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**Michael Ellington**
University of Liverpool, UK

**Chris Florackis**
University of Liverpool, UK

**Costas Milas**
University of Liverpool, UK
The Rimini Centre for Economic Analysis, Italy

# LIQUIDITY SHOCKS AND REAL GDP GROWTH: EVIDENCE FROM A BAYESIAN TIME–VARYING PARAMETER VAR

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

Michael Ellington*, Chris Florackis* and Costas Milas$^{\diamond}$*

**Abstract**

We examine the dynamic impact of liquidity shocks resonating in stock and housing markets on real GDP growth. We fit a Bayesian time-varying parameter VAR model with stochastic volatility to US data from 1970 to 2014. GDP becomes highly sensitive to house market liquidity shocks as disruptions in the sector start to emerge, yet more resilient to stock market liquidity shocks throughout time. We provide substantial evidence in favour of asymmetric responses of GDP growth both across the business cycle, and among business cycle troughs. Stock and house market liquidity shocks explain, on average, 17% and 35% of the variation in GDP during the Great Recession, respectively.

$^{\diamond}$ Corresponding Author
Email addresses:
m.ellington@liverpool.ac.uk
c.florakis@liverpool.ac.uk
costas.milas@liverpool.ac.uk
* *University of Liverpool Management School, UK*

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# 1 Introduction

The links between asset markets and macroeconomic fluctuations are the subject of lengthy debate (see e.g. Bernanke and Blinder (1988)). In light of the 2008 recession (i.e. the Great Recession), liquidity provision is becoming a central topic (see Adrian and Shin (2008); Acharya et al. (2011); Næs et al. (2011)).

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

There are various reasons why liquidity conditions in stock and housing markets can affect the real economy. Stock market liquidity may behave as a signalling process uncovering the information set of investors (Florackis et al., 2014). In times of excess volatility or diminishing confidence regarding the future state of the economy, investors adjust portfolio holdings moving funds from high risk assets into 'safe havens' such as government debt or other short-term fixed income securities (flight to safety). Furthermore if investors expect a negative liquidity shock, portfolio compositions mirror this and greater proportions of wealth move into liquid assets (flight to liquidity); Longstaff (2004). Brunnermeier and Pedersen (2009) develop a model where the provider's ability to supply liquidity depends upon their capital and margin requirements. During periods of financial stress, market liquidity is sensitive to movements in funding conditions leading to mutually reinforcing "liquidity spirals". A "margin spiral" transpires when a shock to funding liquidity results in higher margins, and in turn, tightens speculators' funding constraints. This compels traders to de–lever and provide liquidity to low margin stocks. A "loss spiral" occurs when speculators hold large initial positions that negatively co-vary with customers' demand shocks. A shock to funding liquidity causes speculators to sell more and further reduces prices. Levine and Zervos (1998) propose that investment channels within a liquid secondary market facilitate investment into long-run, generally less liquid, projects that enhance long-term productivity; and subsequently economic growth.

Housing also plays multiple roles in affecting the real economy. First, houses can return capital gains or losses as an asset that directly influence housing wealth. Campbell and Cocco (2007) establish that increases in housing wealth relax borrowing constraints and fuel consumption growth. Similarly Carroll et al. (1992) argue from a precautionary savings motive, that increases in the value of housing wealth increase consumption expenditure. Second, housing can catalyse inter-temporal consumption when credit markets are imperfect. Housing is a pledgeable asset; He et al. (2015) indicate that house prices contain a liquidity premium. Therefore, in equilibrium, people may be willing to pay more than the house's fundamental value because of the financial security this conveys when they need a loan. Moreover purchasing a house requires a sizeable down payment, therefore the buyer's liquidity affects the demand for housing (Stein, 1995). Thus, strong demand in the housing market requires an extensive base of liquidity. Factors contributing to the notion of a housing bubble prior to the Great Recession are: substantial increases in trading volumes, surging prices and, mortgage defaults. With regards to the latter, Mian et al. (2015) states "when major shocks hit the economy and millions of homeowners simultaneously default . . . sales of foreclosed homes could lead to further reductions in house prices, threatening real activity" page 2587[1].

Our main results stem from a Bayesian time-varying parameter VAR model with a stochastic volatility structure. Our model allows for time variation in the autoregressive parameters, structural shocks, contemporaneous relations and the stochastic volatility innovations. We provide robust evidence that stock market liquidity shocks yield sharp contractions to GDP growth. However, the magnitude of the impact is declining. Contrastingly, we document a remarkable structural change between house market liquidity and GDP growth as frictions in the property sector surface in 2005. Our analysis reveals that house market liquidity shocks are most damaging during the depths of the Great Recession. We provide substantial evidence supporting an asymmetric response of GDP to house market liquidity shocks over the business cycle and across business cycle troughs in our sample. We further show that structural stock market and house market liquidity shocks explain, on average, 17% and 35% of the overall variation in GDP growth during the Great Recession. Then, in the period following the Great Recession (i.e. 2009–2014), house market liquidity shocks contribute, on average, 46% to the overall variation in real GDP growth. This implies the fragile recovery in the US is partly attributable to imbalances within the property sector.

Our study aims to contribute to the existing literature in several ways. From a theoretical perspective, our results correspond with the liquidity shock hypothesis in Kiyotaki and Moore (2012). This refers to sudden drops in asset market liquidity that may or may not relate to macroeconomic fundamentals, causing equity prices to fall. Lower asset prices hinder firm's financing abilities through issuing new equities and/or using equity as collateral. Therefore, investment deteriorates, output falls and recession begins. However, in discussing the financial crisis, there is recognition that liquidity conditions in stock and housing markets are both countercyclical with the business cycle (see among others, Jermann and Quadrini (2012); Jaccard (2013); Diaz and Jerez (2013)). The innate appeal of the liquidity shock hypothesis corresponds particularly well with recent business cycles. If asset market liquidity is a causal factor, policymakers can impede the cycle through the direct provision of liquidity to support investment.

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

However, aggregating conditions from different financial markets omits any interaction between financial variables. Implicitly, this ignores important contemporaneous structural links between asset markets. The empirical literature allowing for different financial markets in a VAR framework is small (see e.g Björnland and Leitemo (2009) and Prieto et al. (2016)). Our works extends upon Prieto et al. (2016), who evaluate the effects of asset price shocks to US GDP growth in a time-varying framework. We build on their analysis by isolating the liquidity component from stock and house prices overcoming the complex web of information that nests

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

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

within asset prices (Harvey, 1988).

Conceptually, our work relates to the DSGE literature focussing on financial shocks. Shi (2015) deduces a tractable model able to quantify the effects of financial shocks for the business cycle. Negative shocks to asset liquidity are shown to cause investment, consumption and output to fall. Jaccard (2013) calibrates a DSGE model on Euro area data and evaluates the Great Recession by computing the relative contribution of liquidity shocks. Results imply that the sharp contraction in output was mainly due to negative liquidity shocks originating in the financial sector. Christiano et al. (2010) show that 'financial factors' are key drivers of economic fluctuations. Their main results show that risk shocks–affecting the economy through the investment margin–are the main factor behind economic variations explaining more than 60% of the volatility in US investment; and a third of investment volatility in the Euro area. Furthermore, liquidity shocks display drastic effects on real activity. In particular these shocks reveal a detraction of between 1/3 and 1.5 percentage points of the contraction in US GDP growth.

The paper proceeds as follows: Section 2 shows how we measure liquidity and provides a description of the macroeconomic data. In Section 3, we discuss TVP VARs, prior specification and identification of structural shocks. Empirical analysis and robustness checks are in Sections 4 and 5 respectively. Finally, Section 6 provides concluding comments.

## 2 Measuring Liquidity and Data

For our benchmark analysis, we rely on the Return-to-Volume (RtoV) ratio of Amihud (2002) to measure market liquidity. This ratio captures the price response to $1 trading volume and rests on the theoretical foundation of Kyle's price impact coefficient (Kyle, 1985). Specifically, the price impact coefficient encapsulates the sensitivity of asset prices to the order flow. Amihud (2002) notes that the RtoV ratio is more coarse and less accurate than finer measures of liquidity; such as bid–ask spreads or transaction–by–transaction market impacts. Yet these finer measures of liquidity require vast amounts of high–frequency microstructure data that are not readily available for long periods of time. Pástor and Stambaugh (2003) and Sadka (2006) propose alternative measures of stock market liquidity that capture price impact[3] [4]. Goyenko et al. (2009) provide a comprehensive analysis of an array of high and low frequency liquidity measures. Their findings reveal that the Pástor and Stambaugh (2003) liquidity proxy, among other proxies thought to capture price impact, are dominated by the Amihud (2002) ratio. In fact, Goyenko et al. (2009) "suggest using the Amihud measure... if a researcher wants to capture price impact", page 179.

Furthermore the Amihud (2002) ratio, and implicitly price impact, links well with the models in Kiyotaki and Moore (2012), Jaccard (2013) and Shi (2015). Investing entrepreneurs sell their

[3]In contrast to the Amihud (2002) ratio, increases in the aforementioned constitute a rise in liquidity. Both the Pástor and Stambaugh (2003) and Sadka (2006) liquidity measures are available from the CRSP database. The former and latter are available from 1962 to 2015 and 1983 to 2008, respectively. The contemporaneous correlations between our measure of stock market liquidity and Pastor and Stambaugh's and Sadka's measures are -0.38 and -0.36, respectively. As an additional robustness check we have used the Pástor and Stambaugh (2003) proxy as our measure for stock market liquidity. Results and conclusions are generally consistent to those we report in this paper and are available on request. We have also estimated our benchmark models using the Return-to-turnover ratio proposed in Florackis et al. (2011). These results are consistent with those we present in the paper.

[4]Other measures of liquidity are found in Lesmond et al. (1999) and Roll (1984). Lesmond et al. (1999) and Roll (1984) propose a measure of liquidity based on the frequency of zero returns to proxy an implicit trading cost and an effective spread estimate that depends on the autocovariances of successive returns, respectively. The benefits of both measures are that they require only daily returns. Another widely used measure of liquidity is the relative spread. However, CRSP data to compute the relative spread is only fully available from 1980 which is too short to use in our study. Næs et al. (2011) provide correlations between the Amihud (2002) ratio and the Lesmond et al. (1999) and Roll (1984) liquidity measures of 0.38 and 0.32 respectively. These measures of liquidity are positively correlated since increases capture a decline to market liquidity.

holdings to liquid assets to finance investments due to borrowing constraints. Consequently liquidity relates to the resaleability of assets. The RtoV ratio assumes changes to asset prices depend on the net order flow. Successive orders change the cost of trading which therefore influence the ease of reselling assets. As prices become more sensitive to the order flow, the ease of selling assets declines. In turn the cost of trading increases causing investment to dwindle and output falls.

Adding to this, there is no data available to calculate alternative liquidity measures, such as bid-ask spreads, for the property sector. Therefore, our choice of the Amihud (2002) ratio not only ensures a consistent definition (and measure) of liquidity from both stock and housing markets, but also corresponds well with the causal chain from liquidity shocks to GDP growth outlined in the existing theoretical literature.

We proxy stock market liquidity, $RtoV_t^s$ as:

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

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

To calculate stock market liquidity, we use daily stock price and trading volume data for all common stocks on the New York Stock Exchange (NYSE) from the CRSP database over the time period 1968 to 2014. We implement standard filtering criteria similar to Amihud (2002)[5].

In a similar manner, we estimate house market liquidity, $RtoV_t^h$ as:

$$RtoV_t^h = \frac{|\Delta h_t|}{VOL_t} \tag{2}$$

where $|\Delta h_t|$ is the absolute quarterly change in house prices in quarter $t$ (i.e. house price inflation) and $VOL_t$ is the trading volume (in thousands of units of currency) of houses. We use the Nominal Home Price Index to proxy prices which tracks the prices of single-family homes and is from Robert J. Shiller's webpage. Trading volume is the sum of the volume of sales of new single-family homes and existing single-family homes (available from Thomson Reuters DataStream)[6]. In Appendix A, we report descriptive statistics of the raw estimates of $RtoV_t^s$ and $RtoV_t^h$.

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

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

[6]Available from `http://www.econ.yale.edu/~shiller/data.htm`. From 1975, the Nominal Home Price Index uses Case and Shiller's national house price index that gathers data from the nine US census constituents for single family homes. Before 1975, this index uses the purchasing component of the US Consumer Price Index. Trading volume data is the number of sales of single family homes from the nine constituents (in thousands). To convert into thousands of units of currency we multiply trading volume by the median house price for the USA available from the Federal Reserve Bank of St. Louis.

puzzles (Prieto et al., 2016). We transform our liquidity proxies into % deviations from their respective 3–year moving averages; denoting as $S_t^{illiq}$, $H_t^{illiq}$ respectively; Figure 1 plots our data series.

Table 1 reports descriptive statistics for our macroeconomic and financial data. On average US GDP growth is around 2.75%, it peaks in 1984 at 8.2% and troughs in the depths of the most recent recession at -4.15% (i.e. 2009Q2). House and stock market illiquidity, on average, fluctuate 6.63% and 11.53% below their respective 3–year moving averages. Both measures peak as liquidity dries up during the Great Recession in 2008Q4 at 166.55% and 267.17% respectively. The contemporaneous correlation between GDP growth and stock market and house market illiquidity are -0.35 and -0.05 respectively. Negative correlations with real GDP growth are intuitive, an increase in the Amihud (2002) measure corresponds to worsening liquidity conditions (i.e. the market is more illiquid).

**Table 1: Descriptive Statistics for Macroeconomic Data and Illiquidity Proxies from 1970 to 2014**

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

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

To illustrate, Figure 2 depicts the annual rate of GDP growth along with our proxies of stock and house market liquidity conditions, the Amihud (2002) measure, from 2000 to 2014 respectively. Clearly, we can see that liquidity (illiquidity) is countercyclical (procyclical) with real GDP growth. In particular, liquidity dries up in late 2008–corresponding with the peaks in our stock and house market illiquidity proxies–and these lead the slump in GDP growth by around 1–2 quarters in early 2009.

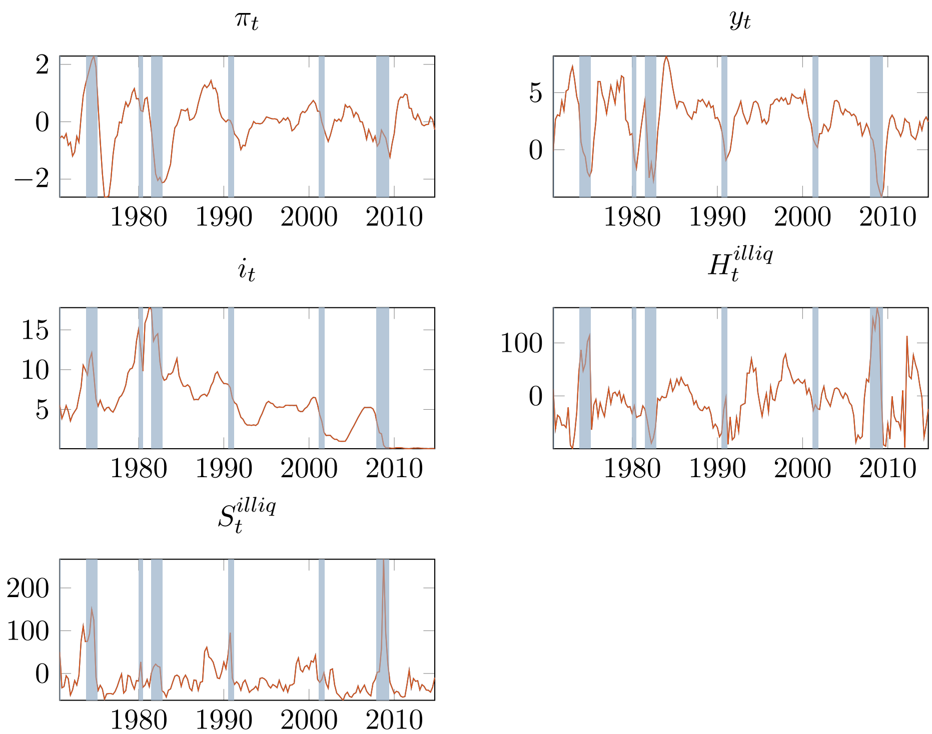


**Figure 1: Macroeconomic and Financial Variables from 1970 to 2014**

Notes: This figure plots the annual rate of US inflation, $\pi_t$; annual real GDP growth, $y_t$; the Federal Funds rate, $i_t$; House Market Illiquidity, $H_t^{illiq}$ and Stock Market Illiquidity, $S_t^{illiq}$. We detrend the annual inflation rate, using a one-sided Kalman filter as in Stock and Watson (1999). Our liquidity proxies are % deviations from their 3–year moving averages, respectively. Grey bars indicate NBER recession dates.

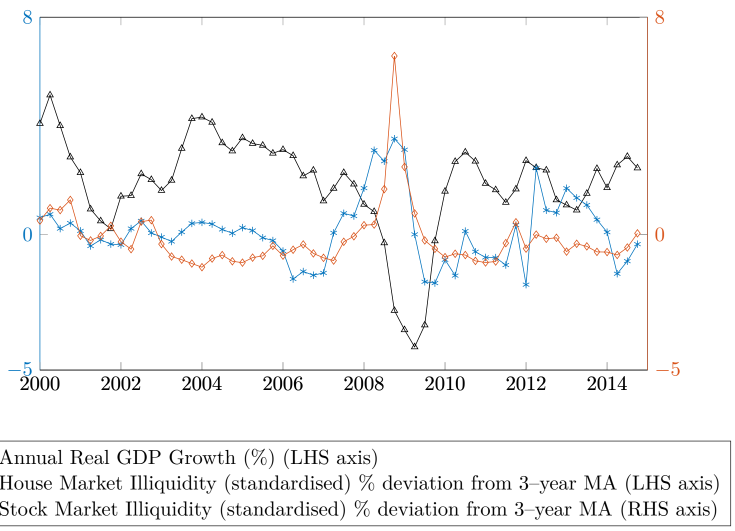


**Figure 2: US Real GDP growth (%), House Market Illiquidity and Stock Market Illiquidity from 2000 to 2014**

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

# 3 Econometric Methodology

## 3.1 A Time-varying Parameter VAR with Stochastic Volatility

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

$$\begin{aligned} y_t &= Z_t'\beta_t + A_t^{-1}\Phi_t\varepsilon_t && (3)\\ \beta_t &= \beta_{t-1} + \upsilon_t, \quad \upsilon_t \backsim N(0,Q) && (4) \end{aligned}$$

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

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

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

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

and collecting the diagonal elements in the vector

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

we assume:

$$\begin{aligned} \alpha_t &= \alpha_{t-1} + \zeta_t, \quad \zeta_t \backsim N(0,S) && (6)\\ \ln\phi_t &= \ln\phi_{t-1} + \eta_t, \quad \eta_t \backsim N(0,W) && (7) \end{aligned}$$

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

$$\begin{bmatrix} \varepsilon_t\\ \upsilon_t\\ \zeta_t\\ \eta_t \end{bmatrix} \backsim N(0,V), \quad V = \begin{bmatrix} I_5 & 0 & 0 & 0\\ 0 & Q & 0 & 0\\ 0 & 0 & S & 0\\ 0 & 0 & 0 & W \end{bmatrix} \quad (8)$$

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

### 3.1.1 Priors

Our prior specification follows closely the specifications in Cogley and Sargent (2005) and Primiceri (2005). We use the first 41 observations (from 1970Q4-1980Q2) to calibrate the initial conditions for the parameters of the model[7]. The initial conditions for the coefficient matrix, $\beta_0$ are the OLS point estimates from a standard VAR. We set $Var(\beta_0)$ as four times the variance of the standard OLS estimates from the training sample. We obtain the prior to initialise $A_0$ in the same manner. We set $\ln \phi_{0,i}$ to have a mean equal to the (logarithmic) standard errors of the OLS estimates (in each equation) to initialise $\beta_0$; its covariance matrix is an $M$-dimensional diagonal matrix where the elements along the main diagonal are equal to 10. Further, setting the degrees of freedom and scale for the inverse-Wishart prior distributions of the hyperparameters; for each of the five blocks of S, the degrees of freedom are $1 + dim(S_i)$. The degrees of freedom for $Q$ are set to $1{+}K$ (i.e. 1 plus the dimension of $\beta_t$), where $K = 55$. $W$ follows an inverse-Gamma distribution with a single degree of freedom with a scale parameter $k_W = .01$. The scale matrices are chosen to be constant fractions of the OLS estimates from the training sample. To summarise:

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

where $IW$ and $IG$ denote the inverse-Wishart and inverse-Gamma distributions respectively. $S_i, i = 1, \ldots, 5$ denote the blocks of $S$. $\hat{A}_{i,OLS}$ denotes the blocks of the OLS estimates of the blocks of the estimate of $\hat{A}$ matrix within the training sample. In line with Primiceri (2005) and Cogley and Sargent (2005), we set $k_Q = .01$ and $k_S = .1$. We allow for 70,000 iterations of the Markov Chain Monte Carlo (MCMC) algorithm discarding the first 60,000 as burn in; of the remaining 10,000 iterations, we sample every $10^{th}$ draw to reduce autocorrelation amongst the draws[8]. Appendix B assesses the convergence properties of the MCMC algorithm.

### 3.2 Identification of Structural Shocks

We add our illiquidity proxies to the macroeconomic data and order our VAR model as follows: the inflation rate, $\pi_t$; output growth, $y_t$; the interest rate $i_t$; house market illiquidity $H_t^{illiq}$ and stock market illiquidity $S_t^{illiq}$ respectively[9]. We assume a block recursive composition of the covariance matrix of structural shocks which is standard in the literature (see among others: Cogley and Sargent (2005), Primiceri (2005), Hubrich and Tetlow (2015) and Prieto et al. (2016)). In our case, we define a liquidity shock as a sudden decline to market liquidity (i.e. an increase in illiquidity). Under this identification scheme, macroeconomic variables are slow to react to liquidity shocks. Our ordering scheme imposes monetary policy reacts slowly to liquidity shocks; typically monetary policy decisions are made every six weeks (Swiston, 2008)[10]. Additionally, ordering our illiquidity variables last in our VAR model is indicative of reality. For example, we observe liquidity shocks in late 2008 and policymakers respond by lowering interest rates in early 2009. Furthermore our liquidity proxies reach their respective peaks at the end of

[7] Our results remain similar when we allow for 50 and 60 observations to calibrate the initial conditions of the model.

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

[9] Ordering $y_t$ before $\pi_t$ yields no differences in the results or conclusions we report in the paper.

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

2008, US GDP growth troughs in early 2009. Therefore we postulate our identification scheme is valid and proceed on this premise; Appendix C reports additional results under an alternative ordering scheme[11].

# 4 Empirical Results

## 4.1 Stochastic Volatility and Changing Dynamics

In what follows, we analyse whether we can characterise time-variation to the size of liquidity shocks or to changing dynamics of the transmission mechanism. Changing shock sizes are captured by the stochastic volatility innovations. The transmission mechanism of these shocks are encapsulated in the impulse response analysis. In Figure 3, we present the posterior median along with the one standard deviation percentiles of the stochastic volatility of liquidity shocks (i.e. the quantiles of the distribution over the draws of $\phi_{4,t}$, $\phi_{5,t}$ respectively). It is clear there is remarkable time-variation in the standard deviation of structural liquidity shocks. Notice that the volatility of house market liquidity shocks in the 2008 recession remains persistently high for at least four years after the recession ends. This resilience may suggest a magnifying and longer lasting impact of house market liquidity shocks following the Great Recession. Figure 3 corroborates with Claessens et al. (2012) in that recessions preceding a property market bust are more extensive, in depth and time, than those without. For example the 2001 recession yields little change in the volatility of house market liquidity shocks. Contrastingly in the same periods, the volatility of shocks to stock market liquidity surge temporarily and then revert back to levels consistent with non–recessionary periods[12].

In Figure 4 we plot the posterior median impulse response functions of GDP growth to liquidity shocks at a five year horizon for each observation in our sample (i.e. 1981Q3-2014Q4). Given an increase in our proxies constitutes a decline in liquidity, a liquidity shock therefore implies a sudden decline in market liquidity. Clearly, shocks to stock market liquidity yield temporarily contractionary effects to GDP growth. Across time the magnitude of stock market liquidity shocks are decreasing, yet the persistence remains similar. This result is consistent with Prieto et al. (2016), who show that stock price shocks also exhibit a decreasing impact on US GDP growth. In fact, they find that the overall contribution of the stock market to the Great Recession plays a negligible role[13]. Nevertheless, the impact of stock market liquidity shocks to GDP growth are significant–relative to 68% posterior credible intervals–across all time periods. Although the impact on GDP lessens throughout time, there are still economically meaningful contractionary effects.

On the other hand, the real effects of house market liquidity shocks are trivial from 1981 to 2005 with the posterior median response of GDP barely fluctuating away from 0. We postulate the inconsequential impact of liquidity shocks on GDP from 1981 to 2000 links with the increasing securitisation of mortgages. However, GDP growth becomes gradually more sensitive to house market liquidity shocks from around 2005 onwards; the impulse response functions' posterior credible intervals indicate significance from 2005Q2 (further results available on request). The transition in impact of house market liquidity shocks aligns closely with disturbances in the housing market. Interestingly, the economic significance of house market liquidity shocks is greatest when GDP is at its (sample) minimum value (i.e. -4.15% in 2009Q2). When GDP growth is at its sample maximum in 1984Q1 notice, from Figure 4, that a liquidity shock spurs

[11]Results are consistent if we place GDP growth before inflation. Ordering GDP and inflation in this manner is consistent with Hubrich and Tetlow (2015) and Prieto et al. (2016).

[12]We report the stochastic volatility of macroeconomic shocks in Appendix C; along with plots of the time-varying parameters and time-varying covariances.

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

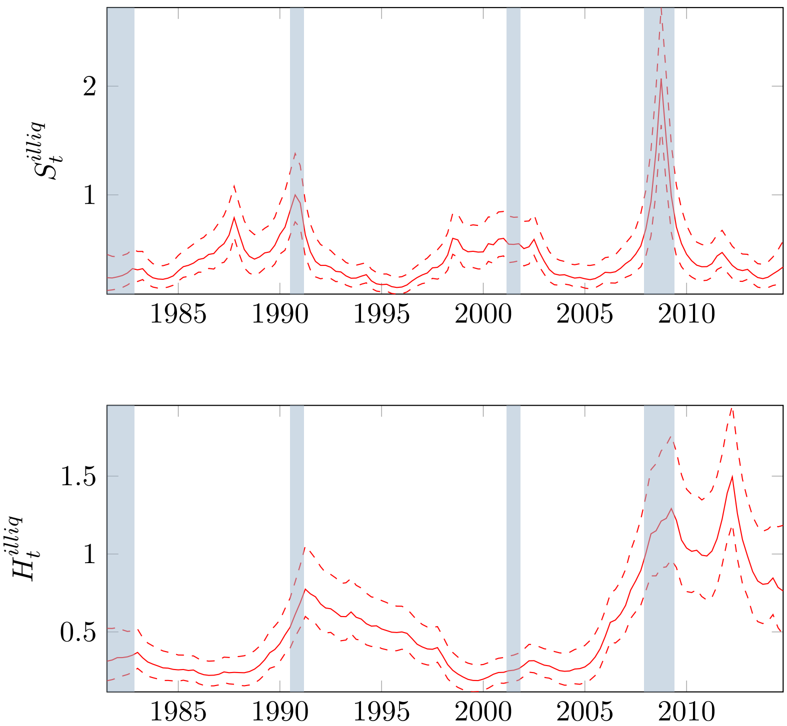


**Figure 3: Stochastic Volatility of Liquidity Shocks from 1981 to 2014**
Notes: This figure shows the median and 1 standard deviation percentiles of the time-varying standard deviations of structural liquidity shocks for Stock Market illiquidity, $S_t^{illiq}$ and House Market illiquidity, $H_t^{illiq}$ from 1981-2014, respectively. Grey bars indicate NBER recession dates.

virtually no response in GDP growth in this period. The difference in the transmission of house market liquidity shocks across our sample indicates there is a structural change in the dynamics between GDP growth and house market liquidity.

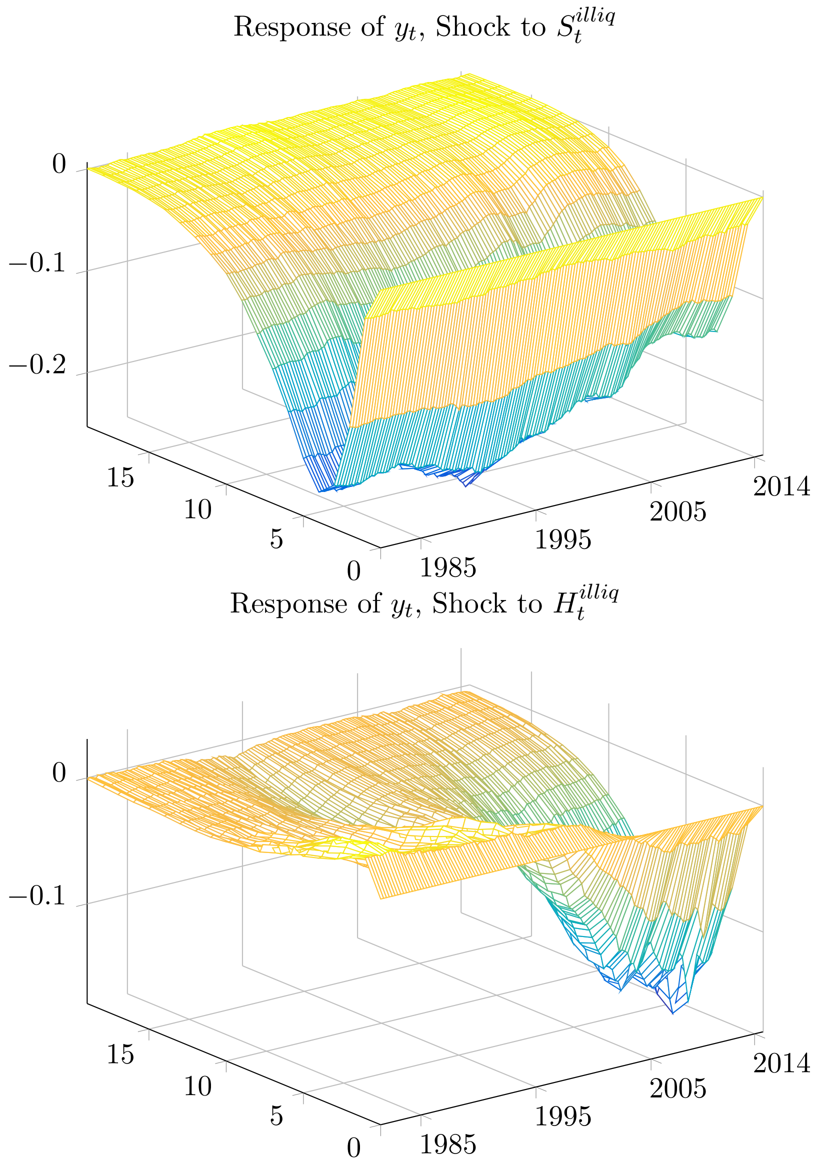


**Figure 4: Impact of Liquidity Shocks on GDP growth 1981 to 2014**
Notes: This figure plots the median impulse response functions of US real GDP growth with respect to: a unit stock and house market liquidity shock respectively. We plot the response along a 5-year horizon for each quarter of our sample 1981Q3-2014Q4. A liquidity shock constitutes a decline in market liquidity (i.e. an increase in illiquidity).

Following the practice of Galí and Gambetti (2009) and Prieto et al. (2016), we plot in Figure 5, the differences in average impulse response of GDP growth to liquidity shocks between different periods stemming from NBER recession dates. This allows us to distinguish if there are differences in the economic impact of liquidity shocks across the business cycle. We compute for each draw of the Gibbs sampler, the average impulse response over each of the periods, take the difference between the averages and then calculate the quantiles over the draws. In the left panel, we compare all recessions excluding the Great Recession with non–recessionary periods. The middle and right panel compare the Great Recession with non–recessionary periods and all other recessions in our sample; this is to evaluate possible heterogeneities in the transmission of liquidity shocks. Our results suggest little difference in the average impact of stock market liquidity shocks across periods. However, this finding is unsurprising since Figure 4 reveals a decline in the susceptibility of GDP to stock market liquidity shocks.

On the other hand, we see asymmetries in the response of GDP to house market liquidity shocks. Our model implies an increasing exposure of GDP to house market liquidity shocks in the post financial crisis period; which links closely with the persistence of the volatility of structural shocks in Figure 3. Clearly, our results show that the impact of house market liquidity shocks on GDP growth are stronger during the Great Recession than non–recessionary periods. Perhaps even more interestingly, Figure 5 shows the effects of house market liquidity shocks onto GDP growth during the Great Recession are more damaging in terms of magnitude and tenacity relative to normal times and other recessions within our sample[14].

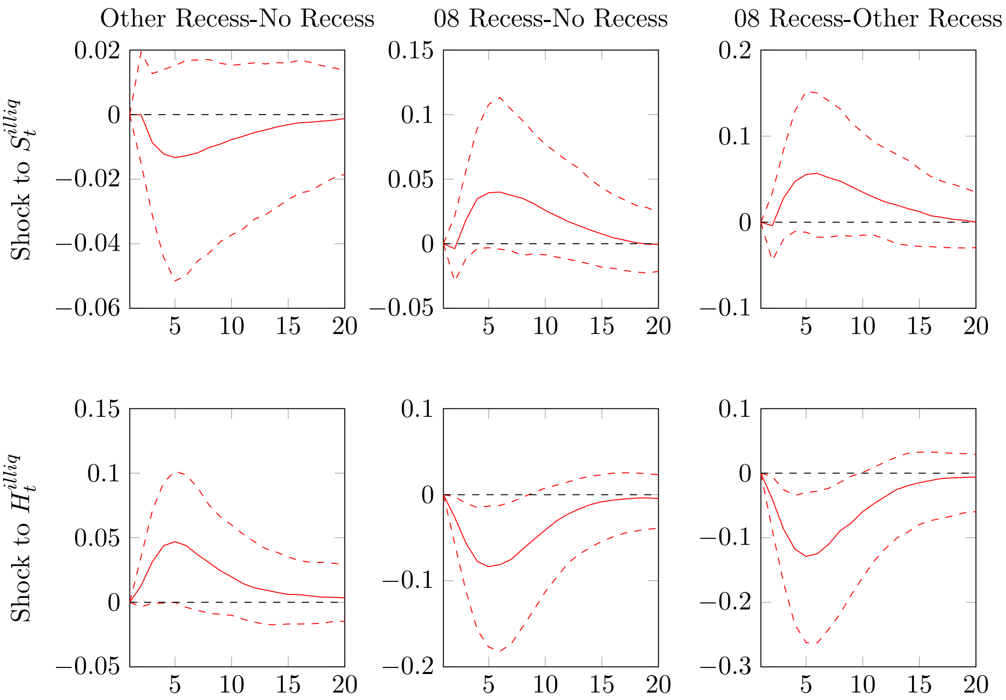


**Figure 5: Impulse Responses of GDP growth: Differences in averages over periods**
Notes: Panels one to three show the averages of differences in impulse responses of GDP growth to liquidity shocks between: other recessionary (i.e. NBER recession dates excluding the Great Recession) and non–recessionary periods (left panel: Other Recess-No Recess); The Great Recession and non–recessionary periods (middle panel: 08 Recess-No Recess) and The Great Recession and other recessionary periods (right panel: 08 Recess-Other Recess) respectively. Recessionary periods are NBER recession dates. We compute the difference in average impulse response as follows: for each draw of the Gibbs sampler, we average the impulse response over each of the selected periods, take the difference between the averages of selected periods and then calculate the quantiles over the draws. A liquidity shock constitutes a decline in market liquidity (i.e. an increase in illiquidity).

In Figure 6, we report the median and one standard deviation percentiles of the contributions of stock and house market liquidity structural shocks to the overall variance of real GDP growth across our sample. Following Benati and Mumtaz (2007), we compute the variance decomposition in the frequency domain by computing, for each quarter, at each iteration of the Gibbs sampler, real GDP's actual spectral density and five counterfactual spectral densities by setting to zero the variances of each of the structural shocks but one[15]. The following discussion

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

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

and analysis refers to the posterior median estimates of the structural variance decompositions. The contribution of stock market liquidity shocks to the variance of GDP varies considerably over our sample. We can see that during the stock market crash of 1987 and the 1991 recession, the structural stock market liquidity shocks account for 20% of the variation in real GDP growth. In 2008 the stock market explains 36% of the variance of real GDP growth; however, this is a temporary shift and by 2010, the fraction of GDP's variance attributable to stock market liquidity shocks is about 5%.

The contribution of house market liquidity shocks to the overall variance of GDP also varies remarkably over our sample. In the 1980s, the fraction of GDP's variance we associate to house market liquidity shocks fluctuates around 10%. Then, following the recession in 1991, the fraction jumps to around 35% and fluctuates around 30% until 1997. In the early 2000s and during the dot com bubble burst, house market liquidity shocks revert back to around 10% of the overall variance of GDP. However as the problems within the property sector start to emerge from 2005, house market liquidity shocks start to have an increasing effect. From 2008 until the end of 2014, house market liquidity shocks explain on average, 46% of the variation in GDP growth.

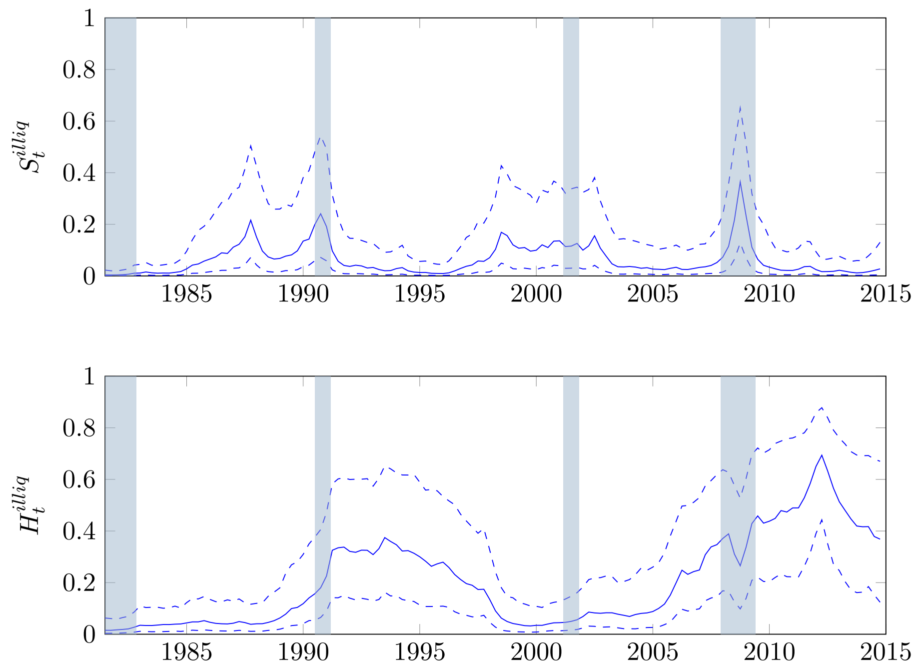


**Figure 6: Contribution of Structural Liquidity Shocks to the Overall Variance of Real GDP Growth from 1981 to 2014**

Notes: This figure plots the median and one standard deviation percentiles of the contribution of structural stock and house market liquidity shocks to real GDP growth from 1981 to 2014. Grey bars indicate NBER recession dates.

The shape of these figures are strikingly similar to the volatility of structural shocks in Figure 3. This implies the majority of the time-variation in the structural variance decomposition is due to changing shock sizes. Taking the results together, the key driving forces to during the Great Recession are structural liquidity shocks. The average contribution of stock and house market liquidity shocks to the variation in GDP growth during the most recent recession are 17% and 35% respectively. The average total contribution of liquidity shocks to the variation in GDP growth is therefore 52%[16]. At the end of our sample (i.e. 2014Q4) the contribution of stock and house market liquidity shocks to GDP growth variance are 2.74% and 36.85%

[16] This is consistent with Figure 2 in Prieto et al. (2016) who find that the total contribution of financial shocks from a forecast error variance decomposition is around 50%.

respectively. From 2009 until 2014, the average contribution of house market liquidity shocks to the variation in real GDP growth is 46%. This, together with Figure 6, suggests the obstinately low rates of GDP growth after the Great Recession are predominantly due to a fragile and sluggish recovery of the US property market[17].

In general, the resilience of GDP to stock market liquidity shocks may reflect a diminishing demand for precautionary savings stemming from less uncertainty (see Arestis et al. (2001)). Further, as financial integration increases, domestic real effects may be offset by international investor participation as risks (and subsequently economic impacts) leak to other economies[18]. The increasing real effects of house market liquidity shocks may arise due to surges in subprime mortgage lending causing increases in debt levels (Mian and Sufi, 2009; Mian et al., 2015). Similarly, increases in the net worth of financial intermediaries due to surges in house prices in the early 2000s facilitates a relax in lending constraints; consequently injecting too much liquidity into the property sector. Coupling with the former, the proliferating sensitivity of GDP to house market liquidity shocks are in line with explanations in Iacoviello and Neri (2010); who maintain housing preference shocks have larger effects on GDP when collateral effects are taken into account.

Overall our results provide substantial evidence that the US property sector has asymmetrical real effects not only across the business cycle, but amongst troughs in business cycles across our sample (see bottom right panel of Figure 5). Furthermore, we show that liquidity conditions in the stock and housing markets contribute heavily to the overall variation in real GDP growth; particularly during crisis periods. Our results with regards to the stock market contrast Prieto et al. (2016) who find that the stock market has negligible explanatory power for US GDP variation during the financial crisis. By isolating the liquidity component from stock prices, we find that stock market liquidity is an important factor in explaining US GDP variance during the Great Recession. The immediate policy implication is that liquidity provision to financial and asset markets is necessary to counteract damaging contractions to GDP growth. Studying the economic impact of liquidity shocks throughout time signals liquidity provision, particularly during the most recent recession, is essential to promote recovery. Our findings justify US policy responses to the turmoil of 2008 such as: injecting liquidity into financial asset markets through Quantitative Easing (QE) policies; providing Fannie Mae and Freddie Mac with capital injections in September 2008; both the Home Affordable Modification and Home Affordable Refinancing Progams (HAMP, HARP) and incentives to reduce principal loans to borrowers whose mortgages exceed their property value.

# 5 Robustness Analysis

## 5.1 The Real Effects of Uncertainty Shocks

There is an implicit relationship between asset market liquidity and asset price uncertainty. For example, Florackis et al. (2014) note a negative correlation between stock market liquidity and volatility; particularly in a bear market. Also, Levine and Zervos (1998) stress that liquidity and uncertainty may possess an important relationship and provide an empirical investigation on the real effects of stock market liquidity and uncertainty. Furthermore, Demirgüç-Kunt and Levine (1996) state that as a result of greater stock market liquidity, less uncertainty associated with investment could reduce saving rates. While less uncertainty proves attractive for risk averse investors, it also diminishes the precautionary motive to save which may deter long term economic growth. However, a more intuitive channel is provided in Arestis et al. (2001). The

[17] The structural variance decomposition of GDP growth from our TVP VAR including corporate bond spreads in Appendix C uncovers that this is not due to liquidity shocks being correlated with credit risk shocks.

[18] An important future avenue would be to quantify real international spillover effects of stock market liquidity shocks.

former note that increases in price uncertainty, possibly as a result of declining liquidity, can hinder an efficient allocation of investment which feeds through into real activity.

Campbell and Cocco (2007) link uncertainty in the housing market to the real economy via the consumption channel. The volatility of house prices corresponds to changes in housing wealth which exhibit a positive correlation with consumption. On the other hand, housing are pledgeable as collateral to obtain credit. Surging prices relax borrowing constraints and allow agents to smooth consumption over the life cycle (Ortalo-Magne and Rady, 2006). Stein (1995) associates uncertainty and liquidity in the property sector under the assumption that a down payment must be made. The multiple equilibria the model implies helps explain large fluctuations in house prices[19]. Diaz and Jerez (2013) establish an intuitive link between liquidity and uncertainty. Their theoretical model is able to reproduce the cyclical time series properties of the US property sector. As liquidity decreases in the property sector before and during the Great Recession, prices fluctuate and volatility intensifies.

Notably, as market liquidity and uncertainty may possess an important connection, it is necessary to investigate the economic impact of uncertainty shocks. If we cannot properly distinguish between the real effects of uncertainty and liquidity shocks, adequate policy recommendations cannot be made. To proxy market uncertainty we estimate an ARCH(1) and GARCH(1,1) model of the absolute value of quarterly stock and house price changes from 1968 to 2014 respectively. Using the absolute value of price changes is shown to predict volatility with greater precision than squared returns (Forsberg and Ghysels, 2007)[20]. We use stock data on the NYSE composite price index (available from Thomson Reuters DataStream); house price data is from Robert J. Shiller's website. We convert stock and house prices into real variables by dividing by the GDP deflator; returns are logarithmic differences. We include lags of the dependent variables in the mean equations of our ARCH and GARCH models to whiten the residuals deleting those that are not statistically significant[21].

Table 2 reports our ARCH(1) and GARCH(1,1) specifications for stock and house price inflation from 1968 to 2014. In addition to parameter estimates, we report the autocorrelations of the residuals up to 8 lags. Note also that we restrict the variance equation to $\rho + \theta = 1$; otherwise the conditional variance is explosive. To keep our analysis consistent our uncertainty proxies are the % deviations from their 3-year moving averages of the conditional volatility from our ARCH(1) and GARCH(1,1) models[22]. We add our uncertainty proxies, $H_t^{\sigma}$, $S_t^{\sigma}$ to our macroeconomic data and liquidity proxies ordered in the following manner: inflation, $\pi_t$; real GDP growth, $y_t$; the interest rate, $i_t$; house market liquidity, $H_t^{illiq}$; house price uncertainty, $H_t^{\sigma}$; stock market liquidity, $S_t^{illiq}$ and stock price uncertainty $S_t^{\sigma}$. Therefore we estimate a 7 variable TVP VAR as in (3)-(8) in the exact manner as before[23].

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

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

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

[22]A widely accepted measure of stock market uncertainty is the VIX index (see among others Connolly et al. (2005)). The VIX index uses option implied volatility of 30-day puts and calls for at the money options for stocks listed on the S&P500 index. However, VIX data starts only in 1990 which is too short to use in our analysis. The contemporaneous correlation (for the sample 1990 to 2014) between the conditional volatility from our ARCH specification of absolute real stock returns and the VIX index is 0.55 respectively. We also consider the annual change in conditional volatilities implied from our models in Table 2. Results are the qualitatively similar to those we report within.

[23]Ordering our uncertainty proxies in this manner implicitly assumes that uncertainty shocks contemporaneously affect liquidity conditions. We postulate this as a valid assumption following the causal chain outlined in Diaz and Jerez (2013). The former note that liquidity shocks can propagate onto current and future price uncertainty. Our results are robust to alternative orderings and the impulse response analysis results in qualitatively similar conclusions; results available on request.

**Table 2: ARCH/GARCH Models of Real Stock and House Price Inflation from 1968 to 2014**

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

| Panel/Eq: | A: $\|\Delta s_t\|$ | | B: $\|\Delta h_t\|$ |
|---|---|---|---|
| Sample: 1968Q1-2014Q4 | | | |
| Mean Eq: | | | |
| $\mu$ | 2.998(0.69) | $\mu$ | 0.345(0.09) |
| $\beta_1$ | 0.152(0.07) | $\beta_1$ | 0.542(0.07) |
| $\beta_2$ | 0.203(0.08) | $\beta_2$ | -0.096(0.06) |
| | | $\beta_3$ | 0.60(0.06) |
| | | $\beta_4$ | -0.38(0.06) |
| Variance Eq: | | | |
| $\omega$ | 12.023(2.63) | $\rho$ | 0.102(0.06) |
| $\rho$ | 0.618(0.33) | $\theta$ | 0.898(0.06) |
| Autocorrelations | | | |
| lag | AC | lag | AC |
| 1 | -0.033 | 1 | 0.003 |
| 2 | 0.093 | 2 | -0.038 |
| 3 | 0.021 | 3 | 0.091 |
| 4 | -0.081 | 4 | 0.046 |
| 5 | -0.017 | 5 | 0.056 |
| 6 | -0.086 | 6 | -0.086 |
| 7 | 0.047 | 7 | 0.018 |
| 8 | -0.083 | 8 | 0.014 |

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

Figure 7 plots the time-varying impact of liquidity and uncertainty shocks from the US stock and housing market onto real GDP growth. Our results reveal that GDP growth responds counter intuitively to stock market uncertainty shocks. Note however that posterior credible intervals contain 0 at every observation. Turning our attention to the real effects of uncertainty shocks from the housing market, the response of real GDP growth remains relatively constant throughout our sample. However, the impact of house price uncertainty shocks on GDP growth increases in the early 2000s. Furthermore, posterior credible intervals indicate significant contractions in GDP growth at every observation of our sample. In comparing the ramifications of liquidity and uncertainty shocks from both the stock and house market, it is clear there are obvious differences in the response of real GDP growth throughout time. In particular, note that the real effects of liquidity shocks are not due to uncertainty within the stock and housing market. Thus, these results imply uncertainty shocks and liquidity shocks from these markets are fundamentally different.

To understand the potential asymmetries of the real effects of uncertainty shocks and liquidity shocks from our 7 variable TVP VAR, we plot in Figure 8 the differences in average impulse responses over different time periods. Our results reveal no asymmetries between the impact of uncertainty shocks in the Great Recession and other recessions in our sample. Moreover, there is no significant difference in average impulse responses between the Great Recession and non–recessionary periods. This implies there are no discernible differences (on average) between uncertainty shocks across the business cycle and over business cycle troughs in our sample. However, we can see that the impact of house market liquidity shocks on GDP growth during the 2008 recession is stronger and more persistent than in normal periods, and other recessions.

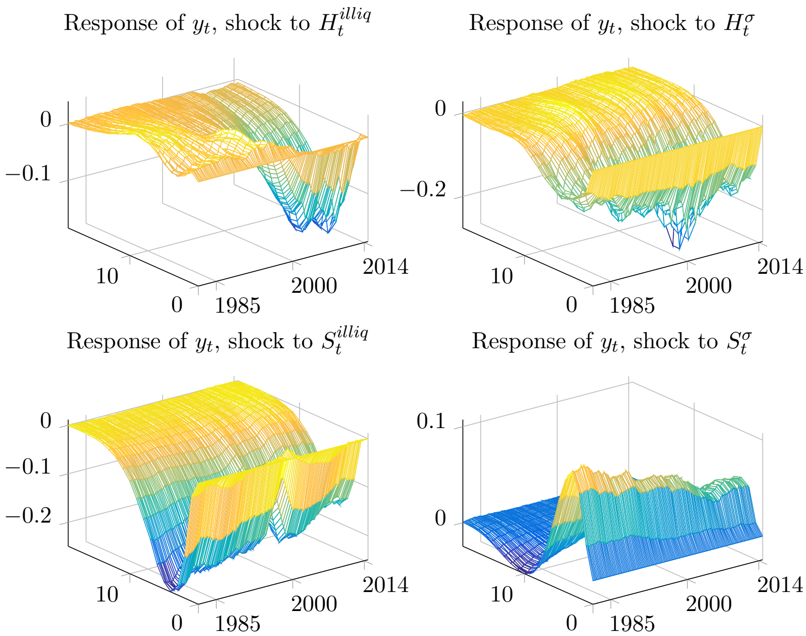


**Figure 7: Impact of Uncertainty and Liquidity Shocks on GDP growth from 1981 to 2014**

Notes: This figure plots the median impulse response functions of US real GDP growth with respect to stock and house market liquidity shocks, $S_t^{illiq}$, $H_t^{illiq}$ and stock market and house market uncertainty shocks, $S_t^{\sigma}$ and a house market uncertainty shock, $H_t^{\sigma}$ respectively. We plot the response along a 5-year horizon for each quarter of our sample 1981Q3-2014Q4. A liquidity shock constitutes a decline in market liquidity (i.e. an increase in illiquidity) and an uncertainty shock constitutes an increase in price uncertainty.

In general these findings reveal that there are stark differences between the real effects of uncertainty shocks relative to liquidity shocks. The results from our 7 variable TVP VAR

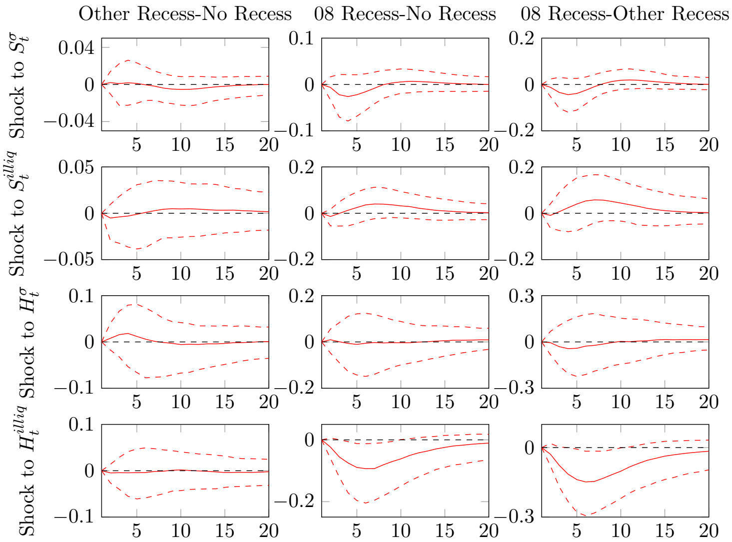


**Figure 8: Impulse Responses of GDP growth: Differences in averages over periods**
Notes: Panels one to three show the averages of differences in impulse responses of GDP growth to liquidity shocks between: other recessionary (i.e. NBER recession dates excluding the Great Recession) and non–recessionary periods (left panel: Other Recess-No Recess); The Great Recession and non–recessionary periods (middle panel: 08 Recess-No Recess) and The Great Recession and other recessionary periods (right panel: 08 Recess-Other Recess) respectively. Recessionary periods are NBER recession dates. We compute the difference in average impulse response as follows: for each draw of the Gibbs sampler, we average the impulse response over each of the selected periods, take the difference between the averages of selected periods and then calculate the quantiles over the draws. A liquidity shock constitutes a decline in market liquidity (i.e. an increase in illiquidity) and an uncertainty shock constitutes an increase in price uncertainty.

further support the analysis from our 5 variable TVP VAR. We can see that the impact of uncertainty shocks remain relatively constant throughout time; and therefore the business cycle. In particular, the response of GDP growth to stock market uncertainty shocks echoes Levine and Zervos (1998) who show a fragile link between stock market uncertainty (relative to stock market liquidity) and economic growth. Our findings with regards to house market uncertainty shocks demonstrate little variation in the contraction of real GDP growth over time. However, the sensitivity of GDP growth to house price uncertainty shocks increases slightly in the early 2000s. This links well with surging house prices in the very same period as a result of relaxes in lending constraints. Nonetheless it is difficult to ascertain asymmetries in the response of GDP growth to uncertainty shocks across the business cycle and different recessions for our sample. Therefore, our analysis reveals the real effects of uncertainty shocks from stock and house markets are fundamentally different to liquidity shocks.

## 5.2 Increasing the Information Set: TVP VAR models with Liquidity Proxies and Financial Factors

The results in previous sections of this paper rely on a relatively small information set. Therefore identification of structural shocks, and their impact on real GDP growth may be misleading; especially with respect to our structural variance decomposition. Hubrich and Tetlow (2015) use the Financial Stress Index (FSI) constructed by the Federal Reserve Board. This index relies on data from 9 variables that account for credit conditions (in the form of interest rate spreads) and the stock market[24]. The FSI is computed as a weighted average of the demeaned data where the weights are a function of the inverse sample standard deviations. However due

[24]See Table 2 in Hubrich and Tetlow (2015).

to data availability, the index may only be computed from 1988; which is too short for our study.

Therefore, to extend our information set, we rely on a quarterly version of the database in McCracken and Ng (2015). We compute financial factors using a subset of the FRED-QD database using principal component analysis. Our dataset contains 74 series that contain information on housing, interest rates, money and credit, household balance sheets, exchange rates and the stock market[25]. Following the test in Bai and Ng (2002), the number of factors present our dataset is 3. We retain only those factors whose eigenvalues are greater than 1, thus leaving us with the first two. We denote our financial factors $F_t^1$ and $F_t^2$ respectively[26]. These factors explain 80.23% of the total variance in our dataset. Specifically, $F_t^1$ and $F_t^2$ explain 46.3% and 33.93% of the overall variation respectively.

In Table 3, we report the average contribution of liquidity and financial factor shocks from our baseline 5 variable TVP VAR model (Model 1) and 3 alternative models (Models 2 to 4) to US real GDP growth volatility during the Great Recession. In Models 2 to 4, we increase the information set and estimate TVP VAR models using inflation, real GDP growth and the Federal Funds rate with combinations of our liquidity proxies ($H_t^{illiq}$, $S_t^{illiq}$ and financial factors, $F_t^1$, $F_t^2$. As we can see from Models 2 to 4, the contribution of liquidity shocks to real GDP growth volatility remains robust to including $F_t^1$ (Model 2), $F_t^2$ (Model 3) and both financial factors (Model 4). We can see that the contribution of structural liquidity shocks to real GDP growth volatility from our baseline model (Model 1) are robust to including additional financial data. There are two noteworthy points in Table 3. The first is that the average contribution of house market liquidity shocks to GDP growth variation in Model 2 falls, relative to Model 1 (i.e. our baseline model), by 5 percentage points; from 35% to 30%. Secondly, the average contribution of stock market liquidity shocks to GDP volatility in Model 4 increases by 6 percentage points (relative to Model 1); from 17% to 23%.

To obtain a better idea of how robust our baseline structural variance decomposition throughout our estimation sample, we plot in Figure 9, the posterior median of the time-varying contributions of stock and house market liquidity shocks to real GDP growth volatility from Models 1 to 4. Clearly, the contribution of stock and house market liquidity shocks to GDP growth variation from Models 2 to 4 remain remarkably similar to our baseline specification. The results from our alternative specifications imply that the impact and magnitude of our structural liquidity shocks on real GDP growth volatility are robust; even when accounting for the financial sector using a large dataset.

Overall, these results reveal that allowing for the financial sector on a broader scale has a negligible effect on the real effects of stock and house market liquidity shocks. Table 3 implies that even when accounting for the broader financial sector, liquidity shocks from stock and housing markets contribute around 50% toward the overall variation in GDP growth during the most recent recession. The plots in Figure 9 demonstrate the robustness of our structural variance decomposition over our full estimation sample. Both Table 3 and Figure 9 provide further support that liquidity shocks resonating from stock and housing markets were the main drivers of the most recent recession. The above not only demonstrates the importance of

[25] Our dataset consists of 74 series because this is the number of financial variables for which we have a balanced panel. The FRED-QD database contains 257 series on macroeconomic and financial variables from 1959 until 2015. Available from `https://research.stlouisfed.org/econ/mccracken/fred-databases/`. We also carry out factor analysis using the data on macroeconomic and financial variables in the FRED-QD database. As for the FRED-MD database in McCracken and Ng (2015), our test reveals there are 8 factors in the FRED-QD database. The leading principal component is a macroeconomic factor that is heavily correlated with US real GDP growth at 0.73. Therefore, we omit the macroeconomic variables from our analysis because of the strong correlations with both real GDP growth and inflation. Additionally, the existing macroeconomic data included in our TVP VAR model provides a feasible indication of an economy's state that is relevant for policymakers.

[26] Our subset of the FRED-QD database implicitly accounts for our credit risk proxy (see Appendix C) since it contains Moody's BAA and AAA corporate bond yields. Factors are remarkably similar when replacing the former with the difference between BAA and AAA corporate bond yields.

allowing time-variation in the structural links between asset markets and the real economy, but also supports our conjecture in allowing for contemporaneous relationships between asset markets themselves.

**Table 3: Average Contribution of Structural Liquidity and Financial Factor Shocks to US real GDP growth Volatility during the Great Recession**

| Variable | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| $H_t^{illiq}$ | 0.35 | 0.30 | 0.35 | 0.35 |
| $S_t^{illiq}$ | 0.17 | 0.18 | 0.15 | 0.23 |
| $F_t^1$ | – | 0.09 | – | 0.08 |
| $F_t^2$ | – | – | 0.11 | 0.04 |
| **Total Average Contributions** | | | | |
| $H_t^{illiq} + S_t^{illiq}$ | 0.52 | 0.48 | 0.50 | 0.58 |

Notes: This table reports the average contribution of structural liquidity and financial factor shocks over the Great Recession. Model 1 is our baseline 5 variable TVP VAR model including inflation, $\pi_t$; real GDP growth, $y_t$; the Federal Funds rate, $i_t$; House market illiquidity, $H_t^{illiq}$ and Stock market illiquidity, $S_t^{illiq}$. Models 2 is a 6 variable TVP VAR including inflation, $\pi_t$; real GDP growth, $y_t$; the Federal Funds rate, $i_t$; House market illiquidity, $H_t^{illiq}$, Stock market illiquidity, $S_t^{illiq}$ and our first financial factor, $F_t^1$. Model 3 is a 6 variable TVP VAR including inflation, $\pi_t$; real GDP growth, $y_t$; the Federal Funds rate, $i_t$; House market illiquidity, $H_t^{illiq}$, Stock market illiquidity, $S_t^{illiq}$ and our second financial factor, $F_t^2$, and Model 4 is a 7 variable TVP VAR including inflation, $\pi_t$; real GDP growth, $y_t$; the Federal Funds rate, $i_t$; House market illiquidity, $H_t^{illiq}$, Stock market illiquidity, $S_t^{illiq}$ and both financial factors, $F_t^1$, $F_t^2$.

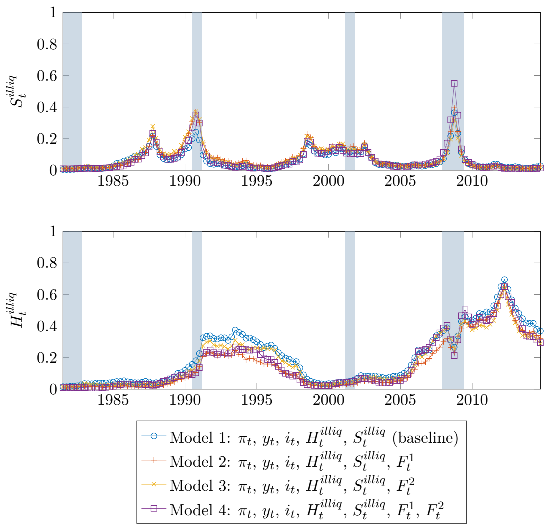


**Figure 9: Contribution of Structural Liquidity Shocks to the Overall Variance of Real GDP Growth from 1981 to 2014; Baseline and Alternative Specifications**

Notes: This figure plots the posterior median time-varying contributions of structural liquidity shocks to US real GDP growth volatility from 1981Q3–2014Q4 from our baseline TVP VAR model (Model 1) and 3 alternative models that include financial factors (Models 2–4). Model 1 includes only our liquidity proxies. Model 2 includes our liquidity proxies and $F_t^1$. Model 3 includes our liquidity proxies and $F_t^2$. Model 4 includes our liquidity proxies and both financial factors, $F_t^1$, $F_t^2$. Grey bars indicate NBER recession dates.

## 6 Conclusions

In this paper we provide insights into the links between asset market liquidity and the real economy using US data by fitting a Bayesian VAR model with time-varying parameters from 1970 to 2014. A summary of our results is as follows: first, we uncover an economically meaningful contractionary impact of stock market liquidity shocks throughout time; however the magnitude is decreasing. Second, our analysis demonstrates a stark change in the structural relationship between real GDP growth and house market liquidity from 2005 as disruptions in the property sector start to emerge. Third, we provide notable evidence of an asymmetric response of GDP growth to house market liquidity across the business cycle and across business cycle troughs. Fourth, counterfactual analysis reveals that structural liquidity shocks contribute the lion's share of variation in GDP growth–particularly during crisis periods. In the most recent recession, the average total contribution of stock and house market liquidity shocks explain 17% and 35% of the variation in real GDP growth respectively. Finally, house market liquidity shocks contributes, on average, 46% of the overall variance in real GDP growth from 2009 onwards. This implies that the fragile recovery in the US is partially due to imbalances within the property sector. Taken together, our analysis sheds light on the need for liquidity provision into asset markets; particularly during recessions preceding a property bust (Claessens et al., 2012). Consequently our study justifies attempts to inject liquidity into the property sector and stock market in response to the Great Recession.

We extend on the main results by showing that the economic impact of stock and house market liquidity shocks are robust to including stock and house price uncertainty proxies. In particular, the response of GDP to uncertainty shocks remains relatively constant throughout time. For policymakers, these results imply that house price uncertainty damages prospects for economic growth which suggests a need to monitor house price volatility. However noting liquidity conditions can propagate house price uncertainty through a variety of factors such as trading delays (Diaz and Jerez, 2013) and relaxes in borrowing constraints (Mian and Sufi, 2009), indicates liquidity provision may feed through into hindering the impact of house price uncertainty shocks. Further, the time-varying contribution of liquidity shocks to GDP growth variation are robust when accounting for the financial sector on a broad scale. Specifically, these results reveal that liquidity shocks were the main driver of GDP growth during the most recent recession. This provides further substance in favour of our conjecture to account for market specific liquidity shocks in empirical analysis.

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

# Appendices

## Appendix A: Raw Illiquidity Estimates

Table A.1 reports descriptive statistics on the raw estimates of our liquidity proxies. In Panel A we report the full sample mean and median along with sub-period means for both $RtoV_t^s$, $RtoV_t^h$ respectively. Panel B reports the contemporaneous correlations between our liquidity proxies from 1968 to 2014 along with sub-period correlations (where we denote correlation as $\rho(RtoV_t^s,\ RtoV_t^h)$). The sub sample means imply liquidity in both the stock and property market are increasing throughout time. The contemporaneous full sample correlation between our raw liquidity proxies is 0.64. Turning our attention to the sub sample correlations, there are substantial differences among decades. In particular the correlation between US stock and house market liquidity from the late 1960s until 1989 is positive; however from 1990 to 1999, correlation is -0.10. In the next decade (i.e. between 2000 and 2009), the correlation is 0.37[27]. Differences in sub sample correlations suggest the market fundamentals are different.

**Table A.1: Descriptive Statistics for Raw Estimates of Illiquidity Proxies from 1968 to 2014**

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

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

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

## Appendix B: Estimation Algorithms

### Posterior Computation of TVP VAR with Stochastic Volatility

To estimate our TVP VAR with stochastic volatility, we use the algorithm developed in Primiceri (2005); notation is consistent with Section 3. The first step is to draw the time-varying coefficients. The density of $\beta_t$, $p(\beta_t)$ can be factored following Carter and Kohn (1994) as:

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

where

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

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

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

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

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

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

because (3) can be written as

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

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

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

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

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

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

Finally, drawing the hyperparameters of the model are from inverse Wishart distributions respectively. In summary, the steps are as follows:

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

**Assessing the Convergence of the MCMC Algorithm**

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

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

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

Figure B.1 plots the inefficiency factors for the time varying coefficients of the VAR (the $\beta_t$), the non zero elements of the matrix $A_t$ and the volatilities ($\phi_{i,t}$'s) respectively–and for the model's hyperparameters, i.e. the free elements of the matrices $Q$, $S$, and $W$ respectively. The figure clearly shows that the autocorrelation of the draws is impeccably low, in the vast majority of cases below 0.8. As stressed in Primiceri (2005) and others, values of the inefficiency factors below 20 are satisfactory.

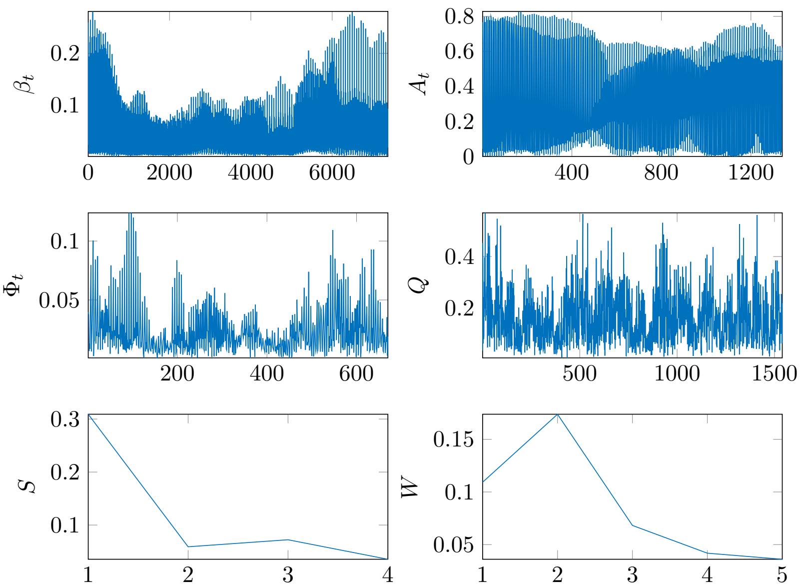


**Figure B.1: Convergence of the MCMC algorithm; Inefficiency Factors**
Notes: This figure shows the inefficiency factors computed for the draws of the elements of the matrices: $\beta_t$, $A_t$, $H_t$, $Q$, $S$ and $W$

## Appendix C: Additional Results

This section reports additional results from our benchmark analysis, along with additional robustness checks. Specifically, we report the stochastic volatility innovations of macroeconomic shocks, parameter evolution and contemporaneous relations. The stochastic volatility innovations of macroeconomic shocks track the size of shocks throughout our estimation sample. Parameter evolution and contemporaneous relations reveal the degree of time–variation within the benchmark model. We include additional robustness checks by presenting the results from an alternative structural identification and a TVP VAR model including corporate bond spreads.

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

In Figure C.1 we plot the median and one deviation percentiles of the time-varying volatility estimates of the structural shocks for our macroeconomic variables. A noteworthy point to consider is the remarkable similarities between the volatility estimates of structural shocks to the interest rate our model implies and those in Justiniano and Primiceri (2008) and Prieto et al. (2016); the former estimates are from a DSGE model.

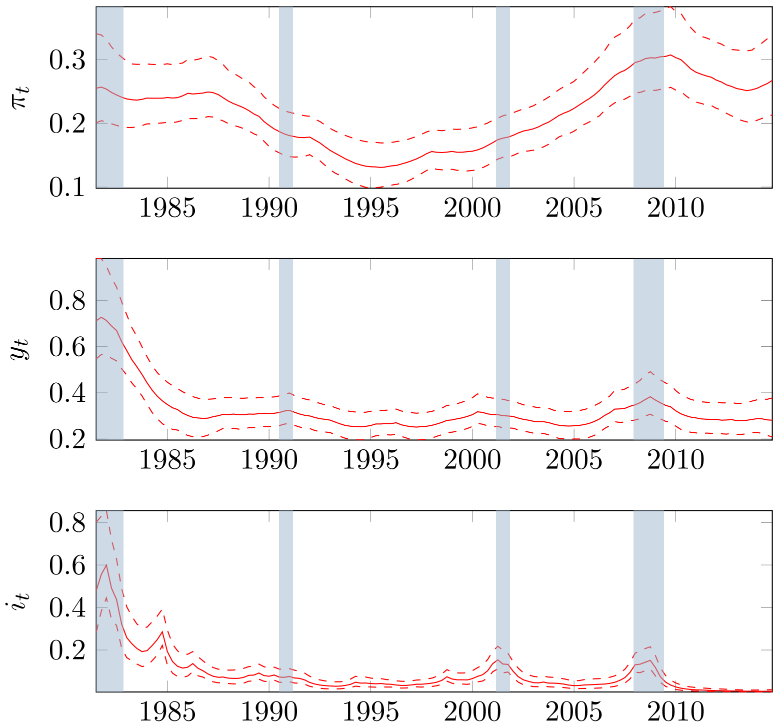


**Figure C.1: Stochastic Volatility of Macroeconomic Shocks from 1981 to 2014**
Notes: This figure shows the median and 1 standard deviation percentiles of the time-varying standard deviations of structural shocks for the inflation rate, $\pi_t$, real GDP growth, $y_t$ and the interest rate, $i_t$ from 1981-2014 respectively. Grey bars indicate NBER recession dates.

Figures C.2 and C.3 plot the evolution of the autoregressive parameters which we sum over lags and the contemporaneous relations between the variables. There is time-variation in both the time-varying coefficient matrices and the contemporaneous relations; as we can see, the degree of variation is more significant in the contemporaneous relations.

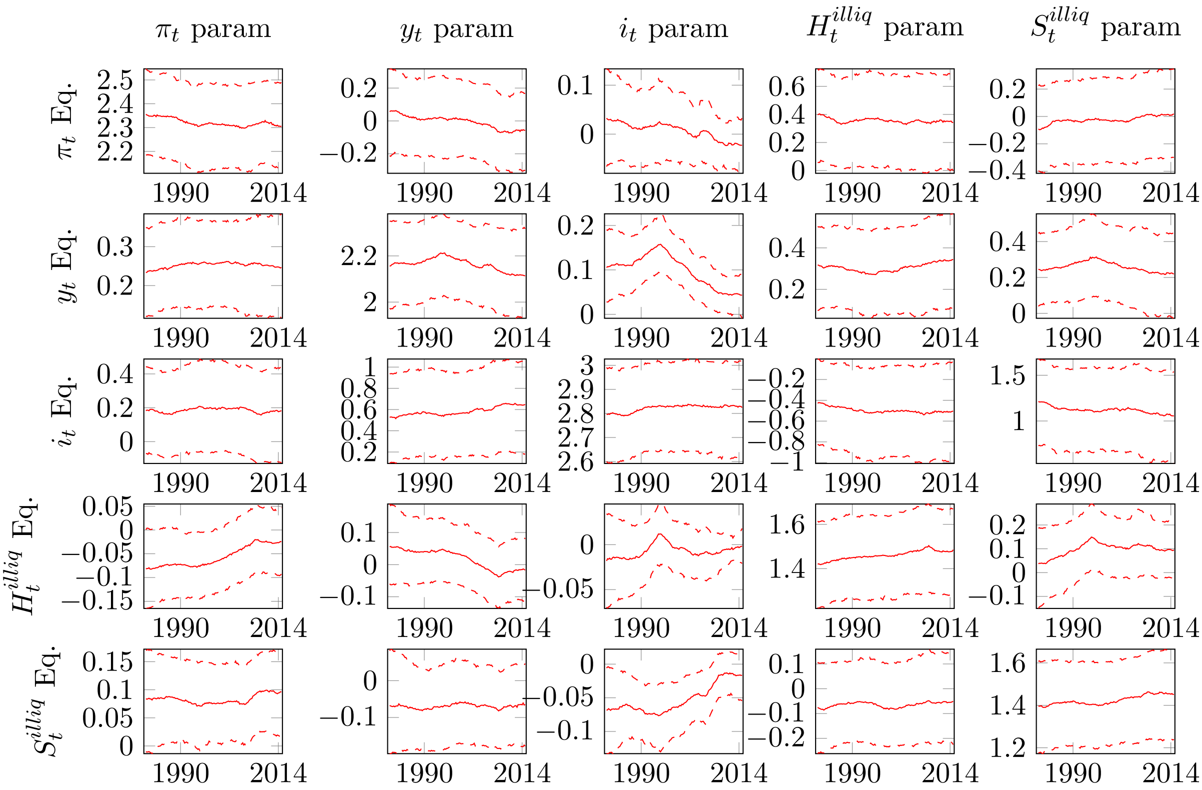


**Figure C.2: Parameter Evolution (elements of $\beta_t$)**
Notes: This figure plots the posterior median (and one standard deviations percentiles) of the autoregressive parameters summing over the lags.

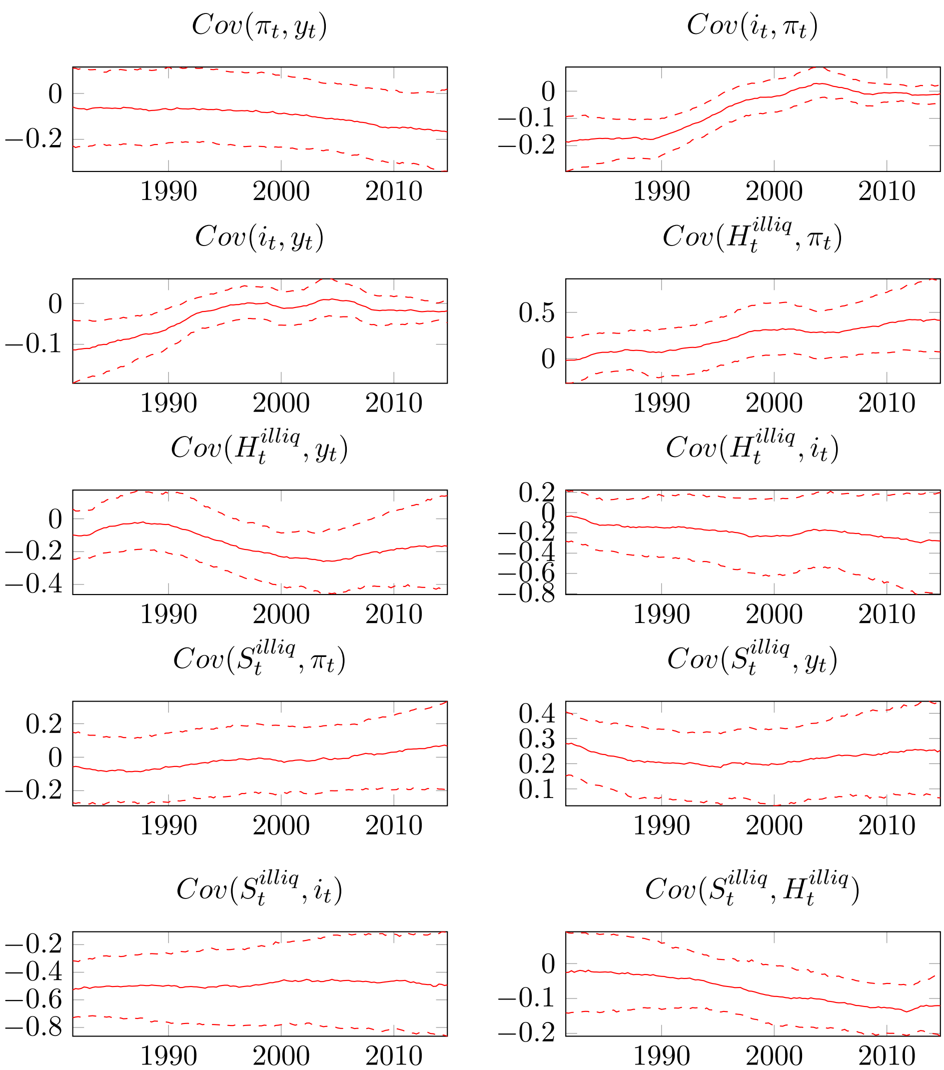


**Figure C.3: Contemporaneous Relations (elements of $A_t$)**
Notes: This figure plots the posterior median (and one standard deviations percentiles) of the contemporaneous relations between our macroeconomic and financial variables.

**Baseline TVP VAR using an Alternative Identification**

The assumptions underpinning our identification scheme requires discussion. Our baseline identification scheme places financial variables after the macroeconomic variables. This implies that our illiquidity proxies react immediately to macroeconomic shocks. Conversely macroeconomic variables are slow to respond to liquidity shocks. Another plausible assumption is that interest rates can react contemporaneously to liquidity shocks within the property sector[28]. Our alternative identification scheme places house market liquidity before the interest rate. Therefore variables enter the VAR in the following order: inflation, $\pi_t$; GDP growth, $y_t$; house market liquidity, $H_t^{illiq}$; the interest rate, $i_t$ and stock market liquidity, $S_t^{illiq}$.

Figure C.4 plots the median impulse response function of GDP to liquidity shocks. Unsurprisingly, the posterior median response of real GDP growth to stock market liquidity shocks remains similar. The impact of house market liquidity shocks under our alternative ordering remain largely similar to those from our baseline identification scheme. The only difference is the posterior median response of GDP in late 2009 reaches a trough considerably lower than the posterior median responses both during the Great Recession and the period following. Apart from this anomaly, the profile of the posterior median impulse response functions remain similar to those we report in the main text.

Figure C.5 plots the differences in average impulse responses of GDP to stock and house market liquidity shocks in different periods under our alternative identification scheme. It is clear that the same conclusions hold as in our baseline analysis for the impact of stock market liquidity shocks on GDP growth during different periods. Conversely, ordering house market liquidity before the interest rate yields different conclusions. In particular, note that our results here suggest no difference in the average impact of house market liquidity shocks between all NBER recessions (excluding the Great Recession) and non–recessionary periods. However, this result is driven by the sensitivity of GDP growth to a house market liquidity shock in late 2009 (see Figure C.4); consequently the response of GDP growth in this time period influences the average impulse response of GDP in non–recessionary periods. Similarly the results yield no difference, on average, between the Great Recession and non–recessionary periods. However, there are differences in the real effects of house market liquidity shocks between the Great Recession and other recessions within our sample. We find that the severity of liquidity shocks, in terms of duration and magnitude, is greater ( on average) in the most recent recession.

[28]Björnland and Leitemo (2009) place house prices before the interest rate in a standard VAR model.

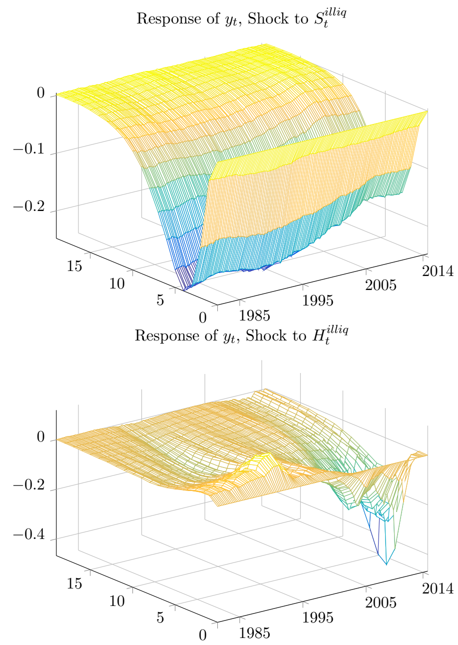


**Figure C.4: Impact of Liquidity Shocks on GDP growth 1981 to 2014**
Notes: This figure plots the median impulse response functions of US real GDP growth with respect to: a unit stock and house market liquidity shock respectively. We plot the response along a 5-year horizon for each quarter of our sample 1981Q3-2014Q4. A liquidity shock constitutes a decline in market liquidity (i.e. an increase in illiquidity).

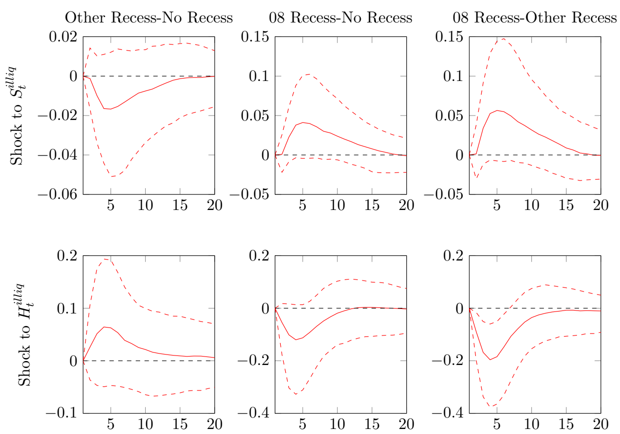


**Figure C.5: Impulse Responses of GDP growth: Differences in averages over periods**
Notes: Panels one to three show the averages of differences in impulse responses of GDP growth to liquidity shocks between: other recessionary (i.e. NBER recession dates excluding the Great Recession) and non–recessionary periods (left panel: Other Recess-No Recess); The Great Recession and non–recessionary periods (middle panel: 08 Recess-No Recess) and The Great Recession and other recessionary periods (right panel: 08 Recess-Other Recess) respectively. Recessionary periods are NBER recession dates. We compute the difference in average impulse response as follows: for each draw of the Gibbs sampler, we average the impulse response over each of the selected periods, take the difference between the averages of selected periods and then calculate the quantiles over the draws. A liquidity shock constitutes a decline in market liquidity (i.e. an increase in illiquidity).

### A TVP VAR Model Including Corporate Bond Spreads

In this section we extend upon our model in the main body of the paper and account for credit risk. To proxy credit risk we use the corporate bond spread, which we measure as the difference between Moody's BAA and AAA corporate bond yields; available from the Federal Reserve Bank of St. Louis. Justiniano et al. (2015) show that both credit market shocks and housing market disturbances are required in order to explain the recent US experience, and match the data. Therefore, omitting credit risk may over exaggerate the impact of our liquidity proxies in the counterfactual structural variance decomposition and influence impulse response analysis.

To investigate further, we estimate a 6 variable TVP VAR model as in (3)–(8) including Moody's BAA-AAA corporate bond yield spread. The results below correspond to the same priors we impose on the system in the main text, variables enter the VAR in the following manner: inflation, $\pi_t$; real GDP growth, $y_t$; the Federal Funds rate, $i_t$; house market illiquidity, $H_t^{illiq}$; corporate bond spread, $CR_t$; and stock market illiquidity, $S_t^{illiq}$ respectively. For the sake of brevity, we do not report convergence diagnostics for the model; however inefficiency factors remain uniformly low. Furthermore, note that the main messages from this analysis are consistent to different orderings of our financial variables. We postulate shocks to the corporate bond spread capture credit conditions worsening which therefore depress real GDP growth.

Figure C.6 plots the posterior median and one standard deviation percentiles of the stochastic volatility of our liquidity and credit risk shocks. In general, the volatility of credit risk shocks surge temporarily in conjunction with the 1999 recession, the period following the burst of the dot-com bubble and the Great Recession respectively. Furthermore, notice the persistent increases from 2005–2009; which implies our model may be picking up disturbances in credit markets before the crash in 2008. Note also that the shape and time-variation in the volatility of our structural liquidity shocks remain similar to Figure 3 in the main text.

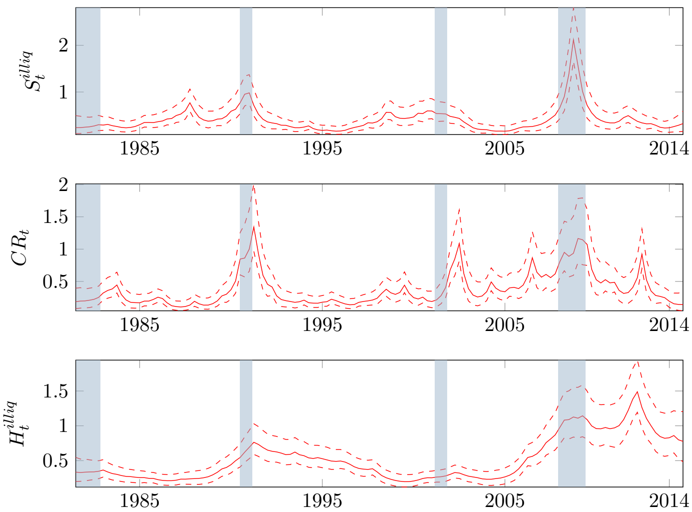


**Figure C.6: Stochastic Volatility of Liquidity and Credit Risk Shocks from 1981 to 2014**

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

In Figure C.7 we plot the posterior median impulse response functions of real GDP growth for every quarter in our sample (i.e. 1981Q3-2014Q4) with respect to liquidity and credit risk shocks. The response of GDP growth with respect to credit risk shocks is in the middle panel of Figure C.7. We can see that shocks to credit risks yield considerable contractions to real GDP growth. The impact of credit risk shocks is greatest immediately following the 2001 recession. Notably, posterior credible intervals (68%) do not include zero for every impulse response function for up to 6 quarters. Turning our attention to the impact of stock and house market liquidity shocks, the shape and profile of the posterior median response of GDP for every observation remains consistent with Figure 4 in the main text.

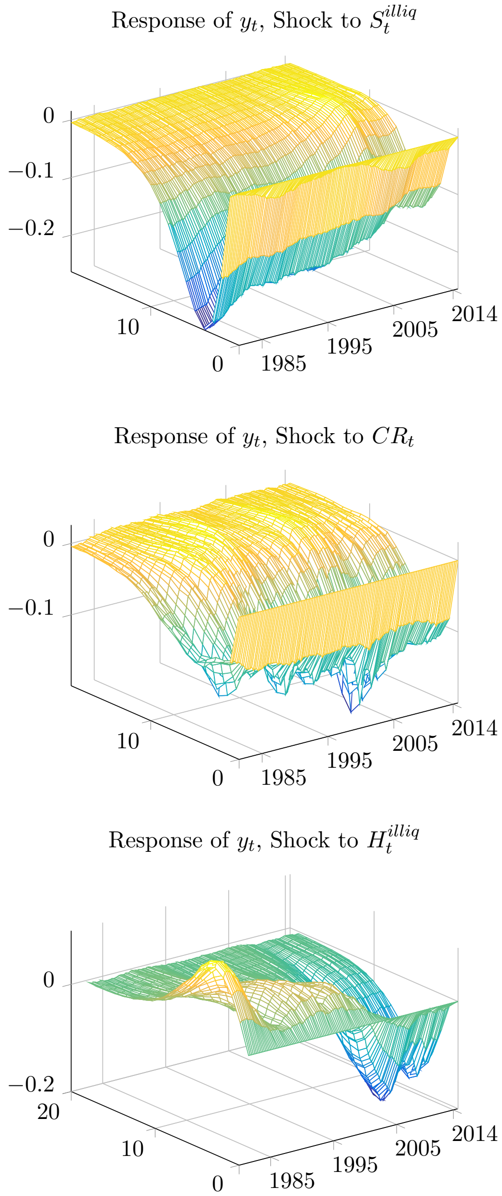


**Figure C.7: Impact of Liquidity and Credit Risk Shocks on GDP growth 1981 to 2014**

Notes: This figure plots the median impulse response functions of US real GDP growth with respect to: a unit stock market liquidity shock; a unit credit risk shock and a unit house market liquidity shock respectively. We plot the response along a 5-year horizon for each quarter of our sample 1981Q3-2014Q4. A liquidity shock constitutes a decline in market liquidity (i.e. an increase in illiquidity).

We show in Figure C.8 the difference in average impulse response functions of real GDP growth to liquidity and credit risk shocks respectively. This is analogous to Figure 5 in the main text and we compute in the exact same manner. Again, the implications are similar to our main results. However, the response of real GDP growth to stock market liquidity shocks is stronger and more persistent in other recessions within our sample (see the top left panel of Figure C.8). This result is unsurprising and intuitive from Figure C.7, since GDP growth becomes more resilient to stock market liquidity shocks throughout time. Adding to this, liquidity shocks in the US housing sector are stronger and more persistent in the most recent recession (see the bottom middle and right panels of Figure C.8) which is consistent with our main analysis. Note also that our analysis in the middle panel of Figure C.8 reports no difference in the sensitivity of GDP growth to credit risk shocks (on average) within our sample.

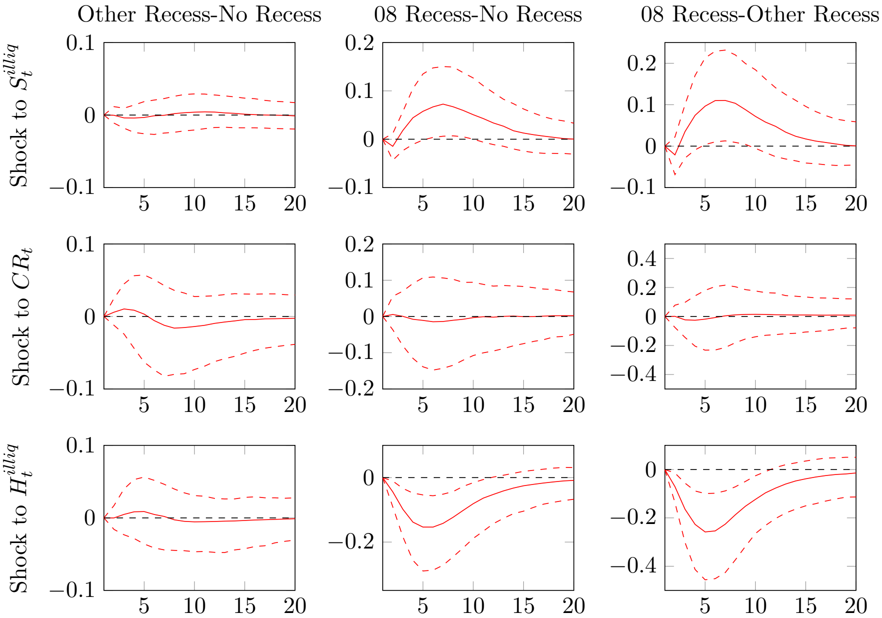


**Figure C.8: Impulse Responses of GDP growth: Differences in averages over periods**

Notes: Panels one to three show the averages of differences in impulse responses of GDP growth to liquidity and credit risk shocks between: other recessionary (i.e. NBER recession dates excluding the Great Recession) and non–recessionary periods (left panel: Other Recess-No Recess); The Great Recession and non–recessionary periods (middle panel: 08 Recess-No Recess) and The Great Recession and other recessionary periods (right panel: 08 Recess-Other Recess) respectively. Recessionary periods are NBER recession dates. We compute the difference in average impulse response as follows: for each draw of the Gibbs sampler, we average the impulse response over each of the selected periods, take the difference between the averages of selected periods and then calculate the quantiles over the draws. A liquidity shock constitutes a decline in market liquidity (i.e. an increase in illiquidity).

A final factor to consider is the robustness of our structural variance decomposition. There is a possibility the financial and asset variables we include in our main model are picking up important information from credit markets. For example, a relaxation (contraction) in credit conditions can aid (hinder) prosperity in the housing market when borrowing constraints are not (are) binding (see Mian and Sufi (2009), Iacoviello and Neri (2010)). Without explicitly accounting for credit risk, there may be over emphasis in the importance of our house market liquidity shocks for the overall variation in GDP growth[29]. Similarly, Justiniano et al. (2015) find that credit shocks are not enough to solely explain the Great Recession and fragile recovery for the US; disturbances in the housing market are thought to help match the data.

Therefore, we follow Benati and Mumtaz (2007) and perform a counterfactual structural variance decomposition of US Real GDP growth directly comparable to Figure 6 in the main body. Figure C.9 reports the time-varying contributions, which we express as the median and one standard deviation percentiles of the distributions, of: stock market liquidity shocks (top panel); credit risk shocks (middle panel); and house market liquidity shocks (bottom panel), to the overall variation in Real GDP growth respectively. The following analysis and comments are with regards to the posterior median estimates of the distributions of our structural variance decomposition. Clearly there is a considerable amount of time-variation in the contributions of our structural liquidity and credit risk shocks.

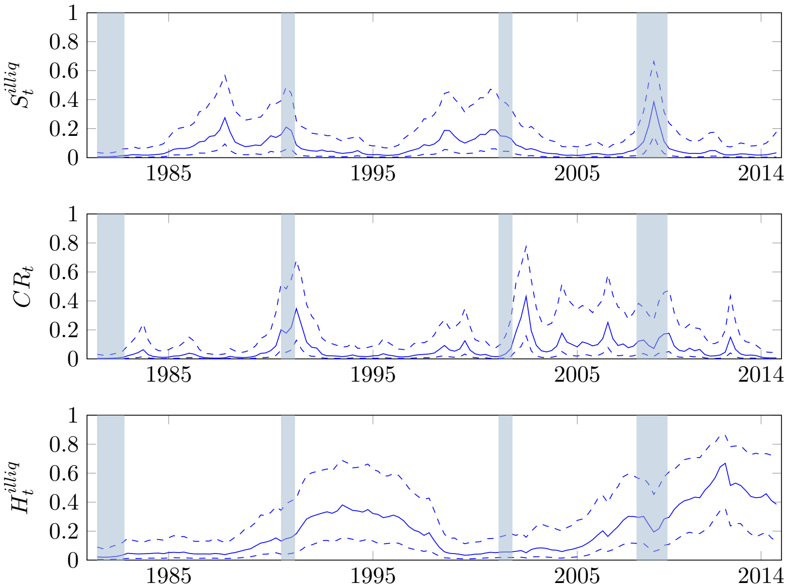


**Figure C.9: Contribution of Structural Liquidity and Credit Risk Shocks to the Overall Variance of Real GDP Growth from 1981 to 2014**

Notes: This figure plots the median and one standard deviation percentiles of the contribution of structural stock market liquidity, credit risk, and house market liquidity shocks to real GDP growth from 1981 to 2014. Grey bars indicate NBER recession dates.

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

In addition, the contribution of credit risk shocks to GDP growth variance surges–particularly

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

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

On average during the most recent recession, stock market liquidity shocks explain 17%; credit risk shocks explain 12.2%, and house market liquidity shocks explain 23.7% of the variance in GDP growth respectively. Therefore the total average contribution of liquidity and credit risk shocks is 52.9%–which is consistent with the 51.6% figure we present in the main body. Overall, the shapes of the changing contributions, resemble the stochastic volatility plots this model implies. Therefore the driving force of time-variation in the contributions are changing shock sizes. Interestingly, both this, and the analysis in the main text uncovers an important role for the stock market in the most recent recession. Contrasting to Prieto et al. (2016) and Justiniano et al. (2015), our analysis reveals that once isolating the liquidity component from stock prices, the stock market is a key explanatory factor for US GDP growth variance during recessions; particularly during 2008 and 2009. This implies that once accounting for stock market conditions through prices and quantities, there is a credible link between the stock market and GDP growth during times of recession.

These results reveal an important structural and episodic relationship between both stock market liquidity shocks and real GDP fluctuations, and credit risk shocks and real GDP variation. To contrast we uncover that the contributions of house market liquidity shocks to GDP growth variance change smoothly in conjunction with changing shock sizes hitting the system throughout time. Combining with the conclusions we report in the main text, this analysis reveals that the impact and real effects liquidity shocks is robust to incorporating credit risk into the model.

# References

Abbate, A., Eickmeier, S., Lemke, W., Marcellino, M., 2016. The Changing International Transmission of Financial Shocks: Evidence from a Classical Time-Varying FAVAR. Journal of Money, Credit and Banking 48 (4), 573–601.

Acharya, V. V., Shin, H. S., Yorulmazer, T., 2011. Crisis Resolution and Bank Liquidity. Review of Financial Studies 24 (6), 2166–2205.

Adrian, T., Shin, H. S., 2008. Liquidity, Monetary Policy, and Financial Cycles. Federal Reserve Bank of New York, Current Issues in Economics and Finance 14, 1–7.

Amihud, Y., 2002. Illiquidity and Stock Returns: Cross-section and Time-series Effects. Journal of Financial Markets 5 (1), 31–56.

Arestis, P., Demetriades, P. O., Luintel, K. B., 2001. Financial Development and Economic Growth: The Role of Stock Markets. Journal of Money, Credit and Banking 33 (1), 16–41.

Bai, J., Ng, S., 2002. Determining the Number of Factors in Approximate Factor Models. Econometrica 70 (1), 191–221.

Balke, N. S., 2000. Credit and Economic Activity: Credit Regimes and Nonlinear Propagation of Shocks. Review of Economics and Statistics 82 (2), 344–349.

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

Bernanke, B. S., Blinder, A. S., 1988. Credit, Money, and Aggregate Demand. American Economic Review 78 (2), 435–39.

Björnland, H. C., Leitemo, K., 2009. Identifying the Interdependence between US Monetary Policy and the Stock Market. Journal of Monetary Economics 56 (2), 275–282.

Brunnermeier, M. K., Pedersen, L. H., 2009. Market Liquidity and Funding Liquidity. Review of Financial Studies 22 (6), 2201–2238.

Campbell, J. Y., Cocco, J. F., 2007. How Do House Prices Affect Consumption? Evidence from Micro Data. Journal of Monetary Economics 54 (3), 591–621.

Carroll, C. D., Hall, R. E., Zeldes, S. P., 1992. The Buffer-Stock Theory of Saving: Some Macroeconomic Evidence. Brookings Papers on Economic Activity 23 (2), 61–156.

Carter, C. K., Kohn, R., 1994. On Gibbs Sampling for State Space Models. Biometrika 81 (3), 541–553.

Christiano, L. J., Motto, R., Rostagno, M., 2010. Financial Factors in Economic Fluctuations. ECB Working Paper, No. 1192.

Claessens, S., Kose, M. A., Terrones, M. E., 2012. How do Business and Financial Cycles Interact? Journal of International Economics 87 (1), 178–190.

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.

Connolly, R., Stivers, C., Sun, L., 2005. Stock Market Uncertainty and the Stock-bond Return Relation. Journal of Financial and Quantitative Analysis 40 (01), 161–194.

Davig, T., Hakkio, C., 2010. What is the Effect of Financial Stress on Economic Activity? Economic Review-Federal Reserve Bank of Kansas City 95 (2), 35–62.

Demirgüç-Kunt, A., Levine, R., 1996. Stock Markets, Corporate Finance, and Economic Growth: An Overview. The World Bank Economic Review 10 (2), 223–239.

Diaz, A., Jerez, B., 2013. House Prices, Sales, and Time On The Market: A Search-Theoretic Framework. International Economic Review 54 (3), 837–872.

Eickmeier, S., Lemke, W., Marcellino, M., 2015. Classical Time-Varying FAVAR Models - Estimation, Forecasting and Structural Analysis. Journal of the Royal Statistical Society, Series A 178 (3), 493–533.

Florackis, C., Giorgioni, G., Kostakis, A., Milas, C., 2014. On Stock Market Illiquidity and Real-Time GDP Growth. Journal of International Money and Finance 44, 210–229.

Florackis, C., Gregoriou, A., Kostakis, A., 2011. Trading Frequency and Asset Pricing on the London Stock Exchange: Evidence from a New Price Impact Ratio. Journal of Banking & Finance 35 (12), 3335–3350.

Forsberg, L., Ghysels, E., 2007. Why do Absolute Returns Predict Volatility so Well? Journal of Financial Econometrics 5 (1), 31–67.

Galí, J., Gambetti, L., 2009. On the Sources of the Great Moderation. American Economic Journal: Macroeconomics 1 (1), 26–57.

Gilchrist, S., Zakrajšek, E., 2012. Credit Spreads and Business Cycle Fluctuations. American Economic Review 102 (4), 1692–1720.

Goyenko, R. Y., Holden, C. W., Trzcinka, C. A., 2009. Do Liquidity Measures Measure Liquidity? Journal of Financial Economics 92 (2), 153–181.

Harvey, C. R., 1988. The Real Term Structure and Consumption Growth. Journal of Financial Economics 22 (2), 305–333.

He, C., Wright, R., Zhu, Y., 2015. Housing and Liquidity. Review of Economic Dynamics 18 (3), 435–455.

Hubrich, K., Tetlow, R. J., 2015. Financial Stress and Economic Dynamics: The Transmission of Crises. Journal of Monetary Economics 70, 100–115.

Iacoviello, M., Neri, S., 2010. Housing Market Spillovers: Evidence from an Estimated DSGE Model. American Economic Journal: Macroeconomics 2 (2), 125–164.

Jaccard, I., 2013. Liquidity Constraints, Risk Premia, and the Macroeconomic Effects of Liquidity Shocks. ECB Working Paper No 1525.

Jermann, U., Quadrini, V., 2012. Macroeconomic Effects of Financial Shocks. American Economic Review 102 (1), 238–271.

Justiniano, A., Primiceri, G. E., 2008. The Time-Varying Volatility of Macroeconomic Fluctuations. American Economic Review 98 (3), 604–641.

Justiniano, A., Primiceri, G. E., Tambalotti, A., 2015. Household Leveraging and Deleveraging. Review of Economic Dynamics 18 (1), 3–20.

Kim, S., Shephard, N., Chib, S., 1998. Stochastic Volatility: Likelihood Inference and Comparison with ARCH Models. Review of Economic Studies 65 (3), 361–393.

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

Kyle, A. S., 1985. Continuous Auctions and Insider Trading. Econometrica 53 (6), 1315–1335.

Lesmond, D. A., Ogden, J. P., Trzcinka, C. A., 1999. A New Estimate of Transaction Costs. Review of Financial Studies 12 (5), 1113–1141.

Levine, R., Zervos, S., 1998. Stock Markets, Banks, and Economic Growth. American Economic Review 88 (3), 537–558.

Longstaff, F. A., 2004. The Flight-to-Liquidity Premium in US Treasury Bond Prices. Journal of Business 77 (3), 511–526.

McCracken, M. W., Ng, S., 2015. FRED-MD: A Monthly Database for Macroeconomic Research. Journal of Business & Economic Statistics (Forthcoming).

Mian, A., Sufi, A., 2009. The Consequences of Mortgage Credit Expansion: Evidence from the US Mortgage Default Crisis. Quarterly Journal of Economics 124 (4), 1449–1496.

Mian, A., Sufi, A., Trebbi, F., 2015. Foreclosures, House Prices, and the Real Economy. Journal of Finance 70 (6), 2587–2634.

Næs, R., Skjeltorp, J. A., Ødegaard, B. A., 2011. Stock Market Liquidity and the Business Cycle. Journal of Finance 66 (1), 139–176.

Ortalo-Magne, F., Rady, S., 2006. Housing Market Dynamics: On the Contribution of Income Shocks and Credit Constraints. Review of Economic Studies 73 (2), 459–485.

Pástor, Ľ., Stambaugh, R. F., 2003. Liquidity Risk and Expected Stock Returns. Journal of Political Economy 111 (3), 642–685.

Prieto, E., Eickmeier, S., Marcellino, M., 2016. Time Variation in Macro-Financial Linkages. Journal of Applied Econometrics DOI: `http://onlinelibrary.wiley.com/doi/10.1002/jae.2499/pdf` (Forthcoming).

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

Roll, R., 1984. A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market. Journal of Finance 39 (4), 1127–1139.

Sadka, R., 2006. Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk. Journal of Financial Economics 80 (2), 309–349.

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

Stein, J. C., 1995. Prices and Trading Volume in the Housing Market: A Model with Down-Payment Effects. Quarterly Journal of Economics 110 (2), 379–406.

Stock, J. H., Watson, M. W., 1999. Forecasting Inflation. Journal of Monetary Economics 44 (2), 293–335.

Stock, J. H., Watson, M. W., 2012. Disentangling the Channels of the 2007-2009 Recession. Brookings Papers on Economic Activity 44, 81–156.

Swiston, A. J., 2008. A US Financial Conditions Index: Putting Credit where Credit is Due. IMF Working Paper No. 08/161.