Australian National University

Crawford School of Public Policy

CAMA

Centre for Applied Macroeconomic Analysis

Investor Sentiment, Volatility and Cross-Market Illiquidity Dynamics: A Threshold Vector Autoregression Approach

CAMA Working Paper 24/2022
March 2022

Lin Qi
Crawford School of Public Policy, ANU
Centre for Applied Macroeconomic Analysis, ANU

Abstract

This paper discusses the role that stock market volatility plays in the linkages between the U.S. stock and Treasury bond markets through liquidity under different regimes of investor sentiment in a threshold vector autoregression model. The baseline analysis shows that the interaction between volatility and illiquidity dynamics coincides with the flight-to-safety phenomenon. Moreover, the empirical evidence in the high investor sentiment regime points to the potential existence of flight-from-maturity where market participants tend to shorten their lending maturities for precautionary purposes. This result is robust under either an exogenously or an endogenously chosen investor sentiment threshold value. Further analysis verifies this relationship in the period after the Global Financial Crisis (GFC) and finds evidence of flight-from-maturity in the medium-term and the short-term bond markets. Finally, this paper finds that an adverse stock market volatility shock increases the probability of moving from a high sentiment to a low sentiment regime. This probability gets higher in the post-GFC era.

Keywords

Liquidity, Flight-from-maturity, Flight-to-safety

JEL Classification

G10, G12, G40, C32

Address for correspondence:

(E) cama.admin@anu.edu.au

ISSN 2206-0332

The Centre for Applied Macroeconomic Analysis in the Crawford School of Public Policy has been established to build strong links between professional macroeconomists. It provides a forum for quality macroeconomic research and discussion of policy issues between academia, government and the private sector.

The Crawford School of Public Policy is the Australian National University's public policy school, serving and influencing Australia, Asia and the Pacific through advanced policy research, graduate and executive education, and policy impact.

Investor Sentiment, Volatility and Cross-Market Illiquidity Dynamics: A Threshold Vector Autoregression Approach

Lin Qi

Crawford School of Public Policy, ANU and

Centre for Applied Macroeconomic Analysis, ANU

Third Draft

November 2021

Abstract

This paper discusses the role that stock market volatility plays in the linkages between the U.S. stock and Treasury bond markets through liquidity under different regimes of investor sentiment in a threshold vector autoregression model. The baseline analysis shows that the interaction between volatility and illiquidity dynamics coincides with the flight-to-safety phenomenon. Moreover, the empirical evidence in the high investor sentiment regime points to the potential existence of flight-from-maturity where market participants tend to shorten their lending maturities for precautionary purposes. This result is robust under either an exogenously or an endogenously chosen investor sentiment threshold value. Further analysis verifies this relationship in the period after the Global Financial Crisis (GFC) and finds evidence of flight-from-maturity in the medium-term and the short-term bond markets. Finally, this paper finds that an adverse stock market volatility shock increases the probability of moving from a high sentiment to a low sentiment regime. This probability gets higher in the post-GFC era.

Keywords: Liquidity, Flight-from-maturity, Flight-to-safety

JEL: G10, G12, G40, C32

1 Introduction

Since the global financial crisis (GFC), financial market liquidity (or illiquidity) has become an important concern for academia, policymakers and market participants. Theoretical papers have outlined the mechanisms where financial market liquidity is a key driving force behind the GFC stock market crash (Brunnermeier and Pedersen, 2009; Brunnermeier and Sannikov, 2014). During this time, monetary authorities in major economies created numerous tools to guarantee the short-term supply of liquidity to systemically important financial institutions (a comprehensive summary of the international monetary policy responses after the GFC is provided by Bank for International Settlements, 2019; and a summary for the monetary policy responses in the U.S. after the COVID-19 crisis is provided by Clarida et al., 2021). Early research (e.g. Engle et al., 2012; Goyenko and Ukhov, 2009) shows that market volatility significantly influences market liquidity and the dynamics between stock and bond markets. However, according to Danielsson et al. (2018), the effects of stock market volatility on investor risk-taking could be asymmetric due to behavioural factors of investors such as over-confidence or optimism. These factors have not been addressed in previous papers on the liquidity dynamics between stock and bond markets. This paper intends to fill this gap to reveal the cross-market dynamics between market liquidity and market volatility. The influence of volatility on other market variables is allowed to be asymmetric under different regimes of investor sentiment in a threshold vector autoregression (TVAR) model. This application focuses on the U.S. stock and Treasury bond market from January 1986 to December 2018.

The illiquidity measure is built on the data collected from the Center for Research in Security Prices (CRSP). Amihud 's (2002) widely used illiquidity measure first constructs individual stock illiquidity measures. The overall stock market illiquidity measure is constructed by aggregating the illiquidity measures of the individual stocks. The relative quoted spread, a standard bond market illiquidity measure, is used for the Treasury bond market. Since the importance of taking into account the bond market yield curve has been found in previous studies (e.g. Goyenko and Ukhov, 2009), this paper examines the Treasury bond market in the short-term, medium-term and long-term. The investor sentiment index, which can approximately measure the extent of optimism or pessimism of investors, is used as the transition variable to distinguish the underlying behavioural states of investors in the TVAR model. Moreover, the model includes the TED spread to capture the potential influence of funding liquidity. Three questions are in particular interest under the TVAR framework:

(1) How do adverse stock market volatility shocks influence cross-market liquidity dynamics across different investor sentiment regimes?

(2) How does the influence of adverse stock market volatility shocks on cross-market liquidity dynamics change after the GFC?

(3) Does an adverse shock to stock market volatility cause a higher probability of moving into a low sentiment regime?

This paper estimates a TVAR model using a threshold value of zero for the investor sentiment index to answer the first question. This threshold is exogenously chosen following early research of Baker and Wurgler (2007), and this model is referred to as the baseline model. In calculating the impulse response functions, the analysis considers two cases. The first is where regime switching between high and low investor sentiment is not allowed, and the second is where regime-switching is allowed. The empirical findings generally confirm the reallocation of investors' portfolios, or flight-to-safety, when an adverse shock happens. Increasing illiquidity in the stock market and decreasing illiquidity in the bond market imply that investors exit the stock market and enter the bond market when faced with an adverse shock. The empirical results highlight the importance of the effect of sentiment. When there is a shock such that the stock market is more volatile, stock market illiquidity increases by less when investors are optimistic compared to when they are pessimistic. Interestingly, the short-term bond market becomes more illiquid in the high sentiment regime, contradicting the flight-to-safety story. A potential explanation for this phenomenon is that the exit of the precautionary short-term lenders causes liquidity evaporation in the short-term money market and its relevant collateral markets, known as flight-from-maturity (Gorton et al., 2021). The robust test using an endogenous threshold value confirms the above findings qualitatively.

The post-GFC situation is investigated by reducing the sample duration to the period starting from January 2009 while keeping other model settings the same as those in the baseline model. The post-GFC era is marked by unconventional monetary policy, tightening regulations, and deepening concerns about financial market liquidity, which may influence investor behaviour. More evidence for flight-from-maturity is found after the GFC. An adverse stock market volatility shock occurring in the high investor sentiment regime leads to the increase of short-term bond illiquidity and medium-term bond illiquidity, implying growing precautionary preparation of investors and narrowing of the choice of safe assets in the post-GFC era compared to full sample results. Moreover, the responses of funding liquidity to the adverse stock market volatility shock are in line with the literature describing how fund providers respond to increasing uncertainty (e.g. Brunnermeier and Pedersen, 2009; Adrian and Shin, 2010).

The third question is addressed by calculating the ex-ante probability of high and low investor sentiment regimes under an adverse stock market volatility shock. Both the full sample and the post-GFC cases are considered. The results show that a sizeable adverse stock market volatility shock will increase the probability of moving to the low sentiment regime by 10% compared to the scenario where there is no shock in the full sample case, while the probability jumps to 20% in the post-GFC era.

This paper substantially contributes to three strands of research. First it confirms the findings of Engle et al. (2012), Adrian et al. (2017) and Danielsson et al. (2018). Engle et al. (2012) and Adrian et al. (2017) find evidence of the influence of volatility in the bond on illiquidity in the bond market. Danielsson et al. (2018) report the asymmetric effects of stock market volatility on the banking sector. In addition to the above papers, which lack discussion about cross-market dynamics, this paper provides further evidence suggesting that the effects from volatility could be cross-market and asymmetric due to behavioural factors. The second strand of research that this paper closely connects with is about liquidity commonality, such as in Chordia et al. (2011) and Goyenko and Ukhov (2009). Chordia et al. (2011) find that U.S. stock and bond market illiquidity comove, and Goyenko et al. (2009) report that the illiquidity in one market has long-run predictive power for the illiquidity in other markets. Both of their models provide little evidence on the significant effect of volatility on illiquidity. The findings of this paper complement this research by providing evidence on liquidity commonality in a model where funding liquidity, investor sentiment and the market state are considered. And finally, the clear demonstration of cross-market liquidity dynamics in high and low sentiment periods supports flight-to-safety, and indirectly, the flight-from-maturity studies (e.g. Baele et al., 2020; Gorton et al., 2021).

The rest of the paper proceeds as follows: Section 2 provides a short review of the literature of the market illiquidity and volatility. Section 3 outlines the TVAR model and the details of the construction of the variables used in the analysis. Section 4 descriptively analyses the data and performs several preliminary tests, Section 5 presents all estimation results, and Section 6 concludes.

2 Brief Literature Review

Classical literature generally argues that financial market illiquidity and volatility are positively correlated (Stoll, 2000; Chordia et al., 2001). The argument that market illiquidity and volatility are correlated is closely related to the findings from two strands of research. The literature from the demand-side focuses on panic selling during periods of financial market turmoil. The literature from the supply-side focuses on the behaviour of financial intermediaries and brokers and dealers. For the supply of liquidity, early research can be traced back to Ho and Stoll (1983), where due to the inventory risk a dealer faces, increasing volatility will lead to decreasing market-making and therefore increasing illiquidity. Gârleanu and Pedersen (2007) show that high volatility induces tighter risk management in financial institutions and therefore lowers the supply of liquidity. Among theoretical papers, Vayanos (2004) presents an asset pricing model where the need to liquidate is linked to volatility. Brunnermeier and Pedersen (2009) suggest that rising volatility may lead to margin requirement tightening and a further downward liquidity spiral. Relevant empirical evidence for stock and bond markets and their cross-market dynamics is provided by Stoll (2000), Chordia et al. (2001), Goyenko et al. (2009), Hameed et al. (2010), Adrian et al. (2017) and recently Nguyen et al. (2020).

Newly developed literature suggests that more detailed research on the relationship between volatility and liquidity is needed due to the influence of behavioural factors. Behavioural factors usually take centre place in building up systemic risk leading to financial crises as demonstrated in the research of the last decade (see a review such as Sufi and Taylor, 2021). For example, Adrian and Shin (2010) show the effects of procyclical mark-to-market leverage of financial intermediaries and the comovement between the marginal adjustment of dealers' balance sheet and financial market risk. In Danielsson et al. (2018), a prolonged period of low financial market volatility may lead to excessive risk-taking in the banking sector and result in a higher probability of crises. Liquidity commonality literature generally suggests that a sentiment shock leads to the increasing comovement of liquidity (see, for example, Karolyi et al., 2012). These findings demonstrate the possibility of asymmetric influence that volatility may have on liquidity in different states of investor sentiment. Moreover, most research as listed above focus on a single market. The lack of cross-market studies on this topic is a substantial research gap.

3 Methodology

This section provides the specification of the TVAR model, introduces the impulse response functions used in the nonlinear scenario and the details of the construction of stock and bond market illiquidity measures and investor sentiment used in the TVAR model. The generalised impulse response function provides a reasonable measure of the influence a shock may bring to the TVAR system where regime switching is allowed. The illiquidity measure proposed in Amihud (2002) is used to depict stock market illiquidity. The illiquidity of the bond market is measured by the relative quoted spreads which is a standard measure. The investor sentiment index following Baker and Wurgler (2006), which proxies investor sentiment, is introduced at last.

3.1 Threshold Vector Autoregression Model

A TVAR model is set up to study the difference between the cross-market liquidity dynamics in high and low sentiment regimes. The model can be expressed by the following equation:

$$Y_t = B_1 + \gamma_1(L)Y_t + (B_2 + \gamma_2(L)Y_t)I(y^*_{t-d} > \theta) + \epsilon_t, \tag{1}$$

where Y_t is a vector containing the endogenous variables. I is an indicator function that equals one if the transition variable y^*, which in this paper is investor sentiment, at the lag order d is greater than the threshold value θ and zero otherwise. The delay parameter d implies the dynamics change at time t when y^* crosses θ at time $t-d$. The dynamics of the system are depicted by the lag polynomials $\gamma_1(L)$ and $\gamma_2(L)$. As an element of Y_t, the evolution of y^*, the investor sentiment, is captured by the TVAR model. The endogenous regime-switching feature of the TVAR brings tractability to the underlying process of market movements, an advantage compared to Markov Switching VARs where the state variable is generally not observed. A TVAR model allows heteroscedasticity across the two regimes as the dynamics within each regime can be described by a linear model shown in the following equation :

$$Y_t = B_1 + \gamma_1(L)Y_t + \epsilon_{1,t} + (B_2 + \gamma_2(L)Y_t + \epsilon_{2,t})I(y^*_{t-d} > \theta). \tag{2}$$

Following early studies such as Chordia et al. (2005) and Goyenko et al. (2009), the variables in vector Y_t is ordered as follows: investor sentiment, funding liquidity, stock market volatility, bond market volatility, stock market returns, bond market returns and the illiquidity of stock market, long-term, medium-term and short-term bond markets. The TED spread is used to indicate the overall funding liquidity condition. The construction of market return and volatility will be outlined in Section 4.

3.2 Generalized Impulse Response Function

The calculation of the impulse response functions in the nonlinear model is quite different from the linear one. In a linear model (for example, a VAR), the system stays in one regime, and shocks do not cause a switch in regime. The impulse response functions in the linear model are thus history-independent and strictly proportional to the size of the shock. However, in a nonlinear model, the system may move to another regime due to a shock. The impulse response functions in the nonlinear case depend on the initial state of the system and the size and sign of the shock, and therefore, are history-dependent.

This paper applies the generalised impulse response functions (GIRFs) developed by Koop et al. (1996) to calculate the impulse response functions in the TVAR model while allowing regime switching. GIRFs are simulation-based and defined as the difference between the conditional expectations of scenarios with and without shocks:

$$GIRF_y(h, \Omega_{t-1}, u_t) = E[y_{t+h}|\Omega_{t-1}, u_t] - E[y_{t+h}|\Omega_{t-1}], \tag{3}$$

where y denotes the responding variable, h denotes the horizon, Ω_{t-1} denotes the information set at $t-1$ and u_t denotes the shock. GIRFs are calculated through the following steps: First, the shocks for the periods within the forecast horizon are simulated by drawing from the variance-covariance matrix of the TVAR model. These shocks are fed into the estimated model for the given initial values to produce a set of forecasts of the variable conditional on the initial values and shock history, denoted as the baseline forecast. Second, the same procedure is repeated except that the shock from the variable of interest has the magnitude of one standard deviation at period 0. The difference between the forecast from the second step and the baseline forecast is the impulse response functions for a set of initial values and certain history of shocks. The two steps above are repeated 500 times to average out the shocks. Subsequently, the impulse response functions are averaged over each regime to produce the impulse response functions conditional only on initial values.

3.3 Stock Market Illiquidity Measure

Since high-frequency microstructure stock price data is not available over a long sample period, market illiquidity must be able to be computed based on daily frequency data, which is an advantage of Amihud's (2002) illiquidity measure. Intuitively the Amihud illiquidity measure adheres to the idea of a liquid market as traders can finish trading with the most negligible impact on price. Amihud (2002) provides evidence that this measure is strongly related to the price impact estimated by microstructure data. Goyenko et al. (2009) investigate a bunch of different illiquidity proxies and finds that the Amihud illiquidity measure outperforms other proxies in measuring price impact. The Amihud illiquidity of stock i in month t is defined as:

$$ILLIQ_t^i = \frac{1}{DAYS_t^i} \sum_{d=1}^{DAYS_t^i} \frac{|R_{td}^i|}{V_{td}^i}, \tag{4}$$

where $DAYS_t^i$ is the number of valid observed trading days in month t, and R_{td}^i and V_{td}^i are respectively the intra-day return, computed by the open and the close price, and the dollar trading volume on the day d in a month t for stock i. The intuition of this measure is that if the stock price moves more in response to less trading volume (value), the stock is more illiquid and therefore has a higher value of $ILLIQ_t^i$. For convenience, the illiquidity measure is multiplied by 10^8. Stock market illiquidity $LIQS$ is computed based on the equal-weighted average of $ILLIQ_t^i$ for all ordinary common shares (share code that start with 10 and 11) listed on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX). When calculating $ILLIQ_t^i$ in month t, only shares with more than 15 valid trading days are included.

3.4 Treasury Market Illiquidity Measure

Treasury market illiquidity is measured by the relative quoted spreads, a standard measure for the bond market. The relative quoted spreads are described as follow:

$$RQS = \frac{ASK - BID}{\frac{1}{2}(ASK + BID)}, \tag{5}$$

where ASK and BID are the quoted ask and bid prices. Monthly bond market illiquidity, denoted as $LIQB$, is the equal-weighted average of the RQS across different securities for each month. In this paper, Treasury market illiquidity is computed conditional on the maturities of the bonds. Short-term bond market illiquidity is the average RQS of the Treasury securities with maturity no longer than one year. Medium-term bond market illiquidity is computed based on the Treasury securities with maturity from two to seven years. Following the tradition in Chordia et al. (2001) and Goyenko et al. (2009), long-term bond market illiquidity is represented by the $LIQB$ of the 10-year Treasury note. In the later sections and the TVAR model, the $LIQB$ for each maturity category has the corresponding suffix: LONG, MEDIUM, and SHORT.

3.5 Investor Sentiment Index

This paper uses the sentiment index first used by Baker and Wurgler (2006) to measure investor sentiment. Baker and Wurgler (2006) develop a sentiment index based on the first principal component of a bucket of investor sentiment proxies in the U.S. financial market. The index is then regressed on core macroeconomic variables to provide a cleaner proxy, which is denoted by $SENT^{\perp}$. The variables for the financial market from which the first principal component is extracted include the value-weighted dividend premium, first-day returns on IPOs, IPO volume, closed-end fund discount and equity share in new issues. By definition, the higher these proxies, the more optimistic are market investors. The macroeconomic variables include the industrial production index, nominal durables consumption, nominal nondurables consumption, nominal services consumption, the NBER recession indicator, employment and the consumer price index. In the earlier version of the sentiment index, Baker and Wurgler (2006, 2007) also use NYSE turnover. However, they dropped this variable in the latest version of the index as the implication of turnover rates changed with the booming of high-frequency institutional trade.

4 Preliminary Analysis

This section provides the information about the data, including summary statistics of the variables, then a brief discussion about the procedure in selecting the threshold value, and non-linearity tests to justified the TVAR model setting.

4.1 Data and Descriptive Analysis

The sample period of this paper is from January 1986 to December 2018, with a total number of observations of $N = 396$. The data for the investor sentiment index $SENT^{\perp}$ is collected from Wurgler's website. The TED spread is collected from FRED, the stock market data is collected from CRSP's Daily Stock file and the Treasury market data is collected from the CRSP's TREASURIES Daily Time Series file. The stock market return series $RETS$ is the value-weighted return on NYSE and AMEX market indices. The bond market return series $RETB$ is calculated based on the 10-year Treasury note. Stock market volatility $VOLS$ and bond market volatility $VOLB$ are the standard deviation of the corresponding return series. The descriptive statistics for the variables in the TVAR model are presented in Table 1.

Table 1: Descriptive statistics

	$SENT^{\perp}$	TED Spread	VOLB	VOLS	RETB	RETS	LIQS	LIQB-LONG	LIQB-MEDIUM	LIQB-SHORT
Mean	0.22	0.54	0.24	0.89	0.49	0.90	0.24	0.06	0.05	0.01
Std. Dev.	0.60	0.39	0.10	0.58	1.19	4.11	0.27	0.03	0.02	0.00
Max	3.20	3.21	0.80	5.14	5.35	12.25	2.06	0.20	0.14	0.02
Median	0.10	0.43	0.22	0.76	0.46	1.43	0.13	0.05	0.04	0.01
Min	-0.89	0.12	0.09	0.26	-2.88	-21.52	0.01	0.03	0.02	0.00
N	396	396	396	396	396	396	396	396	396	396

The correlation matrix is presented in Table 2. The investor sentiment index shows a significant negative correlation with stock market volatility and a significant positive correlation with bond market return and medium-term and short-term bond market illiquidity. Jointly these results suggest that the optimistic financial market is usually accompanied by a tranquil stock market and less trading in the bond market, reflecting the higher risk appetite of investors. The TED spread shows significant correlations with all market variables. The positive correlations between the TED spread and the volatilities of the stock and bond market reflect tightening funding liquidity under increasing risk. The positive correlations of the TED spread with the illiquidities of the stock and bond market reflect the interactions between funding liquidity and market liquidity. The TED spread is positively correlated with bond market returns and negatively correlated with stock returns, pointing to the potential existence of the flight-to-safety phenomenon. Bond market volatility is positively correlated with stock market volatility, implying volatility linkages across the markets. Bond market volatility is also positively correlated with stock market illiquidity and short-term bond illiquidity and is negatively correlated with stock market returns. Stock market volatility has a close relationship with all return and illiquidity series. The bond returns have a positive correlation with all illiquidity variables. The stock and bond illiquidity series are significantly and positively correlated, providing strong evidence of cross-market liquidity dynamics.

4.2 Threshold Value

The threshold value of the transition variable of a TVAR can either be chosen exogenously or estimated endogenously in the model. There is no definite view about which value should be

Table 2: Correlation Table

	$SENT^{\perp}$	TED Spread	VOLB	VOLS	RETB	RETS	LIQS	LIQB-LONG	LIQB-MEDIUM	LIQB-SHORT
$SENT^{\perp}$	1.00									
TED Spread	0.03	1.00								
VOLB	-0.07	0.41	1.00							
VOLS	-0.12	0.44	0.63	1.00						
RETB	0.09	0.17	0.06	0.21	1.00					
RETS	-0.06	-0.13	-0.20	-0.41	-0.06	1.00				
LIQS	0.04	0.16	0.11	0.20	0.17	-0.03	1.00			
LIQB-LONG	0.07	0.43	0.04	-0.08	0.12	0.06	0.19	1.00		
LIQB-MEDIUM	0.16	0.43	0.03	-0.12	0.12	0.09	0.23	0.93	1.00	
LIQB-SHORT	0.09	0.43	0.09	0.01	0.14	0.04	0.14	0.81	0.89	1.00

chosen to distinguish the investor sentiment index into optimistic or pessimistic. In practice, the arbitrary value of zero is usually the threshold (Baker and Wurgler, 2007). Following this literature, the analysis will first be based on the exogenous threshold value of zero. The results where the threshold is endogenously estimated will then be provided.

The endogenous threshold value is determined by a grid search over the possible values of the sentiment index. 20% of the upper and lower bound of the possible values of the sentiment index are trimmed to ensure at least 64 observations in each regime. For each threshold grid point, a TVAR model is estimated using ordinary least squares (OLS). The estimated threshold value θ^* then is determined by the model in which the determinant of the variance-covariance matrix of its estimated residuals is the smallest:

$$\theta^* = \arg\min_{\theta} log|\Omega_{\epsilon}(\theta)|. \tag{6}$$

The estimated threshold value for the sentiment index is -0.21. Figure 1 jointly plots the historical sentiment index and both the exogenous and endogenously estimated threshold values. The low sentiment periods approximately correspond to the recession in the early 1990s and the financial crises aftermaths in 2002 and 2009. On the other hand, the high sentiment periods generally correspond to stable economic performance and financial market booming.

4.3 Nonlinearity Test

A non-linearity test on the TVAR system is performed to find whether the estimated threshold value is meaningful. The null hypothesis is that the coefficients of B_2 and γ_2 in Equation

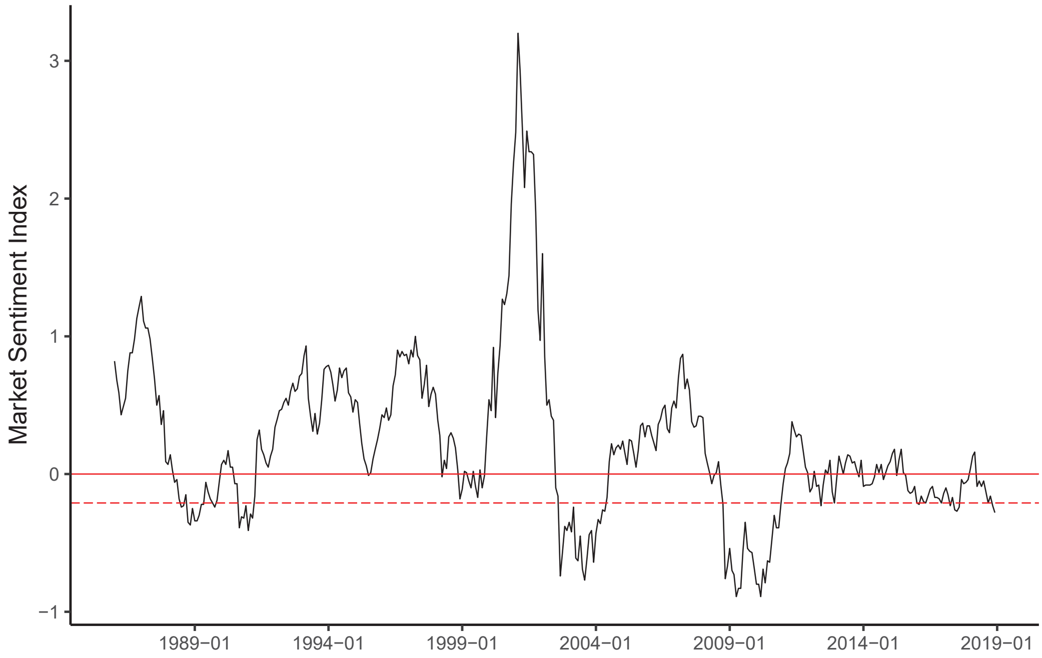

Figure 1: Historical investor sentiment index and threshold values. Note: Solid red horizontal line refers to the exogenous threshold value zero. Dash red horizontal line refers to the threshold value -0.21 endogenously determined in the TVAR model.

1 are equal to zero. In the univariate case, i.e., a threshold autoregression (TAR) system, this hypothesis can be tested by using a sup-F-type (sup-Wald) test first proposed in Hansen (1997, 1999):

$$F_{1m} = T\left(\frac{S_1 - S_m}{S_m}\right), \tag{7}$$

where the S_1 and S_m denote the sum of squared residuals from the estimation of a TAR(1) (one regime, a linear autoregression) model and a TAR(m) model, respectively. This method is extended by Lo and Zivot (2001) to the multivariate case by using the following sup-Likelihood Ratio test (sup-LR, which is equivalent to the sup-Wald):

$$LR_{ij} = T(ln(\det \hat{\Sigma}_i) - ln(\det \hat{\Sigma}_j)), \tag{8}$$

where $\hat{\Sigma}_i$ is the estimated covariance matrix of the TVAR model with i regimes. Therefore the test enables the detection of the non-linearity in a linear VAR system. Since the threshold is

Table 3: Non-Linearity Test for TVAR System and its Individual Equations

Tests	Statistic	p-Values
System		
Linear against 2-Regime Model	297.11	0.000
Equation		
$SENT^{\perp}$	21.85	0.330
TED Spread	64.15	0.000
VOLB	43.08	0.001
VOLS	47.34	0.000
RETB	20.88	0.402
RETS	36.62	0.008
LIQS	57.11	0.000
LIQB-LONG	48.60	0.000
LIQB-MEDIUM	32.92	0.030
LIQB-SHORT	58.54	0.000

unknown at first, according to Hansen (1996), the asymptotic distribution of the sup-LR (sup-Wald) statistic is influenced by the unknown threshold parameter under the null hypothesis of linearity. Instead, Hansen (1996, 1997) suggests a bootstrap procedure to calculate the p-values. The sup-LR test results for the TVAR system and the sup-F test results for each equation in the system are presented in Table 3. The test results provide strong evidence that a threshold effect exists at the whole system level and for most variables in the system.

5 TVAR Estimation

In this section, the regime dependent impulse response functions with the exogenously chosen threshold value are discussed in Section 5.1 to reveal the influence of an adverse stock market volatility shock on other variables. Section 5.1 assumes that the markets stay in the same regime that they are in when the shock occurs. Section 5.2 presents the baseline model where the above assumption is relaxed to allow regime-switching. Section 5.3 reestimates the model when the threshold value to separate investor sentiment into optimistic and pessimistic regimes is endogenously chosen. Section 5.4 focuses on the post-GFC era to investigate if the previous outcomes still stand. Finally, the influence of adverse stock volatility shock on the probability of regime switching is studied in Section 5.5.

5.1 Regime Dependent Impulse Response Functions

Since the process without regime-switching can be described by a linear VAR, the coefficients to generate the regime-dependent impulse response functions are estimated from separate VAR models for each regime. Figure 2 shows the impulse response functions of all endogenous variables during the high and low sentiment regimes after a one standard deviation positive shock to stock market volatility while assuming the financial market stays in the regime that exists when the shock occurs.

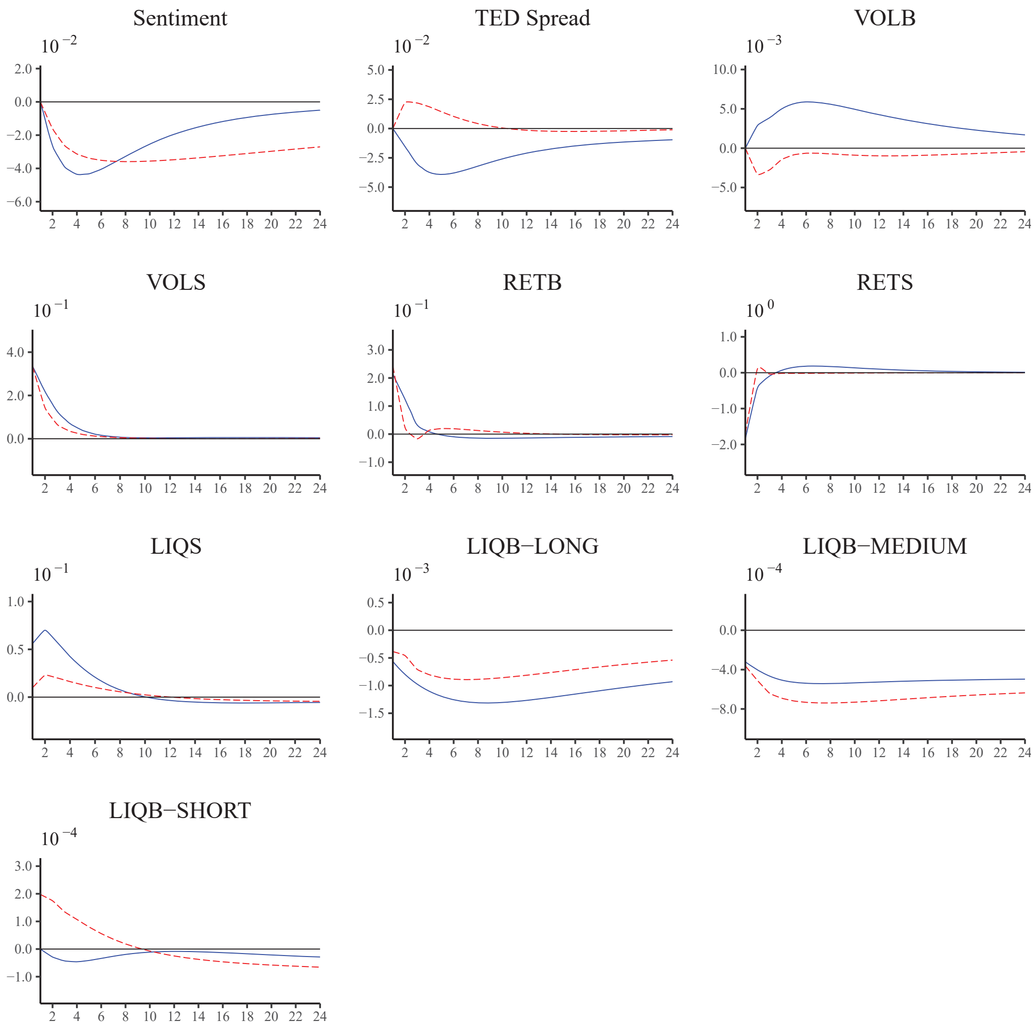

Figure 2: Impact of a one standard deviation positive stock market volatility shock over 24 months with no regime switching. Note: Solid blue lines refer to the low sentiment regime. Dashed red lines refer to the high sentiment regime.

As expected, a positive shock to stock market volatility reduces investor sentiment. This, in turn, leads to higher bond market returns and lower stock market returns. Illiquidity in the stock market rises but falls in the long-term and medium-term bond markets. The responses of stock and bond market returns are transitory, and both converge to zero within a quarter. The reaction of stock market illiquidity lasts for about ten months. The long-term and medium-term bond market illiquidity responses last longer, extending beyond the two-year horizon demonstrated in Figure 2. As a barometer of the economy, increasing stock market volatility implies higher uncertainty and may dampen optimism about future economic performance, leading to the negative response of the investor sentiment index. The increasing bond market returns and decreasing stock market returns jointly provide evidence of the flight-to-safety phenomenon that investors tend to shift to the safer asset in times of increasing uncertainty. The flight-to-safety phenomenon is also reflected by the opposite directions of the stock and bond market illiquidity responses.

For some variables, the signs of their impulse response functions across regimes are different, as shown in Figure 2. The TED spread, bond market volatility and short-term bond market illiquidity respond to the adverse stock market volatility shock in opposite directions across both regimes. The TED spread and short-term bond market illiquidity increase in the high sentiment regime and decrease in the low sentiment regime. Bond market volatility tends to respond positively in the low sentiment regime and negatively in the high sentiment regime. The increasing TED spread indicates tightening funding liquidity, in line with literature such as Brunnermeier and Pedersen (2009), which argues lenders tend to tighten their terms for funding when volatility spikes. The loosening funding condition implied by the negative response of the TED spread in the low sentiment regime seems to contradict these studies. Nevertheless, the negative response of the TED spread is reasonable considering that policy responses from the monetary authority following financial market crises that overlap with low sentiment periods often include the bail-out actions for the systemically important financial institutions and the pumping of liquidity into the market. Stock volatility comoves with bond volatility in the low sentiment regime but not in the high sentiment regime, reflecting higher risk preferences when investors are optimistic.

In the high sentiment regime, unlike long-term and medium-term bond markets in which liquidity conditions improve, the short-term bond market becomes more illiquid in the first few months after the shock. This theoretically exceptional phenomenon is rarely reported or discussed in previous research. A potential explanation comes from the flight-from-maturity phenomenon described by Gorton et al. (2021). Flight-from-maturity refers to market participants keeping the option of a quick quit by shortening the maturity of their lending. This behaviour collectively increases the market fragility at the system level. Gorton et al. (2021) provide empirical evidence that flight-from-maturity was prevalent before the failure of the Lehman Brothers. A deduction from the flight-from-maturity hypothesis is that when an adverse stock market volatility shock happens, the short-term money market is more severely impacted than the medium-term and long-term market because of the sudden quick quit of market participants. The illiquidity in the short-term money market may also spill over to its relevant collateral asset market, including the Treasury bill market. To conclude, the rising illiquidity of the short-term bond market may result from the aftermath of precautionary short-term lending.

In Figure 2, the magnitudes of the impulse response functions which have the same sign across regimes may differ significantly. For example, the responses of stock market illiquidity are stronger in the low sentiment regime than the high sentiment regime, particularly in the first two quarters. The influence from the adverse stock market volatility shock is weaker when investors are optimistic. This finding is in line with Liu (2015) who argues that the stock market is more liquid when investor sentiment is bullish and confident. Long-term bond market illiquidity generally responds stronger in the low sentiment regime, while medium-term bond market illiquidity is stronger in the high sentiment regime.

Different initial regimes lead to the various durations of the effects of shocks shown in the impulse response functions for some endogenous variables. The response of the sentiment index is relatively transitory when the adverse stock market volatility shock occurs in the low sentiment regime. The responses of the TED spread and bond market volatility are more persistent in the low sentiment regime. The responses of the stock and bond market returns last one month longer in the low sentiment regime compared to the high sentiment regime. These differences imply that investors may digest the adverse information faster when they are optimistic or ignore the risk signal due to over-confidence.

5.2 Baseline Model

Figure 3 and 4 presents the GIRFs under the circumstances of one and two standard deviation stock market volatility shocks, respectively. In both figures, the GIRFs start from an initial state of either the high sentiment or the low sentiment regime.

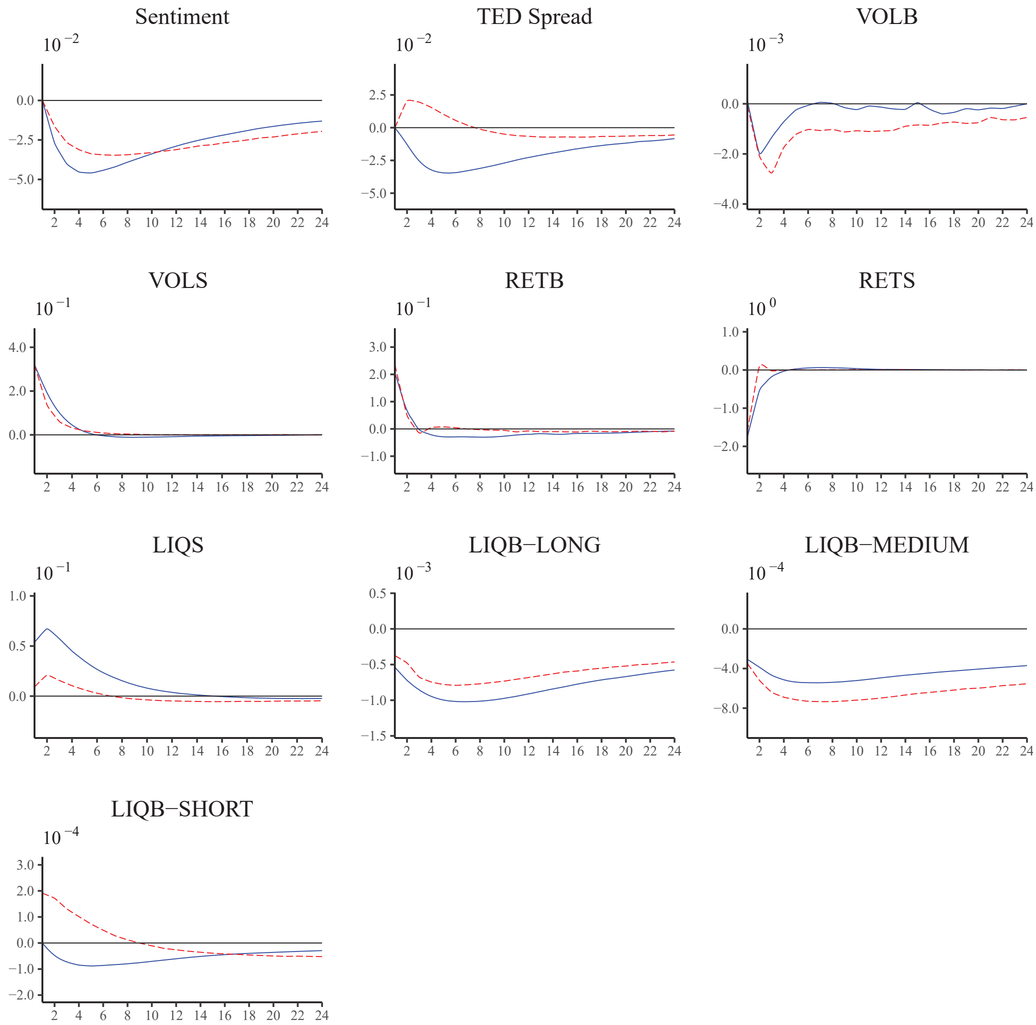

Figure 3: Impact of a one standard deviation positive shock to stock market volatility given different initial states of sentiment over 24 months with regime switching. The model is estimated from January 1986 to December 2018. Note: Solid blue lines refer to the responses where the shock occurs in the low sentiment regime. Dashed red lines refer to the responses where the shock occurs in the high sentiment regime.

A one standard deviation shock to stock market volatility is associated with decreasing investor sentiment in both high and low sentiment regimes. The effect reaches the maximum in the first quarter and then decays slowly over the longer term. Compared to the results in the regime-dependent cases, the GIRFs of investor sentiment across regimes are more similar in shape in the regime-switching case, indicating the mixture of responses in each regime due to regime switching.

Funding liquidity becomes tighter in the high sentiment regime and looser in the low sentiment regime. The response of the TED spread when beginning in the high sentiment regime, rather than converge to zero in regime dependent cases, falls below zero in periods longer than two quarters, indicating loosening funding conditions in the longer term.

The negative response of stock market returns implies that investors prefer to include less risky assets in their portfolios, leading to the sell-off of the higher risk equity assets. The demand for safe assets such as Treasury bonds drives up bond market returns. Bond market volatility dives in the initial month following the shock, reflecting the effect of the portfolio adjustments. The fall in the bond market volatility is more pronounced in the high sentiment regime, indicating when uncertainty in the stock market is high, the demand for safe assets becomes more likely. This demand is more significant while investors are optimistic.

Although stock market liquidity conditions deteriorate as stock market volatility increases, the magnitude of the response is smaller, and the duration of the effect is shorter in the high sentiment regime than in the low sentiment regime. This relatively minor effect reflects that the more optimistic the investors are, the more they tend to continue trading instead of quitting the market when facing increasing uncertainty. The liquidity conditions in the bond market improve in the low sentiment regime, indicating that investors actively trade safe assets as they adjust their portfolios. However, there is an exception that in the case where the initial state is that of high sentiment, the illiquidity of the short-term bond market increases in the first two quarters after the adverse stock market volatility shock. This can be explained by the aftermath of a flight-from-maturity: the quit of the precautionary short-term fund providers causes liquidity evaporation in short-term money market and its relevant collateral markets.

The GIRFs for the two standard deviation stock market volatility shock for the two regimes are shown in Figure 4. The figure mirrors the one standard deviation shock case except for the responses of the bond market volatility. The stock market volatility shock spills over to the bond market in the low sentiment regime. According to the statistics in the descriptive analysis section, a two standard deviation stock market volatility shock usually means an extreme adverse event, which may rationale the co-existence of the cross-market volatility spillover and flight-to-safety.

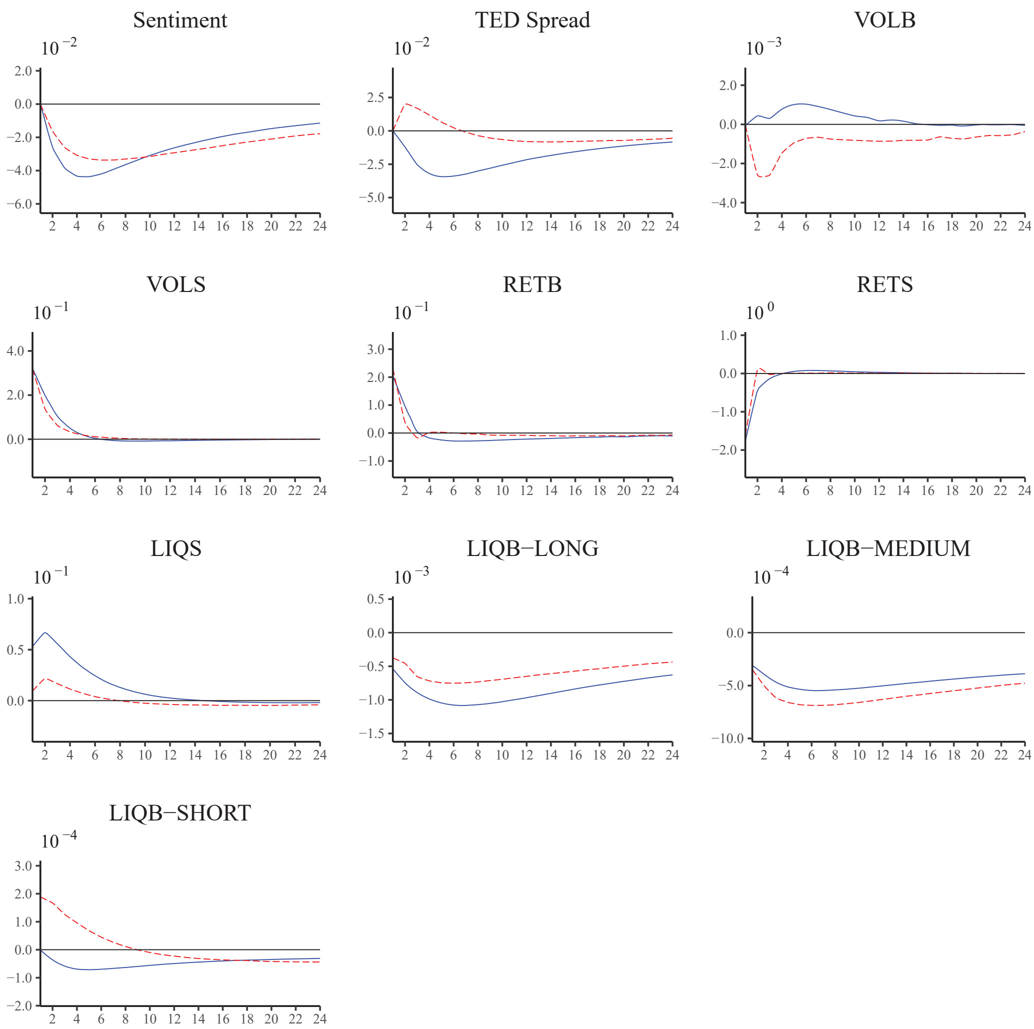

Figure 4: Impact of a two standard deviation positive stock market volatility shock given different initial states of sentiment over 24 months with regime switching. The model is estimated from January 1986 to December 2018. Note: Solid blue lines refer to the responses where the shock occurs in the low sentiment regime. Dashed red lines refer to the responses where the shock occurs in the high sentiment regime.

To illustrate the difference between the GIRFs from one and two standard deviation stock market volatility shocks, Figures 5 and 6 demonstrate these GIRFs starting in the low sentiment and high sentiment regimes, respectively. The GIRFs for the two standard deviation shock is scaled down by a factor of two to allow the direct comparison with GIRFs of one standard deviation shock. The GIRFs of one and two standard deviation shocks mirror each other in most cases. The exceptions are the GIRFs of bond market volatility, which has been discussed above, and short-term bond illiquidity. Short-term bond market illiquidity decreases less when the shock is bigger, implying that the effect from volatility spillover to bond market illiquidity is mainly absorbed by short-term bond market.

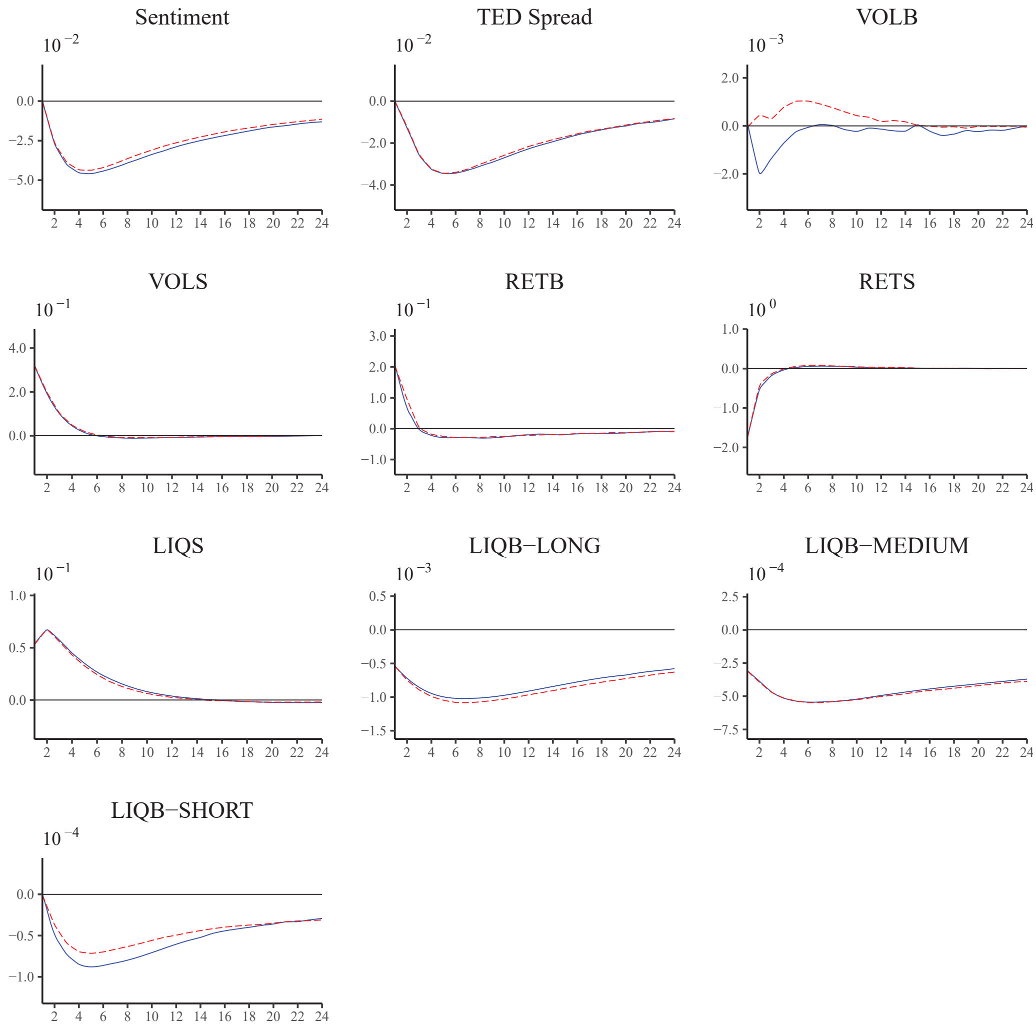

Figure 5: Impact of one and two standard deviation positive stock market volatility shocks initial in the low sentiment regime over 24 months with regime switching. The model is estimated from January 1986 to December 2018. Note: Solid blue lines refer to one standard deviation shock. Dashed red lines refer to two standard deviation shock.

Concluding the analysis in the regime-dependent IRFs and GIRF cases, in response to a positive stock market volatility shock, investor sentiment decreases, and the funding liquidity measured by the TED spread tightens in the high sentiment regime but loosens in

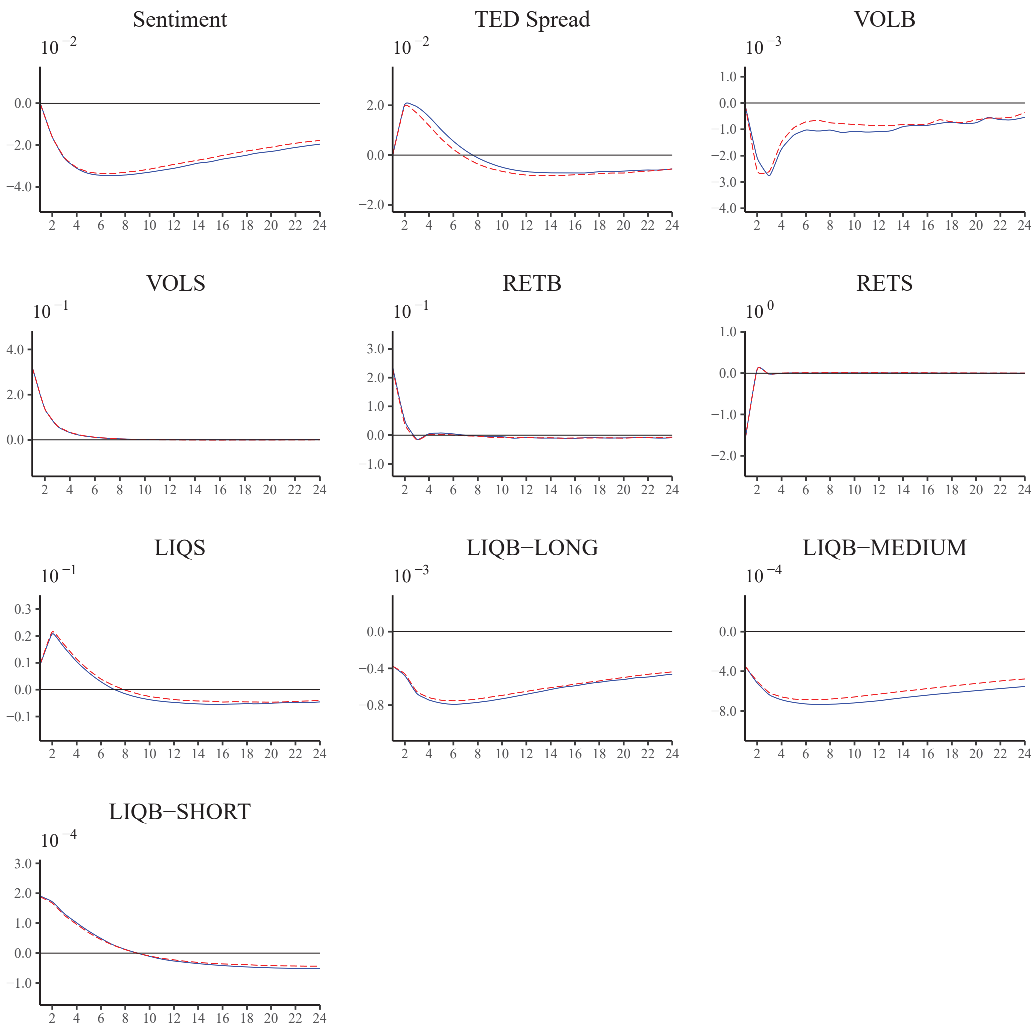

Figure 6: Impact of one and two standard deviation positive stock volatility shocks initial in the high sentiment regime over 24 months with regime switching. The model is estimated from January 1986 to December 2018. Note: Solid blue lines refer to one standard deviation shock. Dashed red lines refer to two standard deviation shock.

the low sentiment regime. The responses of stock and bond market returns are transitory and opposite in directions, and the difference across the regimes is negligible. Bond market volatility is negatively correlated with stock market volatility in most scenarios. However, when investors are pessimistic, the empirical evidence suggests that there are spillovers from the two standard deviation stock market volatility shock to bond market volatility. In terms of liquidity dynamics, stock market illiquidity increases as expected, but the extent is lower in the high sentiment regime than the low sentiment regime. The flight-to-safety phenomenon is found in the low sentiment regime across the yield curve. In the high sentiment regime, while there is flight-to-safety for long-term and medium-term bond markets, the response of the illiquidity for short-term bond market is aligned with the flight-from-maturity story.

5.3 Endogenous Threshold Value

In this section, the exogenously chosen threshold value zero is replaced by the endogenous estimated threshold value of -0.21. The settings for the shocks and the GIRFs remain the same as in the baseline case. Figures 7 and 8 respectively demonstrate the results of the one and two standard deviation shock where the initial state is either the low or high sentiment regime.

Figure 7 and 8 mirror each other, suggesting that the changing magnitude of the stock market volatility shock cause little difference in the GIRFs when the threshold value is endogenously chosen. The initial state causes little difference in the response of stock and bond market return, respectively.

For variables other than market returns, their responses depend on the regime where the shock occurs. The investor sentiment index is lower if the shock happens in the high sentiment regime compared to the low sentiment regime. The TED spread tends to positively respond to the shock in the high sentiment regime, while the response is mostly negative in the low sentiment regime. Bond market volatility responds more in the low sentiment regime. There is evidence that the volatility spillover between stock and bond markets happens when shock magnitude is one standard deviation. Overall, stock market illiquidity increases, and the long-term and medium-term bond market illiquidity falls due to the shock. An exception is that short-term bond market illiquidity increases in the first two months if the initial state

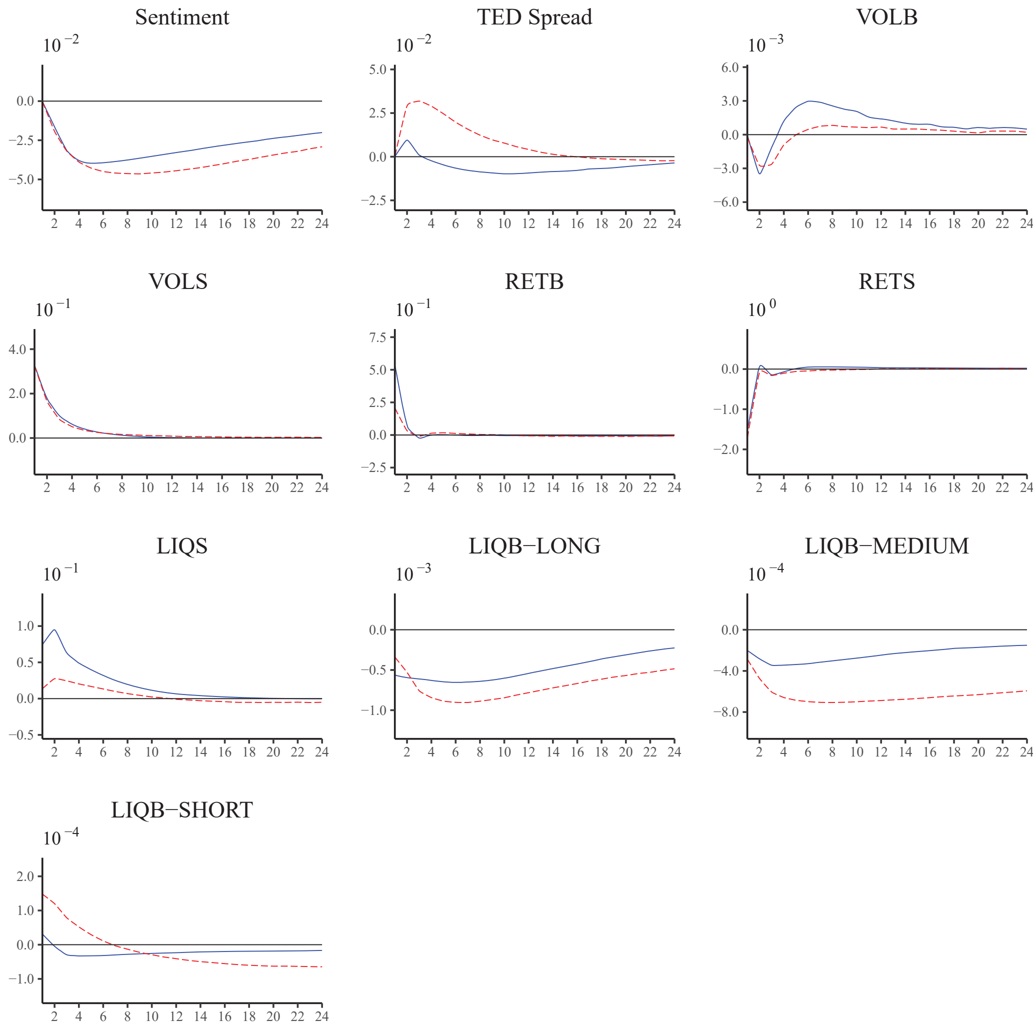

Figure 7: Impact of a one standard deviation positive stock market volatility shock given different initial states of sentiment over 24 months with regime switching. The model is estimated from January 1986 to December 2018 and uses an endogenously chosen threshold value of -0.21. Note: Solid blue lines refer to the responses where the shock occurs in the low sentiment regime. Dashed red lines refer to the responses where the shock occurs in the high sentiment regime.

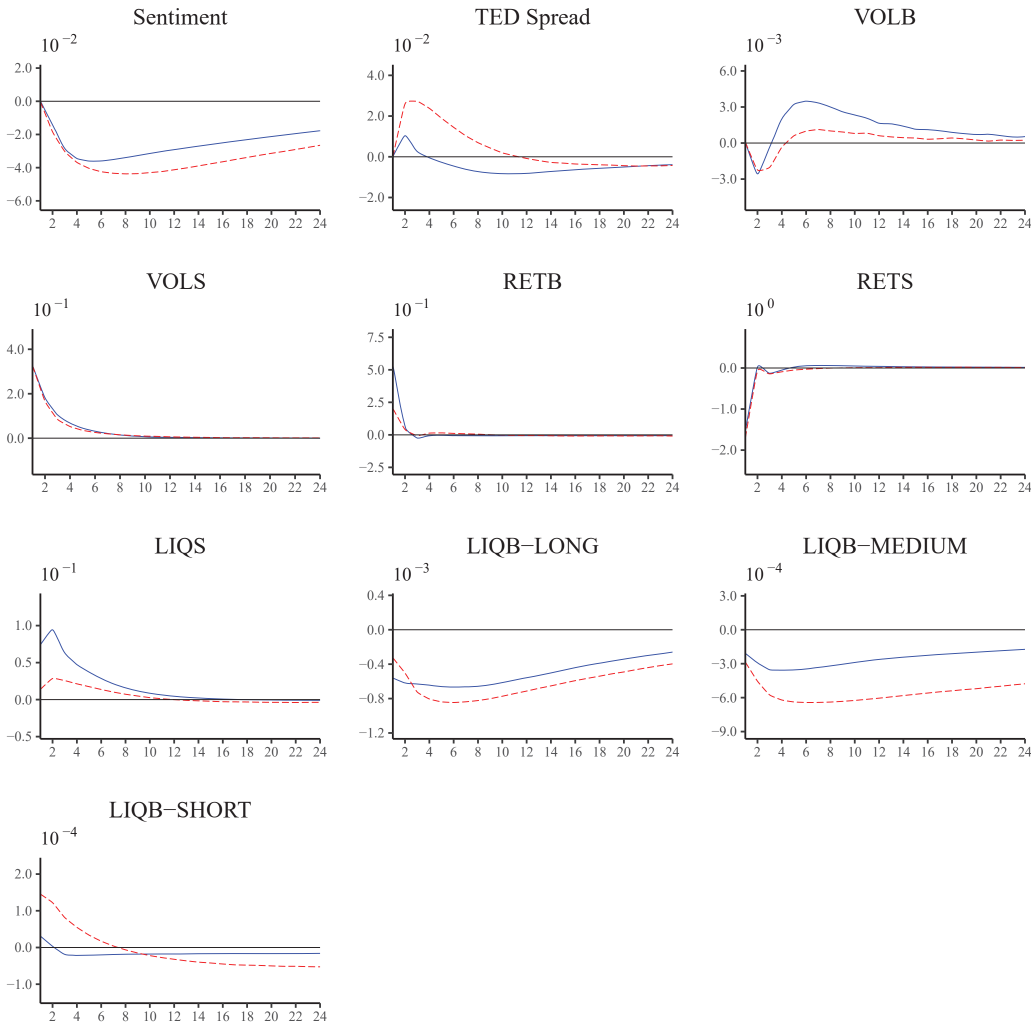

Figure 8: Impact of a two standard deviation positive stock market volatility shock given different initial states of sentiment over 24 months with regime switching. The model is estimated from January 1986 to December 2018 and uses an endogenously chosen threshold value of -0.21. Note: Solid blue lines refer to the responses where the shock occurs in the low sentiment regime. Dashed red lines refer to the responses where the shock occurs in the high sentiment regime.

is the low sentiment regime, or seven months if the initial state is the high sentiment regime and decreases afterwards.

Compared to the baseline case where the threshold is exogenously chosen, the results in the endogenously chosen threshold value case show strong similarities overall. Positive stock market volatility shock causes decreasing investor sentiment, stock market returns and long-term and medium-term bond market illiquidity. It also causes increasing bond market returns and stock market illiquidity. The response of the TED spread turns negative in the low sentiment regime. The response of short-term bond market illiquidity is positive in the short run in the high sentiment regime. This evidence supports the existence of flight-to-safety and the aftermath of flight-from-maturity. However, there are differences in the detail. For example, the endogenously chosen threshold results show the presence of flight-from-maturity in the low sentiment regime. In the long run, the bond market illiquidity across maturities decreases more in the high sentiment regime, which is not defined well in the baseline case. Stock market volatility spillovers happen when the shock is relatively weak.

5.4 Post-GFC Era

In this section, the start date of sample is adjusted to 2009 to investigate the liquidity dynamics after the GFC. The TVAR is re-estimated based on the new sample with the exogenously chosen threshold value zero. Figure 9 and 10 demonstrate the post-GFC GIRFs under one and two positive standard deviation stock market volatility shocks respectively. In both figures, the GIRFs start from an initial state of either high sentiment or low sentiment regime.

The investor sentiment index initially falls in both regimes. Its responses are at a maximum in a quarter and decay over about a year. In the high sentiment regime, the investor sentiment index does not fall as much as it does in the low sentiment regime, reflecting that optimism helps alleviate the adverse impact from an uncertainty shock. The TED spread first positively responds to the shock in both regimes, indicating the tightening funding condition after the shock occurs. The TED spread increases by more in the high sentiment regime than the low, reflecting that post-GFC funding providers increase the funding requirement as a precautionary action when the market is optimistic or over-confident. The impact on the

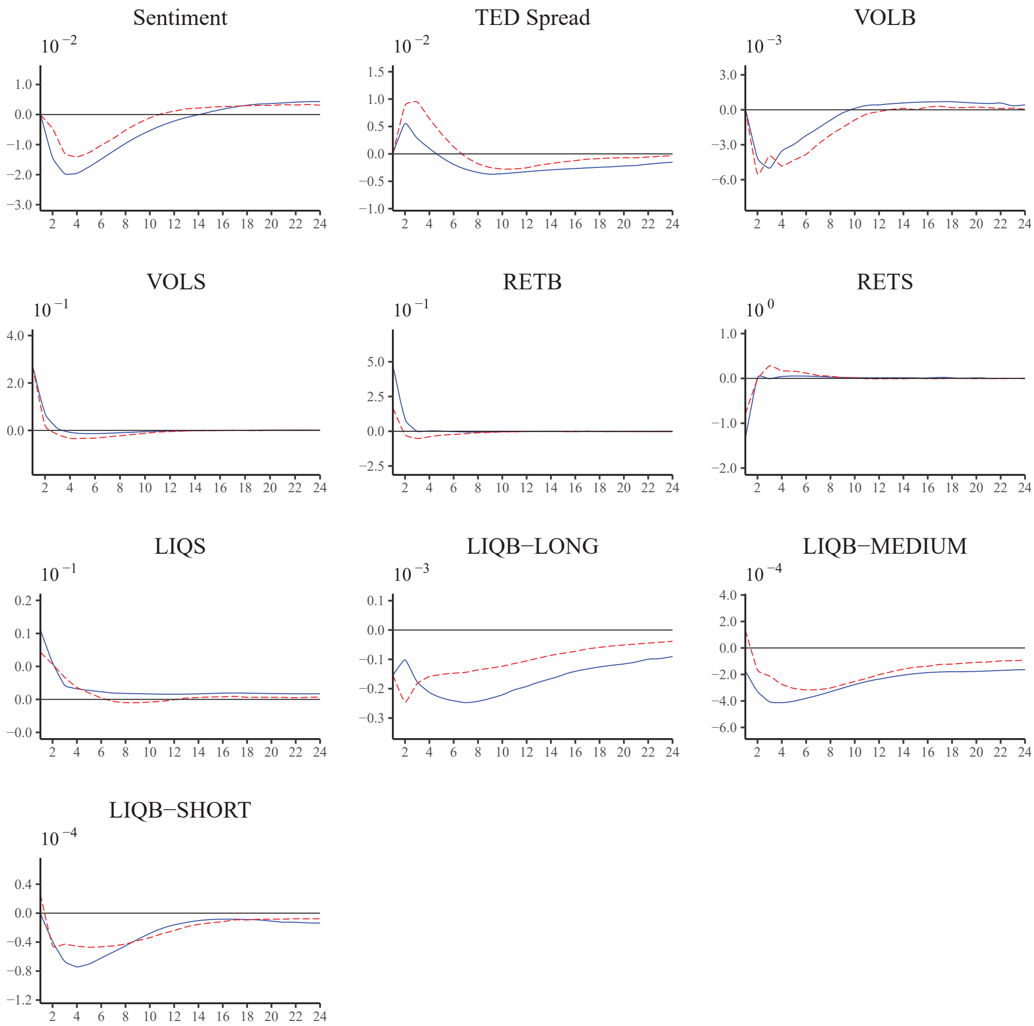

Figure 9: Impact of a one standard deviation positive stock market volatility shock given different initial states of sentiment over 24 months with regime switching. The model is estimated from January 2009 to December 2018. Note: Solid blue lines refer to the responses where the shock occurs in the low sentiment regime. Dashed red lines refer to the responses where the shock occurs in the high sentiment regime.

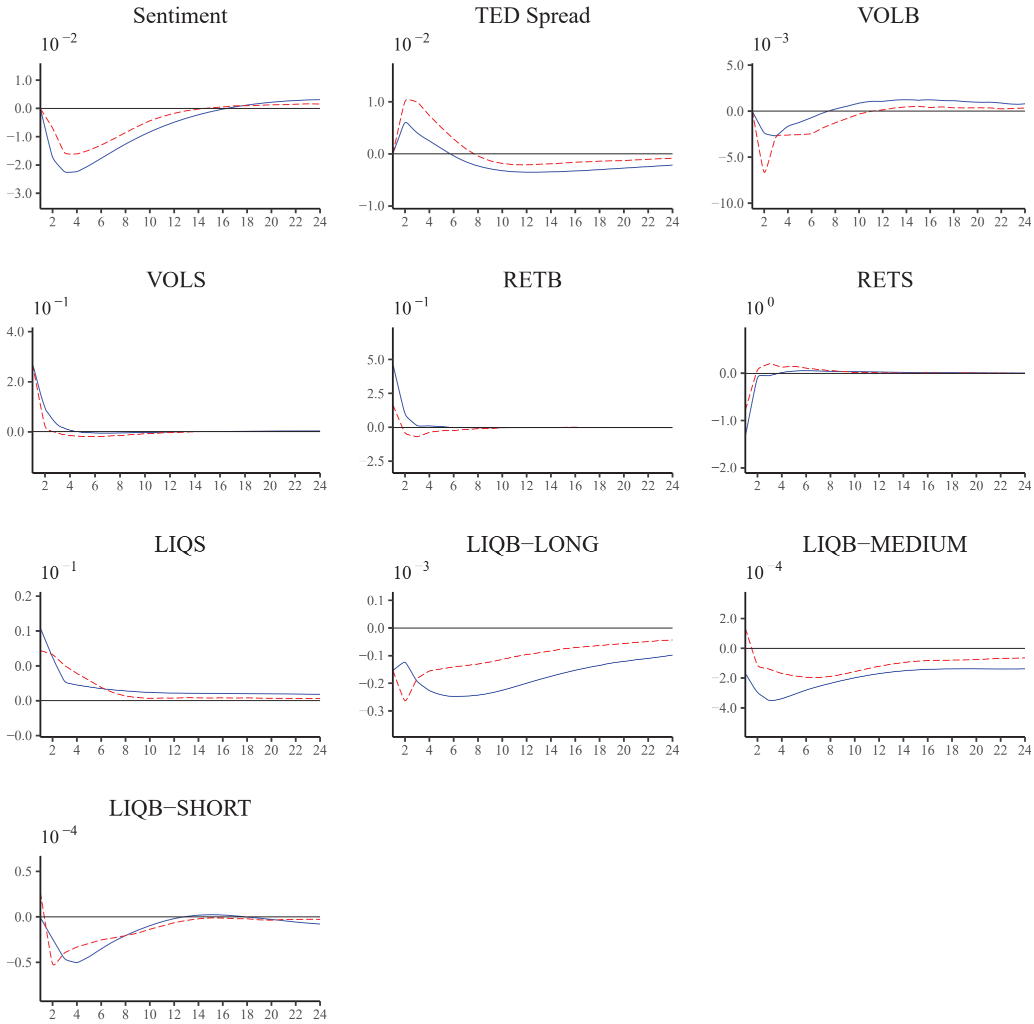

Figure 10: Impact of a two standard deviation positive stock market volatility shock given different initial states of sentiment over 24 months with regime switching. The model is estimated from January 2009 to December 2018. Note: Solid blue lines refer to the responses where the shock occurs in the low sentiment regime. Dashed red lines refer to the responses where the shock occurs in the high sentiment regime.

TED spread lasts about six months before falling as funding liquidity returns to its previous level.

The contradictory signs of responses of returns and illiquidity across markets reflect that investors reallocate the weighting of their portfolios from equity to bond assets. The responses of volatility and illiquidity are overall in the same directions as expected, except that medium-term and short-term bond market illiquidity initially responds positively in the high sentiment regime, implying that the effect of flight-from-maturity is dominion in the short-term after the shock.

Figure 11 and 12 show the GIRFs where the adverse stock market volatility shock occur either in the low or high sentiment regime respectively. The GIRFs under a two standard deviation shock are scaled by two for a direct comparison. The GIRFs result from a two standard deviation shock largely mirrors the GIRFs from a one standard deviation, with noticeable differences in the responses of bond market volatility and medium-term and short-term bond market illiquidity. When the shock occurs in the low sentiment regime, bond market volatility decreases less due to a two standard deviation shock. Furthermore, this is true for bond market volatility after 2+ months if the shock occurs in the high sentiment regime. In both figures, a two standard deviation shock leads to less decreasing for medium-term and short-term bond market illiquidity comparing to one standard deviation shock. The evidence above implies the possibility that the effect of flight-to-safety, while it still largely stands, is partially offset by the cross market volatility spillover or the aftermath of flight-from-maturity.

Compared to the full sample analysis results, the investor sentiment index and the TED spread respond to the shock more consistently. The TED spread no longer decrease due to the shock that occurs in the low sentiment regime. There is evidence that in the low sentiment regime, the volatility spillover from stock to bond market is weaker in the post-GFC era. In addition, the short-term bond market and the medium-term bond market first responds to the shock with an increase in illiquidity in the high sentiment regime, implying that the lending secured by the medium-term and short-term bond assets are disturbed by the exit of investors from the market during times of optimism. The GIRFs show that in the post-GFC era, the impact from this fleeing process on bond market illiquidity last a shorter period.

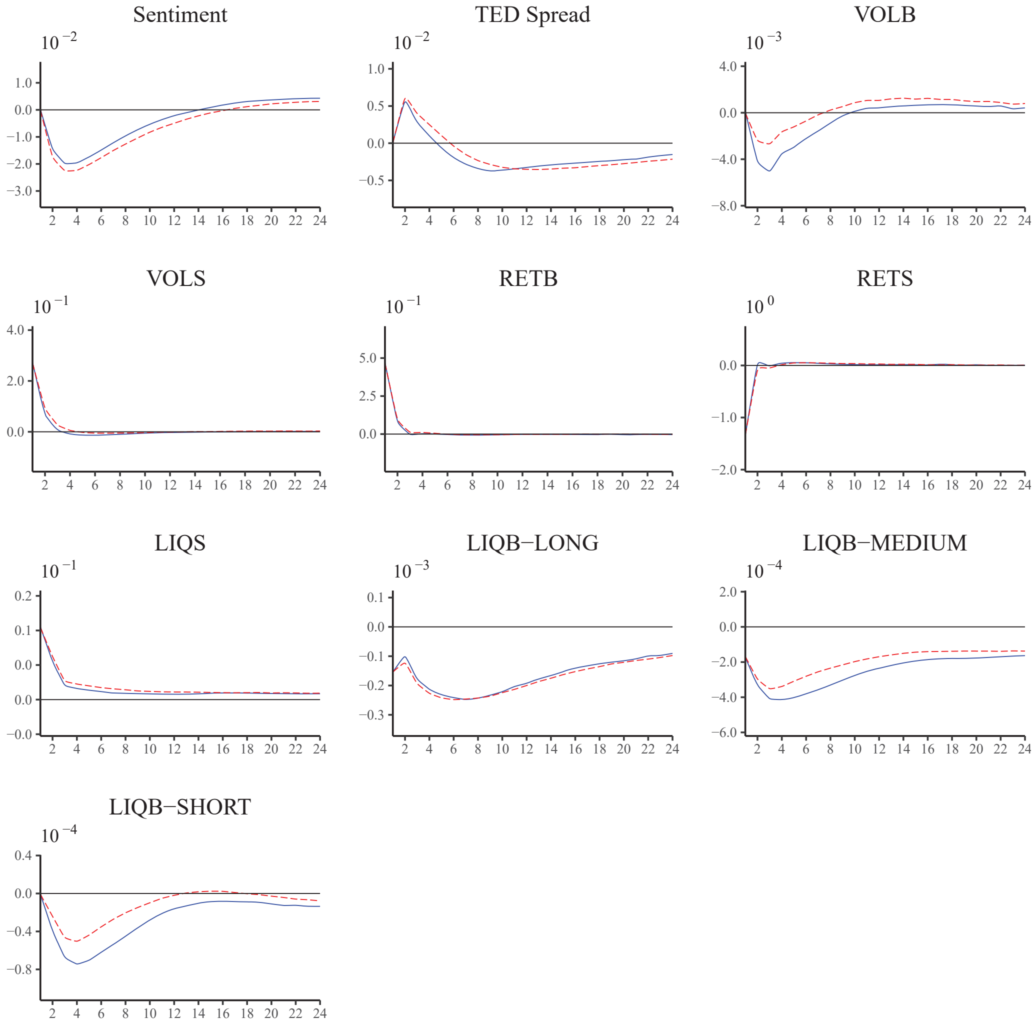

Figure 11: Impact of one and two standard deviation positive stock volatility shocks initial in the low sentiment regime over 24 months with regime switching. The model is estimated from January 2009 to December 2018. Note: Solid blue lines refer to one standard deviation shock. Dashed red lines refer to two standard deviation shock.

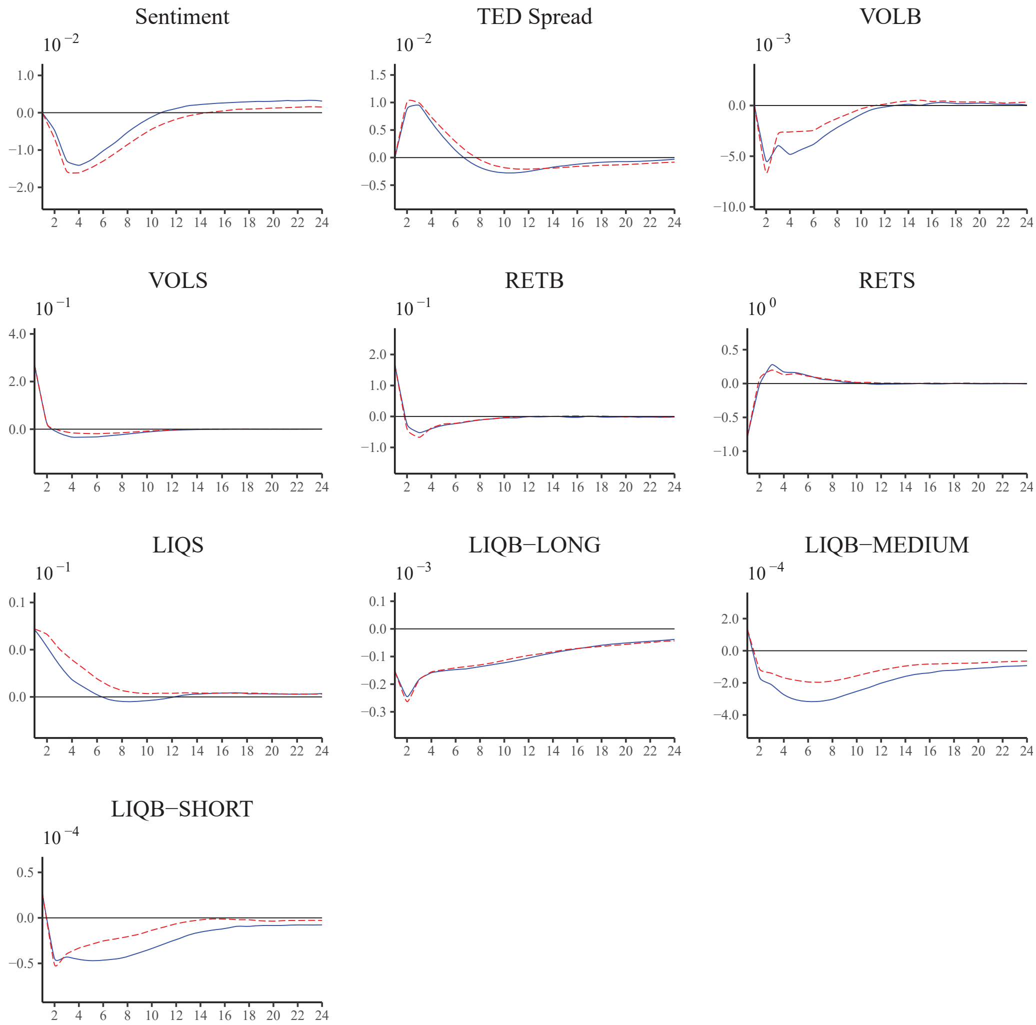

Figure 12: Impact of one and two standard deviation positive stock volatility shocks initial in the high sentiment regime over 24 months with regime switching. The model is estimated from January 2009 to December 2018. Note: Solid blue lines refer to one standard deviation shock. Dashed red lines refer to two standard deviation shock.

5.5 Probability of Regime Switching

This section analyses the influence the positive stock market volatility shock has on the probability of regime switching. The full sample and the post-GFC era are discussed separately. As shown in previous IRFs and GIRFs analyses, a positive stock market volatility shock decreases the investor sentiment index. The specific question of interest is, suppose the financial market is initially in the high sentiment regime, does the positive stock market volatility shock increase the probability of moving from the high to low sentiment regime? Moreover, does this probability in full sample different from it in the post-GFC era?

The probability of the financial market starting in the low sentiment regime is calculated based on the IRFs of each observation. The number of times that the transition variable crosses the threshold value zero is counted. The ex-ante probability of market being in low sentiment regime is calculated by the following equation:

$$P(LowSentimentRegime) = E[I(y^*_{t-d} \leq \theta)|\Omega_{t-1}, u_t], \tag{9}$$

where $I(y^*_{t-d} \leq \theta)$ is the indicator function equals one if the transition variable y^* at lag d is less or equal to the threshold value under the information set Ω_{t-1} and a realization of an exogenous shock u_t.

Figure 13 demonstrates the full-sample probability of regime switching from a high to low sentiment regime under one and two standard deviation shocks and also a zero shock as the baseline. A positive two standard deviation stock market volatility shock increases the probability of regime switching by 10% comparing to the baseline case. In Figure 14 where the post-GFC case is plotted, the probability of regime switch from high to low sentiment regime increases by 20% under the positive two standard deviation shock compared to the baseline. The comparison between the full-sample and post-GFC results suggests that the large stock market volatility shock is more likely to cause investor optimism to turn into pessimism in the recent decade.

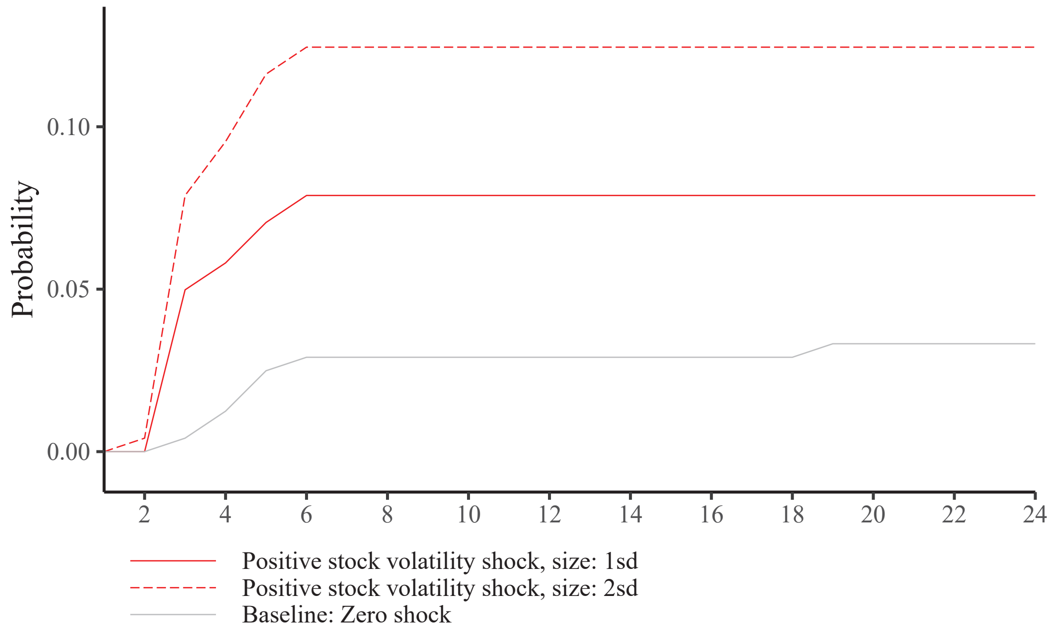

Figure 13: Empirical probability of switching from high to low sentiment regime over 24 months following one and two standard deviation positive stock market volatility shock. The model is estimated from January 1986 to December 2018.

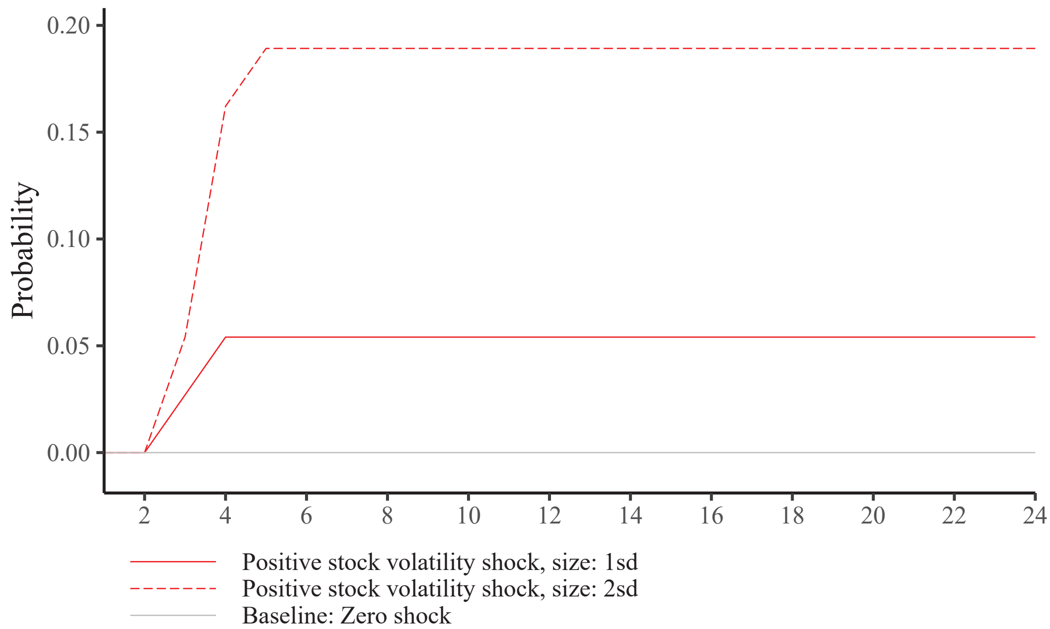

Figure 14: Empirical probability of switching from high to low sentiment regime over 24 months following one and two standard deviation positive stock market volatility shock. The model is estimated from January 2009 to December 2018.

6 Conclusion

This paper examines how stock market volatility may influence cross-market illiquidity dynamics asymmetrically under different investor sentiment regimes in the U.S. from January 1986 to December 2018. A TVAR model is first set up to investigate the dynamics from the year 1986 to 2018. Later the duration of sample is reduced to the period from 2009 to 2018 to show how the dynamics may have changed after GFC. Finally, the potential influence of a stock volatility shock on the probability of regime switching is discussed.

The baseline analysis is conducted based on the total sample and under the exogenously chosen threshold value zero. The results are composed of two parts: the regime dependent IRFs where regime switching is not modelled, and GIRFs where the regime switch is allowed. They jointly suggest that market liquidity, investor sentiment and funding liquidity respond to the adverse stock market volatility shock differently across regimes. Of particular interest, the responses of stock and bond market illiquidity provide evidence suggesting the existence of flight-to-safety and flight-from-maturity phenomenons. The later finding closely relates to the high sentiment regime and is rarely mentioned in previous studies. In the robustness test where the endogenously chosen threshold value is used, the results are qualitatively the same as the baseline.

The analysis for the post-GFC era provides further evidence for flight-from-maturity. While the evidence of flight-from-maturity is only found in the short-term bond market illiquidity in the baseline case, in the post-GFC era, the medium-term and short-term bond market illiquidity both have the responses which are aligned with this effect. Compared to the baseline, the aftermath of flight-from-maturity is more transitory in the post-GFC era and typically lasts no longer than one month. The investor sentiment and the TED spread respond more consistently across the regimes, indicating these variables are less affected by the threshold effect after GFC.

This paper sheds light on the relationship between behavioural factors and cross-market liquidity dynamics. The empirical results suggest that rather than being biased by the investor sentiment, the behaviour of market participants is rationally adjusted according to the investor sentiment, such as taking precautionary actions. Future extension of this research will include a more comprehensive measure of market liquidity, behaviour measure from another perspective, more detailed asset class, and the consideration of macroeconomic factors. It is also worthy of including more countries for comparison.

References

Adrian, T., Fleming, M. J., and Vogt, E. (2017). An Index of Treasury Market Liquidity: 1991-2017. Technical Report 827, Federal Reserve Bank of New York.

Adrian, T. and Shin, H. S. (2010). Liquidity and Leverage. *Journal of Financial Intermediation*, 19(3):418–437.

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

Baele, L., Bekaert, G., Inghelbrecht, K., and Wei, M. (2020). Flights to Safety. *The Review of Financial Studies*, 33(2):689–746.

Baker, M. and Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance*, 61(4):1645–1680.

Baker, M. and Wurgler, J. (2007). Investor Sentiment in the Stock Market. *Journal of Economic Perspectives*, 21(2):129–152.

Bank for International Settlements (2019). *Unconventional Monetary Policy Tools: A Cross-Country Analysis*. Number 63 in CGFS Papers. Bank for International Settlements.

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

Brunnermeier, M. K. and Sannikov, Y. (2014). A Macroeconomic Model with a Financial Sector. *American Economic Review*, 104(2):379–421.

Chordia, T., Roll, R., and Subrahmanyam, A. (2001). Market Liquidity and Trading Activity. *The Journal of Finance*, 56(2):501–530.

Chordia, T., Sarkar, A., and Subrahmanyam, A. (2005). An Empirical Analysis of Stock and Bond Market Liquidity. *The Review of Financial Studies*, 18(1):85–129.

Chordia, T., Sarkar, A., and Subrahmanyam, A. (2011). Liquidity Dynamics and Cross-Autocorrelations. *The Journal of Financial and Quantitative Analysis*, 46(3):709–736.

Clarida, R. H., Duygan-Bump, B., and Scotti, C. (2021). The COVID-19 Crisis and the Federal Reserve's Policy Response. Finance and Economics Discussion Series 2021-035, Board of Governors of the Federal Reserve System (U.S.).

Danielsson, J., Valenzuela, M., and Zer, I. (2018). Learning from History: Volatility and Financial Crises. *The Review of Financial Studies*, 31(7):2774–2805.

Engle, R., Fleming, M., Ghysels, E., and Nguyen, G. (2012). Liquidity, Volatility, and Flights to Safety in the US Treasury Market: Evidence from a New Class of Dynamic Order Book Models. Staff Report 590, Federal Reserve Bank of New York.

Gorton, G., Metrick, A., and Xie, L. (2021). The Flight from Maturity. *Journal of Financial Intermediation*, 47:100872.

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

Goyenko, R. Y. and Ukhov, A. D. (2009). Stock and Bond Market Liquidity: A Long-Run Empirical Analysis. *Journal of Financial and Quantitative Analysis*, 44(1):189–212.

Gârleanu, N. and Pedersen, L. H. (2007). Liquidity and Risk Management. *The American Economic Review*, 97(2):193–197.

Hameed, A., Kang, W., and Viswanathan, S. (2010). Stock Market Declines and Liquidity. *The Journal of Finance*, 65(1):257–293.

Hansen, B. (1997). Inference in TAR Models. *Studies in Nonlinear Dynamics & Econometrics*, 2(1):1–16.

Hansen, B. E. (1996). Inference When a Nuisance Parameter Is Not Identified Under the Null Hypothesis. *Econometrica*, 64(2):413–430.

Ho, T. S. Y. and Stoll, H. R. (1983). The Dynamics of Dealer Markets Under Competition. *The Journal of Finance*, 38(4):1053–1074.

Karolyi, G. A., Lee, K.-H., and van Dijk, M. A. (2012). Understanding Commonality in Liquidity around the World. *Journal of Financial Economics*, 105(1):82–112.

Liu, S. (2015). Investor Sentiment and Stock Market Liquidity. *Journal of Behavioral Finance*, 16:51–67.

Lo, M. C. and Zivot, E. (2001). Threshold Cointegration and Nonlinear Adjustment to the Law of One Price. *Macroeconomic Dynamics*, 5(4):533–576.

Nguyen, G., Engle, R., Fleming, M., and Ghysels, E. (2020). Liquidity and Volatility in the U.S. Treasury Market. *Journal of Econometrics*, 217(2):207–229.

Stoll, H. R. (2000). Presidential Address: Friction. *The Journal of Finance*, 55(4):1479–1514.

Sufi, A. and Taylor, A. M. (2021). Financial Crises: A Survey. Working Paper 29155, National Bureau of Economic Research.

Vayanos, D. (2004). Flight to Quality, Flight to Liquidity, and the Pricing of Risk. Working Paper 10327, National Bureau of Economic Research.