On the Economic Impact of Aggregate Liquidity Shocks: The Case of the UK

Michael Ellington*◇ and Costas Milas*

August 22, 2018

Abstract

We conduct an empirical investigation into the economic implications of aggregate liquidity shocks, through the lens of monetary aggregates, in harmony with conventional monetary policy shocks in an estimated time-varying parameter VAR model. Our results suggest that the transmission of aggregate liquidity shocks changes substantially throughout time with the magnitude of these shocks increasing during recessions. We provide statistically significant evidence in favour of asymmetric contributions of these shocks to macroeconomic fluctuations during the implementation of Quantitative Easing relative to the Great Recession. During this period, aggregate liquidity shocks explain, on average, 32% and 47% of the variance in real GDP and inflation at business cycle frequency, respectively.

◇ Corresponding Author
Email addresses:
m.ellington@liverpool.ac.uk
costas.milas@liverpool.ac.uk
* *University of Liverpool Management School, UK*

JEL Classifications: E32, E44, E47, E52, E58

Keywords: liquidity shocks, time-varying parameter VAR, money growth, sign restrictions

Acknowledgements

We thank the Guest Editor, Theodore Panagiotidis, and three anonymous reviewers for their constructive comments that greatly improved the quality of this paper. We are also grateful to Harris Dellas, Ryland Thomas, and Jane Binner for their invaluable comments. We are grateful to seminar participants at the 2017 Financial Services, Liquidity and Economic Activity Conference held at the Bank of England in May 2017.

1 Introduction

The importance of liquidity for the real economy, and the different transmission channels, has received considerable attention within the literature and more so over the last decade when standard macroeconomic models faced considerable criticism for their inability to understand or even predict events related to financial crises (McKibbin and Stoeckel, 2018). But as former Economic Counsellor and Director of Research at the International Monetary Fund Olivier Blanchard notes, "no model can be all things to all people" (Blanchard (2018), p.43). From a theoretical perspective, Kiyotaki and Moore (2012) and Shi (2015) examine the impact of liquidity shocks using DSGE models. Within these models, liquidity shocks are defined as a sudden decline in the resaleability of assets. From an empirical perspective, Baumeister et al. (2008) investigate the impact of "excess liquidity shocks" for the Euro area. In particular, excess liquidity is captured through broad money, expressed as a deviation from an equilibrium value, and show that these shocks have significant implications for the real economy; particularly output and prices.

In light of the 2008 Recession, and the emergence of unconventional monetary policies such as Quantitative Easing (QE), it is becoming increasingly important to understand how liquidity affects the real economy. This issue is far from trivial as hinted, for instance, by Bank of England Governor Mark Carney in his September 2016 Report to the Treasury Committee by noting that "The Bank's enquiries team has received and responded to almost 1000 letters to the Bank about monetary policy from members of the public."[1] Specifically, unconventional monetary policies involve the central bank buying assets in order to stimulate investment; ultimately feeding through into output. As discussed in Joyce et al. (2012), increases in liquidity follow from a 'portfolio balancing channel' that relies on the assumption of imperfect substitutability among assets in the economy. On an aggregate scale, the sale of long-term government bonds to the central bank (i.e. the Bank of England) causes an increase investor cash holdings, as well as a rise in the amount of notes and circulation. Thus, one would expect an injection of liquidity into the economy to yield surging growth rates of monetary aggregates. Recent studies such as Gambacorta et al. (2014) and Weale and Wieladek (2016) have modelled unconventional monetary policies using data starting post-2008. However, there seems to be little focus on the role of liquidity and money growth which would permit researchers to appraise liquidity throughout time with some historical context.

The main contribution of our paper is to explore the economic impact of aggregate liquidity shocks through the lens of monetary aggregates in a structural vector autoregressive (VAR) model. We identify an aggregate liquidity shock in conjunction with a monetary policy shock, in the spirit of Rubio-Ramirez et al. (2010) and Baumeister and Peersman (2013a), using a combination of contemporaneous sign restrictions and a single zero restriction in a fully generalised framework (Koop et al., 1996). We apply our identification strategy in a structural Bayesian time-varying parameter VAR and investigate the impact of aggregate liquidity shocks for the UK economy from 1955 to 2016.

We summarise our results into three main points: first, we document considerable time-

[1] Available from `https://www.bankofengland.co.uk/-/media/boe/files/about/people/mark-carney/mark-carney-annual-report-2016.pdf?la=en&hash=5FC922C67810E874F196765A0F22273C08A88976`

variation in the transmission of aggregate liquidity shocks for real GDP growth, inflation, and the interest rate. Both real GDP growth and inflation become more sensitive to these shocks during recessionary periods. Second, aggregate liquidity shocks are economically significant and vary considerably over our sample; particularly for inflation. Third, we report substantial differences in the contribution of identified aggregate liquidity shocks to the variance of macroeconomic fundamentals over different frequencies. Following the impact of the Great Recession, aggregate liquidity shocks contribute 32% and 47% toward the variance of real GDP and inflation at business cycle frequency, respectively.

Our paper is related to various streams of literature. First, we contribute to the empirical analysis of liquidity shocks. Ellington et al. (2017) and Ellington (2018) provide substantial evidence in favour of a time-varying response of GDP growth to liquidity shocks stemming from asset markets in the US and UK, respectively. On an aggregate scale using measures of money, Baumeister et al. (2008) and Adalid and Detken (2007) examine the effects of liquidity shocks, and the influence of these shocks on asset price boom and busts, respectively. The former document considerable time-variation in the impact of excess liquidity shocks for the Euro area using an array of different monetary measures. Structural shocks are identified adopting the traditional Cholesky decomposition with money ordered last implying a lagged response of macroeconomic variables. Our work builds on Baumeister et al. (2008), by imposing a set of contemporaneous and zero restrictions on macroeconomic variables.

Second, structural identification of conventional monetary policy shocks using sign restrictions has received considerable attention in the literature following the seminal papers by Canova and De Nicoló (2002) and Uhlig (2005). However, in response to the Great Recession, central banks in the US, UK, Japan and Euro area pursued alternative unconventional expansionary monetary policies. In particular, the authorities made continual attempts to inject liquidity into the economy through the implementation of asset purchase facilities known as Quantitative Easing (QE); see for example, the discussion of Martin and Milas (2012), and Cukierman (2013). Combined with interest rates tending toward their respective zero lower bounds, these expansionary monetary policies cannot be picked up in traditional monetary policy rules.

Studies such as Weale and Wieladek (2016) have made important contributions toward identifying unconventional monetary policy shocks in structural VAR models. Recent extensions allowing simultaneously for sign and zero restrictions are Baumeister and Benati (2013) and Gambacorta et al. (2014). These studies adopt this approach to identify unconventional monetary policy shocks in a time-varying parameter VAR (TVP VAR) and a panel VAR, respectively. Whilst our paper is not the first to implement this strategy, to the best of our knowledge, we are the first to propose an aggregate liquidity shock in conjunction with a conventional monetary policy shock using sign restrictions that are economically plausible.

Third, we contribute to the growing literature recognising that time-varying parameters, covariances, and variances between macroeconomic fundamentals is essential to embed in econometric models (see e.g. Primiceri (2005) and Cogley and Sargent (2005)). A byproduct of this literature are an array of empirical studies, such as Canova and Gambetti (2009), Benati and Mumtaz (2007), and Benati (2008), that estimate macro-econometric models to examine the "good policy or good luck" hypothesis. In general, results are not conflicting; the decline in macroeconomic volatility following the Great Inflation was not a result of effective monetary policies.

Our paper looks to bridge the gap between the former, studies examining the real effects of unconventional monetary policies (see e.g. Kapetanios et al. (2012), Baumeister and Benati (2013), Gambacorta et al. (2014), Meinusch and Tillmann (2016), and Weale and Wieladek (2016)), and monetary policy at the zero lower bound (e.g. Wu and Xia (2016) and Belongia and Ireland (2016)). We provide evidence that our aggregate liquidity shock indirectly captures unconventional monetary policies whilst also holding historical economic importance. Therefore, our study offers an alternative strategy to examine recent monetary policies in a flexible macro-econometric model that can also account for conventional monetary policy shocks.[2]

This study has clear implications for policymakers. Our results demonstrate that aggregate liquidity conditions should be monitored by policymakers. Although the propagation of these shocks changes over time, the economic significance retains historical importance. Moreover, our analysis supports the idea that without unconventional monetary policies, the recovery in GDP from the 2008 recession would have been much more gradual. Thus, consistent with the recommendations in Kapetanios et al. (2012) and Baumeister and Benati (2013), policymakers were right to respond to the financial crisis with large scale asset purchase facilities.

The paper proceeds in the following manner: In Section 2, we discuss data, our econometric specification, and structural identification. Sections 3 and 4 present our empirical results and robustness analysis, respectively. Finally, Section 5 offers concluding comments.

2 Data, Econometric Specification and Structural Identification

2.1 Data

We use UK macroeconomic data from 1955Q1 to 2016Q4 on real GDP, consumer prices, the Bank of England's Policy rate of interest and we construct a break adjusted M4/M4ex series.[3]. All variables enter our model as quarterly growth rates except for the economy's interest rate. We compute the quarterly interest rate in the following manner $i_t = ((1+i_t^{Ann})^{\frac{1}{4}} - 1) \cdot 100$, where i_t^{Ann} is the annual interest rate. To calibrate the initial conditions of the model, we use the first 20 years of data. Therefore the time period our estimated model covers is 1976Q1-2016Q4.[4] Our time-series is dictated by data availability, with our estimation sample containing 4 recessionary periods, as well as the first three rounds of QE implemented by the Bank of England in response to the 2008 recession. In Figure 1, we plot UK data, and within Appendix A Table A1 report

[2]Although conceptually conventional and unconventional monetary policies may not be orthogonal, we do not explicitly identify an unconventional monetary policy shock.

[3]M4ex denotes M4 excluding other intermediate financial corporations. This is the Bank of England's preferred measure of broad money; see `http://www.bankofengland.co.uk/statistics/Pages/iadb/notesiadb/m4_counterparts.aspx`) However these data begin in 1997Q4. Therefore we construct a break-adjusted M4/M4ex series following the methodology outlined in `http://www.bankofengland.co.uk/research/Pages/onebank/threecenturies.aspx`.

[4]Within the TVP VAR literature, it is standard to use the first 10 years of data to calibrate the initial conditions of the model (see e.g. Primiceri (2005), and Cogley and Sargent (2005). We have also estimated our model calibrating the initial conditions using 10 years of data, all results we present in this paper are consistent with these alternative estimates. We opt for a 20 year calibration period in order to capture UK macroeconomic dynamics for a sufficient period following departure from the Bretton Woods system.

the sources and codes of our variables.

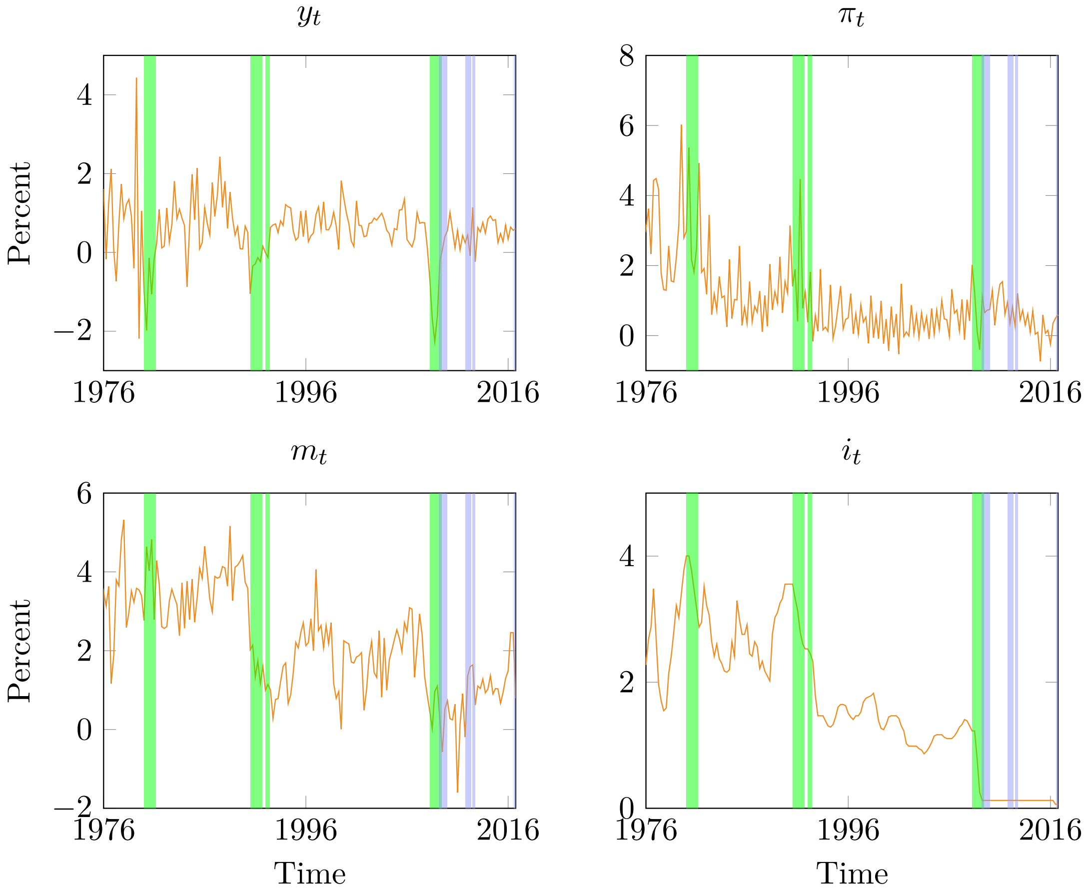

Figure 1: **Macroeconomic Data from 1976Q1 to 2016Q4**
Notes: This figure plots UK macroeconomic data from 1976Q1 to 2016Q4. The top left panel plots the quarterly growth rate of real GDP, y_t; in the top right panel we plot the quarterly growth in consumer price inflation, π_t; the bottom left and right panels plot break adjusted M4/M4ex quarterly growth, m_t; and the Bank of England Bank Rate, i_t, respectively. Green bars indicate UK recession dates and blue bars indicate the three rounds of Quantitative Easing implemented by the Bank of England following the Great Recession.

2.2 A Time–varying Parameter VAR with Stochastic Volatility

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

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

where Y_t is defined as $Y_t \equiv [y_t,\ \pi_t,\ m_t,\ i_t]'$, with y_t being quarterly real GDP growth, π_t is the quarterly rate of consumer price inflation, m_t is the quarterly growth rate of the monetary aggregate, and i_t is the short term interest rate 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).[5] As in Cogley and Sargent

[5]Note that the Schwarz Information Criterion (SIC) favours a lag length of 2 when estimating a conventional VAR over the estimation sample. Note also that we have estimated the model using a lag length of 4 and obtain similar results. The increased dimensionality of this specification increases computation time substantially. In the Appendix, we provide a lag length selection exercise in a Bayesian framework using stochastic shrinkage.

(2005), the VAR's time-varying parameters collected in θ_t evolve as

$$p(\theta_t|\theta_{t-1}, Q) = I(\theta_t)f(\theta_t|\theta_{t-1}, Q) \tag{2}$$

where $I(\theta_t)$ is an indicator function that rejects unstable draws. Therefore, we impose a stability constraint on the VAR where, conditional on the roots of the VAR polynomial lying outside the unit circle, $f(\theta_t|\theta_{t-1}, Q)$ follows a random walk

$$\theta_t = \theta_{t-1} + \nu_t \tag{3}$$

where $\nu_t \backsim N(0, Q)$. Q is a full matrix that allows parameter innovations to be correlated across equations. If $Q = 0$, the model reduces to a constant parameter VAR model with a time-varying covariance matrix. The innovations in (1) follow $\epsilon_t \backsim N(0, \Omega_t)$. Ω_t is the time–varying covariance matrix which we factor as

$$Var(\epsilon_t) \equiv \Omega_t = A_t^{-1}H_t(A_t^{-1})' \tag{4}$$

The structure of the time–varying matrices, H_t and A_t are

$$H_t \equiv \begin{bmatrix} h_{1,t} & 0 & 0 & 0 \\ 0 & h_{2,t} & 0 & 0 \\ 0 & 0 & h_{3,t} & 0 \\ 0 & 0 & 0 & h_{4,t} \end{bmatrix} \quad A_t \equiv \begin{bmatrix} 1 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 \end{bmatrix} \tag{5}$$

in (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

$$\ln h_{i,t} = \ln h_{i,t-1} + \eta_t \tag{6}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t \tag{7}$$

The innovations in the model are jointly normal

$$\begin{bmatrix} u_t \\ \nu_t \\ \zeta_t \\ \eta_t \end{bmatrix} \backsim N(0, V), \quad V = \begin{bmatrix} I_M & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix} \tag{8}$$

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 as a block diagonal matrix

$$S \equiv Var(\zeta_t) = \begin{bmatrix} S_1 & 0_{1\times2} & 0_{1\times3} \\ 0_{2\times1} & S_2 & 0_{2\times3} \\ 0_{3\times1} & 0_{2\times3} & S_3 \end{bmatrix} \tag{9}$$

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. Appendix B reports our choice of priors, an outline of the Markov Chain Monte Carlo (MCMC) posterior simulation algorithm, and convergence diagnostics.

2.3 Structural Identification

Table 1 summarises the impact of a positive, identified, structural shock to our macroeconomic variables. We impose contemporaneous sign restrictions, on a period-by-period basis, to each of our endogenous variables. We posit that an expansionary aggregate liquidity shock contemporaneously increases real GDP and money growth; inflation is unconstrained; and the interest rate does not respond on impact. Note that since we only explicitly identify 2 shocks, which may in fact impact the space spanned by our structural inference. However, we do not wish to assume that the economy may only be hit by M=4 structural shocks. Our partially identified structural model follows, Canova and Gambetti (2009) who characterise a model where there are at least M+1 shocks. In our case, we do not wish to impose a full set of identifying restrictions since we omit variable(s) in this analysis, such as those accounting for the financial sector. Therefore, those two shocks we leave unidentified are a (possibly nonlinear) combination of the remaining structural shocks the economy is subject to.

Table 1: Identification Restrictions

Shock:	Aggregate Liquidity, u_t^L	Monetary Policy, u_t^{MP}
Variable		
y_t	$\geq$0	$\leq$0
π_t	x	$\leq$0
m_t	$\geq$0	$\leq$0
i_t	0	$\geq$0

Notes: This table reports the sign restrictions imposed on the contemporaneous impact of identified structural shocks on to GDP growth, y_t; inflation, π_t; the interest rate, i_t; and broad money growth, m_t. 0 denotes a zero contemporaneous response. The term x denotes no restriction imposed on the contemporaneous impact of the structural shock to the respective variable.

This set of restrictions requires some insight and explanation. Theoretically, negative liquidity shocks in the context of Kiyotaki and Moore (2012) and Shi (2015) cause investment to decline as a result of the resaleability of assets decreasing. As a result, output falls and recession begins. Thus, a sudden increase in the saleability of assets has the opposite effect; thereby providing theoretical premise for our restriction on GDP growth. Naturally, a sudden increase in aggregate liquidity should result in an increase in money growth. There are two possible channels through which this affect translates into increases in money growth following the theoretical underpinnings in Belongia and Ireland (2014). Firstly, an increase in aggregate liquidity implies that banks and financial intermediaries' demands for reserves falls. Secondly, a sudden expansion to liquidity may increase private intermediaries' abilities to provide deposits at a lower cost. The model deduced by Belongia and Ireland (2014) shows that decreases in reserves demand and deposit costs, which are associated with expansions to liquidity, cause money to increase.

There are conflicting theories as to how prices should respond to a sudden increase in aggregate liquidity. Since the source of the liquidity shock is unknown, it may stem from the financial sector. For example, suppose that an increase in aggregate liquidity stems from the velocity of money that ultimately results in surging consumption. We would expect inflation to rise. However, if aggregate liquidity increases as a result of portfolio shifts into generally safer and more liquid assets, there is no economic justification for this to pass through to rising consumer prices. Essentially, the influence of aggregate liquidity shocks on inflation depends on whether supply or demand side factors dominate (see e.g. Gilchrist et al. (2017), Nekarda and Ramey (2013), and Gertler and Karadi (2011) for debates on demand and supply side factors).

By imposing a zero response of the interest rate on impact, we implicitly assume that once a liquidity shock is observed, policymakers can only respond in the following period(s) by increasing the interest rate; conditional on the amount of aggregate liquidity within the economy.[6] This assumption is particularly relevant to the QE policies implemented by central banks; including the Bank of England starting on March 5$^{\text{th}}$ 2009. For a multivariate examination of QE policies in the UK, see Kapetanios et al. (2012). In conjunction with our aggregate liquidity shock, we identify a monetary policy shock following Benati and Mumtaz (2007) and Benati (2008).

To compute our time-varying structural impact matrix, we follow Rubio-Ramirez et al. (2010). Let $\Omega_t = P_t D_t P_t'$ be the eigenvalue-eigenvector decomposition of the VAR's time-varying covariance matrix at time t. We draw an $M \times M$ matrix K from the $N(0,1)$ distribution and compute the QR decomposition of K, normalising the elements of the diagonal matrix R to be positive; the matrix Q is a matrix whose columns are orthogonal to one another. We compute the time-varying structural impact matrix as $A_{0,t} = P_t D_t^{\frac{1}{2}} Q'$. To impose the single zero restriction we compute a deterministic rotation of $A_{0,t}$ along the lines of Baumeister and Peersman (2013a). Specifically we define the rotation matrix, RM as

$$RM = \begin{bmatrix} I_2 & 0_{2\times 2} \\ 0_{2\times 2} & \begin{bmatrix} c & -s \\ s & c \end{bmatrix} \end{bmatrix} \tag{10}$$

where $RM \cdot RM' = I_M$ and

$$c = \frac{A_{0,t}(4,4)}{\sqrt{A_{0,t}(4,3)^2 + A_{0,t}(4,4)^2}} \tag{11}$$

$$s = -\frac{A_{0,t}(4,3)}{\sqrt{A_{0,t}(4,3)^2 + A_{0,t}(4,4)^2}} \tag{12}$$

[6]To the best of our knowledge there is no economic argument to guide our choice for the contemporaneous response of the interes rate. Friedman (1983) states that as a result of surging money growth rates, investors view their increased cash holdings as imperfect substitites an invest into other assets which pushes interest rates down. However, this response would not be contemporaneous.

where $A_{0,t}(i,j)$ notes the (i,j) entry in the prospective impact matrix, $A_{0,t}$ at time t. We obtain a new impact matrix, $\bar{A}_{0,t} = A_{0,t} \cdot RM$ with a zero in the (4,3) position. We carry out our structural analysis in a generalised framework allowing for the propagation of shocks in our impulse response functions. The Monte Carlo integration procedure we use is similar to Koop et al. (1996); we report a more detailed outline of the algorithm in Appendix C.

3 Results

3.1 Model Evaluation

To justify our econometric specification, we conduct a model selection exercise that examines the fit of the model to the data. We use Bayesian DIC statistics (DIC) which is given by

$$\mathrm{DIC} = \bar{\mathrm{D}} + \mathrm{p_D} \tag{13}$$

where $\bar{\mathrm{D}} = -2\mathrm{E}(\ln \mathrm{L}(\Lambda_i)$ which is 2 multiplied by the expected value of the log likelihood function evaluated at parameter draws Λ_i, for each iteration of the MCMC. The second term is a measure of model complexity that approximates the effective number of parameters the model estimates. The lower the DIC, the better the model fit. We report in Table 2, the estimated DIC statistics, along with $\mathrm{p_D}$ and the expected value of the log likelihood function, respectively, for restricted variants of the TVP VAR.

Table 2: Bayesian DIC Statistics for Competing VAR Models of UK Data

	DIC	$\mathrm{p_D}$	$\mathrm{E}(\ln \mathrm{L}(\Lambda_i)$
Linear Bayesian VAR	2828.15	117.98	-1355.08
Linear Bayesian VAR with stochastic volatility	700.58	108.21	-296.19
Linear Bayesian VAR with time-varying covariance matrix	760.71	107.90	-326.41
TVP VAR with constant covariance matrix	2591.42	261.46	-1164.98
TVP VAR with time-varying covariance matrix	-105.79	67.48	86.63

Notes: This table reports the DIC estimates from a battery of VAR models that are nested within the TVP VAR specification. These are a traditional Bayesian VAR model (BVAR), a BVAR with stochastic volatility, a BVAR with time-varying covariance matrix, a TVP VAR with constant covariance matrix, and our specified TVP VAR with time-varying covariance matrix.

As is clear from Table 2, our baseline econometric specification provides the lowest DIC value, thereby indicating this model most favourably fits the data. Note also that the measure of model complexity is substantially lower for our TVP VAR specification (i.e. $\mathrm{p_D}$=67.48), relative to all restricted variant of the TVP VAR model[7]. Having established that our methodology is justified statistically, we proceed in presenting our empirical analysis.

[7] We do not present results from a two-regime Markov-Switching VAR (MS-VAR) as we do not wish to impose the assumption that regimes are the same throughout time. Note that the DIC estimate from the MS-VAR is 762.51.

3.2 Empirical Results

In Figure 2 we plot, the posterior median impulse response functions of real GDP growth, inflation, money growth and the interest rate from 1976Q1 to 2016Q4 over a 20 quarter horizon. The impulse response functions have been normalised to a 1% increase in money growth. It is clear from the first row of Figure 2, the contemporaneous response of UK real GDP growth and inflation varies considerably over our sample. In general, the impact of aggregate liquidity shocks for GDP is stronger during recessions. In particular, quarterly GDP growth increases by 1% in 2008Q2 on impact (when quarterly GDP growth was -0.65%); yet in 2016Q4 the contemporaneous response of GDP is an increase by 0.5% (when the rate of GDP growth was at 0.6%).

To contrast, inflation declines on impact at every observation in our sample. Therefore following Fiore and Tristani (2013), we postulate that the net affect driving the inflationary impact of aggregate liquidity shocks are declines in borrowing costs feeding through into marginal costs that influence firms pricing decisions. This result is consistent with Abbate et al. (2016) who provide robust evidence in favour of expansionary financial shocks causing US inflation to decline.

The response of the interest rate 1-2 quarters following the shock is positive across most observations in our sample. However, note that in some periods following the aggregate liquidity shock the interest rate falls. Following Friedman (1983), if excess cash holdings are realised as a result of an increase in excess money growth, those investors viewing extra cash holdings as a disturbance in their portfolios will invest into other assets; thus causing a decline in the interest rate. In all periods however, interest rates are positive one year following the shock. At longer horizons the response of the interest rate is persistent, and gradually becomes more resilient to these shocks until 1997; when the Bank of England gained operational independence. Then, the sensitivity of the interest rate increases from early 2000 to the end of the sample at these horizons.

In Figure 3 we plot the posterior median, 68% and 95% posterior credible sets for the accumulated 4 quarter response of GDP, inflation and the interest rate from 1976 to 2016. The accumulated impact of aggregate liquidity shocks on to GDP is substantial, with 95% posterior credible sets distinctly above zero. On the contrary, the (dis)inflationary impact of aggregate liquidity shocks is short lived; relative to both 68% and 95% posterior credible sets. During recessions however, the response of inflation is significant. This implies that during recessions firms change their pricing decisions for a longer period of time; arguably to remain competitive. In general our findings are consistent with Abbate et al. (2016) who report a transitory impact of financial shocks for US inflation.

Figure 4 plots the historical contribution of aggregate liquidity shocks to GDP growth, inflation, money growth and the interest rate. The dashed lines represent the actual time series relative to its average growth rate, and the solid blue line reports the estimated cumulative effect of the estimated aggregate liquidity shocks on macroeconomic developments. Thus, the solid line shows how each variable would have evolved if only aggregate liquidity shocks had occurred. The difference between the actual data and the contribution of aggregate liquidity shocks is the cumulative contribution of the composite of monetary policy and other demand

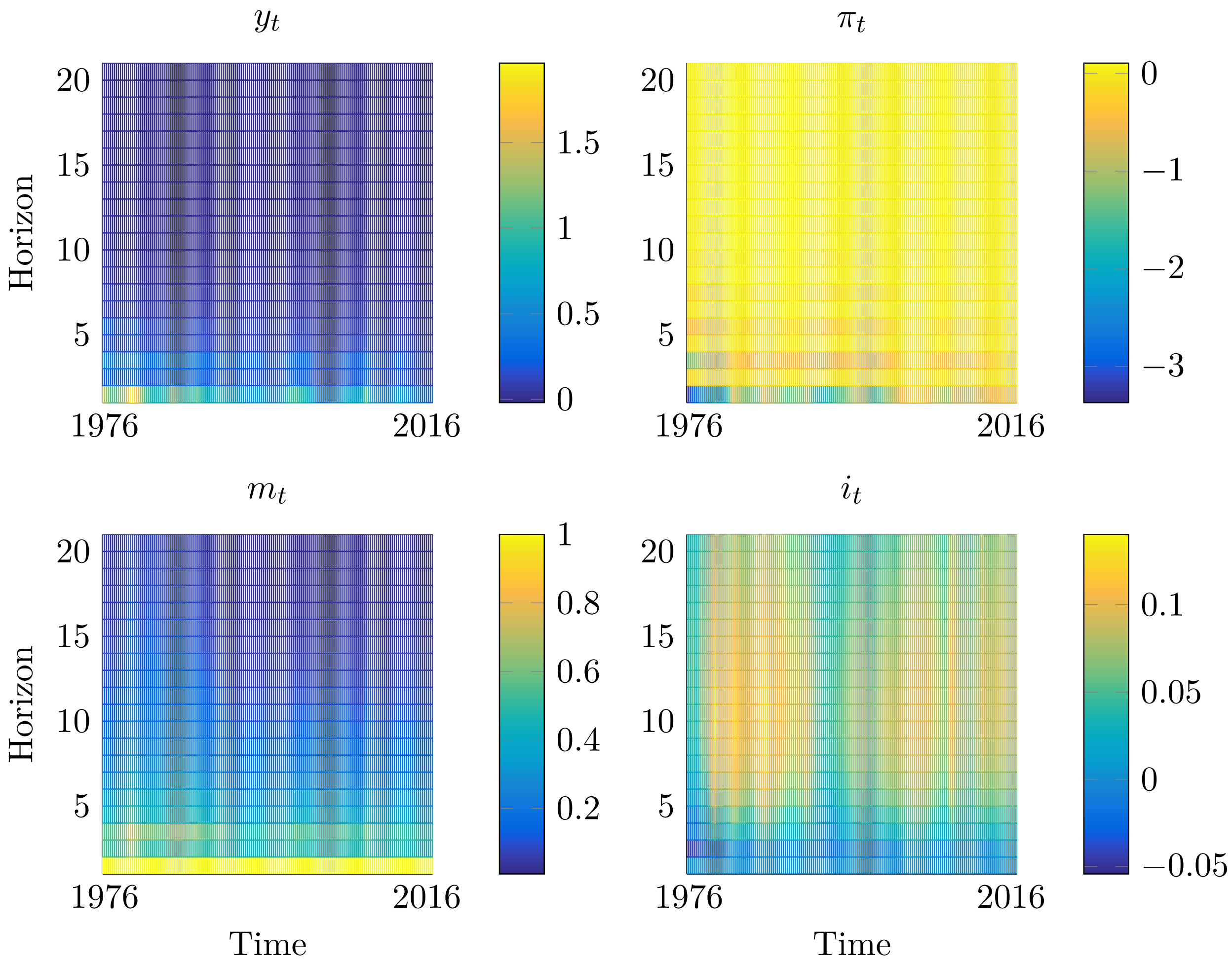

Figure 2: **Posterior Median Response of Macroeconomic Variables with Respect to an Aggregate Liquidity Shock from 1976Q1 to 2016Q4**
Notes: This figure plots heatmaps of the posterior median impulse response function of UK real GDP growth, y_t, consumer price inflation π_t, break-adjusted M4/M4ex, m_t, and the Bank of England Bank Rate, i_t from 1976Q1 to 2016Q4 with respect to an aggregate liquidity shock. We normalise the response of our variables to a 1% increase in m_t. We plot time and horizon along x-axis and y-axis, respectively. The colour bars refer to the magnitude of the response of macroeconomic variables.

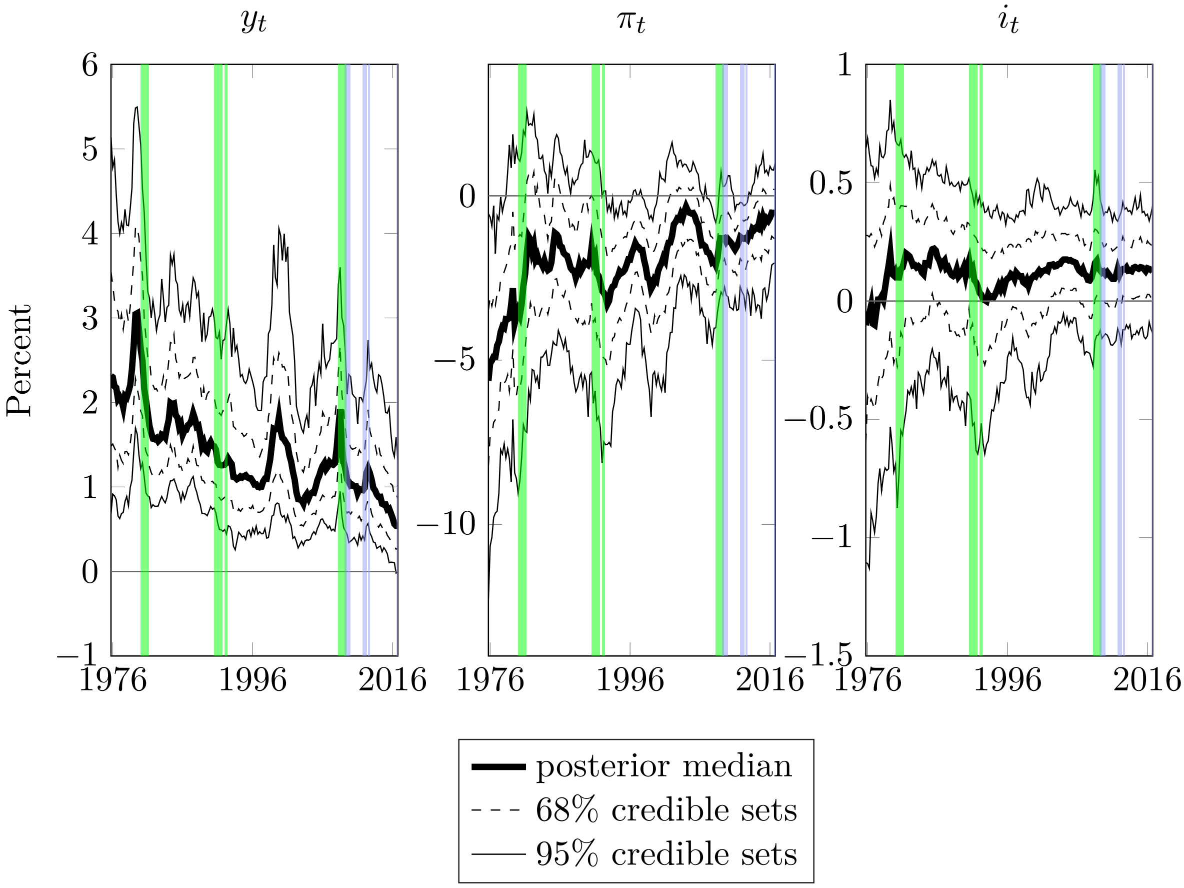

Figure 3: **Accumulated Response of Macroeconomic Variables 4 Quarters after an Aggregate Liquidity Shock from 1976Q1 to 2016Q4**

Notes: This figure plots the posterior median (thick solid line), along with 68% posterior credible sets (dashed lines) and 95% posterior credible sets (solid lines), for the accumulated response of UK real GDP growth, y_t, consumer price inflation, π_t, and the Bank of England Bank Rate, i_t 1 year following an aggregate liquidity shock from 1976Q1 to 2016Q4. Green bars indicate UK recession dates and blue bars indicate the three rounds of Quantitative Easing implemented by the Bank of England following the Great Recession.

shocks.[8]

The overall effect of aggregate liquidity disturbances on real GDP growth, inflation and money growth has been substantial. Note that our assumption of a zero contemporaneous impact of aggregate liquidity shocks on the interest rate is clearly shown in the bottom right panel of Figure 4 which indicates that the interest rate is explained by other shocks. The contribution of aggregate liquidity shocks to GDP, inflation and money surges across recessions in our sample. In particular, these shocks appear to explain the lion's share of macroeconomic variation both during the Great Recession, and during QE periods.

To assess whether our proposed aggregate liquidity shock captures unconventional monetary policies, we report the results from a counterfactual simulation. Had policymakers chosen not to implement successive rounds of asset purchase facilities, the volatility of these shocks would have, arguably, been less turbulent. Therefore, our counterfactual simulation assumes that the standard deviation of estimated structural liquidity shocks remains constant from 2009Q1 until 2016Q4. We set the volatility of the structural liquidity shocks from 2009Q1 to 2016Q4 to the average value of these shocks from 1976Q1 to 2008Q4.[9] Figure 5 reports the posterior median counterfactual simulated path of GDP, Inflation and M4/M4ex, along with their simulated actual values from 2009 to 2016 respectively.

From Figure 5 three points emerge. First, the recovery in UK GDP growth following the Great Recession would have been more gradual. Specifically, GDP growth would have been half a percent smaller than its actual value following the first round of QE. Our finding of subdued rates of GDP growth is consistent with Kapetanios et al. (2012) who show that QE effects on the level of real GDP are around 1.5%. Secondly, inflation would have been more volatile, and higher following QE1 and QE3. This suggests that the more stable rate of inflation that was actually observed as a result of lowering longer term borrowing costs for firms (Abbate et al., 2016). Finally, the recovery in M4/M4ex growth would have taken around two years longer than implied by the actual simulated history. The actual simulated history reports a revival in M4/M4ex growth around 2011Q1, whereas our counterfactual path reveals that money growth would have been 2% lower following the QE3. Based on these findings, and how they link with previous studies, we postulate that our structural liquidity shock indirectly captures the successive rounds of asset purchase facilities implemented by the UK in response to the Great Recession.

In order to assess the relevance of our structural aggregate liquidity shocks for policymakers, we perform a structural variance decomposition in the frequency domain along the lines of Benati and Mumtaz (2007) and Ellington et al. (2017); in Appendix C, we provide more detail of how we compute these decompositions. To examine the changes in the economic significance of our

[8]Following Baumeister and Peersman (2013b) and Canova and Gambetti (2009), we condition on all available information until each respective time period when computing the impulse response function of aggregate liquidity shocks. The impulse response functions are defined as the difference between two conditional expectations, where both contain the entire history up until that point in time. Therefore they trace out the future path of the endogenous variables conditional on the history that reflects the impact of all previous shocks. It is worth mentioning that the influence of aggregate liquidity shocks may be affected by earlier demand and monetary policy shocks whilst monetary policy shocks and demand shocks could be influenced by earlier aggregate liquidity shocks. These indirect effects of earlier shocks are not captured in Figure 4.

[9]We also compute counterfactuals by removing the aggregate liquidity shock from 2009Q1. This assumption leads to the same conclusions as those reported.

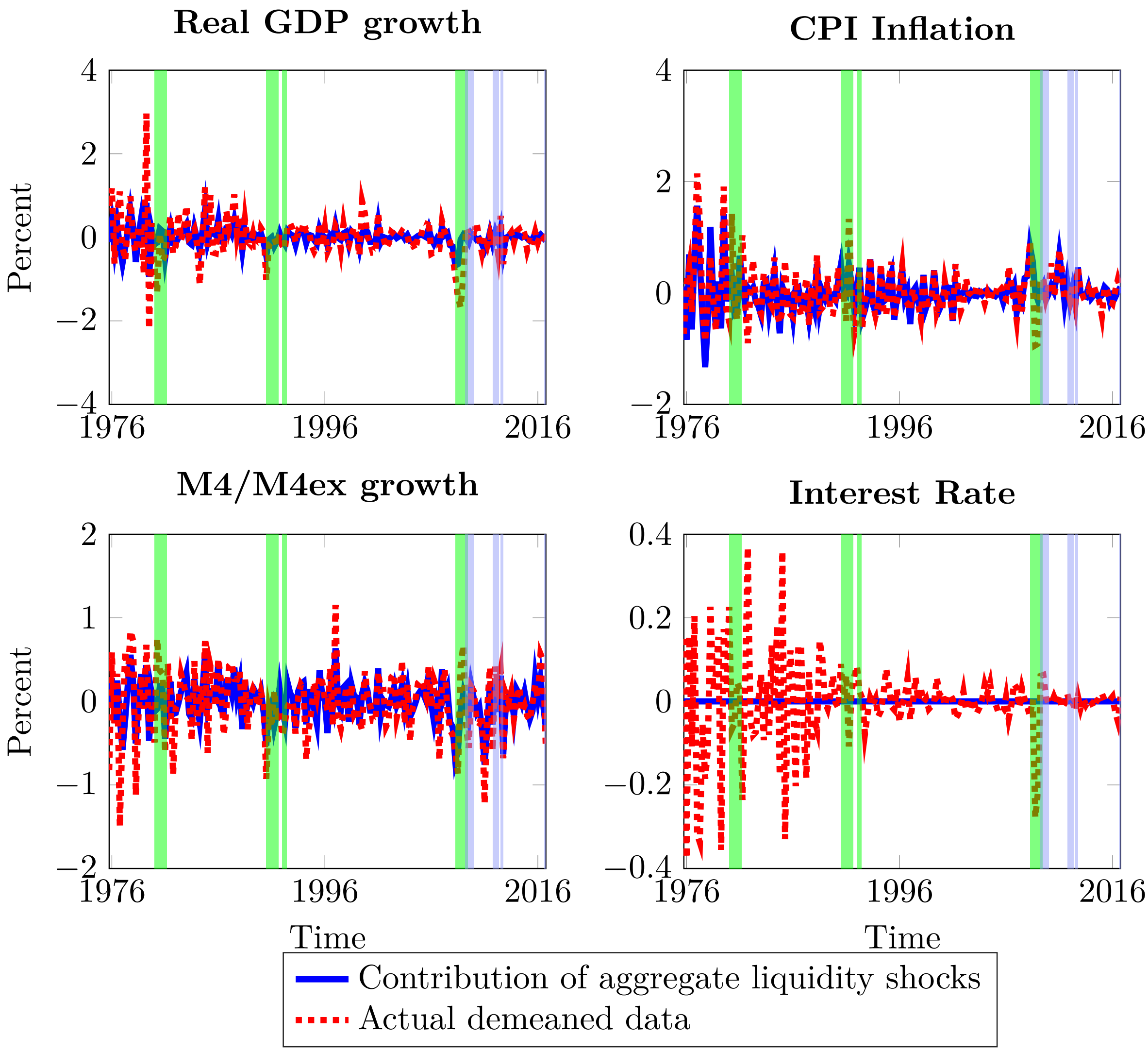

Figure 4: **Historical Decomposition of Macroeconomic Variables from 1976Q1 to 2016Q4; Aggregate Liquidity Shocks**

Notes: This figure plots the posterior median historical decompositions of UK real GDP growth, y_t, consumer price inflation, π_t, break-adjusted M4/M4ex, m_t, and the Bank of England Bank Rate, i_t from 1976Q1 to 2016Q4. "Actual demeaned data" indicates the data have been adjusted for the baseline forecast. Green bars indicate UK recession dates and blue bars indicate the three rounds of Quantitative Easing implemented by the Bank of England following the Great Recession.

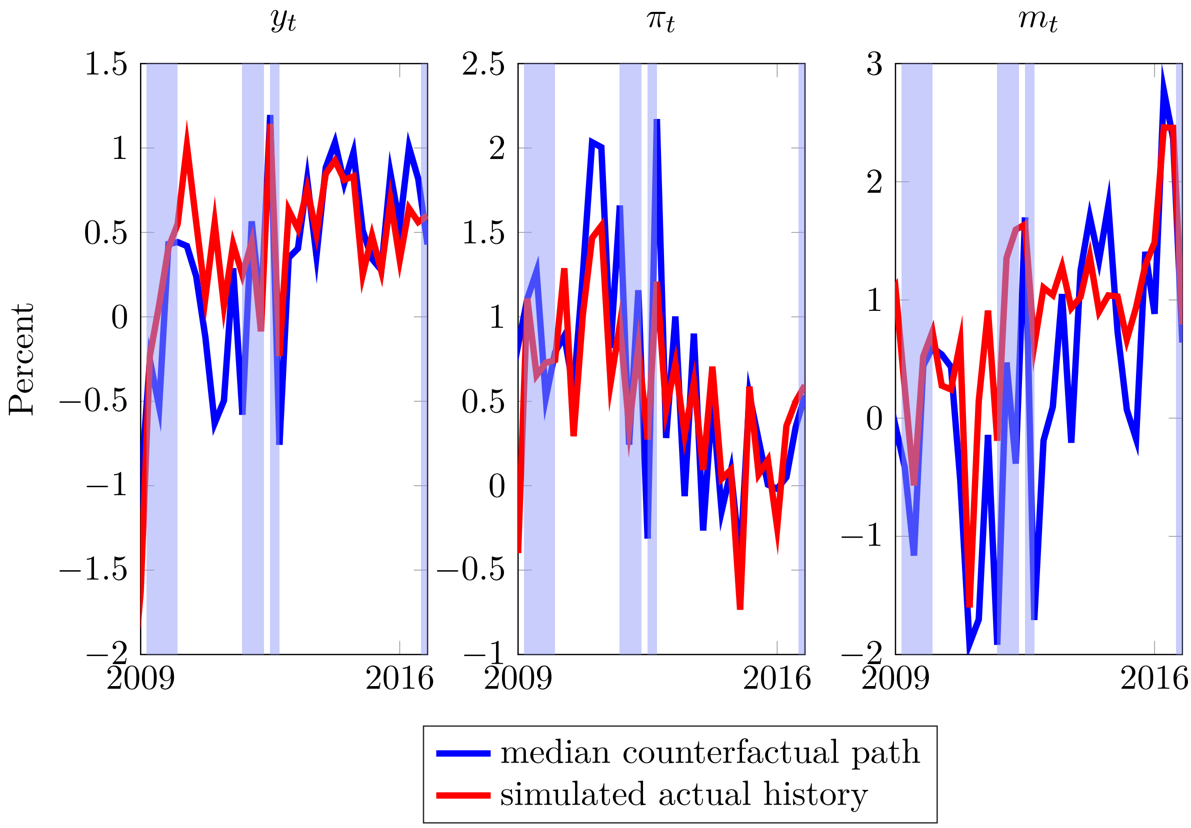

Figure 5: **Counterfactual Simulations of GDP, Inflation and Money Growth 2009Q1 to 2016Q4**

Notes: This figure plots the posterior median counterfactual simulations of UK real GDP growth, y_t, consumer price inflation π_t, and break-adjusted M4/M4ex, m_t by assuming constant volatility of the structural liquidity shock from 2009Q1. We set the volatility of the structural liquidity shock equal to the average value from 1976Q1 to 2008Q4. We also plot the actual simulated values implied by our TVP VAR model. Blue bars indicate rounds of Quantitative Easing.

identified aggregate liquidity shocks over time and frequencies, we plot in Figure 6, the posterior median contribution of these shocks at a business cycle frequency. Following Hamilton (1994) and Mumtaz and Sunder-Plassmann (2013), we define business cycle frequency as 10 quarters.

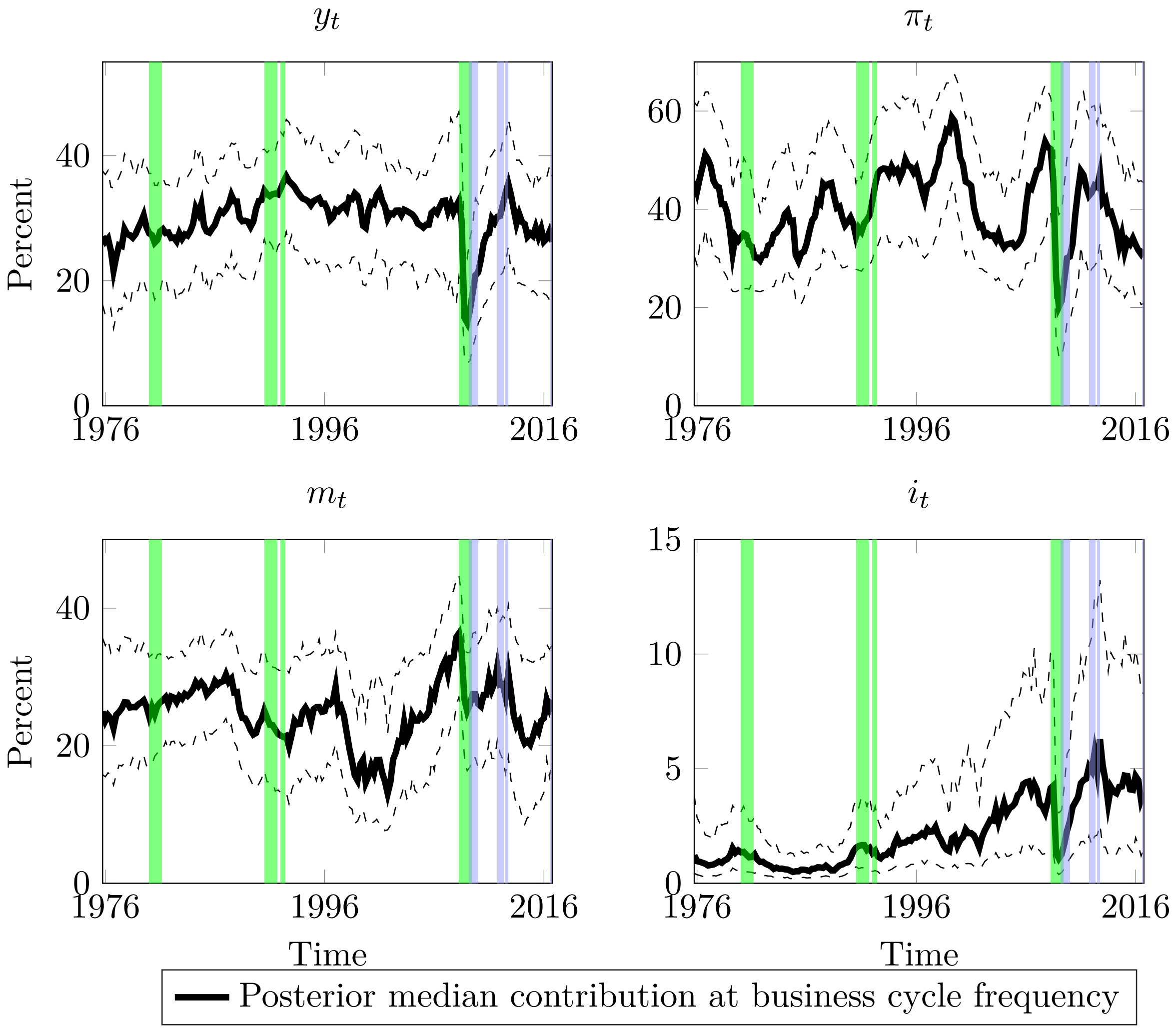

Figure 6: **Contribution of Structural Aggregate Liquidity Shocks to the Variance in Macroeconomic Variables from 1976Q1 to 2016Q4**
Notes: This figure plots the posterior median contribution of structural aggregate liquidity shocks to the variance of UK real GDP growth, y_t; consumer price inflation, π_t; break-adjusted M4/M4ex, m_t; and the Bank of England Bank Rate, i_t at a business cycle frequency from 1976Q1 to 2016Q4. We report the 68% posterior credible intervals of the contribution of aggregate liquidity shocks are business cycle frequency denoted by the black dashed lines. Green bars indicate UK recession dates and blue bars indicate the three rounds of Quantitative Easing implemented by the Bank of England following the Great Recession.

On the whole, our frequency domain variance decompositions have some important implications for policy. First, the stark differences between the contributions at an infinite horizon and business cycle frequency of GDP growth and inflation imply that policymakers should monitor liquidity conditions within the economy over the business cycle. Second the surge in contributions of these shocks to inflation variability from 2009 to 2013 helps explain the falling trend in inflation during the second and third rounds of QE. In the very same period, the importance of these shocks increased for GDP growth, and during the first three rounds of QE. Combining the above with the impulse response analysis, suggests there could be tradeoffs for central banks with the dual mandate of maintaining steady growth and price stability; which is analogous to the implications in Abbate et al. (2016). Third, we document statistically significant differences in the contribution of aggregate liquidity shocks, particularly for GDP growth and inflation. This implies that policymakers' responses should be heterogeneous; conditional on the state of economy; and focus on tailoring policy response to business cycle frequencies.

Following Cogley et al. (2010), we assess the statistical significance of time variation within our structural variance decompositions at a business cycle frequency. In doing so, we account for the entire distribution of the variance decompositions between different periods. We select periods that relate to the financial crisis and QE policies implemented by the Bank of England. Dates relating to the financial crisis are the start and end dates to the recession in the UK, 2008Q2 and 2009Q2 respectively. Similarly, dates relating to QE policies are the first quarter each round of QE started: 2009Q1; 2011Q4; 2012Q3; and 2016Q3. The former three dates are the quarter in which QE1, QE2 and QE3 began. The latter is representative of the asset purchase rounds following the UK's vote to leave the European Union on June 23 2016.

We plot the joint distribution of the contribution of structural liquidity shocks to UK real GDP growth, inflation, money growth and the interest rate in the far left; left; right; and far right columns of Figure 7, respectively. The first row plots the joint distributions in 2008Q2 against 2009Q1. The remaining three rows plot the joint distributions of these shocks in the final quarter of the Great Recession, 2009Q2, against 2011Q4, 2012Q3 and 2016Q3 respectively. Along with the scatterplots, we include a 45° line. The first row of Figure 7 indicates that there is a significant difference in the contribution of structural liquidity shocks to the variance of macroeconomic fundamentals in 2008Q2 and 2009Q1. For GDP growth, inflation and money growth, 95% of the distribution lies below the 45° line indicating that the contribution of aggregate liquidity shocks was greater at the onset of the financial crisis relative to 2009Q1. For the interest rate, time variation is less significant with 90% of the distribution lying below the 45° line.

In the remaining three rows, we plot the joint distribution of our structural variance decompositions of our UK macroeconomic data in the final quarter of the Great Recession against the first quarter of asset purchases following QE1. It is evident from these plots that there are statistically significant differences in the contribution of aggregate liquidity shocks during rounds of asset purchase facilities relative to the Great Recession. More specifically, the contribution of aggregate liquidity shocks is statistically greater, relative to the final quarter of the Great Recession, during all QE periods following QE1. The same conclusion holds for the variance of inflation and money, albeit less so during QE following the UK's decision to leave the European Union in June 2016.

In general, our results provide substantial evidence in support of the findings in Gertler and Karadi (2011) that unconventional monetary policies should only be implemented during times of financial crises. Our structural analysis provides empirical justification for these theoretical findings. Although we do not take a stance on formally identifying an unconventional monetary policy shock, our findings imply that aggregate liquidity shocks capture QE policies. Our analysis sheds light on the ramifications of large scale asset purchases. These findings link well

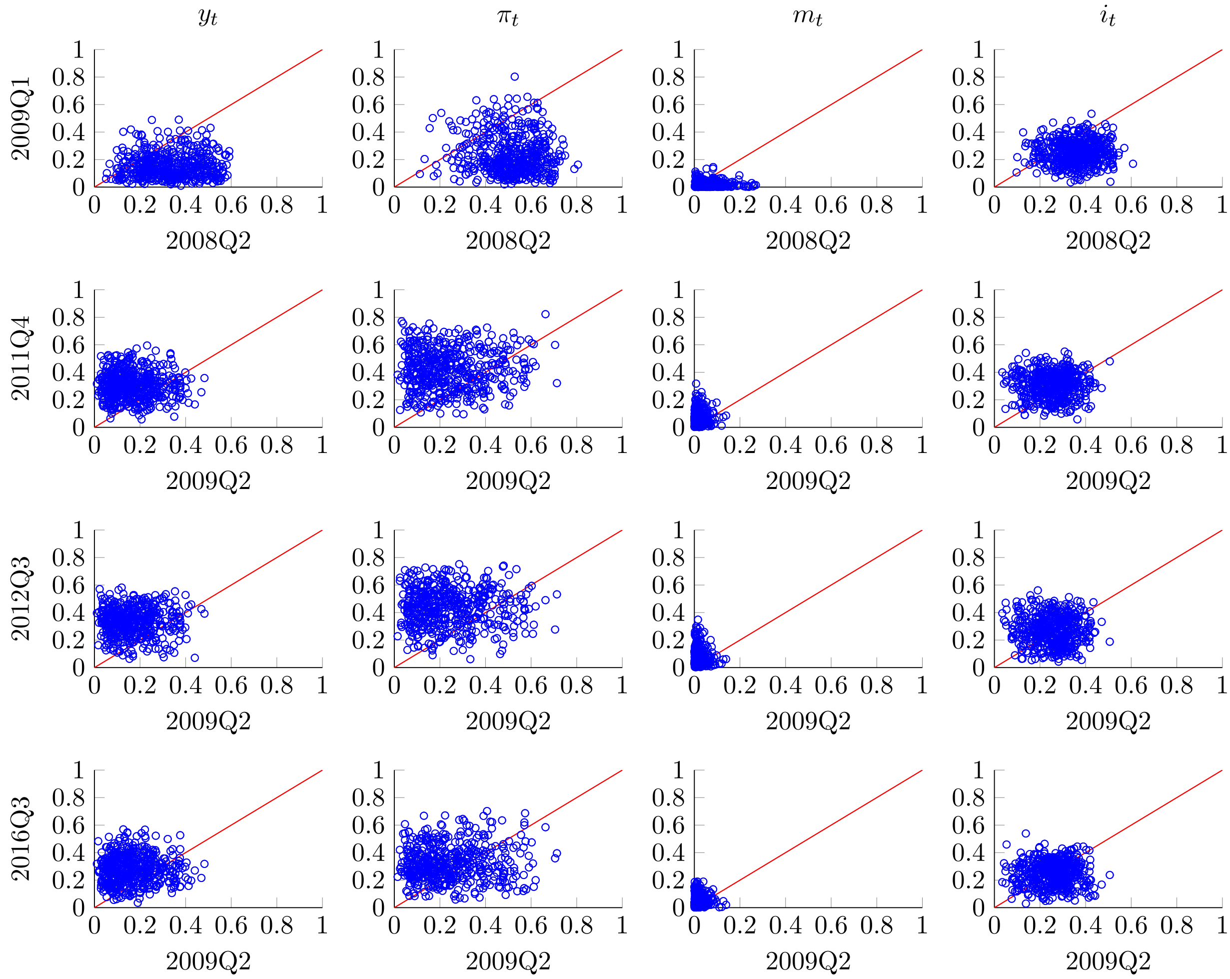

Figure 7: **Assessing the Statistical Significance of Time-variation in the Contribution of Structural Aggregate Liquidity Shocks to the Variance in Macroeconomic Variables at Business Cycle Frequency**

Notes: This figure plots the joint distribution of structural aggregate liquidity shocks to the volatility of UK real GDP growth, y_t in the first column; consumer price inflation, π_t in the second column; break-adjusted M4/M4ex, m_t in the third column; and the Bank of England Bank Rate, i_t in the fourth column, over selected dates at business cycle frequency. The first row plots the joint distribution in 2008Q2 against 2009Q1. The second to fourth rows plot the joint distribution of aggregate liquidity shocks in 2009Q2 against 2011Q4, 2012Q3 and 2016Q3 respectively. Consistent with Hamilton (1994), our definition of business cycle frequency is a 10 quarter horizon, and for each plot we include the 45° line.

with those in Gambacorta et al. (2014), Kapetanios et al. (2012), Baumeister and Benati (2013), and Weale and Wieladek (2016) advocating the implementation of unconventional monetary policies as a response to the financial crisis.

4 Robustness Analysis

4.1 Assessing the Consequences of the Zero-Lower Bound (ZLB)

Given that UK short-term interest rates have been stuck at their zero lower bound for nearly a decade, it is necessary to explore the implications of these on our main results. Therefore, following the 'constant interest rate projections' in Baumeister and Benati (2013), and also used by central banks, we impose a binding ZLB constraint on the UK Bank rate such that it does not respond to structural shocks over a four quarter horizon. The binding constraint is computed by drawing a sequence of monetary policy shocks that exactly neutralise the systematic component of monetary policy. Then, at horizons greater than 4 quarters, we allow the interest rate to move according to what is dictated by the structural monetary policy rule.[10]

In Figure 8, we report the posterior median, 68% posterior credible sets, and 95% posterior credible sets of the four quarter accumulated impulse response functions for GDP growth and inflation from 1976 to 2016; assuming the ZLB is binding for one year following an aggregate liquidity shock. It is clear that the responses of GDP and inflation are similar to those obtained from our baseline results. In particular, there is still substantial time-variation in the transmission mechanism of these shocks that is confluent with the results reported in Figure 3.

The above suggests that our main conclusions are not influenced by the short-term interest rates tending to the ZLB. We have also estimated a model that replaces the UK Bank rate with an estimated shadow rate, as in Wu and Xia (2016). These results conform to those presented here, and in the preceding section.

4.2 Aggregate Liquidity Shocks Identified from a Cholesky Decomposition

To investigate the robustness of our proposed identification scheme, we carry out our structural analysis using a recursive identification scheme. Structural inference is carried out using the same reduced-form estimates to compute our baseline results. The ordering of our variables allows the interest rate to respond contemporaneously to an aggregate liquidity shock. Figure 9 plots the posterior median response of our four endogenous variables with respect to an aggregate liquidity shock identified using a Cholesky decomposition over a 20 quarter horizon. We normalise the response of variables such that the aggregate liquidity shock causes money growth to increase by 1%. Under this approach, the ordering of our variables assumes that GDP growth and inflation react with a lag to aggregate liquidity shocks whereas the interest rate responds contemporaneously.

As we can see from the bottom right panel of Figure 9, the interest rate responds negatively on impact for the first 5 years whereas the impact response from 1980 to 2016 is positive. At longer impulse horizons however, there is a similar decline in the sensitivity of the interest to

[10] These results are robust to imposing a binding constraint of 5-12 quarters.

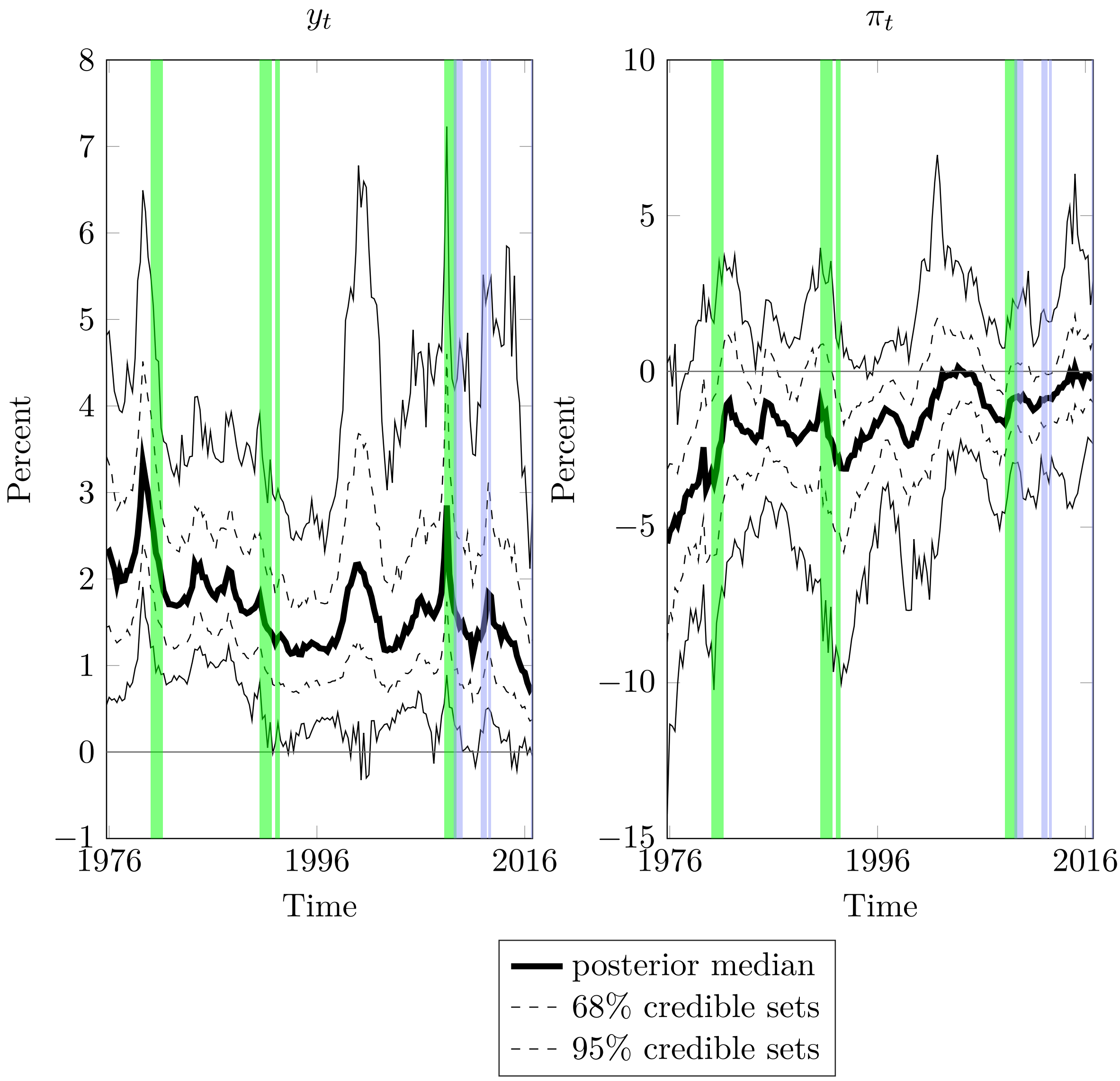

Figure 8: **Accumulated Response of Macroeconomic Variables 4 Quarters after an Aggregate Liquidity Shock from 1976Q1 to 2016Q4**

Notes: This figure plots the posterior median (thick solid line), along with 68% posterior credible sets (dashed lines) and 95% posterior credible sets (solid lines), for the accumulated response of UK real GDP growth, y_t, and consumer price inflation, π_t 1 year following an aggregate liquidity shock from 1976Q1 to 2016Q4. Green bars indicate UK recession dates and blue bars indicate the three rounds of Quantitative Easing implemented by the Bank of England following the Great Recession.

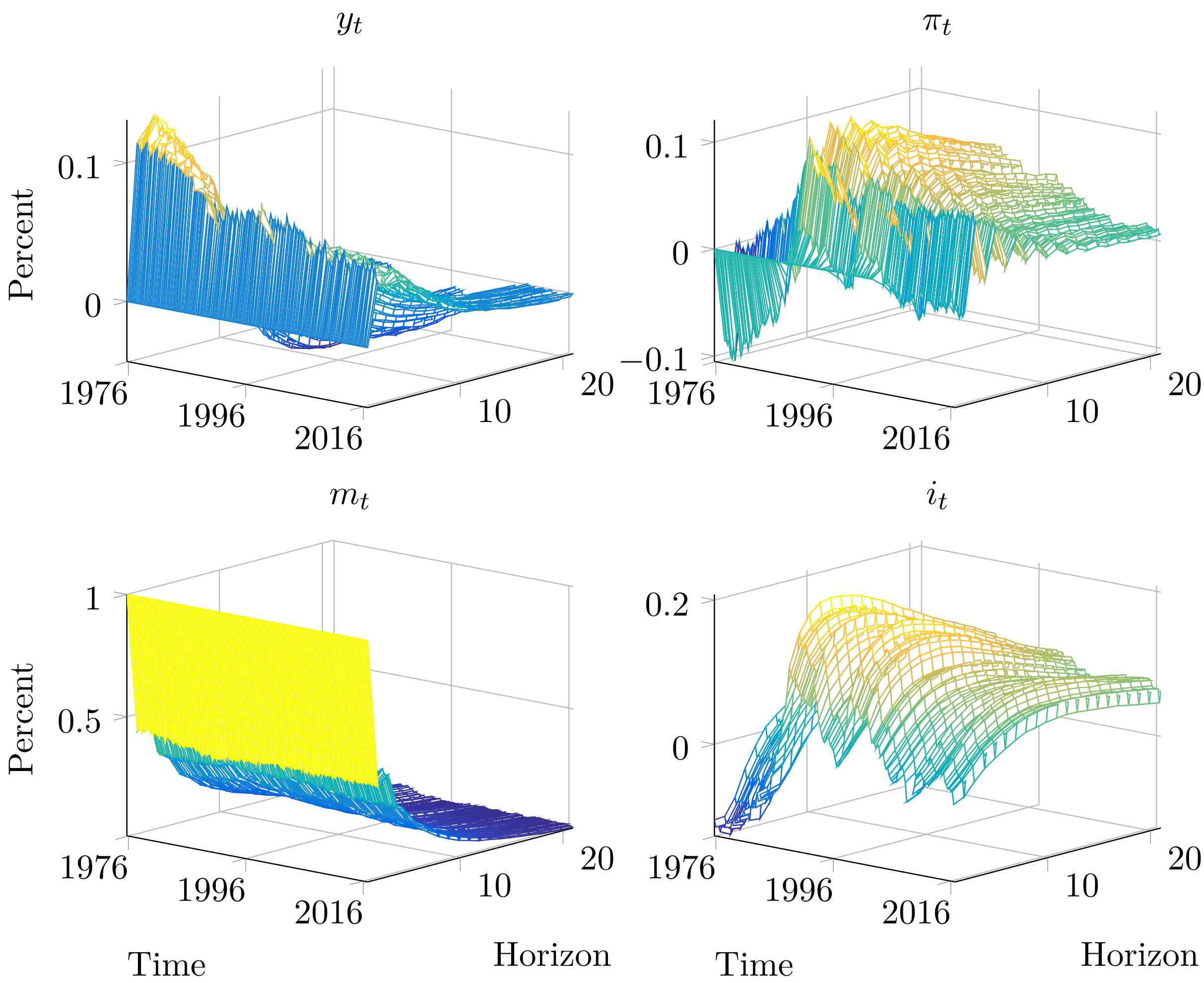

Figure 9: **Posterior Median Response of Macroeconomic Variables with Respect to an Aggregate Liquidity Shock Identified using a Cholesky Decomposition from 1976Q1 to 2016Q4**

Notes: This figure plots the posterior median impulse response function of UK real GDP growth, y_t, consumer price inflation π_t, break-adjusted M4/M4ex, m_t, and the Bank of England Bank Rate, i_t from 1976Q1 to 2016Q4 with respect to an aggregate liquidity shock. We normalise the response of our variables to a 1% increase in m_t. We plot time, horizon and percent along x-axis, y-axis and z-axis, respectively.

aggregate liquidity shocks that we report in our baseline analysis. Turning our attention to the response of GDP growth and inflation, it is clear that GDP becomes more resilient to aggregate liquidity throughout time and the impact of the shock is more persistent during the earlier years of our sample. The effect of these shocks on inflation changes from a negative response in the first decade, to a positive response from 1990 to the end of our sample. It is worth mentioning that sensitivity of inflation declines at longer impulse horizons, however the posterior median response oscillates and appears to be imprecisely determined.[11]

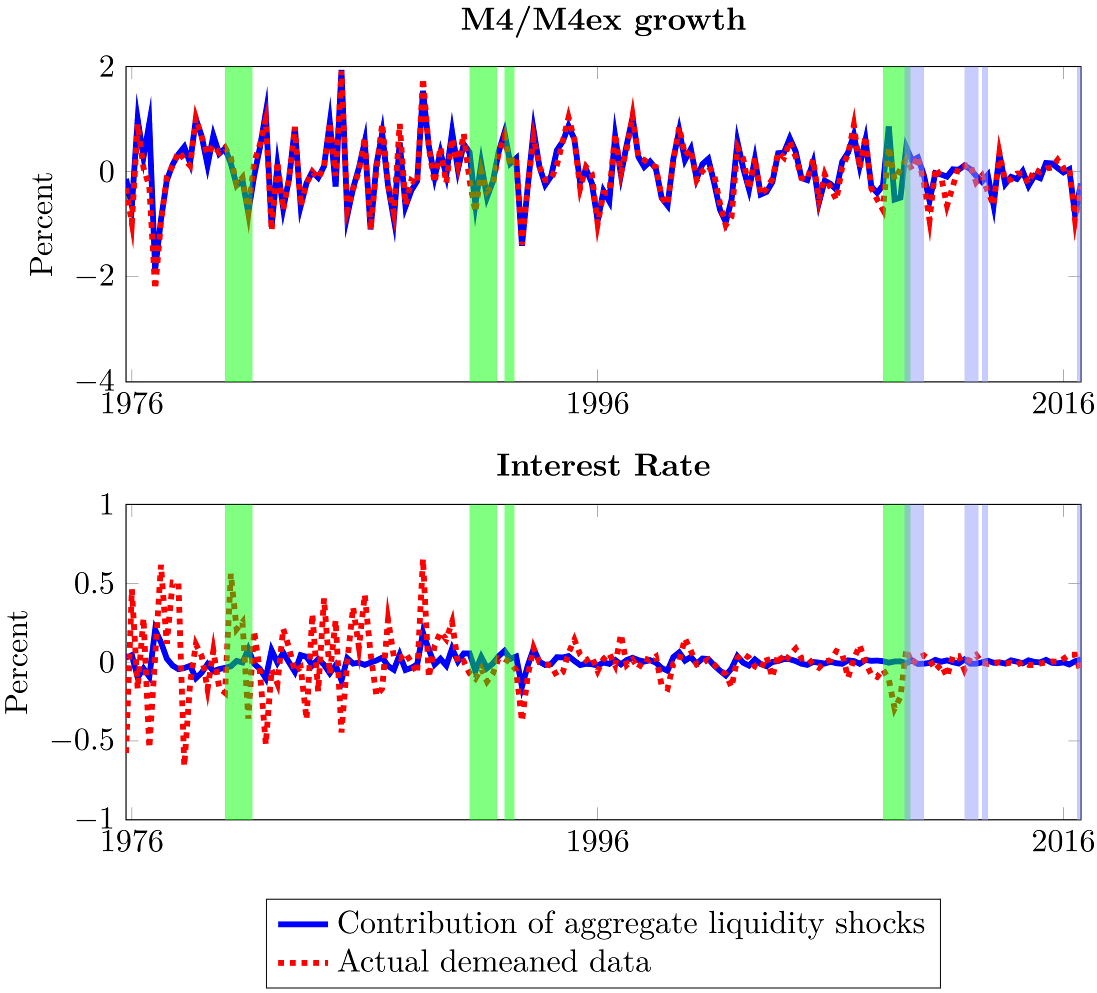

Figure 10: **Historical Decomposition of Money growth and the Interest Rate from 1976Q1 to 2016Q4; Aggregate Liquidity Shocks Identified Using a Cholesky Decomposition**

Notes: This figure plots the posterior median historical decompositions of UK break-adjusted M4/M4ex, m_t, and the Bank of England Bank Rate, i_t from 1976Q1 to 2016Q4. "Actual demeaned data" indicates the data have been adjusted for the baseline forecast. Green bars indicate UK recession dates and blue bars indicate the three rounds of Quantitative Easing implemented by the Bank of England following the Great Recession.

Our proposed identification scheme imposes that aggregate liquidity shocks, on impact, do not contribute to movements in the interest rate. To establish the validity of this assumption,

[11]Note that we cannot benchmark identification schemes against one another in this context. This is because our procedure produces set identification, while taking a Cholesky decomposition produces exact identification. It is however, useful to examine results implied by alternative identification procedures to assess the validity of our main results by assuming a recursive identification scheme and allowing the data guide structural inference

we report the historical decompositions of aggregate liquidity shocks identified using a Cholesky decomposition. In Figure 10, we report the historical contribution of aggregate liquidity shocks to money growth and the interest rate over our sample.

In comparing the results in Figure 10 with the bottom panel of Figure 4, two of noteworthy points emerge. First, we can see that aggregate liquidity shocks appear to contribute substantial proportions of money growth movements. This is consistent under both our proposed identification scheme, and using a Cholesky decomposition. Second, the importance of aggregate liquidity shocks for the level of the interest rate has always been negligible. In particular, note that these shocks appear to contribute very little toward the level of interest rates during the Great Recession. The implication here is that our assumption of a contemporaneous zero restriction on the response of the interest rate is plausible and supported by the data; even in an historical context.

5 Conclusions

In this paper, we conduct an empirical investigation on the influence of aggregate liquidity shocks for the real economy through the lens of monetary aggregates for the UK economy from 1955 to 2016. We fit a Bayesian time-varying parameter VAR model to UK economic data allowing for four sources of uncertainty, and conduct structural inference in a fully non-linear framework. In doing so, we adopt an identification procedure that relies on combining contemporaneous sign restrictions with a single zero restriction.

We summarise our results as follows: First, we provide substantial evidence in favour of a time-varying transmission of aggregate liquidity shocks for real GDP growth and inflation. In particular, both real GDP growth and inflation become sensitive to these shocks during periods of economic downturn. Second, these shocks hold historical substance by contributing significantly macroeconomic movements, and variance. Third, counterfactual simulations indicate that our aggregate liquidity shock indirectly captures unconventional monetary policies. For example, our estimates imply that the recovery in GDP following QE1 would have been more gradual. Fourth, we report substantial differences in the contribution of aggregate liquidity shocks to the variance of macroeconomic fundamentals at a business cycle frequency. At the beginning of the Great Recession these shocks contribute 32% and 47% toward the (business cycle) variability of real GDP and inflation, respectively. Finally, our analysis uncovers statistically significant differences in the percent of variance explained by these shocks during periods of QE relative to the Great Recession.

Our robustness analysis reveals that our results are not driven by ZLB constraints. In particular we adopt a commonly used method in central banks, outlined in Baumeister and Benati (2013), that allows the imposition of a ZLB constraint for a specified number of quarters over the impulse horizon. Adding to this, we conduct structural inference assuming a recursive identification scheme similar to Baumeister et al. (2008) that validates the sign restrictions imposed in our main analysis.

For policymakers, the substantial evidence in favour of time-variation suggests that policy responses to these shocks should be dynamic. Consequently in conjunction with Kapetanios et al. (2012) and Baumeister and Benati (2013), our analysis supports the implementation of Quantitative Easing policies in the UK. Our study builds on the aforementioned in associating time, and frequency, varying macroeconomic variance to identified structural shocks. This paper provides considerable capacity for future research. First, it would be interesting to explore the interconnectedness of financial institutions and markets with aggregate liquidity in a time-varying framework. This would permit an assessment of the dynamics and propagations of liquidity shocks from one sector of the economy to another. Second, linking aggregate liquidity conditions to policy reform would provide key information on the effectiveness of policy response to economic turmoil. Finally in the spirit of Belongia and Ireland (2014), investigating the impact of aggregate liquidity shocks on the monetary business cycle would be of paramount importance to deduce optimal policy responses in a DSGE framework.

Appendices

Appendix A: Data and Sources

Table A1: Data, Codes and Sources for UK Macroeconomic Data
Notes: We compute the quarterly growth rates for all macroeconomic data except for the interest rate. We compute the quarterly interest rate as $i_t = ((1 + i_t^{Ann})^{1/4} - 1) \cdot 100$.

UK Data	**Code**	**Source**
GDP, y_t	ABMI	Office for National Statistics, Quarterly real GDP, millions of pound Sterling. Available: `https://www.ons.gov.uk/economy/grossdomesticproductgdp/timeseries/abmi/ukea`
Inflation, π_t	D7BT	Office for National Statistics, Consumer Price Index Available: `https://www.ons.gov.uk/economy/inflationandpriceindices/timeseries/d7bt/mm23` We splice this measure with the consumer price index in the Bank of England's Three Centuries of Macroeconomic Data. Available: `http://www.bankofengland.co.uk/research/Pages/onebank/threecenturies.aspx`.
Bank rate, i_t	N/A	Bank of England, we convert monthly Bank Rate figures from the Three Centuries of Macroeconomic Data dataset into quarterly observations by taking the average of monthly observations in each respective quarter.
Broad Money, m_t	N/A	Bank of England, we use a break adjusted stock of M4 that splices conventional M4 with the Bank of England's preferred measure M4 excluding Intermediate Other Financial Corporations. We follow the methodology used to construct the break-adjusted stock of broad money in the Three Centuries of Macroeconomic Data. We use the break adjusted M4 series provided by the Bank of England and splice this with M4ex, taken from the Bank of England's Statistical Database, Code: RPQB53Q. Available: `http://www.bankofengland.co.uk/boeapps/iadb/NewInterMed.asp?Travel=NIxSCxSUx`

Appendix B: Priors and Posterior Simulation, Convergence Diagnostics, and Lag Length Selection

Prior Distributions

The priors of the model in (1)–(9) are calibrated on the point estimates of a constant coefficient VAR with 2 lags estimated over the period 1955Q4–1975Q4. We posit that the initial values of the states θ_0, α_0, h_0 are Normal, and independent from one another and from the distributions of the hyperparameters.[12] We set

$$\theta_0 \backsim N\left[\hat{\theta}_{OLS},\ 4 \cdot \hat{V}(\hat{\theta}_{OLS})\right] \tag{14}$$

for α_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

$$\ln h_0 \backsim N(\ln \mu_0, 10 \times I_4) \tag{15}$$

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

$$\alpha_0 \backsim N\left[\tilde{\alpha}_0,\ \tilde{V}(\tilde{\alpha}_0)\right] \tag{16}$$

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, Q is set to follow an inverse–Wishart distribution,

$$Q \backsim IW(\underline{Q}^{-1}, T_0) \tag{17}$$

where $\underline{Q} = (1 + dim(\theta_t)) \cdot \hat{V}(\hat{\theta}_{OLS}) \cdot 3.4 \times 10^{-4}$. The prior degrees of freedom, $(1 + dim(\theta_t))$, are the minimum allowed for the prior to be proper. Our choice of scaling parameter 3.4×10^{-4} is consistent with Cogley and Sargent (2005). We have also estimated our models using different priors, we allowed for a tighter scaling parameter of 1.0×10^{-4} and have also set the degrees of freedom to be the length of the training sample; in our case this is 40. The scaling parameter essentially sets the amount of drift within the θ_t matrices. The results and conclusions presented within the main body are robust to changing the value of the scaling parameter, and the prior degrees of freedom imposed.

The blocks of S are also assumed to follow inverse–Wishart distributions with prior degrees

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

of freedom equal to the minimum allowed (i.e. $1+\dim(S_i)$).

$$S_1 \backsim IW(\underline{S}_1^{-1}, 2) \tag{18}$$
$$S_2 \backsim IW(\underline{S}_2^{-1}, 3) \tag{19}$$
$$S_3 \backsim IW(\underline{S}_3^{-1}, 4) \tag{20}$$

we set S_1, S_2, S_3 in accordance with $\tilde{\alpha}_0$ as in Benati and Mumtaz (2007) such that $\underline{S}_1 = 10^{-3} \times |\tilde{\alpha}_{0,11}|$, $\underline{S}_2 = 10^{-3} \times \text{diag}([|\tilde{\alpha}_{0,21}|,\ |\tilde{\alpha}_{0,31}|]')$, $\underline{S}_3 = 10^{-3} \times\ \text{diag}([|\tilde{\alpha}_{0,41}|,\ |\tilde{\alpha}_{0,51}|,\ |\tilde{\alpha}_{0,61}|]')$. 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,

$$W_{i,i} \backsim IG(\frac{10^{-4}}{2}, \frac{1}{2}) \tag{21}$$

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 (1) is linear with Gaussian innovations with a known covariance matrix. Factoring the density of θ_t, $p(\theta_t)$ in the following manner

$$p(\theta^T|y^T, A^T, H^T, V) = p(\theta_T|Y^T, A^T, H^T, V) \prod_{t=1}^{T-1} p(\theta_t|\theta_{t+1}, Y^t, A^T, H^T, V) \tag{22}$$

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

$$\theta_{t|t+1} = P_{t|t}P_{t+1|t}^{-1}(\theta_{t+1} - \theta_t) \tag{23}$$
$$P_{t|t+1} = P_{t|t} - P_{t|t}P_{t+1|t}^{-1}P_{t|t} \tag{24}$$

which yields, for every t from $T-1$ to 1, the remaining elements in the observation equation (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 (1) can be written as

$$A_t\tilde{Y}_t \equiv A_t(Y_t - X_t'\theta_t) = A_t\epsilon_t \equiv u_t \tag{25}$$
$$Var(u_t) = H_t \tag{26}$$

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

$$\begin{aligned}
\tilde{Y}_{1,t} &= u_{1,t} && (27)\\
\tilde{Y}_{2,t} &= -\alpha_{21,t}\tilde{Y}_{1,t} + u_{2,t} && (28)\\
\tilde{Y}_{3,t} &= -\alpha_{31,t}\tilde{Y}_{1,t} - \alpha_{32,t}\tilde{Y}_{2,t} + u_{3,t} && (29)\\
\tilde{Y}_{4,t} &= -\alpha_{41,t}\tilde{Y}_{1,t} - \alpha_{42,t}\tilde{Y}_{2,t} - \alpha_{43,t}\tilde{Y}_{3,t} + u_{4,t} && (30)
\end{aligned}$$

These observation equations and the state equation (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 et al. (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.

Convergence of the MCMC Algorithm

We allow for 50,000 iterations of the Gibbs sampler keeping every 10^{th} draw, following an initial burn in period of 50,000 iterations. Following Primiceri (2005) we compute the inverse relative numerical efficiency factors for the θ_t, A_t, H_t matrices and for the hyperparameters of the model, Q, S, W. Relative numerical efficiency factors are defined 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. Figure B1 plots the inefficiency factors for our TVP VAR model. It is clear that the autocorrelation among the draws are low, and in the vast majority of cases below 1. As stressed in Primiceri (2005), values of the inefficiency factors below 20 are satisfactory.

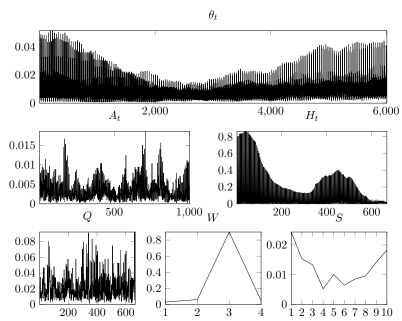

Figure B.1: Convergence of the MCMC Algorithm; Inefficiency Factors
Notes: This figure shows the inefficiency factors computed for the draws of the elements of the matrices: θ_t, A_t, H_t, Q, S and W

As we can see, all of the inefficiency factors are well below 20, therefore we postulate our algorithm has converged to the ergodic distribution.

Lag Length Selection in a Bayesian Framework

In order to justify our lag length of 2 within the TVP VAR, we estimate a traditional Bayesian VAR model over our estimation sample (1955–2016) using the stochastic search shrinkage methodology of George et al. (2008). In particular, this specification allows us to conduct variable selection in a data based manner. Posterior computation allows us to retrieve probabilities of including dependent variables within each respective equation; the reader is referred to their paper for technical details. Table B1 reports the probability of including lagged dependent variable $x = \{y_{t-p},\ \pi_{t-p},\ m_{t-p},\ i_{t-p}\}$ at lag $p = \{1, 2, \ldots, 6\}$ from 3 alternative models. The first model uses 6 lags of dependent variables, and the second and third models use 4 and 2 lags, respectively. We highlight in bold font the posterior inclusion probabilities that exceed 0.51.

As can be seen from Table B1, the VAR using 6 lags contains 17 coefficients that exceed a posterior inclusion probability of 0.51 (i.e. 17.5% of all estimated coefficients). Similarly the model using 4 lags contains 20 of the 65 coefficients surpassing the posterior inclusions probability of 0.51 (or 30.8%). Finally, the model using 2 lags contains 13 of the 39 coefficients that exceed a posterior inclusion probability of 0.51 (or 39.4%). Note also, that for the models estimated with 6 and 4 lags, only 6.25% and 15.625% of coefficients exceeding a lag length of 2 surpass 0.51, respectively.

In general, it is clear across all estimated models, that the majority of lagged dependent variables that exceed a posterior inclusion probability of 0.51 are at lags 1 and 2. Therefore, we postulate that our choice for 2 lags within our TVP VAR is well justified in a data based manner.

Table B1: Stochastic Shrinkage Variable Selection: Inlcusion Probabilities of lagged dependent Variables from Constant Parameter Bayesian VAR models, 1955Q2–2016Q4

Model:	p=6					p=4					p=2			
Dependent Variable:														
	y_t	π_t	m_t	i_t		y_t	π_t	m_t	i_t		y_t	π_t	m_t	i_t
Intercept	**0.9962**	0.0844	**0.7542**	0.3053	Intercept	**0.9962**	0.1006	**0.9432**	0.2105	Intercept	**1.0000**	0.1367	**0.9769**	0.1511
y_{t-1}	0.0850	**0.9267**	**0.7424**	**0.7543**	y_{t-1}	0.0906	**0.9843**	**0.6506**	**0.7716**	y_{t-1}	0.0863	**0.9424**	**0.7127**	0.7379
π_{t-1}	0.0732	**1.0000**	**0.6116**	0.0742	π_{t-1}	0.0853	**1.0000**	**0.6357**	0.0896	π_{t-1}	0.1144	**1.0000**	**0.8306**	0.0955
m_{t-1}	0.1652	0.3656	**0.9643**	**0.9994**	m_{t-1}	0.1164	**0.7638**	**0.9649**	**0.9976**	m_{t-1}	0.0758	**0.9812**	**0.9991**	**1.0000**
i_{t-1}	**0.7433**	0.1813	0.0728	**1.0000**	i_{t-1}	**0.6144**	0.1395	0.0696	**1.0000**	i_{t-1}	0.0957	0.0356	0.1236	**1.0000**
y_{t-2}	0.0784	0.1074	0.1040	**0.6153**	y_{t-2}	0.0830	0.2200	0.1038	**0.6673**	y_{t-2}	0.0981	0.1837	0.1102	**0.7324**
π_{t-2}	0.1270	0.0818	0.2838	0.0841	π_{t-2}	0.2375	0.0912	0.4049	0.0960	π_{t-2}	0.1276	0.0843	0.3300	0.1121
m_{t-2}	0.2895	0.0905	0.4481	**0.7262**	m_{t-2}	0.2541	0.0990	**0.5346**	**0.7360**	m_{t-2}	0.0751	0.0997	**0.9864**	**0.7499**
i_{t-2}	0.2555	0.2161	0.0438	0.1071	i_{t-2}	0.3896	0.3298	0.0448	0.0906	i_{t-2}	0.0613	0.0395	0.0741	0.1230
y_{t-3}	0.4154	0.3198	0.1762	0.1136	y_{t-3}	0.2879	0.2614	0.1427	0.1166					
π_{t-3}	0.1001	0.6782	0.0899	0.1464	π_{t-3}	0.0917	**0.9468**	0.0945	0.1694					
m_{t-3}	0.1964	0.1128	0.8385	0.1526	m_{t-3}	0.1122	0.1208	**0.8234**	0.1645					
i_{t-3}	0.1482	0.0944	0.0441	0.0522	i_{t-3}	0.3482	0.2230	0.0365	0.0473					
y_{t-4}	0.0838	0.0915	0.3551	0.0900	y_{t-4}	0.1069	0.0965	0.3558	0.0857					
π_{t-4}	0.1189	0.0832	0.1106	0.1159	π_{t-4}	0.1454	0.0854	0.1038	0.1090					
m_{t-4}	0.4020	0.3402	0.2084	0.1596	m_{t-4}	0.2555	**0.6195**	0.1999	0.1875					
i_{t-4}	0.0892	0.1249	0.0455	0.0464	i_{t-4}	**0.6542**	**0.8712**	0.0482	0.0547					
y_{t-5}	0.0912	0.1225	0.2560	0.1144										
π_{t-5}	0.1141	**0.9947**	0.2042	0.0672										
m_{t-5}	0.0984	**0.6380**	0.1711	0.3369										
i_{t-5}	0.1433	**0.8234**	0.0526	0.0427										
y_{t-6}	0.0972	0.1415	0.4879	0.3301										
π_{t-6}	0.0900	0.0914	0.2175	0.0752										
m_{t-6}	0.1844	0.8247	0.1186	0.1308										
i_{t-6}	**0.8523**	0.2016	0.0961	0.0563										

Notes: This table reports the posterior mean of including lagged dependent variable $x = \{y_{t-p}, \pi_{t-p}, m_{t-p}, i_{t-p}\}$ at lag $p = \{1, 2, \ldots, 6\}$ from 3 alternative models. The first model uses 6 lags of dependent variables, and the second and third models use 4 and 2 lags, respectively. We highlight in bold font the posterior inclusion probabilities that exceed 0.51. All Bayesian VAR models are estimated using the methods proposed by George et al. (2008).

Appendix C: Outline of Structural Computations

Impulse Response Computation

This Section describes the Monte Carlo integration algorithm we use to compute the time paths of impulse response functions to our four structural shocks. Similar to Koop et al. (1996), we compute the generalised impulse responses as the difference between two conditional expectations, with and without exogenous shocks

$$IRF_{t+j} = E\left[y_{t+j}|\varepsilon_t,\, \omega_t\right] - E\left[y_{t+j}|\omega_t\right] \tag{31}$$

where y_{t+j} contains contains forecasts of the endogenous variables at horizon $j = 1, ..., 20$, ω_t represents the current information set and ε_t is a vector of current disturbance terms. For every point in time, we condition the forecasts on the actual values of the lagged variables and a random draw from the joint posterior distribution of the model parameters and hyperparameters. Specifically, we take 500 random draws of the economy at each point in time. Following each random draw, we simulate stochastically the future paths of the coefficient vector and components of the variance-covariance matrix based on the transition laws 20 quarters into the future. In this manner we are accounting for all of the potential sources of uncertainty stemming from the innovations, variations in lagged coefficients and evolutions in the contemporaneous relations among the endogenous variables.

Following Rubio-Ramirez et al. (2010), we obtain the time-varying impact matrix $A_{0,t}$ in the following manner. Given the current state of the economy, let $\Omega_t = P_t D_t P_t'$ be the eigenvalue-eigenvector decomposition of the VAR's time-varying covariance matrix at time t. We draw an $M \times M$ matrix K from the $N(0, 1)$ distribution and compute the QR decomposition of K, normalising the elements of the diagonal matrix R to be positive; the matrix Q is a matrix whose columns are orthogonal to one another. We compute the time-varying structural impact matrix as $A_{0,t} = P_t D_t^{\frac{1}{2}} Q'$. We then, perform a deterministic rotation of $A_{0,t}$ described in Section 2.3 to give us $\bar{A}_{0,t}$ with a single zero restriction in the (4,3) entry of $\bar{A}_{0,t}$. Given $\bar{A}_{0,t}$ we compute the reduced-form innovations using $\epsilon_t = \bar{A}_{0,t}\varepsilon_t$, where ε_t contains our four structural shocks obtained by drawing from a standard Normal distribution. The impulse response functions are computed by taking the difference between the evolution of the variables with a shock and without a shock. In the former case, the shock is set to $\varepsilon_{i,t} + 1$ and in the latter we consider only $\varepsilon_{i,t}$. From this set of impulse responses, we retain only those that satisfy the whole set of sign restrictions. We retain 100 iterations that satisfy the sign restrictions and then take the mean responses of our endogenous variables over the accepted simulations.

5.1 Computing Structural Variance Decompositions in the Frequency Domain

We compute the structural volatility decompositions as a ratio of the conditional and unconditional spectral densities. Following Cogley and Sargent (2005) the unconditional spectral density of variable $x = \{y_t,\ \pi_t,\ i_t,\ m_t\}$ at frequency ω is given by

$$f_{x,t|T}(\omega) = s_x(I_4 - \tilde{\beta}_{t|T}e^{-i\omega})^{-1}\frac{\bar{A}_{0,t|T}(\bar{A}_{0,t|T})'}{2\pi}\left[(I_4 - \tilde{\beta}_{t|T}e^{-i\omega})^{-1}\right]' s_x' \tag{32}$$

where $\bar{A}_{0,t|T}(\bar{A}_{0,t|T})'$ is the structural impact matrix satisfying our identification restrictions, $\tilde{\beta}_{t|T}$ are the time-varying coefficient matrices, I_4 is a 4×4 identity matrix, and s_x is a row vector selecting the variable of interest. The conditional spectral density of variable $x = \{y_t,\ \pi_t,\ i_t,\ m_t\}$ is

$$\bar{f}_{x,t|T}(\omega) = s_x(I_4 - \tilde{\beta}_{t|T}e^{-i\omega})^{-1}\frac{\underline{A}_{0,t|T}(\underline{A}_{0,t|T})'}{2\pi}\left[(I_4 - \tilde{\beta}_{t|T}e^{-i\omega})^{-1}\right]' s_x' \tag{33}$$

where we replace $\bar{A}_{0,t|T}(\bar{A}_{0,t|T})'$ with $\underline{A}_{0,t|T}(\underline{A}_{0,t|T})'$ which shuts off all structural shocks except for the one of interest. 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. Therefore the contribution of identified structural shocks is given by the ratio

$$\frac{\bar{f}_{x,t|T}(\omega)}{f_{x,t|T}(\omega)} \tag{34}$$

References

Abbate, A., Eickmeier, S., Prieto, E., 2016. Financial Shocks and Inflation Dynamics. Bundesbank Discussion Paper No. 41/2016 Available from `https://papers.ssrn.com/sol3/papers2.cfm?abstract_id=2857845`.

Adalid, R., Detken, C., 2007. Liquidity Shocks and Asset Price Boom/Bust Cycles. ECB Working Paper, No. 732.

Baumeister, C., Benati, L., 2013. Unconventional Monetary Policy and the Great Recession: Estimating the Macroeconomic Effects of a Spread Compression at the Zero Lower Bound. International Journal of Central Banking 9 (2), 165–212.

Baumeister, C., Durinck, E. J., Peersman, G., 2008. Liquidity, Inflation and Asset Prices in a Time-varying Framework for the Euro Area. National Bank of Belgium Working Paper (142).

Baumeister, C., Peersman, G., 2013a. The Role of Time-varying Price Elasticities in Accounting for Volatility Changes in the Crude Oil Market. Journal of Applied Econometrics 28 (7), 1087–1109.

Baumeister, C., Peersman, G., 2013b. Time-varying Effects of Oil Supply Shocks on the US Economy. American Economic Journal: Macroeconomics 5 (4), 1–28.

Belongia, M., Ireland, P., 2016. Circumventing the Zero Lower Bound with Monetary Policy Rules Based on Money. Boston College Working Papers in Economics 2016 (911).

Belongia, M. T., Ireland, P. N., 2014. The Barnett Critique after Three Decades: A New Keynesian Analysis. Journal of Econometrics 183 (1), 5–21.

Benati, L., 2008. The “Great Moderation” in the United Kingdom. Journal of Money, Credit and Banking 40 (1), 121–147.

Benati, L., Mumtaz, H., 2007. US Evolving Macroeconomic Dynamics: A Structural Investigation. ECB Working Paper No. 746.

Blanchard, O., 2018. On the Future of Macroeconomic Models. Oxford Review of Economic Policy 34 (1-2), 43–54.

Canova, F., De Nicoló, G., 2002. Monetary Disturbances Matter for Business Fluctuations in the G-7. Journal of Monetary Economics 49 (6), 1131–1159.

Canova, F., Gambetti, L., 2009. Structural Changes in the US Economy: Is there a Role for Monetary Policy? Journal of Economic Dynamics and Control 33 (2), 477–490.

Cogley, T., Primiceri, G. E., Sargent, T. J., 2010. Inflation-gap Persistence in the US. American Economic Journal: Macroeconomics 2 (1), 43–69.

Cogley, T., Sargent, T. J., 2005. Drifts and Volatilities: Monetary Policies and Outcomes in the post WWII US. Review of Economic Dynamics 8 (2), 262–302.

Cukierman, A., 2013. Monetary Policy and Institutions Before, During, and After the Global Financial Crisis. Journal of Financial Stability 9 (3), 373–384.

Ellington, M., 2018. Financial Market Illiquidity Shocks and Macroeconomic Dynamics: Evidence from the UK. Journal of Banking & Finance 89, 225–236.

Ellington, M., Florackis, C., Milas, C., 2017. Liquidity Shocks and Real GDP Growth: Evidence from a Bayesian Time–varying Parameter VAR. Journal of International Money and Finance 72, 93–117.

Fiore, F. D., Tristani, O., 2013. Optimal Monetary Policy in a Model of the Credit Channel. The Economic Journal 123 (571), 906–931.

Friedman, M., 1983. Monetary Trends in the United States and the United Kingdom: Their Relations to Income, Prices, and Interest Rates. University of Chicago Press.

Gambacorta, L., Hofmann, B., Peersman, G., 2014. The Effectiveness of Unconventional Monetary Policy at the Zero Lower Bound: A Cross-Country Analysis. Journal of Money, Credit and Banking 46 (4), 615–642.

George, E. I., Sun, D., Ni, S., 2008. Bayesian Stochastic Search for VAR Model Restrictions. Journal of Econometrics 142 (1), 553–580.

Gertler, M., Karadi, P., 2011. A Model of Unconventional Monetary Policy. Journal of Monetary Economics 58 (1), 17–34.

Gilchrist, S., Schoenle, R., Sim, J., Zakrajšek, E., 2017. Inflation Dynamics during the Financial Crisis. American Economic Review 107 (3), 785–823.

Hamilton, J. D., 1994. Time Series Analysis. Vol. 2. Princeton University Press, Princeton.

Jacquier, E., Polson, N. G., Rossi, P. E., 2002. Bayesian Analysis of Stochastic Volatility models. Journal of Business & Economic Statistics 20 (1), 69–87.

Joyce, M., Miles, D., Scott, A., Vayanos, D., 2012. Quantitative Easing and Unconventional Monetary Policy–An Introduction. The Economic Journal 122 (564), F271–F288.

Kapetanios, G., Mumtaz, H., Stevens, I., Theodoridis, K., 2012. Assessing the Economy-wide Effects of Quantitative Easing. The Economic Journal 122 (564), F316–F347.

Kiyotaki, N., Moore, J., 2012. Liquidity, Business Cycles, and Monetary Policy. NBER Working Paper Series, No. 17934, National Bureau of Economic Research.

Koop, G., Pesaran, M. H., Potter, S. M., 1996. Impulse Response Analysis in Nonlinear Multivariate Models. Journal of Econometrics 74 (1), 119–147.

Martin, C., Milas, C., 2012. Quantitative Easing: A Sceptical Survey. Oxford Review of Economic Policy 28 (4), 750–764.

McKibbin, W. J., Stoeckel, A., 2018. Modelling a Complex World: Improving Macro-Models. Oxford Review of Economic Policy 34 (1-2), 329–347.

Meinusch, A., Tillmann, P., 2016. The Macroeconomic Impact of Unconventional Monetary Policy Shocks. Journal of Macroeconomics 47, 58–67.

Mumtaz, H., Sunder-Plassmann, L., 2013. Time-varying Dynamics of the Real Exchange Rate: An Empirical Analysis. Journal of Applied Econometrics 28 (3), 498–525.

Nekarda, C. J., Ramey, V. A., 2013. The Cyclical Behavior of the Price-Cost Markup. NBER Working Paper Series, 19099.

Primiceri, G. E., 2005. Time Varying Structural Vector Autoregressions and Monetary Policy. Review of Economic Studies 72 (3), 821–852.

Rubio-Ramirez, J. F., Waggoner, D. F., Zha, T., 2010. Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference. Review of Economic Studies 77 (2), 665–696.

Shi, S., 2015. Liquidity, Assets and Business Cycles. Journal of Monetary Economics 70, 116–132.

Uhlig, H., 2005. What are the Effects of Monetary Policy on Output? results from an Agnostic Identification Procedure. Journal of Monetary Economics 52 (2), 381–419.

Weale, M., Wieladek, T., 2016. What Are the Macroeconomic Effects of Asset Purchases? Journal of Monetary Economics 79, 81–93.

Wu, J. C., Xia, F. D., 2016. Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound. Journal of Money, Credit and Banking 48 (2-3), 253–291.