UNIVERSITY of SOUTHAMPTON

FACULTY OF SOCIAL SCIENCES

SOUTHAMPTON BUSINESS SCHOOL

Essays on Uncertainty and Real Economic Fluctuations

by

Abdullah Alhussaini

Thesis for the degree of Doctor of Philosophy

May 2019

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Abstract

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This thesis focuses on an exhaustive theoretical and empirical scrutiny of the dynamic interdependence between uncertainty and real economic fluctuations. It consists of three main chapters, along with the first introductory chapter.

In the second chapter we propose an analytical framework to study the cointegration relationship between economic uncertainty (various measures) and financial, as well as macroeconomic variables. This chapter contribution builds on establishing a theory-driven analytical framework to demonstrate that a shock to uncertainty can change the equilibrium behaviour of financial and macroeconomic aggregates. An economic system may display heterogenous cointegration structure at various points in the distribution of the growing variable, pointing to the possibility of multiple-steady states and condition-specific policy intervention, rather than being conventionally assumed and estimated. Consequently, another innovation of this chapter is to test and identify the possibility that a heterogenous cointegration relationship may exist across the distribution of the financial/macroeconomic variables, and not only their mean. By employing the recently developed quantile autoregressive distributed lag (QARDL) model to our setting, our empirical examination in the case of the USA confirms that there exist varied speeds of adjustment across different points of the distribution of the economic system.

The third chapter seeks to expand our perception of the impact of economic uncertainty on the growth of macroeconomic variables. In this chapter we exploit long-memory properties in a vector time series to characterize quantitatively important interdependence dynamics between measures of uncertainty and real economic variables. We estimate the impact of this relationship in a system where a shock in these variables has a tendency to converge slowly to the long-run equilibrium, rather than as conventionally predicted or assumed in recent literature. Employing fractionally cointegrated vector autoregressive (FCVAR) model for selected macroeconomic variables and two measures of uncertainty, we find that the dynamic responses of output, employment and stock price to such shocks in uncertainty are negative on average.

In the fourth chapter, we expand our investigation of the uncertainty-economic/financial variables relationship. Specifically, we investigate the dynamic interdependence of the determinants of money demand over time in response to economic uncertainty. We are looking for the chances of a stable money demand, given the fluctuation in persistent uncertainty. In addition, we model the possibility of slow or fast convergence to the steady state of equilibrium of money demand in reaction to uncertainty shocks. Being able to recognize the nature of persistence in uncertainty could lead us to a deeper understanding of the way system interacts with different speeds of convergence of uncertainty shock.

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Declaration of Authorship

I, Abdullah Alhussaini, declare that this thesis with the title 'Essays on Uncertainty and Real Economic Fluctuation' and the work presented in it is my own and has been generated by me as the result of my own original research. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University;
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
- Where I have consulted the published work of others, this is always clearly attributed;
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
- I have acknowledged all main sources of help;
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
- None of this work has been published before submission

Signature: ....

Date: ....

Acknowledgements

I am grateful to many people without whom this thesis might not have been completed.

First and foremost, I would like to express my sincere gratitude to my distinguished supervisor, Professor Tapas Mishra for his constant assistance, exceptional support and wise advice. Without his unconditional support and willingness to assist me patiently, this journey would not have been possible and this thesis would not have been written. Professor Tapas has been a source of joy, motivation and perseverance. I owe a deep debt of gratitude to him for all that he has taught me. I could not ask for more. My appreciation also goes to my second supervisor, Professor Taufiq Choudhry for his guidance and encouragement. His insightful comments and valuable feedback have helped me tremendously. I am also grateful to Dr Nongnuch Tantisantiwong and Dr Si Zhou for their constructive comments, helpful suggestions and constructive criticism.

I would like to extend my special appreciation to Dr Mamata Barhi, Dr Abdulaziz Aldhehayan, Abdulghani Alkindi and Toby Simpson-Silo for their friendship, encouragement and support. I also wish to express my respects to my dedicated mentor, Mr Fawaz Alfawaz for being exceptionally supportive and inspiring.

I am genuinely thankful to the Ministry of Higher Education of Saudi Arabia and the Saudi Arabia Cultural Bureau in London for their financial support during my PhD study. Moreover, I wish to extend my appreciation to the faculty and staff within Southampton Business School.

My special thanks and appreciation to my early teachers, my father and mother, for their endless and unconditional encouragement through my life.

Last, but by no means least, I would like to thank my family: my lovely wife Dalal and my beloved son Tamim for being beside me during this journey. They are a real blessing in my life and a permanent source of happiness.

***To Dalal and Tamim** . . .*

Chapter 1

Introduction

This thesis focuses on the modern and contemporary subject of economic uncertainty. During the last century, substantial episodes of economic uncertainty have occurred across the world at a time when many economists and policymakers have considered it as an obstacle to optimal decisions and accuracy of forecasts (Bloom, 2009). Nowadays, one could say that one of the modern economy features is high economic uncertainty. Uncertainty as a result of global and regional hits results in widespread economic weakness and exacerbates financial volatility. Consequently, it is imperative that policymakers and other stakeholders understand the ramifications of the behaviour of different economic shocks on the economic system. The concept of economic uncertainty is, by nature, both wide and hard to quantify, since it is not directly observable. Knight, writing in 1921, defined uncertainty as an unforecastable risk that is immeasurable, while risk was defined as known likelihood over known time (Knight, reprinted 2012). Jurado et al. (2015) narrowed the concept of economic uncertainty to be the conditional volatility of a shock that is unforecastable from the perspective of economic agents over time; moreover, they believed that there is no objective measure of uncertainty, which thus becomes a challenge to empirical considerations of uncertainty behaviour.

Uncertainty can be a crucial factor affecting the view of current and future financial markets and economic prospects, and can be seen as a leading predictor of aggregate fluctuations. The significance of uncertainty develops from that it is different from risk. Investors and policymakers make decisions based on available information to make an accurate estimation of future outcomes. In a state of fully available information, people can make decisions based on an accurate distribution of outcomes. The problem is when policymakers struggle to form a distribution of economic outcomes due to lack of information, which leads to inaccurate predictions. Therefore, in this thesis, I have utilised an econometric model which takes into consideration the assumption of incomplete information, imperfect market and bounded rationality scenario. In addition, I have used two uncertainty measures: Baker et al's. (2016) subjective index of economic policy uncertainty (EPU), and Jurado et al's. (2015) objective measure of uncertainty. The reason behind using these two measurements is that many of the conventional uncertainty measures carry with them an embedded forecastable part of uncertainty; however, there is no perfect measure.

Recently, a number of researchers have started to investigate the nature of economic uncertainty, and the impact and implications on economic activities. They have been exploring the implications of uncertainty in many facets of macroeconomic and financial life, in both cross-country and cross-sectional settings. They have reached the conclusion that persistent uncertainty influences the cyclicality of the real economy; during periods of high uncertainty, real variables respond negatively to shocks, far worse than in the presence of positive shocks. This asymmetric impact of uncertainty has germinated a string of research that has undertaken serious theoretical and empirical work over the past decade. Consequently, many economists measure uncertainty differently, so the concept automatically has a subjective edge.

Gilchrist et al. (2014) examined the impact of uncertainty in the form of credit spreads on investment in imperfect markets, and they noticed that both uncertainty and financial shocks drive down growth in capital costs through variation in credit spreads. In addition, Bekaert et al. (2009) identified the relationship between uncertainty in consumption and dividend growth and risk preference through interest rates, equity prices and risk premium. They concluded that uncertainty has an effect on the countercyclical volatility of asset returns and risk premium. To investigate the negative side of economic uncertainty, Bloom (2009) and Bloom et al. (2012) analyse the role of uncertainty shocks on both economic activities and recent recession recovery, and their estimations showed that uncertainty shocks decrease the level of investment, hiring and productivity growth, which together lead to recession. However, Bachmann et al. (2013) suggested that recessions raise uncertainty, not the other way around. Baker et al. (2016) developed an aggregate measure of economic policy uncertainty (EPU) to capture the effect of uncertainty on the recent recession recovery, and asked whether it worsens it. They found that economic policy uncertainty puts a strain on aggregate output, investment and hiring, especially for firms that have more exposure to government contracts. Recession, it was found, is the consequence. On the other hand, Born and Pfeifer (2014) found that policy uncertainty has a minor effect on the business cycle. Their findings suggest that the magnitude of uncertainty shocks is too weak to cause any significant dive. They argue that the overall effect of policy uncertainty is ambiguous, as different forces act in opposite directions, and the ability of policy uncertainty to explain business is exaggerated.

In this chapter, I will present a brief summary and background of the research topic, along with the research aim and objective. In addition, I will provide a summary of each chapter, and conclude with the structure of the thesis.

Research Background

Lately, robust empirical and theoretical research has shown that economic and financial uncertainty embedded in any financial and economic system greatly influences their behaviour. Due to the interdependent nature of the economic system, economic uncertainty effects may extend to the whole system and harm the level of investment, hiring and productivity growth (Bloom, 2009; Colombo, 2013; Born and Pfeifer, 2014; Baker et al., 2016). There is a well-established strand of literature on the role of uncertainty at both macro-micro and financial levels. Counter-cyclicality is one of the uncertaintys behaviour features during times of recession. Bloom (2009) and Jurado et al. (2015), among others, found that economic uncertainty measures rise during times of economic slowdown, and fall in times of economic boom. Moreover, Stock and Watson (2012) were of the opinion that economic uncertainty was one of the factors that, to some extent, explained the recession and slow recovery during the 2007 financial crisis. At a time of high economic uncertainty during the recession of 2007, Baker and Bloom (2013) found that the U.S. output was down by at least 1 per cent. Gulen and Ion (2015) reached the conclusion that a third of the decrease in investments during times of high uncertainty could be attributed to economic uncertainty. Likewise, economic uncertainty as a result of global shocks has cast a shadow on the validity of not only economic and financial policies, but also government, firms and individuals' decisions. Economic uncertainty functions intricately through a complex mechanism that impacts market equilibrium via different microeconomic and macroeconomic aggregates. Hence, it is imperative that policymakers and other stakeholders practise uncertainty management by looking before leaping, and understanding the ramifications of different economic and financial policies.

Even though research investigating the impact of economic uncertainty on macroeconomic fluctuation has spiked in recent years, the dynamic interlinks between the real economic variables and persistence uncertainty are far from clear. Shaping economic/financial policy requires a magnifying glass to assess the shock to the system. In other words, despite the well-established long-term relationship between a shock to economic uncertainty and real variables volatility, the magnitude of the shock and the speed of convergence could provide explanations for the stability of the relationship over time, and indeed for equilibrium policy intervention. According to Jones et al. (2014), economic shocks may possibly show persistence behaviour before convergence with the long-term steady state.

Given the fact that economic uncertainty affects economic/financial variables volatility, and given its ability to be a leading predictor of fluctuations, it is essential to study the dynamics of uncertainty and other economic variables through the lens of memory properties. More specifically, it is of high importance to investigate whether uncertainty measures and economic/financial variables have a high/low persistence over time. Long memory characterization refers to the situation where the variables behaviour depends on and is affected by past values, which means that the influences of shock will prolong to the future and take time to converge to zero. Furthermore, as the magnitude of d increases, the more persistent the shock will be. On the other hand, short memory refers to the behaviour of a variable that is just impacted by the immediate past, and the effect does not remain forever. Moreover,the property of long memory can be captured in events that are distant from each other in time, but decay slowly to the long-term level as time increases. In the case of short memory, the effect decays exponentially rather than hyperbolically.

The memory parameter could take on different values, leading to different observations. Current development in the literature sheds light on the possibility of relaxing the assumption of either $I(0)$ stationary series, or $I(1)$ unit root to include the possibility of having a time series where the order of integration could be a non-integer. In a conventional cointegration analysis, all variables are $I(0)$, and if not, they are $I(1)$ and their linear combination are $I(0)$. Given that uncertainty measures are cointegrated with volatilities in the financial market/real economic systems, it is crucial to check whether the co-movement is permanent or not. The reason behind that is to increase our understanding of identifying whether some policy intervention could correct permanent disequilibrium, and lead to a temporary disequilibrium between the cointegration relationship of uncertainty and real economic fluctuations.

In addition, given the cointegration relationship between uncertainty with different measures and macroeconomic and financial variables, it is essential to investigate and identify their behaviour over time. In other words, the impact of economic uncertainty has been examined in the current literature at the conditional mean levels of macroeconomic and financial variables. It is evident that considering the conditional mean of the aggregate would allow us to draw a general conclusion, but it may ignore significant material information between and within different points of the distribution.

Research Aims and Objectives

The aim of this thesis is to investigate theoretically and empirically the interdependent relationships between uncertainty measures and real variables by utilising memory function and heterogeneity co-movement dynamics. By taking this route, this thesis aims to elaborate on the complex topic of economic uncertainty, which is crucial to policy-makers, practitioners and academic researchers.

The aims of each chapter are as follows:

Chapter Two provides a comprehensive analysis of the short-run dynamics, along with the long-run cointegration between uncertainty measures and macroeconomic variables. The analysis focuse on expanding our perception of how persistence and/or low economic uncertainty interact with the economic system and the nature of the equilibrium error-correction at each point of time by employing autoregressive distributed lag (ARDL).

Chapter Three aims to identify the true nature of persistence in economic uncertainty, and enables us to have a deeper understanding of how economic and financial systems react to the shock of uncertainty.

The aim of Chapter Four is to model money demand function as a dynamically interdependent system with possible slowly convergent shocks in view of the recent trend in global economic and financial uncertainty.

Research Objectives

The research objectives of this thesis are stated as a specific set of objectives for each chapter as follows:

The research objectives in Chapter Two are:

- To identify the heterogeneous response of the macroeconomic variables and economic uncertainty measures.
- To empirically estimate the long-run equilibrium relationship between economic variables and uncertainty measures.
- To empirically examine the behaviour of uncertainty measures and macroeconomic variables through their distribution.

The research objectives in Chapter Three are:

- To identify the characteristics of economic/financial variables and uncertainty shocks through long memory properties.
- To empirically quantify the long memory effect within a system of real economic-uncertainty variables.
- To empirically quantify the speed of adjustment behaviour of uncertainty shocks to the system.

The research objectives in Chapter Four are:

- To empirically examine demand function stability given the fluctuations in economic uncertainty.
- To investigate the global economic uncertainty effects on the demand for money determinants.

- To recognise the speed of adjustment to long-run equilibrium in response to a shock in economic uncertainty or other variables, and to model shocks with a slow-convergence property.

The structure of the thesis

Chapter One provides an overview of the concept of economic uncertainty and research context and background.

Chapter Two focuses on the possibility of economic uncertainty and growing economic variables cointegration over time. The co-movement policy implications arise from the nature of the effect of uncertainty shocks over the entire distribution.

Chapter Three sheds light on the dynamic interdependence between macroeconomic aggregate and uncertainty through the lens of memory. This chapter demonstrates how it is essential to identify the persistence of uncertainty shocks and the speed of convergence.

Chapter Four asks the question of how economic uncertainty affects money demand function through other variables. In addition, it examines how the demand for money adjusts or converges to the long-term equilibrium in response to uncertainty shocks, and looks at the speed of adjustment.

Chapter 2

Uncertainty and the Varying Speed of Adjustment of Real Variables

2.1 Introduction

2.1.1 Uncertainty and real-economic cointegration: possibility and implications

Recent research has demonstrated that possible 'cointegration' between growing economic variables (such as per capita output and investment share) has implications for the existence of the type of economic growth (see Lau, 1999 and 2008).[1] A growing body of evidence has also started to emerge lately demonstrating how economic (policy) uncertainty affects an economy's business cycle behaviour and directly contributes to the fluctuations of a number of macroeconomic and monetary variables (see Baker et al. (2016), Bloom (2009) and Jurado et al. (2015) among others). In case of the latter, Bloom (2009) and Jurado et al. (2015) employed the vector autoregression (VAR) framework and studied how a shock to uncertainty affects the long-run growth trajectories of key macroeconomic and monetary variables. What I know little of so far is whether the variables of the VAR system that includes uncertainty are cointegrated and, if so, whether uncertainty and macroeconomic/monetary variables display short-run or long-run cointegration patterns. The undisputed existence of uncertainty and its varying magnitudes of persistence also means that its effects on the growth of the real economic variables are non-unique. Moreover, if uncertainty and the real variables are indeed found to be cointegrated and depict varied patterns at different points of the distribution of the growing variables, then targeted policy intervention may be solicited to bring the economic system to equilibrium. In the current paper, I examine these empirical questions, which to the best of my knowledge, have been emphasised very little in the existing literature.

My work is related to Bekaert et al. (2005), who provided evidence of cointegration (among market returns) that *changes with circumstances*.[2] While my objective is different from Bekaert et al. (2005), it nevertheless outlines a conceptual mechanism that produces heterogenous cointegration structure based on circumstances. I make a distinct contribution to the literature by showing that there is a cointegration between uncertainty and real variables, and that such a cointegration changes over the distribution

[1]Lau (1999) drew attention to the distinguishing characteristics of the cointegration relation generated within endogenous and exogenous growth models. He stated that structural disturbances would leave little effect in the event where cointegration exists within the exogenous model but transmit permanent impact in case cointegration generated by endogenous growth model. For a technical example, He stated, in a system of n variables with r $(1 \geq r \leq n-1)$ cointegrating vectors, the long-run impact matrix for the structural vector moving-average representation, which summarizes the long-run effects of the structural disturbances on the level of observed variables, is of reduced rank of $n-r$ Lau (1999, p. 18). The existence of columns of zero in the long run matrix depends on the growth model and in case it is exogenous, there are r columns equal zero. In contrast, there are no columns of zero in the situation where cointegration is created by endogenous growth model.

[2]The authors demonstrate that market returns become less correlated during market downturns.

of uncertainty.[3] As far as my knowledge on the subject is concerned, I am the first to examine a heterogenous cointegration relationship between uncertainty and real variables. This is important, because evidence of heterogeneity in an economic/financial relationship often amounts to non-unique policy intervention in case a need for stability of the relationship is intended. In view of the growing concern about the persistent effects of uncertainty on real variables, my finding of a heterogeneous cointegration relationship has an important policy implication; depending on the varied speed of adjustment across different points of the distribution of the economic system, a contractionary or expansionary economic/financial policy can be introduced to achieve long-run optimal gain.

There are at least two potential issues involved in this regard. First, is uncertainty exogenous or endogenous to growing economic variables? Following the basic formulation of exogenous growth theory (in Solow-Swan tradition), uncertainty should be exogenous and the distribution of its impact on the variables should follow an $iid\ (0, \sigma^2)$ process. Jurado et al. (2015) and Baker et al. (2016) have already demonstrated that the pattern of fluctuations in many financial and economic aggregates mimic the trajectory of (the measures of) uncertainty. Following these and other recent works, it would be unreasonable to assume that uncertainty has an exogenous influence on the real economic variables. On the other hand, if I allow uncertainty to be either an endogenous response to, or an effect of other growing variables in the system (see Ludvigson et al., 2015), a vector autoregression (VAR) system might identify the nature of economic growth (see Baker et al., 2016). The authors show, using both micro (viz. firm level) and macro strategies, that (policy) uncertainty matters for economic outcomes. For the latter, the authors employ VAR which potentially captures many impact channels, but offers little assurance about the identification of causal effects. The general conclusion is that innovations in policy uncertainty foreshadow declines in investment, output and employment in the United States. The robustness of the univariate results has also been confirmed in the case of a panel data.

A simple argument that may explain the above is that every growing variable, economic or financial, is affected significantly by the fluctuations of uncertainty. If uncertainty is an $I(1)$ process and a real economic variable, say X_t is also an $I(1)$ process, then a linear combination of these variables can be cointegrated. The reason being that it is impossible to dissociate uncertainty from the trajectory of the movement of the growing variables. Hence, whenever a possibility of cointegration arises between uncertainty and X_t, it means that both variables can co-move in the long-run in case there is a disequilibrium error correction mechanism. A number of recent studies have also explored the non-linear/time-varying impact of uncertainty. Among others, Caggiano et

[3]See Antonakakis et al. (2015) for some discussions in the context of housing market returns and Basu and Bundick (2017) for analysis with regard to effective demand.

al. (2014) investigated the effects of uncertainty shocks on U.S. unemployment dynamics, and using Smooth-Transition VARs, demonstrated that uncertainty shocks were much larger than those predicted by standard linear VARs in terms of magnitude of the reaction of the unemployment rate to such shocks, and contribution to the variance of the prediction errors of unemployment at business cycle frequencies.

2.1.2 In search of heterogeneous effects of uncertainty and growth of real economic variables

Caggiano et al. (2014) offered intuitive reasons on why one may expect heterogeneous effects uncertainty on real variables (vice versa) over time. However, their and other related methods do not distinguish between the effects across the distribution of unemployment at various points of time. It was possible that uncertainty shocks exerted large (negative) effects on unemployment during downturn, and small (negative) effects during boom. These varied implications of uncertainty shocks over the entire distribution of unemployment require targeted policy intervention. The focus of my current work is to shed light on this aspect.

In addition, following a recent work by Lau (2008), I recognise that the nature of disequilibrium error corrections in the cointegrated model is a useful tool for identifying whether an exogenous or endogenous economic system exists. Such an identification can inform policymakers of the possible and necessary interventions that need to be adopted to bring the economy into long-run equilibrium. In fact, Lau (2008) showed that the long-run effects of temporary changes in investment share to per capita output indirectly provides the answer regarding the effects of permanent changes in investment share, when per capita output and per capita investment are cointegrated.[4] Moreover Lau (1999) also argued that the endogenous-growth-generating mechanism induces difference stationarity of the variables even though the external impulses are stationary, and it leads to the phenomenon of cointegration. Following the tradition of this literature, one may conclude that similarities or differences in degrees of integration of economic variables in a particular context, and their error-correction mechanism at various parts in the distribution of the economic aggregate can reveal interesting characteristics about the way the economy is affected by exogenous movements or endogenous policy interventions, or by a combination of both. My work is also motivated by the recent methodological development of quantile cointegration structure (Xiao, 2009 and Cho et al., 2015) where attempts have been made to understand the heterogenous nature of cointegration at various points of the distribution of the dependent variable in question. This development is particularly useful in my research,

[4] As an extension of the conventional literature in this regard where distinction between $I(1)$ and $I(0)$ series is made to characterize exogenous or endogenous growth, Cunado et al., (2009) examined the properties of economic growth model using fractional integration ($I(d); 0 < d < 1$) dynamics.

as my interest lies in the study of heterogeneity in the cointegration pattern between uncertainty and real economic variables.

There is a large body of theoretical and empirical literature which has attempted to identify and model the exact source of such 'permanent/temporary' shocks occurring in the economy. Arguments often range from technological change and innovation persistence to demographic dividend and human capital growth, financial sector volatility, and policy intervention, among others. While each of these determinants has its own theoretical and empirical relevance, the role of policy intervention, particularly the role of policy uncertainty, has received vigorous attention in the last decade. Indeed, uncertainty has been found to significantly determine business cycle fluctuations and impact on the persistence nature of growing economic variables (see Bloom (2009); Jurado et al. (2015); Baker et al. (2016)). The existing research in this regard has focused on building theoretical models to establish the relationship between uncertainty and economic fluctuations, and empirically estimating the long-run effects on economic variables of a shock to a measure of uncertainty. Vector autoregression framework has been employed as the main econometric tool in this context.

While the research has found robust evidence of the role of uncertainty in long-term economic and financial fluctuations[5], it is yet to be established whether these variables and uncertainty form long-term (dis)-equilibrium relationships. This is important on several counts. First, in an economic system, the nature of the short-run adjustment mechanism of growing variables to some shocks (that is, the error-correction) under persistent uncertainty can be different from that of the period of low-uncertainty. Second, a shock to uncertainty itself can either permanently or temporarily alter the equilibrium behaviour of the economic system under consideration. Once a policy-maker gains precise knowledge about the nature of co-movement and equilibrium behaviour of economic variables in both the short-run and the long-run, they can design relevant policy to promote monotonic growth. Third, by understanding the true nature of the error-correction term in the economic system under investigation, it will be possible to identify if the economy is characterised by an exogenous or (semi-)endogenous growth system (motivated by the 2008 work of Lau). Fourth, one can clearly establish if uncertainty is cointegrated with the real economic system and hence can enhance our understanding of the definitive role of the short and long-run effects of uncertainty on

[5]See among others, Bloom (2009); Baker et al. (2016); Bloom et al. (2014); and Jurado et al. (2015). Two broad strands of literature may summarize the development in this regard: (i) *the measurement of uncertainty* (subjective and objective measures). (See Baker et al. (2016) and Jurado et al. (2015), for details; (ii) *estimation environment/theory*: general equilibrium theory leading to application of structural vector autoregression (SVAR) approach as in Bloom (2009) and Jurado et al. (2015), measurement error in SVAR (the proxy SVAR approach of Carriero et al. (2015)), and high frequency time series methods (for instance, Bijsterbosch and Guerin (2013); Ko and Lee (2015)). Both (i) and (ii) have been investigated in a single country (Bloom (2009); Bloom et al. (2015); Jurado et al. (2015) for the USA) and cross-country settings, e.g. Ko and Lee (2015); Jones and Olson (2015). The general finding is that uncertainty (measured whichever way) drives real business cycles, is countercylical, and leaves an asymmetric impact on the movement of real activities.

economic variables. The current research paper is aimed at contributing to the existing research in the above-mentioned directions.

To the best of my knowledge, the literature to date has considered examining persistence behaviour and the effect of uncertainty on macroeconomic and/or financial aggregates only at the conditional mean levels, disregarding the information content at other points of the distribution of these variables. The current paper aims to expand on our understanding in this regard by jointly analysing the short-run dynamics and the long-run cointegration by allowing pan-distributional assumptions of these variables. Thus, I consider cointegration analysis within an autoregressive distributed lag (ARDL) framework and under full-distributional assumption.[6] Using this approach, I can gauge, at a minimum, whether policy uncertainty innovations foreshadow weaker macroeconomic performance conditional on standard macro and policy variables.

As a first step towards realising my objective, I examine if the persistence profiles of the 12-variables economic system demonstrate heterogeneous persistence behaviour; for instance, I may find stationary autoregressive dependence for lower quantile and non-stationary dependence at higher quantiles (see Koenker and Xiao, 2006). Such findings would motivate us further to exploit the properties of quantile regression for an understanding of the cointegration relationship in the 12-variables VAR system. Moreover, heterogeneity in the orders of integration of these variables is also an important issue. The ARDL approach best fits the purpose of explicating the cointegration relationship. In the quantile context, Cho et al. (2015) have developed what they term the Quantile ARDL approach to understand error-correction behaviour among time-series variables. I exploit the rich properties of this method in my work in the case of the USA, using monthly data covering 1960:7-2011:12.

The rest of the paper proceeds as follows. Section 2 presents a conceptual framework demonstrating the effect of non-stationary uncertainty shocks on real economic fluctuations. Section 3 presents the data and their characteristics. Section 4 presents estimation strategy, followed by analysis of the empirical results in Section 5. Finally, Section 6 concludes with a summary of the main findings and their implications.

2.2 A conceptual model of cointegration between uncertainty and real economic variables

Is policy uncertainty cointegrated with real economic fluctuations? As such, there are sparse theoretical arguments on how uncertainty forms an essential part of the movements in real variables, except for endogeneous business cycle theory. In this section,

[6] Antonakakis et al. (2016) is an example where quantile ARDL method has been employed in the context of twin deficits hypothesis.

therefore, I develop a conceptual model to demonstrate that a long-memory in uncertainty would enforce a long-memory in real variables, eventually both the systems would depict a cointegration pattern. Finally, we use this conceptual foundation to build our empirical construct. It should be noted that the link between the long-run impact of uncertainty shocks on real economic fluctuations is not straightforward. Only a strong conceptual foundation can lend an empirical construct the needed credibility. This section intends to serve this sole purpose.

In an interesting work, Aizenman and Marion (1993) contend that in the standard neoclassical growth model, policy uncertainty plays no role in determining the long-run growth rate of per capita output. The reason is that policy shocks tend to displace the economy only temporarily from its original growth path, thus leaving no long-lasting impact. In contrast, models of endogenous growth suggest that policies and policy disturbances can have permanent effects on growth (in the limiting case). The implication is that a shock to policy can result in a very slow convergence to the long-run mean, eliciting slow convergence of shocks in macroeconomic processes as well. Whether this convergence pattern is slow enough to leave a permanent impact on the economy[7] is something that needs serious comprehensive theoretical and empirical investigations. For the purpose of this paper, I will propose an approach where I argue that at the conditional distribution of a growing variable, a shock to uncertainty may display varied impacts. Such a possibility of heterogeneous response approximates fluctuations in real economic variables closer than examining the response at the 'mean' of the distribution.

According to Aizenman and Marion (1993), persistent tax uncertainty, along with the fluctuations among low and high tax regimes, are considered among investments and economic growth determinants within an endogenous growth model. Also, the authors noted that asymmetric tax regimes do not influence economic growth without the presence of persistence policy uncertainty.

Let us denote $Z_t = (Z_{1,t}, \ldots, Z_{n,t})'$ as a vector of $n(n \geq 2)$ economic variables of interest (e.g., index of industrial production, real consumption, employment, etc.) observed at time t. I assume that the dynamics of growth in these variables are determined by an endogenous growth mechanism. The key assumption in this regard is that 'shocks' are allowed to exert long-lasting impact on Z_t and policy-interventions are needed to 'stabilise the shocks' so that the balanced growth paths are well-defined.[8] Merton (1975) proposed, using a simple one-sector growth model, asymptotic property of the growth process under persistent uncertainty. He shows that growth models which do not explicitly account for the effects of uncertainty are likely to produce biased moment conditions (such as the mean and variances) leading to inconsistent/inefficient parameter estimates. The outcome is that the predictive power of the model that discounts

[7]Possibly due to the intervention of similar shocks at a time when the earlier shock is in the process of convergence as well.

[8]See Jones (1995) and Ortigueira and Santos (1997), among others, on time series properties of the endogenous growth model and its predictions, respectively.

persistent effects of uncertainty is smaller than the one that explicitly models it. While Merton (1975) examined the case of population growth as a source of uncertainty, the model can be generalized to any source of uncertainty, in particular, Economic Policy Uncertainty, as in my case. The challenge is that one needs to build an economic model where uncertainty enters as a key explanatory variable, or forms a common stochastic component in any growing variable, such as physical capital, human capital, intermediate inputs and technological change, among others.

Let us assume that the source of uncertainty in my case is policy and macroeconomic variations such as Economic Policy Uncertainty measure, as in Baker et al. (2016) and Jurado et al. (2015). (See Section 3 for details). Denote this by U_t. The stochastic process for U_t can be described by a *systematic component*, $\sigma\varsigma(t;h)$ where t is time, h is the length of time between time periods (this one represents the period of survivability of shocks). In addition, also assume that the expected number of uncertainty shocks is constant over time and the same for all variables in the system. Denote this by n. $\sigma\varsigma(t;h)$ represents the common random effects at time t. Moreover, U_t can also be influenced by a *non-systematic* component, $\nu_i\epsilon_i(t;h)$, that is, random effects specific to the i^{th} variable in the system at time t. Combined both components and assuming $U(t) = U$, then

$$U_i(t+h) = nh + \sigma\varsigma(t;h) + \nu_i\epsilon_i(t;h); i = 1,\ldots,N \tag{2.1}$$

The usual assumptions of zero mean and uncorrelated errors over time hold. The stochastic difference equation for uncertainty, U_{it} can be given by $U_i(t+h) - U_i(t) = \sum U_i(t+h)$. Summing the above equation, then gives

$$U(t+h) - U(t) = nUh + \sigma U\varsigma(t;h) + \sum \nu_i\epsilon_i(t;h); i = 1,\ldots,N \tag{2.2}$$

The first two moments of the above equation gives: nUh and $[\sigma^2U^2 + (\frac{1}{U}\sum\nu_i^2)U]h$. If $n\nu_i$ are bounded and are approximately the same size, then $(\frac{1}{U}\sum\nu_i^2)$ is (0/1). Hence for large N one can reasonably neglect the contribution of the non-systematic component in the total variance of U. My next task is to show that a non-mean convergent stochastic shock in U_t can give rise to a non-mean convergent behaviour in X_t.

I assume for simplicity that (shocks to) past uncertainty (U_{t-1}) affect the current value of Z_t. Since uncertainty can affect all variables in any economic system, the following reduced form linear specification of uncertainty-macroeconomic variables can reflect interesting interdependence dynamics.

$$Z_t = \gamma U_{t-1} + \eta_t \tag{2.3}$$

where $\eta_t \sim iid(0, \sigma_\eta^2)$.

Proposition 2.1. *If U_t is non-stationary and have a slow mean convergent property, then Z_t system can also be characterized by non-stationarity (slow-convergence of shocks).*

Basically, I show that the long-run conditional mean and variance of $k-$period cumulative Z is a function of long-memory in U_t.

I obtain the following: The *conditional expectation* of $Z_t^{(k)}$ is

$$\mathbb{E}\left[Z_t^{(k)}\right] = \gamma. \sum_{i=0}^{\infty} \zeta_i^{(k)} \epsilon_{t-1-j+l} \tag{2.4}$$

whereas, the *conditional variance* is:

$$\begin{aligned} &Var_t\left(Z_t^{(k)} - \mathbb{E}\left[Z_t^{(k)}\right]\right) \\ &= \gamma^2. \textstyle\sum_{l=1}^{k}\left(\zeta_{k-l}^{(k)}\right)^2 \sigma_\epsilon^2 + \gamma. \sum_{k-l}^{(k)} \sigma_{\epsilon\eta} + \sigma_\eta^2 \end{aligned} \tag{2.5}$$

Proof

I provide here proof of Proposition 1. I introduce non-stationary long-memory in U_t as an autoregressive fractional cointegrated (ARFIMA) structure:

$$\begin{aligned} &(1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p)(1-L)^d U_t \\ &= (1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q)\epsilon_t \end{aligned} \tag{2.6}$$

with usual definitions: $\mathbb{E}[\eta_t \epsilon_s] = \sigma_{\tau\epsilon}^2$ if $t = s$, 0, otherwise. In the above, L is backward-shift operator, with the usual property that $Ln_t = n_{t-1}, L^2 n_t = n_{t-2}$, etc. Moreover, d is the order of integration. Formally, $(1-L)^d$ can be expressed by power series expansion:

$$(1-L)^d = \sum_{j=0}^{\infty} (-1)^j \left(\frac{d(d-1)(d-2)\dots(d-j+1)}{j!}\right) \tag{2.7}$$

where $\frac{d(d-1)(d-2)\dots(d-j+1)}{j!}$ is the binomial coefficient defined for any real number d and non-negative integer j. The intuitive exposition of $(1-L)^d$ for a time series can be traced via their infinite order MA or AR representations. In this instance, expressing $MA(\infty)$ of $(1-L)^d$ for the time series would mean that I have an expression: $\sum_{j=0}^{\infty} h_j L^j$, where $h_0 = 1$ and

$$h_j = \frac{-d\Gamma(j-d)}{\Gamma(1-d)\Gamma(j+1)} = \frac{j-d-1}{j} h_{j-1}, j \geq 1. \tag{2.8}$$

Equation (2.8) is the impulse response function of the effect of a stochastic shock on Z_t distributed over time. In case, $d = 0$, the series is stationary. A unit root non-stationarity occurs when $d = 1$. For $d \geq 1/2$ a non-stationary long-memory process is characterized, whereas for $d \leq 1/2$ the series contains a stationary long-memory component.

Now, I assume $\phi(L) \neq 0$ for $z \leq 1$. Re-writing (2.6) as $U_t = \phi(L)^{-1}(1-L)^{-d}\theta(L)\epsilon_t$ and denoting $\omega(L) = \phi(L)^{-1}$, where $\omega(L) = \sum_{i=0}^{\infty} \omega_i L^i$ I use the identity $\omega(L)\phi(L) = 1$ to find the unknown coefficients recursively:

$\omega_0 = 1,$
$\omega_1 = \phi_1\omega_0,$
$\omega_2 = \phi_1\omega_1 + \phi_2\omega_0$ and so,
$\omega_i = \phi_1\omega_{i-1} + \cdots + \phi_p\omega_{i-p}$ for $i = p, p+1, \cdots$.

Utilizing $(1-L)^{-d} = \sum_{i=0}^{\infty} \frac{(d+j-1)\cdots(d+1)d}{i!} L^i$ and multiplying $\phi(L)^{-1}$, I get

$$i(1-L)^{-d}\phi(L)^{-1} = \sum_{j=0}^{\infty} z_j L^j \tag{2.9}$$

where
$z_j = 1$ if $j = 0$,
$z_j = \omega_0 \frac{(d+j-1)\cdots(d+1)d}{j!} +$
$\omega_1 \frac{(d+j-2)\cdots(d+1)d}{(j-1)!} + \cdots + \omega_{j-1}d + \omega_j$, otherwise.

finally, for $j \geq 0$, describe
$\psi_j = z_j + z_{j-1}\theta_1 + \cdots z_{j-q}\theta_q$
with $z_{-1} = \cdots = z_{-q} = 0$.

Denote by $Z_t^{(k)}$ the cumulative $k-$period value of, Z_t. Let's use the $MA(\infty)$ representation of Z_t from above:

$$Z_t = \sum_{j=0}^{\infty} \psi_j \epsilon_{t-j}. \tag{2.10}$$

To know the effect of stochastic uncertainty shocks on Z_t, I find that

$Z_t^{(k)} = \sum_{l=1}^{k} y_{t+l} = \gamma. \sum_{l=1}^{k} \sum_{j=0}^{\infty} \psi_j \epsilon_{t-1-j+l} + \sum_{l=1}^{k} \eta_{t+l}$

Representing $\zeta_i^{(k)} \equiv \psi_i + \psi_{i-1} + \cdots + \psi_{i-(k-1)}$,

I can write

$Z_t^{(k)} = \gamma. \sum_{i=0}^{\infty} \zeta_i^{(k)} \epsilon_{t-1-j+l} + \sum_{l=1}^{k} \eta_{t+l}$

The *conditional expectation* of $Z_t^{(k)}$ then equals:

$$\mathbb{E}\left[Z_t^{(k)}\right] = \gamma. \sum_{i=0}^{\infty} \zeta_i^{(k)} \epsilon_{t-1-j+l} \tag{2.11}$$

and the *conditional variance* of $k-$period cumulative macroeconomic variables is:

$$\begin{aligned} &Var_t\left(Z_t^{(k)} - \mathbb{E}\left[Z_t^{(k)}\right]\right) \\ &= \gamma^2 \cdot \textstyle\sum_{l=1}^{k}\left(\zeta_{k-l}^{(k)}\right)^2 \sigma_\epsilon^2 + \gamma \cdot \textstyle\sum_{k-l}^{(k)} \sigma_{\epsilon\eta} + \sigma_\eta^2 \end{aligned} \tag{2.12}$$

Expressed in terms of ζ, macroeconomic variables are now a function of long-memory in uncertainty, which completes the proof. $\square$

2.3 Data characteristics

2.3.1 Data

My empirical investigation involves monthly data for the USA over the period 1960:07-2016:12. The data come from three main sources, viz. Bloom (2009), Baker et al. (2016) and Jurado et al. (2015). Including measures of uncertainty (discussed in detail below), I consider 12 variables in total for my estimation. These variables are described in Table 1.

Table 2.1: Variables Description

Variables	Description
IP	log (real Industrial Production)
EMP	log(Employment)
CONSUMP	log(real consumption)
PCEDEF	log(Per Capita Consumption Expenditure deflator)
NORD	log (real new orders)
WAGE	log(real wage)
HOURS	hours (to proxy labour productivity)
FED	Fed Funds Rate (a measure of interest rate)
SP500	log (S&P 500 Index) to proxy for quarterly corporate profits
M2gr	Growth rate of M2
J-uncertainty	Macroeconomic uncertainty measure based on Jurado et al. (2015)
EPU-Uncertainty	Economic Policy Uncertainty measure based on Baker et al. (2016)

The choice of the variables mentioned above is principally guided by Christiano et al. (2005) and Jurado et al. (2015), who note that the dynamic relationship of these variables has been the focus of extensive macroeconomic research recently. Moreover, these variables, which are a mixture of macroeconomic, monetary and financial aggregates, can broadly describe the dynamic behaviour of a real economic system.

(A) Macroeconomic variables

Among the variables described in Table 1, monthly industrial production (IP) and the PCE deflator (PCEDEF) are intended to measure gross domestic product (GDP), and its deflator. HOURS is used here to serve as a proxy for labour productivity (average hourly earnings is for the manufacturing sector only because - as Jurado et al. (2015) note - the aggregate measure does not go back to 1960. The S&P 500 stock market index is intended to measure corporate profits, whereas federal funds rate is assumed here - following Christiano et al. (2005) as a proxy measure for interest rate. Moreover, real consumption, employment, real wage and growth of M2 are conventional indicators of macroeconomic and monetary variables. Profit is proxied by real new orders (NORD). Finally, uncertainty is measured from both subjective and objective stances. Due to the fact that these measures are relatively novel, in the next section I briefly present their constructs.

(B) Uncertainty

The measurement of uncertainty is exceedingly complex. Bloom (2014, p. 153) rightly asserted that uncertainty is broad and complex to estimate, considering that it is unobservable and has various levels. Indeed, due mainly to its amorphous nature in being associated with the rational behaviour of economic agents and the probable influence of 'exogenous' and 'endogenous' shocks within the economy, the extensive literature on the subject has focused on pseudo-identification of the real uncertainty with various proximus concepts, save for the rigorous developments in the past decade.

Recent research has advanced two popular measures, viz. Economic Policy Uncertainty (EPU) by Baker et al. (2016), and econometric measure of uncertainty by Jurado et al. (2015).[9] I use these two measures for my empirical investigation. Despite the fact that they are based on entirely different concepts (see below for details), I use them here for the purpose of robustness.

(i) Economic Policy Uncertainty

The EPU measure (due to Baker et al., 2015) comprises three components and covers almost all aspects of different sub-measures of uncertainties advanced by various authors/sources. The authors constructed an index from three types of underlying components. The fundamental element of this index is a comprehensive search of nationally representative newspapers in which they monitored newspapers articles, the frequency of news based on economic and business policies, what sort of policy will be undertaken, who will execute the policy decision, and finally the time of implementation. They hunted for some keywords, counted the number of articles, adjusted them and subsequently normalised them to unit standard deviation. The weight of the news based policy uncertainty is $\frac{1}{2}$. The next component is the scheduled tax law expiration based on the Congressional Budget Office (CBO) data of provision for income taxes. The weight of scheduled tax law expirations is $\frac{1}{6}$. The third and fourth parts of the EPU are the forecasters' disagreement about government purchase and inflation. The Federal Reserve Bank of Philadelphias Survey of Professional Forecasters is the source of the data to survey the disagreement. Each component weights $\frac{1}{6}$ in the EPU index.

[9]Ludvigson et al. (2015) have also advanced a measure of financial uncertainty based on econometric measures as in Jurado et al. (2015). Moreover, conventional volatility based measure as in Bloom (2009), and productivity based measures as in Bloom et al. (2012) are also important contributions to the measurement of uncertainty. See, Rossi and Sekhposyan (2015) for description and usefulness of some of these measures in macroeconomic context.

(ii) Econometric measure of uncertainty

Quite distinct from the EPU uncertainty measure (or for that matter any proxy measure, such as implied or realised volatility of stock market returns, the cross-sectional dispersion of firm profits, stock returns, or productivity, or the cross-sectional dispersion of subjective (survey-based) forecasts), an alternative measure has been advanced by Jurado et al. (2015). I denote this as the 'objective' measure of uncertainty. The authors argue that the conventional measures are not the true measure of uncertainty, because "the conditions under which common proxies are likely to be tightly linked to the typical theoretical notion of uncertainty may be quite special" (Jurado et al. 2015, p.1178).

In particular, Jurado et al. (2015) illustrate a $h-$leading period uncertainty in variable $y_{jt} \in Y_t = (y_{1t}, \ldots, y_{N_y t})'$, and express likewise by $U^y_{jt}(h)$, as the conditional volatility of the purely unforecastable element of the future value of the series:

$$U^y_{jt}(h) = \sqrt{E[(y_{jt+h} - E[y_{jt+h}|I_t])^2|I_t]} \tag{2.13}$$

where $E(.|I_t)$ represent the amount of information I_t available at time t. One can then describe an objective measure or index of macroeconomic uncertainty as an aggregation of individual uncertainty at each date. An aggregation weights w_j is used to do the transformation as follows:

$$U^y_t(h) \equiv plim_{N_y \to \infty} \sum_{j=1}^{N_y} w_j U^y_{jt}(h) \tag{2.14}$$

A unique feature of this measure of uncertainty from other aggregate measures is its 'ability to remove forecastable element from a large number of macroeconomic and financial variables'. In fact, a failure to do so can give rise to 'erroneous errors' which are forecastable variations of 'uncertainty'. Jurado et al.'s (2015) measure is arguably a superior econometric estimate of uncertainty, because it appears to be relatively free specification of a robust theoretical model. For the purpose of the current paper, I use both objective and subjective (news-based economic policy uncertainty) measures. The data is available from:

$www.sydneyludvigson.com/data - and - appendixes.$

2.4 Estimation

(A) Identification of non-stationary behaviour at quantiles

Keeping in mind my objective of identifying heterogeneous mean-reversion of the macroeconomic and uncertainty variables, in this section, I employ Koenker and Xiao's (2004) quantile regression framework. This method is known to enjoy power gains over the augmented Dickey-Fuller (ADF) test when the shock exhibits heavy-tailed behaviour. I argue that this procedure enables us to explore the speed of mean reversion for the various series enlisted in Table 1 under different magnitudes and signs of the shock. In other words, Koenker and Xiao's (2004) methodology can reveal a heterogeneous pattern of mean-reversion by explicitly testing for a unit root at different quantiles of the distribution of the variable over time. Here the underlying series is affected by a shock with various sizes and signs.

Denote by Z as the vector of variables described in Table 1. Each variable in Z is indexed by i (I suppress them for the time being). As a starting point, let us consider the ADF regression model for Z a time t, Z_t:

$$Z_t = \beta_1 Z_{t-1} + \sum_{j=1}^{q} \beta_{j+1} \Delta Z_{t-j} + \epsilon_t; t = 1, \ldots, n \tag{2.15}$$

In the above, $\epsilon_t \sim iid(0, \sigma^2)$. In (2.15), β measures the degree of persistence of Z_t . In particular, with $\beta = 1$, a unit root process is observed. Possibility of mean-reversion arises with $|\beta| < 1$. Koenker and Xiao (2004) argue that the degree of mean-reversion can be heterogeneous over the distribution of Z_t. That is, the τ-th quantile of $Z_t|I_{t-1}$ can be expressed as

$$Q_{Z_t}(\tau|\omega_{t-1}) = y_t^{'}\beta(\tau) \tag{2.16}$$

where $y_t = (1, Z_{t-1}, \Delta Z_{t-1}, \ldots, \Delta Z_{t-n})^{'}$ and $\beta(\tau) = (\beta_0(\tau), \beta_1(\tau), \ldots, \beta_{q+1}(\tau))^{'}$. Note that $\beta_0(\tau)$ denotes the τ-th quantile of ϵ, $\beta_1(\tau)$ measures the speed of mean reversion of Z within each quantile, and is dependent on the τ-th quantile under investigation. Moreover, $\beta_1(\tau)$ is estimated by

$$\min \sum_{t=1}^{n} \gamma_\tau (Z_t - y_t^{'}\beta(\tau)) \tag{2.17}$$

where $\gamma_\tau(\epsilon) = \epsilon(\tau - I(\epsilon < 0))$, I is the indicator function. Denote the solution of (2.17) by $\hat{\beta}(\tau)$. Following Koenker and Xiao (2004) the time series properties of Z_t can be tested across τ-th quantile by using the following t-ratio statistic:

$$t_n(\tau) = \frac{\hat{f}(F^{-1}(\tau))}{\sqrt{\tau(1-\tau)}}(Z_{-1}P_yZ_{-1})^{1/2}(\hat{\beta}_1(\tau) - 1) \tag{2.18}$$

where f and F are the density and distribution function of ϵ, Z_{-1} is the vector of lagged dependent variables , P_y is the projection matrix onto the space orthogonal to $y_t = (1, Z_{t-1}, \Delta Z_{t-1}, \ldots, \Delta Z_{t-n})'$. This test statistic can be employed to examine whether unit root exists in each quantile. In sum, the above procedure helps us to dig deeper into the dynamics of the series and investigate possibly different mean-reverting behaviours when the series is hit by different magnitudes and signs of shock at different quantiles. This is in contrast to the conventional unit root tests which only focus on the conditional central tendency.

(B) Estimating non-linearity in cointegration relationship by quantile

Once I have identified that the series follows heterogeneous non-stationary behaviours across the quantile of the distribution of the dependent variable, my next step is to estimate if a long-run equilibrium relationship exists among real macroeconomic variables, and whether such equilibrium behaviours are consistent across the distribution. The necessity of studying the cointegration relationship among growing variables in an economy has been duly established in the work of Lau (1999, 2008), who has demonstrated theoretically that existence and identification of true cointegration structure among these variables can tell us whether an exogenous or endogenous growth system persists. However, a major limitation in Lau (1999, 2008) is the assumption that the economy only approaches a fixed/identified steady-state, whereas in reality one may come across heterogenous steady-states. That is, due to the varied degree of persistence of economic and financial variables over a span of time, the estimated cointegration relationship may also depict heterogenous co-movements.

The idea behind estimating the long-run cointegration relationship between uncertainty and the macroeconomic/financial variables is the fact that the latter variables are likely to display heterogeneous adjustment behaviour to the changes in innovation in uncertainty over time. Indeed, following Koenker and Xiao (2006), it can be argued that the effect of lag of these variables on their current values may vary over the entire distribution of the variable, and can thus display heterogeneous persistence behaviours. Such heterogeneous AR dependence over quantiles not only determines adjustment to long-/short-run equilibria, but also affects such behaviour when other variables (uncertainty in my case) are concerned.

A popular method to study the properties of cointegrated time series is to employ the semiparametric approach of Phillips and Hansen (1990) where a fully modified OLS estimator is used. However, It is currently recognized that Phillips and Hansen's (1990) method does not reveal the short-run interactions of the integrated series, and it only shows the long-run relation, (see Cho et al. (2015) for detailed discussion). As a response to this intricacy, Pesaran and Shin (1998) introduced the ARDL error correction model (ARDLECM). This approach permits one to examine both the long-run relationship and the short-run dynamics in a parametric setting.

Lately, a number of studies, for example, Lee and Zeng (2011), Burdekin and Siklos (2012) and Tsong and Lee (2013) have argued that the conventional cointegration analysis may not be sufficiently informative because it focuses only on the central area of the whole distribution, and therefore the cointegration relationship estimated by focusing on the 'mean' of the distribution can underestimate the true cointegration relationship. This limitation of the conventional quantile regression approach has been resolved by Xiao (2009), who introduced distributional heterogeneity in the cointegration approach in a static regression. This approach, which is known as quantile cointegration method, can be regarded as the quantile counterpart of the estimators proposed respectively by Phillips and Hansen (1990) and Saikkonen (1991). As explained in detail below, such an approach also accounts for non-linearity and structural breaks, the two important determinants in the identification of a true cointegration relationship among variables. An imposing feature of the cointegration mechanism is to estimate the error correction term, mainly because this term can inform us about the way the stochastic shocks within the system may be corrected with certain magnitude over time, or that they may move away from the equilibrium forever. For any economic/financial system to have a stable existence, understanding the way the error correction (ECM) term affects the equilibrium relationship is of key importance (Lau, 1999, 2008).

In this regard, Cho et al. (2015) proposed the dynamic quantile ARDL-ECM (QARDL-ECM), in which it is possible to simultaneously address both the long-run (cointegrating) relationship and the associated short-run dynamics across a range of quantiles in a fully parametric setting.[10] The authors show that QARDL estimators of the short-run dynamic parameters and the long-run cointegrating parameters asymptotically follow the (mixture) normal distribution. I present the general framework of Cho et al. (2015) below.[11]

Denoted by $\mathcal{U}$ as one of the two measures of uncertainty and by $\mathcal{Z}_t$ the vector of the 12-variables mentioned before, the QRADL method of Cho et al. (2015) is described by:

$$Z_t = \alpha_*(\tau) + \sum_{j=1}^{p} \phi_{j*}(\tau) Z_{t-j} + \sum_{j=1}^{q} \theta_{j*}(\tau)' U_{t-j} + V_t(\tau) \tag{2.19}$$

[10]Cho et al. (2015) argue all of the optimal estimation properties in Xiao (2009) are valid in their framework.

[11]Interested readers are referred to Cho et al. (2015) for a detailed understanding of various properties of the QARDL process.

Here $V_t(\tau)$ is the error term and is defined as $Z_t - Q_{Z_t}(\tau|F_{t-1})$. Equation 2.19 can be reformulated to lend empirical analyses as follows:

$$Z_t = \alpha_*(\tau) + \sum_{j=0}^{q-1} W_{t-j}^{'}\delta_{j*}(\tau) + U_t^{'}\gamma_*(\tau) + \sum_{j=1}^{p}\phi_{j*}(\tau)Z_{t-j} + V_t(\tau) \tag{2.20}$$

Here $\gamma_*(\tau) = \sum_{j=0}^{q-1}\theta_{j*}(\tau), W_t = \Delta U_t$, and $\delta_{j*}(\tau) = -\sum_{i=j+1}^{q}\theta_{j*}(\tau)$. These parameters represent short-run dynamics. The long-run relationship between each Z_{it} and uncertainty (U_t) can be captured by reformulating Equation 2 as the following quantile process:

$$Z_t = \mu_*(\tau) + \beta_*(\tau)U_t + R_t(\tau) \tag{2.21}$$

where $\beta_*(\tau) = \gamma_*(\tau)(1 - \sum_{i=1}^{p}\phi_{i*}(\tau))^{-1}$. For details of the properties of this process, see Cho et al. (2015).

Following Cho et al. (2015), I provide some significant implications of allowing both short-run and long-run parameters to be quantile dependence where the parameters could react to fluctuations in economic uncertainty U_t at various positions and times across the distribution. Hence, the (dynamic) conditioning variables change the positions, the range and the spread of the distribution Z_t.

My strategy can be summarised as follows. First, I use the quantile autoregressive (QAR) model proposed by Koenker and Xiao (2006) to estimate the AR coefficients at different quantiles of the distribution for each of the 12 variables. Second, I then use the error-correction with quantile autoregressive distributed lag (QARDL-ECM model proposed by Cho et al. (2015)) for various bivariate systems, each of which involves one uncertainty variable and each of the economic/financial variables.

2.5 Results

2.5.1 Preliminary data characteristics

I begin my analyses of empirical results with preliminary investigation into the trends, correlation and persistence nature of all variables. In Tables 1A and 1B (see Appendix) I have presented descriptive statistics and correlations across various percentiles of the distribution in uncertainty variable. The last three columns in Table 1A present changes in mean across the 25th, 50th and 75th percentiles. It is evident that the mean of all variables differ significantly at 25th, median (50th) and 75th percentiles of the distribution. Moreover, the (static) correlation coefficients (in Table 1B) also give indication of significant heterogeneity (both in magnitudes and signs) across percentiles and over two different measures of uncertainty.

In Figures 1 and 2, I have plotted the autocorrelation functions (ACF). The ACFs display hyperbolic decay and imply that there is a significant effect of the remote past lags on the current value of the series.

Tables 1A and 1B in the appendix present descriptive statistics. The last three columns in Table 1A present changes in mean across the 25th, 50th and 75th percentiles. It is evident that the means of all variables differ significantly at the 25th, median (50th) and 75th percentiles of the distribution. Moreover, the (static) correlation coefficient (in Table 1B) also evinces significant heterogeneity (both in magnitudes and signs) across percentiles and over two different measures of uncertainty. Before proceeding to cointegration analysis, I also tested for unit root in these variables. A DF-GLS test with linear trend and 18 lags (chosen according to Schwert's 1989 criterion) gave rise to the following results: h12:Uncertainty (-3.263[-3.410]), EPU:Uncertainty (-3.153[-3.410]), CPI (-0.731[-3.410]), IP (-2.853[-3.410]), EMP (-0.968[-3.410]), RCONS (-2.455[-3.410]), PCEDEF (-0.795), RNORD (-2.419[-3.410]), hours (-3.378[-3.410]), M2 (-1.198[-3.410]), SP500 (-2.000[-3.410]), FED (-2.607[-3.410]), and WAGE (-2.542[-3.410]). The 5% critical values are in [-]. The results do not support rejection of a unit root at 5% critical level.

My estimation is performed over three sample spans: full-sample (1960:07-2016:12), pre-financial crisis (1960:07-2007:8), and post-financial crisis (2007:09-2016:12). Some authors such as Claessens et al. (2012) preferred a rather broader breakpoint, viz. pre and post-globalization (the period before the mid-1980s being the pre-globalization period). According to Claessens et al. (2011), the reasons for this were threefold, with the noticeable growth in global flows of business and finance since the middle of the 1980s being the first. Second, the years from the beginning of the 1970s to the early 1980s had witnessed sharp volatility in global energy prices, along with contractionary monetary policies in advanced markets. Finally, the second half of the 1980s, and during a period of great moderation and pre-globalization, the swings of business cycle volatilities had lowered substantially. A closer look at the time plots of macroeconomic uncertainty by Jurado et al. (2015) in Figure 1 (top and left panel) clearly shows a shift in the slope of the series since 2008 when the uncertainty indices reached a peak. I also found that the time period around 1980 evinced a breakpoint (conforming to the assumption of Claessens et al. (2012), with pre- and post-globalization as the break point.[12]

[12]In fact, I have performed the Sup-Wald test of Andrews (1993) to test if there was more than one structural break in the uncertainty and other series between 1960:07 and 2011:12. The Sup-Wald test for Jurado et al. (2015) measures of macroeconomic uncertainty showed that the statistic in the first iteration in 2007:08 was larger (20.98) than the second iteration (18.68). Hence, I conclude that there was only one structural break, at year 1983. For EPU uncertainty, I find that the statistic in the first iteration is 24.36 and is greater than the second iteration, 19.34.

Figure 2.1: Autocorrelation Function over time. Full Sample (1960:07-2011:12): Left [Objective measure of uncertainty (h1,h3,h12)(top), EPU measure of Uncertainty (middle), Industrial Production (bottom)], Right[Consumption (top), Employment (middle), and Hours (bottom)].

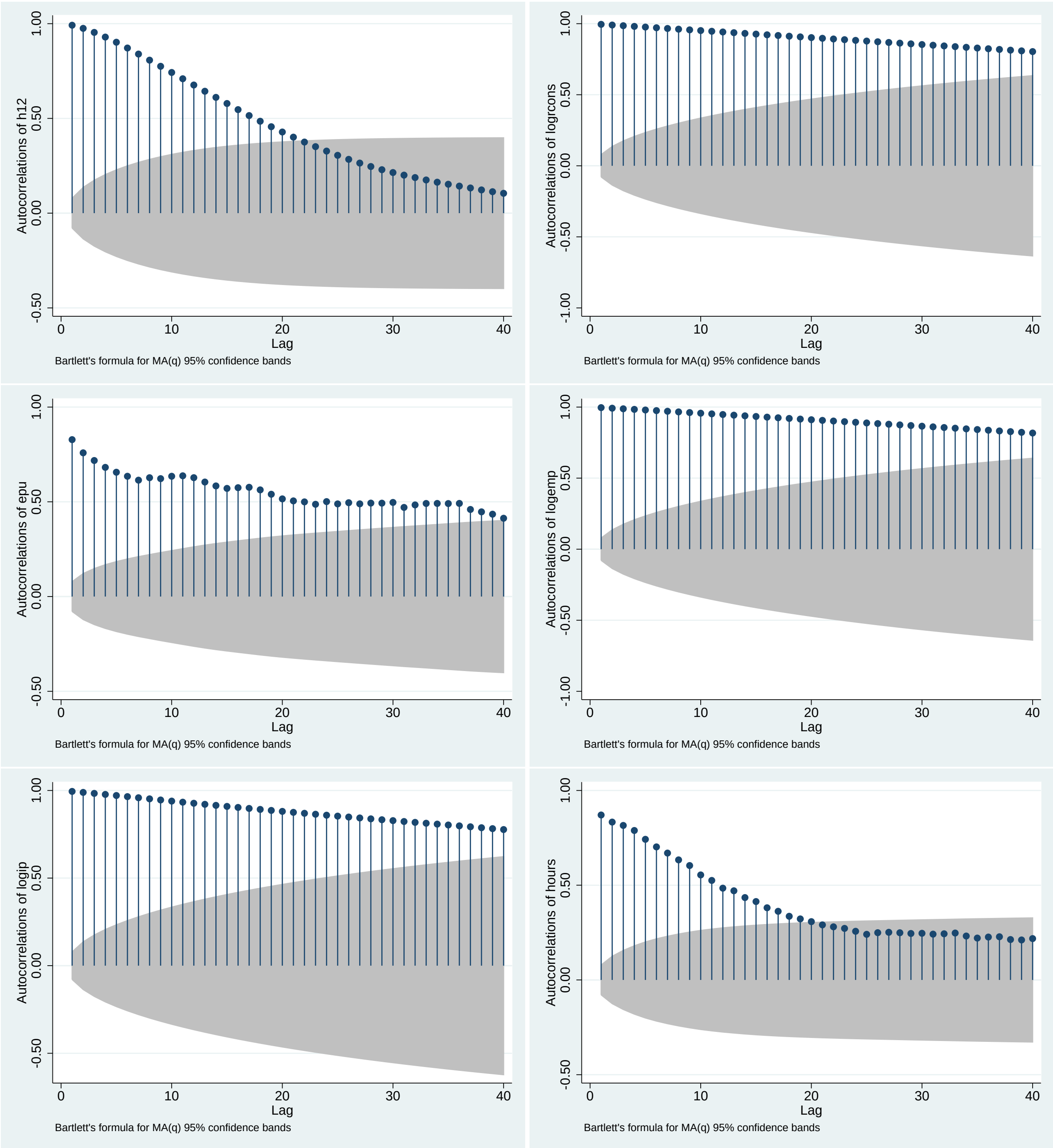
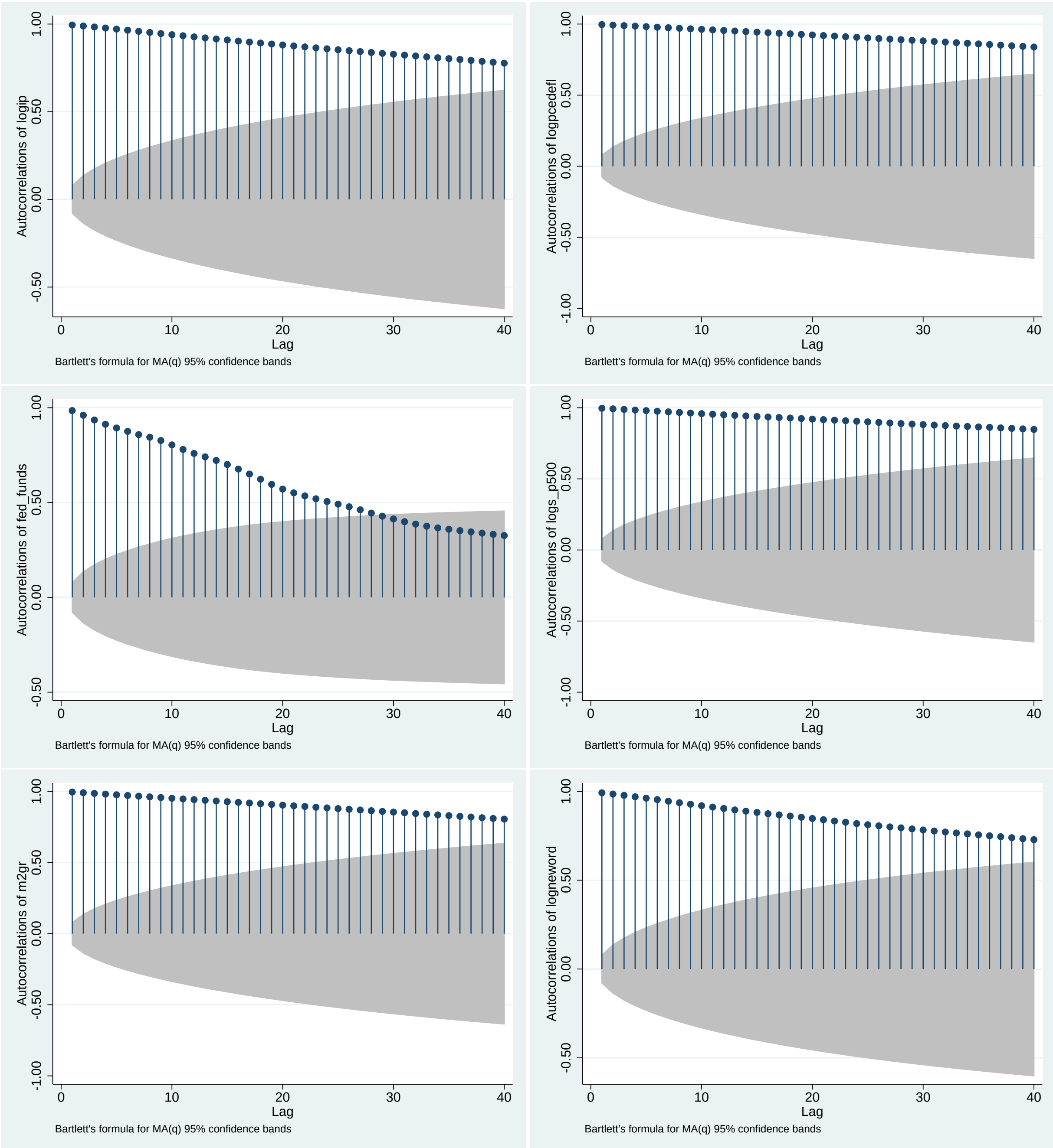


Figure 2.2: Autocorrelation Function. Full Sample (1960:07-2011:12): Left [Industrial production(top), Federal Funds Rate (middle), M2 growth (bottom)], Right[PCE Deflator (top), S&P 500 (middle), and New Orders (bottom)].



2.5.2 Results of quantile unit root test

Before I analyse the results from QARDL regression, I discuss first the heterogeneous nature of autoregressive coefficients across the conditional distribution of the variables. I also perform a Quantile unit root test in an attempt to discover if various parts of the distribution of the variables depict stationary/non-stationary behaviours. There have been numerous arguments about the asymmetric characteristics of some economic and financial time series and their tendency of persistence towards positive shocks rather than negative ones (Enders and Granger, 1998; Koenker and Xiao, 2006). Koenker and Xiao (2006) pointed that the unemployment rate has an asymmetric behaviour of significantly increasing rather than decreasing, due to firms efficiency in raising rather than reducing prices. Consequently, for us to account for heterogeneous behaviour in macroeconomic time series and to identify such asymmetries, it is essential to employ a quantile AR (QAR) process, according to Koenker and Xiao (2006).

Table 2 reports the results of quantile regression for a range of quantiles, including the estimated values of constant term $\beta_0(\tau)$ autoregressive coefficient $\beta_1(\tau)$, their respective p -values, and half-lives. Note that the p -value for $\beta_0(\tau)$ is investigating the null of zero with student-t test, while the counterpart for $\beta_1(\tau)$ is testing the unit-root null with $t_n(\tau)$ statistic. Additionally, for a fair comparison with the results in Table 3, and to avoid possible model misspecification, the optimal lag of the quantile regression for a particular variable is also selected by the MAIC.

I begin the analysis by studying the behaviour of all variables for each quantile. One can readily see that the estimated values for intercept $\beta_0(\tau)$ and autoregressive coefficient $\beta_1(\tau)$ are - in general - heterogeneous across quantiles. For some quantiles, there is an observed consistency of estimates. Recalling that $\beta_0(\tau)$ indicates the magnitude of an observed shock within the τ-th quantile that affects each variable, the negative (positive) sign then represents negative (positive) shocks. This would have resulted from tightened (loosened) economic policy during boom or boost. Furthermore, at the 50% quantile, the magnitude of shock is not significantly different from 0 (considered at the 5% level for all variables). Note that the shocks for the employment variable appear to be the most dispersive (a range of -3.120 to 4.625), while the counterparts for the Wage variable are the most concentrated (which ranges from -1.086 to 2.989). Therefore, the biggest shock that drifts Employment series away from its long-run equilibrium level is the largest one across all variables under study.

Interesting patterns emerge in Table 2 about the estimated values of $\beta_1(\tau)$ and their corresponding unit root tests for other variables. Recall that these are the key to making a judgment of stationarity of the variables in each quantile. I find that the sizes of shocks are different across variables and quantiles. For instance, the shocks to EPU uncertainty depict greater history dependence at higher quantile (0.978 at the 90th quantile) and smaller at lower quantile (0.693 at 10th quantile). The same trend is observed for

Jurado et al.'s (2015) objective uncertainty (h12) although the magnitude of shocks are greater at both the 10th and 90th quantiles for this series in comparison to EPU uncertainty. While both uncertainty measures depict heterogeneous persistence behaviour, h12 measure is observed to be more persistent than EPU uncertainty measure. Figure 3 (top two figures) summarize these conclusions. In Figure 3, I have also presented the pre-crisis (middle two figures) and post-crisis (bottom two figures) estimates of QAR. In general, I observe that the pre-crisis estimates depict relatively smaller persistence than the post-crisis period for EPU uncertainty (at the 10th quantile). For the 90th quantile, the pre-crisis period is observed to be more persistent than that of the post-crisis period. To be precise, in the small quantiles, the estimated values of shock persistence $\beta_1(\tau)$ are way less than unit root with small p -values rejecting the unit-root null at the 5% significance level (mainly for the lower quantiles in variables as PCE deflator, hours and consumption). On the contrary, for large quantiles, the counterparts are approaching to or insignificantly higher than unity and are not significantly distinct from the null hypothesis that the variables function in the style of an integrated process.

In Figures 3-8 I present QAR estimation results. For all variables, the QAR estimates vary between 0.6 (for EPU in post-globalization period, Figure 1) to 1.1 (irrespective of sample classification). In Figure 1, both EPU and Jurado's $h12$ uncertainty variables display monotonic rise in AR coefficients from low to higher quantiles, although $h12$ measure estimates higher persistence at lower quantile (for instance, 0.90 for post-globalization period) than EPU (0.6) at the same level of quantile. Consumption and labour productivity (proxied by 'hours') in Figure 2 present interesting AR dependence: high persistence at lower quantile followed by a monotonic decline at higher quantile across sample stratification. Similar behaviour is observed for employment variable (Figure 3) for full sample, wage (all samples) and S&P 500 (pre-globalization) in Figure 6, new order (Figure 5), and industrial production (full-sample) in Figure 4. In contrast, the growth of M2 and other variables display smaller AR coefficient at lower quantiles and larger coefficient at higher quantiles. These results indicate that the degree of persistence of all variables is heterogeneous. In fact across variables, I find evidence of a mix of $I(d)$ variables (where $0 \geq d < 1$. This latter result calls for the use of ARDL method to find if long-run cointegration relationship exists among the variables.

2.5.3 Results of QARDL estimation

In Tables 3 & 4 (for EPU and Jurado's measures of uncertainty, respectively) I present QARDL results for full-sample as well as for pre- and post-financial crisis periods (for a rolling window length of 624 months to accommodate time-varying pattern). This should allow us to balance the data requirement of the QARDL model and to examine the richest possible range of regime shifts (identified by break points). The full-sample results are the benchmark estimation results. To save space, the results are reported for

Table 2.2: Quantile Unit Root Test Results

Variables	τ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
H12: Jurado et al.	$\beta_0(\tau)$	3.341	-2.073	-1.442	-1.025	-0.323	0.317	0.991	1.877	3.94
(Uncertainty)	p -value	0.000**	0.000**	0.000**	0.004**	0.161	0.198	0.008**	0.000**	0.000**
	$\beta_1(\tau)$	0.865	0.967	0.969	0.974	0.986	0.978	0.996	1.011	1.089
	p -value	0.000**	0.000**	0.000**	0.000**	0.154	0.63	0.986	1	1
EPU: Baker et al.	$\beta_0(\tau)$	-3.083	-1.783	-1.067	-0.588	-0.184	0.32	0.981	1.682	3.026
(Uncertainty)	p -value	0.000**	0.000**	0.000**	0.001**	0.149	0.092*	0.000**	0.000**	0.000**
	$\beta_1(\tau)$	0.693	0.789	0.75	0.751	0.830	0.851	0.870	0.889	0.978
	p -value	0.020**	0.020**	0.000**	0.000**	0.004**	0.034**	0.514	0.814	0.994
CPI	$\beta_0(\tau)$	-2.773	-1.546	-1.012	-0.547	-0.175	0.267	0.68	1.227	2.321
	p -value	0.000**	0.000**	0.000**	0.000**	0.134	0.055*	0.000**	0.000**	0.000**
	$\beta_1(\tau)$	0.702	0.827	0.848	0.877	0.913	0.926	0.974	0.938	1.083
	p -value	0.002**	0.020**	0.014**	0.006**	0.088*	0.124	0.664	0.404	0.968
IP	$\beta_0(\tau)$	-2.528	-1.671	-1.244	-0.562	-0.057	0.389	0.926	1.607	2.913
	p -value	0.000**	0.000**	0.000**	0.002**	0.374	0.018**	0.000**	0.000**	0.000**
	$\beta_1(\tau)$	1.112	0.999	1.000	0.997	0.996	0.997	0.996	0.995	0.902
	p -value	0.014**	0.004**	0.000**	0.002**	0.006**	0.002**	0.024**	0.094	0.5
EMP	$\beta_0(\tau)$	-3.120	-2.332	-1.719	-1.310	-0.306	0.443	1.379	3.091	4.625
	p -value	0.000**	0.000**	0.000**	0.000**	0.206	0.142	0.001**	0.000**	0.000**
	$\beta_1(\tau)$	1.100	0.999	1.000	0.999	0.998	0.997	0.997	0.996	0.885
	p -value	0.006**	0.000**	0.000**	0.000**	0.016**	0.053*	0.076*	0.081*	0.102
CONSUMPTION	$\beta_0(\tau)$	-3.109	-1.782	-1.162	-0.695	-0.03	0.361	0.793	1.642	2.544
	p -value	0.000**	0.000**	0.001**	0.004**	0.45	0.113	0.013**	0.000**	0.000**
	$\beta_1(\tau)$	1.089	1.037	1.011	0.997	0.998	0.999	0.997	0.996	0.886
	p -value	0.000**	0.000**	0.000**	0.000**	0.346	0.864	0.988	0.998	1
PCDEF	$\beta_0(\tau)$	-3.346	-2.359	-1.713	-0.922	-0.528	0.118	0.766	1.681	3.738
	p -value	0.000**	0.000**	0.000**	0.002**	0.051*	0.352	0.016**	0.004**	0.000**
	$\beta_1(\tau)$	0.999	0.999	1.000	0.999	0.999	0.999	1.012	0.999	0.879
	p -value	0.000**	0.000**	0.000**	0.0034***	0.021**	0.076*	0.526	0.978	0.998
RNORD	$\beta_0(\tau)$	-2.997	-2.234	-1.27	-0.745	-0.258	0.517	1.327	2.008	3.318
	p -value	0.000**	0.000**	0.002**	0.028**	0.195	0.056*	0.000**	0.000**	0.000**
	$\beta_1(\tau)$	1.061	0.996	0.995	0.995	0.987	0.976	0.983	0.984	0.866
	p -value	0.002**	0.000**	0.000**	0.014**	0.020**	0.059*	0.066*	0.10	0.081*
HOURS	$\beta_0(\tau)$	-3.112	-2.874	-1.948	-1.189	-0.393	0.205	1.052	1.822	4.823
	p -value	0.000**	0.000**	0.000**	0.003**	0.186	0.305	0.010**	0.005**	0.000**
	$\beta_1(\tau)$	1.000	0.901	1.000	1.000	0.886	1.000	0.889	0.890	0.687
	p -value	0.036**	0.002**	0.002**	0.004**	0.018**	0.12	0.486	0.91	0.986
M2	$\beta_0(\tau)$	-3.44	-2.328	-1.298	-0.711	-0.335	0.303	0.921	1.951	3.985
	p -value	0.000**	0.000**	0.000**	0.008**	0.116	0.133	0.002**	0.000**	0.000**
	$\beta_0(\tau)$	0.997	0.998	0.999	0.999	0.999	0.999	0.999	0.999	1.051
	p -value	0.006**	0.020**	0.004**	0.014**	0.034**	0.332	0.432	0.888	0.926
SP500	$\beta_0(\tau)$		-2.015	-1.571	-0.728	-0.25	0.343	1.246	2.229	4.092
	p -value	0.000**	0.000**	0.000**	0.039**	0.264	0.223	0.002**	0.000**	0.000**
	$\beta_1(\tau)$	0.875	0.998	1.065	1.065	1.011	1.023	1.018	1.075	0.999
	p -value	0.004**	0.000**	0.000**	0.000**	0.012**	0.096*	0.912	1	1
WAGE	$\beta_0(\tau)$		-1.086	-0.877	-0.395	0.221	0.543	0.841	1.338	2.989
	p -value	0.000**	0.000**	0.000**	0.034**	0.122	0.003**	0.000**	0.000**	0.000**
	$\beta_1(\tau)$	1.086	1.053	1.042	0.998	0.997	0.997	0.965	0.958	0.857
	p -value	0.000**	0.004**	0.050**	0.018**	0.0470**	0.0878*	0.0872*	0.090*	0.0984*

Note: All the p -values are calculated with the bootstrap method with 1000 replications. For $\beta_0(\tau)$, the null of zero is tested with the student-t test, while for $\beta_1(\tau)$, the unit-root null is tested with the $t_n(\tau)$ statistic. Statistical significance is denoted by double asterisks (**) for the 5% level and an asterisk (*) for the 10% level. The results reported here are for full sample estimation.

$\tau = 0.25, 0.50, 0.75$. All coefficients are statistically significant at 5% level across quantiles. As explained before, I incorporate location (quantile) asymmetries in the long-run effects of macroeconomic variables. The full-sample estimation results clearly confirm that there is strong evidence of location asymmetries between lower and medium-to-higher quantiles for all parameters. First, the quantile estimates of long-run parameter (of the effect of uncertainty on each variable), $\hat{\beta}(\tau)$ seems to increase monotonically across quantiles for CPI (Table 4 with h12 uncertainty) but decrease (Table 3) with EPU

Table 2.3: QRADL Estimation with EPU Uncertainty

		Full sample			Pre crisis			Post crisis		
		Long	Short	Short	Long	Short	Short	Long	Short	Short
		$\beta*(\tau)$	$\phi*(\tau)$	$\gamma*(\tau)$	$\beta*(\tau)$	$\phi*(\tau)$	$\gamma*(\tau)$	$\beta*(\tau)$	$\phi*(\tau)$	$\gamma*(\tau)$
CPI	$\tau = 0.25$	1.572	0.999	0.000	3.792	0.9990	0.0013	-0.381	0.998	-0.0007
	$\tau = 0.50$	1.555	0.999	0.001	-29.926	1.0000	0.0006	-0.095	0.999	-0.0001
	$\tau = 0.75$	1.546	0.999	0.001	3.245	0.9990	0.0027	32.453	1.000	-0.0005
IP	$\tau = 0.25$	2.265	1.338	-0.003	1.109	1.0000	-0.0055	-0.580	0.998	-0.0012
	$\tau = 0.50$	-3.479	1.265	-0.001	-1.522	0.9980	-0.0020	-0.206	0.997	-0.0005
	$\tau = 0.75$	-1.239	1.103	-0.002	0.298	0.9910	0.0025	-1.676	0.998	-0.0021
EMP	$\tau = 0.25$	0.609	1.000	-0.001	0.458	1.0020	-0.0013	-0.962	0.999	-0.0007
	$\tau = 0.50$	-3.717	0.999	-0.001	1.670	1.0000	-0.0010	-0.270	0.999	-0.0002
	$\tau = 0.75$	-0.335	0.998	0.000	0.201	0.9980	0.0002	-0.452	0.998	-0.0006
RCONS	$\tau = 0.25$	1.947	1.001	-0.002	2.332	1.0009	-0.0020	-2.890	0.998	-0.0020
	$\tau = 0.50$	-1.520	0.999	-0.001	-0.775	0.9994	-0.0005	-0.686	0.997	-0.0013
	$\tau = 0.75$	-0.128	0.997	0.000	0.768	0.9980	0.0015	-0.412	0.996	-0.0011
PCEDEF	$\tau = 0.25$	0.619	2.206	0.000	1.772	0.9990	0.0021	-0.103	0.999	-0.0002
	$\tau = 0.50$	1.290	2.339	0.001	2.278	0.9990	0.0023	-0.086	0.999	-0.0001
	$\tau = 0.75$	1.789	2.339	0.002	2.799	0.9990	0.0029	0.085	0.999	0.0001
RNORD	$\tau = 0.25$	2.187	1.002	-0.004	0.770	1.0081	-0.0062	-0.520	0.980	-0.0095
	$\tau = 0.50$	-0.830	0.998	-0.001	0.375	0.9894	0.0040	-0.402	0.982	-0.0068
	$\tau = 0.75$	-0.113	0.988	-0.001	0.242	0.9716	0.0069	-0.539	0.986	-0.0067
HOURS	$\tau = 0.25$	-0.921	0.959	-0.037	-1.225	0.9040	-0.1171	-2.421	0.941	-0.1388
	$\tau = 0.50$	-0.510	0.950	-0.025	-0.737	0.8880	-0.0829	-0.896	0.948	-0.0458
	$\tau = 0.75$	-0.321	0.925	-0.033	-0.644	0.7990	-0.1293	-0.190	1.000	-0.0180
M2	$\tau = 0.25$	0.432	0.999	0.000	1.320	0.9990	0.0008	0.658	1.000	0.0001
	$\tau = 0.50$	1.465	0.999	0.001	1.558	1.0000	-0.0002	-1.502	1.001	0.0010
	$\tau = 0.75$	1.957	0.999	0.001	0.951	1.0130	-0.0011	-2.500	1.001	0.0021
SP500	$\tau = 0.25$	-6.497	0.998	-0.007	-4.024	0.9980	-0.0067	-2.317	0.990	-0.0212
	$\tau = 0.50$	11.000	0.999	0.003	0.634	0.9870	0.0082	0.662	0.998	0.0012
	$\tau = 0.75$	4.193	0.997	0.010	0.728	0.9720	0.0207	2.932	0.995	0.0121
FED	$\tau = 0.25$	-1.515	0.970	-0.045	3.168	0.9340	0.2101	-5.834	0.974	-0.1546
	$\tau = 0.50$	-5.328	0.991	-0.043	5.033	0.9740	0.1305	-6.257	0.992	-0.0495
	$\tau = 0.75$	3.904	1.016	-0.065	1.274	1.0300	-0.0385	35.623	1.002	-0.0793
WAGE	$\tau = 0.25$	6.064	1.001	-0.002	1.436	1.0032	-0.0045	-1.597	0.999	-0.0020
	$\tau = 0.50$	-35.643	0.999	-0.002	1.947	1.0013	-0.0024	7.124	1.000	-0.0013
	$\tau = 0.75$	-4.145	0.999	-0.001	1.019	1.0017	-0.0018	4.839	1.000	-0.0015

uncertainty. With both measures of uncertainty, monotonic increase in long-run coefficient is observed for PCEDEF, and M2 growth (Tables 3 and 4). Other variables display changes in the sign of long-run coefficients across quantiles implying that change in uncertainty leaves differential negative long-run effects on the growth of real economic activities. When I consider pre- and post-crisis periods in Table 4, I find for instance that $\hat{\beta}(\tau = 0.25)$ is negative (-4.083) for CPI (pre-crisis period) and -5.555 in the post crisis period. These estimates are different from the one in full-sample estimation (13.675) at the 25th quantile. With EPU measure of uncertainty (Table 3) and the case of CPI, $\hat{\beta}(\tau = 0.25)$ = 3.792 (pre-crisis) $>$ 1.572 (full-sample), as well as -0.381 (post-crisis period). Other variables display heterogenous long-run and short-run effects of uncertainty across quantiles.

A detailed examination of the time-varying QARDL results provides important insights: (i) location asymmetries across different quantiles of the conditional distribution of the variables, which were clearly persistent in earlier periods, appear to be less frequent in recent periods. This finding implies that adjustment of shocks to variables due to fluctuations in uncertainty is a long-term process in the USA (see Bloom, 2009; Baker et al., 2016, among others) and the asymmetric adjustment is reflective of the

Table 2.4: QRADL Estimation with Jurado (h12) Uncertainty

		Full sample			Pre crisis			Post crisis		
		Long	Short	Short	Long	Short	Short	Long	Short	Short
		$\beta*(\tau)$	$\phi*(\tau)$	$\gamma*(\tau)$	$\beta*(\tau)$	$\phi*(\tau)$	$\gamma*(\tau)$	$\beta*(\tau)$	$\phi*(\tau)$	$\gamma*(\tau)$
CPI	$\tau = 0.25$	13.675	1.000	0.005	-4.083	1.0050	0.0019	-5.555	0.998	-0.0094
	$\tau = 0.50$	17.522	0.998	0.009	31.208	0.9980	0.0058	0.365	0.998	0.0007
	$\tau = 0.75$	19.499	0.998	0.015	22.809	0.9990	0.0088	9.194	0.998	0.0103
IP	$\tau = 0.25$	37.104	1.001	-0.032	4.524	1.0050	-0.0258	19.651	1.003	-0.0660
	$\tau = 0.50$	-373.498	1.000	-0.026	9.795	1.0020	-0.0212	-505.927	1.000	-0.0530
	$\tau = 0.75$	-4.721	0.999	-0.012	-2.505	0.9980	-0.0100	95.753	1.001	-0.0482
EMP	$\tau = 0.25$	6.655	1.008	-0.005	2.793	1.0020	-0.0065	-14.980	0.999	-0.0086
	$\tau = 0.50$	-13.161	0.999	-0.005	3.653	1.0020	-0.0061	-48.399	0.999	-0.0079
	$\tau = 0.75$	-2.041	0.998	-0.003	2.900	1.0020	-0.0048	-8.793	0.999	-0.0083
RCONS	$\tau = 0.25$	21.714	1.000	-0.021	4.279	1.0044	-0.0187	16.328	1.101	-0.0272
	$\tau = 0.50$	-14.394	0.999	-0.017	6.814	1.0028	-0.0191	-43.956	0.998	-0.0272
	$\tau = 0.75$	-3.813	0.996	-0.009	5.581	1.0029	-0.0164	-3.755	0.995	-0.0134
PCEDEF	$\tau = 0.25$	8.711	0.999	0.004	-12.230	1.0050	0.0030	-3.150	0.998	-0.0055
	$\tau = 0.50$	13.324	0.999	0.008	40.073	1.0000	0.0064	2.184	0.987	0.0024
	$\tau = 0.75$	16.741	0.998	0.010	-60.181	1.0000	0.0066	6.121	0.998	0.0079
RNORD	$\tau = 0.25$	-15.252	0.996	-0.056	4.609	1.0130	-0.0600	-13.496	0.999	-0.0983
	$\tau = 0.50$	-8.569	0.997	-0.029	5.652	1.0064	-0.0359	-7.821	0.987	-0.0998
	$\tau = 0.75$	-2.382	0.989	-0.027	-0.857	0.9809	-0.0164	-6.032	0.987	-0.0858
HOURS	$\tau = 0.25$	-7.525	0.929	-0.530	-3.440	0.8530	-0.5027	-12.355	0.892	-1.3281
	$\tau = 0.50$	-6.364	0.916	-0.535	-3.285	0.8350	-0.5391	-10.197	0.893	-1.0817
	$\tau = 0.75$	-4.795	0.866	-0.643	-3.327	0.7870	-0.7055	-8.439	0.885	-0.9658
M2	$\tau = 0.25$	-0.418	1.000	0.000	-176.475	1.0000	-0.0012	6.110	1.001	-0.0049
	$\tau = 0.50$	6.452	0.998	0.002	7.723	0.9990	0.0009	-17.499	1.001	0.0101
	$\tau = 0.75$	16.478	0.998	0.008	-14.866	1.0003	0.0041	-25.946	1.001	0.0140
SP500	$\tau = 0.25$	-170.414	1.000	-0.062	-19.861	0.9970	-0.0464	-206.907	1.000	-0.1661
	$\tau = 0.50$	-112.783	1.000	0.009	1.671	0.9820	0.0296	-7.942	0.998	-0.0368
	$\tau = 0.75$	-57.521	1.000	0.043	3.628	0.9800	0.0694	6.350	0.998	0.0094
FED	$\tau = 0.25$	-22.111	0.972	-0.603	-71.222	0.9830	-1.1813	-20.574	0.979	-0.4283
	$\tau = 0.50$	-56.153	0.996	-0.203	27.558	0.9570	1.1796	-46.267	0.997	-0.1001
	$\tau = 0.75$	-11.168	1.024	0.268	55.772	0.9410	3.2691	4.303	1.011	-0.0492
WAGE	$\tau = 0.25$	-66.874	1.000	-0.016	10.870	1.0017	-0.0186	-29.657	0.999	-0.0248
	$\tau = 0.50$	-35.959	1.000	-0.011	8.768	1.0017	-0.0149	27.337	1.000	-0.0127
	$\tau = 0.75$	-3.335	0.999	-0.003	3.886	1.0030	-0.0118	10.166	1.000	-0.0039

underlying endogenous economic growth system that responds variedly to the policy interventions. The pre- and post-crisis period estimation shows that the speed of adjustments are greater at the pre-crisis than at the post-crisis period, possibly because of the information cascades and persistent volatility during the latter period.

2.6 Discussion and conclusions

In this paper, I introduce an analytical approach to study the changing cointegration relationship between real variables and uncertainty. At the core of my hypothesis, there is a simple yet policy-relevant argument; if it exists, modelling cointegration relationship between uncertainty and the real variables at the 'mean' level is uninformative, as it does not consider what is happening to this relationship at other points of the distribution. From a theoretical perspective, the existence of a heterogenous cointegration relationship is an indication of varying speed of adjustments, and therefore any planned policy intervention to 'smooth out' stochastic shocks should follow a 'target and needs-based' approach. For instance, when uncertainty is low, an expansionary economic policy may produce greater economic gains from the equilibrium relationship between uncertainty and real variables than when uncertainty is high. Moving across the distribution, a non-unique policy intervention may give rise to better results from 'smoothing-out' effects of shocks, then applying the same policy at each point of the distribution.

Indeed, in my work I find that there is a heterogeneous non-stationary behaviour of variables across the distributions. Examination of cointegration relationship across the distribution showed that a heterogeneous cointegration structure indeed exists; for some quantiles, I find a vanishing cointegration relation, whereas the same exists at other quantiles. An implication is that the economic system depicts heterogeneous adjustment behaviour at various levels of their growth trajectories; at the initial low level of growth one can find a low level of cointegration, but as the economy develops further, the possibility of long-term relationship becomes stronger. Disequilibrium correction of error is stronger at the higher quantile. I checked for the effects of structural break using financial crisis and found that there are significant evidences of asymmetric cointegration.

My work can be seen as an extension of the existing work, yet is distinct in the sense that I focus on characterizing the possibility of cointegration between uncertainty and growing variables as an identification tool for stable long-run growth in an economic system. My strategy and estimation also identifies the fact that non-unique policy intervention might be required to minimize the proliferation of shocks at various points in the distribution of the growth of real economic variables.

Chapter 3

Dynamic Interdependence between Real Economy and Uncertainty: A Fractional Cointegrated VAR Approach

3.1 Introduction

Increasingly, the effect of uncertainty on real economic/financial activities has become an intensely researched topic. Among others, Byeongju (2002), Bloom (2009), Jurado et al. (2015), and Mumtaz and Theodoridis (2016) have investigated the (asymmetric) effects of uncertainty on macroeconomic variations, whereas Giavazzi and McMahon (2012) studied the impact of uncertainty on household saving behaviour from microeconomic perspective. Moreover, investigating the role of economic policy uncertainty (EPU) on financial markets, Brogaard and Detzel (2015) found that EPU is an economically important risk factor for equities, so much so that it can positively forecast log excess market returns. Irrespective of the context of the studies, correctly identifying the nature of persistence[1] in 'uncertainty'[2] can equip a researcher with deeper insights into the way the system interacts with the 'slow/fast-convergence' of uncertainty shocks. This contribution aims to exploit the rich properties of 'fractional process' of a vector time series as an identification tool for persistence, and to demonstrate - both analytically and empirically - that the 'memory' properties of uncertainty shock can determine heterogenous convergence behaviours of macroeconomic aggregates to the steady-state. Such findings are also important in understanding whether specific 'memory' features of uncertainty can identify (exogenous/endogenous) growth generating mechanisms by drawing on the cointegration regression.

3.1.1 The consequences of long-memory uncertainty shock

Why are the effects of long-memory in the uncertainty variable so important in understanding macroeconomic and financial variables' fluctuations? To understand this I follow Granger's (1980) aggregation theorem (a similar theoretical exposition has been presented in Chapter 2). My illustration involves a measure of uncertainty, such as Economic Policy Uncertainty (EPU) index of Baker et al. (2017)[3]. I assume that at subcategorical level i, this index is governed by an autoregressive process (denoted by Z_t):

$$Z_{i,t} = \alpha_{i,1} + \alpha_{i,2} Z_{i,t-1} + u_{i,t} \tag{3.1}$$

$\alpha_{i,2}$ can be 0 or it can be 1. If $\alpha_{i,2}$ is assumed to be distributed as $\beta(u, v)$, then $\frac{1}{N}\sum_1^N Z_{i,t} = Z_t \sim I(d)$. Thus the construction of uncertainty measures (similarly, other macroeconomic aggregates) is subject to Granger's (1980) aggregation theorem, following which I am led to believe that these variables are fractional integrated processes. This needs to be demonstrated empirically. I begin with the plots of ACF in Figures 3 and 4 (in

[1]In other words, it implies a slow decay of the autocorrelation function than one might expect from a pure ARMA process. The latter is characterized by geometric lags.
[2]Details on various measures of uncertainty will be presented in Section 3.
[3]A detailed description of the data will be presented in the following section

the appendix) which reveal that the rate of decline of autocorrelations in successive lags seems closer to hyperbolic than exponential. To strengthen my hypothesis that these variables are generated by long-memory processes or are fractionally integrated, I have also estimated a zero frequency. As it is known, fractional processes have mass at the zero frequency proportional to λ^{-2d} with λ denoting the frequency. As evident in Figures 5 and 6 (in the Appendix), the spectral density plots of all variables depict a concentration of high frequency at zero mass, which is typical of fractionally integrated time series processes. Together, the above plots make us suspect that the series was generated by a long-memory process.

While there is some research on how a fractional integrated framework can be identified with existing growth models using univariate context, the way this property of mean-reversion governs the dynamics of a system in the presence of persistent uncertainty has yet to be investigated. As a starting point, I would like to demonstrate first how long-memory in uncertainty can affect the dynamic behaviour (in terms of constancy of mean and variance) of the aggregate economic system.[4].

Let us denote $X_t = (x_{1,t}, \ldots, x_{n,t})'$ as a vector of $n(n \geq 2)$ economic variables of interest (e.g. the 12-variables I have identified for my analysis) observed at time t, and generated by endogenous growth models. I assume that the evolution of each time series has at least two essential components: growth due to own and system factors (call this Z_t) and growth due to variation in 'uncertainty' (denote this as U_t). Then, for each time series $x_{i,t}$, the evolution is described by: $x_{i,t} = Z^{\alpha}_{i,t} U^{\gamma}_{i,t}$, where under fairly ideal conditions, $\alpha + \gamma = 1$. If one assumes, for the sake of brevity that $Z_{i,t}$ is constant, then any variability in $x_{i,t}$ would be a consequence of fluctuations in $U_{i,t}$. In fact, if one follows the conventional exogenous and the modern 'endogenous' growth theoretic mechanisms, then the nature of persistence of $U_{i,t}$ would be able to identify the true nature of cyclicality of $Y_{i,t}$ and in the process can characterize whether persistence in uncertainty is a leading reason for the source of stochastic exogenous/endogenous growth cycles of real economic activities. While the study of the detailed properties of a fractionally integrated system in characterizing endogenous/exogenous growth could be a subject of separate rigorous research, I present below a simple mechanism to demonstrate that a shock to U_t can spill over to the entire economic system, and depending on the convergence properties of this shock, it can characterize the steady-state behaviour of the growth models. The cointegration equations under the fractional system can identify if there is perpetual growth of at least one variable in the system, which can ensure whether endogenous or exogenous growth mechanisms exist. The following properties can be described based on the arguments above.

I assume for simplicity that (shocks to) past uncertainty (U_{t-1}) affect the current value of X_t. Since uncertainty can affect all variables in any economic system, the following

[4]A generalization of Lau (1999) in long-memory context can be made, however, this is beyond the scope of the current paper

reduced form linear specification of uncertainty-macroeconomic variables can reflect interesting interdependence dynamics.

$$X_t = \gamma U_{t-1} + \eta_t \tag{3.2}$$

where $\eta_t \sim iid(0, \sigma_\eta^2)$. Due to the fact that X_t is a linear function of U_t, then if U_t is characterized by a long-memory process, then X_t system can also be characterized by long-memory. One can in fact show that the long-run conditional mean and variance of $k-$period cumulative X is a function of long-memory in U_t, i.e.,

The *conditional expectation* of $X_t^{(k)}$ is

$$\mathbb{E}\left[X_t^{(k)}\right] = \gamma. \sum_{i=0}^{\infty} \zeta_i^{(k)} \epsilon_{t-1-j+l} \tag{3.3}$$

whereas, the *conditional variance* is:

$$\begin{aligned} &Var_t\left(X_t^{(k)} - \mathbb{E}\left[X_t^{(k)}\right]\right) \\ &= \gamma^2. \textstyle\sum_{l=1}^{k} \left(\zeta_{k-l}^{(k)}\right)^2 \sigma_\epsilon^2 + \gamma. \textstyle\sum_{k-l}^{(k)} \sigma_{\epsilon\eta} + \sigma_\eta^2 \end{aligned} \tag{3.4}$$

This simple, yet intuitive result identifies two points: (i) uncertainty is not exogenous, in fact, it exists and grows due to the complex functioning of the economic system as well as intentional (policy) interventions of agents, and (ii) shocks in uncertainty then determine the equilibrium behaviour of the growing variables in the real economic system. The above framework also leads us to go beyond univariate analysis and adopt an empirical method that is able to characterize the steady-state behaviour of the entire economic system, while still assuming that the variables are long-memory. Section 5 presents a fractional cointegrated VAR (FCVAR) framework of Johansen and Nielsen (2010) to fix ideas motivated by the preliminary empirical evidence of long-memory. I exploit the flexible convergence properties 'fractional process' to formulate and estimate the dynamic relationship between 'uncertainty' and macroeconomic variables. In my work, I employ the recently developed fractionally vector autoregressive (FCVAR) model of Johansen and Nielsen (2012), and characterize the persistence and equilibrium relationship between selected macroeconomic variables and measures of uncertainty. As a result of the characterized equilibrium relationship, I identify whether the macroeconomic system has been generated by endogenous or exogenous growth theoretic mechanisms.

3.1.2 Identification of channels

There are essentially three approaches which one can adopt to identify and model the causal effects between uncertainty and real economic activities. (i) *Timing*: that is, estimating the movements in output, hiring and investment that follow jumps in uncertainty, as in Engel and Rangel (2008), Bloom (2009), Novy and Taylor (2014); (ii) *Structural models*: these are usually calibrated from macro and micro fluctuations to quantify the potential effect of uncertainty shocks (Bloom et al. (2012)). While this approach possesses strong conceptual foundation, like many structural models, it is also sensitive to debatable modelling assumptions; (iii) *Natural experiments*: for instance, the effect of disasters, political coups, changes in trade, and others (see Baker and Bloom (2013) in particular). My conceptual framework broadly relies on the first approach by accommodating the complex interplay of shocks within the system. My primary focus is on the effect of hyperbolic convergence of shocks and their effects on the macroeconomic system.

In fact, as my empirical investigation shows, the persistence profiles of uncertainty are indeed different, depending on various measures. I also find that a unit-root non-stationarity is clearly rejected, thus allowing for the possibility that uncertainty shocks may be characterized by long-memory. Assuming the latter to be true, then the long-memory macroeconomic system would display far more intricate dynamic interdependent behaviour than could be envisaged by the unit-root-led VAR system. The long-memory system displays rich equilibrium dynamics and characterizes quite neatly the 'steady-state' behaviour of many economic time series (see Granger (1980)). Moreover, I know little about how uncertainty drives the (dis)-equilibrium relationship with real economic and financial activities within and across economies[5], particularly when the persistent nature of uncertainty may determine long-run waves and short-run fluctuations in economic activities. In view of the discussed limitations in the literature, my paper is broadly concerned with modeling this equilibrium relationship within the environment of slowly-converging stochastic shocks. The case of my empirical analysis is the USA (given the availability of long-time series data on macro/financial aggregates, as well as both subjective and objective measures of uncertainty spanning more than five decades).

My contribution is distinct from that of the existing literature in one main aspect. It is well-known that attempts to identify the effects of uncertainty shocks in existing empirical work are primarily based on recursive schemes within the framework of vector-autoregressions (VAR).[6] I also follow the broad idea of the recursive scheme of VAR in my setting but relax the limiting assumption of a shock propagation mechanism (i.e. stationarity or unit-root non-stationarity). Rather, I allow a flexible framework within

[5]Bloom (2009) and Baker et al. (2015) provide some arguments and analysis in this regard.

[6]See Bloom (2009), Gilchrist et al. (2014), Bachman et al. (2013), Bekaert et al. (2013), Bloom (2014), and Jurado et al. (2015).

which uncertainty shocks can display a range of 'memory' properties, such as stationary memory, stationary long-memory and non-stationary long-memory.[7] To achieve this, I adopt recent developments in 'long-memory' cointegrated VAR mechanisms where, within the system of macroeconomic and financial aggregates, the dynamic interdependence among the variables would be characterized by an 'adjustment' mechanism of shocks to long-run equilibrium with the possibility of slow convergence. It is common knowledge that such a feature closely approximates real-life evolution of numerous economic and financial variables. Therefore, invoking this feature for understanding dynamic interdependence between 'uncertainty' and real variables, and outlining their equilibrium characteristics under this setting, holds immense significance. In fact, using simple cointegrated VAR, I would have probably dispensed with the long-run effects of uncertainty on various variables (assuming they are stationary because the standard unit-root test said so). Therefore, in most cases, the short-run effects of uncertainty shocks (using cointegrated VAR) can be underestimated to the extent that they discard the possibility of long-memory.

The rest of the paper is organized as follows. Section 2 discusses data and measurement issues of variables, particularly uncertainty. Section 3 presents preliminary observations. Section 4 includes a brief discussion of FCVAR methodology, based on which Section 5 presents and analyses implications of the results. Finally, Section 6 concludes with the main findings of the paper.

3.2 Data and measurements

3.2.1 Data

Similar to Chapter 2, in this chapter, I use monthly data for the USA, comprising 618 months extending over the period 1960:07 to 2011:12. The three sources of my data are Bloom (2009), Baker et al. (2015) and Jurado et al. (2015). A total of 12 variables, containing two measures of uncertainty (to be discussed in details in i and ii) are considered in the estimation. Table 1 provides the list and definition of the variables.

I follow both Christiano et al. (2005) and Jurado et al. (2015) in selecting these variables, which can represent the overall dynamic behaviour of a real economic system. They are a blend of macroeconomic, monetary and financial variables which Christiano et al. (2005) and Jurado et al. (2015) mention as having been recently the centre of dynamic economic relation research. In addition to the 12-variables FCVAR, I also estimate an 8-variables FCVAR (these are the same variables as in Bloom (2009) and Jurado et al. (2015)). Bloom's (2009) 8-variables system is basically a sub-set of the broad

[7] I will discuss the properties and implications of these 'memory' properties in Section 5.

Table 3.1: Variables Description

Variables	Description
IP	log (real Industrial Production)
EMP	log(Employment)
CONSUMP	log(real consumption)
PCEDEF	log(Per Capita Consumption Expenditure deflator)
NORD	log (real new orders)
WAGE	log(real wage)
HOURS	hours (to proxy labour productivity)
FED	Fed Funds Rate (a measure of interest rate)
SP500	log (S&P 500 Index) to proxy for quarterly corporate profits
M2gr	Growth rate of M2
J-uncertainty	Uncertainty measure based on Jurado et al. (2015)
EPU-Uncertainty	EPU: Uncertainty based on Baker et al. (2015)

12-variables system, but differs with respect to ordering mimics (see below). I estimate both systems using two measures of uncertainty.

$$FCVAR-12 = \begin{pmatrix} IP \\ EMP \\ CONSUMP \\ PCEDEF \\ NORD \\ WAGE \\ HOURS \\ FED \\ SP500 \\ M2gr \\ uncertainty \end{pmatrix} ; FCVAR-8 = \begin{pmatrix} SP500 \\ uncertainty \\ FED \\ WAGE \\ CPI \\ HOURS \\ EMP \\ IP \end{pmatrix}$$

(A) Macroeconomic variables

From Table 1, the monthly industrial production (IP) and the PCE deflator (PCEDEF) are used to measure both the gross domestic product (GDP) and the gross domestic product deflator (GDP deflator). HOURS (average hourly earnings) is intended to measure labour productivity for the manufacturing sector, since as Jurado et al. (2015) noticed that the aggregate measure of labour productivity does not extend back to 1960. The S&P 500 stock market index is employed to proxy for quarterly corporate profits, whereas real new orders (NORD) serves as a proxy for profit. Following Christiano et al. (2005), I used federal funds rate as a measure of interest rate. In addition, the variables of real consumption, employment, real wage and growth of M2 are commonly used macroeconomic and monetary summaries. Lastly, I used both the subjective and objective measures of economic uncertainty. In the following section, I present a summary of the concept of uncertainty and the two measures' construction and development.

(B) Uncertainty

Measuring economic uncertainty particularly is a rather challenging and complex process. According to Bloom (2014), what makes the concept of economic uncertainty difficult to quantify is that uncertainty is a complex and unobservable phenomenon which represents both investors' and policymakers' future expectations. Furthermore, the general idea of uncertainty stretches over the scope of macroeconomics, microeconomics and non-economic events. Due to this problem of origin and identification, the exact connection between any measure of uncertainty to economic theory seems limited. However, two new measures of economic uncertainty have emerged recently, viz. Economic Policy Uncertainty (EPU) by Baker et al. (2015), and Econometric measure of uncertainty by Jurado et al. (2015). [8]

In this chapter, I have employed these two measures, a short description of the construction of which is presented next.

(i) Economic Policy Uncertainty

Baker et al. (2015) constructed their uncertainty measure on three components that largely incorporate all aspects of other measures in the literature. The primary component of this index is an extensive newspaper search of news regarding political and economic uncertainty. The authors observed policy-related news and articles from ten national newspapers, monitoring their frequency, exploring the nature of policy adopted and when it would be implemented. They counted the number of articles that contained a set of keywords, then adjusted the number and finally normalised it to a unit standard deviation. The news-based index has the highest weight among other index components. Baker et al. (2015) assigned a weights of $\frac{1}{2}$ to the news policy uncertainty. The next component is the federal tax law provisions expiring in the next 10 years and that is based on the Congressional Budget Office (CBO) data of provision for income taxes. This component has a weight of $\frac{1}{6}$ in the index. The last component of the EPU is a measure of forecasters disagreement on government purchase and inflation. The authors assign a weight of $\frac{1}{6}$ for both disagreements on government purchase and inflation.

[8] Ludvigson et al. (2015) have constructed a measure of uncertainty built on econometric measures that is similar to Jurado et al. (2015). In addition, other measures of uncertainty based on stochastic volatility such as Bloom (2009), or based on output such as Bloom et al. (2012) have added substantially to estimating uncertainty. Rossi and Sekhposyan (2015) provide a detailed review of a number of uncertainty indices and their applications.

(ii) Econometric measure of uncertainty

The econometric measure of uncertainty developed by Jurado et al. (2015) is very different from the economic policy uncertainty EPU, or any of the conventional proxies of uncertainty that is based on the cross-sectional dispersion of firm profits, the cross-sectional dispersion of subjective (survey-based) forecasts, implied or realized volatility of returns, stock market returns, or productivity. As the EPU stands for the "subjective" measure of uncertainty, I denote the econometric measure of uncertainty as being the "objective" one. Jurado et al. (2015) advanced this measure because they claim that the widely used conventional proxies do not reflect the true level of economic uncertainty. The authors demonstrate that "the conditions under which common proxies are likely to be tightly linked to the typical theoretical notion of uncertainty may be quite special" (Jurado et al., 2015, p. 1178). Jurado et al. (2015) exploited a data-rich environment to provide direct econometric estimates of time-varying macroeconomic uncertainty.

To illustrate the construction of their measure , Jurado et al. (2015) defined a $h-$period ahead uncertainty in variable $y_{jt} \in Y_t = (y_{1t}, \ldots, y_{N_y t})'$, and denote the same by $U^y_{jt}(h)$, to be the conditional volatility of the completely unforecastable component of the future value of the series:

$$U^y_{jt}(h) = \sqrt{E[(y_{jt+h} - E[y_{jt+h}|I_t])^2|I_t]} \tag{3.5}$$

where $E(.|I_t)$ is taken with respect to information I_t available to agents at time t. An (objective) measure or index of macroeconomic uncertainty is then described as an aggregation of individual uncertainty at each date using aggregation weights w_j:

$$U^y_t(h) \equiv plim_{N_y \to \infty} \sum_{j=1}^{N_y} w_j U^y_{jt}(h) \tag{3.6}$$

The distinguishing characteristic of this measure of uncertainty from other aggregate measures is its ability to eliminate forecastable components from a large number of macroeconomic and financial variables. Failure to do so often leads to estimates that "erroneously categorize forecastable variations as 'uncertain' ". It is argued that Jurado et al's. measure of uncertainty provides superior econometric estimates of uncertainty that are as free as possible from the structure of specific theoretical models, and from dependency on any single (or small number) of observable economic indicators.

Jurado et al's. estimates display significant independent variations from popular uncertainty proxies, suggesting that much of the variation in the proxies is not driven by uncertainty. Quantitatively important uncertainty episodes appear far more infrequently than indicated by popular uncertainty proxies, but when they do occur, they are larger and more persistent, and are more correlated with real activity. The authors argue that the estimates provide a benchmark with which to evaluate theories where uncertainty plays a role in business cycles.

For the purpose of the current paper, I use both objective and subjective (news-based economic policy uncertainty) measures of uncertainty.

3.3 Preliminary observations

(A) Sample

My study involves both full-sample (1960:07-2011:12) and sub-sample estimations. For the latter, I am particularly interested in understanding the effect of globalization, following which I divide the sample into two distinct periods, *viz.* pre-globalization (1960:07-1985:12) and post-globalization (1986:01-2011:12), assuming 1985 as the demarcation period. According to Claessens et al. (2011), the reasons for this are threefold, with the noticeable growth in global flows of trade and finance since the middle of the 1980s being the first. Second, the period from the beginning of 1970 to the early 1980s had witnessed sharp volatility in global energy prices, along with contractionary monetary policies in advanced economies. Finally, in the second half of the 1980s and during a period of great moderation and pre-globalization, the swings of business cycle volatilities had decreased substantially.[9] Moreover, with one exception (the growth rate of money, M2gr), all the variables which I use to discuss preliminary observations are included in levels. Fractional differences in output, labour productivity, real wages and other variables can be introduced to facilitate FCVAR estimation, but the key properties of the effect of uncertainty shocks to the macroeconomic system remain insensitive to this alternative specification.[10]

(B) Trend and persistence characteristics of data

(i) Trend

In Figures 1 and 2, I have plotted the 12 variables against time. While variables such as the two measures of uncertainty (EPU and H12), Federal Funds Rate and Hours depict noticeable fluctuations over time, other variables depict monotonic growth (around a

[9] Imposition of this exogenous break points is also supported by the Chow test for each of the 12 variables on the AR(1) values. The χ^2 values ranged from 21.121 to 29.039 with p-values = 0.000. Moreover, dynamic Markov Switching regression of these variables also evince that transition from one state to another is non-stationary: high persistence in one state, and low persistence in others. Results are available from the authors on request.

[10] I have undertaken estimation with fractionally differenced variables in the FCVAR estimation, and found that the main implications of the results do not change.

trend). All variables display evidence of changing mean and variances. This is also supported by figures in Tables 1 and 2. The last three columns in Table 1 present changes in mean across the 25th, 50th and 75th percentiles. It is evident that the mean of all variables differ significantly at 25th, median (50th) and 75th percentiles of the distribution. Moreover, the (static) correlation coefficient (in Table 2) also evince significant heterogeneity (both in magnitudes and signs) across percentiles and over two different measures of uncertainty.

Table 3.2: Descriptive statistics

Variables	N	mean	std. dev	min	max	p25	p50	p75
h12: Uncertainty	618	0.959	0.084	0.816	1.267	0.911	0.946	0.981
EPU: Uncertainty	618	1.207	0.453	0.318	3.095	0.930	1.243	1.466
log(CPI)	618	4.510	0.686	3.386	5.425	3.782	4.695	5.104
log(Industrial Production)	618	4.023	0.407	3.094	4.613	3.729	4.008	4.450
log(Employment)	618	11.276	0.290	10.714	11.658	11.033	11.317	11.580
log(real consumption)	618	3.785	0.495	2.844	4.522	3.415	3.811	4.230
log(PCE deflator)	618	3.966	0.613	2.954	4.773	3.312	4.141	4.495
log(new order)	618	11.531	0.307	10.699	11.968	11.318	11.558	11.802
hours	618	40.131	0.567	37.200	41.300	39.800	40.100	40.500
M2 growth	618	7.589	1.009	5.708	9.173	6.709	7.840	8.391
log(S&P 500)	618	5.594	1.101	3.984	7.339	4.579	5.459	6.833
Fed Funds Rate	618	5.667	3.502	0.070	19.100	3.380	5.265	7.600
log(Wage)	618	8.636	0.484	7.694	9.358	8.306	8.676	9.081

Table 3.3: Correlation at various percentiles of uncertainty

	EPU	EPU	EPU	H12	H12	H12
	p25	*p50*	*p75*	*p25*	*p50*	*p75*
CPI	0.601	0.294	-0.059	0.613	-0.150	-0.280
IP	0.689	0.204	-0.062	0.599	-0.188	-0.253
EMP	0.672	0.251	-0.068	0.646	-0.178	-0.296
RCONS	0.674	0.227	-0.037	0.625	-0.215	-0.264
PCEDEF	0.602	0.297	-0.060	0.611	-0.158	-0.299
RNORD	0.682	0.169	-0.070	0.550	-0.290	-0.450
hours	-0.010	-0.042	-0.073	-0.331	-0.522	-0.577
M2	0.657	0.288	-0.041	0.618	-0.178	-0.261
SP500	0.488	0.145	-0.044	0.454	-0.283	-0.314
FED	0.481	0.137	-0.095	0.534	0.730	0.580
WAGE	0.689	0.243	-0.037	0.653	-0.173	-0.224

Figure 3.1: Trend over time. Full Sample (1960:07-2011:12): Left [Objective measure of uncertainty (h1,h3,h12)(top), EPU measure of Uncertainty (middle), Industrial Production (bottom)], Right[Consumption (top), Employment (middle), and Hours (bottom)].

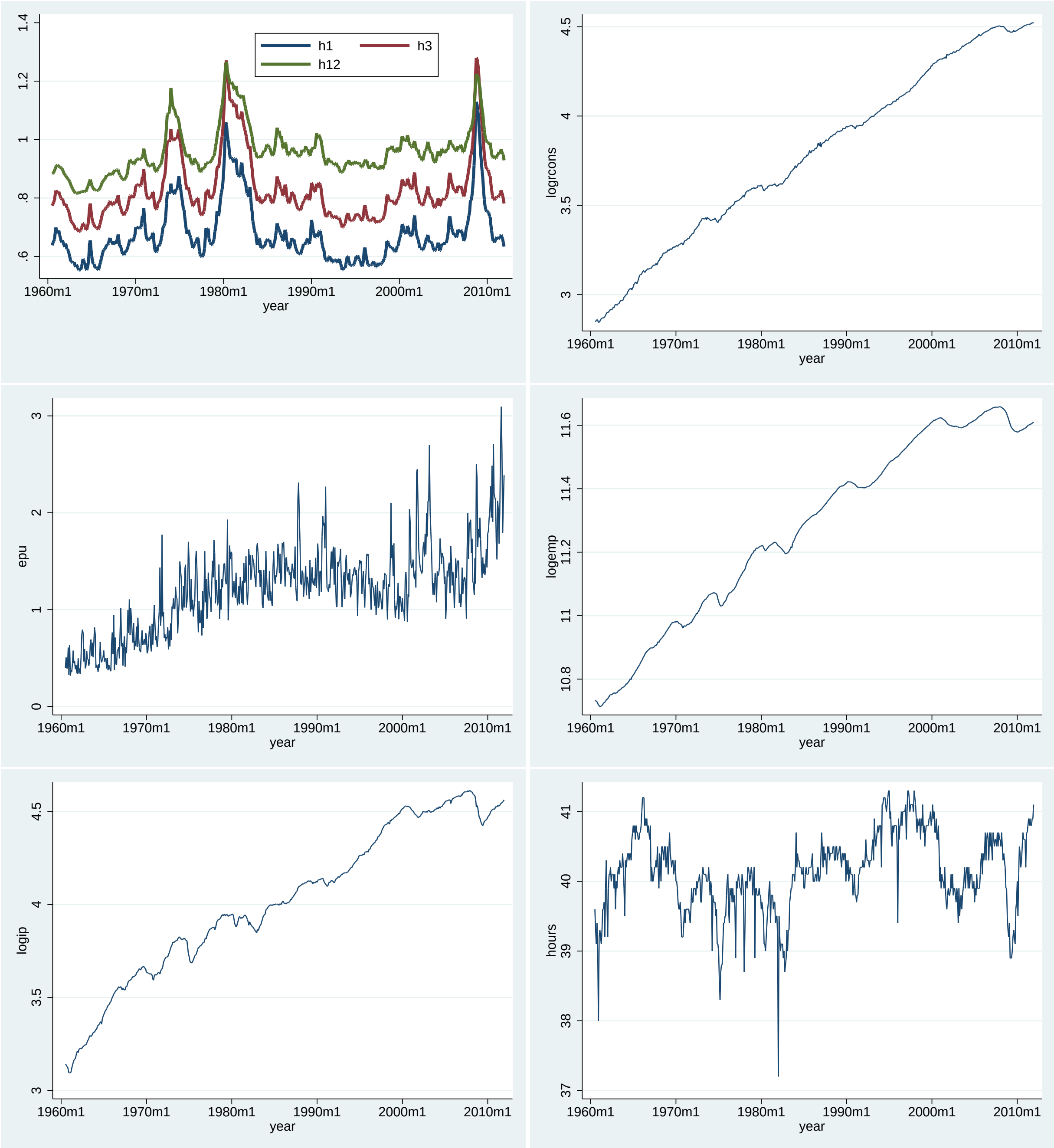
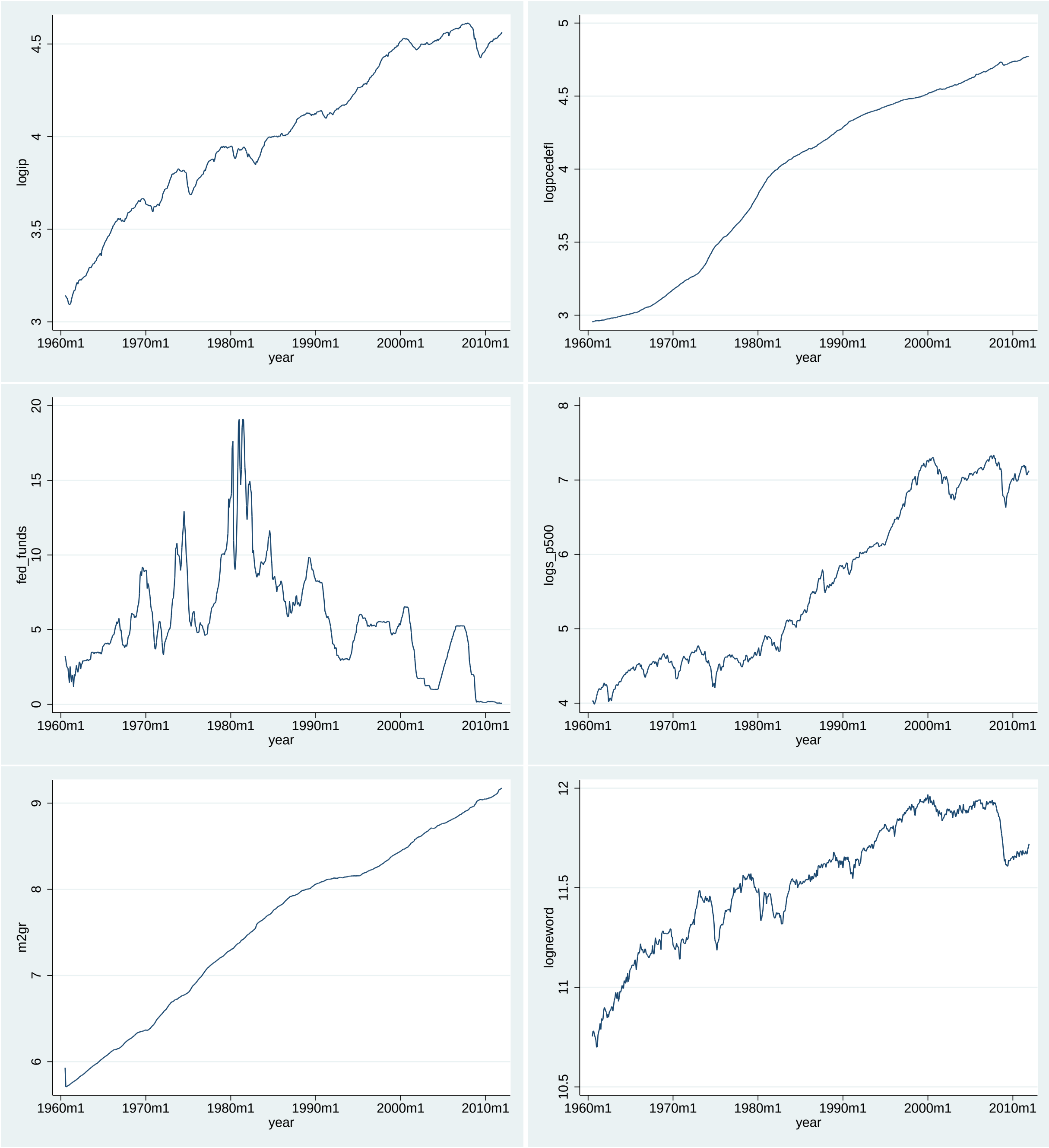


Figure 3.2: Trend over time. Full Sample (1960:07-2011:12): Left [Industrial production(top), Federal Funds Rate (middle), M2 growth (bottom)], Right[PCE Deflator (top), S&P 500 (middle), and New Orders (bottom)].



(ii) Persistence

Moreover, to verify that the FCVAR model (relevant properties of which are presented in the next section) is appropriate for my data, I examine each of my series individually before estimating the full multivariate system. First of all, I have plotted the autocorrelation function (ACF) (see Figures 3 & 4 in Appendix 1) and observe that the ACF of different variables display very slow decay over time.[11] In Figures 5 & 6, I have also presented the spectral density functions, the behaviour of which (i.e. greater mass near zero frequency) also support my initial assumption that these variables depict long-range dependence.

If a time series rejects both stationarity and unit root tests, this might suggest that the series is a fractional process.[12] Although the graphical plots provide informal evidence of the presence of long-memory/fractional integration processes, formal tests need to be carried out. In this regard, I employ two well-known methods, viz. Robinson's (1995) multivariate semiparametric long memory and Phillips' (1999) modified log periodogram regression.[13] The bandwidths used are $\tau = 0.45$, $\tau = 0.55$, and $\tau = 0.65$.[14] The results for each individual series are reported in Table 4.

The estimates in this table are based on the level of all variables except the growth of money supply (logarithmic difference). Variables in the stated forms have been used for estimation in several recent research papers, e.g. Christiano et al. (2005); Jurado et al. (2015), and I have followed the same. From Table 4, it emerges that the estimates of d vary considerably across the 12 variables. Note that both Robinson's (1995) and Phillips' (1999) estimates[15] are significant at the 1% level given the p-value 0.000 for all variables [results not reported to save space]. In case of the EPU measure of uncertainty, both methods present estimates in the range of 0.45-0.97, depending on the bandwidth. In comparison, Jurado15's H12 uncertainty also displays long-memory persistence (the

[11]The shaded area is the 5% significance band.

[12]Prior to obtaining estimates of d, I also tested for unit root in all variables. With linear trend and 18 lags, chosen according to Schwert's (1989) criterion, gave rise to following ADF test results: h12:Uncertainty (-3.263[-3.410]), EPU:Uncertainty (-3.153[-3.410]), CPI (-0.731[-3.410]), IP (-2.853[-3.410]), EMP (-0.968[-3.410]), RCONS (-2.455[-3.410]), PCEDEF (-0.795), RNORD (-2.419[-3.410]), hours (-3.378[-3.410]), M2 (-1.198[-3.410]), SP500 (-2.000[-3.410]), FED (-2.607[-3.410]), WAGE (-2.542[-3.410]). The 5% critical values are in [-]. In addition, I also performed KPSS test for stationary null hypothesis and I reject the hypothesis for each variable at 5% significance level [results not reported].

[13]Robinson (1995) estimates multivariate semiparametric long memory parameters, $d(g)$, of a set of time series. The parameter for each series is estimated from a single log-periodogram regression, which allows the intercept and slope to differ for each series. Phillips (1999) modified the Geweke/Porter-Hudak (GPH, 1983) estimate of the long memory parameter because GPH estimator is inconsistent against $d > 1$. The dependent variable in Phillip's (1999) modified log-periodogram is modified to reflect the distribution of d under the null hypothesis that $d = 1$. The estimator gives rise to a test statistic for $d = 1$, which is a standard normal variate under the null.

[14]Following convention, a choice of $\sqrt{T}$ is employed, although a range of other selections can be made. Accordingly, the nearest bandwidth in my case is 0.4 (with 13 ordinates). To check sensitivity, I also estimate for $\tau = 0.55$ (ordinates= 34), and $\tau = 0.65$ (ordinates =65).

[15]Phillips's (1999) modified log-periodogram estimates are based on trend-extracted series as suggested by the author.

estimates for Robinson's method for instance is in the range of 0.683-1.173). labour productivity variable (proxied by HOURS) also estimates d in the range of 0.323 to 0.808 considering both methods. These values are significantly smaller than 1. Other variables, such as CONSUMP, display estimates which are in the vicinity of 1 using both Robinson's and Phillips' methods. I have also estimated the d for the first-differences of the series (except M2gr, which is in growth form) and have found that d values fluctuate between 0.136 to 0.958 with some series, such as FED evincing over-differencing (results not reported). I therefore use level of variables in the FCVAR estimation in the following section.

Table 3.4: Estimates of fractional integration parameter, d

	$\hat{d}_{Robinson}$	$\hat{d}_{Robinson}$	$\hat{d}_{Robinson}$	$\hat{d}_{Phillips}$	$\hat{d}_{Phillips}$	$\hat{d}_{Phillips}$
	$T^{0.45}$	$T^{0.55}$	$T^{0.65}$	$T^{0.45}$	$T^{0.55}$	$T^{0.65}$
IP	0.946	0.967	1.003	0.788	0.956	1.164
EMP	1.039	1.018	1.019	0.997	0.997	0.995
CONSUMP	1.000	1.006	1.002	0.996	0.982	0.952
PCEDEF	1.052	1.025	1.014	0.968	0.969	0.94
NORD	0.951	0.965	1.025	0.904	0.992	1.096
WAGE	1.017	1.008	1.002	0.997	0.998	0.94
HOURS	0.358	0.693	0.808	0.323	0.599	0.796
FED	0.783	1.084	0.944	0.814	0.919	0.948
SP500	0.976	0.963	0.994	0.963	0.937	0.95
M2gr	1.009	1.000	0.995	0.994	0.987	0.958
EPU	0.676	0.770	0.623	0.979	0.716	0.454
H12	0.683	0.978	1.173	0.819	0.897	0.953

Note: All estimates are significant at 1% level as p-values for each estimate is 0.000

3.4 Econometric Model Specification and Estimation Issues

The starting point of fractional VAR (FCVAR) [see Johansen and Nielsen (2010, 2012, 2014)] is to allow for the possibility that the time series in question are fractionally integrated of order $d \in (0, 1)$ thus avoiding the knife-edge assumption of either stationarity ($d = 0$) or unit root ($d = 1$). Existing works which study the interrelationship between uncertainty (measured in different ways) and macroeconomic/financial variables employ the structural vector autoregressive (SVAR) framework (see Bloom, 2009; Jurado et al., 2015) with the proposition of a new identification scheme, making use of instruments (as in Ludvigson et al., 2015) and accounting for measurement error (see Carriero et al., 2015).

As explicated above, the use of SVAR in such analyses equips us to unravel the dynamic effect of uncertainty shocks on macroeconomic and/or financial variables, but the strict adherence to the propagation mechanism of shocks (i.e. consideration of either stationarity or unit root non-stationarity of variables in the VAR system) limits our understanding of cases where such shocks might display hyperbolic convergence. The study of the properties of long-memory in uncertainty and macroeconomic fluctuations is important, because as Silverberg and Verspagen (2003, p. 2) contend, "it is intermediate between a relatively unstructured stochastic world in which the present is just the summation of unrelated random events in the past (a random walk), and a rigidly predictable deterministic cycle or trend with relatively negligible, mean reverting stochastic disturbances." An imposing feature of long-memory mechanism is that it preserves the notion of the distant past continuing to influence the present in a somewhat law-like fashion. It also allows for developments at a range of time scales, with what appear to be trends at one time scale being revealed to be parts of irregular cycles at longer time scales.

To fully capture these properties within VAR, I employ the FCVAR mechanism of Johansen and Nielsen (2010, 2012, 2014). The properties and predictive capacity of FCVAR have been described in detail in the above mentioned papers. For my purpose I will only focus on the specification of the framework leading to the various hypotheses I will test.

As before, I let $Y_{i,t} = 1, \ldots, T$ be a p-dimensional $I(1)$ time series (for instance, all 12 variables or 8 variables).

$$\Delta Y_t = \alpha\beta^{'} Y_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta Y_{t-i} + \epsilon_t = \alpha\beta^{'} L Y_t + \sum_{i=1}^{k} \Gamma_i \Delta L^i Y_t + \epsilon_t \tag{3.7}$$

The simplest way to introduce the FCVAR model is to replace the difference and lag operators Δ and L in (3.7) by their fractional counterparts, Δ^b and $L_b = 1 - \Delta^b$, respectively. In general, for a time series $Y_{i,t}$

$$(1 - L)^d Y_{i,t} = \epsilon_t \tag{3.8}$$

where $\epsilon_t \sim (0, \sigma^2)$ is a gaussian fractional noise, I may thus study the shock convergence pattern of this system by looking at the decay of the autocovariance function along with the binomial expansion of $(1 - L)^d$, and the implications of limiting values of d are quite well known (in short, $0 < d \leq 1/2$ is a stationary short memory; $1/2 < d \leq 1$ is a long-memory process, whereas $d \geq 1$ is a unit root non-stationary process). I can then obtain

$$\Delta^b Y_t = \alpha\beta^{'} L_b Y_t + \sum_{i=1}^{k} \Gamma_i \Delta^b L_b^i Y_t + \epsilon_t, \tag{3.9}$$

which I apply to $Y_t = \Delta^{d-b} X_t$ such that

$$\Delta^d X_t = \alpha\beta' L_b \Delta^{d-b} X_t + \sum_{i=1}^{k} \Gamma_i \Delta^d L_b^i X_t + \epsilon_t. \tag{3.10}$$

Here, I follow convention and allow ϵ_t to be a p-dimensional iid process with zero mean and a covariance matrix represented by Ω.

Following Jones et al. (2014), I can follow the usual descriptions of the parameters from the CVAR model. Following the authors, α and β are $p \times r$ matrices, where $0 \leq r \leq p$. The columns of β represent the cointegrating relationships in the system, whereas the elements of $\beta' X_t$ represent the long-run equilibria relationship among the variables in the system. Moreover, the coefficients in α and Γ_i denote the rate of adjustment to the steady state and the short-run response of the variables, respectively. I begin with the assumption that $d = b$ and that there is a constant term for the cointegration relationship in the model (4.6). This gives rise to:

$$\Delta^d X_t = \alpha(\beta' L_d X_t + \rho') + \sum_{i=1}^{k} \Gamma_i \Delta^d L_d^i X_t + \epsilon_t. \tag{3.11}$$

In the above, μ can can contribute to the point that X_t initial values' are not observed. The model I estimate is

$$\Delta^d (X_t - \mu) = L_d \alpha\beta' (X_t - \mu) + \sum_{i=1}^{k} \Gamma_i \Delta^d L_d^i (X_t - \mu) + \epsilon_t. \tag{3.12}$$

In this case $\beta'\mu = -\rho'$ represents the mean of the stationary cointegrating relations.

I test a number of hypotheses on the model parameters relevant for my empirical analyses.[16] To facilitate the discussion of hypotheses in the empirical analysis, I describe here the general framework for hypothesis testing on α and β. Hypotheses on β can be formulated as $\beta = H\varphi$, where the known $p \times s$ matrix H specifies the restriction(s) and φ is an $s \times r$ matrix of freely varying parameters. Likewise, the restriction is placed upon each cointegrating relation, and the number of degrees of freedom of the test is expressed as $df = (p - s)r$. In a case when $r > 1$, one can impose various restrictions on β, i.e., $\beta = (H_1\varphi_1, \ldots, H_r\varphi_r)$ for known $p \times s_i$ matrices H_i and $s_i \times 1$ vectors φ_i containing the freely varying parameters in column i of β. In this case the degrees of freedom of the test is $df = \sum_{i=1}^{r}(p - r - s_i + 1)$. Similarly, hypotheses on α can be formulated as $\alpha = A\psi$, where the known matrix A is of dimension $p \times m$ and the matrix of the free parameter ψ is $m \times r$ with $m \geq r$. The degrees of freedom of the test is $df = (p - m)r$.

[16] Johansen and Nielsen (2010) note that the FCVAR model hypothesis testing will follow the general theory of hypothesis testing of the CVAR model. For example, the number of degrees of freedom is equivalent to the number of over-identifying restrictions under the null, and although counting the degrees of freedom is non-standard because of the normalisation required to separately identify, this issue applies in the same way to the CVAR model.

The FCVAR applied in my setting offers many significant advantages in contrast to the SVAR typically employed in the literature (Bloom, 2009; Jurado et al., 2015). Following Jones et al. (2014), the advantages of employing FCVAR are threefold. Firstly, one can decide on the fitting rank of the system that is the number of cointegration relations via statistical tests, such as likelihood ratio (LR) test-statistic. The rank or the long-run equilibrium relation is a stationary linear combination of the nonstationary series of both uncertainty and macroeconomic variables. Secondly, the short-run dynamics along with the adjustment coefficients tell us essential information about variables reaction to shocks based on both speed and magnitude. For example, because of the cointegration relation between economic uncertainty and macroeconomic variables, I find both uncertainty and stock market variables adjust to the long-run equilibrium path when a shock diverges the system towards disequilibrium. Also, I see that interest rate responds exogenously to disequilibrium. Finally, by employing FCVAR, one could assess the fit of the model and especially some of the underlying assumptions, such as serial correlation in residuals.

3.5 Analyses of FCVAR Results

3.5.1 Common characteristics

In this section I present and discuss results from the FCVAR estimation[17] of the effect of long-memory uncertainty on macroeconomic variables.[18] I begin by discussing the results of the 8-variables system, similar to Bloom (2009), and then extend the framework to include additional variables. An 12-variables system, similar to Christiano et al. (2005) and Jurado et al. (2015) is presented next. I consider both EPU and Jurado et al.'s (2015) objective H12 measures of uncertainty for each FCVAR system. Finally, I check the sensitivity of my results over stratified periods of pre- and post-globalization and pre- and post-financial crises. I also note at this point that, unlike Bloom (2009) I have not detrended any variables using the filter of Hodrik and Prescott (1997). I follow the arguments of Jurado et al. (2015) in this regard and assume that the data used in HP filter cover the whole series, so interpretation of the timing would become challenging.

[17]Nielsen et al. (2016) MATLAB FCVAR programme has been used for the purpose. Jones et al. (2014) provides an application of the FCVAR method.

[18]Bachmann and Moscarini (2011) examine how poor economic/financial conditions contribute to the increase in uncertainty. They mainly investigate the mechanism for which the deterioration in economic activity during recessions, for instance, influences firms to seek high-risk investments, which in turn generate more of both dispersion and volatility to income. They argue that firms tend to alter their strategies of profit generation after they experience the first-moment negative shocks. Following this argument, then the first moment shocks are the main reason for fluctuation in economic activities and uncertainty is just a result of that.

3.5.1.1 Model identification and hypotheses

A first step towards describing FCVAR estimation results is to determine the appropriate lag augmentation, k, of the whole system. I applied a general-to-specific testing procedure, for instance, I begin testing with a high lag order and then check in every level for the significance of the coefficient of the highest order lag. The sequential testing motivates us to drop the highest-order lag, if the null hypothesis is rejected, and subsequently, the model is re-estimated until I accept the null hypothesis. Moreover, I examine for possible serial correlation in each step of selecting the lag augmentation by using a multivariate Ljung-Box Q-test. Given the monthly frequency of my data, for this test (presented as $Q_l(h)$ where $h = 12$ lags, I perform the null hypothesis that the residuals are serially correlated. In each model, I start by testing with the highest lag of k = 3. The next step, after the choice of appropriate lag augmentation, is to determine the rank of the system. Once both lag augmentation and rank of the system have been determined, I would then proceed to testing the relevant hypotheses of the FCVAR system.

One such important hypothesis is to test if the model under consideration is cointegrated VAR (CVAR). I expect a rejection of this hypothesis if I believe that the system is actually characterized by fractional dynamics, i.e. FCVAR. Accordingly, I start with hypothesis where I test $H_1^d = 1$. This is paramount to testing the null hypothesis that $d = 1$, i.e. that the model is a CVAR. I can divide the remainder of the hypotheses to test on the cointegration on β parameters and test for weak exogeneity on the parameters. I do not recognise the parameters α and β without further normalisation restrictions (see Johansen, 1995). I place an identification restriction which normalizes the β matrix concerning uncertainty variables. The identification restriction in my results has helped us significantly to both examine and explain the equilibrium relation in the system. Also, exploring the long-run dynamics of each uncertainty variable separately would not be possible without imposing identification restrictions.

The main concern in my case is to find out whether macroeconomic and uncertainty variables construct a stable long-run relation. In case they do, I expect the effect of any (large or small) stochastic shock in uncertainty to macroeconomic variables to eventually vanish (possibly asymptotically). In the case that these variables do not form a stationary long-run equilibrium, then I can posit that shock to uncertainty has left a permanent effect on the growth trajectories of the macroeconomic variables. To test this prediction, I consider the following sub-hypotheses (see Table 5): H_1^d, and $H_1^\beta, \ldots, H_3^\beta$ which form this general hypothesis. H_1^β and H_2^β do not place any restrictions on the β coefficients of economic uncertainty and economic and financial variables, respectively. In case the rank of the system=2 or there are two cointegration relationships, then I examine whether one of the cointegration relations contains either only uncertainty or economic/financial variables, and the other contains either only uncertainty or economic/financial variables. I would confidently assume that I have a long-run equilibrium relation of both economic/financial variables and uncertainty if I eject all of the hypotheses of H_1^β, H_2^β, and H_3^β.

In addition, α denotes the rate of adjustment of the variables to the steady state in reaction to shocks to the system. The endogeneity and exogeneity situation of the variable in the matrix depends on the presence of $j-th, row = 0$. For the parameters α and β I will interchangeably refer to exogeneity as weakly or long-run exogenous. The main idea behind being weakly exogenous is that variables do not react to possible shocks to the system. In Table 5, $H_1^\alpha, \ldots, H_{11}^\alpha$ test whether each of the variables is individually weakly exogenous.

Table 3.5: Hypothesis test

H_1^d	The fractional parameter, d, is equal to one.
H_1^β	Uncertainty variables do not enter the cointegrating relation(s).
H_2^β	Economic/financial variables do not enter the cointegrating relation(s).
	and the other cointegration relation contains only economic/finance variables.
$H_1^\alpha, \ldots, H_{11}^\alpha$	All variables in the VAR including uncertainty are weakly exogenous.

3.5.2 Full Sample Results

3.5.2.1 Lag and rank selection

In Tables 6 and 7 (for EPU and H12 measures of uncertainty, respectively), estimates of d and b are reported for each $lag(k)$ with $rank(r)$ set to the number of variables in the system.[19] I consider here both 8-variables and 12-variables system. The log-likelihood for each lag is shown in column $LogL$. The likelihood ratio (LR) test-statistic is for the null hypothesis Γ_k = 0 with P-value reported in column p-value. This is followed by AIC and BIC information criteria. To account for serial correlation in residuals, I have performed estimation with 12 lags of all variables, firstly because I have monthly observations and secondly, this is consistent with the existing literature (see Jurado et al., 2015 for instance). Once I have established the appropriate lag length I can determine the rank of the system. In Tables 8 and 9 (for EPU and H12 measures of uncertainty, respectively), I report likelihood test results of cointegration equation. The first block of output presents a summary of the model specifications. The second block provides the test results relevant for selecting the appropriate rank. The rank test is intended to give us the information on the number of stationary cointegrating relations. Note that the table is meant to be read sequentially from lowest to highest rank, i.e. from top to bottom.

In case of VAR-8 for instance, I can reject the null of rank 0 against the alternative of rank 8; therefore I move to the test of rank 1 against rank 8. Since this test rejects the

[19] I have imposed restriction of $d = b$.

null hypothesis, I move to the test of rank 2 against 8. This test fails to reject with a P-value of 0.728, so this is the appropriate choice in this case. Similarly, for VAR-12, I proceed in similar fashion, and fail to reject the test of rank 3 against rank 11. With the lags selected, I now move on to unrestricted model estimation.

Table 3.6: Lag Selection Results: 8-variables and 12-variables FCVAR with EPU uncertainty

8-variables FCVAR								
k	r	d	b	LogL	LR	p-value	AIC	BIC
3	8	0.010	0.010	-6403.02	162.43	0.100	13336.05	14508.64
2	8	0.010	0.010	-6484.24	216.80	0.80	13370.48	14259.88
1	8	0.275	0.275	-6592.64	414.73	0.07	13459.28	14065.49
0	8	0.258	0.258	-6800.01	0.00	0.01	13746.01	14069.03
12-variables FCVAR								
k	r	d	b	LogL	LR	p-value	AIC	BIC
3	11	0.011	0.011	14519.65	525.34	0.09	-28047.31	-25851.70
2	11	0.499	0.499	14256.98	415.71	0.07	-27763.96	-26104.08
1	11	0.581	0.581	14049.13	1179.89	0.06	-27590.25	-26465.21
0	11	0.833	0.833	13459.18	0.00	0.01	-26652.36	-26063.67

Table 3.7: Lag Selection Results: VAR-8 and VAR-12 VAR with Objective uncertainty

8-variables VAR								
k	r	d	b	LogL	LR	p-value	AIC	BIC
3	8	0.181	0.181	9886.53	226.46	0.080	-19245.07	-18076.47
2	8	0.595	0.595	9773.3	254.3	0.050	-19146.61	-18261.31
1	8	0.653	0.653	9646.16	667.99	0.010	-19020.31	-18418.31
0	8	1.191	1.191	9312.16	0	0.00	-18480.32	-18161.61
12-variables VAR								
k	r	d	b	LogL	LR	p-value	AIC	BIC
3	11	0.011	0.011	16576.2	587.49	0.08	-32160.41	-29964.87
2	11	0.526	0.526	16282.46	393.89	0.04	-31814.91	-30154.98
1	11	0.685	0.685	16085.51	913.17	0.02	-31663.03	-30538.7
0	11	1.12	1.12	15628.93	0	0.00	-30991.86	-30403.13

Table 3.8: Likelihood Test for Cointegration Rank: 8-variables and 12-variables FCVAR with EPU uncertainty

8-variables FCVAR					
Rank	d	b	Log-likelihood	LR statistic	P-value
0	0.073	0.073	-6807.633	429.981	0.000
1	0.084	0.084	-6729.475	273.665	0.000
2	0.103	0.103	-6680.482	175.680	0.000
3	0.119	0.119	-6643.916	102.547	0.000
4	0.149	0.149	-6612.495	39.705	0.001
5	0.168	0.168	-6599.936	14.588	0.004
6	0.268	0.268	-6594.773	4.262	0.101
7	0.295	0.295	-6593.068	0.851	0.356
8	0.275	0.275	-6592.642	—-	—-
12-variables FCVAR					
Rank	d	b	Log-likelihood	LR statistic	P-value
0	0.363	0.363	14034.555	444.853	0.000
1	0.539	0.539	14080.085	353.793	0.000
2	0.508	0.508	14129.853	254.257	0.000
3	0.303	0.303	14170.768	172.426	0.000
4	0.329	0.329	14193.159	127.645	0.000
5	0.527	0.527	14208.821	96.321	0.102
6	0.531	0.531	14227.313	59.337	0.221
7	0.548	0.548	14240.769	32.425	0.229
8	0.516	0.516	14248.380	17.203	0.346
9	0.499	0.499	14255.526	2.911	0.573
10	0.499	0.499	14256.969	0.024	0.876
11	0.499	0.499	14256.982	—-	—-

Table 3.9: Likelihood Test for Cointegration Rank: 8-variables and 12-variables FCVAR with Objective uncertainty

8-variables FCVAR					
Rank	d	b	Log-likelihood	LR	P-value
0	0.415	0.415	9646.741	253.124	0
1	0.497	0.497	9694.707	157.192	0
2	0.518	0.518	9726.494	93.619	0.728
3	0.564	0.564	9744.968	56.671	0.763
4	0.549	0.549	9758.955	28.696	0.777
5	0.592	0.592	9766.373	13.861	0.809
6	0.592	0.592	9770.637	5.333	0.871
7	0.589	0.589	9772.844	0.918	0.877
8	0.595	0.595	9773.303	—-	0.891
12-variables FCVAR					
Rank	d	b	Log-likelihood	LR	P-value
0	0.414	0.414	16073.378	418.159	0
1	0.499	0.499	16121.912	321.092	0
2	0.482	0.482	16170.92	223.074	0
3	0.538	0.538	16203.017	158.88	0.344
4	0.521	0.521	16227.887	109.141	0.391
5	0.518	0.518	16247.445	70.025	0.523
6	0.538	0.538	16262.771	39.373	0.575
7	0.544	0.544	16271.855	21.206	0.678
8	0.534	0.534	16278.941	7.033	0.699
9	0.526	0.526	16281.204	2.507	0.701
10	0.526	0.526	16282.457	0	0.801
11	0.526	0.526	16282.457	—-	0.876

3.5.2.2 Unrestricted model

In the above, I was concerned with selection of lags and determination of rank of both 8-variables and 12-variables FCVAR systems. Based on these results, I have estimated both *unrestricted* and *restricted* models. In the case of the former, I impose no restrictions on the exogeneity of variables to the FCVAR systems; rather I allow all variables to affect all other variables (including its own) via their lags. In this setting, I am concerned with estimating the effect of (lag of) uncertainty on all variables in the system where I implicitly assume that disintegration of this effect depends linearly on the complex interdependence dynamics of all variables' effects within the system. I will break away from this assumption when I estimate restricted model, where I will introduce various restrictions with respect to the exogeneity of uncertainty and other variables in the system, paving the way to establishing if these variables are - at all - integral to the growth of all variables in the system. To begin with, I discuss results from unrestricted FCVAR.

As mentioned above, the estimations have been performed for both 8-variables and 12-variables systems with both EPU and H12 measures of uncertainty. Starting with the 12-variables system with H12 measure of uncertainty, I have noted from the preceding section that the rank of this system is, $r = 3$ and $k = 2$ (see Table 9). The estimated results are described in Equation (6.1) whereas the equilibrium relation is described in Equation (6.2). I have no evidence of serial correlation in the residual since the Ljung-Box Q-test has a p value of 0.548.

On the right-hand-side of Equation 6.1, I describe the estimated adjustment coefficients $\hat{\alpha}$ is shown by ν_t. This forms a stationary long-run equilibrium given by $\nu_t = \hat{\beta}'(X_t\hat{\mu})$. Moreover, the coefficients forming the long-run equilibrium are often normalized, in my case, with respect to the variable of interest, uncertainty. This is described by the constant term, $\hat{\beta}'\hat{\mu}$. The implication is that uncertainty is increasing in unemployment rates and decreasing in interest rates. I suppress the estimates of $\Gamma_{ii}^{2} = 1$ given that I am concerned with only the long-run dynamics.

Following on from this, I start testing the related hypothesis for my model, which I present in the hypothesis tests table. The first hypothesis is regarding the fitness and specification of my model, and whether it is a fractional or non-fractional process. This can be done by testing if H_1^d, i.e. that $d = 1$ to check whether the CVAR model is sufficient. Test result strongly rejects the hypothesis, implying that the model fractionally processes and CVAR model are not sufficiently specific compared with the FCVAR model. Next, I move on to test whether measures of uncertainty (both EPU and H12) are absent in the long-run equilibria. In this hypothesis, I do not place any restrictions on the coefficient of uncertainty variables. The LR test result of 56.33 for EPU and 71.98 for H12 in 12-var FCVAR suggest that I strongly reject the null hypothesis that uncertainty variables are out of the long-run equilibrium. Accordingly, I start testing the related hypothesis for my model, which I present in the hypothesis tests table. The first

Table 3.10: Hypotheses test: Full Sample

Full sample						
12-variables: FCVAR	EPU: Uncertainty			H12: Uncertainty		
	df	LR	p-value	df	LR	p-value
H_1^d	1	198.558	0	1	77.29	0
H_1^β	6	56.33	0	6	71.98	0
H_2^α	2	25.44	0	2	33.67	0
H_3^α	2	22.19	0	2	29.98	0
H_4^α	2	26.44	0	2	27.65	0
H_5^α	2	19.2	0	2	20.39	0
H_6^α	2	17.36	0	2	18.36	0
H_7^α	2	17.39	0	2	16.32	0
H_8^α	2	2.02	0.298	2	1.98	0.267
H_9^α	2	13.69	0	2	14.98	0
H_{10}^α	2	13.24	0	2	14.56	0.004
H_{11}^α	2	14.69	0	2	15.34	0.002
8-variables: FCVAR	EPU: Uncertainty			H12: Uncertainty		
	df	LR	p-value	df	LR	p-value
H_1^d	1	56.75	0	1	44.12	0
H_1^β	4	49.98	0	6	46.13	0
H_2^α	2	45.12	0	2	42.52	0
H_3^α	2	3.71	0.171	2	1.33	0.211
H_4^α	2	42.87	0	2	38.01	0
H_5^α	2	33.29	0	2	29.68	0
H_6^α	2	23.68	0	2	28.34	0.005
H_7^α	2	19.34	0	2	19.2	0.004
H_8^α	2	17.75	0	2	18.99	0.004

Note: The hypotheses are based on model specification (8 or 12-variables FCVAR). The results are for the full-sample period.

hypothesis is regarding the fitness and specification of my model, and whether it is a fractional or non-fractional process.

As there are no related β hypotheses, I proceed to tests of weak exogeneity on the α coefficients to decide on the variables reaction in the event of uncertainty shocks. I reject exogeneity of all variables, except interest rate (federal funds rate, H_3^α in 8-var FCVAR and H_8^α in 12-variables FCVAR. In both cases, and for both measures of uncertainty I do not reject the null hypothesis of exogeneity. Based on this model, I have estimated the restricted model, the results of which are described in Equation 6.2.

To better understand the α coefficients, take an example of a shock to federal funds that drives the system out of equilibrium. One can notice, from Table 11, a one per cent rise in the fed fund would show a surge in ν_t. I disregard the short-run dynamics in Γ_i and hold everything else fixed. As a reaction to a fractionally lagged rise in ν_t, the fractional change in uncertainty (EPU, for instance) is provided by α coefficient, which in this case is negative and therefore drives the system back to the equilibrium level as

$\nu_t = 0$. Moreover, the positive α coefficient on fed fund (FED) and labour productivity (HOURS) force it to rise and to drive the system to the equilibrium level.

The adjustment size suggests that economic uncertainty shifts to the level of equilibrium at a pace that is faster than the unemployment rate. With the restriction of weak exogeneity upon the fed fund rate, it does not seem to react to shocks to the long-run equilibrium. Fed fund rate reaction could imply that macroeconomic variables respond to the volatilities in uncertainty instead of the swings in the long-run equilibrium.

$$\Delta^{\hat{d}} \left(\begin{bmatrix} iip \\ emp \\ rcons \\ PCE \\ newOrders \\ rwage \\ hours \\ fedfund \\ S\&P500 \\ M2growth \\ Uncertainty(h12) \end{bmatrix} - \begin{bmatrix} 3.158 \\ 10.744 \\ 2.917 \\ 2.953 \\ 10.837 \\ 87.879 \\ 39.385 \\ 0.019 \\ 4.167 \\ 5.938 \\ 0.872 \end{bmatrix} \right) = L_{\hat{d}} \begin{bmatrix} 0.001 \\ 0.001 \\ 0.103 \\ -0.242 \\ -0.002 \\ 0.129 \\ 0.083 \\ -0.003 \\ 0.024 \\ 0.009 \\ 0.004 \end{bmatrix} \nu_t + \sum_{i=1}^{2} + \hat{\Gamma}_i \Delta^{\hat{d}} L_{\hat{d}}^i (X_t - \hat{\mu}) + \hat{\epsilon}_t \tag{3.13}$$

$\hat{d} = 0.482(p = 0.004)$, $Q_\epsilon(12) = 95.381(p = 0.548), LogL = 16203.017$

3.5.2.3 Restricted model

The restriction on β is then specified. There are two points to note here. First, the column length of R_β must equal $p1r$, where $p1 = p + 1$ if a restricted constant is present and $p_1 1 = p$ otherwise; recall that p is the number of variables in the system and r is the number of cointegrating vectors. As before, the restricted model is estimated, the residuals are tested for white noise, and the model under the null is tested against the unrestricted model. With a P-value close to zero, this hypothesis is also strongly rejected.

$$\Delta^{\hat{d}}\left(\begin{bmatrix} iip \\ emp \\ rcons \\ PCE \\ newOrders \\ rwage \\ hours \\ fedfund \\ S\&P500 \\ M2growth \\ Uncertainty(h12) \end{bmatrix} - \begin{bmatrix} 2.989 \\ 9.776 \\ 1.989 \\ 2.908 \\ 10.201 \\ 81.009 \\ 36.308 \\ 0.016 \\ 3.782 \\ 4.366 \\ 0.865 \end{bmatrix}\right) = L_{\hat{d}} \begin{bmatrix} 0.009 \\ 0.006 \\ 0.200 \\ -0.232 \\ -0.002 \\ 0.000 \\ 0.000 \\ -0.001 \\ 0.026 \\ 0.003 \\ 0.002 \end{bmatrix} \nu_t + \sum_{i=1}^{2} + \hat{\Gamma}_i \Delta^{\hat{d}} L^i_{\hat{d}} (X_t - \hat{\mu}) + hat\epsilon_t \tag{3.14}$$

$\hat{d} = 0.501(p = 0.003)$, $Q_\epsilon(12) = 98.366(p = 0.606), LogL = 161012.113$

From the results above one can find that the model specifications are defined accurately and most importantly the absence of serial correlation. Considering the number of restrictions that I have applied, I perform the Likelihood-ratio test for the model with certain restrictions against the unrestricted one. The LR test results prove that the restrictions are suitable by not rejecting the restricted model.

Table 3.11: Equilibrium relation (Partial effect of Uncertainty on Macroeconomic Variables: Full Sample

	12-variables FCVAR				8-variables FCVAR			
	Unrestricted	Unrestricted	Restricted	Restricted	Unrestricted	Unrestricted	Restricted	Restricted
	$\frac{\partial X_i}{\partial U^{H12}}$	$\frac{\partial X_i}{\partial U^{EPU}}$	$\frac{\partial X_i}{\partial U^{H12}}$	$\frac{\partial X_i}{\partial U^{EPU}}$	$\frac{\partial X_i}{\partial U^{H12}}$	$\frac{\partial X_i}{\partial U^{EPU}}$	$\frac{\partial X_i}{\partial U^{H12}}$	$\frac{\partial X_i}{\partial U^{EPU}}$
IP	-7.878	-6.499	-7.566	-6.501	5.981	4.841	5.222	3.798
EMP	2.07	1.308	2.11	1.288	1.091	0.889	0.872	0.704
CONSUMP	1.423	1.401	1.391	1.267				
PCEDEF	-0.247	-0.091	-0.246	-0.085				
NORD	-0.006	-0.002	-0.006	-0.001				
WAGE	-0.2	-0.34	-0.118	-0.33	-1.06	-0.884	-1.02	-0.978
HOURS	-0.019	-0.022	-0.018	-0.02	-0.016	-0.012	-0.011	-0.018
FED	0.533	0.871	0.546	0.797	0.466	0.448	0.398	0.567
SP500	-0.114	-0.198	-0.117	-0.151	-0.261	-0.202	-0.246	-0.289
M2gr	0.063	0.127	0.071	0.119				
CPI	-	-	-	-	2.336	2.591	2.205	2.611

Note: All coefficients are significant at 5% level.

3.5.2.4 Simulation and equilibrium forecast

In this section, I present the simulation results of FCVAR. There are two choices: the first is based on the restriction that the system is characterized by FCVAR not CVAR, i.e. where I test, $d = 1$. The second one is to use one of the restrictions on exogeneity of variables. One can use the interest rate (FED) model, as from my test it appears that this variable is not exogenous. However, to ensure sufficient flexibility, I have used the unrestricted model (while confirming that one but all variables are exogenous) with $d = 1$ imposed as the restriction. The simulated results for both EPU and H12 uncertainty are presented in Figures 7-9 (in the Appendix) (this also considers both 12-variables and 8-variables VAR). The equilibrium forecast based on the final model is also presented in these graphs (left panel). The figures are in the appendix.

Interesting patterns emerge: in general, both EPU and H12 based uncertainty reveal equilibrium adjustment which is fairly volatile. I do not find any specific trend or constancy of equilibrium adjustment due to uncertainty shocks. Interest rate and wages appear to experience very volatile equilibrium adjustment (in fact, there is a substantial degree of non-stationarity in the equilibrium relationship). In the 12-variables model, I find at least two non-stationary equilibria and nine stationary equilibrium relations (the adjustment is fairly flat and the linear predictions do not point to any oscillating pattern). Simulation of the model with 100 steps ahead forecast once again depict volatile patterns for interest rates, employment and productivity, with employment oscillating measurably over other variables in the system (see Figure 9). A similar pattern is noticed for real wages and industrial output (Figure 7 in the appendix).

3.5.3 Robustness check

From the full-sample results, it is clear that (policy) uncertainty significantly affects movement of macroeconomic variables. In particular, I found that output, employment, consumption and labour productivity fall with the rise of uncertainty, whereas the latter seems to motivate the growth of money supply and interest rates. There is mixed evidence of the stationary long-run equilibrium between uncertainty and macroeconomic variables. How sensitive are my results to the alternative definition of uncertainty measure and sample stratification? To account for the effect of the alternative measure, I employ H12 measure of uncertainty, following Jurado et al. (2015). For sample stratification, I am inclined to check the impact of globalization on the possible variable effects on the long-run equilibrium relationship between uncertainty and macroeconomic variables.

3.5.3.1 Alternative measure of uncertainty

As presented in detail in Section 3, (H12), the objective measure of uncertainty advanced by Jurado et al. (2015) is a significant step towards building a possible endogeneity free econometric estimate of uncertainty. I have used this measure to perform the first robustness exercise. The results are presented in Tables 1-11 and discussed in preceding sections. It is worth mentioning here that although I do not find substantive variation in the equilibrium relationship between the two measures, I have noted that the H12 measure displayed far greater magnitude of persistence than the EPU measure.

3.5.3.2 Pre- and post-globalisation period estimation

The second robustness test I am interested in is to stratify the sample to pre- and post-globalization periods (1960:07-1985:12, 1986:01-2011:12, respectively).[20]. Both H12 and EPU uncertainty measures are employed in FCVAR estimations. Led by the results from the full sample estimation, where I find that the effects of all variables under FCVAR-12 and FCVAR-8 were similar, however, for the purpose of sub-sample estimation, I only concentrate on FCVAR-12 (the results of 8-var estimations are available on request from the author). My univariate estimates of fractional integration parameter[21], d (using Robinson's semiparametric method and the bandwidth, $\tau = 0.45$) are presented in Table 13 (in Appendix 2). I choose this bandwidth because this value is close to $\sqrt{T}$ and for which the periodogram ordinates are neither too small nor too big. Key differences in results emerge with respect to persistence behaviour of the uncertainty series, in particular between pre- and post-globalisation periods. The magnitude of persistence for both EPU and H12 measures appear to be larger in the pre-globalisation (0.867, 1.235, respectively) than in the post-globalisation periods (0.604, 0.634, respectively). Moreover, the H12 measure is found to be more persistent than EPU for both periods. However, greater persistence of post-globalisation estimates is observed for variables such as IP, EMP, CONSUMP, NORD, HOURS, and SP500, whereas PCEDEF, WAGE, FED, and M2gr evince greater persistence in the pre-globalization periods. While I may not be able to provide the exact reason for such differences in the results, one possible reason could be the differences in the contribution of trend term in the pre- and post-globalization periods.

In Table 12, I have presented the FCVAR estimation for pre- and post-globalization periods, as well as for both EPU and H12 uncertainty measures. In addition, both 12-variables and 8-variables FCVAR have been estimated. In general, the post-globalization period estimates depict greater negative effects on industrial production, productivity

[20] I have also performed pre- and post-financial crisis (1960:07-2007:07, 2007:08-2011:12, respectively) estimations, but do not obtain substantially different results. The results are available with the author.

[21] Phillips' estimation has also been performed but the results are not included as the differences were not notable.

and output than the pre-globalisation period. This result is expected, and is consistent with earlier studies, athough the investigations were on the post-crisis period (see Bloom (2009) for details). To summarize, the predicted equilibrium relationship in the post-crisis period tends to be more volatile and appears unstable, irrespective of the measure of uncertainty used. Moreover, using both full and sub-sample estimations, I have been able to demonstrate that uncertainty is endogenously affecting the growth of macroeconomic variables. This result is consistent with the mechanism of endogenous growth theory, although uncertainty as a variable was assumed to be broadly exogenous. Using the FCVAR mechanism, I have also been able to establish the missing link between growth theory and general equilibrium method with the flexible method of shock propagation, as in FCVAR. My emphasis on the identification of non-stationary equilibria in both 12-variables and 8-variables model also presented new insights into the way the equilibrium relationship between uncertainty and macroeconomic variables evolves over time. This latter result is not identified in existing research.

Table 3.12: Equilibrium relation: Pre- and post-globalisation periods

Pre-globalisation								
	12-var FCVAR				8-var FCVAR			
	Unrestricted	Unrestricted	Restricted	Restricted	Unrestricted	Unrestricted	Restricted	Restricted
	$\frac{\partial X_i}{\partial U^{H12}}$	$\frac{\partial X_i}{\partial U^{EPU}}$	$\frac{\partial X_i}{\partial U^{H12}}$	$\frac{\partial X_i}{\partial Uncertainty^{EPU}}$	$\frac{\partial X_i}{\partial Uncertainty^{H12}}$	$\frac{\partial X_i}{\partial U^{EPU}}$	$\frac{\partial X_i}{\partial U^{H12}}$	$\frac{\partial X_i}{\partial U^{EPU}}$
IP	-6.881	-6.266	-6.85	-6.191	4.481	3.998	4.001	3.876
EMP	1.05	1.009	1.11	1.012	0.092	0.809	0.867	0.698
CONSUMP	0.987	1.231	0.909	1.201				
PCEDEF	-0.202	-0.102	-0.21	-0.103				
NORD	-0.112	-0.098	-0.16	-0.099				
WAGE	-0.239	-0.229	-0.201	-0.206	-1.21	-0.801	-1.02	-0.909
HOURS	-0.011	-0.016	-0.019	-0.018	-0.017	-0.013	-0.019	-0.017
FED	0.487	0.772	0.467	0.702	0.345	0.412	0.414	0.56
SP500	-0.098	-0.101	-0.091	-0.119	-0.25	-0.201	-0.255	-0.277
M2gr	0.054	0.1	0.05	0.102				
CPI	-	-	-	-	2.311	2.481	2.197	2.232
Post-globalisation								
IP	-7.912	-7.881	-7.901	-7.9	5.213	5.102	5.239	5.22
EMP	0.009	0.009	0.008	0.007	1.191	1.109	1.123	1.222
CONSUMP	0.498	0.496	0.489	0.488				
PCEDEF	-0.272	-0.269	-0.271	-0.27				
NORD	-0.221	-0.21	-0.226	-0.221				
WAGE	-0.239	-0.25	-0.241	-0.258	-1.982	-1.901	-1.776	-1.701
HOURS	-0.121	-0.213	-0.124	-0.223	-0.164	-0.155	-0.235	-0.265
FED	0.501	0.512	0.487	0.498	0.503	0.501	0.45	0.601
SP500	-0.114	-0.118	-0.101	-0.124	-0.269	-0.232	-0.269	-0.345
M2gr	0.112	0.116	0.102	0.12				
CPI	-	-	-	-	2.448	2.556	2.99	3.01

3.6 Conclusions

In this paper I investigated ex-post uncertainty and its impact on the real economy, employing two measures of uncertainty, economic policy uncertainty (EPU) by Baker et al. (2015), and econometric measure of uncertainty by Jurado et al. (2015). Although EPU has recently gained popularity for the analysis of policy-related disturbances, its main drawbacks lie in its inability to reflect 'true uncertainty', because it fails to provide a rationale for the decision-making process by drawing extensively from economy-wide data. Jurado et al. (2015) focus instead on ameliorating these limitations by econometrically extracting the unforecastable component of uncertainty and providing a measure which can be used directly in macroeconomic analysis without subjecting the estimation to possible endogeneity issues.

My analytical model was able to uncover two interesting results. First, it showed that a long-memory in uncertainty series (whichever way measured) can generate a system-wide long-memory shock in macroeconomic variables, making the system exceedingly complex to lend any direct predictive power. Second, by invoking the level and growth effect of uncertainty on macroeconomic system, I was able to show - following leads from recent literature - that the fractional differenced economic system displays properties of endogenous growth mechanism. My model was able to predict that highly persistent uncertainty shocks can generate either a 'cyclical' or a 'monotonic' positive/negative effect on various macroeconomic and financial variables.

My empirical analysis covers fractional cointegrated VAR/VECM with two VAR systems (12-variables and 8-variables), which have been well-investigated in the literature. With two measures of uncertainty and the two VAR systems, my investigation covered both full sample and sub-sample estimations, where the latter was intended to estimate the effects over certain structural changes, viz. globalisation and financial crisis. In general, the two FCVAR systems evinced that 'uncertainty' occupies a central role in the dynamic interdependent behaviour of the macroeconomic systems. My estimates reveal that the VAR systems I have considered are characterized by fractional dynamics, rather than by pure unit root non-stationary behaviour. The post-globalization and post-financial crises effects revealed higher long-memory persistence than the pre-globalization and pre-financial crisis periods. Evidently, these structural changes seem to have infused higher volatility in the behaviour of macroeconomic variables than would have been the case otherwise. The simulated results and the predicted equilibrium relationship among these variables across model estimations and VAR systems evinced fairly unstable behaviour. These results coincide with the Great Moderation period. Indeed, several papers have documented a change in volatility in macroeconomic variables from the mid-1980s until the financial crisis.

Finally, my study has some implications for policy. In light of the estimation of the magnitude of long-memory shocks in uncertainty and other variables, it can be concluded that policies aiming at smoothing out the effect of such shocks should take into consideration the time profile of effects. That is, medium-term countercyclical policies can best limit the proliferation of shocks and contain the persistence leading to system-wide chaos in the long-run.

Chapter 4

Global Policy Uncertainty, Memory and Money Demand: The Saudi Arabian Context

4.1 Introduction

The money demand literature has experienced a robust growth over the past four centuries, investigated primarily in the context of developed economies. There is an observed sparseness of research in both developing countries and countries in the Middle East. The importance of the latter two is significant, especially the Middle East countries, due to their perceived impact on world economies through oil exports and strategic economic positioning in the globe. The Saudi Arabian economy's growing impact on world trade is now well known, and has been sharply felt in recent years, thanks to the dynamics related to 'oil economies'. In view of the recent trend in global economic and financial uncertainty, a characterization of the money demand function for this economy has now become more important than ever. The current chapter hence presents an exhaustive study of the money demand function for Saudi Arabia. A dynamic link with global economic policy uncertainty is established and a predictive outcome of this relationship is well-defined.

Recent developments in the money demand literature have highlighted the effect of economic uncertainty and its contribution to the stability of money demand function. The reason is that fluctuations in uncertainty are highly correlated with the demand for liquidity in any economy. In a definitive way, heightened demand for money reflects on the speed of movement of liquid cash and its impacts on inflation. Macroeconomists, as well as monetary theorists, have consistently argued that uncertainty in an economy impacts the stability property of the demand for money. Indeed, a good deal of empirical research lately has investigated whether economic uncertainty has any impact on the amount of money demanded, and if so, in what way? Thanks to the availability of state-of-the-art econometric tools, in-depth research on the dynamic interdependence of various factors affecting money demand has begun to beget robust predictive power. An analysis using 'co-movement' of variables is one of the direct ways to test for stability in the observed relationship. We exploit recent developments in cointegrated vector autoregression method, and allow free movement of shocks having divergent convergence properties to test for the range of values within which the money demand function is stable.

Stability of money demand has an immediate implication for implementing inflation-targeting policies. However, any inaccurate information on tackling unstable money demand may lead to an inefficient inflation-targeting policy. The result could be a system-wide macroeconomic failure. In this chapter, we build on the econometric development in Chapter 2 with regard to a fractionally cointegrated VAR system, and thoroughly investigate the stability of the money demand function once we include - along with other determinants of money demand - a measure of economic uncertainty. This way, it will be possible to map the effects of shocks on the long-run equilibrium of money.

Thus, a contribution of this research is to introduce the persistent role of uncertainty shocks on money demand behaviour when all determinants of the money demand function are allowed to be dynamically interdependent, and possess significant convergent as well as non-convergent shocks to the long-run mean. Within this environment we study the ability of the money-demand system to converge to a well-defined steady state equilibrium. Our context of investigation is Saudi Arabia (detailed motivation for this country context has been outlined in Section 3). The heterogeneous convergence-pattern of shocks to the long-run mean can be modelled via a fractional integration approach. The cointegration relationship that is confounded on fractional orders of integration would imply that a non-linear and part stable and part unstable money-demand function may exist within the same cointegration domain. For some ranges of values, a fractional cointegration of various determinants of money demand function may imply that an inherent stability of money demand function is possible, whereas in the conventional sense, it may not exist at all. The slow-convergence of shocks within a cointegrated VAR indeed has implications for selective monetary policy, as a policymaker may adopt a differential approach to treating shocks within a money-demand function and map-out strategies to treat the heterogeneous nature of stability of the money demand function.

4.1.1 Context of Saudi Arabia

According to Bloom (2009), uncertainty shocks impact developing countries more than developed nations. The vast majority of recent literature focuses on the case of well-developed economies, such as the U.S. and U.K. One of the features of some developing and emerging economies is the significant and essential role of government in the overall economy (Firth et al. (2013)). The absence of empirical research in the context of developing countries undermines the recognition of some of the economic/financial issues, especially in the phenomenon of globalisation. What makes investigating the role of uncertainty in developing markets exceptionally essential, other than the severity of the shock, is that some of these economies are completely surrounded by uncertainty and political instability.

Being a member of the G-20 group, and the largest oil exporter and producer with a currency pegged to the U.S. dollar, whilst being located in the most unstable region in the world, the case of Saudi Arabia offers a significant and unique setting to investigate the role of uncertainty shocks on money demand. At about nine times the size of the United Kingdom, Saudi Arabia is regarded as among the most influential economies in the world. It is the largest producer and exporter of the primary energy source, and the largest economy in MENA countries. According to The Organization of the Petroleum Exporting Countries (OPEC) Annual Statistical Bulletin (2018), Saudi Arabia has the second largest oil reserve and, as one of the founding members of (OPEC), it has been in the driveing seat in controlling the supply/demand of the crude oil market, according to Mohaddes and Pesaran (2016).

In addition to the wealth of natural resources, Saudi Arabia has a prime strategic location in the intersection of three continents, being the destination of Muslims from around the world. Makkah and Medina, the first and second holy cities of Muslims, are located in the western part of the country, which millions of Muslims visit them every year. The prime position and the wealth of resources do not come free of hurdles, however, and exert significant challenges on the Saudis economy. The economy in Saudi Arabia is government-led, and mostly depends on government spending.

To cover current and capital expenses, the government is heavily dependent on oil revenues, which represented about two-thirds of the total revenue in 2017 and about 90% in 2013. Exposure to oil price fluctuations became a source of uncertainty to the Saudi economy, which could clearly be seen in the low oil prices of 2014/2015. Estimates show the annual deficit and surplus in comparison to oil prices. In addition to oil price fluctuation, Saudi Arabia is bordered by political instability, particularly since the Arab Spring of 2011/2012.

In addition to the above discussion, what makes the Saudi money demand unique is its exchange rate. Saudi Arabia is an open economy and has adopted a fixed exchange rate since 1986, at $3.75. According to Al-Jasser and Banafe (2005), and Jovanovic and Petreski (2012), by adopting a fixed exchange rate, Saudi Arabia has, to some extent, a passive role over monetary, but not fiscal policy. The monetary policy follows closely the U.S. dollar interest rate, since the Saudi Arabia Monetary Agency (SAMA), the Saudi central bank, utilises it to safeguard the exchange rate. Therefore, the central bank has little room for monetary policy manoeuvre. Nevertheless, an open economy with a fixed exchange rate should be able to limit this effect, if it has a high level of forex[1] reserves, according to Jovanovic and Petreski (2012). In the case of Saudi Arabia, which has about $500 Billion in forex reserves, the fourth-largest foreign exchange reserves in the world, could depend on its forex reserve to manage, to some extent, an independent monetary policy.

Being in the Middle East, in an open emerging market deeply reliant on natural resources, with its currency pegged to the U.S. dollar, Saudi Arabia is the perfect setting to investigate the role of shocks in economic uncertainty to the demand of money.

4.1.2 Uncertainty and money demand: general context

To provide a general context of the interlinkage of money demand and its determinants, an insight into the Federal Reserve Bank's policy in the U.S. merits attention. A well-known criticism exists with regard to the Fed's decision to switch its policy in 1979

[1] foreign exchange reserves.

from fixing interest rates to controlling monetary aggregates. Arguably, it missed its inflation target, which prompted severe criticism of the quantity theory of money and its breakdown. However, Friedman (1984) argued that the 'Fed not only should target monetary aggregates but should also aim at achieving a steady and predictable growth rate of those aggregates'. Friedman showed that the unusual volatility of monetary growth gives rise to uncertainty, leading perhaps to an increase in the money holdings of the public and a decline in the velocity of money. Hence, Friedman (1984) identified monetary uncertainty as another determinant of the demand for money. It is possible to argue that if monetary uncertainty could affect the public's desire to hold less money, so too does the uncertainty associated with the job market or production. Choi and Oh (2003) developed a theoretical model and showed that indeed, output uncertainty can also affect the demand for money. The authors showed that uncertainty resulting from output propels the public to face uncertainty in job prospects, forcing them to allocate more of their assets towards holding cash, and less towards other uncertain assets.

Among important oiece of research, by Brggemann and Nautz (1997) examined the impact of monetary uncertainty on the demand for money in the case of Germany. As opposed to Friedmans argument, the authors found monetary uncertainty (which is measured by the volatility of the money supply) has a negative impact on the demand for money in Germany. However, researchers such as Choi and Oh (2003) tested both hypotheses (effects of monetary uncertainty and economic uncertainty) using data from the United States, and found that, while monetary uncertainty increased the demand for money in the USA, economic uncertainty measured by the volatility of real GDP actually decreased it. The authors then went on to demonstrate that both uncertainty measures could have negative/positive effects on money demand, depending upon the degree of substitution between money and other less volatile assets. Other authors (such as Bahmani-Oskooee and Xi (2011)) have tested these hypotheses using cross-country data (such as data from Australia), and have produced similar findings to Choi and Oh (2003). In particular, the authors found that, while both economic uncertainty and monetary uncertainty had *short-run effects* on the demand for money in Australia, only economic uncertainty exerted *long-run positive effects*. Contrasting results appeared in the case of China, where Bahmani-Oskooee et al. (2012) found that while both uncertainty measures had short-run effects, only economic uncertainty had long-run negative effects on the demand for money. Finally, in considering the case of some emerging economies, Bahmani-Oskooee et al. (2015) were able to conclude that both measures of uncertainty possessed more short-run effects than long-run effects.

4.1.3 Why would money stock follow a long-memory?

To explicate this, we follow the development in Chapter 3 and exploit Robinson's (1995) and Granger's (1980) aggregation argument.

Our illustration involves a measure of money demand of a country, indexed by c. We assume that at sub-categorical level i, money demand is governed by an autoregressive process (denoted by Z_t):

$$z_{i,t} = \alpha_{i,1} + \alpha_{i,2} z_{i,t-1} + u_{i,t} \tag{4.1}$$

$\alpha_{i,2}$ can be 0 or it can be 1. If $\alpha_{i,2}$ is assumed to be distributed as $\beta(u, v)$, then $\frac{1}{N}\sum_1^N z_{i,t} = z_t \sim I(d)$. The important point here is that the autoregressive coefficients $\alpha_{i,2}$ differ across i. Some components have coefficients $\alpha_{i,2} \approx 0$ and can be referred to as 'random' components, whereas others have coefficients $\alpha_{i,2} \approx 1$ and are referred to as 'regular' components. If we assume that the distribution of $\alpha_{i,2}$ across components follows a $Beta(u, v)$ distribution, then the aggregate money demand $Z_t = N^{-1}\sum_{i=1}^N z_{i,t}$ is fractionally integrated or order $d = 1 - v$ when N is large. Another related argument is that since money (such as M3) can be observed at a fairly smaller time units, the aggregation can also give rise to a long-memory characteristic.

4.2 Related literature on money demand and stability

The demand for money is based on people's willingness to hold their assets and wealth in the form of cash. In macroeconomic analysis, money demand is an essential tool to implement effective monetary policy. It is crucial to know what encourages people to demand money, and what factors are associated with the increase or decrease in the demand? There are a number of factors which could explain the standard money demand model, including interest rate, income and inflation.

The theoretical expression of money demand is as follows:

$$M^d P = f(Y_p, r_b - r_m, r_e - r_m, \pi_e - r_m) \tag{4.2}$$

In the formula, M^d/P is the choice of real money balance. Y_p denotes wealth or in Friedman's connotation, permanent income, which is theoretically the discounted value for all future incomes. Expected income; represents the expected rate of return of the currency; r_m is the expected rate of return of the stock; r_b is the expected rate of return of the bond; π_e is the expected rate of inflation. Importantly, Friedman (1956) showed that money demand depends crucially on the total wealth level, but 'the total wealth level cannot be specifically measured, so only permanent income can be used instead of unstable expected income'. In theory, money demand will increase as permanent income increases. Taking the case of the USA, Friedman showed that the demand for money is determined, among principal factors, by long-term income, whereas interest rate was found to exert little effect. However, long-term income is stable. Therefore, the long-term demand for money is relatively stable.

Researchers suggest a number of variables to describe money demand function. They suggest that an opportunity cost of holding money, along with inflation and income, forms the backbone of cash demand. Since then, other variables have been introduced to the function, such as exchange rate (Mundell (1963)), monetary uncertainty (Friedman (1984)), and monetary and output uncertainty (Choi and Oh (2003)). Interest rates and income are the two variables that have been widely used in the standard money demand model (Atta-Mensah (2004); Bahmani-Oskooee et al. (2015)). Moreover, the high level of economic uncertainty surrounding the world economy could contribute largely to the stability of the money demand.

Carpenter and Lange (2002) included stock market volatility (as a measure of uncertainty) to examine the effect on the money demand in the U.S. They found a positive relationship between stock market volatility and money demand. The early theoretical work of Choi and Oh (2003) examined the effect of both economic and monetary uncertainty, measured, respectively, by output and money growth volatility on the stability of money demand M1 in the U.S. They found that economic uncertainty has a negative impact, while monetary uncertainty has the opposite effect on money demand. According to Choi and Oh (2003), high uncertainty could increase the precautionary and substitution effects which lead to preference for holding a less volatile and liquid asset. Their findings show that it is crucial to include uncertainty to improve the stability and usefulness of the money demand.

Atta-Mensah (2004) constructed an economic uncertainty index using the volatility of five proxies: stock market, inflation, exchange rate, interest rate and GDP. These proxies were estimated using GARCH to form the index, and to be included in the money demand function for the Canadian economy. He argued that money demand function could be improved with the inclusion of macroeconomic uncertainty. He found that the inclusion of economic uncertainty variable has a short-term impact on money demand. Moreover, Lemke and Greiber (2005) reached the same conclusion that including macroeconomic uncertainty measure improved money demand stability in the U.S. and Europe. Choi and Oh (2003), Atta-Mensah (2004) and Lemke and Greiber (2005) concluded that economic uncertainty has played an important role in determining the demand for money in the long run, since liquidity preference is associated with uncertainty. Nevertheless, in the context of the Euro area, Bruggeman et al. (2003) found no significant long-run relationship between stock market volatility as uncertainty measure and money demand. Carstensen (2006) employed GARCH model to estimate stock market volatility to be included in the money demand, and found that volatility in the stock market and equity return could contribute to money demand stability.

The most recent investigation of the effect of economic and monetary uncertainty on money demand, M3 was by Bahmani Oskooee and Xi (2011). They generated uncertainty measures using both GARCH model, and by taking the volatility of real output and nominal money supply. Then, they added the two measures of uncertainty to the money demand in Australia as additional determinates. They found both uncertainties have short-run effect, while output uncertainty has a long-run impact on Australian money demand. Furthermore, Azim Ozdemir and Saygili (2013) argue that investors' confidence, uncertainty, measured by the volatility of the stock market, inflation, output and GDP could contribute to the stability of the long-run money demand in Turkey. In the context of the coingtegrated VAR, they concluded that the introduction of uncertainty variable in the money demand function is crucial in the estimation of stable money demand. Moreover, with the exclusion of the uncertainty variables, they found no cointegration relation in their model. Similarly, during the time of the recent financial crisis, Cusbert and Rohling (2013) examined what triggers money demand in Australia. They found that money demand increased during times of high uncertainty and financial market stress. Most of the surge in currency is due to precautionary holding during times of economic uncertainty.

4.3 Data and Preliminary evidence

4.3.1 Data

Our study involves monthly data for Saudi Arabia covering 244 months. The sample span is from 1997:01 to 2017:05. For economic policy uncertainty, we employ the Global Economic Policy Uncertainty index as in Baker et al. (2014). We follow the extant literature and propose a general description of money demand function, consisting of five variables in total: Money stock $M2$ (real quantity of M2 monetary aggregate), Disposable income ($RPDI$), inflation (CPI), interest rate (LIR), global economic policy uncertainty (EPU). While exchange rate (ER) is also included in empirical research, we do not use this variable in our money-demand system, as Saudi Arabia's exchange rate is pegged to the U.S. dollar. Moreover, it should be noted that there is no available economic policy uncertainty measure for Saudi Arabia. An alternative would be to follow convention and use volatility in the stock market as a measure of uncertainty. But, research shows that stock market volatility is a poor measure of uncertainty, given that this measure omits political opinion and various macro-monetary decisions taken at the economy-wide level. Being an oil-exporting country, Saudi Arabia's economy is governed significantly by uncertainty at the global level. Therefore, we use global economic policy uncertainty measure, as in Baker et al. (2014). The data have been hand-collected from various volumes of publications/reports of official statistics from Saudi Monetary Agency (SAMA).[2]

[2]Longer time series for variables such as interest rates and disposable income per capita have been gathered after paying a subscription fee.

We assume that the demand for money is positively correlated to disposable income, as from economic theory, we know that higher income leads to higher demand for money (implying higher velocity due to the increasing tendency of spending). Demand for money is also assumed to be negatively related to interest rate (LIR), as LIR captures the opportunity cost of holding money against cash. Moreover, there is another opportunity cost of holding money against real assets - the inflation (measured by $\ln(P_t/P_{t-1})$). The empirical assumption is that demand for money has a negative relationship with inflation, and the same is true with global economic policy uncertainty. With increasing uncertainty, consumers often resort to the strategy of saving (so that they can protect themselves against an uncertain future). This leads to an observed negative empirical relationship with the demand for money. We estimate this five-variables system using our proposed FCVAR model.

4.3.2 Preliminary evidence

In Table 4.1 we present data characteristics and describe the central tendency of each variable, along with the percentile distributions. There is an observed variation in mean across quantiles, for instance, for the global EPU, the 25th percentile of the distribution has a smaller mean of 95.478, whereas at the 75th percentile, the value of the mean rises significantly to 145.804. This tendency of an increase implies a growing level of uncertainty across the whole range of distribution, providing indirect evidence of a rising trend in uncertainty at a global level. The mean M2 remains more or less constant across distribution, with a smaller standard deviation of 0.174. Contrarily, CPI depicts significant variability across percentiles and depicts great volatility represented by very high standard deviation (70.273).

Table 4.1: **Descriptive Statistics**

variables	N	mean	sd	min	max	cv	p25	p50	p75
M2	521	1.830	0.174	1.437	2.208	0.095	1.721	1.792	1.943
RPDI	521	90.099	41.871	30.431	167.021	0.465	53.787	83.393	128.930
LIR	521	4.565	3.339	0.000	14.700	0.731	0.600	4.960	6.550
CPI	521	120.513	70.273	29.150	241.002	0.583	45.600	116.200	179.600
EPU (global)	521	122.114	46.281	30.307	350.712	0.379	95.428	121.740	145.804

In the Appendix, we present various time series plots of money demand and its determinants. We also present ACF, spectral density function and estimates of long-memory, including the rolling window estimation of the memory parameter d (this is done to check for sensitivity of memory estimates to the rolling window size of time). The figures (time series plots) depict conventional pattern of trends implying the presence of stochastic time series. Some variables show a noticeable fluctuation over the time horizon, while others display a growth trend. All variables depict a possible non-mean reversion. The spectral density function is an indirect, but visual way of deciding whether the time series possess significant memory. To infer this, we study whether each series possesses a mass frequency close to the origin, zero. In the event of a significant mass around zero, there is evidence of long-memory. Indeed, mass near origin implies that there are enough observations with long-range dependence at low frequency. At higher frequencies, we expect a small number of observations where higher frequency in the spectral domain implies that very few observations have zero or insignificant time dependent patterns. From this perspective, and having studied the spectral density of all variables within our money demand system, we find that there is irrefutable evidence of significant long-memory.

This conclusion can be strengthened by studying the estimates of d for various bandwidths and window size. We follow the Exact Local Whittle (ELW) of Shimotsu and Phillips (2005) as a semi-parametric estimator to evaluate the memory parameter d in fractionally integrated process. Various tables in the Appendix show the statistics of the 2 steps (ELW) with various bandwidth, viz. $m = T^0.6$, $m = T^0.7$ and $m = T^0.8$. We conclude that with the Exact Local Whittle (ELW) estimator for different bandwidth, we find fractional integration for each series, confirming the presence of long memory in the money-demand system. It is evident that all estimates of d (there are several robustness checks with respect to bandwidth, differencing, demean-detrending and removal of business cycles features) present significant long-memory. These robust findings motivate us to estimate a fractionally cointegrated VAR as opposed to a simple cointegrated VAR. In view of our interest in studying the stability of money demand, a fractional cointegration VAR holds significance in terms of the relative convergence of shocks to the long-run mean and the nature of the cointegration relationship among determinants of $M2$.

4.4 Estimation strategy

Since our objective is to exploit the rich properties of fractionally cointegrated VAR (FCVAR), to minimize repetition we only present here key equations required for the development of our hypotheses. Chapter 3 details the methodological descriptions and outlines various properties of short and long-run adjustment parameters under slow convergence of shocks. Interested readers are referred to Johansen (2008) and Johansen and Nielsen (2012), for details on the usefulness of long-memory in the identification of error corrections and cointegrating relationship(s) among variables. We follow these authors and provide a clear identification of the money demand via the properties of long-memory within the FCVAR model, where various determinants are allowed to be dynamically interdependent over time. The path-dependent structure of variables experiencing slow-convergence of shocks form the key to the modelling and identification of money-demand function.

Denoting money aggregate by y_t and assuming that it is governed solely and exogeneously by *iid* errors, then in the absence of other determinants, the money aggregate, y_t, can be described by a long-memory process:

$$y_t = (1 - L)^{-d}\psi(L)\varepsilon_t \tag{4.3}$$

where $-d > 0$ and $(1 - L)^{-d}\psi(L)$ is the coefficient of ε in different time periods. In the following table, we summarize the consequences of the convergence patterns of shocks (for various values of d, the integration order).

Table 4.2: **Properties of y_t with heterogeneous integration order of d**

d Value	Memory	Stationarity	Mean	Variance	Shock Duration
$d < 0$	Long	Covariance stationary	Mean-reversion	Finite variance	Long-lived
$d = 0$	Short	Covariance stationary	Mean-reversion	Finite variance	Short-lived
$0 < d < 0.5$	Long	Covariance stationary	Mean-reversion	Finite variance	Long-lived
$0.5 \leq d < 1$	Long	Non-stationary	Mean-reversion	Infinite variance	Long-lived
$d = 1$	Long	Non-stationary, unit root process	No Mean-Reversion	Infinite variance	Permanent
$d > 1$	Long	Non-stationary	Non Mean-Reversion	Infinite variance	Permanent

The above table summarizes how a time series, y would behave in the long-run in case of the order of integration, d is neither equal to 0 (stationary and no memory) nor equal to 1 (non-stationary and infinite memory). A researcher basically looks for a value of d that is $\neq 0$ displaying various degrees of memory. In real economic systems, even a small amount of shocks, where $d \leq 0.5$ also creates a problem with regard to the co-evolution of a system. This is because the complex interaction of the system with other variables can lead to systematic chaos in the long-run, unless the small amount of shocks is treated by policy intervention. It is with these insights that we model money demand function within a long-memory vector autoregression, i.e. dynamic interdependence of the demand for money with various determinants, where both the system and the individual determinants are allowed to possess significant memory. The complex nature of evolution and path dependence of the entire system has implications for stability of the whole system.

To model and understand the properties of such a system, we present our equation for money aggregate and other determinants (denoted by a vector of variables embedded in ΔX). We following Johansen's (2008) and Johansen's (2012) cointegrated VAR (CVAR) model, but extended to fractional case (developed in Johansen and Nielsen, 2014). The simple case of CVAR with p lags is presented as:

$$\Delta X_t = \alpha\beta^{'} X_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta X_{t-i} + \varepsilon_t = \alpha\beta^{'} L X_t + \sum_{i=1}^{p} \Gamma_i \Delta L^i X_t + \varepsilon_t \tag{4.4}$$

By applying a transformation: $X_t = \Delta^{d-b} Y_t$ with d as fractional integration order and b as co-fractional order, then $(1-L)^b X_t$ = $(1-L)^b \Delta^{d-b} Y_t$ = $(1-L)^b (1-L)^{d-b} Y_t$ = $(1-L)^d Y_t$ = ε_t. The FCVAR model presented in (3.7) can be re-formulated as:

$$\Delta^d Y_t = \alpha\beta^{'} L_b \Delta^{d-b} Y_t + \sum_{i=1}^{p} \Gamma_i \Delta^d L_b^i Y_t + \varepsilon_t \tag{4.5}$$

It should be noted that the parameters in the FCVAR possess the same interpretations as that in CVAR model. For example, Π represents the cointegration relationship(s). This is a matrix where each element represents a specific cointegration relationship. In cases where we have a three variables system, then one would have at the most two cointegration relationships. This 2×2 Pi would represent how the three variables form a cointegration relationship. Furthermore, Pi can be identified by two sub-parameters: $\Pi = \alpha\beta'$. Note that α and β are $K \times r$ matrices given that r is the rank of Y_t and $0 \leq r \leq K$. In the above, r indicates the number of cointegration(s) in the model, whereas β identifies the cointegrating relationship(s) among variables in Y_t. Furthermore α indicates the adjustment speed, that is adjustment towards the long-run equilibrium of each variable in Y_t. Finally, Γ_i represents the short-run dynamics of a target variable. In the FCVAR model, then, we say that elements of Y_t are fractionally integrated of order d, and the system is cointegrated of order $d - b$. In essence, the FCVAR model helps us characterize (i) the *long-run equilibrium relationship*, $\beta^{'} L_b \Delta^{d-b} Y_t$, (ii) the *short-run adjustment* processes to deviations towards an equilibrium, and (iii) the *short-run dynamics among variables* in a system, such as our money-demand system. The FCVAR is then represented as:

$$\Delta^d Y_t = \alpha(\beta^{'} L_d Y_t + \delta^{'}) + \sum_{i=1}^{p} \Gamma_i \Delta^d L_d^i Y_t + \varepsilon_t \tag{4.6}$$

We conduct a series of hypothesis tests on model parameters. Based on our theoretical framework, the hypothesis tests on α and β are defined as below.

$$\beta = \omega\lambda \tag{4.7}$$

$$\alpha = \tau\theta \tag{4.8}$$

In the above, ω is a $K \times q$ matrix that identifies restriction(s) on the cointegrating relationship(s). For instance, in our particular case of money demand function, if we wish to impose the restriction that interest rates do not enter the cointegration relationship, or that real income does not enter the cointegration relationship, then these variables coefficient effects need to be set to zero in the cointegration equation. This identifying restriction needs to be tested against the more general unrestricted FCVAR model. Likewise, λ is a $q \times r$ matrix defining free varying parameter(s). Note also that K defines the number of variables within the FCVAR system, q presents the number of restriction(s) associated with β, and r denotes the number of rank(s) of Y_t. The table below outlines the specific hypotheses we are aiming to test within our FCVAR model. The hypotheses relate to - as in the conventional CVAR case, but with the exception of fractional order of integration - various exogeneity assumptions are related to the variables within a system (which we explained earlier).

Table 4.3: Hypothesis tests

$H_1 d$	The fractional parameter, d, is equal to one.
$H_1 \beta$	Personal Disposable Income does not enter cointegration relations.
$H_2 \beta$	Interest rates does not enter the cointegrating relation(s).
$H_3 \beta$	Uncertainty does not enter the cointegrating relation(s).
$H_4 \beta$	One cointegrating relation contains only monetary variables.
	and the other cointegrating relation contains only uncertainty.
$H_1 \alpha$	Personal Disposable Income is weakly exogenous.
$H_2 \alpha$	Interest rate is weakly exogenous.
$H_3 \alpha$	Uncertainty is weakly exogenous.

4.4.1 Model determination

The first step to understand the results of a FCVAR estimation is to determine the model specification, which, following convention, is undertaken by choosing (i) the lag order and (ii) the number of (cointegration) ranks in the FCVAR system for each function. The optimal lag order selection makes sure that the model is correctly specified with regard to error correction mechanism, and that there is no correlation of errors, the absence of which might 'mispecify' a model. Therefore, before any VAR estimation, be it a CVAR or a FCVAR, the first step is to determine the 'lag length'. Once an optimal lag order is determined, the next step is to determine the number of cointegration relationships the system has, i.e. we need to decide on the 'rank' of the system. For example, in our money demand function, if we are allowing money demand as a function of real disposable income, interest rates and economic policy uncertainty, then this 4×4 FCVAR system would require the determination of the 'rank', i.e. how many variables within the system form a cointegration relationship. To further explore this, let us assume - as a limiting case that - all variables in the system are independent. This implies that there is neither any amount of path dependence (i.e. a variable's evolution depends on its own path) nor dependence on the lag of other variables. In this case, we expect the system to be of 'full' rank. However, a system with full rank does not describe any form of cointegrating relationship. To ensure this, one should have a rank which is less than a full-rank. In our specific case of 4×4 VAR system, we expect at most 3 cointegration relationships in the sense that one of the variables in the system forms a linear dependence with other variables. Therefore, determination of the 'rank of a system' is very important.

To shed light on the above two steps, we first determine the lag of our money-demand system. We follow convention and begin with the highest lag order (p) so that we can understand the nature of short-run error corrections. In this regard, we draw on Jones et al. (2014) to select the optimal lag order by performing a series of Likelihood Ratio (LR) tests, where we employ a *'general to specific'* strategy. Starting with a general (i.e. very generous lag order, in our case $p = 8$, because empirical literature in money demand show that a system with 8 lags can depict the most general and robust interdependence structure); we then use the LR test to decide - at each step - whether to reject that lag order in favour of one with a smaller lag. In particular, the null hypothesis for each LR test is that the coefficient of the highest lag order (p) is not significant ($H_0 : \Gamma_p = 0$), in contrast to the alternative hypothesis in favour of the significance of Γ_p ($H_1 : \Gamma_p \neq 0$). The process continues until the point where we fail to reject a hypothesis. The chosen rank represents the number of stationary long-run equilibrium relationship(s) among variables within the money-demand system.

It should be noted that whether or not the selected 'lag of the system' is free from any autocorrelation (as we know that the presence of autocorrelation makes coefficient estimates inefficient, although they remain unbiased), we need to perform the conventional $Ljung - BoxQ - test$. We begin with a selection of the number of lags in the test to be 12, that is one year, given the monthly nature of the data (we also tested for higher order lags, for instance 24 lags or two years, and the results remain fundamentally consistent). To choose the best lag order, we employ the conventional information criteria (IC) techniques, such as the Akaike information criteria (AIC) and the Bayesian information criteria (BIC). Once we have decided on the optimal lag orders and ranks of the FCVAR system, we are ready for estimation of a FCVAR system. One estimates - to begin with - an unrestricted FCVAR system, followed by imposition of various restrictions on the model parameters - to correctly identify the money-demand system.

Indeed, Johansen (1995) noted that the parameters of cointegrating relationship(s), viz. α and β, cannot be separately identified without imposition of additional restrictions, viz. normalization of matrix related to Π in the FCVAR equation, i.e. the long-run adjustment coefficients. In our estimations, we impose the identification restriction that normalizes β with regard to $M2$. The necessity of normalization is determined by the fact that our money-demand system has embedded temporal interactions of various determinants which form long-run stationary equilibrium. How significant are the cointegrating parameters (α and β) for the interdependent system? To determine this, we perform a series of hypothesis tests. The LR method is used to either accept or reject a null hypothesis (of exogeneity of the variable in the system).

Table 4.4: **Lag-Order Selection - FCVAR (Demand Function)**

p	K	$\hat{d}$	$LogL$	LR	$P\text{-}value$	AIC	BIC	$PmvQ$
8	5	1.666	-2022.10	68.36	0.004	4956.10	5922.40	0.91
7	5	1.720	-2098.50	39.19	0.292	4927.10	5825.22	0.91
6	5	1.398	-2186.12	76.50	0.000	4877.21	5679.25	0.91
5	5	1.109	-2231.20	55.39	0.051	4877.01	5561.7.18	0.91
4	5	0.599	-2265.10	86.56	0.000	4875.12*	5465.20	0.95
3	5	1.109	-2290.76	86.19	0.000	4892.17	5344.15	0.99
2	5	1.000	-2350.15	82.50	0.000	4910.22	5250.16	0.30
1	5	0.778	-2396.19	84.40	0.000	4922.15	5166.19	0.00
0	5	0.605	-2450.37	0.00	0.000	4940.16	5068.23*	0.00

Note: (i) T: number of observations; (ii) Order of autocorrelation test (white noise test) = 12.

Table 4.5: **Rank Tests - FCVAR (Demand Function)**

$Rank$	$\hat{d}$	$LRstatistic$	$P\text{-}value$
0	0.701	112.550	0
1	0.665	68.592	0.003
2	0.640	45.222	0.049
3	0.621	8.601	0.897
4	0.601	0.010	0.948
5	0.599	—	—-

Note: (i) T: number of observations; (ii) Order of lags = 4.

Following the procedures of model determination as discussed above, we undertake lag order selection of the system, as well as determination of the rank of the system. Noting that our money demand function ($M2$) has the following set of determinants: $M2 = f(inflation(CPI), interestrate(LIR), globaleconomicpolicyuncertainty(EPU), personaldisposableincome(RPDI))$ we run a 5-variables FCVAR system. We first perform the lag order selection, the results of which are presented in Table 4.4. The results of the LR test of selection of optimal lag are guided by the corresponding p-values and various information criteria (such as AIC and BIC). As mentioned earlier, we have a system of 5 variables ($K = 5$ and we test for 8 lags (p), following the suggested maximum limit for a FCVAR system, as in Johansen and Nielsen (2014). We find that p at all lag orders are significant except for $p = 5$ (considering both 1% and 5% levels of significance). For $p = 7$, the lag is significant at only 5% level. Moreover, we find no autocorrelation in residuals, except for the case when $p = 0$ and $p = 1$. That is, for the other order of p, we accept the null hypothesis of no autocorrelation in residuals (as the corresponding p-values are well above both 5% and 10% significance levels). Moreover, guided by these and the minimum AIC value, we choose $p = 4$ as the size of the system. The corresponding system memory (d) is 0.599, implying that the money-demand system - as a whole - possesses significant slow mean-convergent shocks (note that one would have rejected these significant shocks in favour of stationarity in the system following *I(0) - I(1)* mechanism). A further implication is that the stability of the system needs to be investigated by carefully examining the dynamic interaction of all variables within the system when there is a slow-convergence of shocks. Notice that when shocks converge slowly, any abrupt changes in a system due to both external and internal policy changes will lead to further accumulation of shocks, forcing the system perhaps to never return to its long-run mean.

We now turn to the determination of the rank of the system. Table 4.5 presents the results. We have rank of the system ranging from 0 to 5, where the corresponding d and LR statistics are reported. To gauge the significance of the rank (the LR statistics), we also report the p-values. A sequential testing, such as hypothesis of rank=0 against maximum rank of 1 (and so forth until rank = 5), we report the LR statistics. We find that for rank= 2, the LR statistic of 45.222 has a p-value of 0.049. For rank=3, the p-value = 0.897, thus leading us to accept rank=2 as the chosen cointegration rank of the system. To summarize, in our FCVAR system, we choose $p = 4$ and $rank = 2$. For this rank, we have a corresponding value of d=0.640, once again depicting slow-mean convergence of shocks. We will now estimate an unrestricted FCVAR system with these lag and rank orders.

(A) Unrestricted FCVAR

The unrestricted FCVAR system allows us to examine the temporal impact of each determinant within the system - without imposition of an exogeneity restriction. We allow, as chosen by the rank of the system, two stationary cointegrating relationships. Equation (4.9) summarizes the dynamic interdependent structure from unrestricted FCVAR system. It needs to be noted that both $Y_t - \rho$ and α are expanded in matrix form. The column vector ν_t represents $\beta' L_d(Y_t - \rho)$.

For the estimated unrestricted FCVAR, the system memory is 0.640 having a standard error of 0.025 (implying significance at 1% level). Moreover, we do not find any evidence of autocorrelation, given that the Q statistic (with 12 lags) = 401.233 has a p-value of 0.871, accepting the null hypothesis of no autocorrelation. Hence, the estimated model is correctly identified.

Estimated Unrestricted FCVAR model:

$$\Delta^{\hat{d}}\left(\begin{bmatrix} M2^D \\ RPDI \\ Inflation \\ LIR \\ EPU \end{bmatrix} - \begin{bmatrix} 2.806 \\ 0.129 \\ -0.097 \\ -1.126 \\ -0.594 \end{bmatrix}\right) = L_{\hat{d}} \begin{bmatrix} -0.086 & 1.000 \\ 0.259 & -1.019 \\ -0.126 & 0.552 \\ 0.109 & -0.187 \\ 0.069 & 1.938 \end{bmatrix} \begin{bmatrix} \nu_{1t} \\ \nu_{2t} \end{bmatrix} + \sum_{i=1}^{4} \hat{\Gamma}_i \Delta^{\hat{d}} L_{\hat{d}}^{i}(X_t - \hat{\rho}) + \hat{\varepsilon}_t \tag{4.9}$$

$\hat{d} = \underset{(0.025)}{0.640}$, $Q_{\varepsilon}(12) = \underset{(0.871)}{401.233}$, $LogL = -2988.252$

First cointegration relationship: Money demand and its determinants:

$$M2_t^{D*} = -3.640 - 12.600 \times Inflation_t - 1.091 \times LIR_t - 0.129 \times EPU_t + 0.266 \times RPDI_t + \nu_{1t} \tag{4.10}$$

Second cointegration relationship: Disposable income and its determinants:

$$RPDI_t = -2.009 - 9.304 \times Inflation_t - 0.9098 \times LIR_t - 1.002 \times EPU_t + 0.109 \times M2_t t + \nu_{1t} \tag{4.11}$$

A note on the cointegration order of the 5-variables system is in order. The first one corresponds to β, which is normalized by real M2 ($M2^D$). Recall that $M2^{D*}$ denotes the level of money demand in the equilibrium condition achieved. For the first cointegration relationship, (4.13) depicts how determinants in money demand (M2) actually drive the equilibrium level of M2 conditional on $\nu_{1t} = 0$.

Indeed, the cointegrating relationship presented is consistent with empirical results in general, where a negative effect of both interest rate and inflation are normally reported. At the same time, nascent empirical research has also begun to recognize the negative effect of policy uncertainty on money demand on the grounds that higher policy uncertainty serves as a source of greater asymmetric information in the economy, leading people to save more and spend less. This is consistent with the theoretical expectations. Similarly, the second cointegration relationship with regard to disposable income also depicts a positive association between income and money demand, thus summarizing the correct signs of each and every element of the system.

(B) Restricted FCVAR estimation and hypothesis testing

We now turn our attention to testing various restrictions on the FCVAR money-demand system. The restrictions pertain firstly to whether the system has a significant fractional integration (or long-memory). That is, whether our system is a pure CVAR or a FCVAR. Identification of the correct order of integration has implications for slow or fast convergence of disequilibirum shocks to the long-run mean. The other hypotheses correspond to sequentially testing for the exogeneity of each variable in the system, so that we can ascertain the centrality of the determinants of money-demand function and whether with their omission/inclusion, the system is correctly identified. In order to perform restricted FCVAR, we need to thus perform a series of hypothesis tests. Table 4.6 summarizes the results from various hypothesis tests.

Table 4.6: **Hypothesis Test Results of the M2 Demand Function**

	H_D^d	H_{D1}^β	H_{D2}^β	H_{D3}^β	H_{D4}^β	H_{D5}^β	H_{D6}^β
df	1	4	8	2	2	2	2
LR Statistic	29.101	19.287	11.109	9.201	43.112	4.209	96.334
P-Value	0.000***	0.000***	0.023**	0.022**	0.000***	0.241	0.000***
	H_{D1}^α	H_{D2}^α	H_{D3}^α	H_{D4}^α	H_{D5}^α	H_{D6}^α	
df	2	2	2	2	2	2	
LR Statistic	5.115	87.222	21.112	176.201	89.001	59.298	
P-Value	0.221	0.000***	0.007***	0.000***	0.000***	0.000***	

Note: (i) *: significance at the 10% level, **: significance at the 5% level, ***: significance at 1% level; (ii) df: degree of freedom; (iii) LR: Likelihood Ratio test

Note that each hypothesis test reports the likelihood ratio statistic with corresponding p-values. We also report the degrees of freedom associated with each test. The inference we make is as follows: in case we reject a null hypothesis for β, then the concerned variable(s) can enter the equilibrium relationship. Moreover, if we reject the null hypothesis corresponding to α, then it implies that the concerned variable(s) does not correct for disequilibrium error, that is, the variable can be termed as long-run weakly exogenous.

From Table 4.6, it is evident from H_D^d (i.e. if the system has a long-memory), we comfortably reject the null hypothesis of no-memory (or the system is a CVAR) (the LR statistic = 29.101 having a p-value of 0.000 implying rejection at 1% level). We have similar conclusions for the exogeneity of variables except for $H_{D_5}^\beta$ and $H_{D_1}^\alpha$. With these hypotheses testing exgogeneity and weak-identification of some variables, we now estimate a restricted FCVAR system, restricting within the system each variable within both β and α matrix of coefficients, the value of 1 (if the variable does not enter the system or long-run exogeneous), 0, otherwise.

Estimated restricted FCVAR model:

$$\Delta^{\hat{d}}\left(\begin{bmatrix} M2^D \\ RPDI \\ Inflation \\ LIR \\ EPU \end{bmatrix} - \begin{bmatrix} 1.223 \\ 0.109 \\ -0.085 \\ -1.001 \\ -0.394 \end{bmatrix}\right) = L_{\hat{d}} \begin{bmatrix} -0.077 & 0.989 \\ 0.176 & -0.887 \\ -0.098 & 0.243 \\ 0.100 & -0.097 \\ 0.035 & 1.101 \end{bmatrix} \begin{bmatrix} \nu_{1t} \\ \nu_{2t} \end{bmatrix} + \sum_{i=1}^{4} \hat{\Gamma}_i \Delta^{\hat{d}} L_{\hat{d}}^i (X_t - \hat{\rho}) + \hat{\varepsilon}_t \tag{4.12}$$

$\hat{d} = \underset{(0.045)}{0.622}$, $Q_\varepsilon(12) = \underset{(0.554)}{179.029}$, $LogL = -2011.097$

First cointegration relationship: Money demand and its determinants:

$$M2_t^{D*} = -1.232 - 0.980 \times Inflation_t - 1.001 \times LIR_t - 0.349 \times EPU_t + 0.179 \times RPDI_t + \nu_{1t} \tag{4.13}$$

Second cointegration relationship: Disposable income and its determinants:

$$RPDI_t = -1.009 - 2.304 \times Inflation_t - 0.239 \times LIR_t - 0.129 \times EPU_t + 0.162 \times M2_t t + \nu_{1t} \tag{4.14}$$

Similar to the unrestricted FCVAR system, we find that our restricted FCVAR is no different, although the magnitude of coefficients are smaller than the counterparts in unrestricted FCVAR. Equation 4.12 also presents the estimated value of system d, which is 0.622, and this value is very similar to the unrestricted case. The estimated value is significant at 5% level. Moreover, we do not find any evidence of autocorrelated errors. Hence, similar to the unrestricted case, the restricted FCVAR is also correctly identified. The two cointegration relationships also present correct signs of determinants (for instance, negative signs for interest rates, EPU and inflation - as cost to money demand). Overall, the restricted FCVAR, after imposing for various restrictions on possible exogeneity of variables within the system, correctly identified the FCVAR system.

4.5 Conclusions

This paper introduced long-memory mechanism to the study of money demand and uncertainty relationship in the case of Saudi Arabia. The innovation in the paper concerns modelling of shocks with slow-convergence property, as the latter has important implications for stability of the demand-uncertainty relationship. We found that - in general - money demand functions are unstable, given the evidence of strong non-stationary money demand variables and their interest rates. Second, the cointegrated VAR depicted a strong pattern of slow convergence of disequilibrium shocks to the long-run mean. Although we need to perform further robustness checks using the definition of different types of money, at a fundamental level, we found that changes in uncertainty, not the level of uncertainty, co-moves with changes in money demand over time. The growth vs level effects in the relationship has important implications for growth theory in that an endogenous shock, such as policy uncertainty, make the money demand function persistent. However, this type of persistence is not growth-retarding, as evidenced by the interdependence among other macroeconomic aggregates. Rather the endogenous nature of the shocks makes the system non-linear, and unravelling the complex feedback mechanism between uncertainty and real economy becomes complicated. From the policy side, if one can model uncertainty and its evolutionary structure, mapping its impacts on demand for money becomes easier. Ignoring any potential long-memory impact of uncertainty and real variables means that policymakers have under-emphasized the magnitude of shocks, possibly triggering an estimation bias of the impact of uncertainty in real economic fluctuations.

Chapter 5

Conclusions

5.1 Overview and Policy Implications

To reiterate what has been presented in each chapter, in Chapter Two we examined the existence of a cointegration relation between economic uncertainty and real economic and financial variables. Then we moved on to investigate how heterogeneous the dynamic cointegration is across the entire distribution of real variables instead of the mean level. We found that all these variables depict various behaviours across their distributions. In addition, our estimation showed that a heterogeneous cointegration structure indeed exists. For some quantiles, we found a vanishing cointegration relation, whereas the same exists at other quantiles.

Utilising both the subjective and objective measures of economic uncertainty, in Chapter Three we investigated its impact on economic and financial variables within a long memory framework. No matter measure we used, we found that a shock to uncertainty can result in a long memory shock on the macroeconomic/financial variables, which indeed reduces predictive power, due to the system complexity. We also revealed that a cyclical or a monotonic positive/negative effect on various macroeconomic and financial variables can be the result of highly persistent economic uncertainty shocks.

In Chapter Four, we investigated the dynamic interdependence of money demand determinants over time in Saudi Arabia. We tested the stability of the money demand function in response to shocks to global economic uncertainty, and how it adjusts to the long-term equilibrium. Generally, we found money demand function to be unstable, and changes in economic uncertainty are cointegrated with changes in money demand over time.

A policy implication of the various adjustment behaviours could point to the importance of having an in-depth knowledge of the nature of co-movement among growth variables prior to new policy intervention. Moreover, by identifying the speed of adjustment across different points or quantiles of the distribution, policymakers and practitioners should follow a non-unique policy intervention to smooth out the impact of uncertainty shocks. For example, a shock to economic uncertainty might change the equilibrium of the system temporarily or permanently, so policymakers should design policy with regards to short/long run uncertainty impacts.

The main results of the thesis give rise to several policy implications. Recall that this thesis has one core objective: to understand the dynamic linkage between uncertainty and real economic fluctuations. Extant literature does not provide a readily available theory to describe the relationship between policy uncertainty and economic fluctuations, although some ad hoc business cycle types of models are often proposed and empirically examined. In the research presented in this thesis, I have tried to model an uncertainty-real economy linkage by assuming that uncertainty gives rise to information asymmetry in the economy, and through this asymmetry, real economy functions at various levels of inefficiency. A major outcome of such an efficiency is path dependence in fluctuations and its formidable impact on the co-movement of variables in the long-run. This thesis represents a piece of empirical work by modelling both path dependence and the long-run equilibrium behaviour. An immediate policy implication is with respect to the speed of adjustment to shocks to the steady state. The research presented in the various chapters of this thesis shows that there is a slow and very complex adjustment of shocks. The non-linear correction of shocks implies that linear policy interventions may result in partial policy failure and overheating of the economy. A multipronged strategy of 'cooling the economic system' by targeting the slow error correction mechanism of various combinations of real economic integrations could be a robust strategy.

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Appendix A

Supplement to Chapter 2

Table 1A: Descriptive Statistics

Variables	N	mean	std. dev	min	max	p25	p50	p75
h12:Uncertainty	618	0.959	0.084	0.816	1.267	0.911	0.946	0.981
EPU:Uncertainty	618	1.207	0.453	0.318	3.095	0.930	1.243	1.466
CPI	618	4.510	0.686	3.386	5.425	3.782	4.695	5.104
IP	618	4.023	0.407	3.094	4.613	3.729	4.008	4.450
EMP	618	11.276	0.290	10.714	11.658	11.033	11.317	11.580
RCONS	618	3.785	0.495	2.844	4.522	3.415	3.811	4.230
PCEDEF	618	3.966	0.613	2.954	4.773	3.312	4.141	4.495
RNORD	618	11.531	0.307	10.699	11.968	11.318	11.558	11.802
hours	618	40.131	0.567	37.200	41.300	39.800	40.100	40.500
M2	618	7.589	1.009	5.708	9.173	6.709	7.840	8.391
SP500	618	5.594	1.101	3.984	7.339	4.579	5.459	6.833
FED	618	5.667	3.502	0.070	19.100	3.380	5.265	7.600
WAGE	618	8.636	0.484	7.694	9.358	8.306	8.676	9.081

Table 1B: Correlation at various percentiles of uncertainty distribution

	EPU	EPU	EPU	h12	h12	h12
	p25	*p50*	*p75*	*p25*	*p50*	*p75*
CPI	0.601	0.294	-0.059	0.613	-0.150	-0.280
IP	0.689	0.204	-0.062	0.599	-0.188	-0.253
EMP	0.672	0.251	-0.068	0.646	-0.178	-0.296
RCONS	0.674	0.227	-0.037	0.625	-0.215	-0.264
PCEDEF	0.602	0.297	-0.060	0.611	-0.158	-0.299
RNORD	0.682	0.169	-0.070	0.550	-0.290	-0.450
hours	-0.010	-0.042	-0.073	-0.331	-0.522	-0.577
M2	0.657	0.288	-0.041	0.618	-0.178	-0.261
SP500	0.488	0.145	-0.044	0.454	-0.283	-0.314
FED	0.481	0.137	-0.095	0.534	0.730	0.580
WAGE	0.689	0.243	-0.037	0.653	-0.173	-0.224

Figure A.1: Qauntile Autoregression. Left[Jurado uncertainty-h12]. Right[EPU-uncertainty]. Top: Full-sample, Middle: pre-crisis, Bottom: post-crisis.

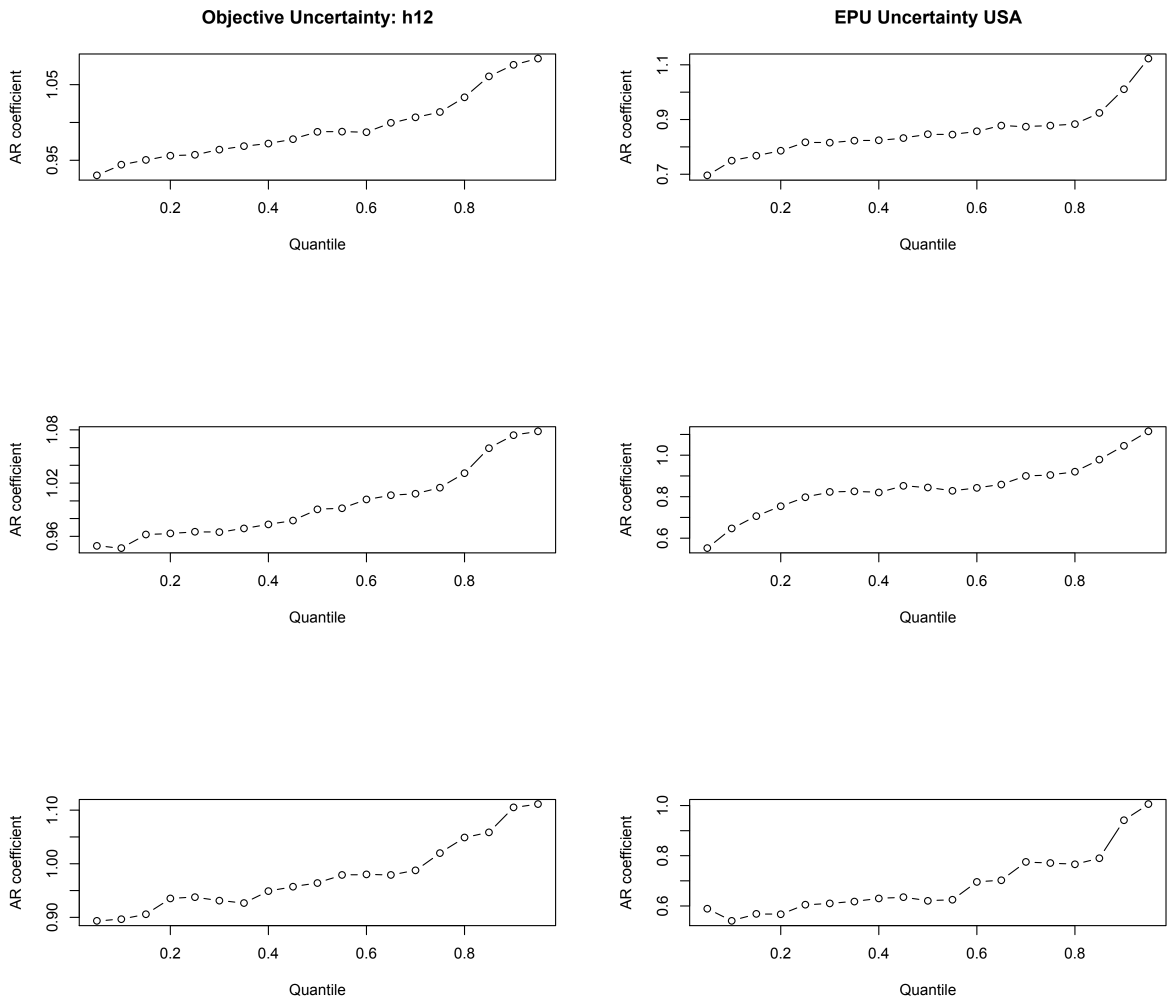


Figure A.2: Qauntile Autoregression. Left[Consumption]. Right[Hours]. Top: Full-sample, Middle: pre-crisis, Bottom: post-crisis.

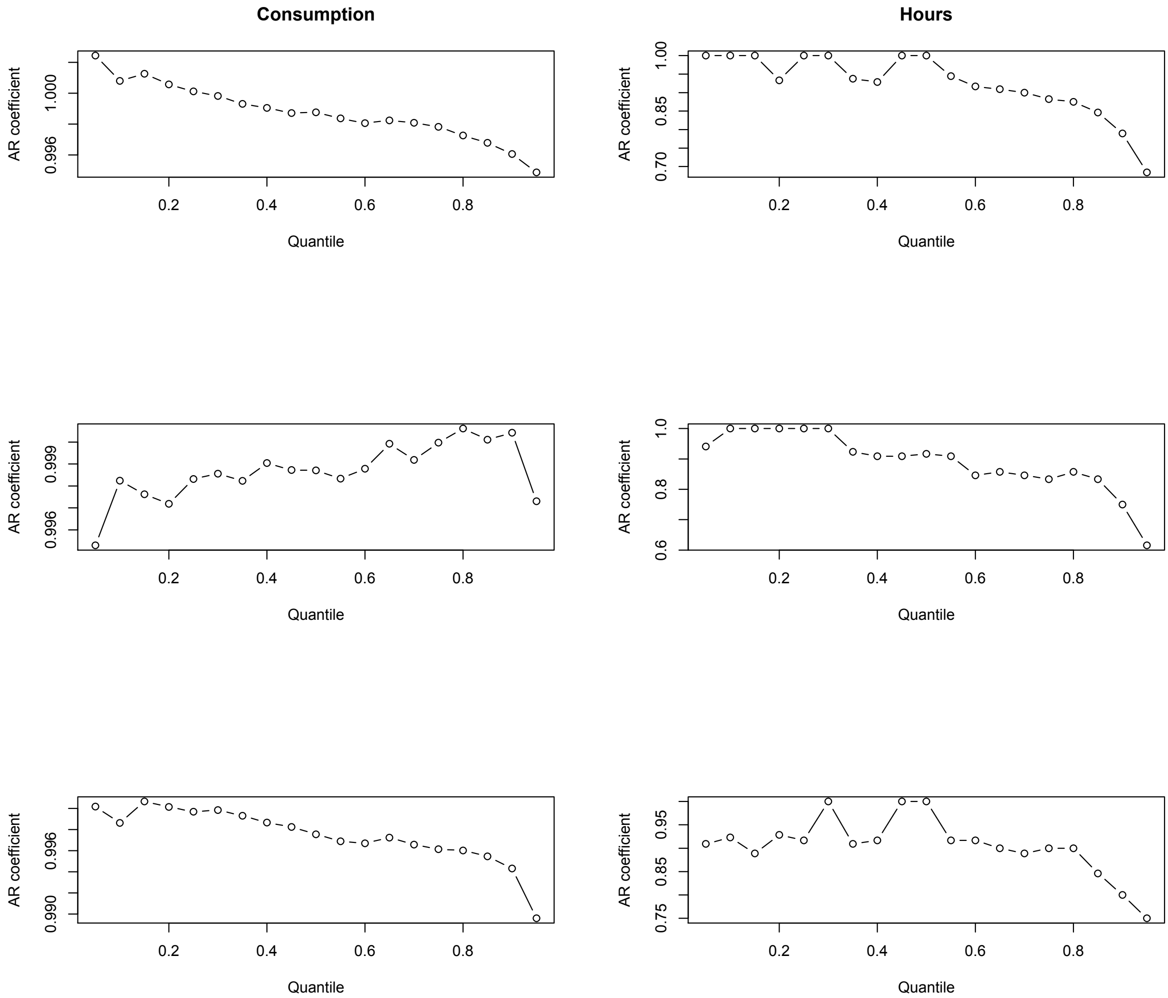


Figure A.3: Qauntile Autoregression. Left[Employment]. Right[Federal-Funds]. Top: Full-sample, Middle: pre-crisis, Bottom: post-crisis.

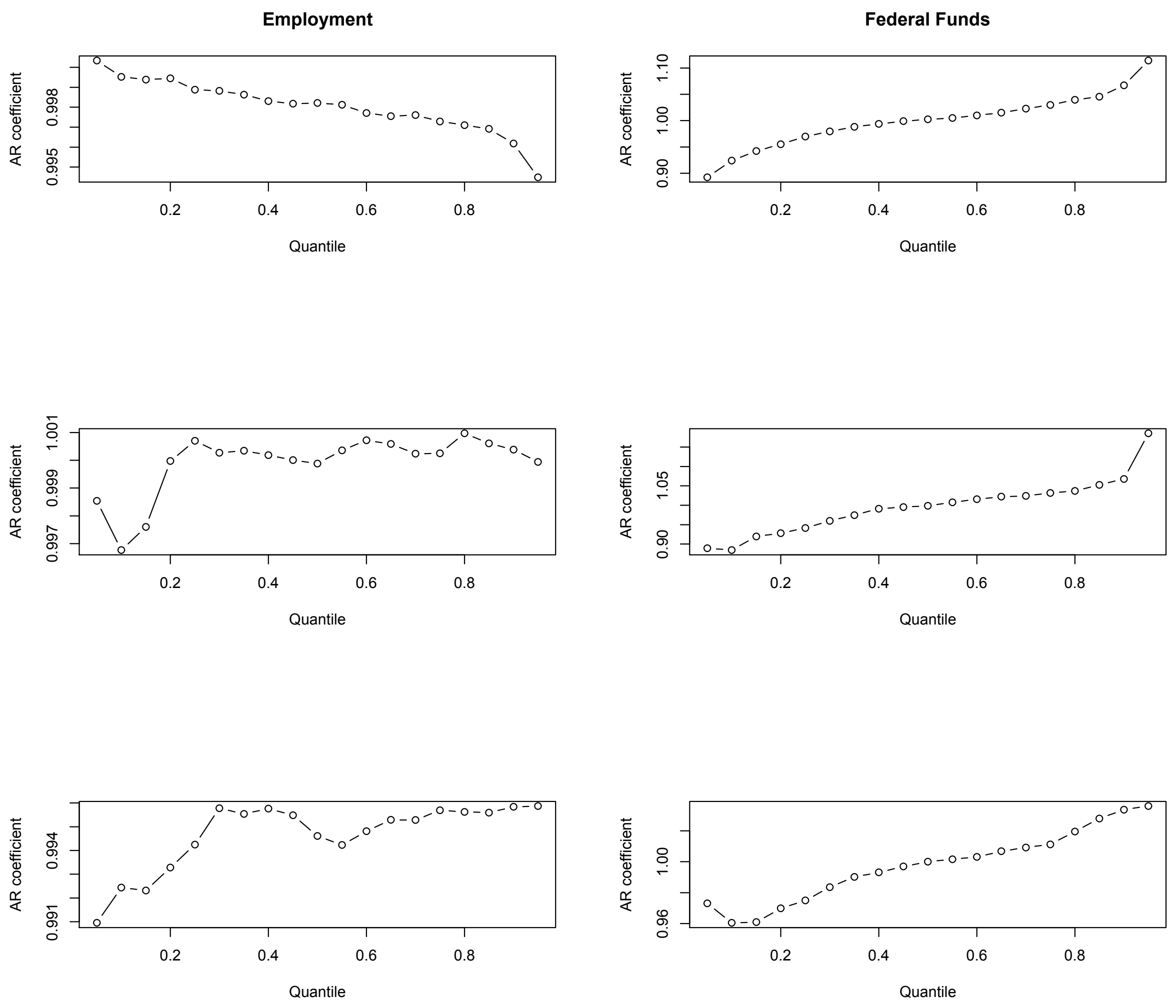


Figure A.4: Qauntile Autoregression. Left[Industrial Production]. Right[M2 Growth]. Top: Full-sample, Middle: pre-crisis, Bottom: post-crisis.

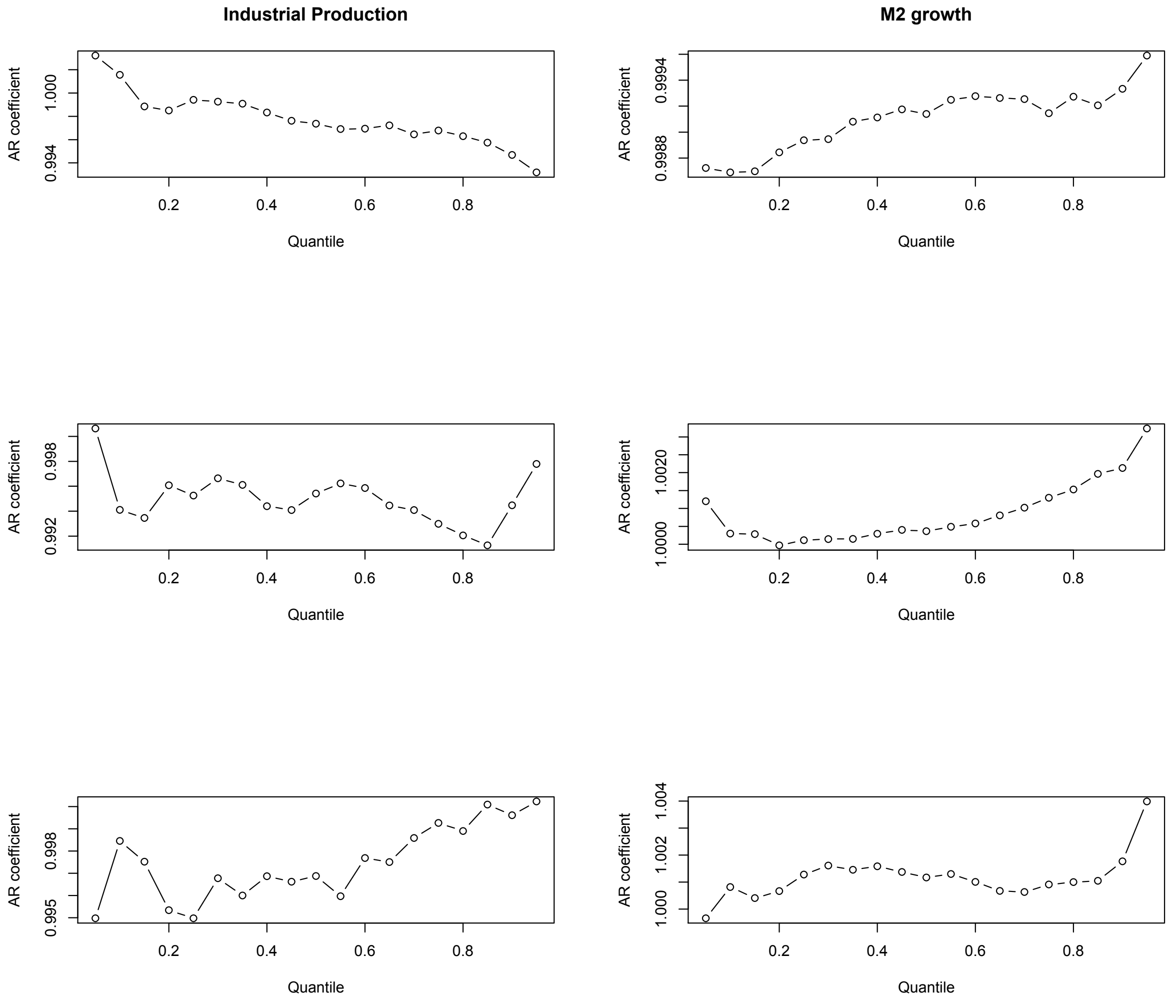


Figure A.5: Qauntile Autoregression. Left[New Order]. Right[PCE-Deflator]. Top: Full-sample, Middle: pre-crisis, Bottom: post-crisis.

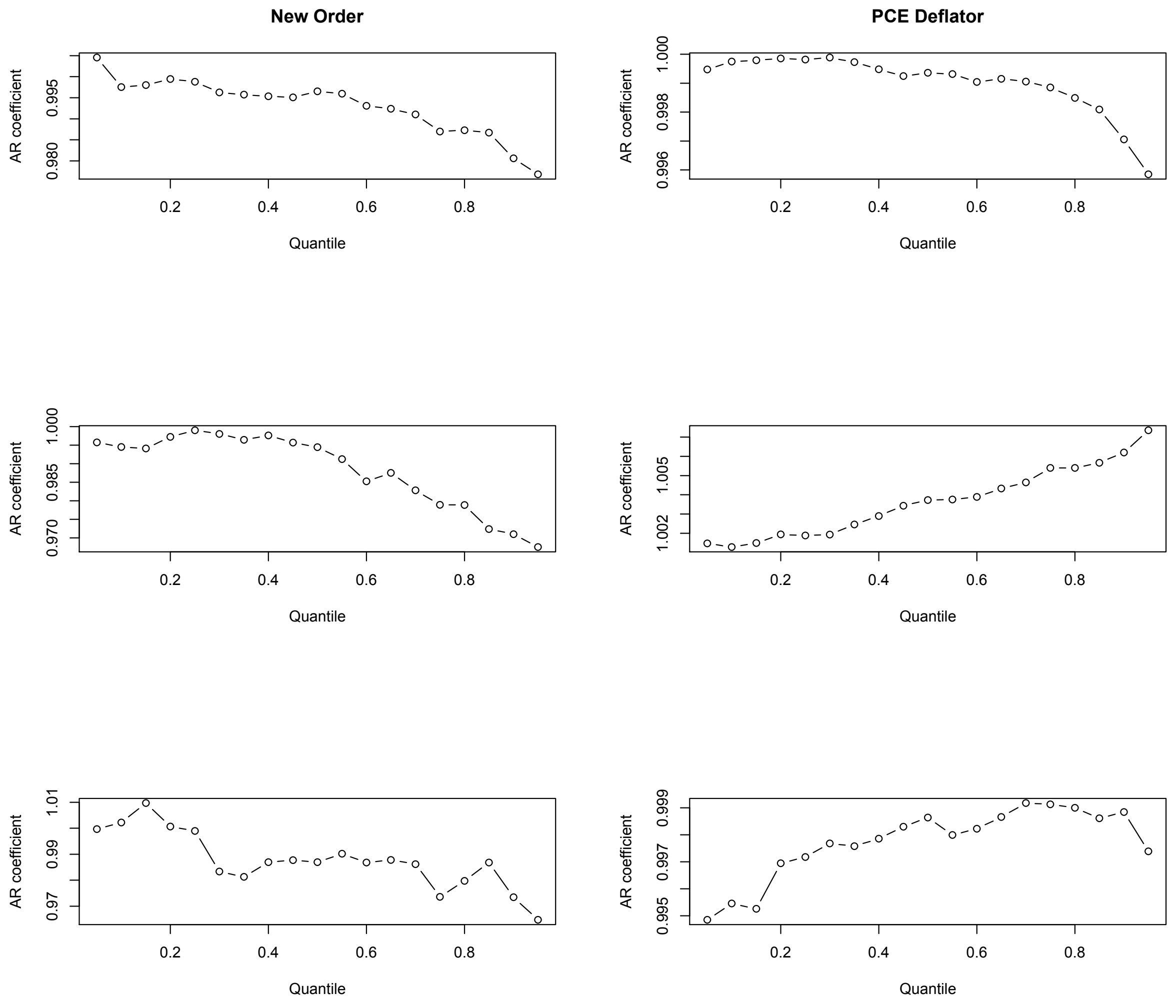
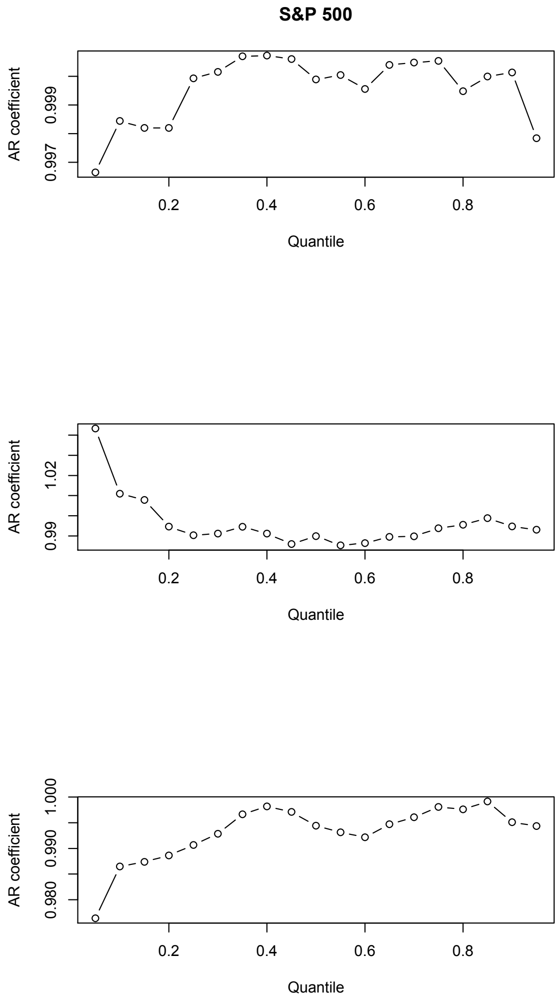


Figure A.6: Qauntile Autoregression. Left[S&P 500]. Right[Real Wage]. Top: Full-sample, Middle: pre-crisis, Bottom: post-crisis.



Appendix B

Supplement to Chapter 3

Figure 4: Autocorrelation Function. Full Sample (1960:07-2011:12): Left [Industrial production(top), Federal Funds Rate (middle), M2 growth (bottom)], Right[PCE Deflator (top), S&P 500 (middle), and New Orders (bottom)].

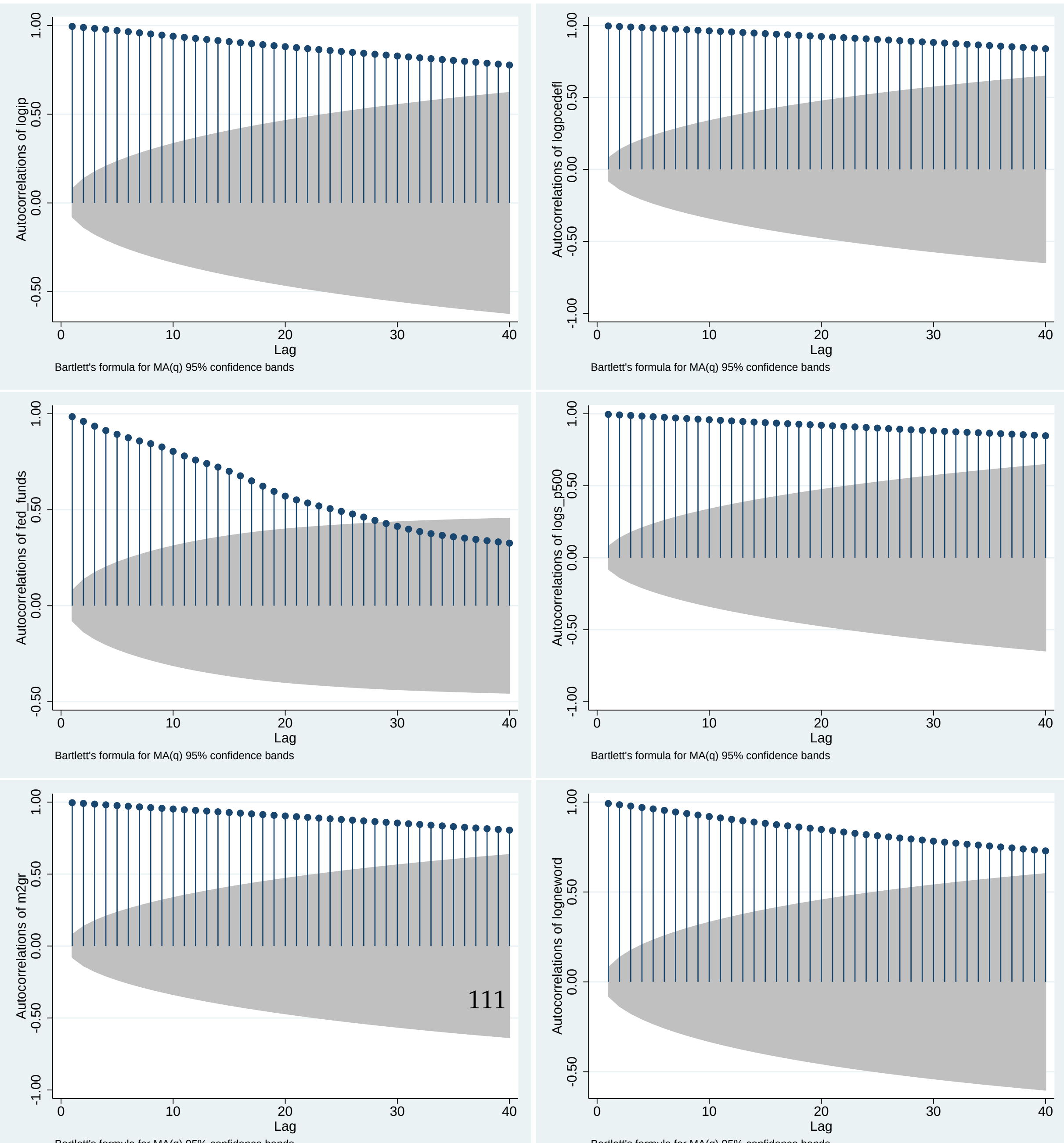


Figure 5: Spectral density. Full Sample (1960:07-2011:12): Left [Objective measure of uncertainty (h1,h3,h12)(top), EPU measure of Uncertainty (middle), Industrial Production (bottom)], Right[Consumption (top), Employment (middle), and Hours (bottom)].

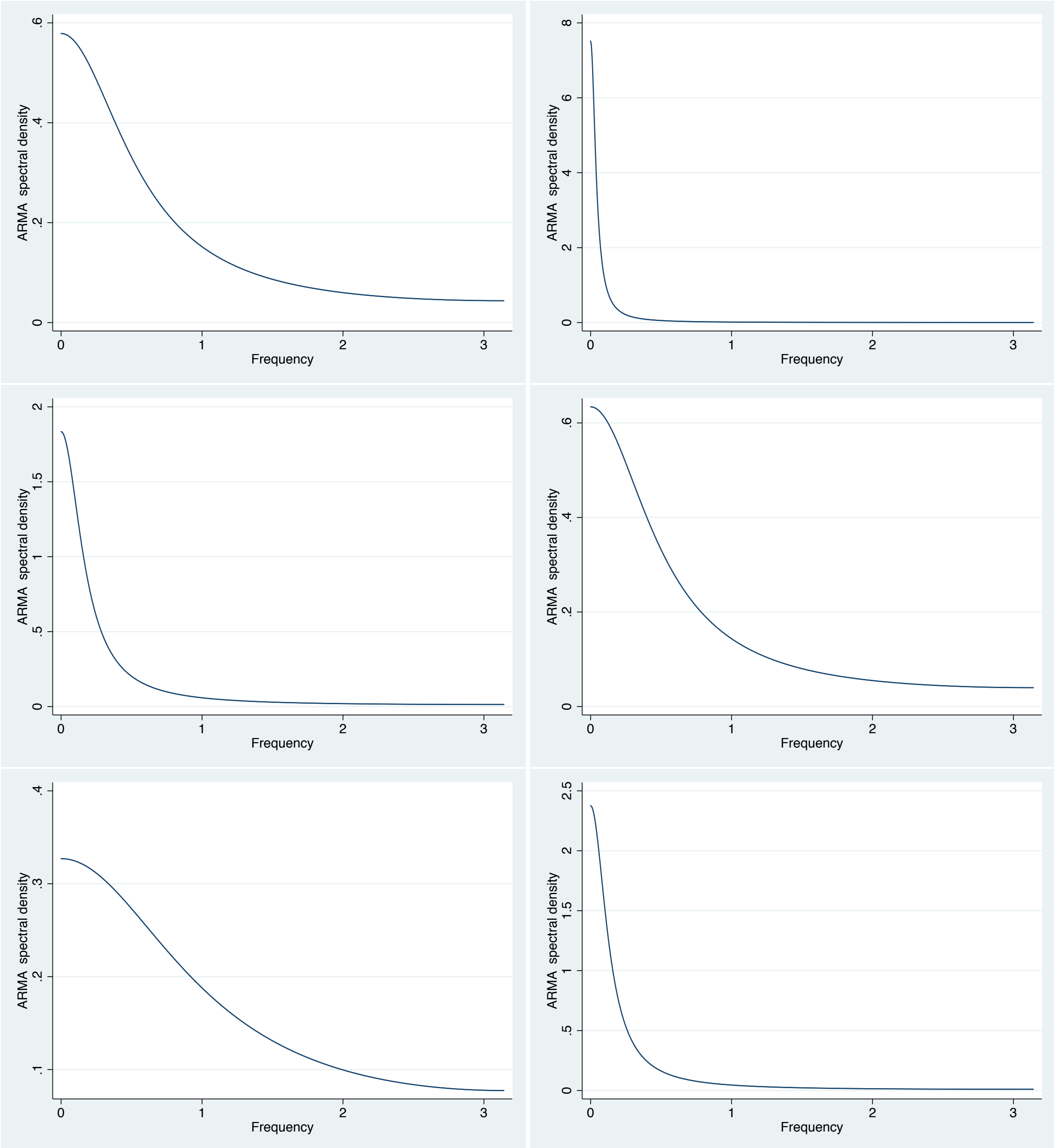


Figure 6: Spectral density. Full Sample (1960:07-2011:12): Left [CPI (top), Federal Funds Rate (middle), M2 growth (bottom)], Right[PCE Deflator (top), S&P 500 (middle), and New Orders (bottom)].

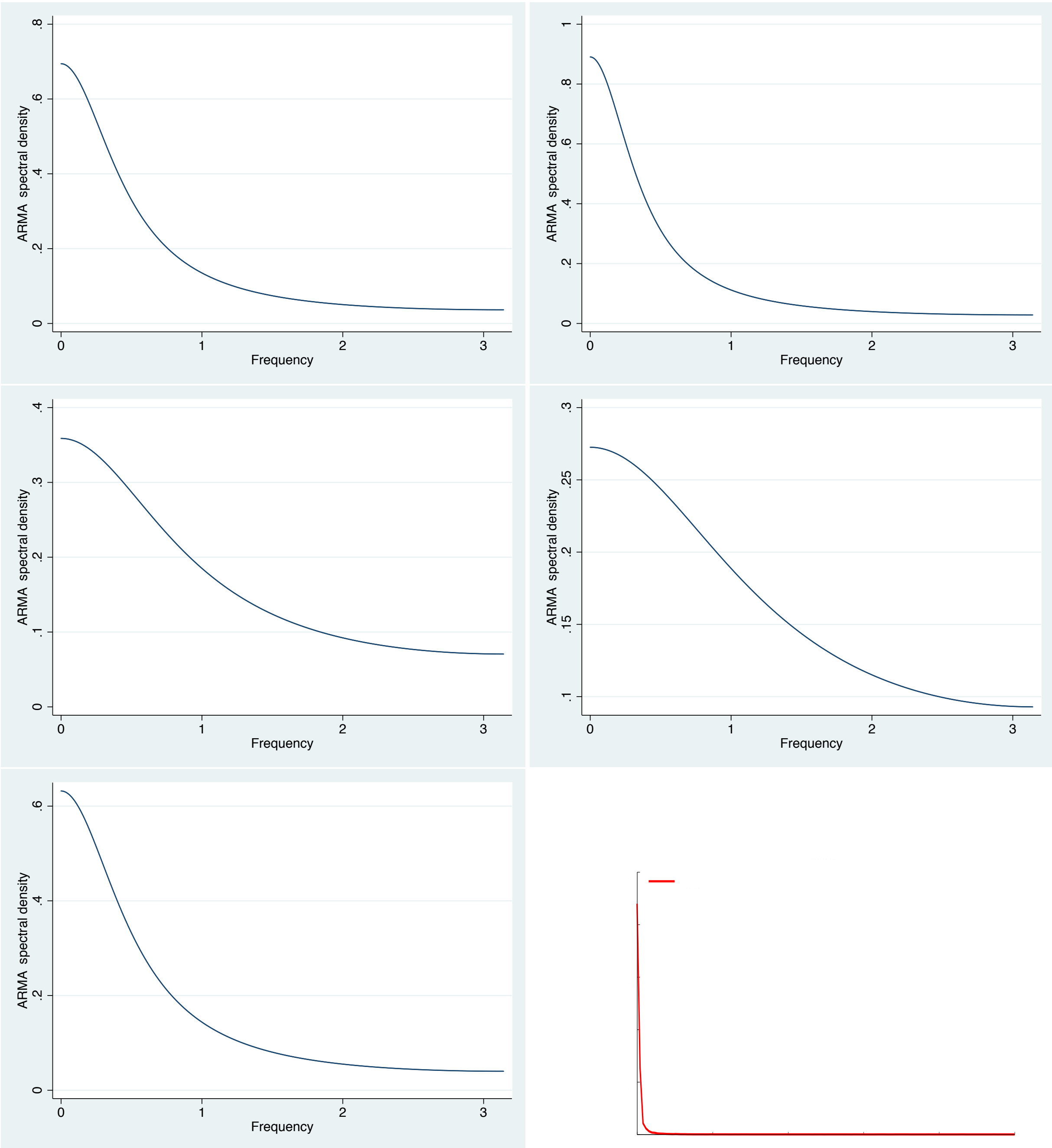


Figure 7: Predicted equilibrium relationship and simulated graphs for 11-var FCVAR. Top panel: Left[equilibrium relation], Right[Simulation for 100 steps]. Bottom panel: Simulation for 500 [left] and 1000 [right] steps respectively: Full Sample and EPU Uncertainty

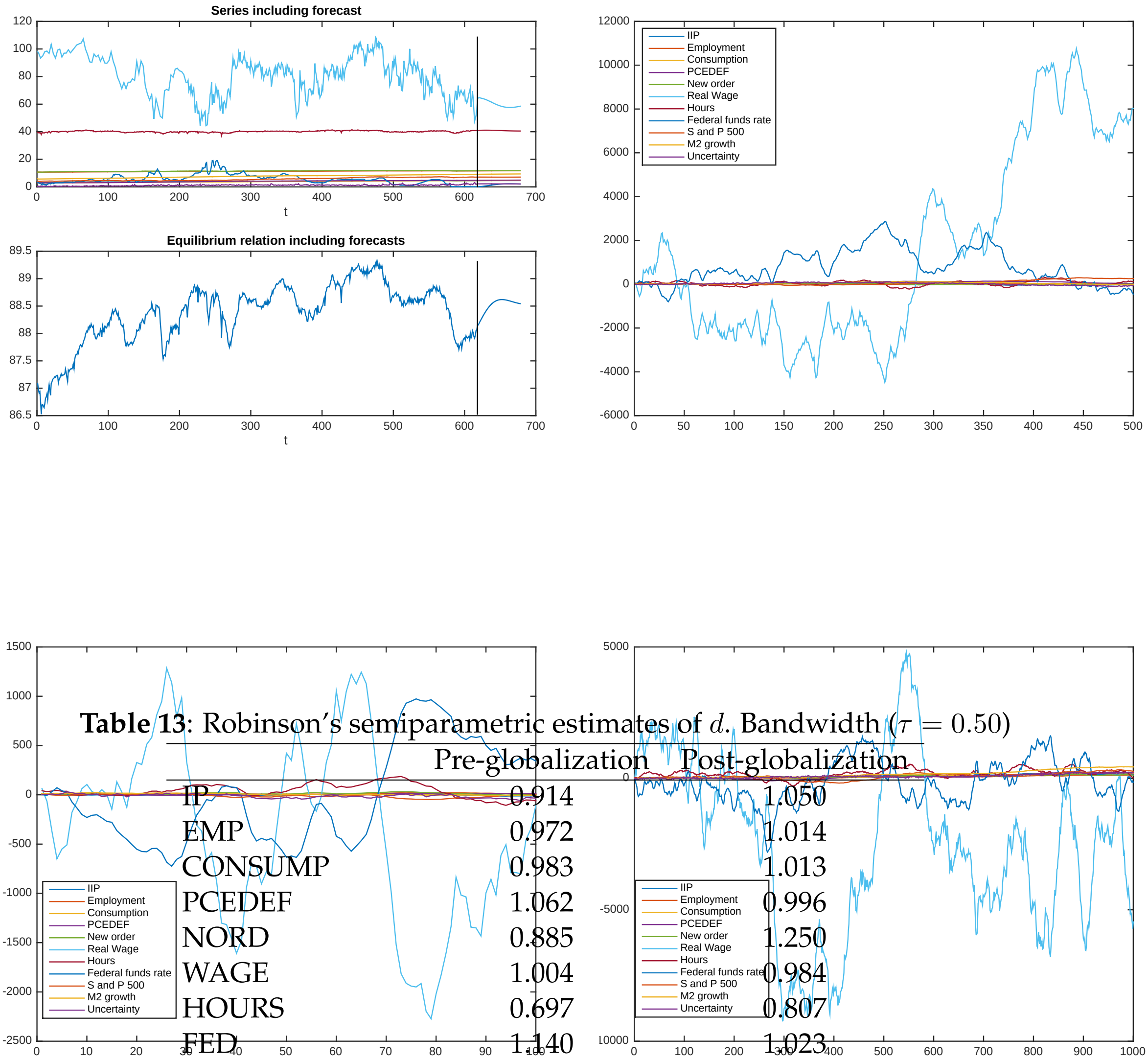


Table 13: Robinson's semiparametric estimates of d. Bandwidth ($\tau = 0.50$)

	Pre-globalization	Post-globalization
IP	0.914	1.050
EMP	0.972	1.014
CONSUMP	0.983	1.013
PCEDEF	1.062	0.996
NORD	0.885	1.250
WAGE	1.004	0.984
HOURS	0.697	0.807
FED	1.140	1.023
SP500	0.771	1.033
M2gr	1.009	0.965
EPU: Uncertainty	0.867	0.604
h12: Uncertainty	1.235	0.634

Note: All estimates are significant at 5% level of significance. The test of equality of d for pre-globalisation period is: F(11,132) = 2.443 Prob $>$ F = 0.0083, and for the post-globalisation period is F(11,180) = 2.5086 Prob $>$ F = 0.0058.

Figure 8: Predicted equilibrium relationship and simulation: Full sample and H12 Uncertainty

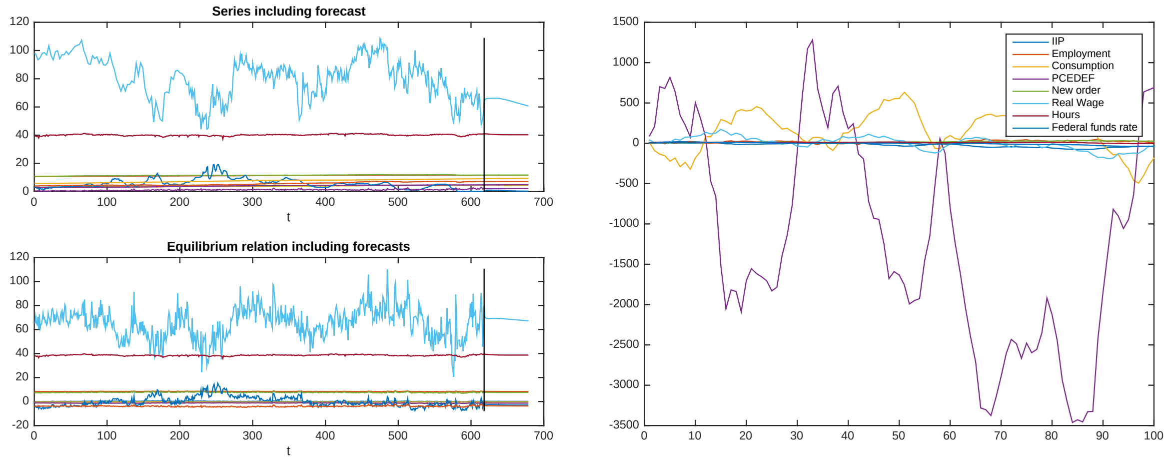
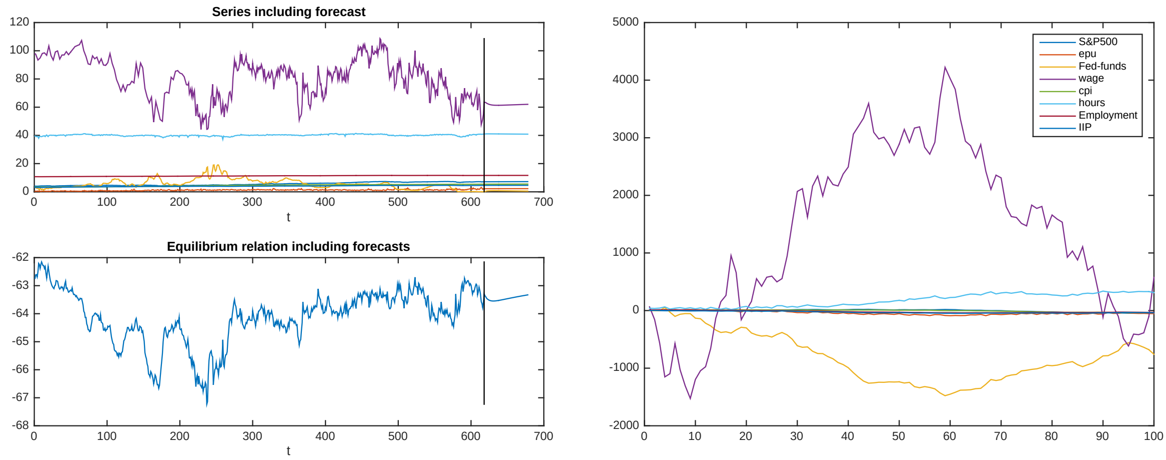


Figure 9: Predicted equilibrium relationship and simulated graphs for 8-var FCVAR. Top panel: Left[equilibrium relation], Right[Simulation for 100 steps]. Bottom panel: Simulation for 500 [left] and 1000 [right] steps respectively: Full Sample and EPU Uncertainty



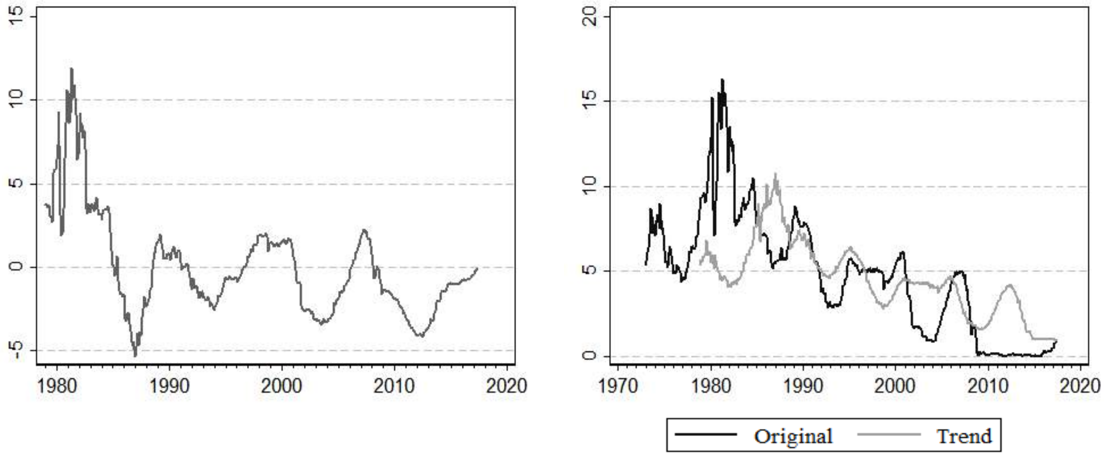
Appendix C

Supplement to Chapter 4

Figure 1 **Cyclical components, trends and original series (Cont'd)**

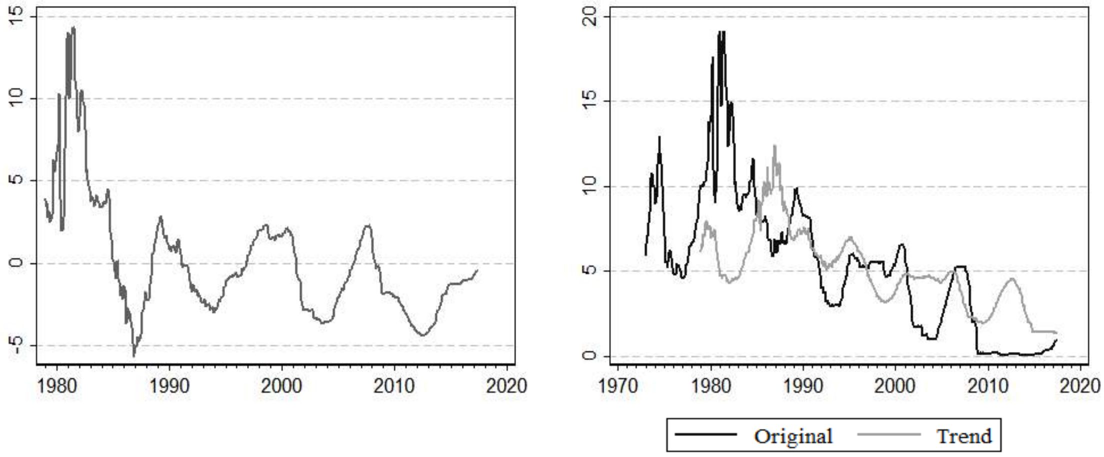
(25) 3-Month Treasury Bill

Cyclical component | Original series and trend



(26) Effective Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted

Cyclical component | Original series and trend



(27) 10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjust

Cyclical component | Original series and trend

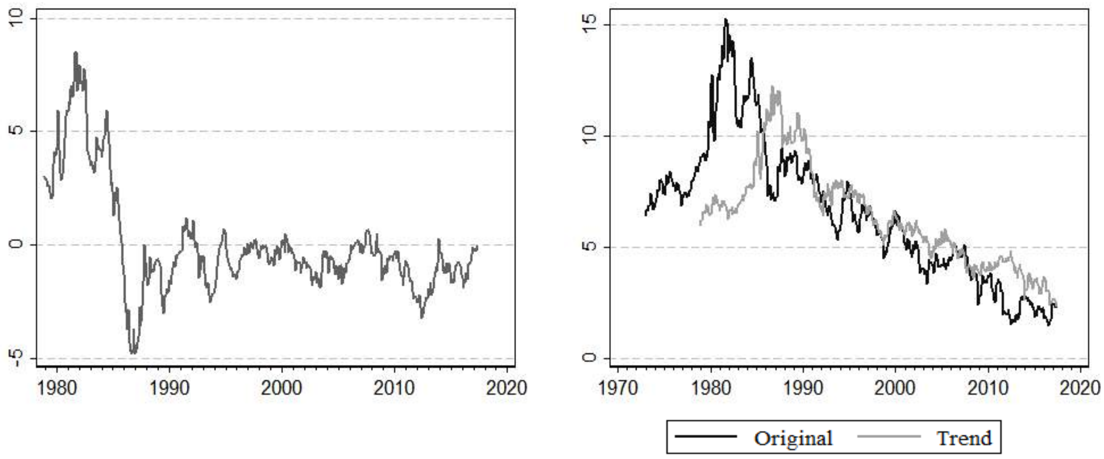
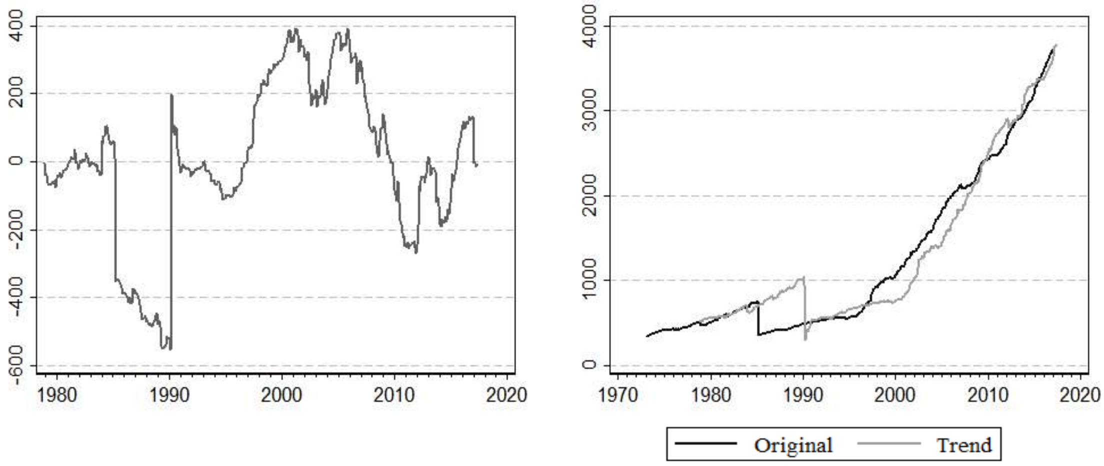


Figure 1 **Cyclical components, trends and original series (Cont'd)**

(28) Small Deposits

Cyclical component — Original series and trend

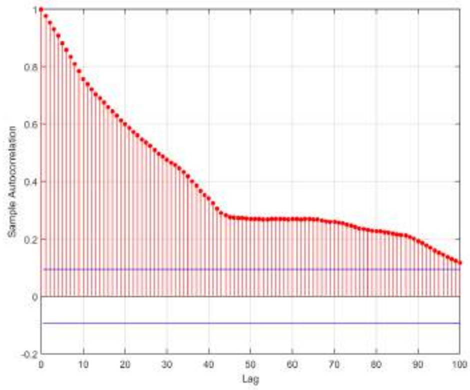


2.2 ACF and periodograms

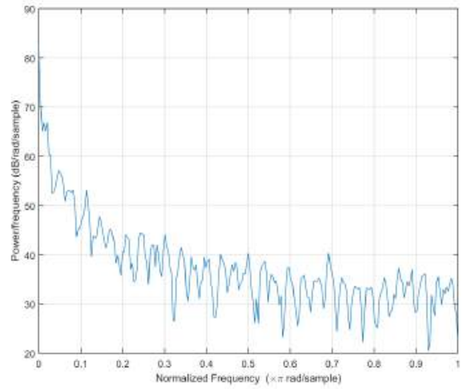
Figure 2 **ACF and periodograms – filtered series**

(1) M1, real

ACF

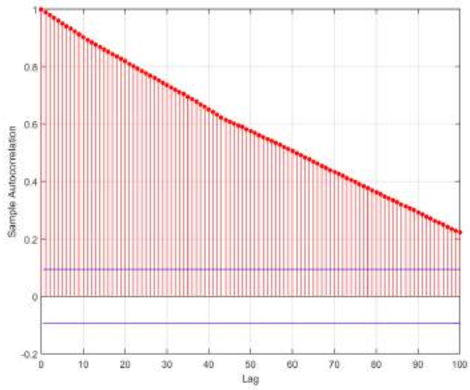


Power spectral density estimate

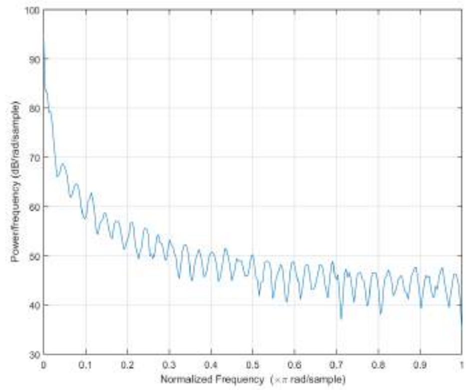


(2) M2, real

ACF

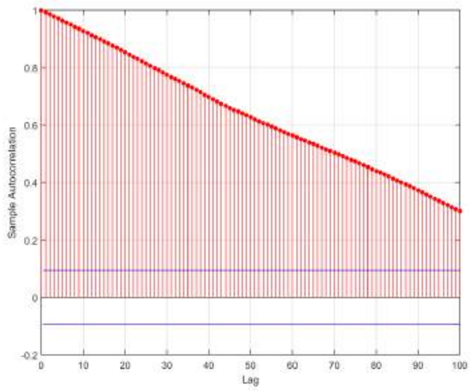


Power spectral density estimate



(3) MZ, real

ACF



Power spectral density estimate

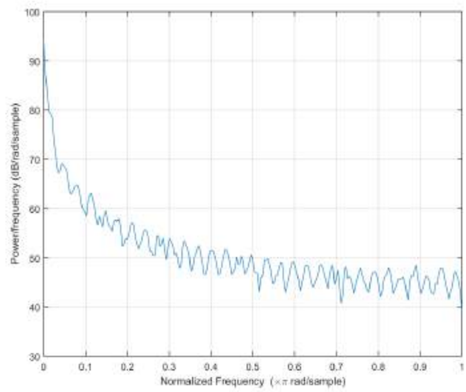
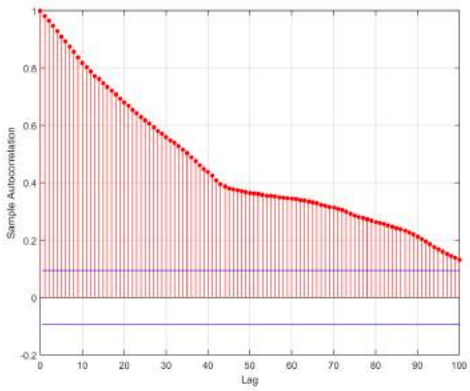


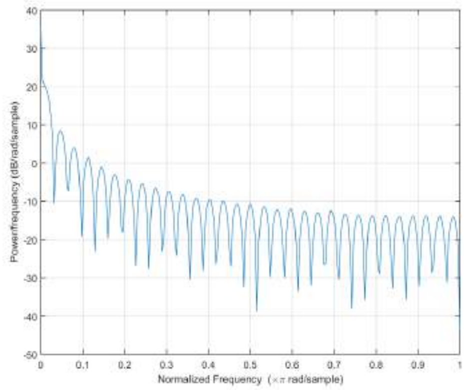
Figure 2 **ACF and periodograms – filtered series (Cont'd)**

(4) Log of real M1

ACF

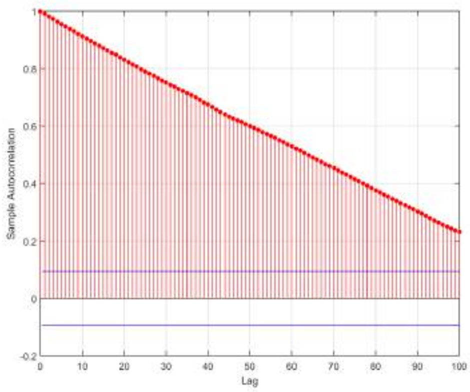


Power spectral density estimate

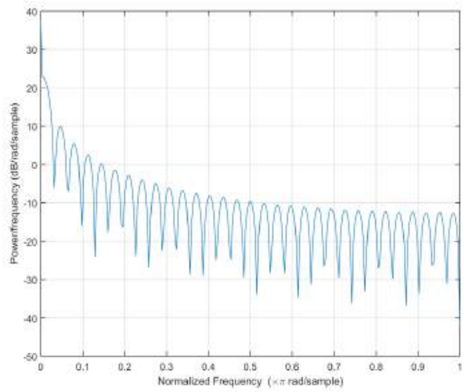


(5) Log of real M2

ACF

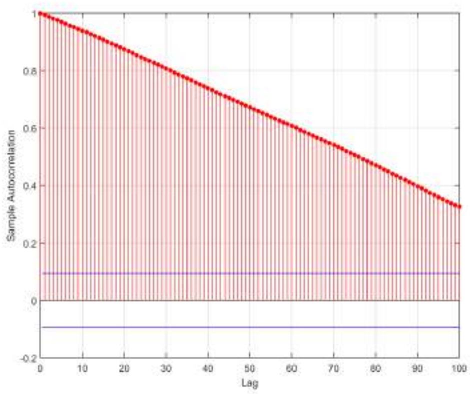


Power spectral density estimate



(6) Log of real MZ

ACF



Power spectral density estimate

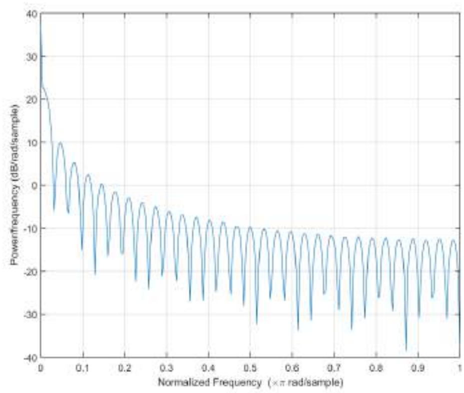
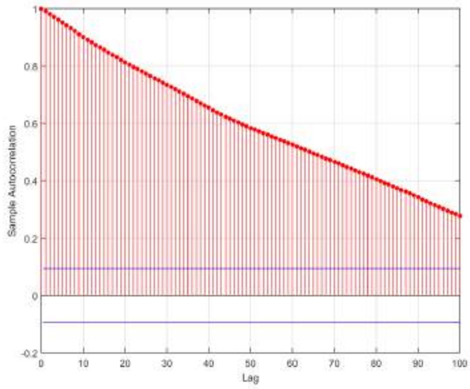


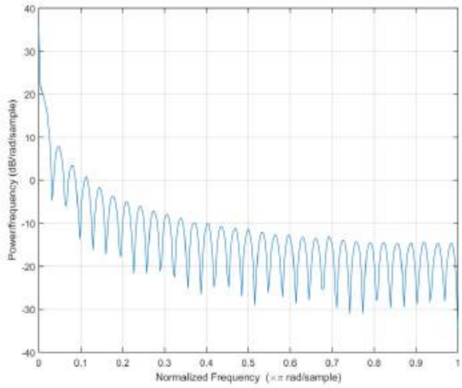
Figure 2 **ACF and periodograms – filtered series (Cont'd)**

(7) Log of M1

ACF

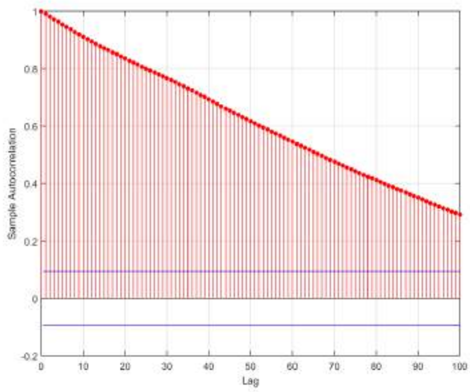


Power spectral density estimate

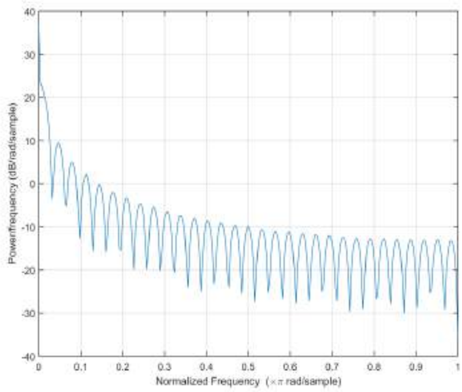


(8) Log of M2

ACF

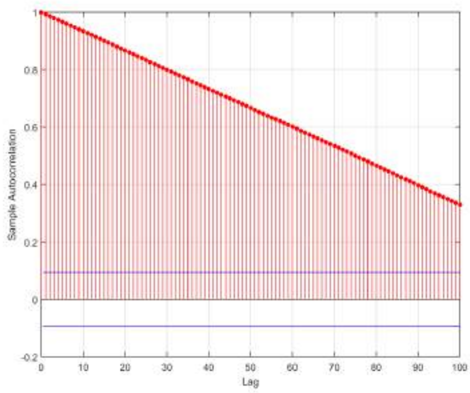


Power spectral density estimate



(9) Log of MZ

ACF



Power spectral density estimate

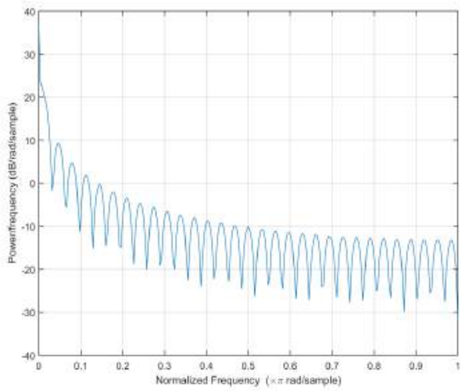
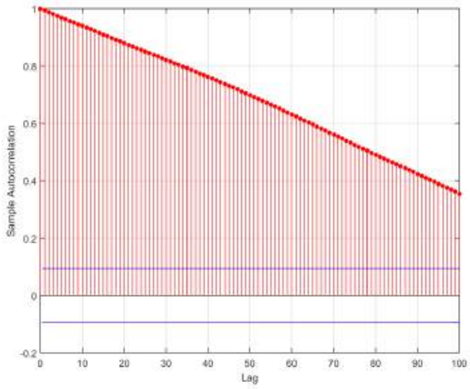


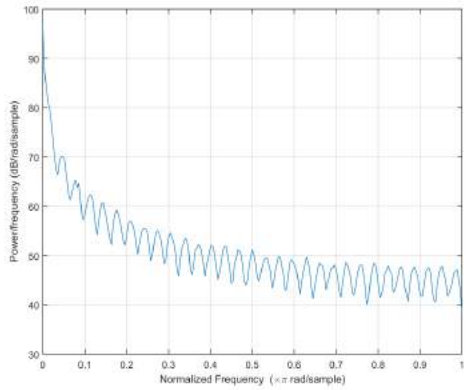
Figure 2 **ACF and periodograms – filtered series (Cont'd)**

(10) Real Personal Disposable Income

ACF

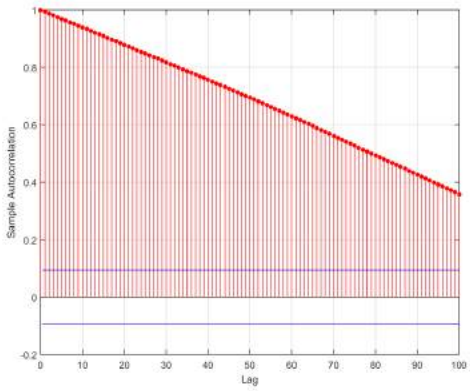


Power spectral density estimate

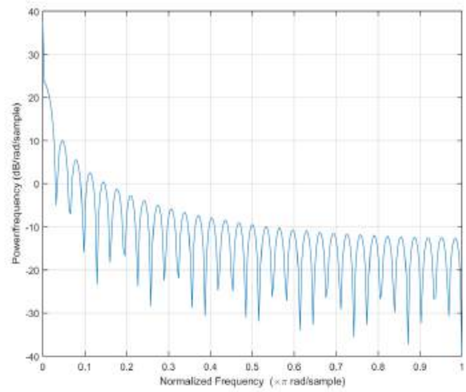


(11) Log of real personal disposable income

ACF

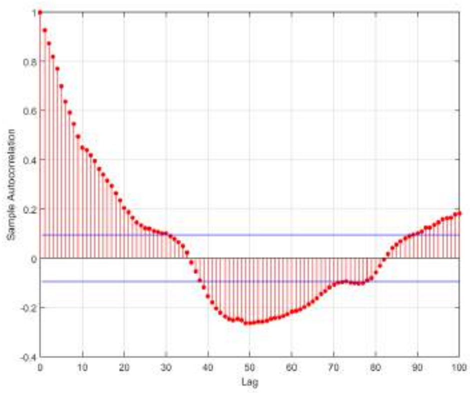


Power spectral density estimate



(12) Economic Policy Uncertainty

ACF



Power spectral density estimate

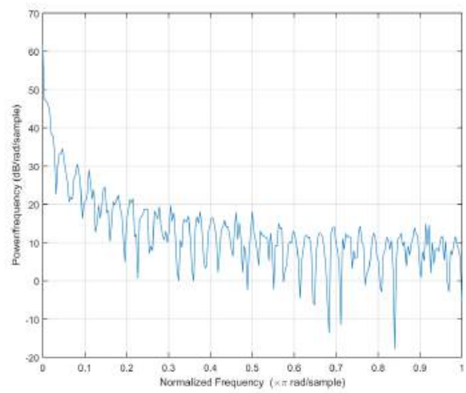
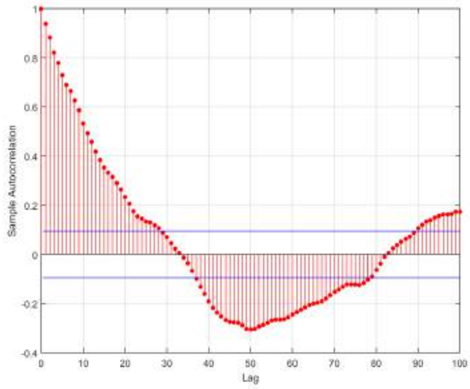


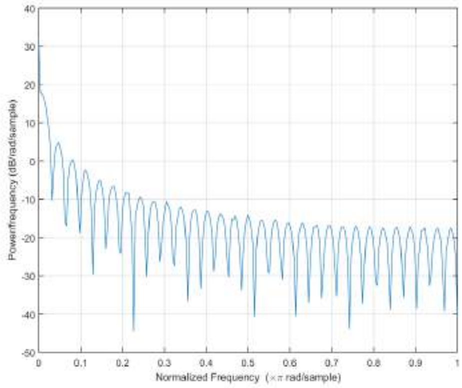
Figure 2 **ACF and periodograms – filtered series (Cont'd)**

(13) Log of EPU

ACF

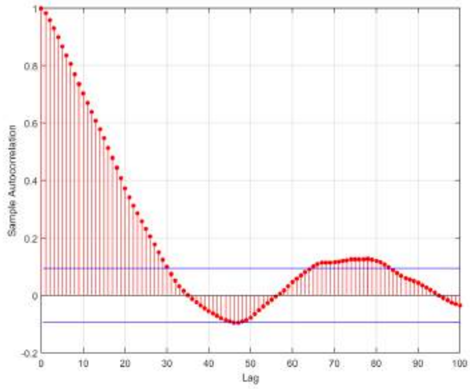


Power spectral density estimate

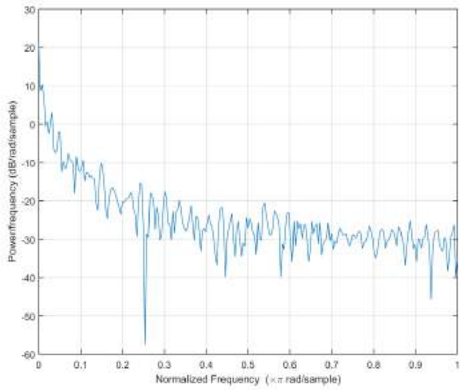


(14) M2 interest rate

ACF

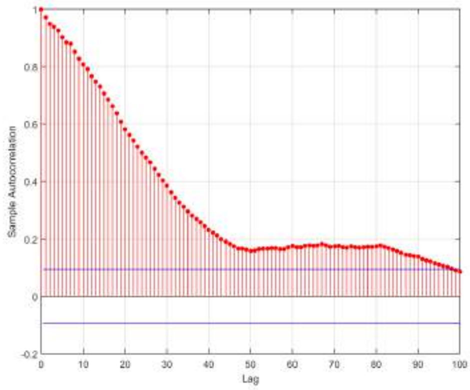


Power spectral density estimate



(15) MZ interest rate

ACF



Power spectral density estimate

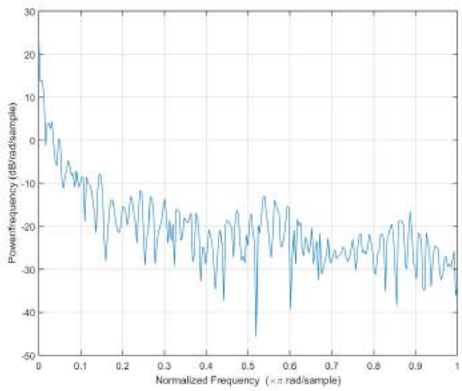
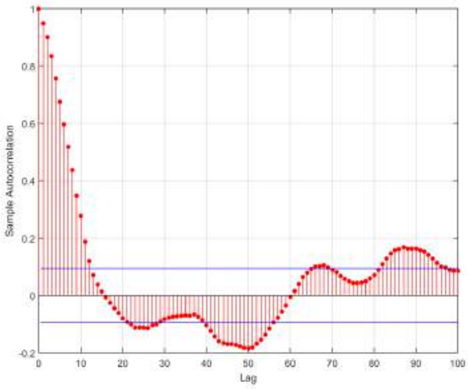


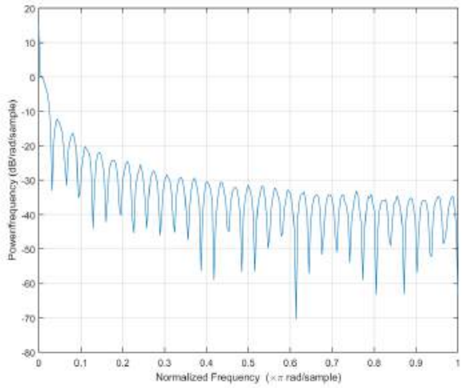
Figure 2 **ACF and periodograms – filtered series (Cont'd)**

(16) Ludvigson Macro Uncertainty: h1

ACF

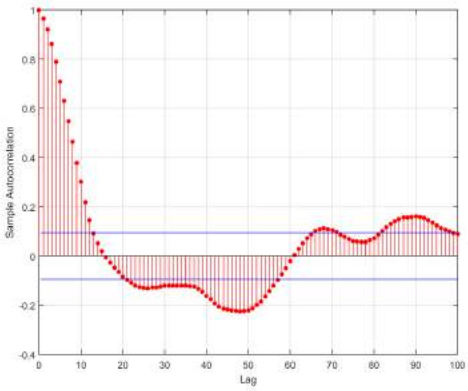


Power spectral density estimate

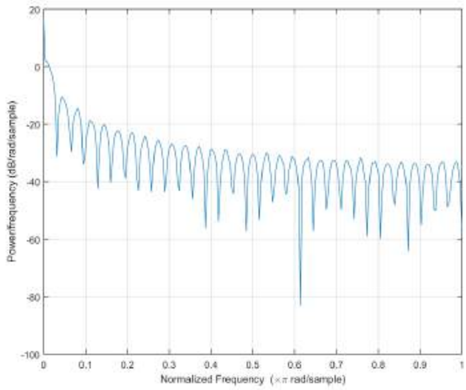


(17) Ludvigson Macro Uncertainty: h3

ACF

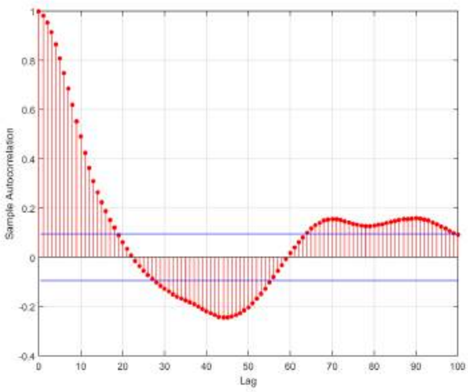


Power spectral density estimate



(18) Ludvigson Macro Uncertainty: h12

ACF



Power spectral density estimate

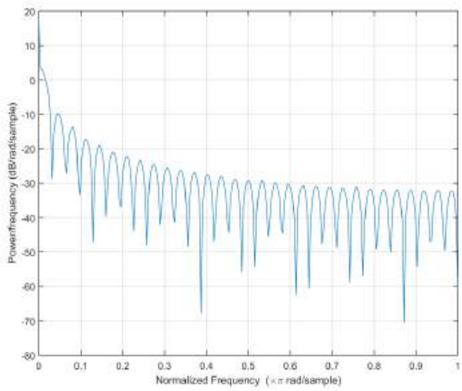
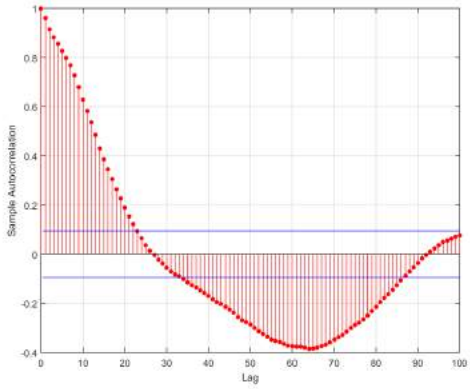


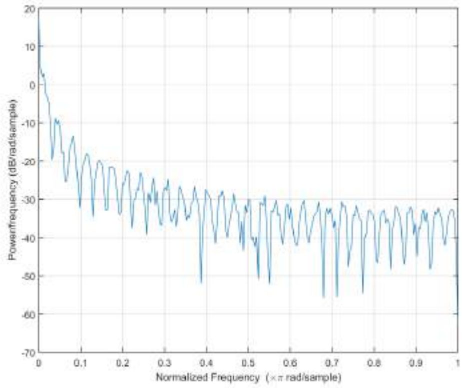
Figure 2 **ACF and periodograms – filtered series (Cont'd)**

(19) Ludvigson Financial Uncertainty: h1

ACF

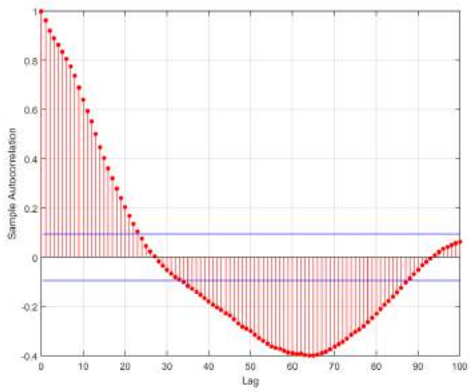


Power spectral density estimate

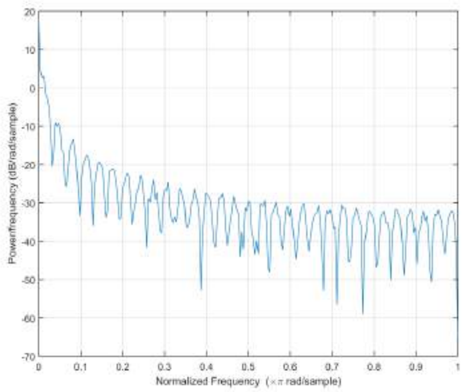


(20) Ludvigson Financial Uncertainty: h3

ACF

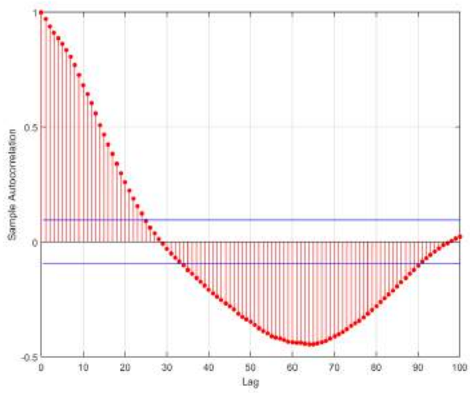


Power spectral density estimate



(21) Ludvigson Financial Uncertainty: h12

ACF



Power spectral density estimate

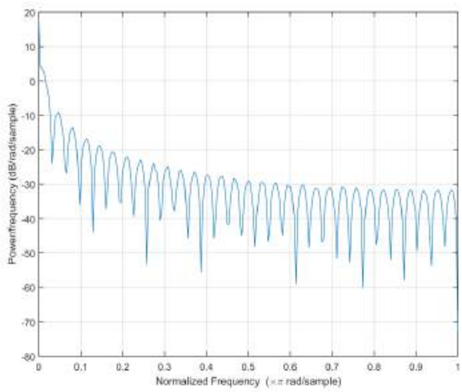
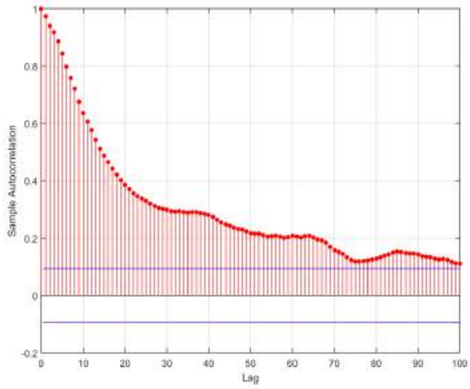


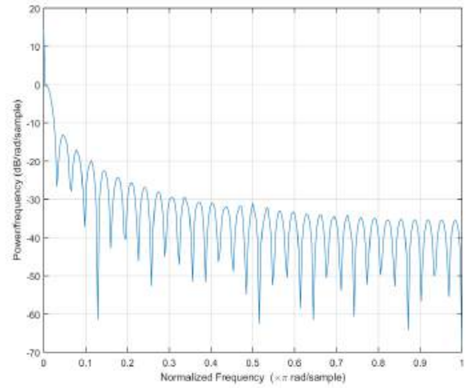
Figure 2 **ACF and periodograms – filtered series (Cont'd)**

(22) Ludvigson Real Uncertainty: h1

ACF

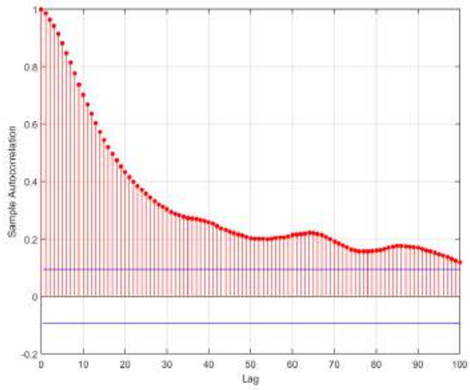


Power spectral density estimate

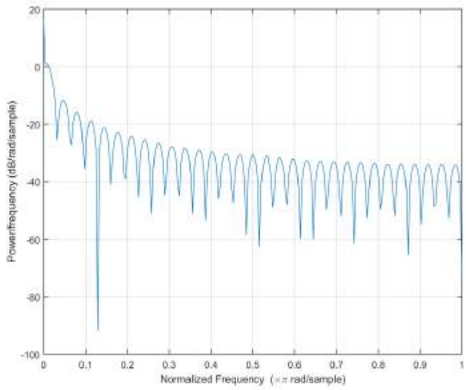


(23) Ludvigson Real Uncertainty: h3

ACF

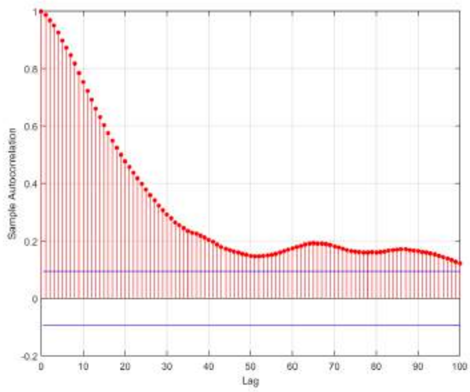


Power spectral density estimate



(24) Ludvigson Real Uncertainty: h12

ACF



Power spectral density estimate

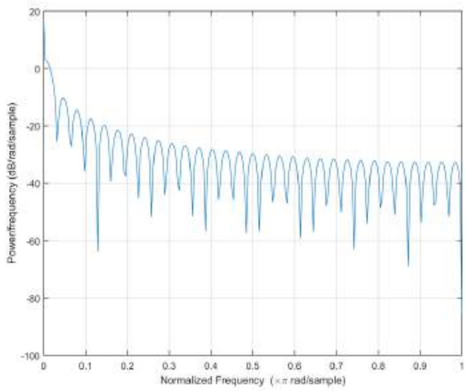
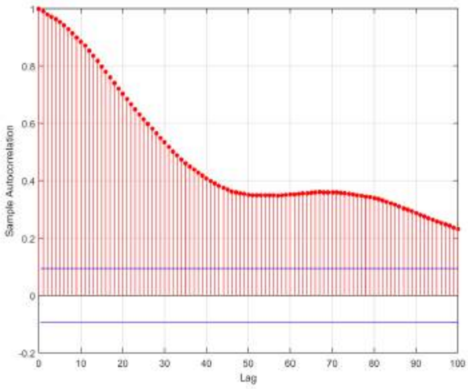


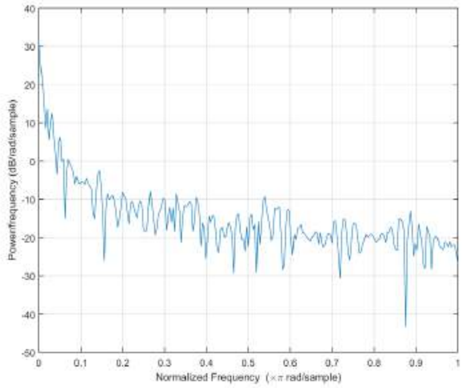
Figure 2 **ACF and periodograms – filtered series (Cont'd)**

(25) 3-Month Treasury Bill

ACF

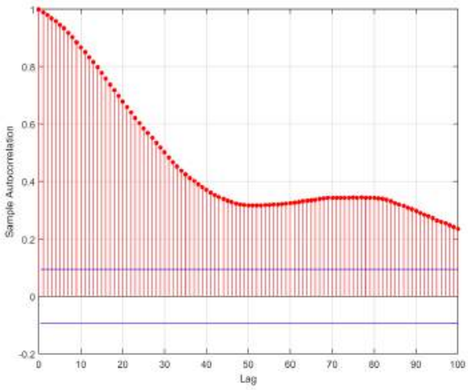


Power spectral density estimate

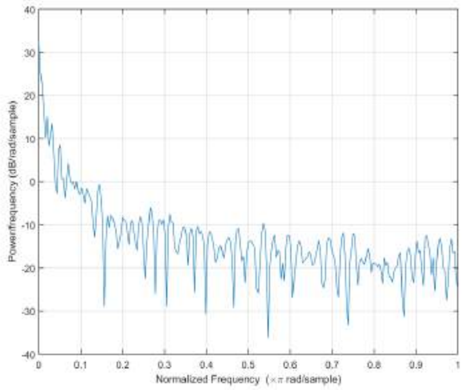


(26) Effective Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted

ACF

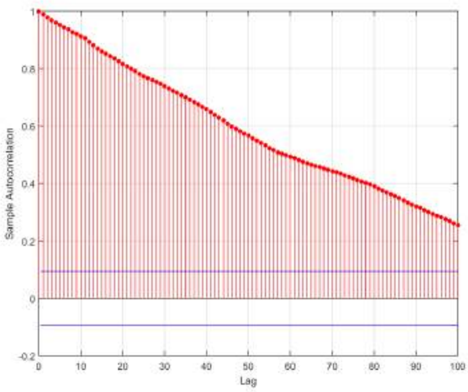


Power spectral density estimate



(27) 10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjust

ACF



Power spectral density estimate

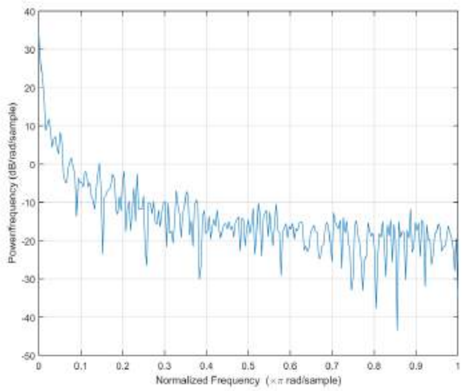
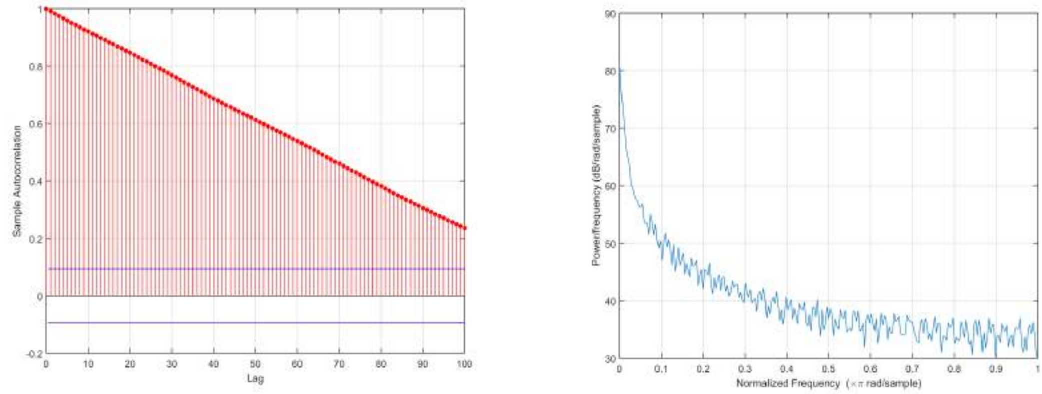


Figure 2 **ACF and periodograms – filtered series (Cont'd)**

(28) Small Deposits

ACF | Power spectral density estimate



Note: Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years)..

2.3 Full sample d estimates

Table 2 **Univariate *d* estimates, monetary aggregates – filtered series**

Bandwidth	**B = 0.4**				**B = 0.45**				**B = 0.5**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
realm1	0.797	0.189	1.344	1.344	0.693	1.364	1.115	1.115	0.787	1.145	1.054	1.054
realm2	0.964	1.065	1.701	1.701	0.924	1.209	1.401	1.401	0.947	1.121	1.352	1.352
realmzm	1.054	1.090	1.389	1.389	1.027	1.175	1.622	1.623	1.032	1.125	1.601	1.601
lnm1	0.921	0.077	1.320	1.320	0.879	0.077	1.034	1.034	0.922	0.077	0.961	0.961
lnm2	0.959	0.071	1.707	1.707	0.904	0.071	0.763	0.763	0.924	0.071	0.733	0.753
lnmzm	1.013	0.105	0.989	0.950	1.009	0.104	1.923	1.923	1.008	0.103	1.626	1.626
lnrealm1	0.894	0.019	1.288	1.288	0.792	0.020	1.122	1.122	0.869	1.006	1.043	1.043
lnrealm2	0.963	0.027	1.759	1.758	0.939	0.027	1.562	1.562	0.973	0.999	1.368	1.368
lnrealmzm	1.071	0.052	1.305	1.306	1.047	0.052	1.552	1.553	1.041	0.051	1.385	1.385

Bandwidth	**B = 0.55**				**B = 0.6**				**B = 0.65**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
realm1	0.797	1.143	1.013	1.013	0.893	1.087	1.053	1.053	0.995	1.009	1.061	1.061
realm2	0.927	1.144	1.171	1.171	0.960	1.045	1.116	1.116	0.969	1.030	1.100	1.100
realmzm	0.999	1.147	1.270	1.270	1.006	1.007	1.097	1.097	1.004	1.022	1.129	1.129
lnm1	0.939	0.077	0.949	0.949	0.964	1.009	1.023	1.023	0.998	1.000	1.037	1.037
lnm2	0.929	0.070	0.759	0.759	0.949	1.012	0.804	0.804	0.954	1.014	0.890	0.890
lnmzm	1.005	0.103	1.267	1.267	0.999	0.102	0.957	0.957	0.996	0.998	1.006	1.006
lnrealm1	0.863	1.011	1.007	1.007	0.924	1.007	1.029	1.029	0.983	1.002	1.034	1.034
lnrealm2	0.951	1.003	1.106	1.106	0.968	1.002	1.000	1.000	0.965	1.006	1.026	1.026
lnrealmzm	1.028	0.990	1.229	1.229	1.009	0.994	1.016	1.016	1.002	1.000	1.065	1.065

Bandwidth	**B = 0.7**				**B = 0.75**				**B = 0.8**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
realm1	0.923	1.060	1.026	1.026	0.994	0.998	1.038	1.038	0.939	1.027	1.025	1.025
realm2	0.954	1.047	1.056	1.056	0.966	1.024	1.074	1.074	0.952	1.025	1.035	1.035
realmzm	0.994	1.013	1.085	1.085	0.986	1.027	1.109	1.109	0.968	1.025	1.076	1.076
lnm1	0.971	1.012	1.017	1.017	0.993	1.010	1.028	1.028	0.962	1.030	1.019	1.019
lnm2	0.947	1.019	0.862	0.862	0.963	1.019	0.996	0.996	0.952	1.033	1.044	1.044
lnmzm	0.989	1.004	1.001	1.001	0.983	1.013	1.074	1.074	0.966	1.029	1.119	1.119
lnrealm1	0.937	1.013	1.021	1.021	0.993	1.012	1.028	1.028	0.941	1.031	1.017	1.017
lnrealm2	0.954	1.011	1.001	1.001	0.966	1.016	1.027	1.027	0.949	1.032	1.004	1.004
lnrealmzm	0.993	1.005	1.038	1.038	0.989	1.013	1.083	1.083	0.970	1.029	1.088	1.088

Note: Univariate d estimates for various bandwidths and various estimators: "LW" = Local Whittle estimator, "ELW" = Exact Local Whittle estimator; "FELW" = Feasible Exact Local Whittle estimator; "2ELW" = 2-step ELW estimator. Column super-headers give the value of the bandwidth (B) used for estimation. Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years).

Table 3 **Univariate *d* estimates, uncertainty variables – filtered series**

Bandwidth	**B = 0.4**				**B = 0.45**				**B = 0.5**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
lnepu	0.424	-0.005	0.625	0.596	0.484	-0.005	0.675	0.633	0.743	0.999	0.779	0.779
ludmach1	0.121	-0.004	0.096	0.096	0.112	-0.006	0.081	0.081	0.276	1.002	0.272	0.272
ludmach3	0.094	-0.004	0.067	0.067	0.106	-0.006	0.079	0.079	0.297	0.994	0.294	0.294
ludmach12	0.230	-0.004	0.227	0.227	0.311	-0.005	0.316	0.316	0.537	0.991	0.639	0.551
ludfin1	0.330	0.002	0.335	0.341	0.634	1.125	0.588	0.816	0.952	1.174	1.173	1.173
ludfin3	0.351	0.001	0.357	0.366	0.665	1.106	0.591	0.841	0.986	1.132	1.207	1.207
ludfin12	0.450	0.000	0.461	0.516	0.791	1.039	0.957	0.957	1.108	1.040	1.341	1.341
ludreal1	0.477	-0.012	0.650	0.527	0.513	-0.012	0.655	0.558	0.592	0.960	0.740	0.734
ludreal3	0.504	-0.011	0.676	0.549	0.564	-0.011	0.703	0.611	0.674	0.970	0.818	0.818
ludreal12	0.556	-0.005	0.705	0.605	0.655	-0.005	0.778	0.777	0.795	0.989	0.951	0.951
Bandwidth	**B = 0.55**				**B = 0.6**				**B = 0.65**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
lnepu	0.790	1.002	0.792	0.792	0.890	1.002	0.899	0.899	0.809	0.999	0.822	0.822
ludmach1	0.485	1.015	0.496	0.496	0.927	1.037	0.953	0.953	1.037	1.027	1.063	1.062
ludmach3	0.543	1.008	0.547	0.556	1.040	1.037	1.067	1.067	1.126	1.032	1.154	1.154
ludmach12	0.793	0.999	0.811	0.811	1.243	1.016	1.227	1.227	1.312	1.019	1.311	1.311
ludfin1	1.243	1.116	1.361	1.361	1.141	1.130	1.273	1.273	0.988	1.094	1.071	1.071
ludfin3	1.252	1.085	1.363	1.363	1.141	1.099	1.272	1.272	1.007	1.078	1.093	1.093
ludfin12	1.274	1.025	1.372	1.372	1.144	1.032	1.278	1.278	1.070	1.031	1.174	1.174
ludreal1	0.707	0.976	0.868	0.868	0.883	0.990	1.047	1.047	1.123	1.004	1.272	1.272
ludreal3	0.847	0.987	1.011	1.011	1.060	0.998	1.225	1.225	1.241	1.008	1.381	1.381
ludreal12	0.999	0.996	1.162	1.162	1.113	1.001	1.214	1.214	1.167	1.006	1.221	1.221
Bandwidth	**B = 0.7**				**B = 0.75**				**B = 0.8**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
lnepu	0.819	1.001	0.840	0.840	0.910	1.022	0.908	0.908	0.858	1.031	0.906	0.906
ludmach1	1.077	1.025	1.112	1.112	1.151	1.033	1.210	1.210	1.089	1.042	1.189	1.189
ludmach3	1.227	1.031	1.264	1.264	1.249	1.034	1.312	1.312	1.159	1.043	1.264	1.264
ludmach12	1.418	1.019	1.448	1.448	1.347	1.023	1.420	1.420	1.225	1.036	1.339	1.339
ludfin1	0.924	1.019	0.963	0.963	0.915	1.062	0.987	0.987	0.881	1.073	0.976	0.976
ludfin3	0.937	1.020	0.975	0.975	0.929	1.056	1.002	1.002	0.894	1.068	0.990	0.990
ludfin12	0.982	1.015	1.019	1.019	0.970	1.032	1.048	1.048	0.927	1.045	1.025	1.025
ludreal1	1.173	1.025	1.103	1.103	1.117	1.032	1.094	1.094	0.896	1.034	0.954	0.954
ludreal3	1.213	1.022	1.165	1.165	1.226	1.029	1.226	1.226	1.022	1.035	1.130	1.130
ludreal12	1.138	1.013	1.127	1.127	1.202	1.021	1.221	1.221	1.032	1.032	1.147	1.147

Note: Univariate d estimates for various bandwidths and various estimators: "LW" = Local Whittle estimator, "ELW" = Exact Local Whittle estimator; "FELW" = Feasible Exact Local Whittle estimator; "2ELW" = 2-step ELW estimator. Column super-headers give the value of the bandwidth (B) used for estimation. Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years).

Table 4 **Univariate *d* estimates, interest rates and other variables – filtered series**

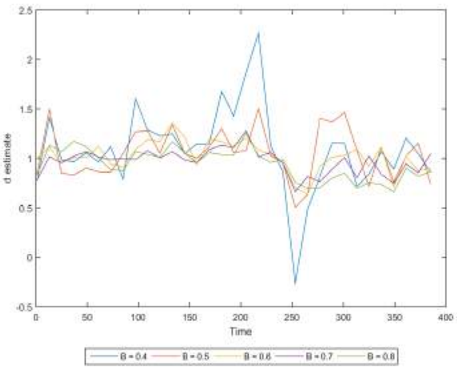
Bandwidth	**B = 0.4**				**B = 0.45**				**B = 0.5**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
interestm2	0.594	0.810	0.621	0.653	0.779	0.878	0.654	0.842	0.896	0.916	1.027	1.027
interestmzm	0.843	0.918	0.779	0.880	0.959	0.968	1.069	1.069	1.036	0.994	1.291	1.291
lnrpdi	1.015	0.034	0.962	0.962	1.014	0.034	0.925	0.925	1.015	0.033	0.903	1.040
tb3ms	0.979	1.026	0.920	0.925	1.084	1.080	1.210	1.210	1.173	1.130	1.663	1.665
fedfunds	0.885	0.952	0.819	0.831	1.018	1.020	1.226	1.227	1.031	1.012	1.566	1.566
gs10	1.129	1.201	1.081	1.081	0.990	1.070	1.035	1.035	1.072	1.109	1.197	1.197
smalldepo	1.029	1.211	1.300	1.300	1.010	1.176	1.244	1.244	1.001	1.145	1.200	1.200
Bandwidth	**B = 0.55**				**B = 0.6**				**B = 0.65**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
interestm2	0.933	0.925	1.117	1.117	0.952	0.942	1.101	1.101	1.042	1.015	1.170	1.170
interestmzm	1.026	0.982	1.327	1.327	1.019	1.000	1.128	1.128	1.031	1.026	1.085	1.085
lnrpdi	1.011	0.994	0.946	0.946	0.994	0.999	0.963	0.963	0.976	1.005	1.001	1.001
tb3ms	1.198	1.147	2.081	2.081	1.151	1.125	1.367	1.367	1.165	1.142	1.402	1.402
fedfunds	1.054	1.026	1.667	1.667	1.098	1.070	1.364	1.364	1.180	1.144	1.401	1.401
gs10	1.067	1.085	1.347	1.347	1.034	1.074	1.052	1.052	0.931	1.003	0.905	0.905
smalldepo	0.991	1.152	1.193	1.193	0.983	1.124	1.149	1.149	0.977	1.114	1.128	1.128
Bandwidth	**B = 0.7**				**B = 0.75**				**B = 0.8**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
interestm2	1.062	1.052	1.134	1.134	1.130	1.112	1.244	1.244	1.040	1.087	1.179	1.179
interestmzm	0.962	0.993	0.973	0.973	0.970	1.015	0.984	0.984	0.789	0.886	0.830	0.830
lnrpdi	0.966	1.010	1.021	1.021	0.977	1.015	0.971	0.971	0.965	1.030	0.991	0.991
tb3ms	1.105	1.107	1.231	1.231	1.007	1.042	1.046	1.046	0.935	1.002	1.001	1.001
fedfunds	1.055	1.065	1.125	1.125	1.022	1.049	1.133	1.133	0.983	1.042	1.106	1.106
gs10	0.992	1.050	0.981	0.981	0.953	1.033	0.934	0.934	0.928	1.024	0.973	0.973
smalldepo	0.971	1.114	1.121	1.121	0.974	1.069	1.095	1.095	0.966	1.057	1.094	1.094

Note: Univariate d estimates for various bandwidths and various estimators: "LW" = Local Whittle estimator, "ELW" = Exact Local Whittle estimator; "FELW" = Feasible Exact Local Whittle estimator; "2ELW" = 2-step ELW estimator. Column super-headers give the value of the bandwidth (B) used for estimation. Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years).

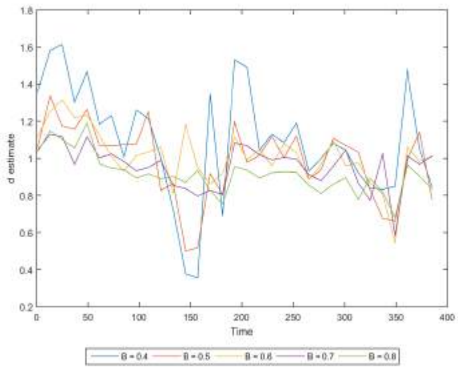
2.4 Rolling-window d estimates

Figure 3 **Rolling-window univariate *d* estimate, LW − filtered series**

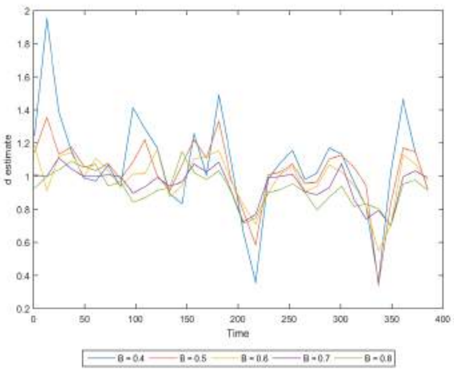
(1) M1, real



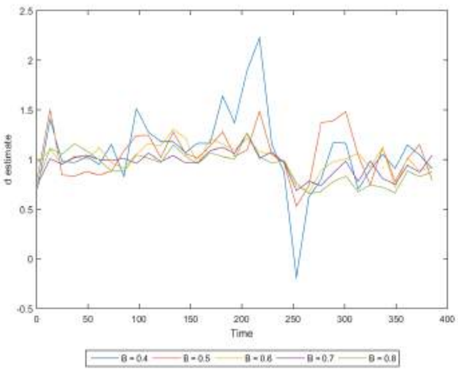
(2) M2, real



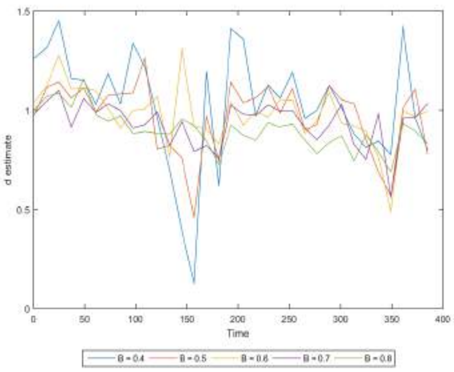
(3) MZ, real



(4) Log of real M1



(5) Log of real M2



(6) Log of real MZ

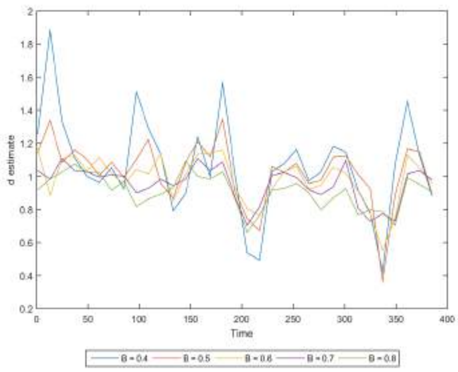
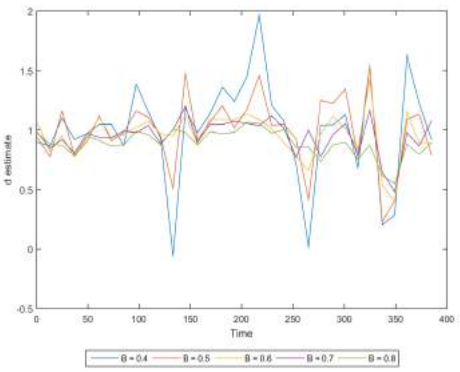
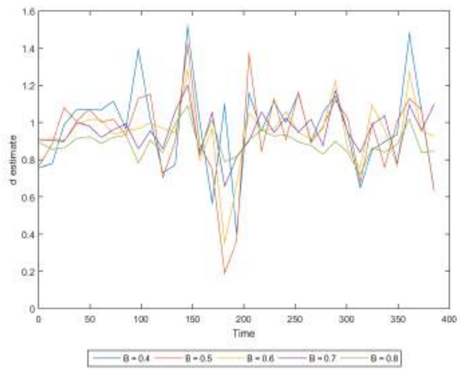


Figure 3 **Rolling-window univariate *d* estimate, LW – filtered series (Cont'd)**

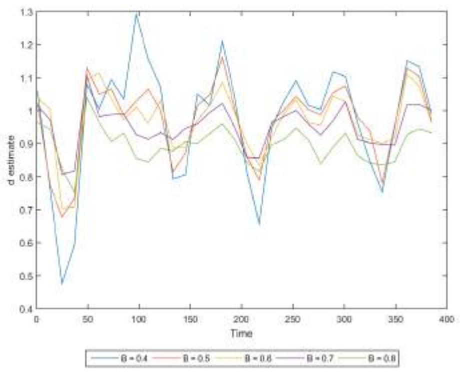
(7) Log of M1



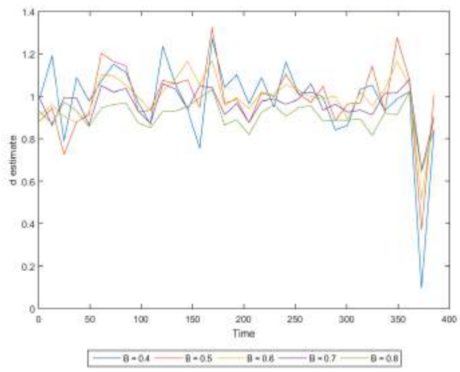
(8) Log of M2



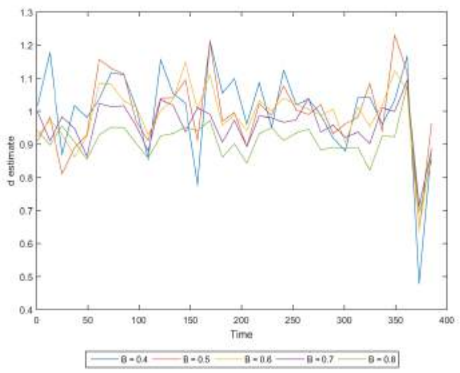
(9) Log of MZ



(10) Real Personal Disposable Income



(11) Log of real personal disposable income



(12) Economic Policy Uncertainty

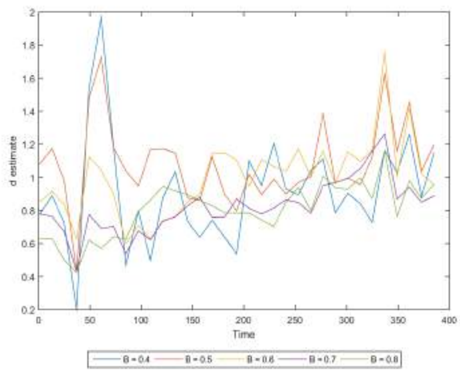
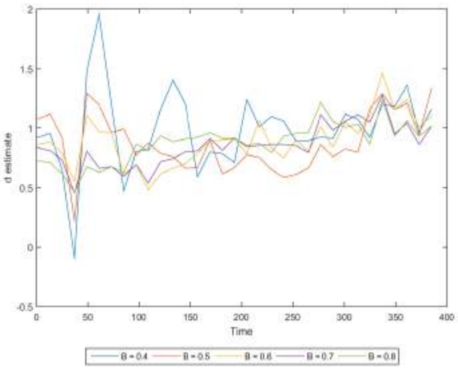
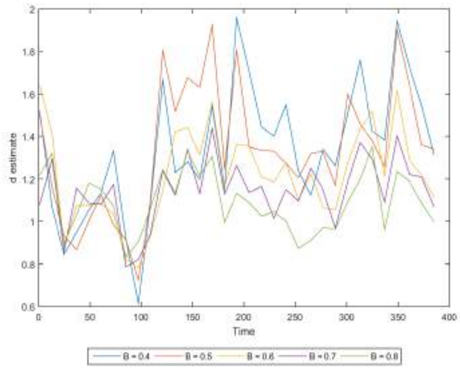


Figure 3 **Rolling-window univariate *d* estimate, LW – filtered series (Cont'd)**

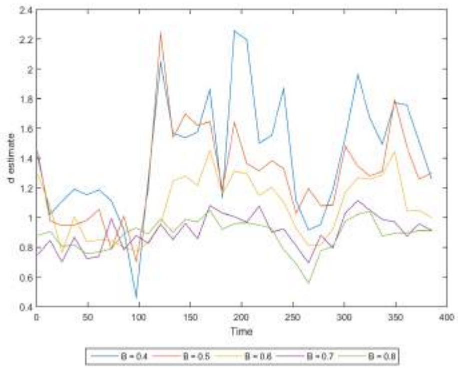
(13) Log of EPU



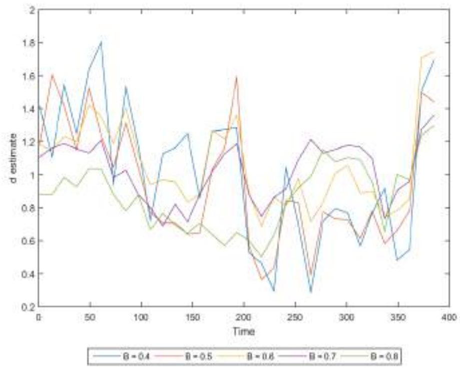
(14) M2 interest rate



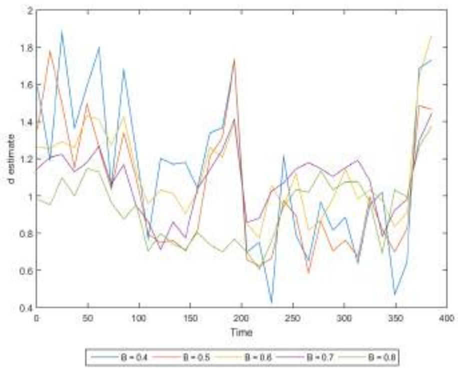
(15) MZ interest rate



(16) Ludvigson Macro Uncertainty: h1



(17) Ludvigson Macro Uncertainty: h3



(18) Ludvigson Macro Uncertainty: h12

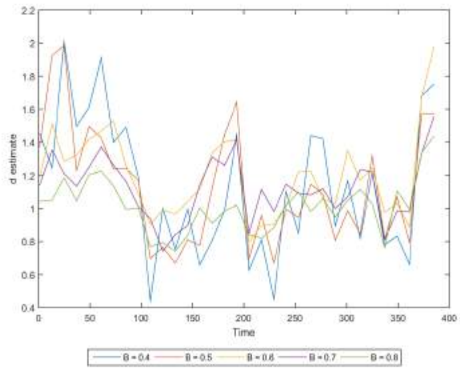
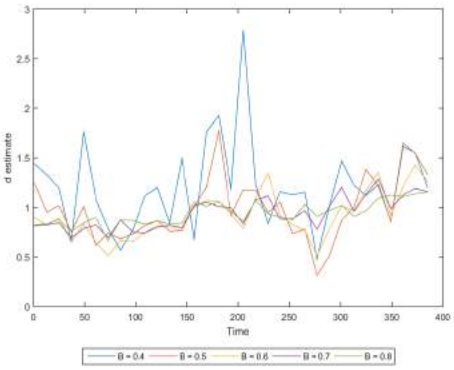
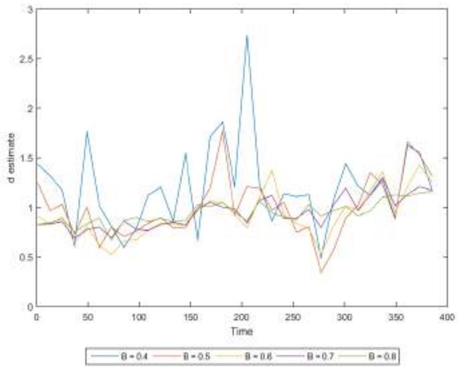


Figure 3 **Rolling-window univariate *d* estimate, LW – filtered series (Cont'd)**

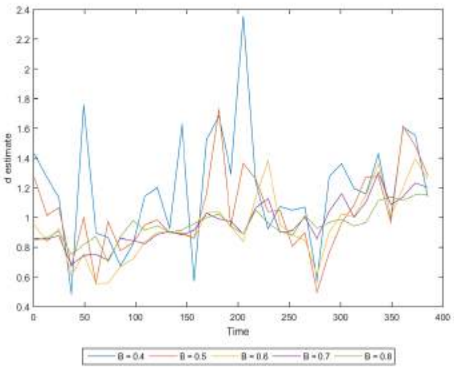
(19) Ludvigson Financial Uncertainty: h1



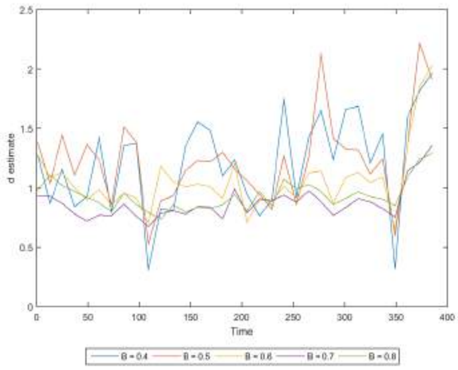
(20) Ludvigson Financial Uncertainty: h3



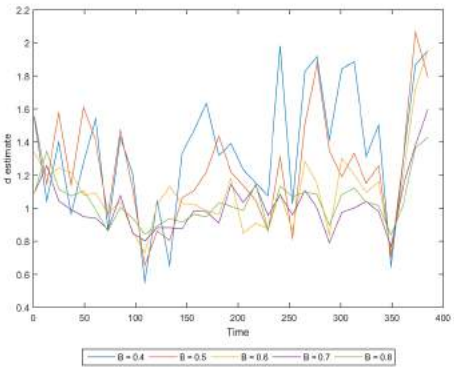
(21) Ludvigson Financial Uncertainty: h12



(22) Ludvigson Real Uncertainty: h1



(23) Ludvigson Real Uncertainty: h3



(24) Ludvigson Real Uncertainty: h12

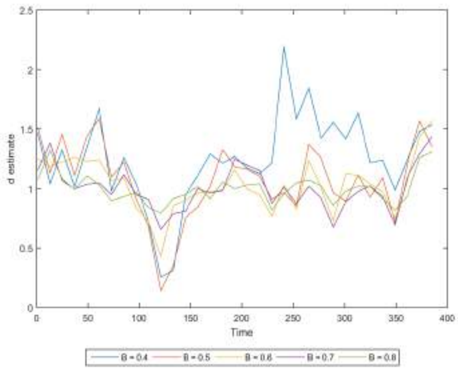
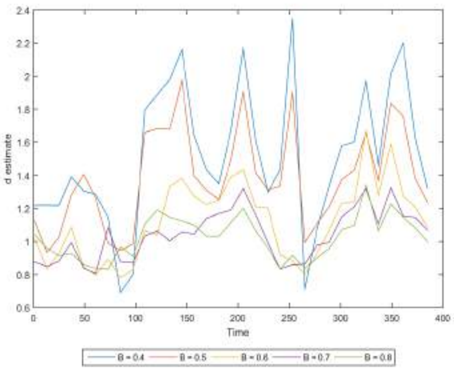
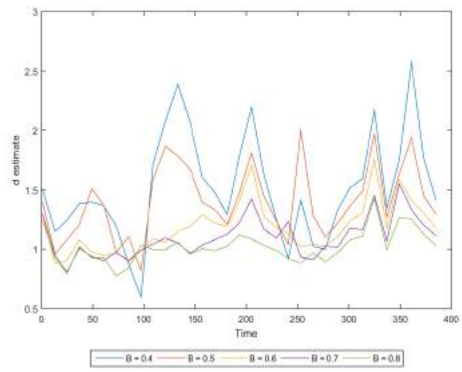


Figure 3 **Rolling-window univariate d estimate, LW – filtered series (Cont'd)**

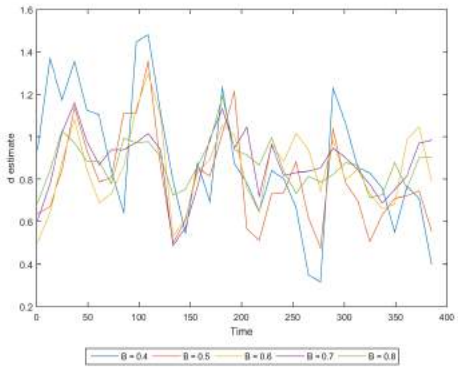
(25) 3-Month Treasury Bill



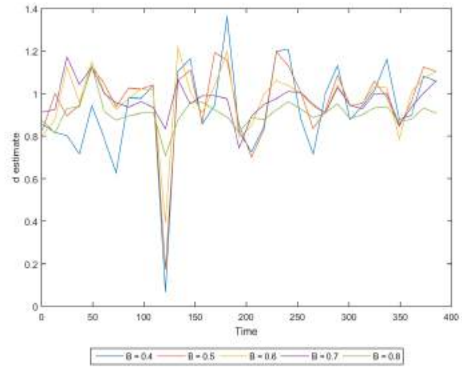
(26) Effective Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted



(27) 10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjust



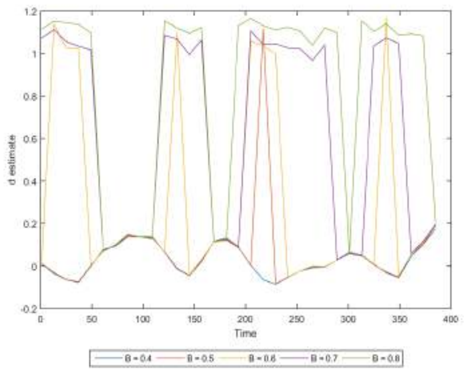
(28) Small Deposits



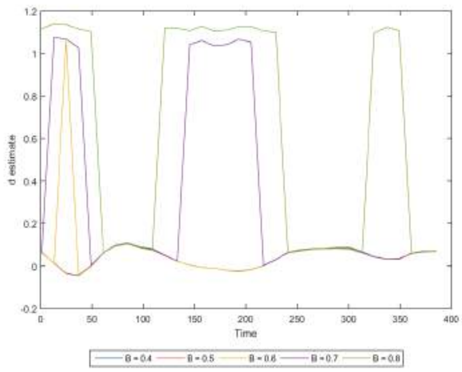
Note: Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years)..

Figure 4 **Rolling-window univariate *d* estimate, ELW − filtered series**

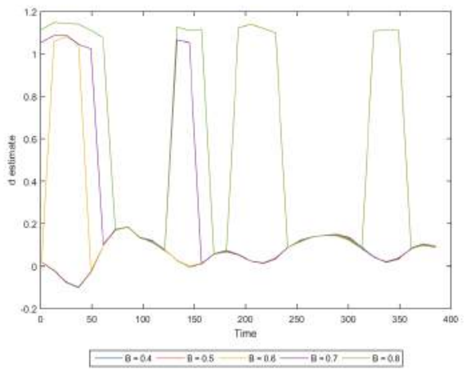
(1) M1, real



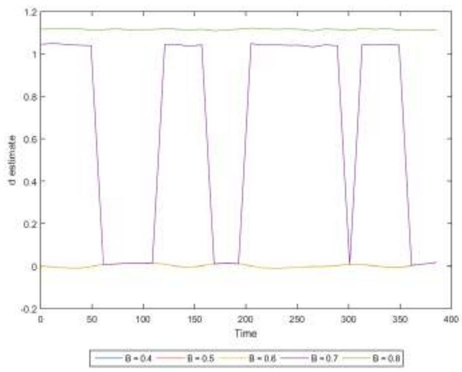
(2) M2, real



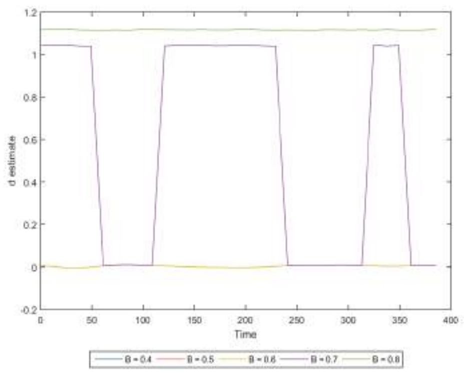
(3) MZ, real



(4) Log of real M1



(5) Log of real M2



(6) Log of real MZ

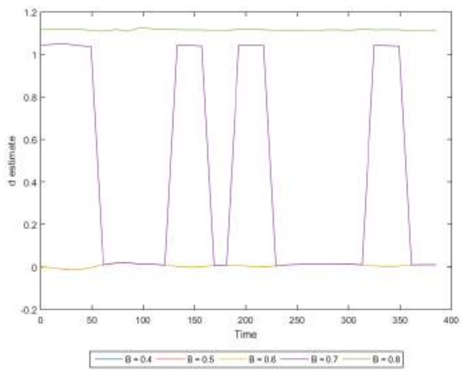
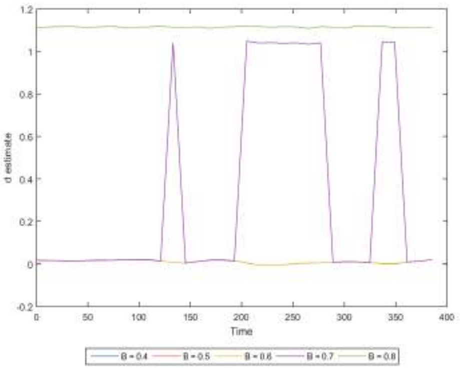
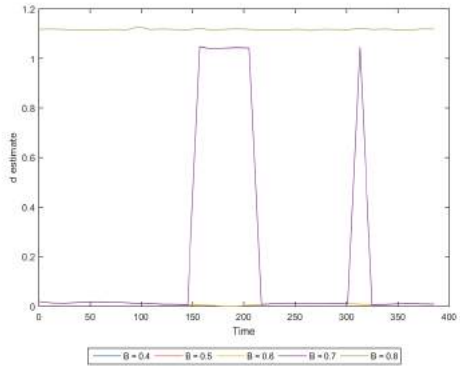


Figure 4 **Rolling-window univariate *d* estimate, ELW – filtered series (Cont'd)**

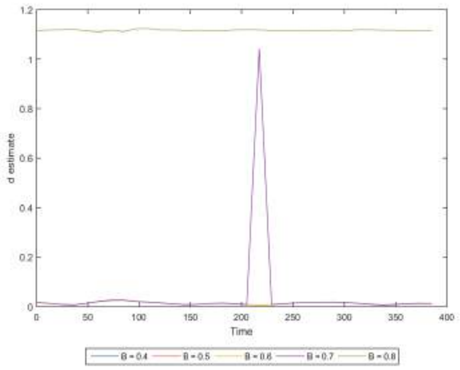
(7) Log of M1



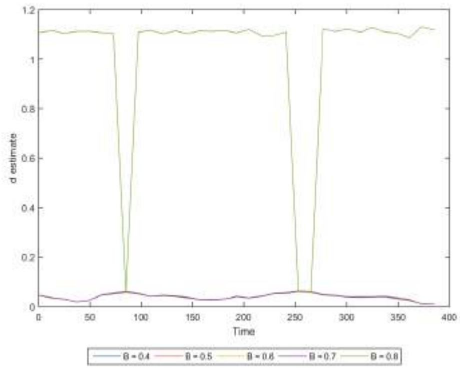
(8) Log of M2



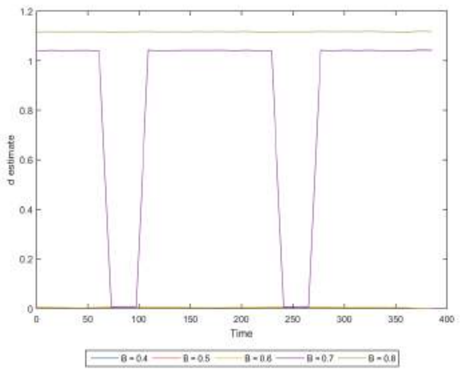
(9) Log of MZ



(10) Real Personal Disposable Income



(11) Log of real personal disposable income



(12) Economic Policy Uncertainty

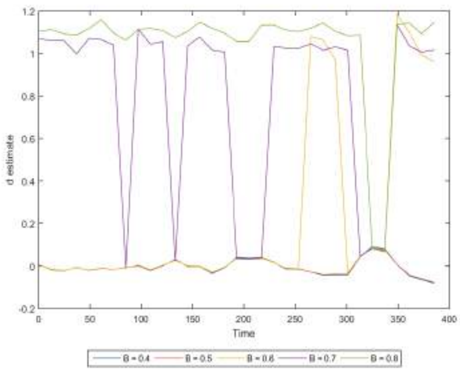
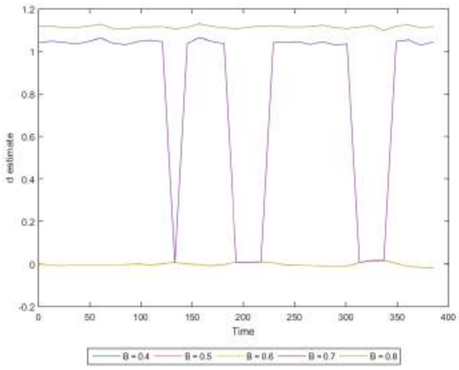
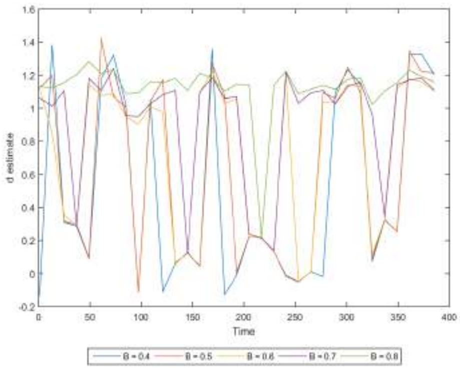


Figure 4 **Rolling-window univariate $\boldsymbol{d}$ estimate, ELW – filtered series (Cont'd)**

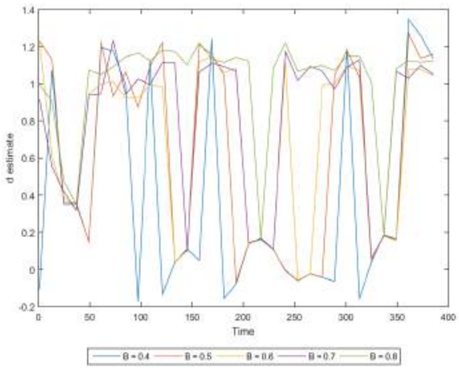
(13) Log of EPU



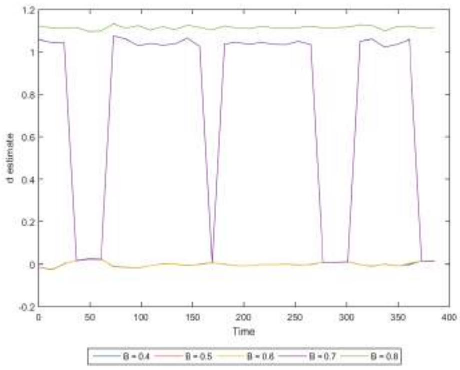
(14) M2 interest rate



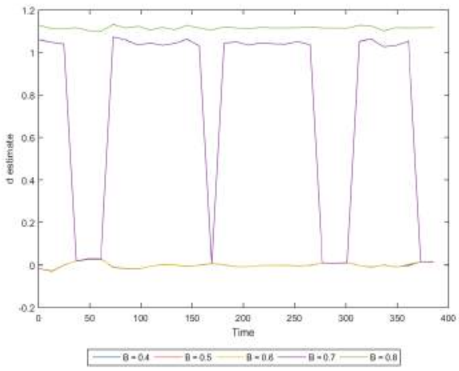
(15) MZ interest rate



(16) Ludvigson Macro Uncertainty: h1



(17) Ludvigson Macro Uncertainty: h3



(18) Ludvigson Macro Uncertainty: h12

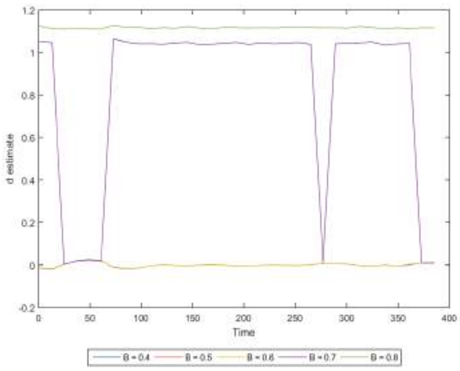
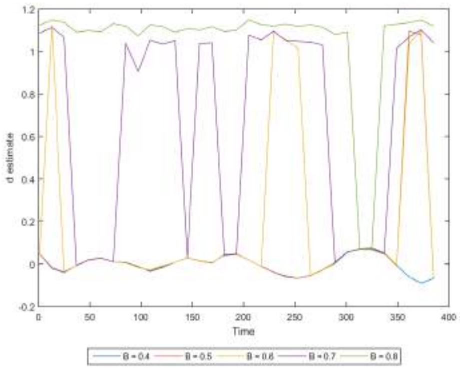
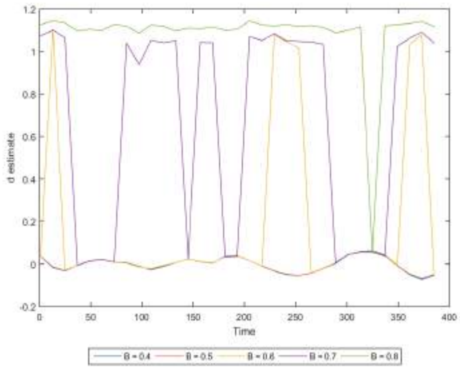


Figure 4 **Rolling-window univariate *d* estimate, ELW – filtered series (Cont'd)**

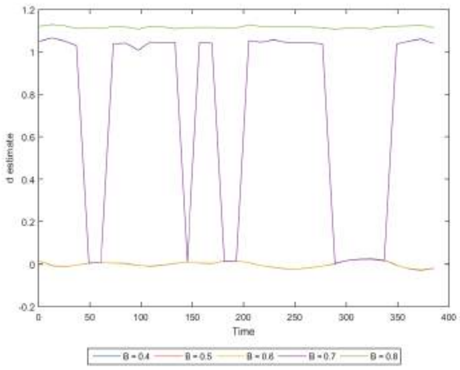
(19) Ludvigson Financial Uncertainty: h1



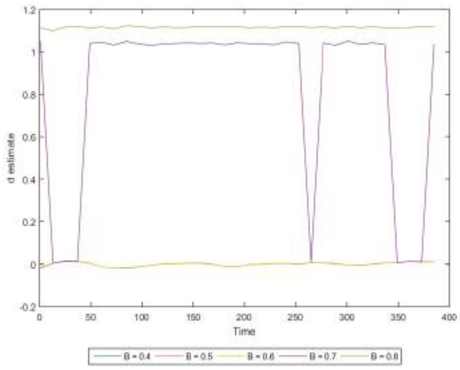
(20) Ludvigson Financial Uncertainty: h3



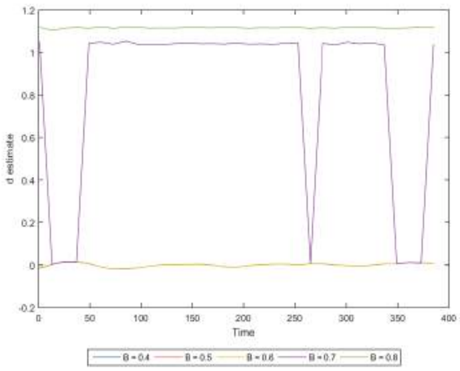
(21) Ludvigson Financial Uncertainty: h12



(22) Ludvigson Real Uncertainty: h1



(23) Ludvigson Real Uncertainty: h3



(24) Ludvigson Real Uncertainty: h12

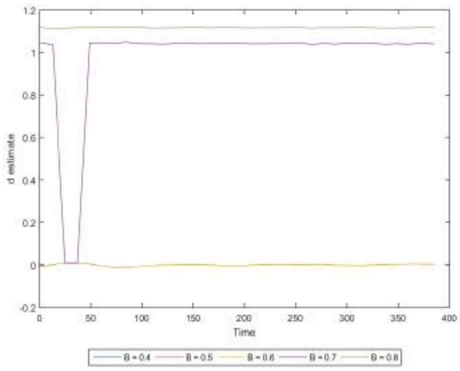
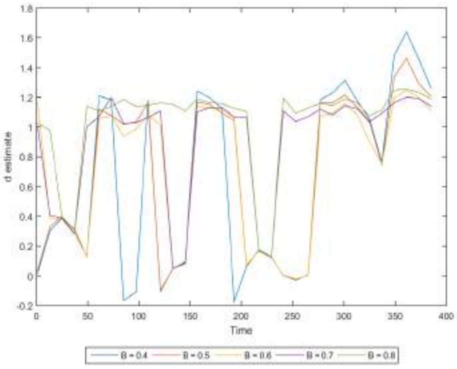
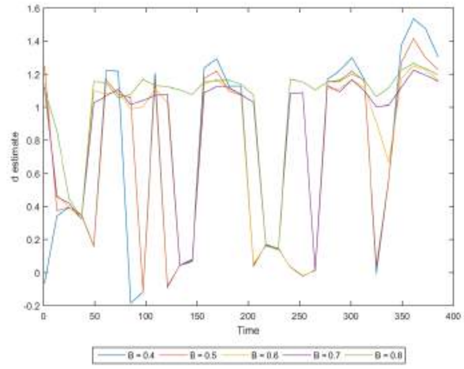


Figure 4 **Rolling-window univariate d estimate, ELW – filtered series (Cont'd)**

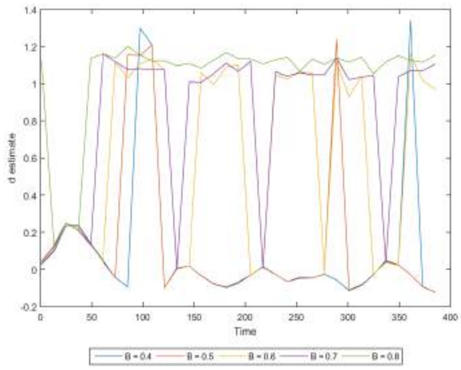
(25) 3-Month Treasury Bill



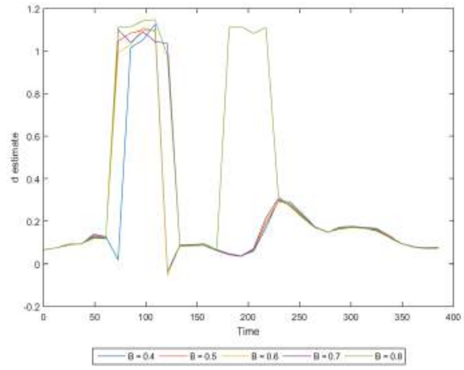
(26) Effective Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted



(27) 10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjust



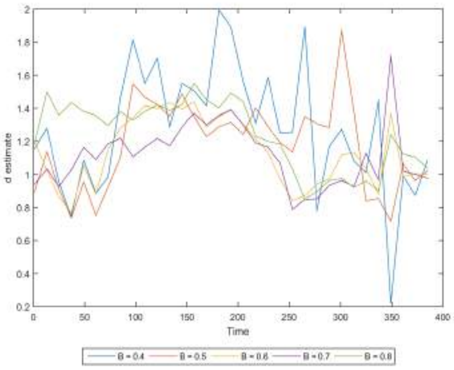
(28) Small Deposits



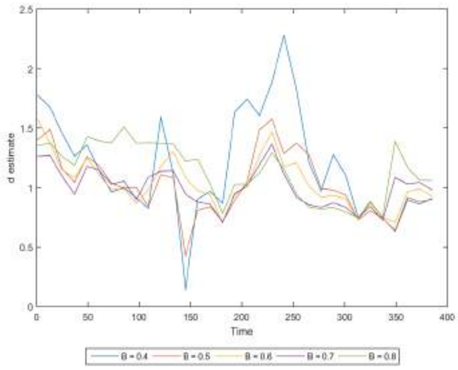
Note: Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years)..

Figure 5 **Rolling-window univariate d estimate, Feasible ELW – filtered series**

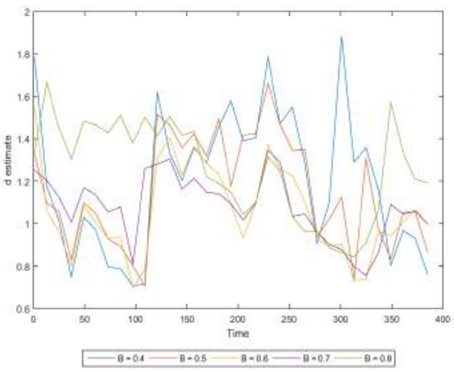
(1) M1, real



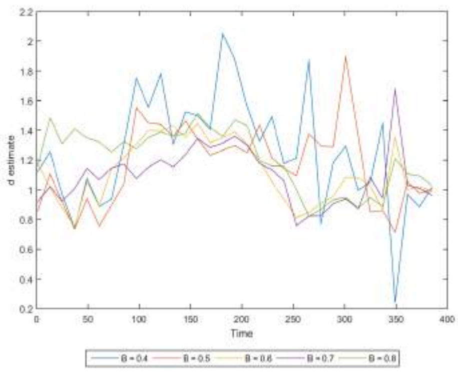
(2) M2, real



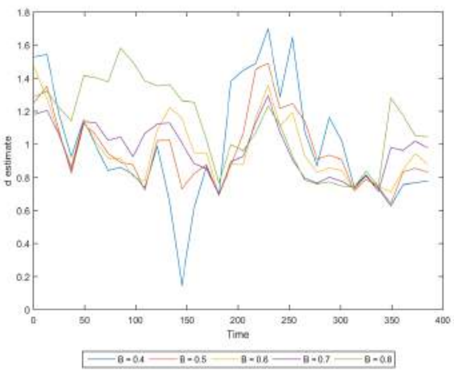
(3) MZ, real



(4) Log of real M1



(5) Log of real M2



(6) Log of real MZ

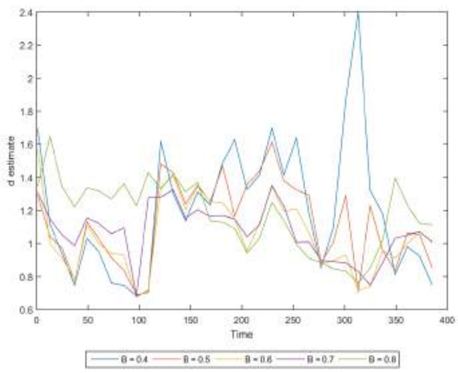
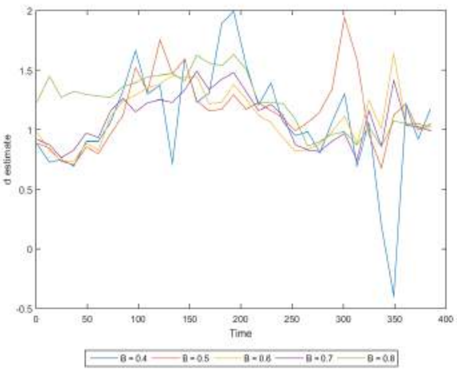
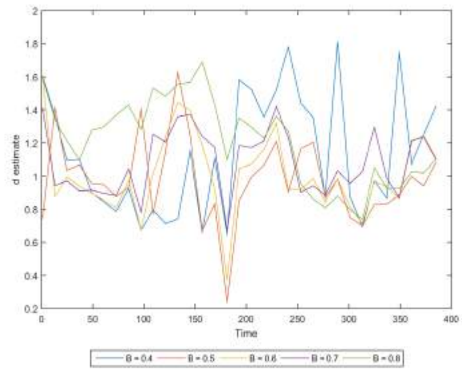


Figure 5 **Rolling-window univariate d estimate, Feasible ELW – filtered series (Cont'd)**

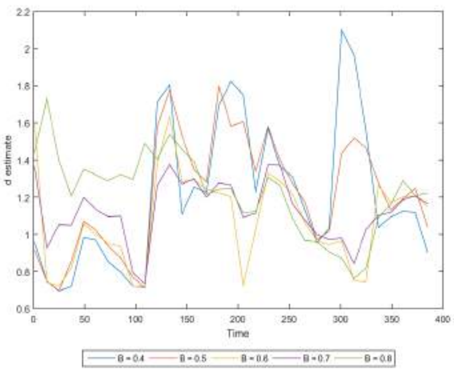
(7) Log of M1



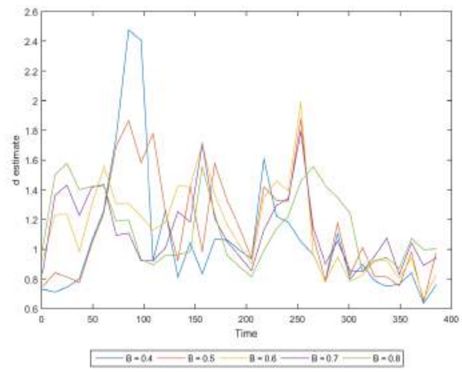
(8) Log of M2



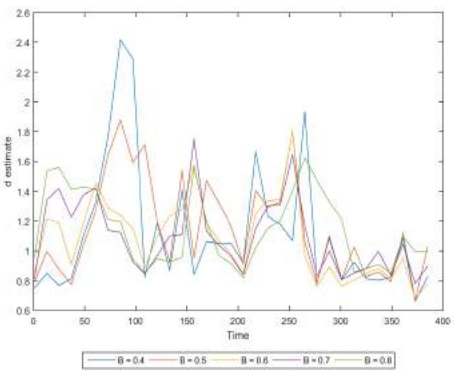
(9) Log of MZ



(10) Real Personal Disposable Income



(11) Log of real personal disposable income



(12) Economic Policy Uncertainty

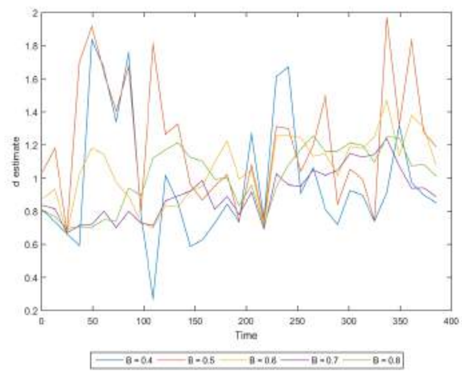
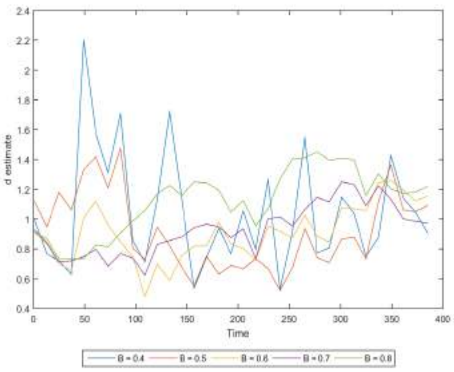
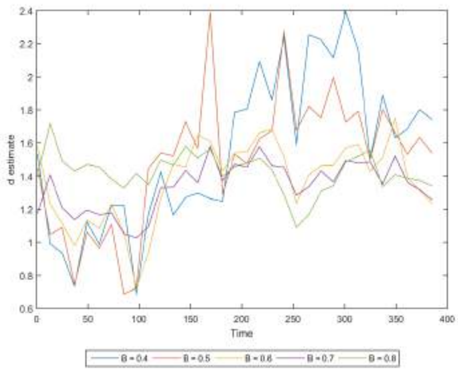


Figure 5 **Rolling-window univariate d estimate, Feasible ELW – filtered series (Cont'd)**

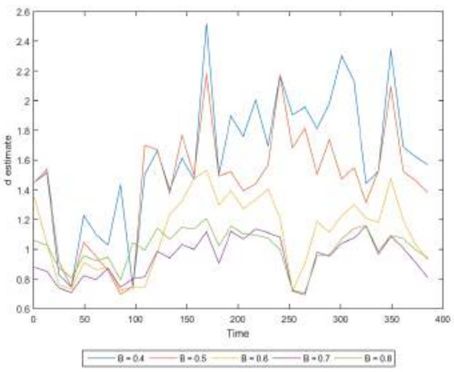
(13) Log of EPU



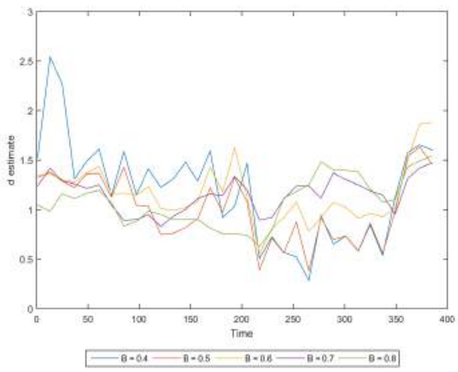
(14) M2 interest rate



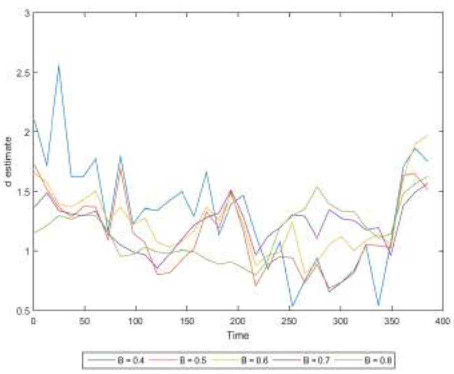
(15) MZ interest rate



(16) Ludvigson Macro Uncertainty: h1



(17) Ludvigson Macro Uncertainty: h3



(18) Ludvigson Macro Uncertainty: h12

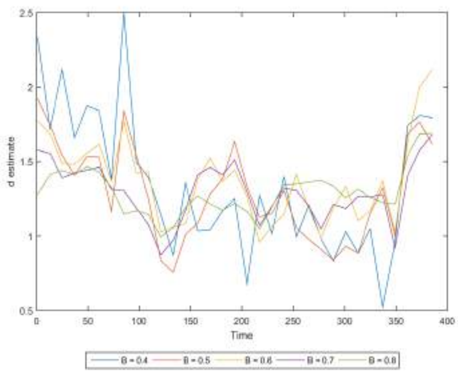
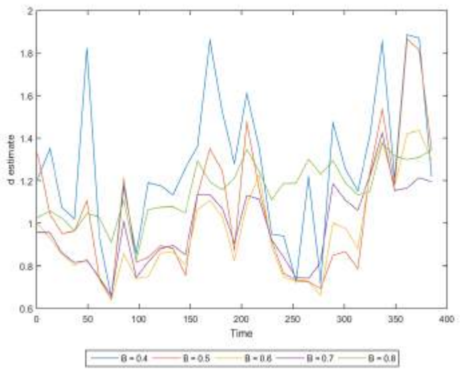
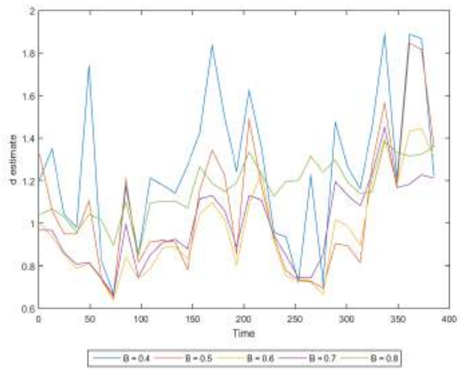


Figure 5 **Rolling-window univariate d estimate, Feasible ELW – filtered series (Cont'd)**

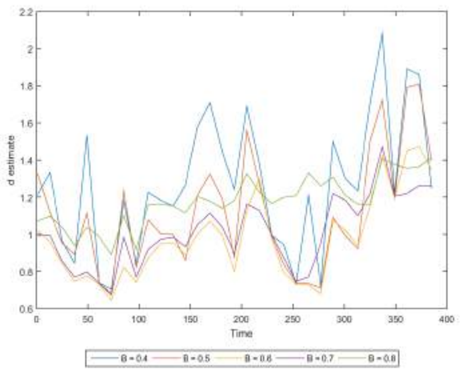
(19) Ludvigson Financial Uncertainty: h1



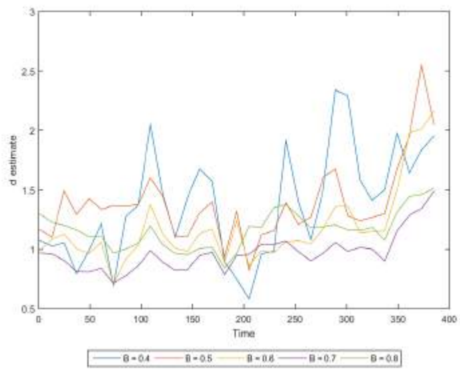
(20) Ludvigson Financial Uncertainty: h3



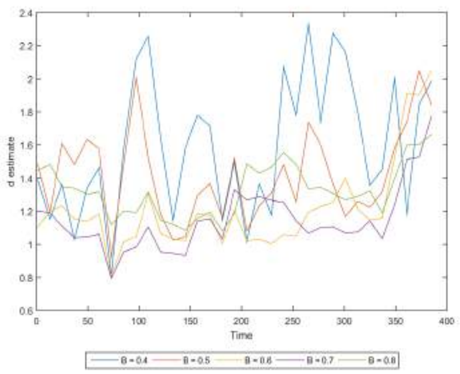
(21) Ludvigson Financial Uncertainty: h12



(22) Ludvigson Real Uncertainty: h1



(23) Ludvigson Real Uncertainty: h3



(24) Ludvigson Real Uncertainty: h12

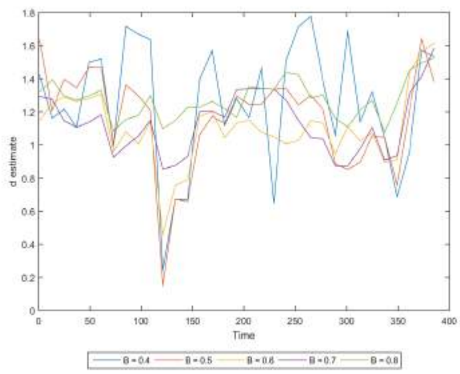
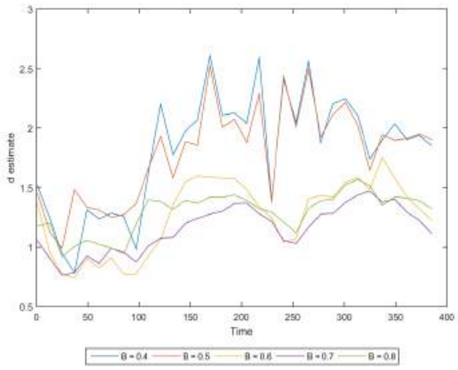
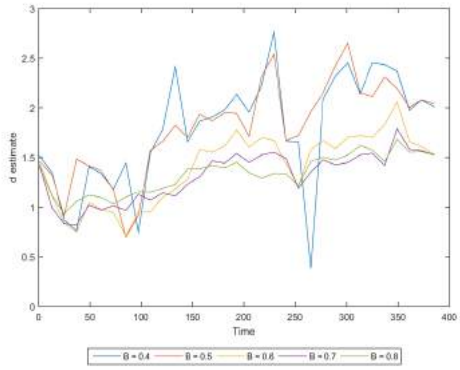


Figure 5 **Rolling-window univariate *d* estimate, Feasible ELW – filtered series (Cont'd)**

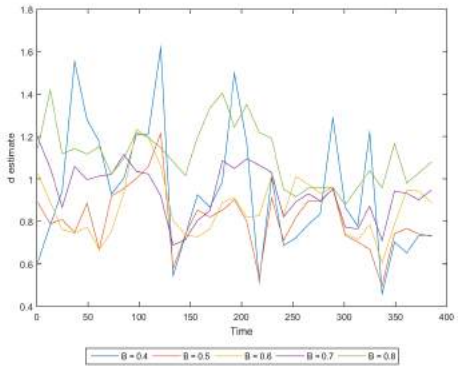
(25) 3-Month Treasury Bill



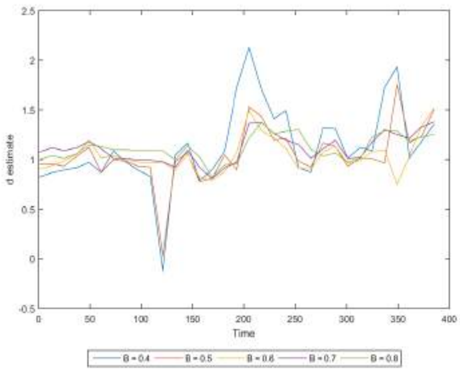
(26) Effective Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted



(27) 10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjust



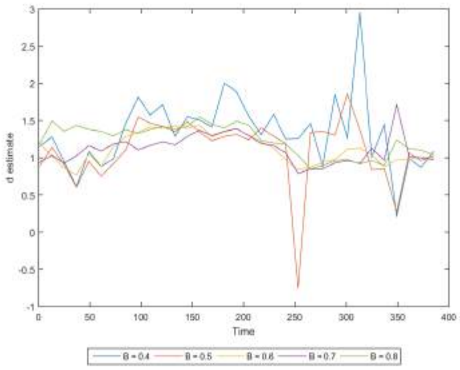
(28) Small Deposits



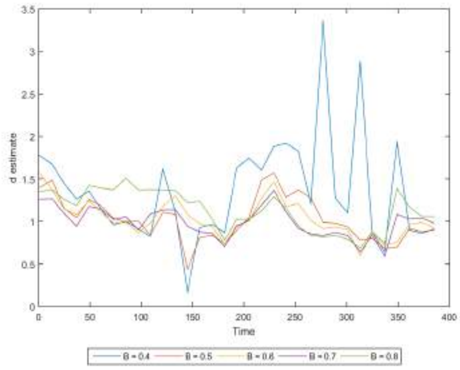
Note: Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years)..

Figure 6 **Rolling-window univariate *d* estimate, 2-stage ELW – filtered series**

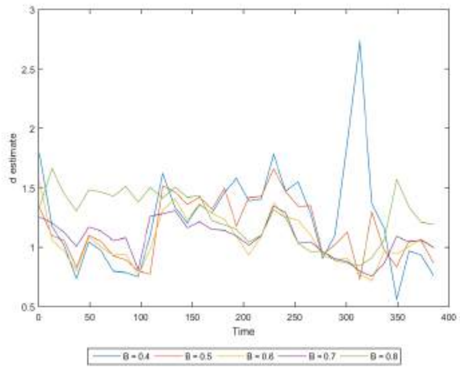
(1) M1, real



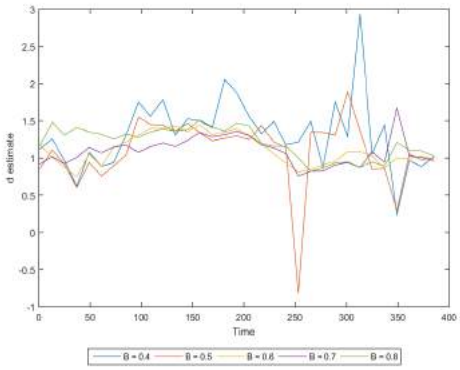
(2) M2, real



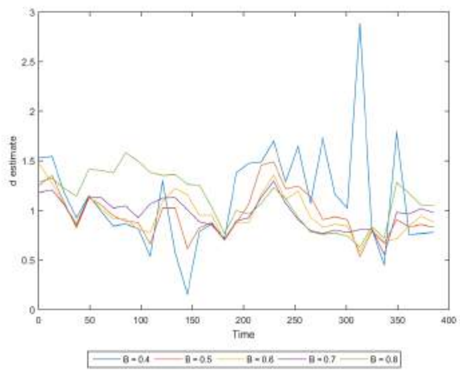
(3) MZ, real



(4) Log of real M1



(5) Log of real M2



(6) Log of real MZ

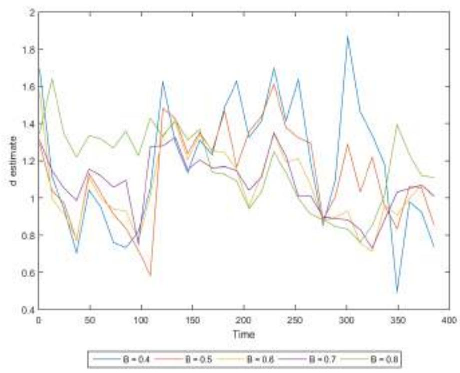
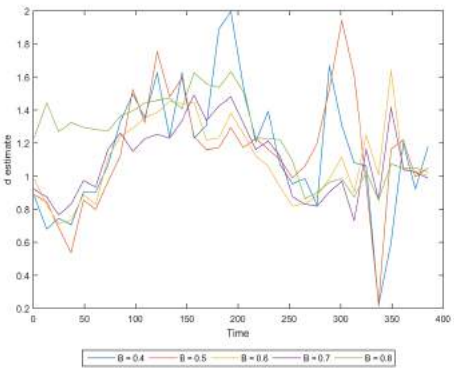
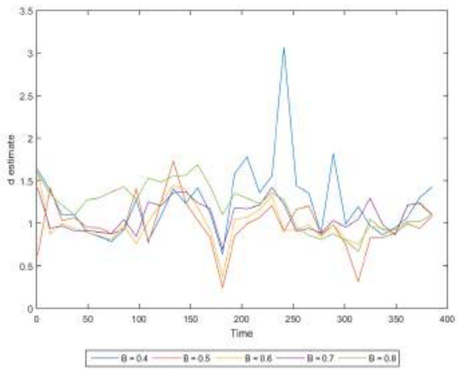


Figure 6 **Rolling-window univariate d estimate, 2-stage ELW – filtered series (Cont'd)**

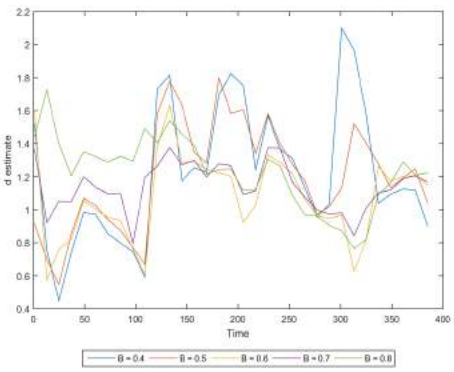
(7) Log of M1



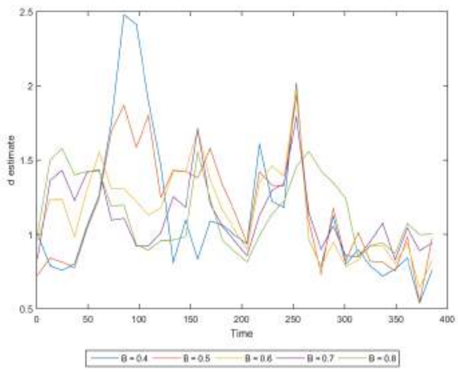
(8) Log of M2



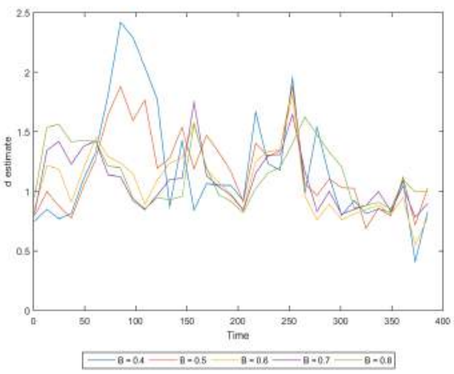
(9) Log of MZ



(10) Real Personal Disposable Income



(11) Log of real personal disposable income



(12) Economic Policy Uncertainty

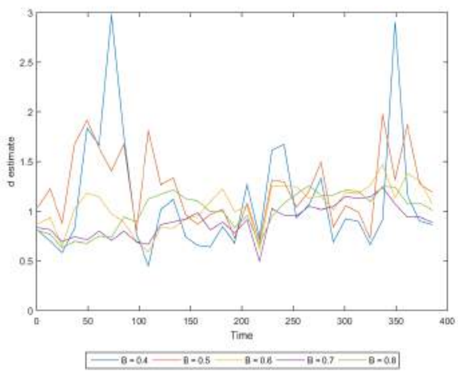
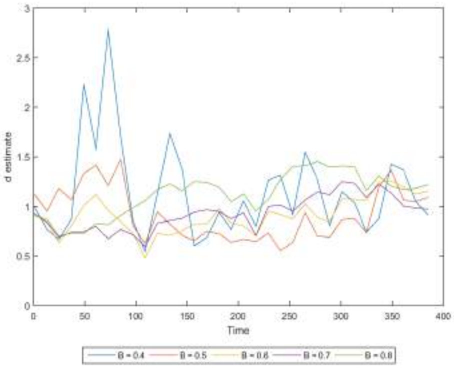
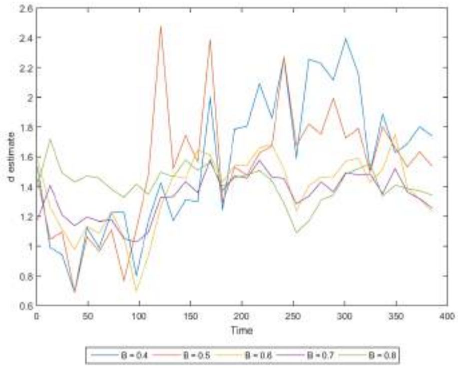


Figure 6 **Rolling-window univariate *d* estimate, 2-stage ELW – filtered series (Cont'd)**

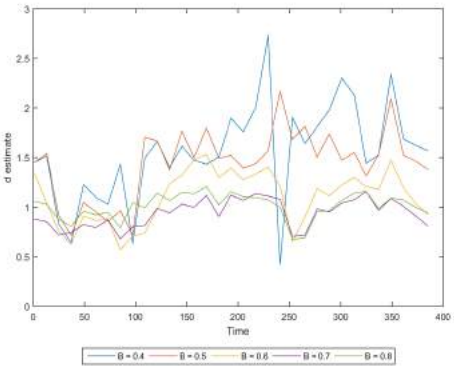
(13) Log of EPU



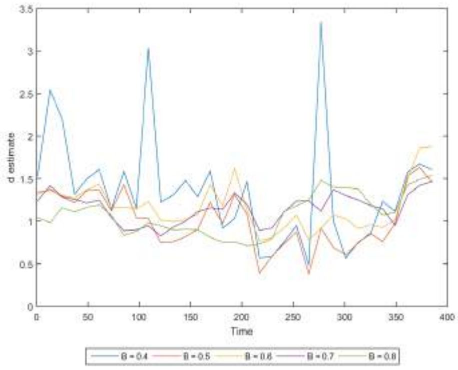
(14) M2 interest rate



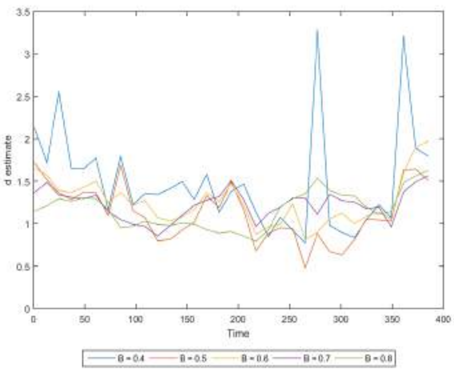
(15) MZ interest rate



(16) Ludvigson Macro Uncertainty: h1



(17) Ludvigson Macro Uncertainty: h3



(18) Ludvigson Macro Uncertainty: h12

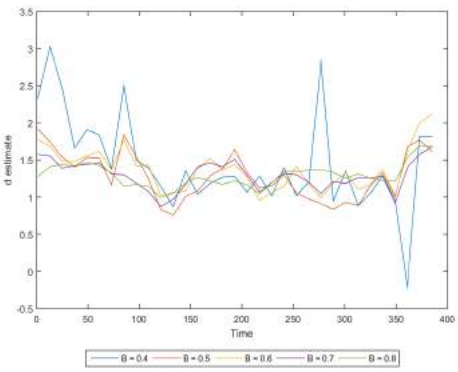
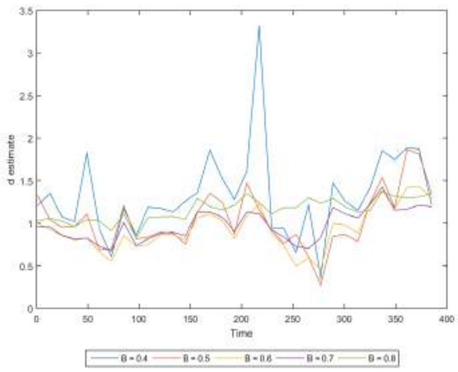
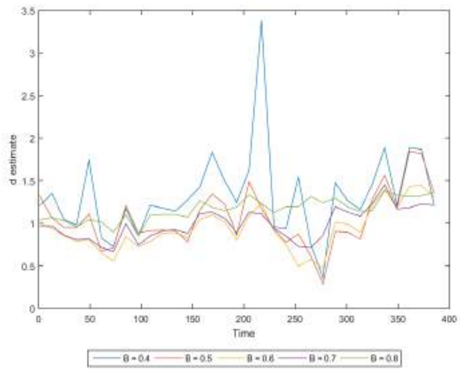


Figure 6 **Rolling-window univariate *d* estimate, 2-stage ELW – filtered series (Cont'd)**

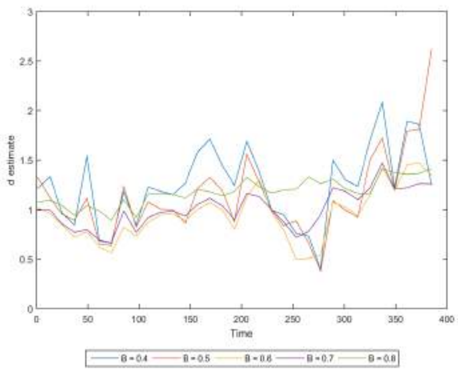
(19) Ludvigson Financial Uncertainty: h1



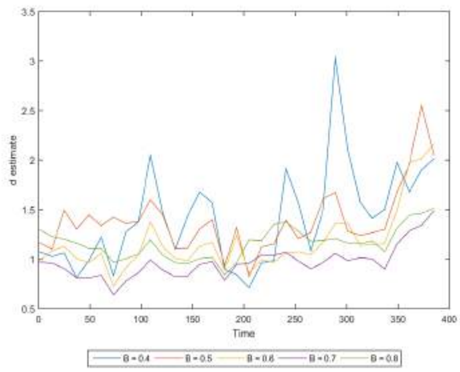
(20) Ludvigson Financial Uncertainty: h3



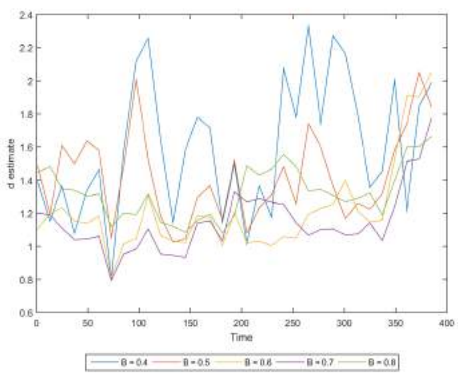
(21) Ludvigson Financial Uncertainty: h12



(22) Ludvigson Real Uncertainty: h1



(23) Ludvigson Real Uncertainty: h3



(24) Ludvigson Real Uncertainty: h12

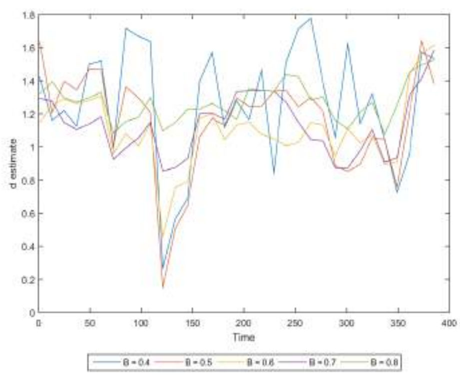
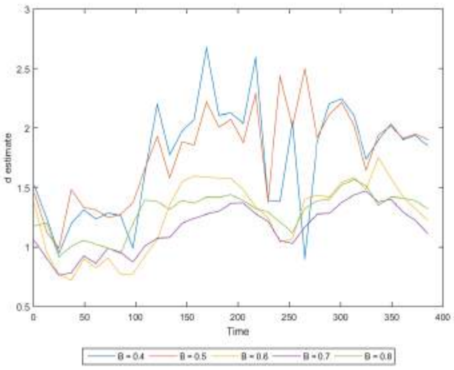
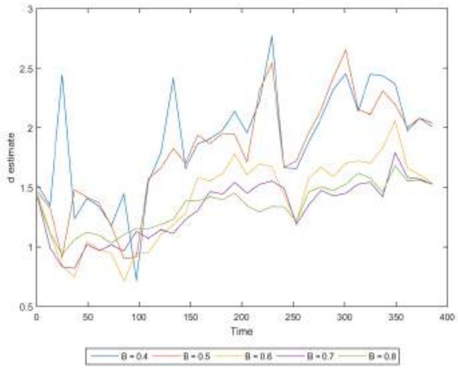


Figure 6 **Rolling-window univariate *d* estimate, 2-stage ELW – filtered series (Cont'd)**

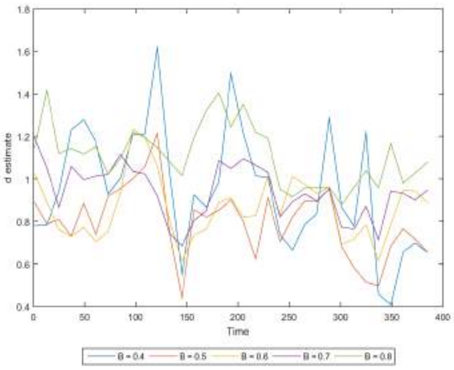
(25) 3-Month Treasury Bill



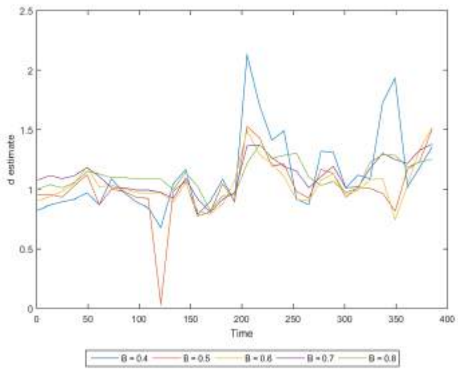
(26) Effective Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted



(27) 10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjust



(28) Small Deposits



Note: Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years)..

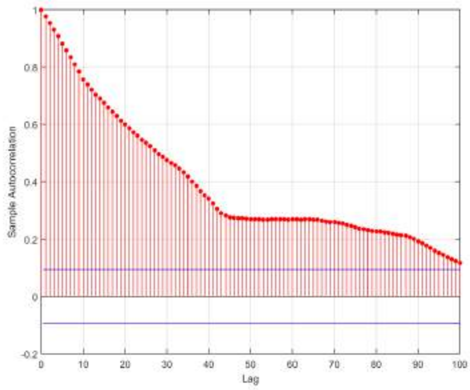
3 Full sample and rolling-window d estimates for filtered, demeaned and detrended series

3.1 ACF and periodograms

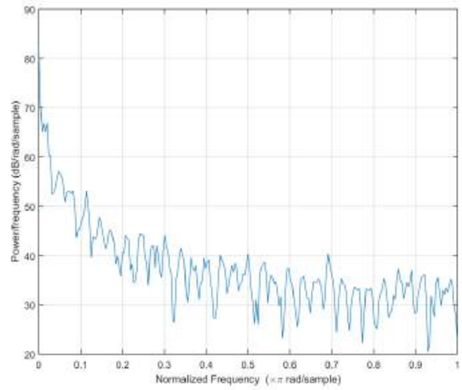
Figure 7 **ACF and periodograms – filtered, demeaned and detrended series**

(1) M1, real

ACF

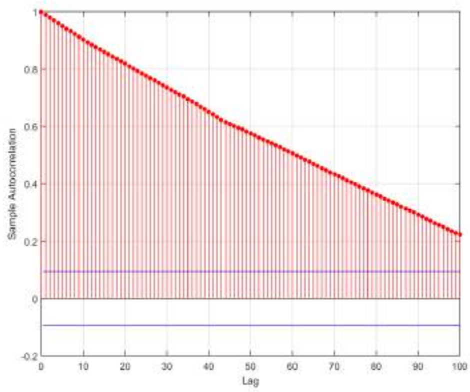


Power spectral density estimate

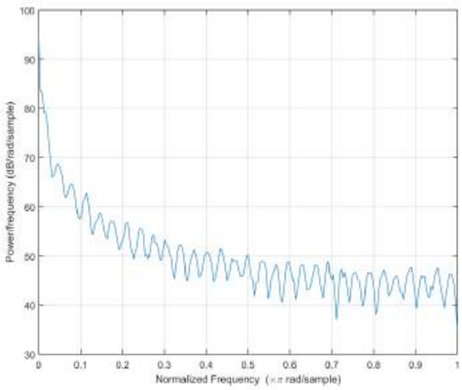


(2) M2, real

ACF

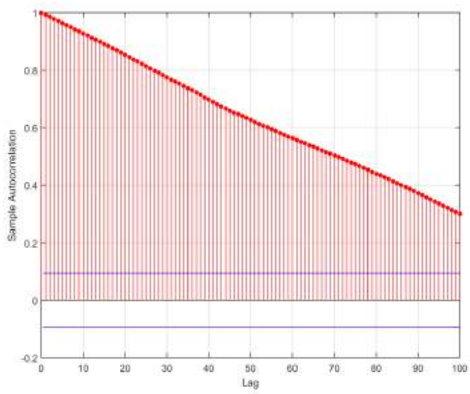


Power spectral density estimate



(3) MZ, real

ACF



Power spectral density estimate

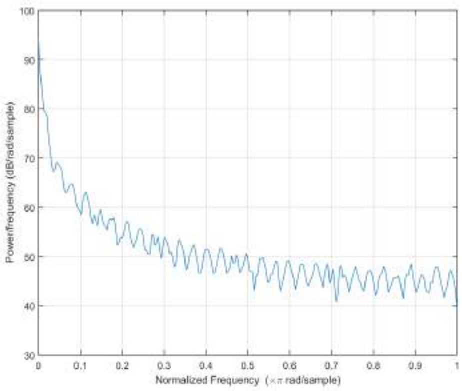
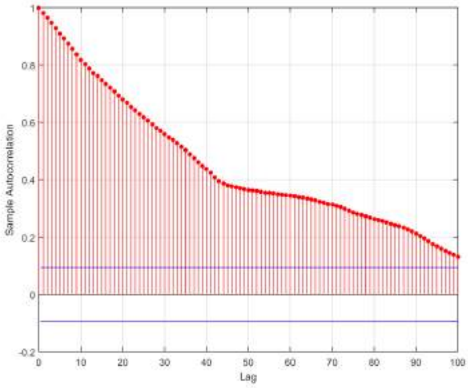


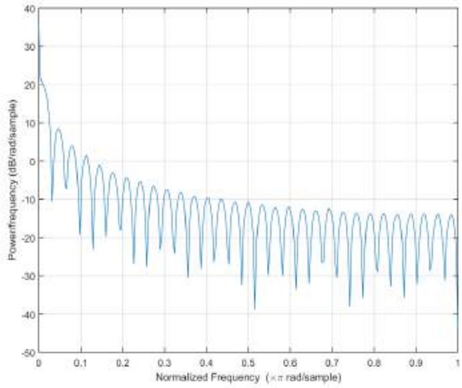
Figure 7 **ACF and periodograms – filtered, demeaned and detrended series (Cont'd)**

(4) Log of real M1

ACF

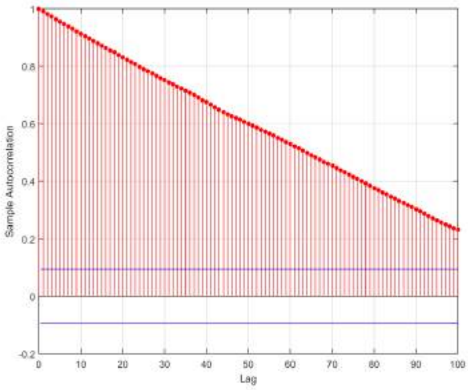


Power spectral density estimate

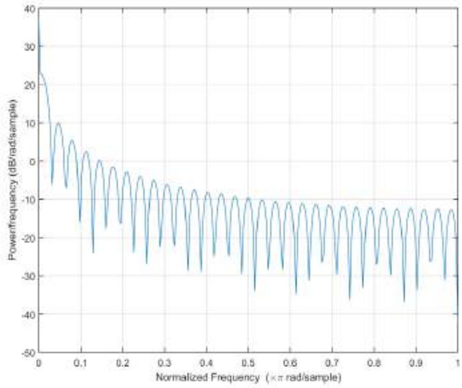


(5) Log of real M2

ACF

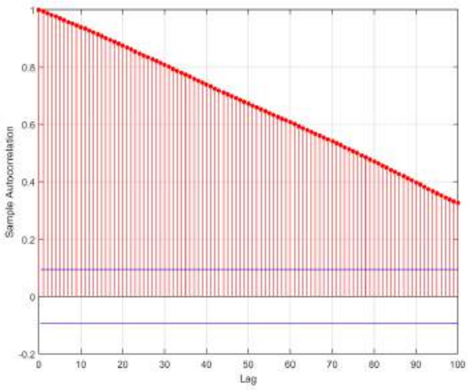


Power spectral density estimate



(6) Log of real MZ

ACF



Power spectral density estimate

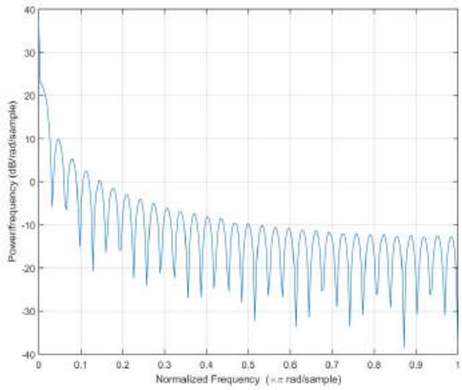
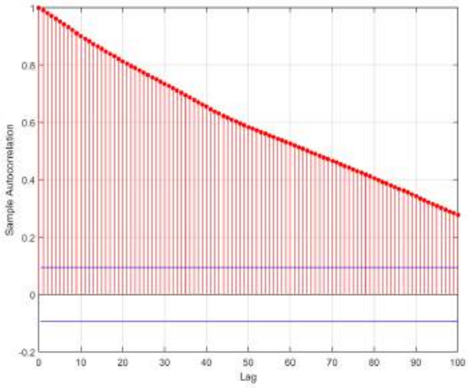


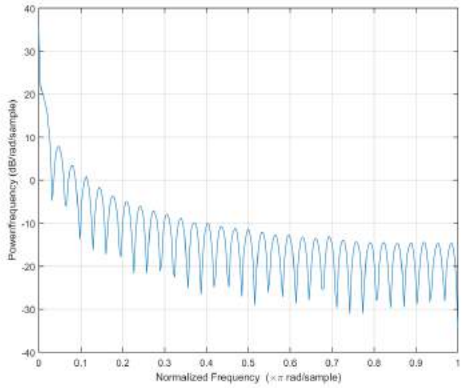
Figure 7 **ACF and periodograms – filtered, demeaned and detrended series (Cont'd)**

(7) Log of M1

ACF

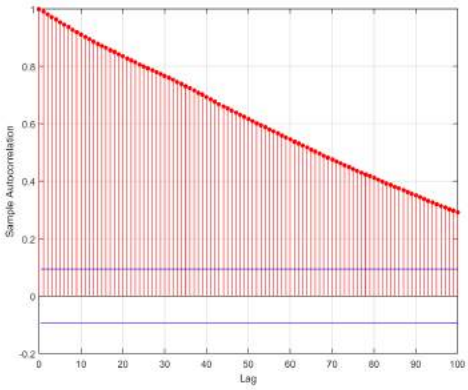


Power spectral density estimate

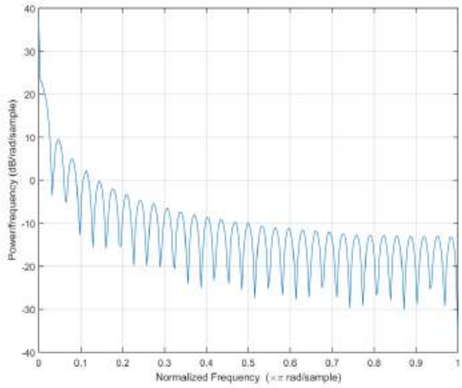


(8) Log of M2

ACF

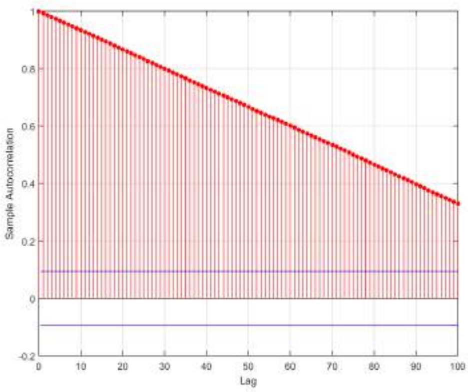


Power spectral density estimate



(9) Log of MZ

ACF



Power spectral density estimate

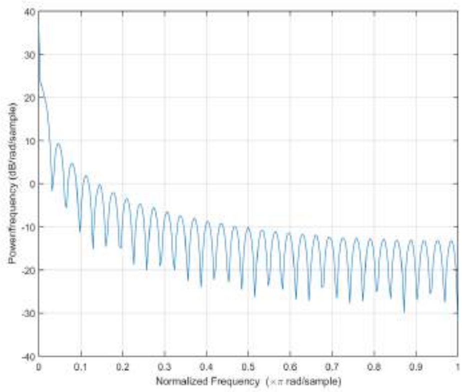
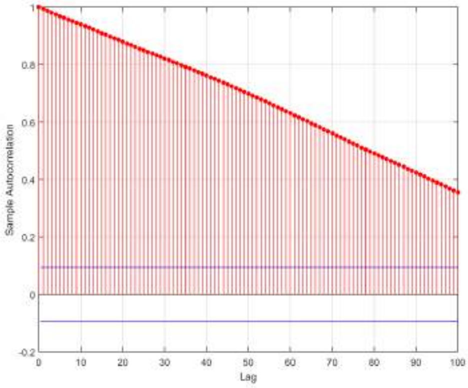


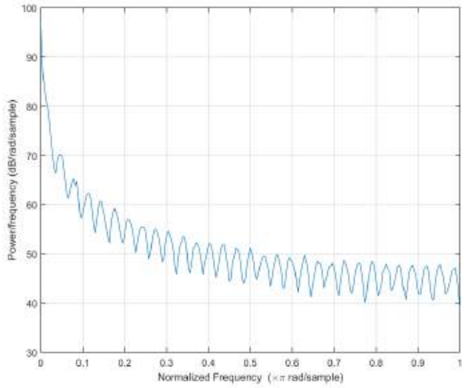
Figure 7 **ACF and periodograms – filtered, demeaned and detrended series (Cont'd)**

(10) Real Personal Disposable Income

ACF

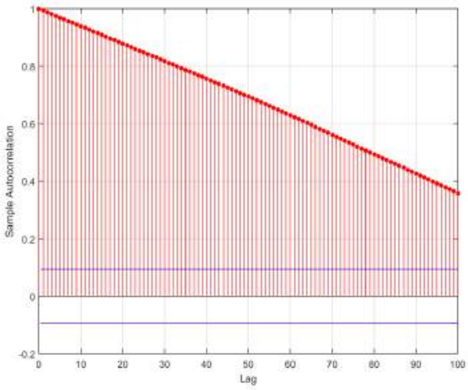


Power spectral density estimate

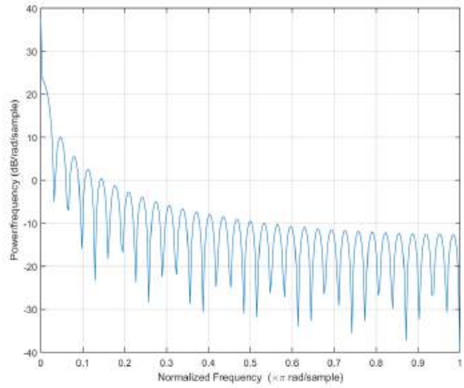


(11) Log of real personal disposable income

ACF

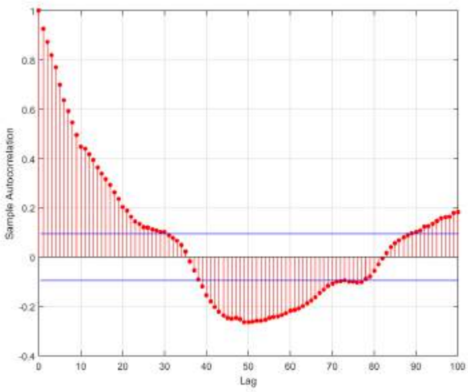


Power spectral density estimate



(12) Economic Policy Uncertainty

ACF



Power spectral density estimate

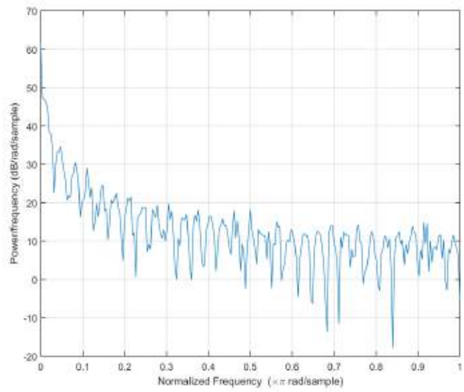
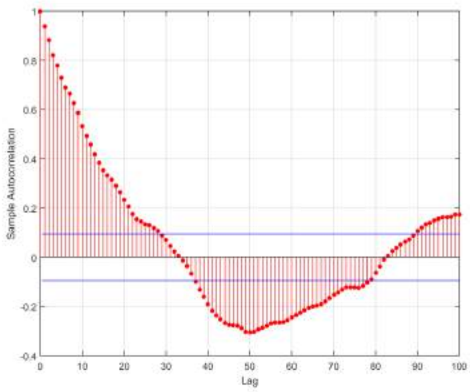


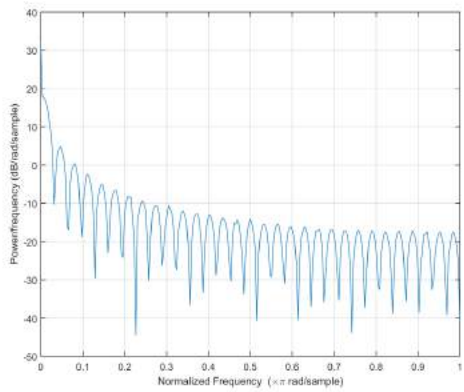
Figure 7 **ACF and periodograms – filtered, demeaned and detrended series (Cont'd)**

(13) Log of EPU

ACF

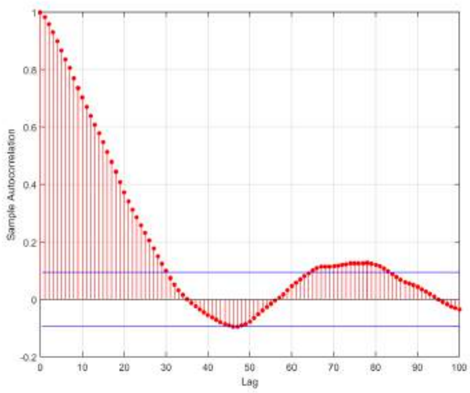


Power spectral density estimate

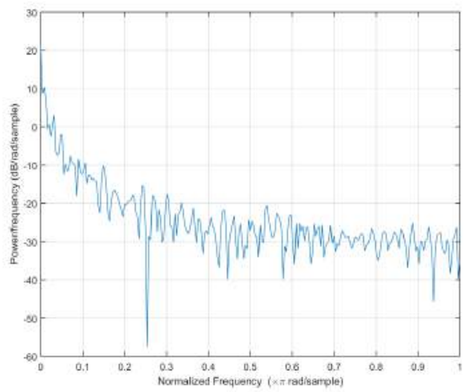


(14) M2 interest rate

ACF

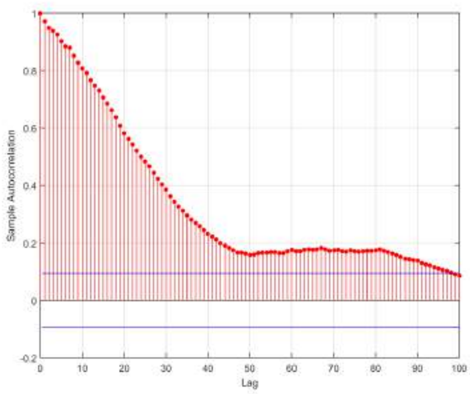


Power spectral density estimate



(15) MZ interest rate

ACF



Power spectral density estimate

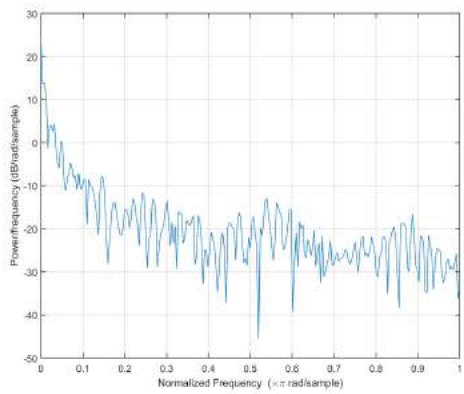
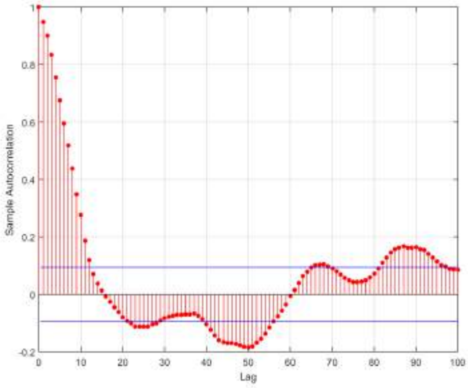


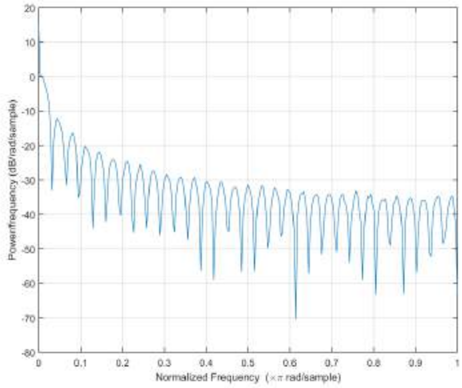
Figure 7 **ACF and periodograms – filtered, demeaned and detrended series (Cont'd)**

(16) Ludvigson Macro Uncertainty: h1

ACF

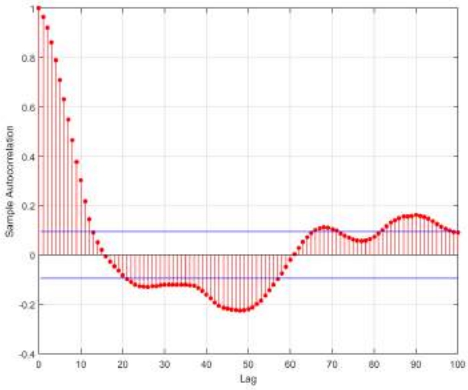


Power spectral density estimate

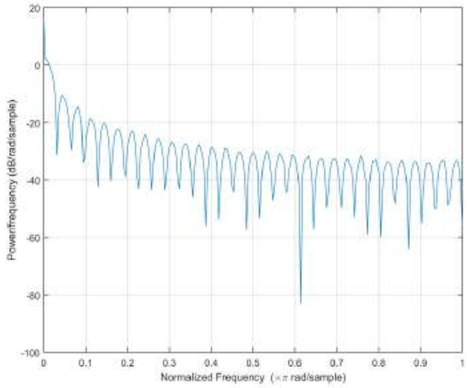


(17) Ludvigson Macro Uncertainty: h3

ACF

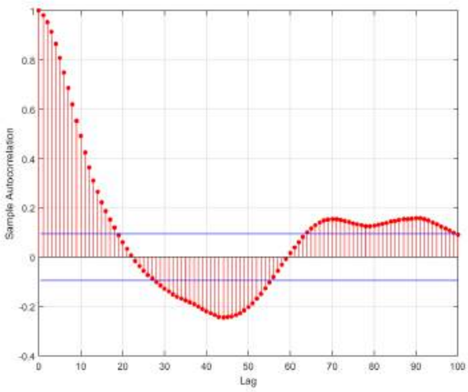


Power spectral density estimate



(18) Ludvigson Macro Uncertainty: h12

ACF



Power spectral density estimate

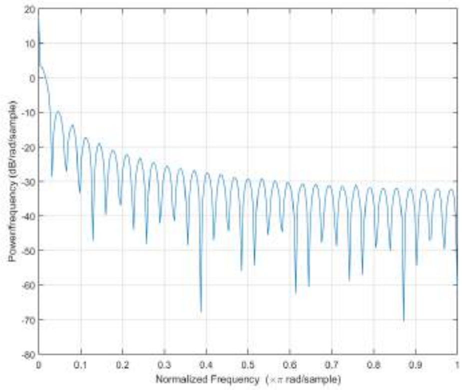
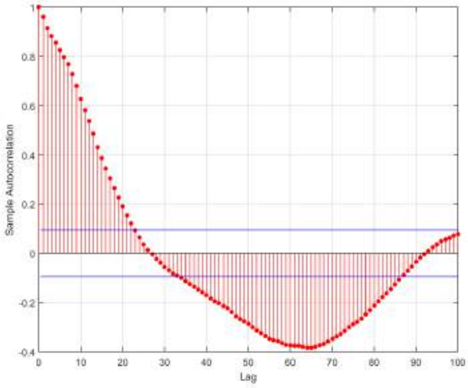


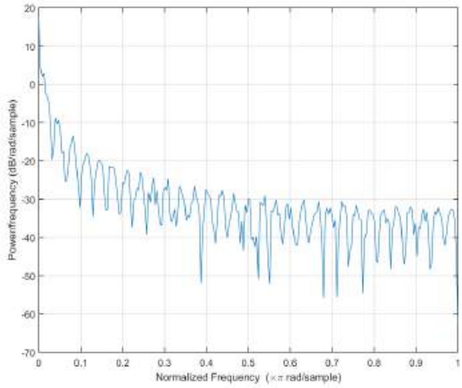
Figure 7 **ACF and periodograms – filtered, demeaned and detrended series (Cont'd)**

(19) Ludvigson Financial Uncertainty: h1

ACF

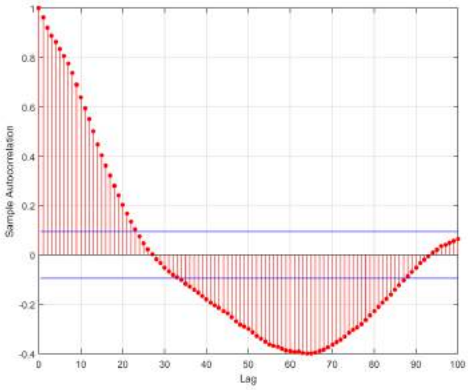


Power spectral density estimate

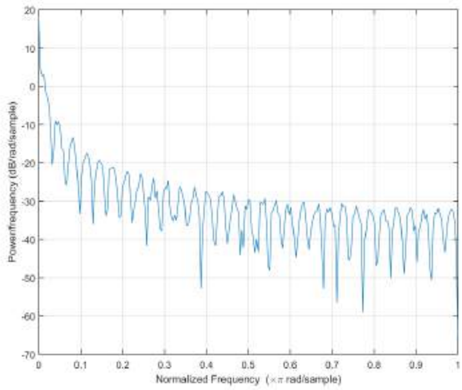


(20) Ludvigson Financial Uncertainty: h3

ACF

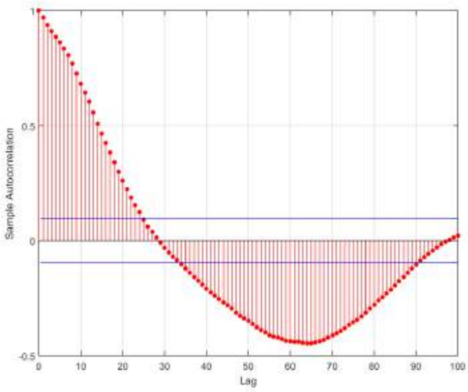


Power spectral density estimate



(21) Ludvigson Financial Uncertainty: h12

ACF



Power spectral density estimate

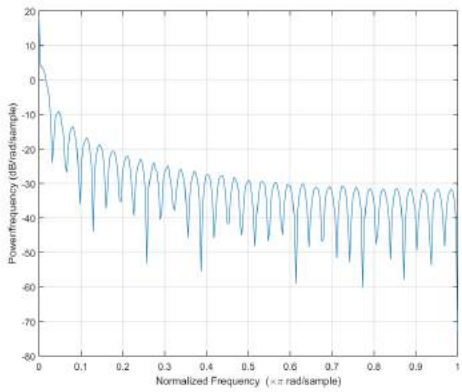
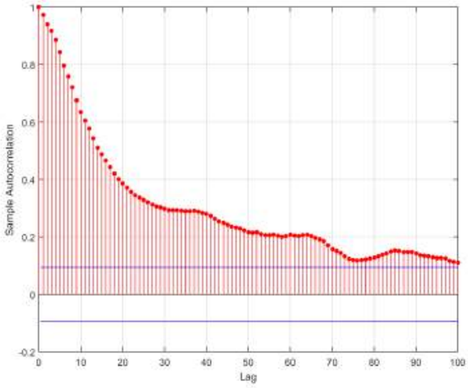


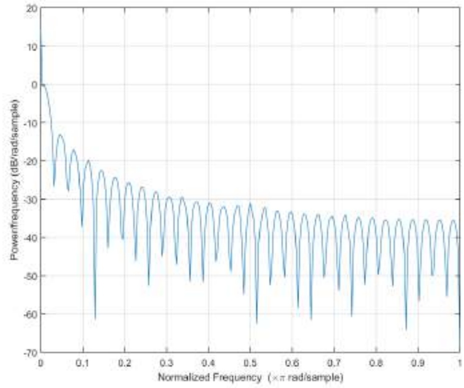
Figure 7 **ACF and periodograms – filtered, demeaned and detrended series (Cont'd)**

(22) Ludvigson Real Uncertainty: h1

ACF

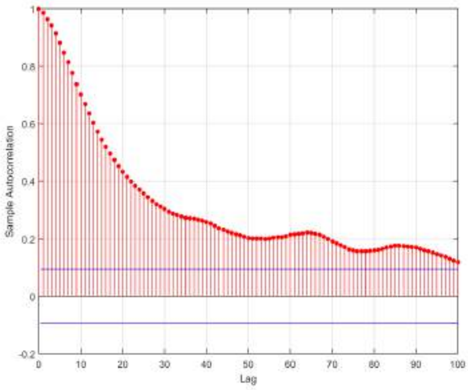


Power spectral density estimate

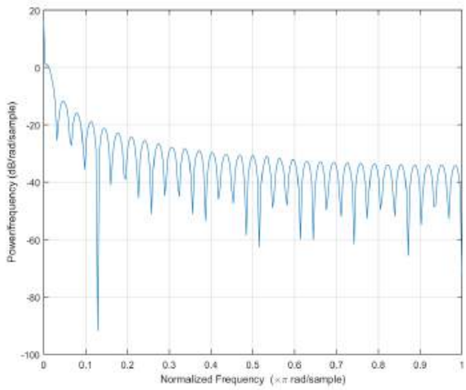


(23) Ludvigson Real Uncertainty: h3

ACF

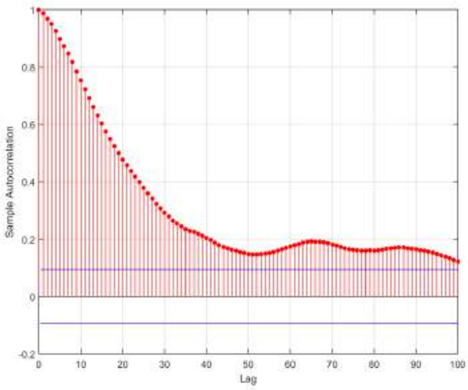


Power spectral density estimate



(24) Ludvigson Real Uncertainty: h12

ACF



Power spectral density estimate

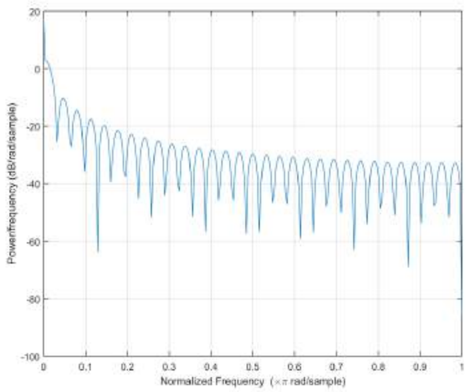
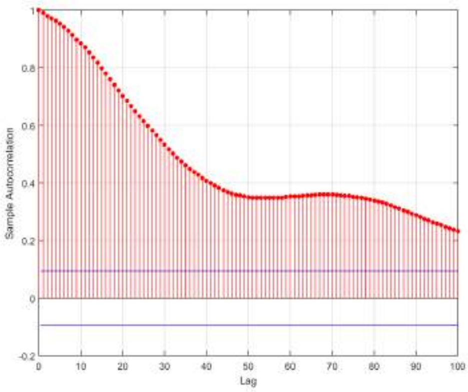


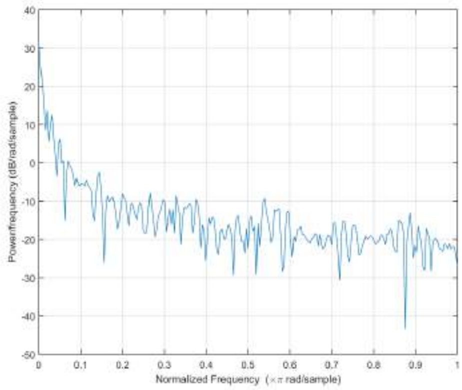
Figure 7 **ACF and periodograms – filtered, demeaned and detrended series (Cont'd)**

(25) 3-Month Treasury Bill

ACF

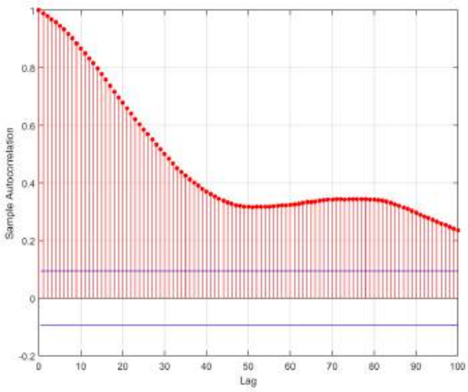


Power spectral density estimate

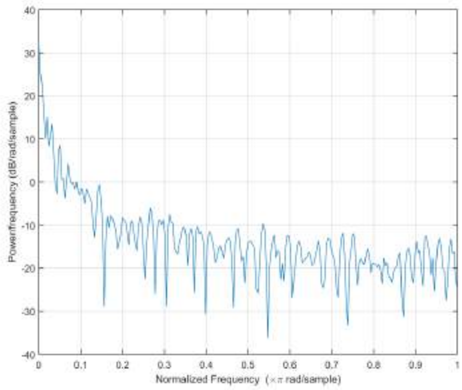


(26) Effective Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted

ACF

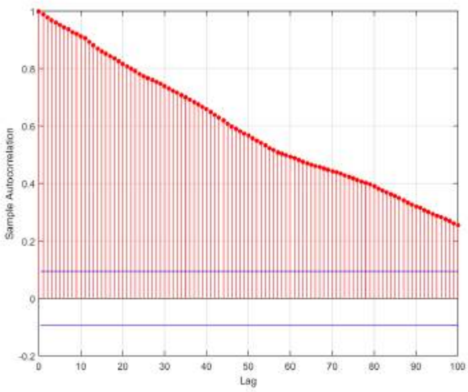


Power spectral density estimate



(27) 10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjust

ACF



Power spectral density estimate

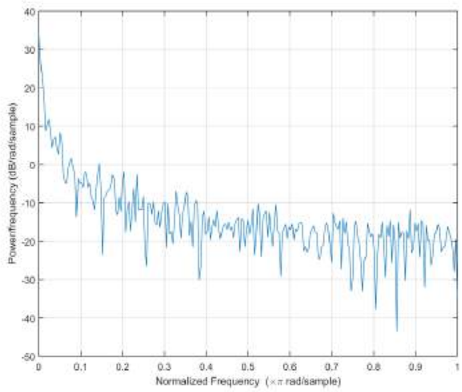
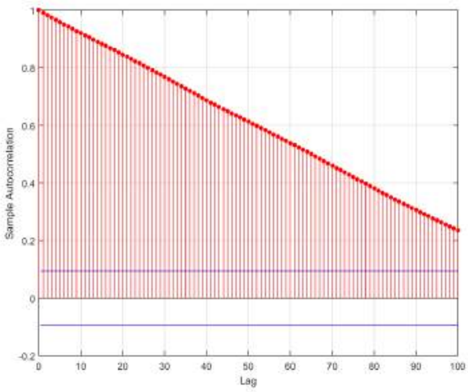


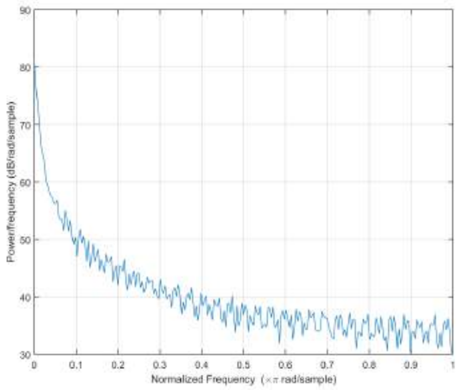
Figure 7 **ACF and periodograms – filtered, demeaned and detrended series (Cont'd)**

(28) Small Deposits

ACF



Power spectral density estimate



Note: Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years), after what they are demeaned and detrended..

3.2 Full sample d estimates

Table 5 **Univariate *d* estimates, monetary aggregates – filtered, demeaned and detrended series**

Bandwidth	**B = 0.4**				**B = 0.45**				**B = 0.5**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
realm1	0.906	1.340	1.332	1.332	0.713	1.121	1.100	1.100	0.811	1.055	1.045	1.045
realm2	1.433	1.605	1.698	1.698	1.094	1.481	1.406	1.406	1.127	1.384	1.367	1.367
realmzm	1.505	1.203	1.478	1.478	1.659	1.320	1.689	1.689	1.653	1.250	1.647	1.647
lnm1	0.994	1.069	1.252	1.252	0.800	0.889	1.037	1.037	0.842	0.897	0.985	0.985
lnm2	1.103	1.108	1.578	1.578	0.698	0.745	1.124	1.124	0.707	0.741	0.997	0.997
lnmzm	1.230	1.310	1.328	1.313	1.772	1.620	1.659	1.659	1.507	1.518	1.538	1.538
lnrealm1	1.044	1.281	1.275	1.275	0.857	1.127	1.107	1.107	0.912	1.042	1.035	1.035
lnrealm2	1.474	1.759	1.765	1.765	1.233	1.557	1.544	1.544	1.261	1.374	1.374	1.374
lnrealmzm	1.235	1.149	1.383	1.387	1.459	1.346	1.595	1.595	1.325	1.258	1.415	1.415
Bandwidth	**B = 0.55**				**B = 0.6**				**B = 0.65**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
realm1	0.807	1.015	1.005	1.005	0.924	1.058	1.052	1.052	1.027	1.058	1.060	1.060
realm2	0.985	1.228	1.177	1.177	1.013	1.129	1.120	1.120	1.011	1.105	1.100	1.100
realmzm	1.281	1.233	1.287	1.287	1.073	1.042	1.089	1.089	1.114	1.065	1.129	1.129
lnm1	0.864	0.902	0.969	0.969	0.953	0.975	1.041	1.041	1.040	1.040	1.046	1.046
lnm2	0.711	0.738	0.963	0.963	0.801	0.818	1.050	1.050	0.838	0.853	1.056	1.056
lnmzm	1.254	1.253	1.260	1.260	0.944	0.955	0.956	0.956	1.013	1.023	1.027	1.027
lnrealm1	0.888	1.007	0.999	0.999	0.956	1.031	1.027	1.027	1.002	1.031	1.032	1.032
lnrealm2	1.020	1.116	1.113	1.113	0.959	1.002	1.000	1.000	0.972	1.031	1.029	1.029
lnrealmzm	1.189	1.159	1.236	1.236	0.973	0.975	0.994	0.994	1.039	1.041	1.058	1.058
Bandwidth	**B = 0.7**				**B = 0.75**				**B = 0.8**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
realm1	0.933	1.028	1.024	1.024	1.003	1.035	1.037	1.037	0.937	1.024	1.024	1.024
realm2	0.954	1.071	1.053	1.053	0.991	1.073	1.073	1.073	0.946	1.034	1.032	1.032
realmzm	1.056	1.043	1.080	1.080	1.073	1.060	1.108	1.108	1.010	1.046	1.073	1.073
lnm1	0.962	0.986	1.023	1.023	1.026	1.049	1.033	1.033	0.955	1.018	1.022	1.022
lnm2	0.807	0.826	0.977	0.977	0.918	0.946	1.045	1.045	0.928	0.991	1.067	1.067
lnmzm	0.995	1.010	1.014	1.014	1.048	1.083	1.086	1.086	1.051	1.120	1.125	1.125
lnrealm1	0.955	1.023	1.019	1.019	0.995	1.024	1.027	1.027	0.936	1.016	1.016	1.015
lnrealm2	0.936	1.003	1.001	1.001	0.971	1.030	1.029	1.029	0.926	1.005	1.004	1.004
lnrealmzm	1.007	1.022	1.030	1.030	1.034	1.060	1.081	1.081	1.013	1.074	1.087	1.087

Note: Univariate d estimates for various bandwidths and various estimators: "LW" = Local Whittle estimator, "ELW" = Exact Local Whittle estimator; "FELW" = Feasible Exact Local Whittle estimator; "2ELW" = 2-step ELW estimator. Column super-headers give the value of the bandwidth (B) used for estimation. Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years), after what they are demeaned and detrended.

Table 6 **Univariate *d* estimates, uncertainty variables – filtered, demeaned and detrended series**

Bandwidth	**B = 0.4**				**B = 0.45**				**B = 0.5**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
lnepu	0.389	0.412	0.412	0.402	0.463	0.571	0.564	0.572	0.708	0.761	0.765	0.765
ludmach1	0.099	0.070	0.070	0.070	0.105	0.063	0.063	0.063	0.273	0.270	0.270	0.270
ludmach3	0.067	0.027	0.027	0.029	0.099	0.057	0.057	0.057	0.296	0.292	0.292	0.292
ludmach12	0.196	0.190	0.190	0.190	0.322	0.308	0.308	0.308	0.548	0.551	0.563	0.551
ludfin1	0.299	0.305	0.305	0.312	0.603	0.606	0.597	0.804	0.914	0.896	1.172	1.172
ludfin3	0.325	0.333	0.333	0.343	0.637	0.640	0.599	0.831	0.952	0.935	1.207	1.207
ludfin12	0.430	0.447	0.447	0.490	0.769	0.775	0.953	0.954	1.078	1.077	1.341	1.341
ludreal1	0.511	0.533	0.622	0.535	0.539	0.565	0.632	0.571	0.639	0.667	0.772	0.772
ludreal3	0.542	0.554	0.647	0.561	0.608	0.624	0.698	0.664	0.742	0.758	0.838	0.838
ludreal12	0.608	0.613	0.682	0.639	0.744	0.750	0.805	0.805	0.895	0.909	0.957	0.957
Bandwidth	**B = 0.55**				**B = 0.6**				**B = 0.65**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
lnepu	0.754	0.779	0.783	0.783	0.873	0.894	0.895	0.895	0.790	0.818	0.818	0.818
ludmach1	0.485	0.494	0.494	0.494	0.912	0.938	0.953	0.952	1.029	1.055	1.062	1.062
ludmach3	0.544	0.553	0.537	0.553	1.018	1.047	1.067	1.066	1.115	1.143	1.154	1.154
ludmach12	0.801	0.811	0.811	0.811	1.206	1.234	1.227	1.227	1.286	1.316	1.311	1.311
ludfin1	1.208	1.173	1.362	1.362	1.115	1.102	1.273	1.273	0.975	0.978	1.070	1.070
ludfin3	1.223	1.194	1.363	1.363	1.118	1.109	1.272	1.272	0.995	0.999	1.093	1.093
ludfin12	1.253	1.250	1.372	1.372	1.127	1.135	1.278	1.278	1.058	1.072	1.174	1.174
ludreal1	0.757	0.792	0.880	0.880	0.937	0.984	1.048	1.048	1.195	1.257	1.271	1.271
ludreal3	0.924	0.952	1.014	1.014	1.145	1.188	1.224	1.224	1.334	1.392	1.380	1.380
ludreal12	1.102	1.135	1.162	1.162	1.179	1.212	1.214	1.214	1.200	1.237	1.221	1.221
Bandwidth	**B = 0.7**				**B = 0.75**				**B = 0.8**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
lnepu	0.805	0.838	0.838	0.838	0.886	0.905	0.907	0.907	0.843	0.905	0.905	0.905
ludmach1	1.073	1.108	1.112	1.112	1.147	1.206	1.210	1.210	1.089	1.188	1.189	1.189
ludmach3	1.219	1.256	1.264	1.264	1.246	1.308	1.312	1.312	1.160	1.263	1.264	1.264
ludmach12	1.412	1.451	1.448	1.448	1.357	1.420	1.420	1.420	1.235	1.338	1.339	1.339
ludfin1	0.922	0.938	0.963	0.963	0.909	0.938	0.987	0.987	0.876	0.933	0.976	0.976
ludfin3	0.934	0.951	0.974	0.974	0.923	0.953	1.001	1.001	0.890	0.948	0.989	0.989
ludfin12	0.979	1.000	1.019	1.019	0.965	1.000	1.048	1.048	0.923	0.985	1.025	1.025
ludreal1	1.147	1.197	1.103	1.103	1.103	1.164	1.094	1.094	0.890	0.971	0.955	0.955
ludreal3	1.186	1.237	1.164	1.164	1.232	1.293	1.226	1.226	1.043	1.131	1.130	1.130
ludreal12	1.116	1.156	1.127	1.127	1.204	1.257	1.221	1.221	1.058	1.147	1.147	1.147

Note: Univariate d estimates for various bandwidths and various estimators: "LW" = Local Whittle estimator, "ELW" = Exact Local Whittle estimator; "FELW" = Feasible Exact Local Whittle estimator; "2ELW" = 2-step ELW estimator. Column super-headers give the value of the bandwidth (B) used for estimation. Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years), after what they are demeaned and detrended.

Table 7 **Univariate *d* estimates, interest rates and other variables – filtered, demeaned and detrended series**

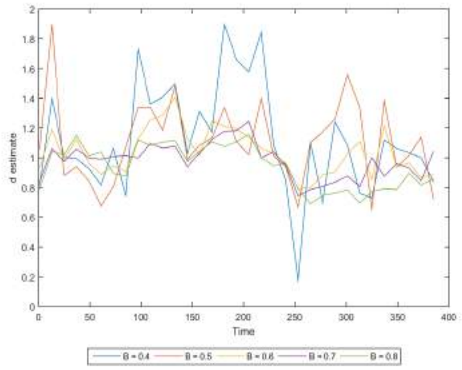
Bandwidth	**B = 0.4**				**B = 0.45**				**B = 0.5**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
interestm2	0.497	0.519	0.506	0.696	0.794	0.822	0.864	0.865	0.963	0.995	1.036	1.036
interestmzm	0.809	0.811	0.838	0.915	1.053	1.061	1.084	1.085	1.248	1.262	1.296	1.296
lnrpdi	1.040	1.151	1.134	1.134	0.904	1.013	0.999	0.999	0.860	0.954	0.941	0.941
tb3ms	0.853	0.849	0.872	0.901	1.206	1.207	1.218	1.218	1.654	1.622	1.669	1.670
fedfunds	0.798	0.798	0.796	0.833	1.220	1.247	1.243	1.244	1.509	1.594	1.573	1.574
gs10	0.938	0.833	1.060	1.060	0.977	0.931	1.004	1.004	1.155	1.093	1.197	1.197
smalldepo	1.332	1.214	1.341	1.341	1.201	1.166	1.255	1.255	1.161	1.138	1.207	1.207
Bandwidth	**B = 0.55**				**B = 0.6**				**B = 0.65**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
interestm2	1.026	1.069	1.121	1.121	1.026	1.064	1.103	1.103	1.113	1.149	1.170	1.170
interestmzm	1.262	1.278	1.329	1.329	1.106	1.117	1.129	1.129	1.069	1.084	1.086	1.086
lnrpdi	1.006	1.096	1.076	1.076	1.066	1.062	1.069	1.069	1.178	1.054	1.088	1.088
tb3ms	2.102	1.986	2.076	2.077	1.354	1.348	1.368	1.368	1.377	1.361	1.403	1.403
fedfunds	1.595	1.694	1.666	1.666	1.349	1.365	1.364	1.364	1.400	1.391	1.400	1.400
gs10	1.357	1.290	1.355	1.355	1.010	0.987	1.045	1.045	0.861	0.860	0.885	0.885
smalldepo	1.140	1.145	1.197	1.197	1.092	1.120	1.148	1.148	1.067	1.112	1.126	1.126
Bandwidth	**B = 0.7**				**B = 0.75**				**B = 0.8**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
interestm2	1.101	1.132	1.134	1.134	1.198	1.250	1.244	1.244	1.082	1.175	1.179	1.179
interestmzm	0.954	0.974	0.975	0.975	0.955	0.987	0.985	0.985	0.769	0.826	0.832	0.832
lnrpdi	1.175	1.029	1.069	1.069	0.969	0.989	0.994	0.994	0.952	1.015	1.015	1.015
tb3ms	1.202	1.213	1.232	1.232	1.010	1.043	1.046	1.046	0.946	1.008	1.001	1.001
fedfunds	1.104	1.125	1.126	1.126	1.096	1.134	1.134	1.134	1.042	1.108	1.107	1.107
gs10	0.932	0.931	0.971	0.971	0.877	0.896	0.924	0.924	0.910	0.963	0.968	0.968
smalldepo	1.055	1.113	1.120	1.120	1.037	1.069	1.093	1.093	1.022	1.057	1.092	1.092

Note: Univariate d estimates for various bandwidths and various estimators: "LW" = Local Whittle estimator, "ELW" = Exact Local Whittle estimator; "FELW" = Feasible Exact Local Whittle estimator; "2ELW" = 2-step ELW estimator. Column super-headers give the value of the bandwidth (B) used for estimation. Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years), after what they are demeaned and detrended.

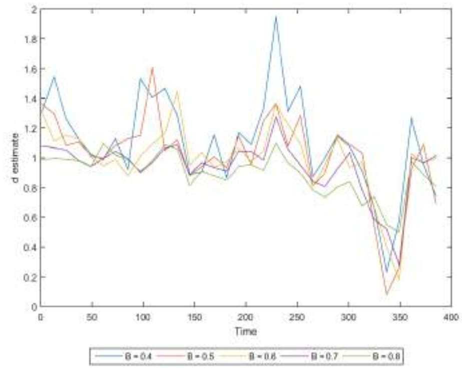
3.3 Rolling-window d estimates

Figure 8 **Rolling-window univariate *d* estimate, LW − filtered, demeaned and detrended series**

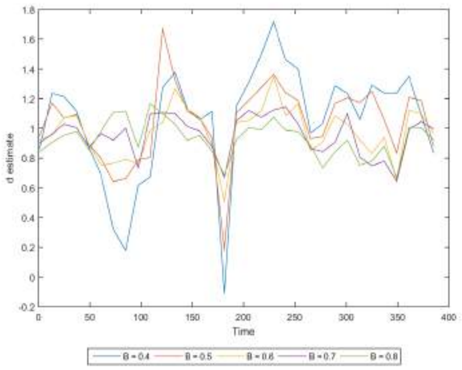
(1) M1, real



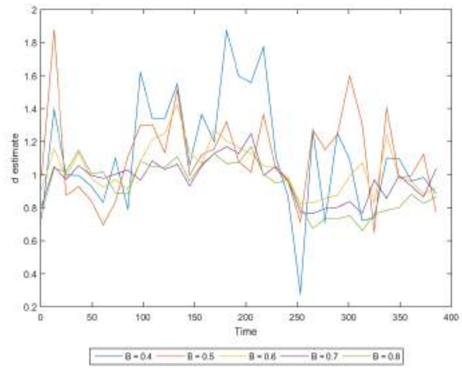
(2) M2, real



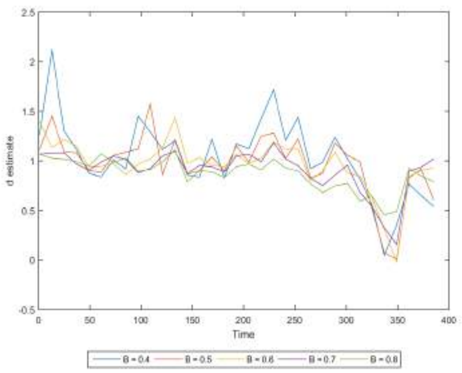
(3) MZ, real



(4) Log of real M1



(5) Log of real M2



(6) Log of real MZ

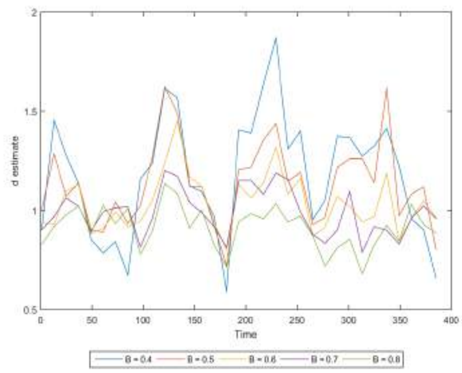
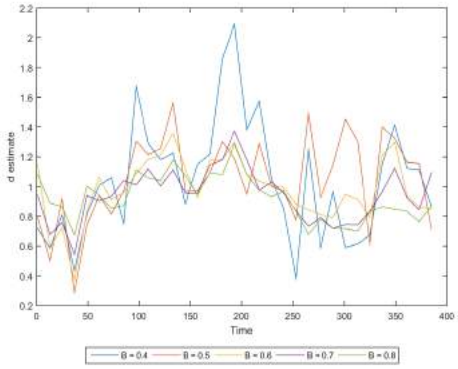
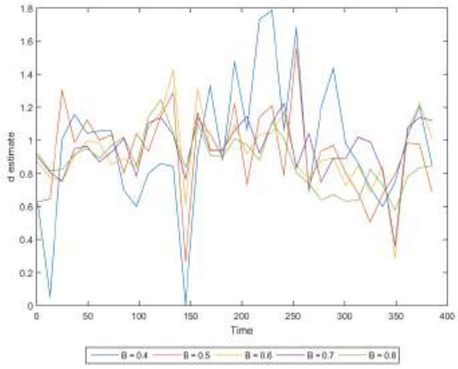


Figure 8 **Rolling-window univariate *d* estimate, LW – filtered, demeaned and detrended series (Cont'd)**

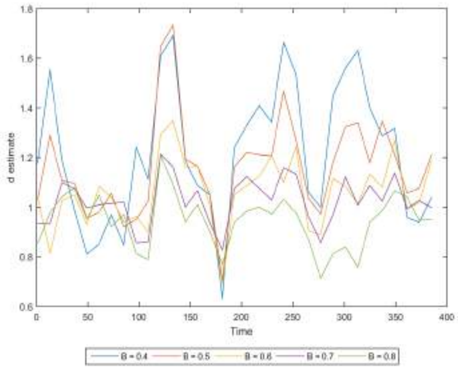
(7) Log of M1



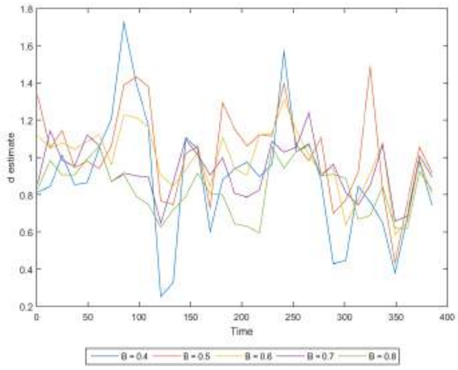
(8) Log of M2



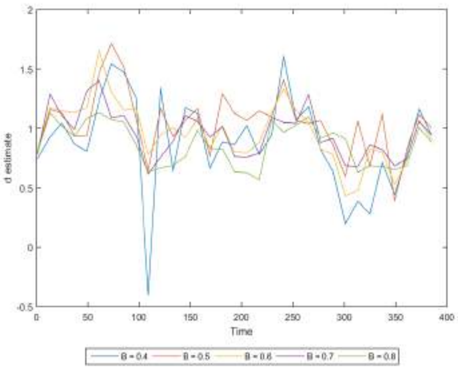
(9) Log of MZ



(10) Real Personal Disposable Income



(11) Log of real personal disposable income



(12) Economic Policy Uncertainty

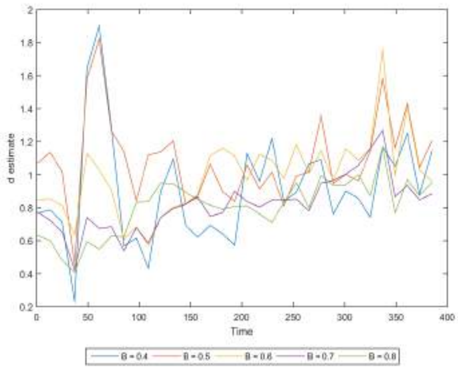
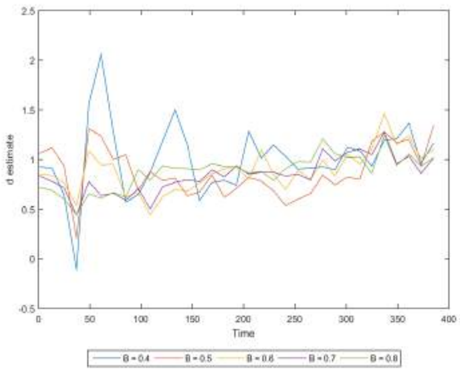
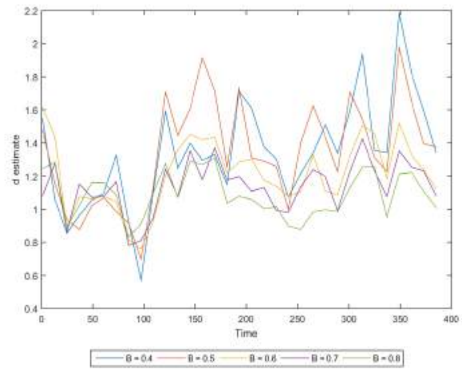


Figure 8 **Rolling-window univariate *d* estimate, LW – filtered, demeaned and detrended series (Cont'd)**

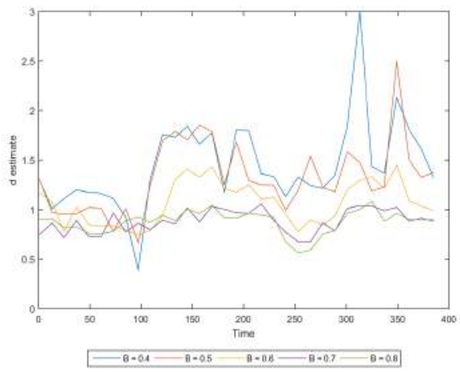
(13) Log of EPU



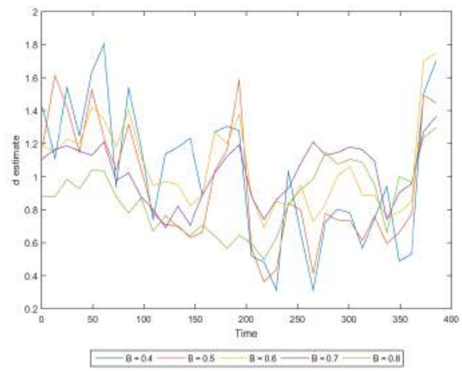
(14) M2 interest rate



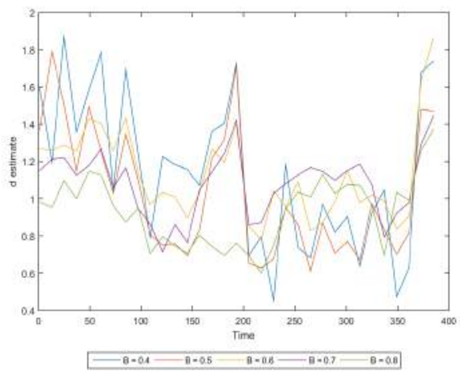
(15) MZ interest rate



(16) Ludvigson Macro Uncertainty: h1



(17) Ludvigson Macro Uncertainty: h3



(18) Ludvigson Macro Uncertainty: h12

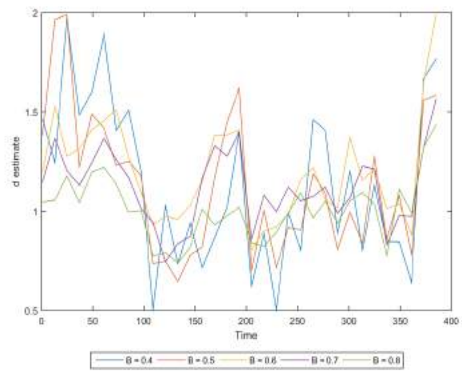
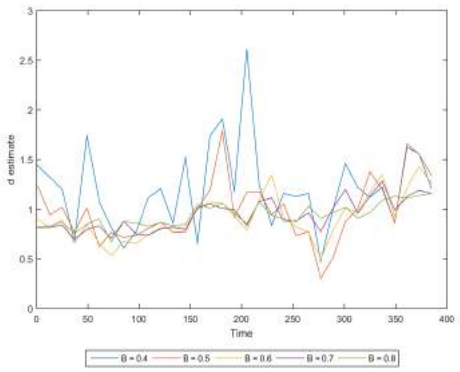
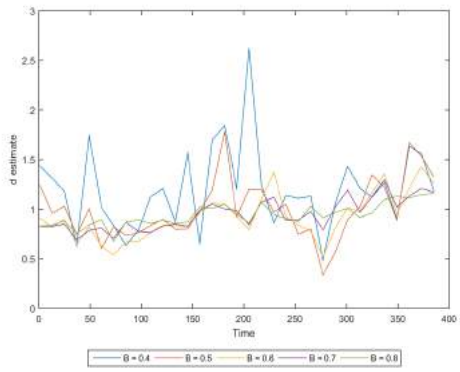


Figure 8 **Rolling-window univariate d estimate, LW – filtered, demeaned and detrended series (Cont'd)**

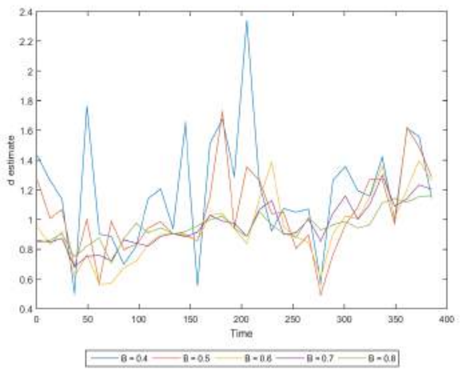
(19) Ludvigson Financial Uncertainty: h1



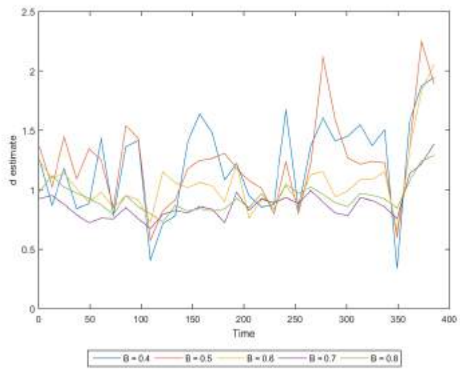
(20) Ludvigson Financial Uncertainty: h3



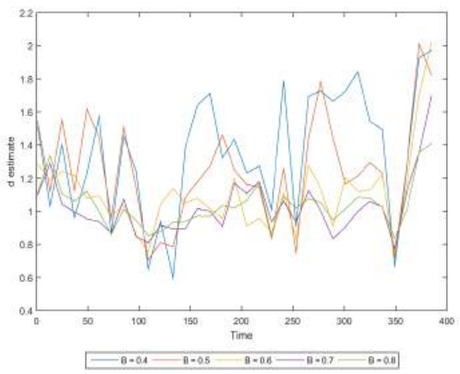
(21) Ludvigson Financial Uncertainty: h12



(22) Ludvigson Real Uncertainty: h1



(23) Ludvigson Real Uncertainty: h3



(24) Ludvigson Real Uncertainty: h12

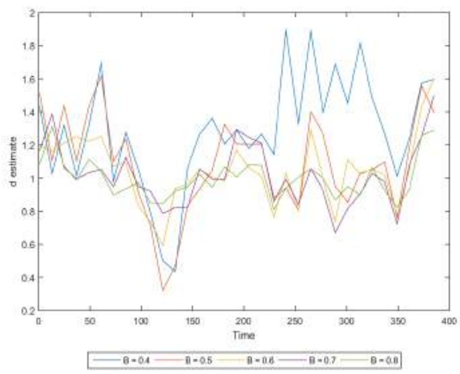
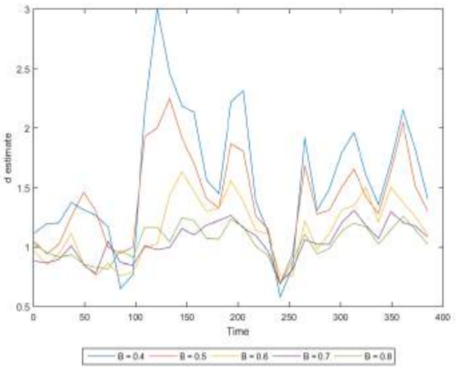
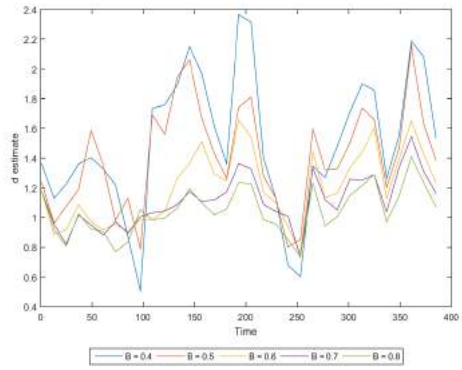


Figure 8 **Rolling-window univariate *d* estimate, LW – filtered, demeaned and detrended series (Cont'd)**

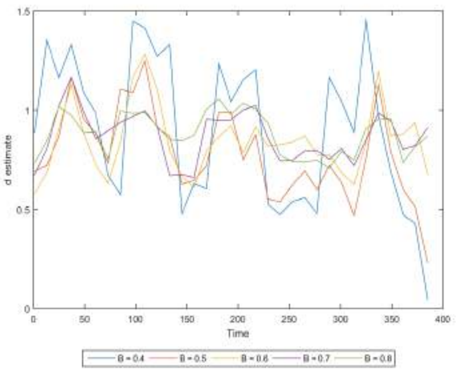
(25) 3-Month Treasury Bill



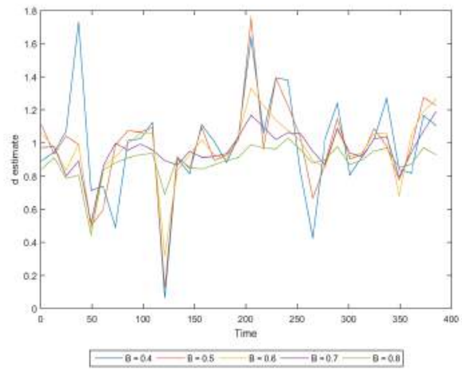
(26) Effective Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted



(27) 10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjust



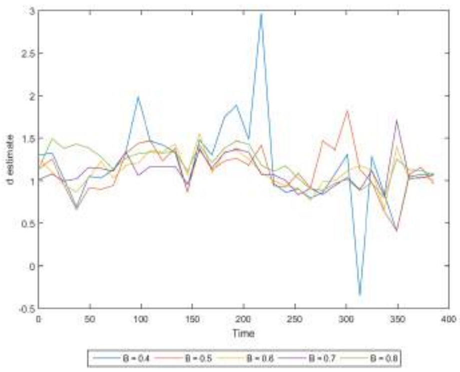
(28) Small Deposits



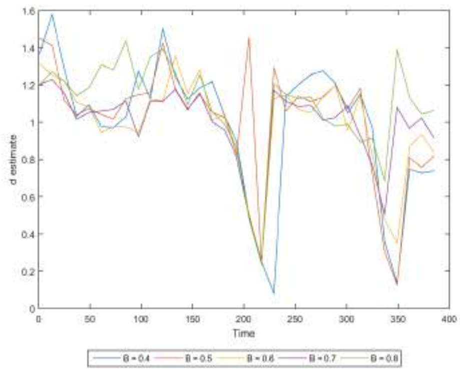
Note: Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years), after what they are demeaned and detrended..

Figure 9 **Rolling-window univariate *d* estimate, ELW – filtered, demeaned and detrended series**

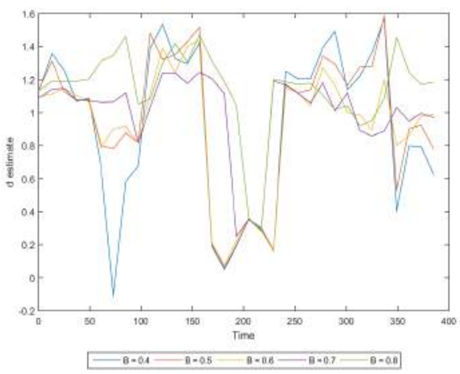
(1) M1, real



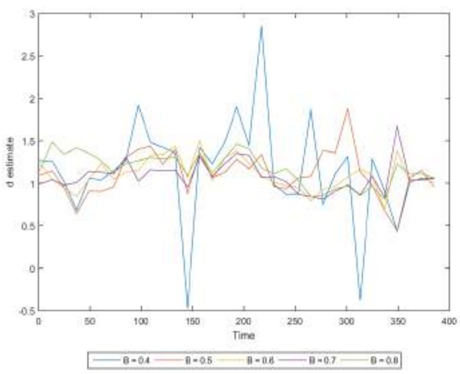
(2) M2, real



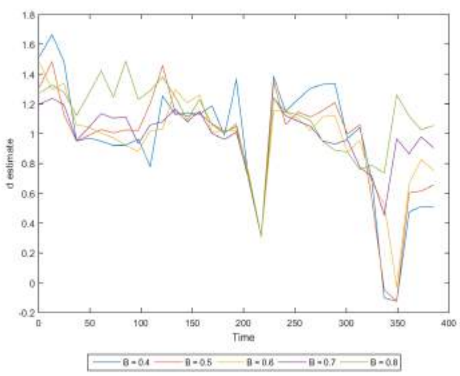
(3) MZ, real



(4) Log of real M1



(5) Log of real M2



(6) Log of real MZ

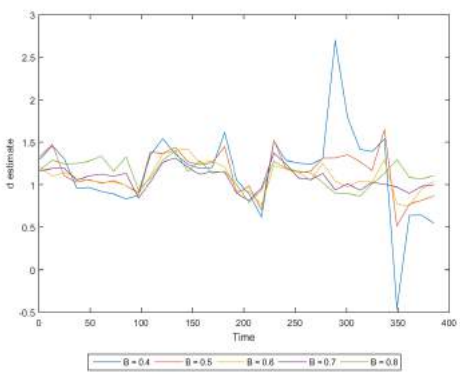
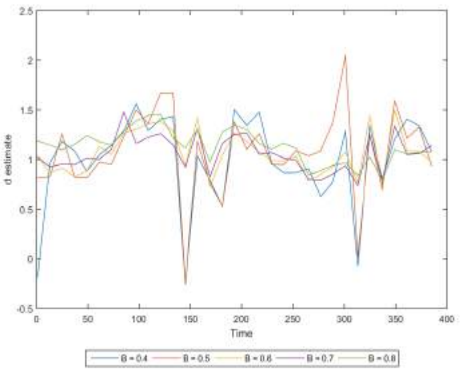
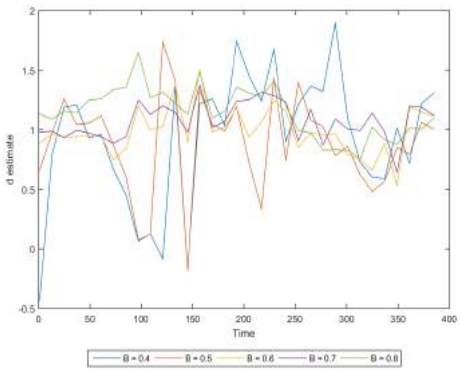


Figure 9 **Rolling-window univariate *d* estimate, ELW – filtered, demeaned and detrended series (Cont'd)**

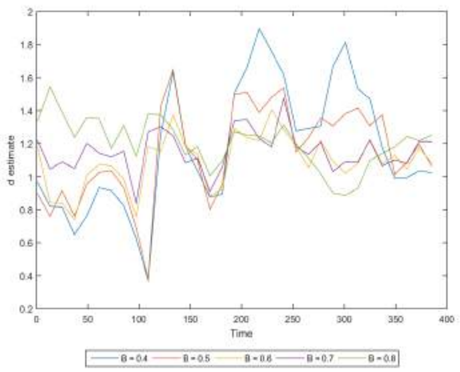
(7) Log of M1



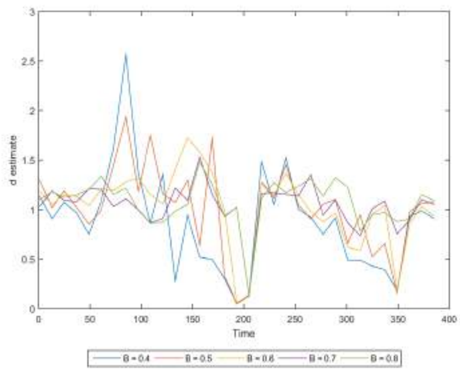
(8) Log of M2



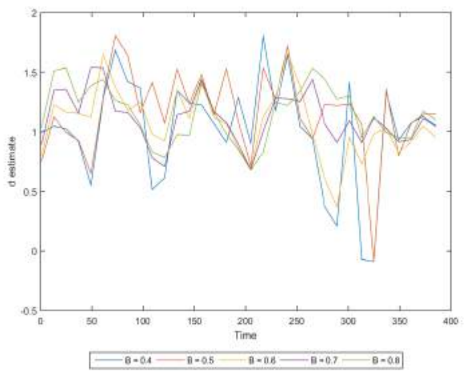
(9) Log of MZ



(10) Real Personal Disposable Income



(11) Log of real personal disposable income



(12) Economic Policy Uncertainty

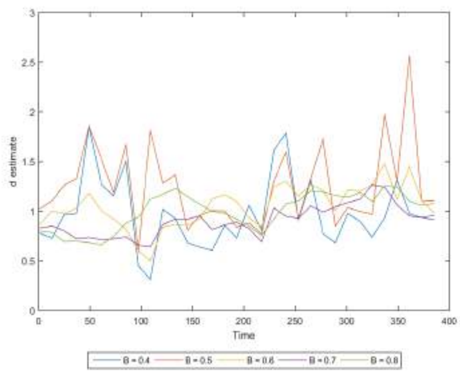
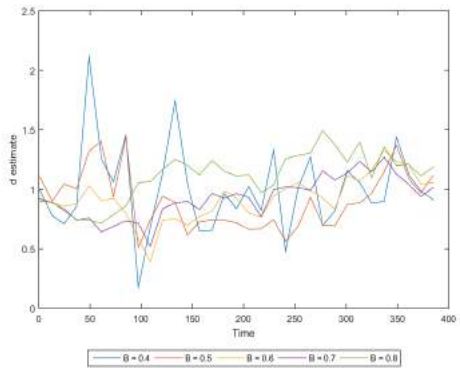
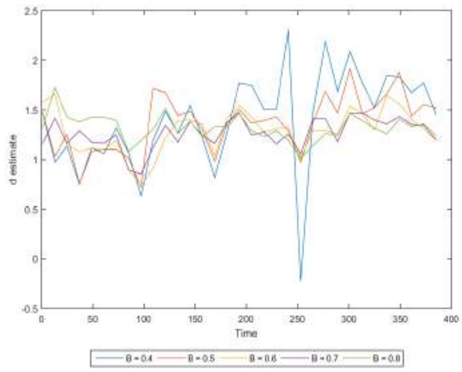


Figure 9 **Rolling-window univariate d estimate, ELW – filtered, demeaned and detrended series (Cont'd)**

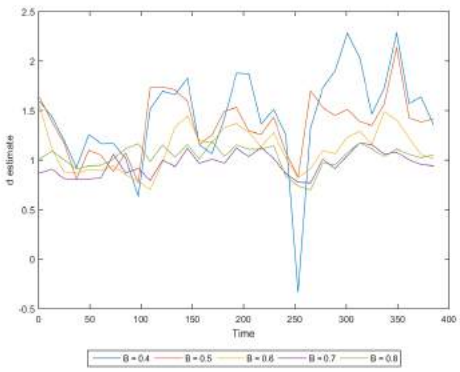
(13) Log of EPU



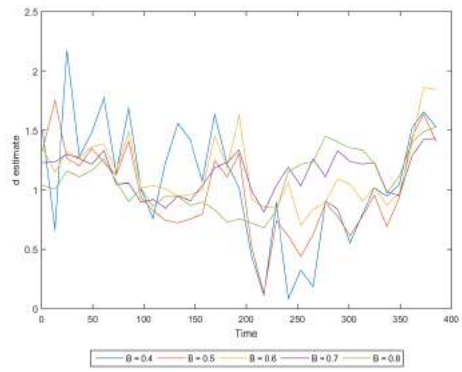
(14) M2 interest rate



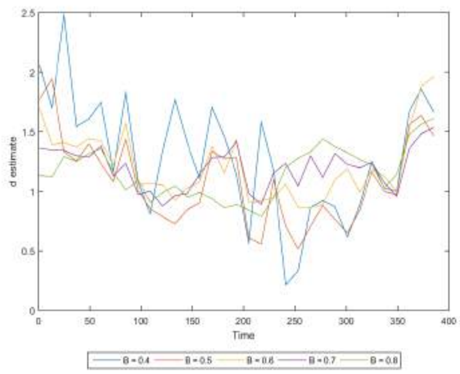
(15) MZ interest rate



(16) Ludvigson Macro Uncertainty: h1



(17) Ludvigson Macro Uncertainty: h3



(18) Ludvigson Macro Uncertainty: h12

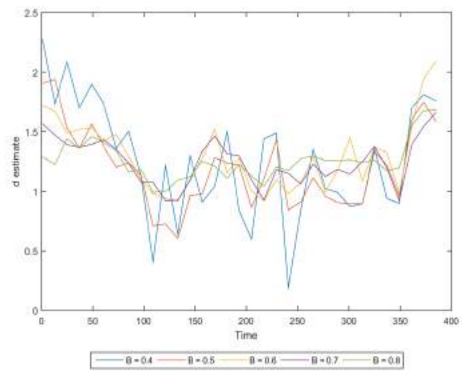
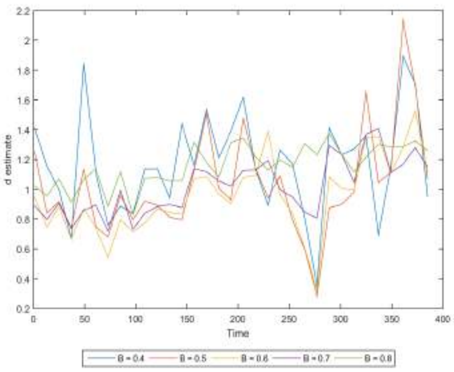
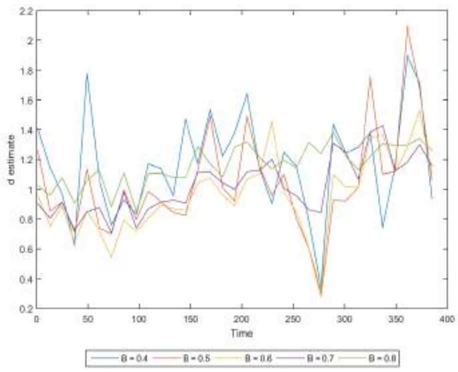


Figure 9 **Rolling-window univariate *d* estimate, ELW – filtered, demeaned and detrended series (Cont'd)**

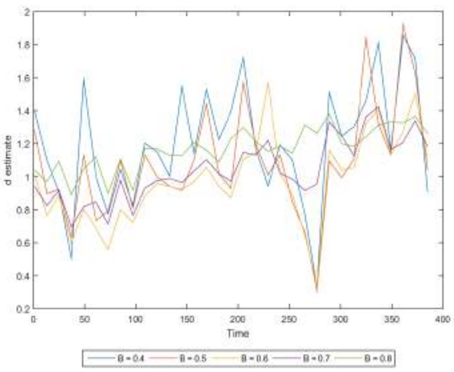
(19) Ludvigson Financial Uncertainty: h1



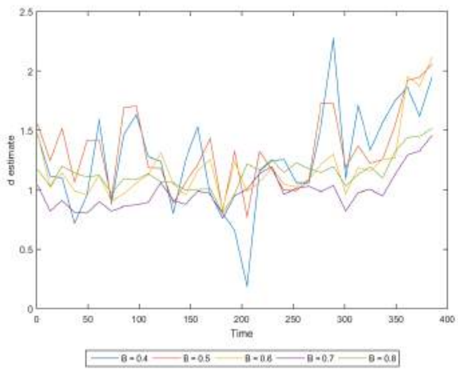
(20) Ludvigson Financial Uncertainty: h3



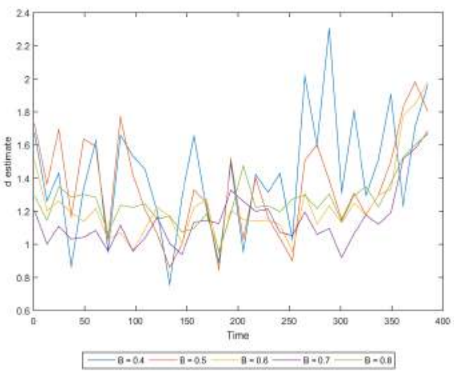
(21) Ludvigson Financial Uncertainty: h12



(22) Ludvigson Real Uncertainty: h1



(23) Ludvigson Real Uncertainty: h3



(24) Ludvigson Real Uncertainty: h12

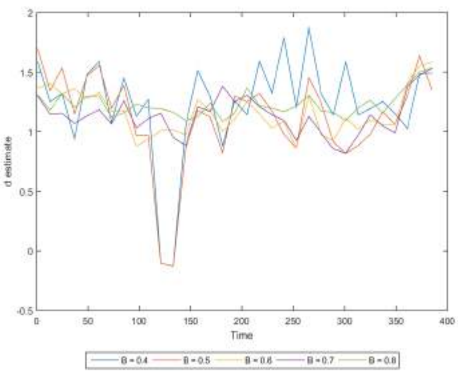
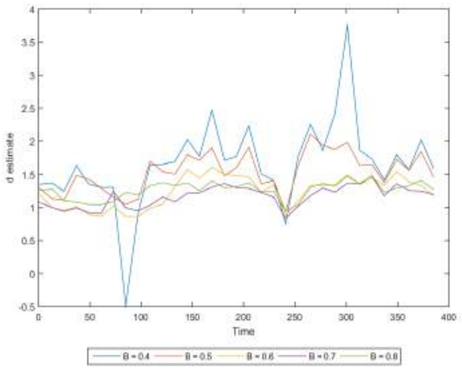
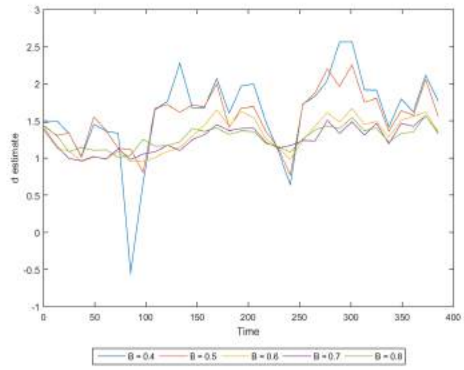


Figure 9 **Rolling-window univariate d estimate, ELW – filtered, demeaned and detrended series (Cont'd)**

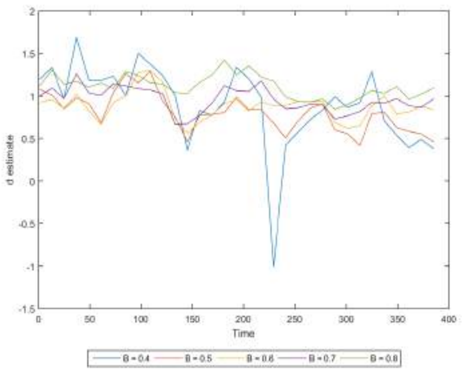
(25) 3-Month Treasury Bill



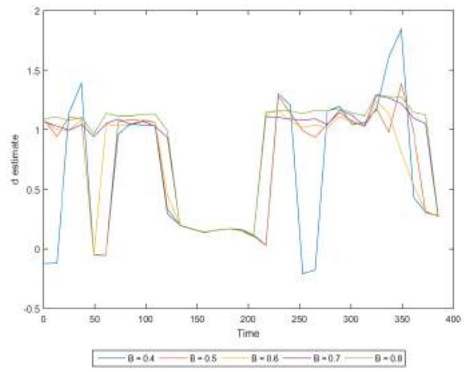
(26) Effective Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted



(27) 10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjust



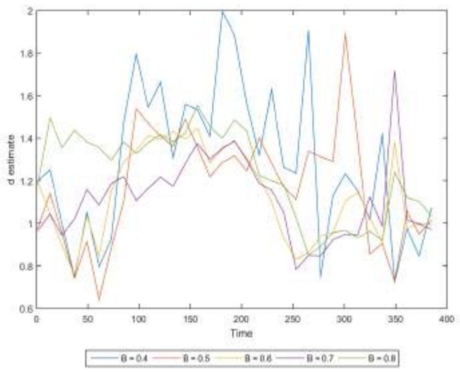
(28) Small Deposits



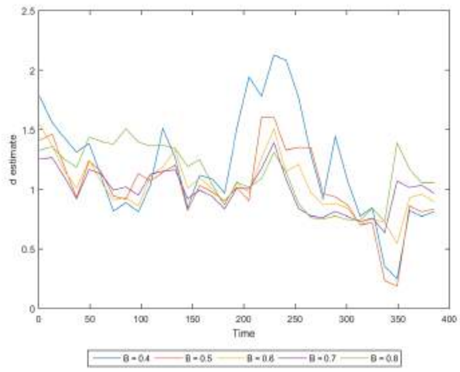
Note: Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years), after what they are demeaned and detrended..

Figure 10 **Rolling-window univariate d estimate, Feasible ELW – filtered, demeaned and detrended series**

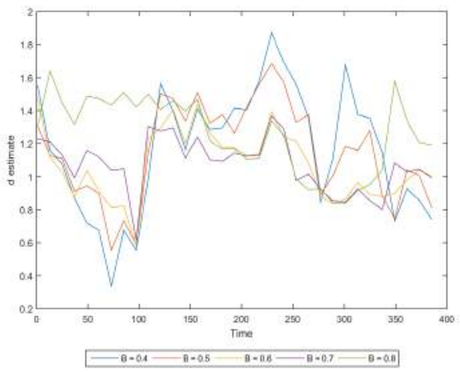
(1) M1, real



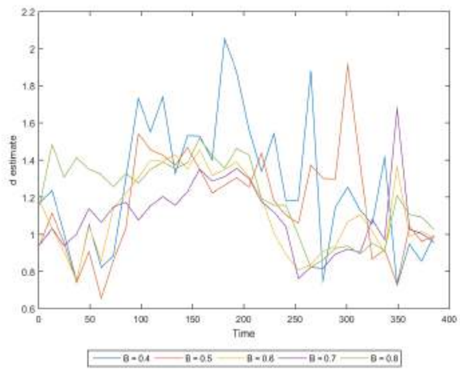
(2) M2, real



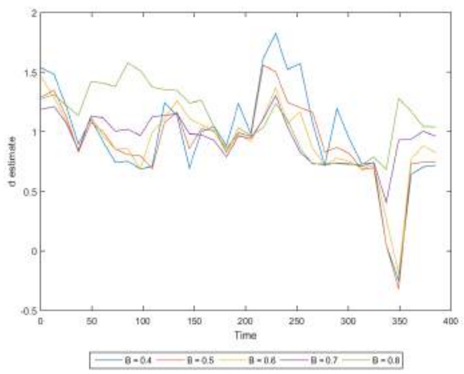
(3) MZ, real



(4) Log of real M1



(5) Log of real M2



(6) Log of real MZ

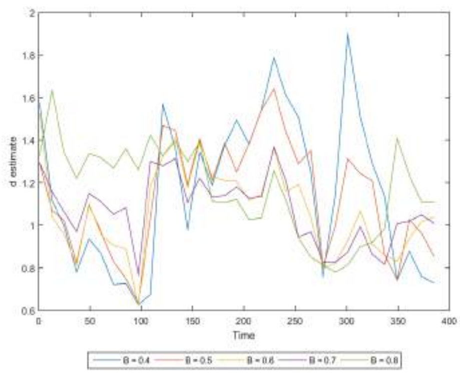
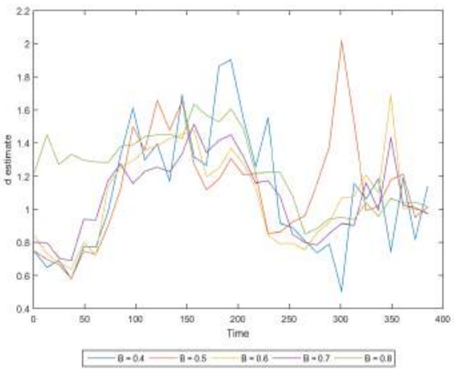
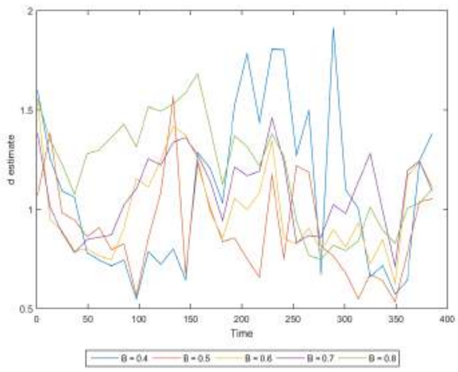


Figure 10 **Rolling-window univariate *d* estimate, Feasible ELW – filtered, demeaned and detrended series (Cont'd)**

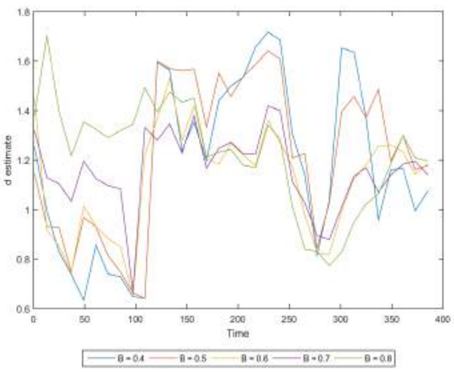
(7) Log of M1



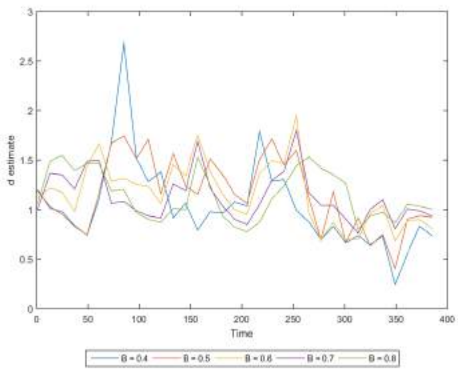
(8) Log of M2



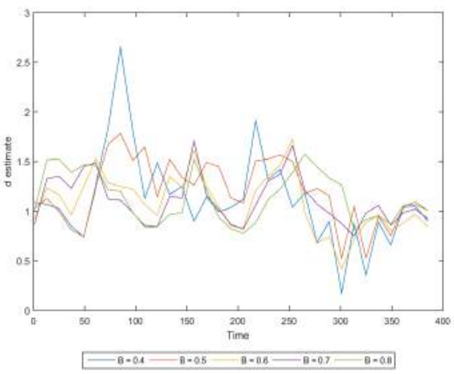
(9) Log of MZ



(10) Real Personal Disposable Income



(11) Log of real personal disposable income



(12) Economic Policy Uncertainty

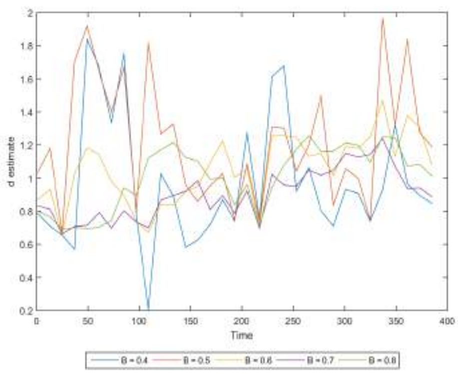
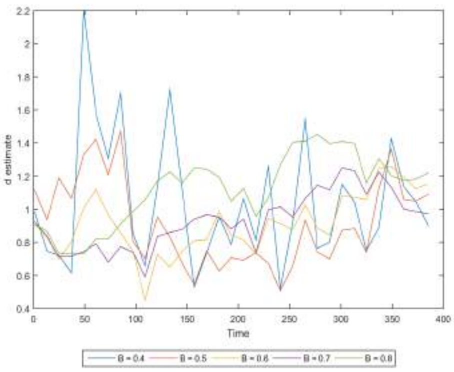
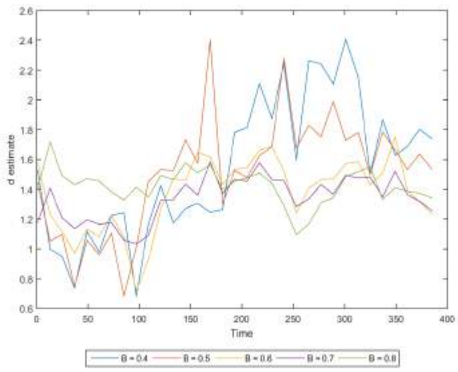


Figure 10 **Rolling-window univariate *d* estimate, Feasible ELW – filtered, demeaned and detrended series (Cont'd)**

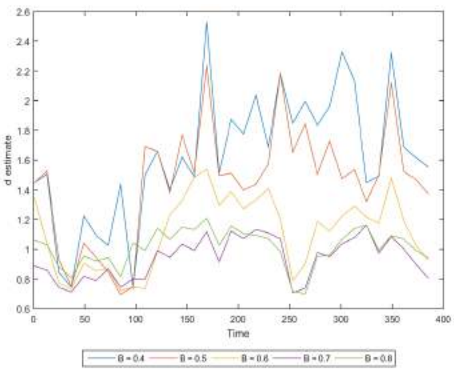
(13) Log of EPU



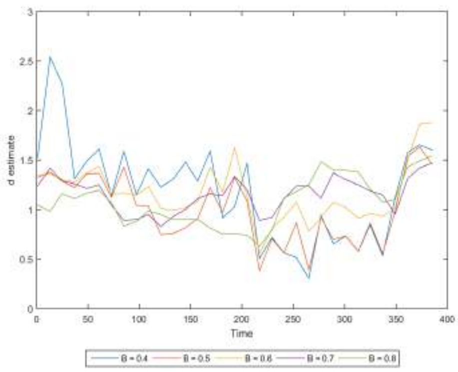
(14) M2 interest rate



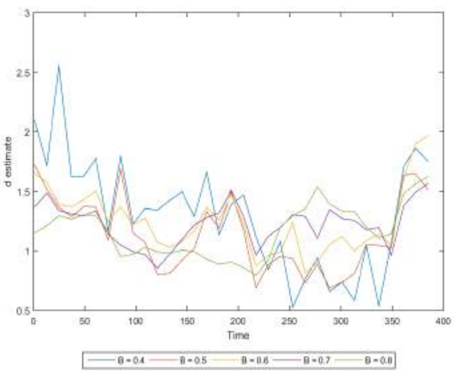
(15) MZ interest rate



(16) Ludvigson Macro Uncertainty: h1



(17) Ludvigson Macro Uncertainty: h3



(18) Ludvigson Macro Uncertainty: h12

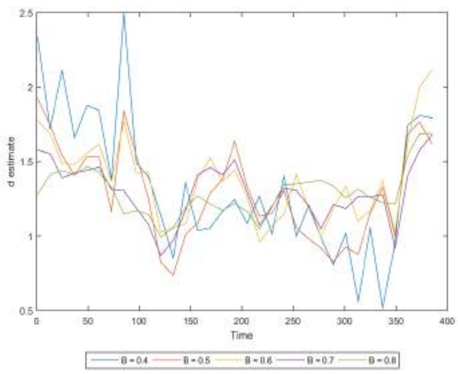
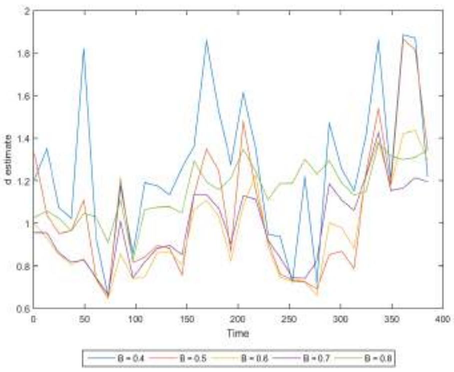
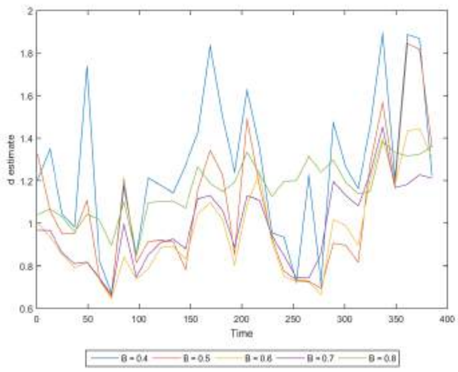


Figure 10 **Rolling-window univariate *d* estimate, Feasible ELW – filtered, demeaned and detrended series (Cont'd)**

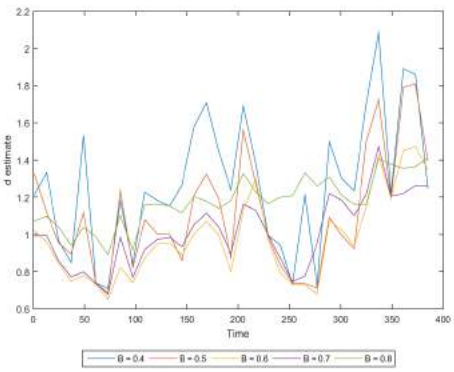
(19) Ludvigson Financial Uncertainty: h1



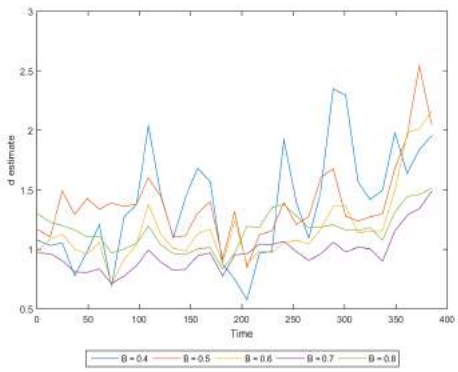
(20) Ludvigson Financial Uncertainty: h3



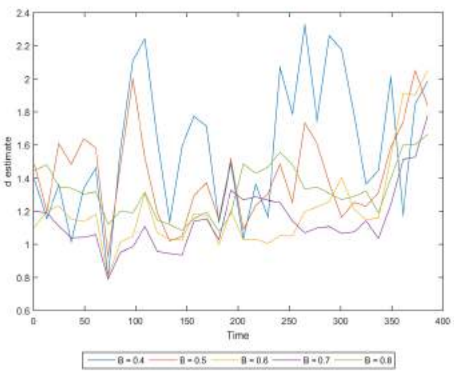
(21) Ludvigson Financial Uncertainty: h12



(22) Ludvigson Real Uncertainty: h1



(23) Ludvigson Real Uncertainty: h3



(24) Ludvigson Real Uncertainty: h12

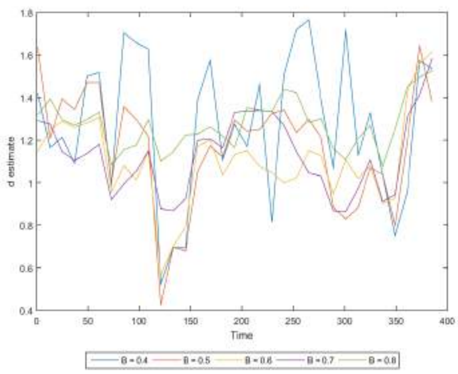
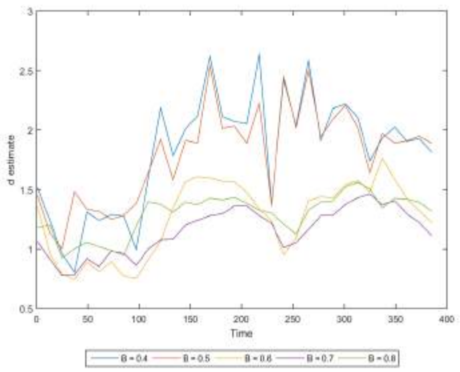
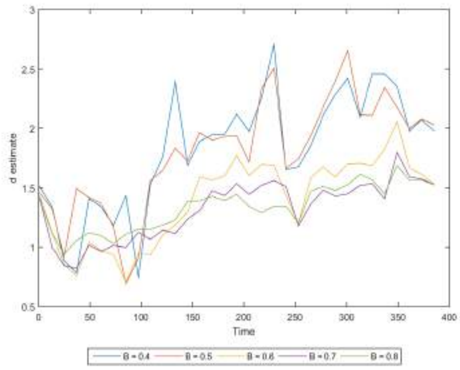


Figure 10 **Rolling-window univariate *d* estimate, Feasible ELW – filtered, demeaned and detrended series (Cont'd)**

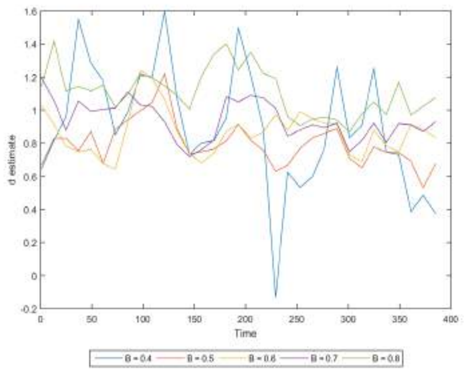
(25) 3-Month Treasury Bill



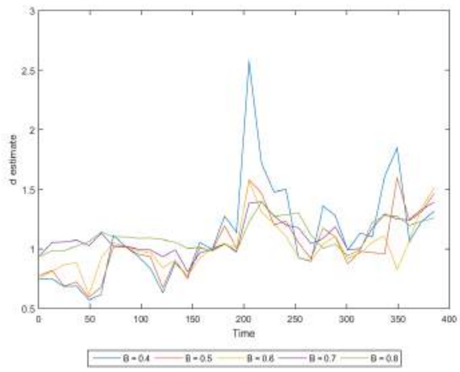
(26) Effective Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted



(27) 10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjust



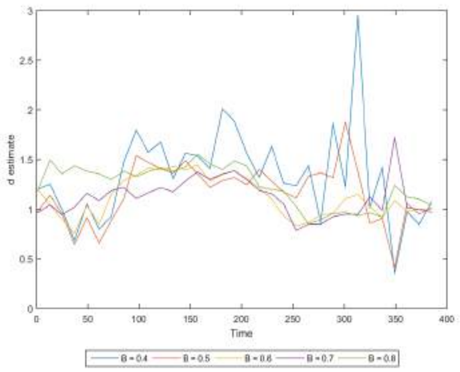
(28) Small Deposits



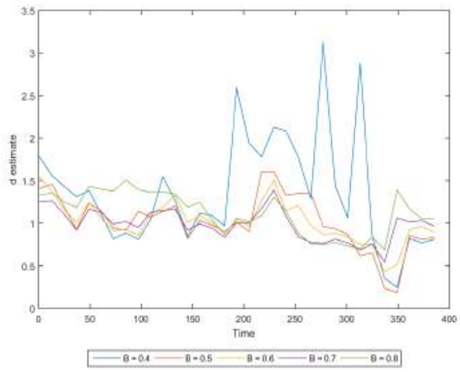
Note: Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years), after what they are demeaned and detrended..

Figure 11 **Rolling-window univariate *d* estimate, 2-stage ELW – filtered, demeaned and detrended series**

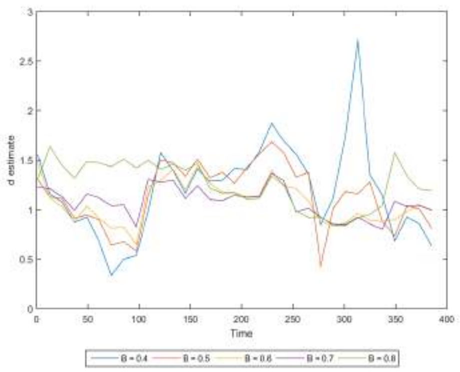
(1) M1, real



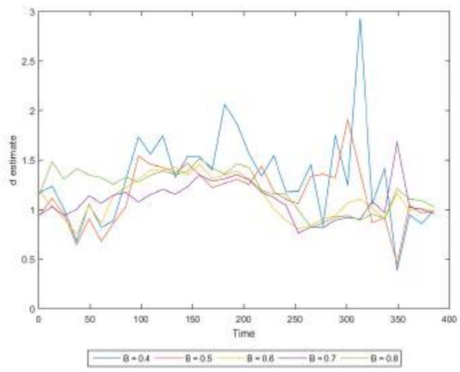
(2) M2, real



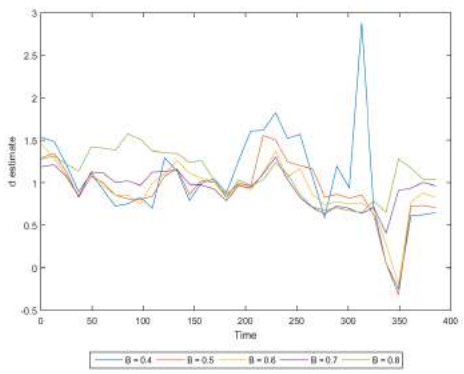
(3) MZ, real



(4) Log of real M1



(5) Log of real M2



(6) Log of real MZ

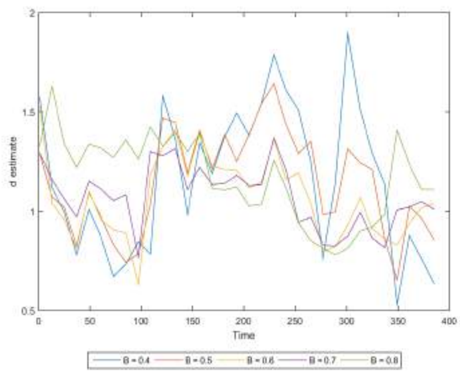
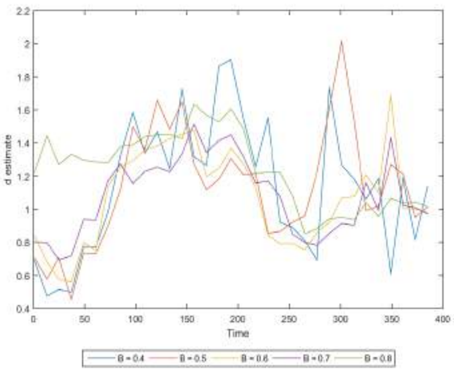
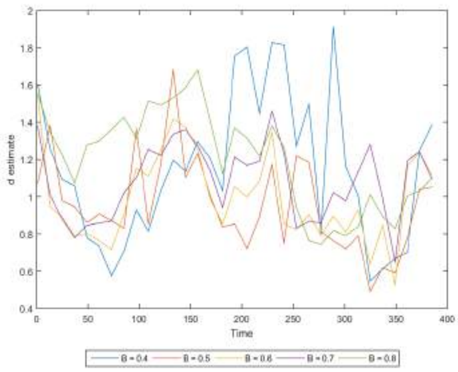


Figure 11 **Rolling-window univariate *d* estimate, 2-stage ELW – filtered, demeaned and detrended series (Cont'd)**

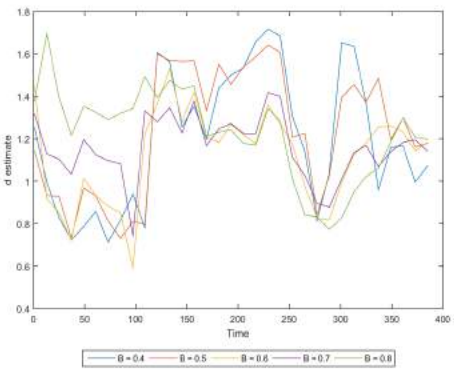
(7) Log of M1



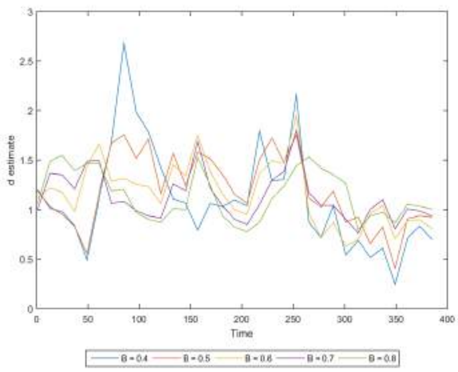
(8) Log of M2



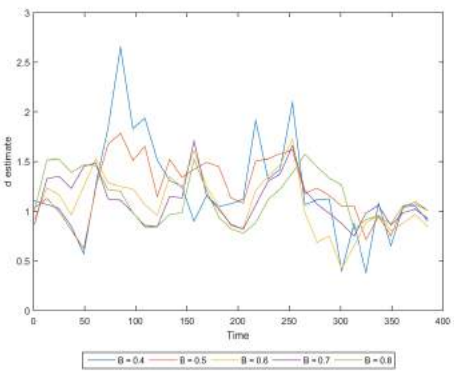
(9) Log of MZ



(10) Real Personal Disposable Income



(11) Log of real personal disposable income



(12) Economic Policy Uncertainty

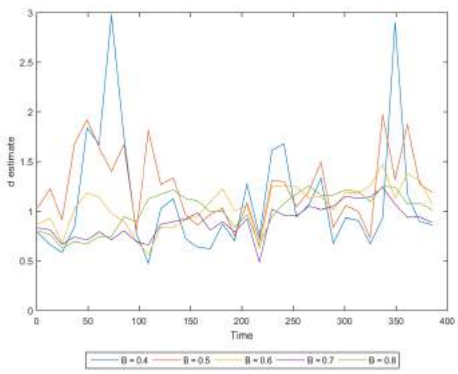
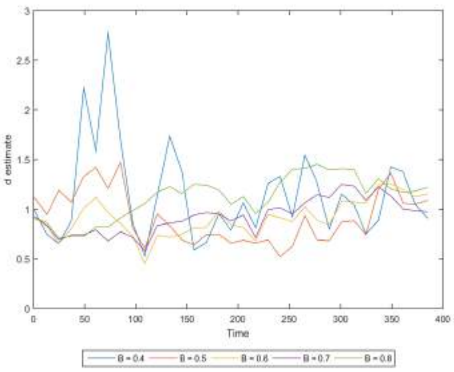
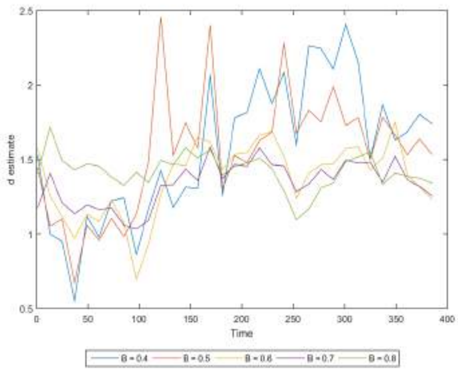


Figure 11 **Rolling-window univariate *d* estimate, 2-stage ELW – filtered, demeaned and detrended series (Cont'd)**

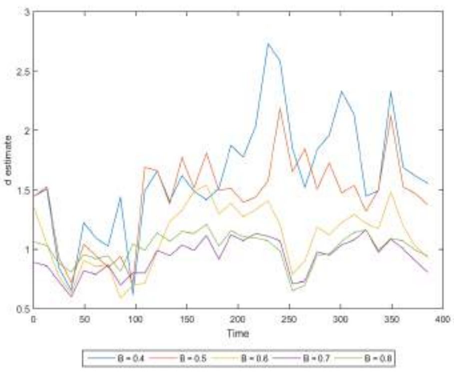
(13) Log of EPU



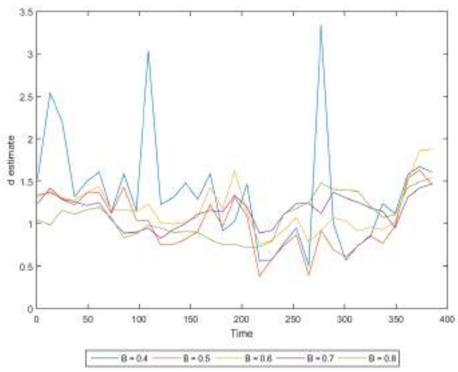
(14) M2 interest rate



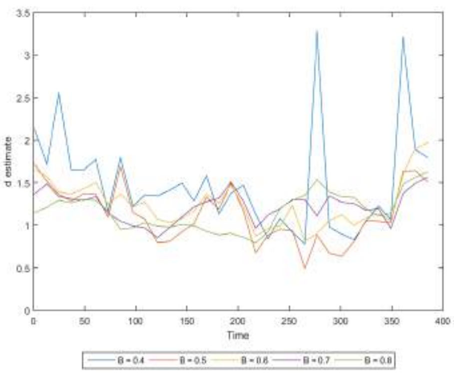
(15) MZ interest rate



(16) Ludvigson Macro Uncertainty: h1



(17) Ludvigson Macro Uncertainty: h3



(18) Ludvigson Macro Uncertainty: h12

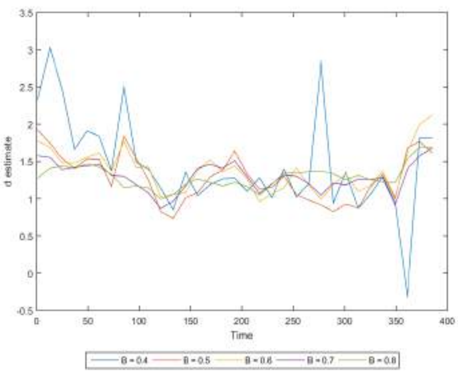
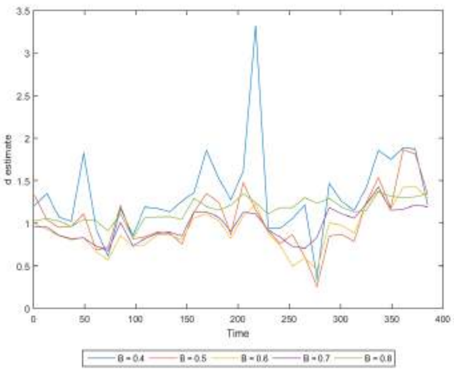
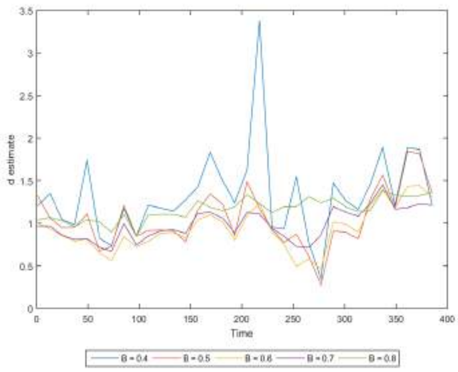


Figure 11 **Rolling-window univariate *d* estimate, 2-stage ELW – filtered, demeaned and detrended series (Cont'd)**

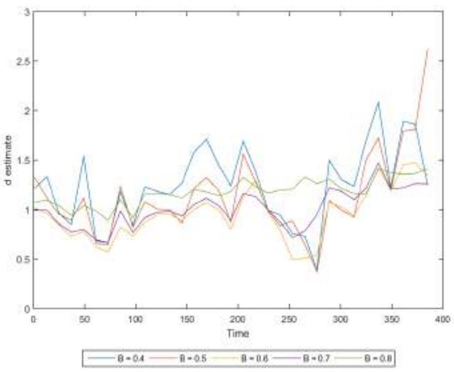
(19) Ludvigson Financial Uncertainty: h1



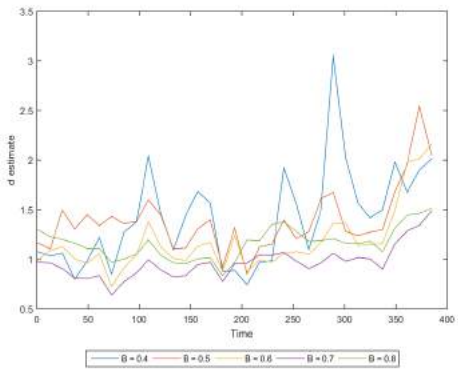
(20) Ludvigson Financial Uncertainty: h3



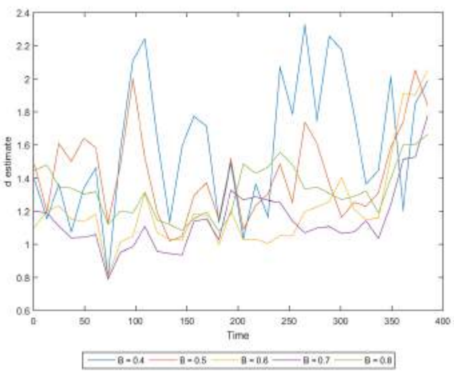
(21) Ludvigson Financial Uncertainty: h12



(22) Ludvigson Real Uncertainty: h1



(23) Ludvigson Real Uncertainty: h3



(24) Ludvigson Real Uncertainty: h12

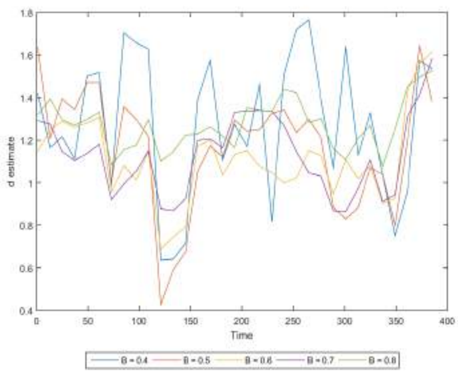
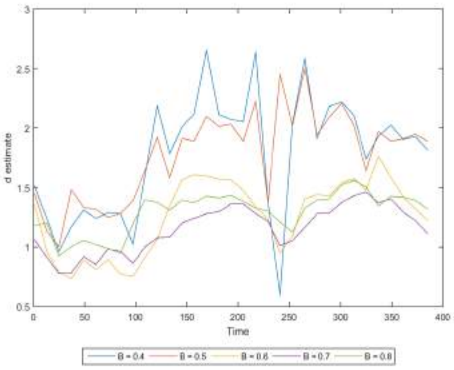
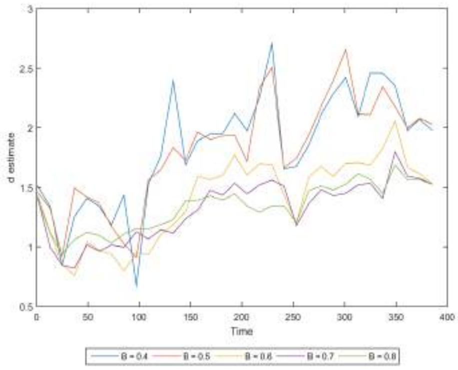


Figure 11 **Rolling-window univariate *d* estimate, 2-stage ELW – filtered, demeaned and detrended series (Cont'd)**

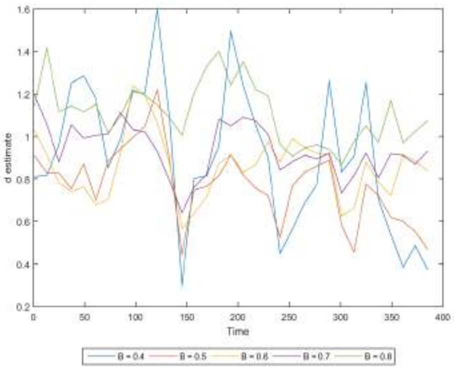
(25) 3-Month Treasury Bill



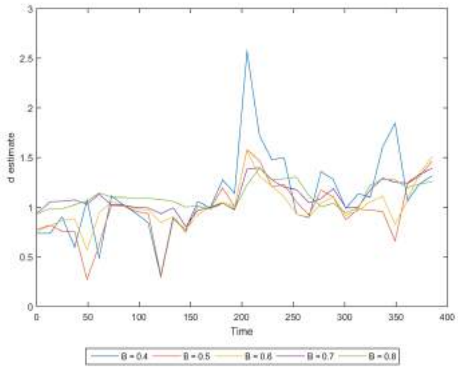
(26) Effective Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted



(27) 10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjust



(28) Small Deposits



Note: Before estimation all series are de-cycled using Hamilton's regression filter tailored for credit cycles (i.e. 5 years), after what they are demeaned and detrended..

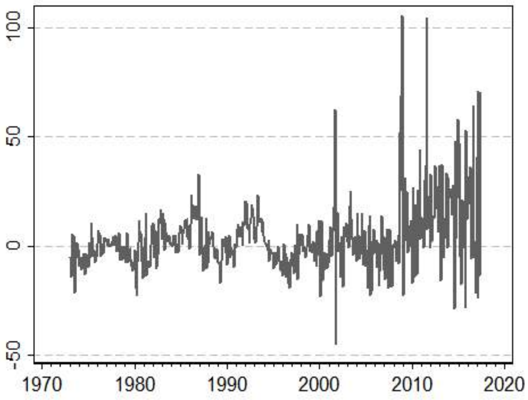
4 Descriptive graphs, full sample and rolling-window d estimates for first-differenced series

4.1 First-differenced and original series

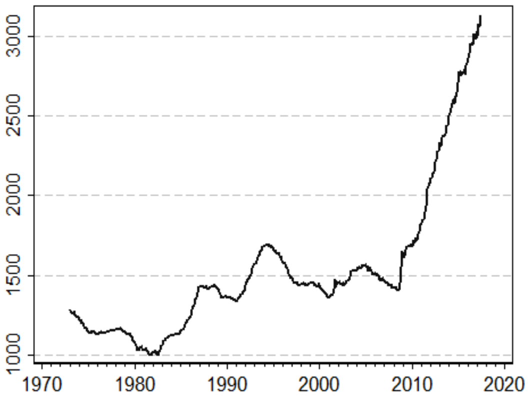
Figure 12 **First differenced and original series**

(1) M1, real

First difference

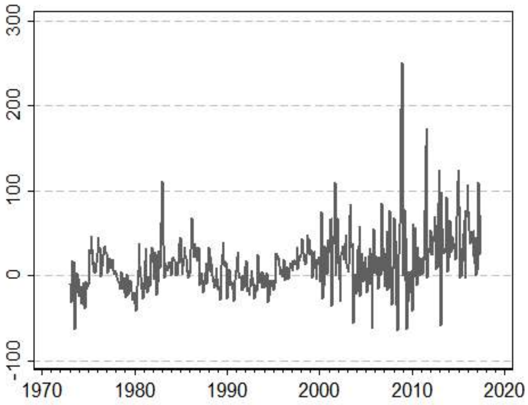


Original series

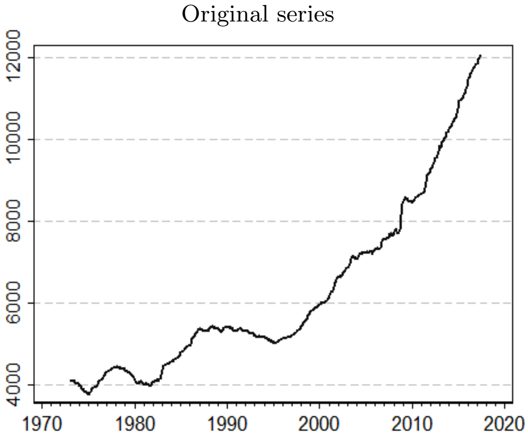


(2) M2, real

First difference

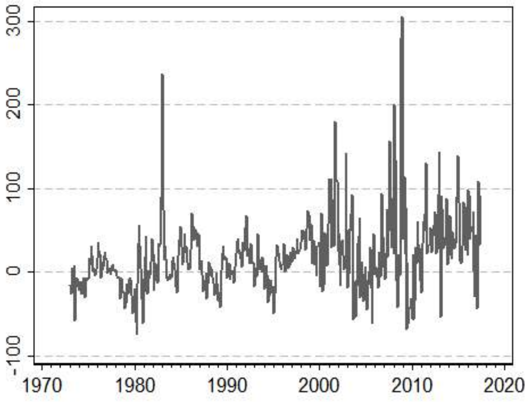


Original series



(3) MZ, real

First difference



Original series

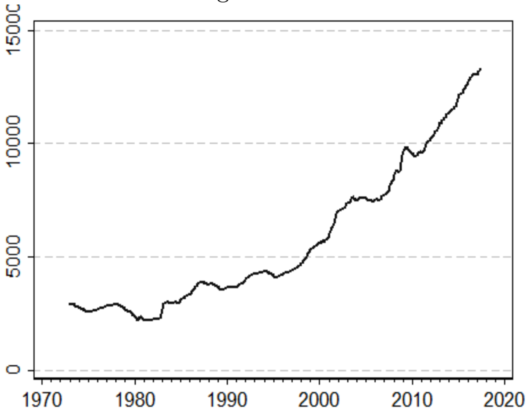
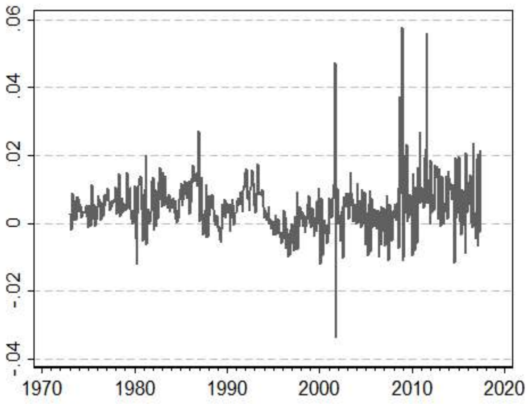


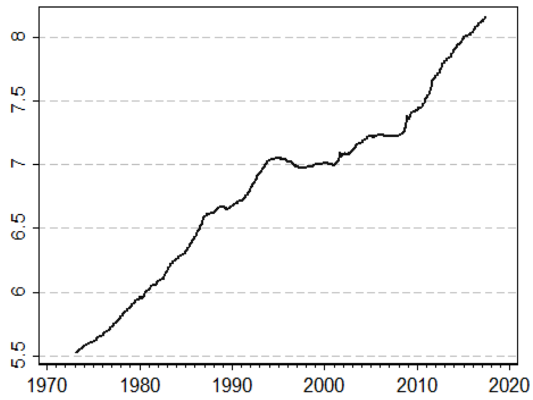
Figure 12 **First differenced and original series (Cont'd)**

(4) Log of M1

First difference

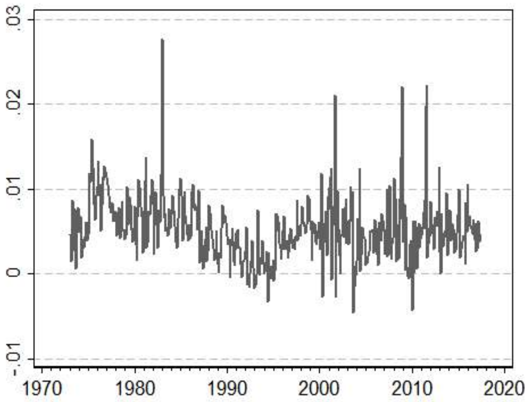


Original series

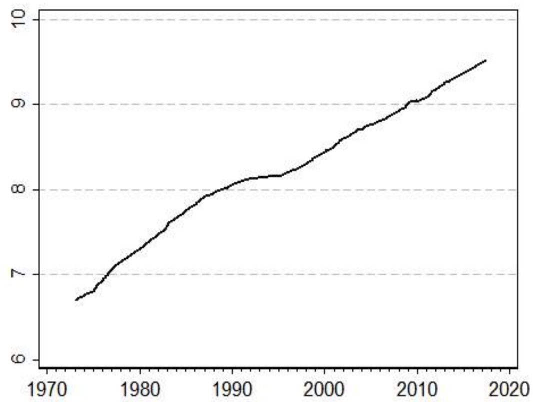


(5) Log of M2

First difference

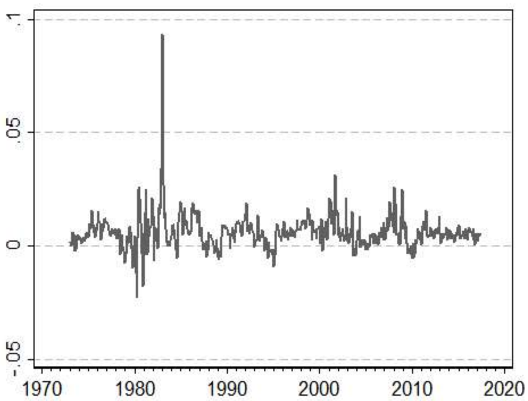


Original series



(6) Log of MZ

First difference



Original series

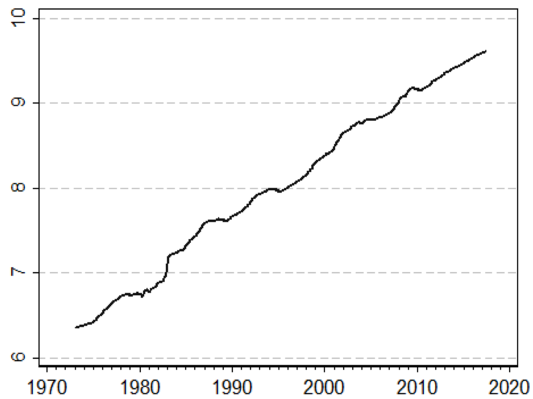
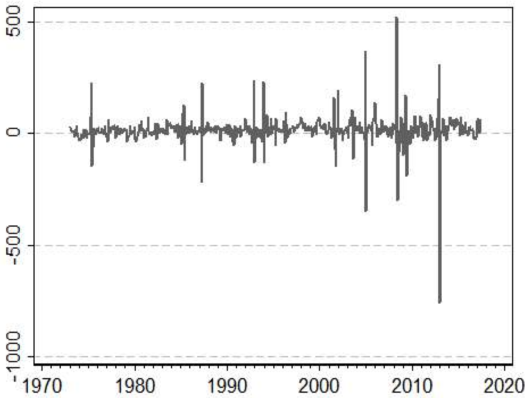


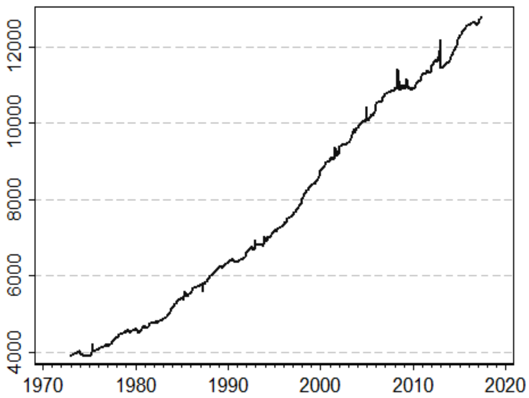
Figure 12 **First differenced and original series (Cont'd)**

(7) Real Personal Disposable Income

First difference

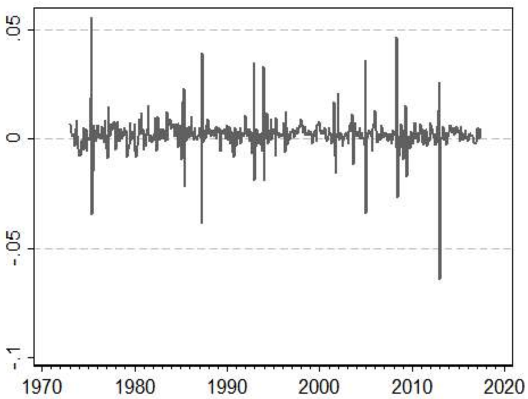


Original series

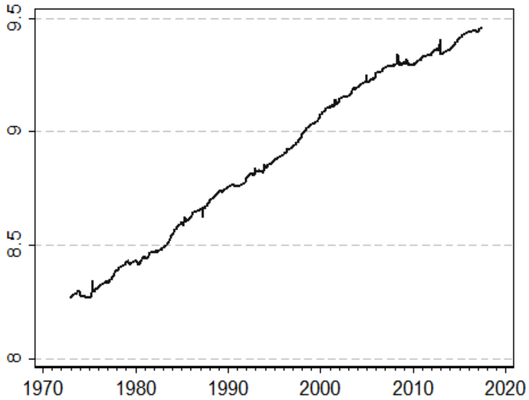


(8) Log of real personal disposable income

First difference

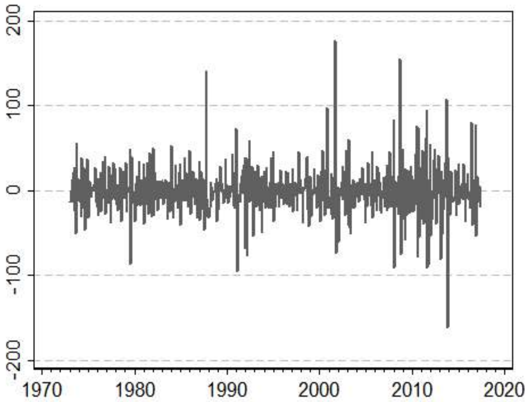


Original series



(9) Economic Policy Uncertainty

First difference



Original series

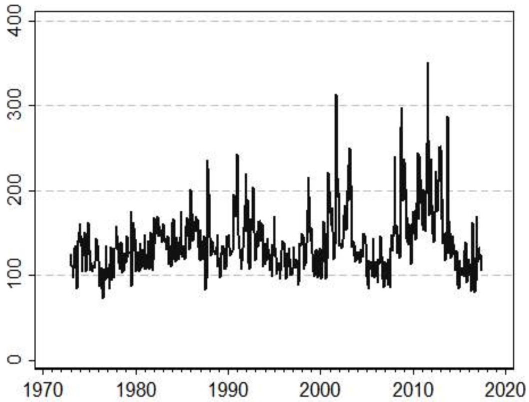
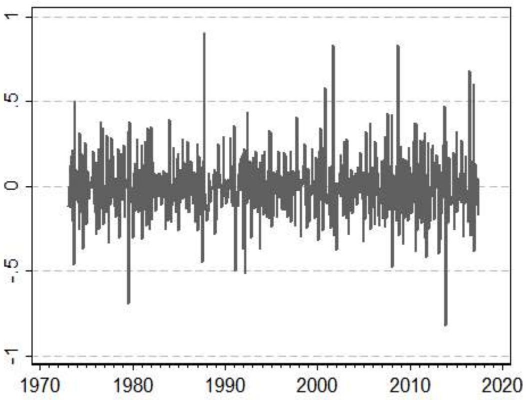


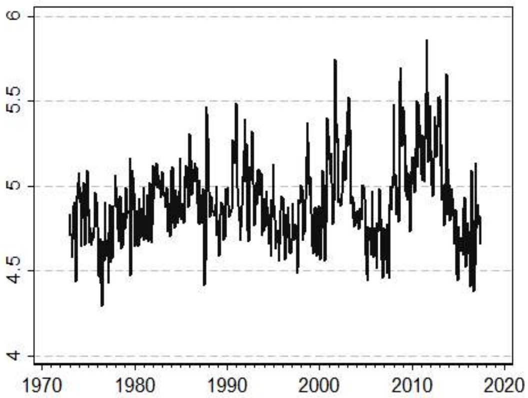
Figure 12 **First differenced and original series (Cont'd)**

(10) Log of EPU

First difference

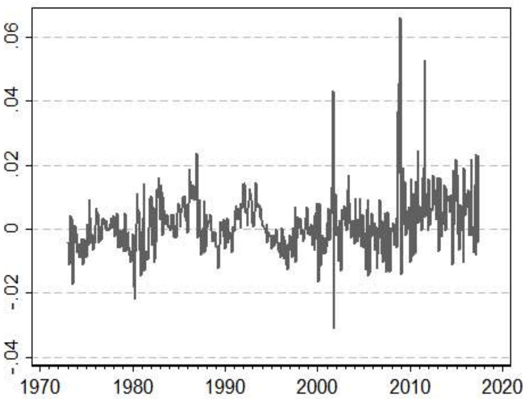


Original series

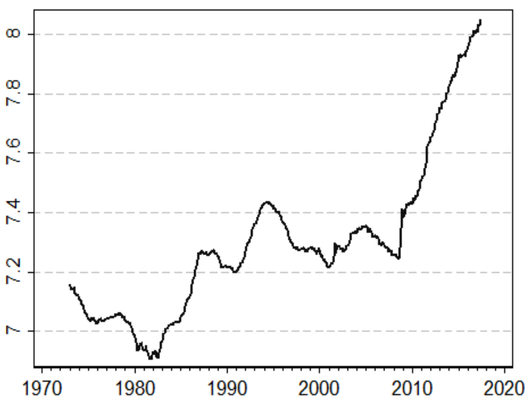


(11) Log of real M1

First difference

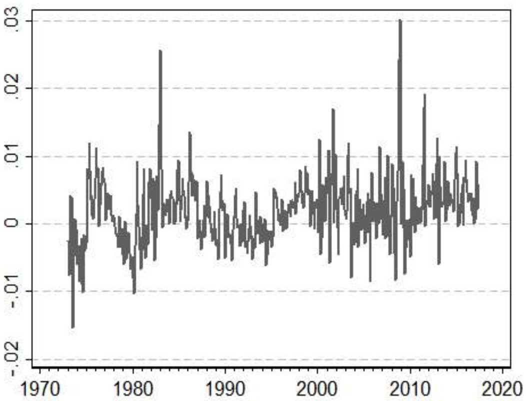


Original series



(12) Log of real M2

First difference



Original series

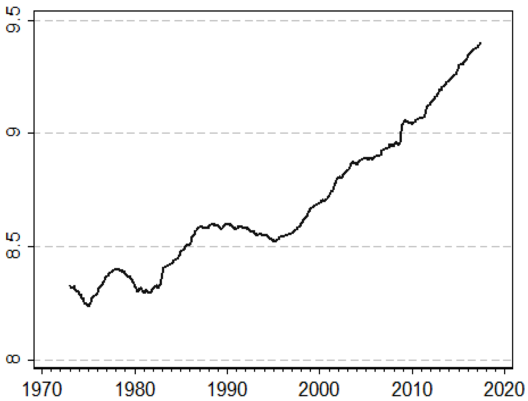
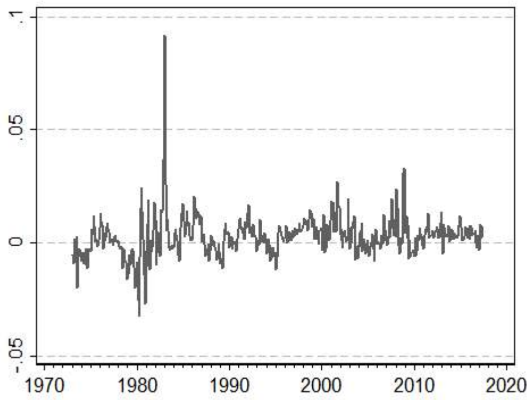


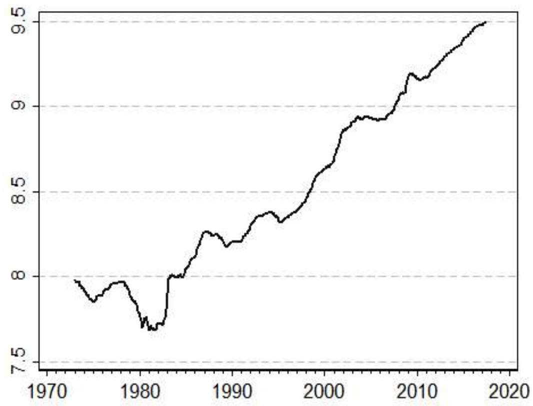
Figure 12 **First differenced and original series (Cont'd)**

(13) Log of real MZ

First difference

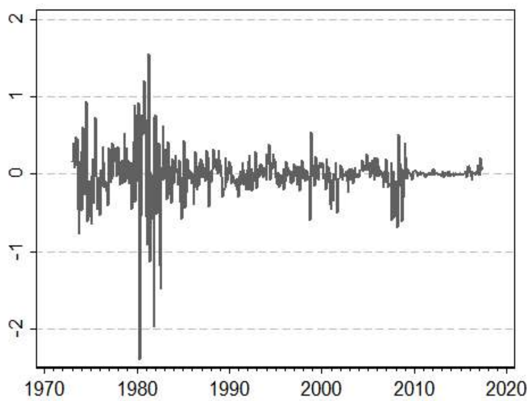


Original series

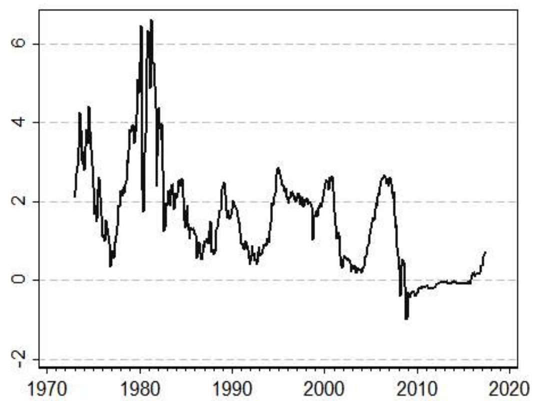


(14) M2 interest rate

First difference

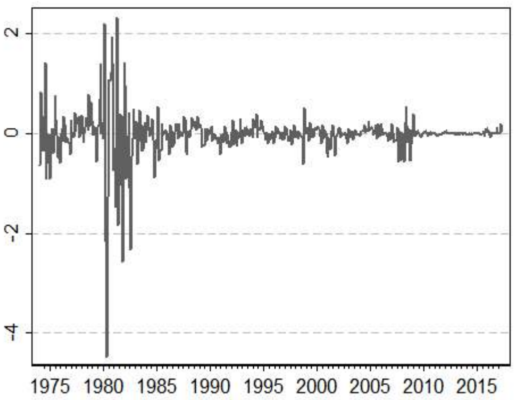


Original series



(15) MZ interest rate

First difference



Original series

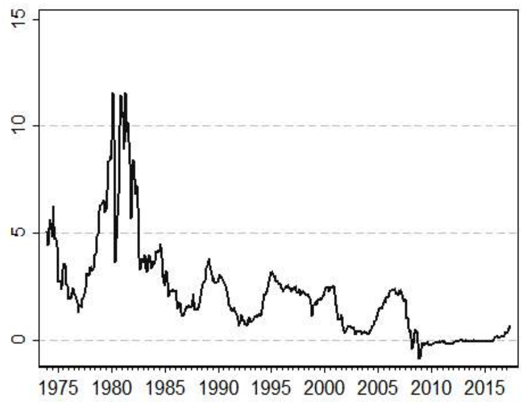
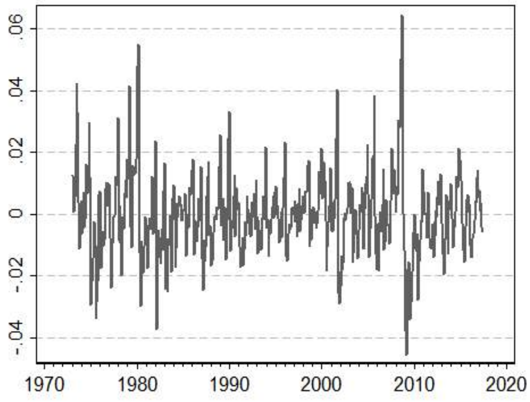


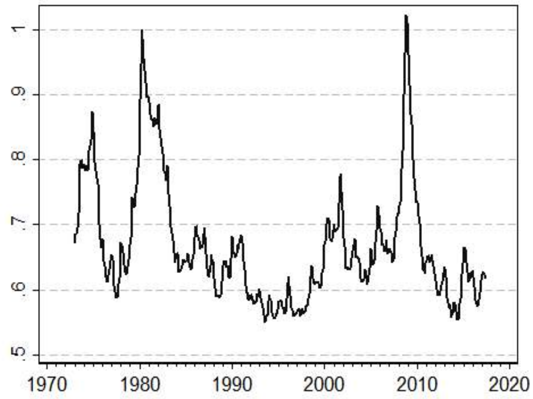
Figure 12 **First differenced and original series (Cont'd)**

(16) Ludvigson Macro Uncertainty: h1

First difference

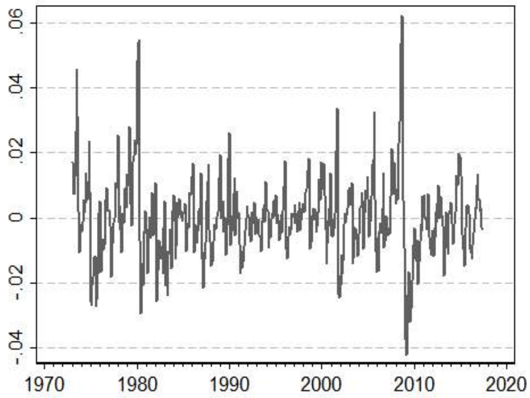


Original series

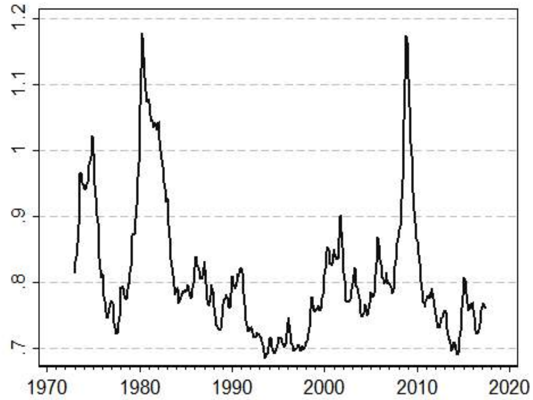


(17) Ludvigson Macro Uncertainty: h3

First difference

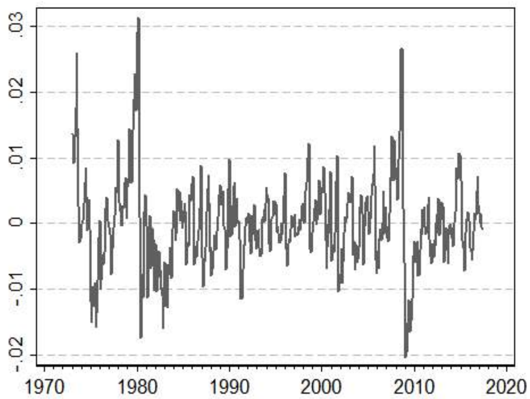


Original series



(18) Ludvigson Macro Uncertainty: h12

First difference



Original series

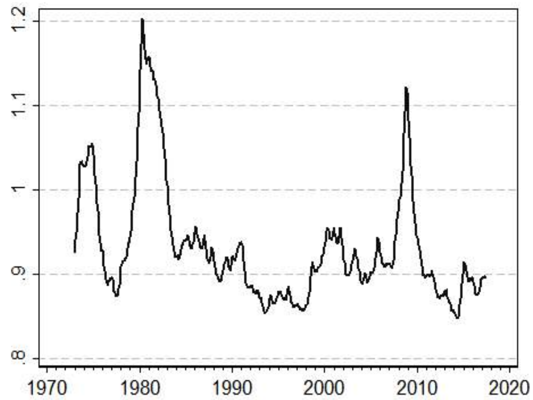
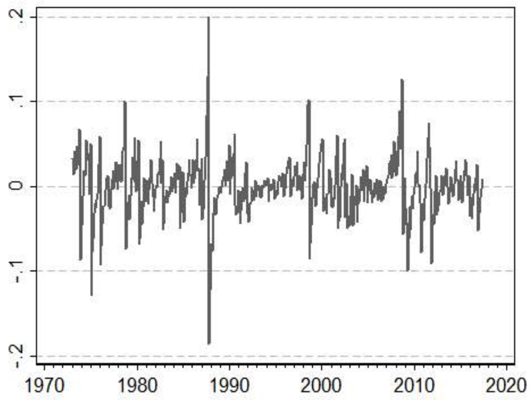


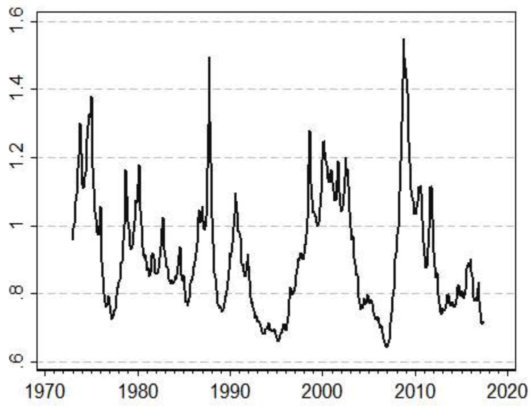
Figure 12 **First differenced and original series (Cont'd)**

(19) Ludvigson Financial Uncertainty: h1

First difference

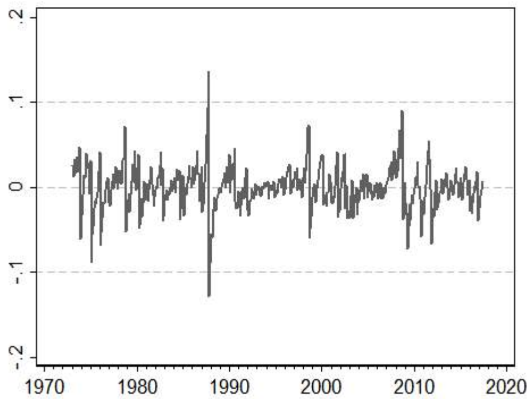


Original series

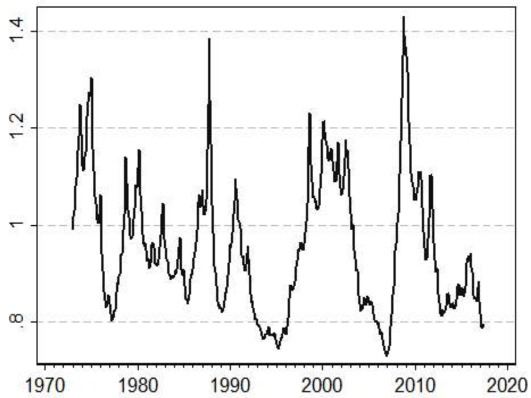


(20) Ludvigson Financial Uncertainty: h3

First difference

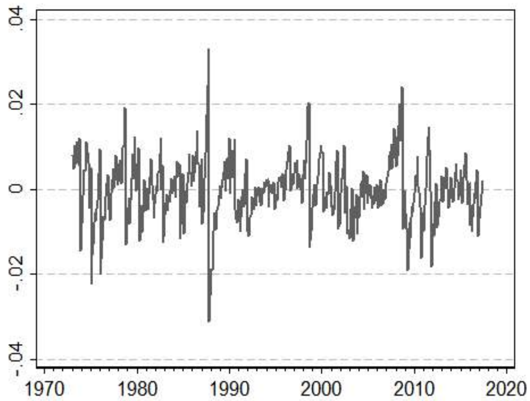


Original series



(21) Ludvigson Financial Uncertainty: h12

First difference



Original series

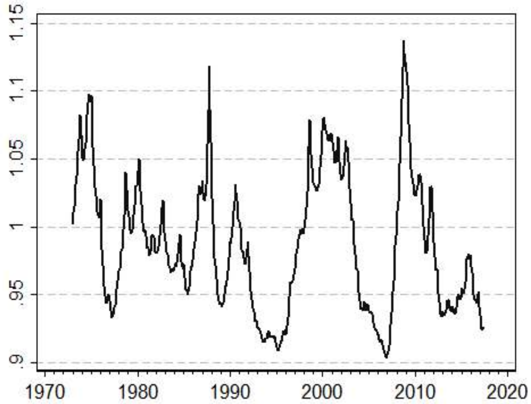
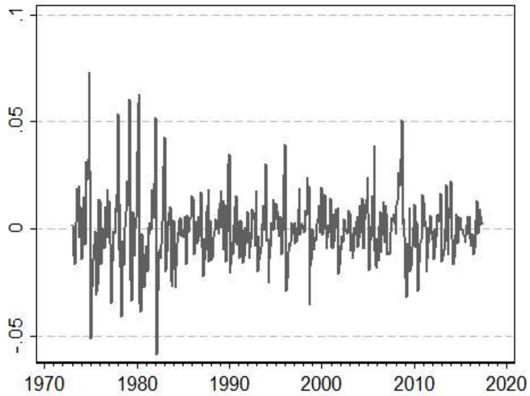


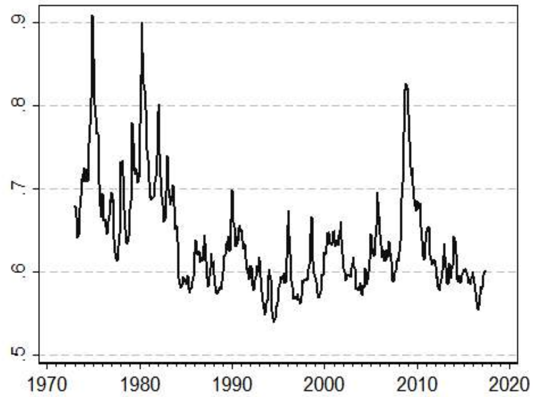
Figure 12 **First differenced and original series (Cont'd)**

(22) Ludvigson Real Uncertainty: h1

First difference

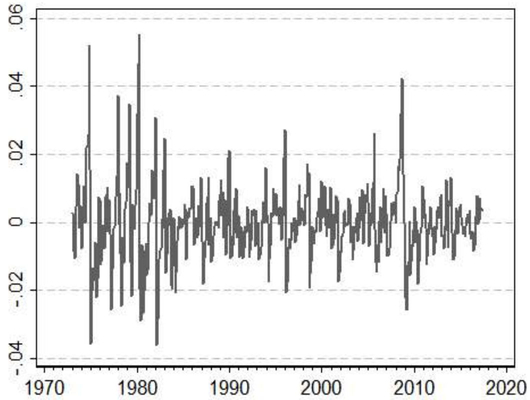


Original series

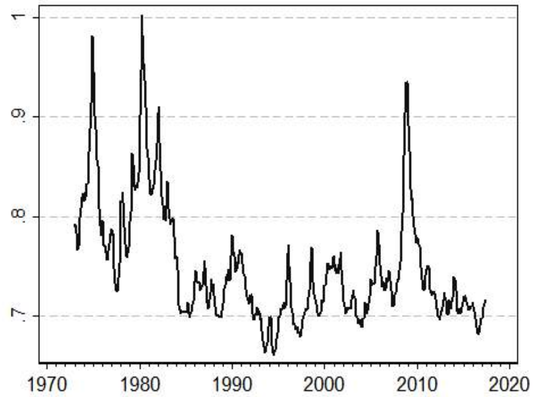


(23) Ludvigson Real Uncertainty: h3

First difference

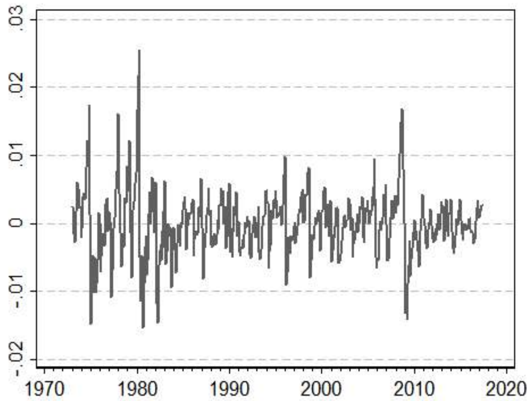


Original series



(24) Ludvigson Real Uncertainty: h12

First difference



Original series

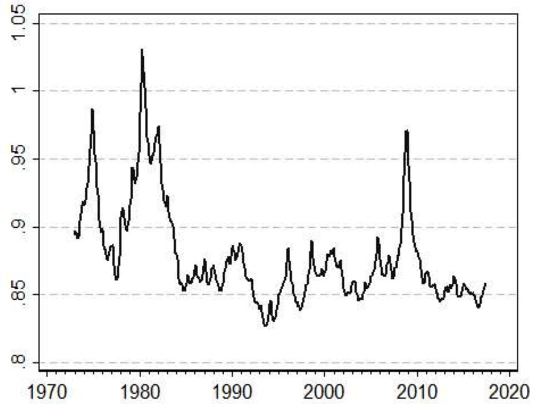
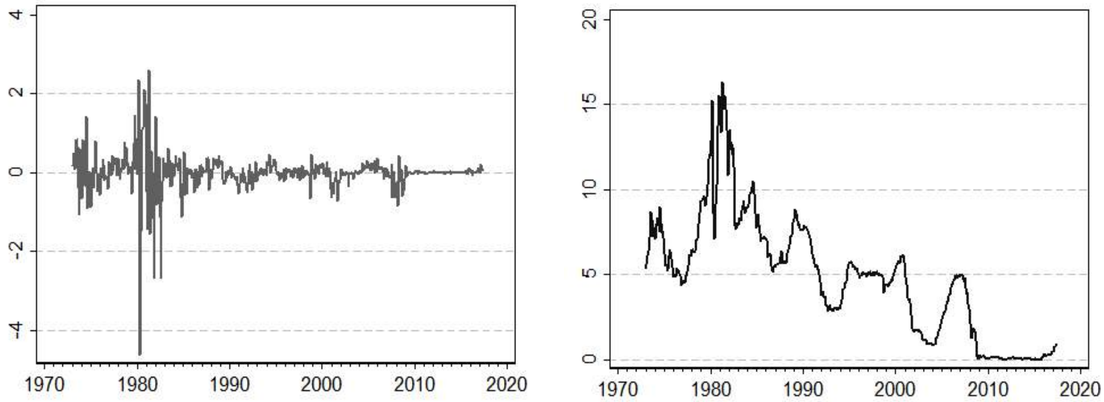


Figure 12 **First differenced and original series (Cont'd)**

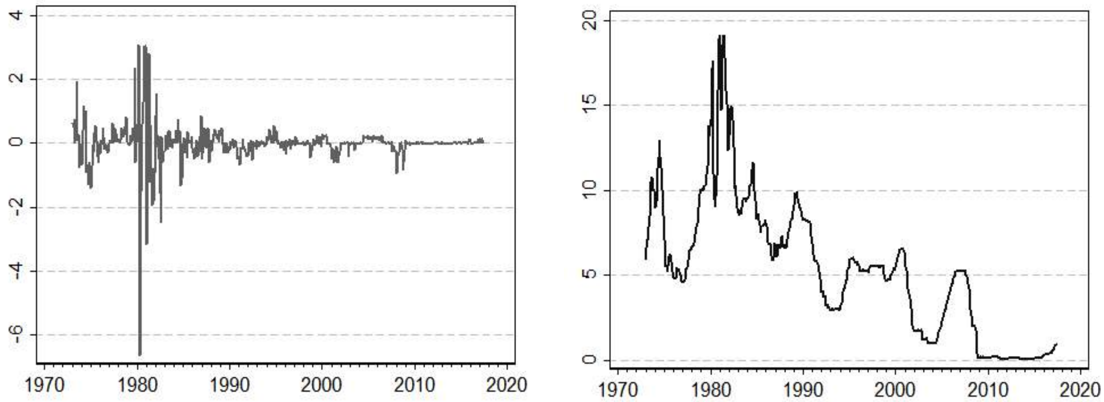
(25) 3-Month Treasury Bill

First difference | Original series



(26) Effective Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted

First difference | Original series



(27) 10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjust

First difference | Original series

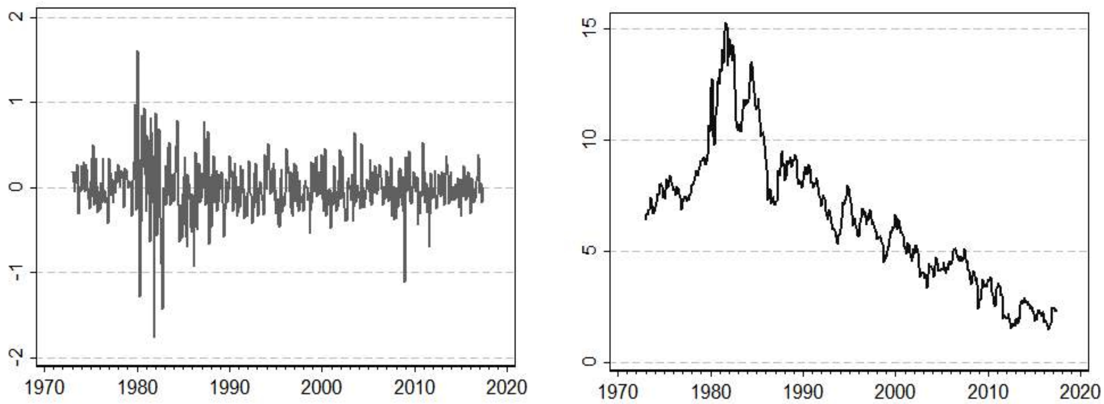
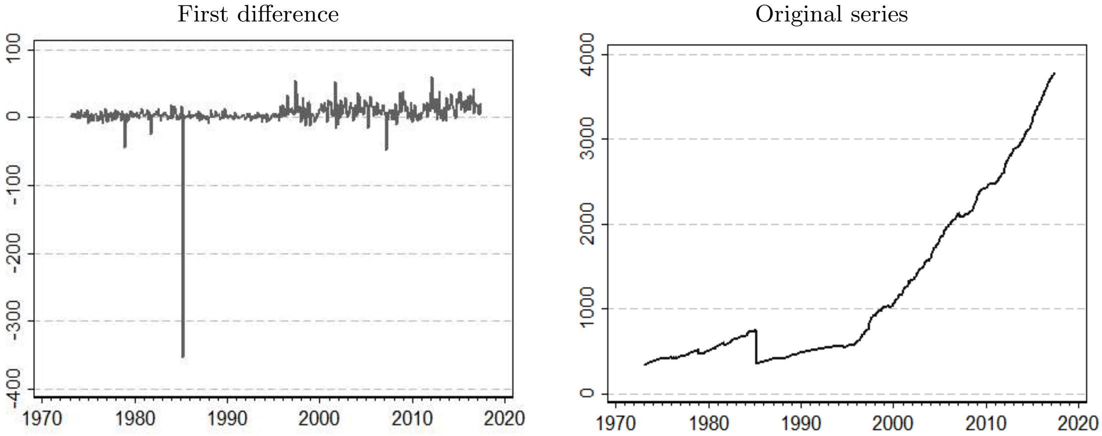


Figure 12 **First differenced and original series (Cont'd)**

(28) Small Deposits

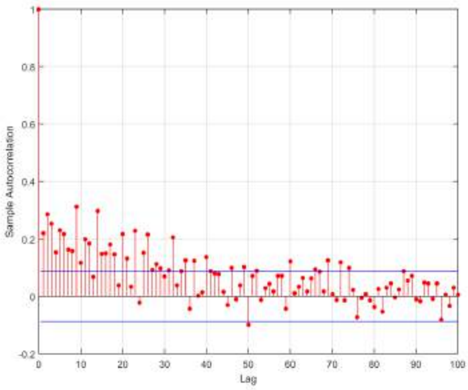


4.2 ACF and periodograms

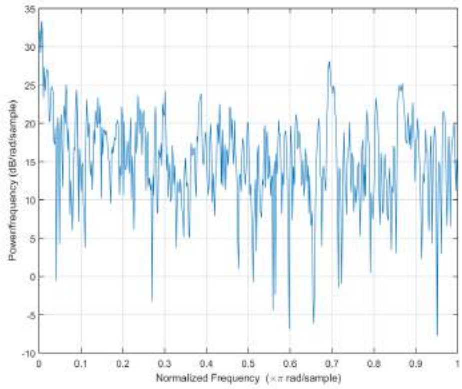
Figure 13 **ACF and periodograms – first-differenced series**

(1) M1, real

ACF

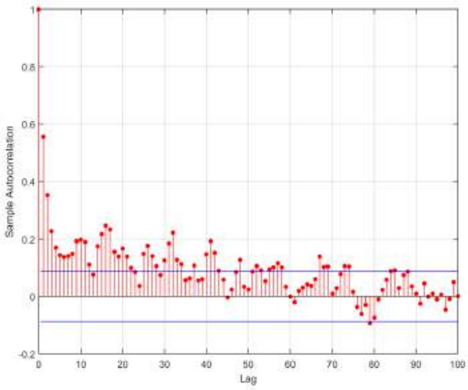


Power spectral density estimate

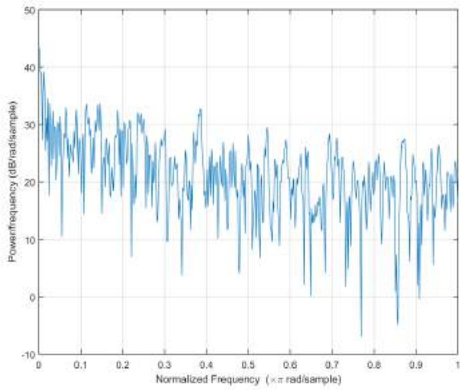


(2) M2, real

ACF

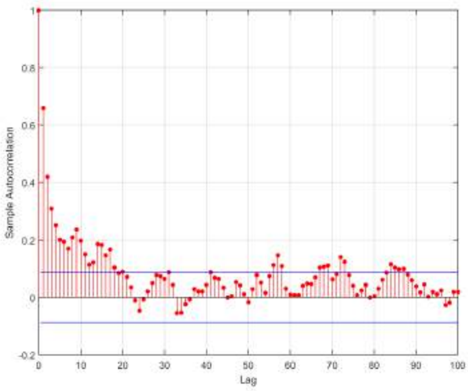


Power spectral density estimate



(3) MZ, real

ACF



Power spectral density estimate

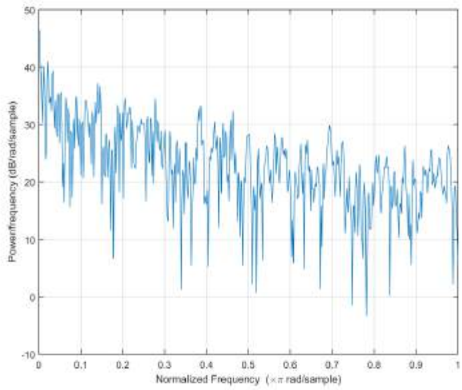
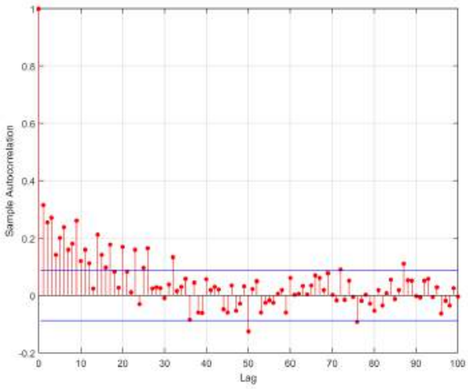


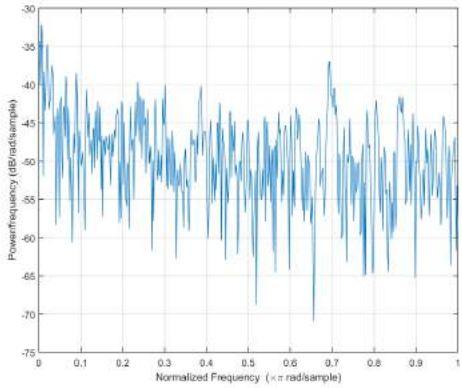
Figure 13 **ACF and periodograms – first-differenced series (Cont'd)**

(4) Log of real M1

ACF

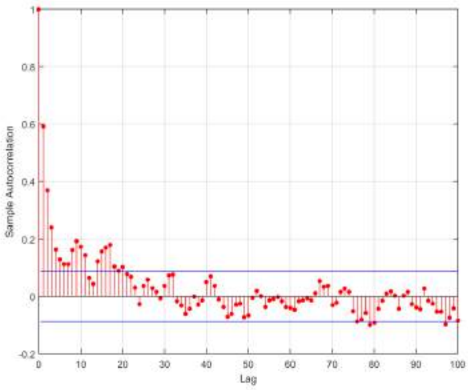


Power spectral density estimate

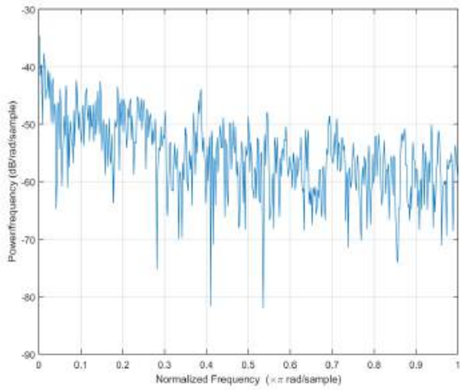


(5) Log of real M2

ACF

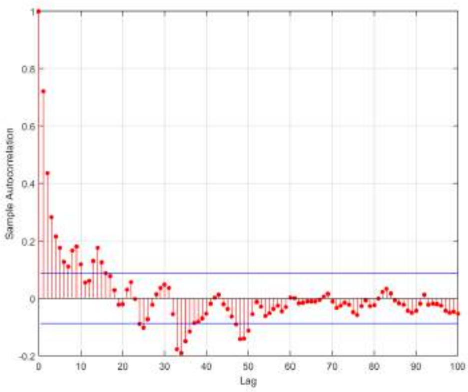


Power spectral density estimate



(6) Log of real MZ

ACF



Power spectral density estimate

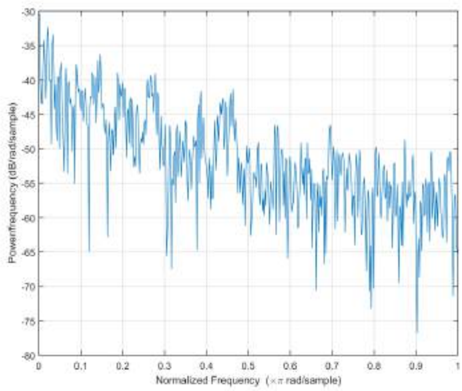
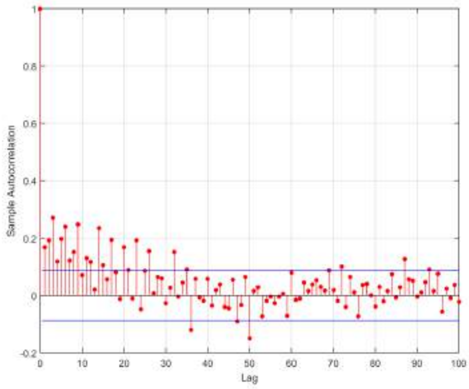


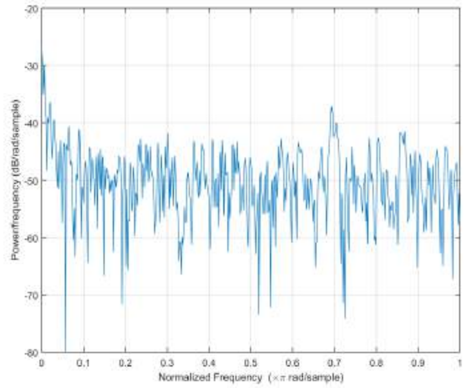
Figure 13 **ACF and periodograms – first-differenced series (Cont'd)**

(7) Log of M1

ACF

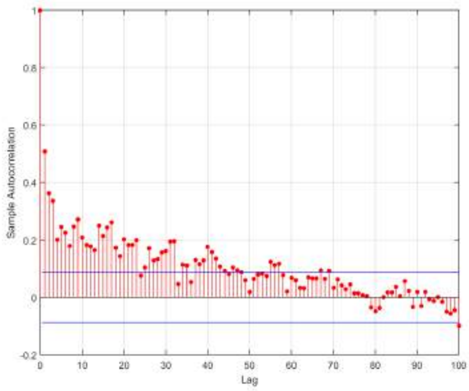


Power spectral density estimate

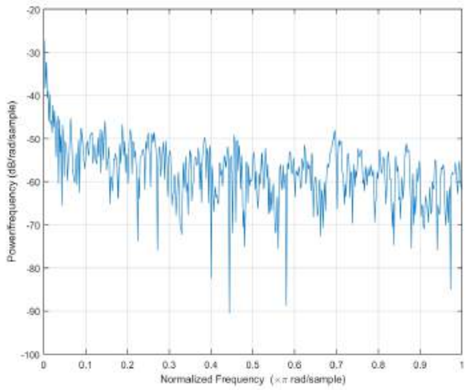


(8) Log of M2

ACF

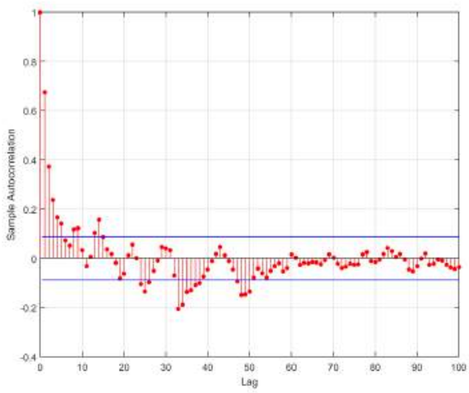


Power spectral density estimate



(9) Log of MZ

ACF



Power spectral density estimate

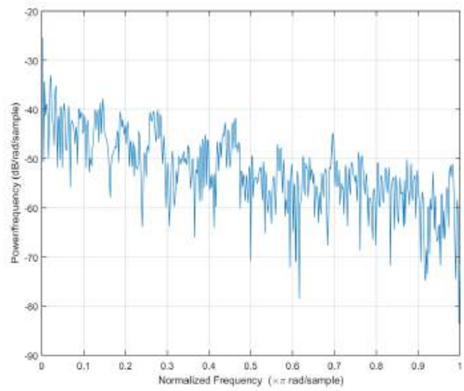
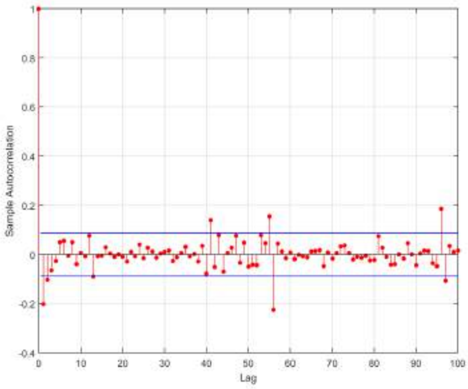


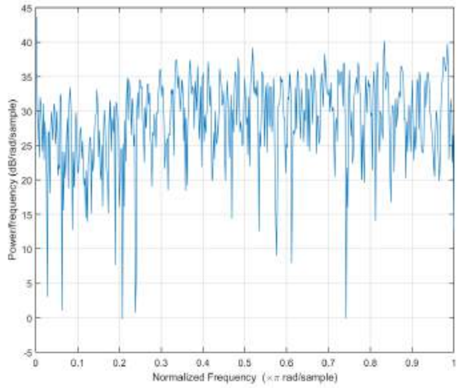
Figure 13 **ACF and periodograms – first-differenced series (Cont'd)**

(10) Real Personal Disposable Income

ACF

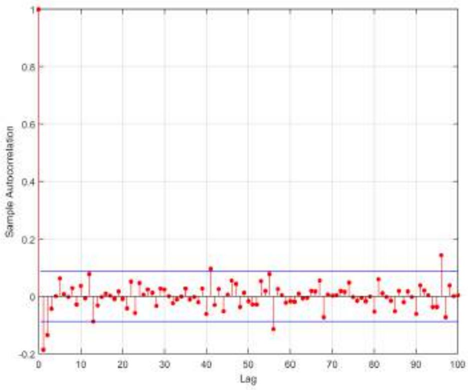


Power spectral density estimate

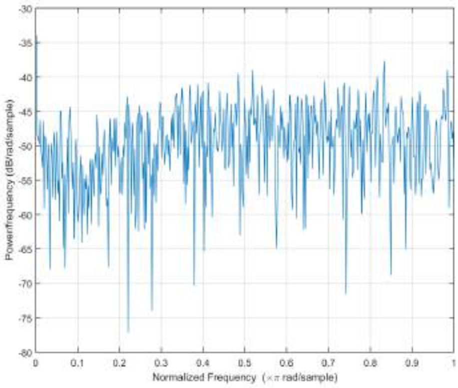


(11) Log of real personal disposable income

ACF

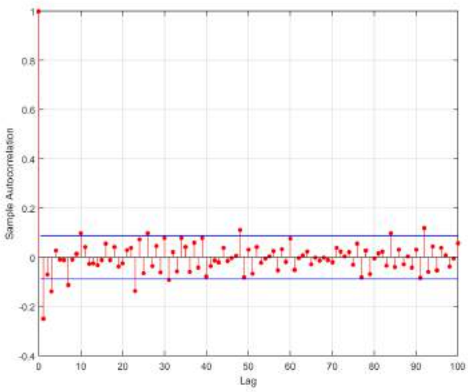


Power spectral density estimate



(12) Economic Policy Uncertainty

ACF



Power spectral density estimate

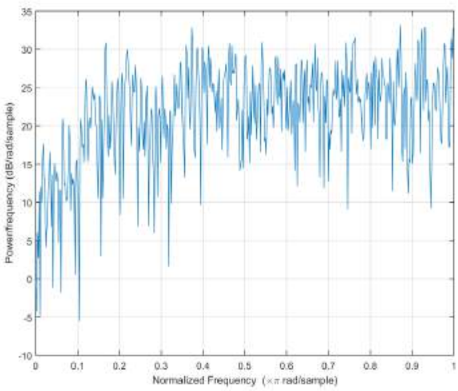
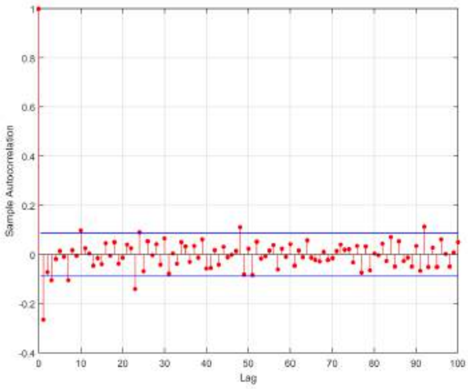


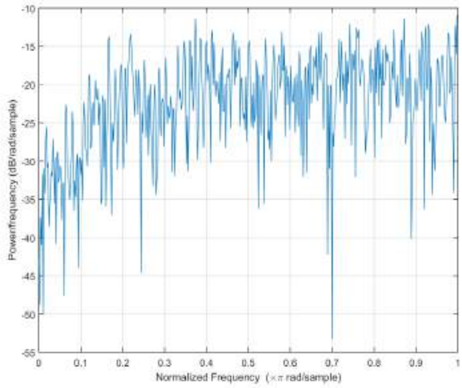
Figure 13 **ACF and periodograms – first-differenced series (Cont'd)**

(13) Log of EPU

ACF

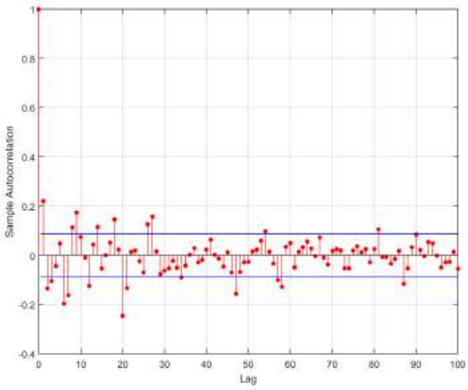


Power spectral density estimate

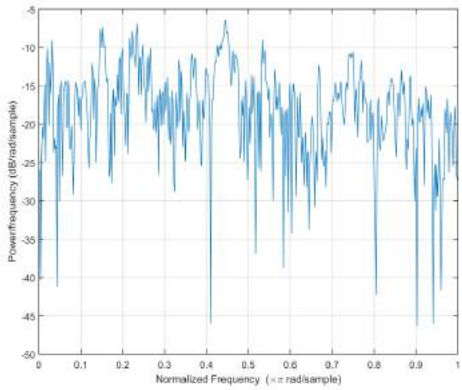


(14) M2 interest rate

ACF

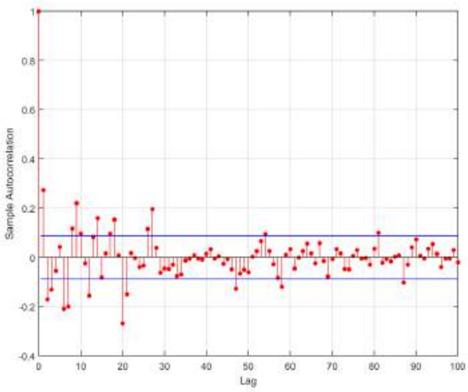


Power spectral density estimate



(15) MZ interest rate

ACF



Power spectral density estimate

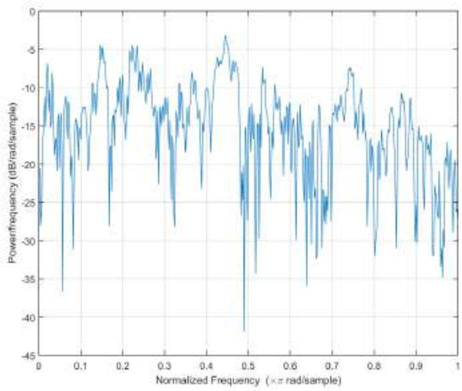
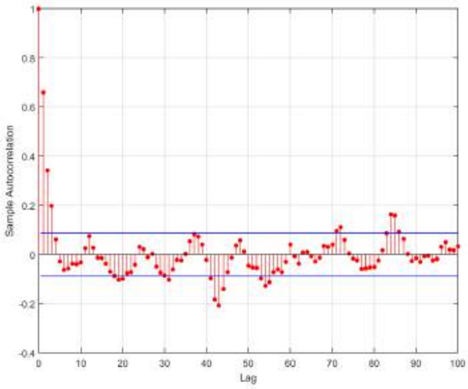


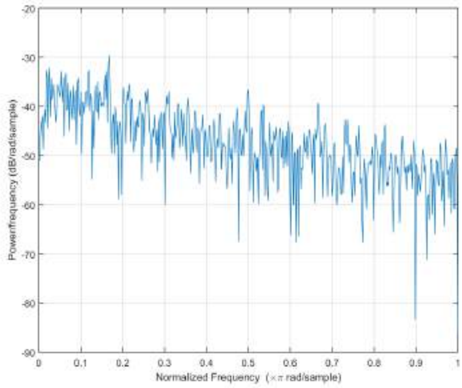
Figure 13 **ACF and periodograms – first-differenced series (Cont'd)**

(16) Ludvigson Macro Uncertainty: h1

ACF

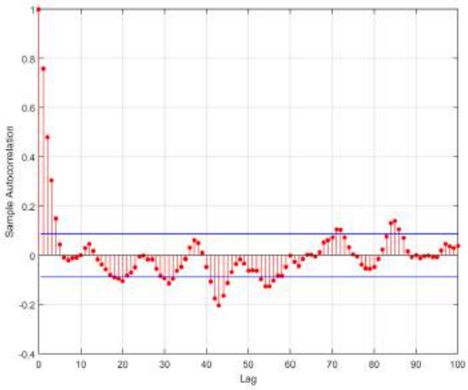


Power spectral density estimate

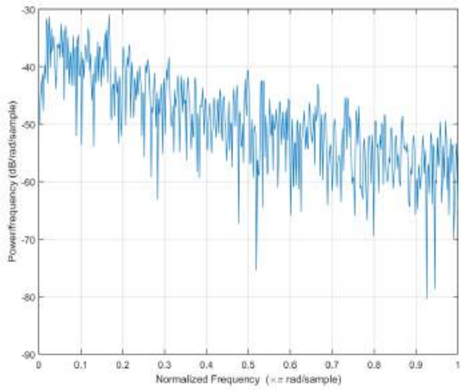


(17) Ludvigson Macro Uncertainty: h3

ACF

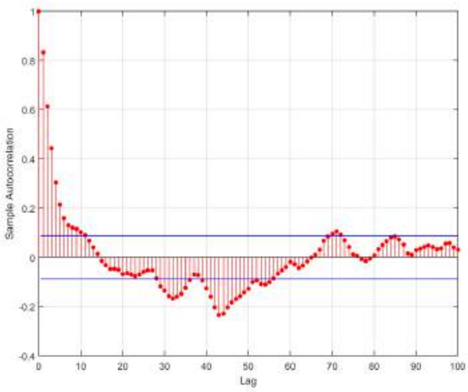


Power spectral density estimate



(18) Ludvigson Macro Uncertainty: h12

ACF



Power spectral density estimate

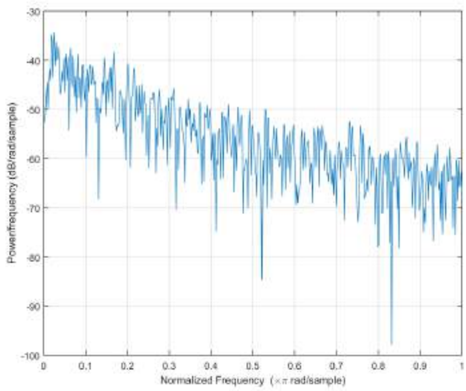
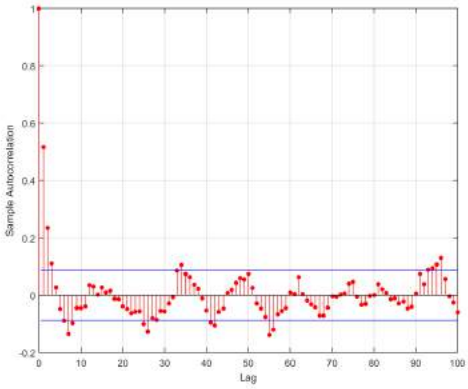


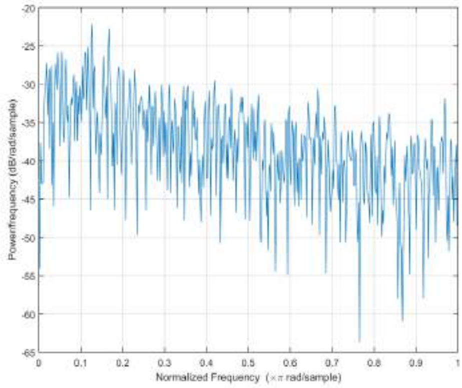
Figure 13 **ACF and periodograms – first-differenced series (Cont'd)**

(19) Ludvigson Financial Uncertainty: h1

ACF

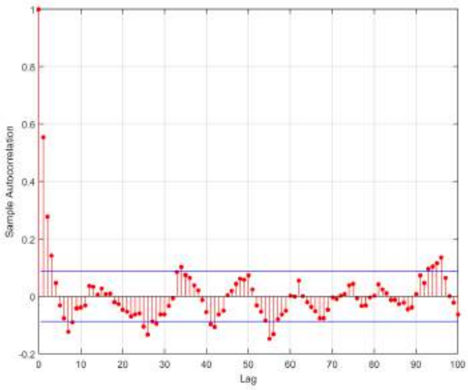


Power spectral density estimate

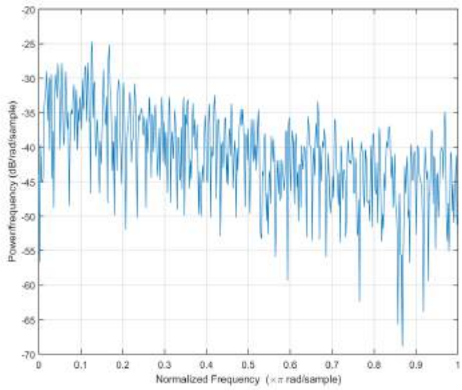


(20) Ludvigson Financial Uncertainty: h3

ACF

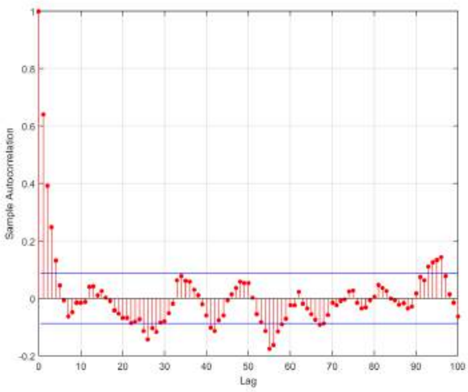


Power spectral density estimate



(21) Ludvigson Financial Uncertainty: h12

ACF



Power spectral density estimate

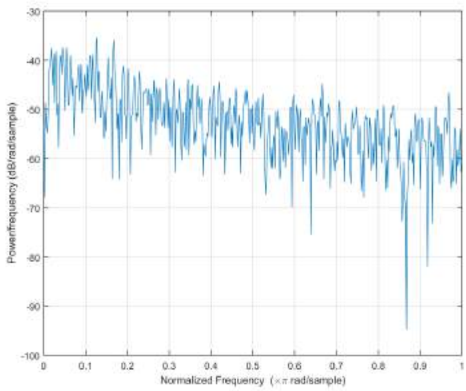
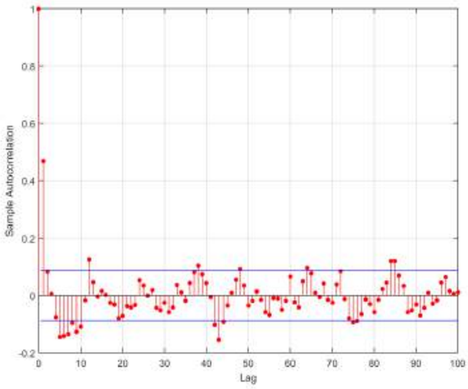


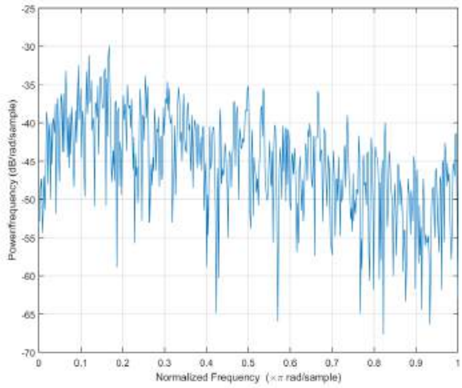
Figure 13 **ACF and periodograms – first-differenced series (Cont'd)**

(22) Ludvigson Real Uncertainty: h1

ACF

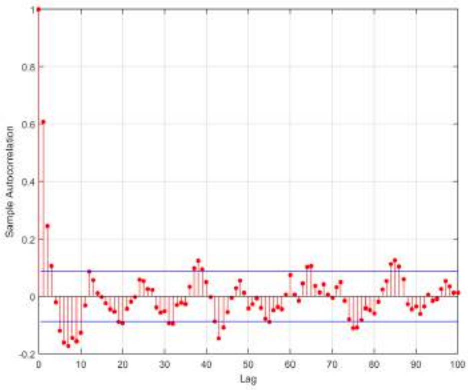


Power spectral density estimate

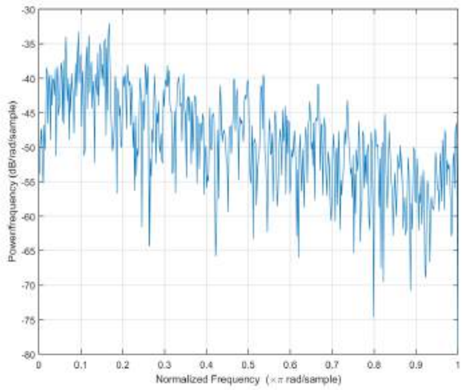


(23) Ludvigson Real Uncertainty: h3

ACF

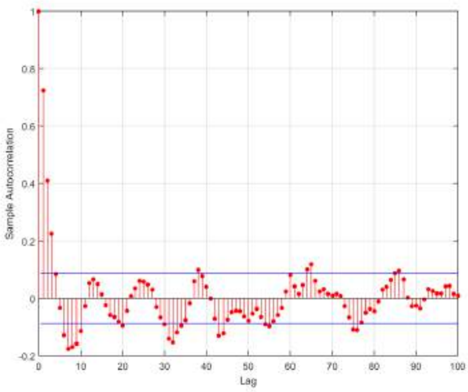


Power spectral density estimate



(24) Ludvigson Real Uncertainty: h12

ACF



Power spectral density estimate

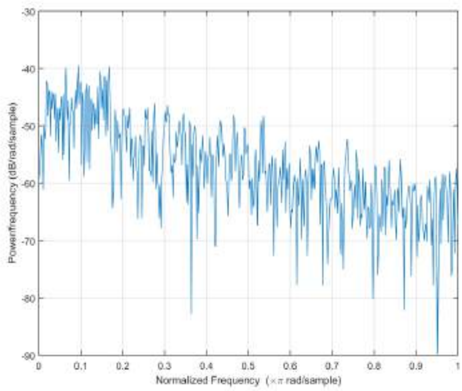
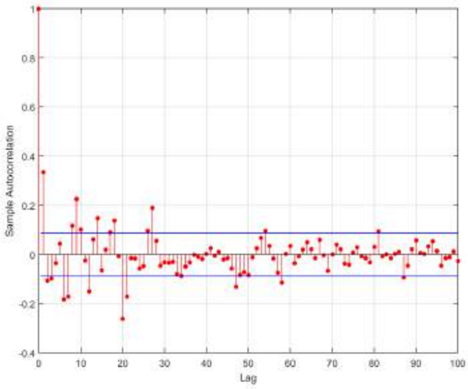


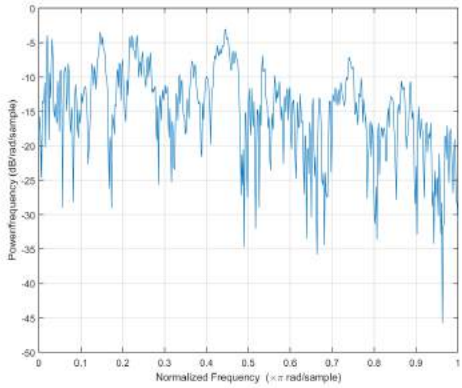
Figure 13 **ACF and periodograms – first-differenced series (Cont'd)**

(25) 3-Month Treasury Bill

ACF

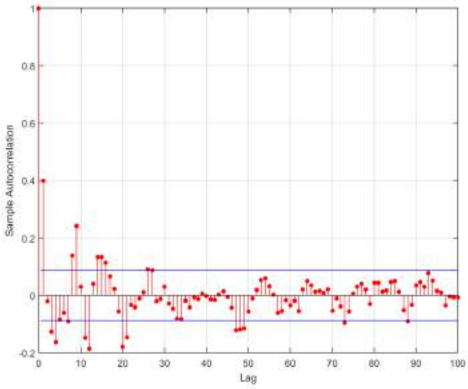


Power spectral density estimate

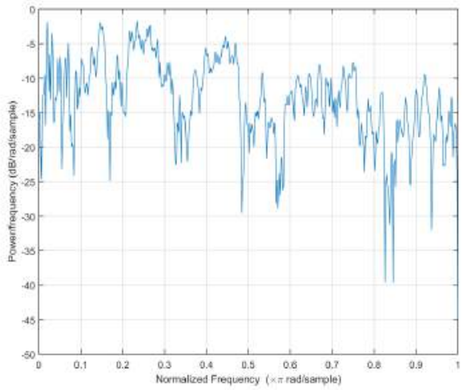


(26) Effective Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted

ACF

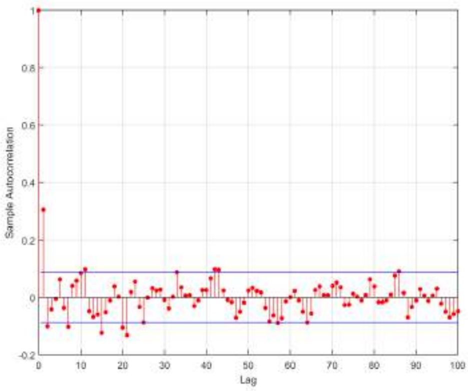


Power spectral density estimate



(27) 10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjust

ACF



Power spectral density estimate

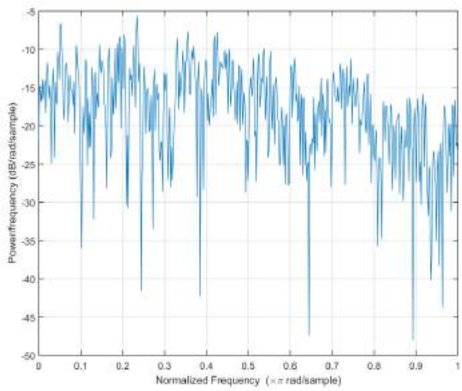
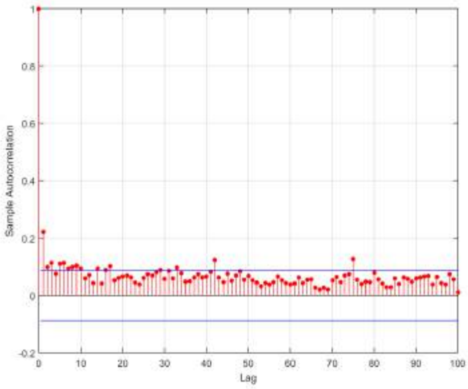


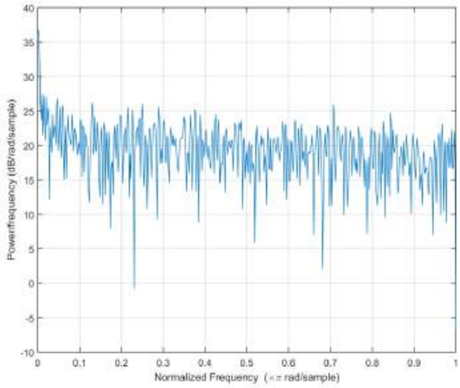
Figure 13 **ACF and periodograms – first-differenced series (Cont'd)**

(28) Small Deposits

ACF



Power spectral density estimate



Note: Before estimation all series are taken in first difference..

4.3 Full sample d estimates

Table 8 **Univariate *d* estimates, monetary aggregates – first-differenced series**

Bandwidth	B = 0.4				B = 0.45				B = 0.5			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
realm1	0.600	0.508	0.542	0.545	0.613	0.466	0.506	0.505	0.584	0.510	0.539	0.540
realm2	0.472	0.507	0.602	0.554	0.509	0.477	0.578	0.531	0.433	0.432	0.574	0.470
realmzm	0.223	0.276	0.298	0.298	0.362	0.322	0.375	0.375	0.431	0.375	0.430	0.430
lnm1	0.488	0.410	0.487	0.487	0.506	0.412	0.465	0.465	0.530	0.477	0.518	0.516
lnm2	0.532	0.720	0.528	0.532	0.597	0.806	0.588	0.594	0.538	0.709	0.531	0.532
lnmzm	-0.189	-0.066	-0.201	-0.201	0.045	-0.029	0.051	0.051	0.198	0.072	0.201	0.201
lnrealm1	0.418	0.472	0.565	0.518	0.529	0.490	0.548	0.525	0.514	0.528	0.577	0.548
lnrealm2	0.276	0.278	0.315	0.315	0.439	0.424	0.465	0.465	0.418	0.439	0.594	0.451
lnrealmzm	0.025	0.111	0.059	0.059	0.229	0.220	0.236	0.236	0.337	0.323	0.343	0.343

Bandwidth	B = 0.55				B = 0.6				B = 0.65			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
realm1	0.495	0.417	0.442	0.442	0.391	0.360	0.377	0.377	0.378	0.361	0.375	0.375
realm2	0.303	0.295	0.317	0.317	0.259	0.261	0.275	0.275	0.253	0.250	0.264	0.264
realmzm	0.364	0.317	0.353	0.353	0.301	0.278	0.301	0.301	0.287	0.272	0.289	0.289
lnm1	0.446	0.421	0.440	0.440	0.435	0.417	0.428	0.428	0.438	0.438	0.443	0.443
lnm2	0.396	0.510	0.393	0.393	0.357	0.444	0.357	0.357	0.333	0.403	0.336	0.336
lnmzm	0.232	0.207	0.234	0.234	0.164	0.144	0.168	0.168	0.232	0.239	0.238	0.238
lnrealm1	0.430	0.422	0.439	0.439	0.418	0.412	0.424	0.424	0.390	0.388	0.398	0.398
lnrealm2	0.289	0.296	0.305	0.305	0.254	0.261	0.267	0.267	0.240	0.243	0.250	0.250
lnrealmzm	0.337	0.327	0.341	0.341	0.232	0.231	0.236	0.236	0.262	0.262	0.268	0.268

Bandwidth	B = 0.7				B = 0.75				B = 0.8			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
realm1	0.303	0.310	0.319	0.319	0.306	0.313	0.321	0.321	0.305	0.324	0.331	0.331
realm2	0.248	0.251	0.262	0.262	0.279	0.286	0.298	0.298	0.345	0.366	0.378	0.378
realmzm	0.300	0.293	0.308	0.308	0.367	0.373	0.386	0.386	0.408	0.439	0.449	0.449
lnm1	0.307	0.318	0.319	0.319	0.288	0.303	0.305	0.305	0.271	0.300	0.301	0.301
lnm2	0.305	0.366	0.312	0.312	0.348	0.418	0.366	0.366	0.371	0.452	0.409	0.409
lnmzm	0.235	0.250	0.247	0.247	0.371	0.406	0.396	0.396	0.399	0.457	0.451	0.451
lnrealm1	0.290	0.298	0.304	0.304	0.296	0.309	0.315	0.315	0.311	0.338	0.343	0.343
lnrealm2	0.251	0.258	0.263	0.263	0.313	0.329	0.335	0.335	0.376	0.413	0.420	0.420
lnrealmzm	0.276	0.282	0.287	0.287	0.394	0.416	0.420	0.420	0.440	0.489	0.493	0.493

Note: Univariate d estimates for various bandwidths and various estimators: "LW" = Local Whittle estimator, "ELW" = Exact Local Whittle estimator; "FELW" = Feasible Exact Local Whittle estimator; "2ELW" = 2-step ELW estimator. Column super-headers give the value of the bandwidth (B) used for estimation. Before estimation all series are taken in first difference.

Table 9 **Univariate *d* estimates, uncertainty variables – first-differenced series**

Bandwidth	**B = 0.4**				**B = 0.45**				**B = 0.5**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
lnepu	-0.175	-0.369	-0.287	-0.287	-0.072	-0.194	-0.170	-0.170	-0.234	-0.320	-0.291	-0.291
ludmach1	-0.438	-0.540	-0.425	-0.425	-0.362	-0.401	-0.355	-0.355	-0.166	-0.174	-0.162	-0.162
ludmach3	-0.434	-0.535	-0.418	-0.418	-0.339	-0.374	-0.330	-0.330	-0.128	-0.134	-0.123	-0.123
ludmach12	-0.443	-0.513	-0.424	-0.425	-0.193	-0.208	-0.181	-0.180	0.040	0.042	0.047	0.047
ludfin1	-0.443	-0.852	-0.469	-0.469	-0.342	-0.521	-0.370	-0.370	-0.201	-0.250	-0.218	-0.218
ludfin3	-0.436	-0.841	-0.464	-0.464	-0.326	-0.493	-0.356	-0.356	-0.175	-0.219	-0.192	-0.192
ludfin12	-0.400	-0.781	-0.436	-0.436	-0.262	-0.383	-0.295	-0.295	-0.089	-0.115	-0.102	-0.102
ludreal1	-0.539	-0.573	-0.530	-0.530	-0.505	-0.526	-0.499	-0.499	-0.420	-0.435	-0.418	-0.418
ludreal3	-0.523	-0.534	-0.519	-0.519	-0.463	-0.470	-0.462	-0.462	-0.361	-0.370	-0.366	-0.366
ludreal12	-0.447	-0.444	-0.453	-0.453	-0.305	-0.318	-0.319	-0.319	-0.194	-0.210	-0.212	-0.212
Bandwidth	**B = 0.55**				**B = 0.6**				**B = 0.65**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
lnepu	-0.331	-0.401	-0.370	-0.370	-0.393	-0.458	-0.425	-0.425	-0.532	-0.603	-0.556	-0.556
ludmach1	-0.105	-0.106	-0.102	-0.102	-0.071	-0.070	-0.067	-0.067	0.020	0.026	0.026	0.026
ludmach3	-0.035	-0.034	-0.032	-0.032	0.012	0.014	0.016	0.016	0.113	0.120	0.120	0.120
ludmach12	0.172	0.176	0.176	0.176	0.223	0.228	0.228	0.228	0.289	0.297	0.296	0.296
ludfin1	-0.167	-0.184	-0.173	-0.173	-0.143	-0.152	-0.146	-0.146	-0.052	-0.050	-0.048	-0.048
ludfin3	-0.129	-0.142	-0.134	-0.134	-0.104	-0.109	-0.105	-0.105	-0.012	-0.007	-0.007	-0.007
ludfin12	-0.008	-0.010	-0.008	-0.008	0.022	0.026	0.026	0.026	0.118	0.127	0.126	0.126
ludreal1	-0.439	-0.450	-0.438	-0.438	-0.415	-0.426	-0.415	-0.415	-0.306	-0.310	-0.305	-0.305
ludreal3	-0.365	-0.370	-0.367	-0.367	-0.329	-0.334	-0.331	-0.331	-0.187	-0.188	-0.187	-0.187
ludreal12	-0.198	-0.206	-0.208	-0.208	-0.183	-0.186	-0.187	-0.187	-0.020	-0.020	-0.020	-0.020
Bandwidth	**B = 0.7**				**B = 0.75**				**B = 0.8**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
lnepu	-0.484	-0.535	-0.506	-0.506	-0.501	-0.541	-0.516	-0.516	-0.465	-0.484	-0.470	-0.470
ludmach1	0.163	0.176	0.176	0.176	0.304	0.332	0.331	0.331	0.400	0.461	0.461	0.461
ludmach3	0.271	0.286	0.286	0.286	0.437	0.468	0.468	0.468	0.551	0.621	0.620	0.621
ludmach12	0.418	0.433	0.433	0.433	0.559	0.592	0.591	0.592	0.689	0.762	0.762	0.762
ludfin1	0.087	0.099	0.099	0.099	0.213	0.241	0.241	0.241	0.295	0.351	0.351	0.351
ludfin3	0.127	0.141	0.141	0.141	0.254	0.283	0.283	0.283	0.339	0.397	0.397	0.397
ludfin12	0.253	0.268	0.268	0.268	0.371	0.402	0.402	0.402	0.454	0.516	0.516	0.516
ludreal1	-0.145	-0.140	-0.139	-0.139	-0.003	0.019	0.019	0.019	0.123	0.174	0.174	0.174
ludreal3	0.011	0.018	0.018	0.018	0.182	0.210	0.210	0.210	0.306	0.368	0.368	0.368
ludreal12	0.191	0.200	0.199	0.199	0.360	0.394	0.394	0.394	0.478	0.549	0.548	0.550

Note: Univariate d estimates for various bandwidths and various estimators: "LW" = Local Whittle estimator, "ELW" = Exact Local Whittle estimator; "FELW" = Feasible Exact Local Whittle estimator; "2ELW" = 2-step ELW estimator. Column super-headers give the value of the bandwidth (B) used for estimation. Before estimation all series are taken in first difference.

Table 10 **Univariate *d* estimates, interest rates and other variables – first-differenced series**

Bandwidth	**B = 0.4**				**B = 0.45**				**B = 0.5**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
interestm2	-0.630	-0.508	-0.667	-0.663	-0.271	-0.261	-0.249	-0.248	0.030	0.052	0.058	0.058
interestmzm	-0.393	-0.353	-0.407	-0.405	-0.063	-0.041	-0.028	-0.027	0.125	0.146	0.150	0.150
lnrpdi	0.118	0.026	0.143	0.143	0.050	-0.005	0.062	0.062	0.012	-0.001	0.014	0.014
tb3ms	-0.333	-0.244	-0.341	-0.341	-0.152	-0.124	-0.148	-0.148	0.044	0.054	0.055	0.055
fedfunds	-0.413	-0.307	-0.419	-0.420	-0.134	-0.114	-0.111	-0.111	0.058	0.069	0.078	0.078
gs10	-0.075	-0.041	-0.074	-0.074	-0.188	-0.140	-0.180	-0.180	-0.098	-0.074	-0.096	-0.096
smalldepo	0.364	0.393	0.416	0.416	0.344	0.330	0.359	0.359	0.333	0.316	0.341	0.341
Bandwidth	**B = 0.55**				**B = 0.6**				**B = 0.65**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
interestm2	0.022	0.026	0.029	0.029	-0.210	-0.209	-0.208	-0.208	-0.193	-0.189	-0.188	-0.188
interestmzm	0.115	0.123	0.125	0.125	-0.213	-0.210	-0.210	-0.210	-0.207	-0.203	-0.202	-0.202
lnrpdi	0.123	0.097	0.135	0.135	0.102	0.086	0.108	0.108	-0.019	-0.007	-0.018	-0.018
tb3ms	0.171	0.177	0.179	0.179	-0.130	-0.123	-0.129	-0.129	-0.116	-0.109	-0.112	-0.112
fedfunds	0.060	0.063	0.065	0.065	-0.155	-0.150	-0.154	-0.154	-0.106	-0.100	-0.102	-0.102
gs10	0.015	0.023	0.016	0.016	0.032	0.038	0.034	0.034	-0.034	-0.025	-0.030	-0.030
smalldepo	0.314	0.293	0.315	0.315	0.285	0.263	0.282	0.282	0.249	0.235	0.250	0.250
Bandwidth	**B = 0.7**				**B = 0.75**				**B = 0.8**			
Variable	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW	LW	ELW	FELW	2ELW
interestm2	-0.168	-0.161	-0.160	-0.160	-0.072	-0.057	-0.057	-0.057	-0.105	-0.078	-0.077	-0.077
interestmzm	-0.190	-0.183	-0.182	-0.182	-0.095	-0.080	-0.080	-0.080	-0.117	-0.090	-0.090	-0.090
lnrpdi	-0.071	-0.042	-0.069	-0.069	-0.152	-0.099	-0.149	-0.150	-0.180	-0.118	-0.169	-0.169
tb3ms	-0.098	-0.090	-0.092	-0.092	0.001	0.018	0.017	0.017	-0.026	0.004	0.004	0.004
fedfunds	-0.167	-0.158	-0.161	-0.161	-0.050	-0.035	-0.035	-0.035	0.036	0.072	0.072	0.072
gs10	-0.005	0.005	0.003	0.003	0.001	0.018	0.016	0.016	-0.000	0.031	0.030	0.030
smalldepo	0.196	0.195	0.204	0.204	0.183	0.188	0.196	0.196	0.177	0.195	0.203	0.203

Note: Univariate *d* estimates for various bandwidths and various estimators: "LW" = Local Whittle estimator, "ELW" = Exact Local Whittle estimator; "FELW" = Feasible Exact Local Whittle estimator; "2ELW" = 2-step ELW estimator. Column super-headers give the value of the bandwidth (B) used for estimation. Before estimation all series are taken in first difference.