Financial Market Illiquidity Shocks and Macroeconomic Dynamics: Evidence from the UK

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Abstract

We examine the link between financial market illiquidity and macroeconomic dynamics by fitting a Bayesian time-varying parameter VAR with stochastic volatility to UK data from 1988Q1 to 2016Q4. We capture liquidity conditions in the stock market using a battery of illiquidity proxies. This paper departs from previous studies examining macro-financial linkages by using theoretically grounded sign restrictions, and conducting structural inference in a non-linear framework. We document both statistically significant differences in the transmission of these shocks, and substantial increases in the economic importance of these shocks during the 2008 recession.

Keywords: stock market illiquidity, time-varying parameter VAR, macro-financial linkages, sign restrictions

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

1. Introduction

The importance of adding financial channels to macroeconomic modelling has only recently received increasing attention. For instance, Federal Reserve Bank of Boston President Eric Rosengren (2010) argued that the seriousness of the recent financial crisis was underestimated by economic forecasters because the provision of liquidity to the real economy was "only crudely incorporated into most macroeconomic modeling" (p.221). Writing in The Financial Times in November 2012, former Bank of England (BoE) Monetary Policy Committee Member Deanne Julius (2012) flagged the importance of adding financial channels in the BoE's econometric model. Both views were reinforced by the Head of the Monetary and Economic Department at the Bank of International Settlements Claudio Borio (2014) who noted that for most of the post-war period "financial factors in general progressively disappeared from macroeconomists' radar screen"(p.182).

The main contribution of this paper is to assess the structural dynamics between financial market illiquidity shocks and macroeconomic fundamentals. We fit a time-varying parameter VAR (TVP VAR) with stochastic volatility to UK macroeconomic data, and two measures of stock market illiquidity, from 1988Q1 to 2016Q4. As noted by Granger (2008), TVP VARs are an attractive modelling strategy since they offer an approximation to any non-linear model. There are two novelties in our approach. First, we identify an illiquidity shock using theoretically grounded contemporaneous sign restrictions. Second, we conduct structural inference in a generalised framework. The above sets our paper aside from the existing literature exploring time-varying macro-financial linkages, such as Prieto et al. (2016) and Ellington et al. (2017). The importance of conducting structural inference in a manner consistent with the modelling

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strategy is twofold. First, structural analysis using linear techniques undermines imposing non-linear relationships on variables within the estimated model. Second, overlooking changes in variances and covariances over the impulse horizon may omit an important transmission mechanism of the shock of interest; thus giving rise to the possibility of distorted policy recommendations.

There are various channels through which stock market illiquidity can affect the real economy. As noted in Ellington et al. (2017), liquidity in the stock market may uncover the information set of investors. During episodes of uncertainty regarding the future state of the economy, investor's portfolio adjustments from high risk assets into safer assets, such as government bonds, may signal their expectations around the wider economy. Adding to this, if investors anticipate a sudden decline in market liquidity, their portfolio compositions may mirror this with greater proportions of wealth directed toward liquid assets. The former and the latter are known as the 'flight to safety' and 'flight to liquidity', respectively (Longstaff, 2004)[1]. Florackis et al. (2014) note that these effects become more prominent during periods of financial tightening where the behaviour of institutional investors and market participants tend to positively covary.

Brunnermeier and Pedersen (2009) deduce a model that links shocks to funding and market liquidity. During periods of financial turmoil, market liquidity becomes highly sensitive to funding conditions which leads to a mutually reinforcing mechanism known as "liquidity spirals." In particular, the interaction between securities' market liquidity and financial intermediaries capacity to provide funding, forces institutional investors to shift greater proportions toward low margin stocks. Furthermore, Levine and Zervos (1998) advocate that a liquid secondary market increases the propensity to invest into longer term less liquid projects. As a result, long-term productivity rises thereby promoting economic growth. From an asset-pricing perspective, Amihud (2002) and Acharya and Pedersen (2005) show that liquidity has a first-order effect on the premium of investors' demands to hold risky assets. Therefore, a liquid stock market can lower cost the of capital for firms, boost higher returns on projects that, subsequently, stimulates productivity and earnings growth (Levine, 1991).

This paper links with three main areas of literature. First, we contribute to empirical studies investigating the explanatory power and forecasting performance of stock market illiquidity. In general, results not only show that stock market illiquidity is linked to the business cycle, but also yields predictive power for future recessionary periods. This supports the view that investors' adjust portfolio holdings across the business cycle, and suggests that liquidity variation links with a 'flight to quality' during slumps. For example,Næs et al. (2011) and Chen et al. (2016a) examine forecasting performance of stock market illiquidity with real activity using US data[2]. The former demonstrate that linear models including stock market illiquidity yield favourable in and out-of-sample properties over and above conventional control variables. The latter estimate a Markov-switching model and find that stock market illiquidity both increases the probability of pushing the economy into recession, and the economy remaining in recession. Both papers find that the illiquidity of small firms yields stronger predictive power for US real activity.

More recently, Chen et al. (2016b) examines the predictive power of a battery of break-adjusted decomposed stock market liquidity proxies for economic activity and stock returns using US data from 1948 to 2015. Their results show that aggregate illiquidity proxies contain information regarding the future state of the economy. Building on this, Apergis et al. (2015) studies the real effects of stock market illiquidity for the UK and German economies, and report both economies slow down as aggregate liquidity dries up. Adding to this, they confirm the findings of Næs et al. (2011) and Chen et al. (2016a), in that the liquidity of small-capitalisation firms is relatively more important than that of large-capitalisation

[1] Kaul and Kayacetin (2017) show that the order flow differential forecasts output growth for the US, over and above illiquidity proxies such as the Amihud (2002) return-to-volume ratio.

[2] Næs et al. (2011) also use Norwegian data.

firms. Focussing on the UK economy, Florackis et al. (2014) examine the forecasting performance of stock market illiquidity for real GDP growth. In particular, they show that a non-linear model with regimes defined by liquidity conditions outperforms an array of forecasting models; including one used by the Bank of England.

Second, the empirical literature is growing with regards to the role of financial markets and the macroeconomy using time-varying models (see e.g. Eickmeier et al. (2015), Hubrich and Tetlow (2015), Abbate et al. (2016a) Prieto et al. (2016) and Ellington et al. (2017)). The aforementioned all identify the structural model assuming a block recursive structure of the VAR's covariance matrices. Our analysis departs from existing studies by using theoretically grounded sign restrictions to identify a financial market illiquidity shock whilst relaxing the assumption that parameters remain constant when implementing structural inference. In relaxing this assumption, we allow for the propagation of other shocks, and account for parameter change over the impulse horizon in the spirit of Koop et al. (1996).

Third, our results correspond well with the DSGE literature incorporating financial frictions. For instance, Jaccard (2013) and Shi (2015) deduce tractable models able to explain the contractionary impact of liquidity shocks by identifying a causal link to real activity through the investment channel. This channel is coherent with the liquidity shock hypothesis in Kiyotaki and Moore (2012) referring to sudden declines in asset market liquidity that cause investment, and consequently, output to fall. Furthermore, results in Christiano et al. (2010a) show that shocks stemming from the financial sector, through the investment margin, contribute more than 60% toward the volatility in US investment; and a contraction of between 0.66 and 1.5 percentage points in US GDP growth. Our results lend themselves to the aforementioned studies, highlighting the importance of accounting for financial market liquidity in macroeconomic models.

Our paper differs from the above in a variety of ways. Those examining the forecasting performance of stock market illiquidity predominantly rely on linear and/or single equation specifications. We extend on this literature by relying on sophisticated and flexible non-linear multivariate models. Perhaps more importantly, this literature contains no discussion on the structural links between financial market illiquidity and the real economy. This paper investigates the structural relationship between financial market illiquidity shocks and the real economy, whilst conducting structural inference in a generalised framework; something that, to the best of our knowledge, is undocumented.

The remainder of this paper proceeds as follows: Section 2 explains how we proxy stock market illiquidity, discusses economic data and provides an outline of our econometric model. Our main results and robustness analysis are reported in Section 3. Finally, Section 4 provides concluding comments.

2. Data and Methodology

2.1. Stock Market Illiquidity and Economic Data

To capture stock market illiquidity, our initial analysis relies on two price impact ratios. The first is the Return-to-Volume (hereafter RtoV) ratio of Amihud (2002). The RtoV ratio captures the price response to, in our case, £1 trading volume. The second measure is the Return-to-Turnover (hereafter RtoTR) ratio proposed in Florackis et al. (2011). Essentially, this measure replaces the denominator in the Amihud (2002) ratio, the trading volume of a stock, with its turnover ratio; eliminating the possibility of any size bias (Florackis et al., 2011). The RtoTR ratio has a similar interpretation to RtoV, in capturing the price response to 1% of turnover[3]. The empirical appeal of these ratios are that they can be easily computed for long periods of time without delving into intradaily or microstructure

[3]For detailed discussion on the advantage of using RtoTR over RtoV in an asset pricing framework, see Florackis et al. (2011).

data. As noted in Amihud (2002) the RtoV ratio, but also the subsequent RtoTR ratio, are more coarse and less accurate than finer measures of liquidity; such as transaction-by-transaction market impacts. However, Goyenko et al. (2009) provide evidence substantial in support of using the Amihud (2002) measure if one wishes to capture price impact.

As well as having empirical appeal, both RtoV and RtoTR have strong theoretical links to the price impact coefficient in Kyle (1985). The price impact coefficient tracks the sensitivity of asset prices to the order flow. Price impact connects well with the propagation of liquidity shocks in the DSGE models of Kiyotaki and Moore (2012), Jaccard (2013) and Shi (2015). Specifically, entrepreneurs sell their holdings for liquid assets to finance investment opportunities due to binding borrowing constraints. As a result, liquidity in these models relates to the resaleability of assets. Price impact ratios assume that the net order flow changes asset prices. As successive orders change trading costs, the ease of reselling assets changes. Specifically, when prices become more sensitive to the order flow, the ease of reselling assets declines. In turn, trading costs rise, investment diminishes and, ultimately, output falls.

We compute stock market illiquidity for all stocks listed on the London Stock Exchange, including delisted stocks, from 1987 to 2016[4]. More formally, RtoV and RtoTR are defined as:

$$\text{RtoV}_{i,D} = \frac{1}{N_D}\sum_{d=1}^{D}\frac{|r_{i,d}|}{\text{VOL}_{i,d}} \tag{1}$$

$$\text{RtoTR}_{i,D} = \frac{1}{N_D}\sum_{d=1}^{D}\frac{|r_{i,d}|}{\text{TR}_{i,d}} \tag{2}$$

where $|r_{i,d}|$ is stock is absolute return on day d; $\text{VOL}_{i,d}$ is stock is trading volume on day d in units of currency; $\text{TR}_{i,d}$ is stock is turnover ratio on day d; N_D is the number of days examined over a period (in our case N_D is three months). We obtain daily stock prices, trading volume, market capitalisation and number of shares outstanding for all stocks listed on the London Stock Exchange from DataStream. We adopt a set of filtering criteria similar to Amihud (2002) that admits individual stocks into our aggregate stock market illiquidity proxies[5]. The aggregate is taken as the cross sectional mean of all individual stocks that meet our filtering criteria. Our baseline price impact ratios include between 93 and 894 stocks with an average of 519 stocks included per year. An increase in both price impact ratios constitutes a decline in market liquidity, therefore both ratios are measures of stock market illiquidity. Figure 1 plots our stock market illiquidity proxies from 1988Q1-2016Q4 expressed as % deviations from their respective 1-year moving averages.

Given our main focus is on the impact of illiquidity shocks for real activity, we omit investment within our baseline results; this is because output is affected through the investment channel(Kiyotaki and Moore, 2012)[6]. Therefore, we use UK macroeconomic data on annual real GDP growth, y_t; the annual rate of consumer price inflation, π_t; and the Bank of England Bank rate, i_t. Real GDP and the consumer price index data are from the Office for National Statistics (ONS) database; the Bank rate is available from the Bank of England's Statistical database[7]. Figure 2 plots UK macroeconomic data from 1988Q1-2016Q4. We also plot in Figure 2, the shadow rate proposed in Wu and Xia (2016).

[4]Our sample is dictated by the availability of data. More specifically, trading volume data on UK stocks is sparse prior to 1987.

[5]Specifically, we admit stocks into our aggregate measures if they have at least 100 days of return and trading volume data in the previous year. We drop stocks with a price less than £5 at the end of the preceding year. Finally, we eliminate outliers by removing stocks' illiquidity estimates that are in the top and bottom 5% tails of the distribution for the current year; conditional on satisfying the former criterion.

[6]In Section 3.2.1 we extend the information and directly include investment into the model, this does not influence the conclusions deduced from our main results.

[7]Our price index data from the ONS is the long term indicator of prices of goods and services (code: CDKO). Our results are robust to replacing consumer price inflation with both retail price inflation, and the GDP deflator.

The former show that the shadow rate is a useful tool to summarise important information regarding monetary policy stance at the zero lower bound (ZLB); we use the shadow rate as part of our robustness checks provided in the Supplementary Materials.

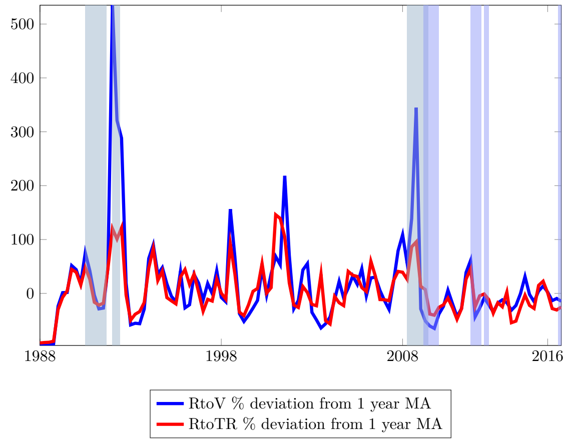

Figure 1: **UK Stock Market Illiquidity, RtoV and RtoTR from 1988 to 2016**
Notes: This figure plots the RtoV and RtoTR ratio for all stocks listed on the London Stock Exchange that meet a standard set of filtering criteria similar to Amihud (2002). Our aggregate illiquidity measures are expressed as the % deviations from their respective 1-year moving averages. Grey 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.

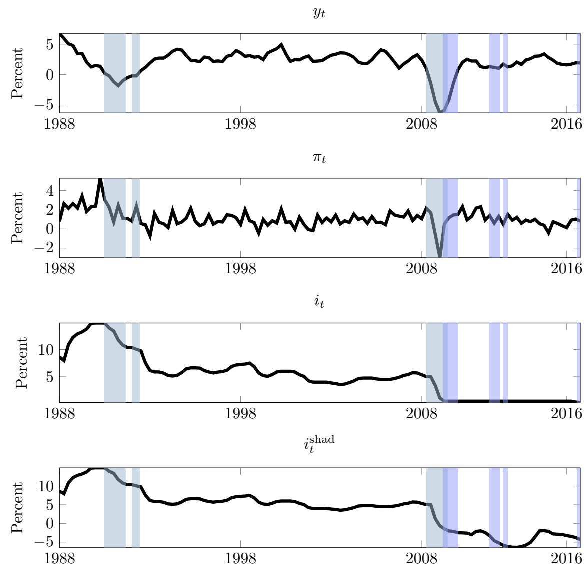

Figure 2: **UK Macroeconomic Data from 1988 to 2016**
Notes: This figure plots the annual rate of UK real GDP growth, y_t (top panel); the annual rate of consumer price inflation, π_t (second panel); the Bank of England Bank rate, i_t (third panel); and the UK shadow rate proposed in Wu and Xia (2016), i_t^{shad} (bottom panel), from 1988Q1-2016Q4. Grey 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:

$$Y_t = \beta_{0,t} + \beta_{1,t} Y_{t-1} + \cdots + \beta_{p,t} Y_{t-p} + \epsilon_t \equiv X_t^{'} \theta_t + \epsilon_t \tag{3}$$

where Y_t is defined as $Y_t \equiv [\pi_t,\ y_t,\ i_t,\ S_t^{illiq}]'$, with π_t being the annual rate of consumer price inflation; y_t is annual real GDP growth; i_t is the short term interest rate; and S_t^{illiq} is stock market illiquidity using either the RtoV_t or RtoTR_t ratio, expressed as the % deviation from their 1-year moving averages, respectively. $X_t = (I_M \otimes (1, Y'_{t-1}, ..., Y'_{t-p}))$ contains lagged values of Y_t and a constant; θ_t is an $M \times Mp$ matrix with $\theta_t = (\beta'_{0,t}, ..., \beta'_{p,t})'$. In our case, $M = 4$, and we set a lag length $p = 2$ which is standard in the TVP VAR literature. As in Cogley and Sargent (2005), the VAR's time-varying parameters are collected in θ_t and evolve as

$$p(\theta_t|\theta_{t-1}, Q) = I(\theta_t)f(\theta_t|\theta_{t-1}, Q) \tag{4}$$

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 driftless random walk[8].

$$\theta_t = \theta_{t-1} + \nu_t \tag{5}$$

where $\nu_t \backsim N(0, Q)$. Q is a full matrix capturing the drift in the states, allowing both parameters within each equation, and across equations to be correlated. If Q=0, the model reduces to a constant parameter VAR with a stochastic volatility structure. The innovations in (3) follow $\epsilon_t \backsim N(0, \Omega_t)$. Ω_t is the time–varying covariance matrix which we factor as

$$Var(\epsilon_t) \equiv \Omega_t = A_t^{-1} H_t (A_t^{-1})' \tag{6}$$

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

$$H_t \equiv \begin{bmatrix} h_{1,t} & 0 & 0 & 0 \\ 0 & h_{2,t} & 0 & 0 \\ 0 & 0 & h_{3,t} & 0 \\ 0 & 0 & 0 & h_{4,t} \end{bmatrix} \quad A_t \equiv \begin{bmatrix} 1 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 \end{bmatrix} \tag{7}$$

in (7), $h_{i,t}$ 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

$$\ln h_{i,t} = \ln h_{i,t-1} + \eta_t \tag{8}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t \tag{9}$$

The innovations in the model are jointly Normal

$$\begin{bmatrix} u_t \\ \nu_t \\ \zeta_t \\ \eta_t \end{bmatrix} \backsim N(0, V), \quad V = \begin{bmatrix} I_M & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix} \tag{10}$$

[8]As Cogley and Sargent (2005) note, adding an indicator function that rejects draws for the coefficient matrices in every t truncates and renormalises the prior. This stability constraint imposes a belief, apriori, that explosive representations of real GDP growth, inflation, the interest rate and stock market illiquidity are implausible. Galí and Gambetti (2009) label this constraint as imposing local stationarity for all time periods, t.

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:

$$S \equiv Var(\zeta_t) = \begin{bmatrix} S_1 & 0_{1\times2} & 0_{1\times3} \\ 0_{2\times1} & S_2 & 0_{2\times3} \\ 0_{3\times1} & 0_{3\times2} & S_3 \end{bmatrix} \tag{11}$$

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. The prior specification of our models are similar to Baumeister and Peersman (2013a) and Cogley and Sargent (2005). To calibrate the initial conditions of the time-varying coefficients, θ_0, we use the first 10 years of data and estimate a constant coefficient VAR model; therefore the effective estimation sample is from 1998Q3 to 2016Q4. The prior mean and variance are set to the OLS estimates from the observations used in the training sample, $\hat{\theta}_{OLS}$ and 4 times the variance of the estimated parameters, $4 \cdot \text{var}(\hat{\theta}_{OLS})$ from the constant coefficient VAR, respectively. Priors on the matrices H_t, A_t, Q, S, W are set consistent with Cogley and Sargent (2005) and details can be found in the Online Appendix. The model is estimated using Bayesian methods allowing for 20,000 iterations of the Gibbs sampler. We discard the initial 10,000 draws as burn in, and of the remaining 10,000 draws, sample every 10^{th} draw to reduce autocorrelation. Also in the Online Appendix, we report an outline of the Markov Chain Monte Carlo (MCMC) posterior simulation algorithm, as well as convergence diagnostics.

2.3. Identification of Structural Shocks

We depart from existing studies examining time-varying macro-financial linkages in two ways. First, we impose contemporaneous sign restrictions in the spirit of Uhlig (2005). Second, we relax the assumption that parameters remain constant over the impulse horizon. More specifically, we adopt a Monte Carlo integration procedure, similar to Koop et al. (1996) and Baumeister and Peersman (2013a), and conduct structural inference in a generalised framework. The prior literature looking to quantify the ramifications of the financial sector for the real economy both identify structural shocks using a Cholesky decomposition, and conduct structural inference in a linear framework (see e.g. Hubrich and Tetlow (2015), Prieto et al. (2016) and Ellington et al. (2017)). Table 1 reports our identification restrictions for the financial market illiquidity shock (hereafter illiquidity shock), u_t^{ILLIQ}. In conjunction with our identified illiquidity shock, we identify a monetary policy shock following Benati (2008).

Table 1: **Contemporaneous Sign Restrictions**
Notes: This table reports the contemporaneous sign restrictions imposed when identifying a stock market illiquidity shock, u_t^{ILLIQ}. S_t^{illiq} represents stock market illiquidity proxied by either the RtoV or RtoTR ratio.

	y_t	π_t	i_t	S_t^{illiq}
u_t^{ILLIQ}	$\leq$	$\leq$	$\leq$	$\geq$
u_t^{MP}	$\leq$	$\leq$	$\geq$	$\geq$

Following the liquidity shock hypothesis in Kiyotaki and Moore (2012), we impose that output responds negatively to increases in illiquidity. Furthermore, we assume that as liquidity declines, inflation and the interest rate fall. Our assumptions on the response of inflation and the interest rate requires further discussion.

We start by noting that there are conflicting theories between the theoretical and empirical results with regards to financial shocks and inflation dynamics. Theoretical models assuming that aggregate demand effects dominate the transmission mechanism, including Gertler and Karadi (2011) and Curdia and Woodford (2010), predict that prices should increase following sudden expansionary financial shocks. Within the former, financial shocks relax banking constraints thereby allowing firms to rent more capital and hire more workers. The surge in labour demand increases wages and consequently puts pressure on prices. The latter, assume that lower borrowing costs give consumers an incentive to borrow to increase consumption, and subsequently, prices.

However, if aggregate supply effects dominate, expansionary financial shocks can lead to falling inflation. Nekarda and Ramey (2013) postulate that the key determinant of firm's pricing decisions are current and expected future marginal costs. Building on this, should firms need to borrow in advance to partially finance wage costs, then marginal costs are also determined by borrowing rates (see e.g. Fiore and Tristani (2013) and Christiano et al. (2010b)). Building on this, Gilchrist et al. (2017) calibrate a model where liquidity constrained (unconstrained) firms increase (decrease) their prices during financial crises. Their results show that inflation, on aggregate increases during financial crises due to the presence of liquidity constrained firms; thereby offering a possible explanation toward the mild disinflation in the US during the financial crisis. Abbate et al. (2016b) provide empirical evidence in support of Gilchrist et al. (2017) and help rationalise why inflation does not rise as a result of expansionary financial shock using the theoretical underpinnings of Nekarda and Ramey (2013) and Fiore and Tristani (2013).

We initially estimated models allowing for the inflation rate to remain unconstrained with respect to an illiquidity shock in light of the above theoretical ambiguities. In this framework, the observed sign of inflation to an illiquidity shock indicates the net effect of the demand and supply side channels. The results obtained by imposing no restriction on inflation are the same as those we report in the next section. This suggests that, for our data, the demand side effects dominate the inflationary impact of illiquidity shocks. Therefore for our analysis we impose, apriori, that financial market illiquidity causes prices to fall following Curdia and Woodford (2010) and Gertler and Karadi (2011).

We postulate that the interest rate declines based on the 'flight to safety' and 'flight to liquidity' considerations in Longstaff (2004). Implicitly, we assume that investors adjust portfolio holdings into safer, more liquid assets such as government bonds or Treasury Bills during illiquid periods. Therefore, the yields on these assets, and consequently interest rates in the economy, falls. Our imposed sign restrictions are supported by the data, and are indicative of reality. For example, in the UK, while our illiquidity measures peak in late 2008, the corresponding trough in inflation and interest rate cuts occur in early 2009. In the Online Appendix we show that identifying illiquidity shocks using a Cholesky decomposition also results in a decline in inflation and the interest rate.

Our identified monetary policy shock modifies that of Benati (2008) by imposing that a contractionary monetary policy shock causes illiquidity in the stock market to rise. We impose this restriction following Hameed et al. (2010), who show that contractionary monetary policy leads to declines in liquidity. We have also implemented structural inference imposing no restriction on the sign of the response of stock market illiquidity and we obtain similar results; available on request. To obtain the time-varying structural impact matrices, we follow the algorithm in Rubio-Ramirez et al. (2010).

Specifically, 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 columns in Q are orthogonal to one another. We compute the time-varying structural impact matrix as $A_{0,t} = P_t D_t^{\frac{1}{2}} Q'$ retaining only those matrices that satisfy our sign restrictions[9].

[9] Appendix B of the supplementary material reports how we compute generalised impulse response functions and provides a structural analysis of monetary policy shocks.

3. Empirical Results

3.1. Baseline Results

Figure 3 reports the posterior median and 10$^{\text{th}}$ and 90$^{\text{th}}$ percentiles of the distribution of estimated illiquidity shocks stemming from our baseline models. As we can see, there are clear positive spikes in the structural errors during the burst of the dot-com bubble in 2001. Furthermore, prior to the Great Recession, structural illiquidity shocks are persistently negative. Thereby suggesting markets were liquid prior to the financial crisis; a widely noted phenomenon during this period and consistent with Borio (2014). Then during the 2008 recession, the estimated shocks are strongly positive in conjunction with the notion that liquidity dried up during the financial crisis. Based on the movements in the estimated illiquidity shocks, we postulate our identification strategy is valid, and indeed captures liquidity conditions within the financial market.

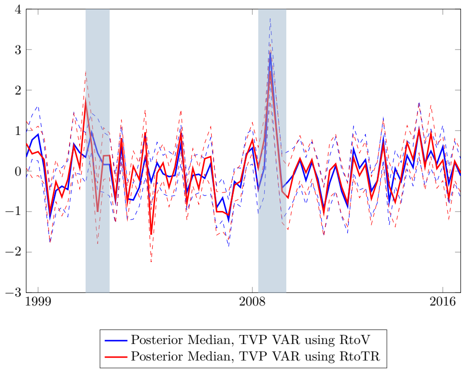

Figure 3: **Posterior Distribution of Structural Illiquidity Shocks from 1998 to 2016**
Notes: This figure plots the posterior median and the 10$^{\text{th}}$ and 90$^{\text{th}}$ percentiles of the distribution of structural illiquidity shocks from 1998Q3-2016Q4. The two grey bars indicate the burst of the dot-com bubble during 2001, and the Great Recession of 2008-2009.

In Figure 4, we report the posterior median impulse response functions of UK macroeconomic variables from 1998Q3-2016Q4 over a 20 quarter horizon. The impulse response functions have been normalised such that the illiquidity shock causes a 200% and 100% deviation in RtoV and RtoTR from their respective 1-year moving averages. Deviations of these sizes are comparable to peaks in late 2008. Panels A and B of Figure 3 report the results from our models that proxy stock market illiquidity using the RtoV and RtoTR ratios, respectively. It is clear that the respective sensitivities of GDP growth, inflation, and the interest rate with respect to illiquidity shocks increase during the 2008-2009 financial crisis. More specifically, in 2008Q4–and notably, immediately following the collapse of Lehman Brothers–the contraction of GDP growth, on impact, is 1.89% and 2.17% from models using RtoV and RtoTR, respectively. In the very same period, these shocks imply inflation falls by 1.78% and 3.79% from our models using RtoV and RtoTR to proxy stock market illiquidity, respectively. Panels A and B clearly show there is a persistent impact of illiquidity shocks on GDP growth and the interest rate. Specifically, the posterior median response of GDP and the interest remains negative for 10 and 20 quarters, respectively. Contrastingly however, the response of inflation is short-lived; lasting around one year.

Figure 5 provides the posterior median and the 80% posterior credible sets (i.e. 10$^{\text{th}}$ and 90$^{\text{th}}$ percentiles) of the distributions of the impulse response functions for real GDP growth, y_t (left column); inflation, π_t (middle column); and the interest rate, i_t (right column), over selected dates from 2001Q1 to 2016Q4. From Figure 5, it is clear that real GDP growth and inflation responds significantly to illiquidity shocks across all periods we consider. However, the response of the interest rate is insignificant in 2016Q4 of our sample for our model using RtoV. For the model using RtoTR there is marginal significance in the

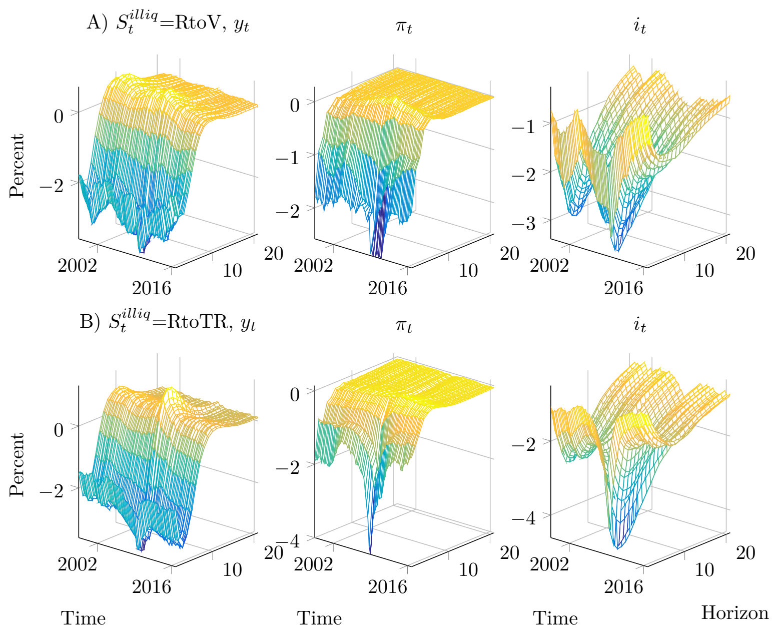

Figure 4: **Impulse Response Functions of Macroeconomic Variables with Respect to an Illiquidity Shock from 1998 to 2016**
Notes: This figure plots the posterior median distribution of the impulse response functions of UK macroeconomic variables with respect to a one standard deviation illiquidity shock from 1998Q3 to 2016Q4 over a 20 quarter horizon. Panel A reports the results from our TVP VAR model using the RtoV ratio in Amihud (2002) to proxy stock market illiquidity. Panel B reports impulse response functions from our TVP VAR model using the RtoTR ratio in Florackis et al. (2011) to proxy stock market illiquidity.

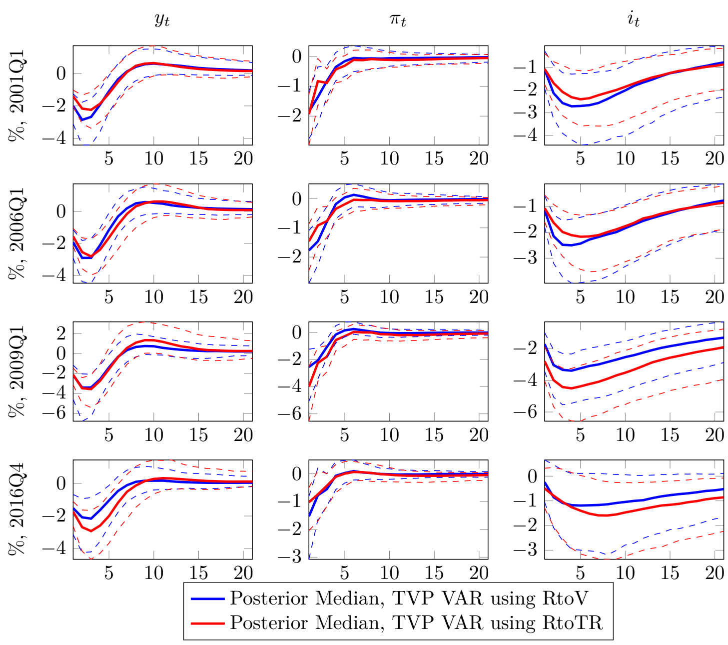

Figure 5: **Impulse Response Functions of Macroeconomic Variables with Respect to an Illiquidity Shock: Selected Dates**
Notes: This figure plots the posterior median and the 10$^{\text{th}}$ and 90$^{\text{th}}$ percentiles of the distribution of the impulse response functions of UK macroeconomic variables with respect to a one standard deviation illiquidity shock over selected dates (i.e. 2001Q1, 2006Q1, 2009Q1, 2016Q4) from 2001 to 2016. The left column presents the impulse response functions of real GDP growth. The middle and right columns report the response of inflation and the interest rate respectively.

response of the interest after 8 quarters[10]. On the whole, Figures 4 and 5 reveal that there is substantial evidence in favour of economically significant time-variation in the response of macroeconomic variables to illiquidity shocks.

Following Cogley et al. (2010), we examine whether there is statistically significant time-variation in the impulse response functions of macroeconomic variables to illiquidity shocks. In doing so we account for the entire posterior distribution at each time period. Figure 6 reports scatterplots of the accumulated 1 year impulse response functions of macroeconomic fundamentals. Panel A uses results from our TVP VAR that proxies stock market illiquidity using the RtoV ratio. Panel B reports results from our TVP VAR that proxies stock market illiquidity using the RtoTR ratio. The first row of Panels A and B reports the accumulated 1 year impulse responses for GDP growth, y_t; the second and third row report the same for inflation, π_t and the interest rate, i_t, over 5 year intervals respectively. Column 1 reports the joint distribution of the accumulated 1 year impulse response functions in 1998Q4 (x-axis) against 2003Q4 (y-axis); columns 2, 3 and 4 reports the joint distribution of the accumulated 1 year impulse response functions in 2003Q4 (x-axis) against 2008Q4 (y-axis), 2008Q4 (x-axis) against 2013Q4 (y-axis), and 2013Q4 (x-axis) against 2016Q4 (y-axis), respectively. We add a 45° line to each scatterplot for ease of interpretation. We characterise statistically significant differences over time when 95%, or more, of the joint distribution lies above or below the 45° line.

Three factors emerge from Figure 6. Firstly, there are no statistical differences in the impulse response functions of UK macroeconomic fundamentals with respect to illiquidity shocks in 1998Q4 relative to 2003Q4, and 2016Q4 relative to 2013Q4. Second, the distribution of impulse response functions in 2008Q4 relative to both 2003Q4 and 2013Q4, reveal that GDP growth and inflation, become more sensitive to these shocks during the Great Recession. More specifically, in Panel A, it is clear that more than 99% of the joint distribution lies below and above the 45° lines in columns 2 and 3 respectively. The same holds for the analogous plots in Panel B. Third, the interest rate is evidently more sensitive to illiquidity shocks during the Great Recession, with the entire joint distribution lying above and below the 45° in columns 2 and 3 respectively. Therefore, this plot provides statistically significant evidence in favour of time-variation in the transmission mechanism of illiquidity shocks during 2008Q4, relative to 2003Q4 and 2013Q4 respectively.

Table 2 reports the posterior median forecast error variance shares, at a 20 quarter horizon (in %) along with the 68% posterior credible intervals, of illiquidity shocks for UK macroeconomic variables at three year intervals. Panels A and B show results from our models where stock market illiquidity is proxied using the RtoV and RtoTR ratios, respectively. To examine the possibility of statistical differences in our choice of price impact ratio, Panel C reports the posterior median and 68% posterior credible intervals of the distributions of relative forecast error variance decompositions (FEVDs)[11]. We compute distributions of relative forecast error variance decompositions (RFEVDs) for our macroeconomic variables from our models using RtoV and RtoTR to proxy stock market illiquidity. More specifically, for every quarter t and each of the states, we scale the forecast error variance decompositions obtained from our model using RtoV by the forecast error variance decompositions from our model using RtoTR.

[10]Note that from 2010Q1 onwards, the response of the interest rate from both models is only marginally significant based on 80% posterior credible sets. We assess the influence of the zero lower bound in the next section.

[11]Relative FEVDs have been used in Rossi and Zubairy (2011) to assess whether fiscal policy changes the forecast error variances of traditional monetary policy shocks. Relative FEVDs in the former are expressed as percentage changes in FEVDs from a VAR model including government spending, and one without. Monetary policy shocks are identified using a Cholesky decomposition with the interest rate ordered last. Our approach differs in that we assess the statistical significance of the shares in forecast error variances accounting for the entire posterior distribution of parameter draws of our TVP VAR models.

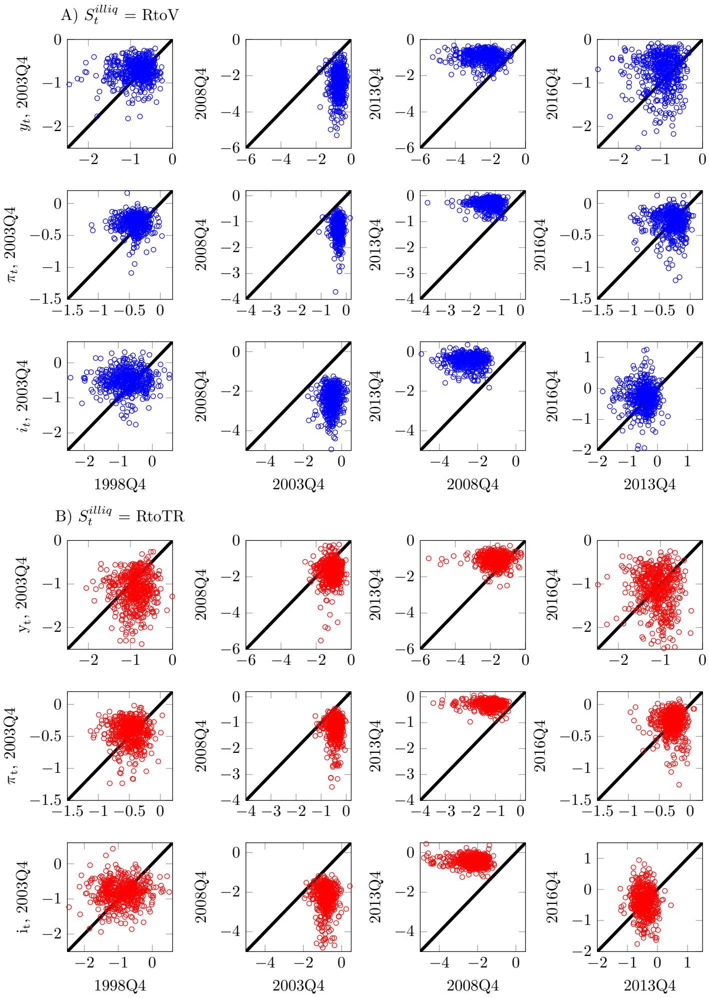

Figure 6: **Scatterplots of Distributions of One Year Accumulated Impulse Response Functions over 5 Year Intervals.**

Notes: This figure reports scatterplots of the one year accumulated impulse response functions of macroeconomic variables with respect to an illiquidity shock. Panel A uses results from our TVP VAR that proxies stock market illiquidity using the RtoV ratio inAmihud (2002). Panel B reports results from our TVP VAR that proxies stock market illiquidity using the RtoTR ratio of Florackis et al. (2011). The first row of Panels A and B reports one year accumulated impulse response functions of GDP growth, y_t; the second and third row report the same for inflation, π_t and the interest rate, i_t respectively over 5 year intervals. Column 1 reports the joint distribution of forecast error variance shares of 1998Q4 (x-axis) against 2003Q4 (y-axis); columns 2, 3 and 4 reports the joint distribution of forecast error variance shares of 2003Q4 (x-axis) against 2008Q4 (y-axis), 2008Q4 (x-axis) against 2013Q4 (y-axis), and 2013Q4 (x-axis) against 2016Q4 (y-axis), respectively. We add a 45° line to each scatterplot for ease of interpretation.

Formally, the RFEVD of illiquidity shocks, u_t^{ILLIQ},for variable i, at horizon h and time t is given by

$$\text{RFEVD}_{ih,t}^{\text{ILLIQ}} = \frac{\text{FEVD}_{ih,t}^{\text{ILLIQ}_0}}{\text{FEVD}_{ih,t}^{\text{ILLIQ}_1}} \tag{12}$$

where $\text{FEVD}_{ih,t}^{\text{ILLIQ}_0}$ denotes the contribution of illiquidity shocks to variable i at horizon h and time t from our model using RtoV; and $\text{FEVD}_{ih,t}^{\text{ILLIQ}_1}$ denotes the contribution of illiquidity shocks to variable i at horizon h and time t from our model using RtoTR. We characterise a statistical difference in the forecast error variance shares if the 68% posterior credible intervals do not include 1.

From Table 2, both Panels A and B reveal that illiquidity shocks are economically meaningful. From Panel A, and turning our attention to posterior median estimates, illiquidity shocks explain 29%, 35% and 56% of the variation in GDP growth, inflation and the interest rate in 2008Q3 respectively. Similarly, from Panel B, these shocks explain, 23%, 29% and 61% of the variance in GDP growth, inflation and the interest rate in 2008Q3, respectively. Overall, Panels A and B suggest there is considerable time-variation in the forecast error variance shares explained by illiquidity shocks. Evidently from Panel C, our results suggest there are no statistical benefits in using the RtoV ratio over the RtoTR ratio (or vice versa).

In general the time profile of the responses of GDP growth and inflation to shocks stemming from the financial sector are consistent with Prieto et al. (2016) and Ellington et al. (2017), whom both use US data. The short-lived response of inflation links well with the theoretical results in Gertler and Karadi (2011). Adding to this, the substantial declines in the interest rate suggest investors perpetually adjust their portfolio holdings in response to illiquidity shocks. Furthermore, the response of the interest rate during the financial crisis implies asymmetries (over time) in the 'flight to safety' and 'flight to liquidity' effects outlined in Longstaff (2004).

Our results also corroborate with Hubrich and Tetlow (2015), Abbate et al. (2016b), and Ellington et al. (2017), who find that during times of elevated financial stress, the ramifications for real activity are amplified. In examining the joint distribution of cumulated impulse response functions, we provide statistically significant evidence in support of an increase in the economic importance of illiquidity shocks during the 2008 recession. It is our conjecture that this episodic response of macroeconomic fundamentals to illiquidity shocks is linked to the reinforcing mechanism between funding and market liquidity proposed in Brunnermeier and Pedersen (2009). We posit that the increased sensitivity of market liquidity to funding liquidity intensifies the transmission mechanism of these shocks for the real economy.

From a policy perspective, and confluent with Claessens et al. (2012), the implication is that liquidity provision during financial crises is necessary to prevent large swings in macroeconomic variation. Therefore our results lend themselves to Kapetanios et al. (2012), by justifying the response of UK policymakers in implementing successive rounds of Quantitative Easing to inject liquidity into the economy. As in Joyce et al. (2012), we argue that investment is stimulated because investors observe increases in their cash holdings in exchange for selling government debt. The increase in cash holdings is used to buy other assets, since investors perceive cash as an imperfect substitute for government debt; known as the portfolio rebalancing channel. Intuitively, as investment increases, so does output. Conceptually this might be thought of as policy response to negate the liquidity shock hypothesis in Kiyotaki and Moore (2012).

Table 2: **Percent Share of Forecast Error Variance Explained by Illiquidity Shocks at a 20 Quarter Horizon, and Relative Forecast Error Variance Decompositions from 1999 to 2016 at 4 Year Intervals**
Notes: Panel A of this table reports the posterior median, along with 68% posterior credible intervals of the percent share of forecast error variance at a 20 quarter horizon of real GDP growth, y_t; inflation, π_t; and the Bank rate, i_t explained by stock market illiquidity shocks using the RtoV ratio in Amihud (2002). Meanwhile Panel B of this table reports the posterior median, along with 68% posterior credible intervals of the percent share of forecast error variance at a 20 quarter horizon of real GDP growth, y_t; inflation, π_t; and the Bank rate, i_t explained by stock market illiquidity shocks using the RtoTR ratio in Florackis et al. (2011). Finally Panel C of this table report the posterior median and 68% posterior credible intervals of the distribution of relative forecast error variance decompositions, also at a 20 quarter horizon. These are computed by taking each of the 500 draws of the forecast error variance of UK macroeconomic variables from our TVP VAR model using RtoV, and dividing each draw by the forecast error variance of the variable of interest from our TVP VAR model using RtoTR. A significant difference in relative FEVDs is observed when the 68% posterior credible intervals do not include 1.

A) TVP VAR using RtoV			
	y_t	π_t	i_t
1999Q3	15.37 [9.16 23.65]	18.98 [12.26 26.71]	33.22 [19.95 53.11]
2002Q3	17.61 [11.38 24.74]	19.92 [14.17 27.03]	33.67 [20.15 51.34]
2005Q3	15.76 [9.28 25.77]	18.07 [11.48 27.09]	37.72 [22.05 53.95]
2008Q3	28.94 [17.52 40.59]	34.97 [23.56 46.59]	55.96 [40.44 67.22]
2011Q3	14.20 [8.16 22.64]	16.99 [10.65 25.41]	27.47 [14.15 45.68]
2014Q3	20.42 [12.26 29.38]	20.47 [13.89 28.79]	28.60 [16.31 44.07]
2016Q4	18.78 [10.81 31.32]	18.77 [11.81 29.42]	24.04 [12.23 40.98]
B) TVP VAR using RtoTR			
	y_t	π_t	i_t
1999Q3	16.28 [9.43 24.81]	19.22 [12.07 26.36]	39.58 [21.05 55.59]
2002Q3	20.30 [12.73 29.01]	22.87 [15.83 32.09]	41.72 [24.91 58.27]
2005Q3	21.43 [13.06 30.79]	23.41 [15.89 34.75]	47.27 [30.04 62.38]
2008Q3	22.99 [13.36 34.71]	29.39 [18.03 40.39]	61.12 [45.19 69.30]
2011Q3	15.06 [8.54 22.33]	17.05 [11.03 25.69]	29.68 [14.63 50.56]
2014Q3	19.91 [13.47 28.80]	20.73 [14.44 29.66]	34.27 [18.38 51.97]
2016Q4	19.95 [11.71 30.68]	19.83 [12.13 30.23]	26.74 [13.07 43.16]
C) RFEVDs: RtoV vs. RtoTR			
	y_t	π_t	i_t
1999Q3	0.98 [0.47 1.87]	1.00 [0.57 1.80]	0.90 [0.48 1.75]
2002Q3	0.84 [0.50 1.62]	0.88 [0.54 1.38]	0.82 [0.44 1.50]
2005Q3	0.77 [0.39 1.45]	0.74 [0.43 1.38]	0.80 [0.45 1.40]
2008Q3	1.28 [0.66 2.24]	1.22 [0.72 2.00]	0.95 [0.64 1.29]
2011Q3	0.95 [0.48 1.99]	0.98 [0.52 1.81]	0.94 [0.42 2.05]
2014Q3	1.02 [0.54 1.73]	0.97 [0.55 1.66]	0.83 [0.42 1.73]
2016Q4	0.96 [0.46 1.97]	0.96 [0.50 1.83]	0.92 [0.42 2.03]

3.2. Robustness Analysis

For the sake of brevity, we provide two robustness checks below; the first extends our initial information set, and the second investigates the impact of alternative proxies. Within the Supplementary Materials, we report a number of different robustness checks to further assess the plausibility of our main results. More specifically based on the findings in Næs et al. (2011) that illiquidity of small capitalisation stocks possess a stronger link with real activity, we construct aggregate illiquidity proxies stemming from small and large stocks. Our results show that there are no statistical or economic differences in the transmission of these shocks. We also provide evidence that our results are not affected by our choice of prior specification or driven by the zero lower bound.

3.2.1. Extending the Information Set

In accounting for only illiquidity within the stock market, our main results rely on a small information set; which may impact the space spanned by the impulse response functions[12]. One stream of the time-varying macrofinancial linkages literature, including Koop and Korobilis (2014), use indices to capture overall financial conditions deriving from large datasets. The former estimate a financial conditions index from a time-varying factor augmented VAR (FAVAR) model incorporating 18 financial series. Adding to this, the transmission of monetary policy and other economic shocks using FAVARs is well documented (see e.g. Korobilis (2013), and Ellis et al. (2014)). The appeal of indices estimated from principal components or factor models are that they permit a large amount of information to be incorporated into econometric models in a parsimonious manner.

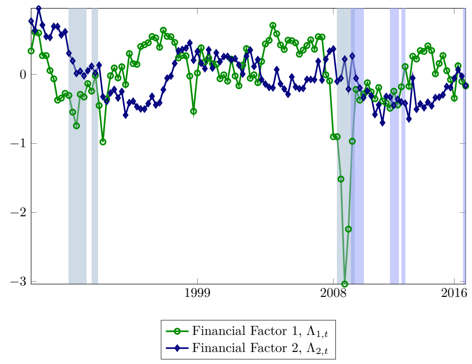

Figure 7: **UK Financial Factors, 1988 to 2016**
Notes: This figure plots the our estimated financial factors, Λ_1, Λ_2 from our constructed financial dataset for the UK economy. Factors are estimated as the first two principal components following the method outlined in McCracken and Ng (2016). Grey 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.

To assess the robustness of financial market illiquidity shocks, we construct a dataset of 19 series capturing the broader UK financial sector and macroeconomy. The variables we include in our dataset are in the spirit of Koop and Korobilis (2014) and Amisano and Geweke (2017); see Appendix C in the Online Appendix for details. Following McCracken and Ng (2016), we estimate static factors via principal components from our dataset. We implement the Expectations Maximisation (EM) algorithm of Stock and Watson (2002) that allows for missing values in the panel of time series. In the spirit of Bai and Ng (2002), we test for the number of factors using the PC_p criteria and find that the number of significant factors is equal to 2[13]. Figure 7 plots our estimated financial factors, Λ_1, Λ_2 from 1988 to 2016.

[12] We thank an anonymous referee for bringing this to our attention.
[13] The PC_p penalty we use in this analysis is the $PC_{p2} = \frac{N+T}{NT}\ln(\min(N,T))$ of Bai and Ng (2002).

We estimate four variants of our baseline model that include either of our financial factors providing us with a slightly larger specification of 5 variables[14]. We also estimate a further two, 5 variable TVP-VAR models by adding investment growth, κ_t to our baseline empirical models; Table 3 reports a summary of our six extended models[15]. These models use the same number of iterations and posterior simulation algorithm as those estimated in previous sections Based on the pro-cyclical nature of our financial factors and investment growth, we impose, on impact, negative signs to: $\Lambda_{1,t}$; $\Lambda_{2,t}$; κ_t, with respect to an illiquidity shock in Models 1-6.

Table 3: **Variables Included in Larger Model Specifications**
Notes: This table reports a summary of variables included into each of our models that include financial factors. y_t is real GDP growth; π_t is inflation; i_t is the interest rate; RtoV_t is stock market illiquidity proxied by the Return-to-Volume ratio in Amihud (2002); RtoTR_t is stock market illiquidity proxied by the Return-to-Turnover ratio in Florackis et al. (2011); $\Lambda_{1,t}$ is our first estimated financial factor; and $\Lambda_{2,t}$ is the second financial factor estimated from our constructed dataset. Included in Models 5 and 6, is annual investment growth, κ_t.

Model 1:	y_t	π_t	i_t	$\Lambda_{1,t}$	RtoV_t
Model 2:	y_t	π_t	i_t	$\Lambda_{1,t}$	RtoTR_t
Model 3:	y_t	π_t	i_t	$\Lambda_{2,t}$	RtoV_t
Model 4:	y_t	π_t	i_t	$\Lambda_{2,t}$	RtoTR_t
Model 5:	y_t	π_t	i_t	κ_t	RtoV_t
Model 6:	y_t	π_t	i_t	κ_t	RtoTR_t

Figure 8 plots the posterior median and 80% posterior credible sets of the impulse response functions of macroeconomic variables from 2001 to 2016 over our selected dates. Panel A reports results from Models 1 and 2; whilst Panels B and C report results from Models 3 and 4, and Models 5 and 6 respectively. We can see from Panels A and B, that the time-variation of the response of macroeconomic variables, particularly GDP growth and inflation, is in the magnitude of the contractions during the 2008 recession. This is similar to the findings of our baseline analysis. It is also noteworthy to mention that the impact of an illiquidity shock on our financial factors yields substantial variation in the magnitude during the financial crisis. From Panel C of Figure 8, we can see that the response of GDP, inflation and the interest rate are similar to those presented in our baseline analysis. These models report negligible time-variation, from posterior median estimates, in the response of investment growth in terms of magnitude and persistence.

On the whole, it is clear that the economic impact of illiquidity shocks is consistent with our main results, even after including extra variables within our models. We show that the time-variation, in terms of magnitude, of the response of GDP growth, inflation and the interest rates are consistent with our main results. In estimating factors from a constructed dataset, we have also documented the contractionary effects these shocks have on a broad panel of macro-financial entities. Notably, model specifications including principal components imply considerable time-variation in the transmission mechanism of illiquidity shocks to the broader macro-financial sector. Overall, these results imply that the space spanned by the impulse response functions generated from our estimated models are not sensitive to including additional variables.

[14] Incorporating both financial factors into the same model leads to convergence issues within the MCMC. This may be due to a combination of the following: i) the relatively short estimation sample; and ii) the strong correlations these factors have with GDP growth and the Bank rate. More specifically, the contemporaneous correlation between $\Lambda_{1,t}$ and y_t is 0.70, and between $\Lambda_{2,t}$ and i_t is 0.63.

[15] We add investment growth to our baseline models following the liquidity shock hypothesis in Kiyotaki and Moore (2012).

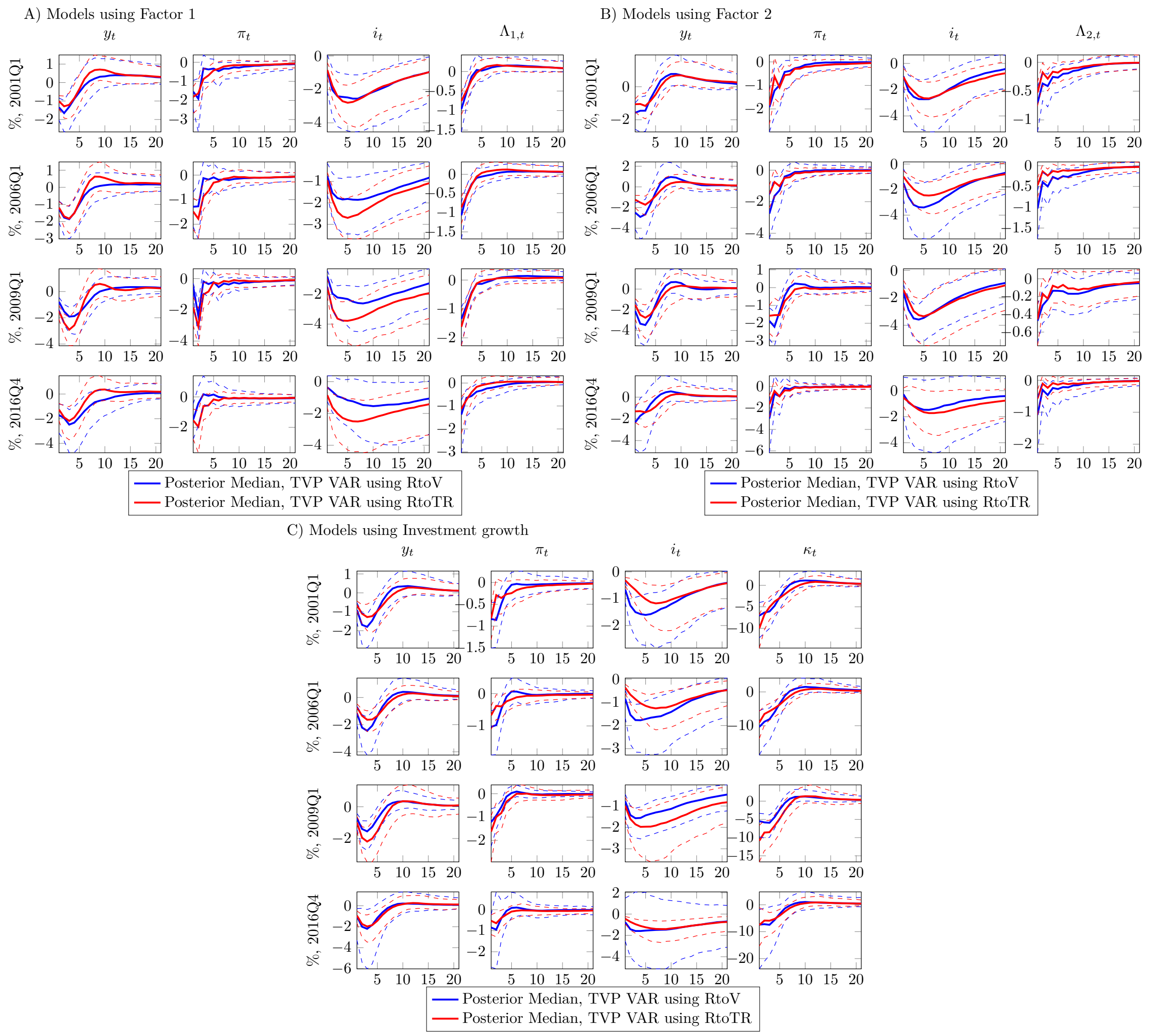

Figure 8: **Impulse Response Functions of Macroeconomic Variables with Respect to an Illiquidity Shock from 1998 to 2016**

Notes: This figure plots the posterior median and the 10^{th} and 90^{th} percentiles of the distribution of the impulse response functions of UK macroeconomic variables with respect to a one standard deviation illiquidity shock over selected dates from 2001 to 2016. Panel A reports results from TVP VARs estimated using Factor 1, $\Lambda_{1,t}$. Panel B reports results from TVP VARs using Factor 2, $\Lambda_{2,t}$. Panel C reports results estimated from TVP VARs that include annual investment growth, κ_t. The left column presents the impulse response functions of real GDP growth. The middle left and middle right columns report the response of inflation and the interest rate respectively. The right columns in Panels A and B report the response of our Factor estimates, and the right column in Panel C reports the response of annual investment growth.

3.2.2. Alternative Illiquidity Proxies

Although price impact is our main focus, we cannot discount other dimensions of liquidity, such as trading costs and market depth, and their influence on real activity. Næs et al. (2011) and Chen et al. (2016b) show that a battery of illiquidity proxies all yield predictive power for US GDP growth. Our study differs from the forecasting literature in that we are looking to investigate the impact of illiquidity in a structural model. Therefore it is necessary to ascertain that our main results are not driven by our choice of proxy. We utilise five alternative measures that capture different dimensions of illiquidity. Our first two measures simply replace the numerator, $|r_{i,d}|$, in RtoV and RtoTR with 1:

$$\mathrm{V}^{-1}_{i,D} = \frac{1}{N_D}\sum_{d=1}^{D}\frac{1}{VOL_{i,d}} \tag{13}$$

$$\mathrm{TR}^{-1}_{i,D} = \frac{1}{N_D}\sum_{d=1}^{D}\frac{1}{TR_{i,d}} \tag{14}$$

These measures are used in Lou and Shu (2017) within an asset pricing study. However, Apergis et al. (2015) uses trading volume and turnover as proxies of liquidity to forecast real activity. Therefore the reciprocal of the trading volume and turnover, are both measures of illiquidity; representing the depth of the market[16].

The following two alternative measures are spread proxies; or measures of transaction costs. The first is the FHT measure proposed in Fong et al. (2017), and the second is the effective spread estimate of Roll (1984). These illiquidity proxies, for the i-th firm are given by:

$$\mathrm{FHT}_{i,D} = 2\hat{\sigma}_{i,D}\Phi^{-1}\left(\frac{1+\mathrm{ZEROS}_{i,D}}{2}\right) \tag{15}$$

$$\mathrm{Roll}_{i,D} = 2\sqrt{-\widehat{\mathrm{COV}}(R_{i,d,D}, R_{i,d-1,D})} \tag{16}$$

In (15), $\hat{\sigma}_{i,t}$ is firm i's daily return volatility over time interval D. $\mathrm{ZEROS}_{i,D}$ is the fraction of zero return days out of total trading days during time interval D, and $\Phi^{-1}(\cdot)$ is the inverse cumulative normal distribution. Before aggregating, we winsorize our proxies by removing firms that are in the top and bottom 5% tails of the distribution for the current year, then we take the cross-sectional average of the remaining stocks to construct our aggregate measures. In (16), $R_{i,d,D}$ ($R_{i,d-1,D}$) is the return for the i-th firm on trading day d (day $d-1$) of time interval D and $\widehat{\mathrm{COV}}$ represents the sample covariance[17].

The FHT measure is a simplified version of the Lesmond et al. (1999) proxy. It is shown to outperform both the former, and an augmented Lesmond et al. (1999) proxy in Goyenko et al. (2009). The intuition behind the FHT measure rests on the idea that a zero return is the result of the true return being in-between the upper bound given by the transaction cost for buying, and the lower bound given by the transaction cost for selling. As can be seen in (16), the FHT measure is an increasing function of return volatility and the proportion of zero returns in the period of examination[18].

Our final alternative illiquidity proxy, in the spirit of Chen et al. (2016b), is the first principal component extracted from our baseline proxies and those discussed above. We estimate our illiquidity factor, ILLIQ^F_t, following McCracken and Ng (2016), Stock and Watson (2002), and Bai and Ng (2002). This factor explains 66.4% of the total variance of the six illiquidity proxies. By construction, ILLIQ^F_t captures and combines each dimension of our individual illiquidity measures. We provide plots of our alternative proxies in the supplementary material.

In Figure 9, we plot the posterior median and 80% posterior credible sets of the impulse response functions of macroeconomic variables stemming from TVP VARs estimated using each of our five alternative illiquidity proxies from 2001Q1 to 2016Q4, at our pre-specified dates. In Panel A we report results using $\mathrm{V}^{-1}, \mathrm{TR}^{-1}$, and Panel B plots impulse response functions from TVP VARs using $\mathrm{FHT}, \mathrm{Roll}, \mathrm{and} \mathrm{ILLIQ}^F$.

[16] We adopt the same filtering criteria for $\mathrm{V}^{-1}_{i,D}$ and $\mathrm{TR}^{-1}_{i,D}$ as we implement for $\mathrm{RtoV}_{i,D}$ and $\mathrm{RtoTR}_{i,D}$.

[17] $\mathrm{Roll}_{i,D}$ is only defined when the first-order autocovariance of daily returns for the corresponding period is negative. Empirically, the first-order sample covariance can be positive. Following Goyenko et al. (2009) and Chen et al. (2016b), we set $\mathrm{Roll}_{i,D}$ to zero when a positive value is observed.

[18] Holding return volatility constant, a greater frequency of zero returns in the period t, implies wider bounds, and therefore a wider spread. Similarly, holding the proportion of zero returns constant, a higher volatility implies that the transaction cost bounds and the bid-ask spread must be larger in order to achieve the same proportion of zero returns.

On the whole, the response of GDP growth, inflation and the interest rate are consistent with our main results. More specifically, across all our alternative measures, the contraction in macroeconomic variables are more severe during 2009Q1 relative to other dates considered in Figure 9. From posterior credible set, differences in the significance of the impulse response functions are negligible, relative to our models using price impact ratios.

These results conform with the findings of Næs et al. (2011), Apergis et al. (2015) and Chen et al. (2016b); the real effects of liquidity are not dependent on the proxy used. Based on the above, we conclude that our main results in examining the structural dynamics of financial market illiquidity is not conditional on the measure. Furthermore, this section reveals that the transmission mechanism of these shocks are episodic in nature, with greater contractions to real activity occurring during the Great Recession, and providing further support for the conclusions of our main analysis.

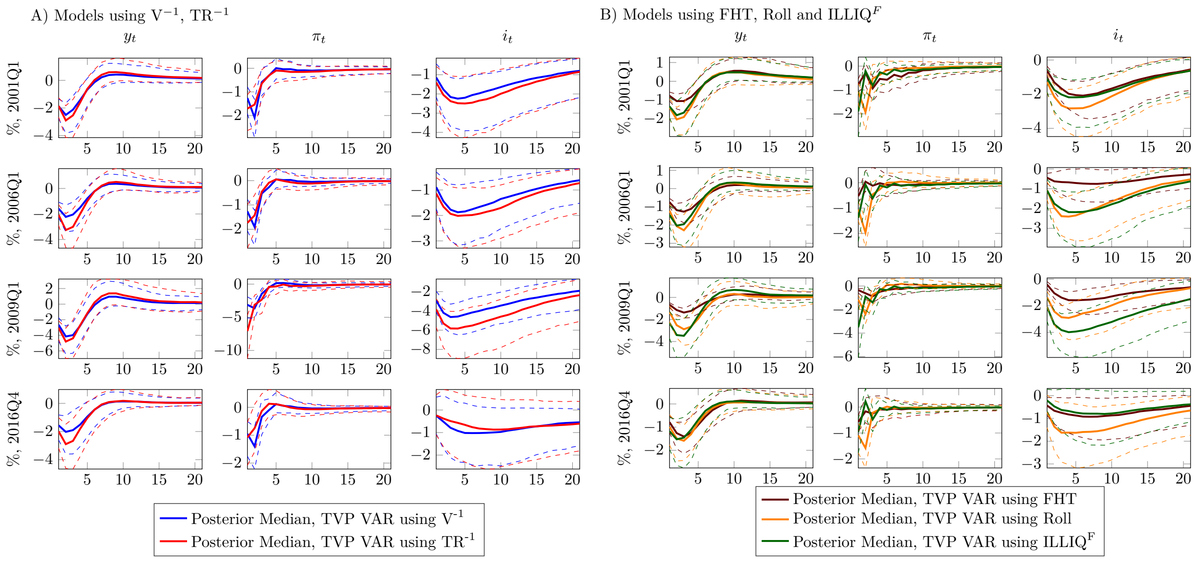

Figure 9: **Impulse Response Functions of Macroeconomic Variables with Respect to an Illiquidity Shock from Models using Alternative Illiquidity Proxies Across Selected Dates**
Notes: This figure plots the posterior median and 80% posterior credible sets of the impulse response functions of GDP (left column); inflation (middle column); and the interest rate (right column), from 2001 to 2016. Panel A reports results from models using V^{-1} and TR^{-1}. Panel B plot impulse response functions stemming from respective models using FHT, Roll, and ILLIQ^{F}.

4. Conclusions

In this paper we fit a Bayesian time-varying parameter VAR with stochastic volatility to UK macroeconomic data, spanning the period 1988Q1-2016Q4, and two proxies of stock market illiquidity; namely the RtoV ratio in Amihud (2002), and the RtoTR ratio in Florackis et al. (2011). We depart from the prior TVP VAR literature examining macro-financial linkages in two ways. First, we identify an illiquidity shock using theoretically grounded contemporaneous sign restrictions, whereas previous studies identify structural shocks using a Cholesky decomposition (see e.g. Hubrich and Tetlow (2015) and Ellington et al. (2017)). Second, we relax the assumption that parameters remain constant over the impulse horizon, and conduct structural inference in a non-linear framework following Koop et al. (1996) and Baumeister and Peersman (2013b).

A summary of our results is as follows: First, illiquidity shocks during the 2008 recession cause annual GDP growth and inflation to decline on impact by 1.89% and 1.78%, respectively. Second, we provide statistically significant evidence in favour of an episodic response of GDP gorwth, inflation and the interest rate in conjunction periods of financial stress. More specifically, the contractionary impact of illiquidity shocks intensifies during the Great Recession. Third, forecast error variance decompositions uncover that the economic importance of these shocks is substantial. Fourth, there are no statistical benefits in using the RtoV ratio in Amihud (2002) over the RtoTR ratio in Florackis et al. (2011); or vice versa. Finally, we find no statistical or economic differences in the transmission of illiquidity shocks from small or large stocks for the real economy.

We assess the consequences of the zero lower bound and show our main conclusions are consistent with: i) imposing a binding constraint zero lower bound constraint within our structural analysis analogous to Baumeister and Benati (2013); and ii) replacing the Bank rate with the shadow rate proposed in Wu and Xia (2016). Furthermore, we conduct a battery of robustness tests and provide substantial support that our results are: not sensitive to the prior specification; our choice of illiquidity proxy; or extending the information set. For policymakers, our study warrants liquidity provision to financial markets during periods of persistent financial stress (Claessens et al., 2012).

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