPUN, VXO

Notes: The IRFs and conditional bands are estimated by author using Gauss (codes retrieved from Jordá's personal webpage, `http://www.econ.ucdavis.edu/faculty/jorda/pubs.html`).
Source: Thomson Reuters Datastream (employment, industrial production, S&P stock market index and VXO), FRED economic database (federal funds rate), Economic Policy Uncertainty website, `http://www.policyuncertainty.com/` (EPUN).

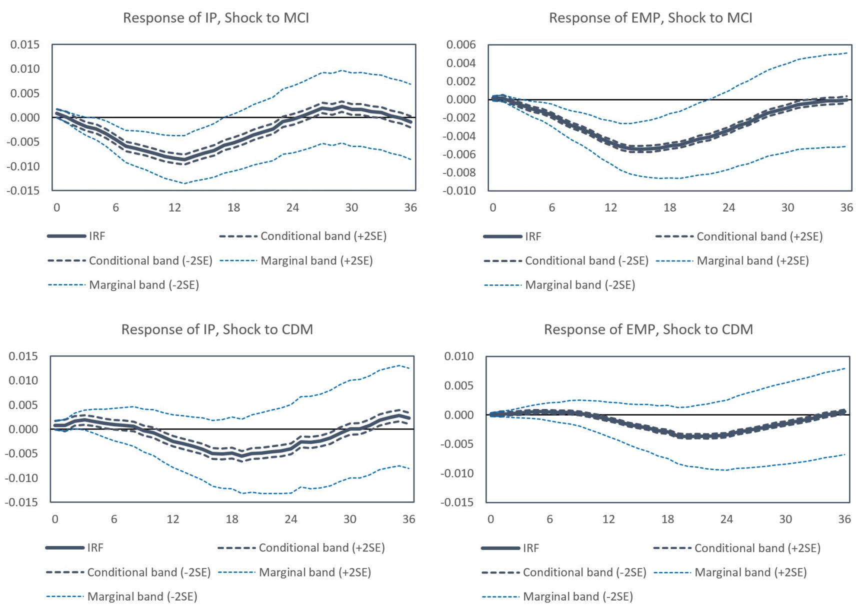

Figure 1.9: IRFs of local projections and conditional bands: MCI, CDM

Notes: The IRFs and conditional bands are estimated by author using Gauss (codes retrieved from Jordá's personal webpage, `http://www.econ.ucdavis.edu/faculty/jorda/pubs.html`).
Source: Thomson Reuters Datastream (employment, industrial production, S&P stock market index and MCI), FRED economic database (federal funds rate), Charemza, Díaz, and Makarova, 2015 (CDM).

Figure 1.10-1.12 illustrate Scheffé fan charts for all uncertainty shocks considered. It shows 95th, 50th and 25th percentiles of the Wald test of joint significants and the impulse responses are calculated by local projections. The results is mostly consistent with the previous findings. 50th and 25th percentile fan charts predict short run negative effects of uncertainty. To all of the uncertainty shocks, employment tends to have long term damages than industrial productions.

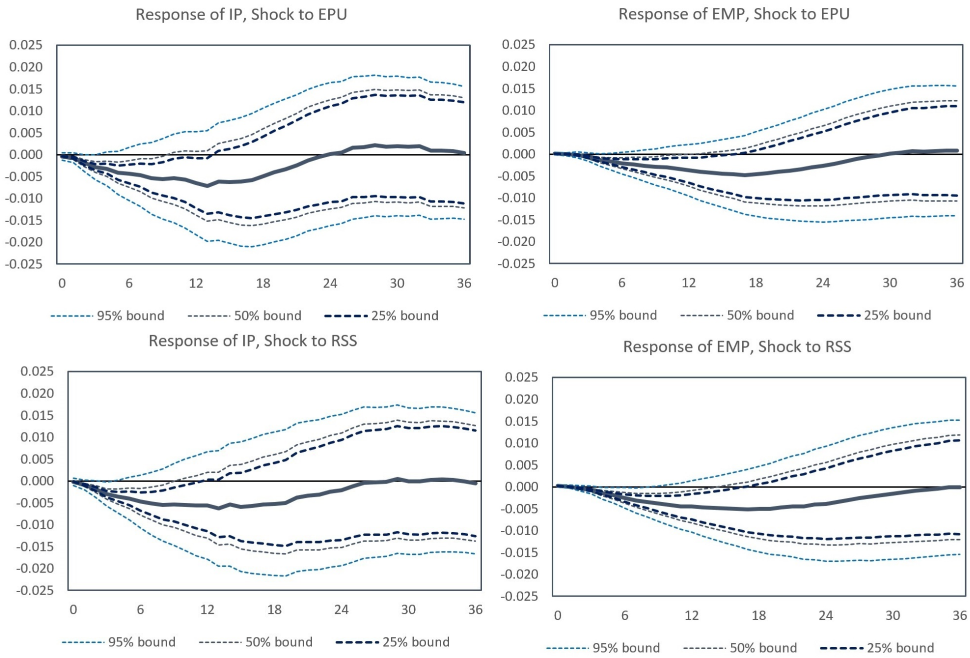

Figure 1.10: Scheffé Fan Chart: EPU, RSS

Notes: The IRFs and Sheffé bands are estimated by author using Gauss (codes retrieved from Jordá's personal webpage, `http://www.econ.ucdavis.edu/faculty/jorda/pubs.html`).
Source: Thomson Reuters Datastream (employment, industrial production, S&P stock market index), FRED economic database (federal funds rate), Economic Policy Uncertainty website, `http://www.policyuncertainty.com/` (EPU) and UCL Centre for Study of Decision-Making Uncertainty (RSS).

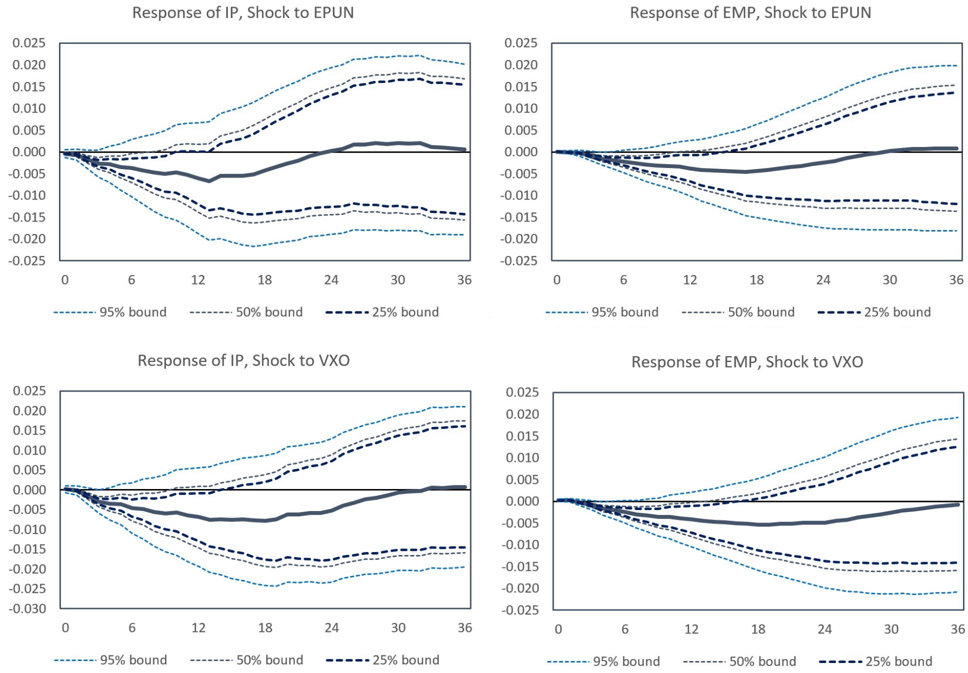

Figure 1.11: Scheffé Fan Chart: EPUN, VXO

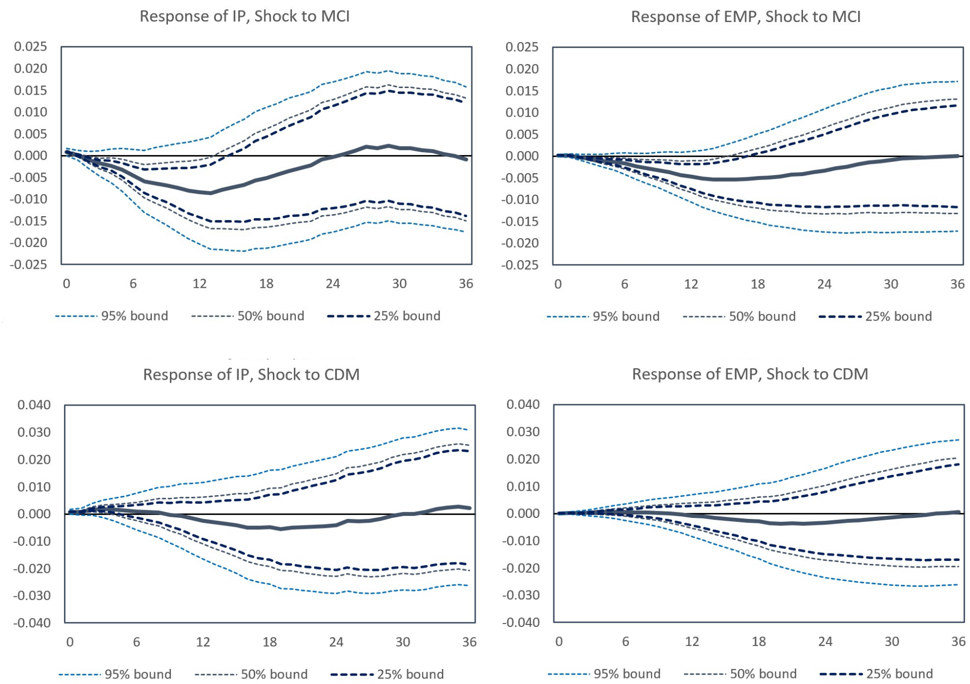

Figure 1.12: Scheffé Fan Chart: MCI, CDM

Notes: The IRFs and Sheffé bands are estimated by author using Gauss (codes retrieved from Jordá's personal webpage, `http://www.econ.ucdavis.edu/faculty/jorda/pubs.html`).
Source: Thomson Reuters Datastream (employment, industrial production, S&P stock market index), FRED economic database (federal funds rate), Economic Policy Uncertainty website, `http://www.policyuncertainty.com/` (EPU) and UCL Centre for Study of Decision-Making Uncertainty (RSS).

Table 1.3 shows the fraction of the uncertainty shocks in explaining the fluctuations in macroeconomic variables, computed by the reduced form VAR model. The left 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.

Table 1.3: Forecast Error Variance Decomposition

	EPU shock				RSS shock			
	Production		Employment		Production		Employment	
	EPU	FFR	EPU	FFR	RSS	FFR	RSS	FFR
h=3	3.45	2.89	2.62	2.49	2.68	0.61	0.64	0.24
h=6	12.55	3.55	13.43	5.28	9.50	2.20	7.08	2.16
h=12	19.26	6.48	20.91	9.96	17.28	9.75	19.96	8.01
h=18	22.11	8.37	23.85	12.76	22.80	16.10	28.35	13.36
h=24	22.96	9.04	25.30	14.17	25.87	17.68	33.58	15.64
max h	27	53	35	63	29	48	34	55
h=max	23.02	9.26	26.05	14.83	26.47	20.08	36.64	17.76

Notes: *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 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.

The right 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.

1.5 Conclusions

This paper investigated various measures of uncertainty and its impact on real economy, focusing mainly on two measures of uncertainty, Economic Policy Uncertainty (EPU) by Baker, Bloom and Davis (2015) and Relative Sentiment Shift (RSS) by Tuckett et al. (2014), Tuckett, Smith, and Nyman (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. Although the two measures show similar trend and high correlation, both linearly and non-linearly, there exist distinctive features among measures due to the differences in the methodology to construct the indices: EPU is sensitive to political events or natural disasters whereas RSS responds more to financial events. Empirical analysis covers the estimation of impulse responses of uncertainty shock to real activity.

Both reduced form VAR and local projections (Jordá, 2005) were applied to estimate the impulse responses. The existing studies hinged on the conventional approach to construct the standard errors for Impulse Response Function (IRF), which could be problematic if the model is misspecified. By estimating the impulse responses with sequential regressions of overlapping points in each adjacent regression, the local projection (Jordá, 2005) could provide consistency and efficiency even in case of misspecification. In addition, simultaneous confidence regions (Jordá, 2009) of the impulse responses are implemented by computing the conditional bands and Sheffé bands. The conditional bands lead the interpretation of confidence bands as the joint significance of the impulse response conditional on the past trajectories.

Results show significant differences in the impact of two different uncertainty measures on the real economy. The magnitude of the RSS shocks on both production and employment is larger and the responses persist longer than EPU. Putting differently, the rebound and overshoot after the downturn of the real activity, *wait-and-see* effect, is more noticeable in EPU than in RSS. It suggests that RSS captures contemporaneous structures among variables in VAR model and consequently explains alternative channels other than *wait-and-see* effect. To account for whether the effect evolves from mean preserving variance, not from bad economic situation itself, the baseline specification includes stock market index to separate out the effect of changes in future expectation of business cycle, assuming stock market returns are forward-looking. The specification of 5 variables with VXO instead of stock market returns captures the second moment shocks. The result is consistent with the theoretical predictions as the volatility is more relevant for the short run negative effect while the expectation of the state of economy is for the persistent negative effects.

1.6 Appendix

1.6.1 Construction of Relative Sentiment Shift (RSS) Index

A Relative Sentiment Shift measure developed in Tuckett et al. (2014), Tuckett, Smith, and Nyman (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 1.4: Examples of emotional words for extracting RSS

Positive Domain	Negative Domain
Amaze	Anxiety
Amazed	Anxious
Attracted	Avoids
Beneficial	Bother
Confident	Distress
Boost	Doubt
Perfect	Threat

The laboratory experiment done by Strauss (2013) back up the idea of word choice. In the experiment, 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.

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

RSS is not influenced by any unintended double counting of documents as it measures the difference between the count of excitement-driven words and anxiety-driven words. The deliberate simplicity of RSS measurement structure helps to retain consistency for extracting sentiment from big data throughout the time period.

1.6.2 Correlation coefficients between CDM and other measures

Table 1.5 illustrates linear correlation between CDM based on different forecasting horizon, from 1 to 12 months, and other uncertainty measures. Table 1.6 summarises Spearman's rank correlation. 1-year-ahead CDM exhibits strongest correlation with other uncertainty measures. This implies that short-term forecast errors are not as much informative as 1-year-horizon forecast errors. Rank correlations between CDM and other measures range from 0.18 to 0.45. The weakest correlation among them is the correlation between RSS and CDM. Unlike other measures show the largest correlation with 1-year-ahead CDM, RSS shows the largest correlation with CDM uncertainty based on 5-month-ahead forecast errors.

Table 1.5: Pearson's correlation coefficients: CDM and other uncertainty measures

horizon	EPU	EPUN	VXO	MCI	RSS	JLN1	JLN3	JLN12
1	0.01	-0.02	-0.01	0.19	0.04	0.28	0.28	0.27
2	0.03	0.03	-0.02	0.09	0.02	0.15	0.15	0.15
3	0.10	0.06	0.02	0.21	-0.01	0.26	0.26	0.25
4	0.22	0.17	0.06	0.27	0.14	0.32	0.32	0.31
5	0.28	0.19	0.13	0.33	**0.18**	0.37	0.37	0.36
6	0.23	0.12	0.11	0.34	0.04	0.40	0.40	0.39
7	0.28	0.18	0.11	0.28	0.06	0.33	0.33	0.32
8	0.31	0.21	0.16	**0.35**	0.08	0.39	0.39	0.37
9	0.31	0.23	0.19	0.35	0.07	0.40	0.40	0.39
10	0.32	0.23	0.23	0.33	0.03	0.37	0.37	0.37
11	0.33	0.25	**0.25**	0.31	0.03	**0.41**	**0.41**	**0.41**
12	**0.34**	**0.26**	0.21	0.32	0.02	0.37	0.37	0.37

Notes: Sample period is 1996m1-2014m12, except RSS (1996m1-2013m11). JLN1 denotes JLN macroeconomic uncertainty based on 1-month-ahead forecast errors. Similarly, JLN3 and JLN12 denotes the measure based on 3-months- and 12-months-ahead forecast errors.

Table 1.6: Rank correlation coefficients: CDM and other uncertainty measures

horizon	EPU	EPUN	VXO	MCI	RSS	JLN1	JLN3	JLN12
1	0.01	-0.04	-0.09	0.17	0.05	0.31	0.31	0.32
2	0.08	0.05	-0.08	0.16	0.06	0.30	0.30	0.29
3	0.14	0.09	-0.07	0.25	0.01	0.29	0.29	0.28
4	0.22	0.15	-0.02	0.31	0.12	0.31	0.31	0.30
5	0.26	0.18	0.03	0.36	**0.18**	0.39	0.39	0.38
6	0.24	0.16	0.04	0.35	0.12	0.42	0.42	0.40
7	0.27	0.20	0.03	0.34	0.13	0.40	0.40	0.37
8	0.29	0.21	0.09	0.38	0.15	0.42	0.42	0.39
9	0.28	0.22	0.19	0.37	0.11	0.40	0.40	0.38
10	0.30	0.24	0.24	0.34	0.11	0.39	0.39	0.37
11	0.34	0.27	0.23	0.36	0.12	0.44	0.44	0.42
12	**0.39**	**0.31**	**0.24**	**0.39**	0.15	**0.45**	**0.45**	**0.43**

Notes: Sample period is 1996m1-2014m12, except RSS (1996m1-2013m11). JLN1 denotes JLN macroeconomic uncertainty based on 1-month-ahead forecast errors. Similarly, JLN3 and JLN12 denotes the measure based on 3-months- and 12-months-ahead forecast errors.

1.6.3 Structural break test for baseline VAR

Chow's breakpoint test attempts to fit the equation separately for each subsample to see whether there are significant differences in estimated equation. This is a simple test for detecting structural break at given date of break. We assume Great Financial Crisis is a major event that may change the behaviour of economic agents. Therefore, by carefully examining time series plots of different uncertainty proxies, July 2008 is set to a given date for Chow's test. In order to conduct tests, each equation in VAR systems (either EPU or RSS as dependent variables) are taken separately. The estimation results with test statistics and significance level is presented in Table 1.7 and 1.8.

Table 1.7: Chow's breakpoint test: EPU

Equation	EPU		Stock		FFR		EMP		IP	
F-stat	1.7920	**	1.5706	**	1.4749	*	1.7671	**	1.9756	***
	0.0122		0.0416		0.0680		0.0141		0.0041	
Wald	53.7596	***	47.1186	**	44.2460	**	53.0121	***	59.2674	***
	0.0049		0.0242		0.0453		0.0059		0.0011	

Notes: The values of the second row of each statistics are significance levels.The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

Table 1.8: Chow's breakpoint test: RSS

Equation	RSS		Stock		FFR		EMP		IP	
F-stat	1.7583	**	2.1171	***	1.5797	**	1.9290	***	2.0351	***
	0.0149		0.0017		0.0396		0.0055		0.0029	
Wald	52.7494	***	63.5135	***	47.3920	**	57.8695	***	61.0545	***
	0.0063		0.0003		0.0228		0.0017		0.0007	

Notes: The values of the second row of each statistics are significance levels. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

Results reject the null hypothesis of no break in July 2008 at 5% significance level. There are many tests for the presence of structural breaks, which are less restrictive and using advanced techniques (see, for example, Quandt-Andrews Breakpoint Test or Global Maximizer Test by Bai and Perron (1998). We leave the further analysis that addresses potential breaks for the future research.

1.6.4 Spectrum analysis

Cramér representation or the spectral representation of a time series y_t is written as follows.

$$y_t = \int_0^{\pi} \alpha(\omega)\cos(\omega t)d\omega + \int_0^{\pi} \beta(\omega)\sin(\omega t)d\omega$$

Where ω denotes the radian angle of $z = x + iy$ in (x, y) space. Given $\alpha(\omega)$, $\beta(\omega)$, any time series y_t can be represented by the above equation. Spectrum is a closely related concept to Cramér representation which measures the contribution to the overall fluctuations in y_t made by the cyclical components, ${y_t}^{\omega}$ over $[0, \pi]$, in particular, specified in terms of frequency. The autocovariance of y_t is defined

$$\gamma(\tau) = E(y_t - \mu_t)(y_{t+\tau} - \mu_{t+\tau})$$

where $E(y_t) = \mu_t$. Applying Fourier transformation,

$$f_y(\omega) = \sum_{\tau=-\infty}^{\infty} \gamma(\tau)e^{-i\omega\tau}$$

Applying inversion formula,

$$\gamma(\tau) = \frac{1}{2\pi}\int_{-\pi}^{\pi} f_y(\omega)e^{i\omega\tau}d\omega$$

The power spectrum of y_t is defined as

$$s_y(\omega) = \frac{1}{2\pi}f_y(\omega)$$

Therefore, the comparison of the height of $s_y(\omega)$ for ω indicates the relative importance of variations at the chosen frequencies in influencing the variation in y_t. For an alternative representation of the spectrum, apply DeMoivre's Theorem to obtain,

$$s_y(\omega) = \frac{1}{2\pi}\sum_{\tau=-\infty}^{\infty} \gamma(\tau)(\cos\omega\tau - i\sin\omega\tau)$$

The autocorrelation function satisfies, $\gamma(\tau) = \gamma(-\tau)$, and using the properties of sin and cos functions, such as $\sin(-\omega) = -\sin(\omega)$, $\cos(-\omega) = \cos(\omega)$, spectrum can be expressed as follows.

$$s_y(\omega) = \frac{1}{2\pi}\left[\gamma(0) + 2\sum_{\tau=1}^{\infty}\gamma(\tau)(\cos\omega\tau)\right]$$

The following relation is connecting ω, radiance, and p, a unit of time period necessary for ${y_t}^{\omega} = \alpha(\omega)\cos(\omega t) + \beta(\omega)\sin(\omega t)$ to complete a cycle.

$$p = \frac{2\pi}{\omega}$$

Thus, the inverse of p $(1/p = \omega/2\pi)$ is the number of cycles completed by ${y_t}^{\omega}$ per period. Business cycles often consider from 6-quarters to 40-quarters cycles which is associated with ω ranging $[2\pi/40, 2\pi/6]$.

Filters can be reflected in frequency domain. Filters are designed to remove the effect of cyclical variation at certain frequencies. First-difference and H-P filters focus on low frequencies and seasonal filters target seasonal frequencies. Suppose linear filter is the linear combination of the original series y_t,

$$y_t{}^f = \sum_{j=-r}^{s} c_j y_{t-j} \equiv C(L) y_t$$

Replacing lag operator with frequency domain expression, $e^{-i\omega j}$, $C(L)$ is expressed by the frequency response function, $C(e^{-i\omega})$. Deriving the spectrum of $y_t{}^f$, where $\{y_t\}$ is mean-zero process with autocovariance, $\{\gamma(\tau)\}_{\tau=-\infty}^{\infty}$.

$$s_{y^f}(\omega) = C(e^{-i\omega}) C(e^{i\omega}) s_y(\omega)$$

Define the gain function,

$$G(\omega) = |C(e^{-i\omega})|$$

where $|C(e^{-i\omega})| = \sqrt{C(e^{-i\omega})C(e^{i\omega})}$. Thus, the spectrum of the filtered series can be linked to the spectrum of the original series by gain function,

$$s_{y^f}(\omega) = G(\omega)^2 s_y(\omega)$$

where $G(\omega)^2$ is the squared gain of the filter. Filters reduce or increase the spectrum of the raw data on a frequency basis. For example, Kaiser and Maravall (2001) proved that the gain function for H-P filter is given by

$$G(\omega) = \left[1 + \left(\frac{\sin(\omega/2)}{\sin(\omega_0/2)}\right)\right]^{-1}$$

where

$$\omega_0 = 2 \arcsin\left(\frac{1}{2\lambda^{1/4}}\right).$$

Band pass (B-P) filter is designed to shut down all fluctuations outside chosen frequency band, between p_l and p_u. The squared gain function satisfies,

$$G(\omega)^2 = \begin{cases} 1, & \omega \in [2\pi/p_u, 2\pi/p_l] \\ 0, & \text{otherwise} \end{cases}$$

Let the ideal symmetric B-P filter for a given frequency range be

$$\alpha(L) = \sum_{j=-\infty}^{\infty} \alpha_j L^j$$

The Fourier transformation gives,

$$\begin{aligned} \alpha(e^{-i\omega}) \equiv \alpha(\omega) &= \sum_{j=-\infty}^{\infty} \alpha_j e^{-i\omega j} \\ &= \alpha_0 + 2\sum_{j=1}^{\infty} \alpha_j \cos(\omega) \end{aligned}$$

It is not feasible to obtain the ideal B-P filter because we need infinite number of observations. Baxter and King (1999) proposed an approach to approximate the ideal B-P filter.

$$A(\omega) = a_0 + 2\sum_{j=1}^{K} a_j \cos(\omega)$$

where

$$A(0) = \sum_{j=-K}^{K} a_j = 0$$

$A(\omega)$ is obtained from the solution for the minimization problem,

$$\min_{a_j} \int_{-\pi}^{\pi} |\alpha(\omega) - A(\omega)|^2 d\omega$$

subject to $A(0) = 0$. The solution is given by

$$\begin{aligned}
a_j &= \alpha_j + \theta, \qquad\qquad j = -K, \cdots, K \\
\alpha_j &= \begin{cases} \frac{2\pi/p_l - 2\pi/p_u}{\pi}, & j = 0 \\ \frac{\sin(\omega 2j) - \sin(\omega 1j)}{\pi j}, & j = \pm 1, \cdots, \pm K \end{cases} \\
\theta &= \frac{-\sum_{j=-K}^{K} \alpha_j}{2K+1}
\end{aligned}$$

For quarterly data, Baxter and King (1999) recommend the Burns–Mitchell (1946, cited in Baxter and King, 1999)'s settings of 6 and 32 quarters for p_l, p_u, and k=12. For monthly data, they recommend 18 and 96 months, with k=12.

The logged series of uncertainty measures are applied for computing the Baxter and King's B-P filtered series. In Figure 1.13, B-P filtered and H-P filtered series of uncertainty indices and proxies are illustrated. The B-P filtered series are much smoother than the H-P filtered ones in all of the uncertainty measures. This result is easily anticipated because Baxter and King's B-P filter is designed to intentionally shut down all other fluctuations outside the business cycle frequency.

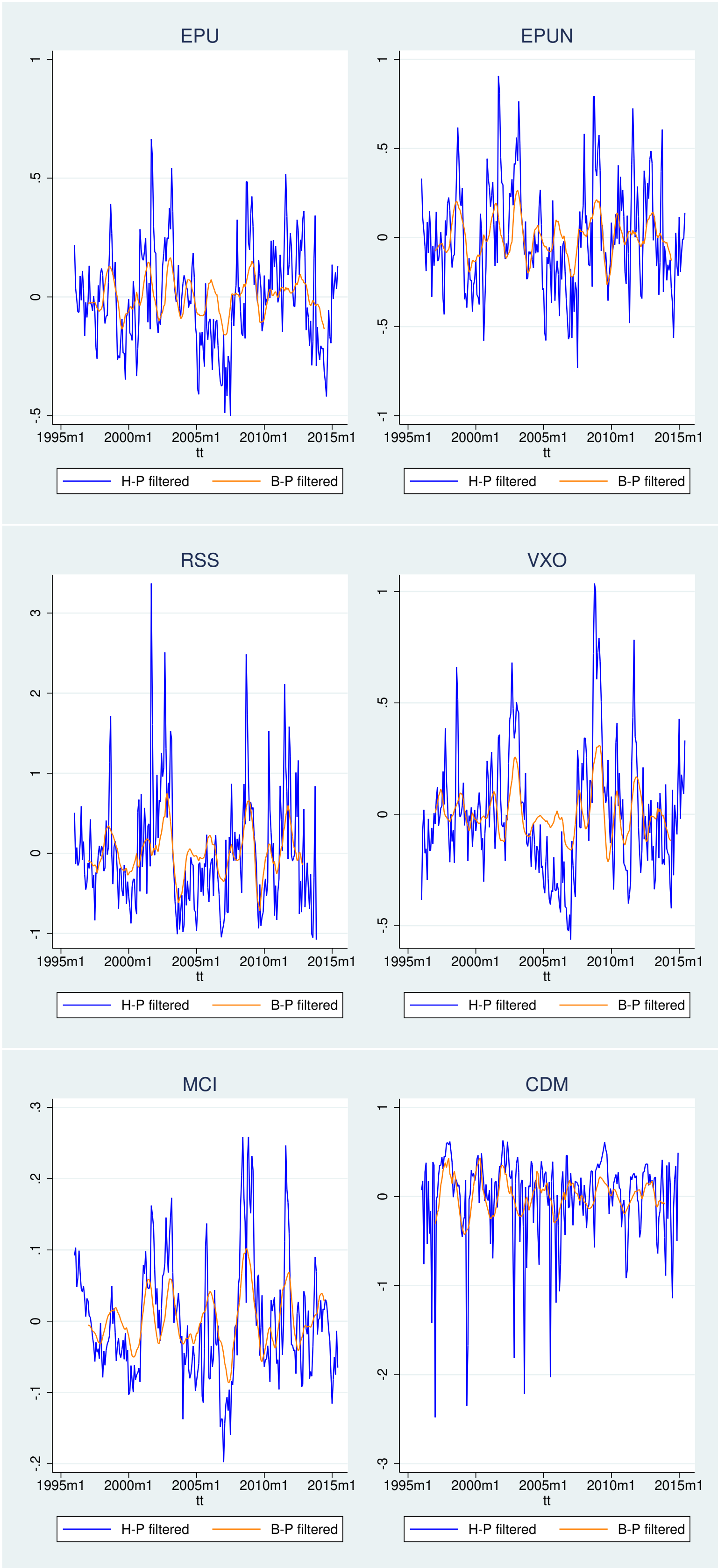

Figure 1.13: H-P filtered and B-P filtered uncertainty measures

Notes: Estimation by author.

Source: Thomson Reuters Datastream (VXO, MCI), Economic Policy Uncertainty website, `http://www.policyuncertainty.com/` (EPU), UCL Centre for Study of Decision-Making Uncertainty (RSS), Charemza, Díaz, and Makarova (2015, CDM)

The spectrum density summarises the persistence and cyclical behaviours of each uncertainty series. Recall previously derived population spectrum of y_t.

$$s_y(\omega) = \frac{1}{2\pi}\left[\gamma(0) + 2\sum_{\tau=1}^{\infty}\gamma(\tau)(\cos\omega\tau)\right]$$

Given the autocovariance function, $\gamma(\tau)$, the spectrum associated with frequencies (ω) can be computed. To obtain the parametric estimation of spectrum, let y_t can be specified by ARMA(p, q) model.

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q}$$

Using the autocovariance-generating function, the population spectrum is given by

$$s_y(\omega) = \frac{\sigma^2}{2\pi}\frac{(1 + \theta_1 e^{-i\omega} + \cdots + \theta_q e^{-iq\omega})}{(1 - \phi_1 e^{-i\omega} - \cdots - \phi_p e^{-ip\omega})}\frac{(1 + \theta_1 e^{i\omega} + \cdots + \theta_q e^{iq\omega})}{(1 - \phi_1 e^{i\omega} - \cdots - \phi_p e^{ip\omega})}$$

The estimates are obtained by estimating ARMA models for each series with Maximum Likelihood Estimation and plugging the estimates, $(\widehat{\sigma^2}, \widehat{\theta}_i, \widehat{\phi}_j)$ for $i = 1, \cdots, q$ and $j = 1, \cdots, p$ into the population spectrum equation, $s_y(\omega)$. If the ARMA model is correctly specified, the estimates of population spectrum will have the same property as the population. The ARMA(p, q) models are specified with small values of p, q as it is known to perform better than big models.

Figure 1.14: Autocorrelation and spectrum of detrended uncertainty measures (1)

Notes: Estimation by author.
Source: Thomson Reuters Datastream (VXO, MCI), Economic Policy Uncertainty website, `http://www.policyuncertainty.com/` (EPU), UCL Centre for Study of Decision-Making Uncertainty (RSS), Charemza, Díaz, and Makarova (2015, CDM)

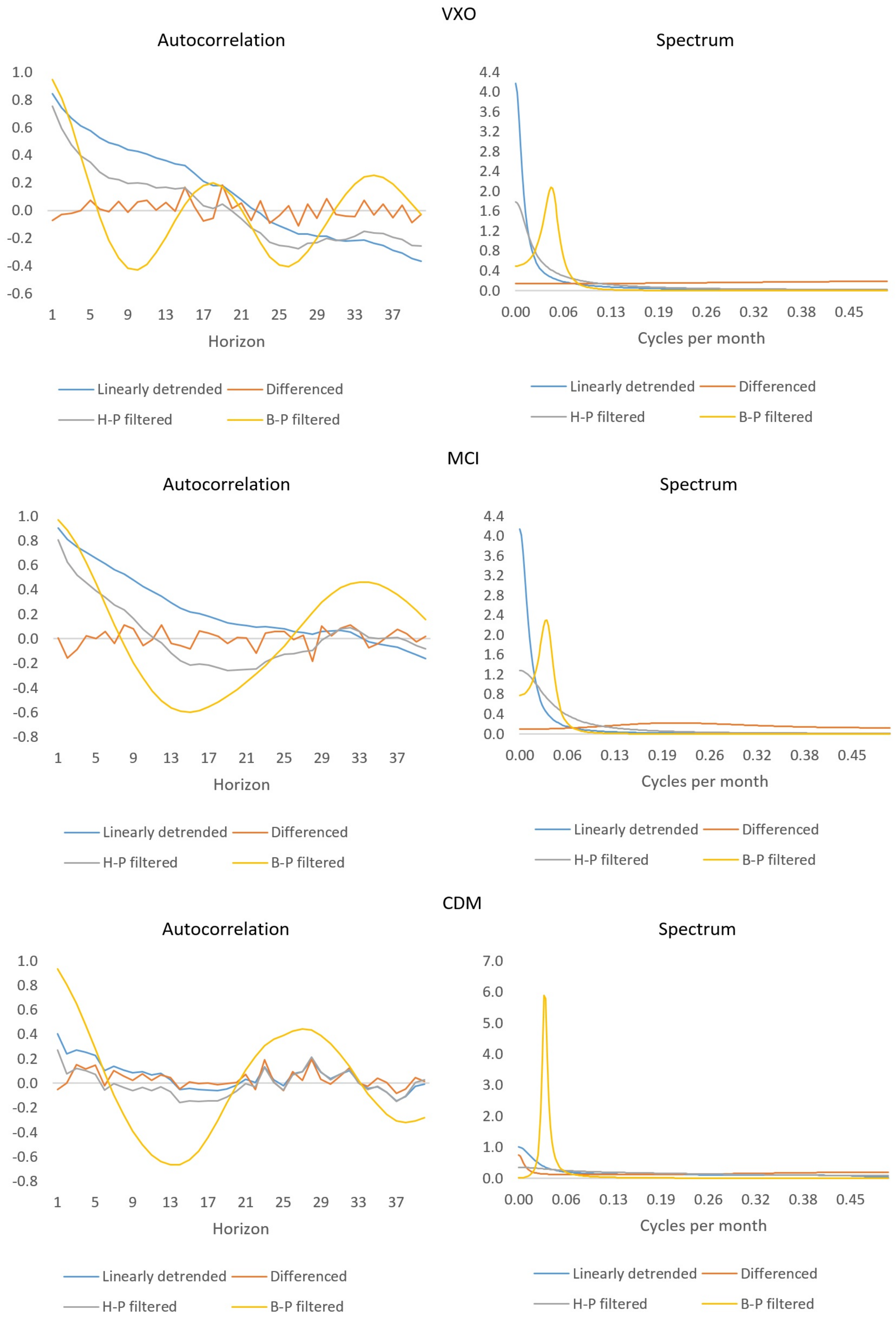

Figure 1.15: Autocorrelation and spectrum of detrended uncertainty measures (2)

Notes: Estimation by author.

Source: Thomson Reuters Datastream (VXO, MCI), Economic Policy Uncertainty website, `http://www.policyuncertainty.com/` (EPU), UCL Centre for Study of Decision-Making Uncertainty (RSS), Charemza, Díaz, and Makarova (2015, CDM) **

1.6.5 VAR model

The general VAR model is constructed as follows (Hamilton, 1994). The equation for a common representation of the VAR(p) is

$$y_t = c + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + \varepsilon_t \tag{1.31}$$

where $\varepsilon_t \sim iidN(0, \Omega)$. c denotes $(n \times 1)$ vector of constants, Φ_j denotes $(n \times n)$ matrix of autoregressive coefficient for $j = 1, 2, \cdots, p$. ε_t is $(n \times 1)$ vector of white noise with

$$\begin{aligned} &E(\varepsilon_t) = 0 \\ &E(\varepsilon_t \varepsilon_\tau') = \begin{cases} \Omega & \text{for } \; t = \tau \\ 0 & \text{otherwise} \end{cases} \end{aligned} \tag{1.32}$$

where Ω is $(n \times n)$ symmetric positive definite matrix.

Using lag operator, VAR can be written in the form

$$\begin{aligned} &[I_n - \Phi_1 L - \Phi_2 L^2 - \cdots - \Phi_p L^p] y_t = c + \varepsilon_t \\ &\Phi(L) y_t = c + \varepsilon_t \end{aligned} \tag{1.33}$$

VAR(p) can be rewritten as VAR(*1*) process by defining

$$\xi_t \equiv \begin{bmatrix} y_t - \mu \\ y_{t-1} - \mu \\ \vdots \\ y_{t-p+1} - \mu \end{bmatrix}$$

$$F \equiv \begin{bmatrix} \Phi_1 & \Phi_2 & \cdots & \Phi_{p-1} & \Phi_p \\ I_n & 0 & \cdots & 0 & 0 \\ 0 & I_n & \cdots & 0 & 0 \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ 0 & 0 & \cdots & I_n & 0 \end{bmatrix} \tag{1.34}$$

$$\nu_t \equiv \begin{bmatrix} \varepsilon_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

where μ is the mean of the vector process, y_t. Then VAR(p) can be written as the following:

$$\xi_t = F \xi_{t-1} + \nu_t \tag{1.35}$$

where

$$E(\nu_t \nu_\tau') = \begin{cases} Q & \text{for } \; t = \tau \\ 0 & \text{otherwise} \end{cases} \tag{1.36}$$

where

$$Q \equiv \begin{bmatrix} \Omega & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{1.37}$$

Recursively expanding equation (1.34) implies

$$\xi_{t+s} = \nu_{t+s} + F\nu_{t+s-1} + F^2\nu_{t+s-2} + \cdots + F^{s-1}\nu_{t+1} + F^s\xi_t + F^{s+1}\xi_{t-1} \tag{1.38}$$

Proposition 1.1: The eigenvalues of F satisfy

$$|I_n\lambda^p - \Phi_1\lambda^{p-1} - \Phi_2\lambda^{p-2} - \cdots - \Phi_p| = 0 \tag{1.39}$$

Therefore, a VAR(p) is covariance stationary if $|\lambda| < 1$ for all values of λ satisfying equation (9).

Proposition 1.2: A VAR(p) is covariance stationary if all values of z satisfying

$$|I_n - \Phi_1 z - \Phi_2 z^2 - \cdots - \Phi_p z^p| = 0 \tag{1.40}$$

lie outside the unit circle.

For the standard maximum likelihood estimation (MLE) and hypothesis testing, assume the Gaussian error. Suppose we observe $(T+p)$ time periods and define $\Pi = [c \;\; \Phi_1 \;\; \Phi_2 \;\; \cdots \;\; \Phi_p]$, so that the likelihood function of observed data $y_{0:T}$ conditional on parameters $\theta = (\Pi, \Omega)$ can be expressed as follows by recursively applying the joint Gaussian densities (denote as f):

$$f(y_T, y_{T-1}, \cdots y_1|y_0, \cdots, y_{-p+1}; \theta) = \prod_{t=1}^{T} f(y_t|y_{t-1}, \cdots, y_{-p+1}; \theta) \tag{1.41}$$

The sample log likelihood is

$$\begin{aligned} \mathscr{L}(\theta) &= \sum_{t=1}^{T} \log f(y_t|y_{t-1}, \cdots, y_{-p+1}; \theta) \\ &= -(Tn/2)\log(2\pi) + (T/2)\log|\Omega^{-1}| \\ &\quad - (1/2)\sum_{t=1}^{T}[(y_t - \Pi' x_t)'\Omega^{-1}(y_t - \Pi' x_t)] \end{aligned} \tag{1.42}$$

where x_t denotes a vector of constant term and p lags of y_t:

$$x_t \equiv \begin{bmatrix} 1 \\ y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{bmatrix} \tag{1.43}$$

Then the maximum likelihood estimator can be obtained by solving the first-order condition for the maximization problem of

$$\hat{\theta}_{MLE} = arg \max_{\theta \in \Theta} f(y_T, y_{T-1}, \cdots y_1 | y_0, \cdots, y_{-p+1}; \theta) \tag{1.44}$$

The $\hat{\Pi}_{MLE}$ becomes the sample analogue of the population linear projection of y_t on a constant and x_t and apply these results to find the $\hat{\Omega}_{MLE}$, which gives us the maximum likelihood estimators identical to OLS estimator.

$$\begin{aligned} \hat{\Pi}_{MLE} &= \left[\sum_{t=1}^{T} y_t x_t' \right] \left[\sum_{t=1}^{T} x_t x_t' \right]^{-1} \\ \hat{\Omega}_{MLE} &= \frac{1}{T} \sum_{t=1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_t{}' \end{aligned} \tag{1.45}$$

Hypothesis testing and the lag length determination, can be conducted using Likelihood Ratio test of estimators as in conventional cases for the ML estimation.

For constructing the impulse response function, recall the MA(∞) representation of the first n rows of the equation with covariance stationarity[22] is as follows:

$$y_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + \cdots = \mu + \Psi(L) \varepsilon_t \tag{1.46}$$

$$\frac{\partial y_{t+s}}{\partial \varepsilon_t{}'} = \Psi_s \tag{1.47}$$

Thus, the row i and column j element of the matrix Ψ_s has the interpretation of a one unit increase in the jth variable's innovation at t for the value of the ith variable at time $t+s$, holding other innovations constant. More precisely, impulse response function is defined as a plot of the row i and column j element of Ψ_s,

$$\frac{\partial y_{i,t+s}}{\partial \varepsilon_{j,t}{}'} \tag{1.48}$$

as a function of s. However, this cannot be interpreted as causal effect because the shocks $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ are contemporaneously correlated. Suppose $\varepsilon_{1,t}$ changed by δ_1, and $\varepsilon_{2,t}$ changed by δ_2, and so on, then combined effect of these effects on the vector y_{t+s} can be expressed by

$$\Delta y_{t+s} = \frac{\partial y_{t+s}}{\partial \varepsilon_{1,t}} \delta_1 + \frac{\partial y_{t+s}}{\partial \varepsilon_{2,t}} \delta_2 + \cdots + \frac{\partial y_{t+s}}{\partial \varepsilon_{n,t}} \delta_n = \Psi_s \delta \tag{1.49}$$

where $\delta = (\delta_1, \delta_2, \cdots, \delta_n)'$. Given the information received about the system as of $t-1$, suppose we are then received the information about the first variable in VAR system at t, e.g. a positive $\varepsilon_{1,t}$. This leads to revision of our expectation on $y_{i,t+s}$ and because the errors are contemporaneously correlated, the new information about $\varepsilon_{1,t}$ affects the values of $\varepsilon_{2,t}, \varepsilon_{3,t}, \cdots, \varepsilon_{n,t}$, which affects the forecast of $y_{i,t+s}$.

[22]If the eigenvalues of F all lie inside the unit circle, i.e. covariance stationary, then $F^s \to 0$ as $s \to \infty$.

In order to back out the causal effect, eliminating the cross-effect by orthogonalisation of the shocks can be considered. For any real symmetric positive definite matrix Ω, there exists a unique lower triangular matrix A with 1's along the diagonal and a unique diagonal matrix D with positive elements along the principal diagonal such that

$$\Omega = ADA' \tag{1.50}$$

With matrix A, construct orthogonalise residuals where

$$u_t \equiv A^{-1}\varepsilon_t \tag{1.51}$$

Since ε_t is uncorrelated with its own lags or lagged values of y, so does u_t. Furthermore, the elements of u_t are uncorrelated with each other,

$$\begin{aligned} E(u_t u_t') &= E(A^{-1}\varepsilon_t \varepsilon_t' A^{-1'}) \\ &= A^{-1}\Omega A'^{-1} \\ &= A^{-1}ADA'A'^{-1} \\ &= D \end{aligned} \tag{1.52}$$

D is diagonal, so that the elements of u_t are mutually uncorrelated.
Rewriting equation (1.50),

$$Au_t = \varepsilon_t$$

$$\begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ a_{21} & 1 & 0 & \cdots & 0 \\ a_{31} & a_{32} & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \cdots & 1 \end{bmatrix} \begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ \vdots \\ u_{nt} \end{bmatrix} = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \vdots \\ \varepsilon_{nt} \end{bmatrix} \tag{1.53}$$

The jth row of the above equation is,

$$u_{jt} = \varepsilon_{jt} - a_{j1}u_{1t} - a_{j2}u_{2t} - \cdots - a_{j,j-1}u_{j-1,t} \tag{1.54}$$

Since $u_t's$ are uncorrelated, u_{jt} can be interpreted as the residuals from a linear projection of ε_{jt} on $u_{1t}, u_{2t}, \cdots, u_{j-1,t}$.

$$\hat{E}(\varepsilon_{jt}|u_{1t}, u_{2t}, \cdots, u_{j-1,t}) = a_{j1}u_{1t} + a_{j2}u_{2t} + \cdots + a_{j,j-1}u_{j-1,t} \tag{1.55}$$

The coefficient from on y_{1t} in a linear projection of y_{jt} on y_{1t} and previous information about $y_t's$ is the same as the coefficient on ε_{1t} in a linear projection of ε_{jt} on ε_{1t} by the formula updating linear projections (see proof in Hamilton (1994) p.321).

$$\frac{\partial \hat{E}(\varepsilon_{jt}|y_{1t}, x_{t-1})}{\partial y_{1t}} = a_{j1} \tag{1.56}$$

where $x_{t-1}' = (y_{t-1}', y_{t-2}', \cdots, y_{t-p}')$. Combining these for $j = 1, 2, \cdots, n$ into a vector,

$$\frac{\partial \hat{E}(\varepsilon_t|y_{1t}, x_{t-1})}{\partial y_{1t}} = \mathbf{a_1} \tag{1.57}$$

where

$$\mathbf{a_1} = \begin{bmatrix} 1 \\ a_{21} \\ a_{31} \\ \vdots \\ a_{n1} \end{bmatrix} \tag{1.58}$$

Rewriting equation (1.56) using equation (1.45) and (1.46) gives,

$$\frac{\partial \hat{E}(y_{t+s}|y_{1t}, x_{t-1})}{\partial y_{1t}} = \Psi_s \mathbf{a_1} \tag{1.59}$$

Due to the recursive structure, the above function can be written in general for $j = 1, 2, \cdots, n$ as follows:

$$\frac{\partial \hat{E}(y_{t+s}|y_{jt}, y_{j-1,t}, \cdots, y_{jt}, x_{t-1})}{\partial y_{1t}} = \Psi_s \mathbf{a_j} \tag{1.60}$$

where $\mathbf{a_j}$ denotes the jth column of the matrix A. The sample estimates of equation (1.59), $\hat{\Psi}_s \hat{\mathbf{a_j}}$, are obtained by estimating $\hat{\Phi}_1, \hat{\Phi}_2, \cdots, \hat{\Phi}_j$ and $\hat{\Omega}$ by OLS and constructing $\hat{\Psi_s}$ by simulating the system. Matrices $\hat{A}$ and $\hat{D}$ satisfying $\hat{\Omega} = \hat{A}\hat{D}\hat{A}'$ can be constructed from estimated $\hat{\Omega}$ using the factorisation algorithm. Practically, the *Cholesky decomposition* of the matrix Ω is often considered.

$$\Omega = AD^{1/2}D^{1/2}A' = PP' \tag{1.61}$$

where $P = AD^{1/2}$ and $D^{1/2}$ is the diagonal matrix whose (i, j) element is the standard deviation of u_{jt}.

Recall equation for MA(∞) representation of VAR model and take the s-period-ahead forecast,

$$y_{t+s} - \hat{y}_{t+s|t} = \varepsilon_{t+s} + \Psi_1 \varepsilon_{t+s-1} + \Psi_2 \varepsilon_{t+s-2} + \cdots + \Psi_{s-1}\varepsilon_{t+1} \tag{1.62}$$

The mean squared error of the s-period-ahead forecast is

$$\begin{aligned} MSE(\hat{y}_{t+s|t}) &= E[(y_{t+s} - \hat{y}_{t+s|t})(y_{t+s} - \hat{y}_{t+s|t})'] \\ &= \Omega + \Psi_1 \Omega \Psi_1' + \Psi_2 \Omega \Psi_2' + \cdots + \Psi_{s-1}\Omega\Psi_{s-1}' \end{aligned} \tag{1.63}$$

where $\Omega = E(\varepsilon_t \varepsilon_t')$. Now consider how the orthogonalised disturbances $(u_{1t}, \cdots, u_{nt})$ contribute to the MSE. Recall and rewrite equation (1.52) and consider the variance-covariance matrix of the errors.

$$\begin{aligned} \varepsilon_t &= Au_t = \mathbf{a_1}u_1 + \mathbf{a_2}u_2 + \cdots + \mathbf{a_n}u_n, \\ \Omega &= E(\varepsilon_t \varepsilon_t') \\ &= \mathbf{a_1}\mathbf{a_1}'Var(u_{1t}) + \cdots + \mathbf{a_n}\mathbf{a_n}'Var(u_{nt}) \end{aligned} \tag{1.64}$$

where $Var(u_{jt})$ is the (j, j) element of the matrix D. Incorporating this equation with equation (1.62) yields,

$$MSE(\hat{y}_{t+s|t}) = \sum_{j=1}^{n} Var(u_{jt}) \cdot [\mathbf{a_j}\mathbf{a_j}' + \Psi_1 \mathbf{a_j}\mathbf{a_j}'\Psi_1' + \cdots + \Psi_{s-1}\mathbf{a_j}\mathbf{a_j}'\Psi_{s-1}'] \tag{1.65}$$

Then with this expression, the Forecast Error Variance Decomposition (FEVD) can be calculated. FEVD reflects the contribution of the jth orthogonalised innovation of the MSE of the s-period-ahead forecasts. For covariance stationary VAR, as $s \to \infty$, $MSE(\hat{y}_{t+s|t})$ converges to the unconditional variance of the vector y_t, thus this can be asymptotically the portion of the total variance in y_t that is due to the disturbance u_j.

The choice of the orders of polynomials in $\Phi(L)$ is vital to specify and estimate parametric VAR model. Traditionally, one way of addressing the trade-off of fit of a model and its degree of parsimony is to select a model that minimises the value of information-theoretic criteria of the form

$$\mathrm{IC}(i) = log(\hat{\sigma_i^2}) + k_i c_T \tag{1.66}$$

Where k_i is the number of parameters in the candidate (nested) model $i = 1, \cdots, M$, and $\hat{\sigma_i^2}$ is the corresponding maximum likelihood estimate of the residual variance.

The penalty term c_T is defined as $c_T = 2/T$ in Akaike Information Criteria (AIC), and as $c_T = ln(T)/T$ in Schwarz Information Criteria (SIC). In addition, Lütkepohl (1993) indicates that overfitting (selecting a higher order lag length than the true lag length) causes an increase in the mean-square forecast errors of the VAR and that underfitting the lag length often generates autocorrelated errors. Hafer and Sheehan (1989) find that the accuracy of forecasts from VAR models varies substantially for alternative lag lengths.

1.6.6 Stationary tests

Assume the following dynamic model for a set of time series:

$$y_t = z_t'\gamma + \nu_t$$
$$\nu_t = \alpha\nu_{t-1} + u_t$$

where $u_t = \sum_{j=0}^{\infty} c_j e_{t-j}$ with $\sum_{j=0}^{\infty} j|c_j| < \infty$, $e_t \sim iid(0, \sigma_e^2)$. In general, the vector z_t is a set of deterministic components, for example, $z_t = (1, t, \ldots, t_p)'$ and $p = 0$ for no trend data or $p = 1$ for linear trending data. The long-run variance for the time series is

$$\sigma^2 = \lim_{t\to\infty} T^{-1}E(\sum_{t=1}^{T} u_t)^2$$

The GLS estimate of γ, $\hat{\gamma}^{GLS}$, can be obtained by the Least Squares regression of detrended variables. In particular, the regression of $y_t^{\bar{\alpha}}$ on $z_t^{\bar{\alpha}}$, where all the variables in the regression are the quasi-differenced series.

$$y_t^{\bar{\alpha}} = y_t - \bar{\alpha}y_t^{\bar{\alpha}}$$
$$z_t^{\bar{\alpha}} = z_t - \bar{\alpha}z_t^{\bar{\alpha}}$$

where $\bar{\alpha} = 1 + \bar{c}/T$, with $\bar{c} = -7$ for $p = 0$ and $\bar{c} = -13.5$ for $p = 1$.[23] ADF^{GLS} (Augmented Dickey-Fuller) test statistics can be constructed using t-statistics associated with $\hat{b}_0$ in the GLS regression estimation.

Assume $y_1 = O_p(1)$, then the null hypothesis of unit root is $H_0 : \alpha = 1$ which can be tested against the alternative, $H_1 : |\alpha| < 1$, using the following test statistics (Ng and Perron, 2001).

$$Z_\alpha = \frac{T^{-1}{y_T}^2 - S_{AR}^2}{2T^{-2}\sum_{t=1}^{T} {y_{t-1}}^2}$$

$$MZ_\alpha^{GLS} = \frac{T^{-1}\tilde{y}_T^2 - S_{AR}^2}{2T^{-2}\sum_{t=1}^{T} \tilde{y}_{t-1}^2}$$

$$MSB^{GLS} = \left(\frac{T^{-2}\sum_{t=1}^{T} \tilde{y}_{t-1}^2}{S_{AR}^2}\right)^{\frac{1}{2}}$$

$$MZ_t^{GLS} = MSB^{GLS} \cdot MZ_\alpha^{GLS}$$

[23]The corresponding values of $\bar{c}$ are given by Elliott, Rothenberg, and Stock (1996, cited in Ng and Perron, 2001, p.1519).

where $\tilde{y}_t = y_t - z_t'\hat{\gamma}^{GLS}$ and $\hat{\gamma}^{GLS}$ is the GLS estimate of γ obtained from the Least Squares regression of detrended variables and S^2_{AR} is the autoregressive spectral density estimate of σ^2.

$$S^2_{AR} = \frac{\hat{\sigma}^2_{ek}}{(1 - \sum_{i=1}^{k} \hat{b}_i)^2}$$

where

$$\hat{\sigma}^2_{ek} = T^{-1} \sum_{t=k+1}^{T} \hat{e}^2_{tk}$$

$\hat{b}_i$, $\hat{e}_{tk}$ are obtained from OLS regression of

$$\Delta\tilde{y}_t = \hat{b_0}\tilde{y}_{t-1} + \sum_{i=1}^{k} \hat{b}_i \Delta\tilde{y}_{t-1} + \hat{e}_{tk}$$

Based on the primary statistics calculated, the feasible point optimal test statistic (Ng and Perron, 2001) can be constructed as follows:

$$P_T = \frac{S(\bar{\alpha}) - \bar{\alpha}S(1)}{{S_{AR}}^2}$$

where $S(\alpha) = \inf_\gamma \sum_{t=1}^{T}(y^\alpha_t - \gamma z^\alpha_t)^2$ and $\bar{\alpha} = 1 + \bar{c}/T$ as defined earlier.

The modified point optimal test statistic, MP_T, also proposed by Ng and Perron (2001), is

$$MP_T = \begin{cases} \dfrac{\bar{c}^2 T^{-2} \sum_{t=1}^{T} \tilde{y}^2_{t-1} - \bar{c}T^{-1}\tilde{y}^2_T}{{S_{AR}}^2} & \text{for} \quad p = 0 \\ \\ \dfrac{\bar{c}^2 T^{-2} \sum_{t=1}^{T} \tilde{y}^2_{t-1} + (1-\bar{c})T^{-1}\tilde{y}^2_T}{{S_{AR}}^2} & \text{for} \quad p = 1 \end{cases}$$

The key decision for constructing the stationarity test statistics is to select the autoregressive order, k. Ng and Perron (2001) found that the exact size is close to nominal size even when there is negative MA (moving average) components and the power of the test for local alternatives is approximately the Gaussian local asymptotic power envelop. Followed by their findings, Ng and Perron (2001) suggested MAIC (modified AIC) for choosing the lag length, which can be summarised as follows[24]:

$$k_{MAIC} = \arg\min_{k \in [0, k_{max}]} MAIC(k)$$

[24] One potential issue regarding the implement of the MAIC is the power reversal problem where the power can be very small for non-local alternatives. Perron and Qu (2007) solve the potential power reversal problem by using GLS detrended data for constructing the autoregression spectral density but for the selection of the autoregressive order k, they proposed using OLS detrended data.The complete elucidation of MAIC would possibly lead to a digression outside the focus of this chapter. For the details of the method, refer to the Ng and Perron (2001) and Perron and Qu (2007).

where

$$MAIC(k) = \ln(\hat{\sigma}_k^2) + \frac{2(\tau_T(k) + k)}{(T - k_{max})}$$
$$\tau_T(k) = (\hat{\sigma}_k^2)^{-1}\hat{b_0}^2 \sum_{k=k_{max}+1}^{T} \tilde{y}_{t-1}^2$$
$$\hat{\sigma}_k^2 = (T - k_{max})^{-1} \sum_{k=k_{max}+1}^{T} \hat{e}_{tk}^2$$
$$k_{max} = \text{int}(12(T/100)^{1/4})$$

Table 1.9: Unit root test statistics: Macroeconomic variables

	Stock				FFR			
	SB1	SB2	NS1	NS2	SB1	SB2	NS1	NS2
PT test	**10.34**	2.91	4.92	2.48	**15.41**	**14.95**	**9.28**	**2.56**
MPT test	**10.13**	2.59	4.96	2.48	**15.36**	**14.69**	**9.36**	**2.57**
ADF test	-1.90	**-5.81**	**-5.61**	**-5.20**	-2.22	-2.28	-2.27	-2.25
ZA test	-19.56	**-156.20**	**-145.85**	**-129.62**	-9.31	-9.73	-9.75	-9.64
MZA test	-5.99	**-52.50**	**-45.12**	**-35.25**	-9.30	-9.72	-9.74	-9.63
MSB test	**0.28**	0.10	0.11	0.12	**0.23**	**0.23**	**0.23**	**0.23**
MZT test	-1.70	**-5.12**	**-4.75**	**-4.20**	-2.15	-2.20	-2.21	-2.19

	IP				EMP			
	SB1	SB2	NS1	NS2	SB1	SB2	NS1	NS2
PT test	**37.17**	5.59	4.13	**2.17**	**6.44**	4.97	4.25	**1.94**
MPT test	**35.05**	5.46	4.01	**1.94**	**6.17**	5.02	4.19	**1.79**
ADF test	-1.40	-3.25	**-3.11**	**-2.39**	-3.17	**-3.44**	**-3.24**	**-2.75**
ZA test	-3.97	**-25.68**	**-22.79**	-14.09	-22.45	**-26.83**	**-22.98**	**-17.98**
MZA test	-3.92	**-25.63**	**-22.75**	-14.07	-22.44	**-26.82**	**-22.97**	**-17.96**
MSB test	**0.35**	0.14	0.15	0.18	**0.15**	0.14	0.15	0.16
MZT test	-1.38	**-3.57**	**-3.37**	**-2.60**	-3.34	**-3.65**	**-3.39**	**-2.95**

Notes: SB1 denotes the linear time trend that is affected by one structural break, which affects both the level and the slope of the time trend. SB2 is the linear time trend that is affected by one structural break, which affects the slope of the time trend. NS1 denotes the linear time trend case, without structural breaks. NS2 denotes the constant case, without structural breaks. PT and MPT test statistics are computed by setting max k = 14, min k = 0, all other test statistics with max k = 5, min k = 0. Bold letters imply rejecting the null hypothesis of unit root at 5% significance level.

Table 1.10: Unit root test statistics: Uncertainty measures

	EPU				EPUN			
	SB1	SB2	NS1	NS2	SB1	SB2	NS1	NS2
PT test	**14.95**	**18.32**	**10.83**	**6.93**	**10.34**	**10.90**	**8.26**	**5.88**
MPT test	**14.77**	**16.83**	**10.62**	**6.23**	**10.13**	**9.91**	**8.04**	**5.26**
ADF test	**-3.92**	**-3.68**	**-3.52**	**-2.56**	**-4.79**	**-4.55**	**-4.30**	**-3.16**
ZA test	**-39.44**	**-34.32**	**-30.58**	**-16.83**	**-58.17**	**-52.44**	**-45.94**	**-24.53**
MZA test	**-29.75**	**-26.12**	**-23.35**	-13.28	**-44.90**	**-40.42**	**-35.50**	**-19.66**
MSB test	0.13	0.14	0.15	0.19	0.11	0.11	0.12	0.16
MZT test	**-3.84**	**-3.60**	**-3.41**	**-2.49**	**-4.74**	**-4.49**	**-4.21**	**-3.08**

	RSS				VXO			
	SB1	SB2	NS1	NS2	SB1	SB2	NS1	NS2
PT test	**8.87**	**7.60**	4.17	**2.09**	**21.44**	**11.18**	**9.32**	**6.67**
MPT test	**8.89**	6.95	4.16	**1.94**	**19.38**	**10.29**	**8.92**	**5.85**
ADF test	**-3.92**	**-3.74**	**-3.61**	**-3.07**	**-4.82**	**-3.74**	**-3.09**	-2.17
ZA test	**-47.35**	**-42.95**	**-39.46**	**-29.30**	**-42.31**	**-34.61**	**-22.78**	-11.00
MZA test	**-27.77**	**-24.97**	**-22.98**	**-16.92**	**-38.32**	**-28.91**	**-19.35**	-9.71
MSB test	0.13	0.14	0.15	0.16	0.11	0.13	0.16	**0.22**
MZT test	**-3.68**	**-3.49**	**-3.36**	**-2.78**	**-4.36**	**-3.78**	**-3.11**	-2.13

	MCI				CDM			
	SB1	SB2	NS1	NS2	SB1	SB2	NS1	NS2
PT test	6.05	5.46	4.31	**2.39**	1.10	3.83	1.97	0.56
MPT test	5.88	5.44	4.20	**2.14**	1.09	3.63	1.98	0.57
ADF test	**-3.80**	**-3.59**	**-3.29**	**-2.53**	**-5.32**	**-4.96**	**-5.24**	**-5.19**
ZA test	**-33.49**	**-29.78**	**-24.51**	-14.80	**-110.58**	**-96.06**	**-106.83**	**-105.01**
MZA test	**-29.41**	**-26.32**	**-21.87**	-13.51	**-50.43**	**-41.34**	**-48.23**	**-46.99**
MSB test	0.13	0.14	0.15	0.19	0.10	0.11	0.10	0.10
MZT test	**-3.82**	**-3.60**	**-3.30**	**-2.51**	**-5.00**	**-4.54**	**-4.89**	**-4.83**

Notes: SB1 denotes the linear time trend that is affected by one structural break, which affects both the level and the slope of the time trend. SB2 is the linear time trend that is affected by one structural break, which affects the slope of the time trend. NS1 denotes the linear time trend case, without structural breaks. NS2 denotes the constant case, without structural breaks. PT and MPT test statistics are computed by setting max $k = 14$, min $k = 0$, all other test statistics with max $k = 5$, min $k = 0$. Bold letters imply rejecting the null hypothesis of unit root at 5% significance level.

1.6.7 The canonical reduced form VAR estimation results

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.

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 (see Figure 1.16).

Table 1.11: Statistics of VAR model: EPU

Equation	No. of parameters	RMSE	R^2	χ^2	$P > \chi^2$
EPU	32	0.531	0.7469	923.46	0.000
Stock (S & P)	32	0.040	0.8908	2553.55	0.000
FFR (Federal Reserve Rate)	32	0.158	0.9841	19361.08	0.000
EMP (Employment)	32	0.002	0.9954	67205.40	0.000
IP (Production)	32	0.006	0.9731	11311.31	0.000

Table 1.12: Statistics of VAR model: RSS

Equation	No. of parameters	RMSE	R^2	χ^2	$P > \chi^2$
RSS	32	0.576	0.7146	443.23	0.000
Stock (S & P)	32	0.038	0.9294	2329.84	0.000
FFR (Federal Reserve Rate)	32	0.120	0.9909	19183.92	0.000
EMP (Employment)	32	0.002	0.9966	52590.69	0.000
IP (Production)	32	0.006	0.9810	9152.25	0.000

Table 1.13: The estimates of VAR coefficients: EPU

	EPU eq.			Stock eq.		
	β	$se(\beta)$		β	$se(\beta)$	
EPU L1	0.7102	0.0576	***	-0.0241	0.0044	***
L2	-0.0474	0.0713		0.0015	0.0054	
L3	0.0046	0.0702		0.0175	0.0053	***
L4	0.1691	0.0715	**	-0.0010	0.0054	
L5	0.0285	0.0732		0.0057	0.0055	
L6	0.0452	0.0635		0.0010	0.0048	
Stock L1	-0.7441	0.7579		0.8853	0.0574	***
L2	0.3110	1.0174		-0.0410	0.0771	
L3	0.4508	1.0108		0.0811	0.0765	
L4	2.3935	1.0032	**	-0.0521	0.0760	
L5	-1.8253	1.0031	*	0.0956	0.0760	
L6	0.4817	0.7428		-0.0550	0.0563	
FFR L1	0.1546	0.1862		-0.0302	0.0141	**
L2	-0.0196	0.3083		0.0340	0.0234	
L3	0.0167	0.3154		0.0076	0.0239	
L4	-0.1586	0.3104		0.0053	0.0235	
L5	0.1276	0.3025		0.0155	0.0229	
L6	-0.0762	0.1840		-0.0252	0.0139	*
EMP L1	-15.2066	21.4835		-0.4576	1.6270	
L2	-12.9173	29.3617		1.0064	2.2237	
L3	33.7067	29.5530		-6.5011	2.2381	***
L4	7.6558	30.0578		4.9904	2.2764	**
L5	-20.4243	29.5553		0.7868	2.2383	
L6	2.5274	19.1359		-0.5662	1.4492	
IP L1	-7.3275	6.4036		-0.2703	0.4850	
L2	2.9126	7.9970		1.3236	0.6056	**
L3	1.4113	8.3590		0.7397	0.6331	
L4	6.1330	8.4305		-1.1334	0.6385	*
L5	-1.0259	8.2182		-0.3980	0.6224	
L6	-2.6789	6.2589		0.2831	0.4740	
trend	0.000	0.000		0.0000	0.0000	
const	-0.132	0.140		0.0003	0.0106	

Notes: The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

[Table Continued]

	FFR eq.			EMP eq.			IP eq.		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
EPU L1	-0.0786	0.0172	***	-0.0002	0.0002		-0.0006	0.0006	
L2	0.0285	0.0213		0.0002	0.0002		-0.0004	0.0007	
L3	0.0102	0.0209		-0.0003	0.0002		-0.0005	0.0007	
L4	0.0084	0.0213		-0.0001	0.0002		-0.0003	0.0007	
L5	0.0041	0.0218		0.0002	0.0002		0.0013	0.0008	*
L6	0.0097	0.0190		0.0001	0.0002		0.0000	0.0007	
Stock L1	0.0707	0.2260		0.0078	0.0024	***	0.0158	0.0079	**
L2	-0.2790	0.3035		0.0023	0.0032		0.0100	0.0106	
L3	0.4879	0.3015		-0.0043	0.0031		-0.0158	0.0105	
L4	-0.9300	0.2992	***	-0.0037	0.0031		-0.0088	0.0104	
L5	0.7590	0.2992	**	0.0016	0.0031		0.0106	0.0104	
L6	-0.3645	0.2216		0.0012	0.0023		0.0045	0.0077	
FFR L1	1.3017	0.0556	***	0.0000	0.0006		0.0031	0.0019	
L2	-0.3674	0.0920	***	0.0016	0.0010	*	-0.0013	0.0032	
L3	0.1127	0.0941		-0.0009	0.0010		-0.0002	0.0033	
L4	-0.0526	0.0926		-0.0006	0.0010		-0.0042	0.0032	
L5	0.0814	0.0902		0.0004	0.0009		0.0072	0.0032	**
L6	-0.1326	0.0549	**	-0.0003	0.0006		-0.0037	0.0019	*
EMP L1	-5.8883	6.4080		0.9439	0.0666	***	0.0382	0.2237	
L2	-1.1437	8.7579		0.1557	0.0911	*	-0.0584	0.3057	
L3	17.6075	8.8149	**	-0.0418	0.0917		-0.4118	0.3077	
L4	-2.3508	8.9655		-0.0125	0.0932		0.3485	0.3130	
L5	1.7541	8.8156		-0.1067	0.0917		0.0312	0.3077	
L6	-7.8210	5.7078		-0.0163	0.0593		-0.0434	0.1993	
IP L1	7.2557	1.9100	***	0.0867	0.0199	***	0.8798	0.0667	***
L2	-3.0587	2.3853		-0.0183	0.0248		0.2617	0.0833	***
L3	-3.2644	2.4933		-0.0192	0.0259		0.1199	0.0870	
L4	-3.0988	2.5146		-0.0244	0.0261		-0.2341	0.0878	***
L5	-1.8037	2.4513		-0.0153	0.0255		-0.0960	0.0856	
L6	4.0019	1.8669	**	0.0257	0.0194		0.0314	0.0652	
trend	0.0000	0.0001		0.0000	0.0000		0.0000	0.0000	
const	-0.0119	0.0419		-0.0004	0.0004		-0.0007	0.0015	

Notes: The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

Table 1.14: The estimates of VAR coefficients: RSS

	EPU eq.			Stock eq.		
	β	$se(\beta)$		β	$se(\beta)$	
EPU L1	0.4129	0.0765	***	0.0314	0.0051	***
L2	0.0389	0.0911		-0.0082	0.0061	
L3	0.1724	0.0900	*	-0.0074	0.0060	
L4	0.1428	0.0909		-0.0032	0.0061	
L5	0.1201	0.0907		-0.0056	0.0061	
L6	0.0419	0.0847		0.0067	0.0057	
Stock L1	-0.9544	1.1486		0.8546	0.0767	***
L2	0.1507	1.5299		-0.0544	0.1021	
L3	-1.5766	1.5161		0.0671	0.1012	
L4	-0.9524	1.4907		-0.0047	0.0995	
L5	-0.5166	1.4602		0.0018	0.0975	
L6	1.4684	1.0794		0.0016	0.0721	
FFR L1	-0.2998	0.3525		-0.0133	0.0235	
L2	0.2348	0.6203		0.0625	0.0414	
L3	-0.4747	0.6457		-0.0713	0.0431	*
L4	1.1235	0.6352	*	0.0277	0.0424	
L5	0.1503	0.6150		0.0085	0.0411	
L6	-0.7649	0.3551	**	-0.0058	0.0237	
EMP L1	-10.1961	29.3256		-0.0441	1.9580	
L2	-6.7989	39.3691		1.6461	2.6286	
L3	35.9032	39.3936		-5.9441	2.6303	**
L4	-55.5313	40.4758		3.8090	2.7025	
L5	31.3698	40.2891		-0.8115	2.6901	
L6	4.3136	25.7794		0.8302	1.7213	
IP L1	6.4427	8.7022		-0.0325	0.5810	
L2	13.6124	10.8248		1.6236	0.7228	**
L3	-15.4878	11.2962		0.1674	0.7542	
L4	-0.1857	11.3995		-1.6773	0.7611	**
L5	5.0641	11.1655		-0.0560	0.7455	
L6	-1.5251	8.5759		0.4918	0.5726	
trend	-0.001	0.001		0.0001	0.0001	*
const	0.351	0.519		-0.0577	0.0346	*

Notes: The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

[Table Continued]

	FFR eq.			EMP eq.			IP eq.		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
EPU L1	0.0467	0.0159	***	0.0000	0.0002		0.0012	0.0008	
L2	-0.0039	0.0189		-0.0001	0.0003		-0.0004	0.0009	
L3	0.0231	0.0187		0.0000	0.0003		0.0003	0.0009	
L4	-0.0179	0.0189		0.0004	0.0003		0.0002	0.0009	
L5	-0.0014	0.0188		-0.0001	0.0003		-0.0005	0.0009	
L6	-0.0108	0.0176		-0.0001	0.0003		-0.0008	0.0008	
Stock L1	0.2108	0.2386		0.0113	0.0035	***	0.0187	0.0114	
L2	-0.0132	0.3178		0.0030	0.0046		0.0101	0.0152	
L3	-0.1695	0.3149		-0.0061	0.0046		-0.0256	0.0150	*
L4	0.0835	0.3096		-0.0047	0.0045		-0.0010	0.0148	
L5	-0.0667	0.3033		0.0014	0.0044		0.0193	0.0145	
L6	0.1872	0.2242		0.0012	0.0032		-0.0063	0.0107	
FFR L1	1.4153	0.0732	***	-0.0007	0.0011		0.0010	0.0035	
L2	-0.3930	0.1288	***	0.0031	0.0019	*	0.0055	0.0061	
L3	-0.0137	0.1341		-0.0010	0.0019		-0.0037	0.0064	
L4	0.0015	0.1319		-0.0025	0.0019		-0.0095	0.0063	
L5	0.0064	0.1277		0.0024	0.0018		0.0153	0.0061	**
L6	-0.0760	0.0738		-0.0012	0.0011		-0.0073	0.0035	**
EMP L1	-12.4838	6.0909	**	0.8921	0.0882	***	-0.0755	0.2905	
L2	2.1610	8.1769		0.1881	0.1184		-0.0399	0.3900	
L3	20.7904	8.1820	**	-0.0361	0.1184		-0.5177	0.3902	
L4	-1.0214	8.4068		0.0210	0.1217		0.5020	0.4009	
L5	2.4893	8.3680		-0.0780	0.1211		0.2175	0.3991	
L6	-10.2379	5.3544	*	-0.0505	0.0775		-0.1770	0.2554	
IP L1	5.7601	1.8074	***	0.1062	0.0262	***	0.8783	0.0862	***
L2	-2.0744	2.2483		-0.0287	0.0325		0.2969	0.1072	***
L3	-1.2667	2.3462		-0.0316	0.0340		0.1203	0.1119	
L4	-4.6239	2.3677	*	-0.0162	0.0343		-0.1755	0.1129	
L5	-2.8735	2.3191		-0.0032	0.0336		-0.1321	0.1106	
L6	4.0146	1.7812	**	0.0029	0.0258		-0.0253	0.0849	
trend	0.0004	0.0002	*	0.0000	0.0000		0.0000	0.0000	
const	-0.1770	0.1078		-0.0014	0.0016		-0.0002	0.0051	

Notes: The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

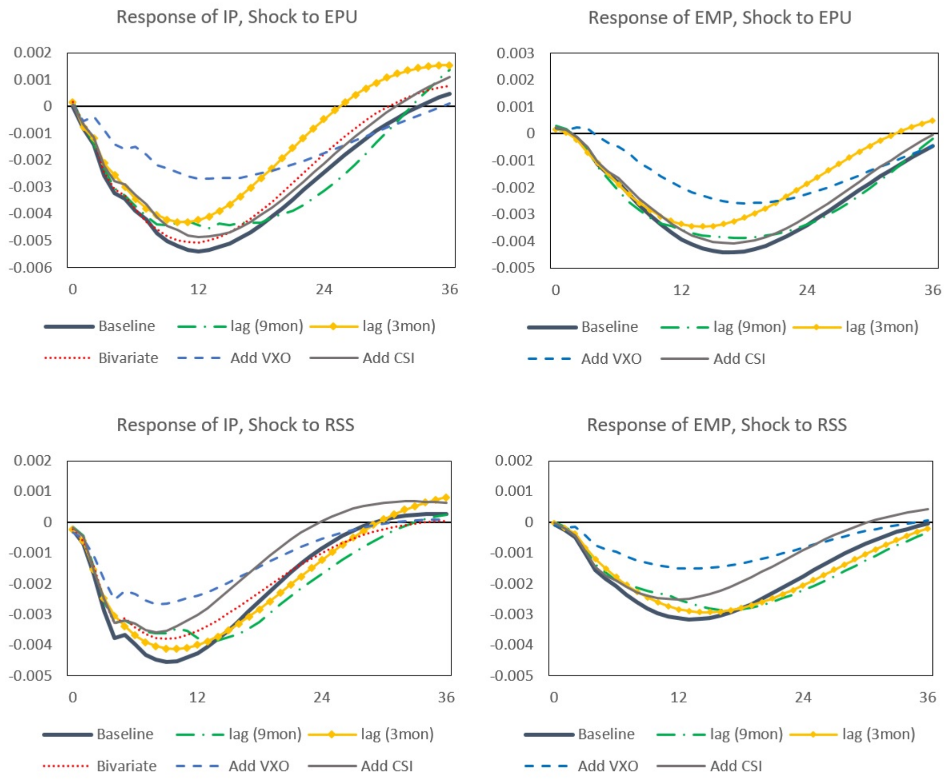

Figure 1.16: The IRFs of different specification

1.6.8 The effects of uncertainty shocks

Figure 1.17-1.18 illustrate the responses to 1 standard deviation increase in uncertainty measures estimated by Jordá's local projection and conditional bands.

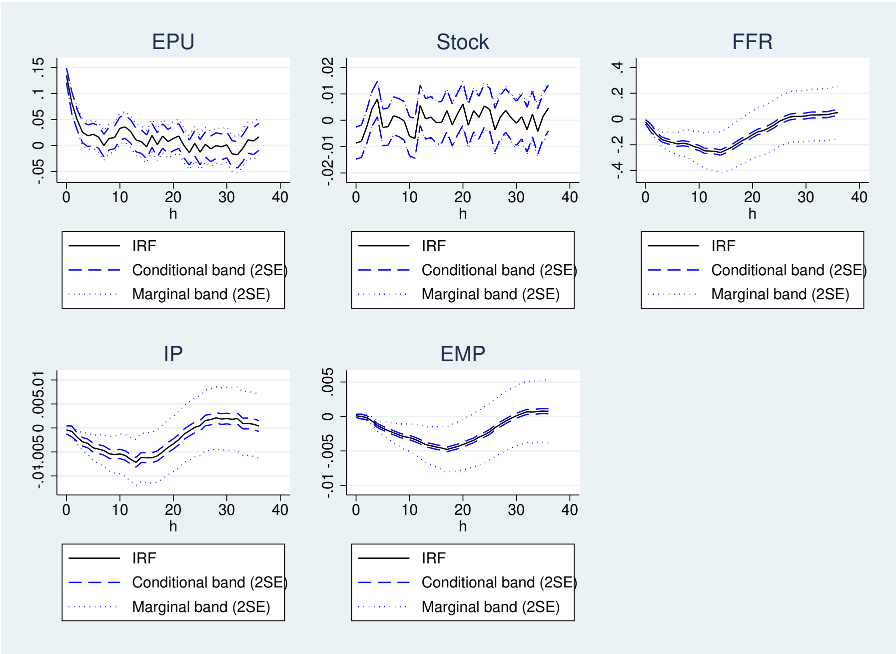

Figure 1.17: The effects of EPU shocks

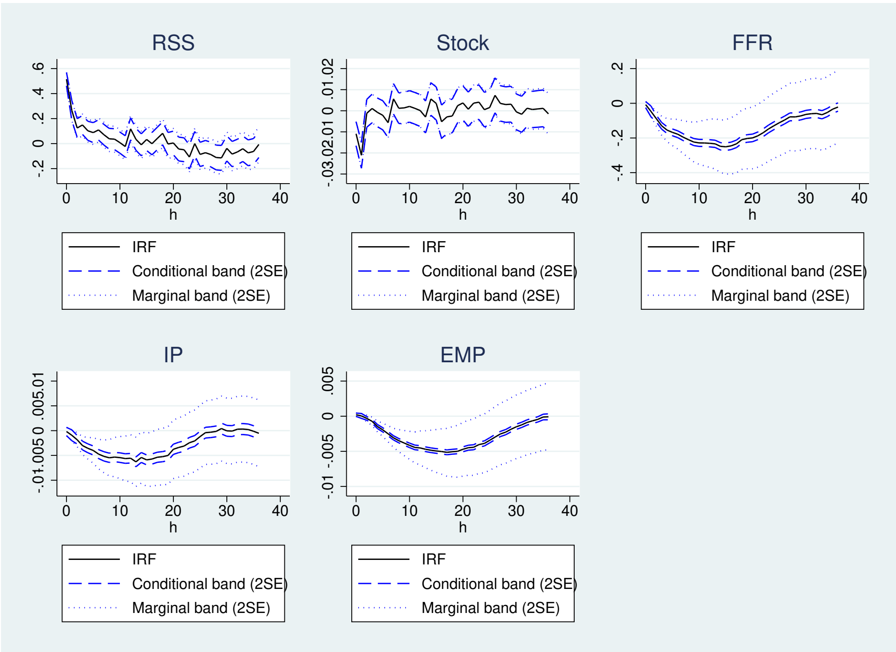

Figure 1.18: The effects of RSS shocks

Chapter 2

The Probabilistic Approach of Dependence Structure in Inflation Uncertainty between the UK and the Euro Area

Abstract

This chapter analyses the dependence structure in inflation uncertainty for the countries bordering a major currency area, in particular, the UK and the euro area. The inflation uncertainty is measured by square forecast errors from bivariate VAR GARCH model using the data from January 1997 to March 2016. The findings suggest that the estimated uncertainty may well be characterised with non-Gaussian density with skewed, heavy tail properties, Two Piece Normal (TPN) and Weighted Skewed Normal (WSN). The goodness-of-fit tests supports the choice of WSN against TPN for both the UK and the euro area inflation uncertainty. The results of estimation of dependence structure suggest that the inflation uncertainty of the UK and the euro area contemporaneously affect one another. Moreover, the simultaneous spillover effects get stronger if it is the uncertainty about the distant future rather than the near future. As for dynamic aspects of spillover effects, the UK inflation uncertainties are highly associated with the leading series of the euro area inflation uncertainty and the euro inflation uncertainties with the lagged series of the UK uncertainty. Without any distributional assumptions, it suggests that the UK inflation uncertainty might contain relevant information for predicting the euro inflation uncertainty with lags, even though it cannot be interpreted solely by causality. Finally, the conditional probability based on the dependence structure is computed using the estimation results. The result suggests that the left tail events of inflation are positively correlated between the two regions. This implies that the appropriate timing of the monetary policy can be driven

if policymakers consider the interconnectedness of the two economies. Since the extra information about the euro inflation uncertainty can lead to a different prediction of the odds of the left tail event for the UK inflation and *vice versa*, the monetary authority can react pre-emptively against the potential influence of the inflation uncertainty of bordering countries.

2.1 Introduction

Inflation in most advanced countries fell significantly and became more stable since late 1980s after experiencing high inflation with high volatility during the period from 1970s to early 1980s. Influenced by Friedman's (1977) paper, Ball (1992) proposed a model where high inflation produces high uncertainty around future inflation through monetary policy channel. Since then, numerous empirical papers have tried to find the evidence that high inflation is associated with high volatility in inflation. The underlying assumption in such empirical studies is that uncertainty in inflation can be well-proxied by volatility. Among them, ARCH-GARCH type econometric framework is widely adopted to investigate that high inflation is associated with higher volatility in inflation.[1]

Facing the Great Moderation in many advanced economies, the discussions about inflation and its volatility were extended to international dimension. For example, Alan Greenspan (2005), the former president of the Federal Reserve Board of the US, pointed out in his speech that globalization and innovation may be important determinants for the lowered inflation and its volatility after mid-1980s in many countries. Since late 1980s and early 1990s, disinflation trend in advanced countries prompted numerous studies (see Rogoff (2003), Levin and Piger (2004) and many more). In particular, Rogoff (2003) underscores the contribution of changes in the conduct of monetary policy across the world in this era.[2] More recently, a large number of studies have contributed to comprehensive understandings of the dependence structure of inflation among countries. They explain such co-movement in inflation by various chan-

[1] For example, Brunner and Hess (1993), Grier and Perry (2000), Elder (2004), Kontonikas (2004), Elder et al. (2005) examined that high inflation leads to high volatility in inflation. On the other hand, Cukierman and Meltzer (1986) suggested the opposite channel that high inflation volatility results in high inflation. Among many, Caporale, Onorante and Paesani (2010), Neanidis and Savva (2011) are the most recent papers on the relationship between inflation uncertainty and inflation level in European countries employing GARCH-type models. Berument, Yalcin and Yildirim (2009) adopted a Stochastic Volatility in Mean model and found that a positive shock in inflation volatility tends to raise inflation level persistently.

[2] The recognition of common trend in inflation was indeed not a novel discovery at that time. After experiencing the acceleration of inflation during 1960-1980, the common trend in inflation among countries was largely investigated as well (see McKinnon (1982), Darby and Lothian (1983), among others).

nels: common macroeconomic shocks (oil price shocks, technological spillovers), trade openness, labour market channel via migration, and exchange rate regimes.[3]

The discussions about the inflation and its uncertainty mainly dealt with inflation volatility, but failed to address how to measure inflation uncertainty *per se*. Whilst volatility measures remained most popular in the literature, there have been some alternative measures suggested. These approaches highlighted that the initial hypothesis of Friedman's (1997) paper was, in fact, that high inflation causes high *unpredictability*, not high *volatility*.[4] This approach underscores that economic agents care about whether inflation becomes less predictable, but are not so much concerned about whether inflation becomes more volatile.

Broadly speaking, unpredictability measures in the previous literature can be drawn from two different sources: (i) forecast error by model, and (ii) disagreement among individual forecasters. The first identification strategy is based on the assumption that uncertainty in a variable can be measured by the *ex post* forecast errors, the components that were not predictable at the moment of forecast (for recent developments, see Jordà, Knüppel and Marcvellino, 2013; Knüppel, 2014; Charemza, Díaz and Makarova, 2014 among others). The second approach considers the dispersion of expectation among individuals as a proxy for uncertainty.[5] If inflation becomes more unpredictable, individuals are likely to have dispersed stance about future path of inflation.

Both measures are intuitively straightforward and useful when constructing uncertainty measure of a specific variable. However, the disagreement measures rely on the survey data with somewhat demanding details because it is essentially density forecast. In order to construct a dispersion index, the data should contain survey responses with distributions, which is unavailable for many countries.[6] Uncertainty by model seems to be less restrictive in terms of obtaining the relevant data. In addition, the selection of forecast model is flexible and researchers can be as explicit as possible in specifying their choice of model.

Upon constructing uncertainty measure by forecast error, one may use conditional volatility of the purely unforecastable components of future values of inflation. It is important to remove entire forecastable components both in mean and variances. After eliminating all the forecastable variations, up to the second moments in this case, one can construct the uncertainty of a variable of choice. Measuring uncertainty by model assumes that if conditional variance of forecasting errors increases, inflation

[3]See Appendix 2.8.1. for related literature.

[4]See Appendix 2.8.1. for related literature.

[5]See Appendix 2.8.1. for related literature.

[6]The Survey of Professional Forecasters (SPF) for the US is widely used for disagreement measure.

uncertainty increases. Furthermore, the desirable forecast model should allow time-varying volatilities in the original series of inflation. This can be resolved by applying ARCH-GARCH type forecasting model.

It is also crucial to take account for the potential dependence structure in international dimensions. In particular, the illustration of the dependence in inflation between the UK and the euro area may provide interesting insights. The UK inflation uncertainty might be related with euro area inflation uncertainty because of the close trade partnership, financial connectedness, and political bonds as the members of the European Union (EU). For the UK, the EU is the largest trade partner, amounting to approximately a half of total export and imports, respectively. Consequently, unprecedented fluctuations in demand in euro area affect UK's exports. Financial linkages between two economies are also very strong. The share of UK banks' exposure to eurozone debt is significantly large and vice versa. Thus, the uncertainty in financial sector of the euro area may lead to disorders in UK financial market as we have seen during European debt crisis in 2009. In addition, geopolitical uncertainties in euro area and/or in the UK may be a common factor which increase the economic uncertainty for both economies. Some examples of the recent important issues are (i) the flood of European immigrants from Middle East and North Africa, (ii) Scottish Independence referendum, and (iii) the UK referendum for leaving the EU (so-called 'Brexit'). Geographical proximity and the fact that the UK is one of the EU member may enhance the effect of the channel that transmits economic uncertainty between two economies.

Besides economic and political connectedness between the UK and the euro area, changes in monetary policy of one economy can be reflected in inflation uncertainty of another through various channels. Since the onset of the global financial crisis in 2008 and European debt crisis in 2009, interconnectedness of monetary policy among countries has been much elevated due to the ambiguous effect of unconventional monetary policy. In order to prop up sluggish demand, both European Central Bank (ECB) and Bank of England, like many other central banks in the world, adopted Quantitative Easing (QE) facing the zero lower bound of policy interest rate. Moreover the negative interest rate policy (NIRP) was adopted by ECB in 2015. In spite of central banks' efforts and hopes, unconventional monetary policies led to the loss of credibility of central banks and disanchoring from inflation target, which can be seen in the much lowered long-term inflation expectation. In the presence of monetary policy uncertainty in the euro area, the independence of the UK monetary policy might also be threatened, which eventually increases monetary policy uncertainty in the UK.

This study aims to develop a simple but sensible measure for inflation uncertainty of the UK and the euro area considering the economic and social linkages between them. To take account for such high associations between two economies, the inflation uncertainty measure is constructed by forecast errors from the bivariate VAR model allowing for time-varying volatility.[7] This 2-variable GARCH type model is parsimonious but could identify the linkages between them up to the second moments. Consequently, the variances of forecasting errors captures conditional variances that is unpredictable at the moment of forecast, *ex post* inflation uncertainty.

One remaining research question is whether the extension to the analysis of the higher moments is possible. The conditional volatility of forecast errors only describes the second moment properties. This can be extended by estimating entire distribution of forecast errors, i.e. probabilistic approach. In fact, the probabilistic approach can bring interesting insights: whether the univariate distribution of forecast errors is likely to be non-Gaussian, whether the joint distribution of the two countries' inflation uncertainty can be constructed.

One of the well-known example of probabilistic approach is inflation fan chart by the Bank of England (2002). It summarizes mean, variance and skewness of inflation forecasts by employing non-Gaussian distribution, Two Piece Normal (TPN) distribution (Britton, Fisher, and Whitley, 1998). Fan chart became a main communication tool for central banks to provide information about their evaluation of future path of inflation: it assess the possibility of the actual realization of inflation being deviated from the mean forecast and the degree of asymmetry of distribution. The evaluation of uncertainty is subject to the judgments of Monetary Policy Committee (MPC) and the main risk factors are described in the Inflation Report: global growth, demand factors, commodity prices, and/or productivity growth. Although fan chart extends the analysis to the higher moments of inflation, the risk factors affecting the moments of inflation distribution cannot be separated out. In addition, the choice of the parametric density, TPN, is rather arbitrary.

One of the novel attempts to shed light on the extension of probabilistic approach, Charemza, Díaz, and Makarova (2014, henceforth CDM) proposes Weighted Skewed Normal (WSN) distributions where the parameters have monetary policy-related interpretation. In the next paper by CDM (2015), they suggested multivariate extension of probabilistic approach in inflation. In general, it is difficult to derive joint distributions between potentially dependent non-Gaussian marginal densities analytically. They overcame the difficulty by applying copula functions to estimate conditional inflation uncertainty for the US and Canada. Copula is the non-parametric technique that has been widely used in finance to analyse dependence between two stock price returns.

[7] By using the inflation data of the UK and the euro area for bivariate VAR GARCH model, we assume closed Fisher effect. Admittedly, the analysis can be extended by considering international Fisher Effect or Purchasing Power Parity index of inflation. However, it is reasonable to estimate inflation uncertainty by CPI inflation since the CB's inflation target is based on CPI inflation in both countries.

Influenced by the work of CDM (2015), this research aims at estimating the conditional probability density function (*pdf*) of inflation, explicitly concerning the interdependence of uncertainty between two countries. The estimated joint density is expected to answer some intriguing questions about the dependence structure of inflation uncertainties between the euro area and the UK. The first question to be addressed is what is the probability that UK inflation being inside its target band conditional on euro inflation being also inside its own target? The computed conditional probability of the UK inflation being inside the target can be compared to the unconditional probability without considering the effect of uncertainty in the euro area. If the conditional probability is larger then the unconditional probability, it may imply that monetary policy target of the Bank of England can be effectively achieved provided that the ECB anchors inflation successfully.

In addition, it may be of interest to discuss the so-called term-structure of the inflation probability. The general conjecture on inflation term-structure may lead us to the following hypothesis: as the forecast horizon increases, both unconditional and conditional probability being inside the target are expected to decrease. This is simply because uncertainty would increase as we predict the further future. The differences between conditional and unconditional probability is also expected to decrease as forecast horizon increases because the additional information about the euro area inflation would no longer improve the predictability when considering distant future.

Moreover, it might be interesting to compare the conditional probability when one of the countries experiences extreme events (either hitting upper limit or lower limit of inflation target). In particular, this chapter focuses on the probability of maintaining inflation target for the UK, considering the odds of hitting the lower bound of inflation target (1%) in the euro area, reflecting the recent deflationary pressure in the region. This leads us to analyse the tail dependence of the inflation between two economies.

The structure of the chapter is as follows. Section 2.2 estimates pseudo out-of-sample forecasts with two-equation VAR BEKK GARCH (1,1) model to obtain measure for inflation uncertainty of the UK and the euro area, respectively. Section 2.3 outlines the estimation strategy of joint density of inflation uncertainty of two regions. Following the sketch outlined in Section 2.3, Section 2.4 discusses the estimation of univariate density of inflation uncertainty. The marginal distributions for each economy's inflation uncertainty are chosen among two non-Gaussian parametric density (Two Piece Normal and Weighted Skew Normal) based on the goodness-of-fit criteria. In Section 2.5, the joint bivariate distribution is estimated using copulas. The copula parameter is estimated by plugging in the probability integral transforms of the marginals into the copula density, using the maximum likelihood method. Section 2.6 conducts experiments using joint density derived in Section 2.5. In particular, conditional probability of the UK inflation being well-anchored or below target rate given the euro area inflation is computed and compared with the unconditional probability. Finally, Section 2.7 concludes with some discussions of future development in the field.

2.2 Estimating Inflation Uncertainty

In a large and growing number of studies, there have been empirical attempts to measure uncertainty in macroeconomic context. The most frequently used proxy for uncertainty is the implied or realised volatility of stock market index, VIX or VXO, calculated by the Chicago Board Options Exchange.[8] It is widely used because it is relatively easy to access and provides high frequency data. However, as several recent studies (see, for example, Bekaert, Hoerova, and Duca (2013), Jurado, Ludvigson and Ng (2015), *inter alia*) pointed out, volatility fails to capture uncertainty *per se* because market sentiment or risk aversion are also important determinant to change the level of volatility. Time-varying volatility index can also be retrieved from the GARCH-type models. The advantage of GARCH-type volatility measure is the potential application to particular economic variables. Time series of volatility for GDP growth, inflation or exchange rate can be constructed depending on the model specification and data used for the estimation of the model. Such approach is shown in some recent papers, including Fountas, Karanasos and Kim (2006) which applied bivariate GARCH model of inflation and output growth to capture time variant nominal and real uncertainty. Despite the broad extension that GARCH model can make, it cannot escape general criticism that the volatility index is not a full representative of uncertainty.

Another stream of studies that pinpoints the measurement of uncertainty is news-based approach. Such measures include Economic Policy Uncertainty (EPU) Index by Baker, Bloom and Davis (2015) and Relative Shift of Sentiment (RSS) Index by Tuckett et al. (2014).[9] The news-based index directly or indirectly exploits the uncertainty-related words presented in the massive archive of newspaper articles. Due to the development in processing big data, this type of uncertainty indices became more easily available for empirical studies. Moreover, the notion of *perceived* uncertainty by economic agent, on which the index is based, is intuitively straightforward. It is attractive also because researchers may related news-based index being exogenous for some circumstances. For instance, unexpected incidents such as natural disasters, wars and/or other geopolitical events can reflect exogenous uncertainty shocks to the economy. However, the uncertainty-related key words in newspapers might be, in fact, endogenous as uncertainty in economic policy tends to increase by other economic factors. Therefore, one need to be careful about interpreting the effect of news-based index causally when

[8]The VIX is based on prices of S&P 500 Index options, whereas VXO is is based on prices of S&P 100 Index options

[9]Refer to the first chapter for the detailed structure of measurement and comparison of the indices.

applying it to empirical models.

Unpredictability measures, mentioned earlier, are potential substitutes of volatility or news-based index. Broadly, they can be classified by two categories: (i) *ex post* forecast error from a model, or (ii) disagreement measure of professional forecasters. Both measures can be constructed to represent *inflation-specific* uncertainty either by evaluating inflation forecast error or by using inflation forecast data from individual forecasters. Unpredictability measures follow the theoretical definition of uncertainty most precisely.

As for the disagreement measures, the key assumption is that each professional forecaster predicts the most likely outcome of economic variables in the future, given all information available. Thus, the variability in the mean forecasts among forecasters represents uncertainty in the prediction in aggregate level. In addition, if these forecasters provide point forecast along with its standard error (or variance), the mean of such estimated variances can also be added up to capture the uncertainty in prediction. The disagreement measures combine individual forecasts to compute uncertainty by adding a variance of means of individual forecasts and a mean of their variances, as initially proposed by Giordani and Söderlind (2003). The data used for constructing uncertainty by disagreement is the Survey of Professional Forecasters (SPF). The overarching assumption for this approach is that each of the forecasters in the survey are independent. However, professional forecasters often share crucial informations available in the market and hence forecasts tend to be centered around the mean. In spite of increasing numbers of studies in this field, the disagreement measure of uncertainty is heavily dependent on rather feeble assumptions.

The *ex post* forecast error from a forecasting model is the uncertainty component which was not predictable at the moment of forecasting. Although the uncertainty measure by forecast errors inherently depends on model selection, it is much more parsimonious to construct compared to other measures, such as news-based index or disagreement measure. The fundamental idea of uncertainty by error can be successfully applied by utilising Stock and Watson's (2007) pseudo out-of-sample forecasting. Pseudo out-of-sample forecasting simulates a real-time forecasting by estimating the model with data up to t to obtain h-step ahead forecast and moving forward to repeatedly make forecasts at $t+1$, $t+2$, and so on, with either rolling or recursive estimation.[10] Therefore, the distribution of forecast errors by such pseudo out-of-sample forecasts can encapsulate uncertainty at each time period. Denote the *ex post* uncertainty measure as follows.

$$U_{t,h} = \Sigma_{t,h}^{1/2} \Sigma_{t|t-h}^{-1/2} e_{t|t-h} \tag{2.1}$$

where $e_{t|t-h}$ is forecast error conditional on the information available at the period of

[10] The rolling window refers to a fixed number of data for each iteration while the recursive window denotes increasing number of data as forecasts moving forward.

the prediction, i.e. the h-period ahead forecasts is made at time $t-h$. $\Sigma_{t,h}$ and $\Sigma_{t|t-h}$ denote the unconditional and conditional variance-covariance matrix of $e_{t|t-h}$. The square root of the unconditional and conditional variance-covariance matrices are used to scale the uncertainty index. Following this conceptual framework, the uncertainty measure for the inflation (π) is simply defined by

$$U_{t,h} = \Sigma_{t,h}^{1/2} \Sigma_{t|t-h}^{-1/2} (\pi_t - \pi_{t|t-h}) \tag{2.2}$$

The inflation forecasts model is chosen by considering the interdependence of the two economies, the UK and the euro area. The forecast errors are generated using bivariate VAR BEKK GARCH (1,1) model. This model ensures the positive definiteness of conditional variance while balancing the trade off between flexibility and parsimony of estimation.[11] Inflation data, retrieved from the Eurostat database (available online: `http://ec.europa.eu/eurostat/data/database`), ranges from January 1997 to March 2016 for both countries with 231 observations in total.[12]

Figure 2.1 shows the evidence of the conditional heteroskedasticity of the inflation series. The inflation for both countries was less volatile and quite well-anchored before the Financial Crisis in 2008. However, in the aftermath of the Great Recession, inflation has become more volatile and the occasions of diverting from the central banks' inflation target have been more frequent. For both countries, inflation series are found to be I(1), so the first differenced data are used for the VAR-GARCH maximum likelihood estimation.[13] Autoregressive order (p) of VAR model is determined by Ljung-Box autocorrelation test for residuals. The minimal number of lags (p) is chosen to ensure the residuals exhibit no autocorrelation at 5% significance level.

Based on the estimated VAR BEKK GARCH (1,1) model[14], the h-step ahead forecasts up to $h = 24$ months are estimated recursively with the initial recursion

[11] Silvennoinen and Teräsvirta's (2009) four classes of multivariate GARCH models are *(i) models which directly specify conditional covariance matrix, (ii) factor models, (iii) constant conditional correlation models, (iv) semi or nonparametric models*. Among the four classes of multivariate GARCH models, the BEKK GARCH model belongs to the first category.

[12] Hwang and Valls Pereira (2006) studied small sample properties of GARCH estimates and suggested 500 observation are needed for GARCH(1,1) models. They found that the maximum likelihood estimator of the GARCH(1,1) model can suffer from negative bias in small sample cases. However, inflation data for euro area are only available from January 1997. In order to robustifying the analysis, acknowledging the limitation of data availability, Appendix 2.8.2 discusses the nonparametric proxies for volatility and compares the uncertainty index by VAR GARCH(1,1) and nonparametric proxy.

[13] Detailed Augmented Dickey-Fuller test results are presented in Appendix 2.8.3.

[14] Notice that there might be breaks in the mean and/or volatility dynamics in the data and, by neglecting the possibility of breaks except 2008 crisis period, misspecification problem may arise. Lamoureux and Lastrapes (1990) argued that the high degree of persistence can be estimated by GARCH due to the failure to account for structural breaks. As for the method of addressing this issues, Clements and Hendry (1999) found that second- or over-differencing the dependent variable can improve the performance of AR models in the case of structural breaks. We leave this for further extension of the thesis.

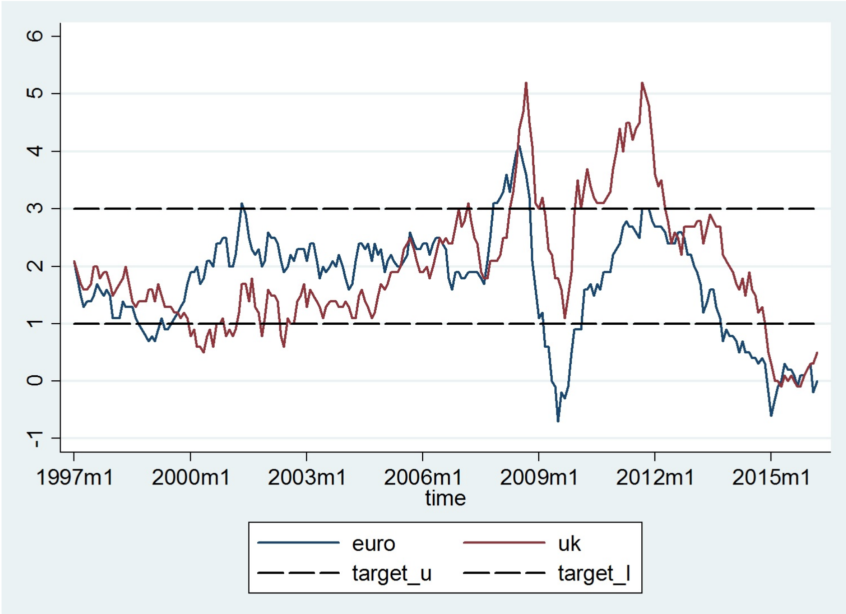

Figure 2.1: Inflation of the UK and the euro area

Source: Eurostat database (`http://ec.europa.eu/eurostat/data/database`). The inflation targets (2%) are obtained based on the announcement of Bank of England (`www.bankofengland.co.uk`), and ECB (`https://www.ecb.europa.eu`). The Bank of England explicitly announces the inflation target band of 1 percentage point from 2% but the European Central Bank does not. In this chapter, the same target band is assumed for both central banks to calculate the conditional probability.

using the first 80 observations in the dataset. Therefore, the forecast yields 151 (= 231 − 80) *one-step-ahead* forecast errors, 150 *two-step-ahead* forecast errors, ... up to 128 *24-step-ahead* forecast errors. The resulting conditional and unconditional variance-covariance matrices ($\Sigma_{t|t-h}$ and $\Sigma_{t,h}$, respectively) are also obtained recursively. The h-step forecasts by maximum likelihood estimation can suffer from spurious dependence when $h > 1$. In order to tackle this issue, Vector Moving Average (VMA) decomposition is used for the estimation of the MSE (Mean Squared Error) matrix of the forecasts (see, for example, Lütkepohl, 2007, p.94).

Table 2.1 shows the descriptive statistics of estimated inflation uncertainty for the selected forecast horizons ($h = 3, 6, 12, 18, 24$).[15] The positive inflation uncertainty implies that the realisation of inflation had not been predicted at the time of forecast and this unanticipated element causes inflation to move upwardly. Similarly, the negative inflation uncertainty measure implies that the realised inflation was much lower than the predicted level from the two-country VAR-GARCH model. The standard deviations of inflation uncertainty are larger for the euro area than those of the UK except 6-month-ahead uncertainty series. For the UK, one-year-ahead inflation uncertainty has the largest second moment with no systematic pattern along increased forecast horizons. However, the euro area inflation uncertainty shows clear tendency of increasing second moments. It exhibits larger standard deviations for the longer horizons.

[15]The table of the descriptive statistics for all forecast horizons is presented in Appendix 2.8.4.

The UK inflation uncertainty shows negative skewness (long left tail) only for short horizons ($h = 3, 6$) but positive skewness when forecast horizons get longer. However, euro area inflation uncertainty exhibits negative skewness for most of the forecast horizons ($h = 3, 6, 12, 18$). Excess kurtosis is evident for the euro inflation uncertainty with horizon 6 and 12 whereas the UK inflation uncertainty exhibits rather moderate magnitude of excess kurtosis only at $h = 12$. These findings suggest that the estimated inflation uncertainty may be better characterised with non-Gaussian density functions that can represent skewness and/or heavy tails.

Table 2.1: Descriptive statistics of inflation uncertainty

	UK				Euro Area			
h	Mean	SD	Skewness	Excess Kurtosis	Mean	SD	Skewness	Excess Kurtosis
3	-0.06	1.00	-0.13	1.12	-0.15	0.69	-0.24	1.82
6	-0.13	1.58	-0.02	1.63	-0.26	1.51	-1.13	4.66
12	-0.09	2.00	0.29	3.48	-0.51	2.95	-1.10	4.98
18	-0.10	1.28	0.36	0.00	-0.83	2.54	-0.35	1.44
24	0.03	1.44	1.19	2.97	-0.76	2.47	0.60	1.63

Figure 2.2: Inflation uncertainty index

Note: Each number at the end of the series stands for the forecast horizon. For example, uk_3 is the UK inflation uncertainty based on three-month-ahead forecasts.

The estimated inflation uncertainty measures (levels) for the selected forecast horizons ($h = 3, 6, 12, 18, 24$) are plotted in Figure 2.2. The inflation uncertainty accelerated in the onset of the Financial Crisis in 2008 for both countries, followed by the significant decline below the average level. Combined with the effect of the Financial Crisis, the surge in commodity price might influence the heightened inflation uncertainty during this period. Similarly, the decline in the inflation uncertainty might be affected by the rapid drop in commodity price after mid-2008 and the European Debt Crisis at the end of 2009. Considering time series of the crude oil price and inflation uncertainty measure for $h = 12$, the decline of oil price in 2009 leads the drop in inflation uncertainty. The lowest level of inflation uncertainty in the euro area occurs earlier than the UK and the magnitude is larger. Although the commodity price could materially explain the inflation uncertainty, the differences in dynamics of inflation uncertainties and oil price might imply that inflation uncertainty cannot be explained solely by the commodity price.

In order to relate important changes in business cycle to the inflation uncertainty, Table 2.2 lays out the date of peaks and troughs in inflation uncertainty for each country. The inflation uncertainty measure computed from short forecast horizon ($h = 3$) fails to distinguish the surge in inflation uncertainty in 2008 due to relatively small variability of the uncertainty series. The maximum level of uncertainty measure occurred approximately in the third quarter of 2008. However, the lowest level of inflation uncertainty was rather diversely situated from 2009 to 2010 depending on the forecast horizons. Since the second upswing of inflation uncertainty after 2009 is observed for several horizons, the dates of the second peak are examined. Comparing the longer horizons ($h = 12, 18, 24$) with similar date of the first peak, the UK inflation uncertainty reached its second peak at around early- to mid-2011. For the euro area, however, the second peaks range from September 2010 to September 2011. The relative size of inflation uncertainty in the second peak is lower than the uncertainty level of the first peak in 2008. For all horizons, the relative size of uncertainty in the second peak compared to the first peak is larger for the euro area than the UK.

The usual (Pearson's) correlation coefficient captures only linear correlation and is known to be not sufficient measure for dependence in cases where there is heavy tail or asymmetric dependences. (Cont, 2001; Boyer et al., 1999). Therefore, the rank correlation coefficients between two countries are computed and presented in Figure 2.3. The average Spearman's correlation coefficient is 0.29 while Kendall's correlation coefficient is 0.21. The uncertainty measure with longer forecast horizon shows higher correlation for both of the coefficients.

Table 2.2: Peak and tough of inflation uncertainty

UK	h=3	h=6	h=12	h=18	h=24
Global max (date, A)	Jan 2010	Jun 2008	Sep 2008	Sep 2008	Sep 2008
Global min (date)	Dec 2008	May 2009	Oct 2009	Feb 2010	Sep 2010
Max after 2009 (date, B)	Jan 2010	Apr 2010	Feb 2011	Sep 2011	Oct 2011
Relative size (B/A)	1.000	0.393	0.254	0.518	0.327

Euro	h=3	h=6	h=12	h=18	h=24
Global max (date, C)	Nov 2007	Jun 2008	Sep 2008	Jul 2008	Sep 2008
Global min (date)	Jan 2009	Mar 2009	Sep 2009	Feb 2010	Sep 2009
Max after 2009 (date, D)	Oct 2009	Mar 2010	Sep 2010	Apr 2011	Sep 2011
Relative size (D/C)	0.723	0.732	0.363	0.646	0.491

Note: *Global max* indicates the date on which the maximum of inflation uncertainty occurs during the whole forecasting periods (September 2003-March 2016). *Global mim* indicates the date on which the minimum of inflation uncertainty occurs during the whole forecasting periods (September 2003-March 2016). *Max after 2009* indicates the date on which the maximum of inflation uncertainty happens after January 2009 to account for the second peak after the financial crisis. *Relative size* indicates the fraction of the uncertainty level at the second peak over the uncertainty level at the initial peak immediately after the Financial Crisis in 2008.

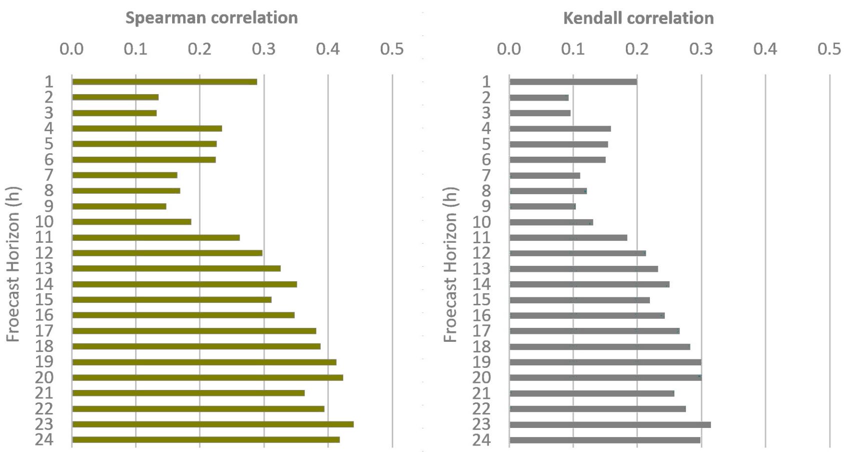

Figure 2.3: Correlation of inflation uncertainty between the UK and the euro area

Notes: Spearman's rank correlation can be defined as $\rho_S(X,Y) = \rho(F_1(X), F_2(Y))$. Kendall's rank correlation is defined as $\rho_\tau(X,Y) = \Pr[(X_1 - X_2)(Y_1 - Y_2) > 0] - \Pr[(X_1 - X_2)(Y_1 - Y_2) < 0]$.

2.3 The Outline of the Estimation Strategy

With the estimated inflation uncertainties of two economies, the joint probability density is to be drawn for examining the probabilistic aspects of inflation uncertainty. In particular, the final aim of the research is to study the density function of inflation uncertainty for one economy conditional on the uncertainty distribution for the other economy. In order to step forward, it is worthwhile to emphasize that the inflation uncertainty measures derived previously exhibit non-Gaussian behaviours. To solve this issue, copula estimation will be adopted. Copulas are well-known, mostly in finance, tools for modeling extremal events, such as risks, and uncertainties. In addition, the multivariate extension in copulas is convenient compared to deriving analytical solutions for combining non-Gaussian densities.

Having such motivation in mind, it might be helpful to sketch the estimation steps because the estimation involves several complex procedures. First, denote inflation uncertainty for the UK and the euro area as U_1 and U_2, respectively. The subscript t and h are omitted for simplicity. Consider continuous bivariate joint cumulative density function (*cdf*) of inflation uncertainties, $F(U_1, U_2)$. The univariate marginals for each inflation uncertainty are denoted as $F_1(U_1)$ and $F_2(U_2)$ with inverse quantile functions, ${F_1}^{-1}$ and ${F_2}^{-1}$. Applying the proposition of probability integral and quantile transformation, the joint *cdf* can be written as follows.[16]

$$\begin{aligned} F(U_1, U_2) &= F({F_1}^{-1}(y_1), {F_2}^{-1}(y_2)) \\ &= \Pr[Y_1 \leq y_1, Y_2 \leq y_2] \\ &= C(y_1, y_2) \end{aligned} \tag{2.3}$$

where $y_1 = F_1(U_1)$, $y_2 = F_2(U_2)$ with a uniform distribution, $\mathcal{U}(0,1)$.[17] C$(\cdot)$ is a copula function that maps the two-dimension support $[0,1]^2$ into the unit interval [0,1].[18]

[16] Let X be a random variable with density F_X. Let F_X^{-1} be the inverse quantile function of F_X:

$$F_X^{-1}(\alpha) = \inf\{x | F_X(x) \geq \alpha\}$$

$\alpha \in (0,1)$. Then,

(1) If F_X is continuous, the random variable Y, defined as $F_X(X)$, has a uniform distribution. $(F_X(X) \sim \mathcal{U}(0,1))$.

(2) For any uniform distribution $Y \sim \mathcal{U}(0,1)$, we have $F_X^{-1}(Y) \sim F_X$.

[17] This implies $U_1 = {F_1}^{-1}(y_1) \sim F_1$, $U_2 = {F_2}^{-1}(y_2) \sim F_2$.

[18] An m-dimensional copula is a function C$(\cdot)$: $[0,1]^m \rightarrow$ [0,1] which satisfies the following conditions:

(1) $C(1, \ldots, 1, a_n, 1, \ldots, 1) = a_n$ for every $n \leq m$;

(2) $C(a_1, \ldots, a_m) = 0$ if $a_n = 0$ for any $n \leq m$;

(3) C is m-increasing.

Rewriting the joint *cdf* of inflation uncertainty to obtain the resulting joint *pdf*,

$$F(U_1, U_2) = C(F_1(U_1), F_2(U_2)) \tag{2.4}$$

then the joint density (*pdf*) of F is given by the following equation.

$$f(U_1, U_2) = c(F_1(U_1), F_2(U_2)) \cdot f_1(U_1) \cdot f_2(U_2) \tag{2.5}$$

where c is the density of the copula, partial derivative of $C(\cdot)$ with respect to y_1, y_2. Denote $\theta = (\theta_1, \theta_2, \alpha)$ be all the parameters of F_1, F_2 and C, respectively. Let $U = \{(U_{1t}, U_{2t})\}_{t=1}^{T}$ denote a sample. The log likelihood function can be written as follows.

$$l(\theta) = \sum_{t=1}^{T} \ln\left(c(F_1(U_1;\theta_1), F_2(U_2;\theta_2);\alpha)\right) + \sum_{t=1}^{T} \Big[\ln\left(f_1(U_{1t};\theta_1)\right) + \ln\left(f_2(U_{2t};\theta_2)\right)\Big] \tag{2.6}$$

Then the Maximum Likelihood Estimator is

$$\hat{\theta}_{\text{MLE}} = \arg \max_{\theta} \; l(U_{1t}, U_{2t}; \theta) \tag{2.7}$$

In theory, the copula parameters can be estimated simultaneously with the parameters in marginal distribution by the maximum likelihood estimation. However, in multi-dimension cases, this might lead to high complexity in computation. Hence, the two-step estimation method or the Inference Function for Margins (IFM) method by Joe and Xu (1996) is applied. As the first step, estimate the univariate marginal distributions.

$$\hat{\theta}_1 = \arg \max_{\theta_1} \sum_{t=1}^{T} \ln\left(f_1(U_{1t};\theta_1)\right) \tag{2.8}$$

$$\hat{\theta}_2 = \arg \max_{\theta_2} \sum_{t=1}^{T} \ln\left(f_2(U_{2t};\theta_2)\right) \tag{2.9}$$

and then given the estimated parameters in the univariate densities, estimate the copula parameter, γ.

$$\hat{\gamma} = \arg \max_{\gamma} \sum_{t=1}^{T} \ln\left(c(F_1(U_1;\hat{\theta}_1), F_2(U_2;\hat{\theta}_2);\gamma)\right) \tag{2.10}$$

The IFM estimator obtained by the two-step estimation, $\theta_{IFM} := (\hat{\theta}_1, \hat{\theta}_2, \hat{\gamma})$, is known to have asymptotically Normal distribution (Joe and Xu, 1996).

The next step is to evaluate the estimated inflation uncertainty measures by fitting them with the marginal (parametric) distributions for each country separately (*step 1*) and eventually to model the dependency of two countries' inflation uncertainty using copula (*step 2*). The detailed estimation procedure is explained in Section 2.4 (*step 1*) and 2.5 (*step 2*).

2.4 Estimating Marginal Density of Inflation Uncertainty

As the first step of IFM method, previously generated inflation uncertainty for individual countries is to be fitted to the marginal density functions. Potential candidates for parametric density functions considered in the research are Two Piece Normal

(TPN; see Wallis, 2004) and Weighted Skewed Normal (WSN; see Charemza, Díaz, and Makarova, 2015). The choice of TPN density follows from the convention of central banks' fan chart. Starting from the Bank of England, fan chart is well-known presentation of the probabilistic forecasts. Fan chart considers both the degree of uncertainty and the balance of uncertainty around the forecast using TPN distribution (Britton, Fisher, and Whitley, 1998). The *pdf* of TPN distribution is defined by (see Wallis, 2004).

$$f_{TPN}(x;\sigma_1,\sigma_2,\mu) = \begin{cases} Aexp\{-(x-\mu)^2/2\sigma_1^2\} & \text{if } x \leq \mu \\ Aexp\{-(x-\mu)^2/2\sigma_2^2\} & \text{if } x > \mu \end{cases}$$

where $A = (\sqrt{2\pi}(\sigma_1+\sigma_2)/2)^{-1}$.[19] If $\sigma_1 = \sigma_2$, it collapses to Normal distribution. If $\sigma_1 < \sigma_2$, the distribution is positively skewed (long right tail).

As an alternative density function, WSN is considered. WSN is the customised distribution which aims at decomposing uncertainty into epistemic and ontological components. Ontological uncertainty refers to complete randomness whereas epistemic uncertainty indicates the uncertainty based on expert knowledge (see Walker et al., 2003). Denote the inflation uncertainty by forecast errors (estimated in Section 2.2) as U, omitting the subscripts, t, h, for simplicity. Decompose U by two components, namely, the baseline forecast error (X) and the signal parts based on revised forecast error (Y) from expert knowledge.

$$U = \underbrace{X}_{\text{baseline forecast error}} + \underbrace{\alpha \cdot Y \cdot I_{Y>m} + \beta \cdot Y \cdot I_{Y<k}}_{\text{Signal part based on revised forecast error}}$$

where $I_{Y>m}$ is an indication function that gives 1 if revised forecast error is larger than a certain threshold, $m \geq 0$. Similarly, $I_{Y<k}$ is an indication function that gives 1 if revised forecast error is smaller than a certain threshold, $k \leq 0$. Hence, the signal part will be switched on for either (i) $Y > m \geq 0$ or (ii) $Y < k \leq 0$. X and Y are bivariate Normal distributions with mean zero, constant and identical variances (σ^2), and correlation coefficient, ρ. This implies that if $\alpha = \beta = 0$, WSN reduces to Normal distribution.

$$\begin{pmatrix} X \\ Y \end{pmatrix} = N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2 & \rho\sigma^2 \\ \rho\sigma^2 & \sigma^2 \end{pmatrix}\right] \tag{2.11}$$

[19] Another representation of the TPN by Britton, Fisher, and Whitley (1998) is as follows.

$$f_{TPN}(x;\gamma,\mu) = \frac{2}{(1/\sqrt{1-\gamma}) + (1/\sqrt{1+\gamma})}\frac{1}{\sqrt{2\pi\sigma^2}}\exp\left[-\frac{1}{2\sigma^2}\left\{(x-\mu)^2 + \gamma\left(\frac{x-\mu}{|x-\mu|}\right)(x-\mu)^2\right\}\right]$$

where γ is skewness ($-1 < \gamma < 1$). It can be shown that the two representations are equivalent by setting the relationship among parameters.

$$\sigma^2 = \sigma_1^2(1+\gamma) = \sigma_2^2(1-\gamma)$$
$$\gamma = \frac{\sigma_2 - \sigma_1}{\sigma_2 + \sigma_1}$$

The key assumption is that the *ex post* inflation uncertainty is the realised uncertainty, once formed by public knowledge and revised based on the expert knowledge through monetary policy decisions. The further underlying assumption is that the central bank makes policy decisions upon the expert knowledge, which will eventually affect the realised uncertainty. For example, assume that baseline forecast error (X) is initially established. If the expert knowledge predicts that forecast error will be, in fact, positive and larger than a threshold ($Y > m \geq 0$), the signal will be turned on and central bank tend to implement hawkish policies ($\alpha Y < 0$ with $\alpha < 0$). The magnitude of the central bank's hawkish response to upside risks of uncertainty is summarised in the parameter, α. Similarly, β depicts the magnitude of the dovish response to downside risks of uncertainty. Furthermore, the comparison between α and β in absolute value will provide interesting intuition. If $|\alpha|$ is greater than $|\beta|$, it implies that the central bank tends to react more aggressively towards the upside risks of inflation uncertainty than downside risks. Figure 2.4 summarises the logics of the decomposition of uncertainty in WSN density.

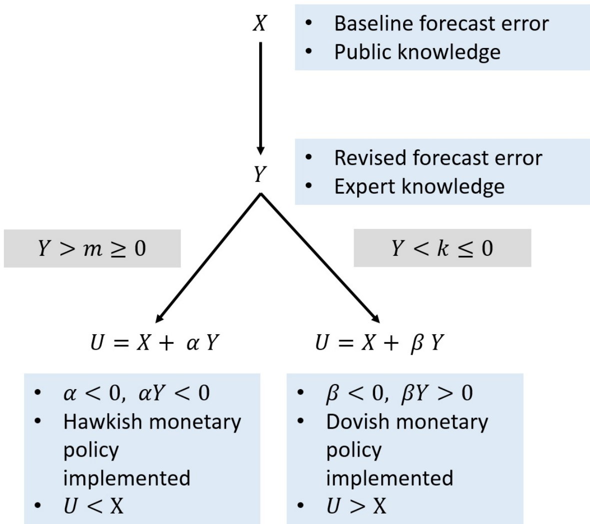

Figure 2.4: Weighted skewed normal distribution

The *pdf* of WSN distribution is as follows (Charemza, Díaz, and Makarova, 2015).

$$\begin{aligned} f_{WSN}(x;\alpha,\beta,m,k,\rho) &= \frac{1}{\sqrt{A_\alpha}}\phi\left(\frac{x}{\sqrt{A_\alpha}}\right)\Phi\left(\frac{B_\alpha x - mA_\alpha}{\sqrt{A_\alpha(1-\rho^2)}}\right) \\ &+ \frac{1}{\sqrt{A_\beta}}\phi\left(\frac{x}{\sqrt{A_\beta}}\right)\Phi\left(\frac{-B_\beta x + kA_\beta}{\sqrt{A_\beta(1-\rho^2)}}\right) \\ &+ \phi(x)\cdot\left[\Phi\left(\frac{m-\rho x}{\sqrt{1-\rho^2}}\right) - \Phi\left(\frac{k-\rho x}{\sqrt{1-\rho^2}}\right)\right] \end{aligned} \tag{2.12}$$

where ϕ and Φ are the *pdf* and *cdf* of standard normal distribution. $A_\tau = 1 + 2\tau\rho + \tau^2$ and $B_\tau = \tau + \rho$ for $\tau = \alpha, \beta$. Notice that the WSN density function in equation (2.12) has five parameters (omitting σ) as it is expressed with the standardised uncertainty series.

The estimation of skewed normal distributions, such as TPN or WSN, by the maximum likelihood is known to be inefficient and numerically very complex (see, for example, Azzalini and Capitanio, 1999, Sartori, 2006, Franceschini and Loperfido, 2014). Therefore, simulation based methods has been largely suggested in the previous studies (see Charemza, Díaz, and Makarova (2014) for related literature). The simulated minimum distance estimators method (SMDE) by Charemza, Díaz, and Makarova (2015) will be applied further on. The SMDE method fits the empirical histograms of inflation uncertainty data to the simulation density function with the chosen minimum distance criterion. The SMDE estimator is defined as follows.

$$\hat{\theta}_{\text{SMDE}} = \arg\ \min_{\theta} \left[\xi \left(HD(d_n, f_{r,\theta}) \right)_{r=1}^{R} \right] \tag{2.13}$$

where d_n is the empirical histogram from the original data, $f_{r,\theta}$ is the simulated Monte Carlo approximation of theoretical densities with total R replications. HD is Hellinger distance measure[20] and ξ denotes the aggregating operator.

Since the number of parameters to be estimated in WSN $(\alpha, \beta, m, k, \rho)$ is larger than that of TPN $(\sigma_1, \sigma_2, \mu)$, it is necessary to impose restrictions on WSN estimation for comparison. In this section and onwards, only α, β, σ in WSN will be estimated by imposing restrictions on ρ and $m = -k = \sigma$. In terms of the restriction on ρ, I consider two different cases: constant ρ $(= 0.75)$ and ρ decaying exponentially from 0.75 to 0.25 as forecast horizon increases.[21] While the first assumption on ρ is straightforward, the second assumption is rather realistic because the covariance between the public and expert knowledge tends to decrease along with the forecast horizons. For the longer term forecasts, the expert knowledge might contain more information uncorrelated to the publicly available information.

Table 2.3 shows the results of the estimation of two marginal distributions with the selected horizons ($h = 6, 12, 18, 24$) and under the assumption of exponentially decreasing ρ.[22] First, the estimated UK WSN parameters for the monetary policy responses to the risks of uncertainty show balanced results. For a shorter horizon ($h = 6$), the absolute value of α is greater than the absolute value of β, implying relatively hawkish monetary policy reactions. For $h = 18$ and 24, the results are the opposite, indicating relatively dovish monetary policy responses in the longer term. For one-year-ahead uncertainty, the responses are balanced. On the contrary, the euro area's WSN result shows $|\alpha| > |\beta|$ for all forecast horizons. It suggests the ECB's the tendency towards hawkish monetary policy in response of upside risk of inflation uncertainty. The estimated σ's of the UK are larger than those of the euro area in

[20]See Basu et al. (2002) for the definition of Hellinger distance measure.

[21]In particular, the computation is based on $\rho_h = 0.25 + \exp\left[\ln(0.75 - 0.25) \cdot h\right]$ where $h = 1, 2, \ldots, 24$.

[22]See Appendix 2.8.5 for the complete results of all forecast horizons and both restrictions on ρ.

shorter horizons ($h = 6, 12$). However, in the longer horizons ($h = 18, 24$), the second moments of the euro area's uncertainty are estimated larger than those of the UK. In particular, the two-year-ahead estimates show a large increase in σ for the euro area whereas the σ stays in the similar level for the UK. This result is consistent with the descriptive statistics results in Section 2.2.

Table 2.3: The estimated parameters of marginal densities

		h=6		h=12		h=18		h=24	
		UK	Euro	UK	Euro	UK	Euro	UK	Euro
WSN	α	-1.81	-3.61	-1.47	-3.19	-0.84	-3.19	-1.00	-0.96
		(0.36)	(1.29)	(0.42)	(0.54)	(0.90)	(0.49)	(0.37)	(0.01)
	β	-0.98	-2.72	-1.38	-0.21	-0.95	0.00	-1.10	-0.01
		(0.46)	(1.01)	(0.69)	(0.17)	(1.54)	(0.00)	(1.09)	(0.02)
	σ	0.99	0.56	1.22	1.47	1.13	1.74	1.07	2.28
		(0.08)	(0.29)	(0.29)	(0.08)	(0.51)	(0.10)	(0.31)	(0.12)
	MD	**1.99**	**13.56**	**14.13**	**22.70**	12.64	**46.18**	6.65	24.86
TPN	σ_1	1.70	0.56	1.58	1.61	3.91	1.07	0.54	1.84
		(0.71)	(0.27)	(0.42)	(1.51)	(0.27)	(0.31)	(0.67)	(0.75)
	σ_2	1.03	2.76	1.78	1.83	0.23	3.99	1.78	2.60
		(0.21)	(1.12)	(0.47)	(0.71)	(0.20)	(0.03)	(0.03)	(0.89)
	μ	0.35	-1.12	-0.26	-0.32	-2.59	-1.18	-0.96	-1.38
		(0.40)	(2.02)	(0.70)	(1.51)	(0.62)	(0.83)	(0.51)	(1.20)
	MD	4.64	39.19	15.37	39.97	**6.56**	55.71	**3.05**	**18.38**
Sample size		146		140		134		128	

Note: MD denotes the minimum distance statistics for the equiprobable null hypothesis against the alternative hypothesis of bumps or dips in the probability. Under the null hypothesis, the MD statistic has an asymptotic χ^2 distribution (Cressie and Read, 1984).

Turning to our attention to the estimated parameters of TPN, the UK TPN shows either $\sigma_1 < \sigma_2$ or $\sigma_1 > \sigma_2$ depending on the forecast horizons without any systematic trend. It is noticeable that σ_1 is much larger than σ_2 for $h = 18$, implying the long left tail. For the euro area, σ_1 is smaller than σ_2 for all horizons, indicating positively skewed (or long right tail) TPN distribution.

Finally, MD statistics can be further analysed as a criterion for the selection of distributions. For the UK, WSN has smaller MD than TPN in the shorter horizons ($h = 6, 12$) while TPN is preferable for the longer horizons. For the euro area, WSN is selected for most horizons with an exception of the case of $h = 24$.

With the estimated parameters of each marginal density, the probability integral transform (*pit's*) are computed in order to examine the goodness-of-fit. The *pit's* are the probability of observing values of random variable being not greater than its realization values. If the forecast density is close to the true but unknown density (either WSN or TPN in this study), *pit's* will be uniform on the interval [0,1]. Figure 2.5 is the box plot of *pit's* for both WSN and TPN as graphical diagnostics. At first glance, the UK inflation uncertainty fits well by WSN density for all horizon. The euro inflation uncertainty data are well matched with the estimated WSN density. TPN distribution seems to be compatible with the UK data for most of horizons with the exception of particular horizons ($h = 1, 2, 14, 15, 18$). The euro inflation uncertainty is not suitable for fitting to TPN density for most of the horizons.

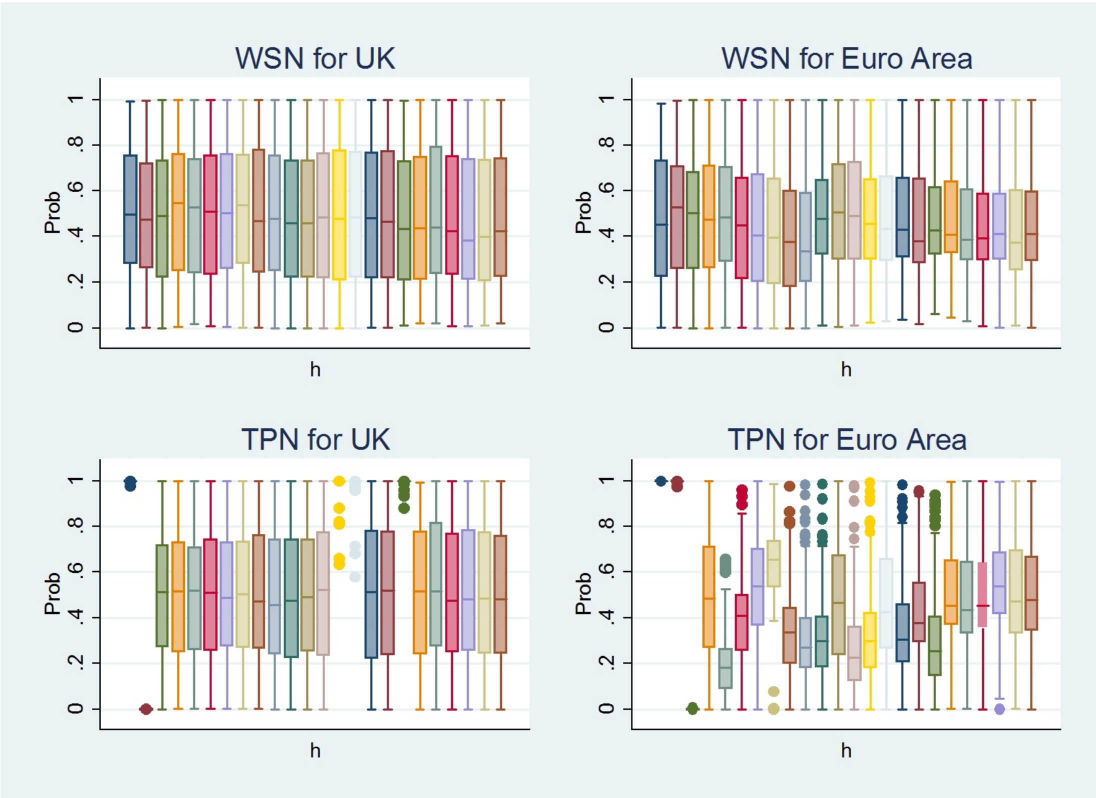

Figure 2.5: The box plot of probability integral transformation

Note: h is horizon of uncertainty index, ranging from 1 to 24. The boxes of each plot indicate IQR (interquantile range) with median. The whiskers are stretched in both sides to 1.5 IQR and the outliers are presented in dots.

In order to formally check the compatibility of the data with the uniform distribution, a simple goodness-of-fit test (the Cramér-von Mises test) using empirical *cdf* is performed further.[23] Table 2.4 presents the test statistics for the selected forecast

[23]Let $X_1, \cdots, X_n$ be *iid* samples from unknown density F. Then whether this empirical density comes from the hypothesized density, F_0, can be tested.

$$H_0\colon\ F = F_0 \qquad \text{vs.} \qquad H_A\colon\ F \neq F_0$$

Under H_0, the Glivenko-Cantelli theorem is satisfied.

$$\sup_t |\hat{F}_n(t) - F_0(t)| \to 0$$

as $n \to \infty$. Thus, discrepancy measures can be used as a test statistics.

horizons ($h = 6, 12, 18, 24$).[24] The simple empirical goodness-of-fit test results support the robustness of parametric estimation. For both WSN and TPN at all of the horizons, the null hypothesis cannot be rejected. Comparison of test statistics also confirms that better fit of WSN over TPN for both economies at most of the forecast horizons.

Table 2.4: Cramér-von Mises statistics for testing uniformity of *pit's*

	h=6		h=12		h=18		h=24	
	UK	Euro	UK	Euro	UK	Euro	UK	Euro
WSN	0.173	0.134	0.194	0.139	0.212	0.140	0.224	0.147
TPN	0.198	0.127	0.223	0.158	0.331	0.177	0.278	0.166

Note: Asymptotic critical values for the Cramér-von Mises statistics are 0.347 at 10% significance level, 0.461 at 5% significance level.

To sum up, the empirical results (including minimum distance statistics, graphical diagnostics of *pit's*, and goodness-of-fit tests) support the choice of WSN against TPN for both the UK and the euro area. Therefore, WSN is chosen as the marginal density for estimating joint density of inflation uncertainty in the next section.

2.5 Estimating Joint Density of Inflation Uncertainty with Copulas

As the second stage of the IFM method, the copula parameters are estimated by maximum likelihood estimation. Recall the equation (2.10) in Section 2.3.

$$\hat{\gamma} = \arg \max_{\gamma} \sum_{t=1}^{T} \ln \left(c(F_1(U_1; \hat{\theta_1}), F_2(U_2; \hat{\theta_2}); \gamma) \right)$$

where $\hat{\theta_1}$, $\hat{\theta_2}$ are the estimated parameters from the marginal densities, F_1, F_2. Thus, the IFM estimator is simply the maximum likelihood estimator of the copula parameter by plugging the parameters of marginal distributions estimated in the first stage. It is widely known that the IMF estimators usually perform well and have asymptotic efficiency (Joe, 2005). It is also worthwhile to notice the limitation of the estimator. The IFM estimator, by its set up, heavily relies on the choice of the marginals.

Frank copula is chosen among other bivariate parametric families, such as Gaus-

The Cramér-von Mises test statistic is

$$C_n \equiv \int (\hat{F}_n(t) - F_0(t))^2 dF_0(t)$$

If the statistics are larger than the critical value, reject the null that the data come from the specific distribution in the null hypothesis.

[24]See Appendix 2.8.6 for the complete results.

sian, Gumbel, Clayton (see Appendix 2.8.7 for the details of the functional forms and the statistical properties of other copulas). Frank copula is a symmetric Archimedean copula[25] and its *cdf* is given by

$$C(y_1, y_2; \gamma) = -\frac{1}{\gamma} \ln \left(1 + \frac{(e^{-\gamma y_1} - 1)(e^{-\gamma y_2} - 1)}{e^{-\gamma} - 1} \right) \tag{2.14}$$

where $\gamma \in (-\infty, +\infty)$. If $\gamma = 0$, it leads to the independence copula. The copula generator for Frank copula, $\varphi(\cdot)$, is

$$\varphi_\gamma(t) = -\ln \left(\frac{e^{-\gamma t} - 1}{e^{-\gamma} - 1} \right) \tag{2.15}$$

The *pdf* of Frank copula is

$$c(y_1, y_2; \gamma) = \frac{-\gamma(e^{-\gamma} - 1)e^{-\gamma(y_1+y_2)}}{((e^{-\gamma y_1} - 1)(e^{-\gamma y_2} - 1) + (e^{\gamma} - 1))^2} \tag{2.16}$$

The dependence structure of the estimated copula can be clearly illustrated by the rank correlations: Kendall's tau (τ) and Spearman's rho (ρ). The analytical closed forms of these rank correlations, which depend on the parameter value, γ, are available for Frank copula as follows.

$$g_\tau(\gamma) = 1 - \frac{4(1 - D_1(\gamma))}{\gamma} \tag{2.17}$$

$$g_\rho(\gamma) = 1 - \frac{12(D_1(\gamma) - D_2(\gamma))}{\gamma} \tag{2.18}$$

where $D_k = kx^{-k} \int_0^x t^k (e^t - 1)^{-1} dt$ is the Debye function. Frank copula is a symmetric Archimedean copula while other two candidates of copulas, Gumbel and Clayton, are considered as asymmetric Archimedean copulas. Gumbel copula exhibits greater dependence in the positive tail than in the negative tail and Clayton exhibits greater dependence in the negative tail than in the positive tail. Based on the properties of each copula, I chose Frank copula because it can identify the asymmetric dependence structure without favouring either upper or lower tail dependence.

The estimation strategy for the comprehensive study of dependence structure in copula is as follows: the copula parameter is estimated (i) by plugging the marginals of the same forecast horizons, and (ii) by plugging the marginals that gives highest rank correlation. The dependence of the inflation uncertainty of two economies can be initially drawn from the forecasts made at the same horizon. This implicitly assumes

[25] A copula C is Archimedean if there exists a convex, decreasing function $\varphi(\cdot) : (0, 1] \to [0, \infty)$ such that

$$C(y_1, y_2) = \varphi^{-1}(\varphi(y_1) + \varphi(y_2))$$

where $\varphi(\cdot)$ is copula generator and $\varphi(1) = 0$. The examples of Archimedean copulas are Gumbel, Frank, and Clayton.

that the uncertainty of one country influences the uncertainty of the other contemporaneously.[26] However, the uncertainty specific to one region may affect the uncertainty of the other region with either some lags or leads. In those circumstances, the joint distribution of the inflation uncertainty of two regions should be driven from the marginals that have the highest explanatory power. Therefore, the latter analytical frame can be viewed as a natural extension to the former. In order to find the matching horizons, the marginal distributions of the UK inflation uncertainty is taken as a benchmark. That is, for each horizons ($h = 1, \dots, 24$) of the UK inflation uncertainty, the rank correlation coefficients are computed pairing with lagged, current, and leading uncertainty of the euro inflation. To facilitate the non linear dependence structure, the Kendall's tau and the Spearman's rho are computed rather than the Pearson's correlation which only accounts for the linear relationships. For copula estimation, the distributions of the UK inflation uncertainty with each horizon will be matched with those of the euro inflation uncertainty with the horizons that deliver the maximum rank correlation.

Several results from this copula estimation can be predicted in advance. The estimated γ will be positive if two uncertainties are related and the increased uncertainty of one economy leads to the higher uncertainty of the other. Considering the term structure of copula parameter, γ may increase as the forecast horizon increases if the uncertainties about the future father away from the time of the forecast are highly dependent as opposed to the uncertainties about the near future being less dependent between two economies. On the other hand, if the uncertainties about the near future is more highly dependent than the uncertainties about the distant future, γ will decrease along with the increasing forecast horizons. Since the rank correlations are increasing functions of γ, the Kendall's tau and the Spearman's rho will also exhibit similar dynamics across horizons as the estimated γ. Comparing the copula estimation of same horizon densities to that of the different horizon densities, it is expected that estimates of γ will be larger in the latter case because the former estimation selects the matching horizons that have the highest rank correlation.

Table 2.5 and Figure 2.6 shows the estimated γ parameter of Frank copula and the rank correlation coefficients estimated according to the first strategy. The copula parameters for all the horizons ($h = 1, \dots, 24$) are estimated to be positive and mostly statistically significant. In particular, for the longer horizons that is larger than $h = 10$, the estimated $\gamma's$ are highly significant. As expected, γ increases, by and large, across

[26] The contemporaneous impact of the inflation uncertainty refers to the rank correlation between two inflation uncertainty indices of the *same horizon*. We use the word *'contemporaneous'* to highlight the comparison between the forecast errors of the same horizon, not *different horizons*, which will be also discussed from p.105. In most papers discussing VAR models, the contemporaneous effect of SVAR often refers to the case where the coefficient matrix that is multiplied by the right hand side variable (y_t) is not identity matrix, so that the variables in vector y_t could be correlated at the same time. Notice that they share the same word *'contemporaneous'* but the usage here is different from the conventional notion of contemporaneous effects in VAR models.

Table 2.5: The estimated parameters of Frank copula

h	γ	se(γ)	CvM	τ	ρ	h	γ	se(γ)	CvM	τ	ρ
1	1.886	0.783	0.091	0.203	0.300	13	2.297	0.838	0.194	0.243	0.358
2	1.022	0.784	0.094	0.112	0.168	14	2.552	0.849	0.210	0.267	0.392
3	0.823	0.751	0.083	0.091	0.136	15	2.401	0.833	0.253	0.253	0.372
4	1.783	0.800	0.120	0.192	0.285	16	2.713	0.841	0.286	0.282	0.413
5	1.984	0.837	0.219	0.212	0.315	17	2.777	0.819	0.333	0.287	0.421
6	1.878	0.830	0.193	0.202	0.299	18	3.017	0.856	0.395	0.309	0.451
7	1.341	0.820	0.151	0.146	0.218	19	3.252	0.860	0.374	0.329	0.478
8	1.539	0.848	0.201	0.167	0.249	20	3.354	0.868	0.460	0.337	0.490
9	1.273	0.830	0.332	0.139	0.208	21	3.326	0.873	0.354	0.335	0.487
10	1.684	0.858	0.425	0.182	0.271	22	3.665	0.893	0.419	0.362	0.523
11	2.167	0.874	0.311	0.230	0.340	23	3.654	0.872	0.463	0.362	0.522
12	2.307	0.876	0.202	0.244	0.360	24	3.784	0.913	0.256	0.372	0.536

Note: Table shows only the results from the assumption that the ρ's in WSN marginals decays exponentially as the forecast horizon increases. See Appendix 2.8.8 for the case of constant ρ for the WSN marginals.

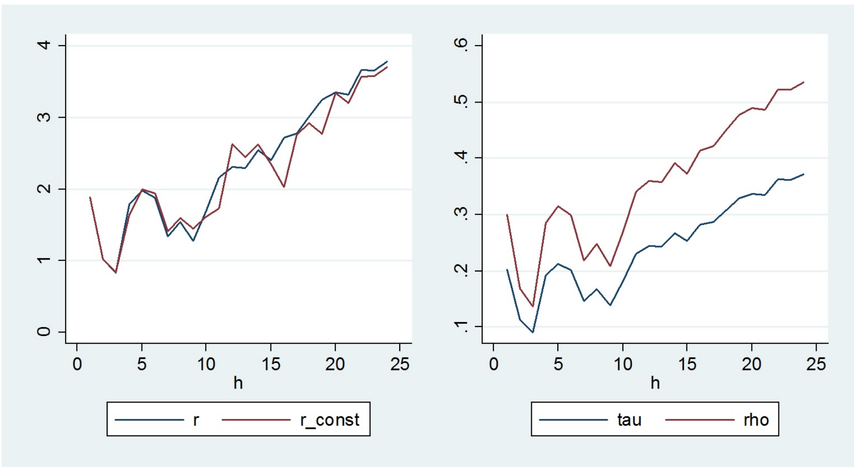

Figure 2.6: Copula parameters and rank correlation: same horizon

Note: r denotes γ parameter of Frank copula based on the assumption of decaying ρ in WSN marginal densities. *r_const* denotes γ parameter of Frank copula assuming constant ρ (=0.75) for the WSN marginal densities. *tau* and *rho* are estimated rank correlation coefficients using the analytical form given in equation (2.17), (2.18).

forecast horizons. In the short term, there are some exceptions. For example, the estimated γ decreases at first and bounces back at around $h = 6$, giving a decrease once again afterwards. However, the longer horizons larger than $h = 12$, show mostly monotonic increase. The uniformity of the estimated joint distribution is also confirmed by the Crémer-von Mises test. The rank correlation coefficients, τ and ρ, exhibit the same trend as the copula parameter. There was no substantial difference in the copula parameter in both cases of assumptions on WSN marginals (decaying ρ and constant ρ), even though the case of constant ρ in WSN marginals seems to be more volatile.

The results imply that the inflation uncertainty of the UK and the euro area contemporaneously affect one another and the simultaneous spillover effects get stronger if it is the uncertainty about the distant future rather than the near future. In the shorter run, there is no systematic relationship between the correlation (or the magnitude of the estimated copula parameter) and forecast horizon. The uncertainties at the forecast horizons $h = 1$ and $h = 5$ exhibit relatively high correlation while the uncertainties at the forecast horizons $h = 3$ being the minimum.

As discussed, a natural extension is to fit copula function with marginals of different horizons which gives highest rank correlation. First, the UK uncertainty is set as a benchmark, from 1-month to 2-years ahead index and then the euro uncertainty as a benchmark in turn. The results reveal certain dynamic aspects of spillover effects between the inflation uncertainties of two economies. Table 2.6 shows the forecast horizons of the euro area inflation uncertainty that have the highest rank correlation coefficients with given horizons of the UK inflation uncertainty.[27] In terms of the Kendall's tau, the short term UK inflation uncertainty series (with forecast horizons less than one year) depends highly on the euro inflation uncertainty series with the forecast horizons from 12 to 14. One-year ahead inflation uncertainty in the UK has the highest correlation with approximately $1\frac{1}{2}$ year ahead uncertainty in the euro area. From 16-months to 2-years ahead inflation uncertainty series of the UK have the highest correlation with 23- to 24-months ahead uncertainty series of the euro area. Spearman's rho criterion yields fairly similar results to the Kendall's tau criterion with a few exceptions in the short term horizons ($h = 1, 3$).

Table 2.7 shows the results by setting the euro area as a benchmark. Both Kendall's tau and Spearman's rho criteria produce quite similar results. Except the horizons, $h = 2, 3$, the euro inflation uncertainty indices at most forecast horizons have the highest correlation with the lagged UK inflation uncertainty series. For example, the 6-months ahead euro inflation uncertainty is highly related to the 3-months ahead UK inflation uncertainty series, the 12-months ahead euro uncertainty to the 7-months ahead UK uncertainty, and 2-years ahead euro uncertainty to the 19-months ahead UK

[27]See Appendix 2.8.9 for the rank correlation coefficients between the UK and the euro area inflation uncertainties across all different horizons.

Table 2.6: The forecast horizons of the euro area inflation uncertainty returning the highest correlation to the UK inflation uncertainty

	Kendall		Spearman			Kendall		Spearman	
UK	$h1$	τ	$h2$	ρ	UK	$h1$	τ	$h2$	ρ
1	12	(0.223)	6	(0.316)	13	19	(0.307)	20	(0.436)
2	12	(0.261)	12	(0.358)	14	20	(0.324)	20	(0.457)
3	12	(0.259)	8	(0.369)	15	20	(0.331)	20	(0.474)
4	13	(0.268)	13	(0.378)	16	23	(0.330)	23	(0.472)
5	14	(0.273)	14	(0.384)	17	23	(0.349)	23	(0.492)
6	14	(0.303)	14	(0.418)	18	23	(0.364)	23	(0.520)
7	14	(0.322)	14	(0.450)	19	23	(0.370)	24	(0.515)
8	14	(0.326)	14	(0.448)	20	24	(0.356)	24	(0.492)
9	14	(0.321)	14	(0.435)	21	24	(0.328)	24	(0.457)
10	14	(0.306)	16	(0.430)	22	24	(0.311)	24	(0.432)
11	14	(0.307)	17	(0.435)	23	23	(0.315)	23	(0.440)
12	17	(0.299)	17	(0.424)	24	24	(0.298)	24	(0.418)

Note: $h1$ refers to the horizons of the euro inflation uncertainty that give the highest Kendall's tau correlation with the UK uncertainty of the given horizon. τ is the Kendall's tau at the horizon $h1$. $h2$ refers to the horizons of the euro inflation uncertainty that give the highest Spearman's rho correlation with the UK uncertainty of the given horizon. ρ is the Spearman's rho at the horizon $h2$.

Table 2.7: The forecast horizons of the UK inflation uncertainty returning the highest correlation to the euro area inflation uncertainty

	Kendall		Spearman			Kendall		Spearman	
Euro	$h1$	τ	$h2$	ρ	Euro	$h1$	τ	$h2$	ρ
1	1	(0.199)	1	(0.289)	13	8	(0.321)	8	(0.439)
2	10	(0.210)	10	(0.305)	14	8	(0.326)	7	(0.450)
3	10	(0.226)	10	(0.322)	15	9	(0.304)	8	(0.429)
4	1	(0.197)	1	(0.289)	16	10	(0.305)	10	(0.430)
5	2	(0.234)	2	(0.339)	17	11	(0.306)	11	(0.435)
6	3	(0.249)	3	(0.358)	18	13	(0.288)	13	(0.407)
7	3	(0.246)	3	(0.346)	19	13	(0.307)	15	(0.432)
8	3	(0.258)	3	(0.369)	20	15	(0.331)	15	(0.474)
9	3	(0.246)	3	(0.348)	21	18	(0.312)	18	(0.447)
10	4	(0.255)	4	(0.359)	22	18	(0.345)	18	(0.487)
11	7	(0.293)	7	(0.394)	23	19	(0.370)	18	(0.520)
12	7	(0.307)	7	(0.422)	24	19	(0.369)	19	(0.515)

Note: $h1$ refers to the horizons of the UK inflation uncertainty that give the highest Kendall's tau correlation with the euro uncertainty of the given horizon. τ is the Kendall's tau at the horizon $h1$. $h2$ refers to the horizons of the UK inflation uncertainty that give the highest Spearman's rho correlation with the euro uncertainty of the given horizon. ρ is the Spearman's rho at the horizon $h2$.

uncertainty. The difference of the horizon (lag) is 3 for the shorter horizons ($h = 4, 5, 6$) euro inflation uncertainty data and becomes little larger for the longer horizons, ranging from 4 to 6.

Bringing the results together, the UK inflation uncertainties are most highly associated with the leading series of the euro area inflation uncertainty and the euro inflation uncertainties with the lagged series of the UK uncertainty. The exact horizon that returns maximum value of rank correlation differs by selecting different benchmarks because the range given for defining maximum changes. Without any distributional assumptions, it suggests that the UK inflation uncertainty might contain relevant information for predicting the euro inflation uncertainty with lags, even though it cannot be interpreted solely by causality.

Figure 2.7: Copula parameters and rank correlation coefficients: combined marginals that have highest correlation

Note: r denotes γ parameter of Frank copula based on the assumption of decaying ρ in WSN marginal densities and combining the same horizon. r_cross denotes γ parameter of Frank copula assuming decaying ρ for the WSN marginal densities and combining different horizons that gives highest correlation. tau and rho are estimated rank correlation coefficients using the analytical form given in equation (2.17), (2.18).

The copula parameters are estimated with the pair that gives the highest correlation. Figure 2.7 presents the results of the estimation in terms of matching horizons based on the Kendall's tau with the UK benchmark.[28] Comparing to the previous results where the copula function is fitted by the same horizon uncertainties for two regions, the $\hat{\gamma}$ is larger for all forecasting horizons. This is reasonable and anticipated result because the matching horizons for two countries' uncertainty are selected to reflect the higher dependence structure. Unlike the same horizon results, $\hat{\gamma}$ increases in the short term as the horizon increases until $h = 10$. The strength of non linear dependence of two uncertainties that is depicted by the copula parameter weakens until it

[28] Even if the benchmark rank correlation coefficients are different, the results for the copula estimation do not change materially. The complete results are in Appendix 2.8.10.

reaches the local minimum at $h = 13$. The maximum value of the estimated γ occurs at $h = 20$.

2.6 Probabilistic Approach: Investigating Inflation Dependence Structure

Based on the estimated marginal and joint densities of inflation uncertainty, one can compute the conditional probability of certain scenarios of inflation outcomes. The subscript for the density functions (f and F) and uncertainty index (U) indicates each region: 1 for the UK and 2 for the euro area. Then, the unconditional probability for the UK inflation being inside [a,b] is computed as follows.

$$\int_a^b \hat{f}_1(U_1)\ dU_1 \tag{2.19}$$

The conditional probability of the UK inflation inside [a,b] given that the euro inflation is inside the same region is

$$\frac{\displaystyle\int_a^b \int_a^b c(\hat{F}_1, \hat{F}_2; \hat{\alpha})\ \hat{f}_1 \cdot \hat{f}_2\ dU_1 dU_2}{\displaystyle\int_a^b \hat{f}_2(U_2)\ dU_2} \tag{2.20}$$

Table 2.8 and Figure 2.8 shows two different scenarios, (i) the inflation below 1% and (ii) the inflation within [1%, 3%] for both economies. The former scenario represents the case of hitting the lower bound of the central banks' target[29] and the latter depicts the case of well-anchored inflation. Each of the horizons, the probabilities are computed by averaging the probabilities across the most recent forecasts, starting from the forecasts made at July 2013. For example, for the forecast horizon $h = 1$, the probabilities of hitting the lower bound (1%) computed at July 2013, August 2013, up to February 2016, are averaged out. Therefore, the total number of entries for the average is 31. The forecasts can be made up to January 2016 for the forecast horizon $h = 2$, thus the total number of entries for the average is 30. Table 2.8 presents both the unconditional and conditional probability of each given scenario with the selected horizons and the complete results are given in Appendix 2.8.11.

[29]The Bank of England and the European Central Bank publish the inflation target on their website. Both set the inflation target of 2% in the medium term. The Bank of England explicitly announces the inflation target band of 1 percentage point from 2% but the European Central Bank does not. In this chapter, the same target band is assumed for both central banks to calculate the conditional probability. See *Monetary Policy Framework of the Bank of England* (Available from: `http://www.bankofengland.co.uk/monetarypolicy/Pages/framework/framework.aspx`) and *Monetary Policy Strategy for the European Central Bank* (Available from: `https://www.ecb.europa.eu/mopo/strategy/html/index.en.html`) for the details.

Table 2.8: The unconditional and conditional probability of the UK inflation

I. The probability of the UK inflation below 1%

	Unconditional	Conditional (same h)	Conditional (different h)	eu h
h=6	0.4867	0.5095	0.5238	14
h=12	0.3863	0.4163	0.4281	17
h=18	0.2663	0.3184	0.3289	23
h=24	0.2387	0.3036	0.3036	24

II. The probability of the UK inflation within [1%, 3%]

	Unconditional	Conditional (same h)	Conditional (different h)	eu h
h=6	0.4224	0.4942	0.5337	14
h=12	0.4150	0.4523	0.4488	17
h=18	0.4457	0.4127	0.3884	23
h=24	0.4179	0.3483	0.3483	24

Note: *Conditional (same h)* indicates the conditional probability calculated using the estimated joint distribution combined by the same horizon univariate densities of the UK and the euro inflation uncertainty. *Conditional (different h)* indicates the conditional probability calculated using the estimated joint distribution combined by the matching univariate densities of the UK and the euro inflation uncertainty which give the highest Kendall's tau rank correlation with each given horizon of the UK inflation uncertainty. *eu h* refers to the selected horizons for the euro inflation uncertainty that gives the highest Kendall's tau correlation with each given horizon of the UK inflation uncertainty.

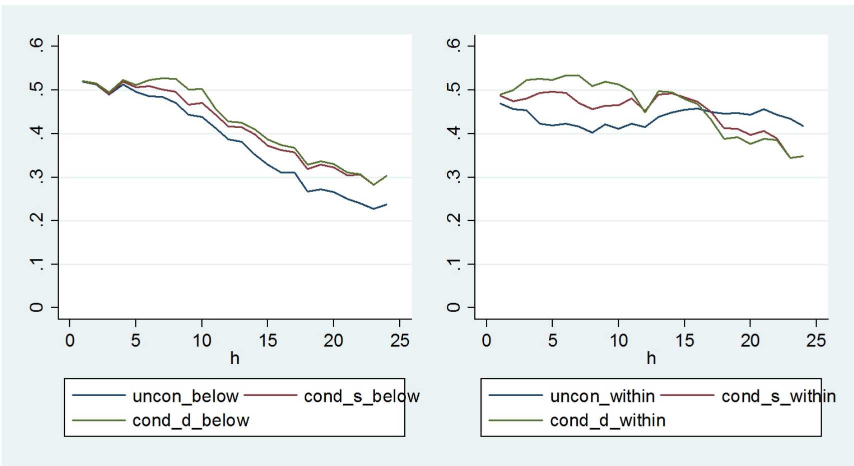

Figure 2.8: The unconditional and conditional probabilities of the UK inflation

Note: The left panel shows the results when the UK inflation is below 1%, and the right panel shows the results when the UK inflation is within target [1%, 3%]. The blue lines are unconditional probability and the red lines are conditional probability computed for the same horizons. The green lines are conditional probability computed for the different horizons when when pairing the two marginal densities.

Both unconditional and conditional probability of the UK inflation below 1% decreases as we forecast further future. This is clearly observed by the downward sloping graphs in the left panel of Figure 2.8. The unconditional probability is lower than the conditional probability for all horizons in the first scenario. For example, the probability of the UK inflation below 1% in two years without considering the dependence structure is approximately 24% while this increases to 31% if it is known that the euro area inflation will also become below 1% in two years. This suggests that the left tail events of inflation are positively correlated between the two regions. The uncertainty of potential downward pressure to the euro inflation below its monetary policy target might create additional downward pressure to the UK inflation.

One important finding of the probabilistic analysis is about when the left tail event is most likely. The unconditional probability of the UK inflation below 1% is at its maximum at $h = 1$ and decreases. However, the conditional probability of the same event computed using the joint density of matching different horizons reaches its largest level at $h = 7$. This implies that the model of univariate inflation density using most recent data anticipates that the UK inflation could be below 1% next month by the highest probability whereas the model which directly takes account for the interaction between the UK and the euro area inflation uncertainty predicts that the same event is most likely to occur 7 months later. The dynamic analysis can suggest the appropriate timing of the monetary policy considering the interconnectedness of the two economies. Since the extra information about the euro inflation uncertainty can lead to a different prediction of the odds of the left tail event for the UK inflation, the monetary authority can react pre-emptively against the potential influence of the euro inflation uncertainty to the UK inflation.

The second case of the UK inflation within the target band yields quite a different picture (see the right panel of Figure 2.8). Unlike the previous scenario, the probabilities do not decrease monotonically as forecast horizon increases. The unconditional probability appears to be flat across all forecast horizons, roughly between 40 and 50 percent. The conditional probabilities are either flat (copula estimated with marginals of the same horizons) or increasing (copula estimated with marginals of the different horizons) for the short forecast horizons. For the longer horizons, the conditional probabilities tend to decline as the forecast horizon increases. Comparing the unconditional and conditional probabilities, unconditional probability of the UK inflation inside the target band is significantly lower than the conditional probability in the short and medium term. However, the long term unconditional probability is larger than the conditional probability. This implies that, for the short forecast horizons, the odds of the UK inflation being within the target range is more likely if the euro inflation is also predicted to be inside the range. Considering the future further ahead (17 months ahead), on the contrary, the odds of the UK inflation inside the target is less likely once it is known that the euro inflation will be well-anchored. It suggests that if the news about the euro area is given, the uncertainty around the inflation in the UK decreases in the near future, but increases in the far future.

2.7 Conclusions

This paper analyses the dependence structure in inflation uncertainty for the countries bordering a major currency area, in particular, the UK and the euro area. The inflation uncertainty is measured by square forecast errors from bivariate VAR GARCH model using the data from January 1997 to March 2016. The findings suggest that the estimated uncertainty may well be characterised with non-Gaussian density with skewed, heavy tail properties. Following the two-step estimation (Inference Functions for Margins, IFM), the uncertainty measures are evaluated by fitting with two different parametric skewed density functions, Two Piece Normal (TPN) and Weighted Skewed Normal (WSN). The goodness-of-fit tests supports the choice of WSN against TPN for both the UK and the euro area inflation uncertainty. The estimated parameters in WSN suggests that the UK monetary policy reactions in the short run show relatively hawkish while in the longer term the responses are rather dovish. For the euro area, the estimation results suggest that the ECB tends to be hawkish in response of upside risk of inflation uncertainty regardless of the forecast horizons.

As the second stage of IFM, the copula parameters are estimated by maximum likelihood estimation. The results imply that the inflation uncertainty of the UK and the euro area contemporaneously affect one another and the simultaneous spillover effects get stronger if it is the uncertainty about the distant future rather than the near future. In the shorter run, there is no systematic relationship between the correlation and forecast horizon. In order to reveal dynamic aspects of spillover effects between the inflation uncertainties of two economies, I fit copula function with marginal densities of different horizons which gives highest rank correlation. The UK inflation uncertainties are most highly associated with the leading series of the euro area inflation uncertainty and the euro inflation uncertainties with the lagged series of the UK uncertainty. Without any distributional assumptions, it suggests that the UK inflation uncertainty might contain relevant information for predicting the euro inflation uncertainty with lags, even though it cannot be interpreted solely by causality.

Finally, the conditional probability accounting for the dependence structure in inflation uncertainties is computed using the estimation results. In particular, I consider the conditional probability of the UK inflation inside a certain interval given that the euro inflation is inside the same interval with two different scenarios: *(i) the inflation hitting the lower bound of the central banks' target and (ii) the case of well-anchored inflation.* The result suggests that the left tail events of inflation are positively correlated between the two regions. The uncertainty of potential downward pressure to the euro inflation below its monetary policy target might create additional downward pressure to the UK inflation. In addition, the appropriate timing of the monetary policy can be driven if policymakers consider the interconnectedness of the two economies. Since the extra information about the euro inflation uncertainty can lead to a different prediction of the odds of the left tail event for the UK inflation, the monetary authority can react pre-emptively against the potential influence of the euro inflation uncertainty to the UK inflation.

2.8 Appendix

2.8.1 Related literature

I. Literature on international co-movement of inflation

Henriksen, Kydland and Sustek (2011) highlighted the possibility that common macroeconomic shocks, such as oil price shock, can lead to similar responses of central banks, resulting inflation co-movement. Henriksen, Kydland, and Sustek (2013) investigated the link between inflation and productivity growth. They found that the international business cycle model with technological spillovers can generate co-movement in inflation across countries. Clearly, trade openness can influence the level of inflation dependence across countries. Melitz and Ottaviano (2008) suggested a model where trade openness decreases firms' mark-ups and lowers inflation. In terms of labour market channel, migration with heterogeneous labour supply elasticities between domestic and foreign labour force can create the dependence of inflation among countries. Bentolila, Dolado, and Jimeno (2008) develop a theoretical model exhibiting downward pressure on inflation when there is a migration boom in a country. Finally, exchange rate regime can be another potential channel for inflation co-movement. Either a fixed exchange rate system or an exchange rate system subject to the stable exchange rates could produce similar monetary policies (see, for example, Canzoneri and Gray, 1985; Calvo and Reinhart, 2002; Devereux and Engel, 2007). In addition, there are some recent empirical studies that has revealed international links of inflation among developed countries (Monacelli and Sala 2009; Ciccarelli and Mojon 2010; Neely and Rapach, 2011; Mumtaz and Surico, 2012).

II. Literature on unpredictability measures of uncertainty

One of the earliest attempt that explores (un)predictability measure as a proxy for uncertainty was Pourgerami and Maskus (1987). They investigated Latin American countries which experienced high inflation and discovered that it is often more likely to fail to predict inflation precisely in countries with high inflation. Ungar and Zilberfarb (1993) proposed three unpredictability measures, such as Absolute Forecast Error (AFE), Squared Forecast Error (SFE) followed by Pagan, Hall, and Trivedi (1983) and Mean Squared Error (MSE) from survey of inflation expectation.

III. Literature on disagreement measures of uncertainty

Holland (1995) explored the dispersion of expectation as a proxy for uncertainty. He suggested that increases in inflation is likely to be followed by the divergence of expectation among individuals, provided that central banks' objective is to minimise welfare losses. For recent work, see Giordani and Söderlind (2003), Engelberg, Manski and Williams (2009), Clements and Harvey (2011), Lahiri, Peng and Sheng (2014).

2.8.2 Nonparametric proxy of inflation volatility

Among nonparametric proxy of volatility, realised variance (or volatility) and standard deviation of rolling windows are discussed here. First, realised variance (RV) is the most widely used proxy for volatility (see Barndorff-Nielsen et al. (2004) for the development of this measure using kernel estimation). RV is defined as the sum of squared returns. For example, the RV of monthly stock market return can be defined as the sum of squared daily returns during a certain month. Therefore, RV is a nonparametric (without assuming any distribution for computing) and a measure of variation over a certain period of time. RV of monthly inflation uncertainty can be measured only if there exist high frequency data for inflation.

Second, standard deviation of rolling windows of certain period can measure volatility without parametric assumptions. This proxy is simple and easily constructed without high frequency data. Therefore, we computed standard deviations of rolling 3-, 6-, 12- and 24-month windows of year-on-year inflation, SD3, SD6, SD12 and SD24, respectively.

In order to compare SD proxies to the inflation uncertainty index constructed using parametric model, bivariate VAR GARCH(1,1), the correlation coefficients are computed in Table 2.9. Mostly, inflation uncertainty is significantly correlated with nonparametric proxy of similar horizon or leading horizons. Figure 2.9-10 plot inflation uncertainty (by VAR GARCH) and nonparametric proxies (by SD). For comparison, inflation uncertainty series are squared and standardised. As seen in the graphs, the two measures of uncertainty are at least showing similar dynamics.

Table 2.9: Correlation coefficients between inflation uncertainty index and nonparametric proxy of inflation volatility

	UK				EURO			
	SD3	SD6	SD12	SD24	SD3	SD6	SD12	SD24
uncer3	0.4253*	0.4933*	0.4536*	0.3412*	0.3268*	0.2521*	0.3380*	0.2305*
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0019	0.0000	0.0047
uncer6	0.3226*	0.3826*	0.5952*	0.3562*	0.2190*	0.4266*	0.3838*	0.2655*
	0.0001	0.0000	0.0000	0.0000	0.0079	0.0000	0.0000	0.0012
uncer12	0.2622*	0.2074	0.3759*	0.3870*	0.1996	0.3104*	0.5416*	0.3337*
	0.0018	0.0140	0.0000	0.0000	0.0180	0.0002	0.0000	0.0001
uncer24	0.1475	0.0533	0.1206	0.1308	0.3012*	0.3422*	0.5169*	0.3772*
	0.0966	0.5503	0.1749	0.1412	0.0005	0.0001	0.0000	0.0000

Notes: SD3, SD6, SD12 and SD24 refer to the standard deviations of rolling 3-, 6-, 12- and 24-month windows of year-on-year inflation. uncer3, uncer6, uncer12, and uncer24 denote inflation uncertainty series computed in Section 2.2.

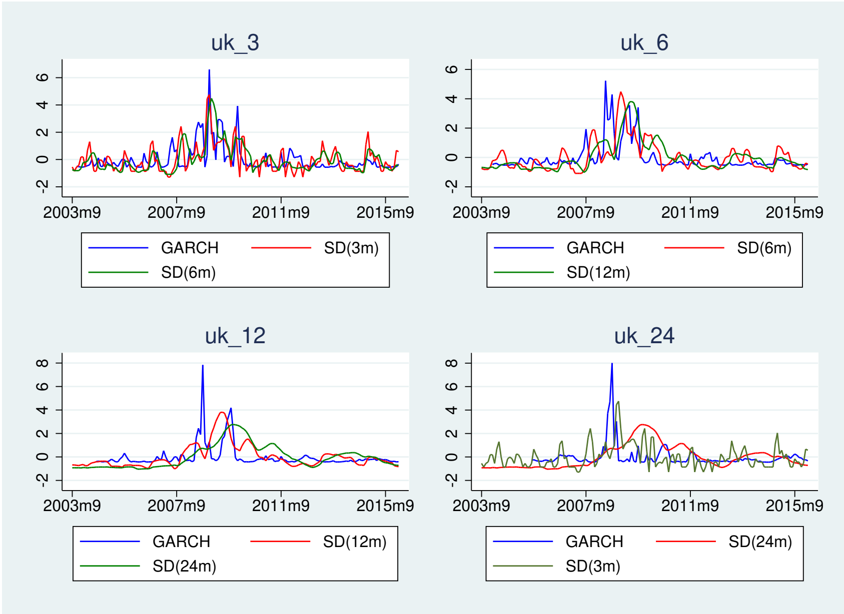

Figure 2.9: The UK inflation uncertainties: Parametric vs nonparametric measures

Notes: GARCH refers to squared and strandardised inflation uncertainty series of different horizons. SD refers to rolling standard deviation. The plots include the SD with same horizon and the ones with highest correlations in Table 2.9.

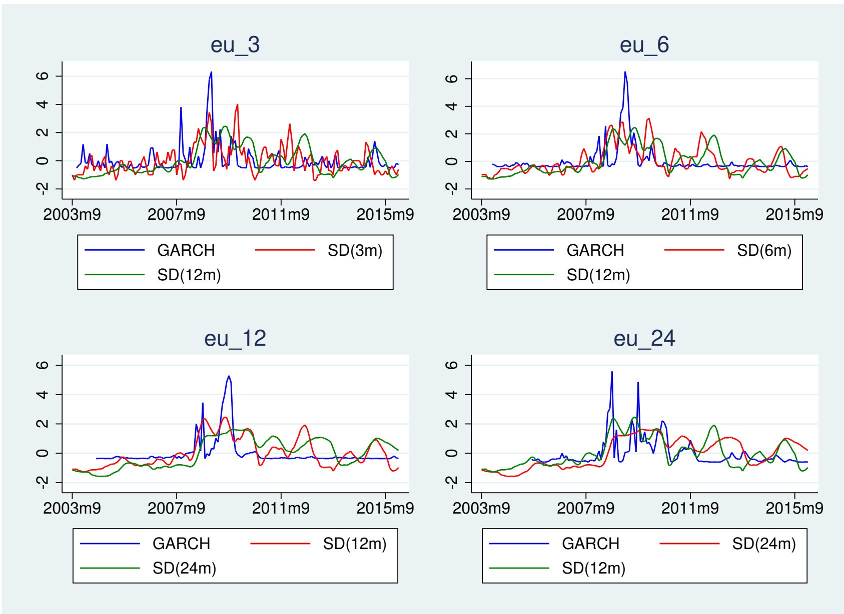

Figure 2.10: The euro area inflation uncertainties: Parametric vs nonparametric measures

Notes: GARCH refers to squared and strandardised inflation uncertainty series of different horizons. SD refers to rolling standard deviation. The plots include the SD with same horizon and the ones with highest correlations in Table 2.9.

2.8.3 The unit root test results

Table 2.10: Augmented Dickey-Fuller test results

	(1)		(2)		Observations
UK	−0.844	(0.806)	−0.224	(0.991)	218
Euro	−1.870	(0.347)	−2.161	(0.512)	218
D.UK	−6.028***	(0.000)	−6.158***	(0.000)	217
D.Euro	−5.742***	(0.000)	−5.877***	(0.000)	217

Notes: D. denotes the first differenced series. (1) assumes the null hypothesis of random walk without drift. (2) assumes the null hypothesis of random walk with or without drift. Both (1) and (2) include 12 lagged differenced terms. MacKinnon approximate p-values are in the parenthesis. *** indicates that the null hypothesis of unit root is rejected at 1% significance level with critical value -3.471.

2.8.4 Descriptive statistics of inflation uncertainty

Table 2.11: The descriptive statistics of inflation uncertainty (all horizons)

	UK				Euro			
Horizon	mean	stdv	skewness	kurtosis	mean	stdv	skewness	kurtosis
1	-0.05	0.43	-0.19	0.35	-0.02	0.41	-0.25	0.42
2	-0.09	0.69	-0.06	0.61	-0.10	0.52	-0.01	0.41
3	-0.06	1.00	-0.13	1.12	-0.15	0.69	-0.24	1.82
4	-0.02	1.20	-0.08	1.24	-0.16	0.90	-0.81	2.95
5	-0.06	1.43	-0.06	1.21	-0.28	1.23	-1.10	4.06
6	-0.13	1.58	-0.02	1.63	-0.26	1.51	-1.13	4.66
7	-0.13	1.75	-0.01	2.22	-0.33	1.81	-1.23	4.99
8	-0.09	1.89	0.09	2.58	-0.45	2.14	-1.17	4.75
9	-0.10	1.97	0.25	3.53	-0.51	2.45	-1.15	5.13
10	-0.13	1.99	0.10	2.84	-0.59	2.68	-1.22	5.14
11	-0.16	2.03	0.09	2.86	-0.63	2.82	-1.32	5.33
12	-0.09	2.00	0.29	3.48	-0.51	2.95	-1.10	4.98
13	-0.14	1.93	0.23	2.81	-0.59	2.97	-1.07	4.66
14	-0.13	1.81	0.45	2.88	-0.73	2.98	-0.96	3.72
15	-0.09	1.70	0.48	3.23	-0.80	2.88	-0.78	3.50
16	-0.06	1.57	0.39	1.77	-0.81	2.76	-0.72	2.79
17	-0.08	1.45	0.40	1.12	-0.90	2.67	-0.59	1.94
18	-0.10	1.28	0.36	0.00	-0.83	2.54	-0.35	1.44
19	-0.08	1.21	0.43	-0.20	-0.85	2.45	-0.12	1.29
20	-0.03	1.24	0.65	0.84	-0.89	2.46	0.24	1.59
21	-0.03	1.24	0.65	1.15	-0.90	2.45	0.30	1.83
22	-0.02	1.33	0.94	2.19	-0.92	2.52	0.51	2.21
23	-0.03	1.37	0.95	1.75	-0.91	2.51	0.57	1.67
24	0.03	1.44	1.19	2.97	-0.76	2.47	0.60	1.63

2.8.5 The estimation results of WSN, TPN distributions

The *pdf* of WSN distribution is as follows (Charemza, Díaz, and Makarova, 2015).

$$
\begin{aligned}
f_{WSN}(x;\alpha,\beta,m,k,\rho) = & \frac{1}{\sqrt{A_\alpha}}\phi\Big(\frac{x}{\sqrt{A_\alpha}}\Big)\Phi\Big(\frac{B_\alpha x - mA_\alpha}{\sqrt{A_\alpha(1-\rho^2)}}\Big) \\
& + \frac{1}{\sqrt{A_\beta}}\phi\Big(\frac{x}{\sqrt{A_\beta}}\Big)\Phi\Big(\frac{-B_\beta x + kA_\beta}{\sqrt{A_\beta(1-\rho^2)}}\Big) \\
& + \phi(x)\cdot\Big[\Phi\Big(\frac{m-\rho x}{\sqrt{1-\rho^2}}\Big) - \Phi\Big(\frac{k-\rho x}{\sqrt{1-\rho^2}}\Big)\Big]
\end{aligned}
$$

where ϕ and Φ are the *pdf* and *cdf* of standard normal distribution. $A_\tau = 1+2\tau\rho+\tau^2$ and $B_\tau = \tau+\rho$ for $\tau = \alpha,\beta$. The estimation is based on the assumption of $m = -k = \sigma$.

The *pdf* of TPN distribution is defined by (see Wallis, 2004)

$$
f_{TPN}(x;\sigma_1,\sigma_2,\mu) = \begin{cases} Aexp\{-(x-\mu)^2/2\sigma_1^2\} & \text{if } x \le \mu \\ Aexp\{-(x-\mu)^2/2\sigma_2^2\} & \text{if } x > \mu \end{cases}
$$

where $A = (\sqrt{2\pi}(\sigma_1+\sigma_2)/2)^{-1}$.

Table 2.12: The estimated parameters of the UK WSN distribution ($\rho = 0.75$)

h	α	β	σ	$se(\alpha)$	$se(\beta)$	$se(\sigma)$	Distance
1	-0.806	-0.413	0.542	0.488	0.719	0.336	4.693
2	-0.921	-0.587	0.872	0.123	0.167	0.302	5.534
3	-2.104	-2.000	0.656	0.076	0.254	0.025	3.031
4	-2.035	-1.454	0.944	0.363	0.046	0.074	4.483
5	-2.607	-1.744	1.012	0.357	0.556	0.140	5.807
6	-2.050	-1.460	1.204	0.094	0.443	0.243	2.496
7	-1.924	-1.268	1.393	0.518	0.039	0.170	2.694
8	-0.409	-0.001	1.747	0.224	0.002	0.059	5.058
9	-2.205	-1.721	1.259	0.396	0.889	0.594	8.627
10	-0.278	-0.011	1.718	0.134	0.035	0.151	9.595
11	-0.807	-0.554	2.070	0.022	0.273	0.046	3.101
12	-1.745	-1.746	1.485	0.047	0.043	0.121	15.053
13	-0.632	-0.351	1.895	0.482	0.603	0.409	6.271
14	-0.877	-0.485	1.922	0.244	0.523	0.496	7.797
15	-0.463	-0.312	1.693	0.559	0.530	0.230	6.182
16	-1.182	-1.140	1.579	0.309	0.442	0.420	3.886
17	-0.906	-0.569	1.733	0.169	0.225	0.103	11.971
18	-1.271	-1.465	1.368	0.029	0.587	0.249	11.305
19	-0.841	-0.583	1.622	1.649	0.832	0.555	10.826
20	-0.679	-0.393	1.577	1.136	0.229	0.413	13.577
21	-1.336	-1.507	1.171	0.176	0.293	0.138	7.297
22	-0.904	-0.602	1.548	0.177	0.121	0.321	14.855
23	-0.913	-0.594	1.604	0.149	0.144	0.511	6.438
24	-1.383	-1.505	1.306	0.326	0.713	0.444	5.935

Table 2.13: The estimated parameters of the UK WSN distribution (ρ decaying exponentially)

h	α	β	σ	$se(\alpha)$	$se(\beta)$	$se(\sigma)$	Distance
1	-0.806	-0.413	0.542	0.488	0.719	0.336	4.693
2	-0.663	-0.280	0.729	0.074	0.886	0.255	5.978
3	-1.981	-1.816	0.553	0.698	0.683	0.301	3.323
4	-1.911	-1.227	0.764	0.534	1.179	0.367	4.462
5	-2.495	-1.473	0.812	0.808	1.117	0.492	4.797
6	-1.806	-0.976	0.992	0.361	0.456	0.077	1.987
7	-1.758	-0.868	1.099	0.514	0.797	0.414	2.994
8	-1.064	-0.542	1.426	0.835	0.311	0.066	5.038
9	-1.945	-1.321	1.048	0.932	0.375	0.255	8.282
10	-1.046	-0.679	1.417	0.778	0.123	0.093	8.932
11	-0.646	-0.376	1.539	0.487	0.327	0.293	3.350
12	-1.466	-1.383	1.219	0.423	0.687	0.291	14.130
13	-0.662	-0.297	1.480	0.437	0.073	0.105	6.696
14	-0.531	-0.122	1.456	0.160	0.387	0.031	8.555
15	-0.527	-0.210	1.399	0.655	0.157	0.151	6.572
16	-0.263	-0.058	1.361	0.179	0.323	0.270	4.345
17	-0.501	-0.148	1.338	0.571	0.038	0.344	12.369
18	-0.837	-0.952	1.129	0.896	1.544	0.511	12.637
19	-0.700	-0.618	1.170	1.328	1.588	0.640	12.052
20	-0.908	-0.741	1.111	0.670	1.199	0.452	14.756
21	-0.650	-0.616	1.106	0.475	1.593	0.439	7.900
22	-0.777	-0.956	1.069	0.074	0.519	0.321	16.175
23	-1.022	-1.245	1.000	0.310	0.617	0.103	7.701
24	-1.004	-1.096	1.067	0.368	1.089	0.313	6.649

Table 2.14: The estimated parameters of the UK TPN distribution

h	σ_1	σ_2	μ	$se(\sigma_1)$	$se(\sigma_2)$	$se(\mu)$	Distance
1	2.597	0.676	-2.537	0.610	0.088	1.590	17.413
2	0.077	3.772	3.942	0.200	0.206	0.174	16.090
3	0.967	0.864	0.014	0.003	0.176	0.461	6.142
4	1.350	0.724	0.443	0.305	0.239	0.116	5.415
5	1.606	0.975	0.405	0.503	0.024	0.237	14.083
6	1.700	1.033	0.354	0.712	0.205	0.399	4.644
7	2.000	0.912	0.674	0.235	0.176	0.613	2.931
8	2.028	1.087	0.611	0.324	0.633	0.415	3.607
9	1.884	1.256	0.370	0.130	0.096	0.348	12.083
10	1.799	1.342	0.278	0.398	0.175	0.638	9.475
11	1.468	1.623	-0.245	0.068	0.957	0.744	3.087
12	1.580	1.778	-0.259	0.422	0.466	0.700	15.373
13	1.125	1.829	-0.721	0.512	0.202	0.762	5.273
14	3.932	0.338	-3.960	0.216	0.533	0.887	6.548
15	3.620	0.506	-3.736	0.313	0.054	0.178	4.996
16	0.988	1.612	-0.570	0.063	0.523	0.284	3.788
17	0.571	1.927	-1.170	0.245	0.510	0.158	7.094
18	3.914	0.234	-2.595	0.272	0.205	0.616	6.562
19	0.357	1.797	-1.210	0.087	0.100	0.283	4.448
20	0.506	1.671	-1.013	0.560	0.298	0.339	9.599
21	0.492	1.582	-0.860	0.515	0.579	0.823	3.460
22	0.163	1.806	-1.350	0.526	0.127	0.729	5.726
23	0.334	1.810	-1.204	0.016	0.140	0.266	1.398
24	0.542	1.775	-0.959	0.673	0.031	0.509	3.049

Table 2.15: The estimated parameters of the euro area WSN distribution ($\rho = 0.75$)

h	α	β	σ	$se(\alpha)$	$se(\beta)$	$se(\sigma)$	Distance
1	-1.711	-1.779	0.362	0.353	0.566	0.104	4.124
2	-1.393	-0.674	0.619	0.357	0.108	0.094	8.297
3	-1.666	-0.632	0.682	0.209	0.479	0.107	8.677
4	-2.240	-1.784	0.582	0.506	0.583	0.211	10.511
5	-2.577	-0.531	0.898	0.561	0.343	0.219	15.702
6	-3.630	-2.824	0.671	0.159	0.176	0.072	13.538
7	-3.712	-2.819	0.731	0.910	0.194	0.262	7.505
8	-3.396	-2.477	0.915	0.114	0.748	0.167	8.838
9	-3.577	-0.468	1.534	0.327	0.467	0.276	33.642
10	0.000	-2.536	2.368	0.000	1.089	0.392	29.984
11	-0.001	-2.600	2.395	0.003	1.391	0.478	33.260
12	-3.920	-3.362	1.259	0.758	0.005	0.591	14.295
13	-3.999	-2.402	1.403	0.002	0.513	0.138	29.535
14	-3.997	-2.422	1.633	0.011	0.438	0.419	37.545
15	-3.924	-0.363	1.804	0.240	0.135	0.122	32.202
16	-0.005	-2.242	2.573	0.017	1.007	0.029	47.987
17	-3.122	-0.302	1.782	0.753	0.058	0.052	35.742
18	-3.339	-2.740	1.519	0.068	0.571	0.230	44.232
19	-2.833	-3.843	1.646	0.356	0.498	0.377	49.468
20	-2.617	-0.383	2.161	0.180	0.200	0.265	52.892
21	-2.466	-0.381	2.191	0.209	0.194	0.170	53.796
22	-1.242	-0.174	2.971	0.625	0.460	0.280	54.737
23	-2.110	-0.174	2.005	0.095	0.044	0.254	18.471
24	-1.196	-0.270	2.845	0.242	0.157	0.118	21.635

Table 2.16: The estimated parameters of the euro area WSN distribution (ρ decaying exponentially)

h	α	β	σ	$se(\alpha)$	$se(\beta)$	$se(\sigma)$	Distance
1	-1.711	-1.779	0.362	0.353	0.566	0.104	4.124
2	-1.019	-0.270	0.537	1.198	0.159	0.351	7.906
3	-1.310	-0.081	0.562	1.106	0.250	0.272	8.560
4	-1.701	-0.473	0.613	0.319	0.484	0.112	8.655
5	-2.441	-0.035	0.730	1.389	0.112	0.259	16.172
6	-3.607	-2.720	0.557	1.288	1.013	0.291	13.557
7	-3.877	-2.855	0.583	0.624	0.933	0.206	7.453
8	-3.665	-2.587	0.716	1.059	0.084	0.214	8.767
9	-1.847	-2.738	0.874	0.781	1.069	0.295	32.560
10	-1.874	-2.807	0.959	0.146	0.275	0.028	38.249
11	-3.592	-0.018	1.464	0.277	0.057	0.055	36.263
12	-3.190	-0.215	1.471	0.537	0.174	0.077	22.704
13	-3.883	-0.035	1.420	0.136	0.112	0.084	32.817
14	-3.800	-0.011	1.574	0.631	0.035	0.403	37.003
15	-3.977	-0.007	1.510	0.434	0.024	0.201	35.622
16	-3.696	-0.009	1.606	0.556	0.029	0.505	50.812
17	-3.015	-0.009	1.479	0.586	0.029	0.102	39.693
18	-3.194	-0.001	1.735	0.488	0.002	0.097	46.176
19	-2.703	-0.013	1.781	0.957	0.040	0.048	50.807
20	-2.189	-0.004	1.817	0.161	0.012	0.161	55.351
21	-1.888	-0.005	1.906	0.102	0.017	0.443	56.032
22	-1.164	-0.003	2.294	0.368	0.009	0.157	58.366
23	-1.781	-0.001	1.731	0.066	0.002	0.109	21.862
24	-0.956	-0.007	2.282	0.012	0.021	0.119	24.855

Table 2.17: The estimated parameters of the euro area TPN distribution

h	σ_1	σ_2	μ	$se(\sigma_1)$	$se(\sigma_2)$	$se(\mu)$	Distance
1	3.978	0.938	-3.722	0.435	0.094	0.879	13.664
2	3.995	0.672	-2.521	0.016	0.075	0.382	11.391
3	0.878	3.982	3.925	0.284	0.057	0.238	12.053
4	0.788	0.654	-0.037	0.568	0.486	0.622	12.447
5	0.556	3.813	-0.537	0.214	0.086	0.831	38.173
6	0.563	2.759	-1.119	0.269	1.122	2.021	39.192
7	1.775	1.130	0.056	0.535	0.496	0.682	41.988
8	0.073	3.990	-4.000	0.178	0.027	0.000	17.248
9	1.371	3.638	-0.760	0.772	1.378	3.161	28.764
10	1.646	3.834	-0.364	0.631	0.021	2.391	28.387
11	1.581	3.973	-0.639	0.585	0.084	0.503	30.421
12	1.607	1.831	-0.319	1.512	0.713	1.514	39.968
13	1.937	3.912	0.327	0.468	0.280	1.496	31.465
14	2.032	3.732	-0.270	0.337	0.343	1.675	41.709
15	1.890	1.655	-0.292	1.120	0.155	0.418	55.842
16	1.607	3.981	-0.963	0.503	0.445	1.527	40.106
17	1.286	3.992	-1.918	0.503	0.024	1.526	53.318
18	1.067	3.989	-1.179	0.313	0.035	0.825	55.714
19	2.413	2.532	-0.846	1.485	0.911	1.156	58.693
20	2.180	2.316	-0.902	0.807	0.226	0.688	58.963
21	2.271	2.302	-0.950	0.084	0.827	0.538	55.974
22	0.086	4.000	-4.000	0.214	0.000	0.000	17.927
23	2.192	2.011	-0.925	0.166	0.737	0.618	17.931
24	1.843	2.601	-1.381	0.748	0.891	1.199	18.385

2.8.6 The Cramér-von Mises test results

Let $X_1, \cdots, X_n$ be *iid* samples from unknown density F. Then whether this empirical density comes from the hypothesized density, F_0, can be tested.

$$H_0\colon\ F = F_0 \quad \text{vs.} \quad H_A\colon\ F \neq F_0$$

Under H_0, the Glivenko-Cantelli theorem is satisfied.

$$\sup_t |\hat{F}_n(t) - F_0(t)| \to 0$$

as $n \to \infty$. Thus, discrepancy measures can be used as a test statistics. The Cramér-von Mises test statistic is

$$C_n \equiv \int (\hat{F}_n(t) - F_0(t))^2 dF_0(t)$$

Table 2.18: Cramer-von Mises test statistics

	UK			Euro		
Horizon	WSN1	WSN2	TPN	WSN1	WSN2	TPN
1	0.185	0.185	0.333	0.164	0.164	0.333
2	0.190	0.190	0.333	0.146	0.147	0.333
3	0.202	0.202	0.194	0.135	0.135	0.333
4	0.202	0.201	0.201	0.148	0.145	0.145
5	0.199	0.201	0.198	0.145	0.144	0.188
6	0.201	0.203	0.198	0.145	0.144	0.127
7	0.206	0.208	0.203	0.148	0.148	0.133
8	0.210	0.211	0.210	0.158	0.158	0.133
9	0.216	0.217	0.211	0.139	0.152	0.142
10	0.218	0.219	0.219	0.159	0.156	0.157
11	0.227	0.228	0.228	0.163	0.144	0.155
12	0.226	0.227	0.223	0.149	0.151	0.158
13	0.245	0.246	0.243	0.154	0.154	0.184
14	0.251	0.254	0.326	0.151	0.152	0.162
15	0.262	0.263	0.326	0.148	0.148	0.157
16	0.270	0.269	0.270	0.178	0.148	0.158
17	0.269	0.268	0.263	0.154	0.156	0.144
18	0.265	0.266	0.331	0.153	0.143	0.177
19	0.267	0.268	0.270	0.150	0.145	0.142
20	0.269	0.271	0.276	0.151	0.153	0.152
21	0.276	0.273	0.279	0.149	0.151	0.148
22	0.276	0.276	0.281	0.151	0.155	0.150
23	0.275	0.276	0.280	0.172	0.175	0.168
24	0.274	0.274	0.278	0.165	0.166	0.166

Notes: WSN1 denotes the computed statistics assuming $\rho = 0.75$. WSN2 denotes the computed statistics assuming ρ decaying exponentially.

2.8.7 Copula functions

The discussions in this section are based on Durrelman, Nikeghbali and Roncalli (2000).

Gaussian copula

$$C(y_1, y_2; \rho) = \int_{-\infty}^{\Phi^{-1}(y_1)} \int_{-\infty}^{\Phi^{-1}(y_2)} \frac{1}{2\pi(1-\rho^2)^{1/2}} \exp\left\{\frac{-(s^2 - 2\rho st + t^2)}{2(1-\rho^2)}\right\} dsdt$$

Where $-1 < \rho < 1$ and Φ is the univariate standard normal distribution function. Two Gaussian marginal variables with Gaussian copula dependence structure, $C_{\rho}^{Ga}(\Phi(y_1), \Phi(y_2))$ is standard bivariate normal density with correlation coefficient ρ. The copula density is given by

$$\begin{aligned} c(y_1, y_2; \rho) :&= \frac{\partial^2}{\partial y_1 \partial y_2} \\ &= \frac{1}{\sqrt{1-\rho^2}} \exp\left\{\frac{2\rho\Phi^{-1}(y_1)\Phi^{-1}(y_2) - \rho^2(\Phi^{-1}(y_1)^2 + \Phi^{-1}(y_2)^2)}{2(1-\rho^2)}\right\} \end{aligned}$$

Archimedean copulas

A copula C is Archimedean if there exists a convex, decreasing function $\varphi(\cdot) : (0, 1] \to [0, \infty)$ such that

$$C(y_1, y_2) = \varphi^{-1}(\varphi(y_1) + \varphi(y_2))$$

where $\varphi(\cdot)$ is copula generator and $\varphi(1) = 0$. (Archimedean: Gumbel, Frank, Clayton)

Frank copula

The Frank copula is a symmetric Archimedean copula given by:

$$C(y_1, y_2; \theta) = -\frac{1}{\theta} \ln\left(1 + \frac{(e^{-\theta y_1} - 1)(e^{-\theta y_2} - 1)}{e^{-\theta} - 1}\right)$$

The generator for Frank copula is

$$\phi_\theta(t) = -\ln\left(\frac{e^{-\theta t} - 1}{e^{-\theta} - 1}\right)$$

The pdf of Frank copula is

$$c(y_1, y_2; \theta) = \frac{-\theta(e^{-\theta} - 1)e^{-\theta(y_1+y_2)}}{((e^{-\theta y_1} - 1)(e^{-\theta y_2} - 1) + (e^{\theta} - 1))^2}$$

Gumbel copula

The Gumbel copula is an asymmetric Archimedean copula, exhibiting greater dependence in the positive tail than in the negative.

$$C(y_1, y_2; \theta) = \exp\left[-\left\{(-\log y_1)^{1/\theta} + (-\log y_2)^{1/\theta}\right\}^{\theta}\right] \tag{2.21}$$

where θ is a dependent parameter, such that $0 < \theta \leq 1$. For $\theta = 1$, the Gumbel copula tends to independece case, i.e. product copula, while $\theta \to \infty$, it tends to be comonotonic. The generator for Gumbel copula is

$$\phi_\theta(t) = (-\ln t)^\theta$$

The density of Gumbel copula is

$$c(y_1, y_2; \theta) = C(y_1, y_2; \theta)$$

where $\tilde{y_1} = -\ln y_1$.

Clayton copula

The Clayton copula is an asymmetric Archimedean copula, exhibiting greater dependence in the negative tail than in the positive. The Clayton copula can be written as

$$C(y_1, y_2; \theta) = \max\left\{(y_1^{-\theta} + y_2^{-\theta} - 1)^{-1/\theta},\ 0\right\} \tag{2.22}$$

where $\theta \in (0, \infty)$. As θ approaches to zero, it tends to be independent copula, whereas if $\theta \to \infty$, it tends to Frechet-Hoeffding upper bound, i.e. perfect negative dependence. The generator for Clayton copula is

$$\phi_\theta(t) = \frac{1}{\theta}(t^{-\theta} - 1)$$

The pdf of Clayton copula is

$$c(y_1, y_2; \theta) = (1+\theta)(y_1 y_2)^{-1-\theta}(y_1^{-\theta} + y_2^{-\theta} - 1)^{-2-1/\theta} \tag{2.23}$$

2.8.8 The estimation results of Frank copula assuming ρ is constant

Table 2.19: Frank copula parameter and rank correlation coefficients

$Horizon$	γ	$se(\gamma)$	CvM	$Kendall$	$Spearman$
1	1.886	0.783	0.091	0.203	0.300
2	1.024	0.785	0.090	0.113	0.168
3	0.830	0.754	0.087	0.092	0.137
4	1.640	0.794	0.138	0.178	0.264
5	1.995	0.839	0.214	0.213	0.316
6	1.939	0.835	0.211	0.208	0.308
7	1.401	0.828	0.154	0.153	0.228
8	1.594	0.853	0.202	0.173	0.257
9	1.449	0.858	0.329	0.158	0.235
10	1.614	0.868	2.060	0.175	0.260
11	1.732	0.829	2.374	0.187	0.278
12	2.632	0.901	0.326	0.274	0.403
13	2.441	0.862	0.358	0.257	0.378
14	2.624	0.872	0.487	0.274	0.402
15	2.355	0.829	0.242	0.248	0.366
16	2.025	0.764	2.936	0.216	0.320
17	2.769	0.819	0.238	0.287	0.420
18	2.915	0.834	1.279	0.300	0.438
19	2.773	0.857	1.210	0.287	0.421
20	3.341	0.873	0.354	0.336	0.488
21	3.197	0.861	0.325	0.324	0.472
22	3.566	0.899	0.261	0.355	0.513
23	3.578	0.876	0.183	0.356	0.514
24	3.708	0.906	0.218	0.366	0.528

2.8.9 The rank correlation coefficients between the UK and the euro inflation uncertainty across all different horizons

Table 2.20: Kendall's τ correlation coefficients

UK/Euro	1	2	3	4	5	6	7	8
1	0.199	0.170	0.119	0.197	0.214	0.218	0.180	0.215
2	0.151	0.093	0.121	0.191	0.234	0.232	0.226	0.236
3	0.084	0.028	0.096	0.184	0.228	0.249	0.246	0.258
4	0.031	-0.043	0.014	0.159	0.202	0.214	0.211	0.232
5	-0.013	-0.086	-0.052	0.069	0.154	0.184	0.168	0.208
6	-0.034	-0.104	-0.070	0.028	0.085	0.151	0.152	0.183
7	-0.081	-0.143	-0.131	-0.038	0.011	0.058	0.111	0.153
8	-0.101	-0.182	-0.171	-0.092	-0.050	-0.002	0.038	0.121
9	-0.094	-0.201	-0.188	-0.139	-0.098	-0.080	-0.037	0.038
10	-0.097	-0.210	-0.226	-0.173	-0.150	-0.127	-0.108	-0.029
11	-0.063	-0.179	-0.199	-0.177	-0.157	-0.149	-0.119	-0.059
12	-0.100	-0.185	-0.197	-0.174	-0.153	-0.154	-0.146	-0.078
13	-0.063	-0.167	-0.179	-0.151	-0.135	-0.149	-0.155	-0.100
14	-0.100	-0.163	-0.199	-0.150	-0.129	-0.140	-0.155	-0.108
15	-0.073	-0.166	-0.205	-0.180	-0.124	-0.134	-0.153	-0.117
16	-0.090	-0.159	-0.201	-0.190	-0.147	-0.136	-0.156	-0.126
17	-0.074	-0.157	-0.204	-0.177	-0.166	-0.164	-0.167	-0.139
18	-0.070	-0.146	-0.200	-0.156	-0.146	-0.165	-0.171	-0.133
19	-0.050	-0.116	-0.167	-0.136	-0.115	-0.130	-0.161	-0.125
20	-0.054	-0.100	-0.126	-0.099	-0.077	-0.085	-0.118	-0.102
21	-0.051	-0.091	-0.115	-0.042	-0.044	-0.051	-0.076	-0.063
22	-0.028	-0.063	-0.067	0.000	0.013	-0.004	-0.025	-0.003
23	-0.069	-0.088	-0.091	0.007	0.044	0.034	-0.002	0.027
24	-0.071	-0.079	-0.081	0.027	0.057	0.061	0.031	0.048

Notes: The top row of the table shows forecast horizons of the euro area inflation uncertainty and the first column shows forecast horizons of the UK inflation uncertainty. Table 2.19 is continued to the next page so that the euro area forecast horizon ranges from 1 to 24.

[Table continued]

UK/Euro	9	10	11	12	13	14	15	16
1	0.176	0.173	0.189	0.223	0.164	0.162	0.129	0.116
2	0.232	0.208	0.226	0.261	0.244	0.204	0.176	0.154
3	0.246	0.243	0.227	0.259	0.251	0.225	0.174	0.173
4	0.235	0.255	0.239	0.259	0.268	0.250	0.216	0.184
5	0.213	0.255	0.266	0.261	0.269	0.273	0.237	0.222
6	0.206	0.243	0.286	0.282	0.296	0.303	0.266	0.243
7	0.180	0.251	0.293	0.307	0.317	0.322	0.287	0.267
8	0.153	0.217	0.283	0.301	0.321	0.326	0.302	0.290
9	0.104	0.180	0.250	0.298	0.306	0.321	0.304	0.302
10	0.022	0.131	0.209	0.256	0.300	0.306	0.293	0.305
11	-0.014	0.071	0.184	0.239	0.279	0.307	0.275	0.295
12	-0.036	0.042	0.130	0.213	0.257	0.281	0.271	0.289
13	-0.069	0.002	0.102	0.165	0.232	0.265	0.248	0.288
14	-0.085	-0.013	0.079	0.148	0.199	0.251	0.236	0.270
15	-0.090	-0.044	0.048	0.118	0.167	0.205	0.220	0.259
16	-0.115	-0.058	0.020	0.088	0.144	0.180	0.183	0.243
17	-0.140	-0.095	-0.012	0.049	0.100	0.136	0.147	0.206
18	-0.132	-0.101	-0.021	0.043	0.087	0.126	0.139	0.203
19	-0.113	-0.087	-0.028	0.019	0.077	0.105	0.107	0.174
20	-0.118	-0.076	-0.044	0.000	0.039	0.077	0.072	0.123
21	-0.093	-0.088	-0.046	-0.014	0.017	0.038	0.029	0.080
22	-0.041	-0.034	-0.010	0.014	0.038	0.056	0.027	0.062
23	0.008	0.001	0.024	0.050	0.063	0.077	0.059	0.073
24	0.025	0.029	0.037	0.055	0.071	0.086	0.052	0.076

[Table continued]

UK/Euro	17	18	19	20	21	22	23	24
1	0.143	0.110	0.130	0.101	0.126	0.127	0.122	0.098
2	0.160	0.148	0.136	0.144	0.128	0.155	0.149	0.129
3	0.148	0.138	0.138	0.134	0.131	0.145	0.158	0.141
4	0.175	0.159	0.160	0.151	0.141	0.147	0.149	0.134
5	0.176	0.164	0.170	0.167	0.152	0.145	0.151	0.129
6	0.214	0.166	0.173	0.170	0.153	0.147	0.144	0.118
7	0.233	0.196	0.176	0.176	0.165	0.152	0.158	0.130
8	0.264	0.222	0.212	0.192	0.169	0.163	0.167	0.148
9	0.288	0.260	0.242	0.226	0.186	0.179	0.183	0.162
10	0.299	0.270	0.263	0.250	0.210	0.191	0.187	0.175
11	0.306	0.286	0.273	0.272	0.232	0.220	0.201	0.188
12	0.299	0.286	0.290	0.278	0.240	0.236	0.223	0.198
13	0.294	0.288	0.307	0.305	0.269	0.267	0.255	0.232
14	0.295	0.282	0.301	0.324	0.293	0.300	0.289	0.270
15	0.283	0.285	0.300	0.331	0.307	0.316	0.319	0.303
16	0.276	0.275	0.294	0.322	0.305	0.321	0.330	0.322
17	0.266	0.271	0.289	0.313	0.309	0.338	0.349	0.341
18	0.247	0.282	0.301	0.318	0.312	0.345	0.364	0.362
19	0.215	0.234	0.300	0.323	0.308	0.338	0.370	0.369
20	0.169	0.187	0.229	0.300	0.286	0.318	0.354	0.356
21	0.131	0.149	0.188	0.236	0.258	0.288	0.320	0.328
22	0.105	0.133	0.167	0.212	0.218	0.276	0.308	0.311
23	0.099	0.122	0.158	0.201	0.206	0.251	0.315	0.311
24	0.073	0.087	0.122	0.163	0.175	0.219	0.262	0.298

Table 2.21: Spearman's ρ correlation coefficients

UK/Euro	1	2	3	4	5	6	7	8
1	0.289	0.250	0.180	0.289	0.312	0.316	0.270	0.312
2	0.216	0.136	0.173	0.279	0.339	0.341	0.332	0.343
3	0.119	0.044	0.132	0.282	0.334	0.358	0.346	0.369
4	0.043	-0.066	0.012	0.234	0.289	0.312	0.297	0.337
5	-0.020	-0.123	-0.083	0.110	0.227	0.266	0.241	0.294
6	-0.042	-0.153	-0.104	0.048	0.138	0.225	0.220	0.262
7	-0.117	-0.211	-0.184	-0.049	0.031	0.100	0.165	0.220
8	-0.140	-0.261	-0.244	-0.125	-0.058	0.010	0.058	0.169
9	-0.135	-0.289	-0.271	-0.190	-0.133	-0.096	-0.040	0.060
10	-0.150	-0.305	-0.322	-0.245	-0.205	-0.160	-0.135	-0.029
11	-0.100	-0.262	-0.292	-0.253	-0.218	-0.197	-0.161	-0.073
12	-0.146	-0.273	-0.286	-0.254	-0.219	-0.206	-0.193	-0.098
13	-0.098	-0.247	-0.263	-0.223	-0.196	-0.207	-0.210	-0.138
14	-0.143	-0.238	-0.291	-0.226	-0.190	-0.204	-0.222	-0.156
15	-0.110	-0.235	-0.293	-0.259	-0.194	-0.198	-0.223	-0.173
16	-0.137	-0.228	-0.286	-0.276	-0.223	-0.205	-0.231	-0.184
17	-0.110	-0.225	-0.287	-0.253	-0.249	-0.238	-0.237	-0.198
18	-0.105	-0.209	-0.286	-0.230	-0.213	-0.234	-0.248	-0.179
19	-0.069	-0.163	-0.239	-0.200	-0.176	-0.190	-0.231	-0.183
20	-0.081	-0.150	-0.190	-0.150	-0.125	-0.132	-0.177	-0.145
21	-0.077	-0.132	-0.179	-0.072	-0.076	-0.083	-0.120	-0.096
22	-0.046	-0.095	-0.106	-0.009	0.016	-0.005	-0.036	-0.011
23	-0.103	-0.128	-0.134	0.009	0.044	0.047	-0.007	0.036
24	-0.099	-0.111	-0.117	0.037	0.078	0.082	0.046	0.067

Notes: The top row of the table shows forecast horizons of the euro area inflation uncertainty and the first column shows forecast horizons of the UK inflation uncertainty. Table 2.20 is continued to cover all of the forecast horizons ($h = 1, \cdots, 24$) for the UK and the euro area.

[Table continued]

UK/Euro	9	10	11	12	13	14	15	16
1	0.258	0.247	0.270	0.315	0.234	0.230	0.177	0.169
2	0.335	0.301	0.311	0.358	0.332	0.279	0.247	0.214
3	0.348	0.348	0.318	0.361	0.351	0.313	0.249	0.245
4	0.331	0.359	0.341	0.366	0.378	0.348	0.302	0.263
5	0.299	0.353	0.371	0.376	0.383	0.384	0.331	0.312
6	0.292	0.338	0.390	0.390	0.414	0.418	0.364	0.343
7	0.253	0.340	0.394	0.422	0.436	0.450	0.399	0.379
8	0.214	0.293	0.375	0.411	0.439	0.448	0.429	0.414
9	0.147	0.249	0.331	0.404	0.416	0.435	0.421	0.428
10	0.041	0.186	0.289	0.354	0.408	0.418	0.405	0.430
11	-0.004	0.111	0.262	0.333	0.379	0.417	0.385	0.413
12	-0.043	0.069	0.185	0.298	0.354	0.384	0.374	0.402
13	-0.090	0.013	0.139	0.232	0.326	0.367	0.344	0.402
14	-0.124	-0.016	0.109	0.203	0.280	0.351	0.334	0.377
15	-0.136	-0.055	0.065	0.165	0.236	0.293	0.312	0.369
16	-0.163	-0.078	0.021	0.121	0.199	0.258	0.262	0.348
17	-0.195	-0.122	-0.016	0.074	0.145	0.202	0.223	0.299
18	-0.177	-0.121	-0.025	0.071	0.129	0.185	0.208	0.291
19	-0.154	-0.109	-0.039	0.034	0.112	0.156	0.163	0.254
20	-0.160	-0.092	-0.049	0.011	0.066	0.123	0.120	0.192
21	-0.128	-0.106	-0.047	-0.007	0.031	0.067	0.063	0.131
22	-0.057	-0.041	-0.010	0.026	0.056	0.087	0.059	0.113
23	0.012	0.013	0.036	0.078	0.100	0.116	0.105	0.127
24	0.036	0.049	0.062	0.088	0.117	0.138	0.094	0.128

[Table continued]

UK/Euro	17	18	19	20	21	22	23	24
1	0.193	0.144	0.184	0.145	0.182	0.173	0.170	0.139
2	0.215	0.202	0.186	0.200	0.186	0.218	0.209	0.182
3	0.207	0.198	0.198	0.187	0.193	0.204	0.226	0.194
4	0.247	0.226	0.230	0.227	0.208	0.213	0.219	0.197
5	0.254	0.236	0.247	0.246	0.225	0.218	0.225	0.195
6	0.304	0.236	0.251	0.256	0.225	0.226	0.222	0.187
7	0.341	0.281	0.262	0.268	0.244	0.243	0.246	0.203
8	0.380	0.323	0.311	0.289	0.259	0.260	0.261	0.232
9	0.407	0.365	0.349	0.337	0.279	0.277	0.283	0.252
10	0.430	0.387	0.384	0.366	0.315	0.295	0.295	0.275
11	0.435	0.403	0.394	0.394	0.339	0.325	0.305	0.283
12	0.424	0.403	0.412	0.404	0.353	0.342	0.332	0.299
13	0.415	0.407	0.429	0.436	0.384	0.384	0.375	0.342
14	0.418	0.398	0.431	0.457	0.410	0.417	0.417	0.387
15	0.405	0.403	0.432	0.474	0.430	0.439	0.454	0.428
16	0.392	0.385	0.427	0.466	0.439	0.455	0.472	0.461
17	0.382	0.382	0.411	0.458	0.440	0.475	0.492	0.484
18	0.355	0.388	0.417	0.451	0.447	0.487	0.520	0.513
19	0.315	0.336	0.413	0.450	0.427	0.476	0.508	0.515
20	0.263	0.277	0.332	0.423	0.401	0.445	0.492	0.492
21	0.206	0.223	0.273	0.344	0.364	0.410	0.445	0.457
22	0.170	0.201	0.241	0.309	0.316	0.394	0.432	0.432
23	0.167	0.189	0.230	0.296	0.302	0.360	0.440	0.434
24	0.135	0.150	0.196	0.253	0.259	0.321	0.379	0.418

2.8.10 The estimation results of Frank copula with matching horizons

Table 2.22: The estimates of Frank copula parameters: matching the same horizons

		Constant ρ				Decaying ρ			
h_{UK}	h_{EU}	γ	$se(\gamma)$	$Kendall$	$Spearman$	γ	$se(\gamma)$	$Kendall$	$Spearman$
1	1	1.886	0.783	0.203	0.300	1.886	0.783	0.203	0.300
2	2	1.024	0.785	0.113	0.168	1.022	0.784	0.112	0.168
3	3	0.830	0.754	0.092	0.137	0.823	0.751	0.091	0.136
4	4	1.640	0.794	0.178	0.264	1.783	0.800	0.192	0.285
5	5	1.995	0.839	0.213	0.316	1.984	0.837	0.212	0.315
6	6	1.939	0.835	0.208	0.308	1.878	0.830	0.202	0.299
7	7	1.401	0.828	0.153	0.228	1.341	0.820	0.146	0.218
8	8	1.594	0.853	0.173	0.257	1.539	0.848	0.167	0.249
9	9	1.449	0.858	0.158	0.235	1.273	0.830	0.139	0.208
10	10	1.614	0.868	0.175	0.260	1.684	0.858	0.182	0.271
11	11	1.732	0.829	0.187	0.278	2.167	0.874	0.230	0.340
12	12	2.632	0.901	0.274	0.403	2.307	0.876	0.244	0.360
13	13	2.441	0.862	0.257	0.378	2.297	0.838	0.243	0.358
14	14	2.624	0.872	0.274	0.402	2.552	0.849	0.267	0.392
15	15	2.355	0.829	0.248	0.366	2.401	0.833	0.253	0.372
16	16	2.025	0.764	0.216	0.320	2.713	0.841	0.282	0.413
17	17	2.769	0.819	0.287	0.420	2.777	0.819	0.287	0.421
18	18	2.915	0.834	0.300	0.438	3.017	0.856	0.309	0.451
19	19	2.773	0.857	0.287	0.421	3.252	0.860	0.329	0.478
20	20	3.341	0.873	0.336	0.488	3.354	0.868	0.337	0.490
21	21	3.197	0.861	0.324	0.472	3.326	0.873	0.335	0.487
22	22	3.566	0.899	0.355	0.513	3.665	0.893	0.362	0.523
23	23	3.578	0.876	0.356	0.514	3.654	0.872	0.362	0.522
24	24	3.708	0.906	0.366	0.528	3.784	0.913	0.372	0.536

Table 2.23: The estimates of Frank copula parameters: matching the horizons with highest Kendall's τ

		Constant ρ				Decaying ρ			
h_{UK}	h_{EU}	γ	$se(\gamma)$	$Kendall$	$Spearman$	γ	$se(\gamma)$	$Kendall$	$Spearman$
1	12	2.429	0.889	0.255	0.376	2.285	0.867	0.242	0.357
2	12	2.885	0.887	0.297	0.435	2.715	0.872	0.282	0.413
3	12	2.921	0.862	0.300	0.439	2.678	0.835	0.279	0.409
4	13	2.924	0.878	0.301	0.439	2.975	0.859	0.305	0.446
5	14	3.154	0.912	0.321	0.467	3.147	0.883	0.320	0.466
6	14	3.510	0.904	0.350	0.507	3.452	0.874	0.345	0.501
7	14	3.647	0.900	0.361	0.522	3.782	0.884	0.372	0.536
8	14	3.864	0.919	0.378	0.544	4.052	0.902	0.392	0.562
9	14	3.988	0.931	0.387	0.556	4.003	0.903	0.388	0.557
10	14	4.040	0.948	0.391	0.561	4.002	0.924	0.388	0.557
11	14	3.700	0.926	0.365	0.527	3.695	0.910	0.365	0.527
12	17	3.709	0.889	0.366	0.528	3.704	0.887	0.366	0.528
13	19	2.878	0.851	0.297	0.434	3.381	0.863	0.340	0.493
14	20	3.493	0.863	0.349	0.505	3.487	0.857	0.348	0.504
15	20	3.589	0.859	0.356	0.515	3.581	0.857	0.356	0.515
16	23	3.544	0.834	0.353	0.511	3.530	0.836	0.352	0.509
17	23	3.771	0.853	0.371	0.534	3.783	0.857	0.372	0.536
18	23	4.000	0.871	0.388	0.557	4.090	0.880	0.395	0.566
19	23	4.035	0.893	0.391	0.561	4.082	0.894	0.394	0.565
20	24	4.126	0.931	0.397	0.569	4.181	0.933	0.401	0.574
21	24	3.820	0.894	0.375	0.539	4.033	0.922	0.391	0.560
22	24	3.768	0.913	0.371	0.534	3.858	0.908	0.377	0.543
23	23	3.578	0.876	0.356	0.514	3.654	0.872	0.362	0.522
24	24	3.708	0.906	0.366	0.528	3.784	0.913	0.372	0.536

2.8.11 The unconditional and conditional probability of the UK inflation in two different cases

Table 2.24: The probabilities of the UK inflation below 1%

	Decaying ρ				Constant ρ			
h_{UK}	$Prob_I$	$Prob_{II}$	$Prob_{III}$	h_{EU}	$Prob_I$	$Prob_{II}$	$Prob_{III}$	h_{EU}
1	0.470	0.487	0.490	12	0.470	0.487	0.492	12
2	0.457	0.474	0.500	12	0.457	0.475	0.503	12
3	0.454	0.480	0.523	12	0.455	0.471	0.511	12
4	0.424	0.493	0.526	13	0.424	0.486	0.522	13
5	0.419	0.496	0.524	14	0.418	0.497	0.525	14
6	0.422	0.494	0.534	14	0.423	0.496	0.534	14
7	0.416	0.471	0.534	14	0.416	0.473	0.534	14
8	0.402	0.457	0.509	14	0.404	0.461	0.509	14
9	0.422	0.463	0.520	14	0.422	0.469	0.502	14
10	0.412	0.465	0.513	14	0.412	0.453	0.526	14
11	0.424	0.481	0.498	14	0.418	0.462	0.523	14
12	0.415	0.452	0.449	17	0.413	0.463	0.475	17
13	0.440	0.491	0.498	19	0.438	0.499	0.507	19
14	0.449	0.492	0.495	20	0.439	0.500	0.518	20
15	0.455	0.483	0.480	20	0.455	0.473	0.463	20
16	0.458	0.474	0.468	23	0.461	0.492	0.531	23
17	0.449	0.449	0.432	23	0.450	0.454	0.436	23
18	0.446	0.413	0.388	23	0.441	0.433	0.425	23
19	0.447	0.412	0.393	23	0.446	0.469	0.479	23
20	0.443	0.398	0.377	24	0.440	0.407	0.388	24
21	0.456	0.406	0.388	24	0.462	0.393	0.373	24
22	0.444	0.389	0.385	24	0.452	0.434	0.431	24
23	0.435	0.345	0.345	23	0.440	0.380	0.380	23
24	0.418	0.348	0.348	24	0.415	0.336	0.336	24

Notes: $Prob_I$ denotes unconditional probability, $Prob_{II}$ conditional probability with same horizons matched between the UK and euro area, and $Prob_{III}$ conditional probability with different horizons matched that yield the highest rank correlation. h_{EU} denotes the matching horizons for euro area.

Table 2.25: The probabilities of the UK inflation between [1%, 3%]

	Decaying ρ				Constant ρ			
h_{UK}	$Prob_I$	$Prob_{II}$	$Prob_{III}$	h_{EU}	$Prob_I$	$Prob_{II}$	$Prob_{III}$	h_{EU}
1	0.520	0.520	0.520	12	0.520	0.520	0.520	12
2	0.513	0.513	0.514	12	0.512	0.513	0.514	12
3	0.490	0.492	0.494	12	0.489	0.491	0.494	12
4	0.512	0.519	0.523	13	0.516	0.525	0.530	13
5	0.496	0.507	0.512	14	0.496	0.506	0.511	14
6	0.487	0.509	0.524	14	0.481	0.505	0.520	14
7	0.483	0.502	0.527	14	0.482	0.501	0.525	14
8	0.471	0.496	0.526	14	0.468	0.494	0.522	14
9	0.444	0.467	0.502	14	0.441	0.454	0.474	14
10	0.438	0.471	0.504	14	0.435	0.503	0.578	14
11	0.414	0.445	0.460	14	0.422	0.510	0.560	14
12	0.386	0.416	0.428	17	0.385	0.432	0.452	17
13	0.381	0.415	0.426	19	0.382	0.434	0.444	19
14	0.352	0.399	0.410	20	0.366	0.438	0.458	20
15	0.330	0.373	0.387	20	0.319	0.357	0.369	20
16	0.311	0.363	0.373	23	0.298	0.416	0.444	23
17	0.311	0.357	0.367	23	0.319	0.361	0.370	23
18	0.266	0.318	0.329	23	0.263	0.329	0.343	23
19	0.273	0.329	0.337	23	0.296	0.379	0.391	23
20	0.265	0.323	0.331	24	0.287	0.342	0.349	24
21	0.249	0.304	0.311	24	0.235	0.280	0.284	24
22	0.241	0.305	0.307	24	0.279	0.346	0.347	24
23	0.228	0.283	0.283	23	0.269	0.322	0.322	23
24	0.239	0.304	0.304	24	0.237	0.295	0.295	24

Notes: $Prob_I$ denotes unconditional probability, $Prob_{II}$ conditional probability with same horizons matched between the UK and euro area, and $Prob_{III}$ conditional probability with different horizons matched that yield the highest rank correlation. h_{EU} denotes the matching horizons for the euro area.

Chapter 3

The Uncertainty and Capital Flows: Evidence of Spillover Effect

Abstract

This chapter examines the long run relationship between gross capital flow and its determinants, focusing on the impact of uncertainty as global and contagion factors. We apply bounds testing approach by Pesaran, Shin, and Smith (2001) allowing for the underlying regressors being either I(0), I(1) or mutually cointegrated. Both gross capital inflows and outflows exhibit significant level relationship with global, contagion and domestic factors and uncertainty spillovers through financial linkages between the UK and the euro area play crucial role in predicting capital flows of the UK.

3.1 Introduction

A seminal paper by Bloom (2009) has provoked burgeoning literature on uncertainty and its effects on real activities in closed economy models. Literature explores the issues of measurement, countercyclicality and theoretical mechanisms behind uncertainty shocks (see, among others, Baker, Bloom and Davis, 2015; Jurado, Ludvigson and Ng, 2015; Clements, 2014; Gilchrist, Sim, and Zakrajšek, 2014). At the same time, a large number of attempts to explain the uncertainty effect on financial markets have been made.[1] However, until most recently, the study of uncertainty in the open economy setting has been strikingly underdeveloped relative to the importance of the role of uncertainty in the dynamics of cross-border capital flows.

[1] See Appendix 3.6.1. for related literature.

Most of existing studies of uncertainty and capital flows mainly focused on setting up theoretical models of *portfolio* capital flows, some of which built on the general equilibrium model of international portfolio allocations.[2] However, they mostly failed to adopt elaborate notions of uncertainty that has recently developed. Theoretical papers overlooked the substantial differences among the various concepts of risk and uncertainty. Moreover, empirical papers largely relied on financial volatility measures as a proxy for uncertainty, which may not reflect precise concept of uncertainty *per se*.[3]

The recent development in measuring different types of uncertainty may shed lights on examining the uncertainty effect on capital flows. Such measures include Economic Policy Uncertainty (EPU) index by Baker, Bloom and Davis (2015), macroeconomic uncertainty by Jurado, Ludvigson and Ng (2015), professional forecasters' disagreement measures by Clements (2014), *inter alia*.[4] Among many, this chapter pay attention to a novel uncertainty measure, Geopolitical Risk (GPR) index by Caldara and Iacoviello (2016).

The econometric models using GPR index have a potential to identify the causal relationship between the geopolitical uncertainty and cross-border capital flows. GPR index is a news-based index that captures worldwide geopolitical tensions and threats. Caldara and Iacoviello found empirical evidence of economic links between GPR index and financial markets (and cross-border flows). That is, an increase in GPR index is associated with an increase in financial market volatility and has adverse effects on global economic activities and cross-border capital flows. In addition, the index is relatively less disturbed by endogeniety problem because it measures the episodes of geopolitical tensions which cannot be predicted directly by macroeconomic conditions contemporaneously.

This study is also related to the traditional literature on capital flows. Literature on push-pull factors of capital flows often distinguishes external (*push*) and domestic (*pull*) factors of capital flows. For emerging countries, the influence from monetary and fiscal policies of advanced economies has considered as important sources of push factors. In addition, the divergence in macroeconomic fundamentals between emerging and advanced countries (i.e. domestic pull factors) are crucial drivers of capital flows. Among recent development in the literature, Forbes and Warnock (2012a) made a clear distinction between global and contagion factors among external (*or push*) factors. Global factors are external determinants that have universal effect on capital flows worldwide and contagion factors are defined over certain regions connected via

[2]See Appendix 3.6.1. for related literature.

[3]See Chapter 1 of this thesis for the discussions about the difference between risk and uncertainty. Makarova (2014) also discussed extensively about the different notions of uncertainty and related concepts.

[4]In general, different measures capture different aspects of uncertainty and the implications of empirical results might vary across the measures.

bilateral relationships. The distinction between the two concept of push factors are crucial because the transmission channels and the effect of global shocks and regional shocks may differ significantly. In the literature, global uncertainty often refers to the uncertainty changes stemming from the United States which has dominant power in the international financial market. The interconnectedness in trade and financial transactions between two countries are common measures for contagion factors from one region to the other. Therefore, we disentangle the impact of contagion factors from that of global uncertainty (geopolitical uncertainty). Furthermore, we identify the contagion in uncertainty and estimate its effect on capital flows.

The other important contribution of the study is that it looks into *gross* capital flows rather than *net* capital flows. Numerous studies analysed determinants of *net* capital flows and examined episodes of sudden and large reversals of *net* capital flows (the mirror image of current account imbalances).[5] Lately, a substantial number of studies have paid more attention to the gross international investment positions rather than the net positions of capital flows.[6] Forbes and Warnock (2012a) found that, despite well-managed net international investment position, large changes in gross assets and liabilities could damage financial stability in crisis episodes. As Fratzscher (2012) pointed out, the incentive of gross capital inflows by foreign investors might differ from the ones of gross capital outflows by domestic investors.[7] In order to study such different underlying forces of capital movement, this research focuses on the gross capital flows.

This chapter particularly examines the dynamics of capital flows in the United Kingdom, acknowledging the close relationship between the UK and the other European Union (EU) countries. As one of the member state of the EU, the UK economy shares the Single Market that allows free movement of goods, services and labour forces while it opted out of the adoption of common currency, euro. As a consequence of such bond, trade between the UK and EU countries constitutes the largest proportion of the total exports and imports.[8] Moreover, the UK takes up the key position of international financial centre within Europe. The UK financial institutions' exposure to the euro area poses great risk to the stability of the financial system in the UK and to the sudden reversal of cross-border capital flows. Thus, the bilateral trade and financial links between the euro area and the United Kingdom might be of a great importance to understand the uncertainty contagion effects on capital flows of the area. Although

[5]See Appendix 3.6.1. for related literature.

[6]See Appendix 3.6.1. for related literature.

[7]Gross capital inflows is defined as net of foreign purchase of domestic assets and foreign sales of domestic assets. Similarly, gross capital outflows can be defined as net of residents' purchase of foreign assets and sales of foreign assets. Obviously, net capital flows is the sum of those two.

[8]In 2015, 44% of the UK's goods and services were exported to the EU, while 53% of imports came to the UK from the EU.

it may be too early to appraise the consequences of the decision of the UK leaving the Single Market (so called, Brexit) by the referendum in June 2016, the examination of uncertainty contagion effects on capital flows would provide meaningful insights.

In terms of the empirical emphasis, this research intends to shed light on the long run relationship of uncertainty factors (both global uncertainty and contagions in uncertainty) and capital flows in the UK. To my knowledge, the long run relationship of the capital flows and uncertainty is less explored in the literature. We employ bounds testing approach of testing level relationship by Pesaran, Shin, and Smith (2001). The model allows for the testing of the existence of a relationship between variables in level irrespective of the underlying regressors being either I(0), I(1), or mutually cointegrated. The conditional error correction model estimation is to be followed to examine the short run dynamics.

Briefly, the research questions to be addressed are as follows. In the long run, does geopolitical uncertainty contain any marginal information about the dynamics of capital flows in the UK, controlling for contagion and domestic factors? Do contagion factors help understanding the Britain's gross capital flows? How to measure the uncertainty contagion due to trade and financial linkages between the UK and the euro area? Does the measured contagion play a significant role in predicting the long run capital flows, holding other factors constant? Do the effects differ by different dependent variables, inflows and outflows? What are other domestic factors that exhibit long run relationship with gross capital flows?

To answer the questions, Section 3.2 examines the definitions and channels of contagion effect. Section 3.3 discusses the empirical strategy and data. Section 3.4 presents the main results and provides robustness checks. Section 3.5 concludes.

3.2 Contagions: Definitions and Channels

Among push factors, it has gained more recognition in the literature that contagion factors among a certain group of countries needs to be taken account for separately from global factors that have worldwide effect. Forbes and Warnock (2012a) clearly drew such a distinction. They defined that global factors are external determinants that have universal effect on international capital flows. Contagion is defined as the consequences due to the shocks from another country or group of countries often with bilateral trade and/or financial relationships. The transmission channels of global and contagion factors may be quite different. For example, changes in global risk appetite may lead to overall contraction of capital inflows in emerging countries while changes in drivers of contagion among the region may have diverse outcomes in capital flows depending on the situation and the degree of linkages among countries. Therefore, the distinction allows the estimation of differential effects from global or contagion factors separately.

Contagion is initially studied by Claessens, Dornbusch and Park (2001) and Claessens and Forbes (2001). The three main issues in the literature are how to define contagion, what is the underlying channel through which the spillover occurs, and how to measure the degree of contagion empirically. In fact, the definition of contagion is a contentious issue.[9] Spillover and interdependence is also related concepts, which are used quite interchangeable with contagion in the literature.[10] Table 3.1. summarises the definition, channels and measures of contagion and other related notions describing dependence structure.

Table 3.1: Definitions, channels and measures of contagion

Paper	Definition	Channels	Measures
Claessens, Dornbusch, and Park (2001)	the spread of market disturbances from one country to the other, a process observed through co-movement in asset prices	(1) Fundamental-based contagion (2) Contagion resulted from the behaviour of investors	(1) Correlation of asset prices (2) Conditional probabilities (3) Volatility spillover (4) Capital flows tests
Forbes (2012)	(1) Interdependence: high correlations across markets during all states of the world (2) Contagion: the spillovers from extreme negative events	(1) Trade channel (2) Bank lending (3) Portfolio investors (4) Wake-up calls	(1) Probability analysis (2) Cross-market correlations (3) VAR models (4) Latent factor/GARCH models (5) Extreme values/Co-exceedance/Jump approach
Rigobon (2016)	(1) Contagion/spillovers: the phenomenon in which a shock from one country is transmitted to another (contagion tends to be more relevant during crises.) (2) Shift-contagion: contagion when there exists parameter instability	(1) Fundamental view: real channels (2) Financial view: bank, capital market, network (3) Coordination view: investors' actions (learning or herding behaviour, multiple equilibrium, political contagion)	(1) Non-parametric methods: correlation, principal components (2) Linear regression models: VAR, ARCH/GARCH models (3) Event studies (4) Probability models (5) New methods: under parameter stability or instability

Spillover and contagion refer to similar phenomenon but contagion is used when the spillover occurs with crises or negative events. The notion of interdependence is more neutral as it simply means high correlation during all states of economy while contagion implicitly (or explicitly) contains negative connotation. Recent paper by Rigobon (2016) defines shift-contagion, which assumes parameter instability.

[9]See Forbes and Rigobon (2002) and Forbes (2012) for the comprehensive summary of various definitions of spillover and/or contagion.

[10]In fact, one very recent paper by Rigobon (2016) is titled "Contagion, Spillover and Interdependence", comprising all three related concepts.

The main focus here is to examine the channels of contagion between two economies and its effect on capital flows while keeping the issue of definition as simple as possible. In the capital flows literature, the main interest is simply to estimate the association between various contagion factors and capital flows controlling for other global and domestic factors. To elaborate on this, I will illustrate the channels of such contagions that are largely discussed in recent studies: trade channel, bank lending channel, and channels that emphasize investors' behavioural aspects.

A large number of theoretical studies have been striving to explain contagion by bilateral trade (see, for example, Glick and Rose, 1999; Forbes, 2002; Abeysinghe and Forbes, 2005; IMF, 2016). The conventional explanation of how bilateral trade linkages affect capital flows (without introducing co-movement in uncertainty) is as follows. Assume country A and B exhibit high economic connection via bilateral trade. Suppose that country A faces significant exogenous negative shock while the economic conditions of country B (and other countries) remain unchanged. Due to adverse prospects of economic growth in A along with weaker home currency, it is likely that portfolio investment shifts abroad and the performance in domestic equity and bond market can be worse off in country A relative to other economies. This may lead to a potential increase in capital inflow to country B like any other countries. It is important to point out that increased capital inflows to country B followed by the initial adverse shock in country A have nothing to do with trade links between two countries. Higher trade share between A and B implies that a large proportion of firms in the stock market in country B export to country A. Therefore, weak demand of A due to unanticipated negative shocks may lead to capital flights from B without any changes in macroeconomic fundamentals of B. If the contagion effect due to trade linkages is significant and larger then the initial effects, capital inflows stops and outflows increases. In the medium term, country A would regain competitiveness due to the devaluation of its currency. As a result, the adjustment in equity market of B takes place, putting more adverse pressure on the dynamics of capital flows.

Besides the adjustment through trade channel, an uncertainty shock to country A can trigger financial market turbulence in country B via bank lending channel. Initial uncertainty shock to country A leads to a rapid reduction in bank credit supply, deteriorating liquidity and causing the upturn of domestic interest rates. These changes in the situations of domestic banking sector can spread to other economies through various means. Banks in the country hit by uncertainty shocks can be forced to diminish lending to foreign borrowers in order to meet capital requirement and other regulations. In addition, domestic banks in other countries can directly reduce lending in the home markets because their balance sheets can be deteriorated by the initial shocks in country A due to cross-border lending. The negative impacts through bank lending channel can be aggravated even more with higher banking leverage. For example, Shin (2012) showed that the leveraging/deleveraging cycle of global banks can play an important role for global financial stability. The universal contraction in bank lending raises cost of capital, impeding firms' investment for both the country where the initial shocks were originated and other foreign countries. Consequently, capital flows can be mainly driven by flight-to-quality incentives, as initially proposed by Bernanke, Gertler, and Gilchrist (1996).[11]

Recent studies have also found that the role of end investors and asset managers is important for explaining contagion effect on global portfolio investments (see IMF, 2015 for comprehensive theoretical background and empirical evidence). Among various explanation of such channels, portfolio rebalancing effect has been widely recognized in the literature. A shock in one country can cause domestic asset prices to drop, leading to redemption threat or actual run by the end investors in other countries. Facing such withdrawals (and/or potential withdrawals), portfolio managers would reduce investments so that the fund can comply with its mandates to maintain certain level of total risk exposures. Through this portfolio rebalancing effect, the asset prices tend to fall in both the stressed country and the other countries, even if they are seemingly unrelated. One recent example other than the US being the origin of uncertainty shock is the spillover effect of Britain's referendum results on leaving the EU (so called 'Brexit'). The decision has significantly influenced the dynamics of international capital flows of neighbouring European countries as well as other large advanced countries such as the US and Japan.

Studies of herding behaviour among investors is one of the earliest attempts focusing on the investors' behaviour. Calvo and Mendoza (2000) suggested that herding behaviour can worsen the condition when the global financial market is hit hard by a negative shock. There have been a large number of theoretical developments in recent studies. Hau and Rey (2008) demonstrated the model where the fund managers have incentives of rebalancing portfolios in order to manage foreign exchange rate risk and equity risk. Bacchetta, Tille and Van Wincoop (2012) and Bacchetta and Van Wincoop (2013) studied risk panics in investor behaviour with an emphasis of self-fulfilling panics and multiple equilibria.

In addition, the wake-up call effect (Goldstein, 1998; Ahnert and Bertsch, 2015) has been largely mentioned as a potential channel of financial spillover. After an extreme event occurs in one country, investors tend to reassess the fundamentals of the whole region which the stressed country is located in and/or is more similar to. As a result of uncertainty shock to one country, a wake-up call for the other related countries can stimulate the immediate capital outflows followed by equity market downside risks and increased credit spreads. In the empirical papers, dummy variables of countries' credit ratings (Forbes, 2012) or the similarities between countries (Dasgupta, Leon-Gonzalez,

[11] Other recent literature in the field are Bruno and Shin (2015), Cerutti, Claessens, Ratnovski (2014), Bordo, Duca, and Koch (2016).

and Shortland, 2011; IMF, 2016) were used to capture the wake-up call effect.

To expand the discussion, contagion in uncertainty and its effect on capital flows can be further introduced. That is, co-movement in uncertainty among a certain group of countries due to trade and financial linkages may also be associated with changes in capital flows. Assume now an increase in uncertainty in country A. An uncertainty shock about the fundamentals of A can halt the firms' investment decision and cause contractions in output and income of country A (wait-and-see effect). An accelerated level of uncertainty of A can prompt hardships in predicting demands for goods and services that are produced domestically and imported alike. This could lead to spillover in uncertainty of country B via trade channel. Uncertainty of two counties may move in tandem also because of financial links via bank lending and/or portfolio investments channel. As a result, wait-and-see effect also applies to country B, slowing down economic activities and potentially resulting in capital movements. The recent examples of such contagion effect can be found without much efforts. Unstable political situations of leading economies in the European Union (EU) brought about increased uncertainty in the region as a whole since the Brexit discussion.

However, it is unclear about the outcomes of the changes in individual contagion factors on co-movement in uncertainty and capital flows. First, it has not been explored in the literature whether and how the economic and financial linkages affect the synchronization of uncertainties of two economies. In addition, the degree of contagion in uncertainty may have heterogeneous effects on capital flows depending on the underlying economic relationship between two countries. This research aims at offering empirical evidence of such associations in contagions in uncertainty and capital flows.

3.3 Empirical Strategy and Data

3.3.1 Empirical models

To address the long run relationship between the gross captial flows and global, contagion and domestic factors, I will employ ARDL model with the bounds testing for the analysis of level relationships by Pesaran, Shin and Smith (2001), henceforth PSS.[12] First, consider a VAR(p) model augmented with deterministic variables such as an intercept and time trends. Notice that PSS model allows the underlying regressors to be either I(0), I(1), or mutually cointegrated. Let $\boldsymbol{z}_t = (c_t, \boldsymbol{x}_t')'$, where c_t is either gross capital inflows (CFI_t) or gross capital outflows (CFO_t), $\boldsymbol{x}_t$ is a vector that contains determinants of capital flows. Determinants consist of three parts: global ($\boldsymbol{G}_t$), contagion

[12] Related recent literature that applied ARDL model for aggregate bank lending is Bordo, Duca, and Koch (2016). However, this paper does not consider bounds testing for the existence of long run relationship.

($\boldsymbol{C}_t$), and domestic factors ($\boldsymbol{D}_t$), so that $\boldsymbol{x}_t' = (\boldsymbol{G}_t, \boldsymbol{C}_t, \boldsymbol{D}_t)$. The list of determinants in the benchmark model is summarised in Table 3.2.[13] A dummy variable is also included to take account for the potential structural break after the Great Financial Crisis in 2008. The dummy variable is defined by $D_{2008,t} = 1$ after 2008q2, 0 otherwise.

$$\Delta c_t = \alpha + \beta_1 t + \beta_2 D_{2008,t} + \pi_{cc} c_{t-1} + \boldsymbol{\pi}_{cx.x} \boldsymbol{x}_{t-1} + \sum_{i=1}^{p} \boldsymbol{\Pi}_i' \boldsymbol{\Delta z}_{t-i} + \boldsymbol{\delta}' \boldsymbol{\Delta x}_t + u_t \quad (3.1)$$

Table 3.2: Determinants of capital flows

Global Factors ($\boldsymbol{G}_t$)	Contagion factors ($\boldsymbol{C}_t$)	Domestic factors ($\boldsymbol{D}_t$)
Global uncertainty	Trade linkages	Domestic growth
Risk-free interest rate	Financial linkages	Inflation
Global growth	International investors' behaviour	Public debt

Several specifications are considered with regards to how contagion factors ($\boldsymbol{C}_t$) are identified in the regression. Initially, three contagion factors (trade linkages, financial linkages and international investors' behavioural aspects) are included directly in the regression equation as appeared in existing capital flows literature (*Spec 1*). In addition to this benchmark model, a novel approach is proposed based on the potential association of uncertainty co-movement with contagion factors (listed above) and capital flows movement.

Uncertainty co-movement index ($Comov$) is measured with the negative of divergence in Economic Policy Uncertainty index (U) by Baker, Bloom and Davis (2015). The co-movement is defined as the absolute value of uncertainty index differences between the UK (i) and other core EU countries (j) in quarter t.

$$Comov_t \equiv -|(\ln U_{i,t} - \ln U_{i,t-1}) - (\ln U_{j,t} - \ln U_{j,t-1})| \quad (3.2)$$

The choice of co-movement index follows the methodology of constructing the business cycle synchronization by Kalemli-Ozcan, Papaioannou and Perri (2013), considering its advantage over the correlation coefficient in the presence of structural breaks. The correlation coefficient on a rolling average basis is likely to be sensitive to the structural breaks and problematic if the number of observations after the break are insufficient (see Doyle and Faust, 2005).

Upon constructing uncertainty co-movement index, a natural conjecture is to infer that co-movement in uncertainty itself is a prospective contagion factor. Grounded on this assumption, the raw series of uncertainty co-movement index can replace the three individual contagion factors in the benchmark model (*Spec 2*). In terms of the notation in equation (3.1), $\boldsymbol{x}_t' = (\boldsymbol{G}_t, \boldsymbol{C}_t, \boldsymbol{D}_t)$, where $\boldsymbol{C}_t$ is $Comov_t$, defined by equation (3.2).

[13]See Appendix 3.6.2. for the examples of push-pull factors in the literature.

Furthermore, two stage estimation is suggested by hypothesizing that uncertainty of two economies with strong economic and financial linkages may be highly synchronized (*Spec 3*). The first step is to show that contagion variables predict synchronization (or co-movement) of uncertainty between two regions. To reveal the association between uncertainty co-movement and traditional contagion factors, the following first-stage regressions are estimated:

$$Comov_t = \beta_0 D_{2008,t} + \beta_1 CoBC_t + \sum_{i=0}^{p} \boldsymbol{\Phi}_i \boldsymbol{C}_{t-i} + \varepsilon_t \tag{3.3}$$

where $Comov_t$ is a time-varying measure of co-movement of uncertainty as defined in equation (3.2). D_{2008} is a dummy variable indicating the structural break after the Great Financial Crisis in 2008, $CoBC$ is the co-movement index of leading indicator of business cycle, and $\boldsymbol{C}_t$ is a vector including three contagion factors. The regression is simple Finite Distributed Lag (FDL) model augmented by business cycle component to control for general macroeconomic fundamentals, expecting to ensure contemporaneous exogeneity. For OLS estimator in FDL model being asymptotically consistent, all variables are required to satisfy weak dependence and stationarity assumption. Therefore, I(0) variables are included as in levels while I(1) variables are first differenced.[14] The appropriate lags of regressors are chosen by information criteria (AIC) and the absence of serial correlation in error term. In addition, the model imposes the restriction on constant term being zero before the 2008 Financial Crisis by excluding intercept term but including dummy variable (D_{2008}). The rationale for implementing regression through the origin (RTO) is based on the assumption that uncertainty is purely random for both countries when there is no changes in contagion factors and other macroeconomic conditions. It is not entirely unjustifiable to assume that the direction and size of the changes in uncertainty of two economies are identical, so that the co-movement index is zero in such cases. The statistical inference of the coefficient on the dummy variable indicates whether there is a significant structural break regarding this assumption after 2008.

Then, in the second stage, the impact of the *predicted* uncertainty co-movement on capital flows is examined. Instead of three individual contagion factors (*Spec 1*) or the raw series of uncertainty co-movement (*Spec 2*), the fitted value of uncertainty co-movement is included in the vector of regressors, $\boldsymbol{x}_t$. Therefore, the determinants vector for two stage approach becomes $\boldsymbol{x}_t' = (\boldsymbol{G}_t, \widehat{\boldsymbol{C}_t}, \boldsymbol{D}_t)$ in equation (3.1), where $\widehat{\boldsymbol{C}_t}$ is obtained by projecting uncertainty co-movement on contagion factors. If contagion factors are indeed an effective predictor of uncertainty co-movement, it could uncover the link between contagion, proxied by uncertainty co-movement, and capital flows.

For all three different specifications in equation (3.1), the next step is to test the long-run level relationship among variables. In order to test the existence of the long

[14]The statistical descriptions of all variables are detailed in Section 3.3.2.

run relationship, it is crucial to define different scenarios for the deterministic intercept and trends. Referring to the notation of PSS, the scenarios are as follows.[15]

Case III: unrestricted intercepts and no trends

$$\Delta c_t = \alpha + \pi_{cc} c_{t-1} + \boldsymbol{\pi}_{cx.x} \boldsymbol{x}_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\Pi}_i' \boldsymbol{\Delta z}_{t-i} + \boldsymbol{\delta}' \boldsymbol{\Delta x}_t + u_t \tag{3.4}$$

Case IV: unrestricted intercepts and restricted trends

$$\Delta c_t = \alpha + \pi_{cc}(c_{t-1} - \gamma_c t) + \boldsymbol{\pi}_{cx.x}(\boldsymbol{x}_{t-1} - \boldsymbol{\gamma}_x t) + \sum_{i=1}^{p-1} \boldsymbol{\Pi}_i' \boldsymbol{\Delta z}_{t-i} + \boldsymbol{\delta}' \boldsymbol{\Delta x}_t + u_t \tag{3.5}$$

Case V: unrestricted intercepts and unrestricted trends

$$\Delta c_t = \alpha + \beta_1 t + \pi_{cc} c_{t-1} + \boldsymbol{\pi}_{cx.x} \boldsymbol{x}_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\Pi}_i' \boldsymbol{\Delta z}_{t-i} + \boldsymbol{\delta}' \boldsymbol{\Delta x}_t + u_t \tag{3.6}$$

Based on each scenario, the test statistics are defined. F_{III} is the F-statistic for testing the null hypothesis, $H_0 : \pi_{cc} = 0$, $\boldsymbol{\pi}_{cx.x} = \mathbf{0}'$ with c_1 set equal to zero. F_{IV} is the F-statistic for testing $H_0 : \pi_{cc} = 0$, $\boldsymbol{\pi}_{cx.x} = \mathbf{0}'$, and $\beta_1 = 0$. F_V is the F-statistic for testing $H_0 : \pi_{cc} = 0, \boldsymbol{\pi}_{cx.x} = \mathbf{0}'$. t_{III} is the t-ratio for testing $\pi_{cc} = 0$ without a deterministic trend in Case III model. t_V is the t-ratio for testing $\pi_{cc} = 0$ with a deterministic trend in Case IV model. The critical value bounds for the statistics are given in the paper by PSS. In testing the coefficients on level relationship, the appropriate lag structure is searched by information criteria and the absence of serial correlation, remaining the coefficients of ECM model unrestricted.

Once hypothesis testing results confirm the long run relationship, the short run dynamics of capital flows adjustment is estimated. For the estimation of the conditional ECM regression associated with the level relationship, the lag orders of an ARDL model are chosen by the AIC criterion without restrictions on coefficients. The regressions are further examined by diagnostic tests for no residual serial correlation, normal errors, heteroscedasticity, and no functional form misspecification test. Based on the estimation results of the conditional ECM, the statistical inference can be performed to provide evidence on the short run dynamics between capital flows and determinants. For example, the estimated coefficient on the equilibrium correction term illustrates the link between long run and short run dynamics. The dynamic stability of the auxiliary equation of the AR (autoregressive) components can be tested to provide information of whether the process converges to long run equilibrium.

[15]For simple representation, dummy variables for structural breaks are omitted in each equations, equation (3.4)-(3.6), but included in the actual estimation

3.3.2 Data

I construct a comprehensive dataset of gross capital flows of the United Kingdom, inflows by foreign agents and outflows by residents, and determinants. As detailed in Table 3.2, the list of determinants are as follows: (i) global factors (global uncertainty, risk-free interest rate, global output growth), (ii) contagion factors (trade linkages, financial linkages, international investors' behaviour), and (iii) domestic factors (GDP growth, inflation, public debt). In addition, I will discuss how to build uncertainty co-movement index for the two stage estimation using Economic Policy Uncertainty index for the UK and the other European countries. Considering the availability of the data, the sample period is set from 1985q1 to 2016q2. The sample period is selected to capture the average long run effect over three decades.[16]

The data of gross capital flows (see Figure 3.1) come from the IMF's Balance of Payments Statistics (BOPS). BOPS includes aggregate and detailed time series of transactions between residents and non-residents. It comprises the goods and services account, the primary income account, the secondary income account, the capital account, and the financial account. The dataset reports the financial flows involving the reporting country's assets and liabilities vis-à-vis non-residents. IMF's Balance of Payment data covers a comprehensive range of financial flows (including FDIs, debt and equity in portfolio flows as well as other investment intermediaries) but captures capital flows between a given country and the rest of the world. Therefore, it is impossible to track bilateral flows using BOPS data.

The gross capital outflows by domestic investors (COF) and inflows by foreign agents (CIF) are computed using the financial account of BOPS data. In particular, it is retrieved by the table of Balance of Payments Analytic Presentation by country for the United Kingdom. COF is equal to the net purchase of foreign assets by domestic agents and CIF is equal to the net purchase of domestic assets by foreign agents. In terms of the sub categories in the Balance of Payments table, COF is the sum of direct investment abroad, portfolio investment assets, other investment assets, and reserve assets. Similarly, CIF is the sum of direct investment in recipient economics, portfolio investment liabilities, and other investment liabilities. Net capital *(in)*flows equals to the difference of gross capital inflows and gross capital outflows.

As for the determinants of capital flows, global uncertainty is one of the important global factors in the literature. Volatility measures, such as VOX by the Chicago Board

[16]Admittedly, during this 30 years of period, there might be more than one breaks other than recent Financial Crisis. The empirical model in Section 3.3.1. introduced only one dummy variable starting from 2008q2 and, consequently, tends to average out the effect of other breaks. However, we focus more on the structural changes after the Financial Crisis, in search of more parsimonious model. The model is already quite heavy with nine explanatory variables except constant, linear time trend, and a dummy.

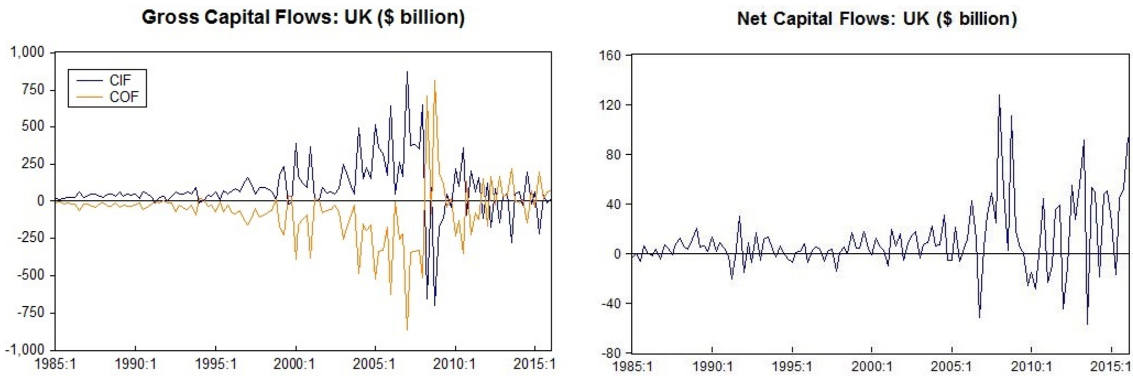

Figure 3.1: Gross and net capital flows

Note: Gross outflows are reported using standard BOP definitions, so that a negative number indicates a gross outflows. Net capital flows equal to gross capital inflows minus gross capital outflows.
Source: IMF BOPS (`http://data.imf.org`).

Options Exchange, are the most commonly used proxy in the capital flows literature. However, it appears to have some drawbacks. Volatility captures both risk and uncertainty that have clearly different implication for economic agents' decision-making. Furthermore, changes in volatility reflects the reactions to shocks in uncertainty or risk, rather than captures the changes in uncertainty itself.[17] Various alternative measures of uncertainty have been proposed in the literature, ranging from news-based index to forecasters' disagreement measures. In general, the decision of which measure to be adopted is largely dependent on the characteristics of a measure and how the chosen measure achieves the aim of the research. In this study, Geopolitical Risk index (GPR) by Caldara and Iacoviello (2016) is selected to capture the uncertainty effect in the international political domain. Increases in instability of international political situation may agitate cross-border movements of capital.

The GPR index is developed based on the assumption that geopolitical risks, such as wars, terrorism, and regional tensions, reflect the exogenous source of uncertainty. It is constructed by counting the words related to geopolitical tensions in major newspapers as a share of total number of articles.[18] The search criteria consists of eight categories, broadly ranging from geopolitical threats and tension to actual events and acts related to geopolitical environment. GPR index is monthly data available from January 1985 to July 2016. As dependent variables are quarterly data, the monthly

[17]See Baker, Bloom and Davis (2015), Jurado, Ludvigson and Ng (2015) for critiques on the use of volatility index as a proxy of uncertainty. Also see Makarova (2014) for detailed discussion of different notion between risk and uncertainty.

[18]For detailed description of methodology, see Caldara and Iacoviello (2016). The list includes 11 national and international newspapers: The Boston Globe, Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, Los Angeles Times, The New York Times, The Times, The Wall Street Journal, and The Washington Post.

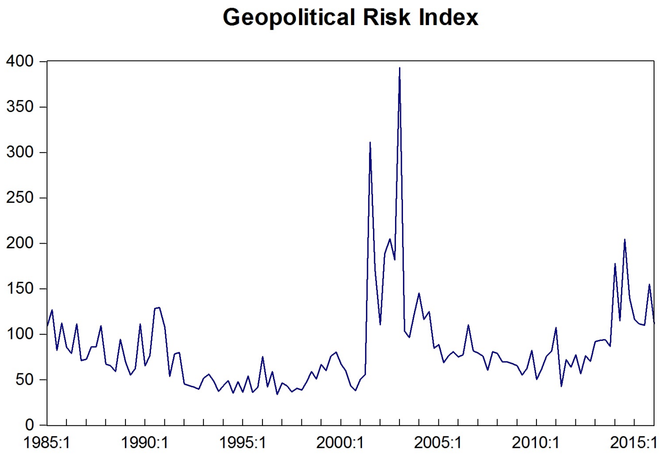

Figure 3.2: Geopolitical Risk Index

Note: The raw data of GPR index is the normalised index to a mean of 100 from 2000 to 2009. Monthly raw data is converted to quarterly data using the last observation of each quarter.
Source: Caldara and Iacoviello. (2016). Measuring Geopolitical Risk, Working paper, Board of Governors of the Federal Reserve Board. (`https://www2.bc.edu/matteo-iacoviello/gpr.htm`).

GPR index is converted using the last observation of each quarter.[19] See Figure 3.2 for quarterly time series plot of GPR index.

As an alternative measure, Global Economic Policy Uncertainty (GEPU) index can be considered. GEPU index is GDP weighted EPU index of 16 countries based on the methodology of Baker, Bloom and Davis (2015).[20] Individual series of EPU is also a news-based index like GPR index, but the search criteria for EPU is the words, 'economic', 'policy' and 'uncertainty', which can be criticized to exhibit endogeneity problem. That is, changes in EPU index may be a consequence of changes in economic condition, not vice versa. Comparing to GEPU index, GPR index is relatively less subject to the economic condition, reflecting mostly exogenous variations. Moreover, GEPU index is only available from January 1997 to December 2016. Therefore, the GEPU index is used for robustness checks later.

The other key global factors are risk-free interest rate and global output growth. As a risk-free rate of investment, the US long term interest rate often used in the literature. The time series of the US 10-year Treasury yield with constant maturity (not seasonally adjusted) is retrieved from Federal Reserve Economic Data (FRED). Global output growth is also an important global factor of capital flows. Several theoretical

[19]The uncertainty indices (GPR, EPU and GEPU) are converted using last observation. Averaging uncertainty (or volatility) proxy may lead to unintended smoothing effect. In order to see the robustness, we computed the long run estimates of the benchmark model (*Spec 1*) with average GPR index and found the estimates are not much different (see Appendix 3.6.8).

[20]The composite index includes 16 countries: Australia, Brazil, Canada, China, France, Germany, India, Ireland, Italy, Japan, Russia, South Korea, Spain, the United Kingdom, and the United States.

paper discussed the role of global growth through innovations in global productivity (see, for example, Albuquerque et al, 2009). The quarterly data of global GDP growth are taken from International Financial Statistics (IFS) dataset by IMF. Both interest rate and global growth rate are available throughout the sample period of 1985q1 to 2016q2. See Figure 3.3 for time series plots of these two global variables.

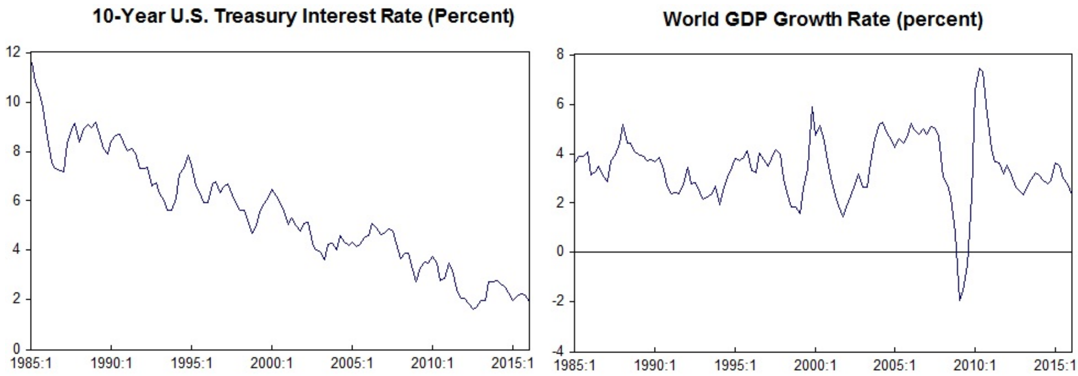

Figure 3.3: Interest rate and global growth

Source: Interest rate data are retrieved from Federal Reserve Economic Data (FRED), (https://fred.stlouisfed.org/), global growth from IMF's IFS dataset (http://data.imf.org).

The contagion factors are trade linkages, financial linkages and international investors' behaviour. The first two variables can be measured only after specifying countries over which the bilateral relationship is defined. While the UK's bilateral trade data are widely available for most European countries, bilateral banking data is accessible only for some core European countries.[21] Therefore, the countries are limited to seven core European countries where the complete bilateral banking data since 1985 is available: Belgium, Germany, Finland, France, Ireland, Luxembourg, and Netherlands.

Trade linkages (TL) are measured by the share of UK's exports to the seven core European countries out of UK's total exports to the rest of the world.[22] The bilateral trade data in domestic currency are obtained from the website of the UK Office for National Statistics (ONS). The data for total exports of the UK to the rest of the world are from IFS database (nominal, seasonally adjusted and in national currency). Due to the availability of bilateral trade data, the time series of trade linkages starts from 1996q1.

$$TL = \frac{\text{Sum of bilateral exports of the UK to each seven core European countries}}{\text{Total UK exports to the rest of the world}}$$

[21]The BIS bilateral banking data are not available between the UK and peripheral European countries, such as Spain, Italy, and Greece.

[22]Alternative measures of trade linkages are bilateral exposure of imports and that of the sum of export and import. However, the time series of these measures are largely similar to the export measure.

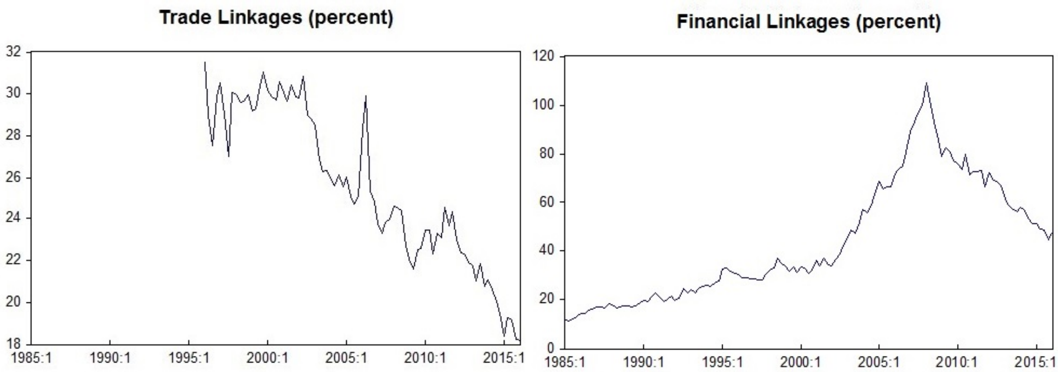

Figure 3.4: Trade linkages and financial linkages

Source: Bilateral exports (ONS, `https://www.ons.gov.uk/`), total exports (IMF IFS, `http://data.imf.org`), bilateral banking flows (Locational Banking Statistics from BIS Statistics Warehouse, `http://stats.bis.org/bis-stats-tool/`), GDP (OECD Statistics, `http://stats.oecd.org/`).

The measures of financial linkages (FL) is constructed based on Locational Banking Statistics (LBS) data by the Bank of International Settlement (BIS). These statistics provide information about outstanding bilateral claims and liabilities of banks located in BIS reporting countries on the unconsolidated basis. The importance of external debt available in the LBS has been emphasized since the GFC. It reports cross-border banking transactions comprising positions within offices under the same global financial institution and many studies found that the expansion in cross-border bank credit explains significant part of financial boom-bust cycle and the vulnerability of financial system. Thus, the contagion effect owing to financial linkages can be effectively summarised by using the LBS statistics. Financial linkages (FL_t) are measured using the sum of bilateral assets and liabilities for all pairs of countries divided by the sum of two countries' GDP.

$$FL_t = \frac{Assets_{i,j,t} + Liabilities_{i,j,t} + Assets_{j,i,t} + Liabilities_{j,i,t}}{GDP_{i,t} + GDP_{j,t}}$$

The international investors' behavioural aspects (re-balancing effect, herding behavior and/or wake-up call effect) are captured by the ratio of international portfolio flows relative to nominal GDP of the UK economy. The international portfolio flows is measured as the sum of gross inflows and gross outflows in portfolio investment. Both portfolio flows (IMF's BOPS) and nominal GDP (OECD Statistics) is in million US dollars. Although this proxy is a broad measure of the share of the UK's cross-border portfolio investments vis-à-vis the rest of the world, it is not restricted to bilateral relationship between the UK and core European countries like the other two contagion factors.

Among various domestic factors, GDP growth, inflation and public debt are considered to keep the model as parsimonious as possible. GDP growth and inflation data

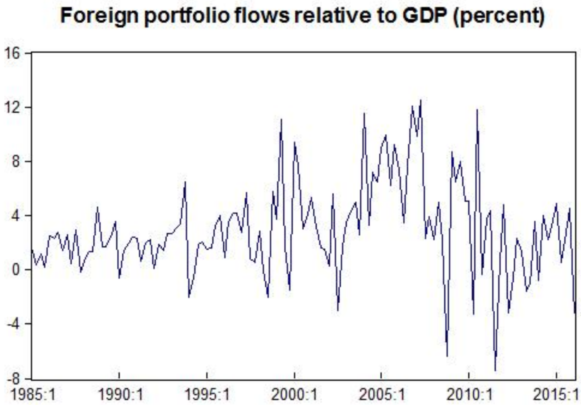

Figure 3.5: International investors' behavioural aspects

Source: Portfolio flows (IMF BOPS database, `http://data.imf.org`) and GDP (OECD statistics, `http://stats.oecd.org/`).

are retrieved from the IMF's IFS database and plotted in Figure 3.6.[23] The public debt to GDP ratio corresponds to quarterly general government consolidated debt data retrieved from the ONS website. Public debt is defined in the Maastricht Treaty as consolidated general government gross debt at nominal (face) value, outstanding at the end of the year. Data for the general government sector are consolidated between sub sectors at the national level and non-seasonally adjusted. Time series of public debt to GDP is plotted in Figure 3.7.

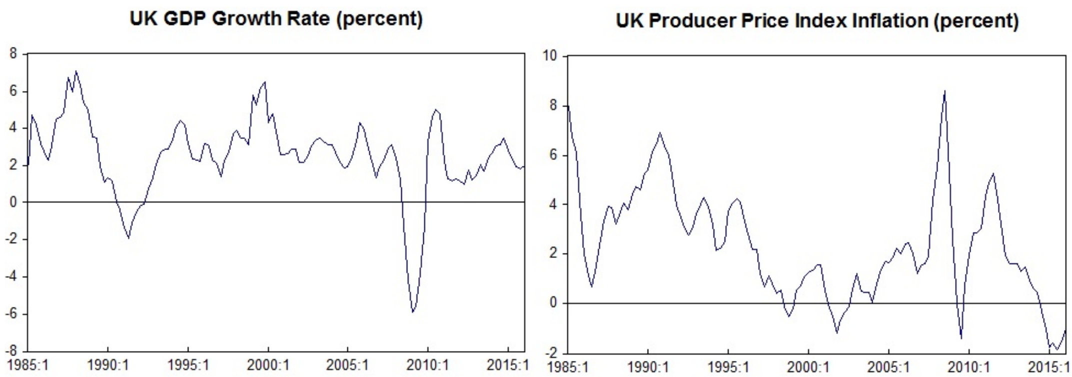

Figure 3.6: GDP growth and inflation

Source: IMF IFS (`http://data.imf.org`).

To examine contagions in uncertainty, uncertainty co-movement index is computed using EPU index. As EPU index is individual country's uncertainty measure, the composite uncertainty index of core EU countries is defined as the GDP-weighted average of national EPU indices. First, I normalise each national-level EPU index to a mean of 100 from 1997 to 2015. Then, using GDP data from the IMF's World Economic

[23] I use Producer Price Index for inflation because Consumer Price inflation data was not available from 1985.

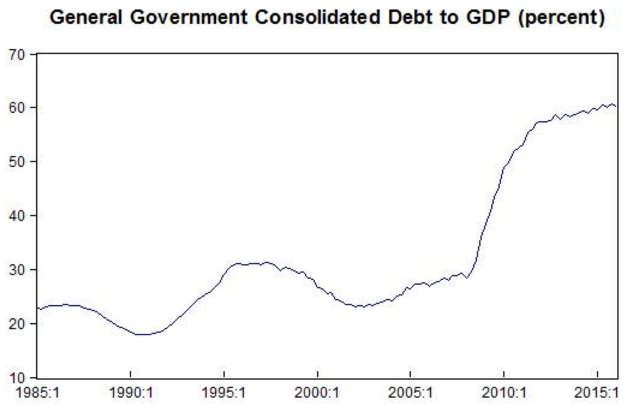

Figure 3.7: Government debt

Source: General government consolidated debt (ONS, `https://www.ons.gov.uk/`), GDP (OECD statistics, `http://stats.oecd.org/`).

Outlook Database, the GDP-weighted average is computed. The left panel of Figure 3.8 shows the EPU index of the UK and the composite EPU index for seven European countries. Monthly EPU data is converted to quarterly data using the last observation of each quarter. Following the definition in equation (3.2), I compute the negative of the absolute value of differences in uncertainty between two regions for each period. The larger the co-movement index is, the greater the uncertainty co-moves.

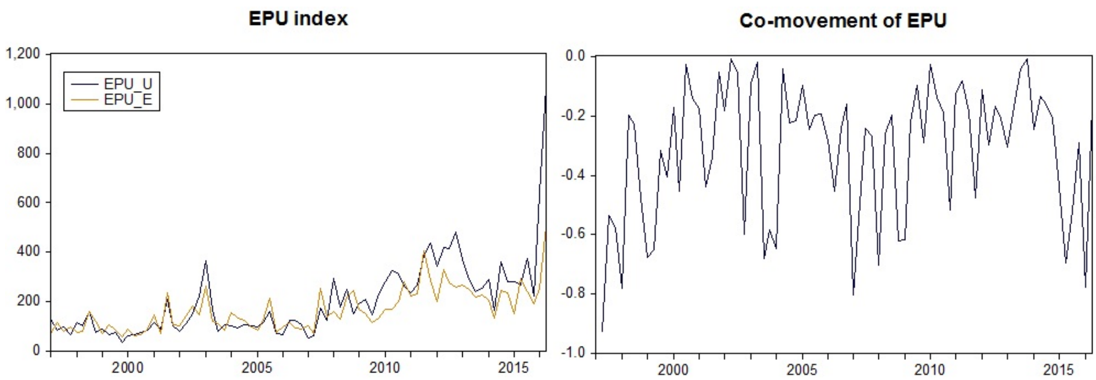

Figure 3.8: Economic Policy Uncertainty index and uncertainty co-movement

Notes: EPU_U is the raw data of UK news-based EPU index. EPU_E is a composite index of seven countries using the current price GDP weight (computed by author). Co-movement index is computed by author using the definition in equation (3.2).
Source: EPU (Baker, Bloom and Davis (2015), `http://www.policyuncertainty.com/`), GDP (IMF, World Economic Outlook Database, `https://www.imf.org/external/pubs/ft/weo/2016/02/weodata/index.aspx`).

The co-movement of the business cycle (Figure 3.9) is constructed using the same definition of uncertainty co-movement with OECD Composite Leading Indicator (CLI). The OECD CLI is designed to summarize the qualitative information of short run economic dynamics. The components are the time series with leading relationship with output growth that are selected based on economic significance, cyclical behaviour, and data quality. The country-level CLIs of six core European countries are retrieved from OECD Statistics and averaged out with equal weights to compute the composite CLI.[24]

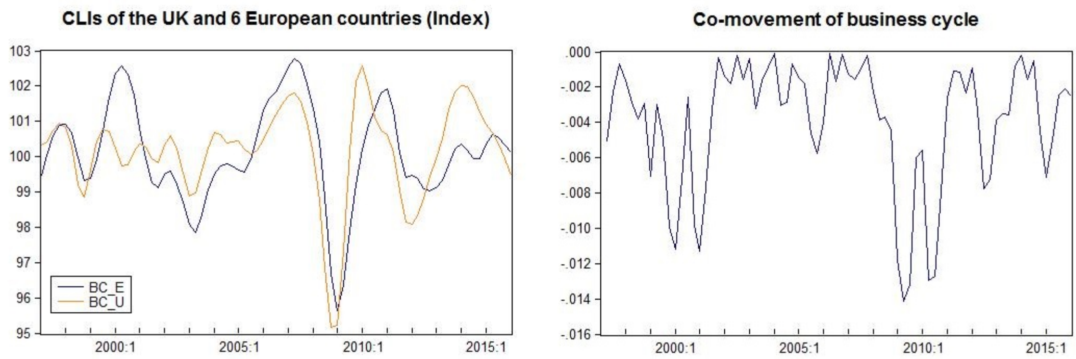

Figure 3.9: OECD Composite Leading Indicator and business cycle co-movement

Notes: BC_U is the raw time series of UK CLI retrieved from OECD database. BC_E is a composite index of six countries (except Luxembourg) using equal weight (computed by author). Co-movement index is computed by author using the definition in equation (3.2).
Source: CLI (OECD statistics, `http://stats.oecd.org/`).

[24]Luxembourg CLI is not available from OECD Statistics Database.

3.4 Estimation Results and Robustness Checks

3.4.1 The long run level relationships between capital flows and determinants

For the estimation of capital flows in the model specification using all individual factors (*Spec 1*), I consider both entire sample (1985q1–2016q2) and sub sample (1997q1–2016q2). The estimation of entire sample excludes trade linkage variable because the data is only available from 1997. Therefore, the determinants are $\boldsymbol{x}_t' = (\boldsymbol{G}_t, \boldsymbol{C}_t, \boldsymbol{D}_t) =$ (GPR_t, i_t, $WGDP_t$, FL_t, inv_t, $DGDP_t$, ppi_t, $debt_t$) in the entire sample model and (GPR_t, i_t, $WGDP_t$, TL_t, FL_t, inv_t, $DGDP_t$, ppi_t, $debt_t$) in the sub sample model. Each group of factors are as follows. GPR_t is Geopolitical Risk index, i_t is long term US interest rate, $WGDP_t$ is global output growth. TL_t and FL_t are trade and financial linkages between the UK and the core European countries, inv_t is international portfolio investment to GDP of the UK. $DGDP_t$ is domestic GDP growth, ppi_t is inflation, and $debt_t$ is public debt to GDP ratio. To make sure that none of the variables are I(2), I conduct Augmented Dickey Fulluer (ADF) and Phillips Perron (PP) unit root test for both entire sample and sub sample period. There is strong evidence of all the variables are either I(0) or I(1).[25] Details of unit root test results by different sample range is provided in Appendix 3.6.3.

In order to test the existence of level relationship, the appropriate lag structure of the unrestricted ECM in equation (3.1) is determined based on information criteria and ensuring the absence of serial correlation in errors. To avoid pre-testing problem, I follow the approach in PSS, holding the coefficients of lagged changes unrestricted. The statistics are shown in Appendix 3.6.4.

First, the appropriate lag length for capital inflows estimation is considered. Akaike's Informationi criteria (AIC) suggest the appropriate lag order is 7 while Schwarz's Bayesian Information Criteria (SBC) suggest 1, irrespective of whether the model includes deterministic trends. However, the LM test for serial correlation does not support the choice of $p = 7$ as the null hypothesis of no autocorrelation is rejecte at 1%. Based on both information criteria and the absence of serial correlation, it seems reasonable to select p to be either 4, 5 or 6. In the sub sample case, the appropriate lags are selected from $p = 1$ to $p = 4$ because the model with higher lags cannot be effectively estimated due to the limited number of observations (*i.e.* the curse of dimensionality).

[25] Notice that, in Chapter 2, the inflation is I(1) while inflation data in Chapter 2 is found to be I(0). The order of integration of inflation data is different in Chapter 2 and Chapter 3 because of the differences in (1) price index on which the computation of inflation is based and (2) data frequency and coverage. In Chapter 2, we use Consumer Price Index (CPI) to compute inflation. The price index is monthly data, ranging from January 1997 to March 2016. The UK inflation data used in Chapter 3 is Producer Price Index (PPI), quarterly data, and the coverage is much wider, 1985q1-2016q2.

According to information criteria, either $p = 4$ or $p = 1$ is the appropriate choice. Similar to the entire sample estimation, the results shows the evidence of autocorrelation in $p = 4$. The SBC statistics of $p = 2$ is not largely different from minimum value of $p = 1$. All in a nutshell, the appropriate lags for the sub sample model is chosen to be $p = 1, 2, 3$. For gross capital outflows estimation, AIC suggests that the appropriate lag order is 7 while SBC suggests 1 for the entire sample case, irrespective of whether the model includes deterministic trends. However, the LM test suggests that errors contain autocorrelation for the lag length $p = 1, 2, 3, 7$. Therefore, the appropriate lag order can be selected among $p = 4, 5, 6$. In the sub sample estimation, the results are similar to the inflows estimation results. The most suitable lag length for both with and without trend can be chosen among $p = 1, 2, 3$.

To test the existence of long run relationships in the level variables, F- and t-tests are performed as constructed in Section 3.3. Table 3.3 shows the F- and t-statistics for chosen lag orders.

Table 3.3: F- and t-statistics for testing the existence of levels equation (*Spec 1*)

Gross Capital Inflows											
Sample: 1985q1 - 2016q2						Sample: 1997q1 - 2016q2					
	With trend			Without trend			With trend			Without trend	
p	F_{IV}	F_V	t_V	F_{III}	t_{III}	p	F_{IV}	F_V	t_V	F_{III}	t_{III}
4	9.90^c	9.78^c	-8.96^c	9.11^c	-8.56^c	1	12.80^c	12.73^c	-10.55^c	12.97^c	-10.63^c
5	7.08^c	7.07^c	-8.01^c	6.36^c	-7.58^c	2	10.53^c	10.34^c	-9.00^c	10.45^c	-9.04^c
6	4.86^c	4.64^c	-5.92^c	3.96^c	-5.41^c	3	3.76^c	3.75^c	-5.05^b	3.54^c	-5.18^c
Gross Capital Outflows											
Sample: 1985q1 - 2016q2						Sample: 1997q1 - 2016q2					
	With trend			Without trend			With trend			Without trend	
p	F_{IV}	F_V	t_V	F_{III}	t_{III}	p	F_{IV}	F_V	t_V	F_{III}	t_{III}
4	6.84^c	6.78^c	-7.31^c	6.17^c	-6.88^c	1	13.32^c	13.16^c	-10.42^c	13.57^c	-10.51^c
5	4.06^c	4.05^c	-6.01^c	3.77^c	-5.77^c	2	8.97^c	8.87^c	-8.12^c	8.84^c	-8.19^c
6	3.50^c	3.25^b	-4.88^b	3.01^b	-4.57^b	3	5.14^c	5.14^c	-4.60^b	4.82^c	-4.70^b

Notes: F_{III} is the F-statistic for testing the null hypothesis, $H_0 : \pi_{cc} = 0$, $\boldsymbol{\pi}_{cx.x} = \mathbf{0}'$ with β_1 set equal to zero. F_{IV} is the F-statistic for testing $H_0 : \pi_{cc} = 0$, $\boldsymbol{\pi}_{cx.x} = \mathbf{0}'$, and $\beta_1 = 0$. F_V is the F-statistic for testing $H_0 : \pi_{cc} = 0, \boldsymbol{\pi}_{cx.x} = \mathbf{0}'$. t_{III} is the t-ratio for testing $\pi_{cc} = 0$ without a deterministic trend. t_V is the t-ratio for testing $\pi_{cc} = 0$ with a deterministic trend. [a] indicates the statistic is smaller than the 0.05 lower bound, [b] denotes the statistic is within the 0.05 bounds and [c] denotes the statistic is greater than the 0.05 upper bound.

The F_{IV} statistics are computed under the null hypothesis of no level relationship and restricting the trend coefficient to zero, while the F_V statistics without restriction on the coefficients on trend. The F-test under case III (F_{III}) is simply based on the estimation models without deterministic trends. The number of regressors used in the estimation of entire sample is eight ($k = 8$). According to the tables provided by PSS (Tables CI and CII), the critical value bounds for F_{III}, F_{IV} and F_V with $k = 8$ at 5% significance level are (2.22, 3.39), (2.38, 3.41) and (2.55, 3.68), respectively. When $k = 8$, the critical value bounds for t_{III} and t_V are (-2.86, -4.72) and (-3.41, -5.10), respectively. The estimation using sub sample from 1997q1, the trade linkage variable is added so it becomes the case of $k = 9$. The critical value bounds for F-tests with $k = 9$ are (2.14, 3.30), (2.30, 3.33), and (2.43, 3.56), respectively for F_{III}, F_{IV} and F_V. The critical value bounds for t-tests (t_{III}, t_V) are (-2.86, -4.88) and (-3.41, -5.15).

For gross capital inflows estimation model with $p = 4, 5, 6$, the null hypotheses under all three different scenarios are rejected at the 0.05 level, irrespective of whether the regressors are I(0)'s, I(1)'s or mutually cointegrated. Both t-test and F-test results confirm the existence of level relationships between capital flows and determinants at 0.05 level, regardless of lag orders for the entire sample capital inflows model. For the sub sample estimation with lag length, $p = 1, 2$, the null hypothesis of no long run relationship is rejected. However, t_V statistics fall in between the upper and lower bound where $p = 3$.

Gross capital outflows results for the entire sample case with lag length $p = 4, 5$ show strong evidence of level relationship of capital outflow and its determinants, irrespective of whether the model has deterministic trend. For $p = 6$, F- and t-statistics indicate that the decision of hypothesis testing is inconclusive. In the sub sample estimation, a model with deterministic trend and lag length $p = 1, 2$ strongly suggests that there exist a long run relationship. However, the test for single hypothesis of $\pi_{cc} = 0$ in the model with $p = 3$ suggests that we fail to reject the null at 0.05 level.

To sum up, the suitable lag lengths of unrestricted models are selected based on information criteria and autocorrelation test. There exists strong evidence of long run relationship when $p = 4$ for entire sample and $p = 2$ for sub sample, irrespective of the model specification. Consequently, the levels relationship is formulated as follows and the estimates are presented in Appendix 3.6.5.

Sample I (1985q1–2016q2)
$c_t = \beta_1 GPR_t + \beta_2 i_t + \beta_3 WGDP_t + \beta_4 FL_t + \beta_5 inv_t + \beta_6 DGDP_t + \beta_7 ppi_t + \beta_8 debt_t$ $+c + \beta_9 t + \beta_{10} d2008 + \hat{v_{1t}}$
Sample II (1997q1–2016q2)
$c_t = \beta_1 GPR_t + \beta_2 i_t + \beta_3 WGDP_t + \beta_4 TL_t + \beta_5 FL_t + \beta_6 inv_t + \beta_7 DGDP_t + \beta_8 ppi_t + \beta_9 debt_t$ $+c + \beta_{10} t + \beta_{11} d2008 + \hat{v_{2t}}$

where $\hat{v_{1t}}$ and $\hat{v_{2t}}$ are the equilibrium correction term.

The estimated long run relationship for capital inflows using entire sample indicates that global uncertainty, world output growth are significant among global factors. The coefficients on uncertainty variables are positive, suggesting procyclicality of global uncertainty shock to gross capital inflows. As geopolitical risk increase globally, the gross capital inflow to the United Kingdom by foreign investors increases, in other words, capital surges. This suggests the flight-to-quality type capital movement considering that the UK financial market is one of the largest international financial centre. In the capital outflows models, the coefficient on geopolitical uncertainty is also significant and positive. Capital outflow by residents increases as the geopolitical tension increases worldwide, i.e. capital flight happens. This might reflect the capital movements towards the US financial market that is relatively safer than the small open economy like the UK from the perspective of the UK residents. The magnitude of estimated effects are smaller than that of the capital inflows estimation, implying that global geopolitical uncertainty is associated with increases in *net* capital inflows to the UK. The global economic growth is correlated with increases in gross capital inflows and outflows but the coefficients are larger for the capital outflows. Hence, in terms of *net* capital flows, the stable global economic growth is countercyclical, being associated with *net* capital outflows. Assuming that the domestic growth rate in the UK is generally lower than the growth rate of other emerging economies, the countercyclicality is simply reflecting the investors' incentive to position a portfolio into the higher return assets. In summary, the two global factors are significant but have different influences on investment motives depending on whether they are either foreign or domestic investors.

In terms of contagion factors, both financial linkages and international investors' behavioural aspects are shown to be highly significant in explaining long run equilibrium of gross capital inflows. The coefficients are positive, implying that gross capital inflows are correlated with higher level of financial connection to the core European countries and increasing role of international portfolio investors' in the financial markets. The contagion are pivotal in determining investment decision by foreign investors and they tend to invest more in the UK assets when the bank lending exposures to the core European countries and the proportion of international investors to portfolio cross-border investment are higher. As for the gross capital outflows estimation, both contagion factors are also significant and positively correlated with capital outflows. Comparing the relative size of the estimated coefficients to the inflows estimation results, the financial linkages with the core European countries via banking sector is procyclical (likely to induce *net* capital inflows) while the international investors' relative position in total cross-border investment is countercyclical (likely to induce *net* capital outflows). These findings are in line with the existing studies regarding contagions, e.g. the leveraging/deleveraging cycle of global banks, the portfolio rebalancing effect, and the wake-up call effect and potentially extend the scope of the domain of research by differentiate investment motivations of foreigners from that of domestic investors.

Among domestic factors, government debt to GDP ratio is statistically significant for both gross capital inflows and outflows. According to the existing theoretical and empirical studies, adverse fiscal positions of a country is often correlated with *net* capital inflows. When sovereign debt is accumulated above the sustainable level, there is a tendency of stop (decreases in gross capital inflows) and flight (increases in gross capital outflows) due to the increased likelihood of sovereign default. The estimated coefficients are positive for both inflows and outflows controlling for the structural changes after 2008. While the positive coefficients for capital outflows seem to be consistent with the literature, the result for inflows is rather counterintuitive and cannot be supported by the existing literature.

In order to explain the results, it can be further examined by comparing the results from the models without the dummy, D_{2008}. Once the structural break after 2008 being ignored, the effect of public debt on capital inflows becomes negative as predicted by most existing theories. Applying simple analysis of omitted variable bias, it is easily deduced that there is a positive correlation between sovereign debt and the dummy.[26] The data also confirms that the level of government debt suddenly escalated after the global crisis in 2008. This finding may help explaining the estimation results that predicts capital surges, not stops, when there is an increase in sovereign debt level in the long run. The seemingly unreasonable estimation results may be due the potential confounding factors that is positively correlated with both the level of sovereign debt and capital inflows.

One possible confounder is the successful implementation of the unconventional monetary and fiscal policy measures after the GFC. In reaction to the unprecedented financial crisis, most of the central banks in advanced economies, including the United Kingdom, adopted Quantitative Easing (QE), allowing for the purchase of assets by the creation of central bank reserves. The public debt data under the EU standard statistics include the recorded *gross* financial liabilities of central and local governments. That is, it includes liquid assets, such as official reserve assets and other cash or cash-like assets. Therefore, the large increase in public debt to GDP ratio may reflect the enlarged balance sheet of the central bank after QE. In addition, some fiscal measures were implemented throughout the course of crisis, including income tax cut for base rate, a temporary cut in Value Added Tax, and Small Enterprise Loan Guarantee Scheme. These measures may have been effective in repairing the financial system, increasing demand and restoring investors' confidence, and consequently leading to capital inflows to the UK financial market. Therefore, the level of debt to GDP ratio may have positive correlation with gross capital inflows in the long run level equation, controlling for the structural break after the GFC. There may also exist a possibility that the capital flows behaves differently in reaction to changes in public debt after the crisis. The model

[26]The OVB is negative ($= -3.64 - 12.20$ comparing (1) and (2). The coefficient on the omitted variable (D_{2008}) is negative in the long regression. Thus, the correlation between the omitted and public debt is positive.

with interaction term between public debt and dummy variable is estimated in the Section 3.4.3. for robustness check.

As noted previously, the level of public debt is positively correlated with capital outflows by domestic investors, implying that domestic investors actually escaped from its own financial markets when government debt to GDP ratio increases. Combined with the positive coefficients on the public debt in the gross capital inflows model, this clearly shows that the underlying motivation of investment decisions by residents may differ from foreign investors. The heterogeneous effects between foreign and domestic investors on capital flows cannot be distinguished in the estimation model for *net* capital flows. The magnitudes of such effects on gross inflows are larger than the effects on gross outflows, suggesting that the capital net inflows as government debt level increases. However, the difference in magnitude of the effects is minimal, especially in case of the specification including deterministic trend.

The model with trade linkages variable (using sub sample) shows some evidence of significant effects of the contagion factors but not the trade linkages itself. Comparing the relative size of the estimated coefficients between inflows and outflows model estimates, the effect of contagion factors on *net* capital flows is similar to the entire sample case: the financial linkages is procyclical while the international investors' role is countercyclical. The global factors are mostly insignificant in the sub sample model. Similar to the entire sample estimation, the coefficients on public debt are positive and statistically significant for both gross capital inflows and outflows. However, the coefficients are larger in outflows than in inflows, suggesting that an increase in sovereign debt level is associated with *net* capital outflows. In the model without the dummy variable, two contagion factors (except trade linkages) and domestic inflation are important determinants for gross capital inflows. Inflation is associated with stops in capital inflows. Similarly, contagion factors and domestic inflation are significant factors for gross capital outflows. The only difference between the results of inflows and outflows is that world output growth is significant at 10% level for capital outflows. This suggests that the residents' cross-border investment decision is more likely to be affected by the global economic growth whereas the decision by foreign investors is relatively less influenced.

In the following, the long run relationship between capital flows and determinants is estimated using the co-movement index as a new proxy for contagion in uncertainty. (*Spec 2*) denotes the model with the raw data of uncertainty co-movement defined in equation (3.2) and (*Spec 3*) denotes the two stage estimation. Notice that the sample period of both specification is 1997q1–2016q2 because the country-level EPU index for constructing the uncertainty co-movement index is available from 1997. In order to check whether any of the variables in the model are I(2), ADF and PP unit root test are conducted (see Appendix 3.6.3). Uncertainty co-movement index and the business cycle co-movement are both I(0) in levels.

Table 3.4: F- and t-statistics for testing the existence of levels equation (*Spec 2*)

Gross capital inflows						Gross capital outflows					
	With trend			Without trend			With trend			Without trend	
p	F_{IV}	F_V	t_V	F_{III}	t_{III}	p	F_{IV}	F_V	t_V	F_{III}	t_{III}
5	5.23^c	5.10^c	-4.77^b	2.41^b	-2.84^a	3	7.02^c	7.00^c	-6.42^c	3.70^c	-4.21^b

Notes: F_{III} is the F-statistic for testing the null hypothesis, $H_0 : \pi_{cc} = 0$, $\boldsymbol{\pi}_{cx.x} = \mathbf{0}'$ with β_1 set equal to zero. F_{IV} is the F-statistic for testing $H_0 : \pi_{cc} = 0$, $\boldsymbol{\pi}_{cx.x} = \mathbf{0}'$, and $\beta_1 = 0$. F_V is the F-statistic for testing $H_0 : \pi_{cc} = 0, \boldsymbol{\pi}_{cx.x} = \mathbf{0}'$. t_{III} is the t-ratio for testing $\pi_{cc} = 0$ without a deterministic trend. t_V is the t-ratio for testing $\pi_{cc} = 0$ with a deterministic trend. [a] indicates the statistic is smaller than the 0.05 lower bound, [b] denotes the statistic is within the 0.05 bounds and [c] denotes the statistic is greater than the 0.05 upper bound.

By information criteria and the absence of serial correlation, the appropriate lag order for gross capital inflows and outflows estimation is $p = 5$ and $p = 3$.[27] The test results of the existence of levels relationship are shown in Table 3.4. From PSS, the critical value bounds are F_{IV}(2.50, 3.50), F_V(2.69, 3.83), t_V(-3.41, -4.85). The case without deterministic trend, the critical values are F_{III}(2.32, 3.50), and t_{III}(-2.86, -4.57) at 5% significance level. The result suggest weak evidence for long run relationship between the gross capital flows and determinants, especially for the capital inflows model with deterministic trend where the null of no level relationship is either cannot be rejected or remain indecisive.

The levels relationship is formulated as follows:

$$\begin{aligned} c_t = {} & \beta_1 GPR_t + \beta_2 i_t + \beta_3 WGDP_t + \beta_4 Comov_t + \beta_5 DGDP_t + \beta_6 ppi_t + \beta_7 debt_t \\ & + c + \beta_8 t + \beta_9 d2008 + \hat{v}_t \end{aligned}$$

where $\hat{v}_t$ is the equilibrium correction term.

Although the long run relationship is likely to be absent in (*Spec 2*), the estimates of the long run level relationship for (*Spec 2*) models are given in Appendix 3.6.5 Table 3.23-3.24. The uncertainty contagion factor is no longer significant in any specifications. Including the dummy variable for recent financial crisis, global output growth is the only factor that is highly significant except the dummy itself. World GDP growth is positively correlated with both gross inflows and outflows. Comparing the magnitude of effects between gross inflows and outflows, it is suggested that the increased level of world growth rate is likely to be associated with *net* capital outflows. This is identical to the results in (*Spec 1*).

In addition to global output growth, public debt to GDP ratio is significant in the

[27] In Appendix 3.6.4, Table 3.15 shows the statistics for selecting the lag order in (*Spec 2*).

long run level of gross capital flows in the models without the dummy. The coefficients for gross inflows model are negative, supporting the countercyclicality argument: the higher the sovereign debt is, the more the capital inflows decreases. However, the gross capital outflows also decreases (retrenchment) as the government debt increases. The coefficients are larger in absolute value for inflows than outflows, suggesting decreases in *net* inflows. In case of the capital outflows, the estimation results differ with respect to different specifications. For example, The model with trend only indicates that world output growth, domestic inflation and public debt to GDP ratio are important determinants.

In (*Spec 3*), the two stage estimation is introduced to uncover the relationship between traditional contagion factors and uncertainty co-movement index and to connect this relationship with capital flows dynamics. The first stage estimation results is presented below with estimates and the standard errors in parentheses. Based on AIC and the absence of serial correlation, the suitable lag of the prediction model is selected ($p = 4$).[28] The estimation method is least squares with HAC standard errors and covariances. In order to capture the bilateral contagion between the UK and the core European countries, the international investors' behavioural factor is excluded in the estimation.[29]

$$\begin{aligned}\widehat{Comov}_t = &\underset{(0.067)}{-0.215}\, D_{2008,t} + \underset{(8.356)}{29.723} CoBC_t \\ &+ \underset{(0.023)}{0.012}\Delta TL_t + \underset{(0.048)}{0.026}\Delta TL_{t-1} + \underset{(0.034)}{0.042}\Delta TL_{t-2} + \underset{(0.025)}{0.028}\Delta TL_{t-3} + \underset{(0.033)}{0.002}\Delta TL_{t-4} \\ &\underset{(0.010)}{-0.009}\, \Delta FL_t \underset{(0.009)}{-0.016}\, \Delta FL_{t-1} \underset{(0.009)}{-0.011}\, \Delta FL_{t-2} \underset{(0.007)}{-0.020}\, \Delta FL_{t-3} \underset{(0.007)}{-0.016}\, \Delta FL_{t-4}\end{aligned}$$

After controlling for the current business cycle component, only financial linkages are significant. Although the trade linkages variable and its lags are insignificant, they are not excluded in the first stage linear projection to keep the variations from the real economic connections between the two regions. The financial linkages and its lags are jointly significant and the coefficients are negative. This implies that increases in the exposure to the core European countries via bank lending are likely to reduce the degree of uncertainty dependence. This is a notable finding. Most literature suggests that financial integration may smoothen the uncertainty faced by the individual parts of the system by providing the cross-ownership structure to share the risks. The first stage estimation results also suggest that the dependence in uncertainty among the individual components in the system gets weaker as financial integration is developed,

[28] There could be numerous alternatives for the suitable first stage models. I compared AIC among different unrestricted models and choose the ones that have minimum AIC statistics with no evidence of autocorrelation.

[29] In addition, the coefficients on *inv* are all insignificant empirically.

at least for the example of the banking system among the UK and the core European countries.

The second stage estimation is the long run equilibrium estimation while replacing $Comov_t$ in (*Spec 2*) with the projected co-movement index in the first stage $\widehat{Comov}_t$. The statistics for selecting the lag orders for the two stage estimation (*Spec 3*) are shown in Appendix 3.6.4 Table 3.16. The appropriate lag length for the two stage estimation is $p = 3$ for both capital inflows and outflows based on the AIC while ensuring there is no autocorrelation in the errors.

Table 3.5: F- and t-statistics for testing the existence of levels equation (*Spec 3*)

Gross capital inflows						Gross capital outflows					
	With trend			Without trend			With trend			Without trend	
p	F_{IV}	F_V	t_V	F_{III}	t_{III}	p	F_{IV}	F_V	t_V	F_{III}	t_{III}
3	7.52^c	7.38^c	-5.96^c	3.97^c	-4.58^c	3	9.10^c	9.00^c	-6.31^c	5.38^c	-4.56^b

Notes: F_{III} is the F-statistic for testing the null hypothesis, $H_0 : \pi_{cc} = 0$, $\boldsymbol{\pi}_{cx.x} = \mathbf{0}'$ with β_1 set equal to zero. F_{IV} is the F-statistic for testing $H_0 : \pi_{cc} = 0$, $\boldsymbol{\pi}_{cx.x} = \mathbf{0}'$, and $\beta_1 = 0$. F_V is the F-statistic for testing $H_0 : \pi_{cc} = 0, \boldsymbol{\pi}_{cx.x} = \mathbf{0}'$. t_{III} is the t-ratio for testing $\pi_{cc} = 0$ without a deterministic trend. t_V is the t-ratio for testing $\pi_{cc} = 0$ with a deterministic trend. [a] indicates the statistic is smaller than the 0.05 lower bound, [b] denotes the statistic is within the 0.05 bounds and [c] denotes the statistic is greater than the 0.05 upper bound.

The test statistics for the level relationship is provided in Table 3.5. In (*Spec 3*), the evidence of the existence of long run relationship is stronger than (*Spec 2*) case. Based on the bounds of critical values provided by PSS, the null hypothesis of absence of long run relationship is rejected at 5% significance level.

The levels relationship is formulated as follows:

$$\begin{aligned} c_t = {} & \beta_1 GPR_t + \beta_2 i_t + \beta_3 WGDP_t + \beta_4 \widehat{Comov}_t + \beta_5 DGDP_t + \beta_6 ppi_t + \beta_7 debt_t \\ & + c + \beta_8 t + \beta_9 d2008 + \hat{v}_t \end{aligned}$$

where $\hat{v}_t$ is the equilibrium correction term.

The estimates of the long run equilibrium for (*Spec 3*) are presented in Appendix 3.6.5 Table 3.25-3.26. Both gross capital inflows and outflows are mainly explained by global output growth, uncertainty contagion and sovereign debt. The coefficient on the uncertainty contagion factor is negative and significant at 10% level for the models with the dummy and trend. This implies that the foreign investors' capital movements towards the UK decreases and the residents' cross-border investments decreases as the uncertainty co-movement increases. In other words, uncertainty contagion due to trade and financial links within European countries is associated with stops in capital inflows and retrenchment in capital outflows. The coefficient of gross outflows model is relatively larger in absolute value than that of gross inflows model, suggesting that *net* capital inflows. This seems consistent with the results in (*Spec 1*): financial linkages are procyclical in terms of *net* capital flows.

Among global factors, only world output growth is positively correlate to gross capital flows. The size of the coefficients is bigger in gross capital outflows than inflows and consequently suggesting that global economic growth is likely to induce increases *net* capital outflows. The countercyclicality of global growth to net capital flows is consistent with the findings in (*Spec 1*). However, geopolitical uncertainty is no longer significant determinant for capital flows after controlling for the uncertainty co-movement as a contagion factor. This is because EPU index may capture important variations in the geopolitical uncertainty.

Domestic factors, GDP growth and public debt, are also significantly associated with capital flows in the long run. The effect of fiscal position on the capital flows is similar to the benchmark model (*Spec 1*). In the models with dummy variable, the coefficients are significantly different from zero and positive. Comparing the magnitude of such effects, the higher sovereign debt ratio is associated with *net* capital outflows in the model with both trend and the dummy. In the model with only the dummy but without trend, the implication to *net* capital flows are the same as (*Spec 1*). The estimation results suggest that domestic output growth is negatively correlated with gross capital flows, but only significant to gross capital outflows. As domestic output grows stronger, residents are likely to retrench, increasing domestic asset positions relative to foreign asset positions. In terms of *net* capital flows, the domestic GDP growth is procyclical: increased level of domestic output growth is associated with net capital inflows.

In short, uncertainty contagion becomes significant and positively correlated with capital flows in (*spec 3*) while the raw uncertainty contagion factor is insignificant in (*Spec 2*). Individual contagion factors are significant in (*Spec 1*). Global growth is important for both inflows and outflows estimation of long run levels equilibrium in all specifications (*Spec 1-3*). Among the pull factors, sovereign debt is the crucial factors on both capital inflows and outflows. The further theoretical and empirical investigation may uncover the underlying mechanism of the long run relationship between gross capital flows and various factors.

3.4.2 The short run dynamics between capital flows and determinants

For the subsequent estimation, ARDL approach in Pesaran and Shin (1999) is adopted. Setting the lag length for unrestricted model as p, the appropriate orders of autoregressive components in an conditional ARDL model are selected among the $p^{(k+1)}$, where k is the number of variables excluding the dependent variable. Therefore, the orders of an ARDL model are selected among the 4^9 models for entire sample in (*Spec 1*) and 2^{10} for sub sample in (*Spec 1*). In case of (*Spec 2*) and (*Spec 3*), the lag length for unrestricted model is $p = 5$ for the model of capital inflows in (*Spec 2*) and $p = 3$ for the model of outflows in (*Spec 2*), inflows and outflows in (*Spec 3*). Therefore, the orders of ARDL models are selected among 5^8 models and 3^8 models, respectively. The selection criteria is AIC. Appendix 3.6.6 Table 3.31-3.32 indicates the resulting lag lengths for each case.

After deciding the appropriate lag lengths for each regressors, the conditional error correction model (ECM) is estimated including the one-period lagged residual, $\widehat{v_{t-1}}$, from the long run equilibrium. The regression results are given in Table 3.33-3.40 in Appendix 3.6.7. To check whether the capital flows converge towards the equilibrium described by the long run relationships, the inverse roots of AR components are also provided in the notes under corresponding tables.

For the estimation of capital inflows in (*Spec 1*) using the entire sample, error correction terms are all significant as expected. The two contagion factors and domestic GDP growth are significant, irrespective of the inclusion of the dummy and deterministic trend. In the model with the dummy, lags of capital inflows and inflation are significant in short term correction in addition to the contagion and domestic GDP growth. In the model without the dummy, the first lag of world GDP and government debt are significant. The sub sample estimation of gross capital inflows shows that error correction terms are all significant. Risk-free interest rate and contagion factors (excluding trade linkages) are important short term determinants in models with and without the dummy. In the case of no dummy model, global uncertainty, world GDP and domestic GDP growth are significant. Trade linkage variable is significant in the model that contains dummy and deterministic trend.

In case of capital outflows estimation in (*Spec 1*) using the entire sample, error correction term is only significant for the models without the dummy. Contagion factors and domestic output growth are significant in all specification while lags of capital outflows and inflation is significant in the models with the dummy only. Public debt is significant in the models without dummy. Finally, capital outflows estimation using sub sample, error correction terms, contagion factors (except trade linkages), global risk-free interest rates are significant in all specification. In the models without dummy, the lags of capital outflows, global uncertainty, world GDP and domestic GDP growth are significant.

To sum up the results from the benchmark model (*Spec 1*), financial linkages and international investors' behavioural factors are significant regardless of sample range and model specification whether the dummy and/or deterministic trend are included. This suggest that contagion factors are important not only in determining the long run equilibrium but also in adjustment in the short run dynamics. Domestic output growth is a crucial short-term determinant in the entire sample cases while global long term interest rate is a key short-term factor in the sub sample estimation. Sovereign debt is clearly important factor in long run equilibrium but it does not play a key role in the short run.

The conditional ECM results of (*Spec 2*) shows that the error correction terms are mostly insignificant in inflows model except for the models without the dummy variable. The significant short term factors of gross capital inflows are global interest rate, domestic GDP growth, and inflation. Co-movement in uncertainty seems insignificant in all specifications. In the capital outflows model, the error correction terms are significant. The lags of public debt are also significant in all specifications. In the model without the dummy, global uncertainty and world GDP growth are significant short term factors. Inflation is significant in the model with the dummy. The co-movement index is insignificant for all specifications.

As for the conditional ECM estimation results in (*Spec 3*), both capital inflows and outflows model have significant error correction terms. Co-movement in uncertainty is insignificant in all specifications. In the long run, however, uncertainty contagion is one of the important factors. In the capital inflows models without the dummy variable, the important short-term factors are global interest rate, world GDP growth, domestic GDP, inflation, and government debt. In addition to the error correction terms, the lags of public debt to GDP are significant in explaining short-term changes in capital outflows in all different specifications. In (*Spec 3*), the sovereign debt is important in long- and short-run dynamics of capital outflows.

Finally, comparing (*Spec 3*) results with the benchmark results, uncertainty contagions in (*Spec 3*) are important in the long run relationships but insignificant in the short run movements in capital flows whereas contagion factors in (*Spec 1*) are crucial in both long- and short-term movements in capital flows. The sovereign debt in (*Spec 3*) is important for both long- and short-run dynamics of capital flows but, in (*Spec 1*), it matters only in the long run.

3.4.3 Robustness Checks

For the robustness check, the benchmark model is re-estimated using the Global EPU (GEPU) index instead of geopolitical risk (GPR) index. Denote this specification as (*Spec 4*). The sample range for (*Spec 4*) is 1997q1–2016q2 due to the limited availability of the GEPU index. The model includes trade linkages variable to be compared with the sub sample case of (*Spec 1*). In addition, the differential effect of public debt before and after the Great Financial Crisis is estimated by introducing an interaction term between the dummy (D_{2008}) and public debt variable. Denote this specification as (*Spec 5*). The sample range is from 1985q1 to 2016q2. Therefore, the estimates of (*Spec 5*) can be compared with the entire sample case of (*Spec 1*).

Appendix 3.6.4 Table 3.17 presents the statistics for choosing an appropriate lag order in (*Spec 4*). The suitable lag length is $p = 2$ selected by minimizing the information criteria while ensuring no serial correlation in the error term. For the test of long run level relationship, the critical value bounds when $k = 9$ in PSS is used. Table 3.6 shows that joint and single hypotheses of no level relationship in different scenarios are rejected at 5% significance level. This implies that the significant long run equilibrium exists between gross capital flows and global, contagion and domestic factors even by changing the proxy for global uncertainty from GPR index to GEPU index.

Table 3.6: F- and t-statistics for testing the existence of levels equation (*Spec 4*)

Gross capital inflows						Gross capital outflows					
	With trend			Without trend			With trend			Without trend	
p	F_{IV}	F_V	t_V	F_{III}	t_{III}	p	F_{IV}	F_V	t_V	F_{III}	t_{III}
2	11.85^c	11.78^c	-9.51^c	10.30^c	-8.97^c	2	10.46^c	10.44^c	-8.96^c	8.99^c	-8.44^c

Notes: F_{III} is the F-statistic for testing the null hypothesis, $H_0 : \pi_{cc} = 0$, $\boldsymbol{\pi}_{cx.x} = \mathbf{0}'$ with β_1 set equal to zero. F_{IV} is the F-statistic for testing $H_0 : \pi_{cc} = 0$, $\boldsymbol{\pi}_{cx.x} = \mathbf{0}'$, and $\beta_1 = 0$. F_V is the F-statistic for testing $H_0 : \pi_{cc} = 0, \boldsymbol{\pi}_{cx.x} = \mathbf{0}'$. t_{III} is the t-ratio for testing $\pi_{cc} = 0$ without a deterministic trend. t_V is the t-ratio for testing $\pi_{cc} = 0$ with a deterministic trend. [a] indicates the statistic is smaller than the 0.05 lower bound, [b] denotes the statistic is within the 0.05 bounds and [c] denotes the statistic is greater than the 0.05 upper bound.

The estimates of the long run equilibrium is listed in Appendix 3.6.5 Table 3.27-3.28. Comparing to the sub sample estimates of (*Spec 1*), global uncertainty, proxied by GEPU index, becomes significant in both capital inflows and outflows estimation. The coefficient is positive, implying that an increase in global uncertainty is associated with surges of capital inflows by foreign investors and capital flight by domestic investors. These findings coincide with the results in (*Spec 1*) entire sample case: the flight-to-quality incentives can form different cross-border investment dynamics among foreign and domestic investors. However, the coefficients of GEPU on capital outflows are larger than capital inflows, suggesting *net* capital outflows. This is the opposite to the findings in (*Spec 1*), where global geopolitical uncertainty is likely to induce *net* capital inflows to the UK financial market. The results may reflect the difference in the aspects of uncertainty that are captured distinctively by each index. It is largely recognised in the recent literature that country-level EPU index might be endogenous to domestic economic conditions. GEPU index is constructed using GDP weight and the UK is one of the largest economy in the world. Therefore, the GEPU index may be largely correlated with the UK's domestic economic fundamentals. If GEPU is positively correlated with recessionary pressure in the UK economy, the domestic investors' incentive of reducing the exposures to domestic assets may become stronger than the foreign investors' incentive of flight-to-quality.

The two contagion factors, financial linkages and international investors' aspects, are significant and have positive sign. The increased level of financial contagion factor is likely to be associated with *net* capital inflows while the increased proportion of international investors associated with *net* capital outflows. All of the findings regarding the contagion factors are unchanged from the estimation results in benchmark models with GPR index.

Among domestic factors, increases in sovereign debt level is correlated to increased level of gross capital inflows and outflows. The effect of sovereign debt on gross outflows is larger than gross inflows, suggesting *net* outflows when the government debt increases. This is also the same findings as (*Spec 1*) estimated using sub sample data.

To estimate the conditional ECM with ARDL(c_t, $GEPU_t$, i_t, $WGDP_t$, TL_t, FL_t, inv_t, $DGDP_t$, ppi_t, $debt_t$), the lag orders of autoregressive terms are selected based on AIC. The resulting lags of the conditional ECM is ARDL(2, 1, 2, 2, 1, 2, 2, 1, 1, 2) for capital inflows equation and ARDL(2, 1, 2, 2, 1, 2, 2, 2, 1, 2) for capital outflows equation.

In terms of the short term dynamics (see Table 3.41-3.42 in Appendix 3.6.7), the error correction terms are significant in both capital inflows and outflows estimation. GEPU and contagion factors (excluding trade linkages) are important factors in the short run. On the contrary, in the benchmark model, GPR index is only significant for some specification. Instead, risk-free interest rate and contagion factors are significant in the conditional ECM in the benchmark model (*Spec 1*).

In the ECM specifications without the dummy, other variables are also significant. World output growth and public debt are significant in the capital inflows equations of (*Spec 4*), whereas global uncertainty (GPR index), world output growth and domestic output growth are important in (*Spec 1*). As for capital outflows equations in (*Spec 4*), world GDP and all three domestic factors are found to be significant while lags of capital outflows, global uncertainty, world GDP growth and domestic GDP growth in (*Spec 1*).

To summarize, the choice of the proxy for global uncertainty does not decay the significance of contagion factors on gross capital movements both in the long-run and the short-run. However, the effect of other global and domestic factors on the capital flows may change by switching between different measures for global uncertainty. GPR and GEPU captures different aspects of uncertainty and as discussed previously. Since EPU index can suffer from potential endogeniety by construction, the estimation results in (*Spec 4*) should be interpreted with caution.

Finally, the entire sample estimation with an interaction term is performed (*Spec*

5).[30] Define $pdebt_t \equiv D_{2008} \times debt_t$, so that the variables included in the model are (c_t, GPR_t, i_t, $WGDP_t$, FL_t, inv_t, $DGDP_t$, ppi_t, $debt_t$, $pdebt_t$). Based on information criteria and the absence of the autocorrelation, the appropriate lag lengths are chosen as $p = 2, 4$. The relevant statistics are presented in Table 3.18 in Appendix 3.6.4. To test the existence of long run relationships in the level variables, F- and t-tests are performed. The critical value bounds are the same as (*Spec 4*) as $k = 9$ as it includes $pdebt_t$ but excludes TL_t. The test statistics in Table 3.7 confirms the existence of long run relationship when $p = 2$, regardless whether the model has deterministic trend or not.

Table 3.7: F- and t-statistics for testing the existence of levels equation (*Spec 5*)

Gross capital inflows						Gross capital outflows					
	With trend			Without trend			With trend			Without trend	
p	F_{IV}	F_V	t_V	F_{III}	t_{III}	p	F_{IV}	F_V	t_V	F_{III}	t_{III}
2	10.25^c	10.04^c	-9.53^c	9.28^c	-9.10^c	2	7.86^c	7.65^c	-8.25^c	7.01^c	-7.84^c
4	5.06^c	5.04^c	-6.22^c	4.65^c	-5.95^c	4	4.09^c	4.05^c	-5.10^c	3.55^c	-4.71^b

Notes: F_{III} is the F-statistic for testing the null hypothesis, $H_0 : \pi_{cc} = 0$, $\boldsymbol{\pi}_{cx.x} = \mathbf{0}'$ with β_1 set equal to zero. F_{IV} is the F-statistic for testing $H_0 : \pi_{cc} = 0$, $\boldsymbol{\pi}_{cx.x} = \mathbf{0}'$, and $\beta_1 = 0$. F_V is the F-statistic for testing $H_0 : \pi_{cc} = 0, \boldsymbol{\pi}_{cx.x} = \mathbf{0}'$. t_{III} is the t-ratio for testing $\pi_{cc} = 0$ without a deterministic trend. t_V is the t-ratio for testing $\pi_{cc} = 0$ with a deterministic trend. [a] indicates the statistic is smaller than the 0.05 lower bound, [b] denotes the statistic is within the 0.05 bounds and [c] denotes the statistic is greater than the 0.05 upper bound.

The long run relationships are summarised in Appendix 3.6.5. Table 3.29-3.30. The contagion factors are still significant in explaining the changes in gross capital flows. The differential effect of public debt before and after the GFC is captured by the estimated coefficient on $pdebt_t$ term. It is significant and positive. That is, in the post-crisis period, the increased level of public debt is correlated with higher level of gross capital inflows while the correlation is nearly zero in the pre-crisis period. As discussed in the benchmark model, this might reveal the effectiveness of expansionary monetary and fiscal policies in response to the global financial crisis to retain investment from abroad. The gross capital outflow estimation result (positive coefficient) suggests that the elevated level of domestic government debt might stimulate capital flight of domestic investors. The difference in the magnitude of the coefficients on *pdebt* between inflows and outflows indicates that the increased level of sovereign debt is likely to induce *net* capital inflows after the GFC. However, there is no significant long run relationship between sovereign debt and net capital flows before the GFC.

For the estimation of short-term dynamics, the lag orders of autoregressive terms

[30] Admittedly, we cannot rule out the potential slope differential effect on other variables, such as political risk. The extension could be further investigated by introducing an interaction term of dummy and GPR index, in this case.

in the conditional ECM are selected based on AIC: ARDL(2, 1, 1, 2, 2, 2, 2, 1, 1, 1) for capital inflows and ARDL(2, 1, 1, 2, 2, 2, 1, 1, 1, 1) for capital outflows. The estimates of the conditional ECM are shown in Appendix 3.6.7. Table 3.43-3.44. The results of capital inflows and outflows are mostly homogeneous: the error correction terms and contagion factors are significant, domestic GDP growth and the interaction between dummy and public debt to GDP ($pdebt_t$) are significant. In (*Spec 1*), government debt does not have significant short run impact on both gross capital inflows and outflows. This suggest the changes of how government debt is associated with short run dynamics of capital flows.

3.5 Conclusions

The research on the effect of uncertainty in open economy setting is rapidly growing area after the Great Financial Crisis in 2008. However, most studies are limited by focusing on theoretical models of cross-border portfolio asset allocation. Empirically, volatility measures are largely employed for uncertainty proxy, failing to incorporate recent developments in measuring uncertainty based on appropriate definition. This research aims at making a contribution towards the on-going discussions in empirical literature on uncertainty and capital flows. It emphasized the impact of geopolitical uncertainty and uncertainty co-movement among major European countries on the UK's gross capital movements. In particular, it implemented the bounds testing approach by Pesaran, Shin and Smith (2001) to examine whether there is long run relationship between uncertainty factors and gross capital flows. The main findings are summarised as follows.

First, in the long run, global uncertainty, proxied by Geopolitical Risk (GPR) index, contains important information about cross-border investments after controlling for other factors. The correlation can be interpreted causally because GPR index reflects exogenous source of uncertainty. The results suggest that higher level of geopolitical uncertainty increases inflows by foreign investors but leads to capital flight by domestic investors. In terms of *net* capital flows, the flight-to-quality motives of foreign investors (a large-scale surge in capital inflows) tend to be stronger than the incentives of residents' capital flight to safer assets.

Second, contagion factors, such as financial linkages and end investors' behavioural aspects, are important long run factors of cross-border investment decisions in the UK. Gross capital inflows and outflows are positively correlated with the degree of financial links to the core European countries and with the end portfolio investors' proportion. The higher degree of banking sector integration among the UK and other European countries may induce *net* capital inflows to the UK in the long run while the increased role of international end investors and asset managers may prompt *net* capital outflows from the UK financial market. These findings may draw some key policy implications regarding the recent Brexit decision. Due to the potential loss of access to EU single financial market, the UK's financial linkages to other core European countries may weaken and, therefore, it may experience large stops in gross capital inflows in the long run.

Third, contagion in uncertainty measured by the co-movement of EPU between the UK and core European countries has significant and positive correlation with capital flows in the two stage estimation. Uncertainty contagion due to trade and financial links within European countries is associated with stops in capital inflows and retrenchment in capital outflows. In terms of the *net* flows, as the uncertainty contagion between the two economies increases, *net* capital inflows increases. The theoretical mechanism of how the economic and financial linkages affect the co-movement in uncertainty is left to the future research.

Finally, in the short run, capital flows dynamics are mostly stable and help convergence towards the long run equilibrium. In the benchmark model, contagion factors are crucial to long- and short-term dynamics of gross capital flows while sovereign debt is only important for long run relationships. On the contrary, in the model with uncertainty co-movement index, contagions in uncertainty matters only for long run relationship and sovereign debt is important for both long- and short-run movements in gross capital flows.

3.6 Appendix

3.6.1 Related literature

I. Literature on uncertainty effect on financial markets

Pástor and Veronesi (2013) showed that political uncertainty can affect asset prices and volatility by reducing the value of the implicit put protection that government provides to the financial market. Ulrich (2013) analysed the uncertainty effect on bond markets with a focus on fiscal policy uncertainty. Brogaard and Detzel (2015) documented the relationship between news-based measure of policy uncertainty and equity risk premium. Bordo, Duca, and Koch (2016) examined the bank credit channel of economic policy uncertainty using the US aggregate and individual bank data. In terms of the linkages between real activities and financial market frictions, Alfaro, Bloom and Lin (2016) developed a model that elucidates firms' investment and financial decision making problems in highly uncertain economic situations.

II. Literature on uncertainty and international portfolio allocation

Pástor and Veronesi (2013) showed that, with higher policy uncertainty, agents are less favourable for taking risks, leading to safe-haven capital flows in equity market. Jotikasthira, Lundblad, and Ramadorai (2012) found that the funds domiciled in advanced economies tend to change their asset allocations in emerging markets followed by uncertainty shocks. Gauvin, McLoughlin, and Reinhardt (2014) documented that the spillover effect in portfolio capital flows due to the policy uncertainty shocks in advanced countries differs with respect to the orientation of the policy uncertainty, whether it is from the US or the EU. Gourio, Siemer, and Verdelhan (2013) built a real business cycle model that can explain time-varying aggregate uncertainty, and excess co-movement of asset prices. Recently, Gourio, Siemer, and Verdelhan (2016) extended Gourio, Siemer, and Verdelhan (2013) and Carrière-Swallow and Céspedes (2013) by setting up a model that can unveil the causal relationship of political uncertainty, financial market volatility and capital flows.

III. Literature on net capital flows

A great number of existing literature studied the behaviour of net capital flows. Traditionally, the external factors that affect net capital flows were referred as push factors and domestic determinants as pull factors (Calvo, Leiderman and Reinhart, 1993, 1996; Fernandez-Arias, 1996; Chuhan, Claessens and Mamingi, 1998; Griffin, Nardari and Stulz, 2004, among others). Among many, one of the important advance in the studies of net capital flows is the study of the determinants of sudden stops (or surges) of net capital flows. They are particularly interested in the abrupt reversals in capital flows and its impact on the small open economies. Key discussions are about the definition of sudden stops and how to identify those highly damaging episodes from country-level panel data. The definition of sudden stops of net capital flows varies among researchers. For example, Calvo (1998) defined sudden stops as episodes of a sharp decrease in net capital flows, Calvo, Izquierdo, and Mejia (2004) in terms of output contraction, and Calvo, Izquierdo, and Mejia (2008) a sharp increase in interest rate spread. On the mirror concept of sudden stops, Reinhart and Reinhart (2008) defined bonanzas as a sharp increase in net capital flows.

IV. Literature on gross capital flows

Rothenberg and Warnock (2011) distinguished true sudden stop (gross capital inflow decreases more than gross outflow increase) form sudden flight (gross capital outflows increase more than gross capital inflow decrease). In addition, the study of link between sudden gross capital flows and crisis has been prompted by several researchers in the aftermath of financial crisis in 2008. Milesi-Ferretti and Tille (2011) studied the recent crisis episodes of extreme events in gross capital flows and Broner et al. (2013) examined the relationship between business cycle and capital flows. Among others, Forbes and Warnock (2012a, 2012b) focused on the different incentives of movement in capital flows depending on the type of investors. Incentives of cross-border capital movements may vary by different types of investors with regards to their residence, i.e. domestic or foreign investors. They characterised four extreme episodes of gross capital flows depending on changes in gross outflows and inflows, respectively, and analysed different factors contribute to different extreme events. Surge is defined as a sharp increase in gross capital inflows by foreign investors, stop as a sharp decrease in gross capital inflows by foreign investors, flight as a sharp increase in domestic investors' gross capital outflows and retrenchment as a sudden decrease in gross outflows of domestic investors.

3.6.2 Determinants of capital flows in the literature

Table 3.8: Determinants of capital flows in the traditional literature (push-pull factors)

	Push factors	Pull factors
Real	Global output growth, commodity prices	GDP growth, inflation, fiscal balance, public debt, short-term external debt
Financial	*(Implied or realised)* US stock market volatility, global liquidity, long-term interest rate	Domestic short-term interest rate, bank credit growth, domestic equity market returns, volatility, sovereign CDS speads
Structural/Institutional	International investors' behaviour	Market capitalisation (the ratio of equity market capital to GDP), capital account openness (Chinn and Ito Index), financial risk index by International Country Risk Guide (ICRG)

3.6.3 Unit root test results

Table 3.9: Augmented Dickey Fuller (ADF) test, Sample I

	Level			First differences			
	None	Intercept	Trend, Intercept	None	Intercept	Trend, intercept	Decision
CFI	−1.719*	−2.349	−2.319	−8.078***	−8.041***	−8.008***	$I(1)$
CFO	−1.844*	−2.319	−2.288	−8.322***	−8.283***	−8.254***	$I(1)$
GPR	−1.198	−4.146***	−4.366***	−12.732***	−12.681***	−12.641***	$I(0)$
i	−2.862***	−2.209	−5.453***	−8.311***	−6.734***	−6.666***	$I(0)$
$WGDP$	−0.997	−6.315***	−6.288***	−7.545***	−7.511***	−7.479***	$I(0)$
FL	0.288	−1.310	−0.216	−9.501***	−9.539***	−9.651***	$I(1)$
inv	−2.301**	−3.756***	−3.721**	−14.822***	−14.761***	−14.721***	$I(0)$
$DGDP$	−1.416	−3.057**	−3.160*	−8.779***	−8.740***	−8.702***	$I(0)$
ppi	−1.471	−2.035	−2.636	−9.318***	−9.300***	−9.266***	$I(1)$
$debt$	0.655	−0.658	−2.231	−2.483**	−2.684*	−2.807	$I(1)$

Table 3.10: Augmented Dickey Fuller (ADF) test, Sample II

	Level			First differences			
	None	Intercept	Trend, Intercept	None	Intercept	Trend, intercept	Decision
CFI	−2.932***	−3.500**	−3.671**	−6.484***	−6.438***	−6.395***	$I(0)$
CFO	−1.512	−3.414**	−3.642**	−6.684***	−6.638***	−6.598***	$I(0)$
GPR	−0.846	−3.501**	−3.503**	−10.062***	−10.009***	−9.944***	$I(0)$
i	−1.823*	−1.128	−3.958**	−4.318***	−7.463***	−7.408***	$I(0)$
$WGDP$	−1.154	−4.933***	−4.903***	−6.154***	−6.112***	−6.069***	$I(0)$
TL	−1.251	−1.046	−3.998**	−9.529***	−9.623***	−9.546***	$I(1)$
FL	0.100	−1.321	−0.194	−7.474***	−7.455***	−7.778***	$I(1)$
inv	−1.914*	−7.328***	−7.485***	−11.885***	−11.813***	−11.746***	$I(0)$
$DGDP$	−1.041	−2.083	−2.416	−8.402***	−8.345***	−8.288***	$I(1)$
ppi	−1.757*	−4.068***	−4.080***	−7.096***	−7.088***	−7.040***	$I(0)$
$debt$	0.638	−0.613	−2.334	−2.025**	−2.230	−2.357	$I(1)$
$Comov$	−1.791*	−7.152***	−7.170***	−8.601***	−8.555***	−8.622***	$I(0)$
$coBC$	−1.659**	−3.014**	−2.989	−9.056***	−8.992***	−8.937***	$I(0)$

Notes: Sample I denotes the period 1985q1–2016q2 and Sample II denotes the period 1997q1–2016q2. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively. MacKinnon (1996) critical values are used for rejection of the null hypothesis of unit root. Lag lengths are selected based on Schwarz information criterion.

Table 3.11: Phillips Perron (PP) test, Sample I

	Level			First differences			
	None	Intercept	Trend, Intercept	None	Intercept	Trend, intercept	Decision
CFI	-9.459^{***}	-10.158^{***}	-10.146^{***}	-29.706^{***}	-29.577^{***}	-28.411^{***}	$I(0)$
CFO	-9.423^{***}	-9.907^{***}	-9.880^{***}	-28.707^{***}	-28.582^{***}	-28.492^{***}	$I(0)$
GPR	-2.312^{**}	-6.794^{***}	-6.983^{***}	-41.908^{***}	-41.684^{***}	-45.261^{***}	$I(0)$
i	-2.597^{***}	-2.195	-4.553^{***}	-8.059^{***}	-8.224^{***}	-8.182^{***}	$I(0)$
$WGDP$	-1.066	-3.318^{**}	-3.306^{*}	-7.114^{***}	-7.046^{***}	-6.970^{***}	$I(0)$
FL	-0.015	-1.397	-0.852	-9.905^{***}	-9.924^{***}	-9.987^{***}	$I(1)$
inv	-6.963^{***}	-9.883^{***}	-9.932^{***}	-48.314^{***}	-48.077^{***}	-53.336^{***}	$I(0)$
$DGDP$	-2.005^{**}	-3.326^{**}	-3.444^{*}	-7.576^{***}	-7.544^{***}	-7.542^{***}	$I(0)$
ppi	-2.638^{***}	-3.183^{**}	-3.350^{*}	-6.208^{***}	-7.113^{***}	-7.018^{***}	$I(0)$
$debt$	1.757	0.398	-1.328	-6.505^{***}	-7.033^{***}	-7.416^{***}	$I(1)$

Table 3.12: Phillips Perron (PP) test, Sample II

	Level			First differences			
	None	Intercept	Trend, Intercept	None	Intercept	Trend, intercept	Decision
CFI	-6.846^{***}	-7.886^{***}	-8.104^{***}	-25.642^{***}	-25.467^{***}	-25.316^{***}	$I(0)$
CFO	-6.908^{***}	-7.654^{***}	-7.954^{***}	-22.730^{***}	-22.581^{***}	-22.444^{***}	$I(0)$
GPR	-1.861^{*}	-5.369^{***}	-5.399^{***}	-20.675^{***}	-20.839^{***}	-20.988^{***}	$I(0)$
i	-1.749^{*}	-1.128	-3.161^{*}	-7.538^{***}	-7.633^{***}	-7.573^{***}	$I(0)$
$WGDP$	-1.365	-3.380^{**}	-3.371^{*}	-4.955^{***}	-4.912^{***}	-4.871^{***}	$I(0)$
TL	-2.186^{**}	-0.655	-3.955^{**}	-10.146^{***}	-12.077^{***}	-12.632^{***}	$I(0)$
FL	-0.064	-1.422	-0.452	-7.593^{***}	-7.574^{***}	-7.824^{***}	$I(1)$
inv	-5.261^{***}	-7.765^{***}	-7.882^{***}	-29.377^{***}	-29.232^{***}	-29.573^{***}	$I(0)$
$DGDP$	-2.044^{**}	-3.056^{**}	-3.237^{*}	-5.439^{***}	-5.407^{***}	-5.375^{***}	$I(0)$
ppi	-2.180^{**}	-2.700^{*}	-2.691	-5.116^{***}	-5.088^{***}	-5.055^{***}	$I(0)$
$debt$	1.718	0.357	-1.828	-4.586^{***}	-5.087^{***}	-5.703^{***}	$I(1)$
$Comov$	-3.640^{***}	-7.152^{***}	-7.170^{***}	-30.983^{***}	-32.436^{***}	-34.516^{***}	$I(0)$
$coBC$	-2.357^{**}	-3.556^{***}	-3.534^{**}	-11.716^{***}	-11.539^{***}	-11.428^{***}	$I(0)$

Notes: The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively. MacKinnon (1996) critical values are used for rejection of the null hypothesis of unit root. Bartlett kernel is used to estimate the frequency zero spectrum. The method of selecting the bandwidth is Newey-West automatic variable bandwidth selection.

3.6.4 Statistics for selecting the lag order

Table 3.13: Statistics for selecting the lag order: Gross capital inflows (*Spec 1*)

Sample: 1985q1 - 2016q2								
	With deterministic trends				Without deterministic trends			
p	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$
1	12.07	12.73	0.07	2.15	12.07	12.71	0.57	2.28
2	11.95	12.81	1.79	0.38	12.00	12.85	4.65**	0.08
3	11.97	13.05	1.43	3.14*	12.04	13.09	1.22	1.36
4	11.90	13.19	0.12	0.19	11.94	13.21	0.18	0.01
5	11.88	13.39	1.07	0.39	11.93	13.42	1.79	0.38
6	11.70	13.43	0.13	1.73	11.80	13.50	0.18	1.52
7	11.41	13.36	0.91	8.33***	11.47	13.40	0.68	7.26***
Sample: 1997q1 - 2016q2								
	With deterministic trends				Without deterministic trends			
p	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$
1	12.48	13.45	0.01	0.97	12.46	13.40	0.00	0.99
2	12.23	13.52	0.22	0.40	12.23	13.49	0.06	0.37
3	12.25	13.85	0.99	0.31	12.28	13.86	0.92	0.11
4	11.71	13.64	3.21*	3.45*	11.70	13.60	3.71*	3.57*

Notes: p is the order of lag in the underlying VAR model for equation (1), without any restrictions on the coefficients of lagged changes in determinants. $AIC \equiv -2(l/T) + 2(k/T)$ and $SBC \equiv -2(l/T) + k\ln(T)/T$ denote Akaike's and Schwarz's Bayesian Information Criteria for a given lag order, where l is the value of the log likelihood function, k is number of parameters and T is the sample size. $\chi^2_{SC}(1)$ and $\chi^2_{SC}(4)$ are the LM statistics for testing autocorrelation in the errors for the models including 1 lag and 4 lags, respectively. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

Table 3.14: Statistics for selecting the lag order: Gross capital outflows (*Spec 1*)

Sample: 1985q1 - 2016q2								
	With deterministic trends				Without deterministic trends			
p	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$
1	12.13	12.79	2.25	4.63**	12.12	12.76	3.86**	4.53**
2	12.04	12.91	3.70*	0.38	12.09	12.93	7.73***	0.53
3	12.07	13.15	3.96**	0.30	12.13	13.19	3.45*	0.01
4	12.05	13.35	2.22	0.00	12.10	13.37	1.35	0.09
5	12.12	13.63	2.28	0.00	12.14	13.63	2.14	0.00
6	11.87	13.60	0.15	0.30	11.92	13.63	0.30	0.32
7	11.54	13.49	1.88	5.69**	11.57	13.49	1.22	5.73**
Sample: 1997q1 - 2016q2								
	With deterministic trends				Without deterministic trends			
p	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$
1	12.45	13.42	0.33	0.25	12.42	13.37	0.35	0.26
2	12.30	13.59	0.06	0.75	12.30	13.56	0.00	0.95
3	12.19	13.80	1.45	0.39	12.24	13.82	1.32	0.32
4	11.66	13.59	2.74*	2.82*	11.63	13.53	2.98*	2.81*

Notes: p is the order of lag in the underlying VAR model for equation (1), without any restrictions on the coefficients of lagged changes in determinants. $AIC \equiv -2(l/T) + 2(k/T)$ and $SBC \equiv -2(l/T) + k\ln(T)/T$ denote Akaike's and Schwarz's Bayesian Information Criteria for a given lag order, where l is the value of the log likelihood function, k is number of parameters and T is the sample size. $\chi^2_{SC}(1)$ and $\chi^2_{SC}(4)$ are the LM statistics for testing autocorrelation in the errors for the models including 1 lag and 4 lags, respectively. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

Table 3.15: Statistics for selecting the lag order (*Spec 2*)

Gross capital inflows								
	With deterministic trends				Without deterministic trends			
p	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$
1	13.16	13.97	2.27	5.78**	13.27	14.04	0.75	5.84**
2	12.76	13.82	2.41	0.06	13.16	14.19	0.29	7.81***
3	12.62	13.94	0.01	0.70	13.01	14.30	0.04	0.00
4	12.41	13.99	3.91**	0.92	12.73	14.28	1.80	0.43
5	11.71	13.56	2.61	0.49	12.30	14.11	0.00	0.76
Gross capital outflows								
	With deterministic trends				Without deterministic trends			
p	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$
1	13.24	14.05	2.14	5.88**	13.28	14.06	1.18	6.00**
2	12.81	13.87	2.85*	0.12	13.08	14.11	0.28	5.85**
3	12.56	13.87	0.32	0.45	12.94	14.23	0.06	0.08
4	12.20	13.78	5.24**	1.14	12.63	14.18	1.72	0.23
5	11.37	13.21	4.24**	0.85	12.13	13.95	0.03	0.65

Table 3.16: Statistics for selecting the lag order (*Spec 3*)

Gross capital inflows								
	With deterministic trends				Without deterministic trends			
p	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$
1	13.02	13.84	4.73**	5.67**	13.06	13.85	1.65	4.95**
2	12.62	13.70	2.90*	0.49	13.06	14.11	1.04	3.32*
3	12.37	13.72	1.19	0.31	12.79	14.10	1.49	0.22
4	11.83	13.45	3.43*	0.42	12.21	13.79	2.41	0.13
Gross capital outflows								
	With deterministic trends				Without deterministic trends			
p	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$
1	13.06	13.88	3.47*	5.00**	13.05	13.84	2.19	4.48**
2	12.68	13.76	2.93*	0.31	12.96	14.01	0.34	1.51
3	12.28	13.62	3.08*	0.16	12.65	13.96	2.18	0.04
4	11.58	13.20	4.25**	0.30	11.98	13.57	3.82*	0.00

Notes: p is the order of lag in the underlying VAR model for equation (1), without any restrictions on the coefficients of lagged changes in determinants. $AIC \equiv -2(l/T) + 2(k/T)$ and $SBC \equiv -2(l/T) + k\ln(T)/T$ denote Akaike's and Schwarz's Bayesian Information Criteria for a given lag order, where l is the value of the log likelihood function, k is number of parameters and T is the sample size. $\chi^2_{SC}(1)$ and $\chi^2_{SC}(4)$ are the LM statistics for testing autocorrelation in the errors for the models including 1 lag and 4 lags, respectively. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

Table 3.17: Statistics for selecting the lag order (*Spec 4*)

Capital inflows								
	With deterministic trends				Without deterministic trends			
1	12.64	13.62	0.14	1.07	12.66	**13.61**	0.00	1.07
2	12.30	**13.60**	0.15	0.18	12.41	13.67	0.25	0.01
3	12.30	13.92	0.27	0.09	12.55	14.14	0.25	0.14
4	**11.66**	13.61	2.62	1.45	**11.86**	13.78	1.40	4.61^{**}
Capital outflows								
	With deterministic trends				Without deterministic trends			
p	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$
1	12.66	13.64	0.04	0.91	12.68	**13.63**	0.45	0.94
2	12.38	13.67	0.01	0.01	12.48	13.75	0.72	0.09
3	12.27	13.89	0.67	0.04	12.58	14.16	0.21	0.34
4	**11.54**	**13.49**	2.75^{*}	0.62	**11.97**	13.88	0.98	3.70^{*}

Table 3.18: Statistics for selecting the lag order (*Spec 5*)

Capital inflows								
	With deterministic trends				Without deterministic trends			
1	11.97	**12.70**	4.06^{**}	2.74^{*}	11.97	**12.67**	2.58	2.28
2	**11.89**	12.85	0.40	0.49	11.94	12.88	4.77^{**}	0.00
3	11.92	13.12	0.95	1.91	11.96	13.13	5.95^{**}	0.00
4	11.90	13.34	2.73^{*}	0.07	**11.93**	13.34	1.96	1.46
Capital outflows								
	With deterministic trends				Without deterministic trends			
p	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$	AIC	SBC	$\chi^2_{SC}(1)$	$\chi^2_{SC}(4)$
1	11.96	**12.69**	2.31	4.61^{**}	**11.96**	**12.67**	0.44	4.79^{**}
2	**11.93**	12.89	0.38	0.23	11.97	12.91	1.93	0.56
3	11.94	13.13	4.09^{**}	0.18	11.98	13.16	2.64	0.06
4	11.94	13.38	2.29	0.08	11.99	13.40	1.94	0.03

Notes: p is the order of lag in the underlying VAR model for equation (1), without any restrictions on the coefficients of lagged changes in determinants. $AIC \equiv -2(l/T) + 2(k/T)$ and $SBC \equiv -2(l/T) + k\ln(T)/T$ denote Akaike's and Schwarz's Bayesian Information Criteria for a given lag order, where l is the value of the log likelihood function, k is number of parameters and T is the sample size. $\chi^2_{SC}(1)$ and $\chi^2_{SC}(4)$ are the LM statistics for testing autocorrelation in the errors for the models including 1 lag and 4 lags, respectively. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

3.6.5 Long run estimation results

Table 3.19: Long run estimation: Capital inflows, Sample I (*Spec 1*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
GPR_t	0.51	0.26	*	0.21	0.29		0.45	0.25	*	0.20	0.27	
i_t	-4.43	18.87		-4.52	21.44		2.96	14.75		-2.44	16.70	
$WGDP_t$	27.96	13.06	**	40.99	14.62	***	25.90	12.62	**	40.38	14.03	***
FL_t	3.31	1.24	***	1.84	1.38		2.85	1.00	***	1.71	1.12	
inv_t	16.76	3.97	***	18.05	4.50	***	16.72	3.96	***	18.03	4.48	***
$DGDP_t$	-4.61	8.66		10.28	9.41		-3.34	8.40		10.60	9.14	
ppi_t	2.53	8.84		-12.57	9.61		4.06	8.48		-12.10	9.10	
$debt_t$	12.20	3.29	***	-3.64	2.16	*	11.34	2.98	***	-3.84	1.69	**
c	-415.40	176.13	**	-44.47	186.85		-468.34	154.47	***	-60.20	156.47	
t	-1.03	1.64		-0.29	1.85		-	-		-	-	
D_{2008}	-515.84	87.58	***	-	-		-511.57	87.09	***	-	-	

Table 3.20: Long run estimation: Capital inflows, Sample II (*Spec 1*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
GPR_t	0.47	0.42		0.29	0.48		0.42	0.39		0.17	0.44	
i_t	-14.15	40.38		-10.32	45.84		-8.46	36.12		2.94	41.03	
$WGDP_t$	23.26	20.17		32.38	22.78		21.83	19.55		29.20	22.17	
TL_t	6.45	16.68		6.15	18.94		8.87	14.82		11.76	16.85	
FL_t	4.72	2.21	**	5.58	2.50	**	4.43	2.01	**	4.92	2.29	**
inv_t	18.26	5.44	***	17.57	6.17	***	18.28	5.40	***	17.60	6.15	***
$DGDP_t$	-0.84	17.17		28.75	18.02		-0.70	17.05		29.54	17.91	
ppi_t	-2.60	17.50		-34.13	18.22	*	-1.89	17.25		-32.96	18.06	*
$debt_t$	16.48	5.36	***	0.31	4.53		15.91	5.03	***	-1.26	3.83	
c	-708.03	707.99		-303.54	797.44		-854.83	540.54		-638.10	613.00	
t	-1.29	3.97		-2.96	4.49		-	-		-	-	
D_{2008}	-612.54	135.68	***	-	-		-616.65	134.18	***	-	-	

Notes: (1) includes constant term, deterministic trend and dummy, (2) excludes dummy, (3) excludes deterministic trend, and (4) excludes both deterministic trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

Table 3.21: Long run estimation: Capital outflows, Sample I (*Spec 1*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
GPR_t	0.48	0.26	*	0.20	0.29		0.41	0.25	*	0.17	0.28	
i_t	-5.26	19.08		-5.34	21.50		4.30	14.94		-0.96	16.76	
$WGDP_t$	34.00	13.21	**	46.72	14.67	***	31.34	12.77	**	45.43	14.08	***
FL_t	2.99	1.26	**	1.56	1.39		2.40	1.02	**	1.29	1.12	
inv_t	18.77	4.01	***	20.03	4.51	***	18.71	4.00	***	20.00	4.49	***
$DGDP_t$	-7.40	8.75		7.13	9.43		-5.76	8.50		7.81	9.17	
ppi_t	0.51	8.94		-14.22	9.65		2.49	8.59		-13.24	9.13	
$debt_t$	12.14	3.33	***	-3.31	2.16		11.02	3.02	***	-3.74	1.70	**
c	-402.28	178.12	**	-40.42	187.44		-470.69	156.38	***	-73.60	157.01	
t	-1.34	1.66		-0.61	1.86		-	-		-	-	
D_{2008}	-503.23	88.57	***	-	-		-497.71	88.17	***	-	-	

Table 3.22: Long run estimation: Capital outflows, Sample II (*Spec 1*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
GPR_t	0.51	0.43		0.34	0.47		0.43	0.39		0.20	0.44	
i_t	-16.51	40.84		-12.87	45.73		-7.73	36.58		3.17	40.99	
$WGDP_t$	33.85	20.40		42.52	22.73	*	31.64	19.79		38.67	22.16	*
TL_t	12.09	16.87		11.81	18.89		15.82	15.00		18.59	16.84	
FL_t	4.70	2.24	**	5.52	2.50	**	4.26	2.04	**	4.73	2.29	**
inv_t	20.87	5.50	***	20.21	6.16	***	20.90	5.47	***	20.25	6.14	***
$DGDP_t$	-7.16	17.37		20.99	17.98		-6.95	17.27		21.94	17.89	
ppi_t	-7.06	17.70		-37.05	18.18	**	-5.95	17.46		-35.64	18.05	*
$debt_t$	17.31	5.42	***	1.93	4.51		16.44	5.09	***	0.03	3.83	
c	-867.20	716.09		-482.38	795.52		-1094.06	547.31	**	-887.00	612.45	
t	-1.99	4.02		-3.58	4.48		-	-		-	-	
D_{2008}	-582.75	137.23	***	-	-		-589.10	135.86	***	-	-	

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

Table 3.23: Long run estimation: Capital inflows, Sample II (*Spec 2*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
GPR_t	-0.08	0.46		-0.31	0.51		0.08	0.45		-0.16	0.50	
i_t	-3.01	45.72		-3.31	50.79		-48.78	35.49		-45.82	39.21	
$WGDP_t$	40.42	22.46	*	49.34	24.84	*	59.08	19.23	***	66.59	21.15	***
$Comov$	55.17	95.99		7.29	105.85		62.90	96.88		14.93	106.23	
$DGDP_t$	-16.13	19.14		15.93	19.43		-28.86	17.51		3.80	17.15	
ppi_t	7.72	14.32		-20.84	13.91		7.59	14.47		-20.69	13.98	
$debt_t$	7.52	5.78		-11.09	4.00	***	10.31	5.55	*	-8.31	3.40	**
c	-417.42	415.24		-11.54	448.09		49.61	291.55		418.40	305.86	
t	5.08	3.25		4.72	3.61		-	-		-	-	
D_{2008}	-642.70	156.23	***	-	-		-636.04	157.82	***	-	-	

Table 3.24: Long run estimation: Capital outflows, Sample II (*Spec 2*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
GPR_t	-0.07	0.47		-0.29	0.51		0.05	0.46		-0.18	0.50	
i_t	-2.63	46.80		-2.92	51.45		-36.52	36.03		-33.65	39.48	
$WGDP_t$	51.12	23.00	**	59.76	25.16	**	64.94	19.52	***	72.23	21.30	***
$Comov$	103.17	98.27		56.74	107.23		108.89	98.34		62.26	106.97	
$DGDP_t$	-22.49	19.60		8.59	19.68		-31.92	17.77	*	-0.18	17.27	
ppi_t	2.94	14.66		-24.75	14.09	*	2.85	14.69		-24.64	14.08	*
$debt_t$	8.16	5.92		-9.88	4.05	**	10.23	5.64	*	-7.88	3.43	**
c	-352.84	425.08		40.72	453.94		-7.04	295.94		351.44	307.98	
t	3.76	3.33		3.41	3.66		-	-		-	-	
D_{2008}	-623.19	159.93	***	-	-		-618.26	160.20	***	-	-	

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

Table 3.25: Long run estimation: Capital inflows, Sample II (*Spec 3*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
GPR_t	0.45	0.51		-0.20	0.55		0.57	0.48		0.00	0.53	
i_t	38.38	49.81		3.94	56.19		24.18	45.86		-21.81	51.40	
$WGDP_t$	45.30	23.23	*	47.55	26.51	*	55.10	19.09	***	64.60	21.78	***
$\widehat{Comov}_t$	-397.04	206.08	*	-132.62	225.65		-428.30	201.07	**	-178.07	222.44	
$DGDP_t$	-33.73	21.90		16.08	21.65		-42.59	18.33	**	2.36	17.92	
ppi_t	11.64	14.34		-21.16	14.15		12.20	14.27		-21.27	14.18	
$debt_t$	16.64	7.52	**	-10.36	5.27	*	19.31	6.59	***	-6.63	4.11	
c	-810.68	448.43	*	-93.88	479.15		-649.42	391.43		209.27	396.82	
t	2.67	3.58		4.56	4.06		-	-		-	-	
D_{2008}	-751.82	165.34	***	-	-		-766.15	163.66	***	-	-	

Table 3.26: Long run estimation: Capital outflows, Sample II (*Spec 3*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
GPR_t	0.53	0.52		-0.10	0.56		0.58	0.49		0.03	0.53	
i_t	43.55	51.10		9.83	57.01		37.91	46.88		-6.61	51.86	
$WGDP_t$	58.38	23.83	**	60.58	26.90	**	62.27	19.51	***	71.46	21.97	***
$\widehat{Comov}_t$	-411.08	211.43	*	-152.23	228.97		-423.48	205.54	**	-181.23	224.41	
$DGDP_t$	-42.75	22.47	*	6.01	21.97		-46.26	18.74	**	-2.74	18.08	
ppi_t	7.49	14.71		-24.62	14.36	*	7.71	14.59		-24.69	14.30	*
$debt_t$	18.15	7.72	**	-8.28	5.35		19.21	6.74	***	-5.90	4.14	
c	-798.60	460.08	*	-96.87	486.20		-734.66	400.13	*	96.62	400.33	
t	1.06	3.67		2.91	4.12		-	-		-	-	
D_{2008}	-736.02	169.64	***	-	-		-741.70	167.29	***	-	-	

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

Table 3.27: Long run estimation: Capital inflows, Sample II (*Spec 4*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
$GEPU_t$	1.26	0.69	*	1.28	0.78		1.26	0.68	*	1.27	0.78	
i_t	7.08	42.25		14.38	47.87		6.70	36.52		27.26	41.19	
$WGDP_t$	21.63	19.73		31.54	22.23		21.70	19.22		29.39	21.76	
TL_t	4.08	16.48		2.72	18.68		3.95	14.77		7.03	16.77	
FL_t	4.78	2.15	**	5.84	2.43	**	4.80	2.00	**	5.39	2.27	**
inv_t	21.09	5.64	**	20.66	6.39	**	21.09	5.59	**	20.75	6.36	**
$DGDP_t$	5.88	16.71		33.71	17.59	*	5.90	16.56		33.71	17.50	*
ppi_t	-10.06	17.30		-40.19	18.08	**	-10.12	16.85		-38.72	17.77	**
$debt_t$	13.68	4.75	**	-1.24	3.84		13.70	4.62	**	-2.10	3.47	
c	-854.46	701.57		-459.13	789.17		-845.76	511.81		-743.64	581.06	
t	0.07	3.64		-2.19	4.09		-	-		-	-	
D_{2008}	-596.77	133.00	**	-	-		-596.44	130.73	**	-	-	

Table 3.28: Long run estimation: Capital outflows, Sample II (*Spec 4*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
$GEPU_t$	1.33	0.70	*	1.35	0.78	*	1.33	0.69	*	1.33	0.77	*
i_t	5.56	42.71		12.47	47.70		8.40	36.92		27.97	41.08	
$WGDP_t$	32.02	19.95		41.42	22.16	*	31.50	19.43		38.83	21.70	*
TL_t	9.69	16.66		8.40	18.62		10.66	14.94		13.59	16.73	
FL_t	4.75	2.18	**	5.75	2.42	**	4.64	2.02	**	5.21	2.26	**
inv_t	23.83	5.70	**	23.42	6.37	**	23.85	5.66	**	23.54	6.34	**
$DGDP_t$	0.07	16.89		26.44	17.53		-0.05	16.75		26.44	17.46	
ppi_t	-15.03	17.49		-43.58	18.01	**	-14.57	17.04		-41.81	17.73	**
$debt_t$	14.26	4.80	**	0.12	3.83		14.13	4.67	**	-0.92	3.46	
c	-1021.68	709.19		-647.02	786.37		-1086.64	517.44	**	-989.38	579.57	*
t	-0.50	3.68		-2.64	4.07		-	-		-	-	
D_{2008}	-565.56	134.44	**	-	-		-568.07	132.17	**	-	-	

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

Table 3.29: Long run estimation: Capital inflows, Sample I (*Spec 5*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
GPR_t	0.13	0.27		0.57	0.29	*	0.07	0.26		0.54	0.27	*
i_t	1.14	17.98		-6.97	20.29		10.73	14.19		-2.48	15.81	
$WGDP_t$	13.81	12.99		38.95	13.85	**	11.31	12.65		37.65	13.30	**
FL_t	5.54	1.33	**	1.79	1.31		4.90	1.11	**	1.52	1.06	
inv_t	16.97	3.77	**	17.12	4.26	**	16.91	3.76	**	17.10	4.25	**
$DGDP_t$	2.20	8.43		-2.37	9.49		3.77	8.22		-1.62	9.22	
ppi_t	-2.52	8.51		-0.57	9.62		-0.45	8.16		0.38	9.21	
$debt_t$	-0.84	4.73		12.42	4.67	**	-1.79	4.59		11.90	4.42	**
$pdebt_t$	20.34	5.53	**	-9.14	2.39	**	20.07	5.51	**	-9.10	2.38	**
c	-115.76	186.03		-418.04	202.03	**	-188.92	165.75		-450.23	179.87	**
t	-1.35	1.56		-0.62	1.76		-	-		-	-	
D_{2008}	-1254.74	217.38	**	-	-		-1239.37	216.43	**	-	-	

Table 3.30: Long run estimation: Capital outflows, Sample I (*Spec 5*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
GPR_t	0.13	0.27		0.55	0.29	*	0.06	0.26		0.50	0.28	*
i_t	-0.09	18.36		-7.77	20.39		11.48	14.51		-0.99	15.89	
$WGDP_t$	20.87	13.25		44.70	13.91	**	17.86	12.93		42.74	13.37	**
FL_t	5.06	1.35	**	1.51	1.31		4.30	1.13	**	1.10	1.06	
inv_t	18.96	3.85	**	19.11	4.28	**	18.89	3.85	**	19.07	4.27	**
$DGDP_t$	-1.08	8.60		-5.41	9.54		0.81	8.40		-4.27	9.27	
ppi_t	-4.18	8.69		-2.33	9.67		-1.69	8.34		-0.91	9.26	
$debt_t$	0.04	4.82		12.61	4.70	**	-1.12	4.69		11.82	4.45	**
$pdebt_t$	18.88	5.64	**	-9.06	2.41	**	18.56	5.64	**	-9.00	2.39	**
c	-124.15	189.88		-410.61	202.98	**	-212.36	169.41		-459.16	180.83	**
t	-1.63	1.59		-0.94	1.77		-	-		-	-	
D_{2008}	-1189.11	221.88	**	-	-		-1170.58	221.20	**	-	-	

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

3.6.6 Lag orders of autoregressive terms in the conditional ECM

Table 3.31: Lag orders of autoregressive terms in the conditional ECM (*Spec 1*)

	Capital inflows		Capital outflows	
	Sample I	Sample II	Sample I	Sample II
c_t	4	2	4	2
GPR_t	1	1	1	1
i_t	2	2	2	2
$WGDP_t$	4	2	4	2
TL_t	-	2	-	1
FL_t	2	2	2	2
inv_t	4	2	4	2
$DGDP_t$	4	1	4	1
ppi_t	2	1	2	1
$debt_t$	1	1	1	1

Table 3.32: Lag orders of autoregressive terms in the conditional ECM (*Spec 2, 3*)

	(*Spec 2*)			(*Spec 3*)	
	Inflows	Outflows		Inflows	Outflows
c_t	4	2	c_t	2	2
GPR_t	4	1	GPR_t	1	1
i_t	5	3	i_t	3	3
$WGDP_t$	4	3	$WGDP_t$	3	3
$Comov_t$	5	1	$\widehat{Comov}_t$	3	2
$DGDP_t$	4	1	$DGDP_t$	3	3
ppi_t	5	2	ppi_t	3	3
$debt_t$	2	3	$debt_t$	3	3

Notes: *Spec 2* denotes the modle with contagion in uncertainty using raw series of uncertainty co-movement index. *Spec 3* denotes the modle with contagion in uncertainty using projected uncertainty co-movement index. The selection criteria is AIC.

3.6.7 Short run estimation results

Table 3.33: Equilibrium correction: Capital inflows, Sample I, (*Spec 1*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
c	4.91	29.89		-24.86	22.81		-4.28	15.32		0.04	11.68	
Δc_{t-1}	-0.63	0.24	**	-0.01	0.24		-0.61	0.23	**	-0.02	0.24	
Δc_{t-2}	-0.52	0.21	**	-0.05	0.21		-0.51	0.20	**	-0.05	0.21	
Δc_{t-3}	-0.35	0.17	**	-0.05	0.17		-0.34	0.17	**	-0.04	0.17	
Δc_{t-4}	0.05	0.11		0.16	0.10		0.05	0.11		0.16	0.10	
ΔGPR_t	-0.12	0.28		-0.16	0.25		-0.12	0.27		-0.16	0.25	
ΔGPR_{t-1}	-0.14	0.29		-0.24	0.26		-0.14	0.29		-0.22	0.26	
Δi_t	-14.84	34.40		-22.80	31.03		-14.55	33.97		-19.90	30.98	
Δi_{t-1}	1.92	34.95		-3.37	31.51		-1.80	34.48		-3.73	31.53	
Δi_{t-2}	45.98	34.48		33.26	31.18		41.60	34.45		34.96	31.13	
$\Delta WGDP_t$	16.11	26.14		8.27	23.73		15.82	25.85		6.86	23.76	
$\Delta WGDP_{t-1}$	0.52	23.27		-38.98	22.98	*	-0.58	23.13		-39.84	23.04	*
$\Delta WGDP_{t-2}$	21.40	22.27		-8.33	21.35		20.96	22.05		-7.53	21.35	
$\Delta WGDP_{t-3}$	23.79	22.03		-8.82	21.43		22.95	21.88		-8.19	21.45	
$\Delta WGDP_{t-4}$	24.84	23.56		-0.81	22.21		24.54	23.33		0.06	22.21	
ΔFL_t	17.38	5.26	***	17.49	4.27	***	16.54	4.99	***	17.20	4.27	***
ΔFL_{t-1}	-6.04	5.37		-2.25	4.48		-6.48	5.12		-2.49	4.48	
ΔFL_{t-2}	1.84	5.50		5.06	4.69		1.34	5.24		4.67	4.68	
Δinv_t	15.84	4.08	***	15.27	3.64	***	15.83	4.04	***	15.19	3.65	***
Δinv_{t-1}	13.11	6.98	*	-0.78	6.83		12.82	6.88	*	-0.80	6.84	
Δinv_{t-2}	8.03	7.31		-3.54	6.95		7.73	7.23		-3.74	6.96	
Δinv_{t-3}	5.70	6.17		-2.01	5.69		5.44	6.09		-2.32	5.69	
Δinv_{t-4}	-3.50	4.54		-5.64	4.06		-3.63	4.49		-5.85	4.06	
$\Delta DGDP_t$	53.67	19.14	***	54.01	16.88	***	54.80	18.78	***	54.47	16.88	***
$\Delta DGDP_{t-1}$	33.04	18.77	*	30.69	16.99	*	33.83	18.64	*	30.83	17.00	*
$\Delta DGDP_{t-2}$	-34.91	17.85	*	-24.31	16.28		-34.00	17.76	*	-23.89	16.31	
$\Delta DGDP_{t-3}$	-15.30	17.70		-6.19	16.18		-14.76	17.57		-6.01	16.20	
$\Delta DGDP_{t-4}$	-2.72	16.00		0.94	14.52		-1.78	15.86		0.48	14.52	
Δppi_t	4.97	21.46		-7.22	19.42		6.59	21.07		-5.69	19.39	
Δppi_{t-1}	24.04	22.47		28.70	20.35		24.35	22.26		28.20	20.36	
Δppi_{t-2}	-37.57	20.55	*	-23.51	18.83		-38.28	20.24	*	-24.83	18.81	
$\Delta debt_t$	-28.49	21.89		-39.26	18.26	**	-27.97	21.64		-36.57	18.15	**
$\Delta debt_{t-1}$	17.10	22.12		12.84	19.35		18.13	21.68		17.49	19.06	
$\hat{v}_{t-1}$	-0.57	0.30	*	-1.25	0.27	***	-0.59	0.29	**	-1.23	0.27	***
t	-0.21	0.62		0.41	0.32							
D_{2008}	39.43	62.56					21.18	35.30				

(1) $\bar{R}^2 = 0.7483$, $AIC = 12.70$, $SBC = 13.53$, $\chi^2_{SC}(4) = 8.07[0.089]$, $\chi^2_H = 51.03[0.039]$
Inverted AR Roots $= -.01, -.21 + .81i, -.21 - .81i, -.88$.
(2) $\bar{R}^2 = 0.7931$, $AIC = 12.50$, $SBC = 13.30$, $\chi^2_{SC}(4) = 18.65[0.001]$, $\chi^2_H = 40.91[0.193]$
Inverted AR Roots $= .80, -.16 + .88i, -.16 - .88i, -.92$.
(3) $\bar{R}^2 = 0.7525$, $AIC = 12.67$, $SBC = 13.48$, $\chi^2_{SC}(4) = 7.03[0.134]$, $\chi^2_H = 50.67[0.033]$
Inverted AR Roots $= -.00, -.21 - .82i, -.21 + .82i, -.88$.
(4) $\bar{R}^2 = 0.7928$, $AIC = 12.49$, $SBC = 13.28$, $\chi^2_{SC}(4) = 17.80[0.001]$, $\chi^2_H = 35.42[0.355]$
Inverted AR Roots $= .80, -.16 + .88i, -.16 - .88i, -.92$.

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively. $\bar{R}^2$ is the adjusted squared multiple correlation coefficient, AIC and SBC are Akaike's and Schwarz's Bayesian Information Criteria, $\chi^2_{SC}(4)$ and χ^2_H denote the chi-squared statistics for no autocorrelation test within 4 lags and the chi-squared statistics for homoskedasticity with p-values inside $[\cdot]$.

Table 3.34: Equilibrium correction : Capital inflows, Sample II, (*Spec 1*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
c	-142.18	157.56		-162.99	72.75	**	2.03	32.37		-4.77	18.61	
Δc_{t-1}	0.01	0.30		0.51	0.23	**	0.05	0.30		0.46	0.22	**
Δc_{t-2}	0.00	0.17		0.20	0.13		0.02	0.17		0.17	0.13	
ΔGPR_t	-0.11	0.41		-0.16	0.32		-0.17	0.41		-0.32	0.32	
ΔGPR_{t-1}	-0.62	0.44		-0.79	0.34	**	-0.65	0.44		-0.76	0.35	**
Δi_t	-178.91	86.63	**	-156.07	63.21	**	-160.91	83.08	*	-131.55	63.34	**
Δi_{t-1}	-12.90	77.17		-9.90	58.42		0.31	74.70		-2.42	59.16	
Δi_{t-2}	-1.28	83.20		20.54	62.42		8.27	81.27		27.33	63.18	
$\Delta WGDP_t$	-24.65	41.27		-15.93	31.91		-31.01	40.52		-35.07	31.92	
$\Delta WGDP_{t-1}$	30.66	37.27		-34.84	31.16		27.49	37.01		-44.39	31.96	
$\Delta WGDP_{t-2}$	-24.90	28.38		-88.37	24.16	***	-24.24	28.14		-81.34	24.23	***
ΔTL_t	36.56	25.10		11.40	18.87		35.65	24.77		10.34	18.94	
ΔTL_{t-1}	41.41	23.15	*	19.94	17.64		34.32	22.13		10.24	17.96	
ΔTL_{t-2}	10.95	22.36		8.67	17.33		7.10	21.92		-1.69	17.34	
ΔFL_t	13.21	8.22		22.90	5.09	***	15.46	7.50	**	20.77	5.17	***
ΔFL_{t-1}	-20.84	8.25	**	-6.65	5.45		-18.13	7.54	**	-7.41	5.51	
ΔFL_{t-2}	-0.73	8.59		6.55	6.31		1.50	8.25		4.34	6.26	
Δinv_t	23.87	6.51	***	17.35	5.12	***	22.89	6.33	***	17.73	5.17	***
Δinv_{t-1}	15.10	9.60		-8.04	8.27		12.64	9.20		-6.96	8.29	
Δinv_{t-2}	9.96	7.15		-3.82	5.94		8.43	6.91		-3.45	6.00	
$\Delta DGDP_t$	35.89	32.55		77.45	24.08	***	37.68	32.09		87.27	24.55	***
$\Delta DGDP_{t-1}$	33.47	33.76		23.39	26.12		37.76	33.67		36.96	26.61	
Δppi_t	2.53	36.44		-43.48	28.99		-1.16	35.90		-31.81	28.91	
Δppi_{t-1}	-5.78	32.91		38.17	26.88		-3.15	32.62		38.02	27.29	
$\Delta debt_t$	26.10	35.41		-28.47	24.78		28.37	35.30		-20.04	24.89	
$\Delta debt_{t-1}$	4.95	33.33		-21.73	25.87		3.36	32.81		-6.94	25.62	
$\hat{v}_{t-1}$	-1.43	0.45	***	-2.04	0.30	***	-1.51	0.45	***	-1.96	0.30	***
t	2.21	2.37		1.90	0.83	**						
D_{2008}	-139.37	137.07					-30.09	60.97				

(1) $\bar{R}^2 = 0.6998$, $AIC = 13.38$, $SBC = 14.26$, $\chi^2_{SC}(4) = 3.33[0.505]$, $\chi^2_H = 37.19[0.115]$
Inverted AR Roots $= -.44 + .42i, -.44 - .42i$.
(2) $\bar{R}^2 = 0.8167$, $AIC = 12.88$, $SBC = 13.74$, $\chi^2_{SC}(4) = 1.48[0.831]$, $\chi^2_H = 31.03[0.270]$
Inverted AR Roots $= -.39 - .48i, -.39 + .48i$.
(3) $\bar{R}^2 = 0.7045$, $AIC = 13.35$, $SBC = 14.21$, $\chi^2_{SC}(4) = 4.53[0.339]$, $\chi^2_H = 33.07[0.195]$
Inverted AR Roots $= -.42 - .42i, -.42 + .42i$.
(4) $\bar{R}^2 = 0.8108$, $AIC = 12.90$, $SBC = 13.73$, $\chi^2_{SC}(4) = 3.66[0.454]$, $\chi^2_H = 30.28[0.256]$
Inverted AR Roots $= -.43 - .42i, -.43 + .42i$.

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively. $\bar{R}^2$ is the adjusted squared multiple correlation coefficient, AIC and SBC are Akaike's and Schwarz's Bayesian Information Criteria, $\chi^2_{SC}(4)$ and χ^2_H denote the chi-squared statistics for no autocorrelation test within 4 lags and the chi-squared statistics for homoskedasticity with p-values inside $[\cdot]$.

Table 3.35: Equilibrium correction: Capital outflows, Sample I, (*Spec 1*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
c	3.42	29.71		-22.82	22.99		-5.47	15.33		-2.78	11.67	
Δc_{t-1}	-0.72	0.25	***	-0.09	0.23		-0.69	0.25	***	-0.09	0.23	
Δc_{t-2}	-0.56	0.21	**	-0.10	0.20		-0.54	0.21	**	-0.10	0.20	
Δc_{t-3}	-0.36	0.18	*	-0.07	0.17		-0.35	0.18	*	-0.07	0.17	
Δc_{t-4}	0.06	0.11		0.16	0.10		0.07	0.11		0.16	0.10	
ΔGPR_t	-0.17	0.28		-0.18	0.25		-0.17	0.27		-0.19	0.25	
ΔGPR_{t-1}	-0.03	0.30		-0.14	0.27		-0.03	0.29		-0.12	0.26	
Δi_t	1.58	34.53		-9.96	31.31		1.37	34.06		-6.91	31.05	
Δi_{t-1}	-0.78	35.23		-5.07	31.89		-4.25	34.70		-7.13	31.72	
Δi_{t-2}	43.60	34.74		28.61	31.53		38.92	34.81		28.04	31.34	
$\Delta WGDP_t$	27.44	26.20		21.32	23.88		27.14	25.92		19.69	23.77	
$\Delta WGDP_{t-1}$	7.28	23.59		-31.56	23.35		5.80	23.46		-33.01	23.30	
$\Delta WGDP_{t-2}$	24.73	22.53		-6.34	21.69		23.73	22.34		-6.20	21.56	
$\Delta WGDP_{t-3}$	23.34	22.57		-8.71	21.89		21.99	22.45		-8.64	21.78	
$\Delta WGDP_{t-4}$	23.38	23.98		-0.76	22.51		22.71	23.75		-0.26	22.37	
ΔFL_t	18.45	5.25	***	18.48	4.29	***	17.59	4.97	***	18.16	4.27	***
ΔFL_{t-1}	-6.64	5.44		-3.07	4.60		-7.14	5.16		-3.07	4.58	
ΔFL_{t-2}	0.93	5.59		4.24	4.82		0.47	5.31		4.02	4.78	
Δinv_t	18.42	4.04	***	17.67	3.64	***	18.37	4.00	***	17.61	3.62	***
Δinv_{t-1}	16.25	7.35	**	1.32	7.04		15.58	7.24	**	1.16	6.99	
Δinv_{t-2}	10.04	7.60		-1.98	7.12		9.42	7.51		-2.15	7.07	
Δinv_{t-3}	6.78	6.41		-1.18	5.85		6.32	6.31		-1.36	5.80	
Δinv_{t-4}	-3.56	4.66		-5.94	4.16		-3.79	4.60		-6.05	4.13	
$\Delta DGDP_t$	50.37	19.39	**	49.16	17.20	***	51.04	19.00	***	50.43	17.08	***
$\Delta DGDP_{t-1}$	26.30	18.99		27.30	17.26		27.19	18.87		28.06	17.18	
$\Delta DGDP_{t-2}$	-38.68	17.97	**	-24.78	16.51		-37.43	17.92	**	-23.77	16.47	
$\Delta DGDP_{t-3}$	-16.91	18.02		-5.57	16.53		-16.02	17.91		-5.12	16.47	
$\Delta DGDP_{t-4}$	-2.72	16.01		2.23	14.61		-1.66	15.89		2.20	14.53	
Δppi_t	12.96	21.81		0.18	19.86		14.22	21.37		1.73	19.69	
Δppi_{t-1}	11.85	22.95		16.84	20.89		12.35	22.74		16.47	20.78	
Δppi_{t-2}	-34.50	20.69	*	-19.75	19.06		-34.96	20.37	*	-20.90	18.91	
$\Delta debt_t$	-32.75	21.61		-40.00	18.25	**	-31.68	21.38		-37.88	18.04	**
$\Delta debt_{t-1}$	29.56	21.79		23.57	19.25		30.16	21.35		27.82	18.84	
$\hat{v}_{t-1}$	-0.38	0.30		-1.11	0.26	***	-0.43	0.30		-1.11	0.26	***
t	-0.20	0.62		0.34	0.32							
D_{2008}	32.57	62.48					14.81	35.25				

(1) $\bar{R}^2 = 0.7506$, $AIC = 12.70$, $SBC = 13.53$, $\chi^2_{SC}(4) = 11.95[0.018]$, $\chi^2_H = 55.56[0.015]$
Inverted AR Roots $= -.14, -.20 - .81i, -.20 + .81i, -.87$.
(2) $\bar{R}^2 = 0.7927$, $AIC = 12.51$, $SBC = 13.32$, $\chi^2_{SC}(4) = 21.23[0.000]$, $\chi^2_H = 45.54[0.089]$
Inverted AR Roots $= .79, .13, -.17 - .83i, -.17 + .83i$.
(3) $\bar{R}^2 = 0.7547$, $AIC = 12.67$, $SBC = 13.48$, $\chi^2_{SC}(4) = 9.70[0.046]$, $\chi^2_H = 55.59[0.011]$
Inverted AR Roots $= -.13, -.20 - .82i, -.20 + .82i, -.88$.
(4) $\bar{R}^2 = 0.7948$, $AIC = 12.49$, $SBC = 13.28$, $\chi^2_{SC}(4) = 20.18[0.001]$, $\chi^2_H = 42.34[0.128]$
Inverted AR Roots $= .84, -.15 - .88i, -.15 + .88i, -.92$.

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively. $\bar{R}^2$ is the adjusted squared multiple correlation coefficient, AIC and SBC are Akaike's and Schwarz's Bayesian Information Criteria, $\chi^2_{SC}(4)$ and χ^2_H denote the chi-squared statistics for no autocorrelation test within 4 lags and the chi-squared statistics for homoskedasticity with p-values inside $[\cdot]$.

Table 3.36: Equilibrium correction: Capital outflows, Sample II, (*Spec 1*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
c	-113.45	148.96		-131.45	69.49	*	-1.67	31.15		-6.05	18.05	
Δc_{t-1}	-0.04	0.30		0.46	0.22	**	0.01	0.30		0.40	0.22	*
Δc_{t-2}	-0.02	0.16		0.18	0.13		-0.01	0.16		0.14	0.12	
ΔGPR_t	-0.15	0.40		-0.20	0.31		-0.24	0.39		-0.39	0.31	
ΔGPR_{t-1}	-0.59	0.45		-0.77	0.35	**	-0.63	0.44		-0.75	0.35	**
Δi_t	-160.55	84.47	*	-139.99	62.42	**	-149.78	81.15	*	-120.73	62.07	*
Δi_{t-1}	-7.60	74.87		-2.17	57.68		1.46	72.36		1.45	57.90	
Δi_{t-2}	-12.99	77.52		-5.12	59.15		-10.84	75.45		-8.76	59.43	
$\Delta WGDP_t$	-7.88	40.65		0.47	31.89		-15.09	39.61		-18.94	31.59	
$\Delta WGDP_{t-1}$	33.43	36.76		-31.49	31.42		29.53	36.39		-38.81	31.80	
$\Delta WGDP_{t-2}$	-29.99	27.77		-86.84	23.71	***	-28.13	27.39		-78.77	23.43	***
ΔTL_t	34.58	23.53		11.02	17.82		37.18	23.44		14.73	17.85	
ΔTL_{t-1}	33.55	21.89		13.79	17.09		27.92	21.02		6.83	17.27	
ΔFL_t	14.87	8.04	*	23.00	4.96	***	16.35	7.21	**	21.55	5.00	***
ΔFL_{t-1}	-19.46	8.06	**	-6.42	5.48		-17.33	7.30	**	-6.92	5.48	
ΔFL_{t-2}	-0.98	8.55		5.58	6.34		1.09	8.16		3.91	6.23	
Δinv_t	25.85	6.32	***	19.39	5.06	***	25.30	6.14	***	20.10	5.05	***
Δinv_{t-1}	14.09	9.68		-9.90	8.58		12.21	9.32		-7.76	8.43	
Δinv_{t-2}	8.79	7.04		-5.08	6.02		7.91	6.84		-3.66	5.96	
$\Delta DGDP_t$	28.43	31.57		70.13	24.11	***	31.81	30.83		82.14	24.45	***
$\Delta DGDP_{t-1}$	31.64	32.87		24.68	25.40		37.90	32.80		36.82	25.70	
Δppi_t	6.07	36.31		-37.42	29.13		2.75	35.49		-26.02	28.65	
Δppi_{t-1}	-8.40	32.12		31.29	26.35		-6.64	31.62		27.56	26.26	
$\Delta debt_t$	20.48	34.21		-27.40	24.24		23.22	33.94		-22.26	24.14	
$\Delta debt_{t-1}$	11.47	32.55		-14.50	25.59		11.45	31.78		1.57	24.88	
$\hat{v}_{t-1}$	-1.33	0.44	***	-1.96	0.30	***	-1.44	0.44	***	-1.88	0.29	***
t	1.71	2.25		1.51	0.79	*						
D_{2008}	-113.95	133.25					-30.35	58.48				

(1) $\bar{R}^2 = 0.7092$, $AIC = 13.33$, $SBC = 14.18$, $\chi^2_{SC}(4) = 5.12[0.276]$, $\chi^2_H = 38.61[0.069]$
Inverted AR Roots $= -.45 - .36i, -.45 + .36i$.
(2) $\bar{R}^2 = 0.8178$, $AIC = 12.86$, $SBC = 13.68$, $\chi^2_{SC}(4) = 1.48[0.830]$, $\chi^2_H = 33.56[0.147]$
Inverted AR Roots $= -.39 + .43i, -.39 - .43i$.
(3) $\bar{R}^2 = 0.7168$, $AIC = 13.30$, $SBC = 14.12$, $\chi^2_{SC}(4) = 5.81[0.214]$, $\chi^2_H = 34.65[0.120]$
Inverted AR Roots $= -.42 - .36i, -.42 + .36i$.
(4) $\bar{R}^2 = 0.8160$, $AIC = 12.86$, $SBC = 13.65$, $\chi^2_{SC}(4) = 3.19[0.527]$, $\chi^2_H = 34.49[0.098]$
Inverted AR Roots $= -.08 + .53i, -.08 - .53i$.

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively. $\bar{R}^2$ is the adjusted squared multiple correlation coefficient, AIC and SBC are Akaike's and Schwarz's Bayesian Information Criteria, $\chi^2_{SC}(4)$ and χ^2_H denote the chi-squared statistics for no autocorrelation test within 4 lags and the chi-squared statistics for homoskedasticity with p-values inside $[\cdot]$.

Table 3.37: Equilibrium correction: Capital inflows, Sample II, (*Spec 2*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
c	124.58	335.04		115.15	144.18		39.42	36.70		32.88	24.98	
Δc_{t-1}	-0.76	0.51		-0.13	0.43		-0.77	0.35	**	-0.12	0.36	
Δc_{t-2}	-0.73	0.44		-0.27	0.39		-0.77	0.34	**	-0.29	0.32	
Δc_{t-3}	-0.54	0.35		-0.23	0.31		-0.59	0.30	*	-0.25	0.27	
Δc_{t-4}	0.07	0.22		0.18	0.20		0.03	0.21		0.16	0.18	
ΔGPR_t	-0.54	0.62		-0.83	0.53		-0.45	0.55		-0.75	0.49	
ΔGPR_{t-1}	-0.53	0.85		-0.83	0.70		-0.51	0.70		-0.83	0.63	
ΔGPR_{t-2}	0.90	0.86		0.54	0.76		0.88	0.78		0.56	0.69	
ΔGPR_{t-3}	0.23	0.79		0.10	0.70		0.28	0.73		0.29	0.62	
ΔGPR_{t-4}	0.03	0.80		-0.10	0.69		0.11	0.72		0.10	0.63	
Δi_t	-120.39	117.98		-130.26	103.26		-124.20	108.60		-138.36	95.90	
Δi_{t-1}	119.01	127.03		127.22	110.78		125.63	118.98		154.62	104.87	
Δi_{t-2}	179.04	125.31		182.61	106.31	*	184.70	113.06		214.21	99.96	**
Δi_{t-3}	-87.37	117.58		-10.64	104.62		-60.45	107.59		41.85	102.11	
Δi_{t-4}	219.68	124.93	*	226.10	107.87	**	231.14	111.63	**	244.31	97.98	**
Δi_{t-5}	36.91	134.79		89.04	115.90		57.47	120.94		114.58	108.15	
$\Delta WGDP_t$	11.02	64.81		-24.30	55.00		20.40	55.85		-12.35	50.36	
$\Delta WGDP_{t-1}$	-15.15	61.38		-82.55	58.08		-21.71	55.52		-96.64	56.06	*
$\Delta WGDP_{t-2}$	16.63	61.99		-25.30	55.16		8.78	54.54		-32.37	50.46	
$\Delta WGDP_{t-3}$	22.75	67.27		-27.12	58.84		19.00	57.79		-27.42	54.01	
$\Delta WGDP_{t-4}$	28.74	54.92		-36.66	55.08		24.54	51.85		-47.26	51.63	
$\Delta Comov_t$	-12.28	142.19		-20.26	122.67		-16.38	133.22		-53.12	117.01	
$\Delta Comov_{t-1}$	-210.48	207.16		-195.89	161.06		-213.29	164.46		-240.40	145.92	
$\Delta Comov_{t-2}$	-174.52	241.06		-209.34	167.64		-180.89	163.03		-258.28	147.38	*
$\Delta Comov_{t-3}$	-56.30	245.32		-88.85	186.86		-69.58	181.43		-129.73	161.23	
$\Delta Comov_{t-4}$	-26.15	207.83		-61.98	165.33		-27.74	158.70		-69.12	138.70	
$\Delta Comov_{t-5}$	109.02	171.50		61.54	146.58		113.46	146.12		80.99	126.32	
$\Delta DGDP_t$	97.22	55.13	*	102.53	48.11	**	90.40	52.54	*	89.70	45.20	*
$\Delta DGDP_{t-1}$	73.99	55.80		85.74	46.09	*	77.48	47.50		91.19	42.02	**
$\Delta DGDP_{t-2}$	-67.41	52.17		-43.02	46.48		-58.94	48.79		-35.71	43.54	
$\Delta DGDP_{t-3}$	-35.27	53.51		-17.10	45.40		-33.31	48.11		-22.89	41.41	
$\Delta DGDP_{t-4}$	26.88	49.35		23.85	43.46		27.67	47.14		16.27	40.72	
Δppi_t	39.57	47.85		52.57	42.74		44.38	46.05		71.04	39.74	*
Δppi_{t-1}	29.36	52.36		58.40	47.59		29.11	49.19		61.42	44.35	
Δppi_{t-2}	-137.90	51.79	**	-109.29	45.88	**	-134.11	47.96	***	-101.44	42.97	**
Δppi_{t-3}	65.46	60.64		57.35	53.01		58.78	57.17		50.73	50.40	
Δppi_{t-4}	5.38	56.37		29.94	51.22		7.66	53.76		38.98	47.79	
Δppi_{t-5}	-26.60	54.64		-12.53	48.46		-25.74	49.75		-7.26	43.11	
$\Delta debt_t$	-38.91	57.72		-80.39	45.74	*	-31.81	52.98		-77.79	41.87	*
$\Delta debt_{t-1}$	15.78	44.00		12.42	38.18		17.15	41.70		7.85	35.88	
$\Delta debt_{t-2}$	67.92	54.19		89.73	47.86	*	63.95	51.69		83.02	45.28	*
$\hat{v}_{t-1}$	-0.65	0.63		-1.31	0.46	***	-0.67	0.41		-1.36	0.39	***
t	-1.26	4.37		-1.08	1.57							
D_{2008}	-30.36	159.74					-83.39	63.41				

(1) $\bar{R}^2 = 0.6947$, $AIC = 13.45$, $SBC = 14.85$, $\chi^2_{SC}(4) = 14.91[0.005]$, $\chi^2_H = 34.47[0.820]$
Inverted AR Roots $= -.06 - .94i, -.06 + .94i, -.66, -.90$.
(2) $\bar{R}^2 = 0.7568$, $AIC = 13.23$, $SBC = 14.60$, $\chi^2_{SC}(4) = 0.45[0.978]$, $\chi^2_H = 35.45[0.752]$
Inverted AR Roots $= .56 - .32i, .56 + .32i, -.00 + .96i, -.00 - .96i$.
(3) $\bar{R}^2 = 0.7194$, $AIC = 13.37$, $SBC = 14.74$, $\chi^2_{SC}(4) = 14.57[0.006]$, $\chi^2_H = 29.50[0.927]$
Inverted AR Roots $= -.04 - .93i, -.04 + .93i, -.66, -.91$.
(4) $\bar{R}^2 = 0.7798$, $AIC = 13.14$, $SBC = 14.48$, $\chi^2_{SC}(4) = 1.15[0.887]$, $\chi^2_H = 33.98[0.773]$
Inverted AR Roots $= .52 - .43i, .52 + .43i, .00 + .95i, .00 - .95i$.

[Table 3.37 continued]

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively. $\bar{R}^2$ is the adjusted squared multiple correlation coefficient, AIC and SBC are Akaike's and Schwarz's Bayesian Information Criteria, $\chi^2_{SC}(4)$ and χ^2_H denote the chi-squared statistics for no autocorrelation test within 4 lags and the chi-squared statistics for homoskedasticity with p-values inside $[\cdot]$.

Table 3.38: Equilibrium correction: Capital outflows, Sample II, (*Spec 2*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
c	28.35	162.42		75.49	95.15		12.05	31.24		-0.24	23.97	
Δc_{t-1}	-0.02	0.24		0.17	0.21		-0.13	0.22		0.08	0.21	
Δc_{t-2}	0.01	0.16		0.07	0.14		-0.04	0.15		0.04	0.14	
ΔGPR_t	-0.45	0.52		-0.94	0.47	*	-0.42	0.52		-0.84	0.48	*
ΔGPR_{t-1}	-0.21	0.53		-0.51	0.48		-0.24	0.53		-0.50	0.49	
Δi_t	-71.19	92.20		-130.76	83.44		-92.87	92.18		-143.55	85.28	*
Δi_{t-1}	79.10	98.50		106.10	88.27		123.00	95.54		136.83	88.64	
Δi_{t-2}	-17.65	85.78		32.87	78.24		2.13	85.11		38.39	79.27	
Δi_{t-3}	-11.73	84.26		67.33	72.68		26.07	81.98		87.61	73.22	
$\Delta WGDP_t$	26.64	47.18		-3.37	42.99		31.76	47.35		7.70	43.73	
$\Delta WGDP_{t-1}$	-18.91	41.64		-74.85	40.11	*	-23.62	41.91		-72.77	41.12	*
$\Delta WGDP_{t-2}$	-14.91	37.31		-52.12	35.04		-19.24	37.58		-52.44	35.95	
$\Delta WGDP_{t-3}$	6.91	34.77		-40.64	33.02		5.44	34.98		-36.29	33.65	
$\Delta Comov_t$	10.92	102.02		65.18	93.10		5.88	101.82		59.72	94.55	
$\Delta Comov_{t-1}$	-58.22	109.04		-85.42	98.32		-75.68	106.61		-88.80	99.04	
$\Delta DGDP_t$	-7.19	38.76		44.23	35.24		-12.46	39.24		35.33	35.78	
$\Delta DGDP_{t-1}$	36.99	38.03		44.83	34.66		34.05	38.09		40.72	35.35	
Δppi_t	-9.93	36.47		-13.17	32.84		-4.93	36.57		-6.42	33.64	
Δppi_{t-1}	42.28	43.68		66.08	40.57		35.93	43.67		58.61	41.21	
Δppi_{t-2}	-67.58	38.48	*	-44.98	35.59		-68.55	38.54	*	-46.43	36.20	
$\Delta debt_t$	-27.01	39.26		-102.53	32.98	***	-29.72	39.46		-98.92	33.58	***
$\Delta debt_{t-1}$	0.25	41.27		-25.26	38.30		1.68	41.53		-21.22	39.07	
$\Delta debt_{t-2}$	58.02	40.08		69.74	36.69	*	54.32	40.36		60.84	37.17	
$\Delta debt_{t-3}$	77.56	42.36	*	84.63	38.49	**	73.74	42.61	*	73.04	38.43	*
$\hat{v}_{t-1}$	-1.51	0.34	***	-1.62	0.28	***	-1.32	0.31	***	-1.48	0.26	***
t	-0.30	2.21		-0.95	1.09							
D_{2008}	-104.51	104.77					-109.78	57.02	*			

(1) $\bar{R}^2 = 0.6389$, $AIC = 13.57$, $SBC = 14.41$, $\chi^2_{SC}(4) = 7.56[0.109]$, $\chi^2_H = 31.95[0.195]$
Inverted AR Roots $= -.55 - .51i, -.55 + .51i$.
(2) $\bar{R}^2 = 0.6979$, $AIC = 13.39$, $SBC = 14.19$, $\chi^2_{SC}(4) = 4.86[0.302]$, $\chi^2_H = 23.60[0.543]$
Inverted AR Roots $= .00 + .36i, .00 - .36i$.
(3) $\bar{R}^2 = 0.6339$, $AIC = 13.58$, $SBC = 14.38$, $\chi^2_{SC}(4) = 9.59[0.048]$, $\chi^2_H = 26.15[0.399]$
Inverted AR Roots $= -.51 - .48i, -.51 + .48i$.
(4) $\bar{R}^2 = 0.6843$, $AIC = 13.43$, $SBC = 14.20$, $\chi^2_{SC}(4) = 7.42[0.115]$, $\chi^2_H = 22.86[0.528]$
Inverted AR Roots $= .07 + .24i, .07 - .24i$.

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively. $\bar{R}^2$ is the adjusted squared multiple correlation coefficient, AIC and SBC are Akaike's and Schwarz's Bayesian Information Criteria, $\chi^2_{SC}(4)$ and χ^2_H denote the chi-squared statistics for no autocorrelation test within 4 lags and the chi-squared statistics for homoskedasticity with p-values inside $[\cdot]$.

Table 3.39: Equilibrium correction: Capital inflows, Sample II, (*Spec 3*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
c	26.84	203.06		103.66	109.53		24.13	34.02		14.52	24.35	
Δc_{t-1}	0.06	0.34		0.19	0.24		0.01	0.32		0.08	0.23	
Δc_{t-2}	0.02	0.19		0.07	0.15		0.00	0.18		0.03	0.15	
ΔGPR_t	0.00	0.52		-0.51	0.43		0.08	0.51		-0.36	0.44	
ΔGPR_{t-1}	-0.31	0.57		-0.35	0.48		-0.34	0.55		-0.38	0.49	
Δi_t	-78.73	102.12		-96.53	87.61		-87.78	100.42		-103.61	89.59	
Δi_{t-1}	87.69	100.70		147.01	83.83	*	109.24	97.56		182.66	85.66	**
Δi_{t-2}	27.74	105.12		160.43	89.64	*	44.50	100.28		170.86	91.84	*
Δi_{t-3}	36.59	108.54		131.23	93.23		58.87	105.06		145.25	94.08	
$\Delta WGDP_t$	9.35	54.96		-23.49	45.84		13.11	53.94		-10.32	46.44	
$\Delta WGDP_{t-1}$	-16.55	48.19		-100.04	44.23	**	-25.03	47.17		-102.83	45.70	**
$\Delta WGDP_{t-2}$	-28.44	52.85		-63.52	46.04		-34.24	52.47		-63.23	47.49	
$\Delta WGDP_{t-3}$	-7.82	44.42		-42.32	39.42		-10.72	44.08		-38.46	40.24	
$\Delta \widehat{Comov}_t$	-0.76	287.32		-339.18	245.43		-34.97	278.82		-371.04	252.59	
$\Delta \widehat{Comov}_{t-1}$	-104.75	303.03		-326.96	257.54		-114.26	298.99		-314.15	262.87	
$\Delta \widehat{Comov}_{t-2}$	128.07	302.78		-196.99	257.88		112.33	296.52		-206.27	264.28	
$\Delta \widehat{Comov}_{t-3}$	240.17	300.38		-84.59	261.39		260.47	292.05		-29.32	265.47	
$\Delta DGDP_t$	3.17	43.94		48.90	37.19		-6.14	43.93		36.78	37.43	
$\Delta DGDP_{t-1}$	65.73	45.24		64.23	37.27	*	69.52	44.14		66.15	38.24	*
$\Delta DGDP_{t-2}$	13.32	44.62		-9.12	35.99		16.61	44.47		-9.73	36.65	
$\Delta DGDP_{t-3}$	-0.27	40.26		-36.45	33.71		1.26	39.90		-37.42	34.08	
Δppi_t	-22.97	41.61		-27.15	35.65		-21.15	41.16		-17.90	35.94	
Δppi_{t-1}	45.52	47.98		101.20	42.37	**	44.43	46.94		93.98	43.15	**
Δppi_{t-2}	-68.38	48.79		-34.61	42.30		-69.34	47.75		-37.63	43.08	
Δppi_{t-3}	27.89	50.28		11.13	40.97		23.41	49.32		14.24	40.06	
$\Delta debt_t$	12.93	52.69		-105.00	37.46	***	15.71	52.51		-99.32	38.11	**
$\Delta debt_{t-1}$	-4.35	51.50		-49.53	45.19		-4.05	50.56		-41.81	45.98	
$\Delta debt_{t-2}$	19.46	49.82		82.91	41.56	*	17.63	49.13		70.03	41.82	
$\Delta debt_{t-3}$	76.54	49.73		106.35	43.28	**	72.41	49.10		88.27	43.18	**
$\hat{v}_{t-1}$	-1.68	0.48	***	-1.75	0.31	***	-1.60	0.45	***	-1.58	0.29	***
t	-0.10	2.70		-1.12	1.24							
D_{2008}	-115.45	121.31					-119.40	64.32	*			

(1) $\bar{R}^2 = 0.6394$, $AIC = 13.66$, $SBC = 14.69$, $\chi^2_{SC}(4) = 7.34[0.119]$, $\chi^2_H = 40.64[0.115]$
Inverted AR Roots $= -.50 + .58i, -.50 - .58i$.
(2) $\bar{R}^2 = 0.7331$, $AIC = 13.36$, $SBC = 14.35$, $\chi^2_{SC}(4) = 13.27[0.010]$, $\chi^2_H = 39.38[0.117]$
Inverted AR Roots $= .03 + .74i, .03 - .74i$.
(3) $\bar{R}^2 = 0.6476$, $AIC = 13.64$, $SBC = 14.63$, $\chi^2_{SC}(4) = 8.82[0.066]$, $\chi^2_H = 39.14[0.123]$
Inverted AR Roots $= -.51 - .56i, -.51 + .56i$.
(4) $\bar{R}^2 = 0.7204$, $AIC = 13.40$, $SBC = 14.36$, $\chi^2_{SC}(4) = 17.51[0.002]$, $\chi^2_H = 35.37[0.193]$
Inverted AR Roots $= .05 - .69i, .05 + .69i$.

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively. $\bar{R}^2$ is the adjusted squared multiple correlation coefficient, AIC and SBC are Akaike's and Schwarz's Bayesian Information Criteria, $\chi^2_{SC}(4)$ and χ^2_H denote the chi-squared statistics for no autocorrelation test within 4 lags and the chi-squared statistics for homoskedasticity with p-values inside $[\cdot]$.

Table 3.40: Equilibrium correction: Capital outflows, Sample II, (*Spec 3*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
c	-6.68	195.27		91.44	108.41		18.05	33.88		9.22	24.50	
Δc_{t-1}	0.02	0.33		0.10	0.24		0.01	0.32		0.07	0.23	
Δc_{t-2}	0.00	0.19		0.04	0.15		0.00	0.18		0.03	0.15	
ΔGPR_t	0.05	0.53		-0.42	0.45		0.07	0.52		-0.33	0.45	
ΔGPR_{t-1}	-0.33	0.58		-0.33	0.49		-0.36	0.56		-0.33	0.49	
Δi_t	-49.49	101.58		-64.09	88.65		-52.70	100.13		-66.85	88.89	
Δi_{t-1}	83.23	102.44		149.23	86.18	*	94.76	98.64		169.38	86.19	*
Δi_{t-2}	14.27	104.05		126.84	90.32		23.97	99.87		133.65	90.36	
Δi_{t-3}	42.80	104.21		98.38	90.26		53.44	101.63		106.09	88.33	
$\Delta WGDP_t$	31.74	55.80		-2.89	47.21		31.83	54.07		7.73	46.55	
$\Delta WGDP_{t-1}$	-4.47	48.32		-89.15	45.69	*	-8.76	47.04		-91.04	46.07	*
$\Delta WGDP_{t-2}$	-39.14	51.42		-58.08	44.62		-41.69	51.02		-59.89	45.02	
$\Delta WGDP_{t-3}$	-4.43	45.16		-32.98	40.33		-5.35	44.66		-31.03	40.39	
$\Delta \widehat{Comov}_t$	-25.44	288.47		-353.48	251.38		-43.10	280.67		-375.50	252.91	
$\Delta \widehat{Comov}_{t-1}$	-282.08	282.06		-352.12	241.24		-286.18	278.19		-350.28	240.49	
$\Delta \widehat{Comov}_{t-2}$	312.05	301.02		-59.30	263.64		302.93	293.39		-61.32	264.39	
$\Delta DGDP_t$	3.12	44.06		42.76	37.77		0.25	43.61		37.25	37.58	
$\Delta DGDP_{t-1}$	53.09	46.28		61.06	38.51		55.90	44.98		61.37	38.69	
$\Delta DGDP_{t-2}$	20.67	45.00		-5.28	36.49		22.11	44.60		-5.78	36.44	
$\Delta DGDP_{t-3}$	-10.47	39.50		-38.39	33.07		-10.67	38.98		-41.21	33.00	
Δppi_t	-32.03	40.88		-22.15	35.34		-30.99	40.35		-15.66	34.96	
Δppi_{t-1}	45.97	48.59		87.42	43.25	**	46.71	47.68		84.85	43.29	*
Δppi_{t-2}	-67.63	49.76		-41.56	43.41		-68.73	48.65		-41.39	43.44	
Δppi_{t-3}	41.04	51.20		23.46	42.19		40.27	50.48		29.36	40.69	
$\Delta debt_t$	17.64	52.27		-96.57	38.36	**	19.56	51.78		-93.61	38.03	**
$\Delta debt_{t-1}$	-18.25	48.25		-39.03	42.43		-18.87	47.60		-36.11	42.35	
$\Delta debt_{t-2}$	14.44	49.37		69.63	41.81		12.98	48.78		60.32	41.56	
$\Delta debt_{t-3}$	91.24	47.91	*	98.89	41.30	**	90.15	47.28	*	88.38	40.19	**
$\hat{v}_{t-1}$	-1.58	0.46	***	-1.59	0.30	***	-1.58	0.45	***	-1.54	0.29	***
t	0.32	2.60		-1.00	1.23							
D_{2008}	-127.96	119.88					-114.68	64.34	*			

(1) $\bar{R}^2 = 0.6258$, $AIC = 13.69$, $SBC = 14.68$, $\chi^2_{SC}(4) = 8.36[0.079]$, $\chi^2_H = 41.41[0.080]$
Inverted AR Roots $= -.55 + .56i, -.55 - .56i$.
(2) $\bar{R}^2 = 0.7144$, $AIC = 13.42$, $SBC = 14.37$, $\chi^2_{SC}(4) = 13.14[0.011]$, $\chi^2_H = 34.44[0.224]$
Inverted AR Roots $= .05 + .71i, .05 - .71i$.
(3) $\bar{R}^2 = 0.6351$, $AIC = 13.66$, $SBC = 14.62$, $\chi^2_{SC}(4) = 9.10[0.059]$, $\chi^2_H = 40.24[0.080]$
Inverted AR Roots $= -.55 + .56i, -.55 - .56i$.
(4) $\bar{R}^2 = 0.7131$, $AIC = 13.42$, $SBC = 14.34$, $\chi^2_{SC}(4) = 14.39[0.006]$, $\chi^2_H = 30.70[0.331]$
Inverted AR Roots $= .06 + .65i, .06 - .65i$.

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively. $\bar{R}^2$ is the adjusted squared multiple correlation coefficient, AIC and SBC are Akaike's and Schwarz's Bayesian Information Criteria, $\chi^2_{SC}(4)$ and χ^2_H denote the chi-squared statistics for no autocorrelation test within 4 lags and the chi-squared statistics for homoskedasticity with p-values inside $[\cdot]$.

Table 3.41: Equilibrium correction: Capital inflows, Sample II, (*Spec 4*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
c	-145.23	153.56		-136.54	77.90	*	6.04	32.59		-4.63	19.01	
Δc_{t-1}	0.08	0.30		0.42	0.22	*	0.09	0.30		0.36	0.22	
Δc_{t-2}	0.07	0.17		0.19	0.13		0.07	0.17		0.18	0.13	
$\Delta GEPU_t$	1.51	0.76	*	1.36	0.61	**	1.54	0.76	**	1.46	0.60	**
$\Delta GEPU_{t-1}$	-0.39	0.82		-0.88	0.68		-0.34	0.81		-0.73	0.67	
Δi_t	-115.98	86.50		-78.24	68.18		-91.86	83.19		-51.43	67.35	
Δi_{t-1}	-36.19	73.56		-27.32	59.04		-20.55	72.00		-21.97	59.24	
Δi_{t-2}	52.33	79.12		79.26	63.84		66.06	78.03		84.69	63.93	
$\Delta WGDP_t$	-8.08	38.76		2.04	31.61		-11.22	38.66		-10.98	31.34	
$\Delta WGDP_{t-1}$	37.27	36.52		-13.50	31.41		36.84	36.54		-18.44	31.77	
$\Delta WGDP_{t-2}$	-44.06	30.56		-99.66	27.09	**	-44.72	30.57		-98.84	27.15	**
ΔTL_t	16.70	24.18		-6.73	19.73		13.23	23.96		-7.45	19.51	
ΔTL_{t-1}	35.76	22.69		17.86	18.33		30.15	22.00		11.36	18.41	
ΔFL_t	10.44	8.34		20.98	5.36	**	14.22	7.48	*	19.75	5.40	**
ΔFL_{t-1}	-22.42	8.26	**	-7.69	5.76		-19.30	7.66	**	-8.76	5.73	
ΔFL_{t-2}	0.35	8.52		8.09	6.64		2.34	8.29		6.14	6.52	
Δinv_t	27.24	6.68	**	21.33	5.50	**	26.09	6.59	**	21.23	5.53	**
Δinv_{t-1}	14.98	9.47		-5.34	8.48		12.86	9.23		-3.92	8.45	
Δinv_{t-2}	9.03	6.90		-2.74	6.02		7.71	6.78		-2.23	6.02	
$\Delta DGDP_t$	19.08	32.64		56.60	25.35	**	19.56	32.66		60.11	25.53	**
$\Delta DGDP_{t-1}$	30.32	31.75		11.78	25.97		29.23	31.75		21.03	26.08	
Δppi_t	-8.30	36.87		-51.85	31.03		-11.57	36.74		-42.81	30.74	
Δppi_{t-1}	10.49	33.93		49.17	29.09	*	10.87	33.94		48.42	29.29	
$\Delta debt_t$	8.86	37.03		-53.42	28.84	*	7.89	37.04		-54.71	29.07	*
$\Delta debt_{t-1}$	-0.64	33.49		-21.06	27.59		-2.39	33.47		-13.83	27.52	
$\Delta debt_{t-2}$	36.01	38.78		43.20	31.72		35.35	38.79		58.29	31.28	*
$\hat{v}_{t-1}$	-1.46	0.43	**	-1.82	0.29	**	-1.48	0.43	**	-1.74	0.28	**
t	2.32	2.30		1.58	0.89	*						
D_{2008}	-165.91	135.60					-44.53	63.04				

(1) $\bar{R}^2 = 0.8181$, $AIC = 13.34$, $SBC = 14.23$, $\chi^2_{SC}(4) = 9.71[0.046]$, $\chi^2_H = 33.95[0.203]$
Inverted AR Roots $= -.34 + .41i, -.34 - .41i$.
(2) $\bar{R}^2 = 0.8031$, $AIC = 12.95$, $SBC = 13.81$, $\chi^2_{SC}(4) = 8.18[0.085]$, $\chi^2_H = 19.48[0.852]$
Inverted AR Roots $= -.33 + .50i, -.33 - .50i$.
(3) $\bar{R}^2 = 0.7094$, $AIC = 13.34$, $SBC = 14.20$, $\chi^2_{SC}(4) = 11.23[0.024]$, $\chi^2_H = 28.40[0.391]$
Inverted AR Roots $= -.33 + .40i, -.33 - .40i$.
(4) $\bar{R}^2 = 0.8002$, $AIC = 12.96$, $SBC = 13.78$, $\chi^2_{SC}(4) = 9.83[0.043]$, $\chi^2_H = 16.36[0.927]$
Inverted AR Roots $= -.31 - .45i, -.31 + .45i$.

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively. $\bar{R}^2$ is the adjusted squared multiple correlation coefficient, AIC and SBC are Akaike's and Schwarz's Bayesian Information Criteria, $\chi^2_{SC}(4)$ and χ^2_H denote the chi-squared statistics for no autocorrelation test within 4 lags and the chi-squared statistics for homoskedasticity with p-values inside $[\cdot]$.

Table 3.42: Equilibrium correction: Capital outflows, Sample II, (*Spec 4*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
c	-104.27	156.13		-126.92	77.03		2.91	32.51		-3.94	18.86	
Δc_{t-1}	-0.09	0.31		0.33	0.22		-0.08	0.31		0.26	0.22	
Δc_{t-2}	0.01	0.17		0.19	0.13		0.01	0.17		0.16	0.13	
$\Delta GEPU_t$	1.40	0.79	*	1.23	0.61	**	1.39	0.78	*	1.32	0.60	**
$\Delta GEPU_{t-1}$	-0.27	0.83		-0.90	0.68		-0.26	0.82		-0.73	0.67	
Δi_t	-79.70	88.47		-57.77	67.33		-61.97	83.93		-31.49	66.52	
Δi_{t-1}	-17.03	76.52		-11.18	59.03		-5.19	73.63		-9.14	59.51	
Δi_{t-2}	32.64	79.53		43.90	63.14		39.93	78.06		49.90	63.33	
$\Delta WGDP_t$	-4.44	41.00		5.07	32.03		-8.65	40.26		-7.19	31.86	
$\Delta WGDP_{t-1}$	47.55	37.58		0.41	31.72		47.45	37.34		-4.43	32.26	
$\Delta WGDP_{t-2}$	-30.44	36.64		-69.75	30.44	**	-28.54	36.27		-71.30	30.70	**
ΔTL_t	20.60	25.11		7.06	20.08		19.83	24.88		5.97	19.86	
ΔTL_{t-1}	28.64	22.89		12.54	18.10		24.23	21.99		6.46	18.26	
ΔFL_t	14.77	8.54	*	22.04	5.28	**	17.26	7.52	**	20.88	5.34	**
ΔFL_{t-1}	-20.25	8.35	**	-8.20	5.71		-17.96	7.58	**	-9.12	5.70	
ΔFL_{t-2}	-0.61	8.73		6.62	6.63		0.90	8.44		4.67	6.52	
Δinv_t	29.00	6.74	**	23.46	5.41	**	28.23	6.58	**	23.57	5.45	**
Δinv_{t-1}	16.51	9.99		-4.62	8.72		15.11	9.75		-2.47	8.65	
Δinv_{t-2}	8.35	7.15		-3.97	6.12		7.46	6.97		-2.88	6.11	
$\Delta DGDP_t$	20.72	33.63		52.08	25.48	**	22.42	33.28		55.35	25.71	**
$\Delta DGDP_{t-1}$	31.43	32.15		23.64	25.70		32.22	31.97		31.81	25.96	
$\Delta DGDP_{t-2}$	-31.60	33.42		-48.96	25.36	*	-34.62	32.76		-43.07	25.64	*
Δppi_t	-0.76	37.74		-45.50	31.07		-3.10	37.36		-35.60	30.74	
Δppi_{t-1}	8.82	35.44		54.94	29.93	*	9.97	35.18		51.29	30.09	*
$\Delta debt_t$	-0.91	36.75		-49.01	28.12	*	-1.55	36.48		-50.63	28.43	*
$\Delta debt_{t-1}$	2.06	34.29		-24.39	27.84		0.89	33.93		-15.19	27.77	
$\Delta debt_{t-2}$	37.38	39.66		46.94	31.77		37.65	39.39		60.59	31.44	*
$\hat{v}_{t-1}$	-1.18	0.44	**	-1.70	0.29	**	-1.20	0.44	**	-1.60	0.28	**
t	1.65	2.35		1.48	0.89							
D_{2008}	-117.73	140.70					-32.11	63.85				

(1) $\bar{R}^2 = 0.7100$, $AIC = 13.35$, $SBC = 14.27$, $\chi^2_{SC}(4) = 9.74[0.045]$, $\chi^2_H = 36.77[0.152]$
Inverted AR Roots $= -.35 + .39i, -.35 - .39i$.
(2) $\bar{R}^2 = 0.8118$, $AIC = 12.92$, $SBC = 13.81$, $\chi^2_{SC}(4) = 12.18[0.016]$, $\chi^2_H = 23.78[0.693]$
Inverted AR Roots $= -.19 + .50i, -.19 - .50i$.
(3) $\bar{R}^2 = 0.7140$, $AIC = 13.34$, $SBC = 14.23$, $\chi^2_{SC}(4) = 10.86[0.028]$, $\chi^2_H = 32.02[0.274]$
Inverted AR Roots $= -.31 + .37i, -.31 - .37i$.
(4) $\bar{R}^2 = 0.8081$, $AIC = 12.93$, $SBC = 13.79$, $\chi^2_{SC}(4) = 13.91[0.008]$, $\chi^2_H = 21.89[0.743]$
Inverted AR Roots $= -.21 + .42i, -.21 - .42i$.

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively. $\bar{R}^2$ is the adjusted squared multiple correlation coefficient, AIC and SBC are Akaike's and Schwarz's Bayesian Information Criteria, $\chi^2_{SC}(4)$ and χ^2_H denote the chi-squared statistics for no autocorrelation test within 4 lags and the chi-squared statistics for homoskedasticity with p-values inside $[\cdot]$.

Table 3.43: Equilibrium correction: Capital inflows, Sample I, (*Spec 5*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
c	7.93	23.17		-11.09	20.29		-2.74	12.28		3.56	10.65	
Δc_{t-1}	0.31	0.20		-0.01	0.15		0.38	0.19	*	0.01	0.15	
Δc_{t-2}	0.17	0.10	*	0.06	0.09		0.19	0.10	**	0.07	0.09	
ΔGPR_t	-0.02	0.22		0.05	0.22		-0.05	0.21		0.04	0.22	
ΔGPR_{t-1}	-0.13	0.23		-0.28	0.24		-0.12	0.22		-0.28	0.24	
Δi_t	-22.94	27.60		-19.86	27.45		-20.97	26.49		-17.16	27.17	
Δi_{t-1}	-24.58	27.17		-15.32	27.37		-38.36	26.61		-17.27	27.13	
$\Delta WGDP_t$	-2.70	17.35		6.33	17.68		-6.59	17.02		4.14	17.51	
$\Delta WGDP_{t-1}$	-12.23	17.95		-21.59	18.49		-17.00	17.67		-23.96	18.39	
$\Delta WGDP_{t-2}$	-1.80	15.66		-17.48	16.59		-4.20	15.37		-17.92	16.49	
ΔFL_t	16.39	4.23	**	17.69	3.89	**	14.70	3.98	**	17.51	3.87	**
ΔFL_{t-1}	-10.23	4.54	**	-3.52	3.87		-11.14	4.17	**	-3.53	3.84	
ΔFL_{t-2}	-4.66	4.34		-2.90	4.08		-4.78	4.10		-3.01	4.04	
Δinv_t	15.61	3.11	**	16.28	3.13	**	15.76	3.03	**	16.21	3.11	**
Δinv_{t-1}	-4.94	5.24		0.34	4.78		-5.83	5.12		-0.07	4.73	
Δinv_{t-2}	-1.13	3.52		-0.15	3.53		-1.24	3.43		-0.28	3.50	
$\Delta DGDP_t$	31.78	13.23	**	35.15	13.43	**	36.96	12.94	**	37.23	13.33	**
$\Delta DGDP_{t-1}$	17.70	14.23		21.91	14.59		21.58	14.04		23.49	14.52	
$\Delta DGDP_{t-2}$	-7.60	13.04		-11.72	12.83		-2.26	12.81		-10.71	12.78	
Δppi_t	3.22	16.29		20.77	16.19		5.08	15.89		22.54	16.02	
Δppi_{t-1}	19.45	15.69		12.27	15.75		18.57	15.31		11.81	15.62	
$\Delta debt_t$	-0.24	18.41		-14.09	18.15		0.97	18.03		-12.74	17.98	
$\Delta debt_{t-1}$	7.97	17.47		11.07	17.71		10.89	16.93		13.85	17.38	
$\Delta pdebt_t$	-28.06	4.19	**	-24.91	4.13	**	-27.59	4.05	**	-24.52	4.08	**
$\Delta pdebt_{t-1}$	25.66	6.27	**	10.50	5.59	*	26.66	6.11	**	10.80	5.53	*
$\hat{v}_{t-1}$	-1.53	0.26	**	-1.09	0.19	**	-1.64	0.26	**	-1.12	0.19	**
t	-0.26	0.48		0.25	0.29							
D_{2008}	18.89	52.17					-8.30	30.82				

(1) $\bar{R}^2 = 0.8267$, $AIC = 12.26$, $SBC = 12.90$, $\chi^2_{SC}(4) = 17.59[0.002]$, $\chi^2_H = 43.66[0.022]$
Inverted AR Roots $= -.34 - .26i, -.34 + .26i$.
(2) $\bar{R}^2 = 0.8206$, $AIC = 12.29$, $SBC = 12.91$, $\chi^2_{SC}(4) = 23.82[0.000]$, $\chi^2_H = 33.28[0.154]$
Inverted AR Roots $= -.35 - .18i, -.35 + .18i$.
(3) $\bar{R}^2 = 0.8336$, $AIC = 12.22$, $SBC = 12.83$, $\chi^2_{SC}(4) = 16.33[0.003]$, $\chi^2_H = 36.57[0.082]$
Inverted AR Roots $= -.34 - .26i, -.34 + .26i$.
(4) $\bar{R}^2 = 0.8230$, $AIC = 12.27$, $SBC = 12.87$, $\chi^2_{SC}(4) = 24.27[0.000]$, $\chi^2_H = 23.25[0.563]$
Inverted AR Roots $= -.35 + .19i, -.35 - .19i$.

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively. $\bar{R}^2$ is the adjusted squared multiple correlation coefficient, AIC and SBC are Akaike's and Schwarz's Bayesian Information Criteria, $\chi^2_{SC}(4)$ and χ^2_H denote the chi-squared statistics for no autocorrelation test within 4 lags and the chi-squared statistics for homoskedasticity with p-values inside $[\cdot]$.

Table 3.44: Equilibrium correction: Capital outflows, Sample I, (*Spec 5*)

	(1)			(2)			(3)			(4)		
	β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$		β	$se(\beta)$	
c	5.28	22.52		-11.57	19.46		-5.54	12.00		0.27	10.16	
Δc_{t-1}	0.22	0.17		0.01	0.14		0.27	0.17		0.02	0.14	
Δc_{t-2}	0.16	0.09	*	0.08	0.08		0.17	0.09	*	0.09	0.08	
ΔGPR_t	-0.03	0.21		0.04	0.21		-0.07	0.21		0.03	0.21	
ΔGPR_{t-1}	-0.03	0.23		-0.18	0.23		-0.03	0.22		-0.18	0.23	
Δi_t	-6.74	26.91		-5.93	26.43		-3.59	25.87		-2.63	26.01	
Δi_{t-1}	-33.25	26.39		-27.00	26.27		-45.15	25.76	*	-30.18	25.90	
$\Delta WGDP_t$	13.06	16.95		20.78	16.94		8.62	16.64		18.02	16.70	
$\Delta WGDP_{t-1}$	-13.23	17.32		-23.06	17.56		-16.59	17.02		-25.40	17.38	
$\Delta WGDP_{t-2}$	-7.52	14.02		-23.69	14.36		-7.27	13.72		-23.66	14.19	*
ΔFL_t	18.59	4.09	**	19.39	3.75	**	17.09	3.86	**	19.10	3.71	**
ΔFL_{t-1}	-8.99	4.32	**	-3.77	3.76		-9.57	3.97	**	-3.66	3.72	
ΔFL_{t-2}	-5.12	4.24		-4.09	3.97		-5.05	4.02		-4.01	3.91	
Δinv_t	17.95	2.99	**	18.19	2.98	**	18.27	2.92	**	18.21	2.93	**
Δinv_{t-1}	-4.23	5.06		-0.53	4.64		-4.59	4.90		-0.87	4.56	
Δinv_{t-2}	-1.26	3.52		-0.62	3.47		-1.28	3.43		-0.72	3.42	
$\Delta DGDP_t$	26.10	12.89	**	28.54	12.87	**	32.24	12.66	**	31.56	12.73	**
$\Delta DGDP_{t-1}$	14.26	14.05		17.65	14.08		18.93	13.90		19.95	13.99	
Δppi_t	10.02	16.08		25.40	15.60		11.76	15.66		27.06	15.35	*
Δppi_{t-1}	8.52	15.39		2.61	15.12		8.36	15.02		2.39	14.93	
$\Delta debt_t$	-10.55	17.99		-21.25	17.48		-9.62	17.61		-19.96	17.24	
$\Delta debt_{t-1}$	20.37	16.87		20.85	16.83		23.52	16.35		23.73	16.40	
$\Delta pdebt_t$	-28.72	4.09	**	-25.64	3.94	**	-28.25	3.95	**	-25.30	3.88	**
$\Delta pdebt_{t-1}$	27.18	5.73	**	15.22	5.32	**	27.49	5.56	**	15.32	5.24	**
$\hat{v}_{t-1}$	-1.32	0.23	**	-1.04	0.17	**	-1.39	0.22	**	-1.07	0.17	**
t	-0.26	0.46		0.20	0.27							
D_{2008}	22.33	49.65					-2.34	29.25				

(1) $\bar{R}^2 = 0.8354$, $AIC = 12.21$, $SBC = 12.83$, $\chi^2_{SC}(4) = 20.20[0.001]$, $\chi^2_H = 48.06[0.005]$
Inverted AR Roots $= -.32 - .10i, -.32 + .10i$.
(2) $\bar{R}^2 = 0.8359$, $AIC = 12.20$, $SBC = 12.80$, $\chi^2_{SC}(4) = 23.22[0.000]$, $\chi^2_H = 34.68[0.094]$
Inverted AR Roots $= -.20, -.44$.
(3) $\bar{R}^2 = 0.8421$, $AIC = 12.17$, $SBC = 12.76$, $\chi^2_{SC}(4) = 19.38[0.001]$, $\chi^2_H = 41.47[0.021]$
Inverted AR Roots $= -.31 - .09i, -.31 + .09i$.
(4) $\bar{R}^2 = 0.8395$, $AIC = 12.18$, $SBC = 12.75$, $\chi^2_{SC}(4) = 24.04[0.000]$, $\chi^2_H = 24.19[0.451]$
Inverted AR Roots $= -.00, -.49$.

Notes: (1) excludes deterministic trend and dummy, (2) excludes deterministic trend, (3) excludes dummy and (4) includes constant, trend and dummy. The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively. $\bar{R}^2$ is the adjusted squared multiple correlation coefficient, AIC and SBC are Akaike's and Schwarz's Bayesian Information Criteria, $\chi^2_{SC}(4)$ and χ^2_H denote the chi-squared statistics for no autocorrelation test within 4 lags and the chi-squared statistics for homoskedasticity with p-values inside $[\cdot]$.

3.6.8 Long run estimation with average GPR index

Table 3.45: Long run estimation: Sample I (*Spec 1*)

	Capital Inflows			Capital Outflows		
	β	$se(\beta)$		β	$se(\beta)$	
GPR_t	0.63	0.30	**	0.59	0.30	*
i_t	-4.60	18.82		-5.36	19.05	
$WGDP_t$	27.09	13.00	**	33.16	13.16	**
FL_t	3.32	1.23	***	2.99	1.25	**
inv_t	16.47	3.95	***	18.49	4.00	***
$DGDP_t$	-3.37	8.54		-6.19	8.64	
ppi_t	2.40	8.81		0.37	8.92	
$debt_t$	12.03	3.23	***	11.95	3.27	***
c	-419.41	175.61	**	-404.96	177.77	**
t	-1.04	1.62		-1.32	1.64	
D_{2008}	-510.39	86.68	***	-497.53	87.75	***

Notes: The symbols ***, **, * denote significance level at 1%, 5% and 10%, respectively.

Bibliography

[1] Aastveit, K. A., Natvik, G. J., and Sola, S. (2013). Economic uncertainty and the effectiveness of monetary policy. *Norges Bank Working Paper*, No. 2013/17, Norges Bank.

[2] Abeysinghe, T., and Forbes, K. (2005). Trade Linkages and Output-Multiplier Effects: a Structural VAR Approach with a Focus on Asia. *Review of International Economics*, 13(2), 356-375.

[3] Ahnert, T., and Bertsch, C. (2015). A wake-up call theory of contagion. *Bank of Canada Working Paper*, No. 2015-14, Bank of Canada.

[4] Aikman, D., Haldane, A. G., and Nelson, B. D. (2013). Curbing the credit cycle. *The Economic Journal*, 125(585), 1072-1109.

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

[6] Albuquerque, R., Bauer, G. H., and Schneider, M. (2009). Global private information in international equity markets. *Journal of Financial Economics*, 94(1), 18-46.

[7] Alfaro, I., Bloom, N., and Lin, X. (2016). The Real and Financial Impact of Uncertainty Shocks. Paper presented at Stanford Institute for Theoretical Economics (SITE) 2016 Workshop. Retrieved from `https://site.stanford.edu/sites/default/files/alfaro.pdf`

[8] Arellano, C., Bai, Y., and Kehoe, P. J. (2012). Financial frictions and fluctuations in volatility. *Federal Reserve Bank of Minneapolis Research Department Staff Report*, No. 466.

[9] Azzalini, A., and Capitanio, A. (1999). Statistical applications of the multivariate skew normal distribution. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 61(3), 579-602.

[10] Bacchetta, P., Tille, C., and Van Wincoop, E. (2012). Self-fulfilling risk panics. *The American Economic Review*, 102(7), 3674-3700.

[11] Bacchetta, P., and Van Wincoop, E. (2013). Sudden spikes in global risk. *Journal of international Economics*, 89(2), 511-521.

[12] Bachmann, R., Elstner, S., and Sims, E. R. (2013). Uncertainty and Economic Activity: Evidence from Business Survey Data. *American Economic Journal: Macroeconomics*, 5(2): 217-49.

[13] Bai, J., and Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, 47-78.

[14] Baker, S. R., and Bloom, N. (2013). Does uncertainty reduce growth? Using disasters as natural experiments. *NBER Working Paper*, No. w19475. National Bureau of Economic Research.

[15] Baker, S. R., Bloom, N., and Davis, S. J. (2015). Measuring economic policy uncertainty. *National Bureau of Economic Research*, No. w21633.

[16] Ball, L. (1992). Why does high inflation raise inflation uncertainty? *Journal of Monetary Economics*, 29(3), 371-388.

[17] Bank of England. (2002). *Inflation Report*, May 2002.

[18] 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.

[19] Barsky, R. B., and Sims, E. R. (2012). Information, animal spirits, and the meaning of innovations in consumer confidence. *The American Economic Review*, 102(4), 1343-1377.

[20] Basu, A., Ray, S., Park, C., and Basu, S. (2002). Improved power in multinomial goodness-of-fit tests. *Journal of the Royal Statistical Society: Series D (The Statistician)*, 51(3), 381-393.

[21] Baxter, M., and King, R. G. (1999). Measuring business cycles: approximate band-pass filters for economic time series. *Review of economics and statistics*, 81(4), 575-593.

[22] Beaudry, P., and Portier F. (2006). Stock Prices, News, and Economic Fluctuations. *American Economic Review*, 96(4), 1293–1307.

[23] Bekaert, G., Hoerova, M., and Duca, M. L. (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics*, 60(7), 771-788.

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

[25] Bentolila, S., Dolado, J. J., and Jimeno, J. F. (2008). Does immigration affect the Phillips curve? Some evidence for Spain. *European economic review*, 52(8), 1398-1423.

[26] Berger, D., I. Dew-Becker and S. Giglio. (2016). Contractionary volatility or volatile contractions? *Northwestern University Working Paper.*

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

[28] Bemanke, B., Gertler, M., and Gilchrist, S. (1996). The Financial Accelerator and the Flight to Quality. *The Review of Economics and Statistics*, 78(1), 1-15.

[29] Berument, H., Yalcin, Y., and Yildirim, J. (2009). The effect of inflation uncertainty on inflation: Stochastic volatility in mean model within a dynamic framework. *Economic Modelling*, 26(6), 1201-1207.

[30] Blanchard, O. J. (1993). Consumption and the Recession of 1990 - 1991. *American Economic Review*, 83(2), 270–74.

[31] Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77(3), 623-685.

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

[33] Board of Governors of the Federal Reserve System. (2004). Speeches of Federal Reserve Officials. [Online] Available from: `http://www.federalreserve.gov/BOARDDOCS/speechES/2004/20040220/default.htm`) [Accessed: 8th September 2015].

[34] Bordo, M. D., Duca, J. V., and Koch, C. (2016). Economic Policy Uncertainty and the Credit Channel: Aggregate and Bank Level US Evidence over Several Decades. *NBER Working Paper*, No. w22021. National Bureau of Economic Research.

[35] Boyer B., Gibson M., Loretan M. (1999). Pitfalls in tests for changes in correlation. *Board of Governors of the Federal Reserve System Working Paper*, Vol. 597.

[36] Britton, E., Fisher, P., and Whitley, J. (1998). The Inflation Report projections: understanding the fan chart. Bank of England. *Quarterly Bulletin*, 38(1), 30.

[37] Brogaard, J., and Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science*, 61(1), 3-18.

[38] Broner, F., Didier, T., Erce, A., and Schmukler, S. L. (2013). Gross capital flows: Dynamics and crises. *Journal of Monetary Economics*, 60(1), 113-133.

[39] Brunner, A. D., and Hess, G. D. (1993). Are higher levels of inflation less predictable? A state-dependent conditional heteroscedasticity approach. *Journal of Business and Economic Statistics*, 11(2), 187-197.

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

[41] Bruno, V., and Shin, H. S. (2015). Capital flows and the risk-taking channel of monetary policy. *Journal of Monetary Economics*, 71, 119-132.

[42] Caldara, D., Fuentes-Albero, C., Gilchrist, S., and Zakrajšek, E. (2016). The macroeconomic impact of financial and uncertainty shocks. *European Economic Review*, 88, 185-207.

[43] Caldara, D., and Iacoviello, M. (2016). Measuring Geopolitical Risk. *mimeo*, Retrieved from `https://www2.bc.edu/matteo-iacoviello/gpr_files/GPR_PAPER.pdf`.

[44] Calvo, G. A. (1998). Capital Flows and Capital-Market Crises: The Simple Economics of Sudden Stops. *Journal of Applied Economics*, 35-54 (Nov).

[45] Calvo, G. A., Izquierdo, A., and Mejia, L. F. (2004). On the empirics of sudden stops: the relevance of balance-sheet effects. *NBER Working Paper*, No. w10520, National Bureau of Economic Research.

[46] Calvo, G. A., Izquierdo, A., and Mejía, L. F. (2008). Systemic sudden stops: the relevance of balance-sheet effects and financial integration. *NBER Working Paper*, No. w14026. National Bureau of Economic Research.

[47] Calvo, G. A., Leiderman, L., and Reinhart, C. M. (1993). Capital inflows and real exchange rate appreciation in Latin America: the role of external factors. IMF Staff Papers, 40(1), 108-151.

[48] Calvo, G. A., Leiderman, L., and Reinhart, C. M. (1996). Inflows of Capital to Developing Countries in the 1990s. *The Journal of Economic Perspectives*, 10(2), 123-139.

[49] Calvo, G. A., and Mendoza, E. G. (2000). Rational contagion and the globalization of securities markets. *Journal of international economics*, 51(1), 79-113.

[50] Calvo, G.A. and Reinhart, C.M., (2002). Fear of floating. *Quarterly Journal of Economics*, 117 (2), 379–408.

[51] Canzoneri, M.B. and Gray, J., (1985). Monetary policy games and the consequences of non-cooperative behavior. *International Economic Review*, 26 (3), 547–564.

[52] Caporale, G. M., Onorante, L. and Paesani, P., (2010). Inflation and Inflation Uncertainty in the Euro Area, *ECB Working Paper*, No. 1229.

[53] Carrière-Swallow, Y., and Céspedes, L. F. (2013). The impact of uncertainty shocks in emerging economies. *Journal of International Economics*, 90(2), 316-325.

[54] Carrion-i-Silvestre, J. Ll., Kim, D. and Perron, P. (2009). GLS-based unit root tests with multiple structural breaks under both the null and alternative hypotheses. *Econometric Theory*, 25(06), 1754-1792.

[55] Carroll, C (1996). Buffer-stock saving and the life cycle/permanent income hypothesis. *NBER Working Paper*, No. 5788. National Bureau of Economic Research.

[56] Cerutti, E., Claessens, S., and Ratnovski, L. (2014). Global liquidity and drivers of cross-border bank flows. *IMF Working Papers*, No. 14-69. International Monetary Fund.

[57] Charemza, W., Vela, C. D., and Makarova, S. (2013). Too many skew normal distributions? The practitioner's perspective, *University of Leicester Working Paper*, No. 13/07.

[58] Charemza, W., C. Dáz and S. Makarova (2014). Term structure of inflation forecast uncertainties and skew normal distributions. *University of Leicester Working Paper*, No. 14/01.

[59] Charemza, W., Dáaz, C., and Makarova, S. (2015). Conditional Term Structure of Inflation Forecast Uncertainty: The Copula Approach. *University of Leicester Working Paper*, No. 15/07.

[60] Chong, K., and Tuckett, D. (2015). Constructing conviction through action and narrative: how money managers manage uncertainty and the consequence for financial market functioning. *Socio-Economic Review*, 13(2), 309-330.

[61] Chuhan, P., Claessens, S., and Mamingi, N. (1998). Equity and bond flows to Latin America and Asia: the role of global and country factors. *Journal of Development Economics*, 55(2), 439-463.

[62] Ciccarelli, M., and Mojon, B. (2010). Global inflation. *The Review of Economics and Statistics*, 92(3), 524-535.

[63] Claessens, S., Dornbusch, R. and Park, Y.C., (2001). Contagion: Why crises spread and how this can be stopped. *In International financial contagion* (pp. 19-41). Springer US.

[64] Claessens, S., and Forbes, K. (2001). International financial contagion: An overview of the issues and the book. In *International financial contagion* (pp. 3-17). Springer US.

[65] Clements, M. P. (2014). Forecast Uncertainty - Ex Ante and Ex Post: US Inflation and Output Growth. *Journal of Business and Economic Statistics*, 32(2), 206-216.

[66] Clements, M. P. and Harvey, D. I. (2011). Combining probability forecasts. *International Journal of Forecasting*, 27, 208-233.

[67] Clements, M. P., and Hendry, D. F. (2001). *Forecasting non-stationary economic time series.* MIT Press.

[68] Cogley, T., and Nason, J. M. (1995). Effects of the Hodrick-Prescott filter on trend and difference stationary time series Implications for business cycle research. *Journal of Economic Dynamics and control*, 19(1), 253-278.

[69] Colombo, V. (2013). Economic policy uncertainty in the US: Does it matter for the Euro area? *Economics Letters*, 121(1), 39-42.

[70] Cont, R. (2001). Empirical properties of asset returns: Stylized facts and statistical issues. *Quantitative Finance*, 1, 223–236.

[71] Cukierman, A., and Meltzer, A. H. (1986). A theory of ambiguity, credibility, and inflation under discretion and asymmetric information. *Econometrica: Journal of the Econometric Society*, 1099-1128.

[72] Darby, M. R., and Lothian, J. R. (1983). The international transmission of inflation. *University of Chicago Press*.

[73] Dasgupta, A., Leon-Gonzalez, R., and Shortland, A. (2011). Regionality revisited: An examination of the direction of spread of currency crises. *Journal of international Money and Finance*, 30(5), 831-848.

[74] DeJong, D. N., and Dave, C. (2011). Structural macroeconometrics. *Princeton University Press*, Princeton.

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

[76] Devereux, M.B. and Engel, C., (2007). Expenditure switching vs. real exchange rate stabilization: competing objectives for exchange rate policy. *Journal of Monetary Economics*, 54 (8), 2346–2374.

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

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

[79] Doyle, B. M., and Faust, J. (2005). Breaks in the variability and comovement of G-7 economic growth. *Review of Economics and Statistics*, 87(4), 721-740.

[80] Durrelman, V., Nikeghbali, A. and Roncalli, T. (2000) Which copula is the right one? Available at: `http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1032545`.

[81] Elder, J. (2004), Another perspective on the effects of inflation uncertainty. *Journal of Money, Credit and Banking*, 36, 911-928.

[82] Elder, R., G. Kapetanios, T. Taylor and T. Yates (2005), Assessing the MPC's fan charts. *Bank of England Quarterly Bulletin*, 45, 326-348.

[83] Embrechts, P., McNeil, A., and Straumann, D. (2002) Correlation and dependence in risk management: properties and pitfalls, *Risk management: value at risk and beyond*, pp. 176-223.

[84] Engelberg, J., Manski, C. F., and Williams, J. (2009). Comparing the point predictions and subjective probability distributions of professional forecasters. *Journal of Business and Economic Statistics*, 27(1), 30-41.

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

[86] Federal Deposit Insurance Corporation. (2008). FDIC Press release, July 11 2008. [Online] Available from: `https://www.fdic.gov/news/news/press/2008/pr08056.html` [Accessed: 8th September 2015].

[87] Fernandez-Arias, E. (1996). The new wave of private capital inflows: push or pull? *Journal of development economics*, 48(2), 389-418.

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

[89] Forbes, K. (2012). The "big C": Identifying contagion. *NBER Working Paper*, No. 18465, National Bureau of Economic Research.

[90] Forbes, K. J. and Rigobon, R. (2002). No contagion, only interdependence: measuring stock market comovements. *The journal of Finance*, 57(5), 2223-2261.

[91] Forbes, K. J., and Warnock, F. E. (2012a). Capital flow waves: Surges, stops, flight, and retrenchment. *Journal of International Economics*, 88(2), 235-251.

[92] Forbes, K. J., and Warnock, F. E. (2012b). Debt-and equity-led capital flow episodes. *NBER Working Paper*, No. w18329. National Bureau of Economic Research.

[93] Fountas, S., Karanasos M., and Kim J. (2006). Inflation uncertainty, output growth uncertainty and macroeconomic performance. *Oxford Bulletin of Economics and Statistics*, 68, 319-348.

[94] Franceschini, C., and Loperfido, N. (2014). Testing for normality when the sampled distribution is extended skew-normal. *In Mathematical and Statistical Methods for Actuarial Sciences and Finance*, pp. 159-169. Springer International Publishing.

[95] Fratzscher, M. (2012). Capital flows, push versus pull factors and the global financial crisis. *Journal of International Economics*, 88(2), 341-356.

[96] Friedman, M., (1977). *Nobel lecture: inflation and unemployment.* Journal of Political Economy, 85 (3), 451–472.

[97] Gauvin, L., McLoughlin, C., and Reinhardt, D. (2014). Policy uncertainty spillovers to emerging markets – evidence from capital flows. *Bank of England Working Paper*, No.512.

[98] Gilchrist, S., Sim, J. W., and Zakrajšek, E. (2014). Uncertainty, financial frictions, and investment dynamics. *NBER Working Paper*, No. w20038. National Bureau of Economic Research.

[99] Gilboa, I., and Schmeidler, D. (1989). Maxmin expected utility with non-unique prior. *Journal of mathematical economics*, 18(2), 141-153.

[100] Giordani, P. and Söderlind, P. (2003). Inflation forecast uncertainty. *European Economic Review*, 47, 1037-1059.

[101] Glick, R., and Rose, A. K. (1999). Contagion and trade: Why are currency crises regional?. *Journal of international Money and Finance*, 18(4), 603-617.

[102] Göktaş, P., and Dişbudak, C. (2014). Modelling Inflation Uncertainty with Structural Breaks Case of Turkey (1994–2013). *Mathematical Problems in Engineering*, 2014.

[103] Goldstein, M. (1998). The Asian financial crisis: Causes, cures, and systemic implications (Vol. 55). *Peterson Institute Press: Policy Analyses in International Economics.*

[104] Golinelli, R., and Parigi, G. (2004). Consumer sentiment and economic activity: a cross country comparison. *Journal of Business Cycle Measurement and Analysis*, 1(2): 147-172.

[105] Gourio, F., Siemer, M., and Verdelhan, A. (2013). International risk cycles. *Journal of International Economics*, 89(2), 471-484.

[106] Greco, L. (2011). Minimum Hellinger distance based inference for scalar skew-normal and skew-t distributions. *Test*, 20(1), 120-137.

[107] Greenspan, A (2005). Globalization. *Remarks given at the Council on Foreign Relations, New York, Federal Reserve Board.*

[108] Grier, K. B., and Perry, M. J. (2000). The effects of real and nominal uncertainty on inflation and output growth: some GARCH-M evidence. *Journal of Applied Econometrics*, 15(1), 45-58.

[109] Griffin, J. M., Nardari, F., and Stulz, R. M. (2004). Are daily cross-border equity flows pushed or pulled? *Review of Economics and Statistics*, 86(3), 641-657.

[110] Hafer, R. W., and Sheehan, R. G. (1989). The sensitivity of VAR forecasts to alternative lag structures. *international Journal of Forecasting*, 5(3), 399-408.

[111] Hamilton, J. D. (1994). Time series analysis (Vol. 2). *Princeton university press*. Princeton.

[112] Hansen, L. P., Sargent, T. J., and Tallarini Jr, T. D. (1999). Robust Permanent Income and Pricing. *The Review of Economic Studies*, 66(229), 873.

[113] Hau, H., and Rey, H. (2008). Home bias at the fund level. *NBER Working Paper*, No. w14172. National Bureau of Economic Research.

[114] Henriksen, E. R., Kydland, F. E., Sustek, R. (2011). The high cross-country correlations of prices and interest rates. *University of Nottingham, Centre for Finance, Credit, and Macroeconomics*. Discussion Paper 11/01.

[115] Henriksen, E., Kydland, F. E., and Sustek, R. (2013). Globally correlated nominal fluctuations. *Journal of Monetary Economics*, 60(6), 613-631.

[116] Holland, A. S. (1995). Inflation and uncertainty: tests for temporal ordering. *Journal of Money, Credit and Banking*, 27(3), 827-837.

[117] Hurvich, C. M., and Tsai, C. L. (1993). A corrected Akaike information criterion for vector autoregressive model selection. *Journal of time series analysis*, 14(3), 271-279.

[118] Hwang, S., and Valls Pereira, P. L. (2006). Small sample properties of GARCH estimates and persistence. *The European Journal of Finance*, 12(6-7), 473-494.

[119] ILO, (2013). Global Employment Trends. Recovering from a second jobs dip. *International Labour Office*. Geneva.

[120] ILO, (2014). Global Employment Trends. Risk of a jobless recovery?. *International Labour Office*. (Geneva).

[121] IMF (2015). Global Financial Stability Report, April 2015. International Monetary Fund.

[122] IMF (2016). Global Financial Stability Report, April 2016. International Monetary Fund.

[123] Joe, H. (2005). Asymptotic efficiency of the two-stage estimation method for copula-based models. *Journal of Multivariate Analysis*, 94(2), 401-419.

[124] Joe, H., and Xu, J. J. (1996). The estimation method of inference functions for margins for multivariate models, *Technical report No.166, Department of Statistics, University of British Columbia*, Vancouver.

[125] Jordá, Ó. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 161-182.

[126] Jordá, Ó. (2009). Simultaneous confidence regions for impulse responses. *The Review of Economics and Statistics*, 91(3), 629-647.

[127] Jordá, Ó., Knüppel, M., and Marcellino, M. (2013). Empirical simultaneous prediction regions for path-forecasts. *International journal of forecasting*, 29(3), 456-468.

[128] Jotikasthira, C., Lundblad, C., and Ramadorai, T. (2012). Asset fire sales and purchases and the international transmission of funding shocks. *The Journal of Finance*, 67(6), 2015-2050.

[129] Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring Uncertainty. *The American Economic Review*, 105(3), 1177-1216.

[130] Kalemli-Ozcan, S., Papaioannou, E., and Perri, F. (2013). Global banks and crisis transmission. *Journal of international Economics*, 89(2), 495-510.

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

[132] Knüppel, M. (2014). Efficient estimation of forecast uncertainty based on recent forecast errors. *International Journal of Forecasting*, 30(2), 257-267.

[133] Kontonikas, A. (2004), Inflation and inflation uncertainty in the United Kingdom, evidence from GARCH modelling, *Economic Modelling*, 21, 525-543.

[134] Lahiri, K., Peng, H. and Sheng, X. (2014). Measuring uncertainty of a combined forecast. *paper presented at the workshop Uncertainty and Economic Forecasting, UCL, London*.

[135] Lamoureux, C. G., and Lastrapes, W. D. (1990). Persistence in variance, structural change, and the GARCH model. *Journal of Business and Economic Statistics*, 8(2), 225-234.

[136] Lazear, E. and Spletzer, R. (2011). Hiring, churn and the business cycle. *NBER Working Paper* No. 17910. National Bureau of Economic Research.

[137] Leahy, J. V. and Whited, T. M. (1995). The effect of uncertainty on investment: some stylized facts. *NBER Working Paper*, No. w4986. National Bureau of Economic Research.

[138] Lehmann, E. L. (1966). Some concepts of dependence. *The Annals of Mathematical Statistics*, 1137-1153.

[139] Levin, A. T., and Piger, J. (2004), Is inflation persistence intrinsic in industrial economies? *ECB working paper*, 334.

[140] Ludvigson, S. C., Ma, S., and Ng, S. (2015). Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response? *NBER Working Paper*, No. w21803. National Bureau of Economic Research.

[141] Lütkepohl, H. (1993). Testing for causation between two variables in higher-dimensional VAR models. In *Studies in Applied Econometrics* (pp. 75-91). Physica-Verlag HD.

[142] Lütkepohl, H. (2007). New introduction to multiple time series analysis, Springer Science and Business Media.

[143] Makarova S. (2014). Risk and Uncertainty: Macroeconomic Perspective. *Forthcoming in: Risk and development for European and global economy*, Editor: Juliusz. Kotyński, publisher: AFiBV.

[144] Mas-Colell, A., Whinston, M. D., and Green, J. R. (1995). Microeconomic Theory. Vol. 1. New York: *Oxford university press.*

[145] McKinnon, R. I. (1982). Currency substitution and instability in the world dollar standard. *The American Economic Review*, 72(3), 320-333.

[146] Melitz, M. J. and Ottaviano, G. (2008). Market Size, Trade, and Productivity. *Review of Economic Studies*, 75, 295–316.

[147] Mertens, K., and 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.

[148] Milesi-Ferretti, G. M., and Tille, C. (2011). The great retrenchment: international capital flows during the global financial crisis. *Economic Policy*, 26(66), 289-346.

[149] Monacelli, T., and Sala, L. (2009). The international dimension of inflation: evidence from disaggregated consumer price data. *Journal of Money, Credit and Banking*, 41(s1), 101-120.

[150] Mumtaz, H., and Surico, P. (2012). Evolving International Inflation Dynamics: World and Country-specific Factors. *Journal of the European Economic Association*, 10(4), 716-734.

[151] Neanidis, K. C. and Savva, C. S. (2011), Nominal uncertainty and inflation: the role of European Union membership, *Economics Letters*, 12, 26-30.

[152] Neely, C. J., and Rapach, D. E. (2011). International comovements in inflation rates and country characteristics. *Journal of International Money and Finance*, 30(7), 1471-1490.

[153] Ng, S., and Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power. *Econometrica*, 69(6), 1519-1554.

[154] Nyman R., Gregory D., Kapadia S., Smith R., and Tuckett D. (2014). News and narratives in financial systems. *Workshop on using big data for forecasting and statistics*. Conference material, *mimeo*. [Online] Available from: `https://www.ecb.europa.eu/pub/conferences/past/html/index.en.html` [Accessed: 13th May 2017].

[155] Pagan, A. R., Hall, A. D., and Trivedi, P. K. (1983). Assessing the variability of inflation. *The Review of Economic Studies*, 50(4), 585-596.

[156] Pástor, Ľ., and Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, 110(3), 520-545.

[157] Perron, P. (1989). The great crash, the oil price shock, and the unit root hypothesis. *Econometrica: Journal of the Econometric Society*, 1361-1401.

[158] Perron, P., and Qu, Z. (2007). A simple modification to improve the finite sample properties of Ng and Perron's unit root tests. *Economics letters*, 94(1), 12-19.

[159] Pesaran, M. H., Shin, Y., and Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics*, 16(3), 289-326.

[160] Phillips, P. C., and Jin, S. (2015). Business Cycles, Trend Elimination, and the HP Filter. *Cowles Foundation Discussion Paper*, No. 2005. [Online] Available from: `http://ssrn.com/abstract=2622477` [Accessed: 9th August 2017].

[161] Pourgerami, A., and Maskus, K. E. (1987). The effects of inflation on the predictability of price changes in Latin America: some estimates and policy implications. *World Development*, 15(2), 287-290.

[162] Reinhart, C. M., and Reinhart, V. R. (2008). Capital flow bonanzas: an encompassing view of the past and present, *NBER Working Paper*, No. w14321. National Bureau of Economic Research.

[163] Rigobon, R. (2016). Contagion, spillover and interdependence. *Bank of England Staff Working Paper*, No. 607. Bank of England.

[164] Rogoff, K. S. (2003), Globalization and Global Disinflation (pp. 77–112), *in Proceedings of the Federal Reserve Bank of Kansas City Economic Review* (4th quarter 2003).

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

[166] Rothenberg, A. D., and Warnock, F. E. (2011). Sudden flight and true sudden stops. *Review of International Economics*, 19(3), 509-524.

[167] Sartori, N. (2006). Bias prevention of maximum likelihood estimates for scalar skew normal and skew t distributions. *Journal of Statistical Planning and Inference*, 136(12), 4259-4275.

[168] Savage, L. J. (1972). The foundations of statistics. *Courier Corporation.*

[169] Schmidt, T. (2007). Coping with copulas. *Copulas-From Theory to Application in Finance*, pp. 3-34.

[170] Schmidt, R., and Stadtmüller, U. (2006). Non-parametric Estimation of Tail Dependence. *Scandinavian Journal of Statistics*, 33(2), 307-335.

[171] Schweizer, B. and Sklar, A. (1983). Probabilistic Metric Spaces. North-Holland, New York.

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

[173] Segal, G., Shaliastovich, I., and Yaron, A. (2015). Good and bad uncertainty: Macroeconomic and financial market implications. *Journal of Financial Economics*, 117(2), 369-397.

[174] Shin, H. S. (2012). Global banking glut and loan risk premium. *IMF Economic Review*, 60(2), 155-192. International Monetary Fund.

[175] Silvennoinen, A., and Teräsvirta, T. (2009). Multivariate GARCH models, in (Andersen, T. G., Davis, R. A., Kreiss, J. P., and Mikosch, T. V., eds.) *Handbook of financial time series* (pp. 201-229). Springer Berlin Heidelberg.

[176] Sims, C. A., and Zha, T. (1999). Error bands for impulse responses. *Econometrica*, 67(5), 1113-1155.

[177] Sinha N. (2014). Using big data in finance: Example of sentiment extraction from news articles. *FEDS Notes*. [Online] Available from: `http://www.federalreserve.gov/econresdata/notes/feds-notes/default.html` [Accessed: 13th May 2017].

[178] Stock, J.H., and Watson, M.W. (2007). Why Has U.S. Inflation Become Harder to Forecast? *Journal of Money, Credit, and Banking*, 39, 3-34.

[179] Stock, J. H., and Watson, M. W. (2010). Modeling inflation after the crisis. *NBER working paper*, No. w16488, National Bureau of Economic Research.

[180] 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.*

[181] Summers, L. H. (2014). US economic prospects: Secular stagnation, hysteresis, and the zero lower bound. *Business Economics*, 49(2), 65-73.

[182] Trivedi, P. K. and Zimmer, D. M. (2007). Copula Modeling: An Introduction for Practitioners. *Foundations and trends in econometrics*, Now Publishers Inc.

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

[184] Tuckett, D., Ormerod, P., Nyman R., and Smith, R. E. (2014a). 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.*

[185] Tuckett, D., Smith, R. E., and Nyman, R. (2014b). Tracking phantastic objects: A computer algorithmic investigation of narrative evolution in unstructured data sources. *Social Networks*, 38, 121-133.

[186] Ulrich, M. (2013). How Does the Bond Market Perceive Government Interventions?. *Columbia Business School Research Paper*, (12/42).

[187] Ungar, M., and Zilberfarb, B. Z. (1993). Inflation and Its Unpredictability - Theory and Empirical Evidence. *Journal of Money, Credit and Banking*, 25(4), 709-720.

[188] Van Nieuwerburgh, S., and Veldkamp, L. (2006). Learning asymmetries in real business cycles. *Journal of monetary Economics*, 53(4), 753-772.

[189] Walker, W. E., Harremoës, P., Rotmans, J., van der Sluijs, J. P., van Asselt, M. B., Janssen, P., and Krayer von Krauss, M. P. (2003). Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. *Integrated assessment*, 4(1), 5-17.

[190] Wallis, K. F. (2004). An assessment of Bank of England and National Institute inflation forecast uncertainties. *National Institute Economic Review*, 64-71.

[191] Wallis, K. F. (2005). Combining Density and Interval Forecasts: A Modest Proposal. *Oxford Bulletin of Economics and Statistics*, 67(s1), 983-994.