A Sparse Measure of Liquidity, and the Impact of Monetary Policy
Garo Garabedian\textsuperscript{a,}\textsuperscript{*}

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We incorporate techniques from recent advances in the macroeconomic forecasting literature to acquire a sparse representation of liquidity for the US stock market. This common market liquidity measure allows us to examine the interaction between market and funding liquidity, and to gauge the impact of monetary policy while taking into account these macro-financial linkages. Most importantly, we examine the effects of the Federal Reserve’s recent episodes of unconventional policy, with its large scale asset purchases, using a large-scale Bayesian VAR. We find a differential impact of each quantitative easing period on market liquidity, with a strong positive impact found during the first period, and a detrimental effect on liquidity during QE2. Finally, we also incorporate a Bayesian factor-augmented framework, in order to track back the effect of monetary policy on each individual liquidity measure. Pushing this exercise to the limit, gives us a more detailed insight on the underlying importance of each dimension of liquidity.

Keywords: market liquidity; funding liquidity; monetary policy; transaction costs; price impact; trading volume; macro-finance linkages; financial stability; Bayesian VAR.

JEL Classification: G01, G12, G14, E44

\textsuperscript{*} E-mail addresses: Garo.Garabedian@centralbank.ie
\textsuperscript{a} Monetary Policy Division, Central Bank of Ireland; and Ghent University

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1 Introduction

Despite the popularity of the Large Asset Purchase Programs (LSAPs), their effectiveness has been heavily debated (Kuttner, 2018). More specifically, there are questions on how the effect of these measures on financial markets trickled through to the wider economy (Boneva et al., 2016). One recent strand of literature examines the impact of such unconventional monetary policy measures on Treasury market liquidity, and finds mixed effects. For example, the IMF (2015) highlights that a central bank can take on the role of a large and reliable market maker, but at the same time warn that LSAPs can have adverse effects on liquidity. Christensen and Gillan (2018) point at the possibility for QE programs to reduce priced frictions to trading. While Bonner et al. (2018) warn that the effects of QE are mixed. Moreover, there is increased attention for a liquidity channel in order to explain monetary policy transmission during recent years. We find both empirical and theoretical evidence of this in Gagnon et al. (2011), Adrian et al (2017), and Lagos and Zhang (2018).

The goal of our paper is threefold. Firstly, we construct a sparse measure of market liquidity that incorporates the full set of information on liquidity. This cloud of information is shown in figure 1. We start at the stock level, by constructing market liquidity measures for every firm within the S&P 500, tracking additions and deletions, since 1962. We repeat this exercise for each of the thirty-six individual liquidity measures that we incorporate in our analysis. For each liquidity measure we compute a weighted market liquidity measure across all the S&P500 stocks. We then distill the common factor from these separate market liquidity measures into one sparse metric. Our common stock market liquidity measure typically spikes up dramatically in historical periods of financial stress and accompanying recessions. In this context, we can also investigate the link between market liquidity and funding liquidity, highlighted through multiple measure.

Secondly, we gauge the effect of unconventional monetary policy on liquidity in the setting of a large Bayesian VAR which allows us to incorporate the important macro-financial linkages. We apply conditional forecasting techniques (Waggoner and Zha, 1999) to create a no policy world. This setting also allows for a more structural analysis where we can incorporate impulse response function using a mix of zero and sign restrictions (following D’Amico et al., 2017) in order to analyze the size of the liquidity channel.

Finally, relaxing the idea of sparsity, and incorporating the full set of liquidity

\[1\text{Researchers have also starting looking more broadly at the impact of central bank actions on tail risk (Hattori et al. 2016) and uncertainty (Husted et al., 2017)\]
in a Factor-augmented Bayesian VAR, allows us to pinpoint which dimensions of liquidity get affected most by changes in monetary policy over time. This allows us to better understand the different dimensions of liquidity.

Our paper is set up as follows. Section 2 describes the construction of our stock market liquidity measure by separately aggregating across stocks and measures. This allows us to examine the impact of US unconventional monetary policy on our new liquidity metric in a large Bayesian VAR framework, taking into account the differential impact of each period of quantitative easing, with its distinctive properties. Finally, section 4 describes the importance of each individual liquidity measures, in the context of these macro-financial linkages, and relies on a FAVAR setting.

2 Common Market Liquidity Measure

When thinking about the concept of liquidity, we encounter several dimensions each explaining a specific aspect of liquidity (Kyle, 1985, Pastor and Stambaugh, 2003, Amihud et al., 2005, Fong et al., 2013). This multi-layered nature has inspired empirical economists to construct many different methods to measure this latent concept. However, there is very little unanimity in the literature on how to model this large array of information in a sparse or comprehensive way. We apply state of the art statistical techniques developed over the last decades, and more specifically within the (Bayesian) forecasting literature, in order to extract the most useful signals contained in the information set, without throwing away any useful information. Our approach is similar in spirit to Hallin et al. (2011), but we extend the information set to include most of the existing market liquidity measures in the literature.

2.1 Dynamic Factor Analysis

Dynamic factor models have often been applied in macro-econometrics for both forecasting and structural analysis (Stock and Watson, 2016), and provide a reli-

\[2\] Commonly applied techniques as ridge and lasso analysis, exploring the literature on sparsity and model selection

\[3\] which focuses on the shrinkage of parameters in order to deal with the curse of dimensionality, and the incorporation of prior beliefs

\[4\] We incorporate thirty-six liquidity proxies, as similarly explored by Garabedian and Inghelbrecht (2015) representing eight different spheres of liquidity, based on spread measures, Roll measures, zero returns measures, Fong measures, effective Tick measures, Amihud measures, volume measures, order flow measure. All measures are expressed as such to denote illiquidity, and all measures are constructed on a monthly frequency. For this purpose, we use daily data from the CRSP database, starting from 1962 until the end of 2013.
able statistical framework for the estimation of synthetic indices, for example of business cycle conditions (Bok et al., 2017). A dynamic factor model assumes that many observed variables \((y_{1,t}, \ldots, y_{n,t})\) are driven by a few unobserved dynamic factors \((f_{1,t}, \ldots, f_{r,t})\), while the features that are specific to individual series, such as measurement errors, are captured by idiosyncratic errors \((e_{1,t}, \ldots, e_{n,t})\). We can depict the model through the following equation:

\[
y_{i,t} = \lambda_{i,1} f_{1,t} + \ldots + \lambda_{i,r} f_{r,t} + e_{i,t} \text{ for } i = 1, \ldots, n
\]  

(1)

which links the data \(y_{i,t}\) to the \(r\) latent common factors \(f_{1,t}, \ldots f_{r,t}\), through the factor loadings \(\lambda_{i,1}, \ldots, \lambda_{i,r}\).

Our methodology, where we extract a latent variable from an observable dataset, is close in spirit to the current literature on the natural rate of interest (Holston, Laubach and Williams, 2016), and on shadow rates (Lombardi and Zhu, 2014, Wu and Xia, 2016).  

2.2 Extracting Market Liquidity

The starting point for our sparsity exercise is the large available information set on liquidity, covering a wide range of dimensions, definitions, and proxies. This cloud of information is shown in figure 1. Although our list is not exhaustive, we incorporate thirty-six measures of liquidity that are most widely used in the literature.\(^5\) The individual liquidity measures are summarized in table 3 of the appendix. Following Garabedian and Inghelbrecht (2015), we group the measures according to eight specific dimensions.

Practically, we construct our market liquidity through the following steps. We start at the stock level, by constructing a market liquidity measures for every firm within the S&P 500, tracking additions and deletions, since 1962. As common in the literature, the data is standardized.\(^6\) We repeat this exercise for each of the thirty-six individual liquidity measures that we incorporate in our analysis. This allows us to construct a market capital weighted measure for S&P500 as a whole, \(^{5}\)Given our aim to incorporate liquidity in a macroeconomic set up and to analyse macro-financial spillovers, we merely focus on low frequency liquidity measures, which are at least available on a daily frequency. Moreover, this allows us to get a comparable and easily accessible definition for market liquidity, without availability constraints.\(^{6}\)However, given several institutional changes (tick size, regulatory adjustments) over the sample we are confronted with breakpoints, and we can detect significant shifts in the mean of many liquidity variables over time. This irregularity in the observations is overcome by standardizing over a smaller moving window of 60 observations, equivalent to 5 years.
for every individual liquidity measure in our analysis. Finally, as a last step, we distill the common factor from these separate market liquidity measures by taking the common factor of every market liquidity proxy.

Our aggregation method differs substantially from similar exercises in the past (Korajczyk and Sadka, 2008; Hallin et al., 2011), and is more closely aligned with recent advances in macroeconomics, most prominently described by Stock and Watson (2011). They typically summarize economic activity by a large set of variables, consisting of for example industrial production or harmonized consumer prices, whereby the latter variables can in turn be weighted averages over a basket of goods or activities. This methodology provides a more intuitive way of understanding the different components that make up market liquidity, and does not lump up commonalities across stocks and across measures simultaneously, but carefully separates every step.

Figure 2 depicts our common market liquidity measure together with historical periods of financial stress and recessions (highlighted by the vertical shaded areas and vertical black dotted lines). Liquidity spikes up dramatically in the context of financial duress, as documented in the literature. For example, market liquidity can be affected by asset price drops and induced fire sales, which in turn can lead to liquidity feedback loops. Moreover, collapses in liquidity are often contagious across financial markets (IMF, 2015). Overall, our measure seems successful at picking up the most important episodes throughout the whole sample period, thus exhibiting a capacity to detect dry ups in liquidity caused by different types of financial distress, in a continuously changing financial environment. This gives us additional reassurance on the benefits of incorporating all of the different dimensions of liquidity to construct an all-encompassing measure.

This framework also allows us to investigate the link between market liquidity and funding liquidity, highlighted in figure 3. The upper panel examines the relationship with the excess bond premium (Gilchrist and Zakrajšek, 2012) and the Ted rate on the left hand side, and the noise measure (Hu et al., 2013) on the right hand side. The lower panel highlights the link with the MOVE measure on the left, and with the implied stock market volatility on the right. Although these funding liquidity measures are closely linked with our market liquidity measure, the relation seems markedly strongly during periods of financial stress (Fleming et al., 2018).

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7 We also construct equally weighted market liquidity measures for the S&P500 as a whole, which does not impact the results dramatically.

8 Acharya et al. document that dry ups in liquidity were a significant factor in exacerbating the uncertainty surrounding the valuation of asset-backed securities.
3 Impact of Unconventional Monetary Policy on Market Liquidity

3.1 Large Scale Bayesian VAR

When applying a vector autoregressive (VAR) framework, even systems of a moderate size yield a large number of coefficients that have to be estimated, hence the risk of over-parametrisation. Let $Y_t = (y_{1,t}, y_{2,t}, \ldots, y_{n,t})$ be a $n \times 1$ vector of endogenous data,

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + CX_t + \varepsilon_t \quad (1)$$

where $A_1, A_2, \ldots, A_p$ are $p$ matrices of dimension $n \times n$ containing the parameters for the endogenous variables. Similarly, $C$ is an $n \times m$ matrix with the coefficients for the exogenous regressors, which are captured by an $m \times 1$ vector $X_t$ (featuring the constant terms, the time trends, and other exogenous data series). Lastly, $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \ldots, \varepsilon_{n,t})$ is a vector of residuals following a multivariate normal distribution: $\varepsilon_t \sim N(0, \Psi)$.

In a Bayesian framework, the technique of applying shrinkage offers a practical solution to overcome the curse of dimensionality, through the incorporation of prior beliefs on the coefficients. The standard approach is to utilize a Minnesota prior, as suggested by Litterman (1986). Practically, this boils down to shrinking the diagonal elements of $A_1$ to one, and the remaining coefficients in $A_1, \ldots, A_p$ to zero. This prior specification embodies the belief that more recent lags carry more reliable info in comparison with more distant ones, and that the own lags should be able to explain more of the variation of a given variable than the lags of other variables.

When studying the impact of monetary policy on liquidity, we want to incorporate all of the potential macro-financial variables that can affect this relationship, thus leading to a large number of variables in our VAR framework. Banbura et al. (2010) convincingly demonstrate that a Bayesian VAR (BVAR) is the appropriate tool for allowing researchers to incorporate a large set of macroeconomic and financial variables, and for forecasting and structural analysis when one conditions on a large information set. The theoretical motivation for working with large BVARs can be found with De Mol et al. (2008), who argue that for time series with strong

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9 Every variable in a VAR is explicitly modeled as a function of the other variables, thus capturing all the mutual interlinkages.

10 More technically, shrinkage resolves the problem of inverting an otherwise unstable large covariance matrix.

11 Useful modifications were later proposed by Kadiyala and Karlsson (1997) and Sims and Zha (1998).
collinearity, as present in macroeconomic data, Bayesian forecasts converge to the optimal value as long as the tightness of the prior is increased with the number of variables.

The practical use of a large Bayesian structure is motivated by several reasons. Firstly, several empirical papers determine that adding information helps to improve forecasts (Beauchemin and Zaman, 2011; Bloor and Matheson, 2011), with medium-sized (twenty variable) BVARs already obtaining significant gains (Giannone et al, 2015). Similarly, Christiano et al. (1999) warn of the omission of variables having negative effects on forecasting and structural analysis. Secondly, central banks need to incorporate information from a large number of variables when performing monetary policy decisions (Iversen et al., 2014). Finally, Gambacorta et al. (2014) highlight the added value of including variables capturing uncertainty, financial turmoil and economic risk to unravel exogenous changes in the central bank balance sheet from endogenous interventions. Hence, the inclusion of many macroeconomic and financial variables is necessary to capture possible spillovers between the real and financial economy.

3.1.1 Dummy observation prior

The above mentioned prior structure by Litterman (1986) has three important shortcomings. Firstly, to get the posteriors, the matrix inversion leads to problems, with a $q \times 1$ matrix (for the mean) and a $q \times q$ matrix (for the variance). Therefore, dealing with this step in the Gibbs sampling algorithm dramatically increases the computational burden. Secondly, with the Minnesota prior, no prior covariance is assumed among VAR coefficients. Finally, the Minnesota prior does not allow us to incorporate prior beliefs about the combination of coefficients in each equation or across equations. This is particularly useful when working with unit root processes (the sum of coefficients on lags of the dependent variable in each equation equals one) or cointegrated processes.

Hence, we use a variation of the Minnesota prior, referred to as a dummy observation prior. Intuitively, this prior generates artificial data from the model assumed under the prior, and mixes this with the actual data. Moreover, the weight placed

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12 A comprehensive overview of the technical aspects with respect to the Bayesian estimation can be found in Diepe et al. (2015) and Mumtaz and Blake (2014).

13 With $q = n(np + m)$, $n$ being the number of endogenous variables, $p$ the number of lags, and $m$ the number of exogenous variables.

14 Especially, if we want to estimate our variables in annualized log levels.

15 We modify the code provided by Blake and Mumtaz (2014) to handle the large dataset. Moreover, we include multiple restrictions simultaneously and apply a longer forecasting horizon. We thank Mumtaz for valuable feedback while incorporating these extensions.
on the artificial data determines the tightness of the prior. The biggest advantage of this methodology is that it can match the Minnesota moments (without having matrix inversion issues), while simultaneously being consistent with unit root or cointegration processes. Appendix A2 contains the technical details.

Following Banbura et al (2010), we implement this prior\[16\] by adjoining $T_d$ dummy observations, as expressed in $Y_d$ and $X_d$, to the system:

\[
Y_d = \begin{pmatrix} 
\text{diag} (\delta_1 \sigma_1, \ldots, \delta_n \sigma_n) / \lambda \\
0_{(p-1) \times n} \\
\text{diag} (\sigma_1, \ldots, \sigma_n) \\
0_{1 \times n}
\end{pmatrix} \\
X_d = \begin{pmatrix} 
J_p \otimes \text{diag} (\delta_1 \sigma_1, \ldots, \delta_n \sigma_n) / \lambda \\
0_{n \times np} \\
\text{diag} (\sigma_1, \ldots, \sigma_n) \\
0_{1 \times np}
\end{pmatrix}
\]

(3)

with $J_p = \text{diag} (1, 2, \ldots, p)$. The first block of dummies represents the prior beliefs on the AR coefficients. The second block summarizes the prior for the covariance matrix. Finally, the third block describes the uninformative prior for the intercept. We retrieve the required structures $Y^*$ and $X^*$ by adding dummies $Y_d$ and $X_d$ to the original data:

\[
Y^* = [Y, Y_d], \quad X^* = [X, X_d]
\]

Using this appended data, the conditional distributions can be integrated in the Gibbs sampling algorithm. The results are based on 15000 draws from the Gibbs sampler, with a burn-in of 10000.

### 3.1.2 Conditional Forecasting

When analyzing the impact of unconventional monetary policy, we typically want to compare the real outcomes with an alternative world in which we abstract from the policy measures, in order to approximate the impact of the interventions (Benati and Baumeister, 2013; Kapetanios et al., 2012). In this analysis, we focus on conditional forecasting techniques,\[17\] popularized by Waggoner and Zha (1999), which allow us to examine exogenous paths or to apply shocks to any variable in the system, in a model-consistent manner (Bloor and Matheson, 2011). The inclusion of prior knowledge, even when not perfect, on the future path of certain variables may carry useful information for forecasting. This technique is commonly used by central banks and other institutions (Banbura et al., 2015).

Consider a VAR(1) model (Blake and Muntaz, 2014):

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*\[16\]Where the coefficients have a normal prior and the covariance matrix has a normal inverted Wishart prior: $\text{vec}(B) | \Psi \sim N(\text{vec}(B_0), \Psi \otimes \Omega_0)$, $\Psi \sim iW(S_0, \alpha_0)$.

*\[17\]Popular applications of this methodology can be found in Jarocinski and Smets (2008), Stock and Watson (2012).
with $Y_t$ representing a $T \times N$ matrix of endogenous variables, and $\varepsilon_t$ denoting the uncorrelated structural shocks and $A_0A_0' = \Sigma$.\textsuperscript{18} When we iterate equation (5) $K$ times forward, we retrieve

$$Y_{t+K} = c \sum_{j=0}^{K} B^j_Y + B^jY_{t-1} + A_0 \sum_{j=0}^{K} B^j \varepsilon_{t+K-j} \quad (6)$$

Hence, when we place restrictions on the future path of the $J^{th}$ variable in $Y_t$, this also induces restrictions on the other variables in the system. If we re-structure equation (6) this becomes more visible:

$$Y_{t+K} - c \sum_{j=0}^{K} B^j - B^jY_{t-1} = A_0 \sum_{j=0}^{K} B^j \varepsilon_{t+K-j} \quad (7)$$

When we constrain some of the variables in our dataset to a fixed path, this means that the future innovations on the right hand side of the equation will have restrictions as well. These constraints on future innovations are defined in Waggoner and Zha (1999) as:

$$R\varepsilon = r \quad (8)$$

The elements of $r$ contain the path for the constrained variables minus the unconditional forecasts of the constrained variables. The elements of the matrix $R$ are the impulse responses of the constrained variables to the structural shocks $\varepsilon$ over the desired forecasting horizon. A least square solution for the constrained shocks in (8) is given by Doan et al. (1983):

$$\varepsilon = R' (R'R)^{-1} r \quad (9)$$

Inserting these constrained innovations in equation (5) allow us to calculate the conditional forecasts.

### 3.2 Scenario Analysis

Our sparse representation of liquidity allows us to examine the impact of monetary policy shocks on liquidity, thus unraveling important macro-financial linkages that change over time. Our analysis is related to Christensen and Gillan (2018), which looks at the impact of the recent asset purchase programs on a measure of liquidity premiums in TIPS yields and inflation swap rates.\textsuperscript{19} Practically, we use a seventeen

\textsuperscript{18}$\Sigma$ represents the variance of the reduced VAR residuals.

\textsuperscript{19}Theoretical aspects of this transmission have recently been explored by Lagos and Zhang (2018)
variable Bayesian vector autoregressive system and incorporate dummy observation prior (Banbura et al., 2015). The data is summarized in Table 1. Specifically, we inspect the impact of the recent unconventional monetary policy (UMP) on market liquidity, as measured by the policy rate and variation in the Federal Reserve total assets. The policy variables we incorporate in our analysis are depicted in figure 4 and 5.

More specifically, we differentiate between the three main asset purchase programs by the Federal Reserve, given the distinct differences in size and composition between these programs and the changing macro-financial environment. Table 2 highlights the different periods and its main characteristics. We construct conditional forecasts for each subperiod based on the assumption that both the Federal Funds rate and the Federal Reserve total assets would remain unchanged, thus depicting a counterfactual no policy world. Our analysis shows that QE1 has a strong positive impact on market liquidity, similar to the findings of Gertler and Karadi (2012) for a more general macroeconomic impact. Given the constraint financial market, the impact of a large institution buying up large amounts of subprime and government bonds has positive spillovers on the liquidity of the stock market. In contrast, during QE2 monetary policy seems to have a detrimental effect on monetary policy. Having the continued presence of the Federal Reserve buying up large quantities financial assets, without concern about their price, potentially has perverse price signal or order effects which trickle through to the liquidity of financial markets. During this period, the most severe financial pressure had already somewhat subsided. Moreover, the changed composition of the purchases, focusing on government bonds, also has further depletes the overall supply of safe assets. Finally, the last round of easing has no significant effect on market liquidity in our analysis. In comparison, the program is much smaller in size, and therefore unsurprising that the spillovers of UMP to the liquidity of financial markets are no longer significant. Our results are summarized in figure 6.

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20 However, our framework would also allow us to examine the impact of both conventional and unconventional monetary policy on liquidity across the whole sample period, from mid-60s up to the end of 2013. This would allow us to incorporate multiple historical crisis episodes (oil crisis, the 1987 crisis, the Asian crisis, etc.).

21 QE1 starting from November 2008, QE2 in November 2010, and QE3 from September 2013, to then taper from January 2014 onward, with the program ending in October 2014. Hence, we only look up to the end of 2013 in our analysis of monetary policy shocks.

22 Alternatively, we could perform a more structural analysis (Antolin-Diaz et al., 2018). However, this requires additional assumptions about the response of several variables to these structural shocks, while the above scenario analysis (based on observables is more agnostic in this context.

23 Many authors during this period point at the importance of safe assets as a reliable store of value, a pricing benchmark, collateral in transactions, as well as a key instrument to fulfill capital requirements (Caballero, 2010; Gourinchas and Jeanne, 2012; IMF, 2012).
4 Importance of individual liquidity measures in the analysis of monetary policy

We can further extend our analysis by moving away from our sparse representation, and now explicitly incorporating all individual thirty-six variables in a Bayesian factor augmented VAR setting, where we can look at the impact of monetary policy on each specific liquidity measure separately. Computationally, the estimation is very similar to the above-mentioned methodology. However, in this framework, we can distill the impact of monetary policy on every individual aspect of liquidity. This analysis gives us a better understanding of the importance of each liquidity measure in driving the results above.

5 Conclusion

Our analysis provides a sparse measure of market liquidity that incorporates the full set of information on liquidity. We start at the stock level, by constructing market liquidity measures for every firm within the S&P 500, tracking additions and deletions, since 1962. We repeat this exercise for each of the thirty-six individual liquidity measures that we incorporate in our analysis. For each liquidity measure we compute a weighted market liquidity measure across all the S&P500 stocks. We then distill the common factor from these separate market liquidity measures into one sparse metric. Overall, our measure seems successful at picking up the most important episodes throughout the whole sample period, thus exhibiting a capacity to detect dry ups in liquidity caused by different types of financial distress, in a continuously changing financial environment. This gives us additional reassurance on the benefits of incorporating all of the different dimensions of liquidity to construct an all-encompassing measure. Although our market liquidity measure seems closely linked with well-known concepts of funding liquidity, the relation seems markedly strongly during periods of financial stress.

Our novel liquidity measure allows us to examine the effects of the Federal Reserve’s recent episodes of unconventional policy, with its large scale asset purchases, using a large-scale Bayesian VAR. We find a differential impact of each quantitative easing period on market liquidity, with a strong positive impact found during the first period, and a detrimental effect on liquidity during QE2, and no significant spillovers in QE3. Hence, the presence of a large institution buying up large amounts of financial assets can have a diverging impact on liquidity over time. These effects seem positive when financial markets are in severe distress, and when the purchases
are focused on specific products in which market liquidity has completely dried up, as for example in the Mortgage Backed Securities market during QE1. However, the sustained purchase of assets, and more specifically of government bonds, can have considerable negative spillovers on the liquidity of financial markets, as it provides the market with distorted price signal (order flow) effects, and further depletes the supply of financial assets.

Finally, a Bayesian factor-augmented framework allows us to uncover the effect of monetary policy on each individual liquidity measure. Pushing this exercise to the limit, gives us a more detailed insight on the underlying importance of each dimension of liquidity.
References


Tables and Figures

Table 1: List of the variables included in the BVAR

<table>
<thead>
<tr>
<th>Prices</th>
<th>Labour market</th>
<th>Cyclical</th>
<th>Monetary Policy</th>
<th>Volatility, Uncertainty and Risk (Financial)</th>
<th>Asset Prices</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Oil Prices</td>
<td>4 Civil Unemployment</td>
<td>5 Real Gross Domestic Product (RGDP)</td>
<td>7 Effective FFR</td>
<td>11 Common Market Liquidity Measures</td>
<td>16 Russel 2000 Price Index</td>
</tr>
<tr>
<td>2 Consumer Price Index</td>
<td></td>
<td>6 Industrial Production</td>
<td>8 Federal Reserve Total Assets</td>
<td></td>
<td>17 Real Broad Effective ER</td>
</tr>
<tr>
<td>3 Core PCE</td>
<td></td>
<td></td>
<td>9 Interbank IR Spread</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>10 Non-financial private sector credit</td>
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<td></td>
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</tbody>
</table>

Table 2: Scenario analysis over different subperiods

<table>
<thead>
<tr>
<th>Program</th>
<th>Start (announcement)</th>
<th>Purchases</th>
<th>Length</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 QE1</td>
<td>2008-12 (2008-11, 2009-03\uparrow)</td>
<td>MBS</td>
<td>8Q</td>
</tr>
<tr>
<td>2 QE2</td>
<td>2010-11 (2010-08)</td>
<td>Treasury Securities</td>
<td>8Q</td>
</tr>
<tr>
<td>3 QE3</td>
<td>2012-09 (12)</td>
<td>Bond Purchases</td>
<td>5Q</td>
</tr>
<tr>
<td>4 Taper</td>
<td>2014-01 (2013-06)</td>
<td>Purchases ↓</td>
<td>3Q</td>
</tr>
<tr>
<td>5 QE End</td>
<td>2014-09</td>
<td>-</td>
<td>4Q</td>
</tr>
</tbody>
</table>
Figure 1: Multiple Dimensions of liquidity

The figure depicts the information cloud with all the measures of liquidity incorporated in the analysis.

Figure 2: Market Liquidity and Financial Stress

The figure shows the evolution of our constructed common liquidity measures, together with recessions (highlighted by bars) and important financial stress episodes (depicted by the dotted vertical lines).
Figure 3: Market Liquidity and Funding Liquidity

These figures show the link between our market liquidity measure and multiple measures of funding liquidity. The upper panel examines the relationship with the excess bond premium (Gilchrist and Zakrajšek, 2012) and the Ted rate in the figure on the left, and the noise measure (Hu et al, 2013) in the figure on the right. The lower panel highlights the link with the MOVE measure on the left, and with the implied stock market volatility.
Figure 4: Federal Reserve Balance Sheet Assets

The figure shows the evolution of the Federal Reserve’s Total Assets

Figure 5: Federal Funds Rate

The figure shows the evolution of the Federal Funds rate over time.
Figure 6: Impact of UMP on liquidity

The figure summarizes the conditional forecasts for the subsamples, depicting the different periods of quantitative easing. The blue line depicts the actual historical path of the macroeconomic variable under investigation. The solid grey represents the median conditional forecast, approximating a world with no Fed purchase program. Finally, the dotted gray line portrays the sixty-eight percent credible set of outcomes.
Table 3: Eight liquidity groups representing the different dimensions in our analysis
Following Garabedian and Inghelbrecht (2015), this table reports all of the different groups which are incorporated in the multidimensional liquidity measure. The table provides the most important formulas for their construction.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Proxy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1. Spread Group</strong></td>
<td></td>
</tr>
</tbody>
</table>
| Korajczyk, Sadka (2008) | \[ Q_{\text{spread},i,t} = \frac{1}{n_{i,t}} \sum_{j=1}^{n_{i,t}} \frac{\text{Ask}_{i,j} - \text{Bid}_{i,j}}{m_{i,j}} \]
|               | \[ m_{i,j} = \frac{\text{Ask}_{i,j} + \text{Bid}_{i,j}}{2} \]
|               | \[ E_{\text{spread},i,t} = \frac{1}{n_{i,t}} \sum_{j=1}^{n_{i,t}} \frac{|p_{i,j} - m_{i,j}|}{m_{i,j}} \]
|               | (Both spreads also calculated with high and low prices) |
| Corwin, Schultz (2012) | \[ S = \frac{2(\alpha - 1)}{1 + e^{\alpha}} \]
|               | with \[ \alpha = \frac{\sqrt{2\beta - \gamma}}{3 - 2\sqrt{2}} \] |
| De Nicolò, Ivaschenko (2009) | \[ S = \frac{2(\alpha - 1)}{1 + e^{\alpha}} \]
|               | where is $\beta$ sum (over 2 days) of squared daily log(high/low) |
|               | $\gamma$ is squared log(high/low) but where high (low) is over 2 days |

| **2. Roll Group** |       |
| Roll (1984) | \[ S = 2\sqrt{-\text{cov}(\Delta P_t, \Delta P_{t-1})} \]
| Holden (2009) | \[ \frac{1}{n} \sum_{t=1}^{n} \Delta P_t \Delta P_{t-1} - \Delta P_t^2 \] (Harris, 1990) |
|               | \[ \left\{ \begin{array}{ll} \sqrt{-\text{cov}(\Delta P_t^{**}, \Delta P_{t+1}^{**})} & \text{when Cov}(\Delta P_t^{**}, \Delta P_{t+1}^{**}) < 0 \\ 0 & \text{when Cov}(\Delta P_t^{**}, \Delta P_{t+1}^{**}) > 0 \end{array} \right. \]
|               | \[ \Delta P_t^{**} = \Delta P_t \text{with } \Delta P_t \text{ : adjusted returns} \]
|               | \[ \Delta P_t = z_t \Delta P_t^{**} \text{ with } z_t = \alpha + \beta \left( r_m - r_f \right) + z_t \]
| Corwin and Schultz (2012) | provide extensions on how to treat positive covariances (hence 2 versions of each Roll measure) |

| **3. Zero Return Group** |       |
| Lesmond, Ogden, Trzcinka (1999) | \[ \text{Zeros} = \frac{\text{Number of days with zero return}}{\text{Number of trading days in month}} \]
|               | \[ \text{Zeros PV} = \frac{\text{Number of positive volume days with zero return}}{\text{Number of trading days in month}} \]

| **4. Fong Group** |       |
| Fong, Holden, Trzcinka (2013) | \[ FHT \equiv S = 2\sigma N^{-1} \left( \frac{1+z}{2} \right) \]
|               | \[ \sigma : \text{Std(retuens)}, z : \text{Zeroreturndays/totaldays} \]
|               | \[ N^{-1} : \text{Inverse function of cumulative distribution function} \]
<table>
<thead>
<tr>
<th>Reference</th>
<th>Proxy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>5. Effective tick (etick) Group</strong></td>
<td></td>
</tr>
<tr>
<td>Holden (2009)</td>
<td>based on observed probabilities of special trade prices</td>
</tr>
<tr>
<td></td>
<td>correspondent to the jth spread ($N_j$)</td>
</tr>
<tr>
<td></td>
<td>dependent on fractional 1/8, 1/16 system or decimal</td>
</tr>
<tr>
<td></td>
<td>which are then transformed to constrained probabilities</td>
</tr>
<tr>
<td></td>
<td>$F_j = \frac{N_j}{\sum_{j=1}^{N} N_j}$</td>
</tr>
<tr>
<td><strong>6. Amihud Group</strong></td>
<td></td>
</tr>
<tr>
<td>Amihud (2002)</td>
<td>$\frac{1}{\text{TradingDays}} \sum \text{Abs(DailyReturns)} / \text{DailyDollarVolume}$</td>
</tr>
<tr>
<td>Goyenko, Holden, Trzcinka (2009)</td>
<td>$\text{SpreadProxy} / \text{DailyDollarVolume}$</td>
</tr>
<tr>
<td></td>
<td>in casu: $\text{High} - \text{low Spread Measure} / \text{DailyDollarVolume}$</td>
</tr>
<tr>
<td>Sarr Lybeck (2002)</td>
<td>$L_{HH} = \left[ \frac{P_{\text{max}} - P_{\text{min}}}{P_{\text{min}}} \right] / \left[ \frac{V}{S \times \bar{P}} \right]$</td>
</tr>
<tr>
<td></td>
<td>$V$: total dollar volume, $S$: number of instruments outstanding</td>
</tr>
<tr>
<td></td>
<td>$\bar{P}$: Average closing price of instrument</td>
</tr>
<tr>
<td>Breen, Hodrick, Korajczyk (2000)</td>
<td>$r_{i,t}^{AR} = \theta_t + \phi_t r_{i,t} + BHK_t \text{sign}(r_{i,t}^e) \times \text{vol}_t + \epsilon_t$</td>
</tr>
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<td></td>
<td>$r_{i,t}^{AR} = \theta_t + \phi_t r_{i,t} + BHK_t \text{sign}(r_{i,t}^e) \times \text{turn}_t + \epsilon_t$</td>
</tr>
<tr>
<td>Liu (2006)</td>
<td>$(V_{\text{Volume zero Previous X months}} + \frac{1}{\text{Previous X months Turnover}}) \times \frac{21 \times X}{\text{NoT D}}$</td>
</tr>
<tr>
<td></td>
<td>$\frac{21 \times X}{\text{NoT D}}$: Standardizes amount of trading days in a month to 21</td>
</tr>
<tr>
<td><strong>7. Volume Group</strong></td>
<td></td>
</tr>
<tr>
<td>Datar (1998)</td>
<td>$\frac{\text{Shares Traded}}{\text{Shares Outstanding}}$</td>
</tr>
<tr>
<td><strong>8. Order Flow Measures</strong></td>
<td></td>
</tr>
<tr>
<td>Pastor, Stambaugh (2003)</td>
<td>$r_{i,t+1}^{e} = \theta_t + \phi_t r_{i,t} + \gamma_t \text{sign}(r_{i,t}^e) \times \text{vol}_t$</td>
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