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The asymmetric dynamics of stock–bond liquidity correlation in China: The role of macro-financial determinants☆

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ABSTRACT

Financial asset liquidity and its linkages to general market conditions form an important part of illiquidity risk analysis in financial economics. Cross-asset liquidity linkages are known to impact expected returns and financial market stability. This paper comprehensively investigates the joint dynamics of liquidity in the Chinese stock and T-bond markets, with emphasis on influences from their distinct market structures. I allow the stock–bond liquidity linkages to be dependent on changing market states and macro-financial informational shocks by including both cyclic and asymmetric terms in the predictive framework. For the daily bid–ask spread and quote depth measures constructed from high-frequency trade-and-quote (TAQ) data over the period of 2005–2022, I demonstrate that liquidity correlation is affected by both cross-asset information spillover and volatility linkages. The macro-financial determinants exert a time-varying and asymmetric impact on the information spillover and volatility linkages, which in turn affect cross-asset liquidity correlation.

1. Introduction

The importance of liquidity in the equity markets is documented by a broad spectrum of research in financial economics. Amihud and Mendelson (1986) first discussed the notion that illiquidity may impact stock returns as investors demand a premium for greater trading costs. They and a number of other studies (e.g. Eleswarapu and Reinganum (1993), Brennan and Subrahmanyam (1996), Datar et al. (1998), Eleswarapu (1997), Jacoby et al. (2000)) provided early theoretical and empirical evidence to support the existence of illiquidity premium, defined as the higher required rate of return for relatively illiquid equities, in the cross-section of stocks. From a market microstructure perspective, measures of illiquidity represent the trading costs that market makers bear due to asymmetric information (Kyle, 1985; Glosten and Milgrom, 1985) or inventory risk (Stoll, 1978; Ho and Stoll, 1981; Amihud and Mendelson, 1980). The illiquidity premium is thus a way to compensate for the significant illiquidity costs created by privately informed investors for uninformed investors (Brennan and Subrahmanyam, 1996), or by exceptional market conditions which elevate the risk of inventory holding for the market makers (Amihud et al., 1990).

More recently, a growing number of research have documented significant commonality in the time-series variation of equity liquidity (Chordia et al., 2000, Hasbrouck and Seppi, 2001, Huberman and Halka, 2001) and emphasized the importance of market-wide illiquidity as an undiversifiable, systematic risk factor (Pastor and Stambaugh, 2003, Acharya and Pedersen, 2005, Avramov et al., 2006). In their comprehensive liquidity-adjusted capital asset pricing model(L-CAPM), Acharya and Pedersen (2005) report that the expected return of a security is related not only to its firm-specific liquidity characteristic (the liquidity level), but also importantly to its exposure to systematic liquidity risk (as measured by the covariances of its own return and liquidity with the market return and liquidity). Investors have a natural, utility-based preference for more liquid securities which allow them to exit positions at reasonable costs. During pervasive market declines or liquidity dry-ups, securities which are more sensitive to systematic liquidity risk will experience more pronounced drops in their liquidity levels or returns. Such drops during market crisis periods when wealth has decreased and marginal utility is higher will turn out to be more costly for investors wishing to liquidate their positions. Consequently, investors will demand a systematic illiquidity premium for holding these securities. Empirical evidence associated with systematic illiquidity costs directly related to the discussion above have been put forward by Gibson and Mougeot (2004), Korajczyk and Sadka (2008), and Watanabe and Watanabe (2008) for the U.S. markets, Martínez et al. (2005), Bekaert et al. (2007), Lee (2011), Moshirian et al. (2017),

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and Amihud et al. (2015) for the global markets, and Narayan and Zheng (2010), Ho and Chang (2015), Ma et al. (2018), Li et al. (2019), and Liao et al. (2021) for the Chinese market.

The implications of the time-varying systematic liquidity risk range beyond the return patterns of individual firms. They matter for cross-asset asset pricing, portfolio management, and on a broad scale, financial market stability. Cespa and Foucault (2014) show that as liquidity providers often learn information about an asset from the prices of other assets, a self-reinforcing, positive relationship between price informativeness and liquidity exists that may cause liquidity spillovers and be a source of financial fragility. The financial market is not unfamiliar with what Cespa and Foucault (2014) term as "illiquidity contagion", especially during periods of market crisis, when a small drop in the liquidity of one asset can, through a feedback loop, results in a systematic liquidity crash. In this study, I examine the mechanisms of information spillover and volatility linkages between aggregate liquidity in the Chinese stock and T-bond markets, with a special focus on investigating the determinant factors that drive the dynamic stock–bond liquidity correlation. I relate and contribute to the existing literature on liquidity in three important ways.

Firstly, I furnish a better understanding of the dynamics and implications of liquidity correlation between the stock and T-bond markets, especially during periods of pervasive market declines. Prior research have provided voluminous evidence on commonality in stock liquidity, while only a handful of studies including Chordia et al. (2005), Goyenko and Ukhov (2009), Banti (2016), Liew et al. (2022) have investigated cross-asset liquidity linkages. This study is most related to Chordia et al. (2005), which study the joint dynamics of liquidity, trading activity, and market prices in the U.S. stock and T-bond market. When examining such joint dynamics in the Chinese market, I emphasize the influences from specific Chinese market structures and cyclic market conditions. The rationale for considering the market cyclic effects is based on the widely documented empirical evidence that liquidity is negatively related to volatility (Chordia et al., 2005, Chordia et al., 2002), and may evaporate during times of market crisis when elevated levels of uncertainty tighten the agents' funding constraints (Gromb and Vayanos, 2002, Brunnermeier and Pedersen, 2009, Nagel, 2012). In addition, a large number of studies have shown that illiquidity premiums are higher during market crises, when systematic liquidity risk increases in response to rising market uncertainty (Acharya and Pedersen, 2005, Avramov et al., 2006, Lou and Sadka, 2011, Cao and Petrasek, 2014,Qian et al., 2014; Ma et al., 2018, Li et al., 2019, Dang and Nguyen, 2020). Pervasive market declines may also cause a "flight-to-quality" (Barsky, 1989, Beber et al., 2009) or a "flight-to-liquidity" (Vayanos, 2004), in which investors display a sudden and strong preference for holding safer or more liquid assets. The combined evidence imply that market states may have differentiated effects on cross-asset liquidity correlation, and in turn, future asset returns and economic conditions.

This study also contributes to the nascent literature examining the determinants that influence cross-asset liquidity correlation. Prior research have found that the time-varying commonality in stock liquidity is subject to both supply- (the agents' funding conditions) and demand-side (correlated trading behavior of investors) determinants (Karolyi et al., 2012). Across the assets, studies like Cespa and Foucault (2014) and Brunnermeier and Pedersen (2009) emphasized the importance of price informativeness and volatility in causing liquidity spillovers, while Chordia et al. (2005), Goyenko and Ukhov (2009), Brunnermeier and Pedersen (2009) and Nyborg and Ostberg (2014) analyzed the role of monetary policy shocks. My experiment to test the determinants of cross-asset liquidity correlation is designed to evaluate a number of hypotheses related to the supply- and demand-side explanations discussed above. Specifically, I conjecture that financial (market prices and monetary) informational shocks may exert asymmetric effects on cross-asset liquidity correlation through the mechanisms of both cross-asset learning and hedging. On the one hand, theories of cross-asset learning (Cespa and Foucault, 2014) predict that financial informational shocks on individual asset liquidity make the liquidity of asset pairs interconnected through price informativeness. On the other hand, as stocks and T-bonds are common rival assets with distinct risk and liquidity levels, financial informational shocks might have asymmetric impacts on investors' cross-asset hedging behavior depending on the market state and the direction of the shocks. I test these hypotheses by including both cyclic and asymmetric terms of the macro-financial determinants in the predictive framework.

Moving beyond the level analysis of liquidity spillovers, this study makes a third contribution to the literature by investigating the volatility linkages between cross-asset liquidity. Fleming et al. (1998) suggest that there are strong volatility linkages in the stock, bond, and money markets due to common information, which simultaneously affect expectations and cross-market liquidity by altering the inventory risk borne by market-making agents. In their pioneering work on illiquidity premium, Pastor and Stambaugh (2003) also find that stocks' expected returns are significantly related to their price sensitivity to innovations in systematic liquidity. The cross-asset liquidity volatility linkage is therefore worth investigating as it impacts systematic liquidity risk, and in turn, wider market return dynamics. In this study, I first model the conditional covariance between aggregate stock and T-bond liquidity, and then measure the degree of their dynamic correlation. Critically, I model macro-financial news shocks as the long-term determinants of the conditional covariance. Such a methodological design to explore the role of macro-financial determinants in driving cross-asset volatility linkages and liquidity correlation is new in the literature. Prior studies have analyzed the impacts of macroeconomic news shocks on stock–bond return correlations (e.g. Baele et al. (2010), Yang et al. (2009), Dajcman et al. (2012), Asgharian et al. (2016), Allard et al. (2020)), but none to my knowledge has analyzed such impacts on stock–bond liquidity covariance. Another related strand of literature have used a similar methodological design to test the long-run determinant role of macro-financial factors, but have exclusively focused on examining return linkages in foreign exchange markets (e.g. Celik (2012), Eraslan (2017)), among commodities products (e.g. Yue et al. (2015), Hou et al. (2019), Liu and Lee (2022)), or between commodities and stocks (e.g. Hashmi et al. (2022)).

This study aims to provide a unified framework for analyzing both the information spillover and the volatility linkages between aggregate liquidity in the stock and T-bond markets. I focus on exploring the mechanisms through which macro-financial informational shocks may asymmetrically impact the cross-asset liquidity correlations. I begin the analysis by developing a multivariate vector autoregressive (VAR) model that formalizes the mechanisms of cross-asset information learning and hedging. Under this model, aggregate stock/T-bond market liquidity is regressed on three distinct trade and financial predictors, namely: trading activity, funding liquidity and market prices. All the predictors are multiplied with a binary stock market state variable to obtain respective interaction terms for market state effects analysis. The VAR modeling allows me to examine the joint dynamics of liquidity and market prices, which is superior to simple regression analysis in that I can now investigate not only the determinants of cross-asset liquidity dynamics, but also the impacts of cross-asset liquidity on expected market returns and volatility. When the VAR modeling is completed, the residuals are passed onto a Dynamic Conditional Correlation (DCC)-Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework, which contains both short-run and long-run asymmetric terms, to model the macro-financial news effects on cross-asset liquidity covariance. Finally, based on the conjecture that horizon heterogeneity may impact liquidity correlation as the underlying driving factors of correlation may vary in function of its frequency, I consider the method of wavelet coherence analysis (WCA) to investigate the time–frequency linkages between cross-asset liquidity.

I test the empirical framework in the Chinese stock and T-bond market utilizing a comprehensive and recent set of high-frequency trade-and-quote (TAQ) dataset. I also source daily monetary supply and monthly macro-financial variables from the Wind financial database. The extended dataset allows me to examine the heterogeneous effects of macro-financial factors on cross-asset liquidity correlation in a relatively young and fast-growing market.[1] In addition to the wide data representativeness, I choose to investigate the determinants and implications of liquidity in the Chinese market because of its distinct market features, including the order-driven market structure (Narayan and Zheng, 2010), market segmentation and foreign investment restrictions (Yao et al., 2014, Chan and Kwok, 2005), predominance of small retail investors (Ma et al., 2018, Li et al., 2019, Liao et al. (2021)), weaker investor protection (Ma et al., 2018), and severe trading restrictions.[2] When compared to more developed markets, such a unique market structure and trade restrictions may result in more information asymmetry and higher limits of arbitrage, which will in turn reduce overall market efficiency and liquidity. A large number of studies have explored illiquidity risk in the Chinese stock markets and report significantly high illiquidity premium (see e.g. Narayan and Zheng (2010), Cao and Petrasek (2014), Ho and Chang (2015), Ma et al. (2018), An et al. (2020), Liao et al. (2021), and Zhang and Lence (2022)). Liao et al. (2021), for instance, argue that the larger aggregate illiquidity premium in the Chinese stock market could be explained by theories of behavioral mis-pricing, in which hindered arbitraging activities and behavioral biases (such as speculative trading and herding) of individual investors drive up the illiquidity premium.

Although the empirical analysis of this study is restricted to the Chinese market, its results should shed useful insights about the dynamics and impacts of liquidity correlation in emerging markets in general. Bekaert et al. (2007), for instance, show that liquidity shocks and expected return are significantly and positively correlated in countries with segmented markets, and the correlation effects are not fully eliminated by market liberalization process. The Chinese stock market is also a segmented market with high illiquidity premium, which suggests that the findings on its liquidity dynamics are likely to prove helpful to other emerging markets with similar market structures. In addition, as the time-varying correlation analysis of this study spans from Year 2005 to 2022, which covers important periods of institutional changes in the Chinese financial market, its results may provide extra insights on the effects of institutional changes on liquidity. A number of studies (e.g. Gerace et al. (2015), Qian et al. (2014), Chu et al. (2015), Ma et al. (2018)) have documented the effects of institutional changes on illiquidity premiums and liquidity commonality in China. This study is not going to expand in this regard, but aims to provide empirical evidence that can inspire future research on cross-asset liquidity risks and associated return premiums in the Chinese market.

The empirical results largely confirm the existence of both commonalities and asymmetries in cross-asset liquidity. While commonalities arise from cross-asset information spillovers and common monetary effects, asymmetries are induced by cross-asset hedging behaviors during the market crisis periods. Over longer horizons, positive and negative macro-financial informational shocks exert asymmetric impacts on cross-asset liquidity covariance. The WCA results confirm the importance of macro-financial factors in affecting time–frequency interdependence between liquidity, trading activity, and market prices .

[1] The Chinese stock market have developed rapidly since its two exchanges, the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) were established respectively in 1990 and 1991. As its market capitalization of listed domestic companies increased to US$12.2 trillion and total value of stocks traded reached US$31.6 trillion in 2020 (See http://www.worldbank.org), the Chinese stock market is the second-largest in the world just after the U.S.

[2] Trade restrictions include the T+1 trading rule (Zhang and Lence, 2022)), daily price limit (Li et al., 2019), as well as short-selling and margin trading constraints (Zhao et al., 2014, Chang et al., 2014).

The remainder of this paper is organized as follows. Section 2 describes the liquidity proxies that I construct for the Chinese market. Section 3 presents the empirical results for the VAR analysis. Section 3 develops the DCC-GARCH model and evaluates the conditional liquidity volatility linkages. Section 4 describes the WCA framework and presents the cross-asset liquidity coherence. Section 5 provides a summary and conclusion.

2. Proxying for liquidity in China

As liquidity is not directly observable, the first challenge associated with examining the liquidity dynamics is to find an appropriate liquidity proxy. Vayanos and Wang (2012) suggest that transactions costs are one of the main market imperfections that cause market illiquidity. In the empirical applications of this study, I adopt the quote depth and the bid–ask spread, which are intuitive and heuristic measures of direct transaction costs (Hasbrouck and Seppi, 2001, Liao et al., 2021), as my liquidity proxies. The quote depth directly measures the investors' inventory conditions and the dynamics of the order book (Hautsch, 2012), while bid–ask spread reflects the transaction costs that market makers bear due to inventory risk or asymmetric information. According to the inventory paradigm (Stoll, 1978, Ho and Stoll, 1981, Amihud and Mendelson, 1980), the bid–ask spread, an inverse measure of liquidity, is a source of profit to compensate the market makers for risk exposure and administrative cost. Factors such as large inventory imbalances, inventory overload and market frictions, which influence the risk of holding inventory, may thereby cause changes in the bid–ask spread. The theoretical paradigm of asymmetric information (Kyle, 1985, Glosten and Milgrom, 1985), on the other hand, suggests that in a market where there are both uninformed and insider traders, risk-neutral market makers earn zero expected returns. The market makers, who possess no superior information, set prices as an increasing function of the imbalance in order flow, which may signal private information. The resulting bid–ask spread roughly implies the part of observed returns that uninformed traders anticipate losing to informed traders.

To construct the time series of aggregate market liquidity measures, I use high-frequency trade-and-quote (TAQ) data from China Stock Market & Accounting Research (CSMAR) Level-1 Trade & Quote (GTA_SEL1) Database. The GTA_SEL1 database is based on real-time market data in the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE). I use the TAQ data by bid and ask record covering the period of August 1st, 2005 to June 30th, 2022, a total of 4108 days of approximately 16 terabytes (TB) of trade and quote records. Data entries include trading prices and volumes, five-level bid and ask quote prices and volumes, as well indications of whether a trade is buyer or seller initiated. The high-frequency transaction data allow me to construct direct daily bid–ask spread and quote depth measures that would not have been possible with daily data. In the empirical analysis I also include daily trading volume and order imbalances measure to proxy for trading activity. Using these liquidity and trading activity proxies, Chordia et al. (2002, 2005, 2008) have shown that variations in market returns and volatility affect trading activity, which could thereby influence market liquidity. Brockman et al. (2009) and Chung and Chuwonganant (2014) also analyzed the dynamics and determinants of commonality in liquidity using intraday spread and depth measures. In the Chinese market, the bid–ask spread has been used by studies including Gerace et al. (2015), Li et al. (2019).

The bid–ask spread and quote depth measures of the stock (denoted by the suffix '_S') and T-bond markets (denoted by the suffix '_B') are formally constructed as follows:

- RPD_S /RPD_B (relative spread): the bid–ask spread divided by the mid-point of the quote (in percentage terms), for the stock/T-bond market respectively: $RPD = \frac{(S_1 - B_1)}{(S_1 + B_1)/2} * 100$, where S_1 denotes first best ask price, B_1 denotes first best bid price;

- Depth_S /Depth_B (quote depth): the posted depth in the first five best bid and ask quotes (in million RMB terms), for the stock/T-bond market respectively: $Depth = \frac{\sum_{i=1}^{5}(S_i * SV_i + B_i * BV_i)}{2}$, where S_i denotes Ask Price i, SV_i denotes Ask Size i, B_i denotes Bid Price i, BV_i denotes Bid Size i.

The liquidity measures are calculated first on tick-by-tick basis for each stock/T-bond, and then averaged within the day to get the daily measures. The daily trading activity measures are calculated on the intraday measures directly:

- Volume_S/Volume_B (trading volume): accumulated daily trading volume(in billion RMB terms), for the stock/T-bond market respectively;
- OIB_S /OIB_B (order imbalances): the value of buyer-initiated trades less the value of seller-initiated trades, divided by the total daily value of buy and sell trades, for the stock/T-bond market respectively.

Once the daily measures for each stock/T-bond are acquired, they are averaged (by value-weighting) across all stocks/T-bonds to get the market-wide measures. I use the logarithmic float market capitalization of each stock/T-bond as of the end of the previous calendar year to calculate the value weights.

The stocks that I include are A-share stocks[3] listed in SSE and SZSE. The 6-digit ticker codes for these stocks start with 600, 601, 603, 605 or 688 in SSE, and 00 or 30 in the SZSE. I use treasury bonds traded in either exchange to construct the T-bond time series. They cover ticker codes that start with 009, 010, 019, or 020 in SSE, and 10 in SZSE. The sample is constructed month by month. To be included, a stock/T-bond has to go through three further filtering steps. In each step, an observation that fails to meet the filtering criteria is removed from calculation for the entire month. The filtering criteria for each step are: first, remove the ST-labeled stocks, or the non-active exchange-traded T-bonds[4]; second, remove observations with no float market capitalization as of the end of the previous year; and third, remove observations which do not have active trading records during at least 60% of trading days of the current month. These filtering criteria left us with an average of 2383 stocks and 25 T-bonds across the sample period for the calculation of daily market-wide measures.

Fig. 1 plots the number of observations left in the sample after each of the above-mentioned filtering steps. The size of the stocks sample has been growing steadily from around 1200 observations in mid 2005 to around 4500 observations in mid 2022. There are minor fractions of ST, newly-listed, or inactive stocks in the stocks sample. In contrast, the T-bond sample features a predominance of non-active exchange-traded observations, which could be attributed to the fact that T-bonds are mainly traded in the inter-bank market in China. There is also a comparatively larger fraction of inactive T-bonds which trade less than 60% of days in the current month. The combined evidence suggest that in a relatively illiquid market like the Chinese T-bond, investors concentrate orders on more active T-bonds in the hope of expediating trading.

Table 1, Panel A presents the summary statistics of the aggregate liquidity and trading activity variables. On average, the stock market

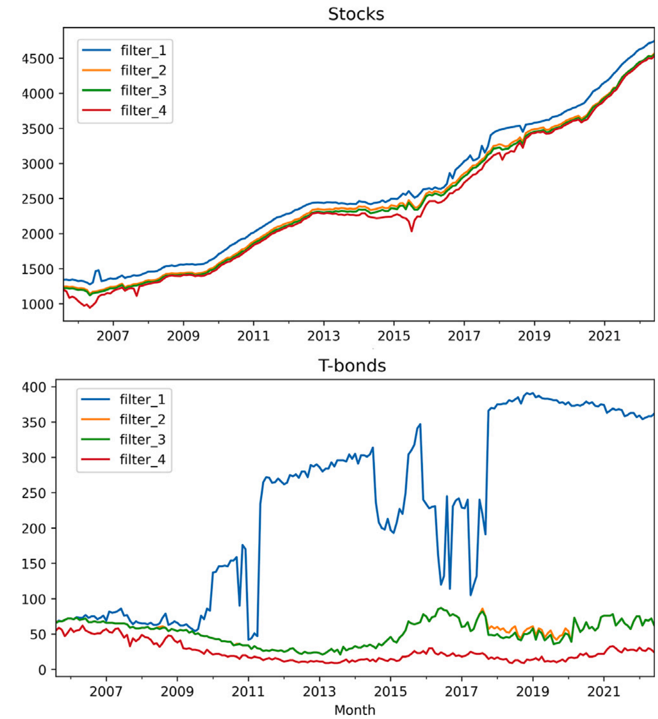

Fig. 1. Sample size after filtering.
Note: This figure plots the month-by-month number of observations left in the sample after four filtering steps. The filtering procedure is: Step 1 : filter equities by the 6-digit ticker code. For the stocks, the ticker codes start with 600, 601, 603, 605 or 688 in SSE, and 00 or 30 in the SZSE; for the T-bonds, the ticker codes start with 009, 010, 019, or 020 in SSE, and 10 in SZSE. Step 2: remove the ST-labeled stocks, or the non-active exchange-traded T-bonds. Step 3: remove observations with no float market capitalization as of the end of the previous year. Step 4: remove observations which do not have active trading records during at least 60% of trading days of the current month.

features a narrower spread, deeper depth and substantially more trading when compared to the T-bond market, indicating a higher level of market liquidity. In addition, both the T-bond liquidity and trading activity variables display more inter-temporal variation, as indicated by their higher coefficients of variation. The traders' level of consensus on the T-bond market position, which is reflected by its order imbalance, is on average on the "buy" side and more time-variant. All the liquidity and trading volume variables are significantly right skewed and exhibit excessive kurtosis. The Augmented Dickey–Fuller (ADF) test statistics confirm the time series stationarity for all variables except the Volume_S. The Ljung–Box test statistics confirm the presence of serial correlation and heteroskedasticity up to 5 lags. To further illustrate the liquidity dynamics, Fig. 2 plots the time series of the daily liquidity and trading activity variables over the entire sample period. Cross-asset liquidity and trading activity measures move in distinct ranges for most of the sample period. Maximum difference in cross-asset co-movement seem to appear in the short periods from Year 2008 to late 2009 (for the RPD) and in Year 2015 (for the Depth), which coincides with the periods of stock market crisis. The T-bond market depth and trading volume have improved significantly since 2019, indicating more active trading.

3. Informational shocks, trade, and liquidity linkages

In this section, I use a multivariate VAR to model the joint dynamics of aggregate liquidity in Chinese stock and T-bond market. Under this model, liquidity linkages could arise from both investors' trading activities and common sources of exogenous informational shocks.

[3] China's A-share stocks are stock shares of domestic Chinese companies that trade on SSE and SZSE. They use the Chinese RMB yuan for valuation and are only available for purchase by domestic investors or specified licensed international investors through the Qualified Foreign Institutional Investor (QFII) system.

[4] Special Treatment, or ST for short, is a label that the stock exchanges use to alert investors of stocks of high financial or operational risks. A T-bond is considered as a non-active exchange-traded asset if it has no trading records in either exchange for the whole month.

Table 1
Summary statistics.

	Mean	SD	CV	Skew	Kurt	ADF	LB(5)	LB^2(5)
Panel A: daily market liquidity and trading activity variables								
RPD_S	0.170	0.050	0.294	1.861	4.830	−3.9***	14432.3***	13704.3***
RPD_B	0.315	0.155	0.492	1.260	2.478	−4.4***	5597 .9***	4221.2***
Depth_S	2.053	0.886	0.432	0.824	2.067	−5.6***	14522.8***	12773.5***
Depth_B	0.743	0.773	1.040	2.621	8.306	−5.0***	13915.4***	10210.9***
Volume_S	0.170	0.127	0.747	2.577	9.749	−1.4	16655.8***	15569.2***
Volume_B	0.028	0.028	1.000	2.970	14.652	−3.8***	11182.0***	4519.8***
OIB_S	-0.031	0.073	−2.355	−0.253	−0.218	−7.8***	633.2***	330.3***
OIB_B	0.058	0.218	3.759	0.089	−0.247	−2.3***	2612.6***	209.1***
Panel B: daily market explanatory variables								
Ret_S	0.030	1.704	56.060	−0.550	3.891	−14.4***	16.7***	564.4***
Ret_B	0.015	0.058	3.898	1.035	26.771	−9.9***	116.2***	285.0***
RV_S	1.237	0.731	0.59	2.231	8.012	−5.7***	9003.9***	6035.6***
RV_B	0.201	0.408	2.029	3.495	18.602	−2.2	14353.8***	5733.8***
Money	1.023	0.600	0.586	1.115	1.022	−2.4	18519.9***	18530.7***

Notes:
- This table presents the descriptive statistics for the daily liquidity and explanatory variables. Panel A describes the daily liquidity and trading activity variables: relative spread (RPD), quote depth (Depth), trading volume (Volume), and order imbalances (OIB). The suffixes "_S" and "_B" denote the stock and T-bond market respectively. Data used to construct these variables are sourced from the GTA_SEL1 TAQ Database. Panel B describes the daily market and monetary explanatory variables: daily market return (Ret), realized market volatility (RV), and 3-month Shibor and 3-month T-bill interest spread (Money). The interest rate and market return measures are constructed from daily data from the Wind database, while the realized market volatility is constructed using data obtained from the GTA_SEL1 Database of 5-minute frequency.
- The first five columns of the table report the mean, standard deviation (SD), coefficient of variation (CV), skewness (Skew), and excess kurtosis(Kurt) for each variable. The Augmented Dickey–Fuller (ADF) statistics test the null hypothesis of unit root in the time series. LB(5) is the Ljung–Box statistic with the lag length equal to 5, to test for autocorrelation. The Ljung–Box squared statistics (LB^2(5)) tests the presence of ARCH effect up to 5 lags. *, **, and *** indicate test significance at the 10%, 5% and 1% level respectively.

Firstly, I examine the interactions between liquidity and trading activity, which are perhaps easy to anticipate because of the trade linkages with inventory risks. The order flow is generally believed to contain informed components and could exert pressure on market makers' inventory with large order imbalances (Chordia et al., 2002), while the trading volume is an important determinant of the inventory level. Both trade measures are closely connected to the theoretical paradigms of price formation, and could therefore induce cross-asset liquidity comovement by affecting the correlated expectations of optimal inventory levels.

Liquidity is also closely linked to exogenous market and monetary informational shocks through the dynamics of inventory risk and trading activity. Prior studies like Chordia et al. (2002, 2005) have found that variations in market returns and volatility affect trading activity, which could thereby influence liquidity. More recently, Chung and Chuwonganant (2014) also show that market uncertainty exerts a significant market-wide impact on liquidity and is an important source of liquidity commonality. Another strand of literature reports that monetary conditions, by affecting the interest rate and the traders' funding state, impact cross-market risk premiums and liquidity simultaneously. Goyenko and Ukhov (2009), for instance, establish a linkage between monetary policy shocks and stock–bond liquidity spillovers. Brunnermeier and Pedersen (2009) prove that tight capital funding can reduce market liquidity as investors become reluctant to take on positions, especially in high-margin securities. Nyborg and Ostberg (2014) further document that a tight interbank market can lead to "liquidity pull-back", which involves increased selling pressure, especially in more liquid securities. I test all these hypotheses in the VAR modeling.

I use the returns and realized volatility of the China Securities Index (CSI) 300 index and the SSE Government Bond Index respectively as empirical proxies for market-wide returns and volatility of the stocks and T-bonds. To proxy for the monetary conditions, I follow Nyborg and Ostberg (2014)'s practice and construct a interbank monetary tightness measure, which is the spread between the three-months Shanghai Interbank Offered Rate (Shibor) and the three-months T-bill rate. The interbank market is important because the effectiveness of the Central Bank's monetary policy depends on the extent to which the interbank market is allocative efficient (Nyborg and Ostberg, 2014). During the financial crisis, for instance, the volume of interbank lending may fall or stay stagnant for fear of lending risk, despite the loose monetary policy adopted by the Central Bank to boost trading. The market return and interest rate measures rely on daily data from the Wind database, while the realized market volatility is constructed using data obtained from the GTA_SEL1 Database of 5-minute frequency. As the Shibor rate starts only from October 9th, 2006, the sample period for liquidity and trade measures are also reduced to start from this date. The acronyms and definitions of market and monetary informational variables are given below:

- Ret_S /Ret_B (market returns): the daily returns of the China Securities Index (CSI) 300 index[5] (ticker code: 000300.SSE/ 399300. SZSE) and the daily returns of the SSE Government Bond Price Index[6] (ticker code: 000012.SSE);
- RV_S /RV_B (market realized volatility): the square root of realized daily volatility of the CSI300 or the SSE Treasury Bond Index based on the intraday five-minute price returns;
- Money: the spread between the three-months Shanghai Interbank Offered Rate (Shibor) and the yield of the three-months treasury bill.

Finally, as a key design to test for possible asymmetries in cross-asset liquidity, I include in the VAR model interaction terms to capture the differentiated effects of informational shocks on liquidity during crisis periods. The interaction terms are obtained by multiplying the trade, market, and monetary information variables with a binary market state indicator, which is constructed by applying the Lunde and Timmermann (2004)'s cycle dating algorithm on the daily CSI300 index

[5] The China Securities Index 300, or CSI300 for short, is composed of 300 stocks with the largest market capitalization and most active trading from the entire basket of listed A share companies in China. Accounting for approximately 70% of the total market capitalization, the CSI300 is widely recognized as representative of the performance of the Chinese stock market.

[6] Constituents for the SSE Government Bond Index are SSE-listed, fixed-rate government bonds with more than one year of remaining maturity. The index is weighted by amounts outstanding and made to reflect the whole government bond market's changes.

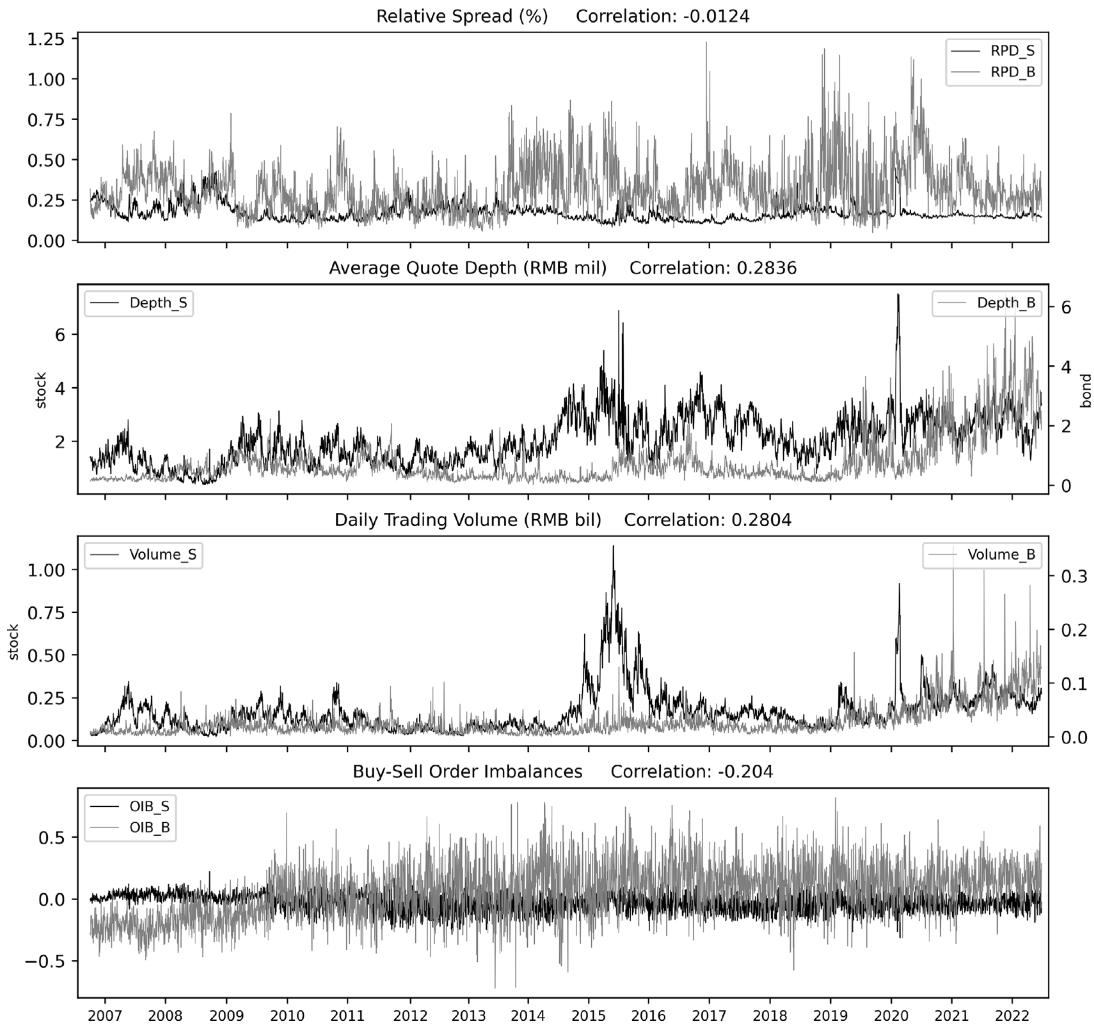

Fig. 2. Liquidity and Trading Activity Dynamics over 2006–2022.
Note: This figure plots the time series for the daily liquidity and trading activity variables over the sample period 2006–2022. The variables include: relative spread (RPD), quote depth (Depth), trading volume (Volume), and order imbalances (OIB). The suffixes "_S" and "_B" denote the stock and T-bond market respectively.

returns (See Appendix for details of the dating algorithm). When the market state indicator equals to 1, it indicates that the market is in a downward track.

The summary statistics of the daily explanatory variables are reported in Table 1, Panel B. The mean and standard deviation of stock market returns are of larger magnitude than those of the T-bond market returns, indicating that stock market tends to have higher and yet more volatile returns. Market risk levels are also higher in the stock market as evidenced by the higher realized volatility. The statistical tests for normality, stationarity, serial correlation and heteroskedasticity render similar qualitative results as those in Panel A.

Table 2 reports pair-wise correlations among the variables for VAR modeling. The stock and T-bond quote depth are significantly and positively related (0.284), suggesting contemporaneous commonalities in cross-asset liquidity. As expected, quote depth in each market is significantly and negatively correlated with their own market spread. The results also reveal strong connections between trading activity and liquidity. Volume_S, for instance, shows high negative correlation(−0.351) with RPD_S and high positive correlation (0.624) with Depth_S, indicating that growing trading volume is associated with increasing market liquidity. In particular, increases in the T-bond market's trading volume and order imbalances are strongly associated with liquidity increases in the stock market, confirming cross-asset correlation. In addition, the results show that cross-asset market returns and volatility are asymmetrically correlated with liquidity. Specifically, high stock liquidity is associated with high returns and low volatility in the stock market, but with low returns and high volatility in the T-bond market, suggesting the presence of cross-asset hedging. Finally, the monetary measure is significantly correlated with the cross-asset trading activity and liquidity measures. The direction of correlation indicates that a tighter interbank monetary market is associated with reduced trading volume, higher selling pressure and lower liquidity in both the stock and T-bond markets.

Table 3 presents results from a twenty-two-equation VAR system with ten monetary and market explanatory variables (Money, c_Money, RV_S, c_RV_S, RV_B, c_RV_B, Ret_S, c_Ret_S, Ret_B and c_Ret_B), eight trade variables (OIB_S, c_OIB_S, OIB_B, c_OIB_B, Volume_S, c_Volume_S, Volume_B, c_Volume_B), and four aggregate liquidity variables (RPD_S, RPD_B, Depth_S and Depth_B). The optimal lag lengths of the endogenous variables are determined by the Akaike's information criterion (AIC) and set to be ten accordingly. Panel A reports the Granger-causality test results. Panel B presents statistical analysis for the VAR residuals. Furthermore, to understand the dynamic impacts of informational shocks on liquidity, we compute and plot in Figs. 3 and 4 respectively impulse response functions (IRFs) for the stock and T-bond quote depth.

I first interpret the results for the explanatory variables without the interaction terms. The Granger causality test results show that aggregate liquidity is not only highly predictable by its lagged values, but also marginally by cross-asset liquidity levels. The relative spread

Table 2
Correlation between liquidity, trading activity and financial explanatory variables.

	RPD_S	RPD_B	Depth_S	Depth_B	Volume_S	Volume_B	OIB_S	OIB_B	Ret_S	Ret_B	RV_S	RV_B	Money
RPD_S	1.000												
RPD_B	−0.012	1.000											
Depth_S	−0.517***	0.173***	1.000										
Depth_B	−0.176***	−0.080***	0.284***	1.000									
Volume_S	−0.351***	0.187***	0.624***	0.231***	1.000								
Volume_B	−0.118***	0.013	0.316***	0.765***	0.280***	1.000							
OIB_S	0.017	0.018	−0.050***	−0.017	0.054***	−0.034**	1.000						
OIB_B	−0.227***	0.050***	0.326***	0.181***	0.147***	0.190***	−0.204***	1.000					
Ret_S	−0.149***	0.010	0.162***	−0.020	0.035**	0.005	0.382***	−0.026*	1.000				
Ret_B	0.083***	−0.002	−0.031**	0.003	−0.009	0.026	−0.001	0.075***	−0.051***	1.000			
RV_S	0.369***	0.045***	−0.374***	−0.117***	0.236***	−0.066***	0.210***	−0.292***	−0.136***	−0.001	1.000		
RV_B	−0.073***	0.160***	0.192***	0.571***	0.245***	0.646***	−0.006	0.097***	−0.022	0.001	0.057***	1.000	
Money	0.149***	−0.098***	−0.259***	−0.3728***	−0.246***	−0.358***	−0.077***	−0.037**	−0.026*	0.038**	−0.040**	−0.366***	1.000

Notes:
- This table reports the Pearson correlation matrix for the time series of the daily variables. The variables include daily liquidity, trade and market explanatory variables: relative spread (RPD), quote depth (Depth), trading volume (Volume), order imbalances (OIB), market return (Ret), realized market volatility (RV), and 3-month Shibor and 3-month T-bill interest spread (Money). The suffixes "_S" and "_B" denote the stock and T-bond market respectively. *, **, and *** indicate test significance at the 10%, 5% and 1% level respectively.

Table 3
VAR estimation results.

	RPD_S	RPD_B	Depth_S	Depth_B	Ret_S	Ret_B	RV_S	RV_B
Panel A: Chi-square statistic from Granger Causality Test.								
Money	**29.18*****	10.25	12.51	**16.66***	**25.43*****	8.61	10.73	4.33
c_Money	**32.56*****	7.98	**19.40****	5.48	**45.32*****	7.85	13.11	9.89
RV_S	11.34	8.58	**21.71****	3.05	**22.52****	**22.00****	**515.35*****	**23.30*****
c_RV_S	**33.93*****	2.61	**34.91*****	7.42	**61.00*****	15.13	68.32	**20.58****
RV_B	5.47	15.10	13.67	**29.94*****	4.01	3.29	**16.86***	**890.88*****
c_RV_B	6.23	10.62	12.35	**23.43*****	2.84	3.07	14.76	**201.97*****
Ret_S	**105.07*****	13.93	**92.91*****	6.41	**16.79***	9.57	**100.59*****	7.32
c_Ret_S	**52.44*****	10.41	**58.21*****	3.70	6.36	**25.29*****	**209.57*****	**29.93*****
Ret_B	13.13	**19.68****	9.31	2.70	10.98	**54.57*****	13.41	6.47
c_Ret_B	14.84	13.84	9.51	5.96	15.24	**24.45*****	**27.28*****	**37.98*****
OIB_S	**32.71*****	10.97	**138.42*****	14.54	8.86	**15.93***	**28.60*****	7.58
c_OIB_S	15.39	12.16	**17.37***	12.68	7.04	**16.63***	**24.56*****	6.93
OIB_B	**18.93****	14.46	**26.83*****	7.57	8.68	**22.41****	**25.17*****	7.54
c_OIB_B	**31.81*****	6.67	15.01	7.79	**16.49***	10.13	14.61	10.88
Volume_S	**72.43*****	6.63	**43.71*****	5.36	6.55	14.47	**49.82*****	**96.19*****
c_Volume_S	**28.07*****	6.19	**69.66*****	7.20	**19.88****	7.89	**31.28*****	49.94
Volume_B	2.48	4.66	3.77	**38.99*****	10.64	4.00	6.50	**17.46***
c_Volume_B	3.35	3.72	3.20	**53.70*****	**17.88***	6.47	8.99	**54.07*****
RPD_S	**14661.74*****	11.96	**45.41*****	7.83	11.36	**21.90****	**27.59*****	**185.80*****
RPD_B	**35.72*****	**2348.08*****	**23.94*****	**16.11***	11.23	7.92	13.44	**15.92***
Depth_S	**24.64*****	**19.98****	**6788.91*****	14.30	10.44	11.80	**31.73*****	**51.02*****
Depth_B	5.00	14.29	12.48	**2707.03*****	5.03	4.20	6.58	12.19
Panel B: Residual diagnosis								
LB(5)	0.08	0.10	1.12	0.90	0.05	0.08	0.77	4.00
$LB^2(5)$	30.42***	401.47***	1253.36***	1733.23***	345.76***	218.23***	512.08***	9.94*

Note: This Table presents results from a twenty-two-equation VAR system with ten market explanatory variables (Money, c_Money, Ret_S, c_Ret_S, Ret_B, c_Ret_B, RV_S, c_RV_S, RV_B and c_RV_B), eight trade variables (OIB_S, c_OIB_S, OIB_B, c_OIB_B, Volume_S, c_Volume_S, Volume_B, c_Volume_B), and four market-wide liquidity variables (RPD_S, RPD_B, Depth_S and Depth_B). The columns are arranged in accordance with variable ordering in the VAR system. The optimal lag lengths of the endogenous variables are determined by the Akaike's information criterion (AIC) and set to be eight. Panel A presents pairwise Granger-causality test results for the null hypothesis that row variable i does not Granger-cause column variable j. Panel B reports the Ljung–Box statistics ($LB^2(5)$) for testing the presence of autocorrelation and the ARCH effects in estimation residuals for up to 5 lags. *, **, and *** indicate test significance at the 10%, 5% and 1% level respectively.

in either the stock or the T-bond market has significant predictive power for their own-market quote depth, which, in joint consideration of their significant negative correlation, implies that a widening spread deters the market clearing process. Across the asset markets, RPD_B significantly cause RPD_S, and Depth_S and RPD_B significantly cause each other, proving the existence of bi-directional liquidity spillovers.

Liquidity is most importantly and significantly predictable by past trading activities. Both the trading volume and order imbalance variables are significantly informative in predicting stock market liquidity. In the T-bond market, the trading volume significantly causes the quote depth. Combined with the evidence from the correlation and IRF analysis, the empirical results are in line with the theoretical predictions that an increased trading volume improves market liquidity by increasing the quote depth; while increases in order imbalance, which reflect growing consensus to take long in the market, play a prominent role in improving quote depth and reducing relative spread. It is important to stress that the OIB_B also exhibits significant predictive power for both RPD_S and Depth_S, suggesting that price pressures caused by changes in the buy-sell order imbalances have implications beyond a single market. They are an important determinant of fluctuations in the cross-asset liquidity as well.

There is clear evidence that monetary and market informational shocks have significant predictive power for cross-asset liquidity. The Money variable significantly Granger-cause and is negatively correlated with both the stock and T-bond quote depth, suggesting that a tighter interbank rate reduces cross-asset liquidity. Particularly, there are very strong associations between stock market liquidity and its own-market returns and volatility. Combined with the correlation and IRF analyses,

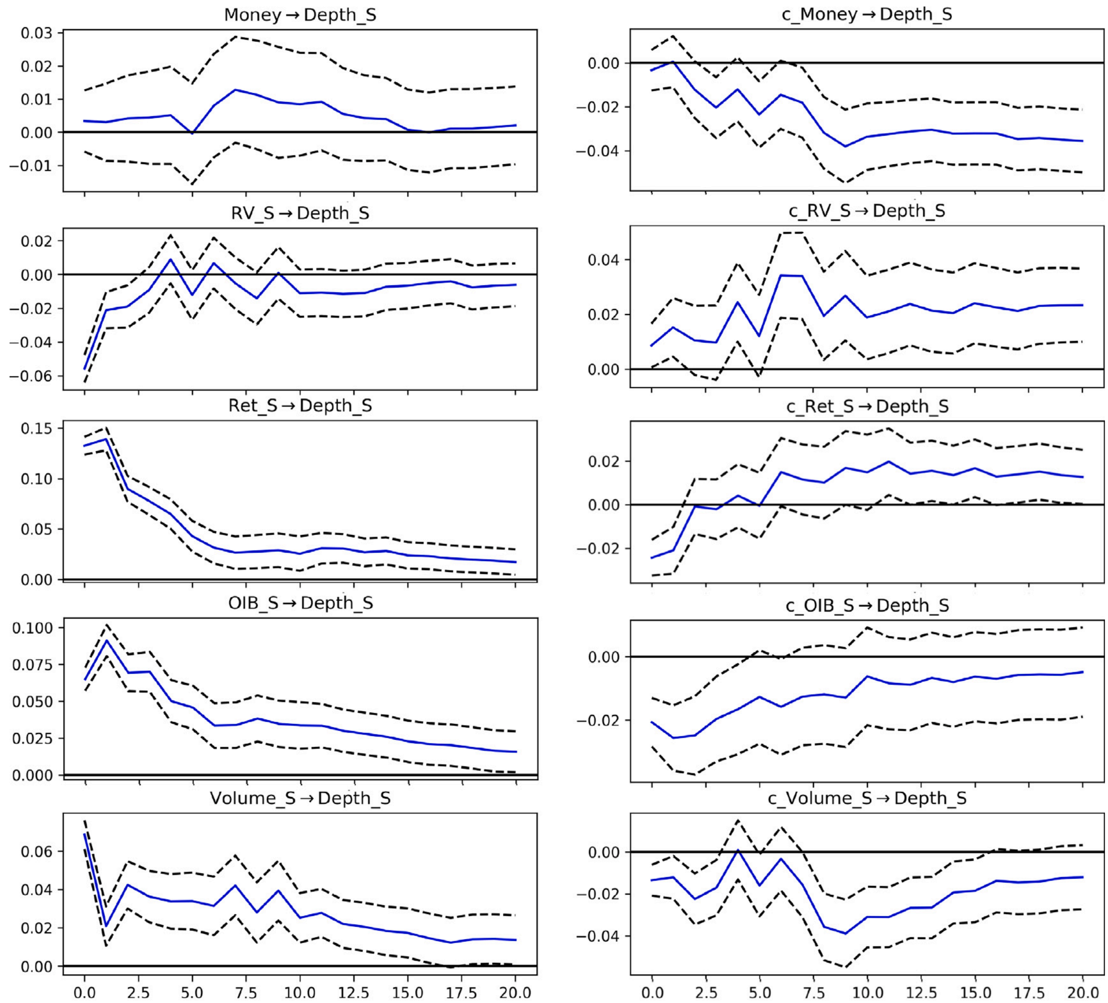

Fig. 3. Impulse response function (IRF) for the stock liquidity.
Note: This impulse response function (IRF) figure illustrates the response of the stock spread (RPD_S) and quote depth (Depth_S) to a one-time, unit standard deviation, positive shock in the endogenous variables for a period of 20 days. The endogenous variables include daily trade, market and monetary explanatory variables: trading volume (Volume), order imbalances (OIB), market return (Ret), realized market volatility (RV), and 3-month SHIBOR and 3-month T-bill interest spread (Money). The prefix "c_" denotes the interaction variables that are obtained by multiplying the binary cycle indicator with respective explanatory variables. The suffixes "_S" denotes the stock market. Monte Carlo two standard error bands are provided to gauge the statistical significance of the responses.

the results suggest that stock market price shocks can cause changes in trading activities and, in turn, fluctuations in liquidity. More specifically, an upward stock market attracts more momentum traders and increases buying pressure, which in turn leads to increased quote depth; while periods of high market volatility increase inventory risks and reduce market liquidity. In the T-bond market, such a pattern is not as evident as its liquidity measures reacts only marginally to market informational shocks. I interpret the combined results as evidence for the impact of investors' arbitraging and risk-hedging behaviors on cross-asset liquidity. The stock market, being more liquid, serves as the chief market for arbitraging and is therefore more sensitive to market informational shocks. The T-bond market, on the contrary, attracts less arbitragers due to its higher trading costs and serves mainly as a market for risk-hedging. In addition, the results also prove that cross-asset liquidity can be predicted by the common monetary factor.

Turning to the effects of the interaction terms, the IRF results for the trade and monetary informational shocks are suggestive of "liquidity pull-back" in the Chinese market. Firstly, the trade informational shocks exert asymmetric impacts on liquidity depending on the market state. Generally, a positive informational shock to the order imbalance and the trading volume improves the quote depth. During the crisis periods, however, such effects are reversed for both markets, indicating that liquidity is going down as investors' trading behaviors alter. In addition, the reversal effect is much stronger and persistent for the stocks market. Secondly, an informational shock to interbank monetary conditions during the crisis periods exerts asymmetric effects on cross-asset liquidity. While the T-bond liquidity has improved slightly in response, the stock liquidity has declined sharply and persistently. The results validate the importance of funding constraints on liquidity provision: "liquidity pull-back" occurs during the crisis periods, and more prominently in the more liquid stock market.

To better understand the interactions between liquidity and market price dynamics, I also report the Granger-causality results for cross-asset market return and volatility. The results provide suggestive evidence that cross-asset learning, which is driven by informational spillover, is an important driver of return commonality. As can be seen, market prices are significantly influenced by cross-asset market returns and volatility, especially during the market downturns. Both the Ret_S and RV_S, for instance, significantly cause Ret_B. The correlation analysis also reveals cross-asset trade and market volatility linkages: Volume_S is significantly correlated with RV_B(0.245), while OIB_B is significantly correlated with RV_S(−0.292). The trade variables also significantly Granger-cause cross-asset market returns and volatility. It is therefore conceivable that investors adjust trading behaviors based on cross-asset price informativeness, which may in turn cause further informational spillovers and affects cross-asset return linkages. Finally,

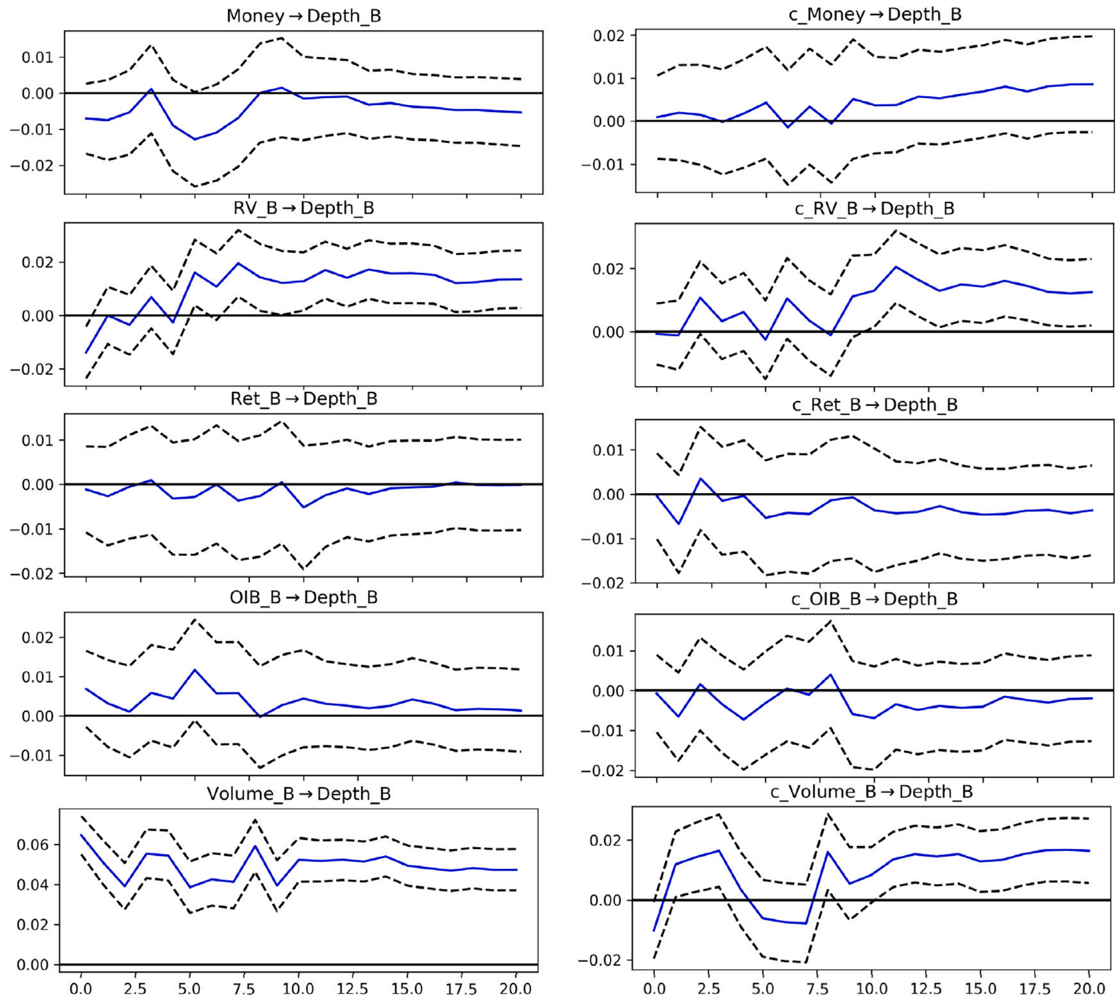

Fig. 4. Impulse response function (IRF) for the T-bond liquidity.
Note: This impulse response function (IRF) figure illustrates the response of the T-Bond spread (RPD_B) and quote depth (Depth_B) to a one-time, unit standard deviation, positive shock in the endogenous variables for a period of 20 days. The endogenous variables include daily trade, market and monetary explanatory variables: trading volume (Volume), order imbalances (OIB), market return (Ret), realized market volatility (RV), and 3-month SHIBOR and 3-month T-bill interest spread (Money). The prefix "c_" denotes the interaction variables that are obtained by multiplying the binary cycle indicator with respective explanatory variables. The suffix "_B" denotes the T-bond market. Monte Carlo two standard error bands are provided to gauge the statistical significance of the responses.

It is important to mention that aggregate liquidity (and stock liquidity in particular) Granger-causes cross-asset market returns and volatility, which validates the informational role of liquidity shocks on predicting future market return and volatility.

In general, the results from the VAR modeling reveal that the effects of monetary conditions, trade, and market informational shocks are not restricted to a single market, they influence cross-asset market dynamics and liquidity linkages as well. Diagnostic tests on VAR residuals reveal that residuals are free from serial correlation up to 5 lags, but significant ARCH effect is present as evidenced by the Ljung Box Q-Statistic in Table 3, Panel B.

4. Macro-financial news shocks and asymmetric liquidity covariance

Thus far I have performed the VAR modeling and examined the effect of cross-asset information spillover on liquidity correlation. In this section, I move on to examine the characteristics and determinants of volatility linkages between the stock and T-bond market liquidity, which has important implications for systematic illiquidity risk analysis. Prior studies have shown that macro-financial news shocks have significant influences on cross-asset return correlations (see e.g. Baele et al. (2010), Yang et al. (2009), Asgharian et al. (2016)). In this section, I use an extended DCC-GARCH model to analyze the effect of a number of monthly macro-financial variables on stock–bond liquidity covariance.

First introduced by Engle and Sheppard (2001), the DCC-GARCH model is an improvement on previous prevailing methods such as multivariate GARCH models and the Constant Conditional Correlation (CCC)-GARCH model (by Engle et al. (1990) and Bollerslev (1990)) by mitigating the problem of dimensionality and relaxing the pre-condition of constant correlation. In order to incorporate monthly macroeconomic fundamentals and long-term covariance effects when modeling the daily liquidity covariance, I further extend the model by applying the Mixed-Data Sampling (MIDAS) approach (Ghysels et al., 2007, Ghysels et al., 2005). In addition, based on observations of the asymmetric conditional volatility phenomenon, where volatility increases more after a negative than after a positive shock of the same magnitude (Cappiello et al., 2006), I include both short-run and long-run asymmetric terms in the DCC-GARCH framework as described in the work of Amendola et al. (2019). The resulting Double Asymmetric GARCH MIDAS (DAGM) model with DCC-MIDAS correlation framework is well suited to examine the asymmetric dynamics of conditional liquidity covariance. The model is estimated by the R statistical software using a two-step quasi-maximum-likelihood (QML) method in the style of Bollerslev and Wooldridge (1992), Engle (2002) and Colacito et al. (2011).

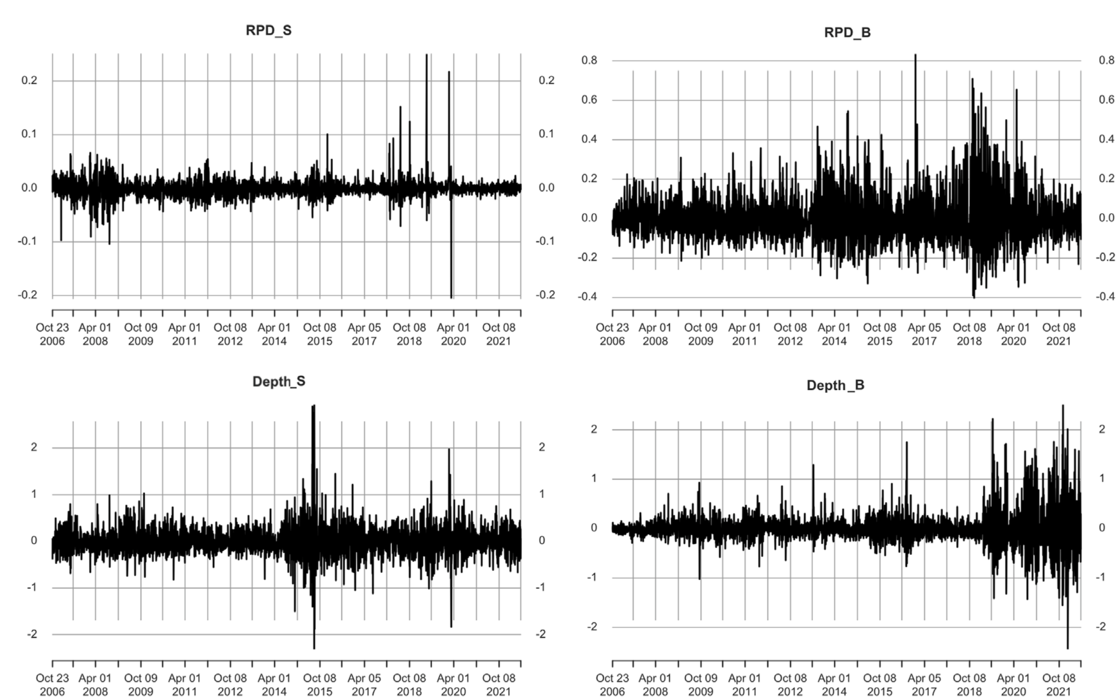

Fig. 5. VAR Residual Plot for the Liquidity Variables.
Note: This figure presents the time series of residuals from the VAR estimation for four market-wide liquidity variables: stock spread (RPD_S), T-bond spread (RPD_B), stock quote depth(Depth_S), and T-bond quote depth(Depth_B).

4.1. The DAGM-DCC-MIDAS model

The DAGM-DCC-MIDAS model is a particular specification of the broad DCC-GARCH based models which are completed in two steps. In the first step, the parameters of the univariate conditional variance are estimated respectively for the stock and T-bond liquidity residuals acquired from Section 3. Fig. 5 presents the residual time series. The conditional variance are modeled by Engle et al. (2013)'s univariate GARCH-MIDAS framework, which extracts two components of volatility in financial returns: one pertaining to short-term volatility that is specified as a mean-reverting GARCH(1,1), and the other to a MIDAS polynomial that applies to long-term macro-financial variables. Consider a return series, $r_{i,t}$, on day i within a lower-frequency period t (in this study set to be a month) is such that:

$$r_{i,t} = \mu_{i,t} + \sqrt{\tau_t \times g_{i,t}}\xi_{i,t}, \forall i = 1, \dots, N_t \quad (1)$$

where $\mu_{i,t}$ represents the conditional mean; N_t is the number of trading days in period t; $\xi_{i,t}$ is the error term, which is conditional on $\Phi_{i-1,t}$ (the information set up to day $i-1$ of period t). The long and short-run components of GARCH are expressed as τ_t and $g_{i,t}$, respectively. We assume $\xi_{i,t}|\ \Phi_{i-1,t}$ to be a Student's t to accommodate the excess kurtosis typical of financial innovations.

In the DAGM framework, possible asymmetries in the conditional variance of the residual time series are captured through three possible channels. The first is by an asymmetric term related to past returns in the short-run component $g_{i,t}$. More specifically, $g_{i,t}$ is specified to follow a unit mean-reverting GARCH(1,1):

$$g_{i,t} = (1-\alpha-\beta-\gamma/2) + (\alpha + \gamma \cdot I_{(r_{i,t}-\mu_{i,t}<0)})\frac{(r_{i,t}-\mu_{i,t})^2}{\tau_t} + \beta g_{i-1,t} \quad (2)$$

where $I(.)$ is an indicator function that equals to 1 if the argument is true. The asymmetric coefficient γ captures the effect that negative short-term information shocks on past returns have on volatility. The constraints $\alpha \geq 0$, $\beta \geq 0$, and $\alpha+\beta+\gamma/2 < 1$ are imposed to assure the positivity of $g_{i,t}$.

The other two channels of asymmetries are provided by the long-run component τ_t, which is defined as a one-sided MIDAS filter of the passed realizations of the monthly macro-financial variable X_t:

$$\tau_t = exp(m + \theta^+ \sum_{k=1}^{K} \varphi_k(\omega_2^+)X_{t-k}I_{(X_{t-k}\geq 0)} + \theta^- \sum_{k=1}^{K} \varphi_k(\omega_2^-)X_{t-k}I_{(X_{t-k}<0)}) \quad (3)$$

where K is the number of lags over which I smooth the X_t, and $\varphi_k(.)$ is a weighting function described by a beta lag polynomial:

$$\varphi_k(\omega_1,\omega_2) = \frac{(k/K)^{\omega_1-1}(1-k/K)^{\omega_2-1}}{\sum_{j=1}^{K}(k/K)^{\omega_1-1}(1-k/K)^{\omega_2-1}}, k = 1, \dots, K \quad (4)$$

The long-run component τ_t captures asymmetric responses to positive and negative changes in X_{t-k} by the sign-specific parameters θ^+ and θ^-. In addition, as the weighting function guarantees a decaying emphasis on X_{t-k} when we set $\omega_1$to 1, possible asymmetries in the rate of decay for X_{t-k} is determined by the parameters ω_2^+ and ω_2^-. The smaller ω_2^+ or ω_2^- is, the smoother the weighting is.

In this study, I consider a number of macro-financial factors related to economic growth, international trade, monetary conditions and consumer confidence as the long-run component. They include:

- Purchasing Managers Index (PMI) : log difference of monthly Purchasing Managers Index;
- international trade (InT): log difference of monthly international trade volume;
- difference in monetary growth (M1–M2): difference between the monthly growth rates of narrow money (M1) and broad money (M2)[7];
- Consumer Confidence Index(CCI) : log difference of monthly Consumer Confidence Index (CCI);

[7] Narrow money (M1) includes circulating currency, non-bank and non-government demand deposits, and money in all store-valued platforms. Broad money (M2) is the sum of M1, savings, foreign currency deposits, and trust funds.

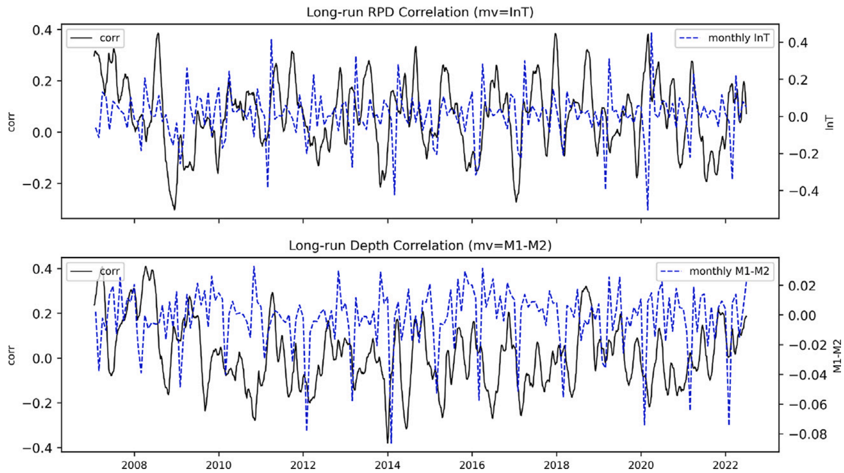

Fig. 6. DCC long-term correlation against Variations of Macroeconomic Variables.
Note: This figure presents the time series of DAGM-DCC-MIDAS-estimated long-run component for the cross-asset liquidity correlations. The estimated time series for RPD and Depth correlation are plotted respectively against the variations of the macroeconomic variable of international trade(InT) and difference in monetary growth (M1–M2) in Panel A and Panel B.

PMI has been widely used as a leading indicator of domestic economic growth. International trade is a common indicator of the general health of the global economy. The monetary supply measure, M1–M2, implies the level of potential funding liquidity and investors' level of optimism in the market. An increasing M1–M2 indicates that investors are more willing to hold the more liquid deposits, which could be readily converted to equity holdings. CCI signals the level of confidence in the prospect of the economy. All the monthly data are sourced from the Wind database.

In the second step of the DAGM-DCC-MIDAS modeling, time-varying correlations are estimated by relying on the lagged values of residuals and covariance matrices. I use Colacito et al. (2011)'s specification of the DCC-MIDAS model, which is a natural extension of Engle (2002)'s DCC model with the application of MIDAS approach. In the DCC-MIDAS, the short-run conditional covariance between two financial returns obeys the autoregressive dynamic structure of DCC, with the intercept specification now extended to reflect the long-run causes of time variation in correlation. More specifically, the conditional covariance between stock and bond liquidity in DCC-MIDAS is now:

$$q_{SB,t} = \bar{\rho}_{SB,t}(1 - a - b) + a\xi_{S,t-1}\xi_{B,t-1} + bq_{SB,t-1} \tag{5}$$

where $\xi_{S,t}$ and $\xi_{B,t}$ are the standardized residuals from the univariate DAGM framework in step 1.

The $\bar{\rho}_{SB,t}$ is the long-run component of the correlation specified as:

$$\bar{\rho}_{SB,t} = \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) C_{SB,t-k} \tag{6}$$

where $C_{SB,t-k}$ is the lagged realized correlation defined as:

$$C_{SB,t} = \frac{\sum_{t-N}^{t} \xi_{S,t-N}\xi_{B,t-N}}{\sqrt{\sum_{t-N}^{t} \xi_{S,t-N}^2}\sqrt{\sum_{t-N}^{t} \xi_{B,t-N}^2}} \tag{7}$$

where N is the number of lagged realizations to use for the standardized residuals forming the realized correlation.

4.2. The DAGM-DCC-MIDAS results

The results for DCC-GARCH modeling are reported for the stock/T-bond relative spread in Table 4, and for the quote depth in Table 5. To measure the success of the DAGM specification in modeling conditional asymmetries in univariate volatility, I also include a GARCH-MIDAS (GM) specification (Engle et al., 2013) for comparison. The GM specification incorporates the long-term effects of macro-variables without the asymmetric terms.

In both cases of the relative spread and the quote depth, the estimated parameters for the short-run components in both GARCH specifications are quite stable and predominantly positive, confirming the presence of GARCH effects in the liquidity residuals. Specifically, for both the stocks (Panel A) and T-bonds (Panel B), the GARCH coefficients on lagged squared error (α) and lagged short-run component (β) are mostly significant at 1% level, implying that short-run volatility is affected not only by the arrival of new information but also strongly by its own lagged values. The asymmetric coefficient (γ) for negative short-run informational shocks is significantly negative, suggesting that short-run volatility could be lower following informational shocks that bring down the liquidity proxy on the previous day. Additionally, the sum of coefficients on the short-run volatility, measured by ($\alpha + \beta + \gamma/2$), are close to unity for both the stock and T-bond markets, implying that short-run conditional variance are highly persistent. Furthermore, the results of DCC-MIDAS estimates in Panel C show that, consistent with most empirical research, the short-run auto-correlation coefficient b is significantly positive and close to unity, indicating strong persistence in short-run correlations.

A comparison of the estimated parameters for the long-run components of the GM and DAGM specifications provide strong evidence for the presence of asymmetric macro-financial effects. The θ^+ and θ^- parameters in the DAGM specifications, which capture the sign-specific macro-financial effects on conditional volatility, are significant and opposite-signed in several cases. Take the effects of international trade on the stock relative spread (Panel A, Table 4) for instance, the θ coefficient in the GM-InT specification is insignificant, but both the θ^+ and θ^- coefficients in the DAGM-InT specification are highly significant and with opposite signs. This indicates that the international trade exerts asymmetric impacts on long-run volatility of stock market liquidity depending on whether its changes are positive or negative. In addition, the estimates of w_2 also change significantly, suggesting that the degree of smoothing for the InT effects varies depending on the signs of its changes. Such asymmetries in sign-specific effects of macroeconomic news are also witnessed in the other three DAGM specifications.

Another intriguing result is the asymmetric responses of cross-asset liquidity volatility to macro-financial news shocks. In several of the DAGM specifications, the coefficients for the long-term GARCH component are opposite-signed for the stock and T-bond market. In Table 4, for instance, the θ^+ and θ^- coefficients for the DAGM-M1–M2 specification are opposite-signed for the RPD_S and the RPD_B respectively, indicating significant difference in the effects of funding liquidity across assets. Such a pattern of asymmetric impacts are also

Table 4
DCC-GARCH estimation results for stock and T-bond spread (RPD_S and RPD_B).

	GM-PMI	DAGM-PMI	GM-InT	DAGM-InT	GM-M1–M2	DAGM-M1–M2	GM-CCI	DAGM-CCI
Panel A: RPD_S volatility								
α	0.318***	0.319***	0.322***	0.323***	0.319***	0.321***	0.314***	0.316***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
β	0.800***	0.800***	0.800***	0.798***	0.801***	0.791***	0.805***	0.799***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
γ	−0.263***	−0.267***	−0.268***	−0.269***	−0.266*	−0.276***	−0.266***	−0.273***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.052)*	*(0.000)*	*(0.000)*	*(0.000)*
m	−7.661***	−7.661***	−7.582***	−6.887***	−7.632***	−6.993***	−7.718***	−7.177***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
θ	−6.699		−0.879		−10.189		6.863	
	(0.690)		*(0.638)*		*(0.136)*		*(0.912)*	
w_2	4.997		**11.402*****		1.001		5.785	
	(0.173)		*(0.000)*		*(0.996)*		*(0.768)*	
θ^{+}		**−10.804*****		**−8.230*****		**−102.741*****		**−59.509*****
		(0.000)		*(0.000)*		*(0.000)*		*(0.000)*
w_2^{+}		**2.376*****		1.010		**1.001*****		**2.529*****
		(0.000)		*(0.743)*		*(0.000)*		*(0.000)*
θ^{-}		**−10.069*****		**7.755***		**58.937*****		**47.736*****
		(0.000)		*(0.056)*		*(0.000)*		*(0.000)*
w_2^{-}		1.002		**1.140*****		**1.153*****		1.420
		(0.339)		*(0.006)*		*(0.000)*		*(0.140)*
Panel B: RPD_B volatility								
α	0.115	0.120**	0.119***	0.117***	0.117***	0.118***	0.116***	0.117***
	(0.498)	*(0.016)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.000)*
β	0.898***	0.891***	0.894***	0.895***	0.896***	0.894***	0.896***	0.896***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
γ	−0.073	−0.074	−0.075***	−0.073***	−0.073***	−0.074***	−0.072***	−0.082***
	(0.768)	*(0.356)*	*(0.000)*	*(0.002)*	*(0.000)*	*(0.000)*	*(0.006)*	*(0.000)*
m	−4.701***	−4.510***	−4.670***	−4.350***	−4.687***	−4.825***	−4.694***	−5.215***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
θ	10.466		−2.452		**2.728*****		−2.267	
	(0.994)		*(0.254)*		*(0.000)*		*(0.235)*	
w_2	**2.846*****		1.003		**1.003*****		5.105	
	(0.000)		*(0.323)*		*(0.000)*		*(0.965)*	
θ^{+}		−6.790		**−6.688***		**11.543*****		**31.486*****
		(0.948)		*(0.066)*		*(0.000)*		*(0.000)*
w_2^{+}		1.002		1.002		1.001		**1.655****
		(0.993)		*(0.238)*		*(0.502)*		*(0.018)*
θ^{-}		**9.601*****		0.128		**−8.041*****		**−32.187*****
		(0.000)		*(0.979)*		*(0.000)*		*(0.000)*
w_2^{-}		4.943		1.193		**1.789*****		1.001
		(0.985)		*(0.118)*		*(0.000)*		*(0.537)*
Panel C: DCC parameterization								
a	0.003	0.004	0.003	0.001	0.001	0.003	0.004	0.005
	(0.469)	*(0.229)*	*(0.468)*	*(0.991)*	*(0.942)*	*(0.391)*	*(0.378)*	*(0.119)*
b	0.996***	0.995***	0.996***	0.999***	0.998***	0.996***	0.995***	0.994***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
w_2	1.972	1.970	1.977***	1.978	1.972***	1.054***	1.972***	1.957
	(0.808)	*(0.846)*	*(0.000)*	*(0.891)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.928)*
AIC	16246.09	16239.32	16235.41	16247.81	16257.48	16257.91	16318.62	16215.41

Notes:
- This table presents the DCC-GARCH model estimation results for the RPD_S and RPD_B. Panel A and B reports the results of univariate conditional volatility modeled by two comparative GARCH specifications: GARCH-MIDAS (GM) and Double Asymmetric GARCH-MIDAS (DAGM). Four macroeconomic variables, namely, Purchasing Managers Index (PMI), international trade (InT), difference in monetary growth (M1–M2) and Consumer Confidence Index (CCI) are to measure their impacts on the long-term component of conditional volatility. Significant θ and w coefficients are highlighted in bold numbers.
- Panel C reports the results of the bivariate DCC-MIDAS model. The number of lagged realizations of macro-financial variables entering the long-run equation is K = 18. We use a moving window of 20 lags of standardized residuals to form the realized correlation (RC), and use 60 RC to construct the long-run component(i.e. N = 20 and K = 60). The final row report the Akaike's information criterion (AIC) scores. The italic numbers in brackets denote the p-values. *, **, and *** indicate test significance at the 10%, 5% and 1% level respectively.

witnessed in the DAGM-CCI specification for the relative spread. As both M1–M2 and CCI imply consumers' level of confidence in the financial market, the results suggest that liquidity volatility across the assets are asymmetrically impacted when consumer confidence changes.

To illustrate the relationship between cross-asset liquidity correlation and the macro-financial news shocks, Fig. 6 respectively plots the DCC-estimated time series of long-run stock–bond liquidity correlation against the variations of InT and M1–M2. The figure gives suggestive evidence that the long-run liquidity correlation tends to be small and negative following trends of weak global economy or narrowing M1–M2. In the later half of 2008 during the financial crisis, for instance, the long-run correlation plummets amid decreasing InT. Since the beginning of 2009, as the Chinese economy gradually recovers in response to the government's massive economic stimulus package,[8] the

[8] In November 2008, in an effort to offset adverse impacts of global financial crisis and boost domestic demand, the Chinese Government announced a massive economic stimulus package estimated at 4 trillion RMB yuan (about 570 billion U.S. dollars). The stimulus package, which included plans to loosen credit conditions, cut taxes and finance infrastructure spending, was scheduled to be spent over the next two years that followed.

Table 5
DCC-GARCH estimation results for stock and T-bond quote depth (Depth_S and Depth_B).

	GM-PMI	DAGM-PMI	GM-InT	DAGM-InT	GM-M1–M2	DAGM-M1–M2	GM-CCI	DAGM-CCI
Panel A: Depth_S volatility								
α	0.089^{***}	0.066^{***}	0.064^{***}	0.065^{***}	0.065^{*}	0.065^{***}	0.068	0.067^{***}
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.052)*	*(0.000)*	*(0.525)*	*(0.003)*
β	0.934^{***}	0.941^{***}	0.940^{***}	0.939^{***}	0.947^{***}	0.942^{***}	0.939^{***}	0.938^{***}
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
γ	-0.048^{***}	-0.040^{***}	-0.041^{***}	-0.041^{***}	-0.039^{**}	-0.043^{***}	−0.040	−0.040
	(0.009)	*(0.003)*	*(0.002)*	*(0.002)*	*(0.025)*	*(0.002)*	*(0.214)*	*(0.595)*
m	−0.519	-2.6872^{***}	-2.687^{***}	-2.854^{***}	-2.801^{***}	-3.256^{***}	−2.683	-2.624^{***}
	(0.484)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.414)*	*(0.000)*
θ	0.351		**-13.335^{***}**		**-12.908^{***}**		0.929	
	(0.127)		*(0.008)*		*(0.000)*		*(1.000)*	
w_2	**2.063^{***}**		**1.106^{***}**		6.983		1.667	
	(0.003)		*(0.000)*		*(0.933)*		*(1.000)*	
θ^+		−0.737		**-10.732^{***}**		**39.103^{***}**		−10.414
		(0.949)		*(0.000)*		*(0.000)*		*(0.741)*
w_2^+		**1.128^{***}**		**1.002^{***}**		1.946		1.002
		(0.000)		*(0.008)*		*(0.125)*		*(0.203)*
θ^-		**6.765^{***}**		**-14.302^{***}**		**-28.616^{***}**		8.581
		(0.000)		*(0.000)*		*(0.000)*		*(0.940)*
w_2^-		6.683		**1.212^{***}**		**5.353^{***}**		1.168
		(0.557)		*(0.000)*		*(0.000)*		*(0.994)*
Panel B: Depth_B volatility								
α	0.140^{***}	0.143^{**}	0.145^{***}	0.146^{**}	0.136	0.152^{***}	0.138^{***}	0.142^{***}
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.275)*	*(0.000)*	*(0.00)*	*(0.000)*
β	0.888^{***}	0.886^{***}	0.884^{***}	0.883^{***}	0.890^{***}	0.878^{***}	0.889^{***}	0.886^{***}
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
γ	-0.083^{***}	-0.085^{***}	-0.0836^{***}	-0.087^{***}	−0.080	-0.092^{***}	-0.083^{***}	-0.087^{***}
	(0.007)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.333)*	*(0.000)*	*(0.000)*	*(0.000)*
m	-3.298^{***}	-2.877^{***}	-3.217^{***}	-3.705^{***}	-3.318^{***}	-4.475^{***}	-3.303^{***}	-3.863^{***}
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.002)*	*(0.000)*	*(0.000)*	*(0.000)*
θ	3.371		−7.036		7.293		**-22.963^{***}**	
	(0.930)		*(0.687)*		*(0.973)*		*(0.000)*	
w_2	**6.325^{***}**		**1.002^{**}**		**12.822^{**}**		**2.707^{***}**	
	(0.000)		*(0.013)*		*(0.049)*		*(0.002)*	
θ^+		**-35.223^{***}**		−1.602		**91.992^{***}**		**37.739^{***}**
		(0.000)		*(0.229)*		*(0.000)*		*(0.000)*
w_2^+		1.754		**1.394^{*}**		**1.001^{*}**		1.001
		(0.267)		*(0.074)*		*(0.096)*		*(0.649)*
θ^-		5.287		**-12.468^{***}**		**-88.476^{***}**		**-39.031^{***}**
		(0.640)		*(0.000)*		*(0.000)*		*(0.000)*
w_2^-		**34.930^{***}**		1.001		**1.001^{*}**		**2.319^{***}**
		(0.006)		*(0.515)*		*(0.085)*		*(0.000)*
Panel C: DCC parameterization								
a	0.001	0.001	0.003	0.001	0.001	0.001	0.001	0.001
	(0.982)	*(0.999)*	*(0.992)*	*(0.991)*	*(0.983)*	*(0.978)*	*(0.986)*	*(0.999)*
b	0.998^{***}	0.998^{***}	0.999^{***}	0.999^{***}	0.999^{***}	0.999^{***}	0.998^{***}	0.999^{***}
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
w_2	2.576^{***}	2.028	2.162	3.905^{***}	2.174^{***}	1.977^{***}	2.847^{***}	2.206
	(0.000)	*(0.851)*	*(0.927)*	*(0.891)*	*(0.603)*	*(0.000)*	*(0.000)*	*(0.409)*
AIC	15027.38	15595.32	15560.03	15547.48	15635.84	15449.91	15596.73	15514.00

Notes:
- This table presents the DCC-GARCH model estimation results for the Depth_S and Depth_B. Panel A and B reports the results of univariate conditional volatility modeled by two comparative GARCH specifications: GARCH-MIDAS (GM) and Double Asymmetric GARCH-MIDAS (DAGM). Four macroeconomic variables, namely, Purchasing Managers Index (PMI), international trade (InT), difference in monetary growth (M1–M2) and Consumer Confidence Index (CCI) are to measure their impacts on the long-term component of conditional volatility. Significant θ and w coefficients are highlighted in bold numbers.
-Panel C reports the results of the bivariate DCC-MIDAS model. The number of lagged realizations of macro-financial variables entering the long-run equation is K = 18. We use a moving window of 20 lags of standardized residuals to form the realized correlation (RC), and use 60 RC to construct the long-run component(i.e. N = 20 and K = 60). The final row report the Akaike's information criterion (AIC) scores. The italic numbers in brackets denote the p-values. *, **, and *** indicate test significance at the 10%, 5% and 1% level respectively.

liquidity correlation steers into a rapid upward trend. In mid 2011, however, in response to the falling InT and decreasing M1–M2 due to monetary tightening,[9] the cross-asset liquidity correlation (and the RPD correlation in particular) falls quickly from 0.3 to −0.2 by 2012. From the Year 2012 to 2014, as the monetary policy loosens and the economy stabilizes, the InT fluctuates within a narrow range and the RPD correlation steers into a general upward track. In the early 2014, both the InT and the M1–M2 witness a sharp decline, which soon leads to decreasing RPD and Depth correlation in the year that follows. From mid 2015 to the beginning of 2016, in another well-documented Chinese stock market crisis, cross-asset RPD correlation witnesses a sharp decline. The correlation steadily climbs uphill in 2016 and 2017 as the market gradually recovers. The upward trend is then reversed around mid 2018 as the US–China trade friction strikes the market and impacts general economic conditions and consumer confidence. Both the RPD

[9] Starting from 2011, in a bid to curb the high inflation that resulted from past two years of economic stimulus and check excessive lending, the People's Bank of China (PBOC), China's central bank, set on a series of monetary tightening measures. By July 2011, the PBOC had raised banks' reserve requirement ratio for six consecutive times to a level of 21.5%.

and Depth correlation then set on a fluctuating pattern that are largely in line with the InT and M1–M2 trends. In the beginning of 2020, both the InT and M1–M2 decline quickly amid the Covid-19 pandemic, which subsequently influence the RPD and Depth Correlation.

5. Horizon heterogeneity and liquidity correlation

The previous two sections have examined the time-varying information and volatility linkages between cross-asset liquidity. It is reasonable to expect, however, that horizon heterogeneity may impact cross-asset liquidity correlation as the underlying driving factors of the liquidity linkages may vary in function of its frequency. Chakrabarty et al. (2015) document that horizon heterogeneity is instrumental behind the stability and clearing of the market and affects the interdependencies of financial time series. In this section, I adopt a new approach to investigate the dynamic correlation between cross-asset liquidity, trade and market informational variables from a horizon heterogeneous perspective. The method of wavelet-based multi-scale analysis also serves as a robustness check for the results found in previous sections.

5.1. Wavelet coherence analysis (WCA)

As an improvement on the traditional Windowed Fourier Transform (WFT) which is commonly used to extract local-frequency information from a signal, the wavelet transform is a tool for analyzing time series that contain non-stationary power at many different frequencies (Daubechies, 1990). The wavelet coherence analysis (WCA), which is built on the basis of wavelet transform, is a bi-variate framework that can be effectively used to identify regions of high co-movement between two time series in the time–frequency space. Rua and Nunes (2009) are among the first to use the WCA in analyzing co-movements among international financial markets. The WCA methodology used in this section largely follows the practices pioneered by Torrence and Compo (1998), Torrence and Webster (1999).

To begin the WCA, a suitable function that has zero mean and is localized in both time and frequency space needs to be specified as the base wavelet function (Farge, 1992). Following the common practices in financial studies (Rua and Nunes, 2009, Mensi et al., 2018), I choose the Morlet wavelet $\varphi_0(t)$, which consists of a plane wave modulated by a Gaussian:

$$\varphi_0(t) = \frac{1}{\pi^{1/4}} e^{i\omega_0 t} e^{-t^2/2} \tag{8}$$

where t is the non-dimensional time parameter and ω_0 is the central frequency. Following the convention in previous studies, I set ω_0 to 6 to provide a good balance between time and frequency localization.

For a given time series x_t with equal time spacing δt and time length T, the *continuous wavelet transform (CWT)*of x_t is defined as the convolution of x_t with a scaled and translated version of $\varphi_0(t)$:

$$W_x(t,s) = \sqrt{\frac{\delta t}{s}} \sum_{t'=0}^{T-1} x_{t'} \varphi_0 \left[\frac{(t'-t)\delta t}{s} \right] \tag{9}$$

where t is the localized time index indicating the exact position of the wavelet, s is scale parameter that determines the degree to which the wavelet is stretched. A higher s implies a more stretched wavelet which is more appropriate for detecting lower frequencies. $\frac{1}{\sqrt{s}}$ is the normalization factor ensuring that $\varphi_0(t)$ has unit energy. By varying s and t, the CWT can show both the amplitude of any features versus the scale and how this amplitude varies with time.

The wavelet transform $W(t,s)$ is complex, and hence can be divided into real part $\Re\{W(t,s)\}$, imaginary part $\Im\{W(t,s)\}$, and phase $tan^{-1}\left[\Im\{W(t,s)\}/\Re\{W(t,s)\}\right]$. The *wavelet power spectrum*, $|W(t,s)|^2$, which is defined as the absolute squared amplitude of the wavelet transform, measures the time series variance at each scale (period) and along the time index.

Based on the concept of CWT of single time series, the *cross wavelet spectrum* of two time series x_t and y_t is defined as:

$$W_{xy}(t,s) = W_x(t,s) W_y^*(t,s) \tag{10}$$

where the asterisk ($*$) denotes the complex conjugate.

The *cross-wavelet power*, which reveals the area in the time-scale space where the two time series show high common power, is defined as $\left|W_{xy}(t,s)\right|$. Confidence levels for the cross-wavelet power can be derived from the square root of the product of two chi-square distributions.

With the tools of CWT and *cross wavelet power* in hand, the *wavelet squared coherence* and *wavelet coherence phase* between two financial time series can be formally defined as:

$$R^2(t,s) = \frac{\left|S(s^{-1} W_{xy(t,s)})\right|^2}{S(s^{-1}\left|W_{x(t,s)}\right|^2) S(s^{-1}\left|W_{y(t,s)}\right|^2)} \tag{11}$$

$$\varphi_{xy}(t,s) = tan^{-1} \frac{\Im\left\{S(s^{-1} W_{xy(t,s)})\right\}}{\Re\left\{S(s^{-1} W_{xy(t,s)})\right\}} \tag{12}$$

where $S(.)$ is the smoothing parameter.

The *wavelet squared coherence*, $R^2(t,s)$, represents the regions in the times-scale space where two selected time series co-move. I therefore consider it as a suitable measure for identifying both the frequency bands and the time intervals within which the stock and T-bond liquidity are covarying. The coherence measure is especially useful for identifying time-scale intervals where wavelet power spectra of both time series show low power yet still display high coherency. $R^2(t,s)$ fluctuates within the range $[0,1]$, with values close to zero indicating a weak correlation and values close to one corresponding to high correlation.

The *wavelet coherence phase*, $\varphi_{xy}(t,s)$, which indicates the phase difference between the two given time series, is used as a measure of the lead–lag and causality relationships between the variables in the time–frequency space. The judgment rules are: (1) if $\varphi_{xy}(t,s) = 0$, x_t and y_t move together at the specified time–frequency; (2) if $\varphi_{xy}(t,s) \in \{\pi, -\pi\}$, x_t and y_t are in anti-phase relation; (3) if $\varphi_{xy}(t,s) \in \left(0, \frac{\pi}{2}\right)$ or $\varphi_{xy}(t,s) \in \left(-\pi, -\frac{\pi}{2}\right)$, x_t and y_t are positively related but x_t leads y_t; (4) if $\varphi_{xy}(t,s) \in \left(-\frac{\pi}{2}, 0\right)$or $\varphi_{xy}(t,s) \in \left(\frac{\pi}{2}, \pi\right)$, then the lead–lag relationship reverts and y_t is leading.

5.2. The WCA results

Fig. 7 plots the wavelet coherence and phase between RPD_S and various financial time series including RPD_B, OIB_S, Volume_S, Ret_S and RV_S. The color code reflects the strength of coherence ranging from low (purple) to high power (yellow), and on a scale of 0 to 1. The black contours show the 5% significance level. The wavelet coherence phase, which indicates the direction of interdependence and the lead–lag relationships between the two financial time series, are indicated by the phase arrows. This study follows the convention of arrow plotting as adopted by Torrence and Webster (1999), in which the phase arrows rotate clockwise with the "north" origin. If the arrow points upwards (to the north), the series are in phase (moving together in the same direction). Contrarily, anti-phase relationships, which indicate negative correlation, are signaled by downward-pointing arrows. Moreover, if the arrow points right (East), the series are in-phase but the RPD_S is leading. In contrast to that, arrows pointing left signal a leading position for the RPD_S.

The results largely confirm the inter-connective relations found by the VAR analysis in Section 2. Specifically, the first Panel shows that cross-asset liquidity coherence is only significant in certain time–frequency space. In contrast, the other panels reveal very strong coherence over the entire sample period between stock liquidity and stock market dynamics. In addition, the direction of the coherence, which

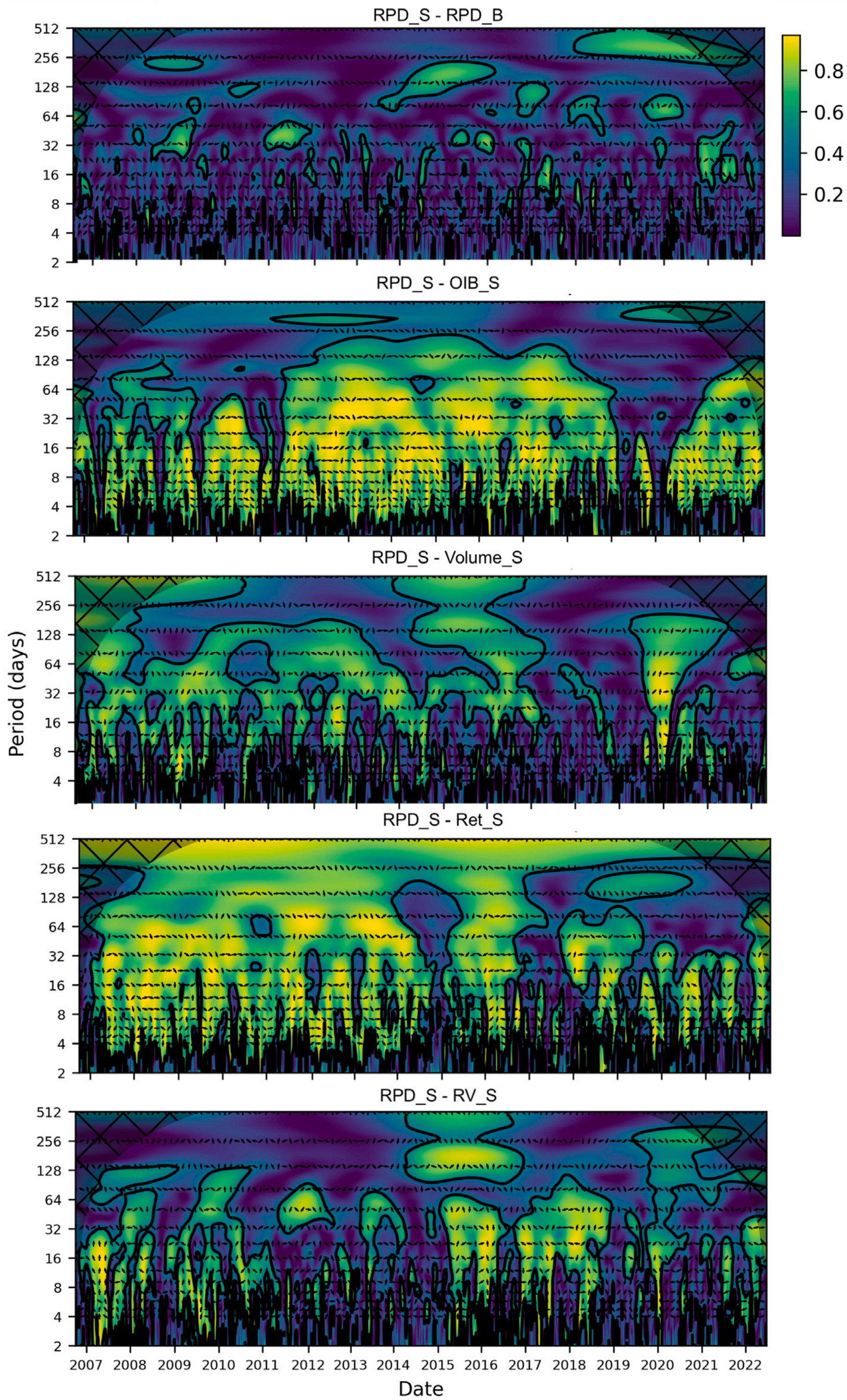

Fig. 7. Cross Wavelet Coherence for RPD_S.
Note: This figure plots the wavelet coherence and phase between RPD_S and various financial time series including RPD_B, OIB_S, Volume_S, Ret_S and RV_S. The color code reflects the strength of coherence ranging from low (purple) to high power (yellow), and on a scale of 0 to 1 (as indicated by the scale bar on the upper right corner). The black contours show the 5% significance level. Monte Carlo simulations are used to assess the statistical significance of the local coherence in the time–frequency domain. The phase arrows, which are plotted following the convention as adopted by Torrence and Webster (1999), rotate clockwise with "north" origin. If the arrow points upwards (to the north), the series are in phase (moving together in the same direction). Contrarily, anti-phase relationships, which indicate negative correlation, are signaled by downward(south)-pointing arrows. Moreover, if the arrow points right (East), the series are in-phase but the RPD_S is leading. In contrast to that, arrows pointing left signal a leading position for the respective financial time series. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

are indicated by the wavelet coherence phase arrows, are also largely in line with the theoretical predictions and empirical findings. Take the RPD_S coherence with the Ret_S for instance, the phase arrows are pointing mostly downwards, especially during the market crisis periods such as in 2008, 2011,2016 and 2018, indicating that RPD_S and Ret_S generally move in opposite directions. In the same period, the phase arrows indicating the direction of the RPD_S and RV_S coherence are mostly pointing upward. The combined evidence are consistent with empirical financial downturns which feature declining returns, increasing volatility and rising illiquidity. In other periods, the phase arrows for the RPD_S and Ret_S in the highly significant contour regions also point rightward, suggesting that an increasing RPD_S leads Ret_S changes in the same direction. Such a lead–lag relationship is consistent with the classic proposition in the asset pricing literature which states that illiquidity may impact stock returns through a premium for greater trading costs (e.g. Amihud and Mendelson (1986), (Pastor and Stambaugh, 2003), Acharya and Pedersen (2005)).

The two trading activity variables demonstrate significant coherence with stock liquidity, but with varying coherence phases. The phase arrows are mostly downward-pointing, indicating that in most cases an increasing order imbalance/trading volume is associated with improving market liquidity. On some occasions, however, the phase arrows can point to other directions, suggesting that trading activity may be in phase with market liquidity and a lead–lag relation exists. As has been discussed in Section 2, the effects of trading activity on market liquidity may vary depending on the market state, as the changing market dynamics alter investors' expectations and trading behavior. The WCA results reflect the importance of time and horizon heterogeneity in affecting investors' expectations.

It is also worth noting that the trading activity variables show strong coherence with stock liquidity mostly in the higher frequency (shorter horizon) region of less than 64 days, while the market variables such as the Ret_S could maintain high coherence with stock liquidity even over the long horizon of 512 days. This reveals the changing importance of trading activity and market factors in influencing liquidity subject to horizon heterogeneity. Furthermore, a closer look at the cross-asset RPD coherence in Panel 1 reveals that when the economy is strong, cross-asset liquidity tends to co-move over a horizon of about 1 to 3 months; during the stock market downturn, however, liquidity flows in the opposite direction across assets over a short horizons of about 1 to 2 weeks. This observation, in combination with findings in Sections 2 and 3, reveals that macro-financial conditions and investors' trading behaviors work in tandem to influence the strength and phase of liquidity coherence in the time–frequency space.

6. Conclusions

Financial market liquidity has long been recognized as a priced factor (Amihud and Mendelson, 1986, Eleswarapu and Reinganum, 1993). More recently, the literature has emphasized the importance of market-wide liquidity as a systematic risk factor (Pastor and Stambaugh, 2003, Acharya and Pedersen, 2005, Avramov et al., 2006). Empirical research confirm that liquidity is negatively related to volatility (Chordia et al., 2005, 2002) and may even evaporate during times of financial turmoil when market uncertainty is very high (Nagel, 2012), leading eventually to a systematic liquidity crash (Cespa and Foucault, 2014). To the extent that cross-asset liquidity co-moves, it has important market implications and pose immediate questions. What are the factors that influence such co-movement, and how do the influences differ depending on market states and investment horizons? In this study, I use a multivariate VAR model with a GARCH-MIDAS error structure to estimate both the first- and second-moment linkages between stock and T-bond liquidity in China. I seek to ascertain the extent to which liquidity fluctuations are caused by cross-asset information spillovers and macro-financial news shocks. I also use both a DCC-MIDAS and a wavelet coherence framework to analyze the nature and dynamics of cross-asset liquidity correlation, and while doing so, provide some suggestive evidence about its sources.

To conclude, I find both commonalities and asymmetries in cross-asset liquidity provision, which lead to time- and horizon-varying liquidity correlation. The empirical results from the VAR estimation provide weak evidence of direct stock–bond liquidity causality but strong evidence that the predictability of market-wide liquidity emanates from trade, market and monetary informational shocks. The evidence validate the importance of cross-asset learning, which is driven by informational spillover, as investors adjust portfolio strategies based on the price informativeness of other assets. During the stock market crisis periods, however, both the market information (returns and volatility) and the common monetary factor exert asymmetric impacts on cross-asset liquidity. More specifically, higher market volatility and tighter interbank monetary rates during the crisis periods induce liquidity outflow from equity markets to different degrees, resulting in asymmetric liquidity co-movement. The results validate the importance of what Nyborg and Ostberg (2014) term as "liquidity pull-back" in the Chinese market, in which monetary tightening increased asset selling pressure, especially for the more liquid stocks.

In the GARCH-MIDAS estimation for cross-asset volatility linkages, I focus on the comparative performances of the DAGM and GM specifications to analyze the possible asymmetries in cross-asset liquidity volatility. I find unambiguous support for the hypothesis that long-term conditional volatility in the equity markets are influenced by general macro-financial conditions. A comparison of the variable coefficients for GM and DAGM specifications also confirms the existence of asymmetric responses of cross-asset liquidity volatility to positive and negative macro-financial news shocks. Furthermore, the results from the DCC-MIDAS estimation suggest that long-run cross-asset liquidity correlation tends to be small and negative following trends of weak global economy or narrowing M1–M2.

Finally, the WCA results capture important dynamics of interdependence between liquidity, trade and market prices in the Chinese stock and T-bond market over heterogeneous horizons. The results confirm the findings of the VAR analysis that aggregate levels of asset liquidity should contain predictive signals for future market returns and economic activity. In addition, the WCA reveals that while macroeconomic factors influence mid- and long-run liquidity correlation, investors' risk-hedging trading behaviors during financial downturns play a significant role in influencing liquidity correlation in the short-run. The results emphasize the importance of both macro-financial determinants and behavioral factors on influencing the asymmetric dynamics of cross-asset liquidity interdependence in China.

The findings on cross-asset liquidity linkages have practical implications for researchers, investors, and regulators. For researchers, understanding the sources of liquidity commonalities and asymmetries may shed light on risk premiums and asset pricing. These issues are also important for investors who need to reconsider the pricing of illiquidity risks in cross-asset hedging and portfolio rebalancing. The results may serve as a potential input for policy makers, who need to consider the impacts of macro-financial policies on cross-asset liquidity co-movement, and subsequently, the stability of the financial market in general.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data

Appendix. The cycle-dating algorithm of Lunde and Timmermann (2004)

The Lunde and Timmermann (2004)'s algorithm for dating business cycles is realized by tracking price changes and identifying alternating peaks and toughs in a market index. Bull and bear markets are identified by examining whether a minimum threshold of price changes has

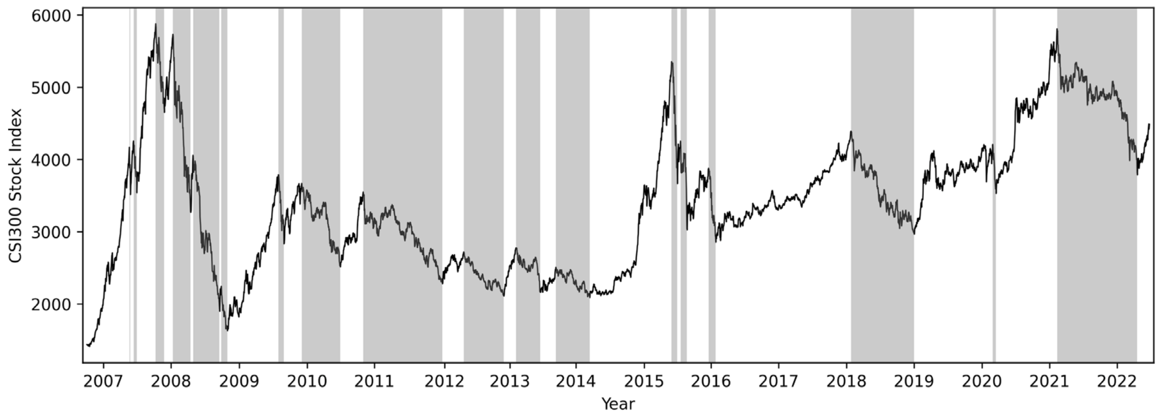

Fig. A.8. Bull/bear market states as indicated by the CSI300 index.
Note: This figure identifies the bull/bear market states in the Chinese stock market as represented by the CSI300 index using the (Lunde and Timmermann, 2004)'s cycle-dating algorithm. The gray-shaded areas mark the periods of bear states.

been met since the last peak or trough. More specifically, let λ_1 be the pre-set threshold of price changes that triggers a switch from a bear to a bull state and λ_2 be the threshold of price changes that triggers the opposite (bull-to-bear) switch, the cycle detection program for a market index P_t uses an iterative search procedure that can be summarized as:

1. Suppose P_t starts with a bear state and the last observed extreme value before period t was a trough, P^{min}:
   - if the current index value $P_t < P^{min}$, update the trough so $P^{min} = P_t$;
   - if P_t is bigger than P^{min} by more than the give threshold λ_1, then identify P_t as a new peak: $P^{max} = P_t$;
   - if neither of above conditions is satisfied, no update takes place and the program now moves to P_{t+1}.
2. Suppose P_t starts with a bull state and the last observed extreme value before period t was a peak, P^{max}:
   - if the current index value $P_t > P^{max}$, update the peak so $P^{max} = P_t$;
   - if P_t is smaller than P^{max} by more than the give threshold λ_2, then identify P_t as a new trough: $P^{min} = P_t$;
   - if neither of above conditions is satisfied, no update takes place and the program now moves to P_{t+1}.

In this study, I set λ_1 and λ_2 to be 15%. Under the above tracking rules, the periods between a trough and a peak are defined bullish while the periods between a peak and a trough are defined as bearish. To determine whether the market index P_t starts with a bear or bull state, peaks and troughs are identified using the algorithm from P_0 and their numbers counted. Whichever state count reaches 3 first is defined as the initial state. The identified market states (gray-shaded areas for bear states) for the Chinese stock market (as represented by the CSI300 index) using the above-described Lunde and Timmermann (2004)'s algorithm is plotted in Fig. A.8.

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