

# The Negative Relation Between Abnormal Volume and Return in Cryptocurrency

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## Abstract

In contrast to the positive relationship between abnormal volume and returns in equities (e.g. [Gervais et al., 2001](#)), we document a *negative* relation in cryptocurrencies. Our results are not explained by common risk factors nor by various coin characteristics. We interpret abnormal trading volume as investor disagreement and find evidence in support of [Miller \(1977\)](#)'s model: when short sale constraints are binding, high abnormal volume (high disagreement) assets experience lower future returns. Further supporting [Miller \(1977\)](#), these same conditions associate with higher contemporaneous order imbalance, and ex-post decreases in both buying and selling activities, with the former exceeding the latter in magnitude. By contrast, the effect of high disagreement disappears after a coin's margin trading is activated. Our results are important because they underscore the difference between equities and cryptocurrencies in the interpretation of abnormal volume.

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# 1 Introduction

In stock markets, the influential “high-volume return premium”, first identified by [Gervais et al. \(2001\)](#), indicates that unusually (i.e. abnormally) high trading volume over a day or a week associates with higher future returns. One explanation for this premium is based on [Merton \(1987\)](#)’s investor recognition hypothesis ([Gervais et al., 2001](#); [Lerman et al., 2010](#); [Kaniel et al., 2012](#); [Wang, 2021](#); [Israeli et al., 2022](#)): a positive shock in the stock’s trading activity increases its visibility, resulting in greater demand for the stock and an increase in price.<sup>1</sup> Alternatively, some studies interpret the abnormal volume return premium as compensation for risk, with opinion divergence ([Garfinkel & Sokobin, 2006](#); [Banerjee & Kremer, 2010](#)) or information uncertainty ([Jiang et al., 2005](#); [Schneider, 2009](#)) proxied by abnormally high trading volume.

Surprisingly, using Binance data we find a *negative* relation between abnormal trading volume and expected cryptocurrency returns in the cross section.<sup>2</sup> When we form daily quintile portfolios of coins on the basis of abnormal volume, the difference between the highest and lowest quintile portfolios’ next-day returns is always negative. In excess returns it is  $-0.498\%$  (t-statistic =  $-7.20$ ); when risk-adjusted, the CAPM alpha is  $-0.491\%$  (t-statistic =  $-7.21$ ), the three-factor alpha is  $-0.464\%$  (t-statistic of =  $-7.00$ ), and the DGTW alpha is  $-0.459\%$  (t-statistic =  $-7.29$ ).<sup>3</sup> This negative high-volume return relation persists

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<sup>1</sup>[Merton \(1987\)](#) posits that investors have incomplete information and thus only hold stocks they are familiar with. Hence, investors will be under-diversified and demand a higher rate of return for bearing unsystematic risk, i.e., holding securities they are unfamiliar with. An increase in investor awareness (visibility) increases its investor base, leading to a reduction in the cost of capital and an increase in the firm’s market value.

<sup>2</sup>We discuss the Binance sample in Section 2.1.

<sup>3</sup>The CAPM alpha and the three-factor alpha are constructed following the approach of [Y. Liu et al. \(2022\)](#), and the DGTW alpha is constructed following the approach of [Daniel et al. \(1997\)](#).

after controlling (via Fama/Macbeth regressions) for liquidity and other individual coin characteristics.<sup>4</sup> In addition, our results using portfolio sorts and cross-sectional regressions are robust to subsample analysis. The stark contrast between our cryptocurrency results on the high-volume return relation, and the inferences from a large literature studying *equity* high-volume return relations, motivates further analysis.

We hypothesize that a coin’s abnormal trading volume *primarily* reflects differences of opinion on its value. In particular, cryptocurrency valuation is made difficult by the lack of two characteristics common to other asset categories: cash flows; and information about their future expected amounts. This is because most coins do not offer rights on dividends, provide no earnings to project, and receive few professional forecasts from analysts on a regular basis (Cong et al., 2021). Combined, this absence of relatively hard information is simultaneously likely to increase both investors’ disagreement about a cryptocurrency’s value and the relative importance of disagreement for said value. Recent work by Biais et al. (2023) highlights this. They construct a model in which a coin’s fundamental value is its stream of transaction benefits depending on its expected prices, and find that *only* 5% of the variation in Bitcoin’s returns can be attributed to changes in such fundamentals. Put differently, the vast majority of return variation of Bitcoin is driven by differential investor interpretations or opinions. We therefore seek to explain the observed negative relation between abnormal volume and returns in cryptocurrency, by focusing on models that link asset returns with investor disagreement.

We specifically invoke price-optimism models,<sup>5</sup> to interpret the negative relation between

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<sup>4</sup>Short-term reversal, market capitalization, momentum, idiosyncratic volatility, abnormal google search volume, and demand for lottery coins.

<sup>5</sup>Primarily Miller (1977), but also Mayshar (1983); Morris (1996); Viswanathan (2001); Chen et al. (2002); Scheinkman & Xiong (2003); and Hong et al. (2006)

abnormal trading volume (high investor disagreement) and expected coin returns. Specifically, [Miller \(1977\)](#) posits that asset prices mainly reflect the opinions of optimists since pessimistic opinions are suppressed by short sale constraints. Hence, high disagreement will drive prices temporarily above fundamental values and result in low future returns. Using a coin’s abnormal trading volume as proxy for investor disagreement, we show that it is negatively related to ex-post cryptocurrency returns, consistent with [Miller \(1977\)](#)’s model.<sup>6</sup>

There is strong precedence for using abnormal trading volume to proxy disagreement; it is one of the most widely used market-based measures for differences of opinion in the accounting and finance literatures.<sup>7</sup> Intuitively, it is hard to explain why investors would trade in the first place without some source of disagreement involved. [Garfinkel \(2009\)](#) in particular assesses the construct validity of unexplained trading volume by showing it aligns well with a direct disagreement measure constructed from proprietary data on investors’ orders.<sup>8</sup> [Cookson & Niessner \(2020\)](#) and especially [Cookson & Niessner \(2023\)](#) provide more targeted finance evidence: a direct measure of disagreement constructed from StockTwits is strongly correlated with abnormal trading volume.

Given this prima facie evidence supporting [Miller \(1977\)](#), we turn our attention to addressing alternative explanations and threats to identification. We begin by recognizing that cryptocurrency trading was dominated by retail investors in the earlier part of their existence. Since retail investors rarely short, they buy cryptocurrencies that draw their

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<sup>6</sup>We empirically focus on short-sale-constrained coins, after the full-sample results.

<sup>7</sup>See [Beaver \(1968\)](#), [L. S. Bamber \(1987\)](#), [Ajinkya et al. \(1991\)](#), [L. S. Bamber et al. \(1997\)](#), [Garfinkel & Sokobin \(2006\)](#), and [L. Bamber et al. \(2011\)](#) in accounting. Finance work in this line includes [Karpoff \(1987\)](#), [Harris & Raviv \(1993\)](#), [Kandel & Pearson \(1995\)](#), [Bessembinder et al. \(1996\)](#), [Goetzmann & Massa \(2005\)](#), [Garfinkel \(2009\)](#), [Berkman et al. \(2009\)](#), [Atmaz & Basak \(2018\)](#), and [Han et al. \(2022\)](#).

<sup>8</sup>He also shows it dominates other disagreement measures including return variation, bid-ask spread, and analyst forecast dispersion. In particular, return variation and analyst forecast dispersion are negatively related to his direct disagreement measure.

attention today, pushing up trading volume and creating positive price pressure (Barber & Odean, 2008). The prices then revert tomorrow (Barber et al., 2022), explaining the negative high-volume return relation. To address this alternative interpretation concern, we use abnormal Google search volume, public crypto news releases, and absolute daily return to proxy for retail investor attention. We then utilize the decomposition approach of Hou & Loh (2016) to examine what fraction of the negative high-volume return relation can be explained by retail investor attention. We find that the first two measures do not explain any of the negative relation between high-volume and return. On the other hand, absolute daily return as a proxy for retail investor attention explains around 42.5% of the negative relation. While this fraction is non-zero, it is less than half, implying that the majority of the negative high-volume return relation is driven by opinion divergence. This is despite the well-documented positive correlation of absolute daily return with trading volume (Karpoff, 1987). Overall, the results suggest that retail investor attention fails to subsume the opinion-divergence explanation for the negative high-volume return relation.

Our next tests of Miller (1977) are predicated on the necessity of short sale constraints for the model to work.<sup>9</sup> Sourcing our data from the Binance trading platform and the coins on it helps us here, since there is an element of exogeneity to short-sale constraints in this sample. Specifically, shorting a coin is not feasible until Binance publicly announces the activation of the coin’s margin trading services.<sup>10</sup> We thus first document that the negative high-volume

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<sup>9</sup>Without short sale constraints, both optimists and pessimists’ beliefs will be incorporated into stock prices and thus no overpricing of assets will occur.

<sup>10</sup>Binance does not mention their criteria for initiating a coin’s margin trading, and it seems implausible that Binance is simply responding to the shorting needs of pessimists in the market. In particular, in our sample period (August, 2018 to December, 2021) a coin’s margin interest rates are typically fixed except for few occasional adjustments after the coin becomes shortable on Binance. In comparison, short interest rates appear more endogenous recently (in 2023), since Binance recently announced a dynamic margin interest rate system which states that ”Effective from 2023-03-01 06:00 (UTC), users can expect hourly interest rate

return relation is concentrated in coin-day observations without available margin trading services.

This concentration of the negative relation between abnormal volume and returns *among short-sale constrained coins*, raises questions of comparability with the full cross section of equity sample’s positive relation. Therefore, in order to foster appropriate comparison, we run our main Fama/Macbeth regressions on a sub-sample of *equities* that more closely resemble cryptos. We find that stocks with low institutional ownership and lacking exchange-traded put options – in short, ”crypto-like” stocks in terms of short sale constraints – still exhibit a *positive* relation between abnormal trading volume and expected stock returns in the cross section. Cryptos are again different from equities – with a more reasonable comparison sample – in terms of their high-volume return relation. This strongly suggests that support for [Miller \(1977\)](#) is clearer when abnormal volume is largely driven by investor opinion divergence.

We also conduct event-study (time-series diff) tests, focusing on coins that transition from “not shortable” to “shortable” in our sample period. This subsample allows us to focus on coins with a natural counterpart (itself), with the only difference being whether it is constrained from being sold short or not.<sup>11</sup> Given the necessity of the Binance exchange’s decision, we simply construct a dummy variable for short-ability of the coin (prior to margin trading activation versus after margin trading activation of the coin). We expect the negative relation between high disagreement and expected coin returns to present only when coins are subject to short sale constraints, and to disappear once a coin is margin

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updates on the Margin Data page based on current market conditions...”

<sup>11</sup>We recognize that this is not a DiD with an untreated counterfactual both pre- and post. We discuss the challenge to developing such an appropriate counterfactual below.

trading activated (impediments to short sales are removed). This is indeed what we find. When short-selling restrictions are present, a one-standard-deviation increase in abnormal trading volume decreases the next-day return by 0.319%, controlling for coin characteristics. By contrast, when a coin’s margin trading is available, high abnormal trading volume does not result in lower future returns.

We provide two other perspectives to support [Miller \(1977\)](#).<sup>12</sup> First we take advantage of directional trade data on Binance to examine a second implication of his paper: the overpricing of high disagreement assets results from a widening gap between buying and selling activities in the presence of short-sale constraints. Put differently, directional order imbalance should be increasing in disagreement when short selling is prohibited in the coin. We find this too. Before the release of short selling constraints, coins with high abnormal trading volume are associated with higher contemporaneous order imbalance in both trades and in volume, even after controlling for order imbalance persistence and coin characteristics. When short sale constraints are removed, there is no statistically significant relation between abnormal trading volume and order imbalance measures.

Finally, we explore the mechanism contemplated by [Miller \(1977\)](#) when linking abnormal trading volume with lower future coin returns: the lower expected return following high disagreement is achieved via resolution of disagreement. When high disagreement subsides, the proportion of investors with extreme valuations of the asset decreases, reducing both buying and selling activities. However, we should see a smaller decrease in selling activities since pessimists with the lowest valuations of the asset were previously restrained from selling

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<sup>12</sup>These tests utilize the sample of coins that migrate from short-constrained to shortable. We do so for the tighter comparison benefits noted above.

(by the short sale constraint). Consistent with this mechanism, we find that in the presence of short sale constraints, high abnormal trading volume (today) decreases subsequent buying and selling activities (tomorrow), with the decrease in buying activities larger in magnitude.<sup>13</sup> On the other hand, when margin trading is activated, we do not observe diminutions of buying and selling activities following high abnormal trading volume.

Our paper makes several contributions. First, we contribute to the literature studying the high-volume return relation. In contrast to the high-volume return premium (Gervais et al., 2001; Lerman et al., 2010; Kaniel et al., 2012; Wang, 2021; Israeli et al., 2022; Garfinkel & Sokobin, 2006; Banerjee & Kremer, 2010; Jiang et al., 2005; Schneider, 2009) in stocks, we instead document a negative relation between high-volume and return in the cross section of cryptocurrencies.<sup>14</sup> We find that the negative relation persists after controlling for their (Y. Liu et al. (2022)’s) three-factor model, as well as coin characteristics that are known to predict returns.

Hence, our paper also contributes to the burgeoning literature studying cross-sectional returns of cryptocurrencies. For example, Y. Liu & Tsyvinski (2021) and Y. Liu et al. (2022) study size and momentum factors’ influences. Following Baker & Wurgler (2006), sentiment proxies such as direct Bitcoin sentiment (from Sentix) or even general (Twitter) happiness, have also been linked to cryptocurrency returns (Naeem et al., 2021; Anamika et al., 2023). But while extant work has studied the role of investor disagreement in other asset

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<sup>13</sup>The reduction in both buying and selling activities following high abnormal trading volume is in sharp contrast to the common explanation for the high-volume return premium in stock markets that unusually high volume increases visibility and investor base.

<sup>14</sup>We are the first to show this robustly. While Y. Liu et al. (2022) document that high *dollar trading volume* coins earn lower returns compared to low dollar trading volume coins, they find that the return difference is subsumed by their proposed three-factor model. Moreover, they find that neither raw volume nor turnover ratio exhibit return predictive power. Our paper complements their findings by focusing on “abnormal” trading volume to mitigate the concern that raw volume or turnover may also capture liquidity.



pricing settings, there is little evidence on its role in the cross-sectional pricing of individual cryptocurrencies. We offer the first empirical study of it by invoking price-optimism disagreement models to explain the negative high-volume return relation.

Finally, we provide unique supporting evidence for [Miller \(1977\)](#). We emphasize the equally important roles of high disagreement and the presence of short sale constraints to produce overpricing. We also provide layers of evidence on trading activities consistent with his implications, using directional trade information. Hence, our paper complements the disagreement studies ([Mayshar, 1983](#); [Morris, 1996](#); [Viswanathan, 2001](#); [Boehme et al., 2006](#); [Chen et al., 2002](#); [Diether et al., 2002](#); [Scheinkman & Xiong, 2003](#); [Hong et al., 2006](#); [Cookson et al., 2022](#)) that support [Miller \(1977\)](#) in other asset classes, while casting some doubts on opposite conclusions ( [Anderson et al., 2005](#); [Doukas et al., 2006](#); [Garfinkel & Sokobin, 2006](#); [David, 2008](#); [Banerjee, 2011](#); [Carlin et al., 2014](#); [Gao et al., 2019](#)) represented by [Varian \(1985\)](#). Notably, none of these papers study cryptocurrency returns where investor opinion divergence likely carries outsize importance for asset valuation and for abnormal volume.

## 2 Data

### 2.1 Sample Selection

We collect hourly closing prices of all spot trading cryptocurrency pairs on [Binance.com](#) from [CoinAPI.io](#). Although our analysis and control variables are daily, the hourly information is useful when we seek daily measures of coin volatility, liquidity, and demand for lottery-like coins (all requiring intraday hourly returns). Hourly data translates into daily data under

the assumption of UTC+00:00 as midnight (following CoinAPI’s daily dataset definition). At the time of our data collection process, Binance was the largest cryptocurrency exchange in the world and had the highest overall exchange rating on several third-party aggregator websites such as CoinCap, CoinGecko, and CoinMarketCap.<sup>15</sup>

We recognize the recent SEC’s suit against Binance platforms.<sup>16</sup> However, the “wash trading” charges in the SEC 136-page filing are brought against the Binance.US platform, while our sample comes from the Binance.com platform (Binance, hereafter) data.<sup>17</sup> That being said, it is unlikely that Binance and other cryptocurrency exchanges are not susceptible to any wash trading. However, our findings in Section 3.5.1 provide evidence that the volume-return relation is unlikely to be explained by the wash-trade effect.

The sample period is from July 1, 2018 through December 31, 2021. Each cryptocurrency trading pair (X/Y) consists of a base asset (X) and a quote asset (Y). The trading volume and price of the pair are measured in X and denominated in Y, respectively. For a given base asset, there can be more than one quote asset. For example, “ETH/BTC” and “ETH/USDT” are both active trading pairs on Binance.

Since trading pairs with the same base asset have almost perfect return comovement due to market efficiency, we treat such cryptocurrencies as the same. We thus only focus on trading pairs with BTC as the quote asset. The main advantage of this approach is that the number of trading pairs quoted in BTC is the largest on Binance. This allows us to maximize the number of base assets in the cross section that we examine. For simplicity,

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<sup>15</sup>According to TokenInsight’s research in October 2019, the actual transaction ratio of Binance is greater than 90%. See <https://tokeninsight.com/en/research/reports/2019-09-crypto-exchange-wash-trading-research>.

<sup>16</sup>See <https://www.sec.gov/files/litigation/complaints/2023/comp-pr2023-101.pdf>.

<sup>17</sup>Binance.US has a significantly lower trading volume than Binance.com due to its limited user base (only for U.S. customers). In addition, Binance.US also offers fewer cryptocurrencies and trading pairs than Binance.com.

we refer to base assets as coins throughout the paper. Since coin prices in our sample are all denominated in BTC, we adjust their prices by multiplying by the contemporaneous exchange rate between BTC and US dollars.

The trade data on these coins also comes from CoinAPI.io. The advantage of our collected trade data is that volume and the direction of each trade (buyer-initiated or seller-initiated) are recorded. This enables us to examine trading activity in greater depth with more clarity than usual. In particular, we do not have to rely on an algorithm to classify trades, such as the commonly used one by [Lee & Ready \(1991\)](#).

We require that coins be traded on Binance for at least one month before we include it in our sample. Thus the effective sample period is August 1st, 2018 through December 31st, 2021. We further exclude leverage coins, and also coins with missing price or volume data.<sup>18</sup> Market capitalization information and circulating supply data comes from CoinMarketCap. To ensure our results are not driven by small coin we eliminate those with market capitalization less than \$1 million at the end of the previous months following [Y. Liu & Tsyvinski \(2021\)](#) and [Y. Liu et al. \(2022\)](#). Our final sample consists of 356 coins.

To construct common risk factors for the whole coin market, we obtain price and market capitalization data from CoinMarketCap. We follow the approach of [Y. Liu et al. \(2022\)](#) to construct daily risk factors: the market factor (CMKT), the size factor (CSMB), and the momentum factor (CMOM). The details are in the Appendix.

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<sup>18</sup>Our empirical results are robust to the exclusion of stablecoins.

## 2.2 Abnormal Trading Volume (ABVOL)

In this section, we construct our measure of unexpected trading activity, recognizing that raw trading activity may largely capture liquidity trading needs.<sup>19</sup> First, we focus on turnover instead of raw volume to account for cross-sectional variation in coin trading. Second, we also subtract from it, coin turnover measured over a reference period  $([t - 30, t - 1])$ , to remove likely liquidity-oriented turnover. The specific calculation of a coin’s daily abnormal turnover is:

$$\text{Change in turnover}_{i,t} = \frac{\text{Volume}_{i,t}}{\text{Circulating supply}_{i,t}} - \frac{1}{30} \sum_{j=i-1}^{i-30} \frac{\text{Volume}_{j,t}}{\text{Circulating supply}_{j,t}}, \quad (1)$$

where  $i$  refers to the coin and  $t$  refers to the day. Change in turnover is thus a coin’s daily turnover minus the prior 30-day average turnover (as proxy for liquidity). This netting approach recognizes that coins with high trading volume are reasonably more liquid<sup>20</sup> and that some research ties liquidity fluctuations to asset returns.<sup>21</sup> Finally, we standardize Change in turnover by its time-series standard deviation calculated over the prior 30 days. This reflects potential cross-sectional variation in coin trading volatility.<sup>22</sup> Hence, abnormal trading volume (ABVOL) for coin  $i$  on day  $t$  is defined as follows:

$$\text{ABVOL}_{i,t} = \frac{\text{Change in turnover}_{i,t}}{\sigma_{i,t}}. \quad (2)$$

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<sup>19</sup>See Benston & Hagerman (1974), Branch & Freed (1977), and Petersen & Fialkowski (1994).

<sup>20</sup>For equity market versions of this, see Tkac (1999), Lee & Swaminathan (2000), Gebhardt et al. (2001), Garfinkel & Sokobin (2006), and Garfinkel (2009).

<sup>21</sup>See Brennan et al. (1998), Chordia et al. (2000), Chordia et al. (2001), and Hasbrouck & Seppi (2001).

<sup>22</sup>Our results are robust to different-length windows (7 days, 15 days, 45 days) for the calculation of the first and second moments of coin turnover.

## 2.3 Defining Coin Characteristics

We begin this section by noting that our excess return measure is standard; it is the daily coin return minus the daily imputed risk-free return (from U.S. Treasuries). We then define several cryptocurrency characteristics (i.e. controls) for use in our regressions.

Following [Jegadeesh \(1990\)](#), short-term reversal (REV) is defined as the coin return in the previous day - i.e. the day prior to the portfolio formation day. Following [Jegadeesh & Titman \(1993\)](#), momentum (MOM) is the cumulative return of a coin over a period of 11 days ending one day prior to the portfolio formation day. MCAP is a coin's market capitalization at the end of the previous month prior to the portfolio formation day.

We follow [Amihud \(2002\)](#) to calculate an illiquidity (ILLIQ) control. It is the daily average of absolute hourly return, divided by dollar trading volume on a day.

$$\text{ILLIQ}_{i,t} = 10^6 \times \text{Avg} \left[ \frac{|R_{i,h}|}{DV_{i,h}} \right], \quad (3)$$

where  $R_{i,h}$  and  $DV_{i,h}$  are the hourly return and dollar trading volume for coin  $i$  in hour  $h$ , respectively. We require at least 15 observations to construct ILLIQ.

We follow [Ang et al. \(2006\)](#) to calculate daily idiosyncratic volatility (IVOL). For coin  $i$  on day  $t$ , it is the standard deviation of hourly residuals estimated from the following regression:

$$R_{i,h} - r_{f,h} = \alpha_i + \beta_i(R_{M,h} - r_{f,h}) + \epsilon_{i,h}, \quad (4)$$

where  $R_{i,h}$  and  $R_{M,h}$  are the hourly return on coin  $i$  and the coin market hourly return

(value-weighted) respectively. We require at least 15 observations to construct IVOL.

Following [Da et al. \(2011\)](#), we control for investor attention using Google search volume. For each coin, we specifically compute abnormal Google search volume index (ASVI) as the Google search volume index on a day minus its median search volume index during the past week.<sup>23</sup> We set ASVI for a coin to zero if its is missing.

Finally, we follow [Bali et al. \(2011\)](#) to measure demand for lottery-like coins using MAX, calculated as a coin’s maximum hourly return during that day.

## 2.4 Summary Statistics

Table 1 presents summary statistics on our sample. Panel A details the time-series averages of coin characteristics. Panel B shows the quarterly time series of coins we study, their average and median market caps, as well as similar information at the coin market level. Notably, ABVOL has a time-series mean of 0.168 and median of  $-0.279$ , clearly indicating right-skewed distribution of ABVOL.<sup>24</sup>

Panel B shows our growing cross-section of coins throughout the sample period. We start with 138 coins in the third quarter of 2018 and end with 301 coins in the fourth quarter of 2021. The number of coins and mean/median market capitalization of the coin market, are generally within norms from other studies (e.g., [Y. Liu & Tsyvinski, 2021](#); [Y. Liu et al., 2022](#)). While our sample on average captures about 14% of the coins in the market, the mean/median market capitalization of our sample coins is relatively larger than that of the overall market’s. This is due to the listing requirements on Binance<sup>25</sup>, which essentially rule

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<sup>23</sup>We use the coin symbol found on Binance as the Google search term. The results are robust to using the coin symbol along with BTC (the quote asset) as the search term.

<sup>24</sup>The time-series averages of the t-statistics for the null hypothesis that  $ABVOL = 0$  is 0.16.

<sup>25</sup>“...We want good coins listed on Binance, such as coins with a proven team, a useful product,

out coins with smaller size and lower user adoption. Overall, the total market capitalization in our sample on average accounts for about 34% of the total market capitalization of the coin market.

## 3 Empirical Results

### 3.1 Portfolio Analysis

First, we examine the predictive power of abnormal trading volume (ABVOL) over future excess coin returns using portfolio sorts. For each day, we form quintile portfolios by sorting individual coins based on their abnormal trading volume (ABVOL) in the previous day, where quintile 1 contains coins with the lowest 20% of ABVOL and quintile 5 contains coins with the highest 20% of ABVOL. Then, we examine the average portfolio returns within each ABVOL quintile.<sup>26</sup>

Panel A of Table 2 reports the results, and Newey & West (1987) t-statistics with eight lags are reported in parentheses.<sup>27</sup> The first column shows that when moving from the lowest to the highest ABVOL quintile, the average excess return decreases monotonically (with the exception of the third ABVOL quintile). Coins in the lowest ABVOL quintile generate an average excess return of 0.542% per day, whereas coins in the highest ABVOL quintile generate an average excess return of 0.044% per day. The average return difference

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and a large user base...” See the “How to Get Your Coin Listed on Binance.com” section in <https://www.binance.com/en/support/faq/> for more details.

<sup>26</sup>The effect of delisting is minor, since Binance publicly announces a coin’s delisting decision one week prior to its actual delisting. To the best of our knowledge, all of the delistings of spot trading pairs on Binance in our sample are anticipated.

<sup>27</sup>Following Andrews (1991), we use  $0.75 \times T^{1/3}$  to compute the optimal lag. With the number of days (T) in our sample period being 1248 days, the optimal lag is 8.07. Our results are robust to all values of lags ranging from 1 to 24.

between the highest and the lowest ABVOL quintile is  $-0.498\%$  per day with a t-statistic of  $-7.20$ .

In addition to excess returns, we compute three types of risk-adjusted returns. CAPM alpha is the intercept from the regression of excess portfolio returns on a constant and the cryptocurrency excess market return (CMKT). Three-factor alpha is the intercept from the regression of excess portfolio returns on a constant, the cryptocurrency excess market return (CMKT), the size factor (CSMB), and the momentum factor (CMOM). In addition, we follow the approach of [Daniel et al. \(1997\)](#) to compute the characteristic-based return measure of each ABVOL portfolio. In particular, each day we sort coins in the coin market into  $10 \times 10 = 100$  portfolios based on their coin size and momentum measured at the end of previous day.<sup>28</sup> Each coin is assigned to a benchmark portfolio according to its coin size and momentum rank. We compute the DGTW alpha for a coin as the difference between its realized daily return and the realized value-weighted return for the matching benchmark portfolio. The DGTW alpha of a portfolio is the average DGTW alpha of the coins in the portfolio.

As shown in the second, third, and fourth columns of Table 2, the average CAPM alpha, three-factor alpha, and DGTW alpha also exhibit a decreasing pattern of returns when moving from the lowest to the highest ABVOL quintile.<sup>29</sup> Specifically, the average daily return differential between the highest and the lowest ABVOL quintile is  $-0.491\%$  (t-statistic  $= -7.21$ ),  $-0.464\%$  (t-statistic  $= -7.00$ ), and  $-0.459\%$  (t-statistic  $= -7.29$ ), respectively.

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<sup>28</sup>Here we follow [Daniel et al. \(1997\)](#) and use sequential sorts (first coin size, then momentum). Using an independent sort does not qualitatively affect the results in the paper.

<sup>29</sup>Note that the average three-factor alphas of all ABVOL quintiles are negative. This is due to the size effect in cryptocurrency ([Y. Liu & Tsyvinski, 2021](#) and [Y. Liu et al., 2022](#)) that larger coins earn significantly lower returns compared to smaller coins. As documented in Panel B of Table 1, the coins in our Binance sample have relatively larger coin size compared to the coin market and thus have lower returns.



The results of Panel A indicate that the return differential between the highest and lowest ABVOL quintile is significantly negative, and is not driven by common risk factors in the cryptocurrency market. This negative high-volume return relation in cryptocurrencies is in stark contrast to the positive high-volume return relation in stocks (Gervais et al., 2001; Lerman et al., 2010; Kaniel et al., 2012; Wang, 2021; Israeli et al., 2022).

An important question is whether the return patterns we document are robust to longer windows of analysis. We therefore examine whether the negative return difference between the top and bottom ABVOL quintiles persists under longer holding periods, following the approach of Jegadeesh & Titman (1993).<sup>30</sup> Table IA.1 in the internet appendix shows that for holding periods up to 19 days, the differences in average returns (excess return, CAPM alpha, three-factor alpha, and DGTW alpha) between the highest and lowest ABVOL quintile remain negative and statistically significant. The result suggests that the negative relation between ABVOL and expected coin returns is not caused by a statistical fluke or bid-ask bounce. Nevertheless, the strongest underperformance appears in the first day (or two) after portfolio formation on ABVOL. Thus, our remaining tests conservatively fixate on the day after ABVOL calculation.

Interpreting ABVOL as investor disagreement, Panel A of Table 2 provides preliminary evidence in support of price-optimism models represented by Miller (1977). That is, high disagreement coins, as represented by high ABVOL, are overvalued relative to their fundamental values as long as there are frictions in the cryptocurrency market that prevent pessimists

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<sup>30</sup>In particular, we vary the number of holding days for each ABVOL portfolio after it has been formed. For example, when we hold for the portfolio for 3 days, the portfolio return in day  $t$  is the average excess return of the quintile portfolios formed in  $t - 1$ ,  $t - 2$ , and  $t - 3$ . Hence, each quintile portfolio changes one-third of its composition each day.

from selling the coin short. Hence, those coins experience significantly lower future returns.<sup>31</sup>

### 3.2 Average Coin Characteristics

In addition to our portfolio based return tests, below we use the Fama-Macbeth framework and consider more controls known to influence returns. Thus it is useful to understand how these variables may be correlated with our key metric of ABVOL. In this section we examine average values of coin characteristics within each ABVOL quintile. Panel B of Table 2 presents these relationships.

First we note that most of our coin characteristic controls appear to be monotonic in relation to ABVOL. For example, moving from the lowest to the highest ABVOL quintile, average contemporaneous return (REV) increases from  $-0.770\%$  to  $3.763\%$  per day. This is consistent with [Miller \(1977\)](#)'s hypothesis that asset prices of high disagreement assets are mainly set by optimists and thus are biased upward. In addition, momentum (MOM), idiosyncratic volatility (IVOL), abnormal google search volume index (ASVI), and demand for lottery coins (MAX) all increase monotonically with abnormal volume (ABVOL). The fact that REV, IVOL, and MAX all increase with ABVOL is somewhat expected since past studies document that stock trading volume is contemporaneously related to return ([Ying, 1966](#); [Westerfield, 1977](#)) and volatility ([Clark, 1973](#); [Tauchen & Pitts, 1983](#); [Karpoff, 1987](#); [Gallant et al., 1992](#); [Andersen, 1996](#)). In the opposite direction, average illiquidity (ILLIQ) decreases monotonically with ABVOL. Finally, we note a U-shape between average market capitalization (MCAP) and the ABVOL quintile. Average MCAP is largest (1.643 billions) within the lowest ABVOL quintile, and second largest (1.244 billions) within the highest

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<sup>31</sup>We address the empirical role of short constraints below, beginning with Table 5.

ABVOL quintile.

Overall, coins with high disagreement (high ABVOL) tend to perform better in the past, have higher return volatility, receive more investor attention, experience higher extreme hourly returns, and are more liquid. We control for the potential absorbing effects of these correlated (with ABVOL) variables, in our next tests.

### 3.3 Fama-Macbeth Cross-Sectional Regressions

In this section, we examine whether the underperformance of high ABVOL coins in the cross section is simply capturing the effect of other coin characteristics on their returns. We explore short-term reversal (REV), market capitalization (MCAP), momentum (MOM), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), abnormal google search volume index (ASVI), and demand for lottery coins (MAX), as potential controls.

We choose the controls based on past research linking them with either coin or stock returns. For example, [Y. Liu & Tsyvinski \(2021\)](#) and [Y. Liu et al. \(2022\)](#) find qualitatively similar size (e.g, [Fama & French, 1992, 1993](#)), momentum (e.g., [Jegadeesh & Titman, 1993, 2001, 2002](#)), and investor attention (e.g., [Da et al., 2011](#)) effects in the coin market. In addition, [Bianchi et al. \(2022\)](#) find that coins exhibit return reversals (e.g., [Jegadeesh, 1990](#); [Lehmann, 1990](#)) over short horizons. Other commonly-known return predictors in the stock market appear to possess insignificant return predicting power in the cross section of coins. For example, according to [Amihud \(2002\)](#), investors should demand compensation for holding less liquid stocks; [Bali et al. \(2011\)](#) document a negative cross-sectional relation between the maximum daily return over the previous month and expected stock returns; [Ang et al.](#)

(2006) and [Ang et al. \(2009\)](#) document a negative relation between idiosyncratic volatility and subsequent stock returns in the cross section. However, [Y. Liu et al. \(2022\)](#) find no significant cross-sectional relationship between any of the above three characteristics (ILLIQ, MAX, and IVOL) and weekly coin returns.

We run [Fama & MacBeth \(1973\)](#) regressions of excess coin returns on ABVOL along with those coin characteristics. For every day, we perform the following cross-sectional (i.e. across coins) regressions:

$$\text{RET}_{i,t+1} = \alpha_t + \beta_t \times \text{ABVOL}_{i,t} + \beta_{c,t} \times \text{Controls}_{i,t} + \epsilon_{i,t+1}, \quad (5)$$

where  $i$  refers to the coin,  $t$  refers to the day, and RET refers to the daily excess return. We include one control variable at a time in columns 1 to 8, and then all controls in column 9. The former helps us assess comparability with extant coin research. The latter asks whether ABVOL is incrementally important. In all regressions, the main variable of interest is ABVOL. The coefficient on this variable captures the difference in next-day excess coin returns based on the level of ABVOL, after controlling for various coin characteristics.

Table 3 reports the time-series averages of the slope coefficients, with the [Newey & West \(1987\)](#) adjusted t-statistics reported in parentheses. In column 1, the average slope,  $\beta$ , from the daily regressions of next-day excess returns on ABVOL alone is  $-0.179$  with a t-statistic of  $-9.72$ . Next, the relation between ABVOL and future coin returns is examined jointly with each of the seven coin characteristics. This joint examination can be viewed as an alternative to bivariate portfolio analysis since the number of coins in the cross section is too few to perform a  $5 \times 5$  double sort. In each specification, the coefficients on ABVOL remain

negative (ranging from  $-0.108$  to  $-0.184$ ) and are all statistically significant at the 1% level. On the other hand, the coefficient on REV is significantly negative ( $-0.057$  with a t-statistic of  $-8.39$ ), indicating that coins exhibit strong short-term reversals.<sup>32</sup> The coefficient on ASVI is significantly positive ( $0.007$  with a t-statistic of  $2.10$ ), suggesting that coins with higher investor attention experience higher future returns. The coefficients on the other variables are statistically indistinguishable from zero.

Of primary interest is the last column in Table 3, which reports the results for the full specification with ABVOL and all seven coin characteristics. The average slope coefficient on ABVOL is  $-0.120$  with a t-statistic of  $-5.61$ , indicating that ABVOL significantly and negatively predicts next-day coin returns after controlling for all coin characteristics simultaneously. Overall, the [Fama & MacBeth \(1973\)](#) cross-sectional regressions provide strong evidence for a significantly negative relation between ABVOL and future coin returns.<sup>33</sup>

### 3.4 Alternative Explanation: Retail Investor Attention

The negative relation between ABVOL and future coin excess returns in the previous sections is consistent with [Miller \(1977\)](#)’s hypothesis that high disagreement assets are overpriced and thus have lower expected returns. In this section, we examine an alternative explanation for this negative relation.

Since retail crypto investors tend to over-react (e.g., [Kogan et al., 2023](#)), attention-grabbing positive news about crypto could generate excess trading volume and create positive price

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<sup>32</sup>We revisit the importance of reversals below in section 3.4, as we explore alternative interpretations of our results.

<sup>33</sup>Introducing a quadratic term to the regression appears to add little to the explanatory power and does not change the significantly negative coefficient on ABVOL. In addition, to control for short-term reversals non-linearly, we run untabulated analyses including the absolute value of reversal as an additional control variable in the regression. The coefficient on ABVOL remains significantly negative.

pressure at the same time (e.g., [Barber & Odean, 2008](#)). This could be followed by reversal in the following days (e.g., [Barber et al., 2022](#)). Hence, it is possible that abnormal trading volume consists of positive-attention-induced volume, and thus the negative relation between ABVOL and next-day coin returns largely reflects retail investor attention rather than investor disagreement.

### 3.4.1 Data: Three Measures of Retail Investor Attention

To study this alternative explanation, we examine what fraction of the negative relation between ABVOL and future coin excess returns can be explained by retail investor attention. We consider three measures of retail investor attention. The first measure is the abnormal Google search volume index (ASVI) defined as in Section 2.3, which is commonly used as a proxy for retail investor attention (e.g., [H. Liu et al., 2023](#)).

For our second measure, we note that retail investors likely pay attention to crypto news releases.<sup>34</sup> We obtain public news events for the coins in our sample from Cryptorank, which contains coin news events from 31 major news sites.<sup>35</sup> We manually eliminate news that contains no new information to investors (e.g., past price analyses, price forecasts, and regular market updates). Among 223,476 coin-day observations in our sample, there are 17,240 coin-day observations with at least one news event. We define our second measure of retail investor attention,  $NEWS_{i,t}$ , as the logarithm of one plus number of news events of coin  $i$  on day  $t$ .<sup>36</sup>

For our third measure, we recognize the fact that small coins are not heavily searched

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<sup>34</sup>[Biais et al. \(2023\)](#) is consistent with this.

<sup>35</sup><https://cryptorank.io/>

<sup>36</sup>The skewness of the number of news events is 10.80.

and often do not have crypto news releases. Hence, we consider  $\text{ABSREV}_{i,t}$ , defined as the absolute value of daily return of coin  $i$  on day  $t$ .<sup>37</sup> Large values of  $\text{ABSREV}$  should be associated with higher level of retail investor attention.

### 3.4.2 Measuring Importance of Retail Investor Attention

We follow the econometric approach in [Hou & Loh \(2016\)](#) to examine how retail investor attention plays a role in the negative relation between  $\text{ABVOL}$  and future coin excess returns. [Hou & Loh \(2016\)](#) provide a simple unified framework to evaluate multiple possible explanations of any number of return puzzles. Their approach also quantifies the fraction of the puzzle that is explained by each candidate explanation. The fractions sum to one, allowing evaluation of the relative importance of multiple candidate explanations for a documented return-relation. We apply their technique to study the role of retail investor attention in the negative  $\text{ABVOL}$ -return relation.

Specifically, for every day  $t$ , we first perform the following cross-sectional daily regressions:

$$\text{RET}_{i,t+1} = \alpha_t + \beta_t \text{ABVOL}_{i,t} + \epsilon_{i,t+1}, \quad (6)$$

where  $i$  refers to the coin,  $t$  refers to the day, and  $\text{RET}$  refers to the daily excess return.

Next, we regress  $\text{ABVOL}_{i,t}$  on a measure of retail investor attention ( $\text{RIA}_{i,t}$ ):

$$\text{ABVOL}_{i,t} = a_t + \delta_t \text{RIA}_{i,t} + \mu_{i,t}, \quad (7)$$

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<sup>37</sup>Since we are predicting coin return on day  $t+1$ , the absolute value of daily return on day  $t$  is essentially the absolute value of reversal. We thank an anonymous referee for suggesting this interpretation of reversal.

where  $RIA_{i,t}$  is proxied by either  $ASVI_{i,t}$ ,  $NEWS_{i,t}$ , or  $ABSREV_{i,t}$ . After obtaining the regression coefficient estimates, we decompose  $ABVOL_{i,t}$  into two orthogonal components:  $\delta_t RIA_{i,t}$  is the component of  $ABVOL_{i,t}$  that is related to the retail investor attention while  $(\alpha_t + \mu_{i,t})$  is the residual component of  $ABVOL_{i,t}$  that is unrelated to retail investor attention.

The final step is to use the linearity of covariances to decompose the  $\beta_t$  from equation (6) into two components: the part that is related to retail investor attention ( $\beta_t^{RIA}$ ) and the residual part that is unrelated to retail investor attention ( $\beta_t^r$ ). Specifically,

$$\begin{aligned}\beta_t &= \frac{Cov[RET_{i,t+1}, ABVOL_{i,t}]}{Var(ABVOL_{i,t})} = \frac{Cov[RET_{i,t+1}, (\delta_t RIA_{i,t} + \alpha_t + \mu_{i,t})]}{Var(ABVOL_{i,t})} \\ &= \frac{Cov[RET_{i,t+1}, \delta_t RIA_{i,t}]}{Var(ABVOL_{i,t})} + \frac{Cov[RET_{i,t+1}, (\alpha_t + \mu_{i,t})]}{Var(ABVOL_{i,t})} \\ &= \beta_t^{RIA} + \beta_t^r.\end{aligned}\tag{8}$$

Therefore,  $\beta_t^{RIA}/\beta_t$  measures the fraction of the ABVOL-return relation explained by retail investor attention (RIA), and  $\beta_t^r/\beta_t$  measures the “residual” fraction of the ABVOL-return relation left unexplained by retail investor attention. By construction, these two fractions sum to one.

We follow [Hou & Loh \(2016\)](#) and use the standard multivariate delta method based on Taylor series expansions to derive means and variances of the two fractions:

$$\begin{aligned}E\left(\frac{\beta_t^{RIA}}{\beta_t}\right) &\approx \frac{E(\beta_t^{RIA})}{E(\beta_t)}, \quad E\left(\frac{\beta_t^r}{\beta_t}\right) \approx \frac{E(\beta_t^r)}{E(\beta_t)}, \\ Var\left(\frac{\beta_t^{RIA}}{\beta_t}\right) &\approx \left(\frac{E(\beta_t^{RIA})}{E(\beta_t)}\right)^2 \times \left(\frac{Var(\beta_t^{RIA})}{(E(\beta_t^{RIA}))^2} + \frac{Var(\beta_t)}{(E(\beta_t))^2} - 2\frac{Cov(\beta_t^{RIA}, \beta_t)}{(E(\beta_t^{RIA})E(\beta_t))}\right), \\ Var\left(\frac{\beta_t^r}{\beta_t}\right) &\approx \left(\frac{E(\beta_t^r)}{E(\beta_t)}\right)^2 \times \left(\frac{Var(\beta_t^r)}{(E(\beta_t^r))^2} + \frac{Var(\beta_t)}{(E(\beta_t))^2} - 2\frac{Cov(\beta_t^r, \beta_t)}{(E(\beta_t^r)E(\beta_t))}\right).\end{aligned}\tag{9}$$



We then use the sample mean, variance, and covariances obtained from the respective time series (over  $T$  days) of  $\beta_t$ ,  $\beta_t^{\text{RIA}}$ , and  $\beta_t^r$  to compute the estimated means and variances of the two fractions:

$$\begin{aligned}\hat{E}\left(\frac{\beta_t^{\text{RIA}}}{\beta_t}\right) &\approx \frac{\overline{\beta_t^{\text{RIA}}}}{\overline{\beta_t}}, \quad \hat{E}\left(\frac{\beta_t^r}{\beta_t}\right) \approx \frac{\overline{\beta_t^r}}{\overline{\beta_t}}, \\ \hat{Var}\left(\frac{\beta_t^{\text{RIA}}}{\beta_t}\right) &\approx \frac{1}{T} \left(\frac{\overline{\beta_t^{\text{RIA}}}}{\overline{\beta_t}}\right)^2 \times \left(\frac{s_{\beta_t^{\text{RIA}}}^2}{\overline{\beta_t^{\text{RIA}}}^2} + \frac{s_{\beta_t}^2}{\overline{\beta_t}^2} - 2\frac{\hat{\rho}_{\beta_t^{\text{RIA}}, \beta_t} s_{\beta_t^{\text{RIA}}} s_{\beta_t}}{\overline{\beta_t^{\text{RIA}}} \overline{\beta_t}}\right), \\ \hat{Var}\left(\frac{\beta_t^r}{\beta_t}\right) &\approx \frac{1}{T} \left(\frac{\overline{\beta_t^r}}{\overline{\beta_t}}\right)^2 \times \left(\frac{s_{\beta_t^r}^2}{\overline{\beta_t^r}^2} + \frac{s_{\beta_t}^2}{\overline{\beta_t}^2} - 2\frac{\hat{\rho}_{\beta_t^r, \beta_t} s_{\beta_t^r} s_{\beta_t}}{\overline{\beta_t^r} \overline{\beta_t}}\right).\end{aligned}\tag{10}$$

The time-series average of  $\beta_t^{\text{RIA}}$  divided by the time-series average of  $\beta_t$  measures the fraction of the negative ABVOL- excess return relation explained by the RIA variable. The time-series average of  $\beta_t^r$  divided by the time-series average of  $\beta_t$  measures the fraction of the relation left unexplained by the RIA variable.

The two fractions along with their statistical significance provide an empirical test for the alternative explanation. If the return-predicting power of ABVOL is mostly driven by retail investor attention, then the fraction  $\beta_t^{\text{RIA}}/\beta_t$  will be large and significantly different from zero, while the fraction  $\beta_t^r/\beta_t$  will be small and statistically indistinguishable from zero.

Table 4 reports the results of this decomposition exercise. Stage 1 regresses day  $t + 1$  coin excess returns on day  $t$  ABVOL. This regression is the same Fama-Macbeth regression in column 1 of Table 3. The average coefficient on ABVOL is  $-0.179$  with a t-statistic of  $-9.72$ .

In Stage 2, we add a RIA variable to the cross-sectional regressions. This is identical to adding a control variable in columns 2 to 8 in Table 3. We see that the average coefficients

on ABVOL remain negative (ranging from -0.184 to -0.139) and statistically significant (t-statistics ranging from -10.06 to -7.16) across three measures of RIA, which indicates that RIA cannot *fully* explain the negative ABVOL-return relation. One thing worth mentioning is the magnitude of the average coefficient on ABVOL becomes smaller when we use ABSREV as the RIA measure. This implies that ABSREV may help account for a fraction of the negative relation between ABVOL and future coin returns.

Next, we use the decomposition methodology to assess specifically what fraction of the negative ABVOL-return relation is captured by retail investor attention. In Stage 3, we regress ABVOL on each measure of RIA each day. When using ASVI as the RIA measure, the average coefficient on RIA is statistically indistinguishable from zero. When using NEWS as the RIA measure, the average coefficient on RIA is 0.074 with a t-statistic of 2.98, suggesting that part of ABVOL is positively and significantly related the number of public news releases of a stock.

When using ABSREV as the RIA measure, the average coefficient on RIA is 0.193 with a t-statistic of 10.40. The adjusted R-squared shows that 21.5% of the variation in ABVOL can be explained by ABSREV. The result is expected as many studies have documented a significantly positive relation between volume and the magnitude of return (e.g., [Karpoff, 1987](#)) in the stock market. As a result, ABSREV may be a range-based measure of ABVOL by construction.

We then use the estimated coefficients from Stage 3 to separate  $ABVOL_{i,t}$  in each day into two orthogonal components:  $\delta_t RIA_{i,t}$  is the component of ABVOL that is related to RIA, and  $(\alpha_t + \mu_{i,t})$  is the residual component of ABVOL that is unrelated to RIA.

In Stage 4, we use the two above two components to decompose the Stage 1 ABVOL

coefficient ( $\beta_t$ ) into a component that is related to RIA ( $\beta_t^{\text{RIA}}$ ) and a residual component ( $\beta_t^{\text{r}}$ ). When using ASVI as the RIA measure, the time-series average of  $\beta_t^{\text{RIA}}$  is negative but very close to zero and only accounts for 0.1% (t-statistic = 0.20) of the time-series average of  $\beta_t$  ( $-0.179$ ). On the other hand, the fraction of the Stage 1 coefficient attributable to the residual component is 99.9% (t-statistic of 105.67). Hence, we conclude that ASVI only explains 0.1% of the negative ABVOL-return relation. Turning to the second RIA measure, NEWS, we find that the portion of the negative ABVOL-return relation explained by NEWS is -2.2%, suggesting that NEWS does not account for the negative ABVOL-return relation either.

On the other hand, we find that ABSREV explains around 42.5% (t-statistic = 8.89) of the negative relation between ABVOL and future coin excess returns. However, even if ABSREV fully captures retail investor attention, a solid 57.5% (t-statistic = 11.31) of the negative ABVOL-return relation is left unexplained, indicating that opinion divergence plays an important role in the negative return predicting power of abnormal trading volume. As a result, the results in Table 4 mitigate the concern that the negative return predicting power of abnormal trading volume results from retail investor attention.<sup>38</sup>

In addition, the positive contemporaneous relation between the number of public news events and ABVOL in Stage 3 is consistent with implications of several theory papers. For example, [Holthausen & Verrecchia \(1990\)](#) model how public announcements can influence traders through an informedness effect (the extent to which investors become more knowledgeable), and a consensus effect (the extent of agreement among investors). In particular, they find

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<sup>38</sup>As a robustness check, we include all three RIA variables in a single regression and perform the decomposition exercise again. ASVI, NEWS, and ABSREV explains  $-0.2\%$  (t-statistic =  $-0.28$ ),  $-2.0\%$  (t-statistic =  $-1.64$ ), and  $42.7\%$  (t-statistic =  $8.93$ ) of the negative ABVOL-return relation, respectively. The residual component, on the other hand, explains  $59.5\%$  (t-statistic =  $11.95$ ) of the negative relation.

that both greater informedness and reduced consensus (more divergent opinions) generate higher trading volume. Since cryptocurrencies lack cash flows and accounting information to infer their fundamental values, it seems *implausible* that upon receiving more news investors will have more precise information about the coin. Hence, an increase in trading volume mainly reflects disagreement among investors. [Kim & Verrecchia \(1994\)](#), [Harris & Raviv \(1993\)](#), and [Kandel & Pearson \(1995\)](#) also predict that when investors receive more information around announcements, they may have different interpretations of the information, thus resulting in an increase in volume.

## 3.5 The Role of Short Sale Constraints

### 3.5.1 Short selling on Binance

According to [Miller \(1977\)](#)'s hypothesis, high disagreement leads to overpricing since the opinions of pessimists cannot be fully incorporated into prices due to short-selling restrictions. If pessimistic investors are less restrained from selling short, high disagreement is less likely to result in lower future returns. To examine this implication, we first discuss the mechanics of short-selling restrictions on Binance.

One can sell short a coin via the margin trading services on Binance. The activation timing of a coin's margin trading services is determined by Binance. In order to borrow coins from a third party on Binance, one must first provide collateral, and then pay back those coins along with interest on the borrowing afterwards. There are 10 tiers of borrowing interest rates and maximum borrowing limits. These are based on the VIP tier of an investor, which is a step-wise increasing function of the investor's 30 days spot trading volume, futures

trading volume, and BNB balance.<sup>39</sup>

Although we hand collect the time-series of daily borrowing interest rates from the Binance website, we refrain from using the rate to directly quantify the level of short-selling restrictions (for each coin) for two reasons. First, the historical data of tier composition, maximum borrowing limits, and shorting volume (demand or supply) for each coin is not available. Second, most shortable coins' borrowing interest rates are fixed except for an occasional adjustment, and thus do not exhibit much time-series variation.<sup>40</sup> Instead, we define a coin as "constrained" on a given day as a simple dummy (equal to one) if the coin's borrowing interest rate is not available on Binance (one cannot borrow on Binance to sell short the coin) on that day.

We first provide a *broad* view of the relevance of short sale constraints for disagreement's influence on returns. Specifically, we use the proportion of constrained coins in the cross section (the number of constrained coins divided by the number of all coins in our sample) to measure the level of short-selling difficulty in the market as a whole. We then examine whether this "market-wide short sale constraint average" appears related to underperformance of high disagreement coins through time.

To analyze the underperformance of high disagreement coins through time, we calculate the average return differences between the highest and the lowest ABVOL quintile. Returns are measured four ways: the excess return, the CAPM alpha, the three-factor alpha, and the DGTW alpha. For the CAMP alpha and the three-factor alpha on day  $t$ , we first estimate risk loadings based on returns in the  $[t-60, t-15]$  window, requiring at least 30 observations.

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<sup>39</sup><https://www.binance.com/en/fee/schedule>.

<sup>40</sup>Binance recently announced that "Effective from 2023-03-01 06:00 (UTC), users can expect hourly interest rate updates on the Margin Data page based on current market conditions...". Hence, one should expect the dynamic margin interest rates to be more reflective of concurrent shorting supply and demand.

Then, we adjust coin returns on day  $t$  to the benchmark factors using the estimated risk loadings.

Figure 1 plots for each quarter, the average daily return differential between the highest and the lowest ABVOL quintile and daily proportion of constrained coins. We find that both the underperformance of high ABVOL coins and the proportion of constrained coins have a decreasing trend, thus providing preliminary support for an implication of [Miller \(1977\)](#) that the underperformance of high disagreement coins gets weaker when short sale constraints are removed. In particular, about 85% of coins in our sample are short sale constrained until mid-2020, and the underperformance of high (relative to low) ABVOL coins is economically and statistically significant. By contrast, from the latter half of 2020 and continuing through the end of our sample, the proportion of shortable coins climbs rapidly and the underperformance dissipates by at least half.

### 3.5.2 Short-constrained coins

The results in Figure 1 indicate that the decreasingly strict short-selling restrictions on Binance weakens the underperformance of high disagreement coins at an aggregate level. We now examine how short-selling restrictions shapes the effect of high disagreement on future coin returns on the individual coin level. If high abnormal trading volume indeed proxies for high disagreement in coins, then one should expect the negative relation between ABVOL and future coin returns to exist among the short-constrained coins, but not among shortable coins.

To examine this hypothesis, we restrict our sample to constrained coin-day observations (around 60% of the full sample), re-run the regressions in equation (5), and report the

results in Table 5. First, the coefficients on ABVOL are all negative (ranging from  $-0.228$  to  $-0.127$ ) and statistically significant at the 1% level. In addition, they are larger in magnitude compared to the corresponding specifications in Table 3. This is because Table 3 also contains observations with no impediments to short sales, which according to [Miller \(1977\)](#) should not result in lower future coin returns. As a result, the negative relation between ABVOL and future coin returns is weaker in Table 3 due to the averaging across samples.<sup>41</sup>

### 3.5.3 Crypto-like, short-constrained stocks

We next compare the ABVOL-return patterns we find in cryptos with those in stocks that are likely to be similarly short-constrained. We construct this short constrained equities sample as follows. For each day in the sample period (August 1st, 2018 through December 31st, 2021), we sort common stocks traded on the three major exchanges (NYSE, NASDAQ, and AMEX) into ten deciles based on their most recent institutional ownership ratio (IOR). We then select the stocks in the bottom decile (those with the lowest IOR). Since institutional investors are major securities lenders to retail investors, stocks in the bottom IOR decile tend to have the highest short-selling constraints ([Nagel, 2005](#)). We also exclude stock-day observations if the stock has exchange-traded put options available on the given day (which would enable investors to express their negative beliefs). Finally, we exclude stocks with price per share less than 10 dollars as of the previous month-end, to ensure that our results are not driven by small or illiquid stocks. We are left with 541 distinct stocks.

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<sup>41</sup>In untabulated analyses, we limit our sample to shortable coins and re-run the regressions in equation (5). As expected, the relation between ABVOL and future coin returns is statistically indistinguishable from zero.

We compute ABVOL and other characteristics for stocks the same way as we did for cryptocurrencies (Sections 2.2 and 2.3). The data is from CRSP, Compustat, and TAQ. We further include book-to-market ratio as a control variable, given its long-standing documented influence on equity returns. We run [Fama & MacBeth \(1973\)](#) regressions of excess stocks returns on ABVOL along with the stock characteristics, as in equation (5).

Table 6 reports the time-series averages of the slope coefficients, with the [Newey & West \(1987\)](#) adjusted t-statistics reported in parentheses. We find that the coefficients on ABVOL across different specifications range from 0.046 to 0.062 and are statistically significant (t-statistic ranging from 2.79 to 4.79), indicating a positive ABVOL-return relation in “crypto-like” stocks. This result suggests that the negative relation between abnormal volume and next-day returns we find in cryptocurrencies are unlikely to be *strictly* explained by their low institutional ownership or high short sale constraints. Rather, it is likely that the dramatically different result is driven by the fact that cryptocurrencies lack “fundamentals”, and thus their high abnormal trading volume is due to high disagreement.<sup>42</sup>

### 3.6 The Movers Subsample - Deeper Exploration

[Miller \(1977\)](#)’s hypothesis indicates that high disagreement associates with overpricing only when short sale constraints are present. In this section we examine this implication in more detail by focusing on the “movers” subsample. Movers are coins that experience a transition stage (their margin trading services are activated some time during the sample period).

Among the 356 coins in our sample, 153 coins are movers and they account for around 57%

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<sup>42</sup>[Cookson et al. \(2022\)](#), on the other hand, show evidence of Miller-like price effects in equity markets at the daily frequency with their disagreement measure, i.e., more disagreement is associated with negative future returns. This is perhaps because their StockTwits measure on average captures disagreement of unsophisticated/uninformed traders. Those traders tend to speculate more and thus resemble crypto traders.



of coin-day observations in our sample. This allows us to use the same coin as a benchmark when evaluating the effect of investor disagreement on certain characteristics from pre- to post- relaxation of short sale constraints.<sup>43</sup> This facilitates our event-study analysis.

### 3.6.1 Disagreement, short-selling restrictions, and overpricing

We first examine the relation between disagreement and future coin returns by running the following regression for the movers, one for prior to, and the other for after, the allowance of their margin trading services:

$$\text{Return}_{i,t+1} = \beta_0 + \beta_1 \text{ABVOL}_{i,t} + \beta_c \text{Controls}_{i,t} + c_i + c_t + \epsilon_{i,t+1}, \quad (11)$$

where  $i$  refers to the coin and  $t$  refers to the day. We use four measures of returns: the excess return (RET), the CAPM alpha, the three-factor alpha, and the DGTW alpha. Control variables include short-term reversal, market capitalization, momentum, illiquidity, idiosyncratic volatility, abnormal google search volume index, and demand for lottery coins. We include both coin and day fixed effects, and standard errors are double-clustered by coin and day.

In [Miller \(1977\)](#), the negative relation between disagreement and lower future return exists only when pessimists are forced to stay on the sidelines. If pessimists can freely trade on their negative beliefs, the negative volume-return relation should disappear. Thus,  $\beta_1$  should be significantly negative for movers prior to the allowance of margin trading services

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<sup>43</sup>Notably, in the movers subsample the number of constrained coin-day observations is about the same as the number of shortable coin-day observations. Hence, for each coin we have on average the same number of observations before and after the activation of its margin trading. In addition, the activation of a coin's margin trading services on Binance is less likely to be so endogenous as we see in equities, where governance matters ([Grullon et al., 2015](#)).

while becoming indistinguishable from zero after the relaxations of short sale constraints. Panel A of Table 7 supports this prediction. The coefficients on ABVOL are negative (ranging from  $-0.097$  to  $-0.049$ ) and statistically significant (t-statistics ranging from  $-2.97$  to  $-2.24$ ) prior to the allowance of margin trading services, while becoming indistinguishable from zero after the relaxation of short sale constraints.

Next, we construct the dummy variable, CONSTRAINT, to be one if the coin is short sale constrained (i.e. before Binance activates margin trading services on the coin), and zero otherwise. We further create an interactive of CONSTRAINT with ABVOL to measure the influence of investor disagreement when the coin is constrained, on ex-post returns. Then, we run the following regression:

$$\begin{aligned} \text{Return}_{i,t+1} = & \beta_0 + \beta_1 \text{ABVOL}_{i,t} + \beta_2 \text{CONSTRAINT}_{i,t} + \beta_3 \text{ABVOL}_{i,t} \times \text{CONSTRAINT}_{i,t} \\ & + \beta_c \text{Controls}_{i,t} + c_i + c_t + \epsilon_{i,t+1}, \end{aligned} \tag{12}$$

where  $i$  refers to the coin and  $t$  refers to the day. We use four measures of returns: the excess return (RET), the CAPM alpha, the three-factor alpha, and the DGTW alpha. Control variables include short-term reversal, market capitalization, momentum, illiquidity, idiosyncratic volatility, abnormal google search volume index, and demand for lottery coins. We include both coin and day fixed effects, and standard errors are double-clustered by coin and day.<sup>44</sup>

Our expectation is that when short-selling restrictions are present (CONSTRAINT =

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<sup>44</sup>We use an event study (time-series diff) because of the concentrated nature (i.e. spike) of shortable coins in the second half of 2020. Put differently, there are very few coins that are shortable before 2020:q3. Thus we don't have a well-populated counterfactual sample when we need it.

1), high disagreement coins will be overpriced and earn lower future returns as opinions converge ex-post. In contrast, if short-selling restrictions are removed ( $\text{CONSTRAINT} = 0$ ), the negative relation between disagreement and future coin returns will disappear. Therefore, the coefficient  $\beta_3$  on the interaction term,  $\text{ABVOL} \times \text{CONSTRAINT}$ , should be negative and statistically significant, while the coefficient on  $\text{ABVOL}$  should be statistically indistinguishable from zero.

Panel B of Table 7 reports the results. In the first column we find support of our prediction; the coefficient on the interaction term is  $-0.080$  with a t-statistic of  $-3.27$ , while the coefficient on  $\text{ABVOL}$  is indistinguishable from zero. To calibrate the economic significance, the standard deviation of  $\text{ABVOL}$  for the models in Table 6 is 3.99. Hence, when short-selling restrictions are present, a one-standard-deviation increase in  $\text{ABVOL}$  decreases next-day return by  $|3.99 \times (-0.080)| = 0.319\%$ . We find similar results in columns 3, 5, and 7 when using CAPM alpha, three-factor alpha, and DGTW alpha as our return measure, respectively. In particular, the coefficients on the interaction term are negative (ranging from  $-0.095$  to  $-0.071$ ) and statistically significant (t-statistics ranging from  $-2.96$  to  $-2.72$ ), while the coefficients on  $\text{ABVOL}$  are insignificantly different from zero.

When all control variables are included in columns 2, 4, 6, and 8, the coefficients on the interaction term remain negative (ranging from  $-0.062$  to  $-0.040$ ) and are all statistically significant at the 5% level (t-statistics ranging from  $-2.59$  to  $-2.07$ ). On the other hand, both the coefficients on  $\text{ABVOL}$  and  $\text{CONSTRAINT}$  are indistinguishable from zero, indicating that neither high disagreement nor the presence of short-selling restrictions is *independently* sufficient to generate overpricing.<sup>45</sup>

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<sup>45</sup>For robustness, we run the same regressions while excluding the pre-event window  $[t-7, t-1]$  just before

The results in Table 7 also allow us to distinguish [Miller \(1977\)](#)’s hypothesis from an alternative explanation for the negative abnormal volume-return relation that might be based on wash-trading. In particular, unusually high volume due to wash trades ([Amiram et al., 2021](#); [Le Pennec et al., 2021](#); [Chen et al., 2022](#); [Cong et al., 2023](#)) drives up the contemporaneous price, which is followed by a reversal as arbitrageurs take advantage of price differences across various exchanges. However, the striking sensitivity of the abnormal volume-return relation to the activation of margin trading services on Binance cannot be explained, at least without further assumptions, by the cross-exchange arbitrage hypothesis. In fact, if the lower expected returns of coins with ”fake abnormal volume” are mainly driven by arbitrageurs, then eliminating limits to arbitrage (the relaxation of short sale constraints) on Binance should theoretically result in even lower expected returns. In Table 7, however, the negative volume-return relation becomes weaker and even disappears after a coin’s margin trading has been activated on Binance.

### 3.6.2 Disagreement, short-selling restrictions, and order imbalance at time ”t”

Key to [Miller \(1977\)](#)’s arguments linking disagreement, short sales constraints, and overpricing at time ”t”, are two factors. First, higher disagreement associates with more extreme evaluations of an asset.<sup>46</sup> Second, in the presence of short-sale constraints, pessimists are

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Binance margin allowance dates. This is in deference to [Savor & Wilson \(2013, 2016\)](#), who note that potential information leakage prior to announcements can create a more serious signal extraction problem, increasing risk and driving up returns. In our case, that could contaminate the use of pre-event same-coin observations as the benchmark/control in the volume-return relation. The results are qualitatively the same.

<sup>46</sup>[Miller \(1977\)](#): ”... the number of people with extremely pessimistic evaluations of a stock are likely to increase with the divergence of opinion about a stock, ...”. More recent theories align with [Miller \(1977\)](#) by arguing that disagreement is high when investors’ interpretations of a public signal are more dispersed or their private signals are more distributed. For example, in [Banerjee & Kremer \(2010\)](#)’s model, investors’ interpretations of a public signal are drawn from a normal distribution with mean zero and standard deviation of  $\lambda$ . In [Golez & Goyenko \(2022\)](#)’s model, a continuum of investors’ private signals are drawn from a normal distribution with mean zero and standard deviation of  $\frac{1}{q}$ . Higher disagreement is associated with a larger  $\lambda$

restrained from selling short while optimists can freely trade on their positive beliefs.<sup>47</sup>

Combined, the overpricing of high disagreement assets (at time "t") stems from a surfeit of buying pressure relative to selling pressure.

Testing these underpinnings is feasible with our data because we have directional trade information. We expect an increased asymmetry between buying and selling activities as disagreement increases, when short sales are prohibited. This is what we look for as a "measurable" outcome, to infer the theoretical underpinning between ABVOL and disagreement.

Using the directional trade data, we construct two order imbalance (OIB) measures for each coin  $i$  on each day  $t$ :

$$\text{OIBVOL}_{i,t} = \frac{\text{BVOL}_{i,t} - \text{SVOL}_{i,t}}{\text{BVOL}_{i,t} + \text{SVOL}_{i,t}}, \quad (13)$$

$$\text{OIBTRD}_{i,t} = \frac{\text{BTRD}_{i,t} - \text{STRD}_{i,t}}{\text{BTRD}_{i,t} + \text{STRD}_{i,t}}, \quad (14)$$

where BVOL (SVOL) is the buyer-initiated (seller-initiated) trading volume and BTRD (STRD) is the buyer-initiated (seller-initiated) number of trades. Next, we run the following regression:

$$\begin{aligned} \text{OIB}_{i,t} = & \beta_0 + \beta_1 \text{ABVOL}_{i,t} + \beta_2 \text{CONSTRAINT}_{i,t} + \beta_3 \text{ABVOL}_{i,t} \times \text{CONSTRAINT}_{i,t} \\ & + \beta_4 \text{OIB}_{i,t-1} + \beta_c \text{Controls}_{i,t-1} + c_i + c_t + \epsilon_{i,t}, \end{aligned} \quad (15)$$

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or a smaller  $q$ .

<sup>47</sup>See also [Hong & Stein \(2007\)](#): "...the intuition is that market prices are driven by the optimists, so if the optimists become more optimistic, prices must go up, even if at the same time the pessimists become more pessimistic."

where  $i$  refers to the coin and  $t$  refers to the day. We use either OIBVOL or OIBTRD as the order imbalance (OIB, in %) measure. Including the lagged order imbalance term,  $OIB_{t-1}$ , aims to control for the well-known persistence in order imbalance. Control variables include short-term reversal, market capitalization, momentum, illiquidity, idiosyncratic volatility, abnormal google search volume index, and demand for lottery coins. We include both coin and day fixed effects, and standard errors are double-clustered by coin and day. The sample is the "movers", same as that used in Table 7.

Table 8 reports the results. In the first two columns where the dependent variable is OIBVOL, the coefficients on the interaction term,  $ABVOL \times CONSTRAINT$ , are 0.159 (t-statistic = 10.90) and 0.162 (t-statistic = 11.03) with and without control variables respectively. This indicates a positive and statistically significant relation between ABVOL and OIBVOL in the presence of short-selling restrictions ( $CONSTRAINT = 1$ ). High disagreement associates with greater order imbalance when a coin is short sale constrained, consistent with [Miller \(1977\)](#). The results are similar when we use OIBTRD to proxy for order imbalance. The coefficients on the interaction term in the last two columns are positive (0.307 and 0.313) and statistically significant at the 1% level (t-statistics = 2.97 and 2.20).

The effects of control variables align with expectations. The coefficients on  $OIBVOL_{t-1}$  and  $OIBTRD_{t-1}$  are significantly positive, confirming the existence of order imbalance persistence.<sup>48</sup> On the other hand, the coefficients on ABVOL and CONSTRAINT are insignificantly different from zero in all but one case (and marginally in that exception), indicating that trading activities are more asymmetric - show higher order imbalance - only when both high disagreement and short-selling restrictions are present.

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<sup>48</sup>The inclusion of more lagged order imbalance terms does not change the results qualitatively.

The results of Table 8 indicate that high investor disagreement, as measured by high ABVOL, is associated with more positive gap between buying and selling in the presence of suppressed short sales. This provides further support for the model by [Miller \(1977\)](#).

### 3.6.3 Disagreement, short-selling restrictions, and *subsequent* trading activities

In this section, we examine the mechanism in [Miller \(1977\)](#) linking investor disagreement and short-sale constraints with ex-post underperformance; it stems from resolution of disagreement. In particular, when investors' expectations around the value of an asset converge, we should see fewer investors with extreme valuations, thus reducing both buying and selling activities. However, the decrease in buying activities should be larger in magnitude since pessimists with the lowest evaluations of the asset were ex-ante inhibited from selling by the short-sale constraints.

Following this logic, we examine whether - in the presence of short sale constraints - high disagreement coins exhibit subsequent decreases in both buyer-initiated and seller-initiated trades, with the decrease in the former being larger in magnitude.<sup>49</sup> To test this implication, we first construct the following four variables for coin  $i$  at any day  $t + 1$ , which capture how

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<sup>49</sup>On the other hand, if the lower expected returns of high volume coins are driven by cross-exchange arbitrage activities rather than [Miller \(1977\)](#)'s mechanism, we'd expect subsequent selling activities to increase instead of decreasing.

buying and selling activities evolve from day  $t$  to  $t + 1$ :

$$\Delta \text{BVOL}_{i,t+1} = \left( \frac{\text{BVOL}_{i,t+1} - \text{BVOL}_{i,t}}{\text{BVOL}_{i,t}} \right) \times 100\%, \quad (16)$$

$$\Delta \text{SVOL}_{i,t+1} = \left( \frac{\text{SVOL}_{i,t+1} - \text{SVOL}_{i,t}}{\text{SVOL}_{i,t}} \right) \times 100\%, \quad (17)$$

$$\Delta \text{BTRD}_{i,t+1} = \left( \frac{\text{BTRD}_{i,t+1} - \text{BTRD}_{i,t}}{\text{BTRD}_{i,t}} \right) \times 100\%, \quad (18)$$

$$\Delta \text{STRD}_{i,t+1} = \left( \frac{\text{STRD}_{i,t+1} - \text{STRD}_{i,t}}{\text{STRD}_{i,t}} \right) \times 100\%. \quad (19)$$

In particular,  $\Delta \text{BVOL}_{i,t+1}$  ( $\Delta \text{SVOL}_{i,t+1}$ ) represents the percentage change in buyer-initiated (seller-initiated) volume of coin  $i$  from day  $t$  to  $t + 1$ , and  $\Delta \text{BTRD}_{i,t+1}$  ( $\Delta \text{STRD}_{i,t+1}$ ) represents the percentage change in number of buyer-initiated (seller-initiated) trades of coin  $i$  from day  $t$  to  $t + 1$ .<sup>50</sup> Then we run the following two regressions:

$$\begin{aligned} \Delta \text{VOL}_{i,t+1} = & \beta_0 + \beta_1 \text{ABVOL}_{i,t} + \beta_2 \text{CONSTRAINT}_{i,t} + \beta_3 \text{ABVOL}_{i,t} \times \text{CONSTRAINT}_{i,t} \\ & + \beta_4 \Delta \text{VOL}_{i,t} + \beta_c \text{Controls}_{i,t} + c_i + c_t + \epsilon_{i,t+1}, \end{aligned} \quad (20)$$

and

$$\begin{aligned} \Delta \text{TRD}_{i,t+1} = & \beta_0 + \beta_1 \text{ABVOL}_{i,t} + \beta_2 \text{CONSTRAINT}_{i,t} + \beta_3 \text{ABVOL}_{i,t} \times \text{CONSTRAINT}_{i,t} \\ & + \beta_4 \Delta \text{TRD}_{i,t} + \beta_c \text{Controls}_{i,t} + c_i + c_t + \epsilon_{i,t+1}, \end{aligned} \quad (21)$$

where  $i$  refers to the coin and  $t$  refers to the day. We use three change in trading volume

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<sup>50</sup>We use raw percentage change in the purpose of better presenting the economic significance of the regression results. For robustness check, we use natural logarithm difference instead of raw percentage change. The results are qualitatively similar.



( $\Delta\text{VOL}$ ) measures:  $\Delta\text{BVOL}$ ,  $\Delta\text{SVOL}$ , and  $\Delta\text{BVOL} - \Delta\text{SVOL}$ , and three change in number of trades ( $\Delta\text{TRD}$ ) measures:  $\Delta\text{BTRD}$ ,  $\Delta\text{STRD}$ , and  $\Delta\text{BTRD} - \Delta\text{STRD}$ . Including the lagged terms,  $\Delta\text{VOL}_t$  and  $\Delta\text{TRD}_t$ , aims to control for the persistence in trading activities. Control variables are short-term reversal, market capitalization, momentum, illiquidity, idiosyncratic volatility, abnormal google search volume index, and demand for lottery coins. We include both coin and day fixed effects, and standard errors are double-clustered by coin and day.

Panel A of Table 9 reports the regression results of equation (20). In columns 1 to 4, the coefficients on the interaction term,  $\text{ABVOL} \times \text{CONSTRAINT}$ , are negative and statistically significant, both with and without control variables. This indicates that when short-selling restrictions are binding ( $\text{CONSTRAINT} = 1$ ),  $\text{ABVOL}$  decreases subsequent buyer-initiated and seller-initiated trading volume. In particular, using columns 1 and 3, a one-standard-deviation increase in  $\text{ABVOL}$  results in a  $|3.99 \times (-6.483)| = 25.795\%$  decrease in buyer-initiated volume and a  $|3.99 \times (-4.670)| = 18.633\%$  decrease in seller-initiated volume, when controlling for persistence in trading activities. Crucially, buyer-initiated volume decreases by 7.162% more compared to seller-initiated volume.<sup>51</sup> When we further include the control variables in the last column, the coefficient on the interaction term remains negative and statistically significant at the 5% level (t-statistic =  $-2.17$ ). In contrast, the coefficients on  $\text{ABVOL}$  alone in all specifications are insignificantly different from zero, again stressing the role of short-selling restrictions in [Miller \(1977\)](#)'s model.<sup>52</sup>

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<sup>51</sup>This can also be computed using the coefficient on the interaction term ( $3.99 \times (-1.795) = -7.162\%$ ) from the fifth column where  $\Delta\text{BVOL}_{t+1} - \Delta\text{SVOL}_{t+1}$  is the dependent variable.

<sup>52</sup>Unreported tests exploring change in order imbalance from  $t$  to  $t+1$  confirm that during a coin's constrained window, when  $\text{ABVOL}$  is higher on day  $t$ , there is more convergence (shrinking OIB) *the next day*. This supports our study of next-day returns after measuring  $\text{ABVOL}$ , in our main tests.

Panel B of Table 9 reports the regression results of equation (21). Consistent with the results in Panel A, we find that in the presence of short-selling restrictions, a one-standard-deviation increase in ABVOL reduces subsequent number of buyer-initiated and seller-initiated trades by  $|3.99 \times (-4.211)| = 16.802\%$  and  $|3.99 \times (-3.325)| = 13.267\%$ , respectively. In addition, the negative and statistically significant coefficients on the interaction term in the last two columns indicate that the decline in the number of buyer-initiated trades is larger in magnitude compared to the decline in the number seller-initiated trades.

Overall, the results in Table 9 indicate that when disagreement is high and short sale constraints bind, then belief convergence should present ex-post. We see this result in trading declines with the buying activity declining more than the selling activity.

## 4 Conclusion

In contrast to the high-volume return premium documented in stock markets, we find that abnormal trading volume (ABVOL) is negatively related to cross-sectional cryptocurrency expected returns. This negative relation cannot be explained by common risk factors nor various coin characteristics including size, short-term reversal, momentum, illiquidity, investor attention, idiosyncratic volatility, and demand for lottery-like coins. This significantly negative relation refutes an interpretation of ABVOL as visibility, risk, or information uncertainty, which are common explanations for a positive high-volume return relation. Liquidity doesn't appear to provide an explanation either, since we are focusing on unusual trading volume rather than raw trading volume.

Considering the speculative nature of cryptocurrencies, we interpret a coin's increased

trading activity as investor disagreement on its value. In particular, the negative high-volume return relation supports [Miller \(1977\)](#)’s hypothesis; when disagreement is high, the opinions of pessimists will fail to be incorporated into asset prices due to short-selling restrictions, resulting in overpricing and lower subsequent returns of those assets. A decomposition exercise indicates that different measures of retail investor attention do not explain this negative relation.

[Miller \(1977\)](#)’s hypothesis also implies that when frictions that prevent pessimists from selling short are relaxed, the underperformance of high disagreement assets should subside. Consistent with this, we find that the negative abnormal volume return relation is concentrated in the coin-day observations when margin trading is not allowed. By contrast, coins (and coin-days) where margin trading is allowed do not exhibit this relation. We also find that “crypto-like” stocks in terms of their short sale constraints (low institutional ownership and lacking exchange-traded put options), exhibit a positive instead of negative volume-return relation in the cross section. This further emphasizes the role of investor disagreement as the likely dominant force in cryptocurrencies’ abnormal trading volume.

To examine the role of short-selling restrictions at a finer level, we study coins that transition from “not shortable” to “shortable” in our sample. We find that the negative abnormal volume return relation exists only when both high disagreement and short-selling restrictions are present, while neither of the two is independently sufficient to produce the result. This sample also enables utilization of directional trades data to test whether trading activities are linked to disagreement in a manner consistent with [Miller \(1977\)](#). First, in the presence of short sale constraints, high disagreement is *contemporaneously* associated with more asymmetric trading activities, since pessimists cannot freely trade

on their negative beliefs. We find that when short-selling restrictions are present, order imbalance for volume and trade are increasing in ABVOL, even after controlling for order imbalance persistence. Second, the lower ex-post returns of high disagreement assets imply resolution of disagreement. [Miller \(1977\)](#) indicates that increased disagreement leads to a larger increase in buying activities relative to selling activities due to short sale constraints. Therefore, ex-post we should observe a larger decrease in buying activities relative to selling activities (i.e. convergence of beliefs), to align with this condition. We find that in the presence of short-selling restrictions, both buying and selling activities of coins decline following high ABVOL, but with the decrease in former showing much larger magnitude than the decrease in latter.

Some questions remain unresolved in this paper. For example, why is there a resolution of disagreement following high disagreement given that there are no regular informative disclosures such as earnings announcements in the cryptocurrency market? In addition, is the formation of “crypto bubbles” related to unresolved high disagreement? We leave these interesting questions for future research.

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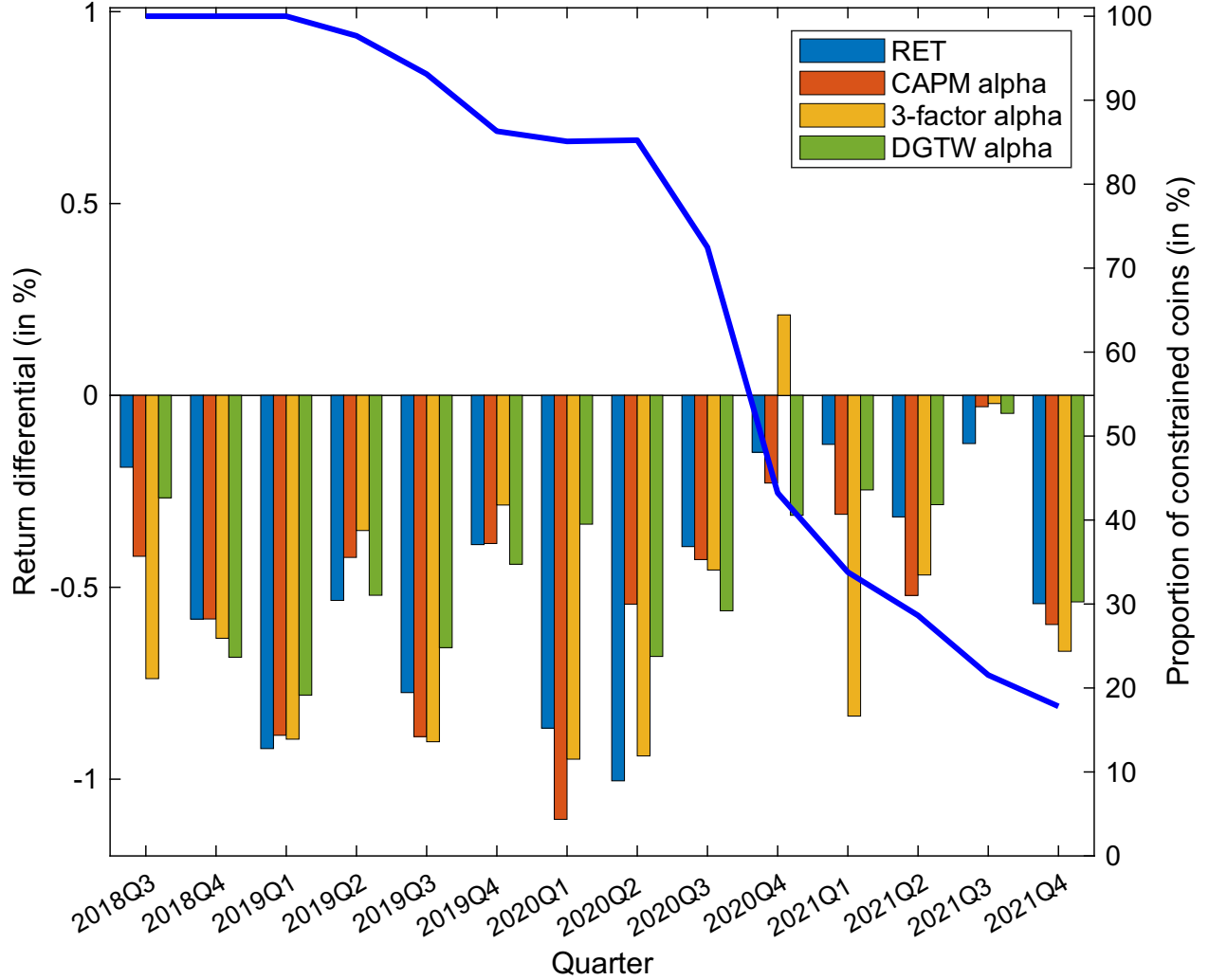
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# Appendix

We construct daily common risk factors in the cryptocurrency market following the approach of [Y. Liu et al. \(2022\)](#). We require that the coins have information on price, volume, and market capitalization. We further exclude coins with market capitalization of less than \$1 million. The cryptocurrency excess market return factor (CMKT) is the difference between the value-weighted coin market return and the daily risk-free rate implied from the one-month Treasury bill rate. The size factor (CSMB) is the difference between returns on portfolios of small and large coins, where the portfolios are formed daily based on coin market capitalization, into the smallest 30%, the middle 40%, and largest 30% of coins on the market. To calculate the momentum factor (CMOM), we use six value-weighted portfolios formed on first size and then on prior two-to-twelve days of returns. Specifically, each day we first sort coins into two size portfolios (small 50% and big 50%) and then within each size portfolio we form three prior return portfolios (the lowest 30%, middle 40% and highest 30%). The momentum factor is constructed as the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. In particular,  $CMOM = 1/2(\text{Small High} + \text{Big High}) - 1/2(\text{Small Low} + \text{Big Low})$ .

## The Volume-Return Relation and Proportion of Constrained Coins



**Figure 1. The Volume-Return Relation and Proportion of Constrained Coins.** For each day, quintile portfolios are formed by sorting individual coins based on their abnormal trading volume (ABVOL) in the previous day. ABVOL is defined as the daily turnover ratio minus the average turnover ratio over the past 30 days, divided by the standard deviation of daily turnover ratio over the past 30 days. The figure plots for each quarter the average return differences between the high (top 20%) and low (bottom 20%) ABVOL coins as well as the proportion of constrained coins (blue line) in the sample. We use four measures of returns (all in %): the excess return (RET), the CAPM alpha, the three-factor alpha, and the DGTW alpha. A coin is constrained if its margin trading is not available on Binance (one cannot borrow on Binance to sell short the coin). The sample period is 2018Q3 to December 2021Q4.

**Table 1. Summary Statistics.** Panel A presents the time-series averages of summary statistics for various coin characteristics, including abnormal trading volume (ABVOL), short-term reversal (REV, in %), market capitalization (MCAP, in billions), momentum (MOM, in %), illiquidity (ILLIQ, scaled by  $10^6$ ), idiosyncratic volatility (IVOL, in %), abnormal google search volume index (ASVI), and demand for lottery coins (MAX, in %). ABVOL is defined as the daily turnover ratio minus the average turnover ratio over the past 30 days, divided by the standard deviation of daily turnover ratio over the past 30 days. Other coin characteristics are defined in Section 2.1. Panel B presents the number of individual coins and mean/median market capitalization (MCAP, in billions) at the end of each quarter for the sample and the coin market. The sample period is August 1st, 2018 to December 31st, 2021.

Panel A: Coin characteristics					
	Mean	SD	P25	Median	P75
ABVOL	0.168	2.116	-0.590	-0.279	0.247
REV	0.479	5.728	-2.345	-0.329	2.182
MCAP	1.185	7.129	0.027	0.085	0.350
MOM	3.171	19.869	-6.895	-0.395	8.147
ILLIQ	22.461	129.095	0.268	0.986	3.847
IVOL	1.303	1.213	0.706	0.986	1.453
ASVI	1.174	6.176	0.003	0.003	0.018
MAX	3.765	3.382	2.064	2.831	4.222

Panel B: Number of coins and coin size by quarter					
Year	Quarter	Sample		Coin market	
		Number	Market Cap mean (median)	Number	Market Cap mean (median)
2018	Q3	138	0.809 (0.067)	1,121	0.565 (0.015)
2018	Q4	142	0.496 (0.031)	1,142	0.394 (0.012)
2019	Q1	142	0.338 (0.022)	1,031	0.271 (0.007)
2019	Q2	140	0.527 (0.041)	1,145	0.197 (0.005)
2019	Q3	151	0.545 (0.031)	1,168	0.161 (0.005)
2019	Q4	156	0.360 (0.019)	1,084	0.255 (0.006)
2020	Q1	166	0.408 (0.020)	1,086	0.313 (0.005)
2020	Q2	170	0.345 (0.017)	1,119	0.254 (0.005)
2020	Q3	192	0.524 (0.039)	1,392	0.274 (0.005)
2020	Q4	222	0.651 (0.049)	1,516	0.281 (0.006)
2021	Q1	248	1.407 (0.080)	1,956	0.318 (0.007)
2021	Q2	262	2.827 (0.212)	2,051	0.432 (0.007)
2021	Q3	282	2.748 (0.163)	1,986	0.990 (0.011)
2021	Q4	301	4.060 (0.299)	2,212	1.148 (0.015)

**Table 2. Returns and Characteristics on Portfolios of Coins Sorted by Abnormal Trading Volume.** For each day, quintile portfolios are formed by sorting individual coins based on their abnormal trading volume (ABVOL) in the previous day, where quintile 1 contains coins with the lowest 20% ABVOL and quintile 5 contains coins with the highest 20% ABVOL. ABVOL is defined as the daily turnover ratio minus the average turnover ratio over the past 30 days, divided by the standard deviation of daily turnover ratio over the past 30 days. Panel A presents the average excess daily return (RET), CAPM alpha, three-factor alpha, and DGTW alpha for each ABVOL quintile portfolio. Portfolio returns are equal-weighted. CAPM alpha is the intercept from regressing excess portfolio returns on a constant and cryptocurrency excess market return (CMKT). Three-factor alpha is the intercept from regressing excess portfolio returns on a constant, CMKT, the size factor (CSMB), and the momentum factor (CMOM). CMKT, CSMB, and CMOM are constructed following the approach of [Y. Liu et al. \(2022\)](#). A coin’s DGTW alpha is the difference between a coin’s return and the value-weighted return of its matching  $10 \times 10$  coin size/momentum portfolio following the approach of [Daniel et al. \(1997\)](#). Panel B reports for each ABVOL quintile the time-series averages of coin characteristics, including ABVOL, short-term reversal (REV, in %), market capitalization (MCAP, in billions), momentum (MOM, in %), illiquidity (ILLIQ, scaled by  $10^6$ ), idiosyncratic volatility (IVOL, in %), abnormal google search volume index (ASVI), and demand for lottery coins (MAX, in %). [Newey & West \(1987\)](#) adjusted t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively. The sample is all coins meeting the requirements in Section 2.1 and the sample period is August 1st, 2018 to December 31st, 2021.

Panel A: Average returns across ABVOL quintiles								
ABVOL quintiles	RET	CAPM alpha	Three-factor alpha	DGTW alpha				
Q1 (Low)	0.542** (2.10)	0.158 (0.68)	-0.531*** (-3.63)	0.257 (1.34)				
Q2	0.518** (2.30)	0.142 (0.72)	-0.565*** (-4.37)	0.246 (1.32)				
Q3	0.567** (2.48)	0.186 (0.95)	-0.524*** (-4.11)	0.275 (1.47)				
Q4	0.485** (2.12)	0.099 (0.51)	-0.605*** (-4.84)	0.171 (0.92)				
Q5 (High)	0.044 (0.19)	-0.333 (-1.63)	-0.994*** (-7.10)	-0.202 (-1.05)				
Q5-Q1	-0.498*** (-7.20)	-0.491*** (-7.21)	-0.464*** (-7.00)	-0.459*** (-7.29)				
Panel B: Average coin characteristics across ABVOL quintiles								
ABVOL quintiles	ABVOL	REV	MCAP	MOM	ILLIQ	IVOL	ASVI	MAX
Q1 (Low)	-0.884	-0.770	1.643	-1.186	28.993	0.988	1.022	2.746
Q2	-0.531	-0.590	1.038	0.670	27.450	1.098	1.037	3.010
Q3	-0.275	-0.327	0.851	2.910	23.196	1.174	1.046	3.269
Q4	0.121	0.334	1.159	5.259	18.451	1.319	1.181	3.771
Q5 (High)	2.421	3.763	1.244	8.204	14.171	1.939	1.579	6.045

**Table 3. Fama-Macbeth Cross-Sectional Regressions: Coins.** This table reports the time-series averages of the slope coefficients obtained from

$$\text{RET}_{i,t+1} = \beta_{0,t} + \beta_1 \text{ABVOL}_{i,t} + \beta_c \text{Controls}_{i,t} + \epsilon_{i,t+1},$$

where  $i$  refers to coin  $i$  and  $t$  refers to day  $t$ . The dependent variable is excess return (RET, in %). Abnormal trading volume (ABVOL) is defined as the daily turnover ratio minus the average turnover ratio over the past 30 days, divided by the standard deviation of daily turnover ratio over the past 30 days. The control variables are short-term reversal (REV, in %), market capitalization (MCAP, in log), momentum (MOM, in %), illiquidity (ILLIQ, scaled by  $10^6$ ), idiosyncratic volatility (IVOL, in %), abnormal google search volume index (ASVI), and demand for lottery coins (MAX, in %). [Newey & West \(1987\)](#) adjusted t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively. The sample is all coins meeting the requirements in Section 2.1 and the sample period is August 1st, 2018 to December 31st, 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ABVOL	-0.179*** (-9.72)	-0.108*** (-5.44)	-0.183*** (-10.74)	-0.184*** (-10.44)	-0.175*** (-9.38)	-0.175*** (-9.42)	-0.181*** (-9.80)	-0.163*** (-6.69)	-0.120*** (-5.61)
REV		-0.057*** (-8.39)							-0.054*** (-8.14)
MCAP			-0.025 (-1.36)						-0.007 (-0.38)
MOM				0.002 (0.98)					-0.000 (-0.07)
ILLIQ					0.030 (1.05)				0.081*** (4.22)
IVOL						-0.007 (-0.17)			-0.003 (-0.07)
ASVI							0.007** (2.10)		0.007* (1.98)
MAX								-0.012 (-0.83)	0.000 (0.03)
Intercept	0.439* (1.88)	0.347 (1.37)	0.887* (1.89)	0.354 (1.52)	0.395* (1.80)	0.443** (2.06)	0.431* (1.83)	0.491** (2.36)	0.333 (0.79)
Observations	223,476	223,476	223,476	223,476	223,476	223,476	223,476	223,476	223,476
Adjusted R <sup>2</sup>	0.020	0.049	0.038	0.045	0.026	0.048	0.023	0.044	0.120

**Table 4. Is the negative ABVOL-return relation driven by retail investor attention? A decomposition exercise.** Using coin-level Fama-Macbeth cross-sectional regressions, the negative relation between abnormal trading volume (ABVOL) and next-day excess returns is decomposed into a component that is related to retail investor attention (RIA) and a residual component. Stage 1 regresses day t+1 excess returns on day t ABVOL ( $RET_{i,t+1} = \alpha_t + \beta_t ABVOL_{i,t} + \epsilon_{i,t+1}$ ). Stage 2 adds a RIA variable ( $RIA_{i,t}$ ) to the regression. Stage 3 regresses ABVOL on the RIA variable to decompose  $ABVOL_{i,t}$  into two orthogonal components ( $ABVOL_{i,t} = a_t + \delta_t RIA_{i,t} + \mu_{i,t}$ ). In Stage 4, the  $\beta_t$  coefficient from Stage 1 is decomposed as:  $\beta_t = \frac{Cov[RET_{i,t+1}, ABVOL_{i,t}]}{Var(ABVOL_{i,t})} = \frac{Cov[RET_{i,t+1}, \delta_t RIA_{i,t}]}{Var(ABVOL_{i,t})} + \frac{Cov[RET_{i,t+1}, (\alpha_t + \mu_{i,t})]}{Var(ABVOL_{i,t})} = \beta_t^{RIA} + \beta_t^r$ . The time-series average of  $\beta_t^{RIA}$  divided by the time-series average of  $\beta_t$  then measures the fraction of the negative ABVOL-return relation explained by the RIA variable, and the time-series average of  $\beta_t^r$  divided by the time-series average of  $\beta_t$  measures the fraction of the relation left unexplained by the RIA variable, with the standard errors of the fractions being determined using the multivariate delta method. Abnormal trading volume (ABVOL) is defined as the daily turnover ratio minus the average turnover ratio over the past 30 days, divided by the standard deviation of daily turnover ratio over the past 30 days. ASVI is the abnormal Google search volume. NEWS is the logarithm of one plus number of daily news events. ABSREV is the absolute value of daily return. Time-series averages of estimated coefficients are reported with t-statistics in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively. The sample is all coins meeting the requirements in Section 2.1 and the sample period is August 1st, 2018 to December 31st, 2021.

Stage	Description		Retail investor attention (RIA) variables					
			ASVI		NEWS		ABSREV	
1	Next-day excess return on ABVOL	Intercept	0.439*	(1.88)	0.439*	(1.88)	0.439*	(1.88)
		ABVOL	-0.179***	(-9.72)	-0.179***	(-9.72)	-0.179***	(-9.72)
2	Add RIA variable	Intercept	0.431*	(1.84)	0.422*	(1.80)	0.467*	(1.86)
		ABVOL	-0.181***	(-9.80)	-0.184***	(-10.06)	-0.139***	(-7.16)
		RIA	0.007**	(2.10)	0.145***	(3.16)	-0.018**	(-2.54)
3	ABVOL on RIA variable	Intercept	0.133***	(4.28)	0.159***	(4.89)	-0.921***	(-2.66)
		RIA	0.032	(1.32)	0.074***	(2.98)	0.193***	(10.40)
		Adj. R <sup>2</sup>	0.4%		0.7%		21.5%	
4	Decompose Stage 1 coefficient	RIA	-0.000		0.004		-0.076	
			0.1%	(0.20)	-2.2%	(-1.51)	42.5%***	(8.89)
		Residual	-0.179		-0.183		-0.103	
			99.9%***	(105.67)	102.2%***	(79.40)	57.5%***	(11.31)
		Total	-0.179		-0.179		-0.179	
			100%	(-9.72)	100%	(-9.72)	100%	(-9.72)



**Table 5. Fama-Macbeth Cross-Sectional Regressions: Short-Constrained Coins.** In this table, the sample is all coin-day observations that meet the requirements in Section 2.1 and whose margin trading is unavailable on Binance (one cannot borrow on Binance to sell short the coin). The table reports the time-series averages of the slope coefficients obtained from

$$\text{RET}_{i,t+1} = \beta_{0,t} + \beta_1 \text{ABVOL}_{i,t} + \beta_c \text{Controls}_{i,t} + \epsilon_{i,t+1},$$

where  $i$  refers to coin  $i$  and  $t$  refers to day  $t$ . The dependent variable is excess return (RET, in %). Abnormal trading volume (ABVOL) is defined as the daily turnover ratio minus the average turnover ratio over the past 30 days, divided by the standard deviation of daily turnover ratio over the past 30 days. The control variables are short-term reversal (REV, in %), market capitalization (MCAP, in log), momentum (MOM, in %), illiquidity (ILLIQ, scaled by  $10^6$ ), idiosyncratic volatility (IVOL, in %), abnormal google search volume index (ASVI), and demand for lottery coins (MAX, in %). [Newey & West \(1987\)](#) adjusted t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively. The sample period is August 1st, 2018 to December 31st, 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ABVOL	-0.224*** (-8.00)	-0.127*** (-4.52)	-0.228*** (-8.24)	-0.240*** (-7.60)	-0.226*** (-7.95)	-0.216*** (-6.62)	-0.228*** (-7.93)	-0.200*** (-6.08)	-0.185*** (-4.44)
REV		-0.076*** (-8.32)							-0.074*** (-7.39)
MCAP			-0.025 (-1.36)						0.003 (0.09)
MOM				0.002 (0.85)					-0.002 (-0.88)
ILLIQ					0.091* (1.89)				-0.014 (-0.28)
IVOL						0.011 (0.23)			-0.002 (-0.03)
ASVI							0.001 (0.17)		0.006 (1.03)
MAX								-0.008 (-0.51)	0.010 (0.53)
Intercept	0.403* (1.71)	0.302 (1.16)	0.775 (1.38)	0.328 (1.38)	0.342 (1.55)	0.401* (1.88)	0.402* (1.69)	0.449** (2.15)	0.129 (0.23)
Observations	133,596	133,596	133,596	133,596	133,596	133,596	133,596	133,596	133,596
Adjusted R <sup>2</sup>	0.026	0.063	0.041	0.056	0.031	0.061	0.031	0.057	0.145

**Table 6. Fama-Macbeth Cross-Sectional Regressions: Crypto-Like, Short-Constrained Stocks.**

For each day in the sample period (August 1st, 2018 through December 31st, 2021), we sort common stocks traded on the three major exchanges (NYSE, NASDAQ, and AMEX) into ten deciles based on their most recent institutional ownership ratio (IOR) and select the stocks in the bottom decile (those with the lowest IOR). Stock-day observations are excluded if a stock has available exchange-traded put options on the given day. We further exclude stocks with price per share less than 10 dollars as of the previous month-end. This table reports the time-series averages of the slope coefficients obtained from

$$\text{RET}_{i,t+1} = \beta_{0,t} + \beta_1 \text{ABVOL}_{i,t} + \beta_c \text{Controls}_{i,t} + \epsilon_{i,t+1},$$

where  $i$  refers to stock  $i$  and  $t$  refers to day  $t$ . The dependent variable is excess return (RET, in %). Abnormal trading volume (ABVOL) is defined as the daily turnover ratio minus the average turnover ratio over the past 30 days, divided by the standard deviation of daily turnover ratio over the past 30 days. The control variables are short-term reversal (REV, in %), market capitalization (MCAP, in log), momentum (MOM, in %), illiquidity (ILLIQ, scaled by  $10^6$ ), idiosyncratic volatility (IVOL, in %), abnormal google search volume index (ASVI), demand for lottery stocks (MAX, in %), and book-to-market ratio (BM, in log). We mimic the calculation approach for coins when constructing ABVOL and the first seven control variables. The book-to-market (BM) ratio from July of year  $t$  through June of year  $t + 1$ , is computed as the shareholders' book value of equity plus deferred taxes and investment tax credit (if available) minus the book value of preferred stock at the end of the last fiscal year,  $t - 1$ , divided by the market value of equity at the end of December of year  $t - 1$ . Depending on availability, the redemption, liquidation, or par value is used to estimate the book value of preferred stock. [Newey & West \(1987\)](#) adjusted t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ABVOL	0.055*** (2.85)	0.062*** (3.20)	0.055*** (2.86)	0.055*** (2.80)	0.047*** (3.41)	0.046*** (3.74)	0.054*** (2.79)	0.047*** (3.70)	0.056*** (2.90)	0.056*** (4.79)
REV		-0.112*** (-13.74)								-0.128*** (-16.38)
MCAP			-0.007 (-0.69)							0.008 (0.57)
MOM				-0.005** (-2.19)						-0.010*** (-3.53)
ILLIQ					0.000 (0.37)					-0.000 (-1.07)
IVOL						-0.003 (-1.42)				-0.002 (-0.18)
ASVI							-0.001 (-0.29)			-0.000 (-0.11)
MAX								-0.001** (-2.23)		-0.000 (-0.02)
BM									0.062** (2.56)	0.066*** (2.61)
Intercept	0.031 (0.76)	0.014 (0.28)	0.068 (1.06)	0.543** (2.20)	0.030 (0.71)	0.036 (0.86)	0.031 (0.76)	0.036 (0.87)	0.068* (1.71)	0.946*** (3.34)
Observations	114,679	114,679	114,679	114,679	114,679	114,679	114,679	114,679	114,679	114,679
Adjusted $R^2$	0.009	0.055	0.013	0.041	0.014	0.022	0.011	0.021	0.030	0.121

**Table 7. The Volume-Return Relation: Movers.** In this table, the sample is all coins that meet the requirements in Section 2.1 and whose margin trading transitions from unavailable to available on Binance in our sample period (August 1st, 2018 to December 31st, 2021). Panel A splits the coin-day observations into two groups (those prior to and after the relaxations of margin trading) and presents coefficient estimates from the following regression:

$$\text{Return}_{i,t+1} = \beta_0 + \beta_1 \text{ABVOL}_{i,t} + \beta_c \text{Controls}_{i,t} + c_i + c_t + \epsilon_{i,t+1}.$$

Panel B presents coefficient estimates from the following regression:

$$\text{Return}_{i,t+1} = \beta_0 + \beta_1 \text{ABVOL}_{i,t} + \beta_2 \text{CONSTRAINT}_{i,t} + \beta_3 \text{ABVOL}_{i,t} \times \text{CONSTRAINT}_{i,t} + \beta_c \text{Controls}_{i,t} + c_i + c_t + \epsilon_{i,t+1}.$$

In both panels,  $i$  refers to coin  $i$  and  $t$  refers to day  $t$ . We use four measures of returns (all in %): Excess return (RET), the CAPM alpha, the three-factor alpha, and the DGTW alpha. Abnormal trading volume (ABVOL) is defined as the daily turnover ratio minus the average turnover ratio over the past 30 days, divided by the standard deviation of daily turnover ratio over the past 30 days. The control variables are defined as before. The existence of short sale constraint (CONSTRAINT) is a dummy variable that equals one if the coin's margin trading is not available on Binance (one cannot borrow on Binance to sell short the coin) and zero otherwise. We include both coin and day fixed effects. Standard errors are double-clustered by coin and day. We present the t-statistics in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Pre- and post-relaxation of margin trading services								
	Before relaxation				After relaxation			
	RET <sub>t+1</sub>	CAPM $\alpha_{t+1}$	3-factor $\alpha_{t+1}$	DGTW $\alpha_{t+1}$	RET <sub>t+1</sub>	CAPM $\alpha_{t+1}$	3-factor $\alpha_{t+1}$	DGTW $\alpha_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ABVOL <sub>t</sub>	-0.079*** (-2.97)	-0.065** (-2.61)	-0.097** (-2.24)	-0.049** (-2.39)	0.004 (0.78)	0.004 (0.72)	0.006 (1.06)	-0.001 (-0.15)
MCAP <sub>t</sub>	-0.566*** (-3.66)	-0.554*** (-4.00)	-0.268 (-1.41)	-0.352*** (-2.74)	-0.584*** (-5.63)	-0.601*** (-5.10)	-0.448*** (-3.06)	-0.500*** (-5.43)
REV <sub>t</sub>	-0.009 (-1.17)	-0.015 (-0.95)	-0.023 (-1.23)	-0.022 (-1.40)	-0.020 (-1.32)	-0.021 (-1.50)	-0.016 (-1.06)	-0.023 (-1.59)
MOM <sub>t</sub>	-0.004* (-1.80)	-0.003 (-1.27)	-0.005 (-1.24)	-0.006** (-2.18)	-0.002 (-0.76)	-0.003 (-1.14)	-0.002 (-0.70)	-0.007*** (-2.83)
ILLIQ <sub>t</sub>	0.001 (0.94)	-0.000 (-0.37)	0.000 (0.33)	0.000 (0.45)	0.001 (0.96)	0.001 (0.71)	0.001 (0.80)	-0.001 (-0.56)
IVOL <sub>t</sub>	0.296* (1.67)	0.125 (1.10)	0.379 (1.54)	0.149 (1.19)	0.054 (0.45)	0.041 (0.34)	0.068 (0.48)	0.035 (0.31)
ASVI <sub>t</sub>	-0.000 (-0.06)	0.006 (0.81)	-0.004 (-0.36)	0.001 (0.10)	0.016*** (3.71)	0.017*** (3.68)	0.017*** (3.59)	0.016*** (3.84)
MAX <sub>t</sub>	-0.085** (-2.53)	-0.050* (-1.77)	-0.081** (-2.11)	-0.063** (-2.24)	-0.068** (-2.24)	-0.072** (-2.37)	-0.095*** (-3.01)	-0.049* (-1.72)
Coin Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Day Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	62,488	56,964	56,964	62,488	65,204	64,853	64,853	65,204
Adjusted R <sup>2</sup>	0.696	0.783	0.769	0.585	0.586	0.476	0.466	0.371

Table 7. The Volume-Return Relation: Movers. (continued)

Panel B: A single setting with dummies and interactive								
	RET <sub>t+1</sub>		CAPM $\alpha_{t+1}$		3-factor $\alpha_{t+1}$		DGTW $\alpha_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ABVOL <sub>t</sub>	-0.005 (-0.44)	-0.000 (-0.02)	-0.007 (-0.55)	0.000 (0.04)	-0.007 (-0.48)	0.002 (0.19)	-0.010 (-0.84)	-0.003 (-0.37)
CONSTRAINT <sub>t</sub>	0.227*** (2.75)	0.100 (1.15)	0.262*** (2.74)	0.144 (1.44)	0.278** (2.15)	0.204 (1.57)	0.142 (1.35)	0.055 (0.52)
ABVOL <sub>t</sub> × CONSTRAINT <sub>t</sub>	-0.080*** (-3.27)	-0.056** (-2.59)	-0.073*** (-2.96)	-0.042** (-2.23)	-0.095*** (-2.72)	-0.062** (-2.07)	-0.071*** (-2.93)	-0.040** (-2.18)
MCAP <sub>t</sub>		-0.323*** (-6.21)		-0.373*** (-6.08)		-0.226*** (-3.14)		-0.253*** (-5.17)
REV <sub>t</sub>		-0.010 (-1.18)		-0.017 (-1.45)		-0.017 (-1.30)		-0.021* (-1.81)
MOM <sub>t</sub>		-0.001 (-0.70)		-0.001 (-0.85)		-0.001 (-0.60)		-0.006*** (-2.98)
ILLIQ <sub>t</sub>		0.001 (0.90)		-0.000 (-0.73)		0.000 (0.22)		0.000 (0.17)
IVOL <sub>t</sub>		0.191 (1.44)		0.084 (0.98)		0.128 (1.18)		0.105 (1.32)
ASVI <sub>t</sub>		0.011*** (3.39)		0.014*** (3.81)		0.011** (2.53)		0.011*** (3.38)
MAX <sub>t</sub>		-0.084*** (-2.87)		-0.064*** (-3.04)		-0.078*** (-3.39)		-0.058*** (-2.96)
Coin Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Day Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	127,693	127,693	121,819	121,819	121,819	121,819	127,693	127,693
Adjusted R <sup>2</sup>	0.657	0.657	0.660	0.661	0.650	0.651	0.511	0.511

**Table 8. Order Imbalance and Abnormal Trading Volume.** In this table, the sample is all coins that meet the requirements in Section 2.1 and whose margin trading transitions from unavailable to available on Binance in our sample period (August 1st, 2018 to December 31st, 2021). This table presents coefficient estimates from the following regression:

$$\begin{aligned} \text{OIB}_{i,t} = & \beta_0 + \beta_1 \text{ABVOL}_{i,t} + \beta_2 \text{CONSTRAINT}_{i,t} + \beta_3 \text{ABVOL}_{i,t} \times \text{CONSTRAINT}_{i,t} \\ & + \beta_4 \text{OIB}_{i,t-1} + \beta_c \text{Controls}_{i,t-1} + c_i + c_t + \epsilon_{i,t}, \end{aligned}$$

where  $i$  refers to coin  $i$  and  $t$  refers to day  $t$ . We use two order imbalance (OIB) measures: OIBVOL (order imbalance in volume, in %) and OIBTRD (order imbalance in trades, in %). Abnormal trading volume (ABVOL) is defined as the daily turnover ratio minus the average turnover ratio over the past 30 days, divided by the standard deviation of daily turnover ratio over the past 30 days. The existence of short sale constraint (CONSTRAINT) is a dummy variable that equals one if the coin's margin trading is not available on Binance (one cannot borrow on Binance to sell short the coin) and zero otherwise. The control variables are short-term reversal (REV, in %), market capitalization (MCAP, in log), momentum (MOM, in %), illiquidity (ILLIQ, scaled by  $10^6$ ), idiosyncratic volatility (IVOL, in %), abnormal google search volume index (ASVI), and demand for lottery coins (MAX, in %). We include both coin and day fixed effects. Standard errors are double-clustered by coin and day. We present the t-statistics in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively.

	OIBVOL <sub>t</sub>		OIBTRD <sub>t</sub>	
	(1)	(2)	(3)	(4)
ABVOL <sub>t</sub>	0.087 (1.07)	0.094 (1.08)	0.071 (1.03)	0.077 (1.04)
CONSTRAINT <sub>t</sub>	0.103 (0.32)	0.449 (1.31)	0.596* (1.72)	0.530 (1.53)
ABVOL <sub>t</sub> × CONSTRAINT <sub>t</sub>	0.436*** (3.18)	0.448*** (3.11)	0.307*** (2.97)	0.313*** (2.90)
OIBVOL <sub>t-1</sub>	0.159*** (10.90)	0.162*** (11.03)		
OIBTRD <sub>t-1</sub>			0.351*** (19.25)	0.356*** (18.92)
MCAP <sub>t-1</sub>		1.081*** (3.92)		-0.021 (-0.10)
REV <sub>t-1</sub>		-0.078*** (-2.83)		-0.098*** (-3.50)
MOM <sub>t-1</sub>		0.004 (1.35)		-0.000 (-0.19)
ILLIQ <sub>t-1</sub>		-0.001 (-1.36)		-0.001 (-1.41)
IVOL <sub>t-1</sub>		0.687*** (4.08)		0.874*** (4.93)
ASVI <sub>t-1</sub>		0.007 (1.59)		-0.000 (-0.08)
MAX <sub>t-1</sub>		-0.142*** (-3.75)		-0.131*** (-2.87)
Coin Fixed Effects	Y	Y	Y	Y
Day Fixed Effects	Y	Y	Y	Y
Observations	128,385	128,233	128,385	128,233
Adjusted R <sup>2</sup>	0.124	0.127	0.229	0.231

**Table 9. Trading Activities (Volume and Number of Trades) following Abnormal Trading Volume.** In this table, the sample is all coins that meet the requirements in Section 2.1 and whose margin trading transitions from unavailable to available on Binance in our sample period (August 1st, 2018 to December 31st, 2021). Panel A presents coefficient estimates from the following regression:

$$\Delta\text{VOL}_{i,t+1} = \beta_0 + \beta_1\text{ABVOL}_{i,t} + \beta_2\text{CONSTRAINT}_{i,t} + \beta_3\text{ABVOL}_{i,t} \times \text{CONSTRAINT}_{i,t} + \beta_4\Delta\text{VOL}_{i,t} + \beta_c\text{Controls}_{i,t} + c_i + c_t + \epsilon_{i,t+1},$$

and Panel B presents coefficient estimates from the following regression:

$$\Delta\text{TRD}_{i,t+1} = \beta_0 + \beta_1\text{ABVOL}_{i,t} + \beta_2\text{CONSTRAINT}_{i,t} + \beta_3\text{ABVOL}_{i,t} \times \text{CONSTRAINT}_{i,t} + \beta_4\Delta\text{TRD}_{i,t} + \beta_c\text{Controls}_{i,t} + c_i + c_t + \epsilon_{i,t+1}.$$

In both panels,  $i$  refers to coin  $i$  and  $t$  refers to day  $t$ . We examine three change in trading volume ( $\Delta\text{VOL}_{t+1}$ ) measures:  $\Delta\text{BVOL}_{t+1}$  (percentage change in buyer-initiated volume from  $t$  to  $t+1$ ),  $\Delta\text{SVOL}_{t+1}$  (percentage change in seller-initiated volume from  $t$  to  $t+1$ ), and  $\Delta\text{BVOL}_{t+1} - \Delta\text{SVOL}_{t+1}$ , and three change in number of trades ( $\Delta\text{TRD}_{t+1}$ ) measures:  $\Delta\text{BTRD}_{t+1}$  (percentage change in number of buyer-initiated trades from  $t$  to  $t+1$ ),  $\Delta\text{STRD}_{t+1}$  (percentage change in number of seller-initiated trades from  $t$  to  $t+1$ ), and  $\Delta\text{BTRD}_{t+1} - \Delta\text{STRD}_{t+1}$ . Abnormal trading volume (ABVOL) is defined as the daily turnover ratio minus the average turnover ratio over the past 30 days, divided by the standard deviation of daily turnover ratio over the past 30 days. The existence of short sale constraint (CONSTRAINT) is a dummy variable that equals one if the coin's margin trading is not available on Binance (one cannot borrow on Binance to sell short the coin) and zero otherwise. The control variables are defined as before. We include both coin and day fixed effects. Standard errors are double-clustered by coin and day. We present the  $t$ -statistics in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Trading volume following abnormal trading volume						
	$\Delta\text{BVOL}_{t+1}$		$\Delta\text{SVOL}_{t+1}$		$\Delta\text{BVOL}_{t+1} - \Delta\text{SVOL}_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{ABVOL}_t$	-1.415 (-1.11)	-0.077 (-1.05)	-1.122 (-1.13)	-0.840 (-1.08)	-0.293 (-1.02)	-0.207 (-0.83)
$\text{CONSTRAINT}_t$	19.485*** (3.14)	13.160** (2.47)	9.162*** (3.26)	5.518** (2.08)	10.322** (2.48)	6.069* (1.96)
$\text{ABVOL}_t \times \text{CONSTRAINT}_t$	-6.465*** (-3.25)	-4.109*** (-2.69)	-4.670*** (-3.16)	-3.239** (-2.55)	-1.795*** (-3.12)	-1.478** (-2.17)
$\Delta\text{BVOL}_t$	0.000** (2.00)	0.000** (2.57)				
$\Delta\text{SVOL}_t$			-0.000 (-0.90)	0.000 (0.02)		
$\Delta\text{BVOL}_t - \Delta\text{SVOL}_t$					-0.000* (-1.88)	-0.000** (-2.56)
$\text{MCAP}_t$		-10.016*** (-3.48)		-11.561*** (-6.46)		-2.075 (-1.20)
$\text{REV}_t$		1.532*** (3.13)		1.602*** (5.59)		-0.845*** (-2.93)
$\text{MOM}_t$		-0.232*** (-3.18)		-0.126*** (-3.00)		-0.121*** (-2.85)
$\text{ILLIQ}_t$		0.217*** (3.55)		0.078*** (6.05)		0.144** (2.54)
$\text{IVOL}_t$		-3.110 (-0.32)		-12.852** (-2.05)		9.345* (1.82)
$\text{ASVI}_t$		0.088 (0.85)		0.008 (0.18)		0.080 (0.88)
$\text{MAX}_t$		-3.338*** (-2.62)		-1.849* (-1.94)		-1.615** (-2.05)
Coin Fixed Effects	Y	Y	Y	Y	Y	Y
Day Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	128,125	128,125	128,124	128,124	128,124	128,124
Adjusted R <sup>2</sup>	0.022	0.030	0.042	0.048	0.007	0.013

**Table 9. Trading Activities (Volume and Number of Trades) following Abnormal Trading Volume. (continued)**

Panel B: Number of trades following abnormal trading volume						
	$\Delta\text{BTRD}_{t+1}$		$\Delta\text{STRD}_{t+1}$		$\Delta\text{BTRD}_{t+1} - \Delta\text{STRD}_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{ABVOL}_t$	-0.974 (-1.07)	-0.645 (-0.97)	-0.795 (-1.11)	-0.540 (-1.04)	-0.189 (-0.90)	-0.110 (-0.65)
$\text{CONSTRAINT}_t$	12.002*** (3.77)	8.962** (2.57)	6.724*** (3.32)	4.839** (2.12)	5.244*** (2.96)	4.101** (2.33)
$\text{ABVOL}_t \times \text{CONSTRAINT}_t$	-4.211*** (-3.06)	-2.652** (-2.42)	-3.325*** (-3.09)	-2.008** (-2.28)	-0.933*** (-2.78)	-0.670** (-2.08)
$\Delta\text{BTRD}_t$	-0.001 (-1.00)	-0.001 (-1.00)				
$\Delta\text{STRD}_t$			-0.000 (-1.14)	-0.000 (-1.01)		
$\Delta\text{BTRD}_t - \Delta\text{STRD}_t$					-0.000 (-1.17)	-0.000 (-1.42)
$\text{MCAP}_t$		-11.129*** (-5.31)		-8.911*** (-6.94)		-2.213* (-1.90)
$\text{REV}_t$		1.171*** (3.73)		1.645*** (6.22)		-0.480*** (-2.79)
$\text{MOM}_t$		-0.118*** (-3.66)		-0.061*** (-2.97)		-0.057*** (-3.22)
$\text{ILLIQ}_t$		0.053*** (6.31)		0.045*** (8.07)		0.008 (0.92)
$\text{IVOL}_t$		-12.790*** (-3.38)		-16.106*** (-5.53)		3.313 (1.49)
$\text{ASVI}_t$		0.061 (0.98)		0.048 (1.05)		0.014 (0.40)
$\text{MAX}_t$		-1.523** (-2.55)		-0.889 (-1.63)		-0.651* (-1.67)
Coin Fixed Effects	Y	Y	Y	Y	Y	Y
Day Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	128,125	128,125	128,124	128,124	128,124	128,124
Adjusted R-squared	0.020	0.025	0.044	0.051	0.007	0.008

**Table IA1. Different Holding Periods.** For each day, quintile portfolios are formed by sorting individual coins based on their abnormal trading volume (ABVOL) in the previous day, where quintile 1 contains coins with the lowest 20% ABVOL and quintile 5 contains coins with the highest 20% ABVOL. ABVOL is defined as the daily turnover ratio minus the average turnover ratio over the past 30 days, divided by the standard deviation of daily turnover ratio over the past 30 days. The coins are then held in the portfolio for  $H$  days, with  $1/H$ th of each portfolio reinvested daily. For each holding period  $H$ , the table presents the difference in average excess daily return (RET), CAPM alpha, three-factor alpha, and DGTW alpha between quintile 5 and quintile 1. Portfolio returns are equal-weighted. CAPM alpha is the intercept from regressing excess portfolio returns on a constant and cryptocurrency excess market return (CMKT). Three-factor alpha is the intercept from regressing excess portfolio returns on a constant, CMKT, the size factor (CSMB), and the momentum factor (CMOM). CMKT, CSMB, and CMOM are constructed following the approach of [Y. Liu et al. \(2022\)](#). A coin's DGTW alpha is the difference between a coin's return and the value-weighted return of its matching  $10 \times 10$  coin size/momentum portfolio following the approach of [Daniel et al. \(1997\)](#). [Newey & West \(1987\)](#) adjusted t-statistics are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively. The sample is all coins meeting the requirements in Section 2.1 and the sample period is August 1st, 2018 to December 31st, 2021.

Holding period	RET	t-value	CAPM $\alpha$	t-value	3-factor $\alpha$	t-value	DGTW $\alpha$	t-value
1 day	-0.498***	(-7.20)	-0.491***	(-7.21)	-0.464***	(-7.00)	-0.459***	(-7.29)
2 days	-0.434***	(-6.99)	-0.428***	(-7.03)	-0.394***	(-7.01)	-0.391***	(-7.77)
3 days	-0.283***	(-5.50)	-0.279***	(-5.54)	-0.255***	(-5.30)	-0.294***	(-6.90)
4 days	-0.224***	(-4.42)	-0.221***	(-4.44)	-0.194***	(-4.36)	-0.239***	(-6.44)
5 days	-0.182***	(-3.58)	-0.181***	(-3.60)	-0.153***	(-3.50)	-0.208***	(-6.04)
6 days	-0.158***	(-3.29)	-0.157***	(-3.30)	-0.136***	(-3.19)	-0.186***	(-5.31)
7 days	-0.153***	(-3.23)	-0.152***	(-3.25)	-0.130***	(-3.15)	-0.184***	(-5.01)
8 days	-0.143***	(-3.24)	-0.143***	(-3.28)	-0.125***	(-3.16)	-0.179***	(-4.89)
9 days	-0.134***	(-3.17)	-0.133***	(-3.20)	-0.124***	(-3.20)	-0.168***	(-4.54)
10 days	-0.118***	(-2.82)	-0.117***	(-2.84)	-0.111***	(-2.88)	-0.143***	(-3.86)
11 days	-0.109***	(-2.76)	-0.108***	(-2.79)	-0.104***	(-2.76)	-0.138***	(-3.85)
12 days	-0.099***	(-2.69)	-0.099***	(-2.73)	-0.095***	(-2.63)	-0.131***	(-3.91)
13 days	-0.082**	(-2.49)	-0.082**	(-2.52)	-0.079**	(-2.30)	-0.119***	(-3.74)
14 days	-0.073**	(-2.31)	-0.073**	(-2.34)	-0.069**	(-2.08)	-0.109***	(-3.54)
15 days	-0.071**	(-2.33)	-0.070**	(-2.35)	-0.067**	(-2.08)	-0.101***	(-3.31)
16 days	-0.066**	(-2.36)	-0.066**	(-2.39)	-0.064**	(-2.09)	-0.101***	(-3.58)
17 days	-0.063**	(-2.34)	-0.063**	(-2.37)	-0.061**	(-2.03)	-0.097***	(-3.65)
18 days	-0.054**	(-2.17)	-0.054**	(-2.19)	-0.052*	(-1.85)	-0.093***	(-3.66)
19 days	-0.049**	(-2.05)	-0.049**	(-2.07)	-0.048*	(-1.75)	-0.084***	(-3.33)
20 days	-0.044*	(-1.90)	-0.044*	(-1.93)	-0.043	(-1.64)	-0.082***	(-3.34)