Citation for published version

Chuliá Soler, H., Koser, C. & Uribe, J.M. (2020). Uncovering the time-varying relationship between commonality in liquidity and volatility. International Review of Financial Analysis, 69(), 1-9. doi: 10.1016/j.irfa.2020.101466

DOI
https://doi.org/10.1016/j.irfa.2020.101466

Uncovering the time-varying relationship between commonality in liquidity and volatility

Abstract

This study examines the dynamic linkages between commonality in liquidity in international stock markets and market volatility. Using a recently proposed liquidity measure as input in a variance decomposition exercise, we show that innovations to liquidity in most markets are induced predominately by inter-market innovations. We also find that commonality in liquidity peaks immediately after large market downturns, coinciding with periods of crisis. The results from a dynamic Granger causality test indicate that the relationship between commonality in liquidity and market volatility is bi-directional and time-varying. We show that while volatility Granger-causes commonality in liquidity throughout the entire sample period, market volatility is enhanced by commonality in liquidity only in sub-periods. Our results are helpful for practitioners and policy makers.

Keywords: Systemic Liquidity, Market Liquidity, Spillover Index, Granger Causality, Financial Crisis, Variance Decomposition

JEL Codes: C10, C32, G01, G15

1. Introduction

Liquidity and commonality among financial assets are a first-order consideration in the decision-making process of investors and market makers, and in the designing of optimal policy frameworks by regulators. Market liquidity is the ability to trade large quantities of an asset without changing its equilibrium price and, as such, it constitutes a crucial feature of any financial asset. It is of great importance for an investor's portfolio choices and policy considerations. In recent decades, empirical studies have shown that stock returns carry a premium for liquidity (see Amihud and Mendelson, 1986; Eleswarapu and Reinganum, 1993; Brennan and Subrahmanyam, 1996; Datar et al., 1998; Amihud, 2002).[1] Studies by Chordia et al. (2000), Amihud (2002), Hasbrouck and Seppi (2001) and Huberman and Halka (2001) find that the level of liquidity co-moves among similar stocks and across time, while studies by Acharya and Pedersen (2005), Holmstrom and Tirole (2001) and Pastor and Stambaugh (2003) show that stocks are exposed to a systemic (market-wide) level of liquidity.

Commonality in liquidity can be defined as the co-movement in liquidity among individual stocks (Karolyi et al., 2012). From a theoretical perspective, Acharya and Pedersen (2005) develop an asset pricing model in which investors are willing to pay a higher premium for stocks that allow them to curtail positions at a relatively lower cost during systemic market declines or liquidity dry-ups. As in any asset pricing model liquidity becomes a systematic factor of common variation among stocks and therefore merits research efforts. The literature has pointed out two fundamental sources of common variation, demand or supply-side driven. Demand-generated commonality can be attributed to correlated trading behavior (Chordia et al., 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001). According to this branch of the literature, large trading orders across a wide range of markets put significant pressure on the inventory of dealers, inducing variation in inventory levels and leading to co-movements in the level of liquidity. Studies by Kamara et al. (2008) and Koch et al. (2016) stress the increasing importance of institutional investors and their index-related trading as a source of demand-oriented co-movements in liquidity. The latter authors find that stocks held by mutual funds, traded in similar time patterns, experience larger trade imbalances and, hence, give rise to commonality in liquidity. Supply-generated commonality in liquidity, on the other hand, can be related to funding constraints in the provision of liquidity by financial intermediaries. Studies by Coughenour and Saad (2004) and Hammed

[1] Amihud and Mendelson (1986) were the pioneers in bridging market microstructure and asset pricing. Eleswarapu and Reingamum (1993) examined the seasonality effects of this same measure, while Brennan and Subrahmanyam (1996) incorporated it into a Fama-French factors framework. Using the turnover rate, research by Datar et al. (1998) and Brennan et al. (1998) further examined the role of liquidity for stock returns.

et al. (2010) report a rise in liquidity commonality within industries, when returns in other industries are large and negative. Furthermore, they argue that this phenomenon of spillovers in the level of illiquidity in industries is partial proof of commonality as the dry-up in funding liquidity affects all stocks.

Empirical evidence of commonality in liquidity focuses primarily on the U.S. financial markets. To the best of our knowledge, the only relevant exceptions are the studies by Brockman et al. (2009) and Karolyi et al. (2012). Brockman et al. (2009) investigate the extent to which commonality is a global vs. local phenomenon and identify the sources of commonality both within and across countries. Karolyi et al. (2012) examine commonality in liquidity in 40 countries and link global commonality to a variety of capital market conditions. Their study provides a comprehensive view of liquidity commonality and its intra-market determinants across time and countries. Yet, the literature to date has not provided reliable empirics that can shed light on the dynamic nature of the relationship between commonality in liquidity and market volatility.

Here, we offer solid, novel empirical evidence of the causal relationship between global commonality in liquidity in international stock markets and global market volatility and we show that this relationship is time-varying and that it displays feedback effects during episodes of crisis. Unlike the scarce extant literature studying commonality in liquidity around the world (i.e. Brockman et al., 2009 and Karolyi et al., 2012), we propose measuring commonality in liquidity *dynamically*. To do so, we construct systemic liquidity measures based on individual stocks for every market in a sample of nine mature markets,[2] following a recently proposed market liquidity indicator developed by Abdi and Ranaldo (2017). We then use these country-specific liquidity measures as inputs in a variance decomposition exercise, which allows us to break down the total variation in liquidity for each market into its own liquidity shocks and foreign-market liquidity shocks. We estimate a global commonality index that reflects liquidity spillovers across these nine major stock markets and which, in line with Diebold and Yilmaz (2012), is constructed as the sum of cross-variance shares in liquidity for all markets in our sample. This allows us to clearly decompose intra- and inter-market spillover effects and their relative strengths. Next, we relate our commonality index to a measure of aggregate global market volatility using data for the same markets. To carry out

[2] We consider the market capitalization of NASDAQ, NYSE, EURONEXT, Deutsche Boerse AG, Six Swiss Exchange, LSE, BME, TMX Group and Japan Exchange Group Inc., which represents 67.3% of total world stock market capitalization, as reported by the World Federation of Exchanges in December 2018.

this step, we use a dynamic Granger causality test, as proposed by Hurn et al. (2016), which allows us to detect directional causality in a time-varying fashion between commonality and market volatility.

Several novel, significant insights can be drawn from our main results. First, we show that the relationship between commonality in liquidity and market volatility is complex and time-varying. That is, we document that volatility Granger-causes commonality in liquidity throughout the entire sample period. This is consistent with theoretical models, including, for example, that developed by Brunnermeier and Pedersen (2009). In this framework, high market volatility leads to an increase in commonality as a consequence of a reduction in the provision of liquidity available for all financial intermediaries. Second, for the first time, we are able to document that commonality in liquidity also Granger-causes volatility, and that this occurred in the aftermath of the Global Financial Crisis, coinciding with high levels of uncertainty in European bond markets. This finding might be interpreted as evidence of the existence of adverse loop effects in which shocks to stock market liquidity endogenously cause stock market volatility and vice versa. Such a feedback effect sheds new light on the endogenous nature of financial shocks arising during crisis episodes, which we show are intensified by liquidity considerations.

In addition to the main finding outlined above, we also show (as expected) that global commonality in liquidity peaks during episodes of market turmoil and that it remains at very high levels even after peaks in market liquidity have fallen. Indeed, we document high levels of commonality in liquidity from the beginning to the end of the subprime crisis. Global commonality remains high even when market specific liquidity measures have returned to their pre-crisis levels. We also find that three-quarters of the variation in market liquidity depends on foreign market liquidity shocks, which provides a more cross-market oriented explanation of commonality. Finally, we show that the measure proposed by Abdi and Ranaldo (2017) performs very well when measuring liquidity in several international stock markets, in the sense that it provides sensible results consistent with our knowledge of these markets and their dynamics between July 2000 and December 2016.

The rest of this paper is organized as follows: Section 2 lays out the methodology used in our analysis. Section 3 describes the data. Section 4 discusses the empirical results and, finally, Section 5 concludes.

2. Methodology

We divide our empirical investigation into three sections. First, we calculate commonality in liquidity for each of the nine stock markets in our sample (Canada, Germany, France, Italy, Japan, Spain, Switzerland, the U.K. and the U.S.), using the bid-ask spread proposed by Abdi and Ranaldo (2017). This sample includes seven of the world's advanced economies (G7) and represent 67.3% of total world stock market capitalization. We then estimate global commonality in liquidity, following Diebold and Yilmaz (2012). Finally, we use the new time-varying Granger causality test, as developed by Hurn et al. (2016), to investigate the dynamic causality between commonality in liquidity and market volatility.

2.1. Systemic Liquidity

To measure systemic liquidity risk, we follow a recently proposed estimator for market liquidity, as developed by Abdi and Ranaldo (2017). Their method is based on close, high and low prices and bridges the well-established bid-ask spread formulated by Roll (1984) and the more recent High-Low (HL) spread developed by Corwin and Schultz (2012). This measure has several advantages over competing alternatives. For example, compared to other low-frequency estimates, this method uses wider information (i.e. close, high, and low prices), it provides the highest cross-sectional and average time-series correlations with the TAQ effective spread, and it delivers the most accurate estimates for less liquid stocks.

Abdi and Ranaldo's (2017) measure is based on the same theoretical assumptions as those made for the spread modelled by Roll (1984). The effective spread s is estimated as

$$s = 2\sqrt{E(c_t - \eta_t)(c_t - \eta_{t+1})} \quad (1)$$

where c_t represents the daily observed close log-price, and η_t refers to the mid-range, defined as the mean of daily high and low log-prices. Although this closed-form solution of the bid-ask spread measure is similar to Roll's (1984) autocovariance measure, it builds on the covariance of consecutive close-to-midrange prices rather than on close-to-close prices.

Owing to errors in the estimation procedure, some estimates of equation (1) are negative. Following Corwin and Schultz (2012), Abdi and Ranaldo (2017) propose two versions of the spread. In the first – known as the *two-day corrected* version – negative two-day estimates are set to zero and then the average of the two-day calculated spreads is taken. In the second – known as the *monthly corrected* version – negative monthly estimates are set to zero. Equations (2) and (3) show how the spreads are calculated:

$$\widehat{s}_{two\ days\ corrected} = \frac{1}{N}\sum_{t=1}^{N} \widehat{s}_t\ ,\ \widehat{s}_t = \sqrt{\max\{4(c_t - \eta_t)(c_t - \eta_{t+1}), 0\}} \tag{2}$$

$$\widehat{s}_{monthly\ corrected} = \sqrt{max\left\{4\frac{1}{N}\sum_{t=1}^{N}(c_t - \eta_t)(c_t - \eta_{t+1}), 0\right\}} \tag{3}$$

where N is the number of trading days in a month. Finally, we calculate a monthly country-specific systemic liquidity measure as the equally weighted average of the monthly spread of individual stocks.

2.2 Global commonality in liquidity

Our approach to estimating commonality in liquidity is based on the methodology introduced by Diebold and Yilmaz (2012), which builds on the seminal work on VAR models by Sim (1980) and the notion of variance decomposition. The starting point for the analysis is the following VAR(p):

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t \tag{4}$$

where $x_t = (x_{1t}, x_{2t}, \dots \dots, x_{Kt})$ is a vector of K endogenous variables, Φ_i is a $K\ x\ K$ matrix of parameters to be estimated, and ε_t is a vector of disturbances that has the property of being independently and identically distributed (i.i.d.) over time, $t\ =\ 1, \dots T$, with zero mean and Σ is a covariance matrix. If the VAR model is covariance stationary, we can derive the moving average representation of model (5), which is given by

$$x_t = \sum_{i=0}^{\infty} \mathrm{A}_i \varepsilon_{t-i} \tag{5}$$

where $A_i = (\Phi_1 A_{i-1} +\ \Phi_2 A_{i-2}, \dots \dots\ \Phi_p A_{i-p})$, A_0 is the $K\ x\ K$ identity matrix and $A_i = 0$ for $i < 0$. Variance decomposition allows us to break down the h-step ahead forecast error variance into *own variance shares*, the fraction of the forecast error variance in forecasting y_i due to shocks to y_i, for i=1, 2, …, N, and cross variance shares, or spillovers, the fraction of the forecast error variance in forecasting y_i due to shocks to y_j for j=1, 2, …, N and $j \neq i$.

Diebold and Yilmaz (2009) proposed using Cholesky decomposition to break down the variance. However, Cholesky decomposition is sensitive to ordering. Diebold and Yilmaz (2012) resolve this ordering problem by exploiting the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), in which variance decomposition is invariant to the ordering of the variables. Variable j's contribution to i's h-step ahead generalized forecast error variance decomposition is given by:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_i^{'}A_h\Sigma e_j)^2}{\sum_{h=0}^{H-1}(e_i^{'}A_h\Sigma A_h^{'}e_i)} \tag{6}$$

where Σ is defined as the covariance matrix of the error vector ε, σ_{ij} is the (estimated) standard deviation of the error term for the variable *j*, and e_i is a selection vector with a value of one on the *i*-th element and zero otherwise. The sum of contributions to the variance of the forecast error of each market do not necessarily add up to one; thus, we normalize each entry of the variance decomposition matrix as

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N}\theta_{ij}(H)} \tag{7}$$

where $\sum_{j=1}^{N}\tilde{\theta}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N}\tilde{\theta}_{ij}(H) = N$.

This normalization enables us to construct the following volatility spillover measures:

- The *total spillover index* which measures the contribution of spillovers of shocks across all markets to the total forecast error variance:

$$TS\ (H) = \frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}(H)} \cdot 100 \tag{8}$$

- The *directional spillovers* received by market i from all other markets j:

$$DS_{i\leftarrow j}(H) = \frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}(H)} \cdot 100 \tag{9}$$

- The *directional spillovers* transmitted by market i to all other markets j:

$$DS_{i\rightarrow j}(H) = \frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}(H)} \cdot 100 \tag{10}$$

- The *net spillover*, namely the difference between the gross shocks transmitted to and the gross shocks received from all other markets, which identifies whether a market is a receiver/transmitter of shocks from/to the rest of the markets being examined. The net spillover index from market *i* to all other markets *j* is obtained by subtracting equation (9) from equation (10):

$$NS_i\,(H) = DS_{i\rightarrow j}(H) - DS_{i\leftarrow j}(H) \tag{11}$$

2.3. Global Market Volatility

Our measure of volatility is based on the traditional realized volatility (RV) estimator, as explained, for example, in Andersen and Todorov (2010). This has been shown to be a useful methodology for estimating and forecasting conditional variances for risk management and asset pricing.[3] The RV estimator can be expressed as:

$$\mathrm{RV}_{\mathrm{monthly}} = \sqrt{\textstyle\sum_{\mathrm{t}=1}^{\mathrm{N}} \mathrm{r}_{\mathrm{t}}^{2}} \tag{12}$$

where $\mathrm{r_t}$ are the log returns and N is the number of trading days per month. In order to examine the time-varying relationship between commonality in liquidity in international stock markets and market volatility, we need to aggregate individual volatilities and, to do so, we employ principal component analysis, taking the first component as our measure of global market volatility.

2.4. Dynamic Granger Causality

To analyze the dynamic relationship between commonality in liquidity in international stock markets and global market volatility, we follow the methodology proposed by Hurn et al. (2016). While emphasizing that the Granger causality test is highly sensitive to the time horizon of its estimation, they propose considering time dynamics to detect periods of instability in the causal relationship. The method proposed is based on an intensive recursive calculation of Wald test statistics for all sub-samples in a backward-looking manner in which the final observation of all samples is the (current) observation of interest.

The traditional testing for Granger causality within a VAR system (as for the instance described in equation 4) involves the following null hypotheses:

$$H_0\colon y_{it} \nrightarrow y_{jt} \quad \phi_{l,ij} = 0 \text{ for } i \neq j \text{ and } l = 1, \dots, p, \tag{13}$$

[3] See Liu et al. (2015) and references therein.

where the causality runs from variable *i* to variable *j*, and the reverse causality between the two variables is given by

$$H_0: y_{jt} \nrightarrow y_{ji} \quad \phi_{l,ij} = 0 \text{ for } i \neq j \text{ and } l = 1, \dots, p, \tag{14}$$

where the symbol $\nrightarrow$ means "does not Granger cause". This hypothesis can be contrasted with the data by constructing a traditional Wald statistic (W) to test it against the alternative of at least one significant coefficient. Hurn et al. (2016) and Shi et al. (2016) compare different statistics for the data-driven discovery of change points in causal relationships and they conclude in favor of a rolling window estimation of the traditional Wald statistics. Namely, for each observation of interest $f \in [f_0, 1]$, where f_0 is the minimum window size that is required to estimate the model, the Wald statistics are computed using subsamples of the original data set. The starting and ending points of the regression are defined as f_1 and f_2, respectively, and the Wald statistic for the subsample starting at f_1 and ending at f_2 is denoted W_{f_1,f_2}. The ending point of the regression f_2 is fixed on the observation of interest (the date on which we want to test for causality). Therefore, as the observation of interest moves forward from f_0 to 1, the starting point of the regression follows and keeps a constant distance from f_2, i.e.$f_1 = f_2 - f_w$, where f_w is the fraction that represents the window size that is used for the regression. Hurn et al. (2016) show that within a stationary VAR system under the assumptions of homoscedasticity, conditional heteroskedasticity of an unknown form, or unconditional heteroskedasticity, W_{f_1,f_2} has a limiting distribution that is given by the following:

$$W_{f_1,f_2} \Longrightarrow \left[\frac{W_d(f_2)-W_d(f_1)}{(f_2-f_1)^{1/2}}\right]\left[\frac{W_d(f_2)-W_d(f_1)}{(f_2-f_1)^{1/2}}\right], \tag{15}$$

where W_d is a vector Brownian motion with covariance matrix I_d and d is the number of restrictions under the null (as in 4 and 5). Hence, if causality is detected, its sign (positive or negative) is identified, as well as its intensity. Finally, the testing framework considers the potential heteroskedasticity (conditional and unconditional) of the data, thereby reducing the potential for incorrect inferences.

Inferences regarding the presence of Granger causality for this observation rely on the supremum taken over the values of all the test statistics in the entire recursion. As the sample period moves forward, all subsamples more forward and the calculation rolls ahead in a changing rolling window framework – hence its name, 'recursive rolling algorithm'. The estimation procedure is based on a VAR model framework in which the selection of the lag order is obtained using the Bayesian Information Criterion (BIC). As in Hurn et al. (2016), the 5% critical value sequences over time are obtained through bootstrapping with 500 replications.

3. Data

We collect daily close, high and low prices, for the period July 2000 through to December 2016, for the following markets (Canada, Germany, France, Italy, Japan, Spain, Switzerland, the U.K. and the U.S.). We confine our sample of stocks to those listed in the country's specific major stock market index. To obtain a measure of market-wide liquidity in each stock market, we first calculate the daily spreads of our restricted set of stocks defined above and aggregate them on a monthly basis. Then, we sum the monthly stock-specific spreads and weight them equally by the number of stocks in each market so as to obtain a monthly market-wide aggregate spread for each market.

The number of stocks in each index is subject to fluctuations over the entire sample period. This reflects the fact that some firms have gone public after the sample start date while others have recently been delisted for reasons of financial restructuring or the merging of business activities. We control for these possibilities by adjusting the weighting over time. In compliance with the screening principles proposed by Karolyi et al. (2012), we aim to obtain a broad range of stocks within each country while avoiding any differences in trading behavior or conventions. In keeping with this objective, we also exclude depositary receipts (DRs), real estate investment trusts (REITs), investment funds and preferred stocks from our sampling. Moreover, we exclude stocks with price data for less than 24 months, although this is rarely applicable. The monthly spread estimates for U.S. stocks are taken from Angelo Ranaldo's website.[4] All other daily price data for stocks are extracted from Datastream. Our final sample of stocks outside of the U.S. consists of 505 stocks from eight different countries.

4. Results

In this section we report our empirical results. We first provide the reader with insights into the dynamics of market liquidity for selected countries. Then, we present our measure of

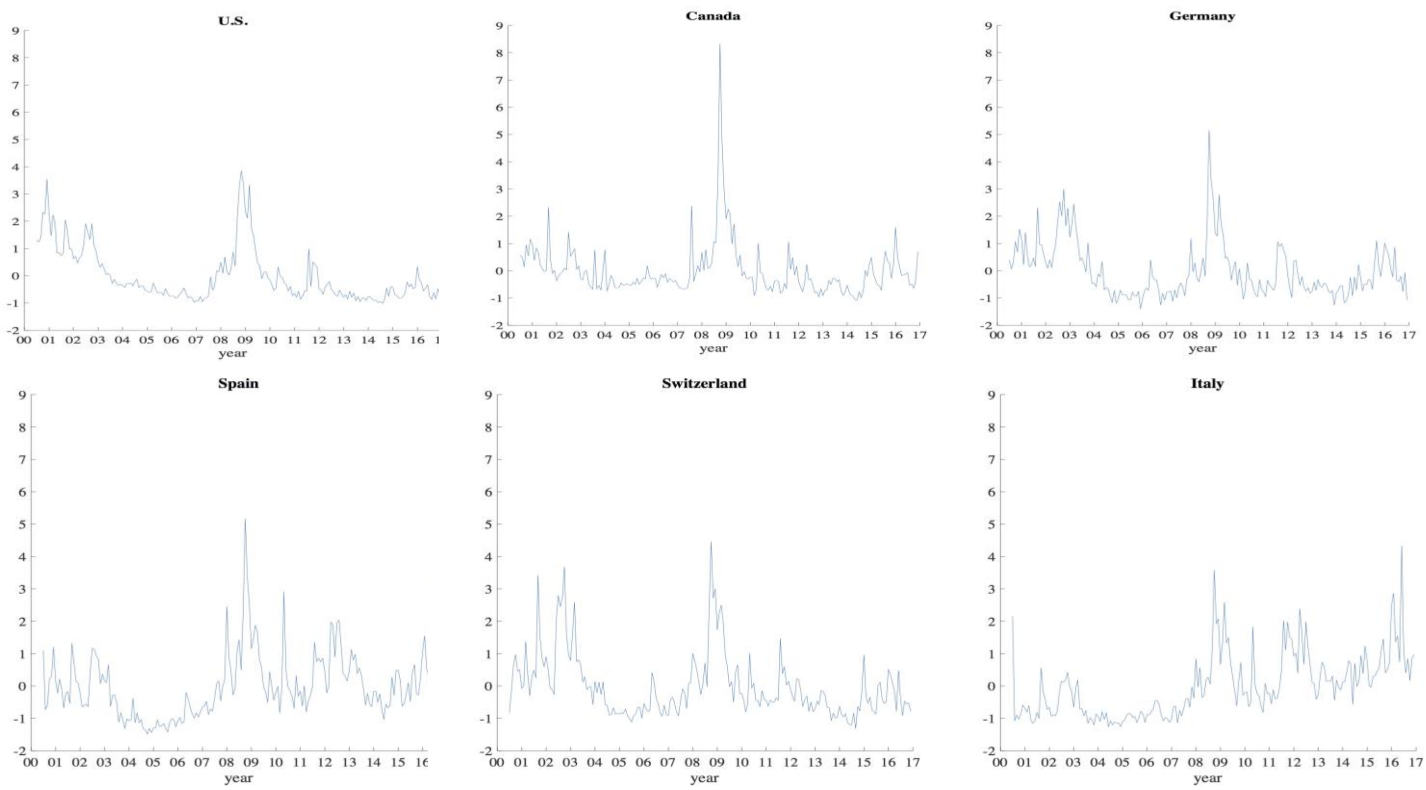
[4] https://sbf.unisg.ch/en/lehrstuehle/lehrstuhl_ranaldo/homepage_ranaldo/research-material

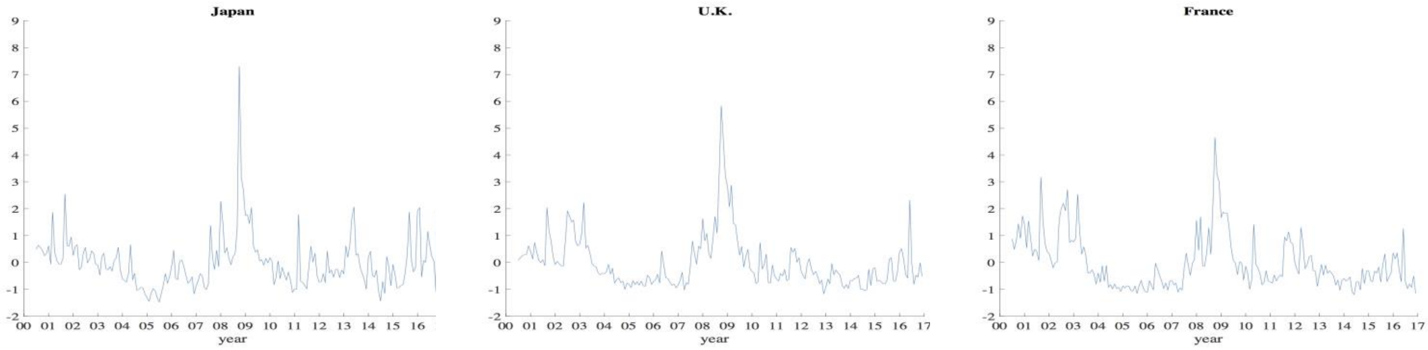
global commonality in liquidity. Finally, we describe the time-varying relationship between global commonality in liquidity and aggregate market volatility.

4.1 Liquidity Measure

Figure 1 shows the estimated market liquidity for each country in our sample. An increase in the spread is associated with a higher level of illiquidity in the respective stock market. We observe that market liquidity is substantially higher in some periods than in others and tends to decrease during financial crises. For example, market illiquidity was high in the U.S., Switzerland, Germany and France during the dot-com bubble. Likewise, for all countries, illiquidity dramatically increased during the financial crisis of 2008-2009. It is also noteworthy that Italy exhibited higher illiquidity than the rest of the countries between 2011-2017. Table A1 shows the descriptive statistics of market systemic liquidity for each country. Our results show that market illiquidity was higher and more volatile during the financial crisis (2008-2009) than before or after it. The U.S., Canada, Germany and Japan are the countries with the lowest levels of market liquidity during this sub-period. Interestingly, the mean and the standard deviation during the post-crisis period are lower than during the pre-crisis period (except for the peripheral countries in our sample, Italy and Spain, due to the European Sovereign debt crisis).

Figure 1: Dynamics of market wide liquidity





Note: Time-series variation in market liquidity for select countries. Monthly country-specific liquidity measures are calculated as the equally weighted average of the monthly spread of individual stocks. The sample runs from July 2000 to December 2016. For illustrative purposes, the liquidity measures in the plots are standardized.

4.2 Global commonality in liquidity

Table 1 shows the estimation results for the full-sample spillover analysis based on a 6-month-ahead forecast error variance decomposition. Element $ijth$ of the matrix represents the contribution to the forecast error variance of market i from shocks to market j. The diagonal elements display the intra-market spillovers, where ($i = j$). The off-diagonal elements of the matrix show the cross-market spillovers. The row sums (labelled "From others") represent the total spillovers received by the respective market as denoted in this particular row, whereas the column sums (labelled "To others") represent the sum of spillovers transmitted by market i in the respective column. The difference between the column and the row sum represents the net spillover. It describes whether the respective market has transmitted (received) more shocks to (from) all of its counterparts. Finally, the total spillover statistic, shown in the bottom-right corner, indicates the degree of interconnection between the system of variables, i.e. our measures of systemic market liquidity.

As can be observed, the inter-market spillovers are higher than the intra-market spillovers, since both the column *from others* and the row *to others* display higher figures than those on the diagonal. This means that variation in market-wide liquidity depends mainly on global sources of liquidity innovations. This result contrasts with findings reported by Brockman et al. (2009) who show that local sources of commonality represent roughly 39% of the firm's total commonality in liquidity, while global sources contribute around 19%.[5] We also observe

[5] This contrasting result could be due to the different methodologies followed by each study. To analyze the relative impact of the local and global components of commonality on the liquidity of individual firms,

that the "contribution from others" figures are quite similar across countries, with Switzerland being the largest receiver of liquidity spillovers. However, the "contribution to others" figures show interesting differences across countries. The largest transmitters are Germany, the U.K., France and Canada and, in fact, the "net contribution" row also shows them to be the largest transmitter countries.

Table 1. Global commonality in liquidity

	US	CA	GER	SP	SWI	IT	JP	UK	FR	From others
US	18.82	15.53	13.02	8.47	9.40	5.61	4.58	11.73	12.79	81.17
CA	10.40	25.06	11.48	8.27	7.51	7.18	7.38	13.26	9.43	74.92
GER	10.32	10.77	18.86	8.95	11.92	7.90	5.45	12.31	13.48	81.13
SP	8.34	9.92	11.30	16.96	9.27	12.94	5.60	12.37	13.25	83.03
SWI	9.58	9.99	15.15	9.67	16.14	7.50	4.24	13.53	14.17	83.85
IT	7.19	10.23	11.43	14.03	8.16	20.20	5.52	11.98	11.22	79.79
JP	7.19	13.16	12.81	9.46	7.69	7.41	21.42	11.77	9.04	78.57
UK	8.60	12.88	13.06	10.95	10.16	9.03	5.37	17.39	12.51	82.60
FR	10.35	9.99	14.57	11.39	11.71	8.27	4.34	12.90	16.43	83.56
To Others	90.82	117.58	121.71	98.19	92.00	86.09	63.94	117.28	112.37	Total Spillover =
Net cont. (to-from)	9.65	42.64	40.57	15.15	8.15	6.30	-14.63	34.67	28.80	80.96

Note: Columns show the market producing the shock and rows the market receiving the shock. The diagonal elements represent intra-market spillovers while the off-diagonal elements represent the pairwise liquidity directional spillovers. The table shows the 6-month ahead forecast error variance decomposition, based on a VAR model with a lag length of 2, following the Akaike's information criterion (AIC).

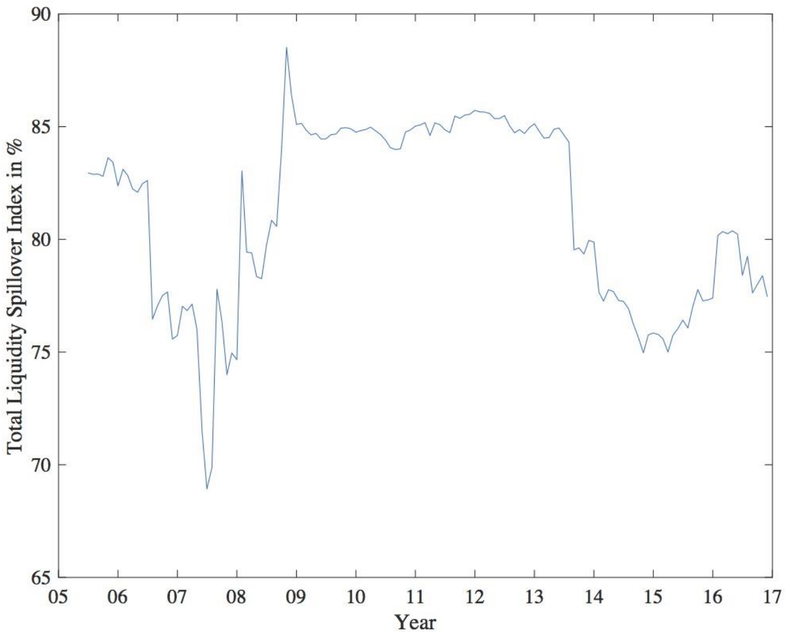
The above results point to a more cross-market oriented explanation of commonality in liquidity. From the demand-side perspective, this favors the hypothesis that large institutional investors, holding large-cap stocks from a variety of markets in their portfolio, can influence the systemic level of liquidity across markets by inducing high volume-related buy-sell trade imbalances (see Koch et al., 2016). From a supply-side perspective, a liquidity contagion effect from one market to another provides evidence that tightness of funding liquidity affects all securities across different markets (see Hameed et al., 2010). Finally, the total liquidity spillover (displayed in the bottom right-hand corner of Table 1) indicates that on average, across our entire sample, 80.96% of the total variance forecast errors come from

Brockman et al. (2009) perform univariate time series regressions. Here, our methodology is based on a VAR model, the main advantages of which are that all the variables in the system are treated as endogenous variables, which provides a systematic way to capture rich dynamics in multiple time series by way of the lag structure.

cross-market liquidity spillovers, which gives an idea of the degree of cross-market connectedness. This result contrasts with the results reported by Diebold and Yilmaz (2009) in terms of volatility and return spillovers across different global equity markets. These authors conclude that, on average, around 40% of forecast error variance comes from cross-spillovers, as regards both returns and volatilities. Our results suggest that liquidity connectedness across national markets is much higher than that of returns and volatilities.

The static analysis provides a good characterization of the spillovers over the full sample period. However, as this study investigates commonality in liquidity over a period affected by extreme economic events, including the global financial crisis, it seems fairly unlikely that liquidity spillovers will not change over time. To assess the time-varying nature of commonality, we estimate the VAR using a 60-month rolling window and a 6-month forecasting predictive horizon for the underlying variance decomposition.[6] From this, we obtain the total dynamic spillover index, which serves as our proxy for commonality in liquidity.

Figure 2: Global commonality in liquidity



Note: Monthly total spillover index. Window length equals 60 months.

Figure 2 shows the total liquidity spillover index obtained from the rolling window estimation. It clearly highlights the changing dynamics over the sample period, with the level

[6] The results are robust to the use of a 60-month rolling window and a 10-month forecasting horizon.

of commonality in liquidity mostly oscillating between 70 and 87%. The low peak at the beginning of 2008 can be associated with the liquidity constraints faced by Bear Stearns, while the collapse of Lehman Brothers in September 2008 is associated with an even steeper increase in commonality in illiquidity. This increment is consistent with the findings of Hameed et al. (2010), indicating that peaks in commonality in liquidity often result from large negative market returns and coincide with liquidity crises. Thus, the dynamics show that commonality in liquidity increases during episodes of market turmoil. Our empirical findings are coherent with the theoretical discussion in Brunnermeier and Pedersen (2009), where funding and market liquidity interact with each other, leading to higher margins and less capital-intensive trading positions in periods of crisis, which in turn leads to tight funding constraints and to changing levels in market-wide liquidity as funding liquidity diminishes.

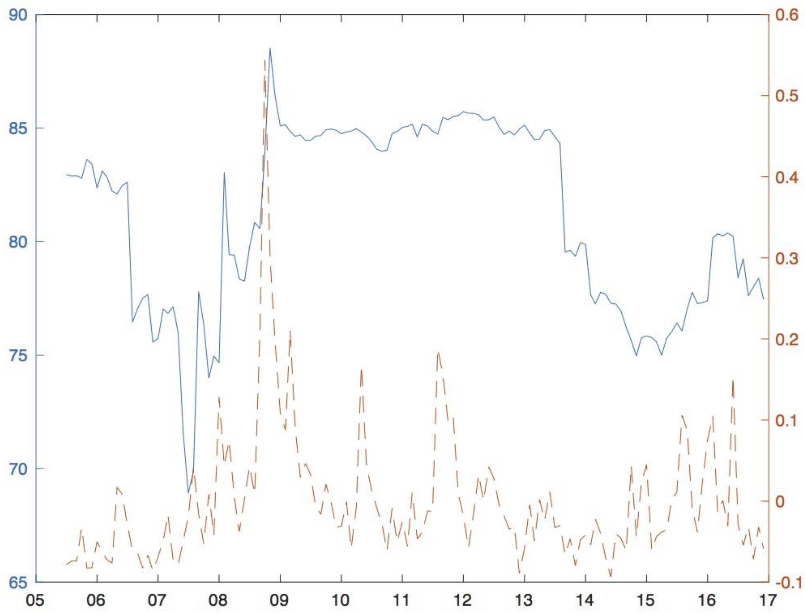
Interestingly, we also observe that commonality is very persistent and that it remains at high levels even after market turmoil and funding tightness has passed. In fact, it remains at high levels even though the level of market-wide illiquidity in each country declined substantially after the effects of the Lehman Brother collapse, to moderate levels (see Figure 1). Commonality continues being high during the European sovereign debt crisis. Investors seem to chase liquidity by rushing from periods of flight-to-quality to periods of flight-to-liquidity, running from the Eurozone bond markets back to equities which, in turn, keeps commonality high. Goyenko and Ukhov (2009), who analyze the dynamics between stock and bond market liquidity in the U.S. market, show that positive shocks to the level of illiquidity in the stock market reduce illiquidity in the bond market. Following a period of persistence in commonality in liquidity, a downward shift is observed at the end 2013, suggesting the normalization of conditions in both the bond and equity markets. The level of market commonality in the last few months of the sample is similar to that recorded in the months leading up to the global financial crisis.

4.3 Dynamics between global commonality in liquidity and global market volatility

Figure 3 shows the joint dynamics of global commonality in liquidity and global market volatility. We observe an increase in both trends during the financial crisis, although the upward trend starts earlier in the case of commonality in liquidity. Remarkably, we find that while volatility returns to lower levels, albeit with sudden peaks, levels of commonality in liquidity remain persistent. To analyze the time-varying relationship between the two, we use the dynamic Granger causality test proposed by Hurn et al. (2016).

Our proxy for global market volatility is the first principal component factor of realized market volatilities in the nine stock markets.[7] Figure 4 displays the dynamic Wald test statistics proposed by Hurn et al. (2016) for the detection of instability in the causal relationship between two time series, namely commonality in liquidity and market volatility. The sequence of t-statistics starts in May 2007, as the first 22 months are used as the minimum window size.[8]

Figure 3. Global Commonality in Liquidity and Global Market Volatility



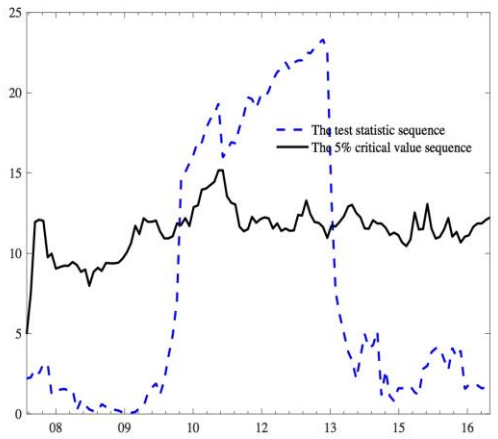
Note: This figure shows the index for global commonality in liquidity (solid line) and the proxy for global market volatility (dashed line).

We observe that global market volatility Granger-causes commonality in liquidity throughout the entire sample period. This is in line with the theoretical model developed by Brunnermeier and Pedersen (2009), in which high market volatility leads to an increase in commonality as a consequence of a reduction in the provision of liquidity available for all financial intermediaries. Conversely, and for the first time, we find that commonality in liquidity Granger-causes volatility only from late 2009 to 2013, that is, in the aftermaths of

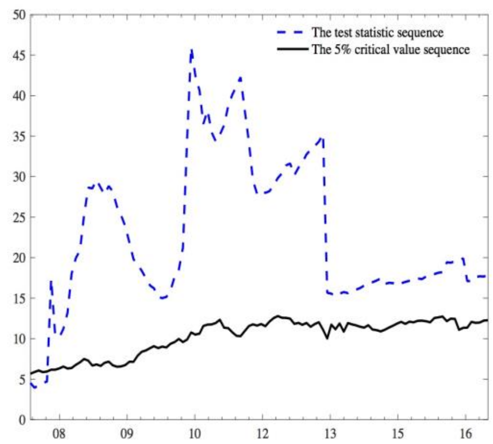
[7] As a robustness check, we have also calculated an equally weighted average volatility index for the same sampling countries, and the results (available upon request) were found to hold.
[8] Our initial sample starts in July 2000. We use 60 months in our rolling window estimation to obtain the total dynamic liquidity spillover. Using this index as input into the dynamic Granger test, we then take an additional 22 months as the minimum window size to perform the dynamic causality test.

the global financial crisis and during the European sovereign debt crisis. These feedback effects between commonality in liquidity and volatility coincide with periods of high commonality in liquidity in global markets. This finding might be interpreted as evidence of the existence of adverse loop effects in which shocks to stock market liquidity endogenously cause stock market volatility and vice versa. Such a feedback effect sheds new light on the endogenous nature of financial shocks arising during episodes of crisis, which we show are aggravated by liquidity considerations.

Figure 4. Test statistic sequences of the time-varying Granger causality test between commonality in liquidity and volatility



(a) Commonality in Liquidity to Volatility



(b) Volatility to Commonality in Liquidity

Note: The lag selection is determined using the BIC. The sequences are calculated using a recursive rolling procedure from May 2007 to December 2016.

5. Conclusion

We document a dynamic relationship between global commonality in liquidity and global market volatility in a sample of nine stock markets, representing most of the world's stock market capitalization. Our results show that global commonality in liquidity and market volatility share a dynamic bi-directional relationship. Market volatility Granger-causes commonality in liquidity as a general rule (i.e. throughout the whole sample period), while commonality Granger-causes market volatility only during sub-periods of crises and their aftermaths. This latter relationship raises a warning about the presence of endogenously enhanced adverse loop effects between commonality and liquidity during crises, which are documented and measured here for the first time.

We also find that variation in market-wide liquidity depends predominantly on inter-market liquidity innovations, which reveals the relative strength of the propagation of liquidity shocks originating from foreign stock markets. Illiquidity shocks are indeed shown to propagate more strongly than volatility and return shocks extensively analyzed by the previous literature. These strong liquidity linkages provide support for both a demand-side explanation of commonality (i.e. correlated trading behavior and the increasing importance of institutional investors in the market) and a supply-side explanation (i.e. funding constraints and liquidity spirals). The dynamics show that commonality in liquidity increases after large market downturns and peaks during episodes of market turmoil and funding tightness. We also observe that commonality is highly persistent and that it remains at high levels even after market turmoil has passed.

Our results should prove helpful for practitioners, as the relationships identified herein can usefully be taken into account in portfolio risk management. They might also be useful for policy makers as they highlight the high level of commonality across markets, which stresses the importance of designing an integrated policy framework to prevent common sources of liquidity shortage in global financial markets. Indeed, from a regulatory point of view, our results call for a closer monitoring of market wide liquidity from an integrated and coordinated perspective. Commonality means that liquidity dry-outs are likely to be correlated and therefore the provision of liquidity during crisis episodes, frequently fostered by domestic monetary policy authorities as to preserve the normal functioning of national financial markets, should be certainly addressed in a coordinated way across different markets and countries. The relatively high transmission of liquidity shocks (compared to price shocks) invites regulators and market participants to think of (i)liquidity as a prominent feature of financial markets that impact different assets and markets simultaneously, and therefore, that makes it harder to diversify risk.

Our results in this regard also emphasize the possibility of market contagion, and shock transmission, explained by the market liquidity channel. That is, market liquidity and systemic commonality appear to be crucial factors underlying market return and volatility co-movements frequently reported by the literature. In other words, our main findings provide support for liquidity as a theoretical factor explaining returns co-movements in stock markets.

Here we study commonality in liquidity of stocks, however analyzing commonality across different asset classes can complement our results. In this way, international investors would be able to reach diversification benefits unexplored here, by diversifying liquidity risk across asset classes (bonds, commodities, etc.) instead of across countries (in which case we document relatively low room for diversification).

6. References

Abdi, F., & Ranaldo, A. (2017). A simple estimation of bid-ask spreads from daily close, high, and low prices. *The Review of Financial Studies*, 30 (12), 4437–4480.

Acharya, V. V., & Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, 77 (2), 375–410.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5 (1), 31–56.

Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, 17 (2), 223–249.

Andersen, T., Todorov, V. (2010). Realized volatility and multipower variation, in Encyclopedia of Quantitative Finance, ed. by R. Cont (Wiley, New York), 1494-1500.

Brennan, M. J., Chordia, T., & Subrahmanyam, A. (1998). Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of Financial Economics*, 49 (3), 345–373.

Brennan, M. J., & Subrahmanyam, A. (1996). Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics*, 41 (3), 441–464.

Brockman, P., Chung, D.Y., & Pérignon, C. (2009). Commonality in liquidity: A global perspective. *Journal of Financial and Quantitative Analysis*, 44 (4), 851-882.

Brunnermeier, M. K., & Pedersen, L. H. (2009). Funding liquidity and market liquidity. *Review of Financial Studies*, 22 (6), 2201–2238.

Chordia, T., Roll, R., & Subrahmanyam, A. (2000). Commonality in liquidity. *Journal of Financial Economics*, 56 (1), 3–28.

Corwin, S. A., & Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *The Journal of Finance*, 67 (2), 719–760.

Coughenour, J. F., & Saad, M. M. (2004). Common market makers and commonality in liquidity. *Journal of Financial Economics*, 73 (1), 37–69.

Datar, V. T., Naik, N. Y., & Radcliffe, R. (1998). Liquidity and stock returns: An alternative test. *Journal of Financial Markets*, 1 (2), 203–219.

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119 (534), 158–171.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28 (1), 57–66.

Eleswarapu, V. R., & Reinganum, M. R. (1993). The seasonal behavior of the liquidity premium in asset pricing. *Journal of Financial Economics*, 34 (3), 373–386.

Goyenko, R. Y., & Ukhov, A. D. (2009). Stock and bond market liquidity: A long-run empirical analysis. *Journal of Financial and Quantitative Analysis*, 44 (1), 189–212.

Hameed, A., Kang, W., & Viswanathan, S. (2010). Stock market declines and liquidity. *The Journal of Finance*, 65 (1), 257–293.

Hasbrouck, J., & Seppi, D. J. (2001). Common factors in prices, order flows, and liquidity. *Journal of financial Economics*, 59 (3), 383–411.

Holmström, B., & Tirole, J. (2001). Lapm: A liquidity-based asset pricing model. *The Journal of Finance*, 56 (5), 1837–1867.

Huberman, G., & Halka, D. (2001). Systematic liquidity. *Journal of Financial Research*, 24 (2), 161–178.

Hurn, S., Phillips, P. C., & Shi, S.-P. (2016). Change detection and the causal impact of the yield curve. *Journal of Time Series Analysis*, 39 (6), 966–987.

Kamara, A., Lou, X., & Sadka, R. (2008). The divergence of liquidity commonality in the cross-section of stocks. *Journal of Financial Economics*, 89 (3), 444–466.

Karolyi, G. A., Lee, K.-H., & Van Dijk, M. A. (2012). Understanding commonality in liquidity around the world. *Journal of Financial Economics*, 105 (1), 82–112.

Koch, A., Ruenzi, S., & Starks, L. (2016). Commonality in liquidity: a demand-side explanation. *The Review of Financial Studies*, 29 (8), 1943–1974.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74 (1), 119–147.

Liu, L.Y., Patton, A.J., Sheppard, K. (2015). Does anything beat 5-minute RV? A comparison of realized measures across multiple asset classes. *Journal of Econometrics*, 187(1), 293-311.

Pastor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, 111 (3), 642–685.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58 (1), 17–29.

Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of finance*, 39 (4), 1127–1139.

Shi S., Hurn, S., & Phillips, C.B. (2016). Causal change detection in possibly integrated systems: revisiting the money-income relationship, Macquarie University Faculty of Business & Economics Research Paper. Available at

SSRN: https://ssrn.com/abstract=3237213 or http://dx.doi.org/10.2139/ssrn.3237213
Sims, C. A. (1980). Macroeconomics and reality. *Econometrica*, 48 (1), 1–48.

Appendix

Table A1: Summary Statistics of Commonality in Liquidity

	Mean	**Median**	**St.Dev.**	**Min**	**Max**	**Skewness**	**Kurtosis**
				Pre-Financial Crisis (2000-2007)			
US	1.740	1.430	0.671	0.907	3.866	0.894	2.998
CA	1.140	1.060	0.279	0.795	23.261	1.520	5.943
GER	1.830	1.790	0.628	0.894	3.521	0.675	2.673
ES	0.790	0.741	0.264	0.433	1.462	0.830	2.714
SWI	1.076	0.972	0.482	0.536	2.683	1.311	4.351
ITA	0.611	0.553	0.208	0.396	1.800	2.749	13.63
JPN	1.235	1.225	0.318	0.668	2.463	0.650	4.497
UK	1.180	1.130	0.362	0.706	2.246	1.032	3.551
FR	1.290	1.170	0.520	0.680	2.820	0.886	3.016
				Financial Crisis (2008-2009)			
US	1.940	1.660	0.880	0.930	4.070	1.001	3.041
CA	1.590	1.250	0.900	0.820	5.310	2.322	9.390
GER	1.980	1.720	0.830	1.060	5.380	1.556	5.380
ES	1.200	1.040	0.490	0.660	2.871	1.448	5.210
SWI	1.290	1.080	0.570	0.620	3.035	1.210	3.914
ITA	1.030	0.920	0.440	0.450	2.383	1.110	3.920
JPN	1.630	1.497	0.675	0.880	4.580	2.368	10.57
UK	1.650	1.470	0.730	0.700	3.956	1.291	4.564
FR	1.540	1.300	0.660	0.710	3.560	1.100	3.892
				Post-Financial Crisis (2010-2016)			
US	1.199	1.165	0.240	0.883	2.192	1.628	6.239
CA	1.004	0.964	0.259	0.628	1.959	1.195	4.629
GER	1.528	1.436	0.343	0.971	2.394	0.948	3.171
ES	1.057	0.983	0.300	0.601	2.103	1.325	4.930
SWI	0.856	0.824	0.227	0.447	1.692	1.128	4.837
ITA	1.145	1.082	0.362	0.578	2.690	1.375	6.028
JPN	1.254	1.166	0.359	0.687	2.247	1.259	4.269
UK	1.001	0.950	0.244	0.636	2.289	2.102	10.886
FR	1.090	1.030	0.290	0.660	1.950	1.257	4.231
				Full Sample (2000-2017)			
US	1.547	1.296	0.654	0.883	4.069	1.656	5.451
CA	1.167	1.034	0.498	0.628	5.313	4.076	28.90
GER	1.730	1.546	0.600	0.894	4.821	1.605	6.649
ES	0.979	0.916	0.367	0.433	2.871	1.442	6.643
SWI	1.034	0.901	0.482	0.447	3.035	1.771	6.448
ITA	0.914	0.841	0.411	0.399	2.690	1.207	4.771
JPN	1.325	1.257	0.447	0.669	4.583	2.585	16.713
UK	1.190	1.061	0.475	0.636	3.956	2.344	10.878
FR	1.250	1.100	0.500	0.660	3.560	1.504	5.613

Note: This table reports summary statistics for the liquidity measure proposed by Abdi and Ranaldo (2017). Our dataset spans from July 2000 to December 2016.