UNIVERSITY OF LIVERPOOL

Essays in Money, Liquidity and the Wider Economy

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Declaration of Authorship

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Abstract

Faculty of Humanities & Social Sciences

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Essays in Money, Liquidity and the Wider Economy

by Michael ELLINGTON

The thesis investigates the impact of money and liquidity for the wider economy. Chapter 1 discusses the primary motivations of this work, introduces the content of the chapters, and briefly positions each essay. Following the brief overview, Chapter 2 uses tools from the classical theory of inflation for UK data. We provide an empirical comparison between broad money and Divisia money aggregates from both a domestic and global scale for two measures of UK inflation. We find that global liquidity yields inflationary pressures in the UK over and above the impact of domestic monetary conditions and spare capacity. Our non–linear models show that monetary effects are dependent on the state of domestic liquidity within the economy. Our empirical findings point against the immediate risk of strong inflationary pressures.

In Chapter 3, we provide a comprehensive reduced–form and structural analysis of evolving macroeconomic dynamics using theoretically founded Divisia money aggregates and a time series spanning the Great Recession. We fit a Bayesian time–varying parameter VAR model with stochastic volatility to US and UK data from 1979 to 2015. Models using Divisia money growth rates pseudo–forecast GDP growth and inflation with a higher precision than simple–sum aggregates up to a 2–year horizon. Structural variance decompositions reveal that monetary policy shocks during the Great Recession contribute the lion's share of variation in real GDP growth and inflation volatility.

Chapter 4 examines the dynamic impact of liquidity shocks resonating in stock and housing markets on real GDP growth. We fit a Bayesian time–varying parameter VAR model with stochastic volatility to US data from 1970 to 2014. GDP becomes highly sensitive to house market liquidity shocks as disruptions in the sector start to emerge, yet more resilient to stock market liquidity shocks throughout time. We provide substantial evidence in favour of asymmetric responses of GDP growth both across the business cycle, and among business cycle troughs. Stock and house market liquidity shocks, on average, explain 15% and 36% of the variation in real GDP growth during the Great Recession respectively.

Finally, Chapter 5 provides concluding comments and suggestions for future research.

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To my family, with love

Chapter 1

Introduction

This thesis explores the impact of money and liquidity conditions on the wider economy. The primary motivations of this work stem from the financial turmoil in 2008 and following policy responses by the Federal Reserve and Bank of England respectively. Since the Great Recession, both the real effects of liquidity conditions, and measuring monetary aggregates in a theoretically consistent manner are becoming key research areas (see e.g. Longstaff, 2004, Næs, Skjeltorp, and Ødegaard, 2011, Florackis et al., 2014, Barnett, 1980, Barnett and Chauvet, 2011 and Barnett, Chauvet, and Leiva-Leon, 2016). In conjunction with this, the necessity of accounting for different sources of time–variation, or structural breaks, in econometric models is also becoming a prime topic (see, among many others Primiceri, 2005, Milas, 2009, Barnett, Groen, and Mumtaz, 2010, Abbate et al., 2016). We offer three empirical essays that contribute to these strands of literature.

In Chapter 2, we provide a concise examination of movements in liquidity through the lens of monetary aggregates. We model the rates of UK Retail Price Inflation (RPI) and Consumer Price Inflation (CPI) using both linear and regime–switching models. Our time series sample for RPI inflation spans from 1983 to 2014, and for CPI inflation from 1989 to 2014 respectively. Motivation of this work derives from UK policy response to the financial turmoil in 2008. This consisted of three rounds of Quantitative Easing (QE) summing to £375bn, preceded by cuts to the policy rate, which froze at 0.5% in March 2009. During the first round of QE broad money (M4) growth did not rise, however Divisia money did. This raises the question: what measure of money matters for UK inflation? Our study builds on Milas, 2009 who finds that UK CPI inflation dynamics are dependent on the rate of broad money (M4) growth. Following the recommendations in the aforementioned, we compare the econometric properties of UK inflation and Divisia money growth with UK inflation and broad money growth respectively.

Specifically, we borrow from the classical theory of inflation and connect prices to the interactions in the demand and supply of money. Following the theoretical underpinnings in Friedman, 1988 and Setzer and Greiber, 2007, we include financial assets and housing into our money demand specifications. Our choice of these variables is coherent with the views expressed in Goodhart and Hofmann, 2008. In particular, one of the preconditions for the financial turmoil being inflated and persistent asset prices. We combine the classical theory of inflation with standard Phillips curve analysis and also relax the assumption that the UK economy is closed. In doing so, we construct global liquidity aggregates following D'Agostino and Surico, 2009. Modelling the UK economy in an open–economy framework implicitly assumes a channel through which fluctuations, in international flows, and more integrated financial markets can be captured. Setzer and Greiber, 2007 note that movements in the money supply of one nation has the possibility to be absorbed elsewhere, and that contemporaneous shifts in major economy's money supplies can result in spillovers to domestic inflation rates. Belke, Orth, and Setzer, 2010 posit that domestic money aggregates are becoming increasingly more difficult to interpret because of increases in the volume of international capital flows. Therefore extending the information set and accounting for spillovers in international money movements is intuitive.

Our initial results show that linear models fail to document any real significant relationship between inflation, money (both domestic and global) and spare capacity. However, we find that both CPI and RPI inflation exhibit regime–switching behaviour and estimate Quadratic Logistic Smooth–Transition Autoregressive (QLSTAR) models where inflation regimes are governed by domestic money movements. Interestingly, we find that both the RPI and CPI inflationary process are conditional on domestic money movements. More specifically, when domestic money growth is contained between two endogenously determined thresholds, inflation is well specified by a standard Phillips curve augmented with global money movements. Yet when money growth surpass these thresholds, domestic monetary conditions dominate the inflationary process. Additionally, we show that our non–linear models are not capturing high and low inflation regimes, by comparing the time–varying impact of alternative specifications of regime–switching models. Finally from a purely econometric perspective, we find no evidence in favour of using Divisia money over conventional simple–sum aggregates.

In Chapter 3, we extend our investigation of the empirical properties of Divisia indices. In spite of the theoretical benefits of Divisia money, the Federal Reserve and the Bank of England maintain focusing their attention on theoretically flawed simple–sum (or broad) measures of money. Adding to this, there is growing literature advocating Divisia indices and that these measures of money could better signal financial crises (e.g. Barnett and Chauvet, 2011). Chapter 3 explores the evolution of macroeconomic dynamics in the US and UK economies from 1979 to 2015. We fit Bayesian Time–varying Parameter VAR (TVP–VAR) models with a stochastic volatility structure. This study directly extends Benati and Mumtaz, 2007 and Benati, 2008 by estimating economic systems of real GDP growth, GDP deflator inflation, the 3–month Treasury Bill rate, and replacing atheoretical simple–sum measures of money with Divisia money growth respectively. By employing this methodology, we offer a Bayesian time–varying analysis of macroeconomic fundamentals using Divisia indices; a novel feature of this study. We set out to answer the following questions: Can we predict real GDP growth and inflation with more precision using theoretically sound measures of money? Are there differences in the transmission mechanism of monetary policy shocks throughout time, and how do these shocks influence macroeconomic volatility?

In answering these questions, Chapter 3 contributes to three main areas of empirical literature. To begin with, we extend the previous work of Cogley and Sargent, 2005, Primiceri, 2005, Bianchi, Mumtaz, and Surico, 2009 and Barnett, Groen, and Mumtaz, 2010 by offering a time–varying Bayesian perspective of evolving macroeconomic dynamics of over the Great Recession and the following recovery period for the US and UK economies, respectively. The aforementioned consider post–WWII data and examine the Great Inflation and Great Moderation. Second, we add to the existing forecasting literature advocating the use of Divisia indices in macro–econometric models (e.g. Schunk, 2001, Albuquerque, Baumann, and Seitz, 2015, Florackis et al., 2014 and Barnett, Chauvet, and Leiva-Leon, 2016). Finally, our results correspond well with studies employing structural VAR (SVAR) models using Divisia money (e.g. Keating et al., 2014, Belongia and Ireland, 2015 and Belongia and Ireland, 2016).

Our results in Chapter 3 support the use of Divisia indices over simple–sum measures of money. We provide an in–depth reduced–form and structural analysis of US and UK economies using Divisia money growth, and compare these results by replacing Divisia money growth rates with the economy's broad money growth rate, respectively. Our analysis reverberates the importance of allowing for time–variation in the parameters, covariances, and volatilities. Specifically, we link the persistence of our macroeconomic data to the dynamic predictability of our TVP–VAR models. Notably, we find clear differences in the pseudo–forecastability of the US and UK economies at the beginning and end of our sample. Likewise, our analysis shows significant differences in the transmission of monetary policy shocks during the Great Recession and the final year of our sample. We also show that systems using Divisia money produce more accurate pseudo–forecasts than those using simple–sum counterparts which emphasises the importance of measuring money correctly. Finally, we offer time–varying variance decompositions of US and UK macroeconomic data in the frequency domain as in Barnett, Groen, and Mumtaz, 2010, and show that monetary policy shocks during the 2008 recession explain 60% and 42% of real GDP growth volatility in the US and UK, respectively.

In the final Chapter of this thesis, Chapter 4, we assess the influence of stock and house market liquidity shocks on US real GDP growth throughout time from 1970 to 2014, using a TVP–VAR model, allowing for four sources of uncertainty. We construct proxies of aggregate stock market liquidity conditions, using daily data for all common stocks listed on the New York Stock Exchange (NYSE), from 1968 to 2014 using the Amihud, 2002 measure. In a similar manner, we propose a price–impact ratio to capture liquidity movements in the US property sector from 1968 to 2014. The prime contribution of this essay is to explore the real effects of liquidity shocks from stock and house markets on US real GDP growth over time. To the best of our knowledge, there are no empirical studies on the economic impact of market specific liquidity shocks. The majority of existing literature focuses on the explanatory and forecasting performance (see e.g. Næs, Skjeltorp, and Ødegaard, 2011 and Florackis et al., 2014). Uncovering a link between market specific liquidity shocks is of major importance for policymakers. If structural links between market specific liquidity shocks and the real economy are conditional on time (or the business cycle), model misspecification can result in erroneous inference and policy recommendations.

Chapter 4 extends the empirical literature accounting for time–varying macro–financial linkages. Conventionally, empirical studies accounting for the financial sector of an economy typically capture conditions through one variable that aggregates the financial sector into one financial 'conditions' or 'stress' proxy (e.g. Hubrich and Tetlow, 2015). However, aggregating financial conditions from different asset markets immediately omits any contemporaneous links between those markets themselves. Therefore, we cannot distinguish between the impact of shocks from individual markets that build the proxy. Empirical literature allowing for different asset markets is small, but growing (see e.g. Björnland and Leitemo, 2009 and Prieto, Eickmeier, and Marcellino, 2016). We extend the work of Prieto, Eickmeier, and Marcellino, 2016, and isolate the liquidity component from stock and house prices overcoming the complex web of information contained in the asset's price (Harvey, 1988).

Liquidity conditions in stock markets is thought to affect the real economy through a variety of different channels. Florackis et al., 2014 state that stock market liquidity can behave as a signalling process revealing the information set of investors. During periods of excess uncertainty or depleting confidence regarding the future state of the economy, investors adjust portfolio holdings and move funds from high risk assets into 'safe havens'; known as flight to safety. Similarly, if investors anticipate sharp declines in liquidity, then portfolio compositions change with more funds being allocated to liquid assets; known as flight to liquidity (Longstaff, 2004). Adding to this, Brunnermeier and Pedersen, 2009 establish a reinforcing mechanism between funding and market liquidity during periods of financial stress. A shock to funding liquidity causes providers to shift liquidity provision into low margin stocks.

Additionally, liquidity in the housing market can also affect the real economy. He, Wright, and Zhu, 2015 state that house prices contain a liquidity premium. In equilibrium, people will be willing to pay more than the fair value of the house since owning a house signals financial security; a favourable factor in obtaining credit. Likewise purchasing a house requires a substantial down payment, therefore the liquidity of the prospective buyer directly influences the demand for housing. Stein, 1995 deduces a tractable model under the assumption a deposit is required to participate on the housing market. The theoretical model reveals that demand in the housing market is sensitive to the extent of market participants liquidity. Diaz and Jerez, 2013 formulate a model able to reproduce the cyclical time series properties of the US housing market using the median number of months to sale (i.e. time–on–the–market) as a proxy for liquidity. In particular they form an intuitive link between liquidity and uncertainty in the housing market, and show that as liquidity decreases in the US property sector before and during the 2008 recession, volatility intensifies and the real effects of shocks propagate onto future periods.

The findings in Chapter 4 highlight the importance in accounting for different asset markets in models because the transmission of market specific liquidity shocks is indeed different. Stock market liquidity shocks result in contractionary effects for real GDP growth across every observation of our sample, although the impact is declining throughout time. Furthermore, we show that liquidity shocks from the US housing market result in contractionary effects from 2005 onwards; the response of real GDP growth pre–2005 is negligible to these shocks. Building on this, we document distinct differences in the real effects of liquidity and uncertainty shocks. We show that uncertainty shocks from the US stock market yield a counter–intuitive response of GDP growth, which supports the findings in Levine and Zervos, 1998; a robust link between stock market liquidity and the real economy. In a similar manner, comparing the response of US real GDP growth to house market liquidity shocks with uncertainty shocks, uncovers a distinct structural change in the relationship between house market liquidity shocks and real GDP growth; a change that uncertainty shocks and real GDP growth do not possess. Therefore we argue that our liquidity proxy is, in fact, capturing liquidity conditions and not price uncertainty. Finally, structural variance decompositions report that stock and house market liquidity shocks explain, on average, 15% and 36% of real GDP growth variation during the financial crisis, respectively.

The rest of this thesis proceeds as follows: In Chapter 2, we investigate the links between global liquidity, money growth and UK inflation. We provide insights into the evolution of US and UK macroeconomic dynamics using correctly measured monetary statistics, in Chapter 3. In Chapter 4, we focus on the real effects of market specific liquidity shocks on the US economy. Chapter 5 offers concluding comments and directions for future research. To enhance the reader's experience of this thesis, we make each chapter self–contained. Therefore we (re)introduce variables, notations and acronyms in each chapter. Where possible, we use the same acronyms across chapters to aid readability.

Chapter 2

Global Liquidity, Money Growth and UK Inflation

2.1 Introduction

The recent global financial crisis witnessed a detrimental shock to liquidity and credit conditions followed by a somewhat staggered recovery. In response to the financial turmoil, monetary policymakers in major economies pursued an unprecedented path of interest rate cuts and repeated rounds of asset purchase facilities involving, predominantly, the purchase of long-term government bonds and other related assets (more commonly known as Quantitative Easing, (QE)). Preconditions for this global phenomenon, as observed by Goodhart and Hofmann, 2008, consisted of inflated asset prices, house price persistence, surging money growth rates, and low capital market yields. This implies that asset markets were "awash with liquidity". Common to other developed countries, the UK's experience of the financial trauma comprised of a prolonged recession followed by a fragile recovery. The UK's response to the financial crisis saw the government attempt to stimulate the property sector through schemes such as 'help to buy' (HTB). This provides equity loans of up to 20% of a property's value (on properties up to the value of £600,000), given the buyer has 5% of the value of the property as a deposit (with the remaining 75% requiring a mortgage). This is consistent with the view, alluded to by Bank of England (BoE) Governor Mark Carney in the June 2014 Financial Stability Report press conference that historically, recessions preceded by a property bust are more severe than those without[1].

In parallel with this, the UK's monetary policy response consisted of successive interest rate cuts which froze at 0.5% on March 5th 2009 and have remained there since; along with three rounds of QE from March 2009 to July 2012 summing to £375bn. QE is thought to work via three main channels: the macro–policy/news channel; the signalling channel, and the portfolio rebalancing channel (for a critical analysis see e.g.

[1]The UK housing market is thought to affect the economy through three channels: domestic demand (documented in the BoE's November 2013 Inflation Report as having prospects for medium–term inflationary pressure); financial stability; and debt levels and resource allocation.

Martin and Milas, 2012). However, during the first round of QE, M4 (or broad money) growth, the usual monetary aggregate monitored by the Monetary Policy Committee (MPC), did not pick up. Yet Divisia money did, thus raising the question as to what measure of money matters for inflation. Divisia money assigns weights to the component assets of M4 in accordance to their liquidity, such that those bearing higher interest payments (thought to be less useful for transaction purposes) are allocated a lower weight. With this in mind, Hancock, 2005 argue that compared with M4, Divisia money has a closer relationship to expenditure[2].

A monetary explanation of inflation requires a classical approach toward price growth. The classical theory of inflation links the aggregate price level to the interactions of the demand for and supply of money. This characterises inflation towards its appropriate definition; an erosion of the purchasing power of money. Our approach, however, utilises the classical theory alongside standard Phillips curve equations that attribute current inflation to expected inflation and the output gap. Another novelty in our approach is the construction and inclusion of global money movements. It is reasonable to assume the UK is an open economy that is receptive to fluctuations in international capital flows, and more integrated financial markets. As noted in Giese and Tuxen, 2007, the integration of financial markets and fluctuations in the money supply of one country has the potential to be absorbed by demand elsewhere. More importantly, contemporaneous shifts in the money supply of major economies could result in spillover effects into domestic rates of inflation. Furthermore, global aggregates are thought to embody cross–country movements in monetary aggregates as a result of capital flows between different regions. This can hinder dissemination of the link between inflation, money and output (Sousa and Zaghini, 2008). Belke, Orth, and Setzer, 2010 argue that domestic money aggregates/national liquidity have become more difficult to interpret due to the vast increase in the volume of international capital flows. To the best of our knowledge, there are no studies examining (simultaneously) global and domestic liquidity effects onto a nation's inflationary dynamics.

The main contribution of this chapter looks to offer a "classical" explanation of inflation, by comparing the relationship between broad money and Divisia money, with two measures of UK inflation (using retail and consumer prices indices (RPI, CPI)), from 1983Q4–2014Q1 and 1989Q2–2014Q1, respectively. We show that housing and financial assets exhibit wealth effects on the demand for money, based on the theoretical arguments in Friedman, 1988 and Setzer and Greiber, 2007. We add an international dimension to our approach by constructing proxies of global liquidity following D'Agostino and Surico, 2009. We employ non–linear models to allow for asymmetric adjustment of inflation expectations, domestic and global liquidity, and spare capacity; depending on liquidity conditions within the UK economy. However, we diverge

[2]There are various theoretical motivations for the use of Divisia aggregates. For surveys advocating their attractiveness; see e.g. Barnett, 1980; Belongia, 1996; Drake and Mills, 2005.

from the aforementioned in that we focus on the inflationary impact of liquidity conditions over and above excessive demand, proxied by the output gap, from both an international and domestic perspective. Inflation dynamics are modelled both in a linear and regime–switching framework. This also distinguishes our chapter from previous UK inflation studies, namely Osborn and Sensier, 2009 who consider regime–switching with respect to a time trend and past inflation, and Milas, 2009 who considers regime–switching with respect to M4 growth and M4 disequilibria without allowing for the effects of the property sector, financial asset markets, or international liquidity effects.

Our results are summarised as follows: First, global liquidity yields inflationary pressures in the UK over and above the impact of domestic monetary conditions and spare capacity. Second, the demand for money is positively influenced by the property sector and financial asset markets. Third, in general, our results show that when domestic liquidity is contained within sensible bounds, inflation is well specified by a standard Phillips curve. Yet, when liquidity surpasses these bounds, domestic monetary effects become prominent. However, our results imply inflation expectations are independent of liquidity conditions. More specifically, CPI inflation is mainly driven by spare capacity considerations and global liquidity effects when M4 growth is contained within regime boundaries. On the other hand, domestic monetary effects dictate inflation movements when M4 growth is either “too high" or “too low". Fourth, we find empirical evidence in favour of M4 money (over Divisia money) in modelling UK CPI inflation.

The implications of our results are that the Bank of England’s MPC should monitor closely domestic money growth as the inflationary effects of both domestic, and global liquidity, depend on money growth boundaries. Further, noting that UK CPI inflation dynamics are currently governed by a monetary regime in which money growth is weak, our empirical findings point against the immediate risk of strong inflationary pressures. With this in mind (and at the time of writing), the BoE’s MPC are not under immediate pressure to raise the policy interest rate; in fact, before the July 2016 Inflation Report, there was speculation of interest rate cuts to 0.25% following the UK’s vote to leave the European Union. The rest of this chapter is organised as follows. Section 2.2 provides a brief description of the data, money demand equations and global liquidity. Section 2.3 gives a discussion of the econometric methodology. Section 2.4 reports our empirical findings. Finally, section 2.5 provides a summary, discusses policy implications and outlines potential avenues for future research.

2.2 Data Description, Money Demand and Global Liquidity

2.2.1 Data Description

We use quarterly data over the period 1983Q4–2014Q1 (for models of RPI inflation) and 1989Q2–2014Q1 (for models of CPI inflation). We adopt a break adjusted M4/M4^{ex} series which splices M4^{ex} (the BoE's preferred broad money measure) with aggregate M4[3]. The former along with Divisia money, the 10–year and 5–year government bonds and the 3–month Treasury Bill rates are available from the BoE's database. The RPI, CPI and GDP series are available from the Office for National Statistics (ONS). FTSE All–Share prices, house prices and the house price–earnings ratio are available from Thomson Reuters DataStream. Figure 2.1 plots the annual rates of RPI and CPI inflation along with the output gap estimate. Figure 2.2 plots the UK annual M4/M4^{ex} and Divisia money growth rates.

Our output gap measure is constructed as the proportional difference between GDP and the average of two alternative measures of equilibrium output; the Hodrick and Prescott, 1997 trend and a simple quadratic trend[4]. It is worth mentioning here some policy issues and difficulties occurring in the measurement of the output gap. Orphanides, 2003 demonstrates how short term policies focussing predominantly on the output gap have previously failed policymakers (in the US). Further, Orphanides and Van Norden, 2002 discuss the unreliability of output gap estimates in real–time, as information becomes more readily available and revisions reveal a clearer picture of the economy's true position within the business cycle. This is particularly relevant for the post–2007 period within our sample in which major revisions to UK GDP data have occurred.

[3]Specifically, we splice headline M4 with M4^{ex} since M4^{ex} data starts in 1997Q4. To construct our break adjusted UK broad money series, we follow the procedure at `http://www.bankofengland.co.uk/statistics/Pages/iadb/notesiadb/Break_adjusted_levels_data.aspx`.

[4]The Hodrick and Prescott, 1997 approximation of the output gap was thought to under–estimate the amount of spare capacity, and the quadratic trend approximation was deemed as an over–estimate; see also Ahmad, Martin, and Milas, 2014. We also considered the Office for Budget Responsibility's output gap estimate in earlier analysis; models using this output gap produced parameter estimates similar to those reported here, yet they resulted in inferior statistical fit.

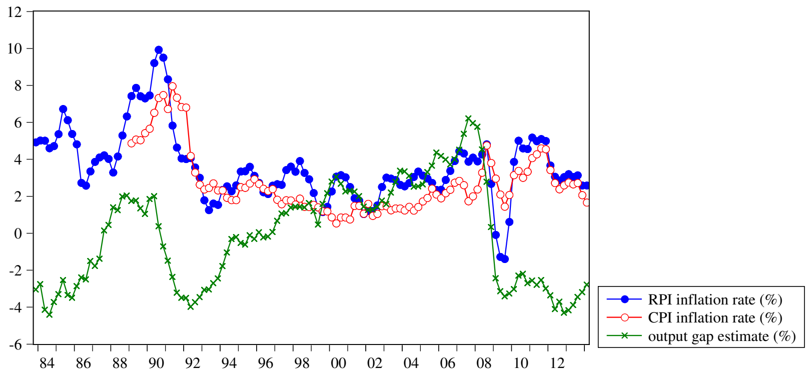

FIGURE 2.1: **Annual UK Rates of Inflation (%) and the Output Gap Estimate (%) from 1983 to 2014**
Notes: This Figure plots UK RPI and CPI annual rates of inflation along with our estimate of the output gap which is an equally weighted average of a Hodrick and Prescott, 1997 and quadratic trend respectively from 1983Q4–2014Q1 respectively.

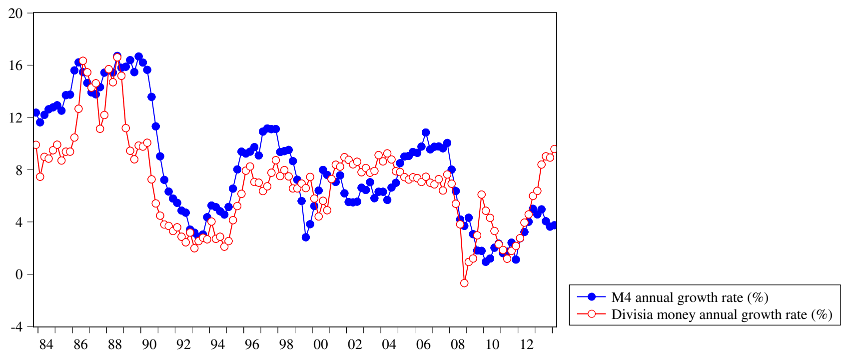

FIGURE 2.2: **Annual UK Money Growth Rates (%), from 1983 to 2014**
Notes: This Figure plots annual UK broad and Divisia money growth rates from 1983Q4–2014Q1 respectively.

2.2.2 The Demand for Money

Bernanke and Blinder, 1988 characterise the biggest challenge to the classical theory of inflation as the "Achilles heel of Monetarism". This stems from ambiguous stability of the money demand equation. For the UK, specifications using conventional variables by, for example, Haldrup, 1994 only amplify this issue. However, a stable money demand function implies the ability for inflation targeting nations (such as the UK, USA and the Euro area) to extract information regarding medium–term (and even long–term) price stability. Friedman, 1988 and Setzer and Greiber, 2007 offer theoretical underpinnings for the inclusion of financial assets and housing variables into money demand specifications. Additionally, Sousa, 2010 states that financial markets embed content regarding agent's expectations on a number of issues including economic activity and inflation. Furthermore, an economy's housing market represent major assets within households' portfolios, from which direct utility is derived. This only echoes the importance of these markets which are paramount for monetary policy; and the demand for money. Thus, we advocate their inclusion into UK money demand functions. Our expectation is that housing and financial assets should exhibit wealth effects onto the demand for money. The observed sign upon estimation indicates the dominant net effect. This assumption is not new; empirical specifications, as in Dreger and Wolters, 2010; Dreger and Wolters, 2014 show housing and financial assets exhibit wealth effects on Euro area money demand. Our "money disequilibrium" constructions are the residuals (multiplied by 100) from the Engle and Granger, 1987 long–run regressions given by[5]:

$$\begin{aligned}
diseq_t^{rpi,M4} &= (m4-p^{rpi})_t + 11.30 - 1.40y_t - 0.05(i^{10yr} - i^{5yr})_t - 0.12h_t - 0.13f_t \quad (2.1)\\
diseq_t^{rpi,DM} &= (dm-p^{rpi})_t + 11.72 - 0.81y_t - 0.07(i^{10yr} - i^{5yr})_t - 0.33h_t - 0.05f_t \quad (2.2)\\
diseq_t^{cpi,M4} &= (m4-p^{cpi})_t + 12.81 - 1.72y_t - 0.01(i^{10yr} - i^{3m})_t - 0.13h(p/e)_t \quad (2.3)\\
diseq_t^{cpi,DM} &= (dm-p^{cpi})_t + 14.50 - 1.28y_t - 0.01(i^{10yr} - i^{3m})_t - 0.40h(p/e)_t \quad (2.4)
\end{aligned}$$

where $diseq_t^{x,y}$ is the money disequilibrium construction, the x superscript denotes the price index used and the y superscript denotes the money aggregate used in each specification; $(m4-p^x)_t$, $(dm-p^x)_t$ denote the log level of real M4 and real Divisia money balances where the x superscript denotes the price index used as a proxy for prices; y_t is the log level of real GDP; i_t^{10yr}, i_t^{5yr} are the 10–year and 5–year government bond rates, respectively and i_t^{3m} is the 3–month Treasury Bill rate. The interest rate differential used in specifications (2.1)–(2.4) is therefore the slope of the respective term structures. The variable h_t is the log level of real standardised average UK house prices; f_t is the log level of real stock prices proxied by the FTSE All–Share index and $h(p/e)_t$ is the log level of the UK house price–earnings ratio (calculated as the average standardised house price scaled by the average earnings of a full–time male UK employee).

Figure 2.3 plots the house price–earnings ratio, real house prices and real asset (FTSE

[5] All variables within these systems were confirmed to be unit root processes. To save space, we refrain from reporting the test results (these are available on request).

All–Share) prices (in logs); we note the rapid increase in all three indices pre–2007, followed by an abrupt decline afterwards. The FTSE All–Share index bounces back up rapidly since QE implementation whereas the housing variables only show a gradual increase. Figure 2.4 plots the interest rate spreads. All variables enter with either the correct theoretical or anticipated sign and the magnitude of each variable is also consistent with existing empirical applications (e.g. Milas, 2009)[6].

Table 2.1 reports a battery of tests that explore the stationarity properties of the disequilibrium constructions. The tests reported are: the EGS test Elliott, Rothenberg, and Stock, 1996; the KPSS test (Kwiatkowski et al., 1992) and the ERS test (Elliott, Rothenberg, and Stock, 1996). The former and the latter test the null hypothesis of a unit root, whereas the KPSS test, tests the null hypothesis of stationarity[7]. As can be seen from Table 2.1, tests results in columns 2–4 confirm that the money disequilibria are stationary. However, there appears to be some ambiguity in column 1 where only around half of the test statistics confirm marginal stationarity of the money disequilibrium (using RPI and M4 in construction). As a form of robustness analysis, we turned to the Johansen, 1988; Johansen, 1995 methodology. All VAR estimates support evidence of cointegration with at least one of the tests (either Johansen's λ–trace or λ–max test) in favour of one cointegrating vector (for the sake of brevity, we do not report these results but are available on request)[8].

[6]Specifications are quite different depending on which price index nominal money holdings are deflated. One possibility is the time horizon considered for each sample. To investigate this further, we estimated the long–run regressions as in (2.3) and (2.4) deflating money holdings by retail prices for the sample 1988Q1–2014Q1. Results were quantitatively similar to those reported in (2.3) and (2.4).

[7]For (2.1), Augmented Dickey Fuller (ADF) test statistics are: ADF(0 lag)=-2.25, ADF(1 lag)=-2.67, ADF(2 lags)=-2.66. For (2.2), ADF test statistics are: ADF(0 lag)=-2.68, ADF(1 lag)=-2.62, ADF(2 lags)=-2.87. For (2.3), ADF test statistics are: ADF(0 lag)=-2.11, ADF(1 lag)=-2.83, ADF(2 lags)=-2.84. For (2.4), ADF test statistics are: ADF(0 lag)=-1.45, ADF(1 lag)=-1.64, ADF(2 lags)=-2.05. The MacKinnon, 1991 5% critical value for (2.1)–(2.2) is -4.53 and for (2.3)–(2.4) is -4.20, ADF tests were unable to reject the null hypothesis in these cases; we return to this issue below when reporting our non–linear model estimates.

[8]From a statistical point of view, it should be noted that money disequilibrium constructions without the property sector and financial asset variables show much clearer evidence of non–stationarity (detailed results are available on request). For VAR estimates using log levels of Divisia money, cointegration was conditional on the inclusion of trend into the cointegrating vector.

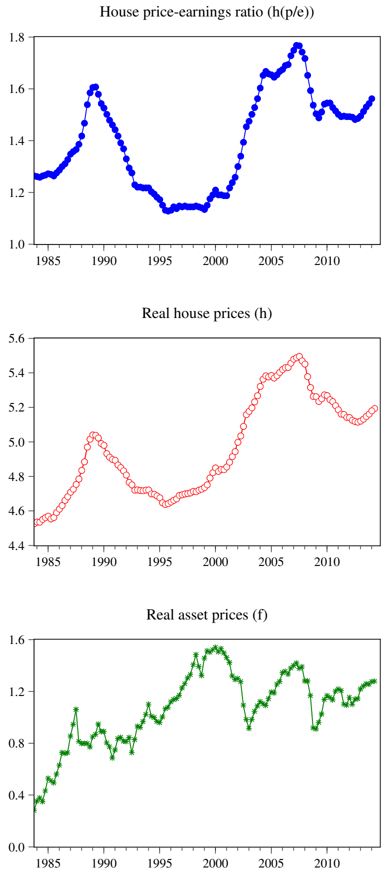

FIGURE 2.3: **UK House Price to Earnings Ratio, Real House Prices and Real Asset Prices from 1983 to 2014**
Notes: This Figure plots the logarithmic values of the the UK house price–earnings ratio, real house prices and real stock prices from 1983Q4–2014Q1 respectively.

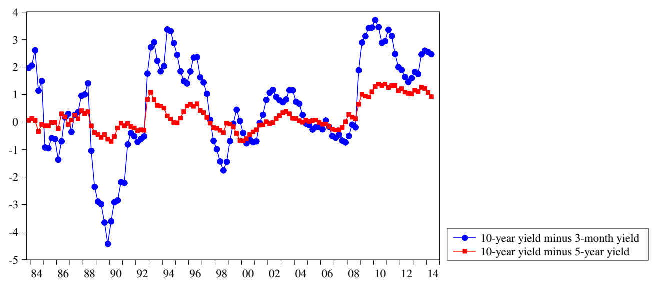

FIGURE 2.4: **Interest Rate Spreads from 1983 to 2014**
Notes: This Figure plots the 10–year government bond yield minus the 5–year government bond yield and the 10–year government bond yields minus the 3–month Treasury Bill rate from 1983Q4–2014Q1 respectively.

TABLE 2.1: Stationarity Tests for Money Disequilibria

Sample:	1983Q1–2014Q1		1988Q1–2014Q1	
	$diseq_t^{rpi,M4}$	$diseq_t^{rpi,DM}$	$diseq_t^{cpi,M4}$	$diseq_t^{cpi,DM}$
EGS[a]				
Lag length				
0	-1.27	-2.07**	-1.00	-1.49
2	-1.71*	-2.31**	-1.70*	-2.07**
4	-1.65*	-1.79*	-1.84*	-2.15**
6	-1.33	-1.56	-1.88*	-2.15**
KPSS[b]	0.13	0.13	0.15	0.20
Bandwidth	8	8	8	8
ERS[c]				
Lag length				
0	10.26	4.11*	15.58	5.04
2	4.68	2.84**	4.83	2.61**
4	3.77*	2.92**	2.83**	1.84***
6	4.46	2.53**	2.20**	1.44***

[a] The 10%, 5% and 1% critical values for the EGS test are -1.61, -1.94 and -2.58, respectively
[b] The 10%, 5% and 1% critical values for the KPSS test are 0.347, 0.463 and 0.739, respectively
[c] The 10%, 5% and 1% critical values for the ERS point optimal are 4.20, 3.12 and 1.94, respectively

Notes: Stationarity tests for the money disequilibrium constructions in (2.1)–(2.4). The EGS test is a unit root test developed by Elliott, Rothenberg, and Stock, 1996. This test works off generalised least squares (GLS) detrending the residuals before running the ADF test equation. The KPSS test is an LM–type test proposed by Kwiatkowski et al., 1992 with the null hypothesis that the data is trend stationary. The ERS test (Elliott, Rothenberg, and Stock, 1996) is a point optimal test that works off quasi–differenced data before running two test regressions. In order to test the null hypothesis of a unit root, the test statistic is then computed as the difference of the sum of squared residuals of the test equation under the alternative hypothesis and under the null hypothesis of conventional ADF tests scaled by an estimator of residual spectrum at frequency zero. In this case we used an autoregressive spectral density estimator. *, ** and *** denote a rejection of the null hypothesis at 10%, 5% and 1% significance, respectively.

Figures 2.5 and 2.6 plot the money disequilibrium constructions as in (2.1)–(2.4). Plots in both Figures show that mean crossings are relatively frequent with substantially more variability in the money disequilibria using real M4 balances. Positive deviations from the long–term equilibrium show excess money holdings within the economy possibly linked to the risk of inflationary pressures. On the other hand, negative deviations from the long–run equilibrium imply a lack of money holding in the economy possibly linked to a period of disinflation.

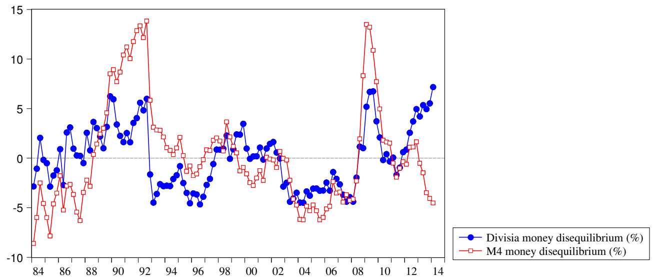

FIGURE 2.5: **Money Disequilibrium using RPI as a Proxy for Prices (%) from 1983 to 2014**
Notes: This Figure plots the money disequilibrium constructions which are computed as the residuals from the Engle and Granger, 1987 long–run regressions (multiplied by 100) in equations 2.1 and 2.2 from 1983Q4–2014Q1 respectively.

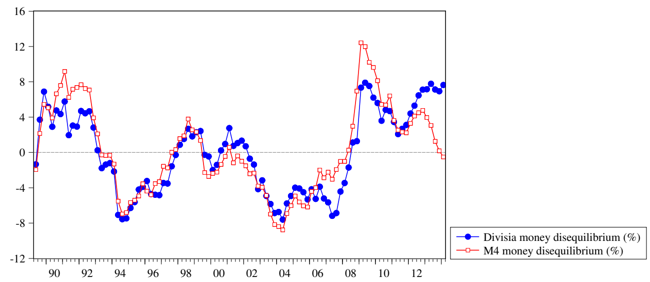

FIGURE 2.6: **Money Disequilibrium using CPI as a Proxy for Prices (%) from 1989 to 2014**
Notes: This Figure plots the money disequilibrium constructions which are computed as the residuals from the Engle and Granger, 1987 long–run regressions (multiplied by 100) in equations 2.3 and 2.4 from 1989Q2–2014Q1 respectively.

Notice (from Figures 2.5 and 2.6) that, towards the end of the sample, there is considerable divergence between M4 money disequilibria and Divisia money disequilibria. In the former case, money has reverted towards equilibrium (or is now moving below equilibrium). In the latter case, however, money is above equilibrium. These differences arise because Divisia money holds greater informational content regarding liquidity conditions/perceptions in the UK that M4 cannot capture. This stems from the assumption nested within simple–sum monetary aggregates. That is, component assets are assumed perfectly substitutable. This condition is noted to be strongly rejected (empirically) in Belongia, 1996. The implication of the above helps explain this divergence between M4 and Divisia disequilibria. Money disequilibria utilising Divisia aggregates are capturing purely internal substitution effects between component assets of M4, from illiquid to liquid components; possibly through the portfolio rebalancing channel of QE[9].

[9]This may be driven by the closer relationship Divisia money has with aggregate spending; as noted by Florackis et al., 2014

2.2.3 Global Liquidity

Next, we turn our attention to measures of global liquidity. Monetary aggregates and GDP data for the constructions of global liquidity are from the Organisation for Economic Co-operation and Development (OECD) and the Centre for Financial Stability (CFS). The levels of broad and Divisia global liquidity are given by:

$$gl_t^{broad} = \sum_{i=1}^{4} \omega_{i,t} m_{i,t} \tag{2.5}$$

$$\omega_{i,t} = GDP_{i,t}/GDP_t^{Agg} \tag{2.6}$$

and

$$gl_t^{Divisia} = dm_{US,t} \tag{2.7}$$

In (2.5) $m_{i,t}$ represents the level of country i's money aggregate converted at PPP exchange rates (i= Canada, US, Japan and the Euro area; we use the term "country" in a loose manner for the Euro area). This is then weighted by $\omega_{i,t}$ which is country i's share in an aggregated GDP series, GDP_t^{Agg} (i.e. $GDP_{i,t}/GDP_t^{Agg}$) in (2.6). Similarly in (2.7), global Divisia is approximated by US Divisia money, $dm_{US,t}$, converted at PPP exchange rates.

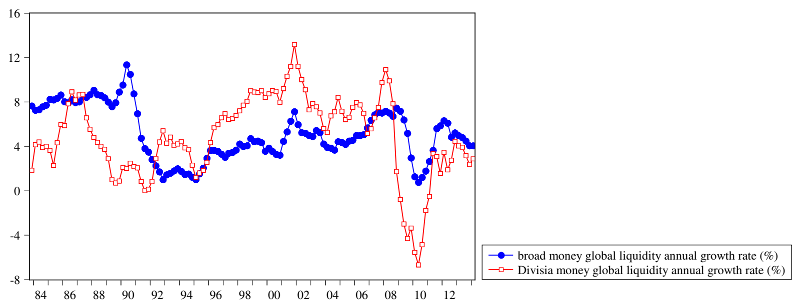

FIGURE 2.7: **Global Liquidity Growth Rates (%) from 1983 to 2014**
Notes: This Figure plots the annual growth rates of broad money and Divisia money global liquidity from 1983Q4–2014Q1 respectively.

Figure 2.7 plots the annual growth in broad and Divisia money global liquidity, where the annual growth rates of (2.5) and (2.7) used in our models of UK inflation, are denoted as GL_t^{broad}, and GL_t^{DM} respectively. Notice the sharp decline in both proxies of global liquidity at the time of the financial crisis. Furthermore, our proxies show that the decline in global Divisia is more severe than that for global broad money; possibly explained by the differences in weighting schemes for each series (for global broad money we rely on four countries whereas for global Divisia we rely solely on the US). For both proxies, there is a surge post–2009 (back into positive growth rates for global

Divisia), suggesting these variables are picking up QE effects. Notably, the surge is more abrupt in global Divisia growth, indicating a quicker response of this aggregate to expansionary monetary policies[10].

2.3 Econometric Methodology

Our analysis starts with a linear model of the form:

$$\pi_t^x \quad = \quad \beta_0 + \beta_i^{'} X_{t-l} + \nu_t \tag{2.8}$$

where π_t^x is the annual rate of inflation, the x superscript denotes the price index the rate of inflation derives from; X_{t-l} is a vector of control variables, namely: lagged inflation π_t; M4 growth ($M4_t$); Divisia money growth (DM_t); global liquidity growth ($GL_t^{broad}/GL_t^{Divisia}$), or the rate of change (acceleration) of global liquidity growth; the output gap (gap_t) (or the rate of change in the output gap); and the money disequilibrium ($diseq_t$)[11]. $\beta_i^{'}$ denotes the coefficient associated to the respective control variable, where the subscript ($i = \pi_t,\ M4_t,\ DM_t,\ GL_t,\ gap_t,\ diseq_t$), and ν_t is an error term[12].

Specifications are then subject to a battery of diagnostics testing whether the model's parameters are time invariant (see Lin and Teräsvirta, 1994) or neglect any potential non–linearity (using tests for fourth order ARCH effects and bootstrapped p–values of the BDS (see Brock et al., 1996) independence test based upon varying correlation dimensions). Upon rejection of parameter constancy in favour of parameters that change smoothly throughout time, we consider non–linear models that allow for possible asymmetries relative to a given transition variable. More formally, inflation is modelled as:

$$\pi_t^x \quad = \quad \beta_0 + \left(\beta_{i,1}^{'} X_{t-l}\right) \alpha_{t-l}^{\delta} + \left(\beta_{i,2}^{'} X_{t-l}\right) (1 - \alpha_{t-l}^{\delta}) + \eta_t \tag{2.9}$$

where

$$\alpha_{t-l}^{\delta} \quad = \quad 1 - \left[1 + \exp\left\{-\gamma((\delta_{t-l} - \tau_1)(\delta_{t-l} - \tau_2))/\sigma_{\delta_{t-l}}^2\right\}\right]^{-1} \tag{2.10}$$

[10]However, the rapid response of global Divisia might also rest on the fact that the proxy utilises only the US Divisia aggregate for which we have data. This might be picking the sizeable QE policies of the Fed. Indeed, in June 2014, the balance sheet of the Fed stood at $4.4 trillion, five times its pre–crisis size.

[11]The rate of change in the output gap eradicates any measurement error in the approximation and may be regarded as more favourable than the raw output gap estimate (see e.g. Walsh, 2003); our models of RPI inflation favoured the output gap's first difference. For proxies of global liquidity, the acceleration rate of global liquidity resulted in a preferable statistical fit for models using the CPI measure of inflation.

[12]Regressors do not explicitly share a common lag length. We include lagged values of all variables up to lag 4; empirical specifications are given in Table 2.2. Model selection criteria were based on the empirical models that yielded the best statistical fit in terms of the regression standard error and the Akaike Information Criterion (AIC).

Equation (2.9) states that inflation is modelled as a weighted average of two linear models. X_{t-l} are the regressors from the linear specification in (2.8), δ_{t-l} is the transition variable and η_t is an error term. α^{δ}_{t-l}, as defined in (2.10), is the quadratic logistic transition function as discussed in Dijk, Teräsvirta, and Franses, 2002. According to (2.9) and (2.10), inflation exhibits regime–switching behaviour depending on whether δ_{t-l} is between or outside of two endogenously determined regime boundaries $\tau_1,\ \tau_2$ where $\tau_1 < \tau_2$; with regime weights given by α^{δ}_{t-l} and $(1-\alpha^{\delta}_{t-l})$, respectively. When δ_{t-l} is between τ_1 and τ_2, $\alpha^{\delta}_{t-l} \to 1$ and the inflationary impact is given by $\beta^{'}_{i,1}$. When δ_{t-l} is outside of the regime boundaries, $\alpha^{\delta}_{t-l} \to 0$ and inflation is given by $\beta^{'}_{i,2}$. The parameter $\gamma(\gamma > 0)$ determines how rapid the transition is from one regime to another and is made scale–free by dividing (2.10) by the variance of δ_{t-l}[13]. This type of model allows us to assess the impact of spare capacity, domestic and global money movements during a "contained regime" and an "uncontained regime". Since the focus of this study is on the link between UK inflation and liquidity conditions, we consider regime–switching behaviour with respect to liquidity variables (that is, M4 money growth, Divisia money growth, the money disequilibria constructions, and our proxies for global liquidity)[14].

In general, our models might be thought of as augmented Phillips curve type equations. Our non–linear specifications allow for asymmetric adjustment of parameters based upon observable variables. In considering liquidity proxies as the transition variables, our model implies that the policymaker can identify what is driving the dynamic behaviour of inflation throughout time. Thus, in contrast to (say) Markov–Switching models, which are based upon unobserved variables defining regimes, our model may be used to make informed monetary policy decisions, conditional on states of domestic liquidity.

[13]Notice in (2.10), as $\gamma \to \infty$, the models become Threshold Autoregressive (TAR) type models as a special case.

[14]We abstain from reporting results of these non–linear models simply because our models with domestic liquidity transition variables (a) exhibit a better statistical fit in terms of parameter constancy and (b) have important economic meaning for policy–makers. We omitted the output gap as a possible candidate as there is already evidence within the literature that inflation does not adjust asymmetrically to movements in the output gap (see Clements and Sensier, 2003).

2.4 Empirical Evidence

2.4.1 Results

Our empirical specifications for different versions of the linear model in (2.8) are reported in Table 2.2. We report four versions of the linear model, two models of RPI inflation and two models of CPI inflation, using combinations of: M4 growth; Divisia money growth; the output gap; global liquidity; and the money disequilibrium. In all models reported, inflation is highly persistent (measured by the coefficient on lagged inflation which acts as a proxy for forward–looking expectations; see e.g. Blanchard, 1990). Models of RPI inflation, reported in columns i) and ii), show that Divisia money growth is statistically significant and has a more prominent inflationary impact than M4 growth. Columns iii) and iv) show instead that M4 seems to exert a stronger and more significant impact on CPI inflation than Divisia money growth.

The impact of the rate of change in the output gap is strong and highly significant for models of RPI inflation. For CPI inflation, instead, the output gap is found to exert a positive impact; however, this is statistically weak. In all models, money disequilibria have a positive (inflationary) but nevertheless, statistically insignificant effect; we return to this issue below as we find (for some non–linear models) cointegration effects when money growth drops outside a range of thresholds. Only for CPI inflation model iv), global liquidity, proxied by the rate of change in US Divisia growth, exerts a statistically significant impact.

All linear models show evidence of residual autocorrelation and heteroskedasticity based on tests for *AR* and *ARCH* effects[15]. Bootstrapped *p*–values from the BDS tests report no evidence of independence (with the exception of models iii) and iv))[16]. There is also substantial evidence that parameters of each respective model vary throughout time. The only exception is model ii) where test results imply parameters are time–invariant[17].

Having rejected parameter constancy, we proceed by estimating non–linear specifications of the inflation models discussed in Table 2.2. We report the tests for the appropriate lag length of transition variable candidates (i.e. domestic money growth or money disequilibria) and functional form of the logistic function in Section 2.6.1 Appendix A (see Dijk, Teräsvirta, and Franses, 2002) for details)[18]. For models of RPI

[15]All *t*–ratios reported in Table 2.2 and Table 2.3 below are based on Newey–West Heteroskedasticity and Autocorrelation robust standard errors.

[16]These tests are implemented as an indication for any non–linearity neglected by the models (see e.g. Clements and Sensier, 2003).

[17]Given this model rejects the null for AR, ARCH and BDS tests, we also proceed to test for regime–switching behaviour.

[18]Lagged transition variable candidates of up to and including 6 lags were considered, see Section 2.6.1 Appendix A for further details.

TABLE 2.2: Linear Estimates of UK Inflation

$$
\begin{aligned}
i)\ \pi_t^{rpi} &= \beta_0 + \beta_\pi \pi_{t-1}^{rpi} + \beta_{M4} M4_{t-1} + \beta_{gap}\Delta gap_{t-1} + \beta_{GL} GL_{t-4}^{broad} + \beta_{diseq} diseq_{t-3}^{rpi,M4} + \nu_t \\
ii)\ \pi_t^{rpi} &= \beta_0 + \beta_\pi \pi_{t-1}^{rpi} + \beta_{DM} DM_{t-1} + \beta_{gap}\Delta gap_{t-1} + \beta_{GL}\Delta GL_{t-1}^{Divisia} + \beta_{diseq} diseq_{t-3}^{rpi,DM} + \nu_t \\
iii)\ \pi_t^{cpi} &= \beta_0 + \beta_\pi \pi_{t-1}^{cpi} + \beta_{M4} M4_{t-1} + \beta_{gap} gap_{t-1} + \beta_{GL}\Delta GL_{t-4}^{broad} + \beta_{diseq} diseq_{t-4}^{cpi,M4} + \nu_t \\
iv)\ \pi_t^{cpi} &= \beta_0 + \beta_\pi \pi_{t-1}^{cpi} + \beta_{DM} DM_{t-1} + \beta_{gap} gap_{t-1} + \beta_{GL}\Delta GL_{t-1}^{Divisia} + \beta_{diseq} diseq_{t-3}^{cpi,DM} + \nu_t
\end{aligned}
$$

Sample:	1983Q4–2014Q1		1989Q2–2014Q1	
Dependent:	π_t^{rpi}		π_t^{cpi}	
	$i)$	$ii)$	$iii)$	$iv)$
β_0	-0.01 (-0.06)	-0.002 (-0.01)	-0.12 (-0.87)	-0.05 (-0.26)
β_π	0.87 (16.67)	0.88 (15.17)	0.91 (18.70)	0.94 (19.52)
β_{M4}	0.03 (1.14)		0.05 (1.75)	
β_{DM}		0.06 (2.61)		0.03 (1.12)
β_{gap}	0.45 (2.90)	0.31 (3.45)	0.04 (1.27)	0.04 (1.44)
β_{GL}	0.04 (0.74)	0.08 (1.37)	0.09 (0.81)	0.09 (1.98)
β_{diseq}	0.02 (0.89)	0.05 (1.11)	0.03 (1.36)	0.02 (0.71)
$\bar{R}^2$	0.86	0.87	0.91	0.90
Regression S.E	0.71	0.69	0.52	0.52
AIC	2.20	2.13	1.58	1.59
PC *F*–test *p*–value	0.00	0.27	0.00	0.00
AR(4) *p*–value	0.00	0.00	0.01	0.00
ARCH(4) *p*–value	0.01	0.02	0.02	0.07
BDS	[bootstrapped *p*–values]			
Dimension				
2	0.02	0.01	0.10	0.03
3	0.04	0.05	0.27	0.10
4	0.05	0.12	0.35	0.11
5	0.02	0.08	0.11	0.04
6	0.02	0.06	0.05	0.02

Notes: Estimates of linear models for UK RPI and CPI inflation from 1983Q4–2014Q1 and 1989Q2–2014Q1, respectively. *t*–ratios are given in parentheses (Newey–West Heteroskedasticity standard errors). AIC stands for Akaike Information Criterion. PC is an *F*–test for parameter constancy testing the statistical significance of the cross product of all regressors in the linear model and a time trend, a quadratic trend and a cubic trend (Lin and Teräsvirta, 1994). AR(4) is an *F*–test for fourth order serial correlation. ARCH(4) is an *F*–test for fourth order ARCH effects. BDS (Brock et al., 1996) is a test for independence of the residuals from the linear model based on correlation dimension 2–6; bootstrapped *p*–values are reported based on 10,000 repetitions.

inflation and M4, and both models of CPI inflation, our reported specifications use domestic money growth rates as the transition variable. For the model of RPI inflation and Divisia money growth, we utilise the money disequilibrium term as the transition variable[19].

Furthermore, we report additional diagnostics to assess the adequacy of the estimated non–linear models. First, we subject each of the non–linear models to an *F*–test with the null, H_0: No remaining non–linearity (based on the statistical significance of the cross product of the regressors in the non–linear model and the respective transition variable; see Dijk, Teräsvirta, and Franses, 2002)[20]. Second, we test the non–linear model against a linear model via an *F*–test ($H_0 : \beta^{'}_{i,1} = \beta^{'}_{i,2}$ such that there is no difference in the impact of regressors across regimes). Third, we report the ratio of standard deviation of the estimated residuals from the non–linear model and the linear model, $\hat{\sigma}_{NL}/\hat{\sigma}_L$. This assesses the fit of the non–linear model conditional on the AIC for the regime–switching model being less than its linear counterpart.

[19]The non–linear models reported in Table 2.3 provided the most favourable statistical fit. For these models, sequential tests do not favour potential transition candidates over one another.

[20]Assuming a common transition variable for regimes.

Table 2.3 reports the non–linear estimates of the baseline specifications reported in Table 2.2. Columns $i)$–$ii)$ report the non–linear models of RPI inflation using M4 growth and Divisia money growth, respectively and columns $iii)$–$iv)$ report the non–linear models of CPI inflation using M4 growth and Divisia money growth, respectively[21]. First, consider specification $i)$ in Table 2.3. This allows for regime–switching behaviour of RPI inflation relative to M4 growth being within, or outside of, the band of thresholds τ_1, and τ_2[22]. The model indicates that when M4 growth is contained between 2.34% and 7.60%, inflation is driven by global liquidity effects (*t*–ratio=1.61). In the uncontained regime, inflation is driven by M4 growth (*t*–ratio=2.37)[23]. Lagged inflation and the output gap exert significant but, nevertheless, regime–independent effects. As indicated in the second half of Table 2.3, diagnostics for specification $i)$ reveal that the model is only marginally favourable over its linear baseline. Although the model's parameters are time–invariant, the inability to reject no remaining non–linearity is negligible.

Consider next specification $ii)$ in Table 2.3. Regime–switching dynamics depend on whether the money disequilibrium is between (or outside of) -2.86% (*t*–ratio=-16.33) and 2.40% (*t*–ratio=11.38). When domestic liquidity is contained, inflation is driven by lagged inflation (regime–independent), Divisia money growth (*t*–ratio=1.19), global Divisia (*t*–ratio=1.40), and the output gap (*t*–ratio=4.38) respectively. When the money disequilibrium exceeds either boundary, the output gap effects diminish sharply (since γ=11.25) and inflation is governed by domestic liquidity effects. Divisia money growth in this uncontained regime is highly significant (*t*–ratio=3.07)[24]. Diagnostics imply that parameters are constant and the non–linearity is adequately captured.

Next we turn our attention to models of CPI inflation. Specification $iii)$ allows for regime–switching behaviour depending on whether M4 growth is between (or surpasses) the statistically significant thresholds of 7.34% and 12.89% respectively. The smoothing parameter is estimated at 23.94 (*t*–ratio=0.86), suggesting a sharp transition from one regime to another. When M4 growth is contained, inflation is determined by past inflation (again regime–independent), the output gap and global liquidity effects (both statistically significant). When M4 growth surpasses one of the thresholds, domestic liquidity effects significantly dominate the inflationary process ($\beta_{M4,2}$=0.08, *t*–ratio=5.97, $\beta_{diseq,2}$=0.05, *t*–ratio=2.79). Diagnostics for this model imply no remaining

[21]We found statistical evidence across all models in Table 2.3, that inflation persistence was not regime dependent based on an *F*–test under the null hypothesis $H_0 : \beta^{'}_{\pi,1} = \beta^{'}_{\pi,2}$.

[22]As in Dijk, Teräsvirta, and Franses, 2002 to examine whether we have sensible regimes we order the values of the transition candidate then trim the highest and lowest 15% of values. So long as at least 30% of the trimmed values lie in one regime, we deem them sensible. For specification $i)$, 45% of $M4_{t-6}$ observations are within the contained regime. For specification $ii)$, 55% of $diseq^{rpi,DM}_{t-2}$ observations are in the contained regime. For specification $iii)$, 43% of $M4_{t-6}$ observations lie within the contained regime and for specification $iv)$, 60% of DM_{t-2} are within the contained regime.

[23]The γ estimate in the models reported in Table 2.3 is shown to be insignificant. Dijk, Teräsvirta, and Franses, 2002 discuss the difficulty in getting accurate estimates of γ. The likelihood function is very insensitive to γ and therefore, precise estimation of this parameter is unlikely.

[24]We tested $H_0 : \beta_{DM,1} = \beta_{DM,2}$, *p*–value=0.02. This is the only model where asymmetric adjustment of domestic money growth was found to be statistically significant.

TABLE 2.3: Non–linear Estimates of UK Inflation

Sample:	1983Q4–2014Q1		1989Q2–2014Q1	
Dependent:	π_t^{rpi}		π_t^{cpi}	
	i)	*ii)*	*iii)*	*iv)*
β_0	-0.20 (-0.84)	0.08 (0.33)	-0.12 (-1.45)	0.08 (1.09)
β_π	0.88 (16.51)	0.87 (16.33)	0.87 (24.09)	0.89 (22.66)
β_{gap}	0.34 (2.68)			0.06 (2.79)
Regime when	$\tau_1 < M4_{t-6}$ $< \tau_2$	$\tau_1 < diseq_{t-2}$ $< \tau_2$	$\tau_1 < M4_{t-6}$ $< \tau_2$	$\tau_1 < DM_{t-5}$ $< \tau_2$
$\beta_{DM,1}$		0.03 (1.19)		
$\beta_{gap,1}$		0.49 (4.38)	0.10 (2.20)	
$\beta_{GL,1}$	0.16 (1.61)	0.09 (1.40)	0.44 (2.60)	0.15 (3.31)
Regime when	$\tau_1 > M4_{t-6}$, $\tau_2 < M4_{t-6}$	$\tau_1 > diseq_{t-2}$, $\tau_2 < diseq_{t-2}$	$\tau_1 > M4_{t-6}$, $\tau_2 < M4_{t-6}$	$\tau_1 > DM_{t-5}$, $\tau_2 < DM_{t-5}$
$\beta_{M4,2}$	0.07 (2.37)		0.08 (5.97)	
$\beta_{DM,2}$		0.09 (3.07)		0.07 (3.43)
$\beta_{diseq,2}$		0.07 (1.34)	0.05 (2.79)	0.03 (1.28)
γ	11.22 (0.78)	11.25 (0.86)	23.94 (0.86)	24.05 (0.64)
τ_1	2.34 (4.15)	-2.86 (-16.33)	7.34 (41.11)	4.05 (26.79)
τ_2	7.60 (16.09)	2.40 (11.38)	12.89 (3.89)	8.93 (85.88)
$\bar{R}^2$	0.87	0.89	0.93	0.92
Regression S.E	0.69	0.65	0.43	0.49
AIC	2.14	2.04	1.26	1.48
PC *F*–test *p*–value	0.66	0.11	0.42	0.3
AR(4) *p*–value	0.00	0.00	0.16	0.02
ARCH(4) *p*–value	0.01	0.03	0.45	0.04
NRNL *F*–test *p*–value	0.06	0.37	0.28	0.21
LIN *F*–test *p*–value	0.24	0.00	0.01	0.01
$\hat{\sigma}_{NL}/\hat{\sigma}_L$	0.96	0.93	0.83	0.92
BDS	[bootstrapped *p*–values]			
Dimension				
2	0.04	0.17	0.52	0.03
3	0.13	0.89	0.79	0.05
4	0.14	0.68	0.43	0.04
5	0.04	0.99	0.27	0.02
6	0.03	0.74	0.20	0.02

Notes: Estimates of non–linear models for UK inflation from 1983Q4–2014Q1 and 1989Q2–2014Q1, respectively. *t*–ratios are given in parentheses (Newey–West standard errors). PC is an *F*–test for parameter constancy testing the statistical significance of the cross product of all regressors in the non–linear model and time trend, (Eitrheim and Teräsvirta, 1996). AR(4) is an *F*–test for fourth order serial correlation. ARCH(4) is an *F*–test for fourth order ARCH effects. NRNL is an *F*–test for testing no remaining non–linearity. This involves testing the statistical significance of the cross product of the regressors in the non–linear model and the transition variable used (see Dijk, Teräsvirta, and Franses, 2002). LIN is an *F*–test indicating whether the model may be simplified to a linear model. $\hat{\sigma}_{NL}/\hat{\sigma}_L$ is the ratio of estimated volatility within the residuals generated from the non–linear model and the linear baseline. BDS (see Brock et al., 1996) is a test for independence of the residuals from the linear model based on correlation dimension 2–6; bootstrapped *p*–values are reported based on 10,000 repetitions.

non–linearity (p–value=0.45), parameters are time-invariant (p–value=0.42) and cannot be simplified to a linear model (p–value=0.01). Furthermore, this model is free from autocorrelation as indicated by the AR(4) test (p–value=0.16)[25].

In specification $iv)$ Table 2.3, regime–switching dynamics are conditional on whether annual Divisia growth is between (or drifts away from) the statistically significant regime boundaries of 4.05% and 8.93%. When Divisia growth is contained between 4.05% and 8.93%, inflation is driven by lagged inflation, the output gap (both regime–independent and statistically significant) and a strong inflationary impact stemming from global liquidity (i.e. $\beta_{GL,1}$=0.15) (which is regime–dependent and statistically significant). When Divisia growth surpasses a regime boundary, there is a sharp switch (γ=24.05) from global liquidity effects to domestic liquidity effects (more specifically, $\beta_{DM,2}$=0.07, t–ratio=3.43, $\beta_{diseq,2}$=0.03, t–ratio=1.28). Diagnostics for specification $iv)$ imply that the model has constant parameters, there is no remaining non–linearity and the model cannot be simplified to a linear specification.

By comparing specification $i)$ with specification $ii)$, we notice that models of RPI inflation with domestic Divisia outperform those with M4 money in terms of fit (AIC, $\bar{R}^2$, regression standard error and $\hat{\sigma}_{NL}/\hat{\sigma}_L$). Furthermore specification $ii)$ also outperforms specification $i)$ in terms of diagnostics (i.e. parameter constancy (PC), AR, ARCH, no remaining non–linearity (NRNL), test against linear model (LIN), and BDS tests). However, by comparing specification $iii)$ with specification $iv)$, we notice that models of CPI inflation with domestic M4 outperform those using domestic Divisia.

Notice the difference between M4 and Divisia regime boundaries for models of CPI inflation; this arises due to less variability within the Divisia money series. Yet, the contained regime across both models allows for 5.5% and 4.9% between regime boundaries[26]. Thus, it is unsurprising to observe quantitatively different thresholds; what our thresholds seem to capture are ranges of "sensible" money growth. Theoretically, the Divisia index should be less volatile than its simple–sum counterpart (in fact sample volatilities confirm this: σ_{M4}=3.53 $>$ σ_{DM}=2.52). In effect the weighting component insulates the Divisia index from large surges in (illiquid) capital flows.

Following on from the above discussion, a number of conclusions can be drawn. Firstly, from specification $ii)$, when domestic liquidity conditions are contained within approximately +/- 2.5% of the long run money equilibrium, RPI inflation is driven by the output gap and domestic and global liquidity conditions (the inflationary impact of the latter are statistically weak). Yet, when there is a divergence of persistently high (or low) money disequilibrium, the output gap effects diminish. Within this uncontained regime, domestic Divisia growth exerts a significantly strong inflationary impact (notice, $\beta_{DM,2} > \beta_{DM,1}$); as does the money disequilibrium.

[25] In fact this model is free from autocorrelation up to order 12.

[26] For specification $i)$ in Table 2.3, there is 5.3% between regime boundaries.

Secondly, from specification $iii)$, when domestic M4 growth is between 7.34% and 12.89%, CPI inflation is driven by the output gap and global liquidity effects. However, when money growth drifts away from “sensible" bounds, domestic liquidity factors govern CPI inflation dynamics. In fact, the domestic liquidity effects are highly significant. More specifically, note the impact of the money disequilibrium on CPI inflation ($\beta_{diseq,2}$=0.05, t–ratio=2.79); this implies that cointegration effects are “on" only when “too much" or “too little" domestic M4 growth is observed.

In general, our non–linear models reveal that when domestic liquidity conditions are contained within sensible boundaries, inflation is well defined by a Phillips curve augmented by global liquidity effects. Our models reveal that global liquidity effects exert a strong inflationary impact when domestic liquidity is contained. However, when there is “too much" (or “too little") liquidity within the economy, there is a shift from global liquidity to domestic liquidity factors. Overall our results suggest that monetary movements (both domestic and global) matter for UK inflation over and above spare capacity. Therefore our results advocate a “classical" explanation of inflation; but it is regime–dependent. In particular, the monetary effects on UK inflation are conditional on the state of domestic liquidity. Yet, our models imply that inflation expectations are regime–independent, such that domestic liquidity conditions do not change agent's expectations for future inflation. From a policy perspective, the Bank of England's MPC should closely monitor these thresholds in order to avoid any strong inflationary impact on the UK economy.

To obtain a better idea of how domestic liquidity (M4 growth) and global liquidity have affected UK CPI inflation throughout time, Figure 2.8 plots the implied regime–switching impacts. Regime–switching effects for broad money global liquidity are calculated as $\beta_{GL,1}\alpha^{M4}_{t-6} + \beta_{GL,2}(1 - \alpha^{M4}_{t-6})$, with $\beta_{GL,1}$=0.44, $\beta_{GL,2}$=0. For M4 money growth, the regime–switching impacts are calculated as $\beta_{M4,1}\alpha^{M4}_{t-6} + \beta_{M4,2}(1 - \alpha^{M4}_{t-6})$, with $\beta_{M4,1}$=0, $\beta_{M4,2}$=0.08. The thresholds, τ_1, τ_2 are τ_1=7.34%, τ_2=12.89%, and the smoothing parameter, γ is γ=23.94. Notice that between 2000 and early 2005 (largely prior to the financial crisis), M4 growth fluctuated initially close to the lower regime bound; in this case, inflation dynamics were dictated by global liquidity, domestic money effects, and indeed output gap movements.

Since 2009, however, and despite QE injections, domestic M4 growth has remained weak and below the lower regime boundary. In this case, the very (admittedly slow) surge in M4 growth has impacted on inflation, whereas, global liquidity effects have been negligible. Notice our M4 money disequilibrium from Figure 2.6 is fluctuating slightly below zero (i.e. 2014Q1). Combining this with low M4 growth and persistent inflation expectations, our model explains why a significant rise in inflation has been avoided. Thus it should not come as a surprise that since 2012, CPI inflation recorded an average of 1.62% (0.38 percentage points below the 2% target), and, in fact, moved below the target throughout 2014. With current (in 2016Q1) M4 growth at 1.37% and

CPI inflation at 0.30%, our model implies that there is no significant or immediate inflationary pressure for the UK economy. In fact our model correctly indicated that inflation would remain low throughout 2015 in conjunction with weak M4 growth rates.

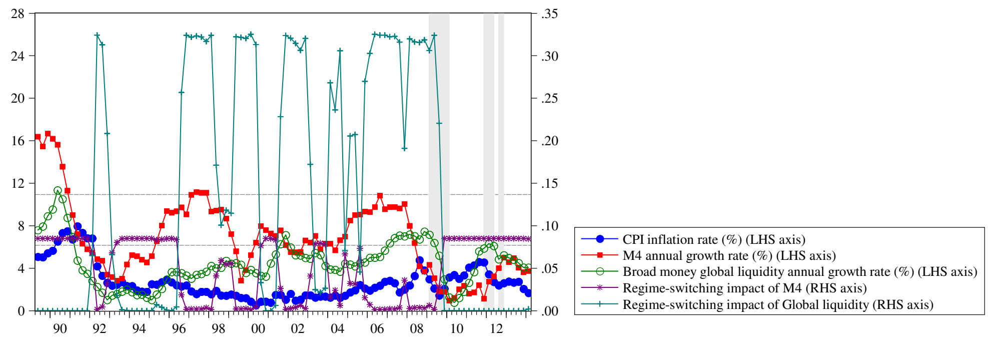

FIGURE 2.8: **Regime–switching Impact of Global and Domestic Money Growth using $M4_{t-6}$ as Transition Variable from 1983 to 2014** Notes: This figure shows the regime–switching impact of broad money global liquidity and M4 annual growth from 1989Q2–2014Q1 calculated as $\beta_{GL,1}\alpha^{M4}_{t-6} + \beta_{GL,2}(1-\alpha^{M4}_{t-6})$, with $\beta_{GL,1}$=0.44, $\beta_{GL,2}$=0, and $\beta_{M4,1}\alpha^{M4}_{t-6} + \beta_{M4,2}(1-\alpha^{M4}_{t-6})$, with $\beta_{M4,1}$=0, $\beta_{M4,2}$=0.08, τ_1=7.34%, τ_2=12.89% and γ=23.94 respectively. These are based on the estimates reported in Table 2.3 $iii)$ for the non–linear model that includes the annual growth rate of broad money global liquidity and the annual growth rate of M4, using M4 growth as the transition variable. Shaded areas indicate the periods of QE.

2.4.2 Robustness Analysis

In order to assess the adequacy of our preferred non–linear models, we report alternative specifications which allow for regime switching behaviour in terms of past inflation. This provides a useful check that our non–linear specifications are not picking up regimes of high and low inflation; particularly for RPI inflation. The functional form of α^{δ}_{t-l} for non–linear models using RPI inflation is as in (2.10). For models of CPI inflation, tests favoured a logistic function of the form:

$$\alpha^{\delta}_{t-l} \quad = \quad 1 - \left[1 + \exp\left\{-\gamma(\delta_{t-l} - \tau_1)/\sigma_{\delta_{t-l}}\right\}\right]^{-1} \tag{2.11}$$

According to (2.11) regime–switching behaviour depends on whether δ_{t-l} is below or above τ_1. Thus inflation is modelled as in (2.9) given by the regime weights α^{δ}_{t-l} and $(1-\alpha^{\delta}_{t-l})$, respectively. When $\delta_{t-l} < \tau_1$, $\alpha^{\delta}_{t-l} \rightarrow 1$ and the inflationary impact is given by $\beta^{'}_{i,1}$ (and vice versa when $\delta_{t-l} > \tau_1$).

Table 2.4 reports the parameter estimates and diagnostics of our alternatively specified non–linear models. Model $i)$ in Table 2.4 is directly comparable with specification $ii)$ in Table 2.3. Model $ii)$ in Table 2.4 is directly comparable with specification $iii)$ in

Table 2.3. By comparing specification $ii)$ in Table 2.3 with model $i)$ in Table 2.4, we notice the alternative model in Table 2.4 seems to fit the data preferably relative to our specification in Table 2.3. However, diagnostics reveal that model $i)$ in Table 2.4 does not capture the non–linearity sufficiently[27]. Therefore the model is misspecified and the ability to make informed policy decisions is (arguably) questionable.

To assess whether our preferred model of RPI inflation is capturing high and low inflation regimes, Figures 2.9 and 2.10 plots the regime–switching impact of specification $ii)$ in Table 2.3 (see Figure 2.9) and model $i)$ in Table 2.4 (see Figure 2.10). If the regime–switching behaviour in liquidity (both domestic and global) from specification $ii)$ in Table 2.3 looked similar to model $i)$ in Table 2.4, then our non–linear model would be tracking regimes of high and low inflation. Figure 2.10 shows pronounced effects of Divisia money and effects from global Divisia during the late 1980s, then minimal effects from global Divisia from around 1990 to 2006. Then from 2007 onwards, we observe multiple regime changes as inflation surpasses its lower regime boundary before rising above its upper boundary, in 2010, after the financial crisis.

If our model in Figure 2.9 was only capturing these regimes, we would expect the regime–switching impacts to be similar for both models. It is clear that the implied regimes from these models are quite different. More specifically, throughout the Great Moderation, our model exhibits an abundance of regime–switching behaviour. Therefore specification $ii)$ in Table 2.3 is indeed capturing liquidity regimes as oppose to inflation regimes.

Now considering the model $ii)$ in Table 2.4, CPI inflation is given by an AR(1) process until inflationary expectations surpass 2.61%, in which case, output gap, domestic and global liquidity effects become the drivers of inflation. However, the test for parameter constancy is marginally rejected at conventional levels, thus policy recommendations cannot be made. Our preferred non–linear model (i.e. specification $iii)$ in Table 2.3) far outperforms model 2 in Table 2.4. The implication here is that it makes sense for policymakers to track liquidity conditions as dictated by specification $iii)$ in Table 2.3[28].

[27] In fact this result implies the presence of multiple regimes; it is beyond the scope of this chapter to investigate this further.

[28] Finally, we allowed for the annual growth (current and lagged) in the price of oil (in domestic currency) to impact on our inflation models. Oil was found to exert a statistically negligible effect; at the same time, all estimated linear and non–linear models could not reject the null hypothesis, H_0 : of parameter stability (results are available on request).

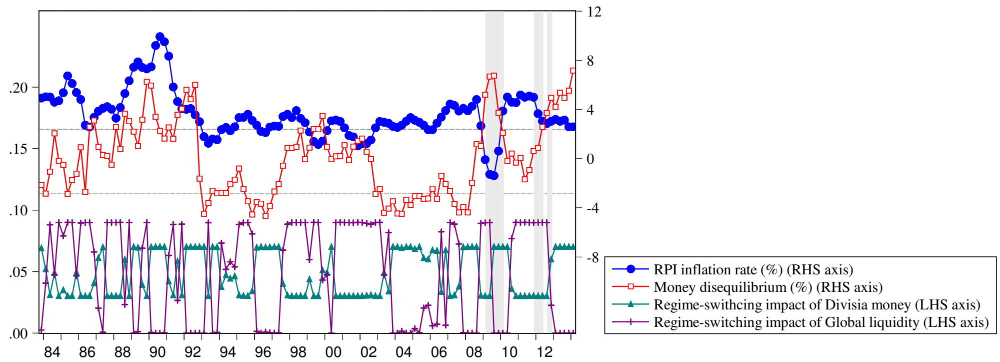

FIGURE 2.9: **Regime–switching Impact of Global and Domestic Money Growth using $diseq^{rpi,DM}_{t-2}$ as Transition Variable from 1983 to 2014**

Notes: This figure shows the regime–switching impact of broad money global liquidity and M4 annual growth from 1983Q4–2014Q1 calculated as $\beta_{GL,1}\alpha^{diseq}_{t-2} + \beta_{GL,2}(1-\alpha^{diseq}_{t-2})$, with $\beta_{GL,1}$=0.09, $\beta_{GL,2}$=0 (imposed), and $\beta_{DM,1}\alpha^{diseq}_{t-2} + \beta_{DM,2}(1-\alpha^{diseq}_{t-2})$, with $\beta_{DM,1}$=0.03, $\beta_{DM,2}$=0.09, τ_1=-2.86%, τ_2=2.40% and γ=11.25 respectively. These are based on the estimates reported in Table 2.3 ii) for the non–linear model that includes the annual growth rate of Divisia money global liquidity and the annual growth rate of Divisia money, using the money disequilibrium as the transition variable. Shaded areas indicate the periods of QE.

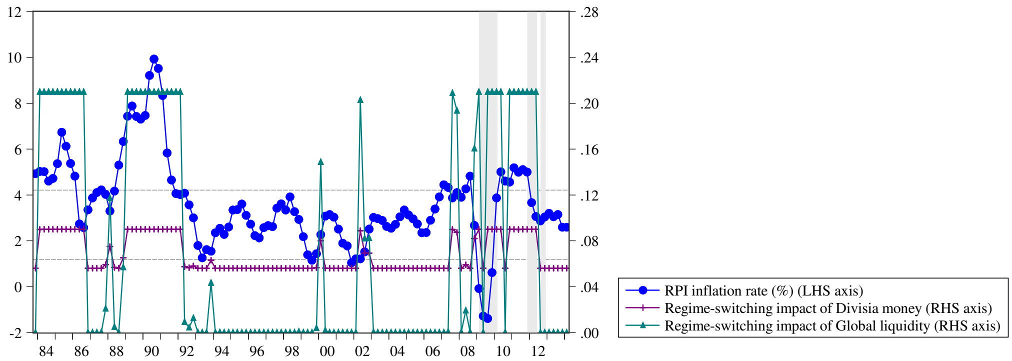

FIGURE 2.10: **Regime–Switching Impact of Global and Domestic Money Growth using π^{rpi}_t as Transition Variable from 1983 to 2014**

Notes: This figure shows the regime–switching impact of broad money global liquidity and M4 annual growth from 1983Q4–2014Q1 calculated as $\beta_{GL,1}\alpha^{\pi}_{t-2}+\beta_{GL,2}(1-\alpha^{\pi}_{t-2})$, with $\beta_{GL,1}$=0 (imposed), $\beta_{GL,2}$=0.21, and $\beta_{DM,1}\alpha^{\pi}_{t-2} + \beta_{DM,2}(1-\alpha^{\pi}_{t-2})$, with $\beta_{DM,1}$=0.06, $\beta_{DM,2}$=0.09, τ_1=1.20%, τ_2=4.21% and γ=29.26 respectively. These are based on the estimates reported in Table 2.4 i) for the non–linear model that includes the annual growth rate of broad money global liquidity and the annual growth rate of M4, using M4 growth as the transition variable. Shaded areas indicate the periods of QE.

TABLE 2.4: Robustness Analysis; Non–linear models using π_t as the Transition Variable

Sample:	1983Q4–2014Q1	1989Q2–2014Q1
Dependent:	π_t^{rpi}	π_t^{cpi}
	$i)$	$ii)$
β_0	0.14 (0.15)	0.33 (3.22)
β_π	0.81 (15.19)	0.80 (12.16)
β_{gap}	0.27 (2.99)	
Regime when	$\tau_1 < \pi_{t-2} < \tau_2$	$\pi_{t-6} < \tau_1$
$\beta_{DM,1}$	0.06 (3.33)	
Regime when	$\tau_1 > \pi_{t-2}$, $\tau_2 < \pi_{t-2}$	$\pi_{t-6} > \tau_2$
$\beta_{M4,2}$		0.05 (1.71)
$\beta_{DM,2}$	0.09 (2.32)	
$\beta_{gap,2}$		0.22(3.43)
β_{GL}	0.21 (5.03)	0.31 (2.95)
$\beta_{diseq,2}$	0.24 (4.68)	0.13 (4.07)
γ	29.26(1.28)	13.95 (2.10)
τ_1	1.20 (21.25)	2.61 (24.22)
τ_2	4.21 (93.65)	
$\bar{R}^2$	0.91	0.92
Regression S.E	0.56	0.45
AIC	1.77	1.31
PC *F*–test *p*–value	0.34	0.05
AR(4) *p*–value	0.00	0.00
ARCH(4) *p*–value	0.68	0.00
NRNL *F*–test *p*–value	0.00	0.45
LIN *F*–test *p*–value	0.00	0.00
$\hat{\sigma}_{NL}/\hat{\sigma}_L$	0.80	0.87

Notes: Estimates of non–linear models for UK inflation from 1983Q4–2014Q1 and 1989Q2–2014Q1, respectively. These are alternative specifications to models ii and iii in Table 2.3. *t*–ratios are given in parentheses (Newey–West standard errors). PC is an *F*–test for parameter constancy testing the statistical significance of the cross product of all regressors in the non–linear model and time trend, (Eitrheim and Teräsvirta, 1996). *AR*(4) and *ARCH*(4) are *F*–tests for fourth order serial correlation and ARCH effects respectively. NRNL is an *F*–test for testing no remaining non–linearity. This involves testing the statistical significance of the cross product of the regressors in the non–linear model and the transition variable (see Dijk, Teräsvirta, and Franses, 2002). LIN is an *F*–test indicating whether the model may be simplified to a linear model. $\hat{\sigma}_{NL}/\hat{\sigma}_L$ is the ratio of estimated volatility within the residuals generated from the non–linear model and the linear baseline.

2.5 Conclusions

This chapter uses a classical approach to examine UK inflation and provides an empirical comparison of the effects of domestic and global liquidity effects through the lens of money aggregates. We find statistically significant evidence that global liquidity yields inflationary pressures in the UK over and above the impact of domestic liquidity and the output gap. Domestic monetary effects are regime–switching and dominant when domestic liquidity is uncontained. However, inflation expectations are independent of liquidity conditions; this indicates that regimes of “too high" or “too low" money growth do not alter expectations. Regime–switching dynamics dependent on monetary conditions are shown to be robust to models utilising previous inflation expectations to dictate asymmetric adjustment. Our empirical results suggest that M4 money growth dominates Divisia money growth (from an econometric perspective) in modelling UK CPI inflation.

From a policy perspective, the MPC should monitor domestic money growth as the inflationary effects of both domestic money and global liquidity depend on money growth boundaries. Our results show that UK CPI inflation dynamics are currently governed by a monetary regime in which M4 growth is weak. In this very regime, the impact of both the output gap and global liquidity is negligible. Therefore, with M4 growth remaining largely subdued at 1.37% (i.e. annual M4 growth rate for 2016Q1) and CPI inflation fluctuating some 2 percentage points below the target, our findings reveal no immediate risk of inflationary pressures. In fact, our model correctly implied low rates of CPI inflation throughout 2015 in conjunction with weak M4 money growth. The implication of our findings is that the BoE’s MPC are not under immediate pressure to raise the policy interest rate. In fact, following the UK’s vote to leave the European Union, there was speculation before the July 2016 inflation report that the Bank rate would be cut to 0.25%.

Our work can be extended in a number of directions. First, although the focus of our analysis has been what drives inflation in the UK, our model could also prove attractive for a number of countries. Both global and domestic money considerations could be employed in modelling inflation beyond the UK economy. One such candidate is the Eurozone economy which, since early 2013, has experienced persistently low inflation. Indeed, Eurozone inflation fell below 2% in February 2013 and since late 2014, has fluctuated around 0%, at the same time when annual M3 growth, at 1.9% in 2014, remained much lower than its 6% historical average. To understand what drives Eurozone’s low inflation, it might be worth examining the impact of international liquidity as well as domestic liquidity along the lines of the models discussed here. Second, it would be interesting to examine the ability of the non–linear models employed here to forecast inflation out–of–sample. These issues are left for future research.

2.6 Appendix to Chapter 2

2.6.1 Appendix A: Additional Results

Here we report test results on the functional form of α^{δ}_{t-l} and delay parameter l in (2.10). There are various popular choices for the functional form of α^{δ}_{t-l}; we consider two. The first is a logistic function as in (2.11), the second is a quadratic logistic function as in (2.10). It should be noted here that there exists another choice, the exponential transition function. The exponential transition function assumes asymmetric adjustment to small and large deviations from the threshold value. Furthermore a non–linear model as in (2.9) collapses to a linear specification if the smoothing parameter in the exponential transition function $\gamma \to \infty$ or $\gamma \to 0$.

Once the linear models are specified, we can test against smooth transition type non–linearity using a third order Taylor expansion:

$$\pi_t = \beta_0^{'} w_t + \beta_1^{'} \tilde{w}_t \delta_{t-l} + \beta_2^{'} \tilde{w}_t \delta_{t-l}^2 + \beta_3^{'} \tilde{w}_t \delta_{t-l}^3 + \epsilon_t \tag{2.12}$$

where $\epsilon_t \backsim^{iid} N(0, \sigma^2)$, w_t are the regressors in the linear specification including the constant, $\tilde{w}_t$ are the regressors in the linear model excluding the constant and δ_{t-l} is the transition variable. The above specification is estimated for l different values and we then test $H_0 : \beta_1^{'} = \beta_2^{'} = \beta_3^{'} = 0$. This is an LM–type test and is carried out for all values of l considered. The test that yields the lowest *p*–value determines the delay parameter of the transition function.

The functional form is found by sequentially testing (2.12) in the following manner:

$$\begin{aligned} H_{03} &: \beta_3^{'} = 0 \\ H_{02} &: \beta_2^{'} = 0 | \beta_3^{'} = 0 \\ H_{01} &: \beta_1^{'} = 0 | \beta_3^{'} = 0,\ \beta_2^{'} = 0 \end{aligned}$$

the decision rule is to choose a quadratic logistic function as in (2.10) if H_{02} yields the lowest *p*–value; otherwise choose the logistic function as in (2.11). We re–estimate the linear specifications in Table 2.2 with the inclusion of the cross product of the regressors and the transition candidate; the squared values of the transition candidate; and the cubed values of the transition candidate, respectively. We assume that inflation adjusts to domestic liquidity conditions (i.e. domestic money growth or the money disequilibrium). The linear specifications in Table 2.2 $i), iii)$ and $iv)$ use domestic money growth (either M4 or Divisia) and $ii)$ uses the money disequilibrium respectively.

Table 2.5 reports the *p*–values of the LM–type sequential tests; numbers highlighted in bold are those that most strongly reject the null hypothesis, H_0. For the sake of brevity, we only report results using the variables discussed above as the transition candidate.

TABLE 2.5: Tests Against Smooth Transition Non–linearity

$$
\begin{aligned}
i)\ \pi_t^{rpi} &= \beta_0 + \beta_\pi \pi_{t-1}^{rpi} + \beta_{M4} M4_{t-1} + \beta_{gap} \Delta gap_{t-1} + \beta_{GL} GL_{t-4}^{broad} + \beta_{diseq} diseq_{t-3}^{rpi,M4} + \nu_t \\
ii)\ \pi_t^{rpi} &= \beta_0 + \beta_\pi \pi_{t-1}^{rpi} + \beta_{DM} DM_{t-1} + \beta_{gap} \Delta gap_{t-1} + \beta_{GL} \Delta GL_{t-1}^{Divisia} + \beta_{diseq} diseq_{t-3}^{rpi,DM} + \nu_t \\
iii)\ \pi_t^{cpi} &= \beta_0 + \beta_\pi \pi_{t-1}^{cpi} + \beta_{M4} M4_{t-1} + \beta_{gap} gap_{t-1} + \beta_{GL} \Delta GL_{t-4}^{broad} + \beta_{diseq} diseq_{t-4}^{cpi,M4} + \nu_t \\
iv)\ \pi_t^{cpi} &= \beta_0 + \beta_\pi \pi_{t-1}^{cpi} + \beta_{DM} DM_{t-1} + \beta_{gap} gap_{t-1} + \beta_{GL} \Delta GL_{t-1}^{Divisia} + \beta_{diseq} diseq_{t-3}^{cpi,DM} + \nu_t
\end{aligned}
$$

Specification:	$i)$					
δ_{t-l}:	$M4_{t-l}$					
l:	1	2	3	4	5	6
Null Hypothesis						
H_0	0.0002	0.0001	0.0025	0.005	0.0001	**3.96E-06**
H_{03}	0.2104	0.2742	0.2287	0.367	0.2482	0.0249
H_{02}	0.0073	0.0199	0.0894	0.0605	0.001	**0.0001**
H_{01}	0.0014	0.0001	0.0019	0.0038	0.002	0.0085

Specification:	$ii)$					
δ_{t-l}:	$diseq_{t-l}^{rpi,DM}$					
l:	1	2	3	4	5	6
Null Hypothesis						
H_0	2.65E-07	**7.62E-15**	1.81E-05	1.94E-06	0.0005	2.29E-13
H_{03}	0.5256	0.0235	0.0096	1.14E-05	0.2642	0.0849
H_{02}	0.021	**0.0018**	0.4194	0.8679	0.0793	2.43E-08
H_{01}	0.047	0.2698	0.1405	0.3847	0.3352	0.54

Specification:	$iii)$					
δ_{t-l}:	$M4_{t-l}$					
l:	1	2	3	4	5	6
Null Hypothesis						
H_0	0.0122	0.0015	0.0004	0.0017	0.0001	**0.0001**
H_{03}	0.3657	0.015	0.001	0.0107	0.0015	0.0885
H_{02}	0.1699	0.6047	0.7833	0.2209	0.0536	**0.0032**
H_{01}	0.0036	0.0019	0.0035	0.0141	0.0095	0.0054

Specification:	$iv)$					
δ_{t-l}:	DM_{t-l}					
l :	1	2	3	4	5	6
Null Hypothesis						
H_0	1.28E-07	6.15E-07	1.68E-07	3.11E-15	**1.57E-24**	1.68E-11
H_{03}	0.2911	0.3876	0.1719	0.2811	0.0093	0.8709
H_{02}	0.4988	0.2448	0.0331	0.0005	**0.0029**	0.0207
H_{01}	0.0003	0.0003	0.0097	0.0152	0.005	0.001

Notes: bold font numbers highlight the lowest p–values from sequentially testing (2.12), $H_{03},\ H_{02},\ H_{01}$. δ_{t-l} denotes the transition variable candidate.

2.6.2 Appendix B: Data and Sources used to Construct Global Liquidity Proxies

Table 2.6 reports the data definitions and sources used to construct our proxies of global liquidity. In order to construct Euro area GDP pre–1995, we spliced the 11 country's aggregated GDP that joined the currency union in 1999 with the published Euro area GDP series commencing from 1995Q1.

TABLE 2.6: Data Sources used to Construct Global Liquidity Proxies

Variable	Definition	Source
Global Divisia Money	USA; Divisia M3	Centre for Financial Stability
Global broad Money	USA; M2	US Federal Reserve
	Japan; M2	OECD
	Canada; M2+	OECD
	Euro Area; M3	Eurostat
GDP	USA	OECD
	Japan	OECD
	Canada	OECD
	Euro Area post 1995Q1	OECD
	Euro Area pre–1995Q1:	
	Austria	OECD
	Belgium	OECD
	Finland	OECD
	France	OECD
	Germany	OECD
	Ireland	OECD
	Italy	OECD
	Luxembourg	OECD
	Netherlands	OECD
	Portugal	OECD
	Spain	OECD
Consumer Prices	USA	OECD
(HICP Euro Area)	UK	OECD
	Japan	OECD
	Canada	OECD
	Euro Area	DataStream
Spot Exchange Rates	USA	Bank of England
	Japan	Bank of England
	Canada	Bank of England
	Euro	Bank of England

Chapter 3

Evolving Macroeconomic Dynamics: A Time–varying Structural Approach using the Correct Measure of Money

3.1 Introduction

Despite the theoretical appeal of Divisia money aggregates originally derived in Barnett, 1980, central banks still focus their attention on atheoretical simple–sum monetary aggregates; more commonly known as broad money aggregates[1]. A growing literature is emerging discouraging the use of simple–sum measures of money and suggest that correctly measured monetary statistics provide better signals for financial crises (see e.g. Barnett and Chauvet, 2011). Divisia indices resolve the innate flaws in broad monetary aggregates that assume the component assets are perfect substitutes for one another. Therefore Divisia indices weight component assets in accordance with their usefulness for transaction expenditure; the more liquid the component asset, the greater the associated weight[2].

In this chapter, we examine the evolution in macroeconomic dynamics, by estimating time–varying parameter VAR models (TVP–VAR) with a stochastic volatility structure, for the US and UK economies as in Benati and Mumtaz, 2007 and Benati, 2008 from 1979 to 2015 respectively. Our New Keynesian systems augment the former and replace theoretically flawed simple–sum monetary aggregates with theoretically founded Divisia indices. Specifically, the questions we want to answer are: Can we predict macroeconomic fundamentals such as real GDP growth and inflation with more precision using

[1]The derivations in Barnett, 1980 are based on superlative index number theory in Diewert, 1976. In this chapter, we use the terms broad and simple–sum interchangeably.

[2]For a full theoretical breakdown of how Divisia indices are constructed see Barnett, 1980 and Barnett and Chauvet, 2011.

Divisia money growth in our systems of the US and UK economies? Are there differences in the transmission mechanism of monetary policy shocks over time, and how do structural shocks affect macroeconomic volatility when using the correct measure of money?

The key contribution of this study is to provide a comprehensive reduced–form and structural analysis of VAR models for the US and UK using correctly measured monetary aggregates in a time–varying framework. To the best of our knowledge, a study using Divisia money growth in a multivariate time–varying framework does not exist. The majority of VAR studies using Divisia indices assume parameters are constant (see e.g. Schunk, 2001, Albuquerque, Baumann, and Seitz, 2015 and Belongia and Ireland, 2015); yet we provide ample evidence in support for a more flexible framework.

We summarise our results into four main findings: First, we link the persistence of US and UK economic data to multivariate R^2 forecastability, and show that there are distinct differences in the overall predictability of macroeconomic fundamentals between 1990 and 2015 respectively. Moreover, in 2015 interest rates in the US and UK are substantially more predictable than in 1990. Second, TVP–VAR models using Divisia money growth provide more accurate (pseudo) forecasts of real GDP growth at 1, 4 and 8–quarter horizons for both respective economies, when comparing them to systems using simple–sum money growth. Adding to this, at 4 and 8–quarter horizons, our models using Divisia money growth produce a range of posterior credible intervals up to 10 percentage points lower than models using conventional broad money growth. Third, we document an evolution in the transmission of monetary policy shocks and note a significant change in the response of inflation, Treasury Bill rates and Divisia money growth in both economies between the periods 2008Q2–2009Q2 and 2014Q2–2015Q2 respectively; thus echoing the need to account for time–variation. Fourth, structural variance decompositions reveal that monetary policy shocks are episodic in their impacts on macroeconomic uncertainty and explain the majority of variation during recessionary periods. During the Great Recession, monetary policy shocks explain 60% and 42% of GDP growth volatility in the US and UK, respectively. In the same period, these shocks explain around 60% of inflation uncertainty in both respective economies.

The structure of the remainder of this chapter is as follows: Section 3.2 provides an overview of related literature. In Section 3.3, we discuss data, our modelling strategy and structural identification. Our empirical results for reduced–form and structural analysis is given in Section 3.4. Following on from this, we consider the robustness of our main results in Section 3.5. Finally, Section 3.6 offers concluding comments.

3.2 Related Literature

Our work relates to three main strands of literature. First, we extend on previous work concentrating on changing macroeconomic dynamics (see e.g. Kim and Nelson, 1999, Cogley and Sargent, 2005, Cogley, 2005, Bianchi, Mumtaz, and Surico, 2009 and Barnett, Groen, and Mumtaz, 2010). We offer a time–varying Bayesian perspective on the evolution of both reduced–form and structural analysis spanning the Great Recession and the following recovery period; whereas the majority of literature focus on post–WWII data. Our work directly extends that of Benati and Mumtaz, 2007 and Benati, 2008. In particular, the former focus on the Great Inflation and following Great Moderation using US macroeconomic data and provides counterfactual evidence supporting the view that the reduced macroeconomic volatility was down to good luck. The latter offers a similar analysis, but for the UK; with the same conclusions holding.

It is not the purpose of this work to provide a counterfactual examination of US and UK economic policies, particularly monetary policies, during the financial crisis. However, an examination of (monetary) policy responses of the US and UK to the 2008 recession may be found in Hamilton and Wu, 2012 and Kapetanios et al., 2012. Our aims are to show that Divisia indices provide greater precision for forecasting purposes and more plausible interpretations from structural analysis over macro–econometric models using simple–sum measures of money. We extend our structural investigation beyond the realm of conventional impulse response analysis and provide time–varying structural variance decompositions of macroeconomic data in the frequency domain in the spirit of Barnett, Groen, and Mumtaz, 2010. The purpose of this is to attribute the impact of identified structural shocks on macroeconomic volatility implied by our TVP–VAR models. This exercise provides an idea of how structural shocks propagate onto macroeconomic uncertainty at high, medium and low frequencies, respectively.

Second, our results are in direct support of existing work on both forecasting and nowcasting using Divisia money. Schunk, 2001 assesses the relative forecasting performance of Divisia indices against simple–sum measures from VAR models to forecast US real GDP and prices. The above authors shows the most accurate forecasting model is one including Divisia indices. Similarly, Albuquerque, Baumann, and Seitz, 2015 forecast US real GDP using different monetary and credit variables in both a single–equation and VAR framework. The best forecasts of real GDP including the financial crisis period are from recursive out–of–sample models including Divisia money aggregates. For the UK, Florackis et al., 2014 show that real–time GDP forecasts from a regime–switching model including Divisia money growth improve the forecasts of those models used by the Bank of England. More recently, a growing trend is to look at nowcasting variables using real–time data. Barnett, Chauvet, and Leiva-Leon, 2016 propose a multivariate nonlinear state space model that produces accurate nowcasts of US nominal GDP when using Divisia indices. On the whole, the policy implications from the above studies are that Divisia indices increase the quality of the information set for forecasting US and UK GDP. Our (in–sample) pseudo–forecasting exercises carried out following Cogley, Primiceri, and Sargent, 2010 conform to this view.

Finally, our results are important for structural studies, both theoretical and empirical, using Divisia indices. Keating et al., 2014 show, using a Dynamic Stochastic General Equilibrium (DSGE) model, that an appropriately parametrised Divisia rule is observationally equivalent to a Taylor rule. Then, the authors estimate a structural VAR (SVAR) model in the spirit of Keating, Kelly, and Valcarcel, 2014. Empirical analysis confirms the theoretical results which have spurred a number of papers to include or replace conventional policy rates (or Treasury Bill rates) with Divisia money as the monetary policy variable (see e.g. Belongia and Ireland, 2015 and Belongia and Ireland, 2016). Results from these studies are not conflicting, these papers confirm plausible monetary policy rules based on monetary aggregates. We do not take a stance on this issue. Our view would be to use both interest rates and money as the central bank's monetary policy tools; especially in light of combining the US Federal Funds rate and UK Bank rate being at their respective zero lower bounds, with the implementation of Quantitative Easing (QE) policies. However, the problem here is how to properly identify a monetary policy shock and an orthogonal shock that captures QE policies through the lens of monetary aggregates. This is a thought provoking topic which we leave for future research. Instead, we give a structural examination of a conventional New Keynesian framework replacing broad money with Divisia money in a fully flexible, time–varying framework. What our analysis provides is substantial evidence in favour of using correctly measured monetary statistics and distinct differences in how structural shocks from these systems affect fluctuations, in macroeconomic variables over different frequencies; a unique element of our study.

3.3 Data and Modelling Strategy

3.3.1 Data

TABLE 3.1: Descriptive Statistics for Macroeconomic Data from 1979 to 2015

Panel A: USA	y_t	π_t	i_t	m_t
Mean	2.60	2.92	4.79	4.72
Median	2.79	2.27	4.88	5.03
Std. Dev	2.06	1.97	3.66	2.84
Skew	-0.68	1.94	0.57	-1.23
Kurt	1.60	3.35	-0.10	3.77
Panel B: UK	y_t	π_t	i_t	m_t
Mean	2.18	4.17	6.68	7.60
Median	2.54	3.10	5.77	7.56
Std. Dev	2.20	3.54	4.36	3.56
Skew	-1.38	2.06	0.26	0.21
Kurt	3.17	4.84	-0.79	-0.16

Notes: This table reports the descriptive statistics for US and UK economic data in Panels A and B from 1979Q1–2015Q2, respectively. y_t is annual real GDP growth; π_t is the annual rate of inflation; i_t is the 3–month Treasury Bill rate; m_t is annual Divisia M4 money growth. Annual growth rates are calculated as annual logarithmic differences.

We use US and UK quarterly data on real GDP growth, y_t; the rate of GDP deflator inflation, π_t; the economy's short–term interest rate which we proxy as the 3–month Treasury Bill rate, i_t; and Divisia M4 money growth, m_t from 1979Q1-2015Q2 (we use the first 10 years of data to calibrate the initial conditions of the model, therefore the model estimation samples cover 1989Q3–2015Q2 respectively). Variables are annual growth rates, which we express as fourth order logarithmic differences, except for the interest rate. All US data is from the Federal Reserve Bank of St Louis except for Divisia M4 (including Treasuries) which is from the Centre for Financial Stability[3]. UK GDP

[3]Divisia M3, M4 excluding Treasuries and M4 including Treasuries are from `http://www.centerforfinancialstability.org/amfm.php` which rely on methods proposed in Barnett, 1980. A discussion of the underlying data and methodologies are in Barnett et al., 2013. Choice of Divisia index is dependent on the application at hand. We opt for the broadest measure following Keating et al., 2014 because Divisia M4 contains a wide variety of component assets through which monetary policy and money demand transmissions can feed into. Note that our analysis does not change when using the alternative measures of Divisia made available by the Centre for Financial Stability–although results are avaialble on request. We choose to report the results using Divisia M4 including Treasuries to keep US analysis consistent with the UK.

and the GDP deflator are from the Office for National Statistics database; the interest rate and Divisia money are from the Bank of England's statistical database[4].

Table 3.1 reports the descriptive statistics of our variables. As we can see, on average, (sample) real GDP growth is higher for the US than the UK. Yet average UK inflation is 1.25 percentage points greater than US inflation within our sample. This is due to rates of UK inflation of around 20% in the early 1980s. On average, the UK Treasury Bill rate is 1.89 percentage points greater (and more volatile) than the US Treasury Bill rate. Yet they have similar estimates of skewness and kurtosis. Divisia M4 growth for the US, is 2.88 percentage points lower, on average, than in the UK. However, the volatilities of Divisia M4 growth are similar.

Figures 3.1 and 3.2 plot US and UK economic data from 1979Q1–2015Q2 respectively; grey bars indicate National Bureau of Economic Research (NBER) recession dates. We add these to our plots of UK data (and where necessary to the following analysis) since UK recession dates are similar to those in the US[5]. Clearly from Figures 3.1 and 3.2, we can see that Divisia money growth tends to decline during recessions. Note also that from 2010, Divisia money growth surges for both economies; possibly capturing the implementation of unconventional monetary policies in the US and UK from late 2008 and early 2009, respectively[6].

[4]We use the Bank of England's preferred Divisia index which includes private non–financial corporations and household sector (code: LPQB6F3). The previous Divisia aggregate (code: LPQVTSP) was discontinued in December 2013.

[5]Sample UK recession dates are: 1980Q1–1981Q3; 1990Q3–1991Q3; and 2008Q2–2009Q2, respectively.

[6]It is beyond the scope of this chapter to assess the impact of QE policies. A detailed discussion on the implications of QE can be found in Joyce et al., 2012. An interesting future avenue of research would be to examine the real effects of QE using Divisia money aggregates.

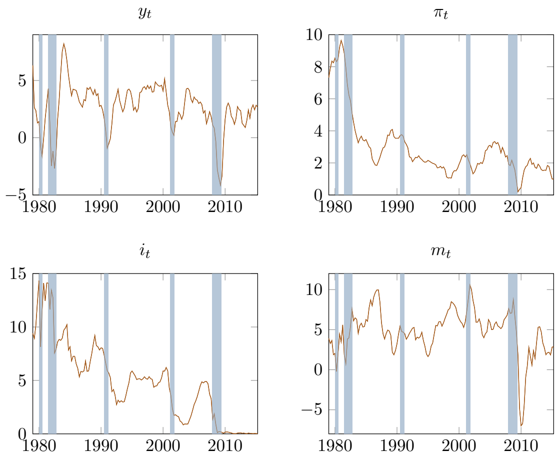

FIGURE 3.1: **US Macroeconomic data from 1979 to 2015**
Notes: This figure plots annual growth rates of US macroeconomic data from 1979Q1–2015Q2 respectively. We express all variables as annual (%) growth rates as fourth order logarithmic differences; except for the interest rate. The top left panel shows Real GDP growth, y_t; the top right panel is the annual rate of GDP deflator inflation, π_t; the bottom left panel is the the US 3–month Treasury Bill rate, i_t, and the bottom right panel is annual Divisia money growth, m_t, respectively. Grey bars indicate NBER recession dates.

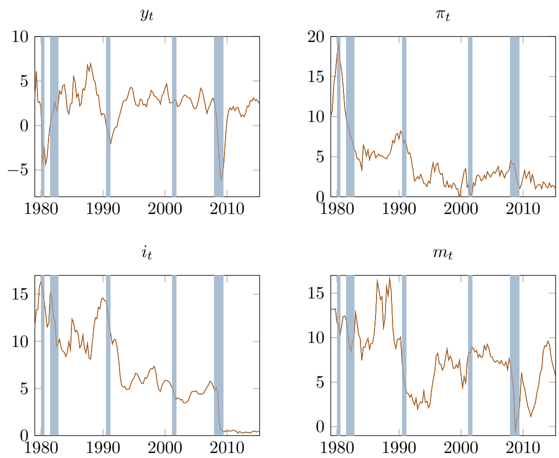

FIGURE 3.2: **UK Macroeconomic data from 1979 to 2015**
Notes: This figure plots annual growth rates of UK macroeconomic data from 1979Q1–2015Q2 respectively. We express all variables as annual (%) growth rates as fourth order logarithmic differences; except for the interest rate. The top left panel shows Real GDP growth, y_t; the top right panel is the annual rate of GDP deflator inflation, π_t; the bottom left panel is the UK 3–month Treasury Bill rate, i_t, and the bottom right panel is annual Divisia money growth, m_t, respectively. Grey bars indicate NBER recession dates.

3.3.2 A Time–varying Parameter VAR with Stochastic Volatility

We work with the following TVP–VAR model with p lags and M variables:

$$Y_t = \beta_{0,t} + \beta_{1,t}Y_{t-1} + \cdots + \beta_{p,t}Y_{t-p} + \epsilon_t \equiv X_t'\theta_t + \epsilon_t \tag{3.1}$$

where Y_t is defined as $Y_t \equiv [y_t,\ \pi_t,\ i_t,\ m_t]'$, with y_t being annual real GDP growth, π_t is the annual rate of GDP deflator inflation, i_t is the short term interest rate (i.e. the 3–month Treasury Bill rate), and m_t is the annual growth of the Divisia money aggregate, respectively. X_t' contains lagged values of Y_t and a constant. In our case, $M = 4$, and we set a lag length $p = 2$ which is consistent with Primiceri, 2005, Benati and Mumtaz, 2007 and Benati, 2008. As in Cogley and Sargent, 2005, the VAR's time–varying parameters are collected in θ_t and evolve as

$$p(\theta_t|\theta_{t-1}, Q) = I(\theta_t)f(\theta_t|\theta_{t-1}, Q) \tag{3.2}$$

where $I(\theta_t)$ is an indicator function that rejects unstable draws. Therefore we impose a stationarity constraint on the VAR where $f(\theta_t|\theta_{t-1}, Q)$ follows a random walk

$$\theta_t = \theta_{t-1} + \nu_t \tag{3.3}$$

where $\nu_t \backsim N(0, Q)$. The innovations in (3.1) follow $\epsilon_t \backsim N(0, \Omega_t)$. Ω_t is the time–varying covariance matrix which we factor as

$$Var(\epsilon_t) \equiv \Omega_t = A_t^{-1}H_t(A_t^{-1})' \tag{3.4}$$

The structure of the time–varying matrices, $A_t,\ H_t$ are:

$$H_t \equiv \begin{bmatrix} h_{1,t} & 0 & 0 & 0 \\ 0 & h_{2,t} & 0 & 0 \\ 0 & 0 & h_{3,t} & 0 \\ 0 & 0 & 0 & h_{4,t} \end{bmatrix} \quad A_t \equiv \begin{bmatrix} 1 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 \end{bmatrix} \tag{3.5}$$

$h_{i,t}$ evolves as a geometric random walk and $\alpha_t \equiv [\alpha_{21,t},\ \alpha_{31,t}, \ldots, \alpha_{43,t}]'$ follows a random walk, respectively

$$\ln h_{i,t} = \ln h_{i,t-1} + \eta_t \tag{3.6}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t \tag{3.7}$$

The innovations in the model are jointly Normal

$$\begin{bmatrix} u_t \\ \nu_t \\ \zeta_t \\ \eta_t \end{bmatrix} \backsim N(0, V), \quad V = \begin{bmatrix} I_M & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix} \tag{3.8}$$

where u_t is such that, $\epsilon_t \equiv A_t^{-1} H_t^{\frac{1}{2}} u_t$. The matrices Q, S, W are all positive definite and we follow Primiceri, 2005 by imposing S is a block diagonal matrix:

$$S \equiv Var(\zeta_t) = \begin{bmatrix} S_1 & 0_{1\times 2} & 0_{1\times 3} \\ 0_{2\times 1} & S_2 & 0_{2\times 3} \\ 0_{3\times 1} & 0_{2\times 3} & S_3 \end{bmatrix} \tag{3.9}$$

where $S_1 \equiv Var(\zeta_{21,t})$, $S_2 \equiv Var([\zeta_{31,t},\ \zeta_{32,t}]')$ and $S_3 \equiv Var([\zeta_{41,t},\ \zeta_{42,t},\ \zeta_{43,t}]')$. This implies that the non–zero and non–unit elements of A_t that belong to different rows evolve independently. This is a simplifying assumption that allows us to estimate (the non–zero and non–unit elements of) A_t equation by equation. We estimate the model in (3.1)–(3.9) via Bayesian methods using 100,000 iterations of the Gibbs sampler using the first 99,000 as burn–in, and save the remaining 1,000 iterations. Appendix A in Section 3.7.1 provides detail for our choices of priors and sketches the Markov–Chain Monte Carlo (MCMC) algorithm to simulate the posterior distribution of hyperparameters and states, conditional on the data. Appendix B in Section 3.7.2 assesses the convergence properties of the MCMC algorithms of our estimated systems using US and UK data.

3.3.3 Structural Identification and Computing Impulse Response Functions

We augment a standard New Keynesian framework of real GDP growth, y_t; the rate of GDP deflator inflation, π_t and the interest rate, i_t with the inclusion of the economy's Divisia money aggregate, m_t. We characterise the structural shocks as in Benati and Mumtaz, 2007 and Benati, 2008, $u_t = [u_t^S,\ u_t^D,\ u_t^{MP},\ u_t^{MD}]'$ as: supply shocks, demand non–policy shocks, monetary policy shocks and money demand shocks, respectively. To identify, we impose sign restrictions (on a period–by–period basis) for the contemporaneous impacts of structural shocks on the four endogenous variables. Table 3.2 summarises the contemporaneous impacts on the variable subject to a positive structural shock.

To compute impulse response functions, we implement the algorithm in Rubio-Ramirez, Waggoner, and Zha, 2010. Let $\Omega_t = P_t D_t P_t'$ be the eigenvalue–eigenvector decomposition of the VAR model's time–varying covariance matrix, Ω_t and let $\tilde{A}_{0,t} = P_t D_t^{\frac{1}{2}}$. We

TABLE 3.2: Sign Restrictions Imposed on Contemporaneous Relationships of Variables

Shock:	u_t^S	u_t^D	u_t^{MP}	u_t^{MD}
Variable				
y_t	$\geq$	$\geq$	$\leq$	$\leq$
π_t	$\leq$	$\geq$	$\leq$	$\leq$
i_t	x	$\geq$	$\geq$	$\geq$
m_t	x	$\geq$	$\leq$	$\geq$

x denotes no constraint on the variable.

then draw an $M \times M$ matrix K from the $N(0,1)$ distribution and take the QR decomposition of K (i.e. $K = Q \cdot R$). We then compute the contemporaneous structural impact matrix, $\bar{A}_{0,t} = \tilde{A}_{0,t} \cdot Q'$. If the draw satisfies our restrictions we keep it, otherwise we discard until the restrictions are satisfied.

3.4 Results

3.4.1 Reduced–Form Evidence

The Evolution of Ω_t

Figures 3.3 and 3.4 provide simple illustrations of the Great Moderation followed by the impact of the financial crisis. Specifically, we plot the time–varying median and one standard deviation bounds of the distribution of the logarithmic determinant of the reduced–form VAR covariance matrix, $\ln|\Omega_t|$ from our models of US and UK data respectively[7]. Following Cogley and Sargent, 2005 we interpret this as the amount of 'noise hitting the system' at each observation of our sample[8]. In general, we can see that prediction variation fluctuates largely throughout time. It is evident that the prediction variance increases during recessions. There are substantial surges from both VAR models at the time the dot–com bubble bursts in 2001, and even more drastic increases during the 2008 recession. Then, following the Great Recession, prediction variation declines sharply in both economies to sample minimum in 2015Q2.

In the US and UK, we can see that the prediction variance starts to increase before the 2008 recession, from 2006. There are two possible interpretations for these results. First, our estimates of each respective TVP–VAR model from the Gibbs sampler are

[7]The one standard deviation bounds are the 16^{th} and 84^{th} percentiles under normality. This covers 68% of the object's distribution under examination.

[8]However, this interpretation can be somewhat misleading. Supposing two shocks hit the system that are linearly dependent, then the log determinant of the variance–covariance matrix will be very small. However, the system may still be very difficult to predict. As in Benati and Mumtaz, 2007 it is not clear how to solve this problem effectively.

two–sided. Therefore, during times of structural breaks, the algorithm 'mixes' past and future states. Second, our models are indirectly, but exactly capturing the underlying turbulences in the financial sector that unwind both respective economies in 2008.

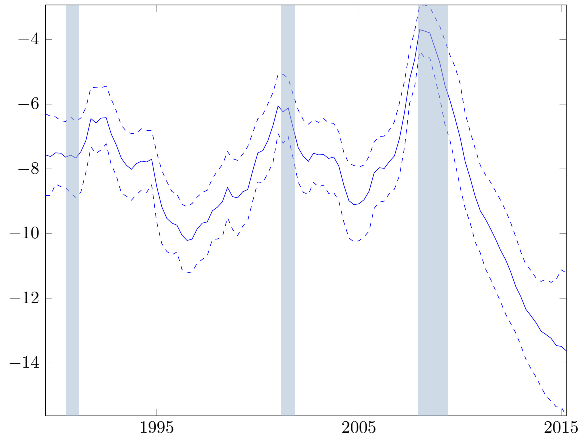

FIGURE 3.3: **Logarithmic Determinant of the Reduced–Form VAR Covariance Matrix,** $\ln|\Omega_t|$ **using US Data from 1989 to 2015**
Notes: This figure shows the median and 1 standard deviation percentiles of the time-varying logarithmic determinant of the estimated reduced–form VAR covariance matrix using US data from 1989Q3–2015Q2 respectively. Grey bars indicate NBER recession dates.

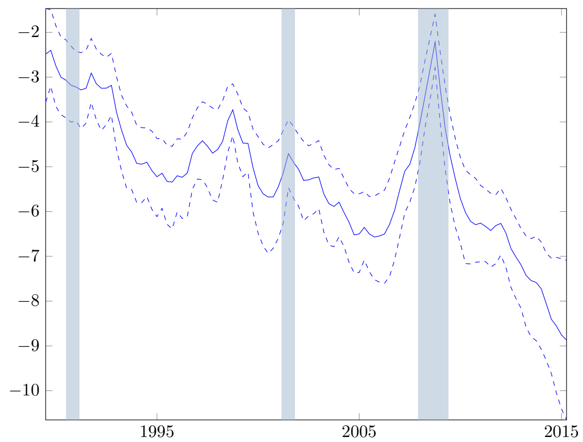

FIGURE 3.4: **Logarithmic Determinant of the Reduced–Form VAR Covariance Matrix,** $\ln|\Omega_t|$ **using UK Data from 1989 to 2015**
Notes: This figure shows the median and 1 standard deviation percentiles of the time-varying logarithmic determinant of the estimated reduced–form VAR covariance matrix using UK data from 1989Q3–2015Q2 respectively. Grey bars indicate NBER recession dates.

The Persistence and Dynamic Predictability of Macroeconomic Fundamentals in the US and UK

Following Cogley and Sargent, 2005, Benati and Mumtaz, 2007 and Baumeister and Peersman, 2013, we approximate the persistence of our macroeconomic variables in the frequency domain calculating each time series' respective spectral densities

$$f_{x,t|T}(\omega) = s_x(I_4 - \tilde{\beta}_{t|T}e^{-i\omega})^{-1}\frac{\Omega_{t|T}}{2\pi}\left[(I_4 - \tilde{\beta}_{t|T}e^{-i\omega})^{-1}\right]' s_x' \tag{3.10}$$

where s_x is a row vector selecting variable $x = \{y_t,\ \pi_t,\ i_t,\ m_t\}$, $\tilde{\beta}_{t|T}$ are the time–varying coefficient matrices, $\Omega_{t|T}$ are the time–varying reduced–form VAR covariance matrices and $\omega \in [0 \quad \pi]$ denotes the frequency window, respectively[9]. We approximate the time–varying persistence of each series, $x = \{y_t,\ \pi_t,\ i_t,\ m_t\}$, by normalising the spectrum for every observation of our sample at $\omega = 0$.

Figures 3.5 and 3.6 plot the median together with the 16^{th} and 84^{th} percentiles of the distribution for the persistence of our macroeconomic variables for the US and UK respectively. We can see from Figure 3.5 how the persistence of US macroeconomic fundamentals evolves over our sample. The persistence of US real GDP growth fluctuates smoothly becoming slightly more persistent in 2015 relative to 1990. Interestingly, the persistence of the interest rate increases substantially throughout time; particularly following the 2008 recession. More specifically, in the latter years of our sample the persistence of the US short–term interest rate doubles from 0.2 in 2008Q2 to 0.4 in 2015Q2 (from posterior median estimates). Contrastingly, note that the spikes in the persistence of GDP deflator inflation and Divisia money growth correspond particularly well with the start of NBER recession dates[10]. In general, the persistence of inflation and Divisia money growth fluctuate around 0.35 and 0.15 respectively (from posterior median estimates).

Turning to Figure 3.6, it is clear there are differences in the persistence of UK macroeconomic fundamentals. The persistence of UK real GDP growth is declining until 2005Q2, then surges during the 2008 recession before reverting back to a constant level of around 0.18 from 2009Q4 until the end of our sample. However, in general, the persistence of inflation and Divisia money growth are slightly declining throughout time. Note also that inflation and Divisia money persistence both surge in the most recent recession and revert sharply back to levels consistent with those before the financial

[9] A series overall variance is given by the integral of the spectral densities over the frequency window, ω.

$$\sigma^2_{x,t|T} = \int_\omega f_{x,t|T}(\omega)d\omega$$

[10] Our estimate of US inflation persistence is similar in shape from 1990–2005 to that of Benati and Mumtaz, 2007.

crisis. Contrarily, interest rate persistence is increasing smoothly throughout our sample. From posterior median estimates, persistence in the interest rate increases from 0.2 in 1989 to 0.45 in 2015.

It is well known that the persistence of a stochastic process relates positively to its R^2 forecastability (see e.g. Barsky, 1987 and Granger and Newbold, 2014). Therefore, we should expect US real GDP growth, inflation and Divisia money growth to remain relatively constant (with slight fluctuations), and the interest rate to become more predictable throughout time. To contrast, the trends in persistence of UK macroeconomic variables automatically imply the predictability of: UK real GDP growth should decrease until 2005Q2 and then start to increase; inflation and Divisia money should exhibit gradual decreases, and the interest rate should substantially increase; we show in Table 3.3 that this has indeed been the case.

Table 3.3 reports the median and one standard deviation percentiles of the (1–quarter ahead) multivariate time–varying R^2 statistics for our US (Panel A) and UK (Panel B) macroeconomic variables at five–year intervals from 1990Q2–2015Q2 respectively. We calculate our R^2 statistics following Cogley, Primiceri, and Sargent, 2010, who postulate that these pseudo–forecasts capture developments in the persistence of a time series process. Furthermore, this measure provides information with regards to the contribution of past shocks to current and future variation of the variable of interest (Diebold and Kilian, 2001)[11].

Perhaps unsurprisingly, the posterior median of the multivariate R^2 statistics in 2015Q2 of the 3–month Treasury Bill rates in both the US and UK are 0.99 and 0.98 respectively. These results are consistent with Benati and Mumtaz, 2007 and Benati, 2008 showing the interest rates are exhibiting close to unit root behaviour. On the other hand, interest rates plummet in the US and UK at the end of 2008 and the beginning of 2009 respectively. Given that, at the time of writing, interest rates in the US and UK are at historical lows (and have been for over 6 years), it is intuitive to observe an increase in predictability of short–term interest rates throughout our sample.

For the US, the pseudo–forecasts for real GDP growth, inflation and Divisia money growth remain relatively constant throughout our sample. However, the predictability of UK real GDP growth and inflation is diminishing throughout time with a decline in the R^2 forecastability of 0.13 and 0.19 percentage points respectively. Further, pseudo–forecasts of UK Divisia money growth are relatively constant from 1995Q2–2015Q2 with posterior median estimates fluctuating around 0.67 respectively.

[11]We deem these statistics as pseudo–forecasts because we omit complications associated with real–time forecasting. However, our objective is to obtain precise estimates, therefore this is not a short–cut; thus, we opt for an ex–post exercise using final–time data and estimate our models using data through the full–sample.

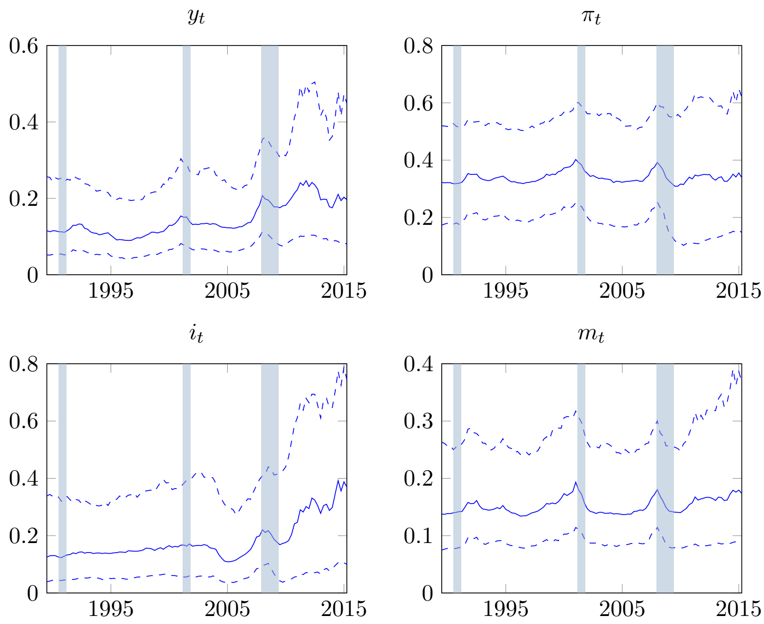

FIGURE 3.5: **Persistence of Macroeconomic Variables using US Data from 1989 to 2015**

Notes: This figure shows the median and 1 standard deviation percentiles of the spectrum at $\omega = 0$ of: real GDP growth, y_t; the rate of GDP deflator inflation, π_t; the 3–month Treasury Bill rate, i_t and Divisia money growth, m_t using US data from 1989Q3–2015Q2 respectively. Grey bars indicate NBER recession dates.

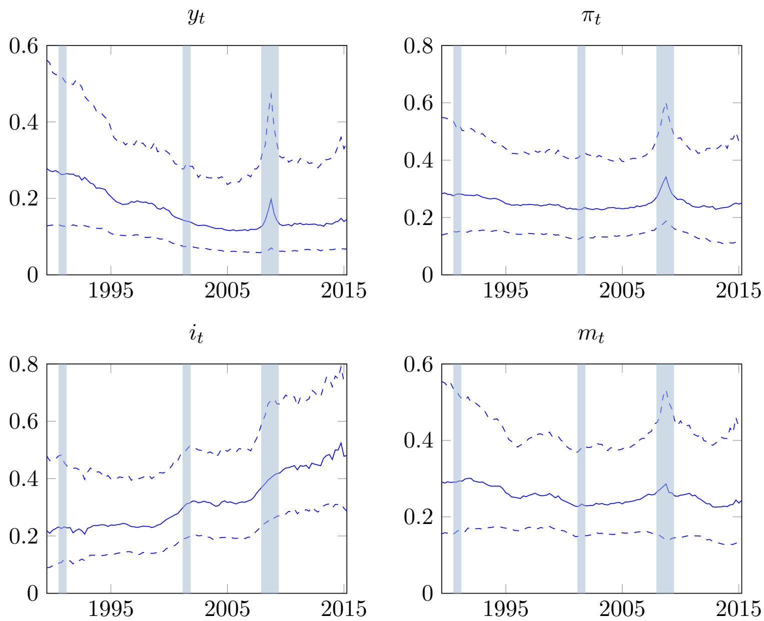

FIGURE 3.6: **Persistence of Macroeconomic Variables using UK Data from 1989 to 2015**

Notes: This figure shows the median and 1 standard deviation percentiles of the spectrum at $\omega = 0$ of: real GDP growth, y_t; the rate of GDP deflator inflation, π_t; the 3–month Treasury Bill rate, i_t and Divisia money growth, m_t using UK data from 1989Q3–2015Q2 respectively. Grey bars indicate NBER recession dates.

TABLE 3.3: Time–varying Multivariate R^2 Statistics for US and UK Macroeconomic Variables

Panel A: USA	y_t	π_t	i_t	m_t
1990Q2	0.64 [0.55 0.75]	0.90 [0.84 0.95]	0.90 [0.80 0.96]	0.76 [0.64 0.86]
1995Q2	0.62 [0.53 0.71]	0.88 [0.82 0.94]	0.92 [0.83 0.97]	0.82 [0.74 0.90]
2000Q2	0.65 [0.56 0.76]	0.89 [0.83 0.95]	0.85 [0.76 0.93]	0.81 [0.73 0.89]
2005Q2	0.65 [0.56 0.74]	0.87 [0.80 0.92]	0.97 [0.94 0.99]	0.73 [0.62 0.82]
2010Q2	0.68 [0.59 0.79]	0.89 [0.81 0.95]	0.98 [0.96 0.99]	0.62 [0.54 0.71]
2015Q2	0.65 [0.55 0.75]	0.85 [0.78 0.92]	0.99 [0.98 0.998]	0.79 [0.67 0.90]
Panel B: UK	y_t	π_t	i_t	m_t
1990Q2	0.85 [0.75 0.93]	0.79 [0.68 0.89]	0.78 [0.66 0.90]	0.76 [0.62 0.88]
1995Q2	0.68 [0.58 0.78]	0.65 [0.54 0.78]	0.85 [0.76 0.93]	0.69 [0.58 0.80]
2000Q2	0.66 [0.57 0.76]	0.64 [0.52 0.77]	0.90 [0.80 0.96]	0.67 [0.56 0.78]
2005Q2	0.65 [0.56 0.74]	0.59 [0.48 0.73]	0.92 [0.83 0.97]	0.66 [0.55 0.78]
2010Q2	0.71 [0.62 0.79]	0.60 [0.47 0.74]	0.94 [0.87 0.98]	0.69 [0.57 0.80]
2015Q2	0.72 [0.61 0.81]	0.60 [0.46 0.76]	0.98 [0.95 0.996]	0.67 [0.54 0.80]

Notes: This table reports the median and one standard deviation percentiles in square parentheses of the distribution of the 1–quarter ahead time–varying multivariate R^2 statistics for US and UK Macroeconomic Fundamentals: annual real GDP growth, y_t; annual GDP deflator inflation, π_t; The 3–month Treasury Bill rate, i_t and annual Divisia money growth, m_t respectively. We report estimates at 5 year intervals spanning our estimation sample.

We follow Cogley, Primiceri, and Sargent, 2010, and determine the significance of a change in the R^2 forecastability of US and UK macroeconomic variables by plotting, in Figures 3.7 and 3.8, the joint distribution of draws of the multivariate R^2 statistics in 1990Q2 (x-axis), against those in 2015Q2 (y-axis) respectively.

In Figure 3.7 it is clear that the distribution of R^2 statistics for US real GDP growth clusters heavily around the $45°$ line thereby indicating little difference in the (pseudo) forecastability of US GDP growth in 1990 and 2015. Similarly, the extent to which there is a significant difference in the forecastability of US Divisia money growth is negligible; although around 65% of the distribution lies above the 45° line. However for US GDP deflator inflation, around 80% of the distribution of R^2 statistics lie below the 45° line. This suggests inflation is more predictable in the earlier years of our sample which is consistent with results in Cogley, Primiceri, and Sargent, 2010 and Stock and Watson, 2007[12]. Clearly and unsurprisingly, the 3–month Treasury Bill rate is more predictable in 2015Q2 with the majority of the distribution congregating above (and away from) the 45° line.

[12]That said, our sample begins only in 1989, whereas both of the former use notably longer time series samples (i.e. 1948Q1–2004Q4 and 1960Q1–2004Q4 respectively). However, the former use quarterly rates and annualised quarterly rates of US inflation respectively. In our case, we use the annual rate, which may influence the relatively high estimates of our multivariate R^2 statistics. Although we use a shorter time series sample, we incorporate the Great Recession and a substantial period following the financial crisis. It is beyond the scope of this chapter to assess in detail the long–run time–series properties of inflation (or the changing dynamics of inflation during and after the recent financial crisis) as documentation on this topic, particularly of postwar US inflation, is heavy (see e.g. Stock and Watson, 2007 and references therein).

For the UK economy, there are a number of differences. First, the distribution of R^2 statistics for real GDP growth show clear evidence of a greater level of predictability in 1990Q2 relative to 2015Q2. Second, the distribution of multivariate R^2 statistics for UK GDP deflator inflation has a wider dispersion than the US (see top right panel of Figure 3.8), yet has a greater R^2 in 1990Q2 relative to 2015Q2; with around 80% of the draws lying below the $45°$ line. However, the distribution of R^2 statistics for UK Divisia money growth reveal no discernible differences in the overall forecastability in 1990Q2 and 2015Q2. Finally, it is clear that the UK 3–month Treasury Bill rate has a multivariate R^2 significantly greater in 2015Q2 than 1990Q2 indicating improvements in pseudo–forecasts.

In general, what can be taken from our reduced–form evidence is that the amount of 'noise hitting the system' varies significantly throughout time for both the US and UK respectively. In particular, sample minimums of $\ln|\Omega_t|$ are in 2015Q2; thereby indicating (possibly) fewer (or smaller) shocks hitting the system thus reducing overall prediction variation. A contributing factor may lie with the historically low levels of interest rates in the US and UK from late 2008 and early 2009 to the end of our sample. Adding to this, we provide evidence of linkages between the persistence and predictability of US and UK macroeconomic fundamentals, which is consistent with Cogley and Sargent, 2005, Benati and Mumtaz, 2007 and Cogley, Primiceri, and Sargent, 2010. Specifically, we document a significant increase in the forecastability (from 1990Q2 relative to 2015Q2) of both US and UK 3–month Treasury Bill rates which is in contrast to the interpretations in Benati and Mumtaz, 2007 and Benati, 2008 since we are taking into account the entire joint distribution of the R^2 statistics[13].

[13]Indeed, plotting the time–varying R^2 statistics for the short–term interest rates (along with other macroeconomic fundamentals) in the US and UK respectively and simply looking at these plots infers little change in the predictability of the 3–month Treasury Bill rates. For the sake of brevity, we do not report these plots, but they are available on request.

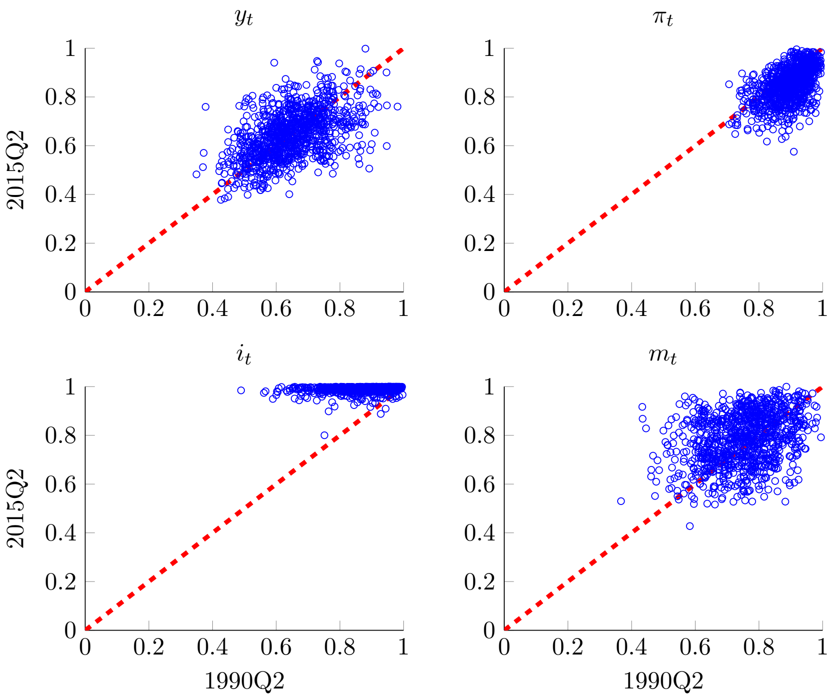

FIGURE 3.7: **Joint Distributions of Multivariate R^2 Statistics for US Macroeconomic Variables 1990Q2, 2015Q2**

Notes: This figure plots the joint distributions of the 1–quarter ahead multivariate R^2 statistics of US real GDP growth, y_t; GDP deflator inflation, π_t; the 3–month Treasury Bill rate, i_t and annual Divisia money growth, m_t for 1990Q2 (x-axis) and 2015Q2 (y-axis) respectively. In addition to the scatter plots, we include a 45° line.

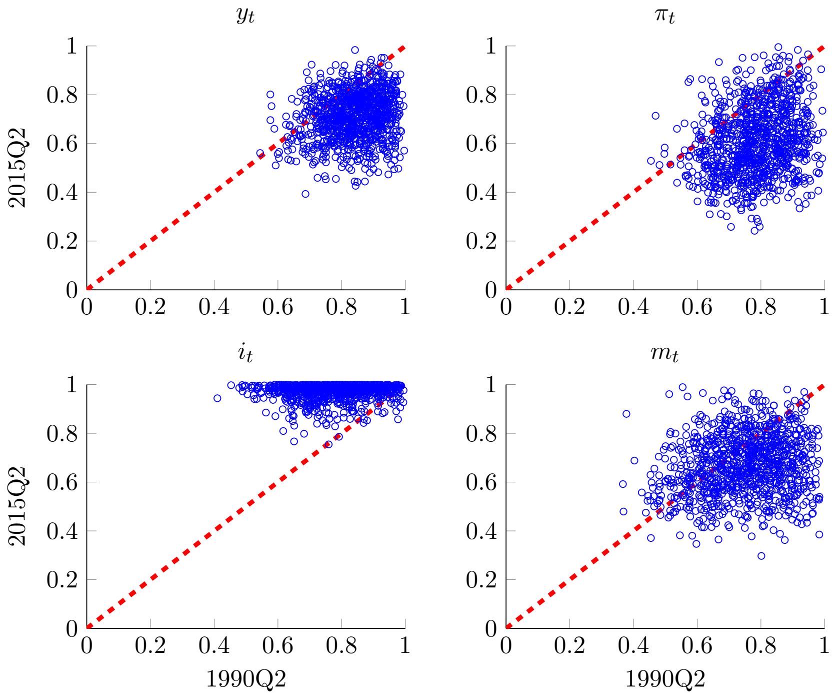

FIGURE 3.8: **Joint Distributions of Multivariate R^2 Statistics for UK Macroeconomic Variables 1990Q2, 2015Q2**

Notes: This figure plots the joint distributions of the 1–quarter ahead multivariate R^2 statistics of UK real GDP growth, y_t; GDP deflator inflation, π_t; the 3–month Treasury Bill rate, i_t and annual Divisia money growth, m_t for 1990Q2 (x-axis) and 2015Q2 (y-axis) respectively. In addition to the scatter plots, we include a $45°$ line.

3.4.2 Structural Evidence

The Transmission of Monetary Policy Shocks

To assess the dynamic transmission of monetary policy shocks in the US and UK, we plot in Figures 3.9 and 3.10 the posterior median of the distribution of the impulse response functions for our macroeconomic data at each observation in our sample, 1989Q3–2015Q2 respectively. As we can see from the top left panels of Figures 3.9 and 3.10, the sensitivity of real GDP growth in both economies varies considerably throughout time. In particular notice that the contractionary impact of monetary policy shocks, in both the US and UK, is greatest during the financial crisis period. Interestingly, the median response of GDP growth in both economies becomes positive around 6 quarters following the shock during the recession; albeit marginal for the UK.

Similarly, the response of inflation (see the top right panels of Figure 3.9 and 3.10) varies remarkably over our sample. Again, the contraction in inflation is greatest during the 2008 recession for both the US and UK. The profile of the median response of both economy's respective 3–month Treasury Bill rates reveal that peaks are predominantly in conjunction with NBER recession dates (see bottom left panels of Figure 3.9 and 3.10). Furthermore, Divisia money growth declines following a monetary policy shock in both the US and UK (see the bottom right panels of Figure 3.9 and 3.10). In the US, the economic impact of monetary policy shocks on Divisia money growth is greater during times of recession. In the UK, there is less variation in the median impulse response functions relative to the US. However, the impact of a monetary policy shock in the most recent recession is clearly distinguishable[14].

[14] Interestingly, the response of UK real GDP growth with respect to a monetary policy shock in 2015Q2 (Figure 3.10) far outweighs the decline in US real GDP growth with respect to a monetary policy shock in 2015Q2 (Figure 3.9). Arguably, there appears to be less pressure on the Bank of England's Monetary Policy Committee (MPC) than on the Federal Open Market Committee (FOMC) to raise the Bank rate at this time. We note that the FOMC raised the target range for the Federal Funds rates by 25 basis points to 0.5% in December 2015 see `https://www.federalreserve.gov/newsevents/press/monetary/20151216a.htm`.

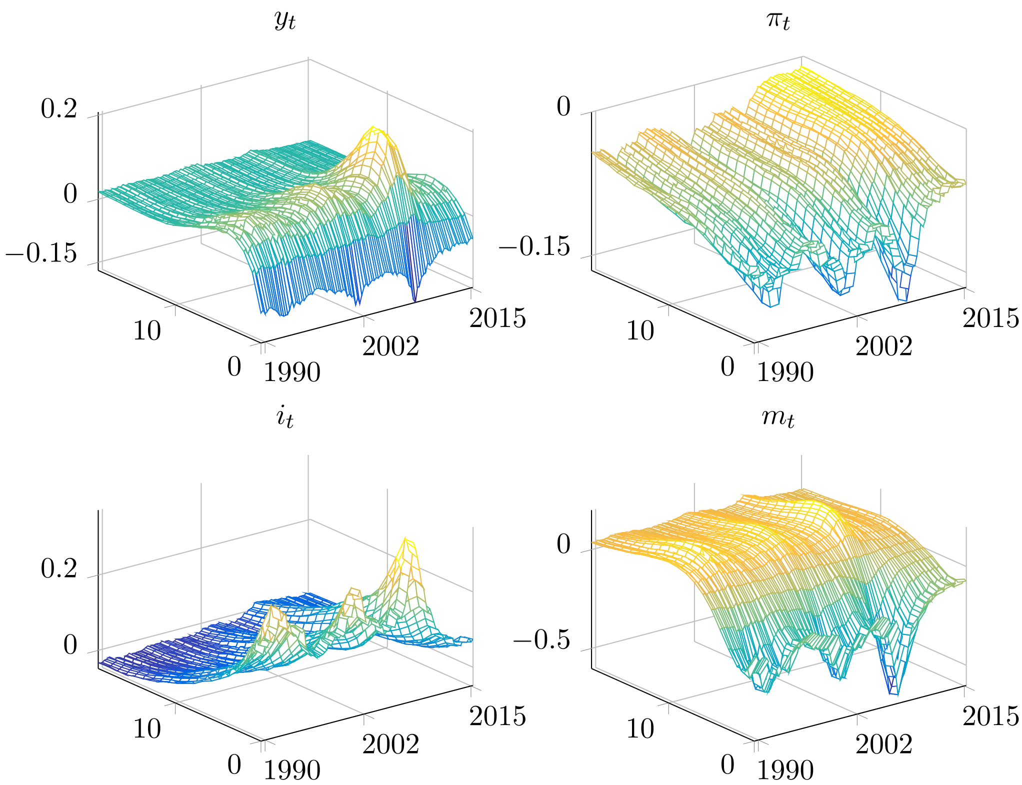

FIGURE 3.9: **Impact of Monetary Policy Shocks for the US Economy from 1989 to 2015**
Notes: This figure plots the median impulse response functions of: real GDP growth; inflation; the interest rate and Divisia money growth to a monetary policy shock. We plot the response along a 20–quarter horizon for each observation of our sample 1989Q3-2015Q2.

In order to assess the extent of the time–variation in the response of monetary policy shocks, we follow Barnett, Groen, and Mumtaz, 2010 and plot the joint distribution of the average one year accumulated response of US and UK macroeconomic data over the most recent recession (i.e. 2008Q2–2009Q2) (x-axis), and the final year in our sample (i.e. 2014Q2–2015Q2) (y-axis), in Figures 3.11 and 3.12 respectively. We choose these time–periods in order to assess the relative economic significance of monetary policy shocks during crisis and non–crisis periods over a one–year horizon[15].

Figure 3.11 reveals that, on average, there is no clear difference in the cumulated response of US real GDP growth during 2008–2009 and 2014–2015 respectively with the distribution being evenly spread across the 45° line. Having said this, the joint distributions of average cumulated impulse response functions of inflation, the interest rate and Divisia money all reveal substantial differences over the most recent recession and subsequent recovery. The impact of monetary policy shocks on inflation and Divisia money growth are more contractionary during the Great Recession relative to the final year in our sample. Specifically, around 70% and 95% of the respective distributions

[15]Specifically, we sum the impulse response function at each observation in our selected periods over a 4–quarter horizon, and then take the average over the time period considered.

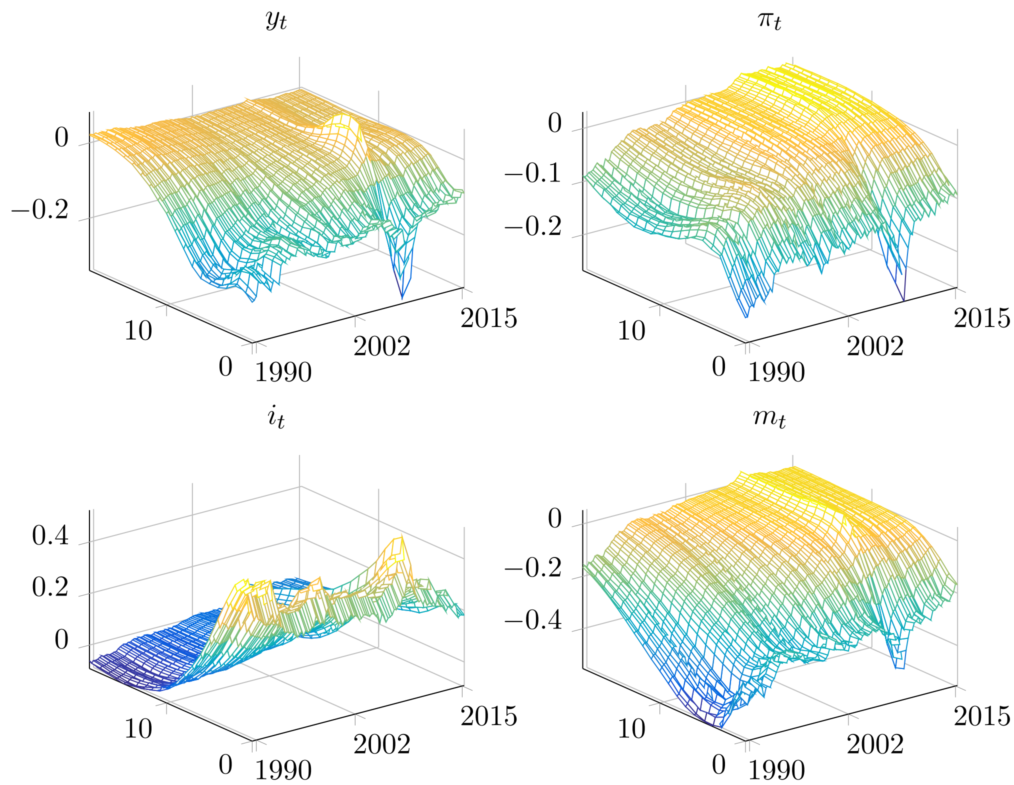

FIGURE 3.10: **Impact of Monetary Policy Shocks for the UK Economy from 1989 to 2015**
Notes: This figure plots the median impulse response functions of: real GDP growth; inflation; the interest rate and Divisia money growth with respect to liquidity shock. We plot the response along a 20–quarter horizon for each observation of our sample 1989Q3-2015Q2.

of the average accumulated impulse response functions of US inflation and Divisia money growth lie above the 45° line. Similarly, the cumulated impact of a monetary policy shock on the interest rate during the Great Recession is greater than in 2014–2015 with almost the entire distribution lying below the 45° line.

In Figure 3.12, it is clear that the average cumulated impact of UK GDP growth, following a monetary policy shock during the Great Recession, is more severe than during the final year of our sample; where 80% of the joint distribution lies above the 45° line. Adding to this, the average cumulated impact of inflation and Divisia money growth is also greater in 2008–2009 relative to 2014–2015. Again, around 80% to 85% of the joint distribution of average cumulated responses of UK inflation and Divisia money growth, are above their respective 45° lines. Finally, as is the case for the US economy, it is also evident that the 4–quarter cumulative impact of a monetary policy shock on the 3–month Treasury Bill rate is greater during the most recent recession.

In general, our results reveal notable time–variation in the transmission of monetary policy shocks in both the US and UK economies. The sign and shapes of our impulse response functions are consistent with Benati and Mumtaz, 2007 and Benati, 2008.

However, we extend conventional impulse response analysis, and examine the average cumulated response of variables following monetary policy shocks over the periods 2008–2009 and 2014–2015 respectively. Our results reveal stark differences in the cumulative impact of monetary policy shocks on macroeconomic fundamentals during the most recent crisis period, and the subsequent recovery which further substantiates the need to account for time–variation.

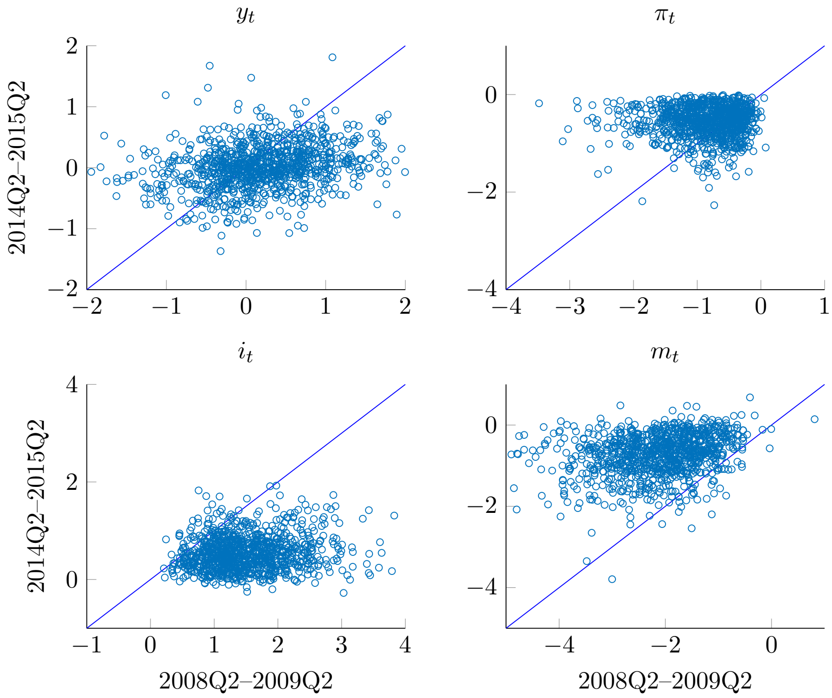

FIGURE 3.11: **Joint Distributions of the Average Accumulated Impulse Responses (4–quarter horizon) of US Macroeconomic Variables to a Monetary Policy Shock during Crisis and Non–crisis Periods**
Notes: This figure plots the joint distributions of the average accumulated 4–quarter impulse response functions of US real GDP growth, y_t; GDP deflator inflation, π_t; the 3–month Treasury Bill rate, i_t and annual Divisia money growth, m_t during the periods 2008Q2–2009Q2 (x-axis) and 2014Q2–2015Q2 (y-axis) respectively. We calculate in the following manner: for every saved draw of the Gibbs sampler, we sum the impulse response function of each macroeconomic variable over a 4–quarter horizon for every observation in our selected period (i.e. 2008Q2,...,2009Q2 and 2014Q2,..., 2015Q2). Then we take the average of the accumulated responses over the period respectively. In addition to the scatter plots, we include a $45°$ line.

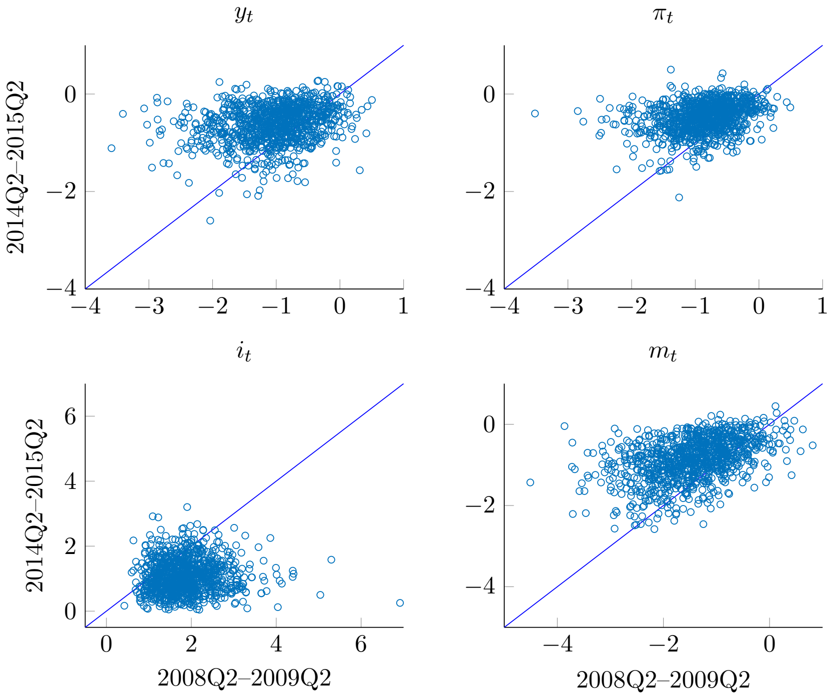

FIGURE 3.12: **Joint Distributions of the Average Accumulated Impulse Responses (4–quarter horizon) of UK Macroeconomic Variables to a Monetary Policy Shock during Crisis and Non–crisis Periods**
Notes: This figure plots the joint distributions of the average accumulated 4–quarter impulse response functions of UK real GDP growth, y_t; GDP deflator inflation, π_t; the 3–month Treasury Bill rate, i_t and annual Divisia money growth, m_t during the periods 2008Q2–2009Q2 (x-axis) and 2014Q2–2015Q2 (y-axis) respectively. We calculate in the following manner: for every saved draw of the Gibbs sampler, we sum the impulse response function of each macroeconomic variable over a 4–quarter horizon for every observation in our selected period (i.e. 2008Q2,...,2009Q2 and 2014Q2,..., 2015Q2). Then we take the average of the accumulated responses over the period respectively. In addition to the scatter plots, we include a $45°$ line.

Structural Variance Decompositions: Assessing the Contribution of Structural Shocks to the Variance in US and UK Macroeconomic Fundamentals

To obtain an idea of how our identified structural shocks contribute to the overall variation of our macroeconomic variables, we report results from a time–varying structural variance decomposition following Barnett, Groen, and Mumtaz, 2010. Specifically, we compute the contribution of each structural shock using the ratio of the conditional and unconditional volatilities of the variable of interest in the frequency domain. The unconditional volatility of variable $x = \{y_t,\ \pi_t,\ i_t,\ m_t\}$ is given by

$$f_{x,t|T}(\omega) = s_x(I_4 - \tilde{\beta}_{t|T}e^{-i\omega})^{-1}\frac{\Omega_{t|T}}{2\pi}\left[(I_4 - \tilde{\beta}_{t|T}e^{-i\omega})^{-1}\right]' s_x' \tag{3.11}$$

where $\Omega_{t|T} = \bar{A}_{0,t|T}H_{t|T}\bar{A}'_{0,t|T}$, $\bar{A}_{0,t|T}$ is a draw of the contemporaneous structural impact matrix that satisfies our sign restrictions; each column of $\bar{A}_{0,t|T}$ is divided by $diag(\bar{A}_{0,t|T})$. $H_{t|T}$ is a diagonal matrix containing the variances of the structural shocks. The conditional volatility of variable $x = \{y_t,\ \pi_t,\ i_t,\ m_t\}$ is

$$\bar{f}_{x,t|T}(\omega) = s_x(I_4 - \tilde{\beta}_{t|T}e^{-i\omega})^{-1}\frac{\bar{\Omega}_{t|T}}{2\pi}\left[(I_4 - \tilde{\beta}_{t|T}e^{-i\omega})^{-1}\right]' s_x' \tag{3.12}$$

where we replace $\Omega_{t|T}$ with $\bar{\Omega}_{t|T} = \bar{A}_{0,t|T}\bar{H}_{t|T}\bar{A}'_{0,t|T}$, $\bar{A}_{0,t|T}$ is consistent with its definition in (3.12). $\bar{H}_{t|T}$ is a diagonal matrix that contains the variances of the shocks shutting off the variances of all structural shocks except for the one of interest[16]. Therefore the contribution of identified structural shocks is given by the ratio

$$\frac{\bar{f}_{x,t|T}(\omega)}{f_{x,t|T}(\omega)} \tag{3.13}$$

In Figure 3.13 and 3.14 we report the time–varying contributions of our structural shocks at different frequencies (which we plot along each individual panel of the z-axes and y-axes respectively; the dates are along the respective x-axes) to the overall variance in US and UK macroeconomic variables we use in our respective TVP–VAR models. This allows us to examine the contribution of each structural shock over all frequency windows (i.e. ω) at every observation in our sample (i.e. t). The sum of the contributions of our identified structural shocks at every ω in each observation t, by construction, is equal to the spectral density of the series of interest (at the given frequency, ω). Therefore, these plots show the influence each identified structural shock has on the volatility of the variable of interest at different frequencies.

Panel 1 of Figure 3.13 and 3.14 show the posterior median contribution of supply shocks to the variance of variables in our US and UK TVP–VAR models respectively.

[16]It is not possible to uniquely identify the innovation variances of our structural shocks. However, it is plausible to compute the TVP–VAR covariance matrix at each point in time that results from setting one or more of the structural innovation variances to zero.

The contribution of supply shocks in the US are highest for inflation in the late 1990s and early 2000s at higher frequencies fluctuating around 55–60%. Then, the contribution drops to below 20% during the financial crisis and increases gradually to around 30% in 2015. Furthermore, supply shocks explain around 50% of real GDP variance, particularly at higher frequencies, throughout our sample; with a slight decline from 2008. In a similar fashion, the contribution of supply shocks to the interest rate is greater at higher frequencies explaining over 50% of the overall variation in the 1990s and early 2000s. During the financial crisis, the contribution to total uncertainty falls to around 2% before gradually rising during the final 5 years of our sample. The contribution of supply shocks to US Divisia money growth fluctuates between 20% and 40% respectively in the first 15 years of our sample, before falling to around 5% at all frequencies throughout the financial crisis.

Turning our attention to the UK, Panel 1 of Figure 3.14 shows the contribution of supply shocks to UK macroeconomic fundamentals, where these shocks make the highest contribution (i.e. around 20%) to inflation in 2005 at a frequency of around 6 quarters[17]. The contribution of supply shocks to UK GDP growth variation follows a similar pattern to that of inflation. In both cases we can see that the contribution of these shocks declines during the financial crisis at all frequencies. Contrastingly, the contribution of supply shocks to the UK Treasury Bill rate and Divisia money growth remains constant throughout our sample.

In Panel 2 of Figure 3.13, we report the contribution of demand shocks onto US economic variables. Notably, demand shocks contribute relatively little to US macroeconomic uncertainty with the greatest contributions of demand shocks, at just over 10% in 2005 for US real GDP growth (at very high and low frequencies) and inflation (at low frequencies). In addition, these shocks explain less than 5% of the overall variation in both the US Treasury Bill rate and Divisia money growth. Panel 2 of Figure 3.14 reports the contribution of demand shocks to UK macroeconomic variables, where the contribution of these shocks is greatest for inflation, typically at low and business cycle frequencies at around 55%[18]. Likewise, the greater contributions of demand shocks for the UK Treasury Bill rate and Divisia money growth are at lower frequencies. The contribution of demand shocks for UK real GDP growth remains constant throughout time, with greater contributions at higher frequencies at every observation.

It is clear from Panel 3 in Figures 3.13 and 3.14 that the contribution of monetary policy shocks to both US and UK macroeconomic uncertainty surge during recessionary

[17] The frequency window we use is $\omega \in [0 \quad \pi]$ where ω is a vector with equal distances between 0 and π split into 52 segments (i.e. half the number of time–series observations in our sample). The largest contributions are made at $\omega = 1.047$ which corresponds to around 6 quarters. Using $2\pi/\omega$, we can calculate the number of quarters associated to each ω.

[18] We define business cycle frequencies as in Borio, 2014 which corresponds to 8 years (or 32 quarters); in our case this is when $\omega \approx 0.2464$. We refer to the long–run at frequency zero (i.e. the infinite horizon) and when $\omega \approx \{0.0616, 0.1232\}$, which correspond to a 25.5 and 12.75 year horizon, respectively.

periods, yet are negligible during non–recessionary periods. The contributions of monetary policy shocks to both US and UK GDP growth during recessions is greatest at low frequencies. For the US, monetary policy shocks at low frequencies explain over 40% of the variance of GDP growth during the three (NBER) recessions our sample covers. Similarly for the UK, the contribution to GDP growth variation fluctuates around 35%–45% during recessions. To contrast, the contribution of monetary policy shocks to both US and UK inflation during recessionary periods is greatest at higher frequencies. In particular, during economic decline, the contribution of monetary policy shocks to US inflation variance reaches 60% at the highest frequency we consider (i.e. 2 quarters); the same holds for the contribution of monetary policy shocks to UK inflation variance during the 2008 recession.

We can see from the third column in Panel 3 of Figures 3.13 and 3.14, monetary policy shocks explain 40% of the variability of both US and UK Treasury Bill rates during the financial crisis; particularly in the long–run. For the US Treasury Bill rate, the contribution of monetary policy shocks during recessions declines at business cycle frequencies, and then starts to increase back to fractions consistent with very low frequencies. The contribution of monetary policy shocks to the variance in the UK Treasury Bill rate is clearly greater during the 2008 recession relative to the 1991 and 2001 recessions in our sample.

The fraction of variance that monetary policy shocks explain of US and UK Divisia money growth are in the fourth columns of Panel 3 in Figures 3.13 and 3.14 respectively. Evidently, we can see the surges in contributions of these shocks onto Divisia money growth are episodic. For the US, monetary policy shocks during recessions explain around 20% of the variance in Divisia money growth at all frequencies. For the UK, it is clear that the contribution of monetary policy shocks to Divisia money growth is greater during the Great Recession relative to other recessions in our sample; explaining around 25% of the overall variance at higher frequencies. At business cycle frequencies however, monetary policy shocks explain around 30% of UK Divisia money growth.

The final rows in Figures 3.13 and 3.14 report the contribution of money demand shocks to US and UK economic volatility. We can see the fraction of variation of US real GDP growth explained by money demand shocks is minor during the 1990s, then from 2008, these shocks explain over 50% of the overall volatility of real GDP growth. In a similar manner, we see the same pattern for the contribution of money demand shocks on US inflation. Notably for real GDP growth and inflation, money demand shocks seem to explain a greater fraction over the short and medium–term from 2008 onwards. The influence these shocks have on the US interest rate are clearly more prominent at medium–term horizons throughout our sample. During the first half of our time series, money demand shocks appear to contribute around 20%, at most, to interest rate variability at high frequencies. Yet from 2008 the impact of money demand shocks at high frequencies surge to over 50%. It is also evident that money demand shocks contribute to the uncertainty around US Divisia money growth from the early 2000s, particularly at medium and short horizons. Following the Great Recession, money demand shocks explain the majority of volatility in Divisia money growth at all frequencies.

Panel 4 in Figure 3.14 reports the proportions of macroeconomic uncertainty attributable to money demand shocks in the UK. It is clear that money demand shocks explain real GDP growth fluctuations at lower frequencies. The fraction of these shocks peak in 2015Q1 and 2015Q2; at 40% over the long–run. Contrarily, these shocks explain substantially larger proportions of inflation volatility at high frequencies. This is greatest at a 2 quarter frequency (i.e. when $\omega = \pi$). Turning our attention to the impact of money demand shocks on UK interest rate and Divisia money growth volatility, it is clear that these shocks bear minimal influence during the 2008 recession. Yet during the 1990s, money demand shocks explain over 50% of interest rate and Divisia money growth uncertainty over the short and medium–term. Then, following the financial crisis (i.e. from 2009 to 2015), the contribution of these shocks surges at short and medium–term horizons to around 60%.

Overall, our structural variance decompositions imply a variety of notable features. Both US and UK macroeconomic uncertainty during the Great Recession are predominantly influenced by monetary policy shocks. In both economies, monetary policy shocks during recessions explain greater proportions of GDP uncertainty at low and business cycle frequencies. In fact, during the 2008 recession, monetary policy shocks explain 60% and 42% of GDP growth volatility in the US and UK respectively. Contrastingly, monetary policy shocks during recessions explain higher proportions of inflation uncertainty over the short–term. During the Great Recession, over 60% of inflation variability is attributable to monetary policy shocks at a 2–quarter frequency.

Our results are consistent with Theodoridis and Mumtaz, 2015, who show that monetary policy shocks increase output, inflation and interest rate volatility using US data to estimate both an SVAR model and DSGE model. However, our analysis offers a variance decomposition that accounts for contributions at different frequencies throughout time. The implications of these results are twofold. First, this equips policymakers with an idea of the influences different structural shocks have on macroeconomic uncertainty throughout time. Second, policy response to shocks, particularly monetary policy shocks, during economic downturn can be tailored to the central bank's initiatives with an idea of how these shocks propagate onto the volatility of real GDP and price growth at different frequencies.

Furthermore, money demand shocks heavily influence interest rate and Divisia money growth volatility both during, and following the financial crisis for both economies. In addition, money demand shocks contribute significantly to US real GDP growth and inflation uncertainty across all frequencies from 2008 until the end of our sample. Yet for the UK, our decompositions reveal that money demand shocks explain uncertainty in real GDP growth more prominently at low and business cycle frequencies. For UK inflation, these shocks are significant drivers in volatility at high frequencies.

Taken together, both the long and shorter–term impact of monetary policy and money demand shocks justify the policy responses pursued by the Federal Reserve and Bank of England following the Great Recession. Specifically, our analysis reveals that monetary policy shocks heavily contribute to real GDP growth and inflation volatility at business cycle and high frequencies, respectively. This implies that lowering interest rates during 2008 and 2009, and injecting liquidity into the economy through QE, influences GDP growth volatility over the long–term and inflation volatility over the short–term. The signalling channel of QE is qualitatively equivalent to cutting interest rates and acts as a credible commitment to keep interest rates low in the future; even after the economy recovers (Krishnamurthy and Vissing-Jorgensen, 2011). Therefore, through the signalling channel of QE, our results imply that policy responses to the 2008 recession may hinder GDP growth variability over the medium to long–run. Consequently, this helps explain the sluggish recoveries in US and UK GDP growth rates from 2009 to 2015[19].

In addition, the portfolio rebalancing channel associated with QE argues that investors rebalance funds with the extra cash attained from selling long–term government bonds. This is because they are not perfect substitutes for one another. Our variance decomposition reveals influential proportions of macroeconomic uncertainty are explained by money demand shocks following the financial crisis. As a result, the rebalancing channel reduces the demand for money by investors, which could hinder the impact(s) of money demand shocks and aid stabilisation. The implications of our analysis are consistent with the results in Kapetanios et al., 2012, and Baumeister and Benati, 2013, who show that without QE policies, GDP growth in the US and UK would have been lower following the financial crisis.

[19]Similarly, the contribution of monetary policy shocks to inflation volatility at high frequencies implies why inflation after the first round of QE in 2009, for both economies, remained stubbornly high.

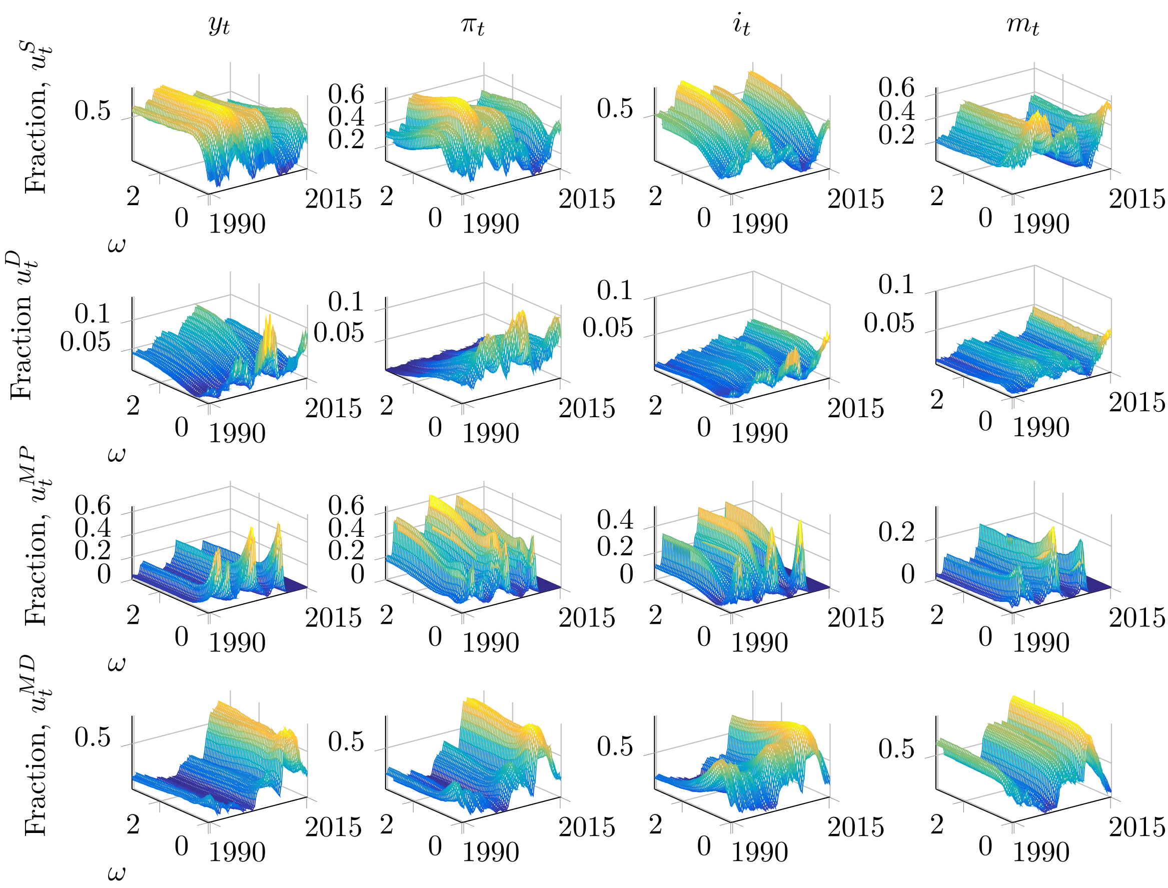

FIGURE 3.13: **Time–varying Contributions of Structural Shocks to the Variance of US Macroeconomic Fundamentals over different Frequencies from 1989 to 2015**

Notes: Panels 1 to 4 show the time–varying contributions of our structural shocks, u_t^S, u_t^D, u_t^{MP}, u_t^{MD} to the overall variation in US real GDP growth, y_t; GDP deflator inflation, π_t, the 3–month Treasury Bill rate, i_t; and Divisia money growth, m_t from 1989Q3–2015Q2 respectively. We report the contributions over the frequency window, $\omega \in [0 \quad \pi]$.

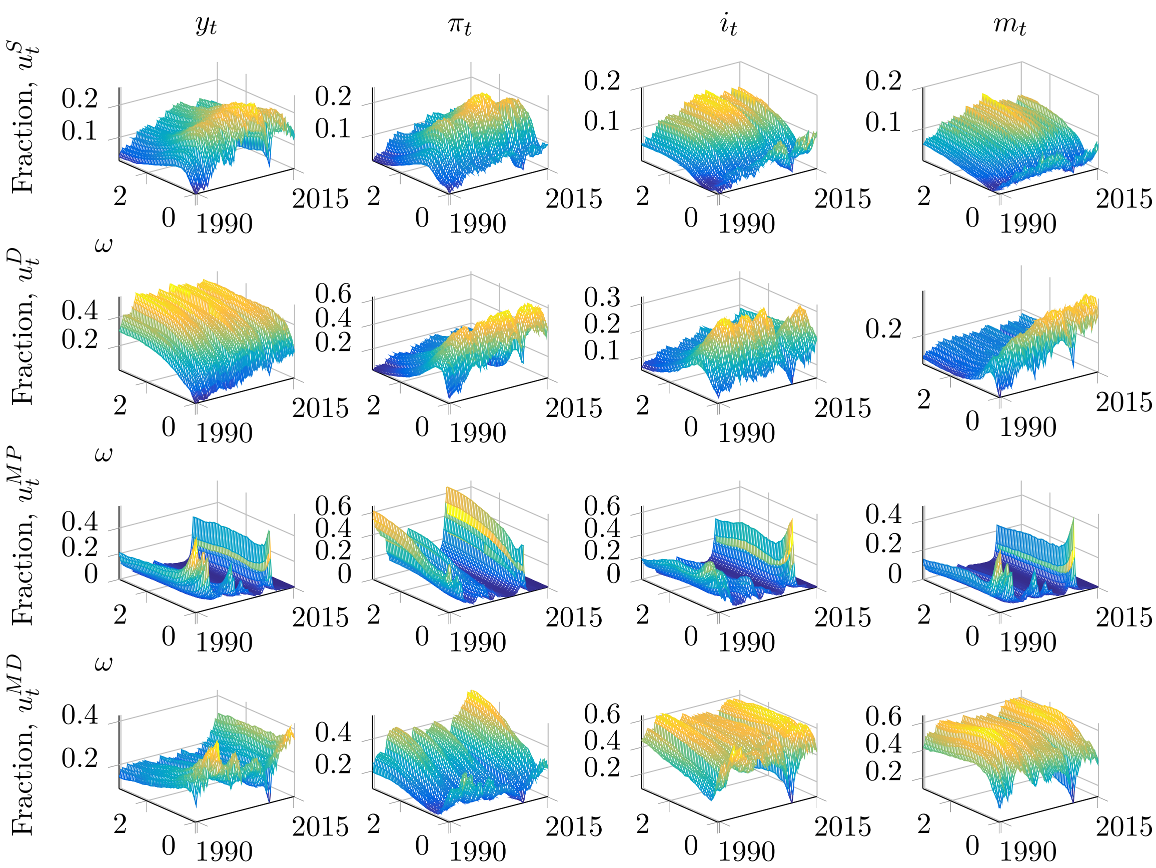

FIGURE 3.14: **Time–varying Contributions of Structural Shocks to the Variance of UK Macroeconomic Fundamentals over different Frequencies from 1989 to 2015**

Notes: Panels 1 to 4 show the time–varying contributions of our structural shocks, u_t^S, u_t^D, u_t^{MP}, u_t^{MD} to the overall variation in US real GDP growth, y_t; GDP deflator inflation, π_t, the 3–month Treasury Bill rate, i_t; and Divisia money growth, m_t from 1989Q3–2015Q2 respectively. We report the contributions over the frequency window, $\omega \in [0 \quad \pi]$.

3.5 Robustness Analysis

3.5.1 Analysis using Simple–sum Monetary Aggregates

To assess the relative empirical benefits of using Divisia aggregates, we compare our main results to systems replacing US and UK Divisia money growth rates with the annual growth of US and UK broad money respectively. For the US we use the same M2 series, which we obtain from the Federal Reserve Bank of St Louis, as Benati and Mumtaz, 2007. For the UK, we construct a break adjusted M4/M4^{ex} series that splices conventional M4 with M4 excluding intermediate other financial corporations (OFCs);

the Bank of England's preferred measure of broad money[20]. All data series used to construct our M4/M4^{ex} measure are available from the Bank of England's statistical database. We then replace Divisia money, m_t in each of our TVP–VAR models with the economy's measure of broad money growth, m_t^b. We re–estimate the model in (3.1)–(3.9) using the priors and algorithm that we outline in Section 3.7.1, Appendix A.

In order to satisfactorily answer whether a system using Divisia aggregates predicts macroeconomic fundamentals with a higher degree of accuracy than those using broad money aggregates, we plot the range of posterior credible intervals from our time–varying multivariate R^2 statistics. Specifically, we compute the range of posterior credible intervals by taking the difference between the 84th and 16th percentiles of the distributions of our multivariate R^2 statistics. Therefore a lower value (or range) implies pseudo–forecasts are estimated with more precision. In Figures 3.15 and 3.16 we plot the range of posterior credible intervals from the 1, 4 and 8–step ahead multivariate R^2 statistics for real GDP growth and inflation for the US and UK. We choose to compare these horizons because the Federal Reserve (and the Bank of England) focus on these horizons, especially when examining inflation (Cogley, Primiceri, and Sargent, 2010)[21].

The top, middle and bottom left Panels of Figures 3.15 and 3.16 correspond to multivariate R^2 statistics at 1–quarter, 4–quarter and 8–quarter horizons for US and UK real GDP growth. In general it is clear, from each Panel, that our TVP–VAR models using Divisia indices produce a lower range of posterior credible intervals for real GDP growth at every horizon. Notably, the range of posterior credible intervals for real GDP growth is considerably lower at 4 and 8–quarter horizons respectively. Specifically, for both economies in the period following the Great Recession, the range of posterior credible intervals from our TVP–VAR models using Divisia money are at least 2 percentage points lower at a 1–quarter horizon. Furthermore, at 4 and 8–quarter horizons, the range of posterior credible intervals for pseudo–forecasts of US and UK real GDP growth are as much as 10 percentage points lower from our systems using Divisia money growth.

The right Panels of Figures 3.15 and 3.16 plot the range of posterior credible intervals of the time–varying multivariate R^2 statistics for US and UK GDP deflator inflation at 1, 4, and 8–quarter horizons. On the whole, there are negligible differences in the precision of pseudo–forecasts of US inflation at all horizons; particularly at 1 and 4–quarter horizons. However, at an 8–quarter horizon until 2005, the range of posterior

[20] We splice headline M4 with M4^{ex} because M4^{ex} data starts in 1997Q4. The method we use to construct our break adjusted UK broad money series is available at `http://www.bankofengland.co.uk/statistics/Pages/iadb/notesiadb/Break_adjusted_levels_data.aspx`.

[21] We do not report the range of posterior credible intervals for the 3–month Treasury Bill rate and Divisia (and broad) money growth since the Federal Reserve and Bank of England are primarily concerned with output and price stability. However for both the US and UK, the range of posterior credible intervals are remarkably similar. For Divisia and broad money growth there are some divergences and the implication of pseudo–forecasts for Divisia money are less precise until 2005 at all horizons. However, from 2005 onwards, the precision of pseudo–forecasts using Divisia money growth are superior than those for broad money growth; results are available upon request.

credible intervals using Divisia money growth is up to 5 percentage points greater than the system using broad money growth. Then, from 2005, the precision of pseudo–forecasts of US inflation from our TVP–VAR using Divisia money growth increases and is comparably lower than our TVP–VAR using broad money growth. To contrast, the precision of pseudo–forecasts of UK GDP deflator inflation using Divisia money growth are greater than those of broad money growth; particularly at 4 and 8–quarter horizons.

Overall the results implied by our TVP–VAR models provide considerable support for using theoretically sound monetary aggregates. Both our systems of the US and UK economies reveal a higher precision in pseudo–forecasts of real GDP growth and inflation. These results are consistent with Schunk, 2001 who shows that VAR models using Divisia money growth better forecasts US real GDP growth. Likewise, our results corroborate with Barnett, Chauvet, and Leiva-Leon, 2016 who show that nowcasts of US nominal real GDP are most accurate when incorporating Divisia money aggregates using an array of non–linear models. Similarly, our results correspond well with Florackis et al., 2014, who show that regime–switching models forecasting UK real GDP growth using Divisia money growth outperform forecasts published by the Bank of England.

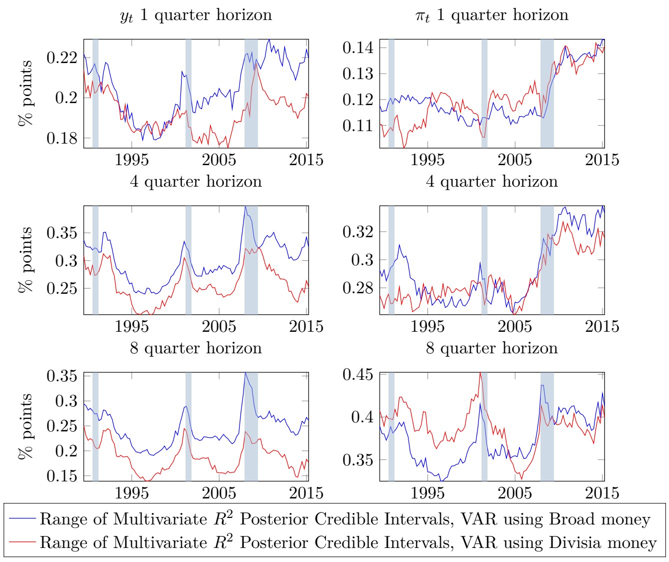

FIGURE 3.15: **Range of Posterior Credible Intervals for Multivariate R^2 statistics using US Data from 1989 to 2015**
Notes: This figure shows the difference between 84^{th} and 16^{th} percentiles of the distributions of the multivariate R^2 statistics for each time series in our VAR models using US data from 1989Q3–2015Q2 respectively. Grey bars indicate NBER recession dates.

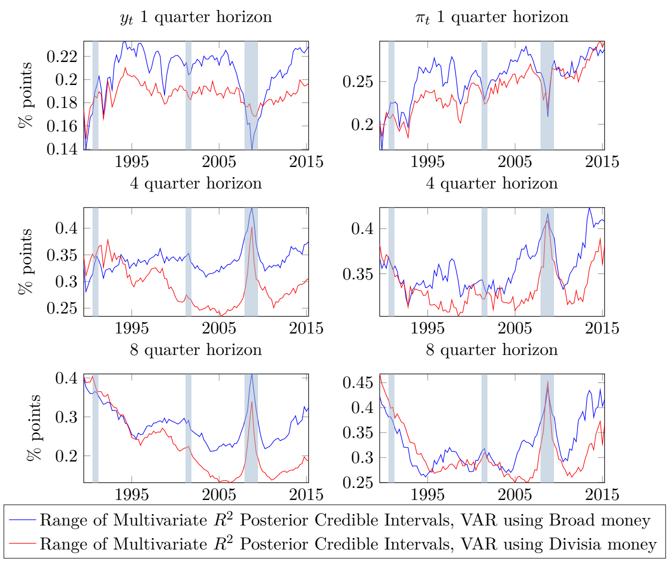

FIGURE 3.16: **Range of Posterior Credible Intervals for Multivariate R^2 statistics using UK Data from 1989 to 2015**
Notes: This figure shows the difference between 84^{th} and 16^{th} percentiles of the distributions of the multivariate R^2 statistics for each time series in our VAR models using UK data from 1989Q3–2015Q2 respectively. Grey bars indicate NBER recession dates.

To establish whether there are substantial differences in the dynamic transmission of monetary policy shocks from TVP–VAR models using broad money aggregates, Figures 3.17 and 3.18 plot the joint distribution of the average one year accumulated response of real GDP growth, y_t; GDP deflator inflation, π_t; the 3–month Treasury Bill rate, i_t and broad money growth, m_t^b over the periods 2008Q2–2009Q2 (x-axis) and 2014Q2–2015Q2 (y-axis), respectively.

Comparing Figure 3.17 with Figure 3.11, and Figure 3.18 with Figure 3.12, it is clear that more of the respective joint distributions of the cumulated impulse response functions lie on, around (or closer to) the 45° lines in Figures 3.17 and 3.18. This indicates less significance in the time–variation of the real effects of monetary policy shocks, from our TVP–VAR models, using broad money aggregates. Our conjecture is that the weighting mechanism inherent in Divisia aggregates not only facilitates closer time–varying covariances with macroeconomic fundamentals, but also more accurately parametrises lagged Divisia money growth rates in the equations within our systems. In general the conclusions from Figures 3.17 and 3.18 are similar to those in Figures 3.11 and 3.12. However, these results echo the findings in Barnett and Chauvet, 2011, who argue that theoretically sound measures of money better signal recessions, and perhaps more importantly, the impact of monetary policy.

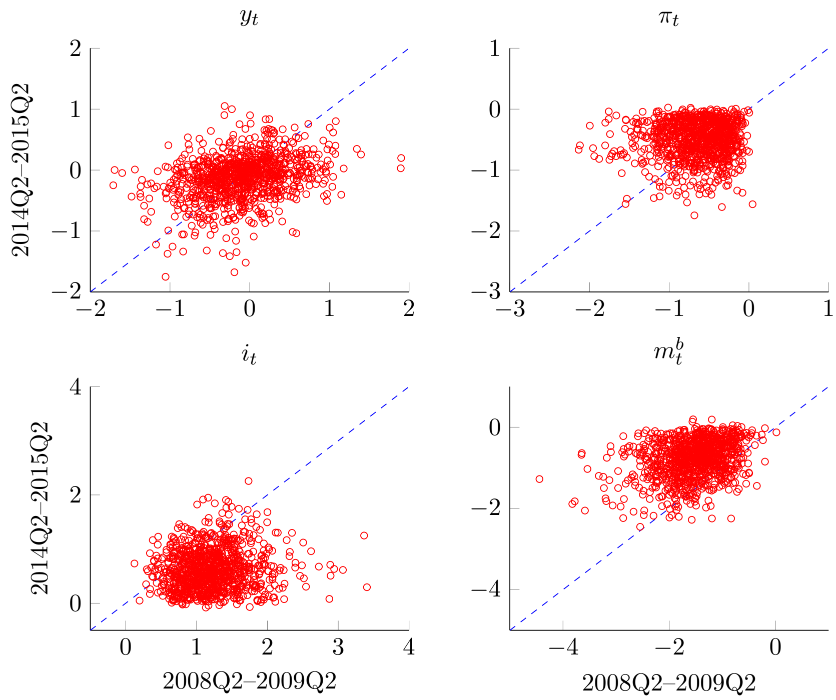

FIGURE 3.17: **Joint Distributions of the Average Accumulated Impulse Responses (4–quarter horizon) of US Macroeconomic Variables during Crisis and Non–crisis Periods**

Notes: This figure plots the joint distributions of the average accumulated 4–quarter impulse response functions of US real GDP growth, y_t; GDP deflator inflation, π_t; the 3–month Treasury Bill rate, i_t and annual broad money growth, m_t^b during the periods 2008Q2–2009Q2 (x-axis) and 2014Q2–2015Q2 (y-axis) respectively. We calculate in the following manner: for every saved draw of the Gibbs sampler, we sum the impulse response function of each macroeconomic variable over a 4–quarter horizon for every observation in our selected period (i.e. 2008Q2,...,2009Q2 and 2014Q2,..., 2015Q2). Then we take the average of the accumulated responses over the period respectively. In addition to the scatter plots, we include a $45°$ line.

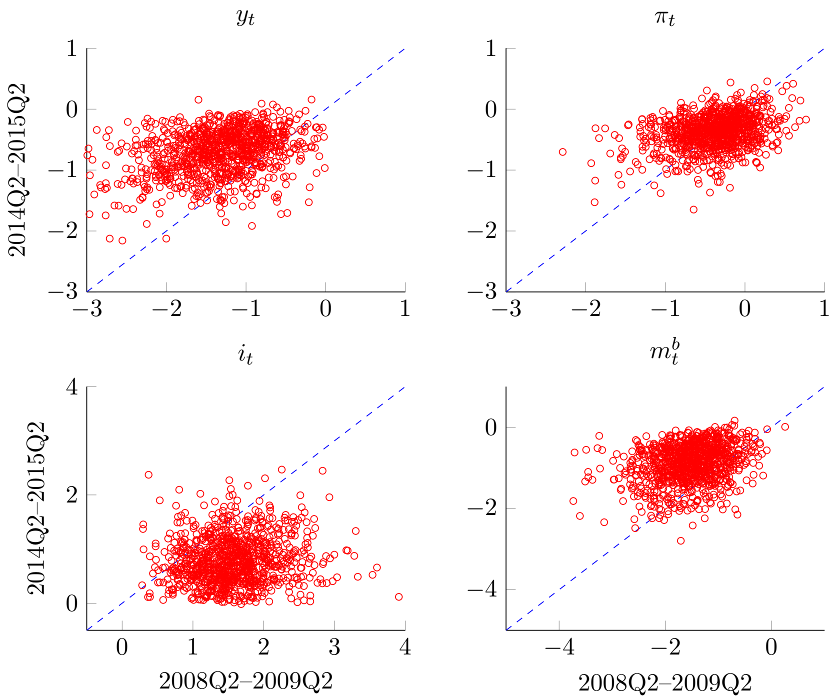

FIGURE 3.18: **Joint Distributions of the Average Accumulated Impulse Responses (4–quarter horizon) of UK Macroeconomic Variables during Crisis and Non–crisis Periods**

Notes: This figure plots the joint distributions of the average accumulated 4–quarter impulse response functions of UK real GDP growth, y_t; GDP deflator inflation, π_t; the 3–month Treasury Bill rate, i_t and annual broad money growth, m_t^b during the periods 2008Q2–2009Q2 (x-axis) and 2014Q2–2015Q2 (y-axis) respectively. We calculate in the following manner: for every saved draw of the Gibbs sampler, we sum the impulse response function of each macroeconomic variable over a 4–quarter horizon for every observation in our selected period (i.e. 2008Q2,...,2009Q2 and 2014Q2,..., 2015Q2). Then we take the average of the accumulated responses over the period respectively. In addition to the scatter plots, we include a $45°$ line.

In order to examine the differences between structural variance decompositions using Divisia and broad money growth, we plot in Figures 3.19 and 3.20 the posterior median of the time–varying contributions our structural shocks possess for US and UK macroeconomic uncertainty. Figure 3.19 is directly comparable with Figure 3.13 and Figure 3.20 is comparable with Figure 3.14. There are a number of notable differences in the shares of variance explained by structural shocks implied by our TVP–VAR models using broad money growth. First, the proportions attributable to supply shocks and demand non–policy shocks to macroeconomic volatility in Figures 3.19 and 3.20 reveal that the impact of these shocks remains relatively constant over different frequencies.

Notably, the impact of demand non–policy shocks on UK GDP growth from our TVP–VAR model using broad money growth (Panel 2 of Figure 3.20), is remarkably different to the influence of these shocks from our TVP–VAR model using Divisia money growth. This result implies that demand–non policy shocks contribute heavily to real

GDP growth variability at low frequencies, and gradually decrease at higher frequencies. This result contrasts the variance decomposition of demand non–policy shocks in Barnett, Groen, and Mumtaz, 2010. However, our variance decomposition of UK real GDP growth in Figure 3.14 is coherent with the former; further supporting the use of Divisia money aggregates. One possible explanation is that systems using broad money growth over approximate the contribution of money demand shocks to UK real GDP growth variation, at higher frequencies, due to the flawed aggregation method used by simple–sum monetary aggregates. Clearly, Figure 3.14 shows the effects of money demand shocks on GDP uncertainty are comparably lower at higher frequencies.

Results implied by our TVP–VAR models using broad money growth indicate that monetary policy shocks during recessions contribute relatively greater proportions to both US and UK real GDP growth volatility at higher frequencies. Furthermore Figure 3.19 and 3.20 show that monetary policy shocks explain lower proportions of inflation uncertainty at higher frequencies than the same shocks generated by our models using Divisia money growth rates. If monetary policy shocks from models using broad money growth contribute substantially less to inflation uncertainty at high frequencies, then results from our models imply inflation is more resilient to changes in the interest rate; especially in the short–term. Assuming central banks use multivariate models that include conventional simple–sum measures to guide monetary policy, then reduced–form and structural counterfactual analysis will likely result in an insensitive response of inflation to movements in the interest rate. Therefore, central bankers and policymakers may conclude that monetary policy is more accommodative, or contractionary, than in reality.

The implication here is that conclusions with regards to the tightness of monetary policy generated by these models may be misleading. If monetary policy shocks contribute less to inflation uncertainty generated by models using simple–sum measures of money, then the impact of raising the interest rate implied by these models may be distorted. Therefore interest rates set by central banks based on models using simple–sum aggregates could, in fact, be more contractionary than previously anticipated. Our analysis corroborates with Barnett and Chauvet, 2011, who argue that monetary policy during the Great Moderation in the US and UK was, indeed, more contractionary than previously thought. We advocate the arguments in the aforementioned in increasing the quality of monetary statistics, and consequently the information set, which guides monetary policy.

On the whole, the structural variance decompositions of US and UK macroeconomic uncertainty, and comparisons of forecast precision, from systems using simple–sum and Divisia money growth provide ample support for using Divisia indices. It is clear from Figures 3.19 and 3.20 that structural shocks exhibit less variation in the frequency domain at every observation in our sample. However, our decompositions of macroeconomic volatility from systems using Divisia growth provide guidance of the impacts of structural shocks throughout time, and at different frequencies. Therefore, policymakers have a better idea of the short, medium and longer–term impacts of structural shocks on macroeconomic fluctuations. Policy response can be tailored to central bank objectives with an idea of the effects these shocks have on macroeconomic uncertainty over different frequencies. Combining this with an increased (pseudo) forecast accuracy, only echoes the importance of correctly measuring money.

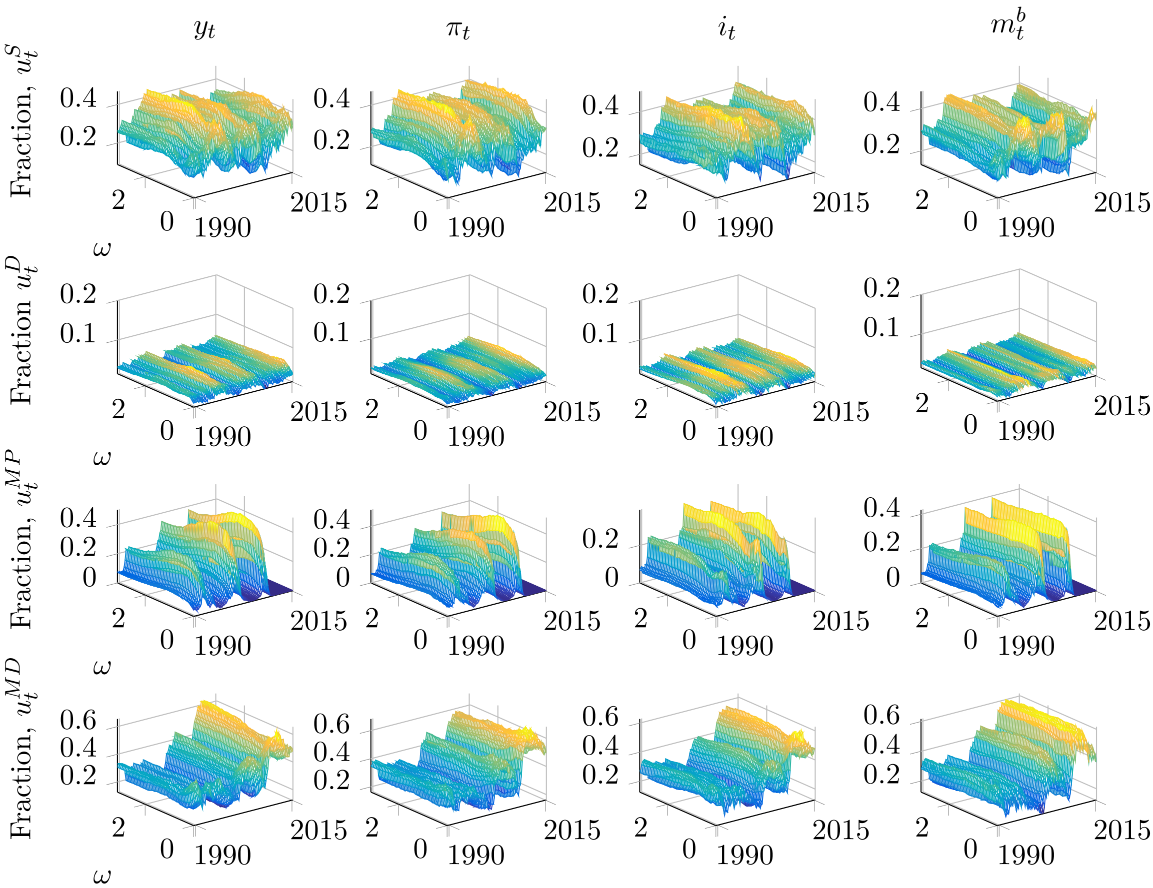

FIGURE 3.19: **Time–varying Contributions of Structural Shocks to the Variance of US Macroeconomic Fundamentals over different Frequencies from 1989 to 2015**

Notes: Panels 1 to 4 show the time–varying contributions of our structural shocks, u_t^S, u_t^D, u_t^{MP}, u_t^{MD} to the overall variation in US real GDP growth, y_t; GDP deflator inflation, π_t, the 3–month Treasury Bill rate, i_t; and broad money growth, m_t^b from 1989Q3–2015Q2 respectively. We report the contributions over the frequency window, $\omega \in [0 \quad \pi]$.

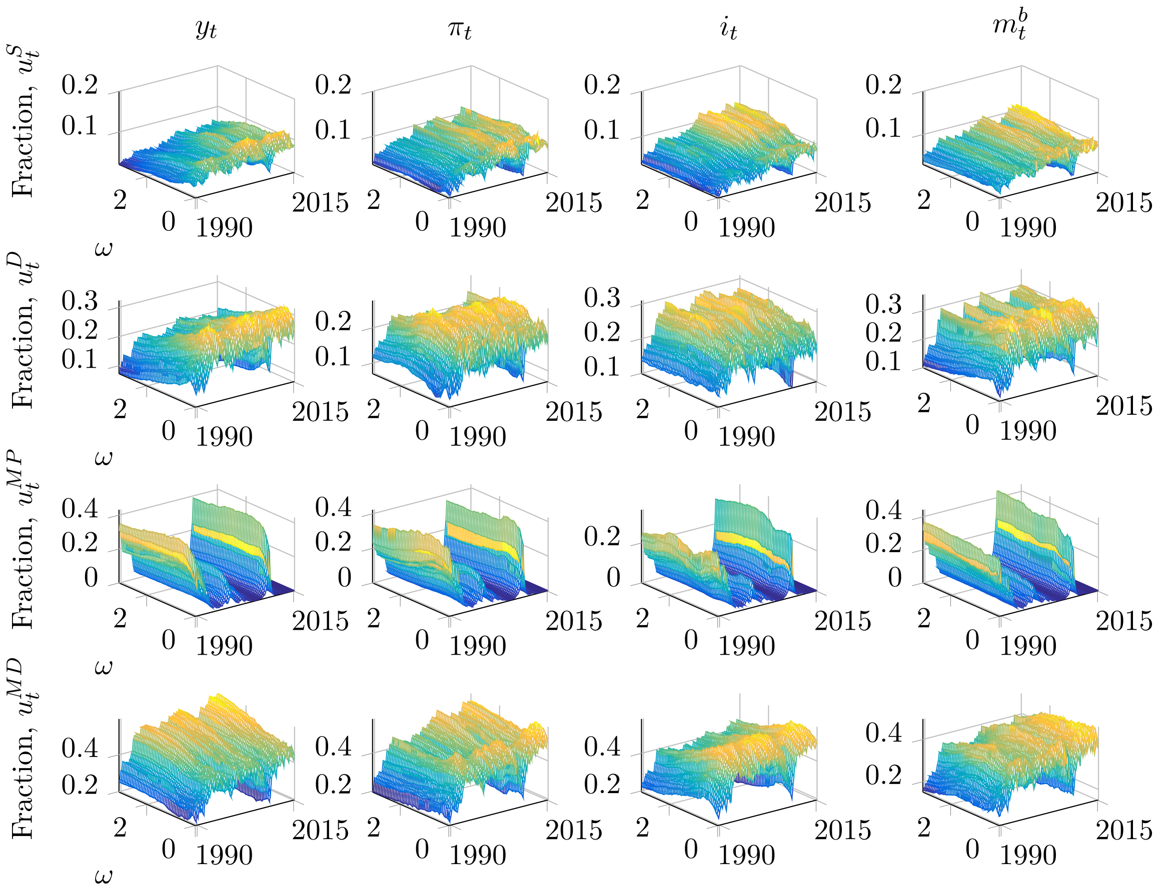

FIGURE 3.20: **Time–varying Contributions of Structural Shocks to the Variance of UK Macroeconomic Fundamentals over different Frequencies from 1989 to 2015**

Notes: Panels 1 to 4 show the time–varying contributions of our structural shocks, u_t^S, u_t^D, u_t^{MP}, u_t^{MD} to the overall variation in US real GDP growth, y_t; GDP deflator inflation, π_t, the 3–month Treasury Bill rate, i_t; and broad money growth, m_t^b from 1989Q3–2015Q2 respectively. We report the contributions over the frequency window, $\omega \in [0 \quad \pi]$.

3.6 Conclusions

In this chapter we provide comprehensive reduced–form and structural insights into evolving US and UK macroeconomic dynamics from 1979 to 2015, using theoretically sound measures of money, Divisia indices. We then test the empirical properties of our baseline systems against those using simple–sum monetary aggregates.

A summary of our results is as follows: First, we link the persistence of US and UK economic data to multivariate R^2 forecastability and, in the spirit of Cogley, Primiceri, and Sargent, 2010, show that there are distinct differences in the overall forecastability of macroeconomic fundamentals between 1990 and 2015; further justifying the conclusions in Schunk, 2001 and Barnett, Chauvet, and Leiva-Leon, 2016. Specifically, in 2015, interest rates in the US and UK are substantially more predictable than in 1990. Second, TVP–VAR models using Divisia money growth provide more accurate (pseudo) forecasts of real GDP growth at 1, 4, and 8–quarter horizons for both economies than systems using broad money aggregates. At 4 and 8–quarter horizons, our baseline models produce a range of posterior credible intervals 10 percentage points lower than models using conventional broad money growth. Third, we track changes in the transmission of monetary policy shocks and note a significant difference in the response of inflation, Treasury Bill rates and Divisia money growth in both economies between the periods 2008Q2–2009Q2 and 2014Q2–2015Q2; thereby vindicating our modelling strategy. Finally, structural variance decompositions reveal that monetary policy shocks are episodic in their impacts on macroeconomic volatility, and explain the majority of variation during recessionary periods. Notably during the Great Recession, monetary policy shocks explain 60% and 42% of GDP growth volatility in the US and UK respectively. In the same period, these shocks explain around 60% of inflation uncertainty in both the US and UK.

The implications of our study lie in two main areas. First, forecasters should consider replacing simple–sum monetary aggregates with Divisia indices, in multivariate analysis, to obtain greater forecast precision. Second, our results outline how monetary policy shocks, on impact, contribute to real GDP growth and inflation uncertainty at different frequencies. Thus, policy response may be guided by the implications these shocks have on economic volatility over different time horizons; conditional on central bank objectives.

Our study provides notable prospects for future research. It would be interesting to see the performance of Divisia money aggregates in a multivariate out–of–sample forecasting exercise that accounts for parameter change. Improving the predictability of macroeconomic fundamentals during times of economic turbulence is of paramount importance to central bankers. Furthermore, a structural analysis incorporating the term–spread into our systems in order to examine the effectiveness of QE could facilitate understanding on the real effects of conventional and unconventional monetary policies in the US and UK.

3.7 Appendix to Chapter 3

3.7.1 Appendix A: Prior Information and Posterior Simulation

Prior Information

We use Bayesian methods to estimate (3.1)–(3.9). One issue in estimating these classes of models is how to deal with the initial conditions. We follow, among others, Primiceri, 2005, Cogley and Sargent, 2005 and Benati and Mumtaz, 2007. We posit that the initial values of the states $\theta_0,\ \alpha_0,\ h_0$ are Normal, and independent from one another and from the distribution of the hyperparameters. To calibrate the initial conditions we estimate a standard (time-invariant) VAR using the first 10 years of data, from 1979Q3–1989Q3[22]. We set

$$\theta_0 \backsim N\left[\hat{\theta}_{OLS},\ 4 \cdot \hat{V}(\hat{\theta}_{OLS})\right] \tag{3.14}$$

for $\alpha_0,\ h_0$, let $\hat{\Sigma}_{OLS}$ be the estimated covariance matrix of the residuals from the time–invariant VAR. Let C be the lower–triangular Choleski factor such that $CC' = \hat{\Sigma}_{OLS}$. We then set

$$\ln h_0 \backsim N(\ln \mu_0, 10 \times I_4) \tag{3.15}$$

where μ_0 collects the logarithms of the squared elements along the diagonal of C. We divide each column of C by the corresponding element on the diagonal; call this matrix $\tilde{C}$. We then set

$$\alpha_0 \backsim N\left[\tilde{\alpha}_0,\ \tilde{V}(\tilde{\alpha}_0)\right] \tag{3.16}$$

with $\tilde{\alpha}_0 \equiv [\tilde{\alpha}_{0,11},\ \tilde{\alpha}_{0,21},\ \ldots,\ \tilde{\alpha}_{0,61}]'$ which is a vector collecting all the elements below the diagonal of $\tilde{C}^{-1}$. We assume $\tilde{V}(\tilde{\alpha}_0)$ is diagonal with each element equal to 10 times the absolute value of the corresponding element of $\tilde{\alpha}_0$. This is an arbitrary prior but correctly scales the variance of each element of α_0 to account for their respective magnitudes (Benati and Mumtaz, 2007).

With regards to the hyperparameters, we posit independence between the parameters corresponding to the matrices $Q,\ S,\ W$ purely for convenience. Q is set to follow an

[22]Our results are insensitive to different prior specifications and larger samples of data to calibrate the initial conditions of the model.

inverse–Wishart distribution,

$$Q \backsim IW(\underline{Q}^{-1}, T_0) \tag{3.17}$$

where $\underline{Q} = T_0 \cdot \hat{V}(\hat{\theta}_{OLS}) \cdot 3.4 \times 10^{-4}$, prior degrees of freedom are given by $T_0 = 40$ which is the number of observations used within the training sample. This value minimizes the significance of the prior, thereby maximising the influence of information contained within the sample. Our choice of scaling parameter 3.4×10^{-4} is consistent with Cogley and Sargent, 2005. However, Primiceri, 2005 uses an even tighter scaling parameter of 1.0×10^{-4}. The scaling parameter essentially sets the amount of time–variation within the parameters of the model. There is a growing literature on restricting the amount time-variation prior to estimating this class of models; see e.g. Groen, Paap, and Ravazzolo, 2013. The results and conclusions presented within the main body are robust to reducing the value of the scaling parameter.

The blocks of S are also assumed to follow inverse–Wishart distributions with prior degrees of freedom equal to the minimum allowed (i.e. $1 + \dim(S_i)$).

$$S_1 \backsim IW(\underline{S}_1^{-1}, 2) \tag{3.18}$$
$$S_2 \backsim IW(\underline{S}_2^{-1}, 3) \tag{3.19}$$
$$S_3 \backsim IW(\underline{S}_3^{-1}, 4) \tag{3.20}$$

we set $S_1,\ S_2,\ S_3$ in accordance with $\tilde{\alpha}_0$ as in Benati and Mumtaz, 2007 such that $\underline{S}_1 = 10^{-3} \times |\tilde{\alpha}_{0,11}|$, $\underline{S}_2 = 10^{-3} \times \mathrm{diag}([|\tilde{\alpha}_{0,21}|, |\tilde{\alpha}_{0,31}|]')$, $\underline{S}_3 = 10^{-3} \times$ $\mathrm{diag}([|\tilde{\alpha}_{0,41}|, |\tilde{\alpha}_{0,51}|, |\tilde{\alpha}_{0,61}|]')$. This calibration is consistent with setting $S_1,\ S_2,\ S_3$ to 10^{-4} times the corresponding diagonal block of $\tilde{V}(\tilde{\alpha}_0)$. The variances for the stochastic volatility innovations, as in Cogley and Sargent, 2005, follow an inverse–Gamma distribution for the elements of W,

$$W_{i,i} \backsim IG(\frac{10^{-4}}{2}, \frac{1}{2}) \tag{3.21}$$

Simulating the Posterior Distribution

In order to simulate the posterior distribution of the hyperparameters and states, conditional on the data, we implement the following MCMC. We combine elements from Primiceri, 2005 and Cogley and Sargent, 2005.

1) *Draw elements of θ_t* Conditional on Y^T, α^T and H^T, the observation equation (3.1) is linear with Gaussian innovations with a known covariance matrix. Factoring the density of θ_t, $p(\theta_t)$ in the following manner

$$p(\theta^T | y^T, A^T, H^T, V) = p(\theta_T | Y^T, A^T, H^T, V) \prod_{t=1}^{T-1} p(\theta_t | \theta_{t+1}, Y^t, A^T, H^T, V) \tag{3.22}$$

the Kalman filter recursions pin down the first element on the right hand side of the above; $p(\theta_T|Y^T, A^T, H^T, V) \backsim N(\theta_T, P_T)$, with P_T being the precision matrix of θ_T from the Kalman filter. We compute the remaining elements in the factorisation via backward recursions as in Cogley and Sargent, 2005. Since θ_t is conditionally Normal we have

$$\theta_{t|t+1} = P_{t|t}P_{t+1|t}^{-1}(\theta_{t+1} - \theta_t) \quad (3.23)$$

$$P_{t|t+1} = P_{t|t} - P_{t|t}P_{t+1|t}^{-1}P_{t|t} \quad (3.24)$$

which yields, for every t from $T-1$ to 1, the remaining elements in the observation equation (3.1). More precisely, the backward recursion begins with a draw, $\tilde{\theta}_T$ from $N(\theta_T,\ P_T)$. Conditional on $\tilde{\theta}_T$, the above produces $\theta_{T-1|T}$ and $P_{T-1|T}$. This allows us to draw $\tilde{\theta}_{T-1}$ from $N(\theta_{T-1|T},\ P_{T-1|T})$ until t=1.

2) *Drawing elements of* α_t Conditional on Y^T, θ^T and H^T we follow Primiceri, 2005 and note that (3.1) can be written as

$$A_t\tilde{Y}_t \equiv A_t(Y_t - X_t'\theta_t) = A_t\epsilon_t \equiv u_t \quad (3.25)$$

$$Var(u_t) = H_t \quad (3.26)$$

with $\tilde{Y}_t \equiv [\tilde{Y}_{1,t},\ \tilde{Y}_{2,t},\ \tilde{Y}_{3,t},\ \tilde{Y}_{4,t}]'$ and

$$\tilde{Y}_{1,t} = u_{1,t} \quad (3.27)$$

$$\tilde{Y}_{2,t} = -\alpha_{21,t}\tilde{Y}_{1,t} + u_{2,t} \quad (3.28)$$

$$\tilde{Y}_{3,t} = -\alpha_{31,t}\tilde{Y}_{1,t} - \alpha_{32,t}\tilde{Y}_{2,t} + u_{3,t} \quad (3.29)$$

$$\tilde{Y}_{4,t} = -\alpha_{41,t}\tilde{Y}_{1,t} - \alpha_{42,t}\tilde{Y}_{2,t} - \alpha_{43,t}\tilde{Y}_{3,t} + u_{4,t} \quad (3.30)$$

These observation equations and the state equation (3.7) allows us to draw the elements of α_t equation by equation using the same algorithm as above; assuming S is block diagonal.

3) *Drawing elements of* H_t Conditional on Y^T, θ^T and α^T, the orthogonal innovations u_t, $Var(u_t) = H_t$ are observable. We sample, element by element, $h_{i,t}$'s using the algorithm of Jacquier, Polson, and Rossi, 2002; Cogley and Sargent, 2005 provide details in Appendix B.2.5 of their paper.

4) *Drawing the hyperparameters* Conditional on Y^T, θ^T, H_t and α^T, the innovations in θ_t, α_t and $h_{i,t}$'s are observable, which allows us to draw the elements of Q, S_1, S_2, S_3 and the $W_{i,i}$ from their respective distributions.

This MCMC algorithm simulates the posterior distribution conditional on the data by iterating over steps 1)–4). For our estimations in the main text, we use a burn–in period of 99,000 iterations to converge to the ergodic distribution. Following this, we run 1,000 more iterations presenting results on these iterations. We use a large amount of burn–in iterations because sampling the elements of H_t is a single–move algorithm that requires more burn–in draws to ensure convergence.

3.7.2 Appendix B: Convergence Diagnostics

To assess the convergence of the MCMC, we compute the inverse relative numerical efficiency factors (RNEs) for the time–varying coefficients of the VAR models, and for the hyperparameters of the models. We follow Primiceri, 2005 defining the RNEs as

$$RNE = (2\pi)^{-1} \frac{1}{S(0)} \int_{-\pi}^{\pi} S(\omega) d\omega$$

where $S(\omega)$ is the spectral density of the sequence of draws from the Gibbs sampler for the quantity of interest at frequency ω; $S(0)$ is the spectral density of the sequence at frequency zero.

Figures 3.21 and 3.22 plot the inefficiency factors for our US and UK VAR models respectively. Specifically, we plot the time–varying coefficients (the β_t), the non zero elements of the matrix A_t and the volatilities ($h_{i,t}$'s) respectively - and for the model's hyperparameters, i.e. the free elements of the matrices Q, S, and W respectively. Figures 3.21 and 3.22 clearly show that the autocorrelation between the draws is low, and in the vast majority of cases below 1.5. As stressed in Primiceri, 2005 and others, values of the inefficiency factors below 20 are satisfactory.

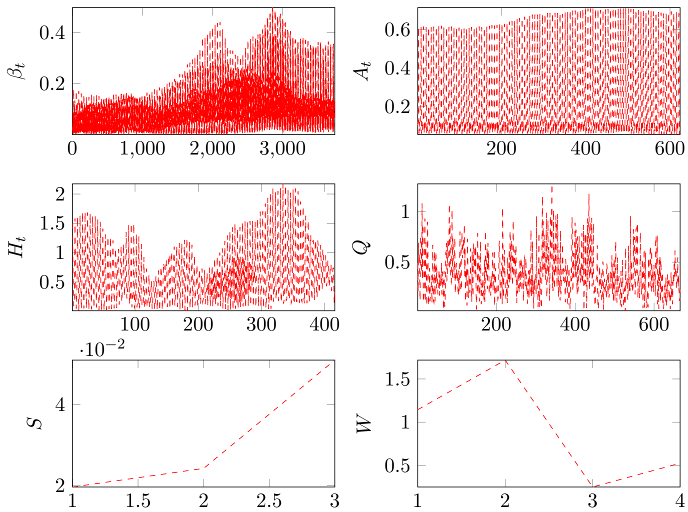

FIGURE 3.21: **Convergence of the MCMC Algorithm using US Data; Inefficiency Factors**
Notes: This figure shows the inefficiency factors computed for the draws of the elements of the matrices: β_t, A_t, H_t, Q, S and W

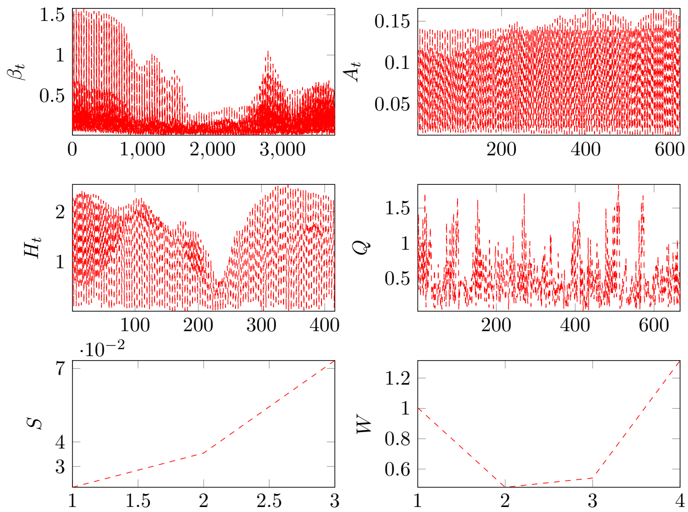

FIGURE 3.22: **Convergence of the MCMC Algorithm using UK Data; Inefficiency Factors**
Notes: This figure shows the inefficiency factors computed for the draws of the elements of the matrices: β_t, A_t, H_t, Q, S and W

Chapter 4

Liquidity Shocks and Real GDP Growth: Evidence from a Bayesian Time–varying Parameter VAR

4.1 Introduction

The links between asset markets and macroeconomic fluctuations are the subject of lengthy debate (see e.g. Bernanke and Blinder, 1988). In light of the 2008 recession (i.e. the Great Recession), liquidity provision is becoming a central topic (see Adrian and Shin, 2008; Acharya, Shin, and Yorulmazer, 2011; Næs, Skjeltorp, and Ødegaard, 2011). Figure 4.1 depicts the annual rate of real GDP growth along with our proxies of stock and house market liquidity conditions, the Amihud, 2002 measure, from 2000 to 2014. An increase in these measures constitutes a decline to liquidity (i.e. an increase in illiquidity). Clearly, we can see that liquidity (illiquidity) is countercyclical (procyclical) with real GDP growth. In particular, liquidity dries up in late 2008, corresponding with the peaks in our stock and house market liquidity proxies, and these lead the slump in GDP growth by around 1–2 quarters in early 2009.

The prime contribution of this chapter is to assess the effects of liquidity shocks stemming from stock and house markets on real GDP growth throughout time. Our empirical study examines the impact of liquidity shocks for the US economy from 1970 to 2014. Our sample captures prosperous and recessionary periods; as well as the recovery period following the financial crisis. To the best of our knowledge, there is no document of an empirical investigation on the effects of liquidity shocks on the real economy. In fact the majority of the literature concentrates on explanatory and forecasting performance (e.g. Næs, Skjeltorp, and Ødegaard, 2011 and Florackis et al., 2014). The importance of understanding the dynamics of liquidity shocks and the real economy is twofold. First, the structural links between asset market liquidity and the real economy may be dependent on the business cycle. Second, model misspecification can result in erroneous inference and policy recommendations.

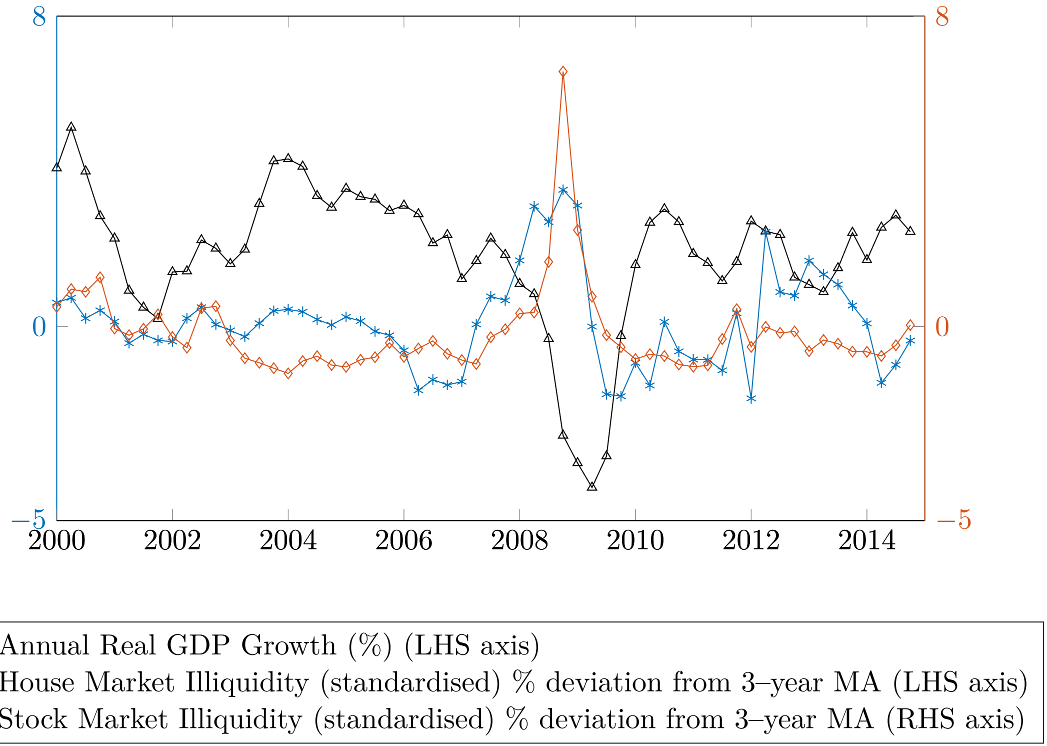

FIGURE 4.1: **US Real GDP growth (%), House Market Illiquidity and Stock Market Illiquidity from 2000 to 2014**
Notes: This figure plots the annual % growth rate of US real GDP (LHS axis), House market illiquidity (expressed as the standardised % from its 3–year moving average) (LHS axis) and Stock market illiquidity (expressed as the standardised % deviation from its 3–year moving average) (RHS axis) from 2000 to 2014.

There are various reasons why liquidity conditions in stock and housing markets can affect the real economy. Firstly, stock market liquidity may behave as a signalling process uncovering the information set of investors (Florackis et al., 2014). In times of excess volatility or diminishing confidence regarding the future state of the economy, investors adjust portfolio holdings moving funds from high risk assets into 'safe havens' such as government debt or other short-term fixed income securities (flight to safety). Furthermore if investors expect a liquidity shock (which we define as a sudden decline to liquidity), portfolio compositions mirror this and greater proportions of wealth move into liquid assets (flight to liquidity); Longstaff, 2004. Brunnermeier and Pedersen, 2009 develop a model where the provider's ability to supply liquidity depends on their capital and margin requirements. During periods of financial stress, a reinforcing mechanism between funding and market liquidity leads to liquidity spirals. A shock to funding liquidity forces providers to shift liquidity provision into low margin stocks. On the other hand, Levine and Zervos, 1998 propose that investment channels within a liquid secondary market facilitate investment into long–run (generally less liquid) projects that enhance long–term productivity; and subsequently economic growth.

Housing also plays multiple roles in affecting the real economy. First, houses can return capital gains or losses as an asset that directly influence housing wealth. Campbell and Cocco, 2007 establish that increases in housing wealth relax borrowing constraints and fuel consumption growth. Similarly Carroll, Hall, and Zeldes, 1992 argue from a precautionary savings motive, that increases in the value of housing wealth increase consumption expenditure. Second, housing can catalyse inter–temporal consumption when credit markets are imperfect. Housing is a pledgeable asset, He, Wright, and Zhu, 2015 allege that house prices contain a liquidity premium. Therefore, in equilibrium, people may be willing to pay more than the house's fundamental value because of the financial security this conveys when they need a loan. Moreover purchasing a house requires a sizeable down payment, therefore the buyer's liquidity affects the demand for housing (Stein, 1995). Thus strong demand in the housing market requires an extensive base of liquidity. Factors contributing to the notion of a housing bubble prior to the Great Recession are: substantial increases in trading volumes, surging prices and, mortgage defaults. With regards to the latter, Mian, Sufi, and Trebbi, 2015 states "when major shocks hit the economy and millions of homeowners simultaneously default ... sales of foreclosed homes could lead to further reductions in house prices, threatening real activity"[1].

Our main results stem from a Bayesian time–varying parameter VAR (TVP–VAR) model with a stochastic volatility structure. Our model allows for time–variation in the autoregressive parameters, structural shocks, contemporaneous relations and the stochastic volatility innovations. We provide robust evidence that stock market liquidity shocks yield damaging contractions to real GDP growth at each observation of our sample. However, the magnitude of the impact is declining. Contrastingly, we document a remarkable structural change between house market liquidity and real GDP growth as frictions in the property sector surface in 2005. Our analysis reveals that house market liquidity shocks are most damaging during the depths of the Great Recession. We provide substantial evidence supporting an asymmetric response of GDP to house market liquidity shocks over the business cycle and across business cycle troughs in our sample. We further show that structural stock market and house market liquidity shocks explain, on average, 15% and 36% of the overall variation in real GDP growth during the Great Recession.

From a theoretical perspective, our results correspond with the liquidity shock hypothesis in Kiyotaki and Moore, 2012. This refers to sudden drops in asset market liquidity that may or may not relate to macroeconomic fundamentals, causing equity prices to fall. Lower asset prices hinder firms' financing abilities through issuing new equities and/or using equity as collateral. Therefore, investment deteriorates, output falls and recession begins. However, in discussing the financial crisis, there is recognition that

[1] A mortgage contract gives the lender the right to foreclose on a home should the buyer default on repayment obligations.

liquidity conditions in stock and housing markets are both countercyclical with the business cycle (see among others, Jermann and Quadrini, 2012; Jaccard, 2013; Diaz and Jerez, 2013). The innate appeal of the liquidity shock hypothesis corresponds particularly well with recent business cycles. If asset market liquidity is a causal factor, policymakers can impede the cycle through the direct provision of liquidity to support investment.

The empirical literature is relatively small (but growing) with regards to the role of asset markets for the macroeconomy in a time–varying framework (see, among others Balke, 2000, Davig and Hakkio, 2010, Eickmeier, Lemke, and Marcellino, 2015, Abbate et al., 2016). In general, results on the time–variation of financial shocks are not conflicting, the volatilities of structural financial shocks evolve throughout time. A possible explanation is that a financial shock simultaneously effects financial intermediaries, credit conditions and segments of the financial market[2]. However, an abundance of literature accounts for financial conditions through one variable; typically a "financial conditions" aggregate. Hubrich and Tetlow, 2015 emphasise the existence of an episodic relationship between the macroeconomy and financial factors limits the amount of economically (and statistically) significant evidence within the literature. They estimate a Bayesian Markov–Switching VAR model using US data and analyse the effects of financial shocks using the Financial Stress Index. Time–variation is shown to be significant and economically meaningful for financial shocks during "stress events".

However, aggregating conditions from different financial markets omits any interaction between financial variables. Implicitly, this ignores important contemporaneous structural links between asset markets. The empirical literature allowing for different financial markets in a VAR framework is small (see e.g Björnland and Leitemo, 2009 and Prieto, Eickmeier, and Marcellino, 2016). Our works builds upon Prieto, Eickmeier, and Marcellino, 2016, who evaluate the effects of asset price shocks to US GDP growth in a time–varying framework. We extend upon their analysis by isolating the liquidity component from stock and house prices overcoming the complex web of information that nests within asset prices (Harvey, 1988). In particular our proxies of liquidity work on the interaction between prices and quantities. We use the liquidity ratio in Amihud, 2002 which focuses on liquidity in the elasticity domain capturing the resilience of the asset price. The attractiveness of this measure is twofold: first, data is readily available for long periods of time and it is simple to compute . Second, the ratio rests on theoretical foundations of Kyle's price impact coefficient (Goyenko, Holden, and Trzcinka, 2009).

Conceptually, our work relates to the Dynamic Stochastic General Equilibrium (DSGE) literature focussing on financial shocks. Shi, 2015 deduces a tractable model able to quantify the impact of financial shocks over the business cycle. Negative shocks to

[2] In particular, this general consensus corroborates with the findings of Stock and Watson, 2012 who note that the size of the financial shocks were drivers of the financial crisis.

asset liquidity are shown to cause investment, consumption and output to fall. Jaccard, 2013 calibrates a DSGE model using US data and evaluates the Great Recession by computing the relative contribution of liquidity shocks. Results imply that the sharp contraction in output was mainly due to negative liquidity shocks originating in the financial sector. Christiano, Motto, and Rostagno, 2010 show that 'financial factors' are key drivers to economic fluctuations. The main results show that risk shocks, affecting the economy through the investment margin, are the main driver behind economic variations explaining more than 60% of the volatility in US investment; and a third of investment volatility in the Euro area. Furthermore, liquidity shocks display drastic effects on real activity. In particular these shocks reveal a detraction of between 1/3 and 1.5 percentage points of the contraction in US GDP growth.

The structure of the remainder of this chapter is as follows: Section 4.2 shows how we measure liquidity and provides a description of the macroeconomic data. We discuss TVP–VARs, prior specification and identification of structural shocks in section 4.3. Empirical analysis and robustness checks are in Section 4.4 and 4.5 respectively. Finally, Section 4.6 provides concluding comments.

4.2 Measuring Liquidity and Data

To proxy stock market liquidity, we rely on the Return–to–Volume (RtoV) ratio of Amihud, 2002:

$$RtoV_t^s = \frac{1}{N_Y} \sum_{n=1}^{Y} \frac{|r_{i,t}|}{VOL_{i,t}} \tag{4.1}$$

where $|r_{i,t}|$ is the absolute return of stock i on day t, $VOL_{i,t}$ is stock i's trading volume (in units of currency) on day t, Y is the number of days within the trading window. An increase in S_t^{illiq} constitutes a decline in liquidity.

To calculate stock market liquidity, we use daily stock price and trading volume data for all common stocks on the New York Stock Exchange (NYSE) from the CRSP database over the time period 1968 to 2014. We implement standard filtering criteria similar to Amihud, 2002[3].

[3]Specifically, we admit stocks into our estimate if they have at least 200 days of return and trading volume data in the previous year. We also omit stocks with a price less than $5 at the end of the previous year. Finally, we eliminate outliers by removing stock's whose liquidity estimate is in the top and bottom 5% tails of the distribution for the current year (after satisfying the former criterion). Note, results and conclusions remain the same when we eliminate the top and bottom 1% tails of the distribution which is consistent with filtering criteria in Amihud, 2002. We calculate the liquidity measure for each quarter and each security, then take an equally weighted average over the cross section of securities. To calculate our stock market liquidity proxy, we include between 986 and 2613 stocks in each year; the average number of stocks estimating market liquidity is 1805 per year.

In a similar manner, we estimate house market liquidity as:

$$RtoV_t^h = \frac{|\Delta h_t|}{VOL_t} \tag{4.2}$$

where $|\Delta h_t|$ is the absolute quarterly change in house prices in quarter t (i.e. house price inflation) and VOL_t is the trading volume (in thousands of units of currency) of houses in quarter t; an increase in $RtoV_t^h$ corresponds to a decrease in liquidity. We use Case and Shiller's composite national house price index which tracks the prices of single–family homes and is from Robert J. Shiller's webpage. Trading volume is the sum of the volume of sales of new and existing single–family homes (available from Thomson Reuters DataStream)[4]. In Section 4.7.1 Appendix A, we report descriptive statistics of the raw estimates of $RtoV_t^s$, $RtoV_t^h$.

TABLE 4.1: Descriptive Statistics for Macroeconomic Data and Liquidity Proxies from 1970 to 2014

	π_t	y_t	i_t	H_t^{illiq}	S_t^{illiq}
Mean	-0.036	2.751	5.571	-6.632	-11.533
Median	0.047	2.958	5.3	-8.716	-22.933
Max	2.291	8.204	17.79	166.548	267.171
Min	-2.627	-4.147	0.07	-99.566	-62.765
Std.Dev.	0.856	2.22	3.867	49.134	42.411
Skew	-0.532	-0.583	0.676	0.671	2.662
Kurt	4.199	3.715	3.537	4.082	14.186

Notes: This table reports descriptive statistics for US macroeconomic data from 1970Q4–2014Q4. π_t is the annual rate of GDP deflator inflation. This has been detrended using a one–sided Kalman filter as in Stock and Watson, 1999; y_t is the annual rate of real GDP growth; i_t is the Federal Funds rate; H_t^{illiq} is house market liquidity expressed as the % deviation from its 3–year moving average and S_t^{illiq} is stock market liquidity which is also expressed as the % deviation from its 3–year moving average.

Our estimation sample spans from 1970 to 2014 and is reliant upon data availability. We cover four National Bureau of Economic Research (NBER) recessionary periods, including the Great Recession. We gather US economic data on inflation (using the GDP deflator), real GDP and the Federal Funds rate from the Federal Reserve Bank of St. Louis. We convert inflation and GDP into annual growth rates using logarithmic differences. Using a one–sided Kalman filter, we de–trend inflation as in Stock and Watson, 1999. The trend captures inflation expectations and is thought to alleviate price

[4]Case and Shiller's national house price index gathers data from nine US census constituents for single family homes; data is available from `http://www.econ.yale.edu/~shiller/data.htm`. Trading volume data is the number of sales (in thousands), to convert into thousands of units of currency we multiply trading volume by the median house price for the USA available from the Federal Reserve Bank of St. Louis.

puzzles (Prieto, Eickmeier, and Marcellino, 2016). We transform both our liquidity proxies into % deviations from their respective 3–year moving averages; denoting as S_t^{illiq}, H_t^{illiq}. Figure 4.2 plots our data series[5].

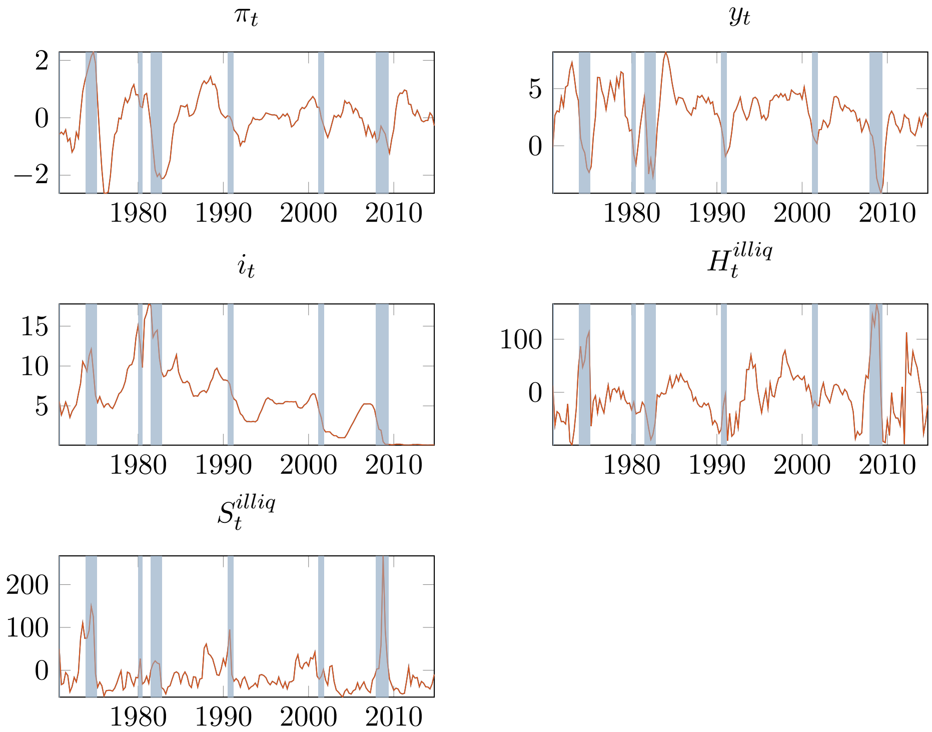

FIGURE 4.2: **Macroeconomic and Financial Variables from 1970 to 2014**
Notes: This figure plots the annual rate of US inflation, π_t; annual real GDP growth, y_t; the Federal Funds rate, i_t; House Market Liquidity, H_t^{illiq} and Stock Market Liquidity, S_t^{illiq}. We detrend the annual inflation rate, using a one-sided Kalman filter as in Stock and Watson, 1999. Our liquidity proxies are % deviations from their 3–year moving averages respectively. Grey bars indicate NBER recession dates.

Table 4.1 reports descriptive statistics for our macroeconomic and financial data. On average US real GDP growth is around 2.75%, it peaks in 1984 at 8.2% and troughs in the depths of the most recent recession at -4.15% (i.e. 2009Q2). House and stock market liquidity, on average, fluctuate 6.63% and 11.53% below their respective 3–year moving averages. Both measures peak as liquidity dries up during the Great Recession in 2008Q4 at 166.59% and 267.17% respectively. The contemporaneous correlation between real GDP growth and stock market and house market liquidity are -0.35 and -0.05 respectively. Negative correlations with real GDP growth are intuitive, an increase in the Amihud, 2002 measure corresponds to worsening liquidity conditions (i.e. the market is more illiquid). The contemporaneous correlation between our liquidity proxies is 0.35.

[5]We also run our analysis using the annual growth rate of our liquidity proxies. Results and conclusions are consistent with the results we report in this chapter. We abstain from reporting these results since during the 2008 recession the annual change in our proxies reach up to 800%.

4.3 Econometric Methodology

4.3.1 A Time–varying Parameter VAR with Stochastic Volatility

Following Primiceri, 2005 the full TVP–VAR with M variables, p lags and t time series observations takes the form:

$$y_t = Z_t'\beta_t + A_t^{-1}\Phi_t\varepsilon_t \tag{4.3}$$

$$\beta_t = \beta_{t-1} + \upsilon_t, \quad \upsilon_t \backsim N(0, Q) \tag{4.4}$$

where $Z_t = I_M \otimes [1, y_{t-1}', \ldots, y_{t-p}']$, $\otimes$ denotes the Kronecker product and I_M is an M dimensional identity matrix; in our case $M = 5$. We set $p = 2$ in line with Cogley and Sargent, 2005; Primiceri, 2005; Hubrich and Tetlow, 2015 and Prieto, Eickmeier, and Marcellino, 2016. The structural shocks of the model, ε_t follow $\varepsilon_t \backsim^{iid} N(0, I_M)$. The coefficients β_t follow driftless random walks. The matrix A_t is an $M \times M$ lower triangular matrix with ones along the diagonal. Below the diagonal elements are the contemporaneous relations of the variables in the model. Φ_t is an $M \times M$ diagonal matrix that contains the reduced form stochastic volatility innovations. In our case, we define the time–varying matrices A_t, Φ_t as:

$$\Phi_t \equiv \begin{bmatrix} \phi_{1,t} & 0 & 0 & 0 & 0 \\ 0 & \phi_{2,t} & 0 & 0 & 0 \\ 0 & 0 & \phi_{3,t} & 0 & 0 \\ 0 & 0 & 0 & \phi_{4,t} & 0 \\ 0 & 0 & 0 & 0 & \phi_{5,t} \end{bmatrix} \quad A_t \equiv \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 & 0 \\ \alpha_{51,t} & \alpha_{52,t} & \alpha_{53,t} & \alpha_{54,t} & 1 \end{bmatrix} \tag{4.5}$$

the contemporaneous relations $\alpha_{ij,t}$ and the volatility innovations $\phi_{i,t}$ drift throughout time. Constructing α_t as the row-wise stacking of elements below the diagonal

$$\alpha_t = [\alpha_{21,t},\ \alpha_{31,t},\ \alpha_{32,t},\ \ldots,\ \alpha_{54,t}]'$$

and collecting the diagonal elements in the vector, ϕ_t

$$\phi_t = [\phi_{1,t},\ \phi_{2,t},\ \phi_{3,t},\ \phi_{4,t},\ \phi_{5,t}]'$$

we assume:

$$\alpha_t = \alpha_{t-1} + \zeta_t, \quad \zeta_t \backsim N(0, S) \tag{4.6}$$

$$\ln\phi_t = \ln\phi_{t-1} + \eta_t, \quad \eta_t \backsim N(0, W) \tag{4.7}$$

The entire system contains four sources of uncertainty that are jointly Normal:

$$\begin{bmatrix} \varepsilon_t \\ \upsilon_t \\ \zeta_t \\ \eta_t \end{bmatrix} \backsim N(0, V), \quad V = \begin{bmatrix} I_5 & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix} \tag{4.8}$$

where I_5 is a $5 \times\ 5$ identity matrix; Q, S, W are all positive definite matrices. S is block diagonal where the blocks correspond to the parameters belonging in each respective equation. This increases the efficiency of the estimation algorithm in Section 4.7.2 Appendix B.

Priors

Our prior specification follows closely the specifications in Cogley and Sargent, 2005 and Primiceri, 2005. We use the first 41 observations (from 1970Q4–1981Q2) to calibrate the initial conditions for the parameters of the model[6]. The initial conditions for the coefficient matrix, β_0 are the OLS point estimates from a standard VAR. We set $Var(\beta_0)$ as four times the variance of the standard OLS estimates from the training sample. We obtain the prior to initialise A_0 in the same manner. We set $\ln \phi_{0,i}$ to have a mean equal to the (logarithmic) standard errors of the OLS estimates (in each equation) to initialise β_0; its covariance matrix is an M-dimensional diagonal matrix where the elements along the main diagonal are equal to 10. Further, setting the degrees of freedom and scale for the inverse–Wishart prior distributions of the hyperparameters; for each of the five blocks of S, the degrees of freedom are $1 + dim(S_i)$. The degrees of freedom for Q are set to 1+K (i.e. 1 plus the dimension of β_t), where $K = 55$. W follows an inverse–Gamma distribution with a single degree of freedom with a scale parameter $k_W = .01$. The scale matrices are chosen to be constant fractions of the OLS estimates from the training sample. To summarise:

[6]Our results remain similar when we allow for 50 and 60 observations to calibrate the initial conditions of the model, and for different values of the hyperparameters.

$$
\begin{aligned}
\beta_0 &\backsim N(\hat{\beta}_{OLS}, 4 \cdot V(\hat{\beta}_{OLS})) \\
A_0 &\backsim N(\hat{A}_{OLS}, 4 \cdot V(\hat{A}_{OLS})) \\
\ln \phi_{0,i} &\backsim N(\ln \hat{\phi}_{OLS,i}, 10) \\
Q &\backsim IW(k_Q^2 \cdot (1+K) \cdot Var(\beta_0), (1+K)) \\
W_{i,i} &\backsim IG\left(\frac{k_W^2}{2}, \frac{1}{2}\right), \; i = 1 \dots M \\
S_i &\backsim IW(k_S^2 \cdot (i+1) \cdot Var(\hat{A}_{i,OLS}), (i+1)), \; i = 1 \dots M-1
\end{aligned}
$$

where IW denotes the inverse–Wishart distribution and $S_i, i = 1, \dots, 5$ denote the blocks of S. $\hat{A}_{i,OLS}$ denotes the blocks of the OLS estimates of the blocks of the estimate of $\hat{A}_{OLS}$ matrix within the training sample following the method in Primiceri, 2005. In line with the former, and Cogley and Sargent, 2005, we set $k_Q = .01$ and $k_S = .1$. We allow for 70,000 iterations of the Markov–Chain Monte Carlo (MCMC) algorithm discarding the first 60,000 as burn–in; of the remaining 10,000 iterations, we sample every 10^{th} draw to reduce autocorrelation amongst the draws[7]. Section 4.7.2, Appendix B assesses the convergence properties of the MCMC algorithm.

4.3.2 Identification of Structural Shocks

We add our liquidity variables to the macroeconomic data and order our TVP–VAR model as follows: the inflation rate, π_t; output growth, y_t; the interest rate i_t; house market liquidity H_t^{illiq} and stock market liquidity S_t^{illiq}. We assume a block recursive composition of the covariance matrix of structural shocks which is standard in the literature (see among others: Cogley and Sargent, 2005, Primiceri, 2005, Hubrich and Tetlow, 2015 and Prieto, Eickmeier, and Marcellino, 2016). In our case, we define a liquidity shock as a sudden decline to liquidity (i.e. an increase in illiquidity). Under this identification scheme, macroeconomic variables are slow to react to liquidity shocks. Notably under this identification scheme, our results are sensitive to ordering; an issue we discuss in Section 4.7.3, Appendix C. Our ordering scheme imposes monetary policy reacts slowly to liquidity shocks; typically monetary policy decisions are made every six weeks (Swiston, 2008)[8]. Additionally, ordering our liquidity variables last in our VAR model is indicative of reality. For example, we observe liquidity shocks in late 2008 and policymakers respond by lowering interest rates in early 2009. Furthermore our liquidity proxies reach their respective peaks at the end of 2008, US real GDP

[7]Our results are robust when setting the scale matrices to different values; larger values of the scale matrices induce a higher degree of time–variation into the model.

[8]The Federal Open Market Committee (FOMC) holds eight meetings throughout the year at regular intervals.

growth troughs in early 2009. Therefore we postulate our identification scheme is valid and proceed on this premise; Section 4.7.3 Appendix C reports additional results under an alternative ordering scheme[9].

4.4 Empirical Results

4.4.1 Stochastic Volatility and Changing Dynamics

In what follows we analyse whether we can characterise time–variation to the size of shocks or to changing dynamics of the transmission mechanism. In Figure 4.3, we present the posterior median along with the one standard deviation percentiles of the stochastic volatility of liquidity shocks (i.e. the quantiles of the distribution over the draws of $\phi_{4,t}, \phi_{5,t}$). It is clear there is remarkable time–variation in the stochastic volatility innovations of liquidity shocks. Notice that the volatility of house market liquidity shocks in the 2008 recession remains persistently high for at least four years after the recession ends. This resilience may suggest a magnifying and longer lasting impact of house market liquidity shocks following the Great Recession. Figure 4.3 corroborates with Claessens, Kose, and Terrones, 2012 in that recessions preceding a property market bust are more extensive, in depth and time, than those without. For example the 2001 recession yields little change in the volatility of house market liquidity shocks. Contrastingly in the same periods, the volatility of shocks to stock market liquidity surge temporarily and then revert back to levels consistent with non–recessionary periods[10].

In Figure 4.4 we plot the posterior median impulse response functions of GDP growth to liquidity shocks at a 5–year horizon for each observation in our sample; which covers the period 1981Q3–2014Q4. Given an increase in our proxies constitutes a decline in liquidity, a liquidity shock therefore implies a sudden decline in market liquidity. Clearly, shocks to stock market liquidity yield temporarily contractionary effects to real GDP growth. Over time the magnitude of the response of real GDP growth with respect to stock market liquidity shocks are decreasing, yet the persistence remains similar. This result is consistent with Prieto, Eickmeier, and Marcellino, 2016, who show that stock price shocks also exhibit a decreasing impact on US real GDP growth. In fact, they find that the overall contribution of the stock market to the Great Recession plays a negligible role[11]. Nevertheless, the impact of stock market liquidity shocks on real GDP

[9]Results are consistent if we place GDP growth before inflation. Ordering GDP and inflation in this manner is uniform to Hubrich and Tetlow, 2015 and Prieto, Eickmeier, and Marcellino, 2016.

[10]We report the stochastic volatility of macroeconomic shocks in Section 4.7.3 Appendix C; along with plots of the time–varying parameters and time–varying covariances.

[11]Our results are similar when we include credit spreads in our model, the credit spread is the difference between Moody's BAA-AAA corporate bond spread. Appendix C in Section 4.7.3 reports the results including credit spreads.

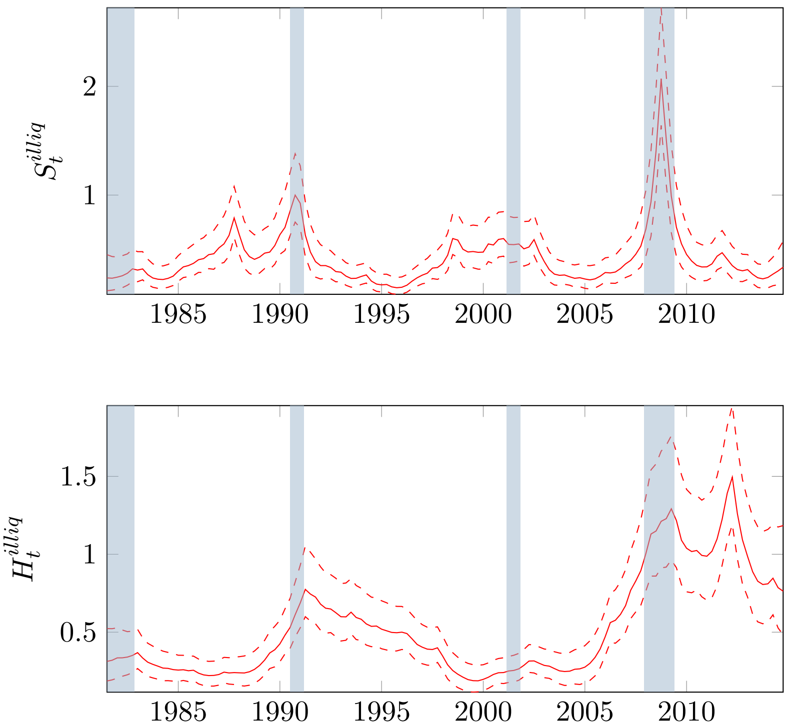

FIGURE 4.3: **Stochastic Volatility of Liquidity Shocks from 1981 to 2014**
Notes: This figure shows the median and 1 standard deviation percentiles of the time–varying standard deviations of structural shocks for Stock Market liquidity, S_t^{illiq} and House Market liquidity, H_t^{illiq} from 1981Q3–2014Q4. Grey bars indicate NBER recession dates.

growth are significant, relative to 68% posterior credible intervals, across all time periods. Although the impact is diminishing throughout time, there are still economically meaningful contractionary effects.

On the other hand, the real effects of house market liquidity shocks are trivial from 1981 to 2005 with the posterior median response of real GDP growth barely fluctuating away from 0. However, GDP growth becomes gradually more sensitive to house market liquidity shocks from around 2005 onwards; the impulse response functions' posterior credible intervals indicate significance from 2005Q2 (further results available on request). The transition in impact of house market liquidity shocks aligns closely with disturbances in the housing market. Interestingly, the economic significance of house market liquidity shocks is greatest when real GDP growth is at its (sample) minimum value (i.e. -4.15% in 2009Q2). To compare, the maximum value of GDP growth in our sample is in 1984Q1, notice in Figure 4.4 that there is virtually no reaction of GDP growth to a liquidity shock in this period. The difference in the transmission of house market liquidity shocks across our sample indicates there is a structural change in the relationship between GDP growth and house market liquidity. We postulate the change in the impact of liquidity shocks on real GDP growth links with the increasing securitisation of mortgages that eventually unwound the US financial sector.

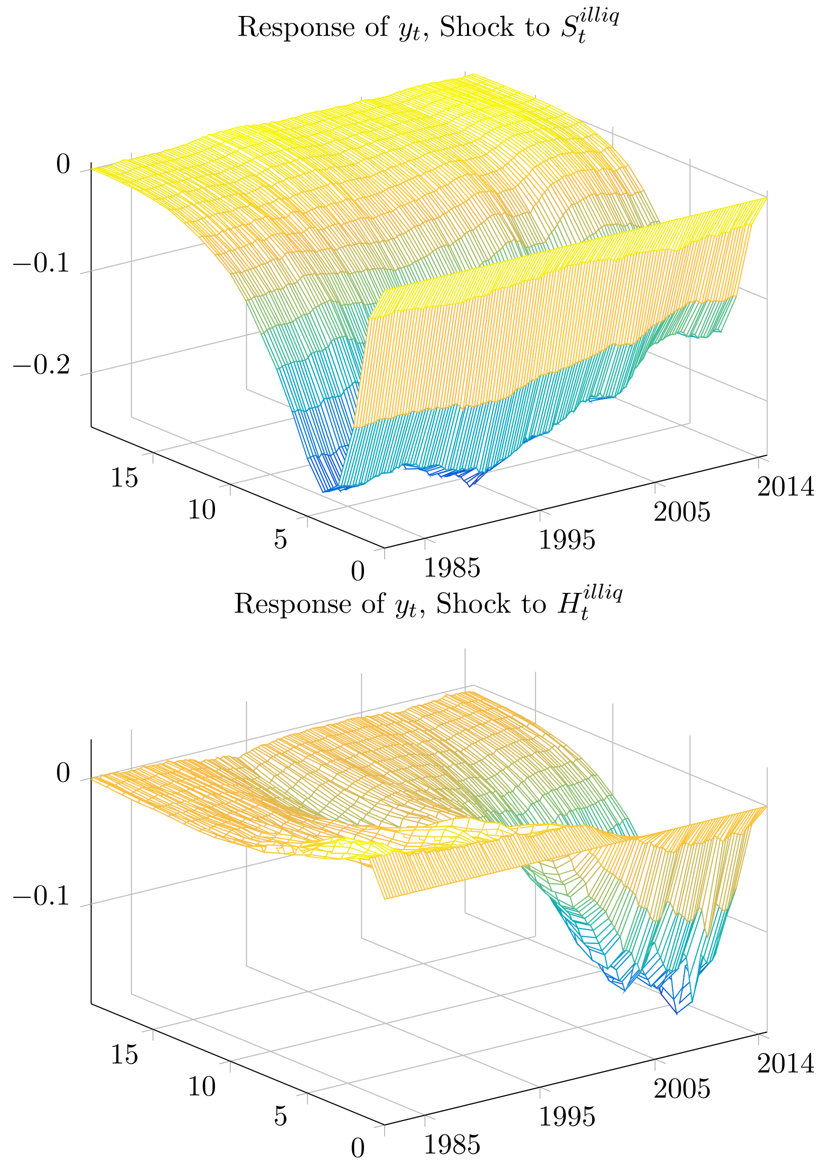

FIGURE 4.4: **Impact of Liquidity Shocks on GDP Growth 1981 to 2014**
Notes: This figure plots the median impulse response functions of US real GDP growth with respect to: a stock market liquidity shock and a house market liquidity shock. We plot the response along a 5–year horizon for each quarter of our sample 1981Q3–2014Q4. We define a liquidity shock as a sudden decline in market liquidity.

Following the practice of Galí and Gambetti, 2009 and Prieto, Eickmeier, and Marcellino, 2016, we plot in Figure 4.5, the differences in average impulse response of GDP growth to liquidity shocks between different periods stemming from NBER recession dates. This allows us to distinguish if there are differences in the economic impact of liquidity shocks across the business cycle. We compute for each draw of the Gibbs sampler, the average impulse response over each of the periods, take the difference between the averages and then calculate the quantiles over the draws. In Panel 1, we compare all recessions excluding the Great Recession with non–recessionary periods. Panel 2 compares the Great Recession with non–recessionary periods, and Panel 3 compares the Great Recession with all other recessions in our sample; this is to evaluate possible heterogeneities in the transmission of liquidity shocks. Our results suggest little difference in the average impact of stock market liquidity shocks across periods. However, this finding is unsurprising since Figure 4.4 reveals a decline in the susceptibility of real GDP growth to stock market liquidity shocks.

On the other hand, we see asymmetries in the response of real GDP growth to house market liquidity shocks. Our model implies an increasing exposure of real GDP growth to house market liquidity shocks in the post financial crisis period; which links closely with the persistence of the volatility of structural shocks in Figure 4.3. Clearly, our results show that the impact of house market liquidity shocks on real GDP growth are stronger during the Great Recession than non–recessionary periods. Perhaps even more interestingly, Figure 4.5 shows the effects of house market liquidity shocks during the Great Recession are more damaging, in terms of magnitude and tenacity, relative to both normal times and other recessions within our sample[12].

In Figure 4.6, we report the median and one standard deviation percentiles of the contributions of stock and house market liquidity structural shocks to the overall variance of real GDP growth across our sample. The discussion following refers to posterior median estimates of the distribution of our structural variance decompositions. Following Benati and Mumtaz, 2007, we compute the variance decomposition in the frequency domain by computing, for each quarter, at each iteration of the Gibbs sampler, real GDP's actual spectral density and the five counterfactual spectral densities by setting to zero the variances of each of the structural shocks but one[13]. The following discussion and analysis refers to the posterior median estimates of the structural variance decompositions. The contribution of stock market liquidity shocks to the variance of real GDP growth varies considerably over our sample. We can see that during the stock market crash of 1987 and the 1991 recession, the structural stock market liquidity shocks account for 20% of the variation in real GDP growth. In 2008 the stock market explains 36% of the variance of real GDP growth; however, this is a temporary shift and by 2010, the fraction of GDP's variance attributable to stock market liquidity shocks is only 5%.

The contribution of house market liquidity shocks to the overall variance of real GDP growth also varies remarkably over our sample. In the 1980s, the fraction of GDP's variance we associate to house market liquidity shocks fluctuates around 10%. Then,

[12]This finding could be partly attributable to our methodology and the length of the most recent recession. Our model allows for smoothly changing parameters throughout time which may, in fact, only capture parameter change over long periods. However, our model implies liquidity shocks in the property sector yield contractionary real effects even after the financial crisis.

[13]Since a series' variance is equal to the integral of its spectral density, we can compute a structural decomposition of GDP growth's variance at each point in time; noting that the sum of the five counterfactual spectral densities is by construction equal to the overall variance of the series in question. It is not possible to uniquely identify the innovation variances of the structural shocks, but it is possible to compute the time–varying covariance matrix of the VAR that results by setting innovation variances to zero.

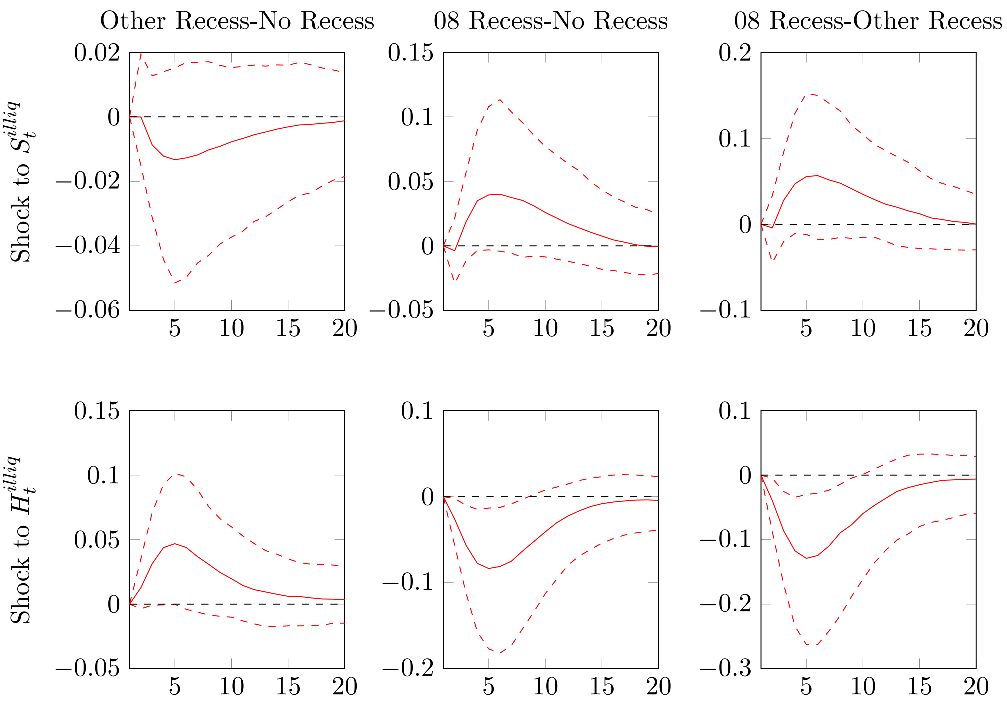

FIGURE 4.5: **Impulse Responses of GDP growth: Differences in averages over periods**

Notes: Panels 1 to 3 show the averages of differences in impulse responses of GDP growth to liquidity shocks between: other recessionary (i.e. NBER recession dates excluding the Great Recession) and non–recessionary periods (Panel 1: Other Recess-No Recess); The Great Recession and non–recessionary periods (Panel 2: 08 Recess-No Recess) and The Great Recession and other recessionary periods (Panel 3: 08 Recess-Other Recess). Recessionary periods are NBER recession dates. We compute as follows: for each draw of the Gibbs sampler, we average the impulse response over each of the selected periods, take the difference between the averages of selected periods and then calculate the quantiles over the draws.

following the recession in 1991, the fraction jumps to around 35% and remains persistently high (i.e. around 30%) until 1997. In the early 2000s and during the dot–com bubble burst, the contribution of house market liquidity shocks revert back to around 10%. However as the problems within the property sector start to emerge from 2005, house market liquidity shocks start to have an increasing effect. From 2008 until the end of 2014, house market liquidity shocks explain on average, 46% of the variation in real GDP growth.

The shape of these figures are strikingly similar to the volatility of structural shocks in Figure 4.3. This implies the majority of the time–variation in the structural variance decompositions is due to changing shock sizes. Taking the results together, the key driving forces to during the Great Recession are structural liquidity shocks. The average contribution of stock and house market liquidity shocks to the variation in GDP

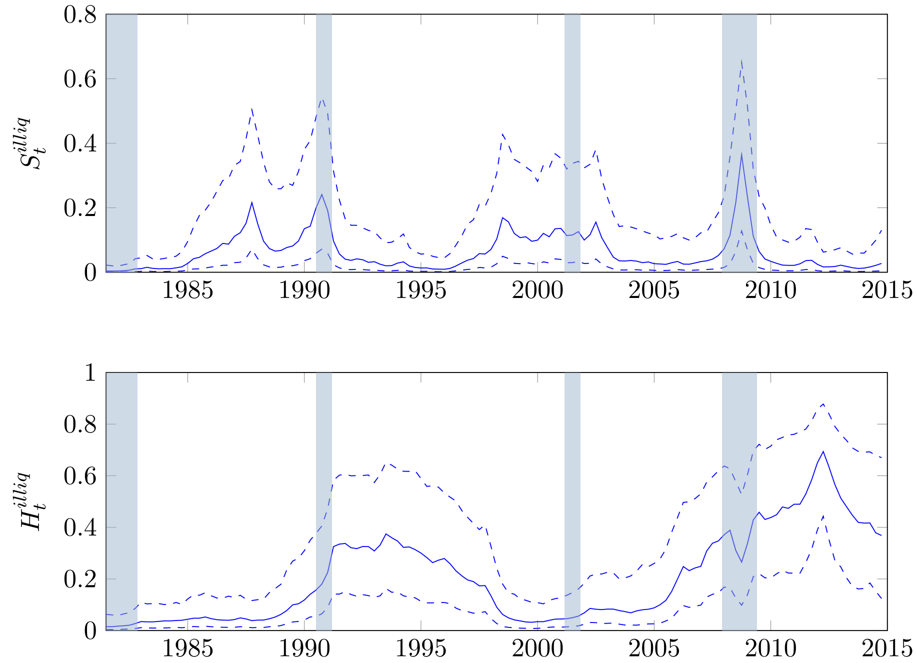

FIGURE 4.6: **Contribution of Structural Liquidity Shocks to the Overall Variance of Real GDP Growth from 1981 to 2014**
Notes: This figure plots the median and one standard deviation percentiles of the contribution of structural stock and house market liquidity shocks to real GDP growth from 1981Q3–2014Q4. Grey bars indicate NBER recession dates.

growth during the most recent recession are 15.36% and 36.34% respectively. The average total contribution of liquidity shocks to the variation in GDP growth is therefore 51.7%[14]. At the end of our sample (i.e. 2014Q4) the contribution of stock and house market liquidity shocks to GDP growth variance are 2.74% and 36.85% respectively. This, together with Figure 4.6, suggests the stubbornly low rates of GDP growth after the Great Recession are predominantly due to a fragile and sluggish recovery of the US property market.

In general, the resilience of real GDP growth to stock market liquidity shocks may reflect a diminishing demand for precautionary savings stemming from less uncertainty (Arestis, Demetriades, and Luintel, 2001). Further, as financial integration increases, domestic real effects may be offset by international investor participation as risks (and subsequently economic impacts) leak to other economies[15]. The increasing real effects of house market liquidity shocks may arise due to surges in subprime mortgage lending causing increases in debt levels (Mian and Sufi, 2009; Mian, Sufi, and Trebbi, 2015). Similarly, increases in the net worth of financial intermediaries due to surges in house prices in the early 2000s facilitates a relax in lending constraints; consequently injecting too much liquidity into the property sector. Coupling with the former, the proliferating

[14] Which is consistent with Figure 2 in Prieto, Eickmeier, and Marcellino, 2016.
[15] An important future avenue would be to quantify real international spillover effects of stock market liquidity shocks.

sensitivity of GDP to house market liquidity shocks are in line with explanations in Iacoviello and Neri, 2010, who maintain housing preference shocks have larger effects on GDP when collateral effects are taken into account.

Overall our results provide substantial evidence that the US property sector has asymmetrical real effects not only across the business cycle, but also amongst business cycle troughs across our sample (see Panel 3 of Figure 4.5). Furthermore, we show that liquidity conditions in the stock and housing markets contribute heavily to the overall variation in real GDP growth; particularly during crisis periods. Our results contrast Prieto, Eickmeier, and Marcellino, 2016 and document that the stock market (i.e. stock market liquidity) is an important factor in explaining US GDP variance during the Great Recession. The immediate policy implication is that liquidity provision to financial and asset markets is necessary to counteract damaging contractions to GDP growth. Studying the economic impact of liquidity shocks throughout time signals liquidity provision, particularly in the property sector, is essential to promote recovery. Our findings justify US policy responses to the turmoil of 2008 such as: injecting liquidity into financial asset markets through Quantitative Easing (QE) policies; providing Fannie Mae and Freddie Mac with capital injections in September 2008; both the Home Affordable Modification and Home Affordable Refinancing Programs (HAMP, HARP) and incentives to reduce principal loans to borrowers whose mortgages exceed their property value.

4.5 Robustness Analysis

4.5.1 The Real Effects of Uncertainty Shocks

There is an implicit relationship between asset market liquidity and asset price uncertainty. For example, Florackis et al., 2014 note a negative correlation between stock market liquidity and volatility; particularly in a bear market. Levine and Zervos, 1998 stress that liquidity and uncertainty may possess an important relationship and provide an empirical investigation on the real effects of stock market liquidity and uncertainty. From a theoretical perspective, Bloom, 2009 links uncertainty shocks to the real economy showing a simulated model matches the estimations from a structural VAR (SVAR) model in terms of magnitude and timing. Additionally, Arestis, Demetriades, and Luintel, 2001 state that increases in uncertainty can hinder an efficient allocation of investment. Furthermore, the former argue that the ambiguous impact of uncertainty on saving establishes a link with liquidity. Therefore, a liquid stock market can decrease uncertainty which reduces the precautionary motive to save; consequently this can hinder economic growth.

Campbell and Cocco, 2007 provide an explanation between house market uncertainty and the real economy via the consumption channel. The volatility of house prices corresponds to changes in housing wealth, which exhibit a positive correlation with consumption. Moreover, a house is pledgeable as collateral to obtain credit. Surging prices relax borrowing constraints and allow agents to smooth consumption over the life cycle (Ortalo-Magne and Rady, 2006). Stein, 1995 associates uncertainty and liquidity in the property sector under the assumption that a down payment must be made. The multiple equilibria the model implies help explain large fluctuations in house prices[16]. Diaz and Jerez, 2013 establish an intuitive link between liquidity and uncertainty. Their theoretical model is able to reproduce the cyclical time series properties of the US property sector. As liquidity decreases in the property sector before and during the Great Recession, prices fluctuate and volatility intensifies.

Notably, as market liquidity and uncertainty may possess an important connection, it is necessary to investigate the economic impact of uncertainty shocks. If we cannot properly distinguish between the real effects of uncertainty and liquidity shocks, adequate policy recommendations cannot be made. To proxy market uncertainty we estimate an ARCH(1) and GARCH(1,1) model of the absolute value of quarterly stock and house price changes from 1968 to 2014 respectively. Using the absolute value of price changes is shown to predict volatility with greater precision than squared returns (Forsberg and Ghysels, 2007)[17]. We use stock data on the NYSE composite price index (available from Thomson Reuters DataStream); house price data is from Robert J. Shiller's website. We convert stock and house prices into real variables by dividing by the GDP deflator; returns are logarithmic differences. We include lags of the dependent variables in the mean equations of our ARCH(1) and GARCH(1,1) models to whiten the residuals; deleting those that are not statistically significant[18].

Table 4.2 reports our ARCH(1) and GARCH(1,1) specifications for stock and house price inflation, and autocorrelation diagnostics, from 1968 to 2014. Note also that we restrict the variance equation in our GARCH(1,1) model of house price inflation to $\rho + \theta = 1$; otherwise the conditional variance is explosive. To keep our analysis consistent, our uncertainty proxies are the % deviations from their 3–year moving averages of the conditional volatilities from our ARCH(1) and GARCH(1,1) models[19]. We replace our liquidity proxies with our uncertainty proxies, σ_t^s, σ_t^h and re-estimate (4.3)–(4.8).

[16]However, the implications for uncertainty are sensitive to parameter values and the initial level of liquidity within the market.

[17]Using absolute returns is also thought to be robust to outliers than volatility measures using squared returns (Florackis et al., 2014). We also estimate specifications using squared real returns, analysis results in the same conclusions to those we report herein.

[18]Initially, we estimate GARCH(1,1) models of the absolute value of real quarterly stock and house price changes, with lags of the dependent variables up to and including 5 lags.

[19]A widely accepted measure of stock market uncertainty is the VIX index (see among others Connolly, Stivers, and Sun, 2005). The VIX index uses option implied volatility of 30–day puts and calls for at the money options for stocks listed on the S&P500 index. However, VIX data starts in 1990 which is too short to use in our analysis. The contemporaneous correlation (from 1990 to 2014) between our proxy for stock market uncertainty and the VIX index is 0.55.

TABLE 4.2: ARCH/GARCH Models of Real Stock and House Price Inflation from 1968 to 2014

$$
\begin{aligned}
|\Delta s_t| &= \mu + \beta_1|\Delta s_{t-1}| + \beta_2|\Delta s_{t-3}| + \nu_t, \\
\sigma^2_{\nu_t} &= \omega + \rho\nu^2_{t-1} \\
|\Delta h_t| &= \mu + \beta_1|\Delta h_{t-1}| + \beta_2|\Delta h_{t-2}| + \beta_3|\Delta h_{t-4}| + \beta_4|\Delta h_{t-5}| + \upsilon_t, \\
\sigma^2_{\upsilon_t} &= \rho\upsilon^2_{t-1} + \theta\sigma^2_{\upsilon_{t-1}}
\end{aligned}
$$

Panel/Eq:		A: $\|\Delta s_t\|$		B: $\|\Delta h_t\|$
Sample: 1968Q1-2014Q4				
Mean Eq:				
	μ	2.998(0.69)	μ	0.345(0.09)
	β_1	0.152(0.07)	β_1	0.542(0.07)
	β_2	0.203(0.08)	β_2	-0.096(0.06)
			β_3	0.60(0.06)
			β_4	-0.38(0.06)
Variance Eq:				
	ω	12.023(2.63)	ρ	0.102(0.06)
	ρ	0.618(0.33)	θ	0.898(0.06)
Autocorrelations				
	lag	AC	lag	AC
	1	-0.033	1	0.003
	2	0.093	2	-0.038
	3	0.021	3	0.091
	4	-0.081	4	0.046
	5	-0.017	5	0.056
	6	-0.086	6	-0.086
	7	0.047	7	0.018
	8	-0.083	8	0.014

Notes: Panel A of this table presents an ARCH(1) model of the absolute value of real stock price inflation using quarterly NYSE composite index returns from 1968 to 2014. Panel B of this table presents a GARCH(1,1) model of the absolute value of quarterly house price inflation using Case & Shiller composite price index from 1968 to 2014. Standard errors are in parantheses. We restrict the variance equation for house price inflation such that $\rho + \theta = 1$. The bottom Panel reports the autocorrelation functions of the residuals up to lag length 8.

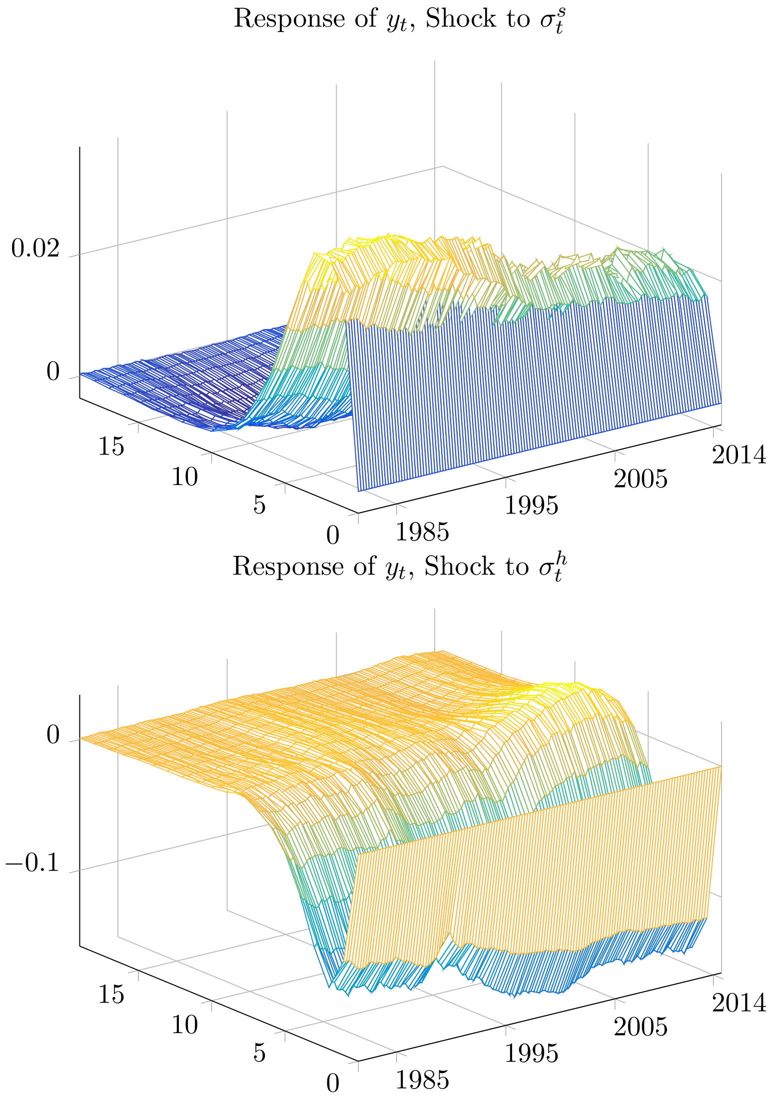

FIGURE 4.7: **Impact of Uncertainty Shocks on GDP growth from 1981 to 2014**

Notes: This figure plots the median impulse response functions of US real GDP growth with respect to a stock market uncertainty shock, σ_t^s and a house market uncertainty shock, σ_t^h. We plot the response along a 5–year horizon for each quarter of our sample 1981Q3–2014Q4. We define a liquidity shock as a sudden decline in market liquidity.

Figure 4.7 plots the posterior median estimates of the impulse response functions of real GDP growth with respect to uncertainty shocks throughout time. Our results reveal that GDP growth responds positively to stock market uncertainty shocks and that the impact is slowly declining across our sample. Moreover the 68% posterior credible intervals of the response of real GDP growth to stock market uncertainty shocks contain 0 over the 5–year horizon in all time periods; indicating no significant response of real GDP growth to stock market uncertainty shocks within our sample. Turning our attention to the real effects of uncertainty shocks in the housing market, the sensitivity of real GDP growth remains relatively similar at each observation. Also the posterior credible intervals of the impulse response functions of real GDP growth to house market uncertainty shocks indicate economically meaningful contractions at every observation in our sample. In comparing the ramifications of property sector uncertainty shocks with liquidity shocks it is clear that there are obvious differences throughout time. In the latter decade of our sample, our results reveal the economic significance of uncertainty and liquidity shocks in the property sector are remarkably similar[20].

To understand the potential asymmetries of the real effects of uncertainty, we plot in Figure 4.8 the differences in average impulse responses over different time periods. Our results reveal no asymmetries between the impact of uncertainty shocks in the Great Recession and other recessions in our sample. Adding to this, there are no prominent differences in average impulse responses between the Great Recession and non–recessionary periods. This implies that, on average, the response of real GDP growth with respect to uncertainty shocks from stock and housing markets are not conditional on the business cycle; or different over business cycle troughs in our sample.

In general these findings reveal that there are stark differences between the real effects of uncertainty shocks relative to liquidity shocks. Our results show the response of real GDP growth to uncertainty shocks do not vary over time; or the business cycle. In particular, the response of real GDP growth to stock market uncertainty shocks echoes Levine and Zervos, 1998 who show a fragile link between stock market uncertainty (relative to stock market liquidity) and economic growth. Our findings with regards to house market uncertainty shocks demonstrate little variation in the contraction of real GDP growth throughout time. Nonetheless it is difficult to ascertain asymmetries in the response of GDP growth to uncertainty shocks across the business cycle and different recessions for our sample. Therefore, our analysis suggests the real effects of uncertainty shocks from stock and house markets are fundamentally different to liquidity shocks.

[20]Note also that we also consider the annual change in conditional volatilities implied from our models in Table 4.2. Results and conclusions are consistent with those we report within.

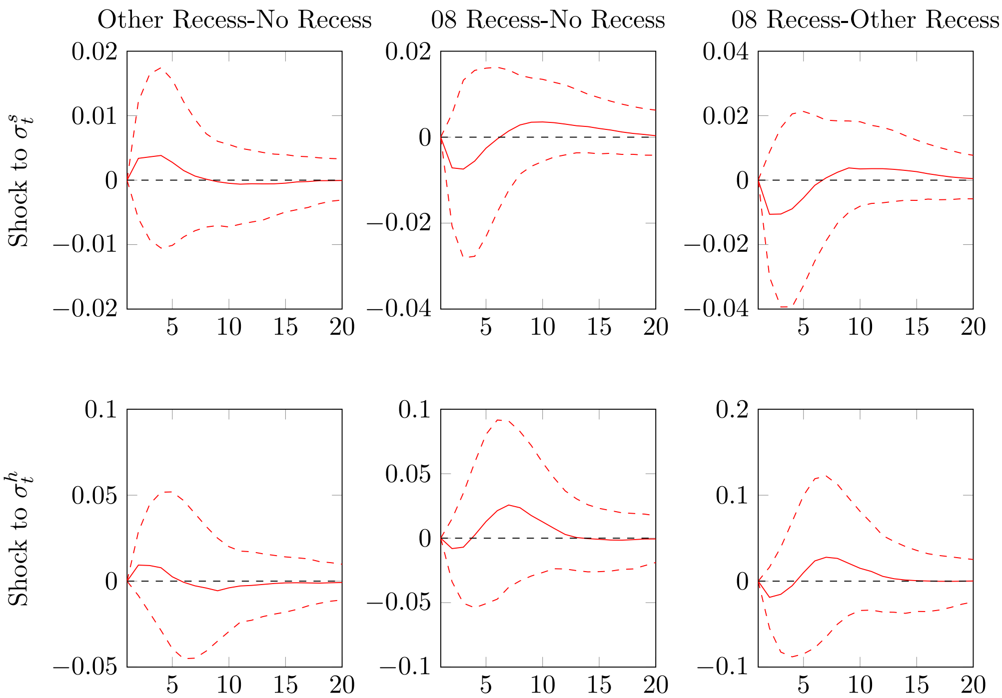

FIGURE 4.8: **Impulse Responses of GDP growth: Differences in averages over periods**

Notes: Panels 1 to 3 show the averages of differences in impulse responses of GDP growth to liquidity shocks between: other recessionary (i.e. NBER recession dates excluding the Great Recession) and non–recessionary periods (Panel 1: Other Recess-No Recess); The Great Recession and non–recessionary periods (Panel 2: 08 Recess-No Recess) and The Great Recession and other recessionary periods (Panel 3: 08 Recess-Other Recess). Recessionary periods are NBER recession dates. We compute as follows: for each draw of the Gibbs sampler, we average the impulse response over each of the selected periods, take the difference between the averages of selected periods and then calculate the quantiles over the draws.

4.5.2 Liquidity Shocks and Inflation

Although the main focus of this chapter is the impact of liquidity shocks on real GDP growth, we examine the inflationary impact of liquidity shocks from stock and housing markets from our baseline TVP–VAR. In Figure 4.9 we plot the impact of stock and house market liquidity shocks for inflation for each observation of our sample. It is clear that stock market liquidity shocks result in temporary increases in inflation for around a year following the shock. The median inflationary impact exhibits some slight time variation, and the 68% posterior credible intervals indicate marginal significance of the response in all time periods. While this might seem counter–intuitive, we postulate that our stock market liquidity proxy is picking up supply side effects of financial tightening. Prieto, Eickmeier, and Marcellino, 2016 argue that the empirical and DSGE literature is ambiguous on the inflationary impact of financial tightening. Demand and supply side factors can contribute to the overall inflationary impact of shocks. Supply side factors are thought to dominate demand factors during the crisis period. A decline in stock market liquidity may imply a lack of access to funds for investment and a lower availability of working capital which is mirrored in increasing loan rates[21].

Gilchrist et al., 2015 develop a DSGE model relaxing the assumption of frictionless financial markets and show that during crisis periods, adverse financial shocks shift the Phillips curve upwards. However, for the 2008 recession in particular, liquidity constrained firm's balance sheets were weak. Typically after contractionary financial shocks, firms have the incentive to drop prices and invest in market share. Yet Gilchrist et al., 2015 argue that firms with weak balance sheets have the incentive to keep share prices high in order to remain profitable. Whilst our stock market liquidity proxy filters out highly illiquid stocks, we do not weight our aggregate based on the 'liquidness' of the stocks. Therefore, our model implies (on aggregate) that supply side effects dominate the demand side effects of financial tightening due to liquidity shocks across our sample[22].

The inflationary impact of house market liquidity shocks varies considerably within our sample. Intuitively if liquidity in the housing sector dries up and prices decline, housing wealth depletes and feeds through into falling consumption levels. Simultaneously as property values decrease the ability to obtain credit diminishes, collateral value falls and households become increasingly constrained. This explanation is in line with Guerrieri and Iacoviello, 2015, who show that negative house price shocks are more detrimental when the borrowing constraint is binding. We propose that the

[21] We also cannot discount the possibility that the response of inflation to stock market liquidity shocks is simply because of the negative correlation with real activity.

[22] An interesting future avenue of research would be to separate our aggregate stock market liquidity proxy into liquid and illiquid firms and assess the impact of liquidity shocks from both proxies. Næs, Skjeltorp, and Ødegaard, 2011 show the predictive power of highly illiquid stocks is richer than liquid stocks.

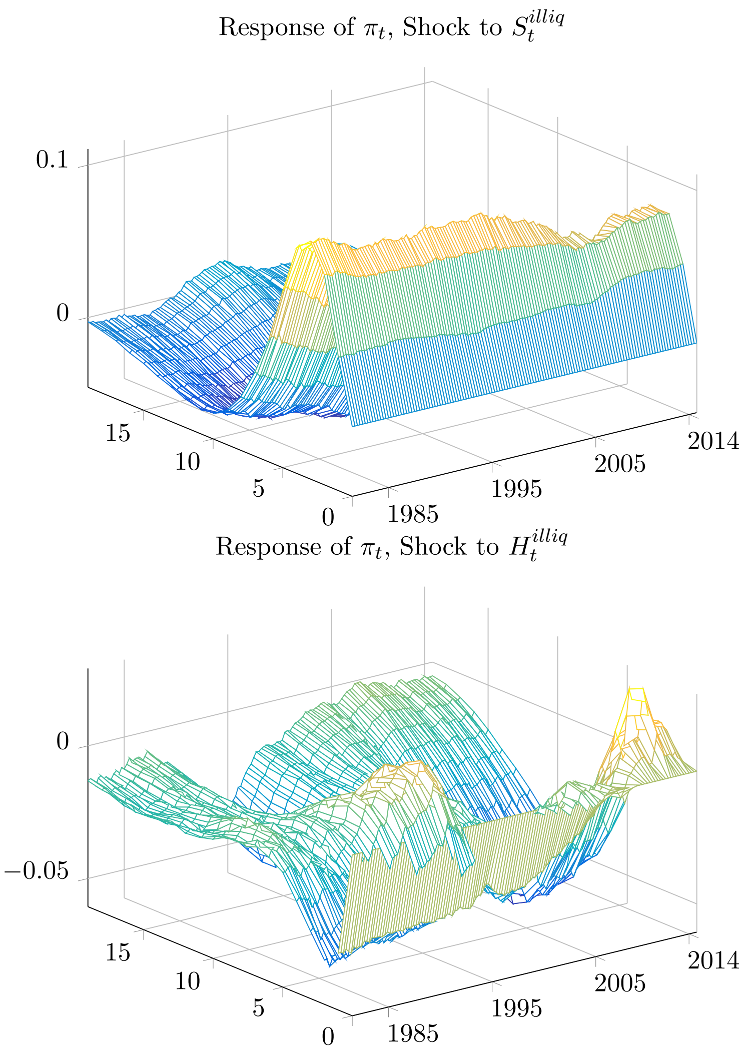

FIGURE 4.9: **Impact of Liquidity shocks on Inflation 1981 to 2014**
Notes: This figure plots the median impulse response functions of US inflation with respect to: a stock market liquidity shock and a house market liquidity shock. We plot the response along a 5–year horizon for each quarter of our estimated sample 1981Q3–2014Q4. We define a liquidity shock as a sudden decline in market liquidity.

effect of house market liquidity shocks work through demand channels thereby decreasing inflation. As borrowing constraints become binding during the Great Recession, the contractions of inflation deepen. Note that from 2008 to the end of our sample, inflation becomes more vulnerable to house market liquidity shocks and the impact duration increases to around three years following the shock. The response of inflation is significant, relative to 68% posterior credible intervals, during the Great Recession around 6 quarters after the shock is observed; thereby indicating a gradual emergence of the disinflationary demand side effects from tightening credit conditions and falling consumption.

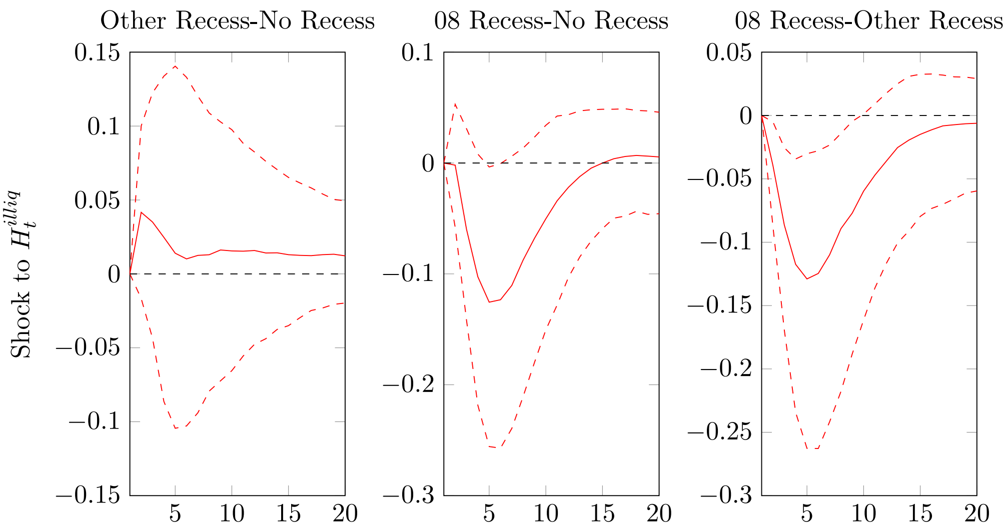

FIGURE 4.10: **Impulse Responses of GDP growth: Differences in averages over periods**

Notes: Columns one to three show the averages of differences in impulse responses of GDP growth to liquidity shocks between: other recessionary (i.e. NBER recession dates excluding the Great Recession) and non-recessionary periods (Panel 1: Other Recess-No Recess); The Great Recession and non-recessionary periods (Panel 2: 08 Recess-No Recess) and The Great Recession and other recessionary periods (Panel 3: 08 Recess-Other Recess). All recessions are defined as NBER recession dates. We compute as follows: for each draw of the Gibbs sampler, we average the impulse response over each of the selected periods, take the difference between the averages of selected periods and then calculate the quantiles over the draws.

Figure 4.10 gives insight into the asymmetrical response of inflation during recessionary periods, these plots further support findings in Guerrieri and Iacoviello, 2015[23]. As we can see, there is little difference in the impact of house market liquidity shocks on inflation to all NBER recessions excluding the 2008 recession and non–recessionary periods. The (dis)inflationary impact of house market liquidity shocks in the Great Recession relative to normal times is marginally significant; referring to 68% posterior credible intervals. However, the inflationary impact of property sector liquidity shocks

[23]We abstain from reporting the results on the inflationary impact of stock market liquidity because there is very little time–variation in the posterior median response of inflation (see Figure 4.9).

is clearly less persistent in all NBER recessions relative to the Great Recession; providing further support with Claessens, Kose, and Terrones, 2012.

Overall, we provide evidence that the inflationary impact of shocks to house market liquidity possess demand side factors in terms of tightening credit conditions thereby reducing price growth. Supply side factors are inherent in our stock market liquidity proxy that influences firm abilities' to obtain credit. Corresponding with Prieto, Eickmeier, and Marcellino, 2016, firms keeping share prices high helps explain the puzzling phenomena of a stubbornly decreasing inflation rate during the Great Recession. Our results further reinforce the challenges for policy outlined in Gilchrist et al., 2015; a tradeoff between output and inflation stabilisation in light of financial hardship.

4.6 Conclusions

In this chapter we provide insights into the links between asset market liquidity and the real economy using US data, by fitting a Bayesian VAR model with time–varying parameters from 1970 to 2014. A summary of our results is as follows: First, stock market liquidity shocks result in economically meaningful contractions to real GDP growth; however, the magnitude is decreasing throughout time. Second, our analysis demonstrates a distinct change in the structural relationship between real GDP growth and house market liquidity from 2005; as disruptions in the property sector start to emerge. Third, we provide notable evidence of an asymmetric response of GDP growth with respect to house market liquidity shocks. In particular, these arise both across the business cycle and among business cycle troughs in our sample. Fourth, counterfactual analysis reveals that structural liquidity shocks contribute the lion's share of variation in GDP growth; particularly during crisis periods. In the most recent recession, on average, stock and house market liquidity shocks explain 15% and 36% of US real GDP growth variation, respectively. Finally, house market liquidity shocks contribute, on average, 46% of the overall variance in real GDP growth from 2008 onwards. This implies that the fragile recovery in the US is partially due to imbalances within the property sector. Taken together, our analysis sheds light on the need for liquidity provision into asset markets; particularly during recessions following a property bust (Claessens, Kose, and Terrones, 2012). Consequently our study justifies attempts to inject liquidity into the property sector and stock market in response to the Great Recession.

We extend upon the main results by showing that the response of GDP to uncertainty shocks does not vary with time, the business cycle, or business cycle troughs in our sample. For policymakers, these results imply that house price uncertainty damages prospects for economic growth, which suggests a need to monitor house price volatility. However, noting that liquidity conditions can propagate through to house price uncertainty through factors such as trading delays (Diaz and Jerez, 2013), and relaxes in borrowing constraints (Mian and Sufi, 2009), indicates liquidity provision may hinder the economic impact of house price uncertainty shocks.

Our work provides considerable scope for future research. First, our results show house market liquidity shocks explain the majority of GDP growth variation in the post–financial crisis period. This supports the use of our house market liquidity proxy for predicting future recessions over and above existing leading economic indicators. Improving forecasts of fundamental macroeconomic indicators would be of great interest to central banks. Delving deeper into the origins of macroeconomic–financial structural dynamics, possibly linking parameter evolution to regulatory reform, would be of paramount importance to examine the effectiveness of policy implementation. Finally, accounting for stock and house market liquidity in a DSGE model provides thought provoking avenues in deducing optimal policy responses to asset market liquidity shocks in a time–varying framework.

4.7 Appendix to Chapter 4

4.7.1 Appendix A: Raw liquidity Estimates

Table 4.3 reports descriptive statistics on the raw estimates of our liquidity proxies. In Panel A, we report the full sample mean and median, along with sub–period means for both $RtoV_t^s$, $RtoV_t^h$. Panel B reports the contemporaneous correlations between our liquidity proxies from 1968 to 2014, along with sub–period correlations (where we denote correlation as $\rho(RtoV_t^s, RtoV_t^h)$). The sub–sample means imply liquidity in both the stock and property market are increasing throughout time. The contemporaneous full sample correlation between our raw liquidity proxies 0.64. Turning our attention to the sub–sample correlations, there are substantial differences among decades. In particular the correlation between US stock and house market liquidity from the late 1960s until 1989 is positive; however from 1990 to 1999, correlation is -0.10. In the next decade (i.e. between 2000 and 2009), the correlation is 0.37[24]. Differences in sub–sample correlations suggest the market fundamentals are different.

[24]The correlation between our liquidity proxies from 2000-2007 is 0.58; during 2008 and 2009 the correlation is 0.68; finally, between the years 2000 and 2014 the correlation is 0.44.

TABLE 4.3: Descriptive Statistics for Raw Estimates of Liquidity Proxies from 1968 to 2014

Panel A: Mean Analysis of Liquidity Proxies					
Full Sample:	**1968-2014**				
	Mean	**Median**	**Skew**	**Kurt**	
$RtoV_t^s$	0.19	0.105	3.124	13.433	
$RtoV_t^h$	0.063	0.019	2.387	5.994	
Sub Sample Means:	**1968-79**	**1980-89**	**1990-99**	**2000-09**	**2010-14**
$RtoV_t^s$	0.486	0.181	0.098	0.023	0.006
$RtoV_t^h$	0.181	0.047	0.011	0.016	0.011
Panel B: Correlation between Liquidity Proxies					
Full Sample:	**1968-2014**				
$\rho(RtoV_t^s,\, RtoV_t^h)$	0.641				
Sub Sample:	**1968-79**	**1980-89**	**1990-99**	**2000-09**	**2010-14**
$\rho(RtoV_t^s,\, RtoV_t^h)$	0.204	0.132	-0.101	0.373	-0.06

Notes: This table reports descriptive statistics for the raw estimates of stock and house market liquidity proxies, $RtoV_t^s$, $RtoV_t^h$ from 1968Q4-2014Q4. We follow Amihud, 2002 in constructing our liquidity proxies as in equations (1) and (2); $RtoV_t^s$ is scaled by 10^6 and $RtoV_t^h$ is scaled by 10^9. Panel A reports mean and median estimates. The top half of Panel A reports full sample estimates of the respective means and medians along with estimates of skewness and kurtosis. The bottom half of Panel A reports sub–sample mean estimates. Panel B reports the contemporaneous correlations between our liquidity proxies, denoted as $\rho(RtoV_t^s,\, RtoV_t^h)$. The first half of Panel B reports the full sample correlation. The second half of Panel B reports sub–sample correlations.

4.7.2 Appendix B: Estimation Algorithms

Posterior Computation of TVP–VAR with Stochastic Volatility

To estimate our TVP–VAR with stochastic volatility, we use the algorithm developed in Primiceri, 2005. Our notation is consistent with the notation in section 4.3. The first step is to draw the time–varying coefficients. Following Carter and Kohn, 1994, the density of β_t, $p(\beta_t)$ can be factored as:

$$p(\beta^T|y^T, A^T, \Phi^T, V) = p(\beta_T|y^T, A^T, \Phi^T, V)\prod_{t=1}^{T-1} p(\beta_t|\beta_{t+1}, y^t, A^T, \Phi^T, V)$$

where

$$\begin{aligned}\beta_t|\beta_{t+1}, y^t, A^T, \Phi^T, V &\backsim N(\beta_{t|t+1}, \Xi_{t|t+1})\\ \beta_{t|t+1} &= E(\beta_t|\beta_{t+1}, y^t, A^T, \Phi^T, V),\\ \Xi_{t|t+1} &= Var(\beta_t|\beta_{t+1}, y^t, A^T, \Phi^T, V).\end{aligned}$$

$E(\cdot)$ & $Var(\cdot)$ denote the expectation and variance operator. The vector, β_t, is drawn using forward and backward Kalman filter recursions. The last recursion of the filter provides the mean and variance of the posterior distribution of β_t.

In order to draw covariance states, S is assumed to be block diagonal and the Kalman filter is applied backward equation by equation. We recursively recover:

$$\begin{aligned}\alpha_{i,t|t+1} &= E(\alpha_{i,t}|\alpha_{i,t+1}, y^t, A^T, \Phi^T, V),\\ \Upsilon_{i,t|t+1} &= Var(\alpha_{i,t}|\alpha_{i,t+1}, y^t, A^T, \Phi^T, V).\end{aligned}$$

here $\alpha_{i,t}$ is the i^{th} block of α_t which corresponds to the coefficients of the i^{th} equation in:

$$\hat{y}_t = X_t\alpha_t + \Phi_t\varepsilon_t$$

because (4.3) can be written as

$$A_t(y_t - Z_t'\beta_t) = A_t\hat{y}_t = \Phi_t\varepsilon_t$$

$\alpha_{i,t}$ is sampled recursively in the same way as sampling the coefficients β_t from the $N(\alpha_{i,t|t+1}, \Upsilon_{i,t|t+1})$.

Drawing volatility states requires sampling from a mixture of 7 Normal distributions (Kim, Shephard, and Chib, 1998). We convert $\hat{y}_t = \Phi_t\varepsilon_t$ into a system of linear equations by squaring and taking logarithms of every element which leads to an approximating state space form:

$$\begin{aligned}\log(\hat{y}_t^2 + 0.001) &= 2\phi_t + \epsilon_t \\ \phi_t &= \phi_{t-1} + \eta_t\end{aligned}$$

where $\epsilon_{i,t} = \log(\varepsilon_{i,t}^2)$. As noted in Primiceri, 2005, the measurement equation innovations are $\log \chi^2(1)$ distributed. The mixture of 7 Normals is now required to transform this equations into a linear Gaussian system as in Kim, Shephard, and Chib, 1998. Now defining $\nu^T = [\nu_1, \ldots, \nu_T]'$ as a matrix of indicator variables that selects which member of the mixture of Normal approximations is used at every point in time. Conditional on β^T, A^T, V, and ν^T, we are now able to recursively recover $\phi_{t|t+1}$ and $\Phi_{t|t+1}$ from a Normal distribution. Note:

$$\begin{aligned}\phi_{t|t+1} &= E(\phi_t|\phi_{t+1}, y^t, A^T, \beta^T, V, \nu^T) \\ \Phi_{t|t+1} &= Var(\phi_t|\phi_{t+1}, y^t, A^T, \beta^T, V, \nu^T)\end{aligned}$$

Finally, we draw the hyperparameters of the model from their inverse–Wishart distributions. In summary, the steps are as follows:

1. Initialise parameters
2. Sample β^T from $p(\beta^T|y^T,\ A^T,\ \Phi^T,\ V)$
3. Sample A^T from $p(A^T|y^T,\ \beta^T,\ \Phi^T,\ V)$
4. Sample Φ^T from $p(\Phi^T|y^T,\ A^T,\ \beta^T,\ \nu^T,\ V)$
5. Sample ν^T from $p(\nu^T|y^T,\ A^T,\ \Phi^T,\ V)$
6. Sample V by sampling $Q,\ W,\ S$
7. Repeat steps 2–6

Assessing the Convergence of the MCMC Algorithm

We compute the inefficiency factors for the draws of states from their respective posterior distributions. Following Primiceri, 2005, we compute the inefficiency factors as the inverse of the relative numerical efficiency (RNE) measure

$$RNE = (2\pi)^{-1} \frac{1}{S(0)} \int_{-\pi}^{\pi} S(\omega) d\omega$$

where $S(\omega)$ is the spectral density of the sequence of draws from the Gibbs sampler for the quantity of interest at frequency ω.

Figure 4.11 plots the inefficiency factors for the time–varying coefficients of the TVP–VAR (the β_t), the non zero elements of the matrix A_t, the volatilities ($\phi_{i,t}$'s), and for the model's hyperparameters, i.e. the free elements of the matrices Q, S, and W. The figure clearly shows that the autocorrelation of the draws is impeccably low, in the vast majority of cases below 0.8. As stressed in Primiceri, 2005 and others, values of the inefficiency factors below 20 are satisfactory.

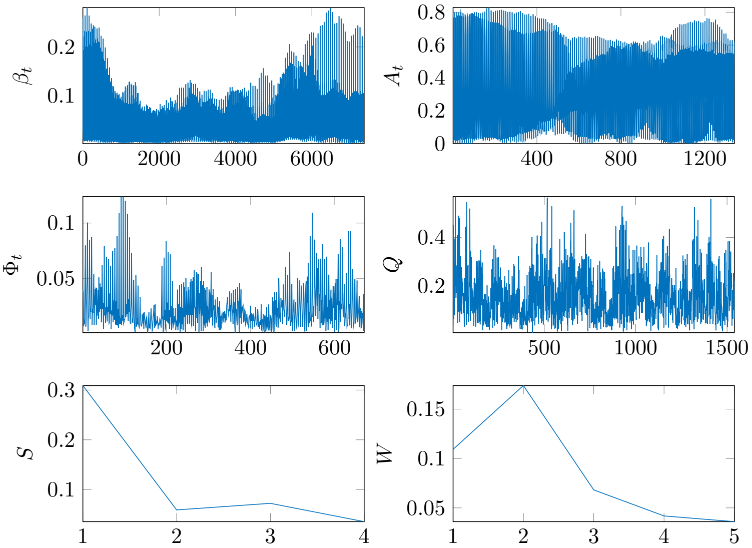

FIGURE 4.11: **Convergence of the MCMC Algorithm; Inefficiency Factors**

Notes: This figure shows the inefficiency factors computed for the draws of the elements of the matrices: β_t, A_t, H_t, Q, S and W

4.7.3 Appendix C: Additional Results

A Standard Bayesian VAR model using Stochastic Search Shrinkage

We start with a standard SVAR with p lags and M variables:

$$By_t = \Gamma_0 + \sum_{i=1}^{p} \Gamma_i y_{t-i} + \varepsilon_t$$

where y_t for $t = 1, \ldots, T$ is an $M \times 1$ vector of M variables, B is an $M \times M$ matrix, Γ_0 is an $M \times 1$ vector, $\Gamma_i, i = (1, 2, ..., p)$ are $M \times M$ matrices and $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, ..., \varepsilon_{M,t})$ are the structural errors from the VAR model. Under the assumption that B is invertible and pre–multiplying both sides of the above by B^{-1} we have the reduced–form VAR(p) model:

$$y_t = A_0 + \sum_{i=1}^{p} A_i y_{t-i} + \epsilon_t$$

where $A_0 = B^{-1}\Gamma_0$, $A_i = B^{-1}\Gamma_i, i = (1, 2, ..., p)$ and $\epsilon_t = B^{-1}\varepsilon_t$ with $\epsilon_t \backsim^{iid} N(0, \Sigma)$. Now we define Y as a $T \times M$ matrix which stacks the T observations for each dependent variable (in a column-wise manner) and E stacking the residuals conformable to Y. Defining $A = (A_0, A_1, \ldots, A_p)'$ and the $T \times K$ matrix X where $K = 1 + Mp$ is the number of coefficients in each equation of the system we have:

$$Y = XA + E$$

Let $\alpha = vec(A)$ which is a vector of KM elements, we can see that the number of parameters to estimate increases exponentially when adding variables to the system. Similarly, Σ has $\frac{M(M+1)}{2}$ elements. In typical macroeconomic applications, the number of parameters to estimate is far greater than the number of time series observations. In this section, we use the algorithm developed in George, Sun, and Ni, 2008; it is commonly referred to as using a Stochastic Search Variable Selection (SSVS) prior. The intuition behind the SSVS prior specifies a hierarchical prior as a mixture of two Normal distributions[25]. Let α_i denote the i^{th} element of α:

$$\alpha_i|\gamma_i \backsim (1 - \gamma_i)N(\underline{\alpha}_i, \kappa_{0,i}^2) + \gamma_i N(\underline{\alpha}_i, \kappa_{1,i}^2)$$

here γ is a dummy variable. It is treated as an unknown parameter and is estimated in a data–based fashion. If $\gamma_i = 0$, then α_i is drawn from the first Normal distribution and drawn from the second Normal distribution if $\gamma_i = 1$. In particular, George, Sun, and Ni, 2008 note that the SSVS aspect of this method arises by choosing $\kappa_{0,i}^2 \ll \kappa_{1,i}^2$. Thus, the coefficient, if drawn from the first Normal is restricted to be virtually zero.

[25] A hierarchical prior is a prior in which the parameters expressing have a prior of their own

Conversely, if the coefficient in α_i is drawn from the second Normal (with an uninformative prior), the coefficient is included within the equation. The prior given above may be written more compactly as:

$$\alpha|\gamma \backsim N(\underline{\alpha}, D)$$

D is a diagonal matrix with d_i denoting the $(i,i)^{th}$ element where:

$$d_i = \begin{cases} \kappa_{0,i}^2 \; if \; \gamma_i = 0 \\ \hline \kappa_{1,i}^2 \; if \; \gamma_i = 1 \end{cases}$$

The prior for $\gamma = (\gamma_1, \ldots, \gamma_{KM})'$ assumes each element is independent of one another and of Bernoulli form such that:

$$Pr(\gamma_i = 1) = \underline{q}_i$$

$$Pr(\gamma_i = 0) = 1 - \underline{q}_i$$

setting $\underline{q}_i = 0.5$ implies each coefficient is equally likely to be included or excluded.

Posterior Computation of the SSVS Algorithm

Here, we sketch out the procedure to compute the posteriors of the SSVS prior Let Λ denote the set of parameters for the VAR model and Λ_{-c} note all the parameters except for c. For the coefficient matrix of the VAR we have

$$\alpha|Y, \Lambda_{-\alpha} \backsim N(\overline{\alpha}, \overline{V}_\alpha)$$

$$\begin{aligned} \overline{V}_\alpha &= [\Sigma^{-1} \otimes (X'X) + D^{-1}]^{-1} \\ \overline{\alpha} &= \overline{V}_\alpha [D^{-1}\underline{\alpha} + vec(X'Y\Sigma^{-1})] \end{aligned}$$

γ_i is independent $\forall i$ Bernoulli random variables:

$$\begin{aligned} Pr(\gamma_i = 1|Y, \Lambda_{-\gamma_i}) &= \overline{q}_i \\ Pr(\gamma_i = 0|Y, \Lambda_{-\gamma_i}) &= (1 - \overline{q}_i) \end{aligned}$$

and

$$\overline{q}_i = \frac{\frac{1}{\kappa_{1,i}} \exp\left(-\frac{\alpha_i^2}{2\kappa_{1,i}^2}\right)}{\frac{1}{\kappa_{1,i}} \exp\left(-\frac{\alpha_i^2}{2\kappa_{1,i}}\right) \underline{q}_i + \frac{1}{\kappa_{0,i}} \exp\left(-\frac{\alpha_i^2}{2\kappa_{0,i}^2}\right) \left(1 - \underline{q}_i\right)}$$

The error covariance matrix is decomposed as:

$$\Sigma^{-1} = \Psi\Psi'$$

where Ψ is upper triangular. A Gamma prior is used for the squared diagonal elements of Ψ. A mixture of two Normal distributions is used for each element above the diagonal. The implication here is that the diagonal elements are included within the model which guarantees Σ^{-1} is positive definite. Define the non zero elements of Ψ as $\psi_{i,j}$ where $\psi = (\psi_{1,1}, \ldots, \psi_{n,n})'$, $\eta_j = (\psi_{1,j}, \ldots, \psi_{j-1,j})'$ for $j = 2, \ldots, n$ and $\eta = (\eta_2', \ldots, \eta_n')'$. These elements are assumed to have prior independence with a Gamma distribution:

$$\psi_{j,j}^2 \backsim G(\underline{a}_j, \underline{b}_j)$$

where $G(\underline{a}_j, \underline{b}_j)$ notes the Gamma distribution with scale and shape parameters $\underline{a}_j, \underline{b}_j$ respectively. In our application, $\underline{a}_j = 0.01$ and $\underline{b}_j = 0.01$; results are robust to the choices of hyperparameters selected. The prior for the off diagonal elements of Ψ takes an identical mixture of two Normals as in α.

$$\eta_j | \omega_j \backsim N(0, L_j)$$

where

$$\begin{aligned} \omega_j &= (\omega_{1,j}, \ldots, \omega_{j-1,j})', \quad \omega_{i,j} \in \{0, 1\} \\ L_j &= diag(l_{1,j}, \ldots, l_{j-1,j}) \end{aligned}$$

where

$$l_{i,j} = \begin{cases} \kappa_{0,ij}^2 \; if \; \omega_{i,j} = 0 \\ \hline \kappa_{1,ij}^2 \; if \; \omega_{i,j} = 1 \end{cases}$$

for $j = 2, \ldots, n$ and $i = 1, \ldots, n-1$. Values of $\kappa_{0,ij}$ and $\kappa_{1,ij}$ are specified as 0.1 and 1 respectively. For $\omega = (\omega_2', \ldots, \omega_n')'$ each element has a Bernoulli form and again is independent from one another thus:

$$\begin{aligned} Pr(\omega_{ij} = 1) &= \underline{q}_i \\ Pr(\omega_{ij} = 0) &= (1 - \underline{q}_i) \end{aligned}$$

We set $\underline{q}_i = 0.5$ allowing each parameter is equally likely to be included or excluded. Note as in George, Sun, and Ni, 2008 ψ_{jj}^2 are independent of one another with:

$$\psi_{jj}^2 | Y, \Lambda_{-\psi_{jj}} \backsim G\left(a_j + 0.5T, \bar{b}_j\right)$$

with

$$\begin{aligned}\overline{b}_j &= b_1 + 0.5 v_{11}, \quad if\; j = 1 \\ \overline{b}_j &= b_1 + 0.5(v_{jj} - v_j'[V_{j-1} + L_j^{-1}]^{-1} v_j), \quad if\; j = 2, \ldots, n\end{aligned}$$

note that $V = (Y - XA)'(Y - XA)$ with elements v_{ij}, $v_j = (v_{1,j}, \ldots, v_{j-1,j})'$, V_j is the upper left block of V (with dimension $j \times j$). The posterior of η can be written in terms of the conditional posteriors of η_j for $j = 2, \ldots, n$ since they are independent of one another and:

$$\eta_j | Y, \Lambda_{-\eta_j} \backsim N(\overline{\eta}_j, \overline{V}_j)$$

$$\begin{aligned}\overline{V}_j &= [V_{j-1} + L_j^{-1}], \\ \overline{\eta}_j &= -\psi_{jj} \overline{V}_j v_j\end{aligned}$$

The posterior for ω_{ij} (independent Bernoulli random variables):

$$\begin{aligned}Pr(\omega_{ij} = 1 | Y, \Lambda_{-\omega_{ij}}) &= \overline{q}_{ij} \\ Pr(\omega_{ij} = 0 | Y, \Lambda_{-\omega_{ij}}) &= (1 - \overline{q}_{ij})\end{aligned}$$

and

$$\overline{q}_i = \frac{\frac{1}{\kappa_{1,ij}} \exp(-\left(\frac{\psi_{ij}^2}{2\kappa_{1,ij}^2}\right)}{\frac{1}{\kappa_{1,ij}} \exp\left(-\frac{\psi_{ij}^2}{2\kappa_{1,ij}}\right) \underline{q}_{ij} + \frac{1}{\kappa_{0,ij}} \exp\left(-\frac{\psi_{ij}^2}{2\kappa_{0,ij}^2}\right) \left(1 - \underline{q}_{ij}\right)}$$

The MCMC algorithm draws sequentially from the posterior distributions reported above.

Standard VAR models over Sub Samples

To obtain an idea of on the sources of time–variation, we estimate constant parameter VAR models using three sub–samples: 1984Q1 to 2006Q4, 1984Q1 to 2014Q4 and 1995Q1 to 2014Q4. We use Bayesian methods to estimate these VAR models and follow the algorithm in George, Sun, and Ni, 2008 implementing the SSVS prior. As in Prieto, Eickmeier, and Marcellino, 2016, 1984Q1 marks the starting point of the Great Moderation. The first sub–sample ends before the Great Recession; the second includes the Great Recession and the third uses the last two decades of our sample. We plot in Figure 4.12, the impulse response functions of GDP growth with respect stock and house market liquidity shocks.

It is clear that there is variation in the response of GDP growth with respect to both liquidity proxies, conditional on the estimation sample. Notice in Panel 1, liquidity shocks have no substantial real effects on US GDP growth during the Great Moderation. From our estimated VAR model using a sample from 1984 to 2014 (in Panel 2), we see that stock market liquidity shocks result in significant contractions of real GDP growth; relative to 68% posterior credible intervals. However, as we can also see in Panel 2, the economic impact of house market liquidity shocks are trivial. Yet, Panel 3 reveals that there are persistently damaging effects of house market liquidity shocks in the latter two decades sample (i.e. from 1995 to 2014). Contrastingly in the very same period, stock market liquidity shocks appear immaterial. Having said this, the remarkable differences in the impact of stock market liquidity shocks on GDP growth support the use of models accounting for time–variation. These findings are also consistent with the main results. Specifically, the constant parameter VAR models are picking up economically meaningful real effects of house market liquidity shocks in the latter years of our sample. Finally, the difference in the shapes of the impulse response functions support the use of a volatility structure that accounts for changing shock sizes; clearly the impact of a 1% standard deviation shock is changing over time.

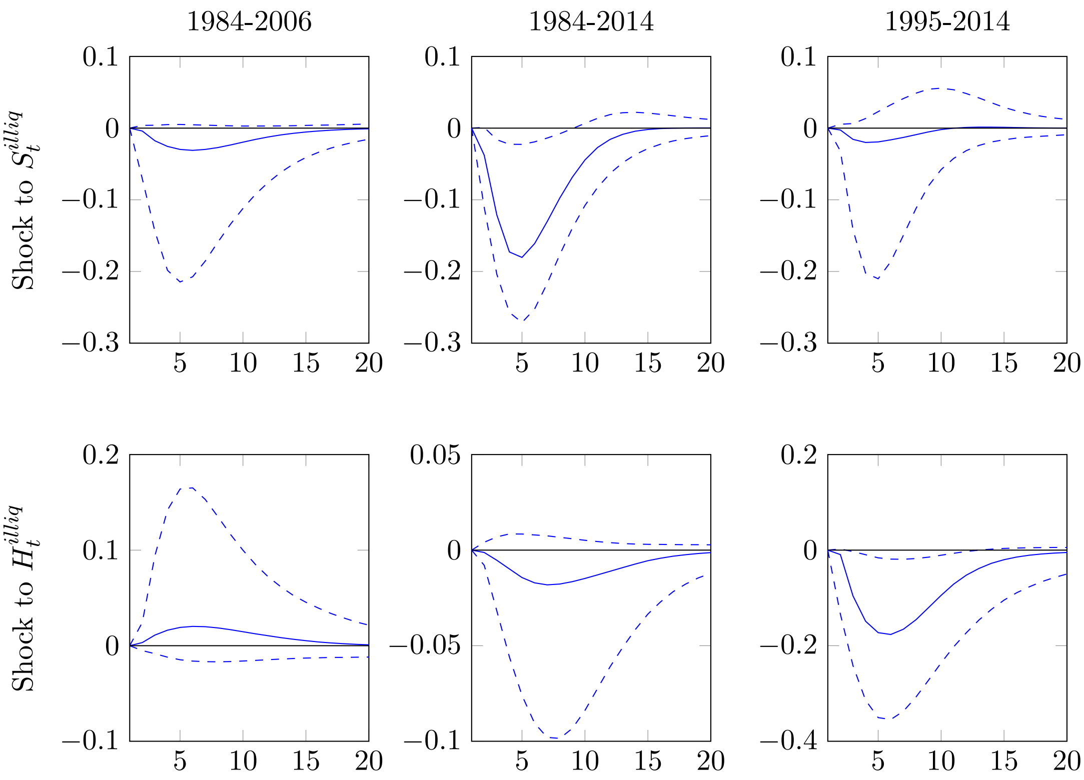

FIGURE 4.12: **Impulse Response Functions of GDP growth from Constant Parameter VAR models in Different Sub Samples**
Notes: This figure plots the posterior median and 1 standard deviations percentiles of the impulse response function of GDP growth with respect to stock and house market liquidity shocks for estimated VAR models using different sub samples. The first sub sample considered is 1984Q1 to 2006Q4 (Panel 1); the second is 1984Q1 to 2014Q4 (Panel 2) and the third is 1995Q1 to 2014Q4 (Panel 3). We define a liquidity shock as a sudden decline in market liquidity.

Stochastic Volatility, Parameter Evolution, and Contemporaneous Relations for our main TVP VAR model

In Figure 4.13, we plot the median and one deviation percentiles of the time–varying volatility estimates of the structural shocks for our macroeconomic variables. A noteworthy point to consider is the remarkable similarities between the volatility estimates of structural shocks to the interest rate implied by our model, and those in Justiniano and Primiceri, 2008 and Prieto, Eickmeier, and Marcellino, 2016; the former estimates are from a DSGE model.

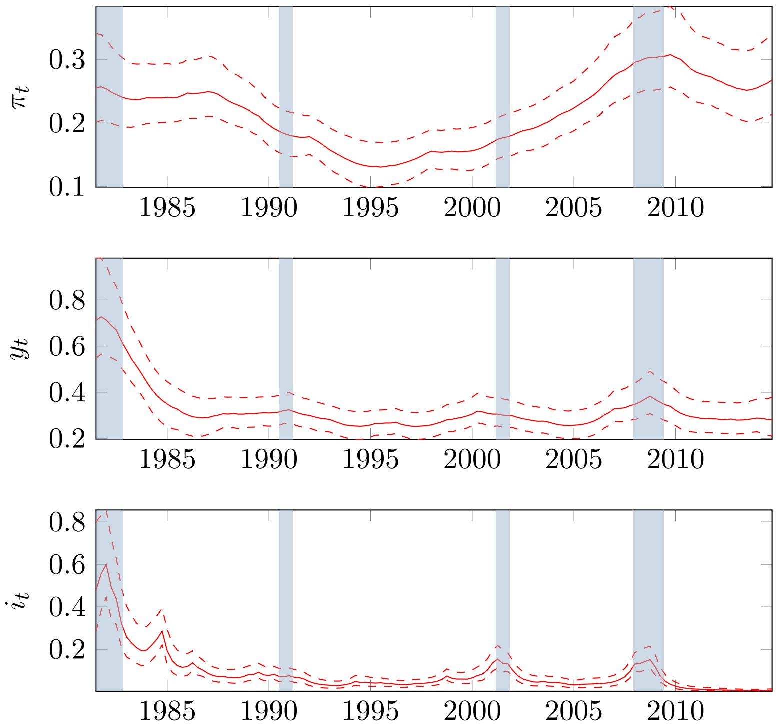

FIGURE 4.13: **Stochastic volatility of Macroeconomic Shocks from 1981 to 2014**
Notes: This figure shows the median and 1 standard deviation percentiles of the time–varying standard deviations of structural shocks for the inflation rate, π_t, real GDP growth, y_t and the interest rate, i_t from 1981Q3–2014Q4. Grey bars indicate NBER recession dates.

Figures 4.14 and 4.15 plot the evolution of the autoregressive parameters which we sum over lags, and the contemporaneous relations between the variables. There is time–variation in both the time–varying coefficient matrices and the contemporaneous relations; as we can see, the degree of variation is more significant in the contemporaneous relations.

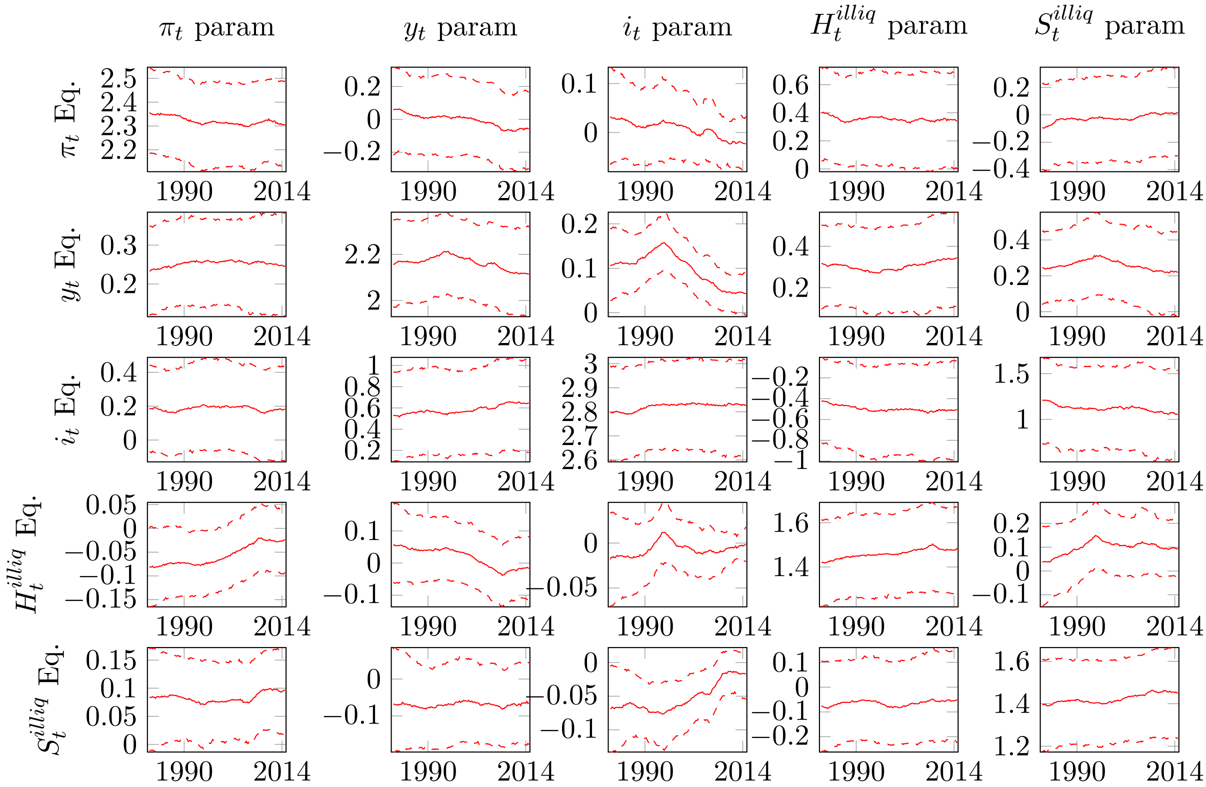

FIGURE 4.14: **Parameter Evolution (elements of β_t)**
Notes: This figure plots the posterior median (and one standard deviations percentiles) of the autoregressive parameters summing over the lags.

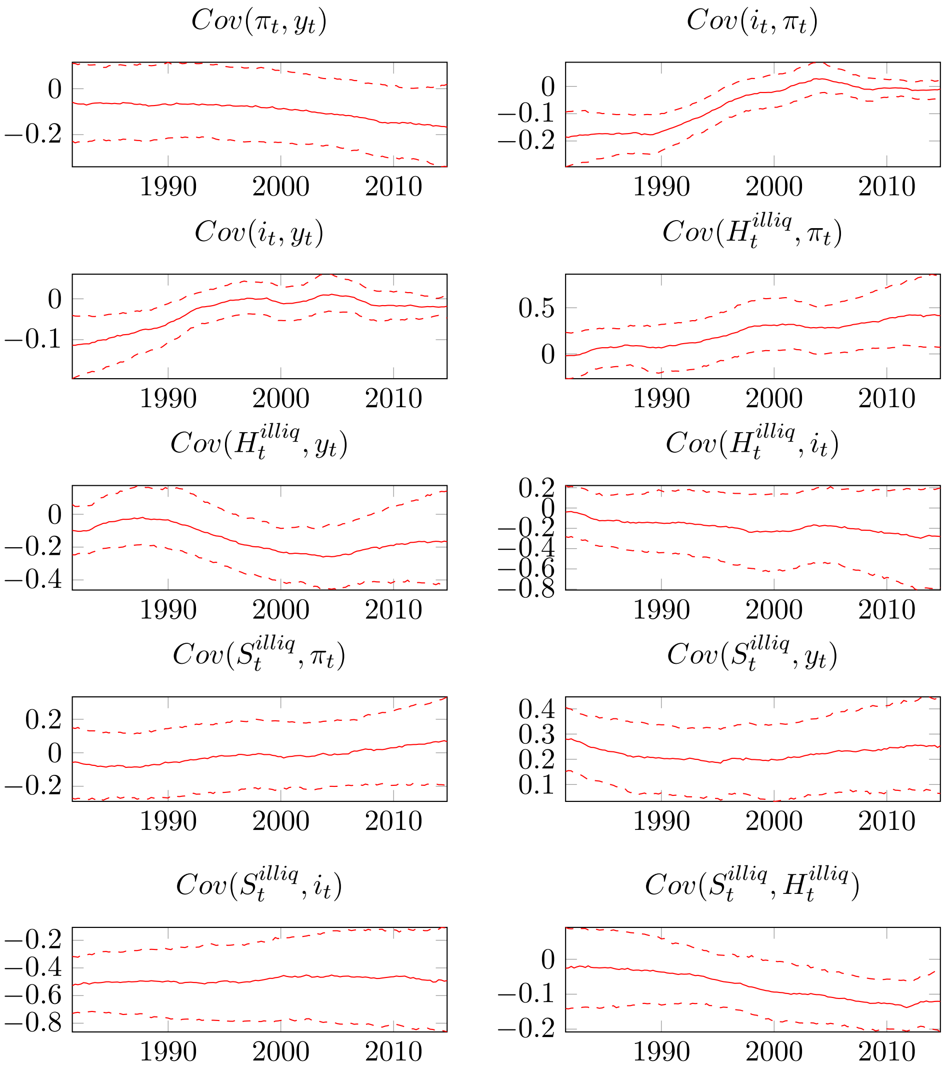

FIGURE 4.15: **Contemporaneous Relations (elements of A_t)**
Notes: This figure plots the posterior median (and one standard deviations percentiles) of the contemporaneous relations between our macroeconomic and financial variables.

The Response of Inflation to Contractionary Monetary Policy Shocks

As we report in the main text, we detrend inflation using a one–sided Kalman filter as in Stock and Watson, 1999. This is thought to alleviate price puzzles that are often apparent in VAR analysis (see Björnland and Leitemo, 2009)[26]. Figure 4.16 plots the posterior median impulse response function of inflation with respect to a contractionary monetary policy shock in all time periods of our sample. Notice that inflation responds marginally positively in all periods; although the response is not significant relative to 68% posterior credible intervals for all observations in our sample. Furthermore, our plot reveals that inflation becomes less sensitive to movements in the interest rate throughout time. This could possibly link to the declining trend in the Federal Funds rate within our sample. In the first observation of our sample (1981Q3) the interest rate is 17.59% and in the last observation the interest rate is 0.1%. Therefore our model suggests that inflation is more sensitive to contractionary monetary policy shocks at higher rates of interest.

An alternative argument is that, with the interest rate approaching its zero lower bound from 2008 until the end of our sample, the Federal Funds rate is not an effective indicator of monetary policy stance. Combining this with QE implementation, suggests that monetary policy from 2008 is even more expansionary than the information content within the interest rate. Therefore, the resilience of inflation to contractionary monetary policy shocks, in the post–financial crisis period, may be partly due to the injections of liquidity into the economy that the interest rate cannot capture.

[26] Analysis using the (raw) annual rate of GDP deflator inflation results in a significant (relative to 68% posterior credible intervals) price puzzle for a year after the shock. Results available on request.

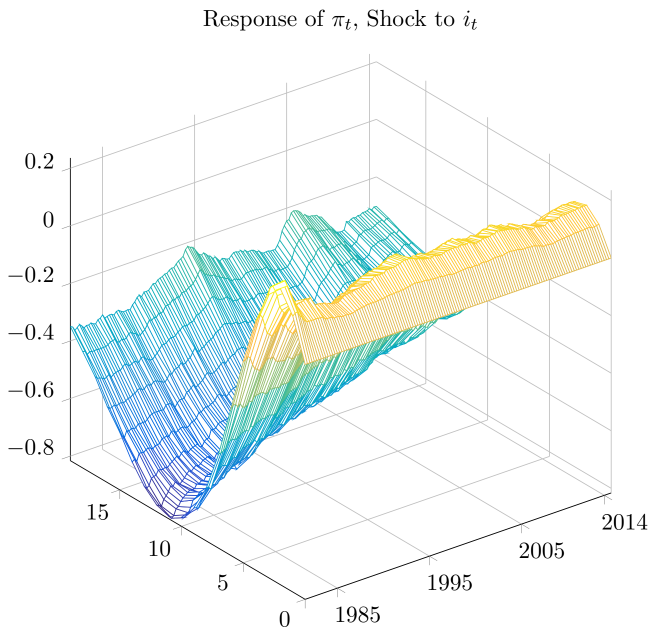

FIGURE 4.16: **Impact of Contractionary Monetary Policy Shocks on Inflation 1981 to 2014**

Notes: This figure plots the median impulse response functions of inflation with respect to a contractionary monetary policy shock. We plot the response along a 5–year horizon for each quarter of our estimated sample 1981Q3–2014Q4.

Baseline TVP–VAR using an Alternative Identification

The assumptions underpinning our identification scheme requires discussion. Our baseline identification scheme places financial variables after the macroeconomic variables. This implies that our liquidity proxies react immediately to macroeconomic shocks. Conversely macroeconomic variables are slow to respond to liquidity shocks. Another plausible assumption is that interest rates can react contemporaneously to liquidity shocks within the property sector[27]. Our alternative identification scheme places house market liquidity before the interest rate. Therefore variables enter the TVP–VAR in the following order: inflation, π_t; GDP growth, y_t; house market liquidity, H_t^{illiq}; the interest rate, i_t and stock market liquidity, S_t^{illiq}.

Figure 4.17 plots the median impulse response function of GDP to liquidity shocks. Unsurprisingly, the posterior median response of real GDP growth to stock market liquidity shocks remains similar. The impact of house market liquidity shocks under our alternative ordering remain largely similar to those from our baseline identification scheme. The only difference is the posterior median response of real GDP growth, in late 2009, reaches a trough considerably lower than the posterior median responses both during the Great Recession and the following period. Apart from this anomaly, the profile of the posterior median impulse response functions remain similar to those we report in the main text[28].

Figure 4.18 plots the differences in average impulse responses of GDP to stock and house market liquidity shocks in different periods under our alternative identification scheme. It is clear that the same conclusions hold as in our baseline analysis for the impact of stock market liquidity shocks on real GDP growth during different periods. Conversely, ordering house market liquidity before the interest rate yields different conclusions. In particular, note that our results here suggest no difference in the average impact of house market liquidity shocks between all NBER recessions (excluding the Great Recession) and non–recessionary periods. However, this result is driven by the sensitivity of GDP growth to a house market liquidity shock in late 2009 (see Figure 4.17); consequently the response of real GDP growth in this time period influences the average impulse response of GDP in non–recessionary periods. Similarly the results yield no difference, on average, between the Great Recession and non–recessionary periods. However, there are differences in the real effects of house market liquidity shocks between the Great Recession and other recessions within our sample. We find that the severity of liquidity shocks, in terms of duration and magnitude, is greater (on average) in the most recent recession.

[27] Björnland and Leitemo, 2009 place house prices before the interest rate in a standard VAR model.
[28] Ordering the interest rate last in our TVP–VAR models reveals qualitatively similar conclusions.

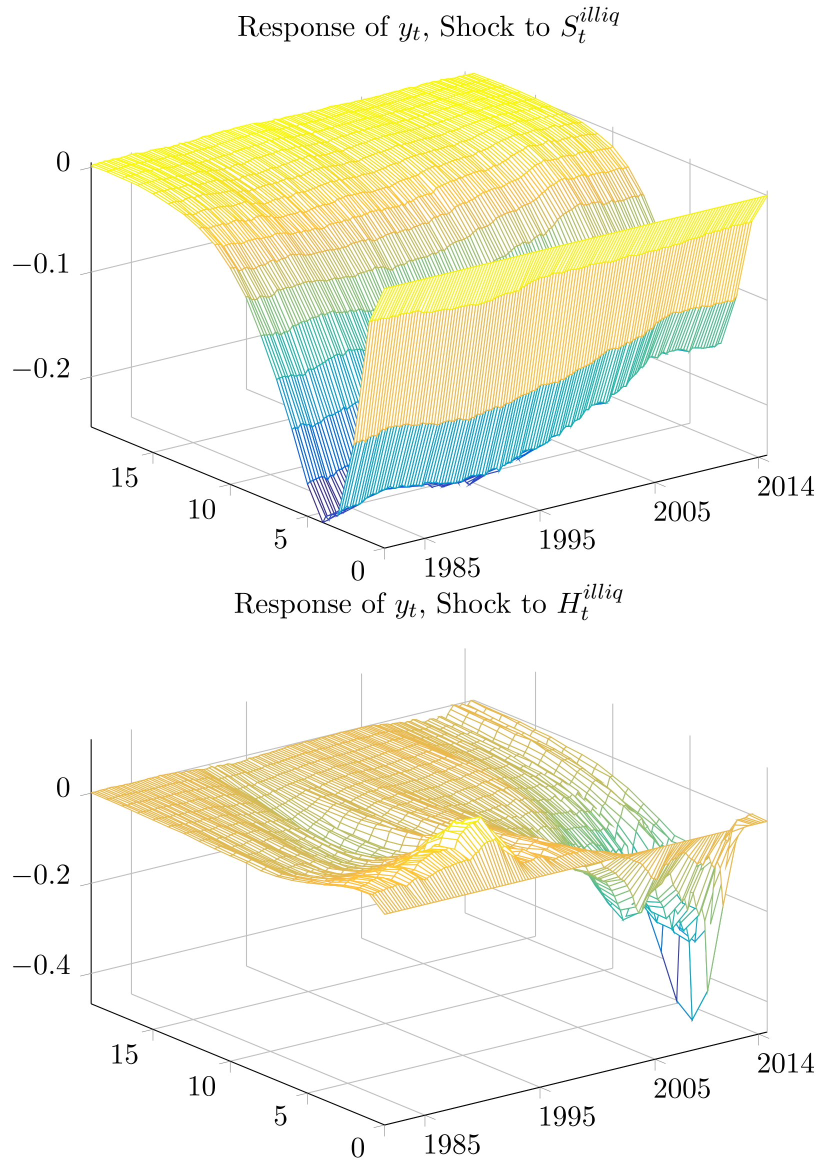

FIGURE 4.17: **Impact of Liquidity shocks on GDP growth 1981 to 2014**
Notes: This figure plots the median impulse response functions of US real GDP growth with respect to: a stock market liquidity shock and a house market liquidity shock. We plot the response along a 5–year horizon for each quarter of our sample 1981Q3–2014Q4. We define a liquidity shock as a sudden decline in market liquidity.

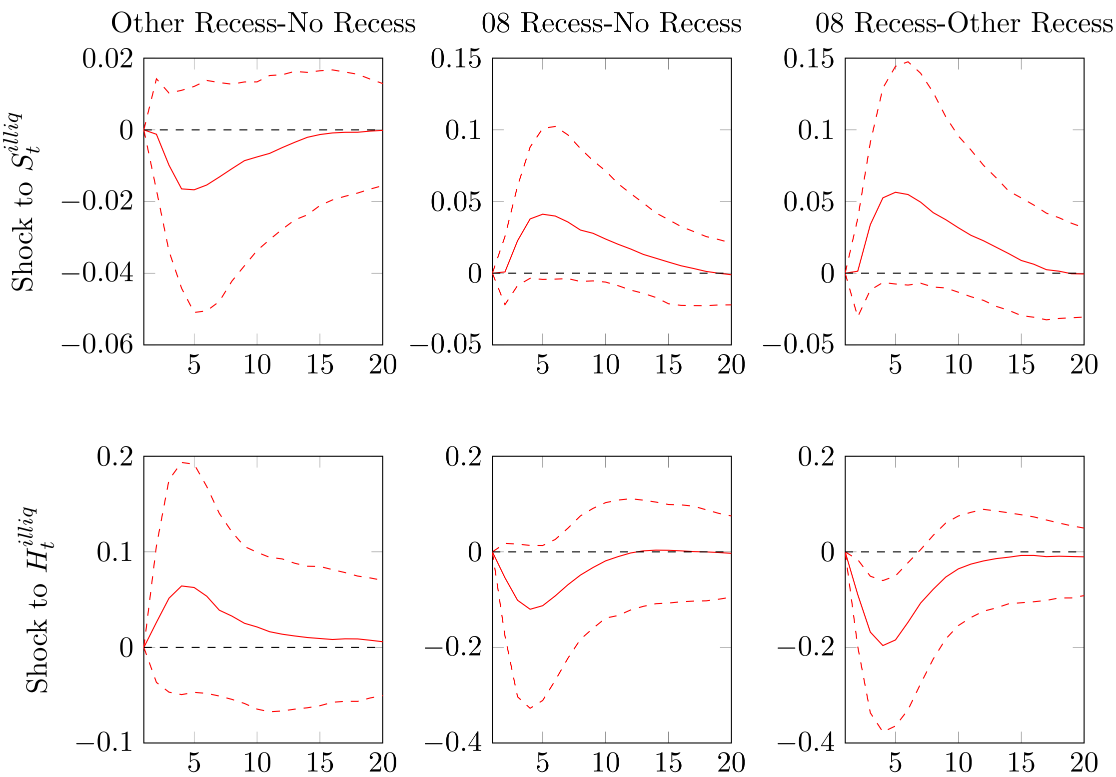

FIGURE 4.18: **Impulse Responses of GDP growth: Differences in averages over periods**

Notes: Panels 1 to 3 show the averages of differences in impulse responses of GDP growth to liquidity shocks between: other recessionary (i.e. NBER recession dates excluding the Great Recession) and non–recessionary periods (Panel 1: Other Recess-No Recess); The Great Recession and non–recessionary periods (Panel 2: 08 Recess-No Recess) and The Great Recession and other recessionary periods (Panel 3: 08 Recess-Other Recess). Recessionary periods are NBER recession dates. We compute as follows: for each draw of the Gibbs sampler, we average the impulse response over each of the selected periods, take the difference between the averages of selected periods and then calculate the quantiles over the draws.

A TVP–VAR Model Including Credit Spreads

In this section we extend upon our model in the main body of the chapter and account for credit risk. To proxy credit risk we use the corporate bond spread, which we measure as the difference between Moody's BAA and AAA corporate bond yields; available from the Federal Reserve Bank of St. Louis. We abstain from reporting results using credit spreads in the main text because of difficulties in isolating the liquidity component from a credit spread[29]. However, omitting credit risk may over exaggerate the impact of our liquidity proxies in our counterfactual structural variance decomposition and influence impulse response analysis.

To investigate further, we estimate a 6–variable TVP–VAR model as in (4.3)–(4.8) including Moody's BAA-AAA corporate bond yield spread. The results below correspond to the same priors we impose on the system in the main text, variables enter the TVP–VAR in the following manner: inflation, π_t; real GDP growth, y_t; the Federal Funds rate, i_t; house market liquidity, H_t^{illiq}; corporate bond spread, CR_t; and stock market liquidity, S_t^{illiq}. For the sake of brevity, we do not report convergence diagnostics for the model; however inefficiency factors remain uniformly low. Furthermore, note that the main messages from this analysis are consistent to different orderings of our financial variables. We postulate shocks to the corporate bond spread capture credit conditions worsening which therefore depress real GDP growth.

Figure 4.19 plots the posterior median and one standard deviation percentiles of the stochastic volatility of our liquidity and credit risk shocks. In general, the volatility of credit risk shocks surge temporarily in conjunction with the 1991 recession, the period following the burst of the dot–com bubble, and the Great Recession. Furthermore, notice the persistent increases from 2005–2009; which implies our model may be picking up disturbances in credit markets before the crash in 2008. Note also that the shape and time–variation in the volatility of our structural liquidity shocks remain similar to Figure 4.3 in the main text.

[29]Schwarz, 2015 proposes a credit spread measure free from the risk component using the KFW yield minus the German sovereign yield.

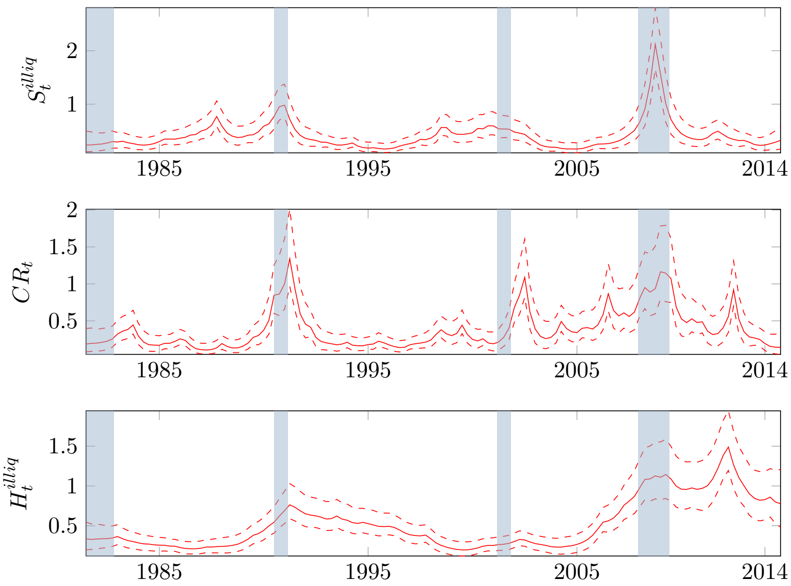

FIGURE 4.19: **Stochastic Volatility of Liquidity and Credit Risk Shocks from 1981 to 2014**

Notes: This figure shows the median and 1 standard deviation percentiles of the time–varying standard deviations of structural shocks for stock market liquidity, S_t^{illiq}; credit risk, CR_t and house market liquidity, H_t^{illiq} from 1981Q3–2014Q4. Grey bars indicate NBER recession dates.

In Figure 4.20, we plot the posterior median impulse response functions of real GDP growth for every quarter in our sample (i.e. 1981Q3–2014Q4), with respect to liquidity and credit risk shocks. We can see that shocks to credit risks yield considerable contractions to real GDP growth. The impact of credit risk shocks is greatest immediately following the 2001 recession. Notably, posterior credible intervals (68%) do not include zero for every impulse response function for up to 6 quarters. Turning our attention to the impact of stock and house market liquidity shocks, the shape and profile of the posterior median response of real GDP growth for every observation remains consistent with Figure 4.4 in the main text.

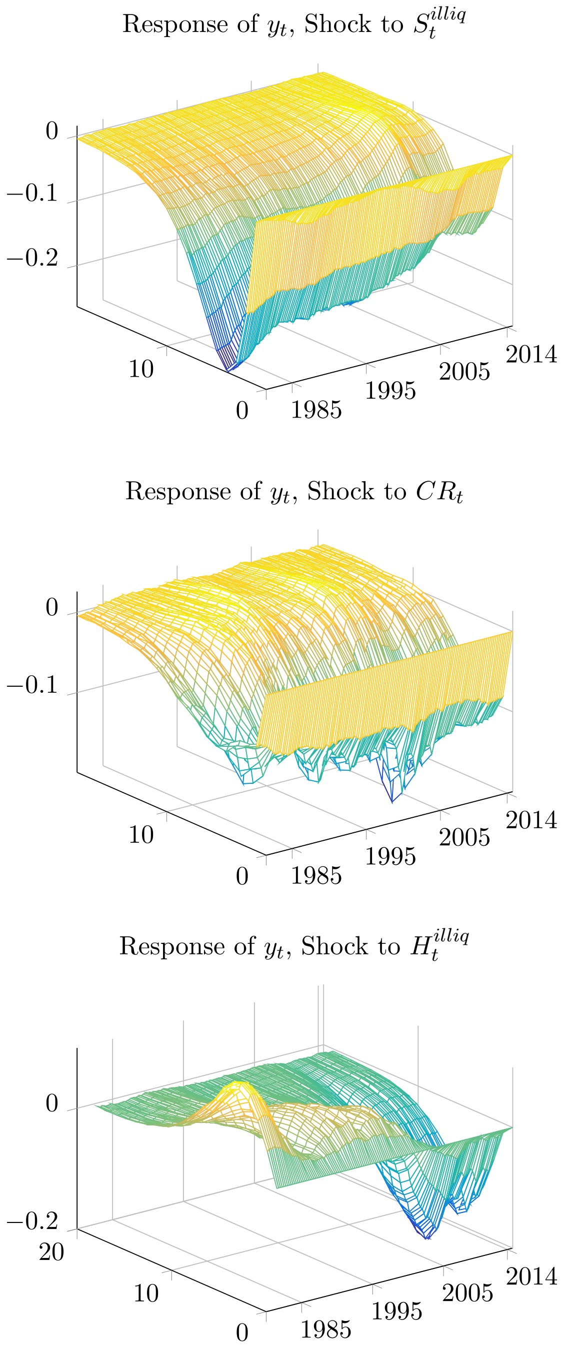

FIGURE 4.20: **Impact of Liquidity and Credit risk Shocks on GDP growth 1981 to 2014**

Notes: This figure plots the median impulse response functions of US real GDP growth with respect to: a stock market liquidity shock; a credit risk shock and a house market liquidity shock. We plot the response along a 5–year horizon for each quarter of our sample 1981Q3–2014Q4. We define a liquidity shock as a sudden decline in market liquidity.

We show, in Figure 4.21, the difference in average impulse response functions of real GDP growth to liquidity and credit risk shocks. This is analogous to Figure 4.5 in the main text and we compute in the exact same manner. Again, the implications are similar to our main results. However, the response of real GDP growth to stock market liquidity shocks, on average, is stronger and more persistent in other recessions within our sample, relative to the Great Recession (see Panel 3 of Figure 4.21). This result is unsurprising and intuitive since, from Figure 4.19, real GDP growth becomes more resilient to stock market liquidity shocks throughout time. Adding to this, liquidity shocks in the US housing sector are stronger and more persistent in the most recent recession (from Panels 2 and 3 of Figure 4.21) which is consistent with our main analysis. Note also that our analysis in Panel 2 of Figure 4.21 reports no difference in the sensitivity of GDP growth to credit risk shocks (on average) within our sample.

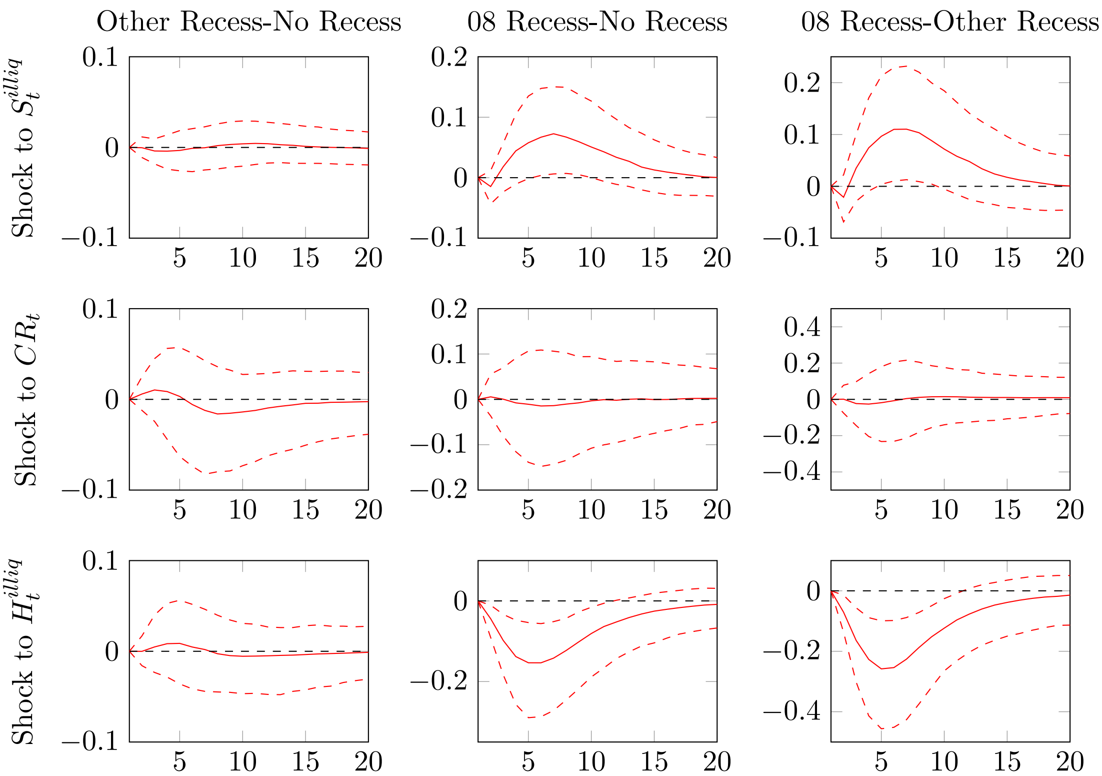

FIGURE 4.21: **Impulse Responses of GDP growth: Differences in averages over periods**

Notes: Panels 1 to 3 show the averages of differences in impulse responses of GDP growth to liquidity shocks between: other recessionary (i.e. NBER recession dates excluding the Great Recession) and non–recessionary periods (Panel 1: Other Recess-No Recess); The Great Recession and non–recessionary periods (Panel 2: 08 Recess-No Recess) and The Great Recession and other recessionary periods (Panel 3: 08 Recess-Other Recess). Recessionary periods are NBER recession dates. We compute as follows: for each draw of the Gibbs sampler, we average the impulse response over each of the selected periods, take the difference between the averages of selected periods and then calculate the quantiles over the draws.

A final factor to consider is the robustness of our structural variance decomposition. There is a possibility the financial and asset variables we include in our main model are picking up important information from credit markets. For example, a relaxation (contraction) in credit conditions can aid (hinder) prosperity in the housing market when borrowing constraints are not (are) binding (see Mian and Sufi, 2009, Iacoviello and Neri, 2010). Without explicitly accounting for credit risk, there may be over emphasis in the importance of our house market liquidity shocks for the overall variation in real GDP growth[30]. Similarly, Justiniano, Primiceri, and Tambalotti, 2015 find that credit shocks are not enough to solely explain the Great Recession and fragile recovery for the US; disturbances in the housing market are thought to help match the data.

Therefore, we follow Benati and Mumtaz, 2007 and perform a counterfactual structural variance decomposition of US real GDP growth directly comparable to Figure 4.6 in the main body. Figure 4.22 reports the time–varying contributions, which we express as the median and one standard deviation percentiles of the distributions, of: stock market liquidity shocks (top Panel); credit risk shocks (middle Panel); and house market liquidity shocks (bottom Panel), to the overall variation in real GDP growth. The following analysis and comments are with regards to the posterior median estimates of the distributions of our structural variance decomposition. Clearly there is a considerable amount of time–variation in the contributions of our structural liquidity and credit risk shocks.

It is evident that the contributions of stock market liquidity shocks are episodic in nature. Notably, a significant proportion of real GDP growth variance (i.e. around 20%) is attributable to stock market liquidity shocks from 1987–1992; corresponding well with the crash of the stock market in 1987 preceding the savings and loan crisis. Furthermore note that in the 2001 recession, the stock market is the main driver of real GDP growth variance. Moving on to the most recent recession, stock market liquidity shocks contribute 38.5% to the overall variance in real GDP growth in 2008Q4, before declining sharply to around 5% following the Great Recession.

In addition, the contribution of credit risk shocks to real GDP growth variance surges, particularly in the earlier years of our sample, with NBER recession dates. Then, following the 2001 recession, the contribution of credit risk shocks increases to 43.12%. From 2005 until late 2009, credit risk shocks are shown to contribute around 20% to the variance in real GDP growth. The deterioration in credit conditions during this time period links well with the findings in Gilchrist and Zakrajšek, 2012. Combining the former, with the increase in subprime mortgage lending, helps explain why both the contributions of house market liquidity shocks and credit risk shocks surge in the late 2000s prior to the Great Recession (Mian and Sufi, 2009; Iacoviello and Neri, 2010). Turning our attention to the bottom Panel, we can see substantial time–variation in the

[30]Although corporate bond spreads do not explicitly capture credit conditions households face, they will give an indication of credit conditions within an economy.

contribution of house market liquidity shocks. Notably, the changing contributions is much more gradual than stock market liquidity and credit risk shocks.

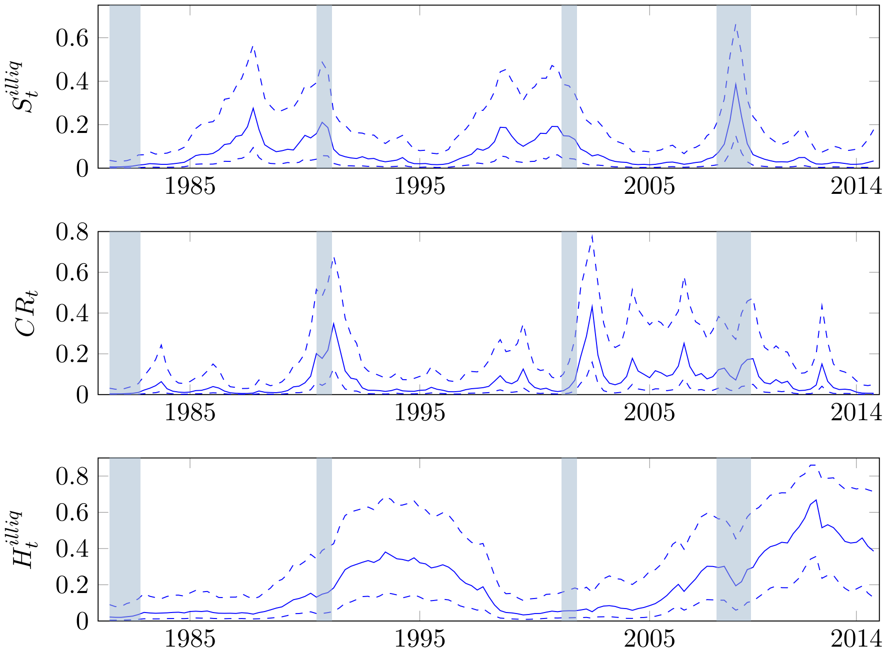

FIGURE 4.22: **Contribution of Structural Liquidity and Credit Risk Shocks to the Overall Variance of Real GDP Growth from 1981 to 2014**
Notes: This figure plots the median and one standard deviation percentiles of the contribution of structural stock market liquidity, credit risk, and house market liquidity shocks to real GDP growth from 1981Q3–2014Q4. Grey bars indicate NBER recession dates.

On average during the most recent recession, stock market liquidity shocks explain 12.87%; credit risk shocks explain 10.93%, and house market liquidity shocks explain 26.48% of the variance in real GDP growth respectively. Therefore the total average contribution of liquidity and credit risk shocks is 50.28%; which is comparable with the total average contribution of liquidity shocks from our main results (i.e. 51.7%). Overall, the shapes of the changing contributions, resemble the stochastic volatility plots this model implies. Therefore the driving force of time–variation in the contributions are changing shock sizes. Interestingly, both this, and the analysis in the main text uncovers an important role for the stock market in the most recent recession. Contrasting to Prieto, Eickmeier, and Marcellino, 2016 and Justiniano, Primiceri, and Tambalotti, 2015, our analysis reveals the stock market (i.e. accounting for liquidity conditions) is a key explanatory factor for US real GDP growth variance during recessions; particularly during 2008 and 2009. This implies that once accounting for stock market conditions through prices and quantities, there is a credible link between the stock market and real GDP growth during times of recession.

These results uncover an important structural and periodic relationship stock market liquidity and credit risk shocks possess with the variance of US real GDP growth. To contrast we uncover that the contributions of house market liquidity shocks to real

GDP growth variance change smoothly in conjunction with changing shock sizes hitting the system throughout time. Combining with the conclusions we report in the main text, this analysis reveals that the impact and real effects liquidity shocks is robust to incorporating credit risk into the model.

Chapter 5

Conclusions and Directions for Future Research

5.1 Concluding Comments

This thesis studies the links between money, liquidity and the wider economy. In Chapter 2 we examine the impact of global liquidity movements, whilst controlling for domestic monetary conditions and spare capacity, on UK RPI inflation (from 1984 to 2014) and CPI inflation (from 1989 to 2014) respectively. In doing so we compare conventional simple–sum (or broad) measures of money with theoretically founded Divisia indices. A summary of our results in Chapter 2 are as follows: First, global liquidity exerts significant inflationary pressures over and above that of domestic monetary conditions and spare capacity. Building on this, we show that housing and financial assets positively influence the demand for money, thereby exhibiting wealth effects. Furthermore, our study highlights a strong non–linear relationship of UK inflation rates with our control variables. In particular inflation exhibits regime–switching behaviour, depending on whether domestic money growth is contained between two endogenously determined thresholds. When money growth is contained, UK inflation is well specified by a standard Phillips curve augmented by movements in global liquidity. Yet, when money surpasses these thresholds, domestic monetary conditions dominate the inflationary process. Finally we show, from a purely econometric specification, models of CPI inflation using M4 money growth dominate those using Divisia money growth.

In Chapter 3, we investigate evolving macroeconomic dynamics of the US and UK economies from 1979 to 2015 respectively. We augment a standard New Keynesian system replacing simple–sum monetary aggregates with Divisia indices. Namely, we provide comprehensive reduced–form and structural analyses, using Bayesian TVP–VAR models with stochastic volatility structures. Our main findings in Chapter 3 are as follows: First, we link the persistence of US and UK economic data to the dynamic multivariate R^2 forecastability of macroeconomic fundamentals, and uncover distinct differences in the predictability over our sample. Second, our TVP–VAR models using Divisia money growth generate more accurate pseudo–forecasts of both US and UK real GDP growth than systems using simple–sum measures of money. At longer forecast horizons, models using Divisia money growth produce a range of posterior credible intervals 10 percentage points lower than those using broad money growth. Third, we show that the transmission of monetary policy shocks has changed since the financial crisis; further justifying the need to account for time–variation. Finally, our structural variance decompositions show that monetary policy shocks explain 60% and 42% of real GDP growth uncertainty at low and business cycle frequencies in the US and UK, respectively. In the very same period, these shocks explain 60% of inflation uncertainty at high frequencies in both respective economies.

The final empirical chapter of this thesis, Chapter 4, constructs proxies of stock and house market illiquidity in the spirit of Amihud, 2002 for the US economy. Then, we add these proxies to US macroeconomic data and estimate a Bayesian TVP–VAR with a stochastic volatility structure from 1970 to 2014, and provide a structural analysis of the real effects of market specific liquidity shocks. In Chapter 4 our results consist of four main findings. First, the contractionary affects of stock market liquidity shocks on US real GDP growth are economically meaningful at every observation in our sample; however, the magnitude is decreasing. Second, we uncover a stark structural change in the relationship between US real GDP growth and house market liquidity shocks from 2005, as turbulences in the property sector start to surface. Third, we provide evidence in support of asymmetries in the response of real GDP growth both across the business cycle and among business cycle troughs in our sample. Namely, these results show that house market liquidity shocks during the 2008 recession are stronger and more persistent than other recessions in our sample. Fourth and finally, stock and house market liquidity shocks contribute, on average, 15% and 36% toward the total volatility in US real GDP growth during the most recent recession, respectively.

Our main findings yield a number of implications for policymakers and central bankers. To begin with, our work in Chapter 2 suggests that UK policymakers should monitor domestic money growth. This is because the inflationary process depends on whether money growth is contained or uncontained. Our results imply that UK CPI inflation is currently governed by a regime where M4 money growth is weak. Therefore, with M4 growth currently low (annual M4 growth in 2016Q1 is 1.37%) and CPI inflation fluctuating very close to zero (the annual rate of CPI inflation in 2016Q1 is 0.30%), our model implies no immediate risk of inflationary pressures. Therefore, the Bank of England's Monetary Policy Committee (MPC) are not under immediate pressure to raise the policy rate of interest. In fact, in the most recent Inflation Report (i.e. July 2016), the MPC unanimously voted to keep the Bank rate at 0.5%; only one MPC member voted to cut interest rates in light of the UK's choice to leave the European Union.

Our analysis in Chapter 3 indicates that forecasters should consider replacing simple–sum monetary aggregates with Divisia money in order to obtain more precise forecasts of US and UK real GDP growth. This supports the view that correctly measured monetary statistics may have better signalled the financial crisis (Barnett and Chauvet, 2011). Our structural variance decompositions uncover how monetary policy shocks contribute to macroeconomic uncertainty across our sample at different frequencies. It is evident that monetary policy shocks sporadically contribute to US and UK economic uncertainty in harmony with recessionary periods. Decomposing real GDP growth and inflation volatility in the frequency domain reveal how monetary policy shocks affect fluctuations over different cycles. Thus policy response, during times of economic downturn, may be guided by the implications these shocks have on economic volatility over different time horizons, conditional on central bank goals.

On the whole, our analysis in Chapter 4 uncovers important links that market specific liquidity shocks have on US real GDP growth. The immediate policy implication is that liquidity provision to financial and asset markets is necessary to counteract the severity of contractions to real GDP growth. In particular, the stark change in the structural links between house market liquidity shocks and US real GDP growth, justifies the market stimulating policies the US implemented following the Great Recession. Furthermore, our structural variance decompositions imply that stock and house market liquidity shocks during the 2008 recession explain a substantial share of US real GDP growth volatility. Thus, providing further substance to US policy responses from 2008. The surges in the contribution of stock market liquidity shocks to real GDP growth variation correspond remarkably well with NBER recessions. This implies liquidity provision to the US stock market during economic downturn is essential to hinder adverse fluctuations in real GDP growth. Finally, the persistence in the proportion of US real GDP growth variance attributable to house market liquidity shocks, implies the fragile recovery in the US is, at least partially, due to imbalances in the property sector; a view shared by Ben Bernanke in the speech “Housing Markets in Transition" on February 10 2012.

5.2 Directions for Future Research

We now discuss several directions for future research that directly extend the findings in this thesis.

5.2.1 Global Liquidity and the UK Economy: Evidence from Bayesian Smooth–Transition VECM models

In Chapter 2 we show that UK inflation dynamics are well specified by Quadratic Logistic Smooth–Transition Autoregressive (QLSTAR) models; assuming domestic money growth governs the regime–switching process. However, the results in this chapter suffer from problems of endogeneity. Therefore an interesting question would be to fit Bayesian Smooth–Transition VECM models to UK data and global liquidity proxies respectively[1]. Gefang, 2012 extends cointegration state space methods in Strachan and Inder, 2004 and uses a collapsed Gibbs sampler as in Koop, León-González, and Strachan, 2009 that accounts for non–linearities. Specifically, Gefang, 2012 examines the relationship between money and output for post–WWII US data and finds substantial evidence in favour of non–linear causality between money and output; with regimes depending on output and price levels. The methodological benefit in using Bayesian methods to fit these models is that the parameters, logistic function, and thresholds can be estimated simultaneously. This overcomes the inaccuracies in sequential testing required when estimating these models using conventional Frequentist methods. Furthermore, we can directly assess the reduced–form and structural properties in order to ascertain whether models using both domestic and global Divisia money preferred over models using simple–sum counterparts. In addition, using multivariate models would allow us determine the impact of purely exogenous global liquidity shocks onto the system, and trace out the regime–dependent implications on domestic macroeconomic fundamentals.

5.2.2 Monetary Policy using Divisia Indices

The in–depth analysis in Chapter 3 may be extended in several directions. On the whole, the study warrants using models that account for time–varying parameters. Therefore when considering multivariate models, the assumption of constant parameters as in Albuquerque, Baumann, and Seitz, 2015 and Keating et al., 2014 may be misleading. Our pseudo–forecasts document substantial improvements in the accuracy of the overall predictability of our TVP–VARs of the US and UK. Thus, it would be interesting to explore the forecasting performance of our models in a full recursive

[1] Implicitly assuming global liquidity is a purely exogenous variable.

out–of–sample forecasting exercise; to confirm the implications of the reduced–form evidence we present in Chapter 3.

Adding to this, there is a growing base of literature replacing interest rates with Divisia indices and user–costs that are directly implied by the aggregating scheme (see e.g. Keating et al., 2014, Keating, Kelly, and Valcarcel, 2014, Belongia and Ireland, 2015 and Belongia and Ireland, 2016). The structural analyses within the aforementioned examine the implications of using Divisia money as the monetary policy indicator, as well as including the user–cost within the information set. Monetary aggregation theory implies, rather than using a single interest rate, the choice of how much money to hold, depends on its user–cost. Keating et al., 2014 shows that the aggregate user–cost of money is a weighted average of interest rate spreads. Furthermore, it is shown in the former, that the user–cost contains much of the same information as the Federal Funds rate with the added advantage that it is not at the zero lower bound. We postulate, replacing the short–term Treasury Bill rates with the user–cost of Divisia in our TVP–VAR models will not only better identify monetary policy shocks (Keating et al., 2014), but also allow for an assessment of monetary policy shocks insulated from the zero lower bound problem.

5.2.3 Market Specific Liquidity Shocks

Chapter 4 provides significant scope for future research. Contrasting Prieto, Eickmeier, and Marcellino, 2016, our analysis uncovers the importance of the US stock market during the 2008 recession and its contribution to economic uncertainty. Specifically examining the liquidity shocks from the US stock and housing market, results in very different interpretations from the aforementioned, and simultaneously overcomes the complex web of information contained within the price of an asset (Harvey, 1988). Therefore, utilising our proxies of liquidity conditions in structural analysis may better inform the economic implications of policy response; specifically tailored to liquidity provision. Furthermore, based on our structural variance decompositions, using our liquidity proxies could substantially improve forecasts of real economic activity, and be useful for predicting future recessions over and above existing leading economic indicators. A deeper insight into the origins of time–variation linking parameter change to regulatory reform would also be beneficial to examine the effectiveness of policy implementation; particularly in real–time. Finally, a theoretical examination of market specific liquidity shocks in a DSGE model, in order to deduce optimal policy responses, is a thought provoking line of future research.

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