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ORIGINAL RESEARCH

Investor attention and cryptocurrency market liquidity: a double-edged sword

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Abstract

This paper explores the double-edged sword effect of investor attention on market liquidity. Based on the analysis on 597 cryptocurrencies from 2014 to 2020, our findings show that static investor attention improves cryptocurrency market liquidity over the next three months by attracting more investors into the market and stimulating buy and sell transactions. By contrast, abnormal attention persistently and negatively affects the liquidity and leads to excessive net buying pressure in the market and a crowded buyers' market, resulting in a sharp deterioration of liquidity. Moreover, these effects intensify during low global economic policy uncertainty periods and for cryptocurrencies with small market capitalization and low idiosyncratic volatility. Overall, our results have important implications for investors, portfolio managers, and policymakers.

Keywords Cryptocurrency markets · Investor attention · Liquidity · Investor trading behavior

JEL Classification G30 · G34

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1 Introduction

Cryptocurrencies have grown popular in recent years, attracting many investors owing to their decentralized structure, anonymity, and low transaction costs. As the number of cryptocurrencies surges, cryptocurrency assets are gradually forming their own "ecosystem", and the dynamics of the cryptocurrency market has gained considerable attention from researchers (Cong & He, 2019; Cong et al., 2021a, 2021b; Grobys & Junttila, 2021; Howell et al., 2020; Liu & Tsyvinski, 2021; Makarov & Schoar, 2020; Sockin & Xiong, 2020).[1] However, existing studies have shown that cryptocurrencies are more regarded as emerging investment assets (Baur et al., 2018; Blau, 2017; Celeste et al., 2020) rather than as a means of payment. Liquidity, which reflects an asset's ability to trade quickly, is crucial for investing in assets. If cryptocurrency assets lack liquidity, it will increase the transaction cost of investors in the market, make the market inefficient, and make the prices easier to be manipulated. As the creation and transaction of cryptocurrencies are entirely supported by blockchain technology, with no official agency to maintain and regulate, an intriguing question arises: will the liquidity of cryptocurrencies be hurt when they suddenly receive a tremendous amount of investor attention? Putting it differently, can the unique transaction mechanism of the cryptocurrency market ensure the stability of its liquidity?

Traditional financial theories usually assume that investors can obtain all relevant information and pay sufficient attention to assets in the process of analysis and reaction. Based on this assumption, the efficient market hypothesis assumes that stock prices fully reflect all relevant information (Fama, 1970). However, behavioral finance theory holds that attention is a scarce cognitive resource due to the limited central cognitive processing capacity of the human brain (Barber & Odean, 2008; Grossman & Stiglitz, 1980; Kahneman & Tversky, 1973). Attention is a necessary prerequisite for recognizing and acquiring information about assets. When faced with numerous alternative assets, investors tend to prioritize assets with more information and higher familiarity. A typical example is the local bias effect (Ackert et al., 2005; Coval & Moskowitz, 1999; Huang et al., 2016; Seasholes & Zhu, 2010), i.e., the tendency of investors to invest in stocks of local firms they know well. Thus, limited investor attention easily influences investors' decision-making behavior (Li & Yu, 2012; Mondria et al., 2010; Peng, 2005; Peng & Xiong, 2006).

Recently, many studies have shown that investor attention has a significant impact on the cryptocurrency markets, including returns (Dastgir et al., 2019; Liu & Tsyvinski, 2021; Philippas et al., 2019; Subramaniam & Chakraborty, 2020; Zhang & Wang, 2020), price discovery (Ibikunle et al., 2020), and volatility (Sabah, 2020; Yao et al., 2021a; Zhang & Wang, 2020). However, little research has focused on the relationship between investor attention and cryptocurrency market liquidity as well as the role of investor attention in different market states. This paper bridges this gap by dividing investor attention into static and abnormal investor attention and exploring the induced impacts on cryptocurrency market liquidity.

Our study extends the literature examining the impact of investor attention on asset liquidity. Merton (1987) proposes the concept of investor cognition and shows that investor attention is related to stock pricing and liquidity. In the traditional stock markets, relevant

[1] For example, Makarov and Schoar (2020) study arbitrage opportunities and price formation in cryptocurrency market. Howell et al. (2020) examine the issuer and initial coin offerings (ICO) characteristics that influence the success of ICOs. Grobys and Junttila (2021) focus on the lottery-like behavior in the cryptocurrency market. Liu and Tsyvinski (2021) explore the influencing factors of cryptocurrency returns. Other studies propose theoretical models applicable to the cryptocurrency market (Cong and He, 2019; Cong et al., 2021a; Cong et al., 2021b; Sockin and Xiong, 2020).

studies indicate that investor attention can enable investors to obtain more effective information, alleviate the problem of information asymmetry, increase investors' trading activity, and thus improve stock liquidity (Aouadi et al., 2013; Bank et al., 2011; Ding & Hou, 2015; Grullon et al., 2004). Specifically, Grullon et al. (2004) employ the firms' advertising expenditure to study the influence of investor attention on stock liquidity. They find that advertising expenditure has a significant positive relationship with the number of investors and stock liquidity. Bank et al. (2011) use the Google search index to measure investor attention and explore the impact of investor attention on stock market liquidity. They find that the increase in Google search leads to an increase in stock trading activities and liquidity, mainly due to the reduction of information asymmetry. In addition, Ding and Hou (2015) indicate that investor attention is a necessary condition for a firm to be recognized. Moreover, investors' attention expands the firm's reputation and significantly improves the stock liquidity. The above research suggests that investors' attention can arouse the interest of potential investors who can collect relevant information to reduce information asymmetry, thus driving them to participate in trading and improve stock liquidity. Due to a large number of cryptocurrencies and the imperfect information transparency, a sustained high level of attention for a particular cryptocurrency over a certain period can attract more investors and lead to more frequent buy and sell activities. Therefore, we expect that static investor attention can enhance the willingness to buy and sell at the same time and thereby improve the liquidity of the cryptocurrency markets.

Previous studies often employ abnormal attention as an alternative proxy of investor attention in the robustness tests (Da et al., 2011; Ding & Hou, 2015; Drake et al., 2012). A consensus is that abnormal attention significantly improves stock liquidity (Adachi et al., 2017; Takeda & Wakao, 2014). However, Cheng et al. (2021a) document that the impact of retail investors' abnormal attention on stock liquidity improvement gradually weakens and even reverses in the long run. For stocks that generate an unusual increase in investor attention, investors buy far more than sell, resulting in mismatched orders and reducing the asset liquidity.

Cryptocurrency markets provide an ideal environment for our study on the double-sided nature of investor attention, due to their specific characteristics such as a larger proportion of retail investors than the stock market,[2] the absence of links to explicit economic fundamentals (Koutmos, 2018; Nadarajah & Chu, 2017), and the speculative trading (Baur et al., 2018; Cheah & Fry, 2015; Corbet et al., 2018; Fry & Cheah, 2016). Moreover, since their trading mechanism is mainly order-driven, the liquidity supply is endogenous and mainly provided by the traders through the submission of orders. Under extreme conditions, investors have no obligation to provide liquidity to keep the market running smoothly. The uniqueness of the cryptocurrency markets' trading mechanism thus makes them more vulnerable to the impact of external events.

The liquidity in the cryptocurrency markets may also worsen due to the crowding effect following an unusual increase in investor attention. On the one hand, the latter drives up investors' net buying behavior because the increased attention helps solve the search problem they face when choosing assets to buy (Barber & Odean, 2008). When a large number of investors gather in the buying direction, the market will become "crowded", and it will be more difficult for the buyer to match the right seller, resulting in increased transaction costs and reduced liquidity. On the other hand, reduced trading frictions can further exacerbate the crowding effect and liquidity deterioration (Afonso, 2011). The increased abnormal attention

[2] Retail investors are more attention-driven than institutional investors (Barber and Odean, 2008), which could result in a stronger and more lasting impact on cryptocurrency liquidity.

can alleviate the search problem and reduce information asymmetry, attracting more buyers to enter the market and leading to a serious imbalance between buying and selling sides.

Our results, based on the analysis of 597 cryptocurrencies over the 2014–2020 period, show that static investor attention significantly improves cryptocurrency liquidity, particularly over the next three months. By contrast, the increased abnormal investor attention significantly reduces cryptocurrency liquidity due to a severe imbalance of buy-sell pressure in the market and the deterioration of cryptocurrency liquidity. This negative impact can last up to 97 days. In addition, we find that static investor attention leads to better improvement of cryptocurrency liquidity for the sample with low economic policy uncertainty, small market capitalization, and low idiosyncratic volatility. As to the negative impact of abnormal investor attention on cryptocurrency liquidity, it is stronger in the sample with high economic policy uncertainty, large market capitalization, and high idiosyncratic volatility.

Overall, the main contributions of this paper are twofold. It first contributes to the literature regarding investor attention's impact on cryptocurrency market liquidity by considering a large dataset of cryptocurrencies.[3] To date, Urquhart (2018) explores the factors leading to the attention of Bitcoin and finds that volatility and trading volume are significant drivers. Lin (2020) finds that past cryptocurrency returns influence future investor attention. Dastgir et al. (2019) document a bi-directional causal relationship between bitcoin attention and returns. Besides, some studies examine the impact of investor attention on the price (Li et al., 2021a; Liu & Tsyvinski, 2021; Philippas et al., 2019; Subramaniam & Chakraborty, 2020), volatility (Sabah, 2020; Shen et al., 2019), and price discovery (Ibikunle et al., 2020) of Bitcoin or a few cryptocurrencies. However, existing studies mainly investigate investor attention's impact on Bitcoin (Choi, 2021; Dastgir et al., 2019; Ibikunle et al., 2020; Philippas et al., 2019; Shen et al., 2019) or major cryptocurrencies (Li et al., 2021a; Subramaniam & Chakraborty, 2020). Among these studies, only Choi (2021) uses intraday data to examine real-time effects of tweets on Bitcoin liquidity and finds evidence that investor attention improves Bitcoin liquidity in real time, and the positive impact decays after approximately an hour.[4]

Second, our study provides unique empirical evidence regarding investor attention's effects on asset liquidity in that investor attention is a double-edged sword for cryptocurrency liquidity. For instance, existing empirical studies on the stock market consistently conclude that both static and abnormal investor attention significantly improve the liquidity in the short term (Adachi et al., 2017; Aouadi et al., 2013; Bank et al., 2011; Ding & Hou, 2015; Ruan & Zhang, 2016). Moreover, the validity of the classic "investor cognition hypothesis" in the stock market suggests that increased attention can enhance the visibility and popularity of firms, expand their investor base, make transactions more active, and thus significantly improve liquidity. However, we find that the abnormal increase in investor attention harms the liquidity of the cryptocurrency market. We argue that this unique finding is associated with cryptocurrency market's special investor structure and specific characteristics. On the one hand, the cryptocurrency market is dominated by retail investors and not supported by

[3] They are selected from an initial dataset of 3,553 cryptocurrencies and account for more than 95% of the total market capitalization of cryptocurrencies. Cryptocurrencies with small market value and low popularity are also included to explore their heterogeneous characteristics in terms of investor attention – liquidity relationship.

[4] Our study differs from Choi (2021) in several aspects. Choi (2021) examines tweets' effects on Bitcoin liquidity, while we use the Google search volume index to measure investor attention, decompose the latter into static attention and abnormal attention, and investigate their effects on the liquidity of a large number of cryptocurrencies. We also bring new empirical insights because the impact of the static and abnormal investor attention on cryptocurrency market liquidity is not alike, which has important implications for trading and regulation policy.

fundamental values, making it more sensitive to investor attention. On the other hand, due to the lack of official market makers and regulatory authorities, cryptocurrency liquidity comes entirely from matching orders submitted by buyers and sellers in the market, and no agency has an obligation to maintain the liquidity and smooth operation of the market. This feature foreshadows the negative impact of abnormal attention on cryptocurrency liquidity. Abnormal attention triggers a large influx of investors, resulting in the accumulation of buy orders and the intensification of net purchase pressure in the market. As a result, it is difficult to quickly match the right seller to complete the transaction and liquidity is poor. Our finding thus confirms the crowding effect in Afonso (2011), broadens a new perspective on the impact of investor attention on liquidity, and has important practical implications. Indeed, they provide a liquidity risk warning for investors and portfolio managers investing in cryptocurrencies, particularly those with large market value and high idiosyncratic volatility during periods of high global economic policy uncertainty. Regulators might, for their part, elaborate policies that help protect investors from losses due to cryptocurrency trading.

The rest of this paper is structured as follows. Section 2 introduces the data source, variable construction, and research design. Section 3 presents our empirical results. Section 4 reports the results of further robustness analysis. Section 5 summarizes the paper and provides potential implications.

2 Data and methodology

2.1 Data source and sample selection

The cryptocurrency data of our sample comes from two datasets. First, we collect the daily trading data of cryptocurrency markets from CoinMarketCap,[5] including opening price, high price, low price, closing price, trading volume and market capitalization. Since CoinMarketCap provides public and comprehensive historical data of daily cryptocurrency transactions, this dataset has been widely used (e.g., Köchling et al., 2019; Liu et al., 2020; Liu & Tsyvinski, 2021; King & Koutmos, 2021).

Second, to analyze the role of investor trading behavior, we employ the U.S. dollar-denominated cryptocurrency 5-min order book and tick-by-tick data from Bitfinex exchange. We obtain this dataset from Kaiko,[6] a private data provider that has been collecting trading information about cryptocurrencies since 2014. In addition, Google search volume index (GSV) measuring investor attention is available from Google Trends.[7]

We exclude cryptocurrencies that have a price history less than a year or have zero Google searches over half of the sample period. Finally, we get 583,003 cryptocurrency-day observations from 597 cryptocurrencies, covering the period from 27 December 2013 to 30 November 2020.[8] These 597 cryptocurrencies account for more than 95% of the total market value of all cryptocurrencies, which can fully reflect the whole picture of the cryptocurrency market. Panel A of Table 12 shows the list of 597 cryptocurrencies.

5 http://www.coinmarketcap.com.

6 Makarov and Schoar (2020), Tiniç et al. (2020) and Akyildirim et al. (2021) also use this database.

7 http://www.google.com/trends.

8 We downloaded daily dataset from April 2013 via coinmarketcap.com. However, since some cryptocurrencies have insufficient data points for our cross-sectional analysis, the earliest date of our sample is 27 December 2013.

It is worth noting that the Kaiko's tick-by-tick data includes the price and the corresponding dollar trading volume for each transaction, a UNIX time stamp in milliseconds and a trade indicator to sign the transaction as buyer- or seller-initiated. An order book snapshots contain all prices and dollar trading volumes of bids and asks within the 5-min period, as well as the price, dollar trading volume and trade indicator of the last transaction. Restricted by the availability of cryptocurrency order book data, we obtained a sample data of only 34 cryptocurrencies from 27 April 2015 to 22 June 2018.[9] The abbreviations of these cryptocurrencies are reported in Panel B of Table 12.

All weekly and monthly variables are averaged from daily variables. In order to mitigate the potential influence of outliers, all continuous variables are winsorized at 1% at both tails.

2.2 Main variables

2.2.1 Investor attention

Phillips and Gorse (2018) employ Wikipedia views as a proxy for investor attention to Bitcoin, Ethereum, Litecoin, and Monero. Shen et al. (2019), Philippas et al. (2019), and Choi (2021) use the number of tweets as a measure for investor attention to Bitcoin. These studies only focus on the measure of investor attention to Bitcoin or a few well-known cryptocurrencies, while our study is based on 597 cryptocurrencies that are actively traded in the cryptocurrency market. Twitter or Wikipedia data can only capture the investor attention of some high-profile cryptocurrencies, which is not sufficient for our study. However, in the cryptocurrency market, there is no unified trading platform that allows investors to trade all cryptocurrency assets freely, so there is no platform that provides scholars with investor attention index calculated by the venue itself. Also, there is a limitation on the number of cryptocurrency social media forums or websites where global investors can discuss and express their views on a particular cryptocurrency. Google search engine, as the largest search engine in the world, provides Google search volume index (GSV) for most cryptocurrencies. Therefore, we follow Urquhart (2018), Ibikunle et al. (2020), Cretarola and Figà-Talamanca (2021), and Liu and Tsyvinski (2021) in employing Google search volume index (GSV) as a primary measure of investor attention on the cryptocurrency market.

Following Da et al. (2011), Ding and Hou (2015), Lin (2020) and (Li et al., 2021a), we use the natural logarithm of Google search volume index (GSV) provided by Google Trends as a proxy for static investor attention. Specifically, we employ the full name of the cryptocurrency as Google search keywords, and then use the web crawler technology to obtain the daily GSV of the corresponding cryptocurrency during the sample period. Meanwhile, in order to capture the abnormal changes of investor attention, we construct the abnormal investor attention index according to Jiang et al. (2019) and Cheng et al. (2021b):

$$D\_ABGSV_{i,t} = \frac{lnAtt_{i,t} - \text{Average}(lnAtt_{i,(t-30,t-1)})}{\text{Average}(lnAtt_{i,(t-30,t-1)})} \tag{1}$$

where $lnAtt_{i,t}$ is daily investor attention to cryptocurrency i on day t, and $Average(lnAtt_{i,(t-30,t-1)})$, the mean of daily investor attention for cryptocurrency i over the past 30 days, denotes the normal or time-trend level of investor attention. Therefore, $D\_ABGSV_{i,t}$ refers to the deviation of investor attention after removing the time trend, namely, abnormal investor attention.

[9] This sample interval is limited because the order book data we purchased from Kaiko is only available from 27 April 2015 to 22 June 2018.

In the robustness test, we construct an alternative measure of abnormal attention ($D\_ABGSV2_{i,t}$) by excluding the time-trend level of investor attention in the past 60 days according to Eq. (1). Moreover, following Da et al. (2011) and Ding and Hou (2015), we calculate the third indicator to measure abnormal attention.

$$D\_ABGSV3_{i,t} = \log(Att_{i,t} + 1) - \log[\mathrm{Med}(Att_{i,t-1}, \ldots, Att_{i,t-60}) + 1] \tag{2}$$

where $Att_{i,t}$ is the daily Google search volume for cryptocurrency i on day t, and $\mathrm{Med}(Att_{i,t-1}, \ldots, Att_{i,t-60})$ is the median of the daily Google search volume for cryptocurrency i over the past 60 days.

Referring to Shen et al. (2019) and Liu and Tsyvinski (2021), we adopt the number of Twitter posts as an alternative proxy for investor attention. We use the web crawler technology to download the daily Twitter post counts of cryptocurrencies from https://bitinfocharts.com/, and finally get the dataset of 230 cryptocurrencies from April 9, 2014 to November 30, 2020. The variable of static attention is the natural logarithm of the daily Twitter post counts plus one, while the construction method of abnormal attention ($D\_ABTweets_{i,t}$) refers to Eq. (1).

2.2.2 Cryptocurrency liquidity

Amihud illiquidity ratio (Amihud, 2002) takes the speed, width and depth of liquidity into consideration and fully reflects the level of three-dimensional composite liquidity, which is also a common proxy for liquidity in the study of cryptocurrency markets (Loi, 2018; Scharnowski, 2021; Tiniç et al. 2020)). Therefore, we also use *Amihud illiquidity ratio* to measure the liquidity of cryptocurrencies, and the specific calculation process is as follows:

$$ILLIQ_{i,t} = \ln\left(\frac{|R_{i,t}|}{Q_{i,t}/10^6} + 1\right) \tag{3}$$

where $R_{i,t}$ and $Q_{i,t}$ are respectively the logarithmic return and dollar trading volume of cryptocurrency i on day t. Considering the great difference of liquidity among different cryptocurrencies, we expand the ratio of the absolute return to the dollar trading volume by 10^6 times, and then take the natural logarithm[10] to get the *Amihud illiquidity ratio*. From the construction of *Amihud illiquidity ratio*, we can intuitively see that cryptocurrencies with poor liquidity need less trading volume to change their prices.

Regarding the robustness tests, we construct alternative liquidity measures. First, we employ the opening and closing prices to calculate Amihud (2002) illiquidity ratio (*lnAmihudOC*) according to Eq. (3)[11]. Second, as the Amihud illiquidity ratio is characterized by extreme value, we take the square root of both *ILLIQ* and *lnAmihudOC* to obtain *adjILLIQ* and *adjlnAmihudOC* according to Hasbrouck (2009) and Asparouhova et al. (2010). Third, the illiquidity index is calculated according to Kyle and Obizhaeva (2016) by the following formula:

$$Kyle_{i,t} = \left[\frac{\overline{\sigma^2_{i,T}(R)}}{\sum_T Q_{i,t}}\right]^{1/3} \tag{4}$$

where T = 30 days, i.e., we use a rolling window of 30 days to calculate *Kyle* for each day. $\overline{\sigma^2_{i,T}(R)}$ is the mean of the squared returns over 30 days, and $\sum_T Q_{i,t}$ is the sum of the dollar

[10] The original illiquidity index calculated by Amihud (2002) has a very high positive skewness (8.708), so we take the natural logarithm following Edmans et al. (2013).

[11] We use the closing price of day t divided by the opening price of day t minus one to get the return of day t.

trading volume. We use the natural logarithm of *Kyle* plus one (*lnKyle*) for regressions, with a larger *lnKyle* implying lower liquidity for cryptocurrencies.

Fourth, we construct three high-frequency liquidity indicators using 5-min order book data: quoted spread, effective spread, and price impact, with the following formulas.

$$QS_{i,t} = \frac{Ask_{i,t} - Bid_{i,t}}{MQ_{i,t}} \tag{5}$$

$$ES_{i,t} = \frac{2 \times \left|Price_{i,t} - MQ_{i,t}\right|}{MQ_{i,t}} \tag{6}$$

$$PI_{i,t} = D_{i,t}^{+} \times \frac{(MQ_{i,t+1} - MQ_{i,t})}{MQ_{i,t}} \tag{7}$$

where $Ask_{i,t}$ and $Bid_{i,t}$ refer to the best ask price and the best bid price for cryptocurrency i at time t, respectively. $MQ_{i,t}$ is the quote midpoint for cryptocurrency i at time t, measured as the mean of $Ask_{i,t}$ and $Bid_{i,t}.Price_{i,t}$ is the price at which cryptocurrency i is traded at time t, and $D_{i,t}^{+}$ is the transaction direction of cryptocurrency i at time t (+ 1 for a buyer-initiated trade and -1 for a seller-initiated trade). Then we average $QS_{i,t}$, $ES_{i,t}$ and $PI_{i,t}$ over the day to get the daily $D\_QS_{i,t+1}$, $D\_ES_{i,t+1}$ and $D\_PI_{i,t+1}$.

2.2.3 Control variables

Following Yao et al. (2019), Ibikunle et al. (2020), Subramaniam and Chakraborty (2020) and Yao et al. (2021b), we add ten control variables that may affect liquidity of the cryptocurrency market into the panel model. Taking the daily variable as an example, the control variables include the market value ($D\_lnSize_{i,t}$), closing price ($D\_lnPrice_{i,t}$), the listing month ($D\_lnAge_{i,t}$), trading volume ($D\_lnVolume_{i,t}$), maximum daily return ($D\_MAX_{i,t}$), reversal ($D\_REVL_{i,t}$), momentum ($D\_MOM_{i,t}$), idiosyncratic volatility ($D\_IVOL_{i,t}$), co-skewness ($D\_Coskew_{i,t}$) and idiosyncratic skewness ($D\_Iskew_{i,t}$) of cryptocurrency i on day t. Specifically, according to Ang et al.(2006), Zhang and Li (2020) and Xing et al. (2021), we define idiosyncratic volatility as the standard deviation of the residuals in Eq. (8). Following Harvey and Siddique (2000), Kumar (2009) and Li et al., (2021b), co-skewness is the component of cryptocurrency i's skewness that is associated with the market portfolio skewness, that is, the estimated $\widehat{\gamma_i}$ from Eq. (9). Idiosyncratic skewness is the rest after eliminating systematic skewness, which is calculated as the skewness of the residual estimated by Eq. (9).

$$R_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{i,t}(R_{m,t} - r_{f,t}) + \varepsilon_{i,t} \tag{8}$$

$$R_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{i,t}(R_{m,t} - r_{f,t}) + \gamma_{i,t}(R_{m,t} - r_{f,t})^2 + \varepsilon_{i,t} \tag{9}$$

where $R_{i,t}$ is the return of cryptocurrency i on day t and $r_{f,t}$ represents the risk-free return on day t, which is measured by US three-month Treasury yield. $R_{m,t}$, the cryptocurrency market return, is the value-weighted average return of all cryptocurrencies traded in the market on day $t.\beta_{i,t}$ denotes the sensitivity of cryptocurrency i to the variance risk of cryptocurrency market, and $\gamma_{i,t}$ indicates the sensitivity of cryptocurrency i to the skewness risk of cryptocurrency market. For each cryptocurrency, we use the within-month daily return data to estimate Eqs. (8) and (9), and the estimates are updated monthly.

2.3 Baseline models

Since static investor attention is primarily aimed to measure the level of investor attention to the cryptocurrency, it has a long-term lasting impact on liquidity of the cryptocurrency market. While abnormal attention focuses on measuring the abnormal change of investor attention, which has a significant impact in the short term. Therefore, this paper explores the impact of static attention on liquidity of the cryptocurrency market on a weekly and monthly basis, and the impact of abnormal attention on a daily basis.

We use a two-way fixed-effect regression model to eliminate the unobserved endogeneity problems associated potentially with individual and time variations of cryptocurrencies. This model also helps explore the internal mechanism of investor attention's impact on cryptocurrency liquidity and conduct conditional analysis considering the heterogeneity among cryptocurrencies. To explore the weekly impact of static investor attention on liquidity of the cryptocurrency market, we construct the following regression model:

$$W\_ILLIQ_{i,t+n} = \lambda_0 + \lambda_1 W\_lnAtt_{i,t} + \sum_k \delta_k W\_Controls_{k,i,t} + \sum Cryptocurrency + \sum Time + \varepsilon_{i,t+n} \tag{10}$$

where $W\_ILLIQ_{i,t+n}$ is the *Amihud illiquidity ratio* of cryptocurrency i in week $t+n$ (n = 0, 1, 2, …), and $W\_lnAtt_{i,t}$ is the static investor attention of cryptocurrency i in week t. $W\_Controls$ is a set of control variables on a weekly basis, including $W\_lnSize_{i,t}$, $W\_lnPrice_{i,t}$, $W\_lnAge_{i,t}$, $W\_lnVolume_{i,t}$, $W\_MAX_{i,t}$, $W\_REVL_{i,t}$, $W\_MOM_{i,t}$, $W\_IVOL_{i,t}$, $W\_Coskew_{i,t}$ and $W\_Iskew_{i,t}$. Table 11 in the "Appendix" provides the definitions and calculation methods of all control variables used in our analysis. $\sum Cryptocurrency$ and $\sum Time$ indicate that cryptocurrency and month fixed effects are controlled to mitigate the impact of the sample's heterogeneity. In addition, the standard errors are clustered at the cryptocurrency level, as proposed by Petersen (2009).

To explore the long-term impact of static investor attention on liquidity of the cryptocurrency market, we construct a similar model on a monthly basis:

$$M\_ILLIQ_{i,t+n} = \lambda_0 + \lambda_1 M\_lnAtt_{i,t} + \sum_k \delta_k M\_Controls_{k,i,t} + \sum Cryptocurrency + \sum Time + \varepsilon_{i,t+n} \tag{11}$$

where $M\_ILLIQ_{i,t+n}$ is the *Amihud illiquidity ratio* of cryptocurrency i in month $t+n$ (n = 0, 1, 2, …), and $M\_lnAtt_{i,t}$ is the static investor attention of cryptocurrency i in month t. $M\_Controls$ is a set of control variables on a monthly basis, which is similar to the control variables used in the weekly model. Cryptocurrency and month fixed effects are controlled for and the standard errors are clustered at the cryptocurrency level. Table 11 gives a detailed description of the definitions and calculation methods of all variables.

On a daily basis, we adopt a two-way fixed effect model to study the impact of abnormal attention on liquidity of the cryptocurrency market.

$$D\_ILLIQ_{i,t+n} = \lambda_0 + \lambda_1 D\_ABGSV_{i,t} + \sum_k \delta_k D\_Controls_{k,i,t} + \sum Cryptocurrency + \sum Time + \varepsilon_{i,t+n} \tag{12}$$

where $D\_ILLIQ_{i,t+n}$ is the *Amihud illiquidity ratio* of cryptocurrency i on day $t+n$ (n = 0, 1, 2, …), and $D\_ABGSV_{i,t}$ is the abnormal investor attention of cryptocurrency i on day

t. $D\_Controls$ is a set of control variables on a daily basis, which is similar to the control variables used in the weekly and monthly model.[12] The definitions and calculation methods of the corresponding variables are explained in the Table 11.

3 Empirical analyses

3.1 Descriptive statistics and correlations

In this section, we conduct descriptive statistics and correlation analysis on all variables used in the weekly panel regression model of static investor attention. The Table 11 provides the definitions of all corresponding variables.

As can be seen from Table 1, the mean and median of static investor attention (*W_lnAtt*) are close to the maximum, showing a left-skewed distribution. The standard deviations of *W_ILLIQ, W_lnSize, W_lnVolume* and *W_Coskew* are respectively 5.494, 5.209, 4.141 and 21.710, indicating that liquidity, market value, trading volume and co-skewness of different cryptocurrencies are significantly different. In the subsequent study on the impact of investor attention on liquidity of the cryptocurrency market, we need to further consider the heterogeneity among different cryptocurrencies.

Table 2 reports the correlation coefficients of all variables in the weekly regression model based on static investor attention. As reported in the table, there is a significant negative correlation between static investor attention (*W_lnAtt*) and the *Amihud illiquidity ratio* of the cryptocurrency market (*W_ILLIQ*) at the level of 1%, indicating that the higher the static investor attention, the better the liquidity of the cryptocurrency market. Moreover, most of the Pearson correlation coefficients among the variables are less than 0.5, and thus there is no serious multicollinearity problem in the regression model.

3.2 Static investor attention

3.2.1 Weekly effect of static investor attention on cryptocurrency markets' liquidity

We first adopt a two-way fixed effect model to investigate the impact and duration of static investor attention on liquidity of the cryptocurrency market on a weekly basis. To save space, Table 3 only shows the regression results of how static investor attention affects liquidity of the cryptocurrency markets for the current and next 6 weeks. The coefficient of $W\_lnAtt_{i,t}$ is significantly negative at the level of 10% in the cases with n = 0, and the coefficients are significantly negative at the level of 5% in the cases with n = 1, 2, …, 6. The above findings suggest that static investor attention can significantly improve current and future liquidity of the cryptocurrency market. For example, the coefficient of $W\_lnAtt_{i,t}$ in column (2) is − 0.112, which indicates that a one standard deviation increase in static investor attention increases the standard deviation of next week's cryptocurrency market liquidity by 1.415% (0.112 × 0.694/5.494) on average. This evidence is consistent with the conclusion of Bank et al. (2011) and Ding and Hou (2015). Moreover, our untabulated weekly regression results show that static investor attention can significantly boost cryptocurrency liquidity for up to 14 weeks. These results suggest that the higher the static investor attention to a cryptocurrency, the more investors will be inclined to trade with the cryptocurrency they know and are familiar

[12] At the same time, we also control the week fixed effect as robustness tests, and the untabulated results show that the conclusions remain unchanged.

Table 1 Descriptive statistics

Variables	Obs	Mean	Std. dev	Max	Median	Min	Skewness	Kurtosis
W_ILLIQ	81199	4.945	5.494	22.893	3.027	0.000	1.186	3.754
W_lnAtt	81199	3.626	0.694	4.508	3.774	1.273	– 1.093	4.000
W_lnSize	81199	14.065	5.209	22.706	15.178	0.000	– 1.522	5.145
W_lnPrice	81199	0.451	1.019	5.733	0.034	0.000	3.346	14.808
W_lnAge	81199	2.714	0.914	4.304	2.890	0.000	– 0.779	3.352
W_lnVolume	81199	11.348	4.141	21.246	11.570	1.451	– 0.112	2.681
W_MAX	81199	0.295	0.291	1.769	0.200	0.025	2.696	11.813
W_REVL	81199	– 0.050	0.474	1.584	– 0.065	– 1.281	0.546	4.593
W_MOM	81199	– 0.250	1.197	3.593	– 0.255	– 3.144	0.478	4.005
W_IVOL	81199	0.104	0.099	0.583	0.072	0.007	2.504	10.496
W_Coskew	81199	– 2.536	21.710	89.461	– 1.765	– 99.802	– 0.258	11.319
W_Iskew	81199	0.358	0.938	3.253	0.294	– 2.298	0.288	4.098

This table reports the descriptive statistics of all variables used in the weekly regression model of static investor attention. The sample data is obtained from CoinMarketCap and Google Trends, including 81,199 cryptocurrency-week observations from 597 cryptocurrencies, covering the period from October 1, 2014 to November 30, 2020. This table presents the mean, standard deviation, maximum, median, mean, minimum, skewness and kurtosis of each variable. The detailed descriptions of all variables are shown in Table 11

Table 2 Pearson correlation coefficients

	W_ILLIQ	*W_lnAtt*	*W_lnSize*	*W_lnPrice*	*W_lnAge*	*W_lnVolume*	*W_MAX*	*W_REVL*	*W_MOM*	*W_IVOL*	*W_Coskew*	*W_Iskew*
W_ILLIQ	1											
W_lnAtt	− 0.037***	1										
W_lnSize	− 0.453***	− 0.021***	1									
W_lnPrice	− 0.360***	− 0.060***	0.274***	1								
W_lnAge	0.009**	0.028***	0.277***	0.088***	1							
W_lnVolume	− 0.823***	− 0.046***	0.511***	0.398***	0.015***	1						
W_MAX	0.492***	0.002	− 0.292***	− 0.141***	− 0.126***	− 0.407***	1					
W_REVL	− 0.069***	0.034***	0.075***	0.081***	0.055***	0.076***	0.019***	1				
W_MOM	− 0.171***	− 0.012***	0.149***	0.179***	0.046***	0.153***	− 0.023***	0.014***	1			
W_IVOL	0.583***	0.006*	− 0.355***	− 0.182***	− 0.153***	− 0.492***	0.929***	0.020***	− 0.032***	1		
W_Coskew	0.030***	− 0.021***	− 0.016***	0.009***	− 0.014***	− 0.038***	− 0.005	− 0.003	− 0.009**	− 0.003	1	
W_Iskew	− 0.147***	− 0.015***	0.119***	0.057***	0.009***	0.168***	0.186***	0.017***	0.026***	− 0.018***	− 0.110***	1

This table reports the Pearson correlations between all variables used in the weekly regression model of static investor attention. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variable definitions are provided in the Table 11

Table 3 The weekly effect of static investor attention on liquidity of the cryptocurrency market

	Dependent variable = $W\_ILLIQ_{i,t+n}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	n = 0	n = 1	n = 2	n = 3	n = 4	n = 5	n = 6
$W\_lnAtt_{i,t}$	− 0.089*	− 0.112**	− 0.112**	− 0.110**	− 0.106**	− 0.108**	− 0.113**
	(0.047)	(0.047)	(0.047)	(0.048)	(0.048)	(0.049)	(0.050)
$W\_lnSize_{i,t}$	− 0.039***	− 0.040***	− 0.040***	− 0.041***	− 0.041***	− 0.040***	− 0.038***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
$W\_lnPrice_{i,t}$	1.246***	1.214***	1.189***	1.171***	1.148***	1.121***	1.100***
	(0.196)	(0.193)	(0.190)	(0.188)	(0.186)	(0.185)	(0.184)
$W\_lnAge_{i,t}$	0.484***	0.481***	0.483***	0.476***	0.469***	0.463***	0.460***
	(0.090)	(0.090)	(0.090)	(0.092)	(0.092)	(0.093)	(0.094)
$W\_lnVolume_{i,t}$	− 0.953***	− 0.881***	− 0.828***	− 0.790***	− 0.754***	− 0.726***	− 0.701***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.030)	(0.030)	(0.031)
$W\_MAX_{i,t}$	− 1.126***	− 1.463***	− 1.640***	− 1.643***	− 1.621***	− 1.438***	− 1.429***
	(0.208)	(0.220)	(0.218)	(0.232)	(0.241)	(0.236)	(0.236)
$W\_REVL_{i,t}$	− 0.284***	− 0.295***	− 0.289***	− 0.280***	− 0.286***	− 0.293***	− 0.288***
	(0.034)	(0.035)	(0.037)	(0.041)	(0.043)	(0.044)	(0.045)
$W\_MOM_{i,t}$	− 0.246***	− 0.259***	− 0.274***	− 0.281***	− 0.281***	− 0.285***	− 0.285***
	(0.028)	(0.029)	(0.030)	(0.031)	(0.032)	(0.032)	(0.033)

Table 3 (continued)

	Dependent variable = $W\_ILLIQ_{i,t+n}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	n = 0	n = 1	n = 2	n = 3	n = 4	n = 5	n = 6
$W\_IVOL_{i,t}$	11.636***	12.170***	11.985***	11.281***	10.595***	9.540***	9.214***
	(0.797)	(0.841)	(0.855)	(0.902)	(0.928)	(0.920)	(0.918)
$W\_Coskew_{i,t}$	0.001*	0.001*	0.001	0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$W\_Iskew_{i,t}$	− 0.004	− 0.028*	− 0.048***	− 0.058***	− 0.063***	− 0.069***	− 0.056***
	(0.016)	(0.016)	(0.016)	(0.017)	(0.018)	(0.018)	(0.018)
Constant	14.732	14.870	14.576	13.784	13.798	13.502	13.222
	(0.822)	(0.792)	(0.793)	(0.832)	(0.852)	(0.781)	(0.812)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crypt FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	81,199	79,225	78,516	77,879	77,246	76,625	76,015
Adjusted R^2	0.690	0.655	0.618	0.587	0.561	0.539	0.523

This table reports the regression results of how static investor attention affects liquidity of the cryptocurrency market for the current and next 6 weeks. The specific model is constructed as follows:

$W\_ILLIQ_{i,t+n} = \lambda_0 + \lambda_1 W\_lnAtt_{i,t} + \sum_k \delta_k W\_Controls_{k,i,t} + \sum Cryptocurrency + \sum Time + \varepsilon_{i,t+n}$

where $W\_ILLIQ_{i,t+n}$ is the *Amihud illiquidity ratio* of cryptocurrency *i* in week $t+n$ (n = 0, 1, 2, …), and $W\_lnAtt_{i,t}$ is the static investor attention of cryptocurrency *i* in week *t*. $W\_Controls$ is a set of control variables on a weekly basis, including $W\_lnSize_{i,t}$, $W\_lnPrice_{i,t}$, $W\_lnAge_{i,t}$, $W\_lnVolume_{i,t}$, $W\_MAX_{i,t}$, $W\_REVL_{i,t}$, $W\_MOM_{i,t}$, $W\_IVOL_{i,t}$, $W\_Coskew_{i,t}$ and $W\_Iskew_{i,t}$. Cryptocurrency and month fixed effects are controlled, and all variable definitions are shown in Table 11. Standard errors are clustered at the cryptocurrency level and robust standard errors are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

with, resulting in a surge of attention-driven trading behavior, which significantly improves the liquidity of the cryptocurrency markets.

We adopt alternative measures of cryptocurrency liquidity and investor attention to conduct robustness tests, respectively. The regression results, shown in Table 13, indicate that replacing measures of cryptocurrency liquidity and static attention has no impact on our findings, i.e., static attention significantly improves cryptocurrency market liquidity.

3.2.2 The monthly effect of static investor attention on liquidity of the cryptocurrency market

In order to further explore the long-term impact of static investor attention on liquidity of the cryptocurrency markets, we then conduct the empirical analysis on a monthly basis. Similarly, using the two-way fixed effect model, we estimate Eq. (11) and present the regression results in the cases for n = 0, 1, 2, …, 6. As shown in Table 4, the coefficients of $M\_lnAtt_{i,t}$ are significantly negative in the cases where n = 0, 1, 2, 3, 4, while they are no longer significant with n > 4. Therefore, we can see that on a monthly basis, static investor attention also significantly improves the liquidity of the cryptocurrency markets, and this positive effect can last for the next three months. For instance, the coefficient of $M\_lnAtt_{i,t}$ in Column (2) is − 0.204, suggesting that a one standard deviation increase in the monthly static attention is associated with a 2.369% (0.204 × 0.636/5.476) increase in the standard deviation of cryptocurrency liquidity in the following month.[13] This result is in line with the conclusions of weekly regression, verifying the positive effect of static investor attention on the liquidity of the cryptocurrency market and the duration of the impact.

Similar to the weekly robustness test, we adopt *M_lnAmihudOC*, *M_lnKyle, M_adjILLIQ* and *M_adjlnAmihudOC* as alternative measures of cryptocurrency liquidity and use *M_lnTweets* to replace the measure of monthly static attention. All of our monthly results remain robust, according to Table 14.

3.2.3 Channel analysis of static investor attention on a weekly basis

Existing studies suggest that the price dynamics of cryptocurrencies are mainly driven by investors' trading behavior (Baek & Elbeck, 2015; Li et al., 2021a). We thus attempt to identify the role of investor trading behavior in static investor attention's improving effect on liquidity of the cryptocurrency markets. Following Kim et al. (2016) and Chen et al. (2018), we adopt the two-step regression method to conduct the channel tests. Specifically, we first examine the impact of static investor attention on the overall buying and selling activity of investors in the cryptocurrency markets. Then, we test whether the overall buying and selling behavior of investors will affect the liquidity of the cryptocurrency markets. The corresponding model is constructed as follows:

$$W\_lnBuySum_{i,t} or W\_lnSellSum_{i,t} = \lambda_0 + \lambda_1 W\_lnAtt_{i,t} + \sum_k \delta_k W\_Controls_{k,i,t} + \sum Cryptocurrency + \sum Time + \varepsilon_{i,t} \quad (13)$$

$$W\_ILLIQ_{i,t+1} = \lambda_0 + \lambda_1 W\_lnBuySum_{i,t} or W\_lnSellSum_{i,t} + \sum_k \delta_k W\_Controls_{k,i,t}$$

[13] The standard deviations of $M\_lnAtt_{i,t}$ and $M\_ILLIQ_{i,t}$ is 0.636 and 5.476, respectively.

Table 4 The monthly effect of static investor attention on liquidity of the cryptocurrency market

	Dependent variable = $M\_ILLIQ_{i,t+n}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	n = 0	n = 1	n = 2	n = 3	n = 4	n = 5	n = 6
$M\_lnAtt_{i,t}$	− 0.178***	− 0.204***	− 0.174**	− 0.191**	− 0.147*	− 0.141	− 0.155
	(0.068)	(0.069)	(0.073)	(0.078)	(0.086)	(0.095)	(0.094)
$M\_lnSize_{i,t}$	− 0.047***	− 0.044***	− 0.041***	− 0.039***	− 0.027**	− 0.020	− 0.012
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)
$M\_lnPrice_{i,t}$	1.247***	1.182***	1.066***	0.985***	0.891***	0.798***	0.721***
	(0.207)	(0.206)	(0.199)	(0.194)	(0.188)	(0.183)	(0.178)
$M\_lnAge_{i,t}$	0.456***	0.403***	0.437***	0.451***	0.440***	0.390***	0.376***
	(0.083)	(0.086)	(0.090)	(0.094)	(0.098)	(0.100)	(0.102)
$M\_lnVolume_{i,t}$	− 0.978***	− 0.876***	− 0.726***	− 0.618***	− 0.518***	− 0.444***	− 0.383***
	(0.036)	(0.038)	(0.037)	(0.038)	(0.038)	(0.040)	(0.041)
$M\_MAX_{i,t}$	− 0.662***	− 1.346***	− 1.163***	− 1.055***	− 0.859***	− 1.095***	− 1.064***
	(0.212)	(0.260)	(0.261)	(0.271)	(0.285)	(0.288)	(0.301)
$M\_REVL_{i,t}$	− 0.284***	− 0.222***	− 0.255***	− 0.231***	− 0.269***	− 0.265***	− 0.198***
	(0.039)	(0.049)	(0.050)	(0.054)	(0.058)	(0.062)	(0.062)
$M\_MOM_{i,t}$	− 0.256***	− 0.254***	− 0.272***	− 0.268***	− 0.249***	− 0.203***	− 0.176***
	(0.031)	(0.035)	(0.036)	(0.039)	(0.041)	(0.044)	(0.044)
$M\_IVOL_{i,t}$	12.581***	10.519***	8.665***	7.674***	6.668***	6.793***	5.923***
	(0.820)	(0.995)	(1.004)	(1.056)	(1.118)	(1.167)	(1.204)
$M\_Coskew_{i,t}$	0.001	− 0.001	− 0.000	− 0.001	− 0.001	− 0.000	− 0.001

Table 4 (continued)

	Dependent variable = $M\_ILLIQ_{i,t+n}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	n = 0	n = 1	n = 2	n = 3	n = 4	n = 5	n = 6
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$M\_Iskew_{i,t}$	− 0.006	− 0.038**	− 0.031	− 0.025	− 0.029	− 0.009	− 0.000
	(0.017)	(0.019)	(0.020)	(0.018)	(0.023)	(0.024)	(0.024)
Constant	16.152	15.442	14.852	14.555	13.146	12.672	12.395
	(0.868)	(0.831)	(0.948)	(1.020)	(1.031)	(1.071)	(1.175)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crypt FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,176	17,242	16,626	16,033	15,446	14,877	14,307
Adjusted R^2	0.725	0.633	0.550	0.499	0.456	0.426	0.403

This table reports the coefficients of the regression as follows:

$$M\_ILLIQ_{i,t+n} = \lambda_0 + \lambda_1 M\_lnAtt_{i,t} + \sum_k \delta_k M\_Controls_{k,i,t} + \sum Cryptocurrency + \sum Time + \varepsilon_{i,t+n}$$

where $M\_ILLIQ_{i,t+n}$ is the *Amihud illiquidity ratio* of cryptocurrency *i* in month $t + n$ (n = 0, 1, 2, …), and $M\_lnAtt_{i,t}$ is the static investor attention of cryptocurrency *i* in month *t*. $M\_Controls$ is a set of control variables on a monthly basis, which is similar to the control variables used in the weekly model. All variable definitions are shown in Table 11. Cryptocurrency and month fixed effects are controlled for and the standard errors are adjusted at the cryptocurrency level. Robust standard errors are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

$$+\sum Cryptocurrency + \sum Time + \varepsilon_{i,t+1} \quad (14)$$

where $W\_lnBuySum_{i,t}$ and $W\_lnSellSum_{i,t}$ are respectively the total amount of buyer- and seller-initiated trade of cryptocurrency i in week t. $\sum Cryptocurrency$ and $\sum Time$ indicate that cryptocurrency and month fixed effects are controlled for. All variable definitions are shown in Table 11.

The coefficients of $W\_lnAtt_{i,t}$ in columns (1) and (3) of Table 5 are both significantly positive at the 1% level, which implies that static investor attention increases the overall buying and selling activities of investors simultaneously. While the coefficients of $W\_lnBuySum_{i,t}$ in column (2) and $W\_lnSellSum_{i,t}$ in column (4) are both significantly negative at the 1% level, indicating that investors' buying and selling activities enhance the liquidity of the cryptocurrency markets. Intuitively, increased static attention will imply that more investors are interested in cryptocurrency assets and actively search for relevant information, improving their visibility and popularity, further attracting more investors to participate in the market, and expanding the investor base (Ding & Hou, 2015; Grullon et al., 2004). Therefore, static investor attention increases both the buying and selling activity of investors at the same time, which makes investors in the cryptocurrency market trade more actively, thus significantly improving the liquidity of cryptocurrency market.

3.3 Abnormal investor attention

3.3.1 The daily effect of abnormal investor attention on liquidity of the cryptocurrency market

Next, we analyze the impact of abnormal investor attention on liquidity of the cryptocurrency markets. Considering that the abnormal changes in investor attention may have a sudden effect on the liquidity of cryptocurrency markets, we use daily data for regression estimation. The specific regression model is shown in Eq. (12), and we only report the regression results in the cases with n = 0, 1, 2, …, 6 in Table 6. Evidence shows that the coefficients of $D\_ABGSV_{i,t}$ are significantly positive at the level of 1% and 5%, that is, the higher the abnormal investor attention is, the worse the liquidity of the cryptocurrency markets. For example, the coefficient of $D\_ABGSV_{i,t}$ in column (2) is 0.033, which shows that a one standard deviation increase in daily abnormal attention leads to a 0.367% (0.033 × 0.578/5.204) decrease in the standard deviation of next day's cryptocurrency liquidity on average.[14] Moreover, the abnormal investor attention has a stronger weakening effect on the liquidity of cryptocurrencies on the first day with increased attention. The above results preliminarily confirm our previous conjecture that the abnormal increase of investor attention leads to the deterioration of cryptocurrencies' liquidity.

To further explore how long the abnormal investor attention can affect the liquidity of the cryptocurrency market, Table 7 reports the regression results in the cases with n = 10, 20, 30, …, 110. It can be seen that the coefficients of $D\_ABGSV_{i,t}$ are significantly positive in the cases with n ≤ 90, implying that the negative impact of abnormal attention on liquidity of the cryptocurrency market has a certain persistence. In the unreported regression results, we find that the negative impact of abnormal attention on liquidity of the cryptocurrency market persists until the 97th day, and then the impact is no longer robust and significant. The negative impact of abnormal attention on liquidity of the cryptocurrency market lasts much longer than we expected, which also shows the immature characteristics of cryptocurrency markets

[14] The standard deviation of $D\_ABGSV_{i,t}$ is 0.578, and the standard deviation of $D\_ILLIQ_{i,t}$ is 5.204.

Table 5 Channel analysis of static investor attention on a weekly basis

Dependent variables =	$W\_lnBuySum_{i,t}$ (1)	$W\_ILLIQ_{i,t+1}$ (2)	$W\_lnSellSum_{i,t}$ (3)	$W\_ILLIQ_{i,t+1}$ (4)
$W\_lnAtt_{i,t}$	0.149***		0.129***	
	(0.053)		(0.049)	
$W\_lnBuySum_{i,t}$		− 0.033***		
		(0.006)		
$W\_lnSellSum_{i,t}$				− 0.034***
				(0.006)
$W\_lnSize_{i,t}$	0.026*	− 0.001	0.021	− 0.001
	(0.014)	(0.002)	(0.013)	(0.002)
$W\_lnPrice_{i,t}$	1.135***	0.030**	1.088***	0.030**
	(0.077)	(0.015)	(0.072)	(0.015)
$W\_lnAge_{i,t}$	0.021	0.047***	− 0.028	0.045***
	(0.077)	(0.013)	(0.071)	(0.013)
$W\_MAX_{i,t}$	0.197	− 0.276**	0.346	− 0.272**
	(0.626)	(0.109)	(0.583)	(0.110)
$W\_REVL_{i,t}$	0.336***	0.015	0.334***	0.016
	(0.080)	(0.014)	(0.074)	(0.014)
$W\_MOM_{i,t}$	− 0.072*	0.009	− 0.041	0.010
	(0.043)	(0.008)	(0.040)	(0.008)
$W\_IVOL_{i,t}$	9.842***	1.906***	8.951***	1.882***
	(2.240)	(0.395)	(2.088)	(0.395)
$W\_Coskew_{i,t}$	0.002	0.000	− 0.001	− 0.000
	(0.003)	(0.001)	(0.003)	(0.001)
$W\_Iskew_{i,t}$	− 0.032	0.000	− 0.038	0.000
	(0.039)	(0.007)	(0.036)	(0.007)
Constant	9.118***	0.488***	9.156***	0.499***
	(0.825)	(0.147)	(0.769)	(0.149)
Month FE	Yes	Yes	Yes	Yes
Crypt FE	Yes	Yes	Yes	Yes
Observations	1105	1063	1105	1063
Adjusted R^2	0.817	0.072	0.830	0.070

This table shows the role of investor trading behavior in the weekly impact of static investor attention on liquidity of the cryptocurrency market. Columns (1) and (3) respectively report the impact of static investor attention on the investors' buying and selling activities, while columns (2) and (4) respectively show the impact of investors' overall buying and selling behavior on liquidity of the cryptocurrency market. All variable definitions are shown in Table 11. All continuous variables are winsorized at 1% and 99%. Cryptocurrency and month fixed effects are controlled for and the standard errors are adjusted at the cryptocurrency level. Robust standard errors are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

Table 6 The daily effect of abnormal investor attention on liquidity of the cryptocurrency market

	Dependent variable = $D\_ILLIQ_{i,t+n}$						
	(1) n = 0	(2) n = 1	(3) n = 2	(4) n = 3	(5) n = 4	(6) n = 5	(7) n = 6
$D\_ABGSV_{i,t}$	0.041***	0.033***	0.023***	0.018**	0.019**	0.023***	0.025***
	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)
$D\_lnSize_{i,t}$	– 0.024**	– 0.041***	– 0.044***	– 0.045***	– 0.045***	– 0.045***	– 0.045***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
$D\_lnPrice_{i,t}$	1.010***	0.935***	0.927***	0.923***	0.920***	0.918***	0.916***
	(0.176)	(0.167)	(0.165)	(0.164)	(0.163)	(0.163)	(0.163)
$D\_lnAge_{i,t}$	0.309***	0.397***	0.412***	0.419***	0.419***	0.420***	0.420***
	(0.092)	(0.090)	(0.089)	(0.089)	(0.089)	(0.089)	(0.089)
$D\_lnVolume_{i,t}$	– 0.855***	– 0.711***	– 0.684***	– 0.671***	– 0.663***	– 0.657***	– 0.650***
	(0.025)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
$D\_MAX_{i,t}$	– 0.909***	– 1.087***	– 1.128***	– 1.152***	– 1.153***	– 1.146***	– 1.178***
	(0.189)	(0.195)	(0.202)	(0.196)	(0.197)	(0.198)	(0.196)
$D\_REVL_{i,t}$	– 0.213***	– 0.270***	– 0.272***	– 0.274***	– 0.272***	– 0.274***	– 0.272***
	(0.030)	(0.030)	(0.030)	(0.031)	(0.031)	(0.031)	(0.031)
$D\_MOM_{i,t}$	– 0.166***	– 0.205***	– 0.213***	– 0.216***	– 0.219***	– 0.219***	– 0.221***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
$D\_IVOL_{i,t}$	8.211***	9.207***	9.438***	9.502***	9.465***	9.383***	9.418***
	(0.805)	(0.824)	(0.838)	(0.821)	(0.822)	(0.831)	(0.827)
$D\_Coskew_{i,t}$	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$D\_Iskew_{i,t}$	0.007	– 0.007	– 0.014	– 0.016	– 0.022	– 0.025*	– 0.029**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Constant	12.367	11.283	11.135	11.118	10.961	10.983	11.037
	(0.714)	(0.626)	(0.594)	(0.587)	(0.553)	(0.558)	(0.543)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crypt FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	583,003	574,385	572,935	572,055	571,187	570,380	569,667
Adjusted R^2	0.522	0.450	0.439	0.433	0.428	0.424	0.420

This table reports the regression results of how abnormal investor attention affects liquidity of the cryptocurrency market for the current and next 6 days. The specific model is constructed as follows:
$D\_ILLIQ_{i,t+n} = \lambda_0 + \lambda_1 D\_ABGSV_{i,t} + \sum_k \delta_k D\_Controls_{k,i,t} + \sum Cryptocurrency + \sum Time + \varepsilon_{i,t+n}$
where $D\_ILLIQ_{i,t+n}$ is the *Amihud illiquidity ratio* of cryptocurrency i on day $t + n$ (n = 0, 1, 2, …), and $D\_ABGSV_{i,t}$ is the abnormal investor attention of cryptocurrency i on day t. $D\_Controls$ is a set of control variables on a daily basis, which is similar to the control variables used in the weekly and monthly model. All variable definitions are shown in Table 11. All continuous variables are winsorized at 1% and 99%. Cryptocurrency and month fixed effects are controlled for and the standard errors are adjusted at the cryptocurrency level. Robust standard errors are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

Table 7 The impact of abnormal investor attention on liquidity of the cryptocurrency market in the long-term

	Dependent variable = $D\_ILLIQ_{i,t+n}$										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	n = 10	n = 20	n = 30	n = 40	n = 50	n = 60	n = 70	n = 80	n = 90	n = 100	n = 110
$D\_ABGSV_{i,t}$	0.013*	0.026***	0.025***	0.021**	0.022**	0.029***	0.026***	0.017**	0.021**	0.014	0.006
	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.766)
$D\_lnSize_{i,t}$	− 0.046***	− 0.044***	− 0.045***	− 0.043***	− 0.042***	− 0.040***	− 0.039***	− 0.037***	− 0.035***	− 0.034***	− 0.028***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(− 2.590)
$D\_lnPrice_{i,t}$	0.905***	0.888***	0.867***	0.842***	0.817***	0.793***	0.772***	0.748***	0.727***	0.707***	0.681***
	(0.161)	(0.159)	(0.157)	(0.155)	(0.154)	(0.153)	(0.151)	(0.149)	(0.148)	(0.147)	(4.668)
$D\_lnAge_{i,t}$	0.421***	0.397***	0.392***	0.396***	0.394***	0.403***	0.414***	0.408***	0.405***	0.407***	0.388***
	(0.089)	(0.090)	(0.090)	(0.090)	(0.092)	(0.092)	(0.093)	(0.095)	(0.096)	(0.097)	(3.954)
$D\_lnVolume_{i,t}$	− 0.623***	− 0.587***	− 0.552***	− 0.520***	− 0.496***	− 0.469***	− 0.442***	− 0.416***	− 0.397***	− 0.376***	− 0.359***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(− 16.238)
$D\_MAX_{i,t}$	− 1.189***	− 1.065***	− 0.926***	− 0.936***	− 0.908***	− 0.899***	− 0.847***	− 0.849***	− 0.843***	− 0.775***	− 0.821***
	(0.197)	(0.194)	(0.200)	(0.196)	(0.203)	(0.201)	(0.209)	(0.214)	(0.214)	(0.222)	(− 3.450)
$D\_REVL_{i,t}$	− 0.264***	− 0.255***	− 0.244***	− 0.260***	− 0.265***	− 0.269***	− 0.273***	− 0.263***	− 0.249***	− 0.249***	− 0.228***
	(0.032)	(0.035)	(0.037)	(0.038)	(0.040)	(0.040)	(0.041)	(0.042)	(0.045)	(0.047)	(− 4.740)
$D\_MOM_{i,t}$	− 0.229***	− 0.235***	− 0.240***	− 0.238***	− 0.236***	− 0.233***	− 0.234***	− 0.230***	− 0.232***	− 0.229***	− 0.226***
	(0.027)	(0.028)	(0.029)	(0.030)	(0.031)	(0.032)	(0.033)	(0.033)	(0.034)	(0.035)	(− 6.360)

Table 7 (continued)

	Dependent variable = $D\_ILLIQ_{i,t+n}$										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	n = 10	n = 20	n = 30	n = 40	n = 50	n = 60	n = 70	n = 80	n = 90	n = 100	n = 110
$D\_IVOL_{i,t}$	9.208***	8.108***	6.951***	6.680***	6.329***	6.049***	5.722***	5.580***	5.438***	5.032***	4.981***
	(0.822)	(0.820)	(0.847)	(0.826)	(0.857)	(0.844)	(0.851)	(0.866)	(0.878)	(0.920)	(5.081)
$D\_Coskew_{i,t}$	0.001	0.000	0.000	0.000	0.000	0.000	− 0.000	− 0.000	− 0.001	− 0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.011)
$D\_Iskew_{i,t}$	− 0.041***	− 0.067***	− 0.074***	− 0.070***	− 0.068***	− 0.055***	− 0.062***	− 0.062***	− 0.061***	− 0.058***	− 0.045**
	(0.014)	(0.014)	(0.015)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)	(− 2.448)
Constant	11.358***	11.342***	10.925***	10.512***	9.883***	10.483***	10.740***	10.410***	11.093***	10.701***	10.458***
	(0.536)	(0.526)	(0.604)	(0.461)	(0.602)	(0.619)	(0.769)	(0.732)	(0.897)	(0.869)	(12.721)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crypt FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	566,828	560,555	554,306	548,304	542,254	536,364	530,448	524,591	518,704	513,392	507,585
Adjusted R^2	0.403	0.378	0.354	0.338	0.324	0.310	0.298	0.285	0.278	0.268	0.260

We examine the impact of abnormal investor attention on cryptocurrency liquidity in the next 110 days, and this table presents the regression results every 10 days ahead. The detailed definitions of the variables are shown in Table 11. All continuous variables are winsorized at 1% and 99%. Cryptocurrency and month fixed effects are controlled for and the standard errors are adjusted at the cryptocurrency level. Robust standard errors are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively to some extent. With no fixed market makers to provide liquidity, it is difficult to ensure the smooth operational activity in the cryptocurrency market, especially in the face of extreme market conditions. When investor attention to a certain cryptocurrency increases abnormally in the short term, the liquidity of cryptocurrency market will deteriorate easily due to the lack of counterparties in the market.

To test the robustness of the effect of abnormal attention, we replace the measures of cryptocurrency liquidity and investor attention, respectively. The specific regression results are shown in Table 15. The calculation of liquidity indicators in columns (1)-(4) is similar to the robustness tests for static attention. In addition, we use 5-min order book data to construct three high-frequency liquidity indicators: quoted spread (*D_QS*), effective spread (*D_ES*), and price impact (*D_PI*). As for the alternative measures of abnormal attention, we use the Google search volume index to construct *D_ABGSV2* and *D_ABGSV3* according to Eq. (2) and Eq. (3), respectively. Moreover, *D_ABTweets* is then constructed based on Twitter post counts according to Eq. (1). We can see from Table 15 that abnormal attention significantly reduces cryptocurrency liquidity, which is consistent with our baseline regression results.

3.3.2 Channel analysis of abnormal investor attention on a daily basis

From the perspective of investor trading behavior, we analyze the internal mechanism of how abnormal attention impairs the liquidity of cryptocurrency markets. In the case of deteriorating liquidity in the cryptocurrency market, many quoted orders are usually not fulfilled. Only by using the data of unsolved quoted orders we can truly capture the dominant force and imbalance between buyers and sellers in the market. Therefore, different from the static investor attention's mechanism test that use the transaction order data that have been finalized, we utilize the bid and ask order data to reflect the trading intention of investors and the counterbalancing force between the buyers and the sellers in the cryptocurrency market. Inspired by Barber and Odean (2008), we construct $D\_NetBid_{i,t}$ to measure the net buying pressure in the cryptocurrency market, which is calculated as follows:

$$D\_NetBid_{i,t} = \frac{D\_Bid_{i,t} - D\_Ask_{i,t}}{D\_Bid_{i,t} + D\_Ask_{i,t}} \tag{15}$$

where $D\_Bid_{i,t}$ and $D\_Ask_{i,t}$ are respectively the bid and ask dollar volumes of cryptocurrency i on day t. $D\_NetBid_{i,t}$ denotes the net bid quoted amount of cryptocurrency i on day t, which is mainly used to measure the imbalance degree and the direction of pressure between buyer and seller forces in cryptocurrency market. In particular, its absolute value represents the imbalance degree of quoted orders, and its symbol is positive for net buying pressure and negative for net selling pressure.

Similar to the mechanism test of static investor attention, we first study the impact of abnormal attention on the net bid amount in the cryptocurrency market, and then further explore whether the net purchase pressure of investors has an impact on liquidity of the cryptocurrency market.

$$\begin{aligned} D\_NetBid_{i,t} = \lambda_0 + \lambda_1 D\_ABGSV_{i,t} + \sum_k \delta_k D\_Controls_{k,i,t} \\ + \sum Cryptocurrency + \sum Time + \varepsilon_{i,t} \end{aligned} \tag{16}$$

$$D\_ILLIQ_{i,t+1} = \lambda_0 + \lambda_1 D\_NetBid_{i,t} + \sum_k \delta_k D\_Controls_{k,i,t}$$

$$+\sum Cryptocurrency + \sum Time + \varepsilon_{i,t+1} \quad (17)$$

where $D\_NetBid_{i,t}$ is the net bid quoted amount of cryptocurrency i on day t, and $\sum Cryptocurrency$ and $\sum Time$ indicate that cryptocurrency and month fixed effects are controlled for. All variable definitions are shown in Table 11.

From Table 8, we can see that coefficients of $D\_ABGSV_{i,t}$ in Eq. (16) and $D\_NetBid_{i,t}$ in Eq. (17) are significantly positive at the level of 5% and 1%, suggesting that abnormal attention can significantly increase the net bid amount of investors. Then the net bid amount will significantly damage the liquidity of the cryptocurrency market. The fact that abnormal attention significantly reduces cryptocurrency liquidity by increasing net buying pressure in the market is consistent with the "price pressure hypothesis" proposed by Barber and Odean (2008) and the crowding effect (Afonso, 2011). Indeed, abnormal attention can drive a large number of investors to buy cryptocurrencies, resulting in net buying pressure on the market. Since they face higher information search costs when buying cryptocurrencies, most of them only choose to sell their cryptocurrencies and are more likely to be driven by limited attention to buy rather than sell. Moreover, the abnormal increase of investor attention in the short term causes many buyers to gather in the market. In the absence of official market makers in the cryptocurrency market, the congestion of the buying orders makes it more difficult to match the right sellers for transactions. The direct consequence is the increased transaction costs and reduced cryptocurrency liquidity. At the same time, as abnormal attention can alleviate investors' search problems and reduce the level of information asymmetry in the market, it attracts more buyers to enter the cryptocurrency market, resulting in a more severe imbalance in the distribution of investors. This issue amplifies the crowding effect and worsens liquidity in the cryptocurrency market.

4 Conditional analysis

Taking into account the impact of different cryptocurrency characteristics and overall market conditions, we group the samples according to market capitalization, idiosyncratic volatility, and global economic policy uncertainty. Based on the significance of the interaction coefficients of dummy variables, we can determine whether there are significant differences among different groups in the influence of investor attention on liquidity of the cryptocurrency market.

4.1 Conditional analysis of static investor attention on a weekly basis

To conduct conditional analysis of static investor attention on a weekly basis, we construct the dummy variables $W\_LargeCap_{i,t}$, $W\_HighIVOL_{i,t}$ and $W\_HighGEPU_t$ to group the samples according to market capitalization, idiosyncratic volatility and global economic policy uncertainty, respectively. Specifically, $W\_LargeCap_{i,t}$ is a dummy variable that equals one for all sample cryptocurrencies on week t, if the weekly size of cryptocurrency is greater than the weekly median, and zero otherwise. $W\_HighIVOL_{i,t}$ is a dummy variable that equals one for all sample cryptocurrencies on week t, if the idiosyncratic volatility of cryptocurrency is greater than the median, and zero otherwise. $W\_HighGEPU_t$ is a dummy variable that equals one for all sample cryptocurrencies on week t, if the GEPU value in the associated month is greater than the median over all sample months, and zero otherwise. The conditional test results are shown in Table 9. The interaction coefficients of three dummy

Table 8 Channel analysis of abnormal investor attention on a daily basis

Dependent variables =	$D\_NetBid_{i,t}$ (1)	$D\_ILLIQ_{i,t+1}$ (2)
$D\_ABGSV_{i,t}$	0.013**	
	(0.006)	
$D\_NetBid_{i,t}$		0.025***
		(0.007)
$D\_lnSize_{i,t}$	0.003**	− 0.004***
	(0.002)	(0.001)
$D\_lnPrice_{i,t}$	0.007	0.006
	(0.009)	(0.005)
$D\_lnAge_{i,t}$	0.036***	0.037***
	(0.009)	(0.005)
$D\_MAX_{i,t}$	0.219***	− 0.184***
	(0.071)	(0.041)
$D\_REVL_{i,t}$	0.019*	− 0.011*
	(0.010)	(0.006)
$D\_MOM_{i,t}$	− 0.006	0.001
	(0.005)	(0.003)
$D\_IVOL_{i,t}$	− 0.750***	0.683***
	(0.263)	(0.151)
$D\_Coskew_{i,t}$	0.000	0.000
	(0.000)	(0.000)
$D\_Iskew_{i,t}$	− 0.010**	0.005**
	(0.005)	(0.003)
Constant	0.182	0.168***
	(0.113)	(0.063)
Month FE	Yes	Yes
Crypt FE	Yes	Yes
Observations	7026	6737
Adjusted R^2	0.061	0.041

This table shows the role of investor trading behavior in the daily impact of abnormal attention on cryptocurrency liquidity. Column (1) reports the impact of abnormal investor attention on net buying pressure in cryptocurrency market, and column (2) shows the impact of net bid amount on liquidity of the cryptocurrency market. All variable definitions are shown in Table 11. All continuous variables are winsorized at 1% and 99%. Cryptocurrency and month fixed effects are controlled for and the standard errors are adjusted at the cryptocurrency level. Robust standard errors are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

Table 9 Conditional analysis of static investor attention on a weekly basis

Dependent variable =	$W\_ILLIQ_{i,t+1}$		
	(1)	(2)	(3)
$W\_lnAtt_{i,t}$	− 0.117***	− 0.133***	− 0.078***
	(0.019)	(0.019)	(0.018)
$W\_LargeCap_{i,t}$	− 0.457***		
	(0.090)		
$W\_lnAtt_{i,t} \times W\_LargeCap_{i,t}$	0.054**		
	(0.024)		
$W\_HighIVOL_{i,t}$		0.121	
		(0.081)	
$W\_lnAtt_{i,t} \times W\_HighIVOL_{i,t}$		0.072***	
		(0.022)	
$W\_HighGEPU_t$			1.321***
			(0.489)
$W\_lnAtt_{i,t} \times W\_HighGEPU_t$			0.063***
			(0.019)
Constant	15.155***	15.159***	14.193***
	(0.444)	(0.443)	(0.107)
$W\_Controls_{k,i,t}$	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Crypt FE	Yes	Yes	Yes
Observations	84,843	84,843	84,843
Adjusted R^2	0.653	0.655	0.715

This table reports the impact of static investor attention on cryptocurrency liquidity under different cryptocurrency characteristics and aggregate states. $W\_LargeCap_{i,t}$ is a dummy variable that equals one for all sample cryptocurrencies on week t, if the weekly size of cryptocurrency is greater than the weekly median, and zero otherwise. $W\_HighIVOL_{i,t}$ is a dummy variable that equals one for all sample cryptocurrencies on week t, if the idiosyncratic volatility of cryptocurrency is greater than the median, and zero otherwise. $W\_HighGEPU_t$ is a dummy variable that equals one for all sample cryptocurrencies on week t, if the idiosyncratic volatility of cryptocurrency is greater than the median, and zero otherwise. The detailed definitions of the applied variables are shown in Table 11. All continuous variables are winsorized at 1% and 99%. Cryptocurrency and month fixed effects are controlled for and the standard errors are adjusted at the cryptocurrency level. Robust standard errors are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

variables ($W\_LargeCap_{i,t}$, $W\_HighIVOL_{i,t}$ and $W\_HighGEPU_t$) with static investor attention ($W\_lnAtt_{i,t}$) are significantly positive at the level of 5% and 1%, indicating that in the samples with low global economic policy uncertainty, small market capitalization and low idiosyncratic volatility, static investor attention has a more obvious effect on the improvement of cryptocurrency liquidity. For cryptocurrencies with small market value and low idiosyncratic volatility, there are fewer investors holding these cryptocurrencies and their transactions are not active, and thus the marginal impact of investor attention on their liquidity is more intense. Once investors pay attention to these cryptocurrencies, the investor trading activities will have a stronger effect on their liquidity. Similarly, in the period of low global economic policy uncertainty, implying that the global macro-economy is relatively stable, investors have less incentive to invest in cryptocurrency market. At this time, if investors allocate limited attention to some cryptocurrencies, it will greatly stimulate the trading activity of these cryptocurrencies, thus significantly improving the liquidity of the cryptocurrency market.

4.2 Conditional analysis of abnormal investor attention on a daily basis

Similar to the conditional tests of static investor attention, three dummy variables ($D\_LargeCap_{i,t}$, $D\_HighIVOL_{i,t}$ and $D\_HighGEPU_t$) are used in this part to group samples according to market value, idiosyncratic volatility and global economic policy uncertainty, respectively. When $D\_LargeCap_{i,t}$, $D\_HighIVOL_{i,t}$ and $D\_HighGEPU_t$ are equal to 1, they represent respectively the samples with large market value, high idiosyncratic volatility and high global economic policy uncertainty. From Table 10, we can see that the interaction coefficients of three dummy variables with static investor attention are significantly positive at the level of 5% and 1%, indicating that the interaction coefficients of three dummy variables ($D\_LargeCap_{i,t}$, $D\_HighIVOL_{i,t}$ and $D\_HighGEPU_t$) with abnormal investor attention $D\_ABGSV_{i,t}$) are significantly positive at the level of 1% and 5%, implying that in the samples with high global economic policy uncertainty, large market capitalization and high idiosyncratic volatility, abnormal investor attention has more significant negative effects on liquidity of the cryptocurrency market.

These cryptocurrencies with large market value and high idiosyncratic volatility are usually well-known, and they are actively traded by investors. When investor attention suddenly increases, a large number of investors rush into the market to buy cryptocurrency assets, resulting in a serious imbalance of trading pressure. The congestion and heavy competition in the buyers' market increase the transaction cost and damage the liquidity of the cryptocurrency market. This situation is even more exacerbated during the period of high global economic policy uncertainty.

5 Conclusion and policy implications

In this paper, we investigated the impact of investor attention on cryptocurrency liquidity. Our results show that static attention significantly improves cryptocurrency liquidity. This evidence can be explained by the fact that limited attention drives investors to enter the cryptocurrency market and increases their trading activities. On the other hand, increased abnormal attention can seriously damage the cryptocurrency liquidity since it rushes investors to the cryptocurrency market and causes severe net buying price pressure. In the absence of official market makers offering liquidity voluntarily, a crowded buyer's market makes it harder to find the right sellers for transactions and thus worsens liquidity. Our findings differ from the previous literature in that abnormal attention has a significant and long-term negative impact on cryptocurrency liquidity.

In addition, our conditional analysis pointed out that in the samples with low global economic policy uncertainty, small market capitalization, and low idiosyncratic volatility, static investor attention has a more pronounced effect on the improvement of cryptocurrency liquidity. On the contrary, in the samples with high global economic policy uncertainty, large market capitalization, and high idiosyncratic volatility, abnormal investor attention negatively affects cryptocurrency liquidity. Noticeably, cryptocurrencies with large market value and

Table 10 Conditional analysis of abnormal investor attention on a daily basis

Dependent variable =	$D\_ILLIQ_{i,t+1}$		
	(1)	(2)	(3)
$D\_ABGSV_{i,t}$	0.015	0.019**	0.023***
	(0.012)	(0.008)	(0.007)
$D\_LargeCap_{i,t}$	− 1.181***		
	(0.115)		
$D\_ABGSV_{i,t} \times D\_LargeCap_{i,t}$	0.035***		
	(0.013)		
$D\_HighIVOL_{i,t}$		0.396***	
		(0.009)	
$D\_ABGSV_{i,t} \times D\_HighIVOL_{i,t}$		0.024**	
		(0.011)	
$D\_HighGEPU_t$			0.363
			(0.355)
$D\_ABGSV_{i,t} \times D\_HighGEPU_t$			0.023**
			(0.011)
Constant	10.605***	11.088***	10.922***
	(0.586)	(0.352)	(0.041)
$D\_Controls_{k,i,t}$	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Crypt FE	Yes	Yes	Yes
Observations	574,385	574,385	574,385
Adjusted R^2	0.459	0.452	0.450

This table reports the impact of abnormal investor attention on cryptocurrency liquidity under different cryptocurrency characteristics and aggregate states. $D\_LargeCap_{i,t}$ is a dummy variable set to one for all sample cryptocurrencies on day t, if the daily size of cryptocurrency is greater than the daily median, and zero otherwise.$D\_HighIVOL_{i,t}$ is a dummy variable that equals one for all sample cryptocurrencies on day t, if the idiosyncratic volatility of cryptocurrency is greater than the median, and zero otherwise. $D\_HighGEPU_t$ is a dummy variable that equals one for all sample cryptocurrencies on day t, if the GEPU value in the associated month is greater than the median over all sample months, and zero otherwise. The detailed definitions of the applied variables are shown in Table 11. All continuous variables are winsorized at 1% and 99%. Cryptocurrency and month fixed effects are controlled for and the standard errors are adjusted at the cryptocurrency level. Robust standard errors are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

high idiosyncratic volatility easily attract investors' attention. As such, increased abnormal attention is more likely to cause a severe trading imbalance pressure, intensify the crowding effect, and aggravate the deterioration of liquidity. Similarly, cryptocurrencies can also easily attract investor attention due to their ability to diversify investment and hedge macroeconomic risks in periods of high global economic policy uncertainty.

Our results would imply that individual investors should avoid being "locked-in" cryptocurrency markets because limited attention can quickly drive them to chase hot cryptocurrencies. For portfolio managers who consider diversifying their investments or hedging macroeconomic risks, it is essential to pay attention to additional transaction costs arising from cryptocurrency liquidity risk and timely market exiting when the cryptocurrency is overheated. Policymakers should assess the cryptocurrency market's liquidity and instability risks to develop relevant recommendations on cryptocurrency investments, especially when investor attention is overheated. For their part, cryptocurrency exchanges can reflect on improving market liquidity through the presence of market makers.

Given this paper's empirical evidence, future research could develop a theoretical framework to formalize the double-edged sword effect of investor attention. Then, empirically, the impact of static and abnormal investor attention could be gauged more easily with longer tick-by-tick and order book data of more cryptocurrencies. Focusing on the microstructure characteristics of the cryptocurrency market to explore the price behavior differences between cryptocurrencies and traditional assets is another research direction.[15] Finally, due to the segmentation of cryptocurrency exchanges (Makarov & Schoar, 2020), future research can explore the differences in the impact of investor attention on liquidity among different exchanges and their possible dynamic spillovers.

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Appendix

See Tables 11, 12, 13, 14 and 15.

[15] Baek and Elbeck (2015) find that the price behavior of cryptocurrency is more driven by the trading behavior of buyers and sellers and is irrelevant to economic fundamentals. Li et al., (2021a) argue that the price dynamics of cryptocurrencies are mainly dominated by speculation and trend trading.

Table 11 Variable definitions

Variables	Definitions
Cryptocurrency liquidity variables	
$D\_ILLIQ_{i,t}$	The daily Amihud illiquidity, defined as the natural logarithm of expanding the ratio of the absolute return to the dollar trading volume by 10^6 times
$W\_ILLIQ_{i,t}$	The weekly Amihud illiquidity ratio is the average of the daily Amihud illiquidity ratio (*D_ILLIQ*) in week *t*
$M\_ILLIQ_{i,t}$	The monthly Amihud illiquidity ratio is the average of the daily Amihud illiquidity ratio (*D_ILLIQ*) in month *t*
Investor attention variable	
$D\_ABGSV_{i,t}$	The daily abnormal investor attention, defined as the natural logarithm of GSV on day *t* to minus the GSV average value from day *t-30* to day *t-1*, and then divided by the mean of GSV from day *t-30* to day *t-1*. See Eq. (1) for the specific formula
$W\_lnAtt_{i,t}$	The weekly static investor attention, measured as the mean of the natural logarithm of daily Google search volume index for cryptocurrency *i* in week *t*
$M\_lnAtt_{i,t}$	The monthly static investor attention, measured as the mean of the natural logarithm of daily Google search volume index for cryptocurrency *i* in month *t*
Control variables on a daily basis ($D\_Controls_{k,i,t}$)	
$D\_lnSize_{i,t}$	The market value, defined as the natural logarithm of the circulation market value of cryptocurrency *i* on day *t*
$D\_lnPrice_{i,t}$	The closing price, calculated as the natural logarithm of the closing price of cryptocurrency *i* on day *t*
$D\_lnAge_{i,t}$	The listing month, calculated as the natural logarithm of the number of listing months
$D\_lnVolume_{i,t}$	The trading volume, calculated as the natural logarithm of trading volume of cryptocurrency *i* on day *t*
$D\_MAX_{i,t}$	The maximum daily return of cryptocurrency *i* for the month of day *t*
$D\_REVL_{i,t}$	The monthly return on the cryptocurrency *i* over the previous month of day *t*
$D\_MOM_{i,t}$	The momentum of cryptocurrency *i* in the month of day *t*, which is measured as the cumulative return from month m-7 to month m-2

Table 11 (continued)

Variables	Definitions
$D\_IVOL_{i,t}$	Idiosyncratic volatility of cryptocurrency i for the month of day t, defined as the standard deviation of the residual in Eq. (3)
$D\_Coskew_{i,t}$	Co-skewness of cryptocurrency i for the month of day t, measured as the estimated coefficient $\widehat{\gamma_i}$ in Eq. (4)
$D\_Iskew_{i,t}$	Idiosyncratic skewness of cryptocurrency i for the month of day t, defined as the skewness of the residuals of Eq. (4)
Control variables on a weekly basis ($W\_Controls_{k,i,t}$)	
$W\_lnSize_{i,t}$	The weekly size of cryptocurrency i is the average of the daily size(*D_lnSize*) in week t
$W\_lnPrice_{i,t}$	The weekly price of cryptocurrency i is the average of the daily price(*D_lnPrice*) in week t
$W\_lnAge_{i,t}$	The natural logarithm of the number of months from the launch of cryptocurrency i to week t
$W\_lnVolume_{i,t}$	The weekly volume of cryptocurrency i is the average of the volume(*D_lnVolume*) in week t
$W\_MAX_{i,t}$	The maximum weekly return of cryptocurrency i for the month of week t
$W\_REVL_{i,t}$	The monthly return on the cryptocurrency i over the previous month of week t
$W\_MOM_{i,t}$	The momentum of cryptocurrency i in the month of week t, which is measured as the cumulative return from month m-7 to month m-2
$W\_IVOL_{i,t}$	Idiosyncratic volatility of cryptocurrency i for the month of week t, defined as the standard deviation of the residual in Eq. (3)
$W\_Coskew_{i,t}$	Co-skewness of cryptocurrency i for the month of week t, measured as the estimated coefficient $\widehat{\gamma_i}$ in Eq. (4)
$W\_Iskew_{i,t}$	Idiosyncratic skewness of cryptocurrency i for the month of week t, defined as the skewness of the residuals of Eq. (4)
Control variables on a monthly basis ($M\_Controls_{k,i,t}$)	
$M\_lnSize_{i,t}$	The monthly size of cryptocurrency i is the average of the daily size(*D_lnSize*) in month t
$M\_lnPrice_{i,t}$	The monthly price of cryptocurrency i is the average of the daily price(*D_lnPrice*) in month t
$M\_lnAge_{i,t}$	The natural logarithm of the number of months from the launch of cryptocurrency i to month t
$M\_lnVolume_{i,t}$	The monthly volume of cryptocurrency i is the average of the volume(*D_lnVolume*) in month t
$M\_MAX_{i,t}$	The maximum weekly return of cryptocurrency i for the month of week t

Table 11 (continued)

Variables	Definitions
$M\_REVL_{i,t}$	The monthly return on the cryptocurrency i over the previous month of week t
$M\_MOM_{i,t}$	The momentum of cryptocurrency i in the month of week t, which is measured as the cumulative return from month m-7 to month m-2
$M\_IVOL_{i,t}$	Idiosyncratic volatility of cryptocurrency i for the month of week t, defined as the standard deviation of the residual in Eq. (3)
$M\_Coskew_{i,t}$	Co-skewness of cryptocurrency i for the month of week t, measured as the estimated coefficient $\widehat{\gamma_i}$ in Eq. (4)
$M\_Iskew_{i,t}$	Idiosyncratic skewness of cryptocurrency i for the month of week t, defined as the skewness of the residuals of Eq. (4)
Variables of investor trading behavior	
$D\_NetBid_{i,t}$	The daily net-bid amount of cryptocurrency i on day t, defined as the difference between bid and ask amount scaled by total amount of the quote orders
$W\_lnBuySum_{i,t}$	The total amount of buyer-initiated trade of cryptocurrency i in week t
$W\_lnSellSum_{i,t}$	The total amount of seller-initiated trade of cryptocurrency i in week t
Dummy variables of conditional analysis	
$D\_LargeCap_{i,t}$	A dummy variable that equals one for all sample cryptocurrencies on day t, if the daily size of cryptocurrency is greater than the daily median, and zero otherwise
$D\_HighIVOL_{i,t}$	A dummy variable that equals one for all sample cryptocurrencies on day t, if the idiosyncratic volatility of cryptocurrency is greater than the median, and zero otherwise
$D\_HighGEPU_t$	A dummy variable that equals one for all sample cryptocurrencies on day t, if the GEPU value in the associated month is greater than the median over all sample months, and zero otherwise
$W\_LargeCap_{i,t}$	A dummy variable that equals one for all sample cryptocurrencies on week t, if the weekly size of cryptocurrency is greater than the weekly median, and zero otherwise
$W\_HighIVOL_{i,t}$	A dummy variable that equals one for all sample cryptocurrencies on week t, if the idiosyncratic volatility of cryptocurrency is greater than the median, and zero otherwise
$W\_HighGEPU_t$	A dummy variable that equals one for all sample cryptocurrencies on week t, if the GEPU value in the associated month is greater than the median over all sample months, and zero otherwise

This table contains the definitions and calculation methods of all variables used in our study

Table 12 List of cryptocurrencies

Panel A

1SG	1ST	1UP	7E	AC3	ACDC	ACED	ACES	ACM	AD	ADA	ADI	ADN	AEON	AIDOC
AION	AKA	AKRO	ALGO	ALIAS	AMN	AMON	AMPL	ANCT	ANKR	ANT	AOA	ARAW	ARB	ARDR
ARION	ARK	ARNX	ART	ASAFE	ATCC	ATL	ATN	ATOM	ATX	AUC	AUTO	AUX	AVT	AXE
AXIOM	B91	BANCA	BAND	BAT	BAX	BCD	BCH	BCI	BCN	BDG	BDX	BEAM	BEAT	BELA
BIFI	BIS	BIT	BITC	BLAST	BLT	BLUE	BMC	BNB	BNK	BNT	BOLT	BOMB	BOOM	BORA
BOX	BQTX	BRD	BRDG	BSV	BTA	BTC	BTC2	BTCP	BTCT	BTG	BTM	BTO	BTRN	BTT
BU	BUB	BUSD	BZX	CAG	CARAT	CCX	CDT	CEL	CF	CHR	CHZ	CIV	CLAM	CLR
CNNS	CNT	CON	CONI	CONST	COS	COTI	COVA	CPAY	CPX	CRE	CREA	CREDO	CRM	CROAT
CRPT	CS	CTL	CTXC	CV	CVC	D	DACC	DAD	DADI	DAG	DAI	DAM	DAN	DASH
DAT	DCN	DCR	DCT	DDK	DEEX	DEFI	DENT	DEX	DFS	DILI	DIVI	DMD	DMT	DOCK
DOGE	DONU	DOS	DPY	DREP	DRG	DRGN	DSC	DT	DTA	DTEP	DVT	DWS	DYN	DYNMT
EBST	ECC	EDG	EDN	EGCC	EKO	EKT	ELA	ELF	ELY	EMC2	EMT	ENG	ENJ	ENT
ENTS	EOS	EQL	ERC20	ERG	ESP	ESS	ETC	ETG	ETH	EUM	EVC	EVE	EXP	FCT
FDZ	FIII	FIL	FLASH	FLETA	FLO	FLOT	FLP	FOAM	FOTA	FOXT	FREE	FRN	FSN	FTM
FTN	FUN	FUND	FX	FXT	GAP	GAS	GEM	GET	GET	GIC	GIG	GMB	GMB	GNO
GNT	GNY	GOLD	GOT	GPKR	GRFT	GRIN	GRN	GTC	GVT	GZRO	HALO	HAVY	HBAR	HDAC
HEAT	HNST	HOLD	HOT	HUSD	HUSH	HVCO	HYC	HYDRO	IC	ICX	IDEX	IGG	IGNIS	ILC
ILK	INCNT	INK	INT	INX	ION	IOP	IOST	IPSX	IRD	ITC	ITL	IVY	IXT	JOINT
JUL	JUP	JWL	KARMA	KIN	KLKS	KMD	KNC	KNOW	KRB	LA	LALA	LAMB	LBTC	LCC
LEVL	LIFE	LINK	LINKA	LIT	LKK	LOKI	LSK	LTC	LUNA	LUNES	LXT	MAG	MANA	MANNA
MARO	MATIC	MAVRO	MBN	MCO	MER	MESG	MET	METM	MEX	MFT	MGO	MIDAS	MIOTA	MITH

Table 12 (continued)

Panel A

MKR	MLM	MOAC	MOBI	MOIN	MONK	MORE	MSR	MT	MTC	MTL	MTV	MVL	MXC	MYST
MZK	NANO	NAS	NEBL	NEO	NET	NETKO	NEU	NEW	NEWS	NEXO	NGC	NIX	NKC	NKN
NLG	NMR	NODE	NOIZ	NOVA	NPXS	NRG	NRVE	NSD	NTRN	NTY	NUG	NULS	NXS	NXT
OAX	OBITS	OBSR	OCN	ODE	ODEX	OKB	OMNI	OMX	ONE	ONT	ONX	OPAL	OPCT	OPEN
OPT	ORBS	ORS	OST	PAR	PASC	PAT	PAXG	PAY	PC	PENG	PEOS	PERL	PHO	PHR
PHX	PIRL	PIVX	PKT	PLA	PLA	PLBT	PLC	PLR	PLU	PNT	PNY	POA	POLY	POWR
PPC	PPT	PRA	PRE	PROM	PROUD	PST	PTON	PXG	PXL	PZM	QASH	QNT	QTUM	QUBE
RAISE	RALLY	RBIES	RBLX	RC20	RDD	REAL	RED	REM	REN	REP	REPO	REQ	RISE	RLX
ROX	RPD	RSR	RUFF	RUP	RUPX	RVN	S	SAFE	SALT	SBTC	SC	SCL	SEER	SEND
SENSE	SENT	SFCP	SGN	SHARD	SHIFT	SHPING	SHVR	SIX	SKB	SLS	SMART	SMARTUP	SNL	SNM
SNRG	SNT	SOC	SOLVE	SON	SOUL	SPD	SPD	SPHR	SPIKE	SPN	SPT	SSP	STAK	STAR
STEEM	STK	STMX	STORJ	STRAX	STX	STX	SUB	SUSD	SWING	SWM	SXP	TCASH	TEL	TEMCO
TENA	TERA	THETA	TKN	TLOS	TNB	TOK	TOL	TOP	TRX	TRY	TSL	TUBE	UBEX	UBQ
UBTC	UGAS	UNI	UNIFY	UNO	UOS	USDC	USDT	UTK	UTNP	UUU	VEIL	VERA	VET	VIB
VIBE	VIDY	VIEW	VINCI	VITE	VITES	VLD	VLX	VNDC	VOISE	VOL	VOLTZ	VOTE	VRS	VTC
VULC	WABI	WAVES	WAXP	WCO	WHEN	WIKEN	WIN	WINGS	WIRE	WTC	XAP	XAS	XBC	XBTC21
XCN	XEL	XEM	XENO	XLA	XLM	XLR	XMR	XMX	XMY	XNS	XNV	XPC	XPD	XQN
XRP	XSH	XST	XTZ	XUC	XVG	XWP	XYO	XZC	YEE	YOC	YOU	ZAP	ZCL	ZEC
ZEL	ZEN	ZEON	ZER	ZIL	ZINC	ZIP	ZIPT	ZLA	ZNN	ZNZ	ZRX			

Panel B

ANT	AUC	AVT	BAT	BCH	BCI	BTC	BTG	DAT	ELF	EOS	ETC	ETH	FSN	FUN
GNT	KNC	LTC	MKR	NEO	ODE	POA	REP	REQ	SNT	TNB	TRX	UTK	XLM	XMR
XRP	XVG	ZEC	ZRX											

Panel A in this table presents the abbreviation list of 597 cryptocurrencies in the sample used for baseline regressions, which is available from CoinMarketCap. And Panel B reports the list of 34 cryptocurrencies in the intraday high-frequency sample used in channel analysis

Table 13 Weekly robustness checks

Dependent variable =	$W\_lnAmihudOC_{i,t+1}$	$W\_lnKyle_{i,t+1}$	$W\_adjILLIQ_{i,t+1}$	$W\_adjlnAmihudOC_{i,t+1}$	$W\_ILLIQ_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)
$W\_lnAtt_{i,t}$	− 0.113**	− 0.039***	− 0.052**	− 0.052**	
	(0.047)	(0.014)	(0.022)	(0.022)	
$W\_lnTweets_{i,t}$					− 0.021***
					(0.005)
$W\_lnSize_{i,t}$	− 0.041***	− 0.013***	− 0.020***	− 0.020***	− 0.310***
	(0.011)	(0.003)	(0.005)	(0.005)	(0.008)
$W\_lnPrice_{i,t}$	1.209***	0.231***	0.545***	0.542***	1.465***
	(0.192)	(0.059)	(0.090)	(0.089)	(0.018)
$W\_lnAge_{i,t}$	0.485***	0.120***	0.229***	0.231***	0.164***
	(0.089)	(0.026)	(0.042)	(0.042)	(0.017)
$W\_lnVolume_{i,t}$	− 0.880***	− 0.283***	− 0.427***	− 0.426***	− 0.533***
	(0.031)	(0.009)	(0.015)	(0.015)	(0.006)
$W\_MAX_{i,t}$	− 1.433***	− 0.494***	− 0.708***	− 0.693***	− 0.869***
	(0.218)	(0.067)	(0.107)	(0.106)	(0.141)
$W\_REVL_{i,t}$	− 0.301***	− 0.099***	− 0.144***	− 0.147***	− 0.194***
	(0.035)	(0.010)	(0.017)	(0.017)	(0.023)
$W\_MOM_{i,t}$	− 0.256***	− 0.088***	− 0.128***	− 0.126***	− 0.111***

Table 13 (continued)

Dependent variable =	$W\_lnAmihudOC_{i,t+1}$ (1)	$W\_lnKyle_{i,t+1}$ (2)	$W\_adjILLIQ_{i,t+1}$ (3)	$W\_adjlnAmihudOC_{i,t+1}$ (4)	$W\_ILLIQ_{i,t+1}$ (5)
	(0.029)	(0.008)	(0.014)	(0.014)	(0.010)
$W\_IVOL_{i,t}$	11.956***	4.520***	5.920***	5.815***	9.627***
	(0.840)	(0.257)	(0.406)	(0.406)	(0.484)
$W\_Coskew_{i,t}$	0.001*	0.000*	0.001*	0.001*	0.004***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
$W\_Iskew_{i,t}$	− 0.024	− 0.005	− 0.013*	− 0.011	− 0.042***
	(0.016)	(0.005)	(0.008)	(0.008)	(0.009)
Constant	14.841***	5.730***	7.386***	7.374***	13.696***
	(0.780)	(0.238)	(0.368)	(0.363)	(0.182)
Month FE	Yes	Yes	Yes	Yes	Yes
Crypt FE	Yes	Yes	Yes	Yes	Yes
Observations	79,221	79,225	79,225	79,221	23,910
Adjusted R^2	0.655	0.687	0.660	0.660	0.634

In this table, we test the weekly robustness tests of static attention. Columns (1)-(4) show the regression results after including another measures of cryptocurrency liquidity, and column (5) reports the regression after replacing the indicator of static attention. In columns (1) and (2), we use the daily opening and closing prices to construct the Amihud (2002) illiquidity ratio (*W_lnAmihudOC*) and the illiquidity indicator (*W_lnKyle*) constructed by Kyle and Obizhaeva (2016) as alternative proxies for liquidity. Moreover, as the Amihud illiquidity ratio is characterized by extreme value, in columns (3) and (4) we use the method in Hasbrouck (2009) to adjust the two Amihud illiquidity ratios to obtain *W_adjILLIQ* and *W_adjlnAmihudOC*. In column (5), we employ *W_lnTweets* as another measure of static attention, which is the weekly average of the natural logarithm of the daily twitter post counts plus one. The methods for calculating the above variables are detailed in Sect. 2.2.1 and Sect. 2.2.2. Robust standard errors are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

Table 14 Monthly robustness checks

Dependent variable =	$M\_lnAmihudOC_{i,t+1}$ (1)	$M\_lnKyle_{i,t+1}$ (4)	$M\_adjILLIQ_{i,t+1}$ (2)	$M\_adjlnAmihudOC_{i,t+1}$ (3)	$M\_ILLIQ_{i,t+1}$ (5)
$M\_lnAtt_{i,t}$	− 0.204***	− 0.059***	− 0.095***	− 0.094***	
	(0.069)	(0.019)	(0.033)	(0.033)	
$M\_lnTweets_{i,t}$					− 0.025**
					(0.013)
$M\_lnSize_{i,t}$	− 0.046***	− 0.011***	− 0.022***	− 0.022***	− 0.340***
	(0.013)	(0.003)	(0.006)	(0.006)	(0.020)
$M\_lnPrice_{i,t}$	1.181***	0.277***	0.535***	0.534***	1.044***
	(0.205)	(0.056)	(0.096)	(0.096)	(0.050)
$M\_lnAge_{i,t}$	0.405***	0.100***	0.192***	0.193***	0.121***
	(0.086)	(0.023)	(0.040)	(0.040)	(0.037)
$M\_lnVolume_{i,t}$	− 0.874***	− 0.262***	− 0.424***	− 0.423***	− 0.412***
	(0.038)	(0.011)	(0.018)	(0.018)	(0.014)
$M\_MAX_{i,t}$	− 1.328***	− 0.357***	− 0.655***	− 0.646***	− 0.457
	(0.259)	(0.077)	(0.126)	(0.126)	(0.320)
$M\_REVL_{i,t}$	− 0.223***	− 0.082***	− 0.109***	− 0.110***	− 0.103*
	(0.050)	(0.013)	(0.024)	(0.024)	(0.055)
$M\_MOM_{i,t}$	− 0.254***	− 0.084***	− 0.126***	− 0.126***	− 0.095***

Table 14 (continued)

Dependent variable =	$M\_lnAmihudOC_{i,t+1}$ (1)	$M\_lnKyle_{i,t+1}$ (4)	$M\_adjILLIQ_{i,t+1}$ (2)	$M\_adjlnAmihudOC_{i,t+1}$ (3)	$M\_ILLIQ_{i,t+1}$ (5)
	(0.035)	(0.009)	(0.017)	(0.017)	(0.023)
$M\_IVOL_{i,t}$	10.390***	3.051***	5.118***	5.055***	6.892***
	(0.993)	(0.294)	(0.481)	(0.480)	(1.078)
$M\_Coskew_{i,t}$	− 0.001	0.000	− 0.000	− 0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)
$M\_Iskew_{i,t}$	− 0.039**	− 0.016***	− 0.018**	− 0.018**	− 0.023
	(0.019)	(0.005)	(0.009)	(0.009)	(0.019)
Constant	15.412***	5.163***	7.696***	7.681***	12.394***
	(0.829)	(0.219)	(0.382)	(0.381)	(0.388)
Month FE	Yes	Yes	Yes	Yes	Yes
Crypt FE	Yes	Yes	Yes	Yes	Yes
Observations	17,242	17,242	17,242	17,242	5371
Adjusted R^2	0.633	0.692	0.640	0.639	0.489

In this table, we test the monthly robustness tests of static attention. Columns (1)-(4) show the regression results after replacing the indicators of cryptocurrency liquidity, and the dependent variables are *M_lnAmihudOC*, *M_lnKyle*, *M_adjILLIQ* and *M_adjlnAmihudOC* respectively. In column (5), we employ *M_lnTweets* as an alternative measure of static attention, which is the monthly average of the natural logarithm of the daily twitter post counts plus one. The methods for calculating the above variables are detailed in Sect. 2.2.1 and Sect. 2.2.2. Robust standard errors are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

Table 15 Daily robustness checks

Dependent variable =	Alternative measures of cryptocurrency liquidity							Alternative measures of abnormal attention		
	$D\_lnAmihudOC_{i,t+1}$	$D\_lnKyle_{i,t+1}$	$D\_adjILLIQ_{i,t+1}$	$D\_adjlnAmihudOC_{i,t+1}$	$D\_QS_{i,t+1}$	$D\_ES_{i,t+1}$	$D\_PI_{i,t+1}$	$D\_ILLIQ_{i,t+1}$	$D\_ILLIQ_{i,t+1}$	$D\_ILLIQ_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$D\_ABGSV_{i,t}$	0.068***	0.008***	0.016***	0.033***	0.069**	0.091***	0.007***			
	(0.007)	(0.002)	(0.004)	(0.004)	(0.028)	(0.025)	(0.002)			
$D\_ABGSV2_{i,t}$								0.032***		
								(0.008)		
$D\_ABGSV3_{i,t}$									0.027**	
									(0.012)	
D_ABTweets$_{i,t}$										0.009**
										(0.005)
Constant	23.845***	5.121***	5.690***	11.909***	2.853**	2.504**	0.115	11.274***	12.506***	13.645***
	(0.731)	(0.287)	(0.280)	(0.347)	(1.328)	(1.115)	(0.073)	(0.625)	(0.546)	(0.103)
$D\_Controls_{i,t}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crypt FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	574,339	574,339	156,323
Observations	531,115	558,454	574,385	531,115	7375	7347	7035	0.451	0.477	0.441
Adjusted R^2	0.750	0.724	0.447	0.749	0.080	0.059	0.085	0.450	0.477	0.440

This table presents the daily robustness tests of the impact of abnormal attention on cryptocurrency liquidity. Columns (1)-(7) show the regression results for alternative measures of cryptocurrency liquidity, and the dependent variables are *D_lnAmihudOC*, *D_lnKyle*, *D_adjILLIQ*, *D_adjlnAmihudOC*, *D_QS*, *D_ES* and *D_PI* respectively. Columns (8)-(10) present the test results after replacing the abnormal attention indicators, which are *D_ABGSV2*, *D_ABGSV3* and *D_ABTweets* respectively. The methods for calculating the above variables are detailed in Sect. 2.2.1 and Sect. 2.2.2. Robust standard errors are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

References

Ackert, L. F., Church, B. K., Tompkins, J., & Zhang, P. (2005). What's in a name? An experimental examination of investment behavior. *Review of Finance, 9*(2), 281–304.

Adachi, Y., Masuda, M., & Takeda, F. (2017). Google search intensity and its relationship to the returns and liquidity of Japanese startup stocks. *Pacific-Basin Finance Journal, 46*, 243–257.

Afonso, G. (2011). Liquidity and congestion. *Journal of Financial Intermediation, 20*(3), 324–360.

Akyildirim, E., Goncu, A., & Sensoy, A. (2021). Prediction of cryptocurrency returns using machine learning. *Annals of Operations Research, 297*(1), 3–36.

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

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *Journal of Finance, 61*(1), 259–299.

Aouadi, A., Arouri, M., & Teulon, F. (2013). Investor attention and stock market activity: Evidence from France. *Economic Modelling, 35*, 674–681.

Asparouhova, E., Bessembinder, H., & Kalcheva, I. (2010). Liquidity biases in asset pricing tests. *Journal of Financial Economics, 96*(2), 215–237.

Baek, C., & Elbeck, M. (2015). Bitcoins as an investment or speculative vehicle? A First Look. *Applied Economics Letters, 22*(1), 30–34.

Bank, M., Larch, M., & Peter, G. (2011). Google search volume and its influence on liquidity and returns of German stocks. *Financial Markets and Portfolio Management, 25*(3), 239.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies, 21*(2), 785–818.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money, 54*, 177–189.

Blau, B. M. (2017). Price dynamics and speculative trading in bitcoin. *Research in International Business and Finance, 41*, 493–499.

Celeste, V., Corbet, S., & Gurdgiev, C. (2020). Fractal dynamics and wavelet analysis: Deep volatility and return properties of Bitcoin, Ethereum and Ripple. *Quarterly Review of Economics and Finance, 76*, 310–324.

Cheah, E. T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters, 130*, 32–36.

Chen, Y., Xie, Y., You, H., & Zhang, Y. (2018). Does crackdown on corruption reduce stock price crash risk? Evidence from China. *Journal of Corporate Finance, 51*, 125–141.

Cheng, F., Chiao, C., Wang, C., Fang, Z., & Yao, S. (2021a). Does retail investor attention improve stock liquidity? A dynamic perspective. *Economic Modelling, 94*, 170–183.

Cheng, F., Wang, C., Chiao, C., Yao, S., & Fang, Z. (2021b). Retail attention, retail trades, and stock price crash risk. *Emerging Markets Review*, 100821.

Choi, H. (2021). Investor attention and bitcoin liquidity: Evidence from bitcoin tweets. *Finance Research Letters, 39*, 101555.

Cong, L. W., & He, Z. (2019). Blockchain disruption and smart contracts. *Review of Financial Studies, 32*(5), 1754–1797.

Cong, L. W., Li, Y., & Wang, N. (2021a). Tokenomics: Dynamic adoption and valuation. *Review of Financial Studies, 34*(3), 1105–1155.

Cong, L. W., Li, Y., & Wang, N. (2021b). Token-based platform finance. *Journal of Financial Economics*.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters, 165*, 28–34.

Coval, J. D., & Moskowitz, T. J. (1999). Home bias at home: Local equity preference in domestic portfolios. *Journal of Finance, 54*(6), 2045–2073.

Cretarola, A., & Figà-Talamanca, G. (2021). Detecting bubbles in Bitcoin price dynamics via market exuberance. *Annals of Operations Research, 299*(1), 459–479.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *Journal of Finance, 66*(5), 1461–1499.

Dastgir, S., Demir, E., Downing, G., Gozgor, G., & Lau, C. K. M. (2019). The causal relationship between Bitcoin attention and Bitcoin returns: Evidence from the Copula-based Granger causality test. *Finance Research Letters, 28*, 160–164.

Ding, R., & Hou, W. (2015). Retail investor attention and stock liquidity. *Journal of International Financial Markets, Institutions and Money, 37*, 12–26.

Drake, M. S., Roulstone, D. T., & Thornock, J. R. (2012). Investor information demand: Evidence from Google searches around earnings announcements. *Journal of Accounting Research, 50*(4), 1001–1040.

Edmans, A., Fang, V. W., & Zur, E. (2013). The effect of liquidity on governance. *Review of Financial Studies, 26*(6), 1443–1482.
Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance, 25*(2), 383–417.
Fry, J., & Cheah, E. T. (2016). Negative bubbles and shocks in cryptocurrency markets. *International Review of Financial Analysis, 47*, 343–352.
Grobys, K., & Junttila, J. (2021). Speculation and lottery-like demand in cryptocurrency markets. *Journal of International Financial Markets, Institutions and Money, 71*, 101289.
Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *American Economic Review, 70*(3), 393–408.
Grullon, G., Kanatas, G., & Weston, J. P. (2004). Advertising, breadth of ownership, and liquidity. *Review of Financial Studies, 17*(2), 439–461.
Harvey, C. R., & Siddique, A. (2000). Conditional skewness in asset pricing tests. *Journal of Finance, 55*(3), 1263–1295.
Hasbrouck, J. (2009). Trading costs and returns for US equities: Estimating effective costs from daily data. *Journal of Finance, 64*(3), 1445–1477.
Howell, S. T., Niessner, M., & Yermack, D. (2020). Initial coin offerings: Financing growth with cryptocurrency token sales. *Review of Financial Studies, 33*(9), 3925–3974.
Huang, Y., Qiu, H., & Wu, Z. (2016). Local bias in investor attention: Evidence from China's Internet stock message boards. *Journal of Empirical Finance, 38*, 338–354.
Ibikunle, G., McGroarty, F., & Rzayev, K. (2020). More heat than light: Investor attention and bitcoin price discovery. *International Review of Financial Analysis, 69*, 101459.
Jiang, L., Liu, J.Y., Peng, L. & Wang, B. L. (2019). Investor attention and commonalities across asset pricing anomalies. *Working Paper*. Tsinghua University.
Kahneman, D., & Tversky, A. (1973). On the psychology of prediction. *Psychological Review, 80*(4), 237.
Kim, J.B., Luo, L., & Xie, H. (2016). Dividend Payments and Stock Price Crash Risk. *Working paper*.
King, T., & Koutmos, D. (2021). Herding and feedback trading in cryptocurrency markets. *Annals of Operations Research, 300*(1), 79–96.
Köchling, G., Müller, J., & Posch, P. N. (2019). Price delay and market frictions in cryptocurrency markets. *Economics Letters, 174*, 39–41.
Koutmos, D. (2018). Bitcoin returns and transaction activity. *Economics Letters, 167*, 81–85.
Kumar, A. (2009). Who gambles in the stock market? *Journal of Finance, 64*(4), 1889–1933.
Kyle, A. S., & Obizhaeva, A. A. (2016). Market microstructure invariance: Empirical hypotheses. *Econometrica, 84*(4), 1345–1404.
Li, J., & Yu, J. (2012). Investor attention, psychological anchors, and stock return predictability. *Journal of Financial Economics, 104*(2), 401–419.
Li, R., Li, S., Yuan, D., & Zhu, H. (2021a). Investor attention and cryptocurrency: Evidence from wavelet-based quantile Granger causality analysis. *Research in International Business and Finance, 56*, 101389.
Li, Y., Urquhart, A., Wang, P., & Zhang, W. (2021b). MAX momentum in cryptocurrency markets. *International Review of Financial Analysis, 77*, 101829.
Lin, Z. Y. (2020). Investor attention and cryptocurrency performance. *Finance Research Letters*, 101702.
Liu, W., Liang, X., & Cui, G. (2020). Common risk factors in the returns on cryptocurrencies. *Economic Modelling, 86*, 299–305.
Liu, Y., & Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *Review of Financial Studies, 34*(6), 2689–2727.
Loi, H. (2018). The liquidity of bitcoin. *International Journal of Economics and Finance, 10*(1), 13–22.
Makarov, I., & Schoar, A. (2020). Trading and arbitrage in cryptocurrency markets. *Journal of Financial Economics, 135*(2), 293–319.
Merton, R. C. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information. *Journal of Finance, 42*(3), 483–510.
Mondria, J., Wu, T., & Zhang, Y. (2010). The determinants of international investment and attention allocation: Using internet search query data. *Journal of International Economics, 82*(1), 85–95.
Nadarajah, S., & Chu, J. (2017). On the inefficiency of Bitcoin. *Economics Letters, 150*, 6–9.
Peng, L. (2005). Learning with information capacity constraints. *Journal of Financial and Quantitative Analysis, 40*(2), 307–329.
Peng, L., & Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics, 80*(3), 563–602.
Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies, 22*, 435–480.

Philippas, D., Rjiba, H., Guesmi, K., & Goutte, S. (2019). Media attention and Bitcoin prices. *Finance Research Letters, 30*, 37–43.
Phillips, R. C., & Gorse, D. (2018). Cryptocurrency price drivers: Wavelet coherence analysis revisited. *PLoS ONE, 13*(4), e0195200.
Ruan, X., & Zhang, J. E. (2016). Investor attention and market microstructure. *Economics Letters, 149*, 125–130.
Sabah, N. (2020). Cryptocurrency accepting venues, investor attention, and volatility. *Finance Research Letters, 36*, 101339.
Scharnowski, S. (2021). Understanding bitcoin liquidity. *Finance Research Letters, 38*, 101477.
Seasholes, M. S., & Zhu, N. (2010). Individual investors and local bias. *Journal of Finance, 65*(5), 1987–2010.
Shen, D., Urquhart, A., & Wang, P. (2019). Does twitter predict Bitcoin? *Economics Letters, 174*, 118–122.
Sockin, M., & Xiong, W. (2020). A model of cryptocurrencies (No. w26816). *National Bureau of Economic Research*.
Subramaniam, S., & Chakraborty, M. (2020). Investor attention and cryptocurrency returns: Evidence from quantile causality approach. *Journal of Behavioral Finance, 21*(1), 103–115.
Takeda, F., & Wakao, T. (2014). Google search intensity and its relationship with returns and trading volume of Japanese stocks. *Pacific-Basin Finance Journal, 27*, 1–18.
Tiniç, M., Sensoy, A., Akyildirim, E., & Corbet, S. (2020). Adverse Selection in Cryptocurrency Markets. *Working Paper*.
Urquhart, A. (2018). What causes the attention of Bitcoin? *Economics Letters, 166*, 40–44.
Xing, H., Wang, H., Cheng, F., & Yao, S. (2021). Mispricing: failure to capture the risk preferences dependent on market states. *Annals of Operations Research*, 1–26.
Yao, S., Kong, X., Sensoy, A., Akyildirim, E., & Cheng, F. (2021a). Investor attention and idiosyncratic risk in cryptocurrency markets. *European Journal of Finance*, 1–19.
Yao, S., Wang, C., Cui, X., & Fang, Z. (2019). Idiosyncratic skewness, gambling preference, and cross-section of stock returns: Evidence from China. *Pacific-Basin Finance Journal, 53*, 464–483.
Yao, S., Wang, C., Fang, Z., & Chiao, C. (2021b). MAX is not the max under the interference of daily price limits: Evidence from China. *International Review of Economics & Finance, 73*, 348–369.
Zhang, W., & Li, Y. (2020). Is idiosyncratic volatility priced in cryptocurrency markets? *Research in International Business and Finance, 54*, 101252.
Zhang, W., & Wang, P. (2020). Investor attention and the pricing of cryptocurrency market. *Evolutionary and Institutional Economics Review, 17*(2), 445–468.