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Abstract

We analyse the market liquidity level and resilience of US 10-year Treasury bonds. Having checked that five indicators show inconclusive results on the liquidity level, we fit a bivariate CC-GARCH model to evaluate its resilience, that is, how liquidity reacts to financial shocks. According to our results, spillovers from liquidity volatility to returns volatility and vice versa are more intense after the crisis. Further, the volatility persistence of both returns and liquidity becomes lower after the crisis. These results are consistent with the existence of more frequent short-lived episodes of high volatility and more unstable liquidity that is more prone to evaporation.

Keywords: market liquidity, volatility, US Treasuries; CC-GARCH model.

JEL classification: G24, C33.

Resumen

En este trabajo se analiza la liquidez del mercado de deuda pública a diez años en Estados Unidos antes y después de la crisis financiera. Se consideran tanto el nivel como su resistencia, es decir, la forma en que la liquidez reacciona a los *shocks* financieros. Tras analizar cinco indicadores de liquidez, la recuperación de los niveles anteriores a la crisis financiera no es concluyente. La resistencia de la liquidez se estudia a partir de un modelo CC-GARCH bivalente. Según nuestros resultados, la propagación de un repunte de la volatilidad de la liquidez a la volatilidad de los rendimientos (y viceversa) se ha intensificado tras la crisis. Es más, la persistencia de la volatilidad de los rendimientos y de la liquidez es menor tras la crisis. Estos resultados son coherentes con la presencia más habitual de breves episodios de elevada volatilidad, caracterizados por una liquidez de mercado más inestable y propensa a evaporarse.

Palabras clave: liquidez de mercado, deuda pública en Estados Unidos, modelos CC-GARCH.

Códigos JEL: G24, C33.

1 Introduction

Market liquidity may be defined as the ease with which market participants can buy or sell an asset in a market without affecting its price (Elliot, 2015).¹ Market liquidity plays a central role in financial stability. First, impaired market liquidity makes securities trading more difficult by increasing funding costs. Also, a lack of liquidity is a well-known shock amplifier. During upturns, agents perceive that liquidity will remain abundant, which encourages them to gain exposure to apparent liquid assets. When market sentiment changes, liquidity conditions worsen and agents convert securities that were actually illiquid into cash (Nesvetailova, 2008; Houben et al., 2015). Finally, the availability of high quality collateral can be damaged under a low liquid government debt scenario, which could distort the functioning of the financial markets (Anderson et al., 2015).

In recent years, market liquidity has received growing attention given its apparent decline in some markets (IMF, 2015; Fender and Lewrick, 2015). Indeed, some episodes of heightened volatility such as the October 2014 “flash crash” in the US Treasury markets or the so-called “taper tantrum” in the second quarter of 2013 have been associated with the presence of liquidity strains in certain fixed income markets (Adrian et al., 2015). Those events demonstrated that liquidity strains could also affect the most liquid bond markets, even under benign market conditions, and increased the fear of further volatility spikes (Fisher, 2016).

In this paper we study U.S. Treasury debt market liquidity, namely that of the 10-year on-the-run Treasury note, which has centred discussions on the existence of liquidity strains (Engle et al., 2012).² We choose this market for several reasons. First, US 10-year government debt is a safe haven for investors, a key instrument of monetary policy and a source of high-quality collateral. Besides, as it is the most liquid fixed income asset, liquidity strains would likely feed through to other markets. Longstaff (2004) illustrates how investors price this abundant liquidity through the fight-to-liquidity premium in Treasury bond prices.

In addition, in recent years markets have undergone significant structural changes with potential implications for the liquidity conditions of several assets, including Treasuries (IMF, 2015). First, the rise of electronic platforms and new trading techniques, such as automatic trading and high-frequency trading, have made market liquidity less predictable. Second, the profound trans-

¹Market liquidity differs from monetary liquidity, which is related to central banks’ monetary aggregates, or from funding liquidity, which is the ability to obtain funding for a position in a risky asset (Brunnermeier and Pedersen, 2009).

²See, IMF (2015) or Adrian et al. (2017 (a)) for some recent papers that also study market liquidity conditions of US Treasuries.

formation of intermediation, with lower inventories by banks and market-making activities concentrated in fewer clients, together with some of the new regulations that might have discouraged banks from market-making activities,³ could have harmed market liquidity. Finally, the effect on market liquidity of unconventional monetary policies and asset purchases under quantitative easing (QE) programs on market liquidity is not clear.⁴

The main liquidity indicators of US Treasuries do not fully justify the existence of those liquidity strains (Broto and Lamas, 2016; Adrian et al., 2017 (a)), although this result is not conclusive. The main reason for this lack of empirical evidence is that market liquidity is not easy to measure. In fact, it is an unobservable variable that embodies several heterogeneous characteristics (Sarr and Lybek, 2002). Accordingly, a large number of indicators that have been proposed to monitor this multidimensionality. The result is a plethora of indices that usually provide different signals and do not allow for an unequivocal assessment of how liquidity conditions evolve.

Nevertheless, from a financial stability standpoint, the main concern about liquidity is not the level itself but its resilience, that is, the risk of a sharp liquidity decline in response to shocks (IMF, 2015). Even apparently sound markets with ample liquidity can be fragile and prone to evaporation. Therefore, an all-encompassing study of market liquidity should analyze these two dimensions. In this paper, we analyze both the level of liquidity and its resilience. First, we consider five liquidity indicators to gauge its level. Second, we study liquidity resilience by means of a model that relates the volatility of these measures to financial volatility, which helps to disentangle whether liquidity is resilient to stressed market conditions or not. During the financial crisis, more volatile liquidity and prices are expected, whereas these dynamics of both variables in the post-crisis period are not that clear. If market liquidity is resilient to financial shocks, liquidity volatility would scarcely react to market volatility. On the contrary, in a non-resilient scenario, the market would witness a feedback-loop between both variables. Therefore, liquidity volatility, rather than the liquidity level, becomes the key variable of our analysis of resilience.

Many papers have shown the link between the liquidity level and financial volatility. There are two main theoretical explanations. On the one hand, according to the mixture of distribution

³For instance, the leverage ratio might have reduced the weight of low-margin and high-volume activities, like repos (Adrian et al., 2017 (a)), and the restrictions on proprietary trading might have also harmed market-making activities by dealers affected by the Volcker rule (Bao et al., (2016)).

⁴On the one hand, these policies have a positive impact on market liquidity, given the higher funding liquidity by banks (Brunnemeier and Pedersen, 2009) and the lower search frictions that prevent investors from finding counterparts (Lagos et al., 2011). Nevertheless, on the other hand, central banks' purchases generate scarcity of certain assets, which might reduce liquidity. Besides, accommodative policies could increase risk appetite (Bekaert et al., 2013) and might lead to a search for yield by investors that might ultimately boost liquidity risk.

hypothesis (MDH), price volatility and liquidity, proxied by trading volumes, should be positively correlated because of their dependence on the rate of information flow. This explanation justifies the positive correlation between price volatility and volumes found empirically by Clark (1973) and Tauchen and Pitts (1983).⁵ On the other hand, the sequential information arrival hypothesis (SIAH) of Copeland (1976) states that there is a positive correlation between trading volume and price volatility in a sequential manner, as once new information arrives at the markets, intermediate equilibriums occur prior to the final equilibrium, which leads to significant lead-lag relationships between the information flow and the returns.

Regarding the empirical literature, most studies that link returns volatility and liquidity levels fit GARCH-type models. The pioneering work by Lamoureux and Lastrapes (1990) analyze the volatility of 20 traded stocks through a univariate GARCH model where the daily trading volume is an exogenous regressor in the variance equation.⁶ Since then, univariate and multivariate GARCH models alike have been broadly used to study the link between market liquidity and volatility, while model specifications have been enriched over time—see Chuang et al. (2012), Frank et al. (2008) and Engle et al. (2012), among others—.

Although the literature on the link between the liquidity level and financial volatility is extensive, previous studies on the link between liquidity volatility and returns volatility are scarcer. For instance, Akbas et al. (2011) conclude that there is a positive correlation between the volatility of liquidity and expected stock returns. Thus, if liquidity is very volatile and fluctuates within a wide range, investors may be exposed to a relatively higher probability of low liquidity at the time of selling the asset. Therefore, risk-averse investors would require a premium for holding stocks with high liquidity volatility. On the contrary, Chordia et al. (2001) document a negative relationship between both variables using volumes as liquidity indicators. Engle et al. (2012) propose a joint model of liquidity and volatility for the US Treasuries. These papers use volumes or alternative liquidity measures in their specifications.

We focus on this second, less explored branch of the literature. We analyze the dynamics of liquidity volatility and returns volatility before and after the financial crisis, as well as their links, for the US Treasury debt market. To this end, we fit a bivariate GARCH-type model of the family

⁵Whereas Clark (1973) reports a positive link between the square price change and volumes from the cotton futures market, Tauchen and Pitts (1983) shows this relationship using daily data of Treasury-bill futures. Since trading activity also rises as intraday price changes increase, correlation between trading volume and volatility, measured by the variance of daily price changes, is positive.

⁶In Lamoureux and Lastrapes (1990), trading volume is highly significant and volatility persistence tends to disappear once this variable is included.

of constant conditional correlation (CC-) GARCH models by Bollerslev (1990) as proposed by Nakatani (2010). This model allows us to fit returns volatility, liquidity volatility (which serves as a proxy for the stability of liquidity conditions) and their interactions. Through this model we are able to answer some important questions. Has liquidity any role in shaping market volatility? Is liquidity volatility driven by market uncertainty, meaning it would vanish under a shock?

Our results show that the liquidity level of the 10-year note is similar to that of the pre-crisis period. Regarding liquidity resilience, returns of the 10-year note are more volatile than before the crisis, so that they are more prone to jumps. Liquidity volatility measures have changed in a similar manner: in recent years liquidity is more prone to sudden drops, although recoveries are faster than before the crisis. Finally, we explore the link between the volatility of liquidity and that of returns and demonstrate that volatile liquidity conditions exert a stronger influence on financial volatility nowadays than before the crisis. This means that, after the financial crisis, more shifting market conditions in the U.S. Treasury market can be explained by less resilient market liquidity, although other factors might be contributing to this trend.

The rest of the paper is organized as follows. Section 2 describes the main market liquidity indicators and analyzes the market liquidity level of US Treasuries. Then, in Section 3 we present our empirical model to analyze the relationship between both variables. Section 4 summarizes the main results. Finally, section 5 concludes.

2 Market liquidity measures

2.1 Selected market liquidity indicators

Next, we analyze the market liquidity level of US 10-year Treasuries. This analysis poses at least two difficulties. First, market liquidity is not an observable variable. Second, the concept of market liquidity entails several dimensions, so that various proxies are needed to capture all the relevant features. According to Sarr and Lybek (2002), a liquid market should have five characteristics, namely tightness, immediacy, efficiency, depth and breadth. Tightness refers to transaction costs, which are low in liquid markets, whereas immediacy characterizes those markets where trades are executed quickly and in an orderly manner. In an efficient market, prices are able to correct imbalances that move prices from what is warranted by fundamentals and to move rapidly to new equilibrium levels.⁷ Finally, depth is linked to the number of orders, while breadth allows orders to flow with a minimal impact on prices, even if they are large.

Given the heterogeneous characteristics behind the definition of market liquidity, a large number of indicators have been proposed to monitor these aspects (see Sarr and Lybek, 2002). We focus

on five indicators among this variety, one per each feature of market liquidity, to cover the five dimensions. Three of them are based on prices, while the remaining two consist of quantities or a combination of prices and quantities. Table 1 provides further details about their construction and interpretation.

We analyze tightness, immediacy and market efficiency with metrics based on prices. First, we proxy tightness with the estimation of the effective bid-ask spread proposed by Roll (1984), which follows this expression,

$$L_R = 2\sqrt{-Cov(r_t, r_{t-1})}, \quad (1)$$

where r_t is the percentage return on the US 10-year Treasuries, which is given by,

$$r_t = 100 \times (\Delta \ln p_t), \quad (2)$$

where p_t is the interest rate in t and Δ is the difference operator. The intuition behind L_R is based on the fact that in an efficient market the underlying value of an asset fluctuates randomly, whereas trading costs introduce negative serial dependence in market price changes. This indicator is more representative of real transaction costs in a market than other widely used indicators like the quoted bid-ask spread, as the measure by Roll (1984) is an estimation of the effective spread, defined as the execution price and the midpoint of bid and ask quotes.⁸

Second, we use the daily range, denoted as L_{DR} , as a measure of immediacy. We calculate this as the difference between the highest and lowest price in a day, so that a wider range may indicate poor orders execution in a market, or lower liquidity.⁹ Third, we analyze market efficiency with the Market Efficiency Coefficient (MEC), L_{MEC} . The MEC is a ratio between the variances of two returns with different time spans, that is,

$$L_{MEC} = Var(R_t)/(Var(r_t) \times 5), \quad (3)$$

⁷To avoid confusion with the IMF (2015) concept of resilience, which is linked with the resistance of liquidity to shocks, we use the term “efficiency” to denote the same concept that Sarr and Lybek (2002) call “resilience”.

⁸Nevertheless, the covariance of price changes is frequently positive, so that L_R becomes a noisy estimator even in relative large samples (Harris, 1990), which explains why alternative measures, such as the high and low prices spread estimator of Corwin and Schultz (2012), outperform L_R estimation of transaction costs. See Corwin and Schultz (2012) and Schestag et al. (2016) for a comparison of trading costs estimates. However, due to convergence problems our model faces in analyzing liquidity resilience with the Corwin and Schultz (2012) estimator and given the simplicity of L_R , we choose the latter.

⁹Alternatively, Schestag et al. (2016) analyze liquidity immediacy in the U.S. corporate market by means of the interquartile range. We discard this metric due to the lack of intraday data.

where R_t are weekly returns, whereas r_t are daily returns. This indicator is close to one in efficient, liquid markets, whereas substantial departures from unity reveal lower liquidity. The intuition behind L_{MEC} is based on the fact that price movements are more continuous in liquid markets. That is to say, if new information affects equilibrium prices, the transitory changes to that price are minimal in resilient markets. See Sarr and Lybeck (2002) for further details on the interpretation of the MEC coefficient.

With regard to measures that require quantities, we use the trading volume, V_t , to analyze market depth. The volume is the amount of securities traded per period (in US dollars). Finally, we study breadth through the indicator proposed by Amihud (2002), given by,

$$L_A = \frac{|r_t|}{V_t}, \quad (4)$$

which is the ratio of the absolute return in the market to the trading volume, V_t . Sudden spikes in L_A suggest that the market is not able to suitably absorb a given amount of trading orders, so that market breadth would be impaired. By construction, this measure is more volatile than the trading volume, V_t .¹⁰

2.2 The data

Figure 1 represents the five liquidity measures for the 10-year on-the-run Treasury note, together with the daily returns for this maturity. Due to data constraints, L_R , L_{DR} and L_{MEC} are daily, whereas volumes and the Amihud (2002) ratio are weekly. We calculate the metrics based on prices from Bloomberg Generic dataset, which is Bloomberg's market consensus price for government bonds. We obtain volumes from the Primary Dealers release of the Federal Reserve Bank of New York (FRBNY). The release compiles different datasets with a remaining term to final maturity from seven to eleven years, so that the trading volumes include not only the 10-year note but also other securities. However, our measure is representative, as the bulk of trading activity is carried out in the 10-year on-the-run note.¹¹ With regard to the Amihud (2002) ratio, L_A , we use trading volumes in the denominator, whereas we obtain absolute returns from an index by Bank of America that summarizes prices of all outstanding Treasury issues within a similar maturity sector for the numerator.¹² Table 1 summarizes data sources.

¹⁰We drop observations of the last week of each year for V_t and L_A since trading activity is usually abnormally low in these periods.

¹¹From March 2013 to September 2015 the average volume of the 10-year on-the-run Treasury note was 84.7% of the total trading volume of US Treasuries (Brain, et al., 2018).

¹²This index, the BofA Merrill Lynch 7-10 Year US Treasury Index, also excludes TIPS and comprises securities with a remaining term to final maturity greater than or equal to seven years and less than ten years.

The sample period runs from January 2003 to end-June 2016, so that the sample size is 3,465 trading days and 692 weeks for daily and weekly indicators, respectively. We also focus on the pre-crisis period, from January 2003 to May 2007, and the post-crisis period, from April 2009 to June 2016, to gain an insight into liquidity dynamics in periods of calm. We date the beginning of the crisis in June 2007 coinciding with the first evidence on problematic subprime mortgages and mortgage-related securities, more specifically, when two Bear Stearns hedge funds with large holdings of subprime mortgages run large losses.¹³ We consider the end of the crisis in April 2009, after the QE program was launched and expanded in March 2009, which also coincided with an agreement of the G20 on a global stimulus package, which helped to stabilize the markets.

Figure 1 represents the five market liquidity measures. All indices but the MEC exhibit a severe deterioration of the market liquidity level during the financial crisis, around 2008:Q3 and 2009:Q1. Once the financial crisis abated, market liquidity returned to pre-crisis levels. By construction, price-based measures, i.e., L_R , L_{DR} and L_{MEC} , are more erratic and exhibit more volatility spikes than volume-based indicators. These bouts of illiquidity are also frequent after the financial crisis. Volumes have a clearer trend and rapidly recovered after the crisis, but since mid-2013 volumes steadily declined. Nevertheless, in the post-crisis period, the five liquidity indices have fluctuated in a non-homogeneous way, so that it is difficult to clearly characterize market liquidity recovery through Figure 1.¹⁴ This problem is a result of the inherently diverse nature of indicators.¹⁵

To gain greater insight into liquidity dynamics after the crisis, Table 2 contains the mean and standard deviation of the five indicators in the pre-crisis and post-crisis periods. The average price-based measures are slightly higher in the post-crisis period, which suggests that market liquidity conditions worsened. In this same vein, average daily trading volume dropped below pre-crisis levels, and the Amihud ratio, L_A , stabilized at higher levels than before the crisis. Standard deviations of the five indicators are systematically higher post-crisis than pre-crisis. From this evidence it is not possible to disentangle whether these differences in liquidity between the two periods, which are quite modest for both means and standard deviations, are significant. However, while we do not

¹³Namely, in June 2007 S&P and Moody's downgrade over 100 bonds backed by second-lien subprime mortgages.

¹⁴Our findings are in line with Adrian et al. (2017 (a)), who also offer a non-conclusive picture of liquidity conditions in U.S. Treasury securities when comparing market liquidity before and after the financial crisis. Nevertheless, contrary to our evidence, they do not identify a liquidity decline in the aftermath of the crisis. Our analysis is not fully comparable with Adrian et al. (2017 (a)), who focus on the on-the-run 2-, 5- and 10-year Treasury notes.

¹⁵The recent literature proposes synthetic indicators that summarize the information of a set of liquidity measures, which enables the conflicting signals between indicators to be disentangled (see, for instance, Broto and Lamas (2016) who propose a synthetic liquidity index for government and corporate U.S. fixed income based on the methodology for financial stress indicators).

have enough evidence to conclude as to a liquidity deterioration, these descriptive statistics would support this hypothesis.

3 Market liquidity resilience: Empirical model

To study liquidity resilience in the US Treasury market, i.e. the risk of a sharp liquidity decline in response to shocks, we propose a bivariate model that allows us to analyze simultaneously both liquidity volatility and returns volatility. Liquidity volatility serves as a proxy for the uncertainty of the liquidity level. If liquidity had become less resilient after the crisis, we would expect more unstable volatility dynamics in liquidity. We also incorporate US Treasuries returns volatility in the model to analyze its interlinkages to the volatility of market liquidity measures. If liquidity is resilient to stressed conditions, more volatile markets will barely impact liquidity volatility. On the contrary, in a non-resilient liquidity scenario, higher market volatility would affect liquidity volatility, which would react in a feedback loop.

Therefore, we model two dependent variables,

$$\mathbf{Y}_t = \begin{pmatrix} r_t \\ \Delta L_t \end{pmatrix}, \quad (5)$$

where r_t are daily returns and ΔL_t is the first difference of each of the five liquidity indicators, calculated on a daily basis for L_R , L_{DR} and L_{MEC} , and on a weekly basis for V and L_A . Treasuries' returns of the models for V and L_A are also weekly, r_t^w .¹⁶ Table 3 summarizes the main statistics for these variables. All series are asymmetric and/or have excess kurtosis. Box-Pierce Q-statistics for higher order serial correlation suggest the presence of conditional heteroskedasticity in both returns and first differences of liquidity indicators, which evidences the suitability of a GARCH family model.

Specifically, our baseline model is a bivariate ECCC-GARCH (Extended Constant Conditional Correlation GARCH) model as proposed by Nakatani (2010) and Jeantheau (1998), which belongs to the family of conditional correlation (CC-) GARCH models by Bollersvev (1990). The main advantage of the specification by Nakatani (2010) for our empirical problem is that it allows us to analyze volatility transmission among the variables of the model. That is to say, whereas in a standard CCC-GARCH specification the conditional volatility would be modeled as a combination of its squared innovations and volatility, Nakatani (2010) considers that conditional volatility also

¹⁶Weekly returns, r_t^w , are calculated as $100 \times (\Delta \ln p_t^w)$, where p_t^w is a weekly series of Wednesday's interest rates, which is the day of the week when the Federal Reserve releases the data on volumes.

depends on those squared innovations and volatilities of other equations, while keeping the conditional correlation structure constant. Therefore, our proposed bivariate model allows us to study the simultaneous impact of higher liquidity volatility on financial volatility and that of financial volatility on liquidity volatility. This approach is more realistic than previous models where the level of market liquidity affects financial volatility exogenously (see, for instance, Lamoreux and Lastrapes, 1990).¹⁷

First, as usual in the empirical finance literature, we prewhiten the dependent variables with AR and VAR filters,¹⁸

$$\mathbf{Y}_t = \mathbf{A}_0 + \mathbf{A}_1 \mathbf{Y}_{t-1} + \dots + \mathbf{A}_i \mathbf{Y}_{t-i} + \varepsilon_t, \quad (6)$$

where $\varepsilon_t = [\varepsilon_{1t}, \varepsilon_{2t}]'$ and $\varepsilon_t \sim N(0, \mathbf{\Omega})$. Conditional variance equations follow this expression,

$$\begin{aligned} \varepsilon_t \quad | \quad I_{t-1} &\sim N(0, \mathbf{D}_t R \mathbf{D}_t) \\ \mathbf{D}_t &= \text{diag}\{\sqrt{h_{it}}\} \\ \mathbf{h}_t &= \mathbf{C} + \mathbf{A} \varepsilon_{t-1}^2 + \mathbf{B} \mathbf{h}_{t-1} \end{aligned} \quad (7)$$

where R is the constant conditional correlation matrix, \mathbf{D}_t is a diagonal matrix with the conditional variance of returns, h_{1t} , and liquidity, h_{2t} , \mathbf{C} is a (2×1) vector, and \mathbf{A} and \mathbf{B} are (2×2) matrices. If both \mathbf{A} and \mathbf{B} are diagonal, this ECCC-GARCH model collapses into the CCC-GARCH model of Bollerslev (1990). Specifically, our conditional variances follow the proposal by Nakatani (2010) and are given by,

$$\begin{aligned} h_{1t} &= c_1 + \alpha_{11} \varepsilon_{1t-1}^2 + \alpha_{12} \varepsilon_{2t-1}^2 + b_{11} h_{1t-1} + b_{12} h_{2t-1} \\ h_{2t} &= c_2 + \alpha_{22} \varepsilon_{2t-1}^2 + \alpha_{21} \varepsilon_{1t-1}^2 + b_{22} h_{2t-1} + b_{21} h_{1t-1} \end{aligned} \quad (8)$$

where, apart from the determinants of the conditional variance of univariate GARCH models, this specification allows us to arrive at information on the impact of liquidity volatility on returns

¹⁷We choose the CCC-GARCH, which forces conditional correlation to be constant over time, instead of DCC-GARCH (Dynamic Conditional Correlation GARCH) as in our case there is no gain in the use of a DCC model. The DCC-GARCH model is estimated in two steps. In the first step parameters in the variance equations are estimated, while in the second step dynamic correlations are fitted. As our main focus is on volatility spillovers, which are estimated from the variance equations in the first stage, we rule out a DCC-GARCH specification. Besides, tests based on Engle and Sheppard (2001), which are available upon request, suggest that our bivariate dataset has constant conditional correlations rather than time-varying ones.

¹⁸We use Granger-causality tests to choose between AR or VAR filters, hence we use VAR filters when the tests identify feedback between liquidity measures and returns. Otherwise, we employ AR filters. The number of lags is determined using the Akaike information criterion. We have performed all the prewhitening process with E-Views.

volatility through coefficients α_{12} and b_{12} , and that of returns volatility on liquidity volatility, through coefficients α_{21} and b_{21} . Spillovers to financial volatility, h_{1t} , can be the result of past shocks of liquidity measures, α_{12} , and/or of higher liquidity volatility in $(t - 1)$, b_{12} . In the same vein, shocks in returns and returns volatility might influence liquidity volatility through h_{2t} . The model allows us to disentangle whether interlinkages between the two variables have grown after the crisis as well as causality direction. These variables also enable us to analyze the existence of feedback loops between both variables, as a return shock might translate into more uncertain liquidity conditions.

As usual in GARCH-type models, the estimates of $\alpha_{11} + b_{11}$ and $\alpha_{22} + b_{22}$ provide a measure of volatility persistence, so that if this sum is close to one, high volatility tends to be followed by high volatility. A lower persistence after the crisis as proxied by this sum of coefficients might be interpreted as an indicator of more fragile liquidity conditions.

We estimate all parameters simultaneously in R with the `cggarch` package of Nakatani (2014) by maximizing the log-likelihood function of this model. As initial values in the estimation process we choose univariate GARCH estimates for diagonal elements of \mathbf{A} and \mathbf{B} and values slightly above zero for the non-diagonal elements. The modulus of the largest eigenvalue of $\mathbf{A} + \mathbf{B}$ matrix is constrained to be strictly less than one to ensure positive and stationary variances (Nakatani, 2010).¹⁹

4 Results

Next we analyze whether market liquidity has become more fragile after the crisis. We fit the model in equations (6) to (8) for the returns, r_t , and the first differences of the five liquidity measures, L_R , L_{DR} , L_{MEC} , V and L_A . We estimate the model for the full sample, as well as for the pre-crisis period, from January 2003 to May 2007, and the post-crisis period, from April 2009 to June 2016. Tables 4, 5 and 6 report the estimates of the model for the three periods, respectively. Our main interest is in the two calm periods before and after the crisis to analyze to what extent market liquidity dynamics might have changed over time outside stressed periods, so as to ensure that results are not driven by the financial crisis episode.

According to the estimates of α_{11} and b_{11} in Tables 5 and 6, the volatility of the U.S. Treasuries became less persistent after the financial crisis. Persistence, which is approximated by $\hat{\alpha}_{11} + \hat{b}_{11}$, is lower in the post-crisis period for all liquidity indicators except for the estimates with L_{MEC} . This implies that after the crisis calm periods last less than before the crisis, and also that volatility

¹⁹Following the notation in Nakatani (2010), $\lambda(\Gamma_{\mathbf{C}}) < 1$ denotes the stationarity condition, whereas the fourth order moment condition is fulfilled if $\lambda(\Gamma_{\mathbf{C} \otimes \mathbf{C}}) < 1$. See Nakatani (2010) for further details.

shocks in returns impact on financial volatility for shorter periods, so that market turbulence tends to fade away more rapidly than in the past. In other words, market conditions might be more unstable than in the past. We reach similar conclusions on the persistence of liquidity volatility as $\widehat{\alpha}_{22} + \widehat{b}_{22}$ also diminish after the crisis for all liquidity indicators, except for the model with L_{MEC} , although with non-significant coefficients. This result implies that liquidity shocks are less persistent than in the past. In the same vein, calm periods are shorter in the aftermath of the crisis. That is to say, the propensity of liquidity to suddenly evaporate has increased, which confirms fears that liquidity conditions are more fragile in this market segment. On a more positive note, this lower persistence also implies that market liquidity volatility would return to low levels more quickly than in the past.

Spillovers from liquidity volatility to financial volatility, as approximated by \widehat{b}_{12} , are increasingly significant. Thus, according to Table 5, in the pre-crisis period this coefficient is only significant for the models with L_R and V , whereas, as shown in Table 6, in the post-crisis period all estimates for b_{12} except that for L_A are significant. Nevertheless, the Amihud ratio, L_A , is weekly, which might make spillover identification more difficult. Moreover, the impact of financial volatility on liquidity volatility can be analyzed through \widehat{b}_{21} . As stated in Table 5, this coefficient is significant only for L_{DR} in the pre-crisis period, whereas Table 6 indicates that after the crisis \widehat{b}_{21} also becomes significant for the models with L_{MEC} and L_A .

In other words, we identify rising spillovers over time, so that once we estimate the model for the two calm periods, that preceding and that following the crisis, we observe that the influence of liquidity volatility on financial volatility and vice versa has increased. Indeed, in the aftermath of the crisis spillovers are significant in both directions for L_{DR} and L_{MEC} . This means that for the models with the daily range and the MEC, we identify a feedback loop between liquidity volatility and price uncertainty. Specifically, higher liquidity volatility translates into higher financial volatility and, simultaneously, the other way around, so that the more unstable liquidity is, the more volatile returns are, and vice versa.

In any case, according to Table 6, the estimates for b_{12} tend to be larger and more significant than those for b_{21} , except for the model for the Amihud ratio, L_A , which indicates that liquidity volatility dominates these dynamics. This result complements that of Fleming and Remolona (1999) and Fleming and Piazzesi (2005), who state that depth, which we approximate through volumes, tends to disappear prior to economic news announcements. According to our results, liquidity volatility not only reacts to returns volatility, but also plays a major role in exacerbating financial volatility.

Our results are in line with previous publications by some central banks that also find evidence supporting this changing pattern in volatility after the crisis in different markets. For instance, the ECB (2016) also observes a lower persistence of stock market volatility after the announcement of asset purchase programs in the US and the euro area through time-varying estimates of GARCH (1,1) parameters, whereas the BoE (2015) estimates a range of asymmetric GARCH models for UK equity and credit markets to conclude that financial volatility has become more sensitive to news after the crisis.

Important financial stability considerations arise from our findings. The lower volatility persistence of both returns and liquidity after the crisis suggests that financial volatility is more prone to acute, short-lived episodes of market turbulence, meaning that shocks impact volatility more intensely than in the past. Nevertheless, markets also recover more easily from shocks. Further, higher feedback effects between financial volatility and market liquidity in the aftermath of the crisis imply that financial shocks are immediately followed by liquidity strains, which in turn exacerbate market reaction. On a more positive note, episodes of high volatility are less prolonged, potentially reducing the severity of financial strains, which is positive for financial stability. In any event, our results suggest that the market liquidity of US Treasuries has become more fragile even with apparently sound liquidity.

In line with the IMF (2015), the degree of liquidity resilience might be related to some of the recent structural changes in the markets already mentioned in the introduction, such as the lower presence of market makers, or the existence of large mutual fund holdings and concentrated holdings by institutional investors. Moreover, the rise of electronic platforms and new trading strategies, such as automatic trading and high-frequency trading, could have prompted more unstable liquidity conditions in recent years (Joint Staff Report, 2015). On another level, some specific features of the Basel III capital framework, such as the introduction of the leverage ratio, could have contributed to the decline of the liquidity provision by bank-dealers (Adrian et al., 2017 (b)), which is consistent with the increasing interlinkages between the volatility of liquidity and returns. Besides suffering from serious data limitations, the quantification of the significance of those drivers in shaping the link between market liquidity and financial volatility exceeds the scope of this paper.

5 Conclusions

In this paper, we propose a model to analyze the market liquidity level and resilience of US 10-year Treasury bonds, which have been at the core of the discussion about liquidity strains since the “flash crash” of October 2014. First, we calculate five market liquidity indicators that do not show

a clear liquidity drop in the aftermath of the financial crisis. Then, we fit a bivariate CC-GARCH model as proposed by Nakatani (2010) for US 10-year Treasury returns and the first difference of our liquidity measures to evaluate liquidity resilience, i.e. how liquidity reacts to financial shocks. This model approach is useful for understanding the dynamics of returns volatility and liquidity volatility, which proxies the stability of liquidity conditions, as well as their interactions.

We arrive at two main findings. First, after the crisis the volatility persistence of both returns and volatility is lower. Second, spillovers from liquidity volatility to returns volatility and vice versa become more intense after the crisis. Both results are consistent with the existence of more frequent short-lived episodes of high volatility of US Treasuries, and liquidity that is more unstable and more prone to evaporation. Under more recurrent jumps, markets could be subject to more frequent distortions, but they would have a faster recovery than in a high persistence scenario. All in all, our results suggest that despite apparently sound liquidity, the market liquidity of US Treasuries has become more fragile, i.e. more vulnerable to financial shocks.

These results may have financial stability implications regarding the pivotal position of U.S. Treasury debt as a safe asset. These new market liquidity dynamics are also relevant for the liquidity buffer of banks. Thus, since this buffer in some cases consists of a large stock of government securities, poor liquidity in this market during stress episodes could diminish the ability to convert Treasury debt into cash, precisely when it is most needed. Further research to understand the drivers of this lower liquidity resilience, which would be probably related to recent structural changes in those markets, would be needed to propose policy responses that reinforce the resilience of market liquidity.

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Figure 1: Daily returns of the US 10-year Treasury note and five market liquidity measures.

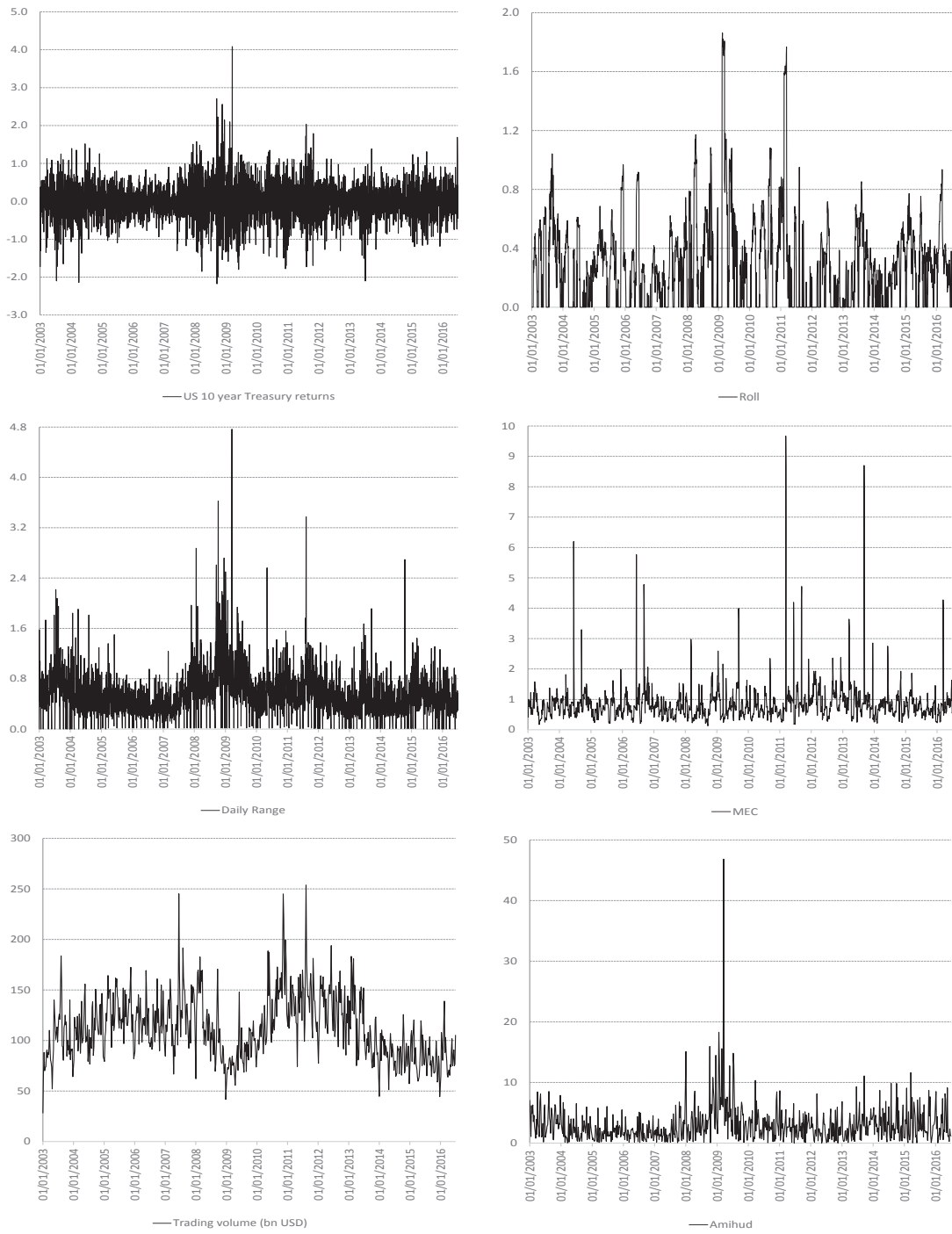


Table 1: Market liquidity measures

Market liquidity measures	Definition	Aspect of liquidity	Interpretation	Source	Frequency
Roll (1984)	Estimation of the effective bid-ask spread based on the covariance of returns over two consecutive days. Covariances are computed over sample periods of three months	Tightness	Wider spreads imply that transaction costs are higher and market liquidity is lower	Bloomberg	Daily
Daily range	Absolute difference between high and low prices each day	Immediacy	Spikes reflect that the market is less able to absorb new orders (less liquidity)	Bloomberg	Daily
Market efficiency coefficient (MEC)	Variance of weekly returns to variance of daily returns. Variances are computed over sample periods of three months	Resilience	Proxy for market efficiency. If close to 1, then prices of a security or asset are able to move fast to their new equilibrium	Bank of America Merrill Lynch	Daily
Volume	Average daily transactions, in USD	Depth	Lower volume reflects poor liquidity conditions	Federal Reserve Bank of New York	Weekly
Amihud (2002)	Absolute return to trading volume	Breadth	Price concession needed to execute trades	Bloomberg (FINRA) Bank of America Merrill Lynch Federal Reserve Bank of New York	Weekly

Table 2: Descriptive statistics of market liquidity indicators.

		L_R	L_{DR}	L_{MEC}	V	L_A
Mean	Total	0.281	0.553	0.828	11.591	2.967
	Pre-crisis	0.244	0.487	0.812	11.621	2.287
	Crisis	0.399	0.795	0.729	11.609	4.537
	Post-crisis	0.274	0.532	0.863	11.567	2.990
SD	Total	0.305	0.343	0.533	0.281	3.085
	Pre-crisis	0.246	0.287	0.482	0.230	1.858
	Crisis	0.432	0.477	0.404	0.312	5.889
	Post-crisis	0.290	0.306	0.585	0.300	2.475
Observations	Total	3465	3465	3465	692	692
	Pre-crisis	1132	1132	1132	227	227
	Crisis	471	471	471	93	93
	Post-crisis	1862	1862	1862	372	372

Notes: L_R is the transaction costs indicator by Roll (1984), L_{DR} is the daily range, L_{MEC} denotes the market efficiency coefficient, V is trading volume expressed in logarithms and L_A stands for the Amihud (2002) ratio. The pre-crisis period runs from January 2003 to May 2007, whereas the post-crisis period covers the time from April 2009 to June 2016.

Table 3: Descriptive statistics of US 10-year bonds' returns and market liquidity indicators.

	Total sample							Pre-crisis period						
	r_t	r_t^w	ΔL_R	ΔL_{DR}	ΔL_{MEC}	ΔV	ΔL_A	r_t	r_t^w	ΔL_R	ΔL_{DR}	ΔL_{MEC}	ΔV	ΔL_A
Mean	0.005	0.105	0.000	0.000	0.000	0.002	-0.009	-0.011	0.059	0.000	0.000	0.000	0.005	-0.031
SD	0.505	0.889	0.107	0.388	0.355	0.216	3.922	0.424	0.743	0.083	0.343	0.324	0.211	2.428
Maximum	4.085	3.743	1.760	3.844	9.064	0.894	40.873	1.519	2.469	0.778	1.578	5.412	0.894	7.013
Minimum	-2.176	-3.321	-0.928	-3.469	-3.067	-0.708	-37.141	-2.143	-2.410	-0.475	-1.531	-2.381	-0.548	-6.081
Skewness	0.081**	0.018	1.162***	0.291***	10.521***	0.093	0.424	-0.379***	-0.073	0.981***	0.166**	8.390***	0.100	0.157
Kurtosis	5.718***	4.035***	39.952***	10.882***	241.581***	3.378***	31.378***	4.896***	3.684	18.629***	5.470	147.136***	3.834***	3.249***
Observations	3465	692	3464	3464	3464	691	691	1132	227	1131	1131	1131	226	226
$Q(10)$	52.743***	18.475***	41.314***	721.100***	338.250***	97.757***	155.260***	11.082	19.481***	20.301***	281.160***	123.960***	21.892***	67.671***
$Q^2(10)$	394.790***	201.650***	9.100	756.220***	75.621***	27.895***	172.780***	73.986***	30.528***	9.466	182.970***	31.826***	7.098	19.679***

	Crisis-period							Post-crisis period						
	r_t	r_t^w	ΔL_R	ΔL_{DR}	ΔL_{MEC}	ΔV	ΔL_A	r_t	r_t^w	ΔL_R	ΔL_{DR}	ΔL_{MEC}	ΔV	ΔL_A
Mean	0.038	0.273	0.002	0.000	-0.001	-0.002	0.103	0.006	0.091	-0.001	0.000	0.000	0.001	-0.023
SD	0.714	1.267	0.154	0.568	0.200	0.232	7.345	0.487	0.855	0.105	0.357	0.400	0.215	3.414
Maximum	4.085	3.743	1.760	3.844	2.168	0.730	40.873	2.032	3.014	1.180	2.289	9.064	0.573	13.671
Minimum	-2.177	-2.586	-0.928	-3.469	-0.853	-0.708	-37.141	-2.104	-3.321	-0.869	-1.422	-3.067	-0.577	-9.076
Skewness	0.567***	0.072	2.451***	0.426***	3.506***	0.143	0.400	-0.204***	-0.190	0.019	0.173***	10.804***	0.078	0.085
Kurtosis	5.593***	2.899***	44.313***	12.256***	44.537***	4.164***	18.461***	3.970***	3.902***	23.451***	5.634***	237.926***	2.842***	3.858***
Observations	471	93	471	471	471	93	93	1862	372	1862	1862	1862	372	372
$Q(10)$	34.049***	9.975***	12.485***	105.160***	36.364***	15.715***	27.355***	20.436***	15.186***	27.830***	352.400***	180.670***	83.498***	113.560***
$Q^2(10)$	15.454	31.653***	0.709	113.540***	14.456	19.670***	22.390***	279.560***	29.313***	23.702***	229.760***	39.639***	23.688***	34.890***

Notes: r_t and r_t^w are the daily and weekly 10-year bond returns, respectively. L_R is the transaction costs indicator by Roll (1984), L_{DR} is the daily range, L_{MEC} denotes the market efficiency coefficient, V is trading volume expressed in logarithms and L_A stands for the Amihud (2002) ratio. All liquidity indicators are expressed in first differences, Δ . $Q(10)$ is the Ljung-Box Q-statistic (with 10 lags) and $Q^2(10)$ is the Ljung-Box Q-statistic (with 10 lags) for the squared returns. ***, **, and * refer to significance at 1%, 5% and 10% level.

Table 4: Estimates of the model for the full sample.

	L_R	L_{DR}	L_{MEC}	V	L_A
c_1	0.012*** (0.003)	0.001 (0.001)	0.001 (0.008)	0.045 (0.146)	0.016 (0.013)
c_2	0.001 (0.017)	0.002 (0.017)	0.001 (0.028)	0.005 (0.040)	0.025 (0.028)
a_{11}	0.043 (0.079)	0.032*** (0.010)	0.032*** (0.002)	0.093 (0.528)	0.065*** (0.001)
a_{22}	0.316*** (0.001)	0.009** (0.004)	0.000 (0.006)	0.023** (0.010)	0.054 (0.196)
a_{12}	0.000 (0.529)	0.008 (0.405)	0.000 (0.251)	0.028 (5.704)	0.000 (0.001)
a_{21}	0.017 (0.032)	0.038 (0.115)	0.000 (0.103)	0.001 (0.074)	0.183*** (0.049)
b_{11}	0.842*** (0.004)	0.957*** (0.019)	0.960*** (0.014)	0.844*** (0.002)	0.909*** (0.336)
b_{22}	0.265*** (0.067)	0.407 (0.351)	0.963*** (0.141)	0.802* (0.426)	0.915*** (0.032)
b_{12}	1.383*** (0.004)	0.013 (0.108)	0.008 (0.052)	0.036*** (0.005)	0.000 (0.589)
b_{21}	0.005 (0.074)	0.151*** (0.017)	0.011*** (0.002)	0.000 (0.032)	0.110*** (0.041)
$LogL$	1188.359	-2616.47	-3233.109	-626.485	-2355.404
T	3464	3464	3464	691	691
$Q_1(10)$	7.948	6.931	7.948	6.331	0.702
$Q_2(10)$	5.693	10.203	5.693	12.949	6.835
$Q_1^2(10)$	11.436	10.541	11.436	21.527**	17.796**
$Q_2^2(10)$	4.456	3.873	4.456	5.281	6.874
$\lambda(\Gamma_C)$	0.964	0.996	0.964	0.937	0.980
$\lambda(\Gamma_{C \otimes C})$	0.940	0.995	0.940	0.896	0.965

Estimation results of the conditional variances of a bivariate ECC-GARCH model (Nakatani, 2010):

$$\begin{aligned}
 h_{1t} &= c_1 + \alpha_{11}\varepsilon_{1t-1}^2 + \alpha_{12}\varepsilon_{2t-1}^2 + b_{11}h_{1t-1} + b_{12}h_{2t-1} \\
 h_{2t} &= c_2 + \alpha_{22}\varepsilon_{2t-1}^2 + \alpha_{21}\varepsilon_{1t-1}^2 + b_{22}h_{2t-1} + b_{21}h_{1t-1}
 \end{aligned}$$

where h_{1t} is the conditional volatility of 10-year US Treasury returns (log difference of prices) and h_{2t} the conditional volatility of the first difference of each of the five liquidity indicators (namely, L_R is the transaction costs indicator by Roll (1984), L_{DR} is the daily range, L_{MEC} denotes the Market efficiency coefficient, V is trading volume expressed in logarithms and L_A stands for the ratio proposed by Amihud (2002)). See Section 2 for further details on these indexes; $LogL$ denotes the value of the log likelihood function; $Q(10)$ denotes the Ljung-Box Q-statistic (with 10 lags) for the standardized residuals; $Q^2(10)$ denotes the Ljung-Box Q-statistic (with 10 lags) for the squared standardized residuals; $\lambda(\Gamma_C)$ and $\lambda(\Gamma_{C \otimes C})$ denote the stationarity and the fourth-order moment conditions, respectively; Standard errors in brackets; ***, **, and * refer to significance at 1%, 5% and 10% level; Estimates of the equations for trading volumes and for the Amihud (2002) ratio are based on weekly data.

Table 5: Estimates of the model for the pre-crisis period, from January 2003 to May 2007.

	L_R	L_{DR}	L_{MEC}	V	L_A
c_1	0.000 (0.001)	0.000 (0.000)	0.009 (0.088)	0.000 (0.053)	0.000 (0.014)
c_2	0.001 (0.018)	0.000 (0.019)	0.086*** (0.028)	0.006 (0.037)	0.062** (0.031)
a_{11}	0.029 0.199	0.006 0.017	0.073*** 0.004	0.043 0.851	0.000 0.006
a_{22}	0.180*** (0.001)	0.000 (0.001)	0.005 (0.366)	0.104*** (0.010)	0.001 (0.110)
a_{12}	0.011 (0.778)	0.013 (0.187)	0.001 (0.878)	0.017 (4.277)	0.011 (0.019)
a_{21}	0.009 (0.024)	0.029 (0.048)	0.003 (0.203)	0.000 (0.134)	0.247** (0.108)
b_{11}	0.950*** (0.008)	0.980*** (0.017)	0.752*** (0.038)	0.901*** (0.004)	0.932*** (0.205)
b_{22}	0.273** (0.123)	0.755*** (0.177)	0.002 (3.990)	0.468 (0.642)	0.928*** (0.098)
b_{12}	0.510*** (0.008)	0.024 (0.051)	0.255 (0.638)	0.961*** (0.024)	0.000 (0.794)
b_{21}	0.008 (0.133)	0.056** (0.023)	0.005 (0.007)	0.013 (0.075)	0.001 (0.043)
$LogL$	757.872	-479.1963	-801.5718	-143.8205	-648.3826
T	1131	1131	1131	226	226
$Q_1(10)$	3.745	4.124	3.279	7.992	4.679
$Q_2(10)$	5.352	5.517	1.325	3.675	9.739
$Q_1^2(10)$	6.038	3.955	10.823	4.897	5.007
$Q_2^2(10)$	1.689	7.274	0.339	12.752	13.171
$\lambda(\Gamma_C)$	0.995	0.999	0.827	0.976	0.984
$\lambda(\Gamma_{C \otimes C})$	0.993	0.998	0.694	0.956	0.968

Estimation results of the conditional variances of a bivariate ECC-GARCH model (Nakatani, 2010):

$$\begin{aligned}
 h_{1t} &= c_1 + \alpha_{11}\varepsilon_{1t-1}^2 + \alpha_{12}\varepsilon_{2t-1}^2 + b_{11}h_{1t-1} + b_{12}h_{2t-1} \\
 h_{2t} &= c_2 + \alpha_{22}\varepsilon_{2t-1}^2 + \alpha_{21}\varepsilon_{1t-1}^2 + b_{22}h_{2t-1} + b_{21}h_{1t-1}
 \end{aligned}$$

where h_{1t} is the conditional volatility of 10-year US Treasury returns (log difference of prices) and h_{2t} the conditional volatility of the first difference of each of the five liquidity indicators (namely, L_R is the transaction costs indicator by Roll (1984), L_{DR} is the daily range, L_{MEC} denotes the Market efficiency coefficient, V is trading volume expressed in logarithms and L_A stands for the ratio proposed by Amihud (2002)). See Section 2 for further details on these indexes; $LogL$ denotes the value of the log likelihood function; $Q(10)$ denotes the Ljung-Box Q-statistic (with 10 lags) for the standardized residuals; $Q^2(10)$ denotes the Ljung-Box Q-statistic (with 10 lags) for the squared standardized residuals; $\lambda(\Gamma_C)$ and $\lambda(\Gamma_{C \otimes C})$ denote the stationarity and the fourth-order moment conditions, respectively; Standard errors in brackets; ***, **, and * refer to significance at 1%, 5% and 10% level; Estimates of the equations for trading volumes and for the Amihud (2002) ratio are based on weekly data.

Table 6: Estimates of the model for the post-crisis period, from April 2009 to June 2016.

	L_R	L_{DR}	L_{MEC}	V	L_A
c_1	0.003 (0.002)	0.000 (0.014)	0.011* (0.006)	0.003 (0.208)	0.224 (0.445)
c_2	0.002 (0.015)	0.011 (0.023)	0.023 (0.031)	0.022 (0.054)	0.168 (0.104)
a_{11}	0.032 (0.311)	0.053** (0.021)	0.037*** (0.004)	0.114 (1.180)	0.033*** (0.005)
a_{22}	0.338*** (0.001)	0.012 (0.010)	0.003 (0.026)	0.122*** (0.012)	0.030 (2.445)
a_{12}	0.315 (0.937)	0.001 (0.539)	0.008 (0.140)	0.729 (7.945)	0.002 (0.043)
a_{21}	0.013 (0.024)	0.032 (0.095)	0.352*** (0.038)	0.002 (0.093)	0.000 (1.096)
b_{11}	0.921*** (0.004)	0.874*** (0.022)	0.849*** (0.235)	0.823*** (0.003)	0.542* (0.325)
b_{22}	0.057 (0.113)	0.606* (0.358)	0.010 (0.057)	0.147 (0.368)	0.844*** (0.211)
b_{12}	0.477*** (0.005)	0.232*** (0.064)	0.145** (0.066)	0.816*** (0.007)	0.002 (5.509)
b_{21}	0.008 (0.091)	0.040** (0.018)	0.025*** (0.008)	0.000 (0.055)	0.908*** (0.028)
$LogL$	683.436	-1377.649	-1509.98	-321.7579	-1270.723
T	1861	1861	1861	371	371
$Q_1(10)$	5.799	5.334	6.644	3.561	1.709
$Q_2(10)$	12.658	9.701	21.184	7.764	16.681
$Q_1^2(10)$	12.204	9.743	11.855	13.343	8.289
$Q_2^2(10)$	4.000	2.678	0.558	5.852	6.420
$\lambda(\Gamma_C)$	0.982	0.974	0.948	0.941	0.885
$\lambda(\Gamma_{C \otimes C})$	0.966	0.953	0.901	0.912	0.785

Estimation results of the conditional variances of a bivariate ECC-GARCH model (Nakatani, 2010):

$$\begin{aligned}
 h_{1t} &= c_1 + \alpha_{11}\varepsilon_{1t-1}^2 + \alpha_{12}\varepsilon_{2t-1}^2 + b_{11}h_{1t-1} + b_{12}h_{2t-1} \\
 h_{2t} &= c_2 + \alpha_{22}\varepsilon_{2t-1}^2 + \alpha_{21}\varepsilon_{1t-1}^2 + b_{22}h_{2t-1} + b_{21}h_{1t-1}
 \end{aligned}$$

where h_{1t} is the conditional volatility of 10-year US Treasury returns (log difference of prices) and h_{2t} the conditional volatility of the first difference of each of the five liquidity indicators (namely, L_R is the transaction costs indicator by Roll (1984), L_{DR} is the daily range, L_{MEC} denotes the Market efficiency coefficient, V is trading volume expressed in logarithms and L_A stands for the ratio proposed by Amihud (2002)). See Section 2 for further details on these indexes; $LogL$ denotes the value of the log likelihood function; $Q(10)$ denotes the Ljung-Box Q-statistic (with 10 lags) for the standardized residuals; $Q^2(10)$ denotes the Ljung-Box Q-statistic (with 10 lags) for the squared standardized residuals; $\lambda(\Gamma_C)$ and $\lambda(\Gamma_{C \otimes C})$ denote the stationarity and the fourth-order moment conditions, respectively; Standard errors in brackets; ***, **, and * refer to significance at 1%, 5% and 10% level; Estimates of the equations for trading volumes and for the Amihud (2002) ratio are based on weekly data.

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