International Review of Financial Analysis 87 (2023) 102532

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Nonlinear market liquidity: An empirical examination

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ARTICLE INFO

JEL codes:
C32
G12
D40

Keywords:
Liquidity indicators
Nonlinear effects
Quantile regressions, liquidity crisis

ABSTRACT

We offer novel indicators of market-wide liquidity. Previous literature uses averages of individual liquidity indicators to track the evolution of market-wide liquidity. Instead, we focus on the tails of the market liquidity distribution. First, we construct aggregate liquidity indicators using low and high quantiles of six liquidity measures (total volume, number of trades, effective spread, realized spread, price impact and lambda). Our results show that market conditions have an asymmetric impact on the tails of the liquidity distribution. In the second part of the study, we test for nonlinearity of the effects of market determinants on market liquidity.

1. Introduction

We contribute to the literature by devising novel, more informative empirical proxies for market-wide liquidity and offering a better understanding of liquidity commonality. To this end, we examine the tails of market liquidity distribution. We provide liquidity indicators that comprehensively track market-wide liquidity by directly considering its nonlinear features. The general hypothesis that underlies our study is simple: changes in market liquidity do not affect all stocks alike. Moreover, the association of market liquidity with the market state is highly nonlinear.

An asset is said to be liquid when it can be sold in relatively large quantities without necessarily experiencing a simultaneous deterioration of its market price. Liquidity is a crucial feature of any security and a particularly fundamental determinant of asset prices (see Amihud and Mendelson (1986), Bekaert, Harvey, and Lundblad (2007), Brennan and Subrahmanyam (1996) and Chordia, Subrahmanyam, and Anshuman (2001)). The literature has provided compelling evidence on the existence of commonality in liquidity between and within different types of assets (see Chordia, Roll, and Subrahmanyam (2001), Hameed, Kang, and Viswanathan (2010) and Hasbrouck and Seppi (2001)), which means that market-wide liquidity can be certainly thought of as a factor that underlies price formation, alongside other traditional factors such as value, growth, profitability, investment or the market itself (see Acharya and Pedersen (2005), Amihud (2002), Amihud and Noh (2020) and Pástor and Stambaugh (2003)).

This prominent role of liquidity in asset pricing naturally calls for liquidity proxies that are able to track the evolution of the phenomenon in the aggregate. Such proxies are useful for market participants, particularly in terms of portfolio choice and risk management, and for regulators, who aim to track market liquidity in real time, so as to be able to foster financial stability. To this end, literature relies on market-wide liquidity indicators, which are estimated as averages of different liquidity proxies calculated on an individual asset basis. For instance, the study of aggregate liquidity evolution in the stock market has resorted to cross-sectional averages of individual stocks' effective and relative bid-ask spread, averages of buy- and sell-price impact indicators, averages of low frequency liquidity measures, or functions of returns and trading value, within a certain time interval (see Chordia, Roll, and Subrahmanyam (2001) and Vayanos and Wang (2013) for a summary of empirical approaches). The different measures aim to capture distinctive dimensions of interest about liquidity, which range from asymmetric information to transaction costs and imperfect competition. These dimensions can be divided into five categories: depth, tightness, resilience, breadth and immediacy (see Fig. 1). Accordingly, when it comes to quantifying the association of market liquidity with other variables that jointly determine market dynamics, such as volatility, past market trends, funding, central bank liquidities or even the day of the

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https://doi.org/10.1016/j.irfa.2023.102532
Received 25 September 2022; Received in revised form 5 December 2022; Accepted 10 January 2023
Available online 20 January 2023
1057-5219/

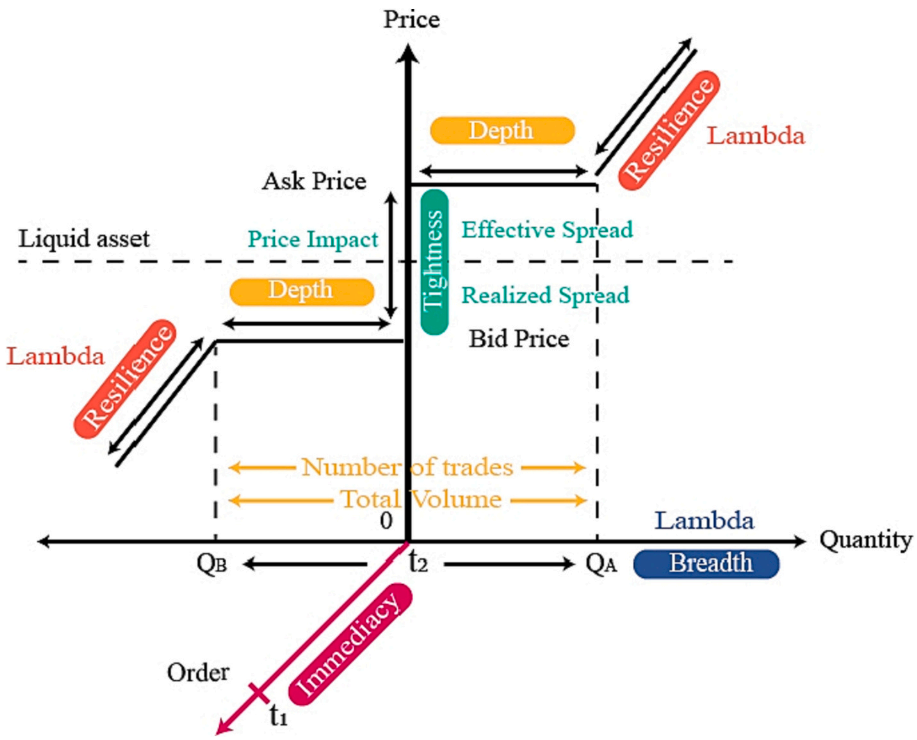


Fig. 1. Liquidity market dimensions.
Note: This figure depicts the five dimensions of liquidity (depth, tightness, resilience, breadth and immediacy), as well as the liquidity measure that addresses each of them. Q_A and Q_B are the quantities traded at the bid and ask prices, respectively. The higher the quantities traded, the broader the market is. The bigger the bid-ask spreads are, the tighter the market is. The depth is related to the amount of buying and seller orders, while a market is considered more or less resilient depending on its ability to absorb and recover from unexpected shocks. Lastly, immediacy measures the difference between when an order is introduced (t_1) and when it is executed (t_2). Adapted from Díaz and Escribano (2020).

week, analyses have also focused on the conditional mean of such relationships (see for instance, Brennan, Chordia, Subrahmanyam, and Tong (2012) and Chordia, Roll, and Subrahmanyam (2001)).

However appealing, this strategy comes at a price. When we exclusively focus on average liquidity in our estimations and market monitoring, we miss out on some of the most interesting and economically relevant features of market-wide liquidity, which are precisely related to its nonlinear nature. Interestingly, this is somehow at odds with the theoretical literature, which has (frequently indirectly) emphasized the nonlinear nature of liquidity, which is thought to result from several market frictions and well-studied limits to arbitrage emerging in incomplete market settings. For instance, we can think of nonlinearities in the provision of liquidity triggered by investors' funding constraints (see Brunnermeier and Pedersen (2009)), equity constraints (see Shleifer and Vishny (1997)), VaR-like risk-taking constraints (see Danielsson, Shin, and Zigrand (2011)) or limited risk-bearing capacity due to inventory risk on the side of market makers (see Huang and Wang (2008) and Weill (2007)); or emerging from cross-learning dynamics involving different asset classes (see Cespa and Foucault (2014)) or even from a time-varying risk aversion (e.g. Guiso, Sapienza, and Zingales (2018)).

A good illustration of the nonlinear nature of market liquidity is found in Vayanos (2004), who emphasizes the sudden preference for liquidity that might be experienced by market participants during episodes of turmoil, which in turn leads to a time-varying liquidity premium. Following Vayanos (2004), when volatility is small, fund managers are not concerned with liquidation because an event in which performance falls below a given risk threshold requires a movement of several orders of magnitude in the fund's performance. However, when volatility increases, liquidation emerges as a concern and managers select their portfolios in a more risk-averse fashion.

In addition, the increasing importance of algorithmic high frequency traders (HFT) and the overall growing presence of artificial intelligence and machines in charge of executing most buying and selling positions in the market, generally associated with more liquid markets and smaller spreads (Baldauf & Mollner, 2020), have also made room for new forms of nonlinearities describing the relationship between market liquidity and market volatility (see Ait-Sahalia and Saalam (2017) and Kirilenko, Kyle, Samadi, and Tuzun (2017)). In particular, HFT appear to provide liquidity and act like traditional market makers while experiencing relevant selling pressures only partially, and stop doing so when the selling pressure becomes too large or the market volatility too high. From that point on, they revert their positions and even seem to contribute to the reduction of overall market liquidity.

Drawing inspiration from the theoretical literature, here we stress the nonlinearities of market-wide liquidity, bearing in mind that the abovementioned nonlinearities in the provision of (and the demand for) liquidity should directly translate into a nonlinear association between market-wide liquidity proxies and the market conditions. Our methodological approach is simple, yet comprehensive. First, we provide novel indicators of aggregate liquidity and we track their evolution in time. Our indicators are based on individual liquidity characteristics, but unlike the previous literature that uses cross-sectional averages to aggregate information, we employ quantiles of liquidity measures on individual asset's basis. By construction, high or low quantiles are better than the average to track the evolution of the market liquidity tails. We then analyze several properties of these indicators, such as the persistence of shocks and the correlations across the various liquidity indicators. In the second part, we turn to the study of the determinants of aggregate market liquidity, allowing the relationship between liquidity and the other market variables to change according to the market *liquidity state*. To this end, we employ conditional quantile regressions (see Koenker and Bassett (1978) and Koenker (2005)) in which a market liquidity indicator is on the left-hand side of the equation and the other market variables are on the right-hand side.

The results of our study can be summarized in two parts. First, we document that market conditions have an asymmetric impact on the tails of the liquidity distribution. Indeed, an episode of market turmoil reduces the liquidity of the already illiquid stocks but increases the liquidity of relatively liquid stocks, which is in line with what can be expected from episodes of flight to liquidity (see Vayanos (2004)). Moreover, we find a markedly different behavior regarding the persistence of liquidity shocks: a liquidity shock is more persistent for relatively illiquid stocks than for the more liquid ones. Second, regarding the main determinants of market liquidity, our market liquidity indicators

Table 1
Liquidity measures.

Liquidity Measure	Formula	Description	Type	Dimension	Source
Total Volume	$k = P_k \times SHR_k$ where P_k is the price of trade k and SHR_k is shares of trade k.	Sum of all trade volume	Liquidity	Depth	WRDS Intraday Indicator Database
Number of Trades	—	Total number of trades during market hours	Liquidity	Depth	WRDS Intraday Indicator Database
Effective Spread	$ES_{AVGi,T} = \frac{1}{N} * \sum_{k=1}^{n} ES_k$ where $ES_k = \frac{2D_k(P_k - M_k)}{M_k}$ and N is the total number of trades of stock i on day T. P_k is the price of trade k, M_k is the bid-ask mid-price $M_k = (B_k + A_k)/2$, B_k is the bidding quote and A_k the asking quote. D_k is defined as follows: $D_k = +1$ if trade k is a buy and $D_k = -1$ if trade k is a sell.	Simple averaged percentage of the effective spreads of a stock in a transaction day	Illiquidity	Tightness	WRDS Intraday Indicator Database
Realized Spread	$RS_{i,T} = \frac{1}{N} * \sum_{k=1}^{n} RS_k$. where $RS_k = \frac{2D_k(P_k - M_{k+5})}{M_k}$ and N is the total number of trades of stock i on day T.	Simple averaged percentage of the realized spreads of a stock in a transaction day	Illiquidity	Tightness	WRDS Intraday Indicator Database
Price Impact	$PI_{i,T} = \frac{1}{N} * \sum_{k=1}^{n} PI_k$, where $PI_k = \frac{2D_k(M_{k+5} - M_k)}{M_k}$ and N is the total number of trades of stock i on day T. M_{k+5} is the bid-ask mid-point five minutes after the *kth* trade.	Simple averaged percentage price impact of a stock in a transaction day	Illiquidity	Tightness	WRDS Intraday Indicator Database
Lambda	$ln\frac{M_{i,t}}{M_{i,t-300}} = \alpha + \lambda_2 * SSqrtDVol + \epsilon$ where $SSqrtDVol = Sgn(\sum_{t-300}^{t} BuyDollar - \sum_{t-300}^{t} SellDollar) \times \sqrt{\left\|\sum_{t-300}^{t} BuyDollar - \sum_{t-300}^{t} SellDollar\right\|}$, and $M_{i,t} = (B_{i,t} + A_{i,t})/2$ is the bid-ask mid-price for stock i at second t.	Price impact coefficient that corresponds to the regression coefficient in the model described in the formula, where the intercept has not been suppressed	Illiquidity	Breadth and resilience	WRDS Intraday Indicator Database

Note: Each measure is classified according to its type and dimension. The liquidity type measures are those in which a higher level of the measure is related with higher levels of liquidity in the market. The opposite holds for the illiquidity type measures: the higher the level of the variable indicates a more illiquid market. The dimension refers to the aspect of liquidity the measure addresses. To sign transactions we rely on (WRDS) Intraday Indicator Database (IID), in particular, using the variable definition provided in the WRDS INTRADAY INDICATOR DATA Millisecond IID V1.0 User Manual (2020), formulas 30 and 31.

respond mainly to variables related to term spread and market risk. Market risk is positively associated with trading activity in a nonlinear fashion. In the case of tightness, resilience and breadth measures, we have that, for instance, market risk increases illiquidity only when the market is already illiquid.

Our results highlight the relevance of studying the tails of aggregate market liquidity for policymakers. We document (and quantify) flight to liquidity. From a risk point of view, central banks should be focusing their liquidity funding decisions on the dynamics of illiquid assets, which have higher liquidation costs and create illiquidity spirals that translate into higher losses, higher margins and volatility in the market (see Brunnermeier and Pedersen (2009)). We provide a simple way to track the effectiveness of interventions in terms of liquidity, which is more informative than previous measures proposed in the literature.

We proceed as follows. First, we describe the methodology followed to construct our cross-sectional liquidity indicators, the quantile regression approach to assess the determinants of market liquidity, and the data used in Section 2. The cross-sectional analysis of market liquidity tails is then presented in Section 3.1, following which we analyze the time series liquidity determinants under different liquidity states in Section 3.2. Section 4 provides an overview of our conclusions.

2. Methods and data

Through the rest of the paper, it is important to bear in mind that we use the term liquidity measure when we refer to the original input liquidity variables (e.g. spreads, volume, number of trades) that we use to construct our indicators. These measures are described in Section 2.1. Instead, we use the term liquidity indicator when we refer to the aggregation of these individual measures in an aggregate series that we can track in time. The procedure to construct our liquidity indicators is described in Section 2.2. Note that we construct two liquidity indictors (high and low) associated to each liquidity measure. We also explore the nonlinear association between the liquidity indicators and market variables. We explain the methodology used to estimate this association in Section 2.3., and describe the market variables on the right-hand-side (RHS) of the equation in Section 2.4. The estimates that describe the association between the market variables and the liquidity indicators are, in turn, divided according to the market liquidity state. The market liquidity state responds to the overall level of liquidity according to a given liquidity indicator.

2.1. Liquidity measures

We employ stocks listed at NYSE, AMEX and NASDAQ from the Wharton Research Data Services' (WRDS) Intraday Indicator Database (IID), which contains intraday transaction data for securities obtained from the NYSE Trade and Quote (TAQ) database. We select the daily measures that average trades and quotes during market hours. Given the robustness of the order statistics to outliers, we are able to conduct all our estimations using the whole universe of stocks from September 10, 2003 to May 31, 2020, without imposing additional filters on the data. Our sample includes at least three periods of interest in terms of liquidity: the global financial crisis, the European debt crisis and the recent coronavirus crisis.

We considered all liquidity measures available in the IID, but opted to present the results for total volume, number of trades, effective spread, realized spread, price impact and lambda (see Table 1), which

Table 2
Liquidity determinants.

Name	Description	Expected Sign	Source
Short rate	The daily first difference in the Federal Funds Rate.	+	Federal Reserve Economic Data (FRED).
Term Spread	The spread between 10-Year Treasury Constant Maturity and the effective Federal Funds Rate.	+	
Quality Spread	The spread between Moody's Seasoned Baa Corporate Bond and 10-Year Treasury Constant Maturity.	+	
VIX	CBOE Volatility Index.	+	
Ted Spread	The spread between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill.	+	
MKT+	Positive state variable of the equity market calculated from the CRSP daily index. Takes the value of one if the index return is positive, and zero otherwise.	−	Authors' own creation based on data from CRSP daily index from WRDS.
MKT-	Negative state variable of the equity market calculated from the CRSP daily index. Takes the value of one if the index return is negative, and zero otherwise.	+	
MA5MKT+	Positive momentum variable of the equity market calculated from the CRSP daily index. Takes de value of one if the past five trading day return is positive, and zero otherwise.	+	
MA5MKT-	Negative momentum variable of the equity market calculated from the CRSP daily index. Takes de value of one if the past five trading day return is negative, and zero otherwise.	+	
Abs(MKT)	Absolute value of market return calculated from the CRSP daily index.	+	
CPI	Indicator variable that takes the value of one the day of the CPI announcement, and zero otherwise.	+	Authors' own creation based on data from Federal Reserve Economic Data (FRED).
GDP	Indicator variable that takes the value of one the day of the GDP announcement, and zero otherwise.	+	
UN	Indicator variable that takes the value of one the day of the unemployment announcement, and zero otherwise.	+	
CPI_12	Indicator variable that takes the value of one two days leading up to the CPI announcement, and zero otherwise.	−	
GDP_12	Indicator variable that takes the value of one two days leading up to the GDP announcement, and zero otherwise.	−	
UN_12	Indicator variable that takes the value of one two days leading up to the unemployment announcement, and zero otherwise.	−	
Holiday	Indicator variable that takes the value of one if one of the following conditions apply: i) if a trading day is a Thursday before an Independence, Christmas, or New Years's Day that falls on a Friday; ii) a Tuesday after a holiday that falls on a weekend or on a Monday; iii) if a holiday falls on a different weekday, the preceding and following trade days, and zero otherwise.	+	
MonThu	Indicator variable that takes the value of zero if the trading day is a Friday, and one otherwise.	−	

Note: the expected sign column presents the anticipated direction effect of each explanatory variable on the level of illiquidity, measured by the different liquidity measures used.

widely reflect the various dimensions of trading activity and liquidity.

Total volume and number of trades are trading activity variables that assess the liquidity dimension of market depth. According to Vayanos and Wang (2013), market imperfections reduce trading volume, while transaction and participation costs reduce trading frequency. Effective spread and realized spread are measures of illiquidity that account mainly for transaction and participation costs. They are related to the liquidity dimension of tightness. Biais, Glosten, and Spatt (2005) show that bid-ask spreads are affected mainly by order-processing costs, asymmetric information, imperfect competition, and market maker risk aversion. Price impact is also a measure of illiquidity that accounts mainly for transaction costs (market tightness). Lastly, lambda is a measure of illiquidity related to the dimensions of resilience and breadth. Kyle (1985) links lambda with the degree of asymmetric information in the market. Our estimations consider 18,268 listed companies during the sample period, and 4209 trading dates.

2.2. Aggregating liquidity of individual assets in liquidity indicators

We employ quantiles of the stocks' liquidity distribution in a given period to construct our liquidity indicators. Quantiles are defined as $Q_y(\theta) = \inf [y|F(y) \geq \theta]$, where y refers to a certain liquidity measure for an individual stock in a given day. We construct "low" and "high" quantiles of two liquidity depth measures (number of trades and total volume), three liquidity tightness measures (the realized and effective bid-ask spread, and the price impact) and lambda. Note that for total volume and number of trades, the lower quantiles are associated with low liquidity, while the higher quantiles are associated with high liquidity. On the contrary, for effective spread, realized spread, price impact and lambda, higher quantiles are related with low liquidity, and lower quantiles with high liquidity· Therefore, each day we order the individual stocks by their level of liquidity (as defined by one of the liquidity measures) and then we select the appropriate quantile to obtain the daily high (low) liquidity indicators that are composed by the most liquid (illiquid) stocks each day. We end up with high and low liquidity indicators for each liquidity measure.

2.3. Nonlinear determinants of liquidity

We employ conditional quantile regressions in which a given aggregate market liquidity indicator is on the left-hand side of the equation and the other market variables are on the right-hand side. Following Koenker and Bassett (1978) and Koenker (2005), we have that:

$$Q_{Y_t|X_t}(\tau) = X_t' \beta(\tau), \tag{1}$$

where $Q_{Y_t|X_t}(\tau)$ is the τ^{th} quantile of the liquidity indicator Y_t, X_t consists of market variables that explain market liquidity, and $\beta(\tau)$ is a vector of coefficients that depends on the quantile τ. Specifically, we analyze the full conditional distribution of our liquidity indicators that are conditional on the term spread, the quality spread, the short-term interest rate, the TED spread, the market implied volatility as measured by VIX, observed volatility, past negative and positive market trends, dates of important macroeconomic announcements regarding prices, unemployment and GDP, and finally, the day of the week.

To illustrate our definition of a liquidity state, consider a given liquidity indicator (high or low) of number of trades. Suppose we fit a quantile regression using this indicator on the LHS of eq. 1 and the market variables are the regressors on the RHS. In this case, the quantile-

Table 3
Descriptive Statistics of Liquidity Indicators.

	Total Volume	Number of Trades	Effective Spread	Realized Spread	Price Impact	Lambda
			Low Liquidity Indicator			
Minimun	618.40	3.00	0.01795	0.01064	0.00641	0.00001
Mean	2197.49	10.00	0.03129	0.02139	0.01302	0.00003
Maximum	6726.60	39.00	0.16454	0.10595	0.09063	0.00015
5th Percentile	1466.16	4.00	0.02044	0.01365	0.00743	0.00002
95th Percentile	3100.00	16.90	0.05281	0.03804	0.02173	0.00005
			High Liquidity Indicator			
Minimun	251,865.20	543.80	0.00017	−0.01290	−0.00917	−0.00028
Mean	1,484,484.433	8195.66	0.00032	−0.00072	−0.00022	−0.00001
Maximum	4114,370.10	28,255.80	0.00135	−0.00003	0.00000	0.00000
5th Percentile	817,948.00	1765.52	0.00019	−0.00165	−0.00055	−0.00002
95th Percentile	2,175,307.12	13,353.92	0.00053	−0.00014	−0.00001	−0.00001

Note: this table shows the descriptive statistics of the 12 liquidity indicators associated to the 6 original liquidity measures. The upper panel show the low liquidity indicators constructed as the 95th percentile of individual effective spread, realized spread, price impact and lambda, and the 10th percentile of individual total volume and number of trades. The lower panel shows the high liquidity indicators, constructed as the 5th percentile of individual effective spread, realized spread, price impact and lambda, and the 90th percentile of individual total volume and number of trades.

slopes associated with high quantiles of number of trades (e.g. $\tau = .95$) can be interpreted as describing a high liquidity state, because they refer to periods of time when the liquidity indicator is high. On the other hand, quantile-slope coefficients related to low quantiles of number of trades (e.g. $\tau = .05$) refer to low liquidity states. This definition of the liquidity states avoids any arbitrary selection of dates to set the states *ex-ante* and allows for all possible variations in the relationship between liquidity and other market variables to freely manifest themselves.

In order to assess the goodness of fit of the quantile regressions we calculate a pseudo R^2, which is a generalization of the coefficient of determination to the case of conditional quantile regression. Following Koenker and Machado (1999), the pseudo R^2 is given by:

$$R^2(\tau) = 1 - \frac{\widehat{V}(\tau)}{\widetilde{V}(\tau)}, \tag{2}$$

where $\widetilde{V}(\tau)$ stands for the weighted sum of the absolute residuals of the restricted model, for the case of the τ quantile, and $\widehat{V}(\tau)$ stands for the weighted sum of the absolute residuals of the unrestricted model (i.e. the model that includes only an intercept within the set of regressors) at quantile τ. Like the traditional R^2, $R^2(\tau)$ lies between zero and one. However, it does not measure the relative success of two models (restricted and unrestricted) for the conditional mean function in terms of residual variance. Instead, it measures the relative success of the corresponding quantile regression model at a specific quantile. Therefore, $R^2(\tau)$ can be seen as a local measure of goodness of fit for a particular quantile, rather than a global measure of the goodness of fit.

2.4. Liquidity determinants

Following Chordia, Roll, and Subrahmanyam (2001), we selected the daily overnight Federal Funds rate, a term structure variable, and a measure of default spread as possible determinants of market liquidity. It is expected for higher long-term interest rates to increase aggregate stock illiquidity by the reallocation of investors' wealth between stock and debt instruments. Moreover, short-term interest rates determine liquidity by affecting the costs of margin trading and short-selling constraints. Regarding default spreads, changes in the quality spread affect the perceived risk of holding assets (see Demsetz (1968), Ho and Stoll (1981) and Stoll (1978) for a detailed analysis of how inventory risks affect liquidity), and hence market liquidity. To also address holding inventory risks, we consider the TED spread as a credit risk indicator. The relationship between risk and quality spread is not linear because once market makers reach a risk limit, they contract their portfolios towards safer assets, withdrawing liquidity from the market. All these variables were retrieved from Federal Reserve Economic Data (FRED).

We also consider the market state as a liquidity determinant. The dynamics of stock prices affect the expectations of market participants, and therefore the composition of portfolios, implying changes in demand for assets. Hence, we include a variable, in absolute terms, of the returns of the market. However, given that the sign of price shifts could affect liquidity differently, we also include variables of positive and negative states in the stock prices. It is expected for illiquidity to increase more in falling markets than it declines in rising markets, since market makers may be more concerned with inventory adjustments in the midst of price declines. Additionally, we consider positive and negative momentum variables to assess the impact of recent price dynamics on trading activity. Theoretically, a positive relationship between momentum and aggregate illiquidity is expected, since arbitrage should be easier when markets are more liquid (see Avramov, Cheng, and Hameed (2016)). All these measures were constructed using data from the Center for Research in Security Prices (CRSP) daily index extracted from WRDS.

Equity market volatility is also a candidate for a determinant of liquidity because a more volatile market could negatively impact trading activity. The literature on the limits of arbitrage (see Gromb and Vayanos (2010)) highlights that traders rely on external capital, such as collateralized debt, to fund their operations. Yet, when shocks affect the value of the collateral, it reduces the funding that agents can access. Therefore, a positive relation between volatility and market illiquidity is expected. To assess the impact of adverse shocks on our liquidity indicators, we include the VIX index (retrieved from FRED).

Information regarding macroeconomic conditions could also determine agents' investment decisions. Therefore, we consider the announcement days (and the days leading up to them) for the Consumer Price Index (CPI), Gross Domestic Product (GDP) and unemployment rate. One might expect for speculative trading to intensify before the announcements. Finally, we include dummy variables for trading days prior to or following holidays and for days of the week (all were constructed using data from FRED). The studies of Admati and Pfleiderer (1989) and Foster and Viswanathan (1990) show that liquidity follows seasonal patterns, which are related to time invested in making trading decisions. That is why we can expect to see lower trading activity and higher illiquidity on Fridays and days before or after a holiday. The explanatory variables considered are presented in Table 2.

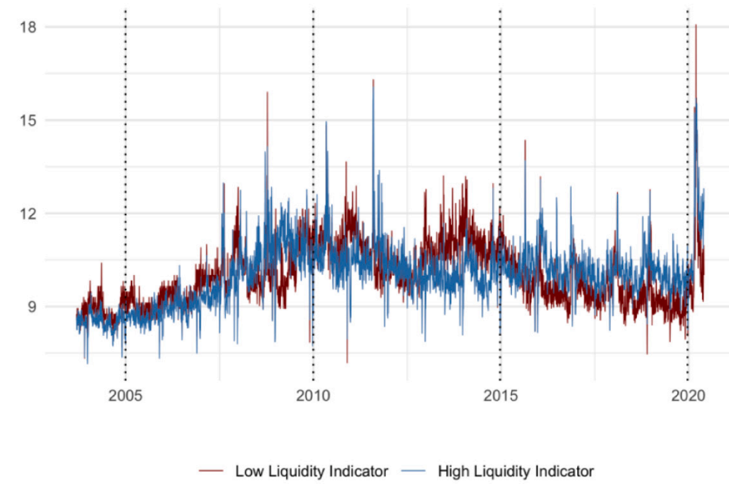
See Table A2 in the Appendix for the descriptive statistics and the Augmented-Dickey Fuller tests for the explanatory variables considered.

3. Results

3.1. Aggregate liquidity indicators

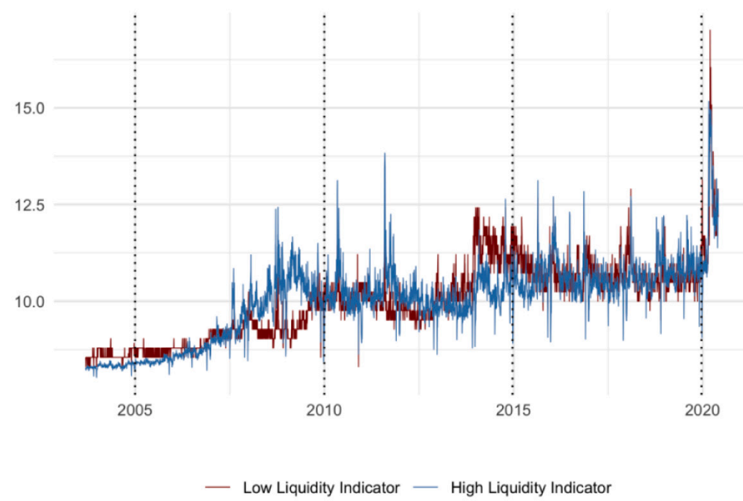
When analyzing the results, it is necessary to recall that the various

A. Total Volume



Note: Low and high liquidity indicators correspond to the 10th and 90th percentiles of the total traded volume, respectively.

B. Number of Trades



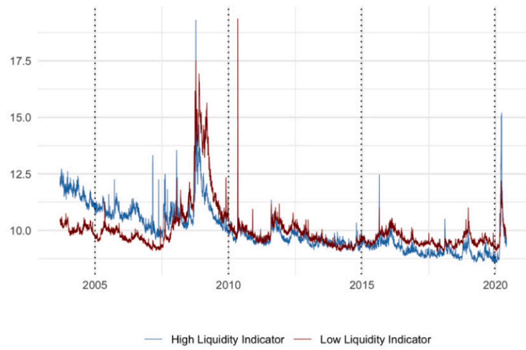
Note: Low and High liquidity indicators correspond to the 10th and 90th percentiles of the number of trades, respectively.

Fig. 2. Depth measures.

dimensions of liquidity can be divided into five categories: depth, tightness, resilience, breadth and immediacy. Total volume and number of trades are related to depth; effective spread, realized spread and price impact to tightness; and lambda to breath and resilience. Table 3 shows the mean, maximum and minimum of the aggregate liquidity indicators estimated at "low" and "high" quantiles. In the case of the tightness and resilience measures, we set the quantiles to 5th and 95th, i.e. $\theta = \{0.05, 0.95\}$. In the case of the two depth measures, we set these values to 10th and 90th, (i.e. higher or lower quantiles were constant in these case, in several days). As can be observed in the table, there is large variability in the liquidity indicators associated to the number of trades and volume. For instance, the liquidity indicator for total volume varies between 618.4 and 6726.6 when we focus on the low quantile of the distribution (i.e. the least traded stocks). Meanwhile, it varies between 251,865.2 and 4114, 370.1 when we focus on the high liquidly indicator (i.e. the most traded stocks). Other liquidity indicators, associated to other liquidity measures, also vary considerably. All of them are negative (except for the effective spread) when we focus on the high liquidity indicators (lower panel) and positive when we focus on the low liquidity indicators (upper panel).

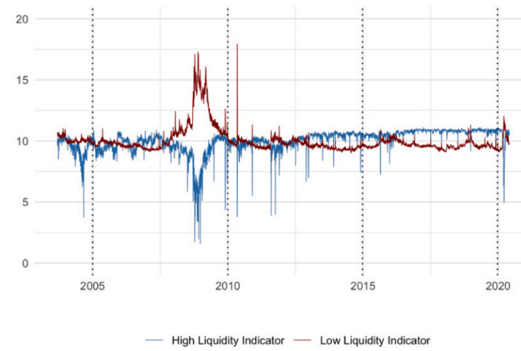
For our next calculations, we standardized all the indicators to have a mean equal to 10 and unit variance. This is just a change in scale of the original units expressed in Table 3, with no other purpose than to facilitate comparisons allowing us to focus on the time dynamics of the

A. Effective Spread



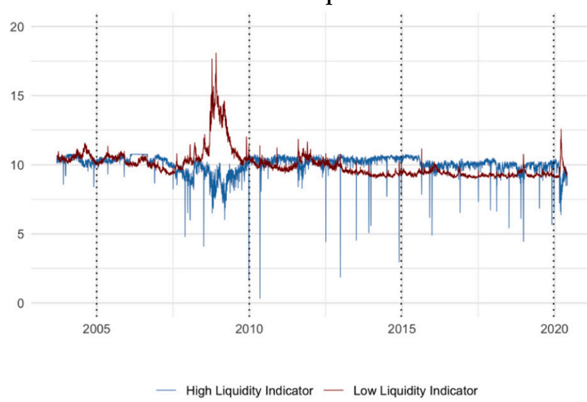
Note: Low and high liquidity indicators correspond to the 95th and 5th percentiles of effective spread, respectively.

B. Realized Spread



Note: Low and high liquidity indicators correspond to 95th and 5th percentiles of realized spread, respectively.

C. Price Impact



Note: Low and high liquidity indicators correspond to the 95th and 5th percentiles of price impact, respectively.

Fig. 3. Tightness measures.

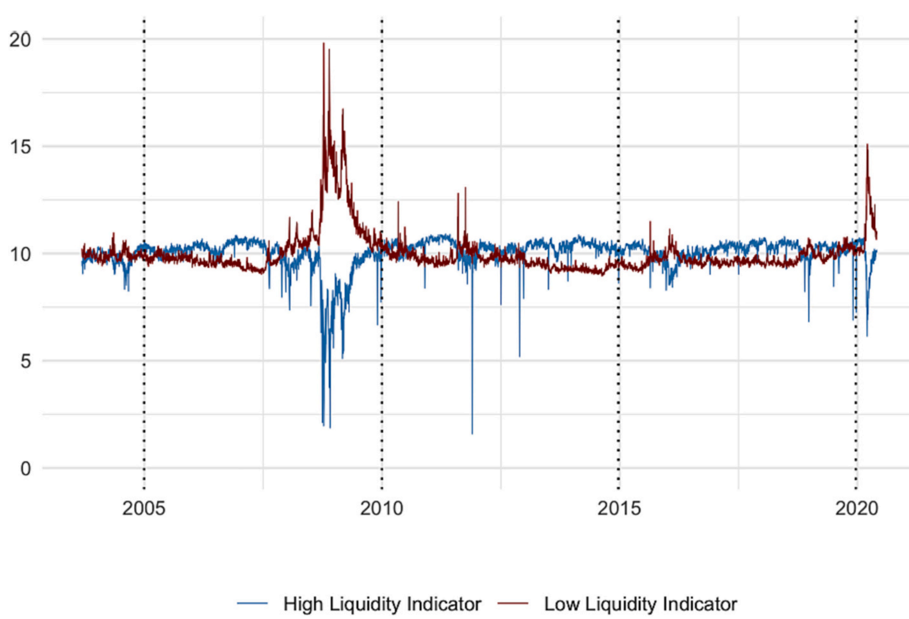


Fig. 4. Resilience Measure- Lambda.
Note: Low and high liquidity indicators correspond to the 95th and 5th percentiles of lambda, respectively.

indicators. We present the indicators from September 2003 to May 2020 in Figs. 2 to 4.

According to expectations, low and high liquidity indicators, share a common trend. Moreover, regarding the two depth measures, volume and total trades, the liquidity indicators increased steadily from 2003 until the global financial crisis in 2008–2009 (see Fig. 2). From that point on, they became cyclical, depicting peaks and troughs, with about a year of amplitude. These cycles do not necessarily coincide for the two

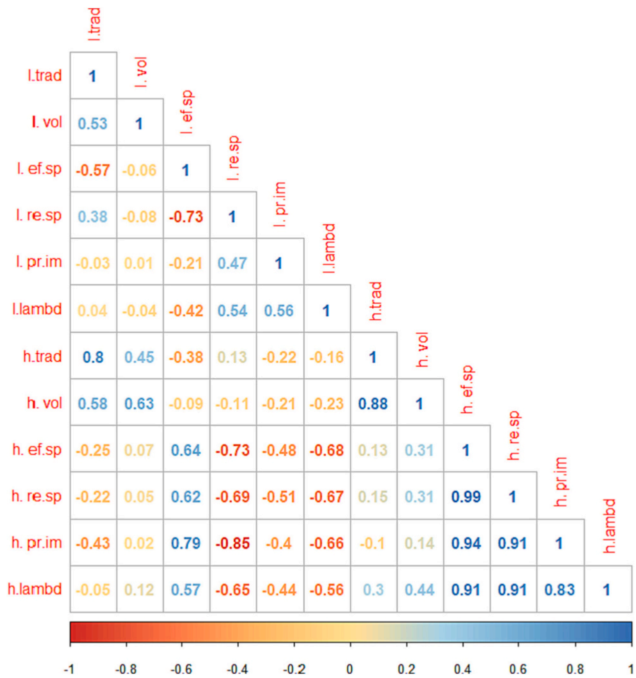


Fig. 5. Correlations between liquidity indicators.
Note: l.trad is Trading Activity low liquidity indicator; l.vol is Volume low liquidity indicator; l. ef.sp. is Effective Spread low liquidity indicator; l. re.sp. is Realized Spread low liquidity indicator; l. pr.im is Price Impact low liquidity indicator; l.lambd is Lambda low liquidity indicator; h.trad is Trading Activity high liquidity indicator; h.vol is Volume high liquidity indicator; h. ef.sp. is Effective Spread high liquidity indicator; h. re.sp. is Realized Spread high liquidity indicator; h. pr.im is Price Impact high liquidity indicator; and h. lambd is Lambda high liquidity indicator.

liquidity indicators associated to each measure. For instance, while volume high liquidity was increasing during 2008–2009 and reached a peak in the latter year, volume low liquidity was decreasing during the same period and reached a trough about the same month. The opposite occurred during 2013 when volume low liquidity peaked and volume high liquidity reached a trough (see Fig. 2, Panel A). The same analysis suits the number of trades (see Fig. 2, Panel B). The fact that the two liquidity indicators of trading activity convey distinctive information is also attested by their correlations. The Pearson's correlation between volume low and high liquidity indicators amounts to 0.63, while in the case of the number of trades it rises to 0.80 (see Fig. 5). In other words, 37% of the time the two tails of volume, represented by high and low volume indicators, do not comove. The same is true for tradig activity 20% of the time.

Focusing on the spreads, the dissimilarities between the two liquidity indicators are also notorious. The Effective Spread low and high liquidity both peaked during the global financial crisis and again during the Covid-19 crisis (see Fig. 3, Panel A). Other than that, they seemed to share a common downward trend during the sample, with cycles that sometimes coincided, as occurred with the depth measures analyzed before, but which are clearly not the same, as witnessed by a correlation between the two indicators equal to 0.64, similar to the correlation between the two liquidity indicators associated to volume (see Fig. 5). Regarding the realized spread, the difference between the two liquidity indicators becomes obvious, because their correlation is negative (−0.69). This occurs because the two indicators behave as a mirror during episodes of market stress. For instance, if we focus on Fig. 3, Panel B, in the wake of the global financial crisis, while the realized spread high liquidity indicator experienced a dramatic reduction, the realized spread low liquidity indicator experienced a notorious increment. The same analysis applies for price impact and lambda. The two tails of price impact present a correlation of −0.40 and between Lambda low and Lambda high there is a correlation of −0.56. The analysis of the correlations above implies that the market state has a clearly differentiated impact on the tails of the liquidity distribution. Indeed, an episode of market turmoil reduces the liquidity of illiquid stocks (i.e. increases the lambda low liquidity indicator) but increases the liquidity of the liquid stocks (i.e. reduces the lambda high liquidity indicator). This is in line with expectations in episodes of flight to liquidity (e.g. Vayanos (2004)). Finally, one can note from Fig. 3, Panel C, and Fig. 4 that episodes of market turmoil, especially those during the global financial crisis, but also at the end of the sample during the Covid-19 crisis, had an asymmetric effect on low and high liquidity indicators. Not only does the effect have a different sign, but also it is also smaller in magnitude for Lambda and Price Impact high liquidity than for their low liquidity counterparts.

Now we turn to the statistical properties of our liquidity indicators. In Table 4 we report the skewness, kurtosis, persistence and half-life in days of shocks for the liquidity indicators associated to each measure. The persistence (β) is estimated using an autoregressive model of order one and corresponds to the coefficient of the first lag in the regression. The half-life corresponds to the number of days the market will take to absorb half the impact of a shock to liquidity and is estimated using the formula $hl = \ log\,(0.5)/\ log\,(\rho)$.

The differences are noteworthy. Regarding the two trading activity measures (number of trades and volume), kurtosis is very similar for the two liquidity indicators (high and low). For its part, skewness is larger for trading low liquidity than for trading high liquidity. The half-life of the shocks in the volume series is 4.23 for the least traded stocks and 5.30 for the heavily traded ones. Regarding lambda high liquidity half-life is less than a day (0.82), while for lambda low liquidity it amounts to 17.50 days. This finding is crucial, as it means that a shock to liquidity is a very persistent phenomenon for relatively illiquid stocks, while it is not for the more liquid stocks. This point is completely missed by analyses that focus on the average liquidity. A similar analysis suits price impact and the realized spread, while the situation is more balanced for

Table 4
Statistical Properties of Shocks to Liquidity Indicators.

	Total Volume	Number of Trades	Effective Spread	Realized Spread	Price Impact	Lambda
			Low Liquidity Indicator			
Skewness	1.0103	0.7100	3.5196	3.5705	3.1195	3.7269
Kurtosis	2.9372	1.9855	15.1208	15.0133	15.5614	17.5571
Rho	0.8488	0.9553	0.9664	0.9663	0.9488	0.9612
Half-life	4.2272	15.1670	20.2706	20.2482	13.1856	17.4953
			High Liquidity Indicator			
Skewness	0.8102	0.1989	1.3352	−4.1797	−13.4282	−22.1604
Kurtosis	2.9735	1.1456	3.3916	44.8762	322.4935	917.2341
Rho	0.8774	0.9530	0.9634	0.8341	0.3011	0.4274
Half-life	5.2984	14.3972	18.5757	3.8208	0.5775	0.8154

Note: This table shows the descriptive statistics of high and low liquidity indicators associated with each liquidity measure.

Table 5
Summary of the Effects of Explanatory Variables on Depth According to the Liquidity State.

	Total Volume						Number of Trades					
	Low liquidity indicator			High liquidity indicator			Low liquidity indicator			High liquidity indicator		
Explanatory Variable	$\tau=$ 0.05	$\tau=$ 0.95	Nonlinear effect	$\tau=$ 0.05	$\tau=$ 0.95	Nonlinear effect	$\tau=$ 0.05	$\tau=$ 0.95	Nonlinear effect	$\tau=$ 0.05	$\tau=$ 0.95	Nonlinear effect
Intercept	+	+	*	+	+	*	+	+	*	+	+	*
Short rate	0	–		0	–	*	0	0		0	–	*
Term Spread	+	+	*	0	+	*	+	+	*	+	+	*
Quality Spread	0	+	*	+	+	*	0	+	*	0	+	*
VIX	+	+	*	+	+	*	+	+	*	+	+	*
Ted Spread	0	–	*	0	–	*	–	0	*	+	+	*
MKT+	0	0		0	+		0	0		+	+	
MKT-	0	0		0	0		0	0		–	–	
MA5MKT+	0	0		0	+		0	0		0	+	
MA5MKT-	0	0		0	0		0	0		+	0	
Abs(MKT)	+	0	*	0	+	*	0	–	*	+	+	*
CPI	+	0		+	0		0	0		0	0	
GDP	0	0		+	0		0	0		0	0	
UN	0	0		0	+		0	+		0	+	
CPI_12	0	0		0	–		0	0		0	–	
GDP_12	+	0		+	0		0	0		0	–	
UN_12	0	0		–	–		0	0		–	–	
Holiday	0	+	*	–	–	*	0	+	*	–	–	*
MonThu	+	0		+	0	*	+	+	*	+	+	
Trend	–	–	*	+	+	*	+	+	*	+	+	*

Note: This table shows the sign of the slope coefficient estimated for the 5th and 95th quantiles (low and high liquidity states, respectively). * is placed when most of the slopes are outside the confidence interval of the median regression, which corresponds to a nonlinear effect.

the effective spread with 18.58 and 20.27 days for its high and low liquidity indicators, respectively. Finally, we also conducted unit root tests for all the indicators, and all of them were found to be trend-stationary, as it suffices to include a linear trend in the test to strongly reject the null of a unit root (see Table A1 in the Appendix).

3.2. Liquidity determinants under different liquidity states

The impact of the explanatory variables on different quantiles of the high and low liquidity indicators was estimated as in Eq. 1. We interpret quantile slopes at low quantiles of trading activity variables (e.g. $\tau = .05$) as describing a low liquidity state, while quantile slopes related to high quantiles of total volume or number of trades (e.g. $\tau = .95$) refer to high liquidity states. Naturally, this interpretation reverts for the other liquidity measures.

We summarize the results in Tables 5-9 by indicating the sign of the effect of each explanatory variable on the low and high liquidity indicators, discriminating, in turn, between those associated to low and high liquidity states. We focus the analysis on the most significant patterns that we detect in the table and the figures. Figs. A1 to A3 show the regression slopes for all the quantiles of the liquidity indicators. Section 3.2.1. presents the analysis of the depth dimension; Section 3.2.2 shows the results of variables in the tightness dimension; and Section 3.2.3. analyzes lambda, which is related to the dimensions of resilience and breadth. Finally, Section 3.2.4. describes the statistical significance of the explanatory variables among all the regressions made and the goodness of fit of the regressions estimated.

3.2.1. Depth

Table 5 indicates the sign of the effect of each explanatory variable on the total volume and number of trades low and high liquidity indicators, differentiating between those associated to low liquidity states and high liquidity states. Additionally, the variables that present a nonlinear effect on the indicators are pointed out. Higher short-term rates decrease volume traded. The more liquid the market state, the more negative the impact of the short rate becomes (see Fig. A1, Panels A and B). For total number of trades, the effect is mainly insignificant. Regarding the Term spread for both liquidity indicators, the relationship is positive (see Fig. A1). The same holds for quality spread most of the times (see Fig. A1, Panel B). The results are in line with the fact that negative shocks in long-term interest rates and default spreads can induce more trading activity by triggering traders' nervousness. VIX also presents a positive relationship with both indicators associated to total volume and number of trades, indicating that higher implied volatility leads to the execution of more buying and selling orders. Additionally, for the three variables (term spread, quality spread and VIX) the relationship is always nonlinear and the impact increases for the high liquidity states (see also Fig. A1). The effect of the absolute value of the market returns on total volume and number of trades is very heterogeneous for the different liquidity states and the two liquidity indicators. Other explanatory variables like TED spread, present, in general, a negative and nonlinear relationship with the depth measures. For positive variables related to market returns, the effect is mainly linear and statistically insignificant. Macroeconomic conditions, CPI, GDP and unemployment announcements, as well as the days prior to such announcements (CPI_12, GDP_12 and UN_12) do not explain either of the indicators (high or low liquidity). Total volume and number of trades high liquidity indicators reduce in the days prior to or following a holiday (see Fig. A1, Panel B and D). Additionally, we find that when the trading day is not a Friday, trading activity is higher. For the Holiday and MonThu variables, the relationship with the measures is mainly nonlinear. Finally, regarding the trend, which measures how fast liquidity indicators evolve in time, the coefficient is positive and changes across the liquidity states.

3.2.2. Tightness

We now analyze three liquidity measures that address market tightness: effective spread, realized spread and price impact. Table 6 summarizes the results in the same way than Table 5, but this time the high liquidity state corresponds to the 5th percentile, and low liquidity state to the 95th percentile. Again, the variables that present a nonlinear effect are pointed out. Short rate and term spread have a low explanatory power on tightness. Term spread's relationship with the liquidity indicators is always negative and significant, except for the high liquidity indicator of realized spread and price impact (see Fig. A2). In the case of the low liquidity indicator (see Fig. A2, Panel A, C and E) the impact of the spread is nonlinear, while for the high liquidity indicator (see Fig. A2, Panel B, D and F) the opposite holds. Quality spread has a

Table 6
Summary of the Effects of Explanatory Variables on Tightness According to the Liquidity State.

	Effective Spread						Realized Spread						Price Impact					
	Low liquidity indicator			High liquidity indicator			Low liquidity indicator			High liquidity indicator			Low liquidity indicator			High liquidity indicator		
Explanatory Variable	τ= 0.05	τ= 0.95	Nonlinear effect	τ= 0.05	τ= 0.95	Nonlinear effect	τ= 0.05	τ= 0.95	Nonlinear effect	τ= 0.05	τ= 0.95	Nonlinear effect	τ= 0.05	τ= 0.95	Nonlinear effect	τ= 0.05	τ= 0.95	Nonlinear effect
Intercept	–	0	*	-	+	*	–	+	*	–	-	*	+	+	*	–	τ= 0.95 +	*
Short rate	0	0		0	–	*	0	0		+	0		0	0		0	0	
Term Spread	–	–	*	–	–		–	0	*	+	0		–	–	*	+	+	
Quality Spread	–	0	*	0	0	*	–	0	*	–	0	*	–	0		–	0	*
VIX	+	+	*	+	+	*	+	+	*	–	–	*	+	+	*	–	–	*
Ted Spread	0	+	*	+	+	*	+	+	*	–	–	*	–	+	*	–	–	*
MKT+	0	0		0	0	*	0	0		+	0		+	0		0	0	
MKT-	–	0	*	0	0		–	0	*	–	0		–	+	*	+	+	
MA5MKT+	0	0		0	0		0	0		0	0		0	0		0	0	
MA5MKT-	0	0		0	0		0	0		0	0		0	0		0	0	
Abs(MKT)	+	0	*	0	–	*	+	+	*	+	+	*	+	–	*	–	–	*
CPI	0	0		0	0		0	0		0	0		0	0		0	0	
GDP	0	0		0	+		0	0		0	0		0	0		+	0	
UN	0	0		0	0		0	0		0	0		0	0		–	0	
CPI_12	0	0		0	0		0	0		0	0		0	0		0	0	
GDP_12	0	0		+	+	*	0	0		0	0		0	0		0	0	
UN_12	0	0		0	0		0	0		0	0		0	0		0	0	
Holiday	+	+	*	0	0		0	+	*	–	0	*	+	+		–	0	*
MonThu	0	–	*	–	–		–	–		0	0	*	0	0		+	0	*
Trend	–	–	*	–	–	*	+	+	*	+	+	*	–	–	*	–	–	*

Note: This table shows the sign of the slope coefficient estimated for the 5th and 95th quantiles (high and low liquidity states, respectively). * is placed when most of the slopes are outside the confidence interval of the median regression, which corresponds to a nonlinear effect.

Table 7
Summary of the Effects of Explanatory Variables on Lambda According to the Liquidity State.

	Lambda					
	Low liquidity indicator			High liquidity indicator		
Explanatory Variable	$\tau=$ 0.05	$\tau=$ 0.95	Nonlinear effect	$\tau=$ 0.05	$\tau=$ 0.95	Nonlinear effect
Intercept	+	+	*	–	–	*
Short rate	–	0		0	0	
Term Spread	–	–	*	–	+	*
Quality Spread	–	0		0	+	*
VIX	+	+	*	–	–	*
Ted Spread	+	+	*	–	–	*
MKT+	+	–	*	0	0	
MKT-	–	0	*	0	0	
MA5MKT+	0	0		0	0	
MA5MKT-	0	0		0	0	*
Abs(MKT)	+	–	*	+	0	*
CPI	0	0		0	0	
GDP	0	0		0	0	
UN	0	0		0	0	
CPI_12	0	0		0	0	
GDP_12	+	0		0	–	
UN_12	0	0		0	0	
Holiday	0	0		–	0	*
MonThu	0	0		+	0	*
Trend	0	–	*	+	–	*

Note: This table shows the sign of the slope coefficient estimated for the 5th and 95th quantiles (high and low liquidity states, respectively). * is placed when most of the slopes are outside the confidence interval of the median regression, which corresponds to a nonlinear effect.

Table 8
Summary of the Explanatory Variables' Significance.

	Significance %	
Variable	Low Liquidity Indicator	High Liquidity Indicator
Intercept	96%	99%
Short rate	7%	12%
Term Spread	89%	96%
Quality Spread	79%	69%
VIX	98%	100%
Ted Spread	97%	70%
MKT+	34%	29%
MKT-	55%	57%
MA5MKT+	8%	12%
MA5MKT-	21%	21%
Abs(MKT)	74%	88%
CPI	11%	9%
GDP	18%	19%
UN	8%	31%
CPI_12	6%	39%
GDP_12	11%	24%
UN_12	16%	26%
Holiday	55%	69%
MonThu	72%	61%
Trend	100%	95%
Total	48%	51%

Note: This table shows the percentage of the number of times that each explanatory variable is statistically significant at a 5% level of confidence, discriminating by liquidity indicators.

negative and nonlinear relationship with this liquidity dimension, yet with betas close to zero through all liquidity states. VIX and TED spread exhibit a positive relationship with the indicators: a shock in the implied volatility of the market or in credit risk makes the bid-ask spreads higher. Moreover, this effect is nonlinear. Only for the high liquidity indicators associated to the realized spread (see Fig. A2, Panel D) and price impact (see Fig. A2, Panel F) the relationship is negative.

On its side, the explanatory variables based on market returns tend to have an effect close to zero in most of the cases. Similarly, CPI

Table 9
Goodness of Fit of the Quantile Regressions.

Liquidity Measure	Low Liquidity Indicator		High Liquidity Indicator	
	Low Liquidity State	High Liquidity State	Low Liquidity State	High Liquidity State
Total Volume	0.1588	0.1766	0.3770	0.4075
Number of Trades	0.4633	0.4638	0.5734	0.5867
Effective Spread	0.4886	0.3283	0.3183	0.2014
Realized Spread	0.4580	0.2898	0.4323	0.4881
Price Impact	0.5735	0.4688	0.2442	0.2861
Lambda	0.4527	0.2946	0.2261	0.3293

Note: This table shows the pseudo R^2, which is a generalization of the coefficient of determination to the case of quantiles.

announcements do not influence any of the liquidity indicators. GDP and unemployment announcements do not tend to impact the liquidity indicators either. Finally, liquidity tends to decrease days prior to or following a holiday.

3.2.3. Breadth and resilience

In this dimension, the most notable effects, which also highlight the asymmetric impact of the explanatory variables on lambda, are associated with the VIX and the Ted Spread (see Table 7). Both have a positive and nonlinear relationship with the low liquidity indicators (Fig. A3, Panel A), and a negative nonlinear effect with high liquidity indicators (Fig. A3, Panel B). In other words, these variables increase illiquidity only when the market is already illiquid. The rest of the effects are either heterogeneous or insignificant.

3.2.4. Statistical significance analysis

Table 8 summarizes the percentage of the number of times that each explanatory variable is statistically significant. On average, 50% of the explanatory variables' betas are statistically significant; i.e. half of the 2280 estimated betas (6 liquidity measures, 20 explanatory variables, 19 percentiles) have explanatory power over the liquidity indicators. Term spread and the risk measures are statistically significant in the vast majority of cases, more frequently than all other variables. VIX is the variable with the highest explanatory power, being significant in 100% of the estimated regressions for the high liquidity indictors, and in 98% for the low liquidity indictors. The variables that have the lowest explanatory power are short rate and the macroeconomic announcement indicator variables.

Regarding the goodness of fit of the quantile regressions, we present the pseudo R^2 estimations in Table 9. For total volume and number of trades, the regression of the high liquidity indicator exhibits a higher goodness of fit than the regression of the low liquidity indicator. Moreover, the high liquidity state regressions always present higher explanatory power than the low liquidity state regressions. For the other four liquidity measures, low liquidity indicators exhibit a higher goodness of fit than high liquidity indicators, except for the high liquidity state of realized spread and lambda.

4. Conclusions

Unlike previous literature that uses averages to aggregate information, we propose market-wide liquidity indicators that emphasize the dissimilar nature of liquidity for low-liquidity stocks and high-liquidity stocks. Our indicators are based upon a wide set of individual liquidity measures (e.g. total volume, number of trades, effective and realized spreads, price impact and lambda). We construct indicators using high and low percentiles of individual-level liquidity measures in a given day, rather than averages. We show that low and high liquidity indicators associated with market depth (i.e. total volume and number of trades) are positively correlated and cyclical. For the other four measures, the low and high liquidity indicators present notorious dissimilarities. Indeed low and high liquidity indicators associated to the realized spread, price impact and lambda, present a negative correlation with each other, which indicates that market conditions have an asymmetric impact on the two tails of the liquidity distribution. Indeed, an episode of market turmoil reduces the liquidity of the already illiquid stocks but increases the liquidity of relatively liquid stocks. We also document that the number of days the market will take to absorb half the impact of a shock differs according to the liquidity of the stocks. Specifically, a liquidity shock is a very persistent phenomenon for relatively illiquid stocks, while it is not for the more liquid ones. This point is completely missed by previous analyses focusing on average market liquidity.

Second, we examine the determinants of our liquidity indicators. To this end, we use conditional quantile regressions. We explore determinants such as implied volatility, recent market trends and funding liquidity. We find that short-term rates have little effect on the liquidity indicators, which rather respond to the term spread, the quality spread, and the VIX. Moreover, most of the relationships that we document are nonlinear. In most of the cases, this means that the impact of explanatory variables tends to increase during high liquidity states.

Our results emphasize the asymmetric responses of liquidity to its determinants according to the assets' liquidity and the market liquidity state. Furthermore, in terms of model adjustment, the overall goodness of fit of our quantile regressions ranges from 16% to 59%, while in Chordia, Roll, and Subrahmanyam (2001) ranges from 18% to 33%, which emphasizes the convenience of our approach.

The measures provided in this document are especially useful for researchers and policymakers seeking to anticipate episodes of financial instability or market fragility, or those interested in measuring the impact of monetary policy, conditioning on the general level of liquidity. These effects largely depend on the type of asset being considered (liquid or illiquid), and market-monitoring conclusions can be very different, depending on the aggregate liquidity measure used. Thus, we enhance the set of policy tools available to central banks, regulators and market participants. From our perspective, researchers should always look at the tails of liquidity distribution, given the nonlinear nature of market liquidity that we have documented.

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

Data will be made available on request.

Acknowledgements

This work was supported by the Spanish Ministry of Science and Innovation under Grant [PID2019-105986GB-C21].

Appendix A. Appendix

Table A1
Augmented Dickey-Fuller Unit Root Test.

	Total Volume	Number of Trades	Effective Spread	Realized Spread	Price Impact	Lambda
			Low Liquidity Indicator			
tau2	−13.2107***	−6.6964***	−5.823***	−5.8233***	−6.8900***	−6.6388***
phi1	87.2629***	22.4608***	16.9562***	16.9585***	23.7406***	22.0393***
			High Liquidity Indicator			
tau2	−13.1631***	−8.1142***	−6.3553***	−13.551***	−30.6333***	−26.1459***
phi1	86.6455***	32.9584***	20.2181***	91.8147***	469.2004***	341.8052***

Note: *** indicates that the null hypothesis is rejected and stationarity at the 1% level is found.

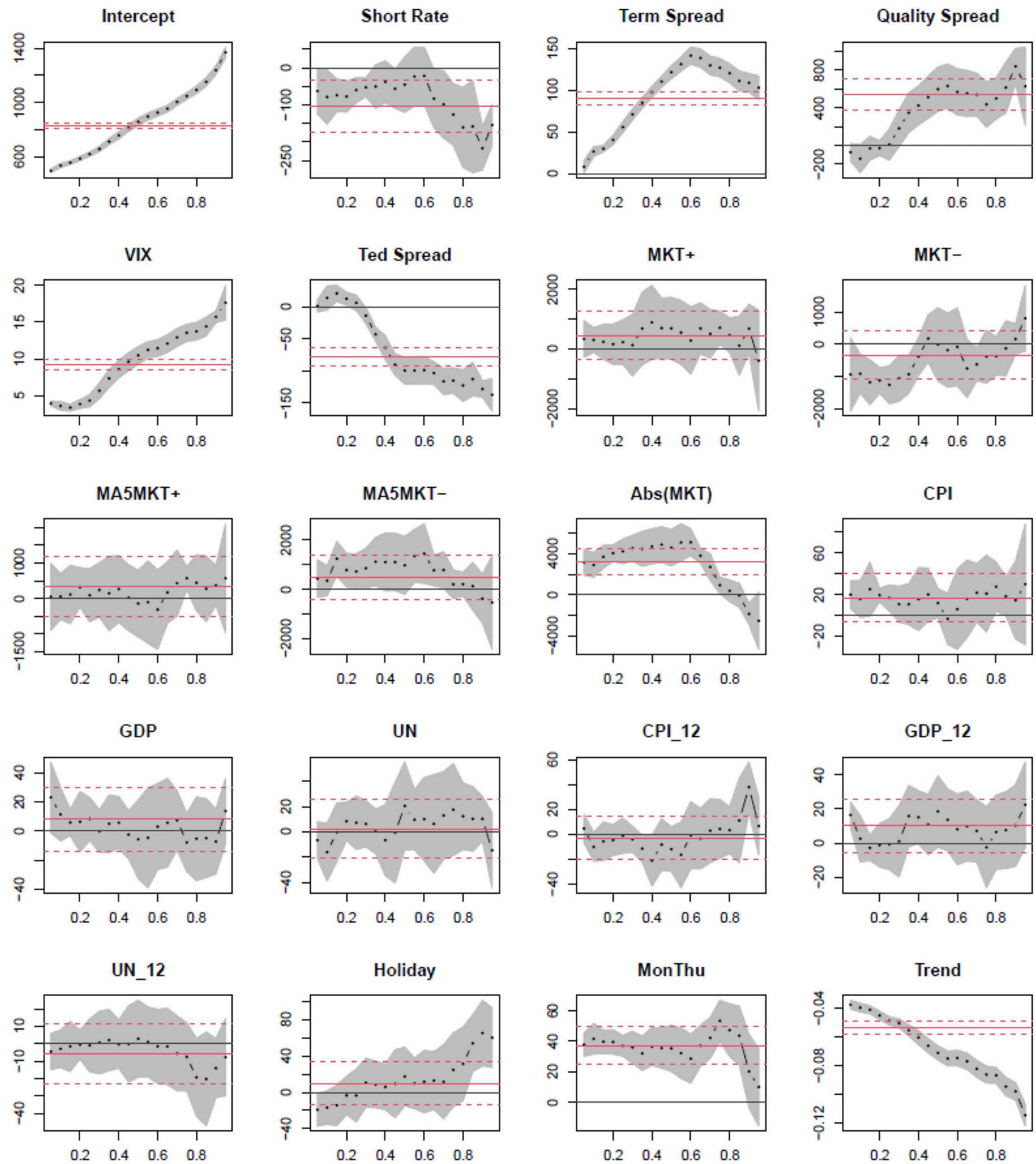
Table A2
Descriptive Statistics and Augmented Dickey-Fuller Unit Root Test of the Explanatory Variables.

	Short Rate	Term Spread	Quality Spread	VIX	Ted Spread	MKT+	MKT-	MA5MKT+	MA5MKT-
Minimun	−0.9500	−1.1800	−0.2000	9.1400	0.0900	0.0000	−0.0895	0.0000	−0.0895
Mean	−0.0002	−0.0006	0.0001	18.5800	0.4407	0.0040	−0.0036	0.0040	−0.0036
Maximum	1.0500	0.9600	0.3800	82.6900	4.5800	0.1135	0.0000	0.1135	0.0000
Std. Dev.	0.0705	0.0914	0.0302	9.1514	0.4306	0.0070	0.0073	0.0070	0.0073
Skewness	−0.8494	0.1476	2.3307	2.7538	3.8449	4.2584	−4.0086	4.2582	−4.0086
Kurtosis	73.6622	35.2109	26.7877	10.0514	20.4660	34.8992	25.1979	34.8963	25.1962
t-ADF	−55.8386***	−2.5338	−34.8835***	−5.5854***	−3.2304***	−31.3328***	−30.4456***	−31.3031***	−30.446***
	Abs(MKT)	CPI	GDP	UN	CPI_12	GDP_12	UN_12	Holiday	MonThu
Minimun	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Mean	0.0075	0.0463	0.0551	0.0456	0.0927	0.1102	0.0912	0.0454	0.7992
Maximum	0.0586	1.0000	1.0000	1.0000	2.0000	2.0000	2.0000	1.0000	1.0000
Std. Dev.	0.0057	0.2102	0.2282	0.2087	0.2908	0.3192	0.2888	0.2082	0.4006
Skewness	3.1199	4.3151	3.8974	4.3539	2.8377	2.6620	2.8678	4.3670	−1.4935
Kurtosis	14.8884	16.6239	13.1929	16.9602	6.1852	5.7695	6.3609	17.0746	0.2307
t-ADF	−6.0927***	−45.7365***	−43.9053***	−45.4971***	−45.7951***	−43.2519***	−45.3803***	−35.2701***	−14.5638***

Note: *** indicates that the null hypothesis is rejected and stationarity at the 1% level is found. VIX is the only variable that is trend-stationary. Term spread is not stationary; the variable has a breakpoint at position 1097. The residuals from the regressions of term spread to a trend until the breakpoint, and after the breakpoint, are stationary.

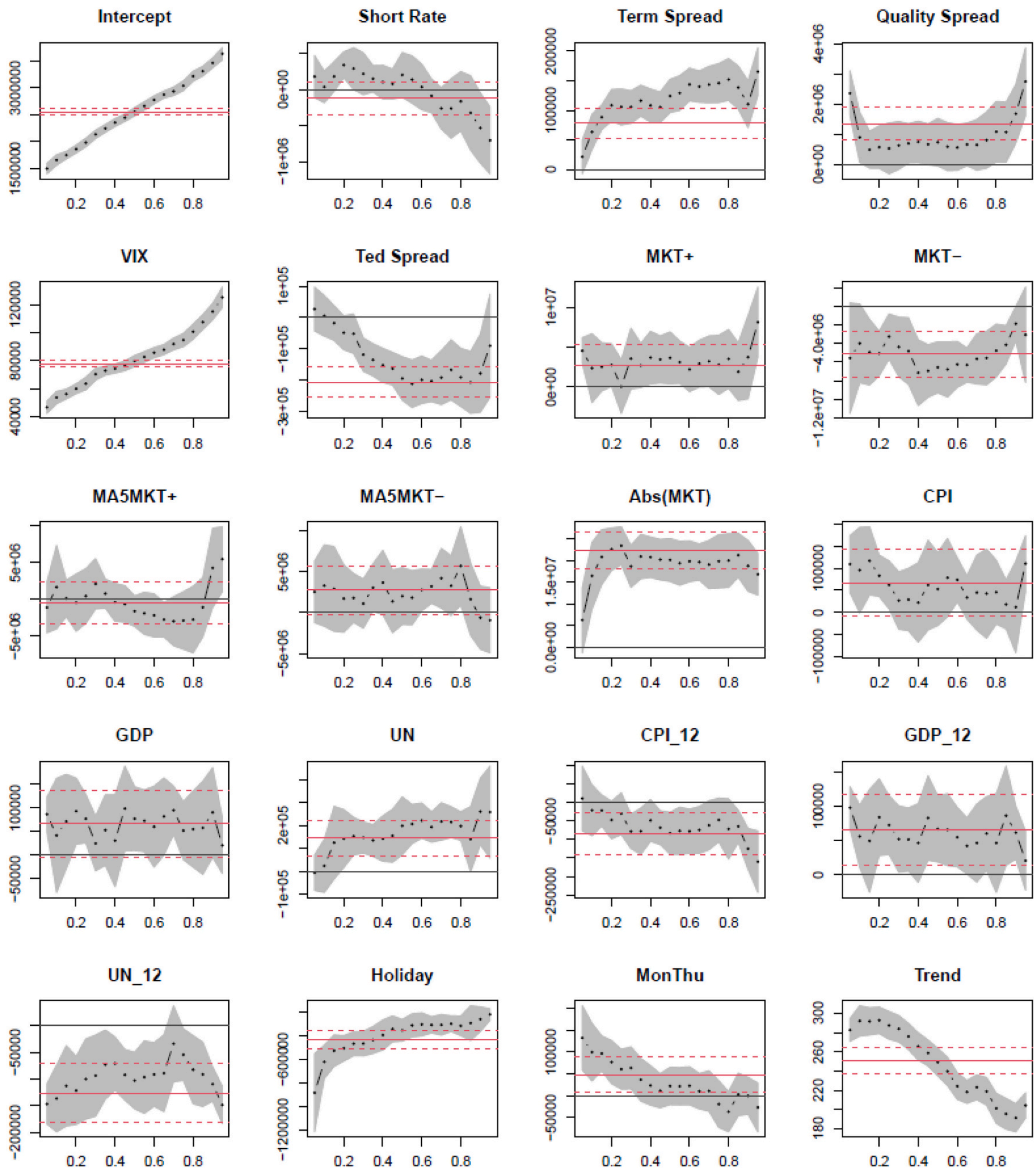
Fig. A1. Effects of the Explanatory Variables on Depth Dimension Liquidity Measures

A. Low Liquidity Indicator – Total Volume Measure



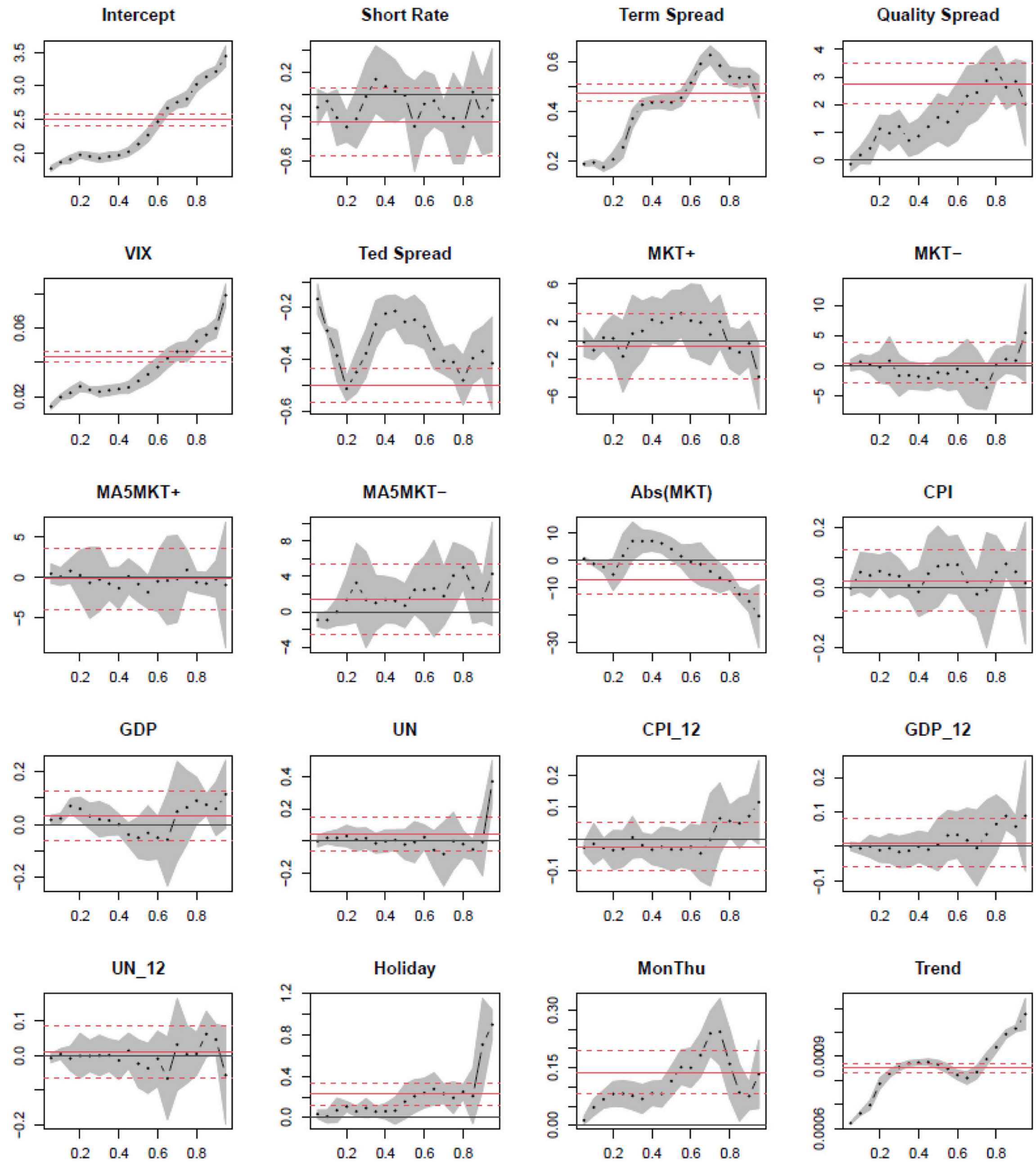
Note: The horizontal axis in each subplot corresponds to a quantile of the liquidity indicator corresponding to a market liquidity state (from the 5th to the 95th percentile, while the vertical axis corresponds to the effect of the variable on the total volume liquidity indicator. The dotted black lines show the varying effects across percentiles, with their respective confidence intervals displayed as shadowed areas. The red solid line is the effect at the median of the measure distribution, which has associated confidence intervals shown as red dotted lines. All the confidence intervals were constructed with 95% confidence.

B. High Liquidity Indicator – Total Volume Measure.



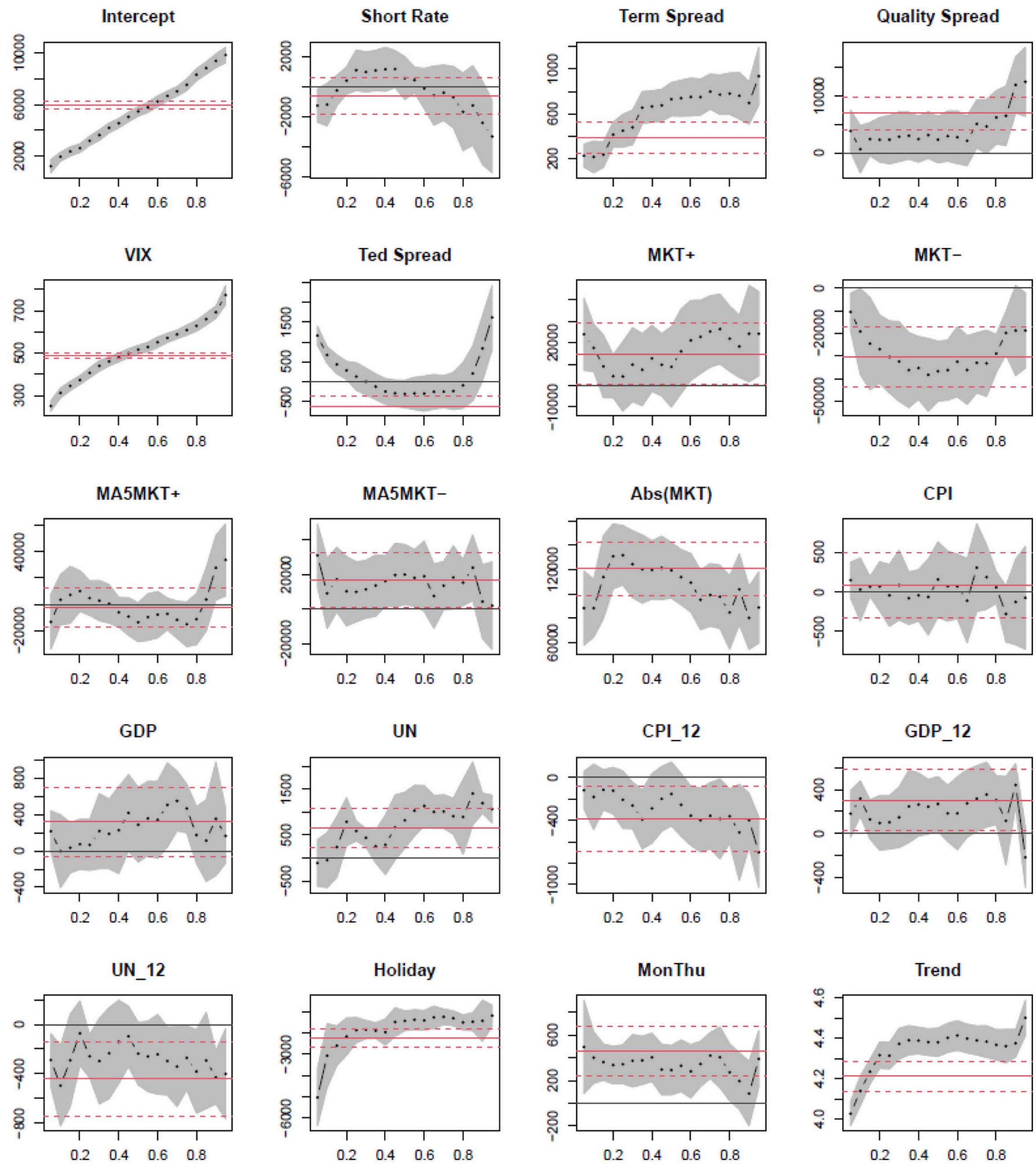
Note: The horizontal axis in each subplot corresponds to a quantile of the liquidity indicator corresponding to a market liquidity state (from the 5th to the 95th percentile, while the vertical axis corresponds to the effect of the variable on the total volume liquidity indicator. The dotted black lines show the varying effects across percentiles, with their respective confidence intervals displayed as shadowed areas. The red solid line is the effect at the median of the measure distribution, which has associated confidence intervals shown as red dotted lines. All the confidence intervals were constructed with 95% confidence.

C. Low Liquidity Indicator – Number of Trades Measure.



Note: The horizontal axis in each subplot corresponds to a quantile of the liquidity indicator corresponding to a market liquidity state (from the 5th to the 95th percentile, while the vertical axis corresponds to the effect of the variable on the number of trades liquidity indicator. The dotted black lines show the varying effects across percentiles, with their respective confidence intervals displayed as shadowed areas. The red solid line is the effect at the median of the measure distribution, which has associated confidence intervals shown as red dotted lines. All the confidence intervals were constructed with 95% confidence.

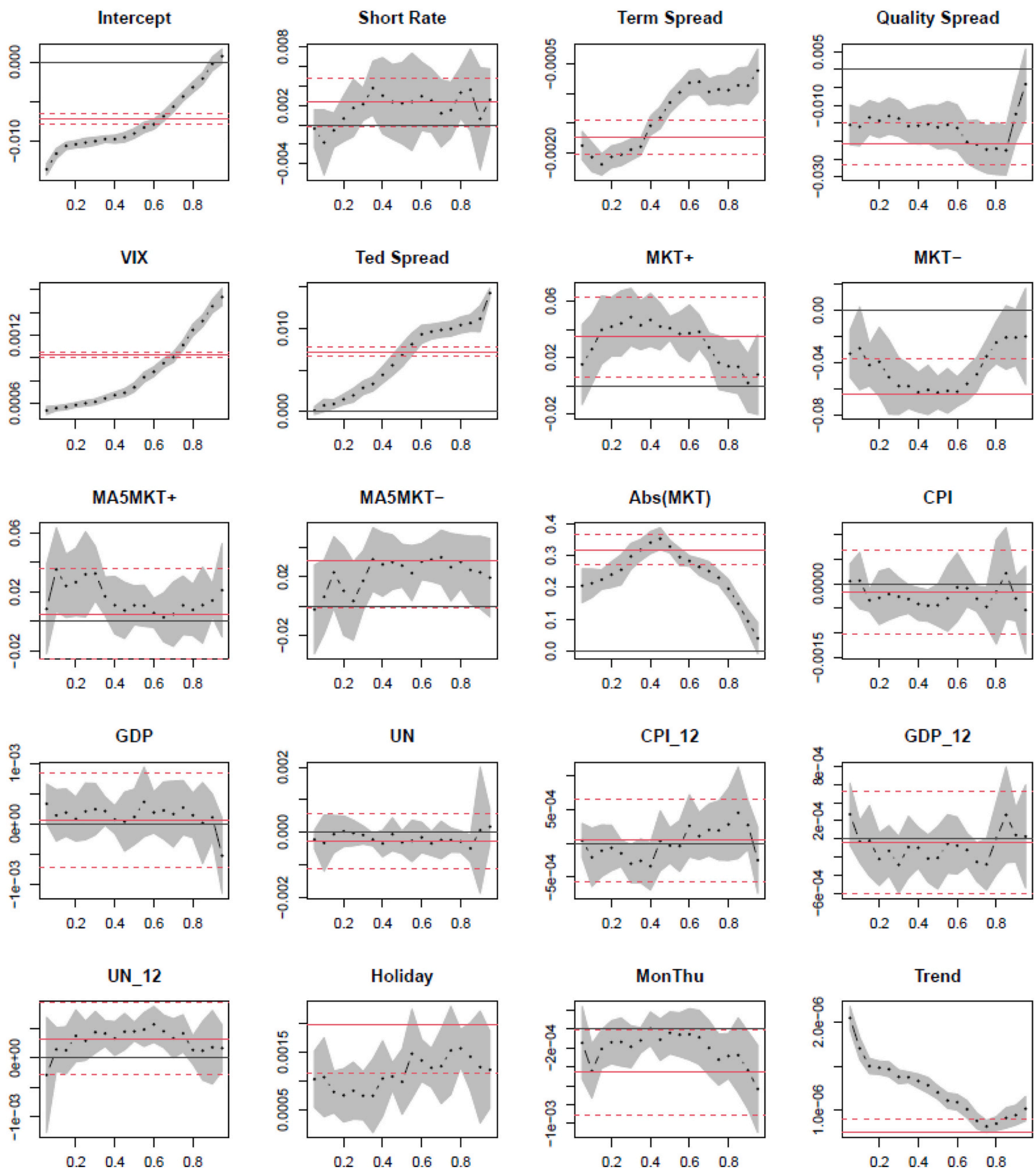
D. High Liquidity Indicator – Number of Trades Measure.



Note: The horizontal axis in each subplot corresponds to a quantile of the liquidity indicator corresponding to a market liquidity state (from the 5th to the 95th percentile, while the vertical axis corresponds to the effect of the variable on the number of trades liquidity indicator. The dotted black lines show the varying effects across percentiles, with their respective confidence intervals displayed as shadowed areas. The red solid line is the effect at the median of the measure distribution, which has associated confidence intervals shown as red dotted lines. All the confidence intervals were constructed with 95% confidence.

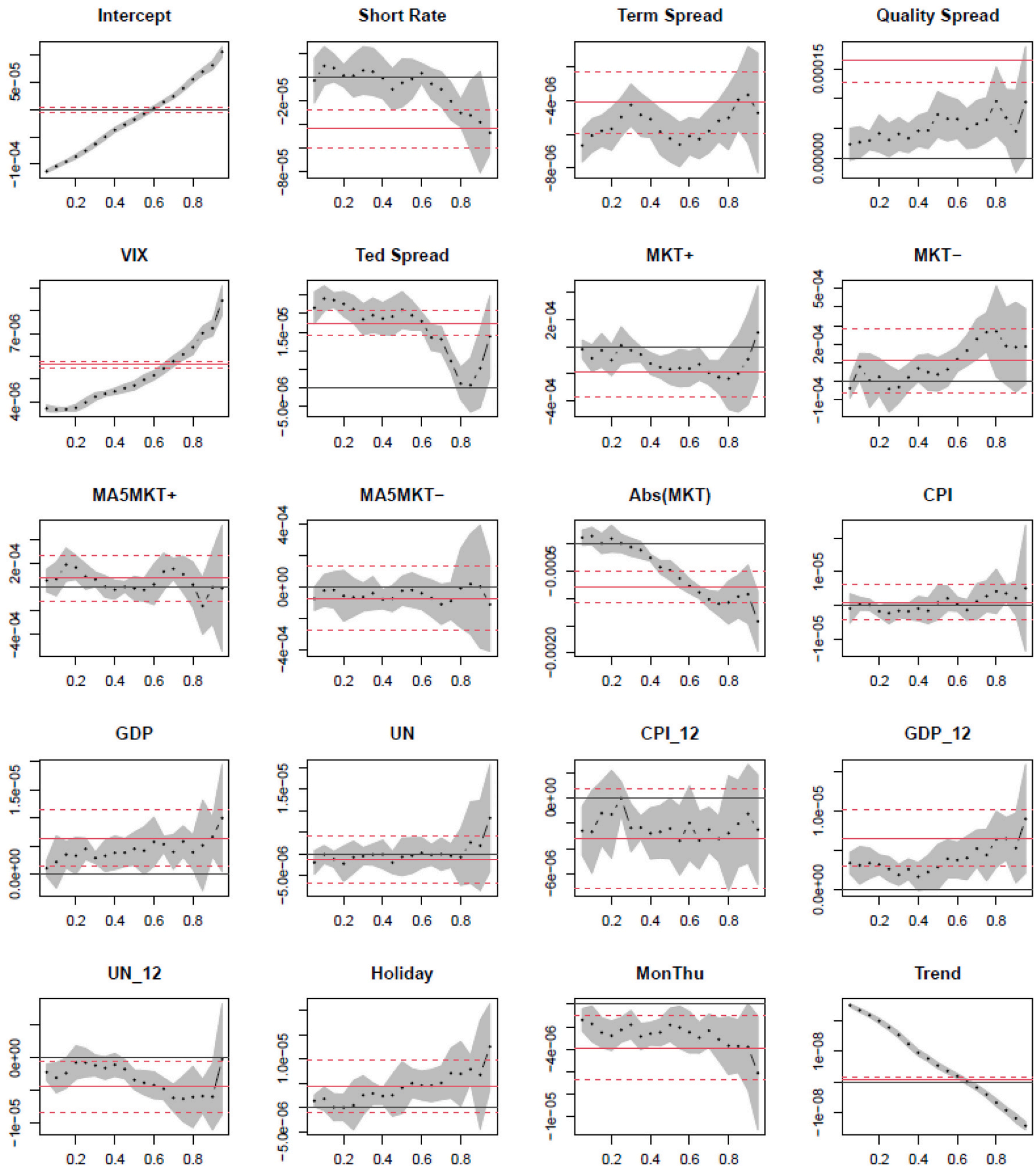
Fig. A2. Effects of the Explanatory Variables on Tightness Dimension Liquidity Measures

A. Low Liquidity Indicator – Effective Spread Measure



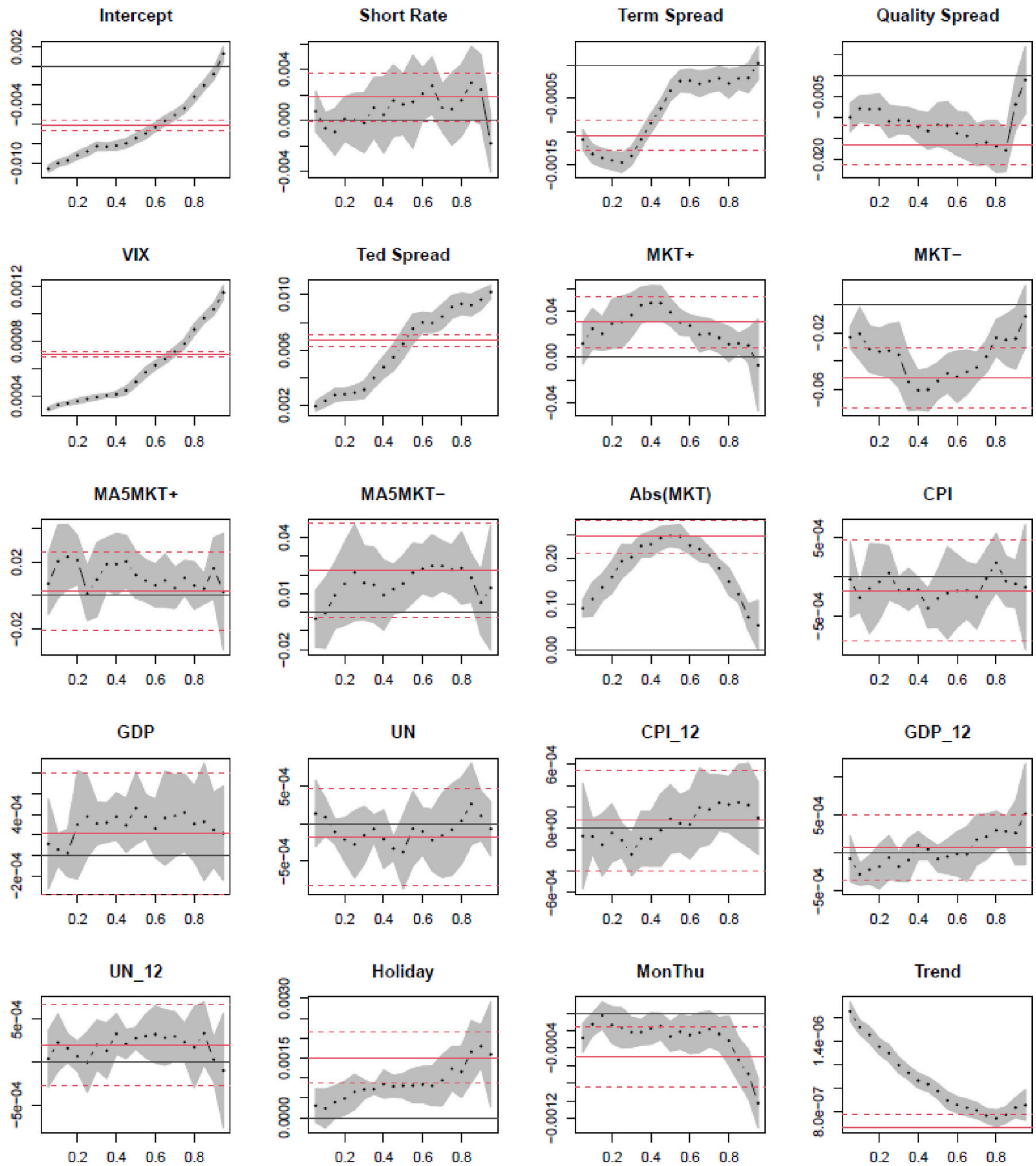
Note: The horizontal axis in each subplot corresponds to a quantile of the liquidity indicator corresponding to a market liquidity state (from the 5th to the 95th percentile, while the vertical axis corresponds to the effect of the variable on the effective spread liquidity indicator. The dotted black lines show the varying effects across percentiles, with their respective confidence intervals displayed as shadowed areas. The red solid line is the effect at the median of the measure distribution, which has associated confidence intervals shown as red dotted lines. All the confidence intervals were constructed with 95% confidence.

B. High Liquidity Indicator – Effective Spread Measure.



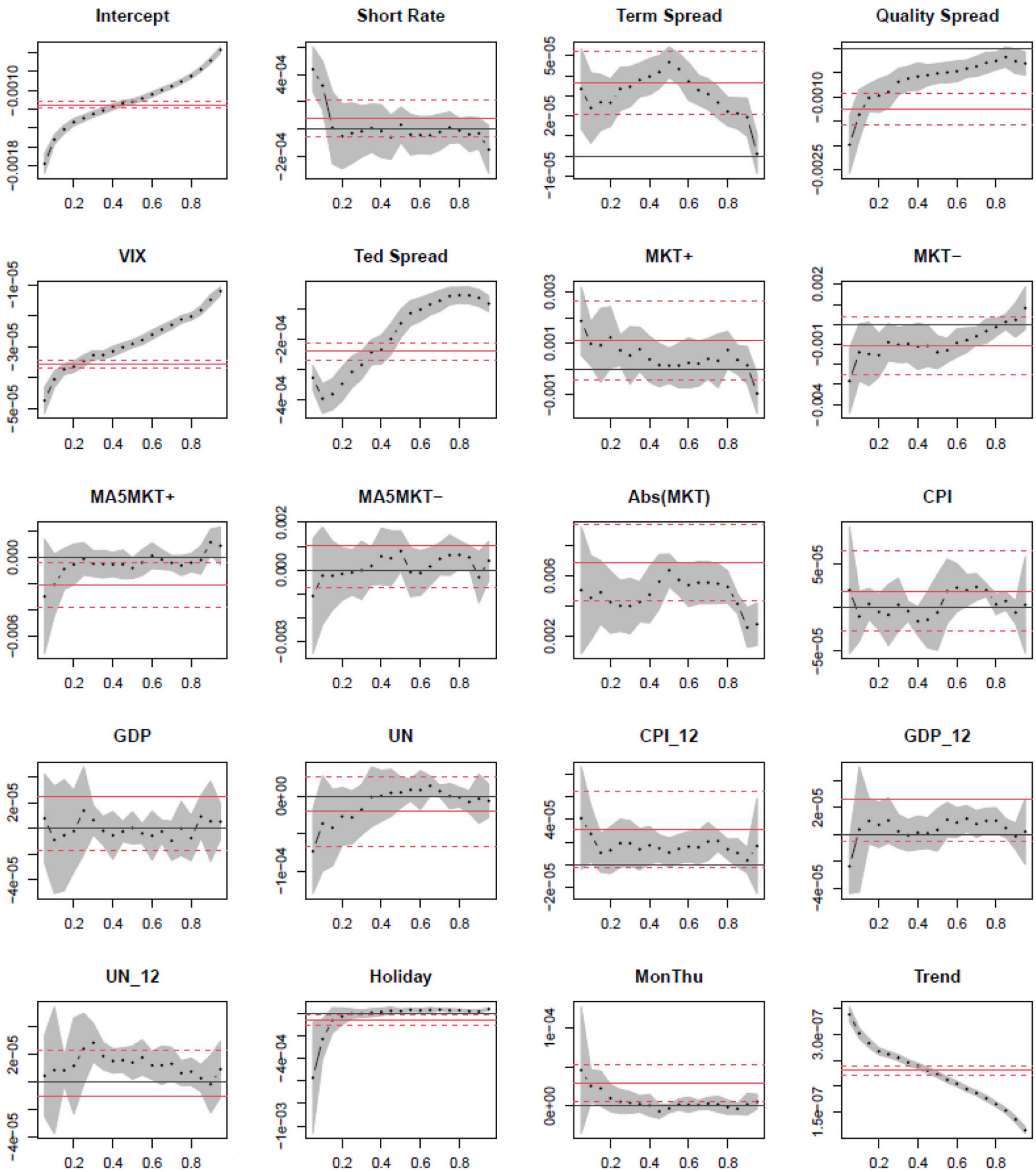
Note: The horizontal axis in each subplot corresponds to a quantile of the liquidity indicator corresponding to a market liquidity state (from the 5th to the 95th percentile, while the vertical axis corresponds to the effect of the variable on the effective spread liquidity indicator. The dotted black lines show the varying effects across percentiles, with their respective confidence intervals displayed as shadowed areas. The red solid line is the effect at the median of the measure distribution, which has associated confidence intervals shown as red dotted lines. All the confidence intervals were constructed with 95% confidence.

C. Low Liquidity Indicator – Realized Spread Measure.



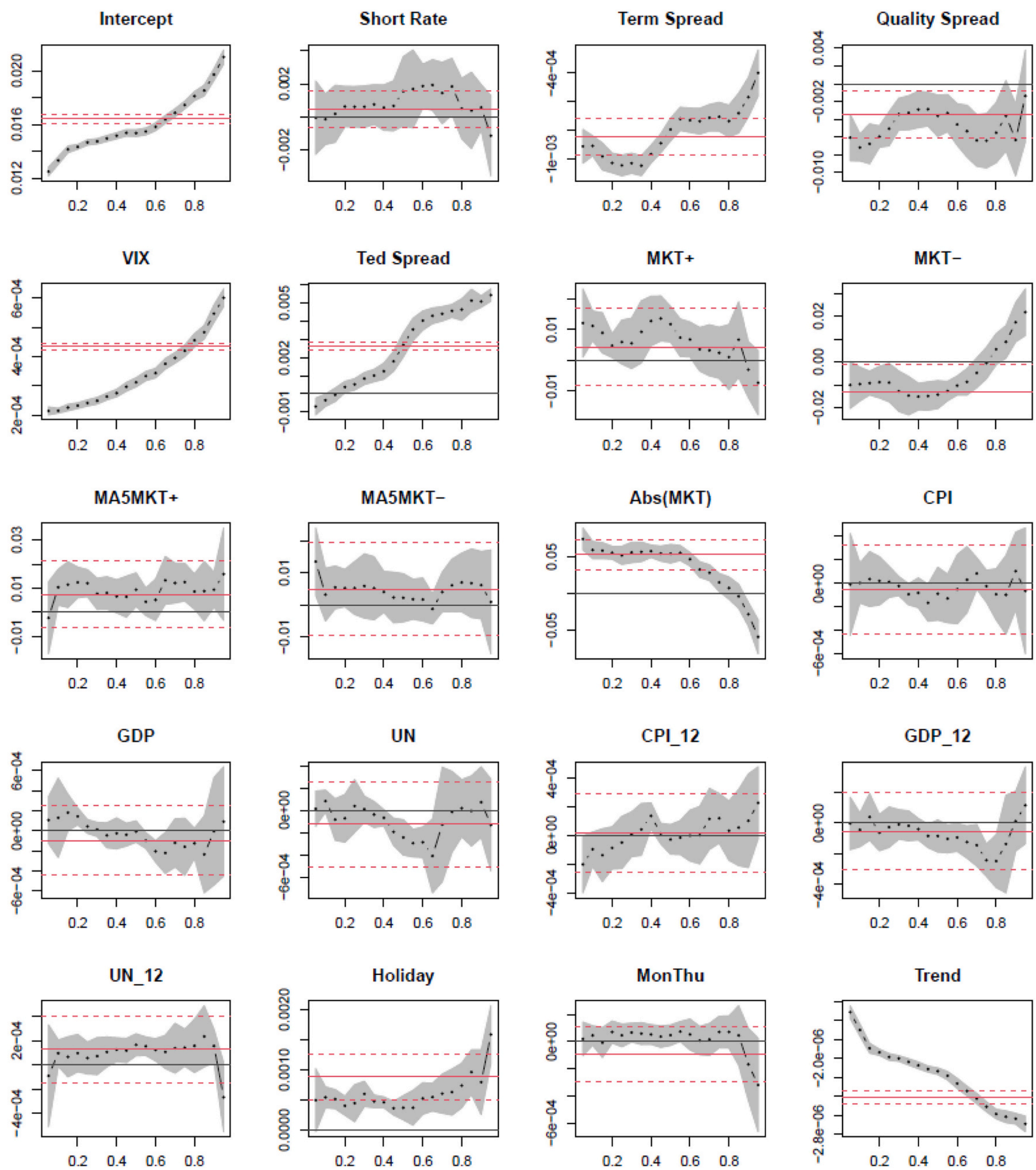
Note: The horizontal axis in each subplot corresponds to a quantile of the liquidity indicator corresponding to a market liquidity state (from the 5th to the 95th percentile, while the vertical axis corresponds to the effect of the variable on the realized spread liquidity indicator. The dotted black lines show the varying effects across percentiles, with their respective confidence intervals displayed as shadowed areas. The red solid line is the effect at the median of the measure distribution, which has associated confidence intervals shown as red dotted lines. All the confidence intervals were constructed with 95% confidence.

D. High Liquidity Indicator – Realized Spread Measure.



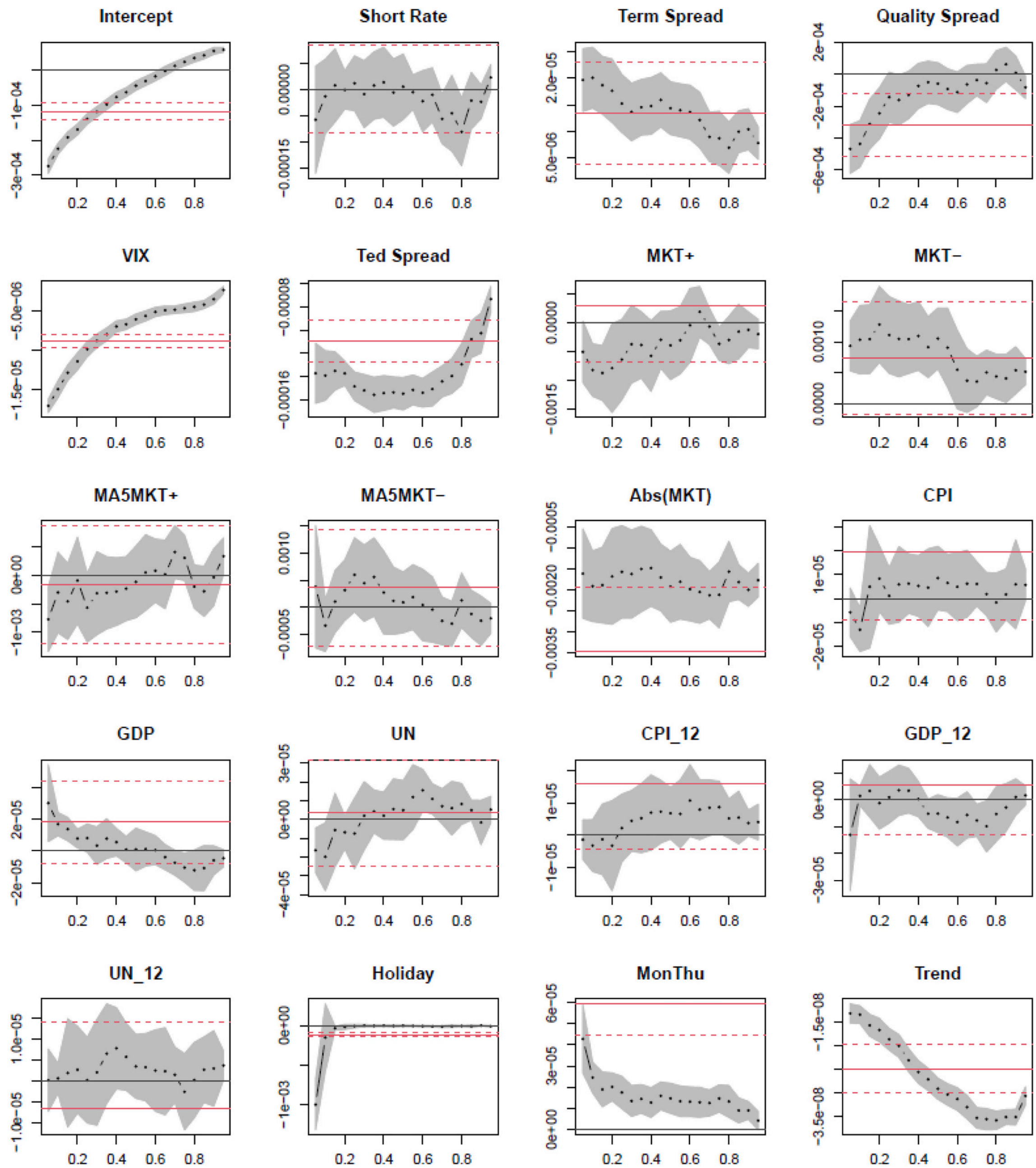
Note: The horizontal axis in each subplot corresponds to a quantile of the liquidity indicator corresponding to a market liquidity state (from the 5th to the 95th percentile, while the vertical axis corresponds to the effect of the variable on the realized spread liquidity indicator. The dotted black lines show the varying effects across percentiles, with their respective confidence intervals displayed as shadowed areas. The red solid line is the effect at the median of the measure distribution, which has associated confidence intervals shown as red dotted lines. All the confidence intervals were constructed with 95% confidence.

E. Low Liquidity Indicator – Price Impact Measure.



Note: The horizontal axis in each subplot corresponds to a quantile of the liquidity indicator corresponding to a market liquidity state (from the 5th to the 95th percentile, while the vertical axis corresponds to the effect of the variable on the price impact liquidity indicator. The dotted black lines show the varying effects across percentiles, with their respective confidence intervals displayed as shadowed areas. The red solid line is the effect at the median of the measure distribution, which has associated confidence intervals shown as red dotted lines. All the confidence intervals were constructed with 95% confidence.

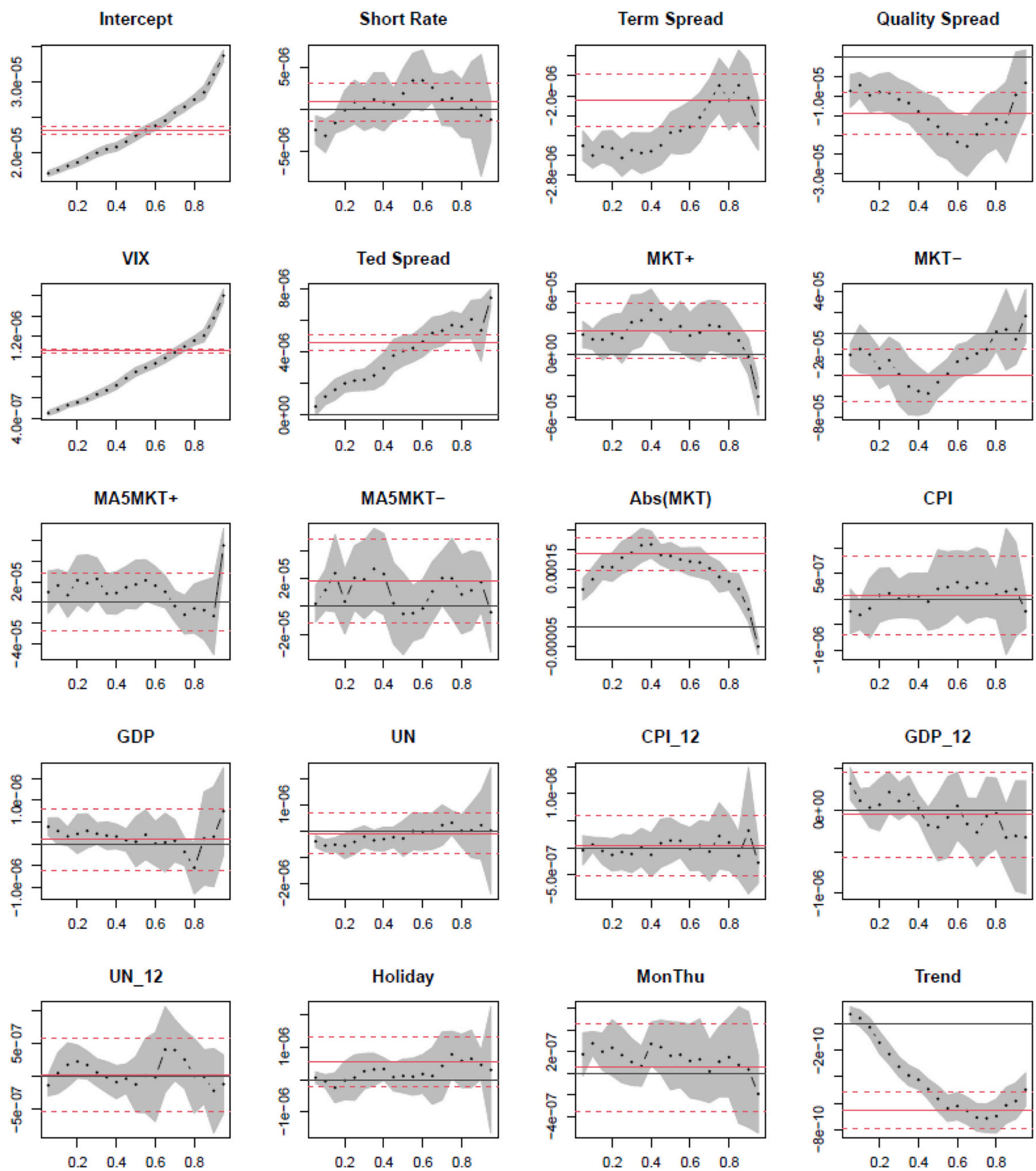
F. High Liquidity Indicator – Price Impact Measure.



Note: The horizontal axis in each subplot corresponds to a quantile of the liquidity indicator corresponding to a market liquidity state (from the 5th to the 95th percentile, while the vertical axis corresponds to the effect of the variable on the price impact liquidity indicator. The dotted black lines show the varying effects across percentiles, with their respective confidence intervals displayed as shadowed areas. The red solid line is the effect at the median of the measure distribution, which has associated confidence intervals shown as red dotted lines. All the confidence intervals were constructed with 95% confidence.

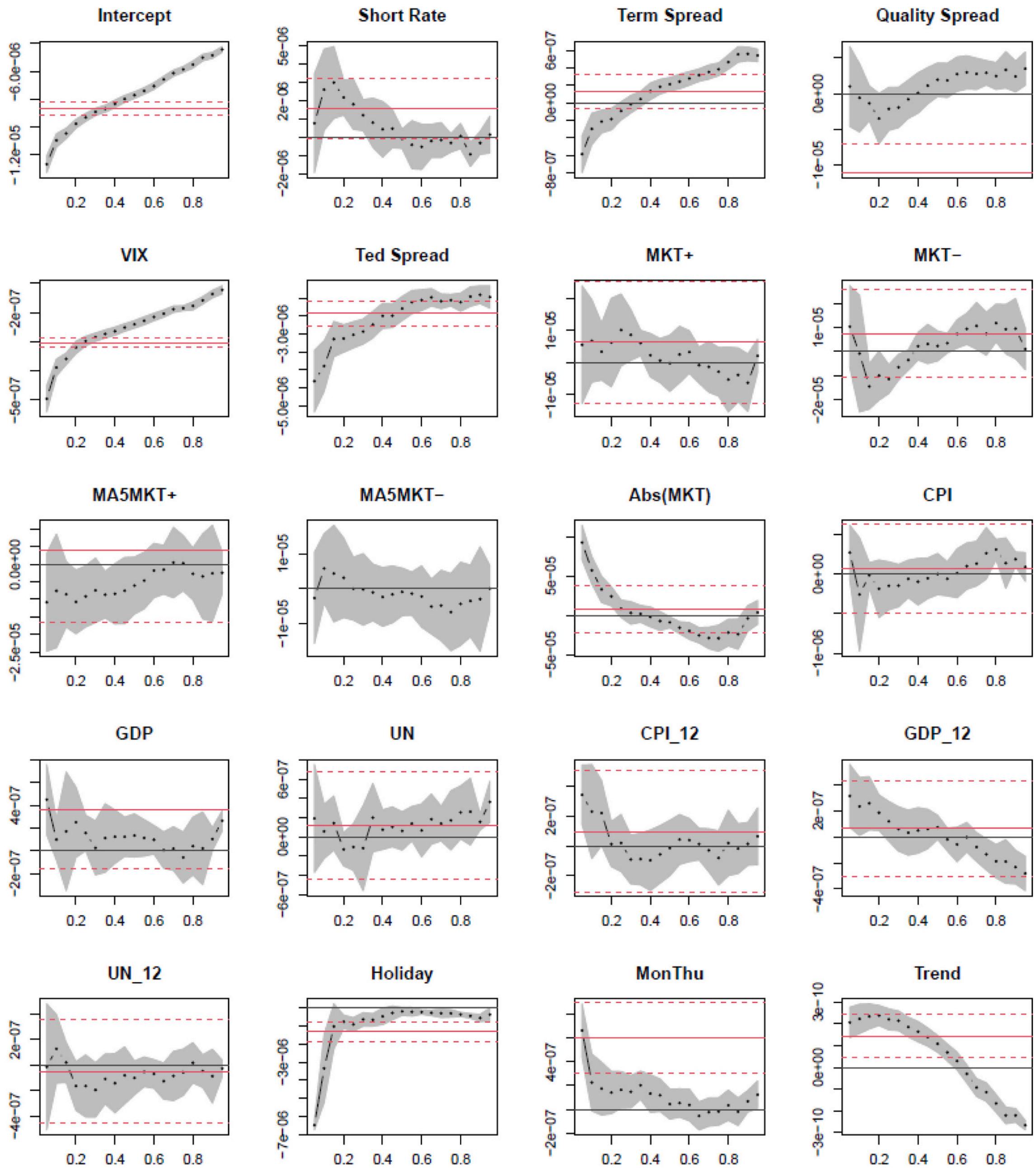
Fig. A3. Effects of the Explanatory Variables on Breadth and Resilience Dimension

A. Low Liquidity Indicator - Lambda



Note: The horizontal axis in each subplot corresponds to a quantile of the illiquidity state of the lambda measure, from the 5th to the 95th percentile, while the vertical axis corresponds to the effect of the variable on the lambda. The dotted black lines show the varying effects across percentiles, with their respective confidence intervals displayed as shadowed areas. The red solid line is the effect at the median of the measure distribution, which has associated confidence intervals shown as red dotted lines. All the confidence intervals were constructed with 95% confidence.

B. High Liquidity Indicator - Lambda.



Note: The horizontal axis in each subplot corresponds to a quantile of the liquidity state of the lambda measure, from the 5th to the 95th percentile, while the vertical axis corresponds to the effect of the variable on the lambda. The dotted black lines show the varying effects across percentiles, with their respective confidence intervals displayed as shadowed areas. The red solid line is the effect at the median of the measure distribution, which has associated confidence intervals shown as red dotted lines. All the confidence intervals were constructed with 95% confidence.

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