The Negative Abnormal Volume Return Relation 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.

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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 the high-volume return 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's shares and an increase in price.[1] Alternatively, some studies interpret the abnormal volume return premium as compensation for risk, manifested in the form of opinion divergence (Garfinkel and Sokobin, 2006; Banerjee and Kremer, 2010) or information uncertainty (Jiang et al., 2005; Schneider, 2009), with each 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.[2] 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 raw 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 $= -7.29$).[3] This negative volume-return relation persists after controlling

[1] 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.

[2] We discuss the Binance sample in Section 2.1.

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

(via Fama/Macbeth regressions) for liquidity and other individual coin characteristics.[4] 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, as 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; Cong and Xiao, 2021; Cong et al., 2022; Sockin and Xiong, 2022; Cong et al., 2023). 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. (2022) 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 (Mayshar, 1983; Morris, 1996; Viswanathan,

[4]Short-term reversal, market capitalization, momentum, idiosyncratic volatility, abnormal google search volume, and demand for lottery coins.

2001; Chen et al., 2002; Scheinkman and Xiong, 2003; Hong et al., 2006) represented by Miller (1977) to interpret the negative relation between abnormal trading volume (high investor disagreement) and expected coin returns. 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.[5]

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 literature.[6] 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.[7] Cookson and Niessner (2020) and especially Cookson and Niessner (2023) provide more targeted finance evidence: a direct measure of disagreement constructed from StockTwits is strongly correlated with abnormal trading volume.

Our tests of Miller (1977) are also predicated on the necessity of short sale constraints for the model to work.[8] Sourcing our data from the Binance trading platform and the coins on it

[5]We empirically focus on short-sale-constrained coins, after the full-sample results.

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

[7]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.

[8]Without short sale constraints, both optimists and pessimists' beliefs will be incorporated into stock

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.[9] We thus first document that the negative volume-return relation is concentrated in coin-day observations without available margin trading services.

Given this prima facie evidence supporting Miller (1977), we turn our attention to robustness and addressing threats to identification. We begin by recognizing that cryptocurrency trading was dominated by retail investors in the earlier part of their existence. This raises the question of appropriate comparison with the full cross-section of equity volume-return relation. We therefore re-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 options – in short, "crypto-like" stocks in terms of short sale constraints – 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 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

prices and thus no overpricing of assets will occur.

[9] 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 updates on the Margin Data page based on current market conditions..."

it is constrained from being sold short or not.[10] 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 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.

Another threat to our conclusions relates to time-series variation in the investor composition of crypto trading. While retail investors dominated trading earlier in our sample window, there was a spike in institutional ownership of cryptos during 2020. Given the importance of institutional investors to both enable short-selling and mitigate behavioral effects in returns, this simultaneity offers an alternative explanation for our results. Specifically, given evidence that retail crypto traders overreact to news (e.g., Kogan et al., 2023) and that pre-2020 most crypto news was positive, the higher abnormal volume may reflect the typical overreaction and the ex-post return-decline represents slow reversal (instead of necessarily supporting Miller, 1977).

In response, we offer two analyses designed to knock down this alternative interpretation. The first confronts the presumption that the volume-overreaction to news drives the return

[10]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.

patterns we observe. We decompose our daily abnormal volume into a news-related piece and a residual.[11] We find that our abnormal volume - return relation is driven by the residual piece, *not the news-related piece that the alternative interpretation would require.* Second, we offer a type of placebo-test that emphasizes potential time-trends in our analysis (i.e. relies on the rather sudden arrival of institutional trading in crypto during 2020). To knock down the alternative interpretation, the cryptocurrencies that were already shortable before 2020 should show no time-trends, and especially not during the year 2020. That is in fact what we find.[12]

We provide two other perspectives to support Miller (1977). 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,

[11]See Section 3.6.1 for details.

[12]Section 3.6.2 provides details. It also discusses how this sudden spike in coins receiving margin trading allowance, undermines formation of appropriate counterfactuals for a more traditional DiD.

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 (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.[13] 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 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 and Sokobin, 2006; Banerjee and Kremer, 2010; Jiang et al., 2005; Schneider, 2009) in stocks, we instead document a negative volume-return relation in the cross section of cryptocurrencies.[14] We find that the negative volume-return relation persists after controlling for their three-factor model, as well as several 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, Liu and Tsyvinski (2021) and Liu et al. (2022) study size and momentum factors' influences, while Cong et al. (2022) add network adoption and a valuation premium to determinants of crypto returns. Following Baker and Wurgler

[13]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.

[14]We are the first to show this robustly. While 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.

(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 and Anamika et al., 2023). But while extant work has studied the role of investor disagreement in other asset 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 volume-return relation.

Our paper emphasizes the equally important roles of high disagreement and the presence of short sale constraints to produce overpricing in Miller (1977), while providing additional 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 and Xiong, 2003; Hong et al., 2006) that support Miller (1977) in other asset classes, while casting some doubts on opposite conclusions (Abel et al., 1989; Anderson et al., 2005; Doukas et al., 2006; Garfinkel and Sokobin, 2006; David, 2008; Banerjee, 2011; Carlin et al., 2014; Gao et al., 2019) represented by Varian (1985).

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.[15]

We recognize the recent SEC's suit against Binance platforms.[16] 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.[17] 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

[15] 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.

[16] See https://www.sec.gov/files/litigation/complaints/2023/comp-pr2023-101.pdf.

[17] 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.

maximize the number of base assets in the cross section that we examine. For simplicity, 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 and 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.[18] 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 Liu and Tsyvinski (2021) and 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 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.

[18]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.[19] 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:

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

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[20] and that some research ties liquidity fluctuations to asset returns.[21] 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.[22] Hence, abnormal trading volume (ABVOL) for coin i on day t is defined as follows:

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

[19] See Benston and Hagerman (1974), Branch and Freed (1977), and Petersen and Fialkowski (1994).

[20] For equity market versions of this, see Tkac (1999), Lee and Swaminathan (2000), Gebhardt et al. (2001), Garfinkel and Sokobin (2006), and Garfinkel (2009).

[21] See Brennan et al. (1998), Chordia et al. (2000), Chordia et al. (2001), and Hasbrouck and Seppi (2001).

[22] 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 Coin Characteristics

We define several cryptocurrency characteristics. Following Jegadeesh (1990), short-term reversal (REV) is defined as the coin return in the previous day prior to the portfolio formation day. Following Jegadeesh and 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.

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

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:

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

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.[23] 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 while 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. In particular, ABVOL has a time-series mean of 0.168 and median of -0.279, clearly indicating right-skewed distribution of ABVOL.[24]

Panel B shows our growing cross-section of coins throughout the sample period. with the number of coins and mean/median market caps. 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., Liu and Tsyvinski, 2021, Liu et al., 2022, and Cong et al., 2022). While our sample on average capturing about 14% coins of the coin market, the mean/median market capitalization is relatively larger. This is due to the listing requirements on Binance[25], which essentially rule out coins with smaller size and lower user adoption. In particular, the total

[23] 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.

[24] The time-series averages of the t-statistics for the null hypothesis that ABVOL = 0 is 0.16.

[25] "...We want good coins listed on Binance, such as coins with a proven team, a useful product, 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.

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 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.[26]

Panel A of Table 2 reports the results, and Newey and West (1987) t-statistics with eight lags are reported in parentheses.[27] 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). In particular, coins in the lowest ABVOL quintile generate an average excess return of 0.542% per day, whereas coins in the highest ABVOL quintile generate a lower average excess return of 0.044% per day. The average return difference between the highest and the lowest ABVOL quintile is −0.498% per day with a t-statistic of −7.20.

[26] 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.

[27] 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.

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.[28] 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 when moving from the lowest to the highest ABVOL quintile.[29] 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.

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

[28]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.

[29]Note that the average three-factor alphas of all ABVOL quintiles are negative. This is due to the size effect in cryptocurrency (Liu and Tsyvinski, 2021 and 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.

cryptocurrency market. This negative volume-return relation in cryptocurrencies is in stark contrast to the positive volume-return relation in stocks (Gervais et al., 2001; Lerman et al., 2010; Kaniel et al., 2012; Wang, 2021; Israeli et al., 2022).

We conjecture that a coin's abnormal trading activity (ABVOL) largely reflects investor disagreement on its underlying value. To test this conjecture, we begin with an important question: why do people trade in the first place? The famous no-trade theorem (Milgrom and Stokey, 1982) states that when the initial asset allocation is Pareto-efficient and agents have common knowledge of rationality, then the arrival of private information will not induce further trade as long as agents interpret information in a similar fashion. However, if agents share different beliefs about the distribution of information conditional on asset values, then there can be trade in the market. Since most cryptocurrencies lack cash flows and do not issue regular disclosures to communicate with the investing public, investors tend to interpret their values in a dissimilar fashion and thus are incentivized to trade. In short, trading activity in a cryptocurrency is highly likely to reflect divergent investor opinions about the cryptocurrency's value.

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 from selling the coin short. Hence, those coins experience significantly lower future returns.[30]

However, Miller (1977)'s hypothesis also implies that *only* high disagreement assets are overpriced; it does not imply that low disagreement assets will be undervalued. This

[30] We address the empirical role of short constraints below, beginning with Table 4.

is because pessimistic investors will consider selling short an asset only when they have extremely pessimistic evaluations of the asset. When divergence of opinion is low, the number of such investors is likely to be very low. Hence, in such cases, asset price is not biased since both sides of the market can trade on their beliefs without restrictions. Consistent with this, we find that the negative and statistically significant difference in returns is mostly driven by the underperformance of the top two ABVOL quintiles.[31] [32] In general, Table 2 provides results that are preliminarily consistent with Miller (1977), notwithstanding our eventual need to recognize and control for short constraints among coins.

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 and Titman (1993).[33] 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

[31] Using analyst earnings forecast dispersion to capture disagreement, Diether et al. (2002) find that the return spread between high-dispersion and low-dispersion stocks is mainly driven by the underperformance of the high-dispersion stocks.

[32] This pattern also helps refute an interpretation of ABVOL as liquidity, since assets with the lowest trading volume are the most illiquid and therefore should command the highest expected returns. In Table 2, it is the coins in the middle ABVOL quintile that experience the highest average excess returns and alphas.

[33] 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.

on the day after ABVOL calculation.

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 and 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

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 stock returns. For example, Liu and Tsyvinski (2021) and Liu et al. (2022) find qualitatively similar size (e.g, Fama and French, 1992, 1993), momentum (e.g., Jegadeesh and 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. On the other hand, 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, 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 and MacBeth (1973) regressions of excess coin returns on ABVOL along with those coin characteristics. In particular, for every day, we perform the following cross-sectional daily regressions:

$$\mathrm{RET}_{i,t+1} = \beta_{0,t} + \beta_{1,t} \times \mathrm{ABVOL}_{i,t} + \beta_{c,t} \times \mathrm{Controls}_{i,t} + \epsilon_{i,t+1}, \tag{5}$$

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 and West (1987) adjusted t-statistics (with eight lags) reported in parentheses. In column 1, the average slope, β_1, 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 bivariate portfolio analysis since the number of coins in the cross section is too few to perform a 5×5 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. 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 and MacBeth (1973) cross-sectional regressions provide strong evidence for a significantly negative relation between ABVOL and future coin returns.[34]

3.4 The Role of Short Sale Constraints

3.4.1 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.

[34]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.

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.[35]

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.[36] 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

[35] https://www.binance.com/en/fee/schedule.

[36] 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.

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. 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.

3.4.2 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 indiviudal 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 4. 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 do 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.[37]

3.4.3 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

[37] 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.

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.

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 and MacBeth (1973) regressions of excess stocks returns on ABVOL along with the stock characteristics, as in equation (5).

Table 5 reports the time-series averages of the slope coefficients, with the Newey and West (1987) adjusted t-statistics (with eight lags) 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.

3.5 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% 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.[38] This facilitates our event-study analysis.

3.5.1 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:

$$\text{Return}_{i,t+1} = \beta_0 + \beta_1 \text{ABVOL}_{i,t} + \beta_c \text{Controls}_{i,t} + c_i + c_t + \epsilon_{i,t+1}, \tag{6}$$

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,

[38] 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).

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, β_1 should be significantly negative for movers prior to the allowance of margin trading services while becoming indistinguishable from zero after the relaxations of short sale constraints. Panel A of Table 6 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:

$$\begin{aligned}\text{Return}_{i,t+1} = \beta_0 + \beta_1\text{ABVOL}_{i,t} + \beta_2\text{CONSTRAINT}_{i,t} + \beta_3\text{ABVOL}_{i,t} \times \text{CONSTRAINT}_{i,t} \\ + \beta_c\text{Controls}_{i,t} + c_i + c_t + \epsilon_{i,t+1}, \quad (7)\end{aligned}$$

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.

Our expectation is that when short-selling restrictions are present (CONSTRAINT = 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 (CONSTRAINT = 0), the negative relation between disagreement and future coin returns will disappear. Therefore, the coefficient β_3 on the interaction term, ABVOL $\times$ CONSTRAINT, should be negative and statistically significant, while the coefficient on ABVOL should be statistically indistinguishable from zero.

Panel B of Table 6 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 ABVOL is indistinguishable from zero. To calibrate the economic significance, the standard deviation of ABVOL for the models in Table 6 is 3.99. Hence, when short-selling restrictions are present, a one-standard-deviation increase in 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 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 ABVOL and CONSTRAINT are indistinguishable from zero, indicating that neither high disagreement nor the presence of short-selling restrictions is *independently* sufficient to generate overpricing.[39]

The results in Table 6 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; 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 6, however, the negative volume-return relation becomes weaker and even disappears after a coin's margin trading has been activated on Binance.

[39]For robustness, we run the same regressions while excluding the pre-event window [t-7, t-1] just before Binance margin allowance dates. This is in deference to Savor and 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.

3.5.2 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.[40] Second, in the presence of short-sale constraints, pessimists are restrained from selling short while optimists can freely trade on their positive beliefs.[41] 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:

$$\mathrm{OIBVOL}_{i,t} = \frac{\mathrm{BVOL}_{i,t} - \mathrm{SVOL}_{i,t}}{\mathrm{BVOL}_{i,t} + \mathrm{SVOL}_{i,t}}, \tag{8}$$

[40] 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 and Kremer (2010)'s model, investors' interpretations of a public signal are drawn from a normal distribution with mean zero and standard deviation of λ. In Golez and 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 λ or a smaller q.

[41] See also Hong and 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."

$$\text{OIBTRD}_{i,t} = \frac{\text{BTRD}_{i,t} - \text{STRD}_{i,t}}{\text{BTRD}_{i,t} + \text{STRD}_{i,t}}, \tag{9}$$

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:

$$\begin{aligned} \text{OIB}_{i,t} = \beta_0 + \beta_1 \text{ABVOL}_{i,t} + \beta_2 \text{CONSTRAINT}_{i,t} + \beta_3 \text{ABVOL}_{i,t} \times \text{CONSTRAINT}_{i,t} \\ + \beta_4 \text{OIB}_{i,t-1} + \beta_c \text{Controls}_{i,t-1} + c_i + c_t + \epsilon_{i,t}, \end{aligned} \tag{10}$$

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 6.

Table 7 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.[42] 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.

The results of Table 7 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).

3.5.3 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

[42] The inclusion of more lagged order imbalance terms does not change the results qualitatively.

trades, with the decrease in the former being larger in magnitude.[43] To test this implication, we first construct the following four variables for coin i at any day $t+1$, which capture how buying and selling activities evolve from day t to $t+1$:

$$\Delta\text{BVOL}_{i,t+1} = (\frac{\text{BVOL}_{i,t+1} - \text{BVOL}_{i,t}}{\text{BVOL}_{i,t}}) \times 100\%, \tag{11}$$

$$\Delta\text{SVOL}_{i,t+1} = (\frac{\text{SVOL}_{i,t+1} - \text{SVOL}_{i,t}}{\text{SVOL}_{i,t}}) \times 100\%, \tag{12}$$

$$\Delta\text{BTRD}_{i,t+1} = (\frac{\text{BTRD}_{i,t+1} - \text{BTRD}_{i,t}}{\text{BTRD}_{i,t}}) \times 100\%, \tag{13}$$

$$\Delta\text{STRD}_{i,t+1} = (\frac{\text{STRD}_{i,t+1} - \text{STRD}_{i,t}}{\text{STRD}_{i,t}}) \times 100\%. \tag{14}$$

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 $t+1$.[44] Then we run the following two regressions:

$$\begin{aligned}\Delta\text{VOL}_{i,t+1} = \beta_0 + \beta_1\text{ABVOL}_{i,t} + \beta_2\text{CONSTRAINT}_{i,t} + \beta_3\text{ABVOL}_{i,t} \times \text{CONSTRAINT}_{i,t}\\ + \beta_4\Delta\text{VOL}_{i,t} + \beta_c\text{Controls}_{i,t} + c_i + c_t + \epsilon_{i,t+1},\end{aligned} \tag{15}$$

[43] 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.

[44] 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.

and

$$\Delta\text{TRD}_{i,t+1} = \beta_0 + \beta_1\text{ABVOL}_{i,t} + \beta_2\text{CONSTRAINT}_{i,t} + \beta_3\text{ABVOL}_{i,t} \times \text{CONSTRAINT}_{i,t} + \beta_4\Delta\text{TRD}_{i,t} + \beta_c\text{Controls}_{i,t} + c_i + c_t + \epsilon_{i,t+1}, \quad (16)$$

where i refers to the coin and t refers to the day. We use three change in trading volume (ΔVOL) measures: ΔBVOL, ΔSVOL, and $\Delta\text{BVOL} - \Delta\text{SVOL}$, and three change in number of trades (ΔTRD) measures: ΔBTRD, ΔSTRD, and $\Delta\text{BTRD} - \Delta\text{STRD}$. Including the lagged terms, ΔVOL_t and ΔTRD_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 8 reports the regression results of equation (15). In columns 1 to 4, the coefficients on the interaction term, ABVOL $\times$ CONSTRAINT, are negative and statistically significant, both with and without control variables. This indicates that when short-selling restrictions are binding (CONSTRAINT = 1), ABVOL decreases subsequent buyer-initiated and seller-initiated trading volume. In particular, using columns 1 and 3, a one-standard-deviation increase in 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.[45] When we further

[45]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.

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 ABVOL alone in all specifications are insignificantly different from zero, again stressing the role of short-selling restrictions in Miller (1977)'s model.[46]

Panel B of Table 8 reports the regression results of equation (16). 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 8 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.

3.6 Two Alternative Explanations

Institutional investors entered crypto trading nearly en masse during the second half of 2020.[47] This could explain our results under two alternative explanations that we now explore.

[46] Unreported tests exploring change in order imbalance from t to t+1 confirm that during a coin's constrained window, when 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 ABVOL, in our main tests.

[47] Which makes a true DiD with counterfactuals untenable.

3.6.1 Is the Negative Abnormal Volume Return Relation Driven by News?

Kogan et al. (2023) show that retail crypto investors overreact, and it is well-known that institutional trading can mitigate behavioral bias in returns. Since institutions were largely absent from crypto before the second half of 2020, and most crypto news during their absence was positive, two things might have occurred. News about crypto could generate excess retail investor trading (overreaction), while returns would generally be positive contemporaneously with reversal after. This mimics the pattern observed in our data, pre-entry of institutional investors, but is not necessarily due to the arguments put forth by Miller (1977).

To knock down this alternative explanation for our observed results, we offer two lines of inquiry. The first one confronts the implication that news-generated abnormal volume is an overreaction that associates with ex-post returns. To do so, we perform a two-step decomposition of ABVOL's negative return predictive power.

We begin by collecting the public news events for the coins in our sample from Cryptorank, which contains coin news events from 31 major news sites.[48] We further 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 8,830 coin-day observations with at least one news event. The low news coverage is unsurprising as crypto news are concentrated in large coins. We then define the news count measure, $\text{NEWS}_{i,t}$, as the logarithm of one plus number of news events of coin i on day t.

In the first step, we run cross-sectional regressions of ABVOL on NEWS and lagged

[48]https://cryptorank.io/

control variables for each day t using the Fama and MacBeth (1973) methodology:

$$\text{ABVOL}_{i,t} = \gamma_{0,t} + \gamma_{1,t} \times \text{NEWS}_{i,t} + \gamma_{c,t-1} \times \text{Controls}_{i,t-1} + u_{i,t}. \tag{17}$$

Next, we compute the two components of $\text{ABVOL}_{i,t}$ as follows:

$$\widehat{\text{ABVOL}}_{i,t}^{news} = \widehat{\gamma_{1,t}} \times \text{NEWS}_{i,t}, \tag{18}$$

$$\widehat{\text{ABVOL}}_{i,t}^{other} = \text{ABVOL}_{i,t} - \widehat{\text{ABVOL}}_{i,t}^{news}, \tag{19}$$

where $\widehat{\text{ABVOL}}_{i,t}^{news}$ ($\widehat{\text{ABVOL}}_{i,t}^{other}$) represents the part of ABVOL associated (unassociated) with news arrival for coin i on day t. In the second stage, we replace $\text{ABVOL}_{i,t}$ with $\widehat{\text{ABVOL}}_{i,t}^{news}$ and $\widehat{\text{ABVOL}}_{i,t}^{other}$ and perform the following Fama and MacBeth (1973) regression:

$$\text{RET}_{i,t+1} = \delta_{0,t} + \delta_{1,t} \times \widehat{\text{ABVOL}}_{i,t}^{news} + \delta_{2,t} \times \widehat{\text{ABVOL}}_{i,t}^{other} + \delta_{c,t} \times \text{Controls}_{i,t} + \eta_{i,t+1}, \tag{20}$$

where the coefficients in equation (20) reveal the contribution of each component of ABVOL to future coin returns.

Table 9 reports the decomposition results. Panel A covers the full sample period, while panels B and C cover $2018Q3 - 2020Q2$ and $2020Q3 - 2021Q4$, respectively.[49] In Panel A's first stage regression, the coefficient on NEWS is positive and statistically significant, indicating that abnormal trading volume is higher when there are more public news events. Turning to the second stage of the decomposition, we see that the coefficient on ABVOL (news) is indistinguishable from zero, while the coefficient on ABVOL (other) is negative and

[49]We discuss the logic behind the sample period splitting, in 3.6.2.

statistically significant. The results indicate that news-related ABVOL does not contribute to the ex-post negative coin returns, hence rejecting the alternative explanation that retail investors' overreaction to news is driving the negative volume-return relation.

3.6.2 Time Variation in the ABVOL - Returns Relation

The spike entry of institutional owners into crypto trading also enables a bifurcated view of our ABVOL (and its components) - return relation. In Panels B and C of Table 9, we re-estimate the two-step analysis that was in Panel A, but for the time windows preceding and following mass entry of institutional traders in crypto. The pre-window is from the start of our sample through the second quarter of 2020, and post-window is from the third quarter of 2020 through the end of our sample (year-end 2021). Our full-sample results (from Panel A) appear driven by the pre-institutions-entry window. The coefficient on ABVOL (other) is negative and significant in the earlier window, but not the later one.

While this result suggests a time-trend complication to our story - i.e. that institutional entry associated with reduction of behavioral patterns in returns generally, and not necessarily due to Miller (1977) - we now offer two counter-arguments. First, the significance is on ABVOL (other), which is not the news-related volume, and this mitigates concern about overreaction to news driving our results. Second, this result is for the full sample and not just the short-constrained coins (which are integral to Miller (1977)'s story).

We therefore create a sub-sample of coins that *were already shortable before* the spike entry of institutions into crypto. Think of this as a sort of placebo group. We then explore the ABVOL - return relation for these shortable coins. If the alternative hypothesis - that there's something systematically different after institutions' entry into crypto trading, but that is unrelated to Miller (1977) and which drives our results - holds water, then *this sub-sample* should show a negative ABVOL - return relation before the spike entry and a diminution of the effect after 2020Q2. It does not. In fact, the relation before spike entry of institutions is insignificant and so is the relation after spike entry.[50]

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. In contrast, when frictions that prevent pessimists from selling short are relaxed, the underperformance of

[50]Results available from authors, upon reasonable request.

high disagreement assets should subside. Consistently, the negative abnormal volume return relation is concentrated in the coin observations whose margin trading is not allowed.

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. In addition, we utilize directional trades data to examine 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 as 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 (trading volume or number of trades) of coins decline following high ABVOL, with the decrease in former significantly exceeding 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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Appendix

We construct daily common risk factors in the cryptocurrency market following the approach of 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) 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, $\text{CMOM} = 1/2(\text{Small High} + \text{Big High}) - 1/2(\text{Small Low} + \text{Big Low})$.

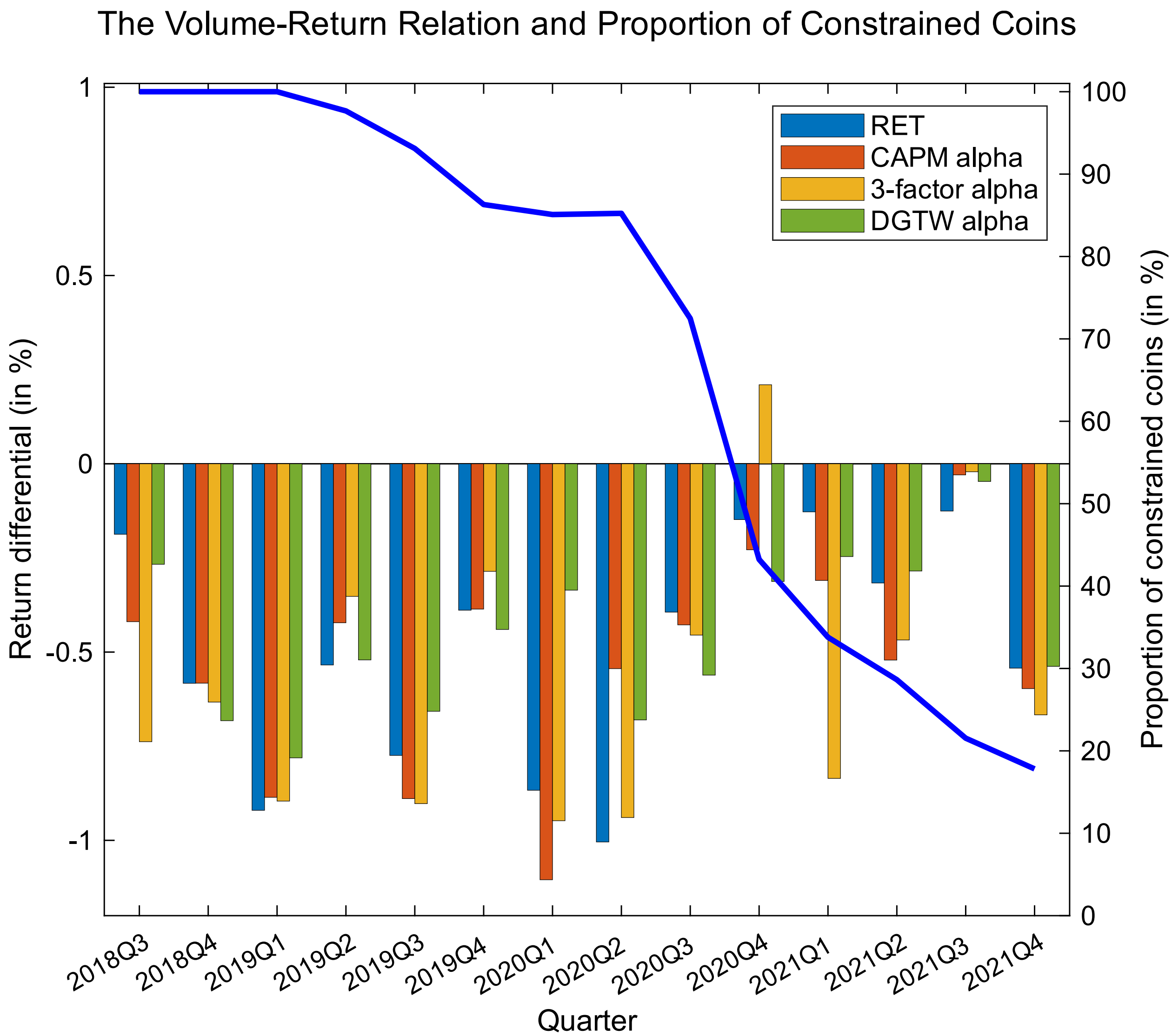

Figure 1. The Volume-Return Relation and Proportion of Constrained Coins. For each day, quintile portfolios are formed by sorting individual coins based on their abnormal trading volume (ABVOL) in the previous day. ABVOL is defined as the daily turnover ratio minus the average turnover ratio over the 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

		Sample		Coin market	
Year	Quarter	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 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 × 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 and 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**	0.158	-0.531***	0.257
	(2.10)	(0.68)	(-3.63)	(1.34)
Q2	0.518**	0.142	-0.565***	0.246
	(2.30)	(0.72)	(-4.37)	(1.32)
Q3	0.567**	0.186	-0.524***	0.275
	(2.48)	(0.95)	(-4.11)	(1.47)
Q4	0.485**	0.099	-0.605***	0.171
	(2.12)	(0.51)	(-4.84)	(0.92)
Q5 (High)	0.044	-0.333	-0.994***	-0.202
	(0.19)	(-1.63)	(-7.10)	(-1.05)
Q5–Q1	-0.498***	-0.491***	-0.464***	-0.459***
	(-7.20)	(-7.21)	(-7.00)	(-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 and 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***	-0.108***	-0.183***	-0.184***	-0.175***	-0.175***	-0.181***	-0.163***	-0.120***
	(-9.72)	(-5.44)	(-10.74)	(-10.44)	(-9.38)	(-9.42)	(-9.80)	(-6.69)	(-5.61)
REV		-0.057***							-0.054***
		(-8.39)							(-8.14)
MCAP			-0.025						-0.007
			(-1.36)						(-0.38)
MOM				0.002					-0.000
				(0.98)					(-0.07)
ILLIQ					0.030				0.081***
					(1.05)				(4.22)
IVOL						-0.007			-0.003
						(-0.17)			(-0.07)
ASVI							0.007**		0.007*
							(2.10)		(1.98)
MAX								-0.012	0.000
								(-0.83)	(0.03)
Intercept	0.439*	0.347	0.887*	0.354	0.395*	0.443**	0.431*	0.491**	0.333
	(1.88)	(1.37)	(1.89)	(1.52)	(1.80)	(2.06)	(1.83)	(2.36)	(0.79)
Observations	223,476	223,476	223,476	223,476	223,476	223,476	223,476	223,476	223,476
Adjusted R^2	0.020	0.049	0.038	0.045	0.026	0.048	0.023	0.044	0.120

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

Table 5. 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 and 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***	0.062***	0.055***	0.055***	0.047***	0.046***	0.054***	0.047***	0.056***	0.056***
	(2.85)	(3.20)	(2.86)	(2.80)	(3.41)	(3.74)	(2.79)	(3.70)	(2.90)	(4.79)
REV		-0.112***								-0.128***
		(-13.74)								(-16.38)
MCAP			-0.007							0.008
			(-0.69)							(0.57)
MOM				-0.005**						-0.010***
				(-2.19)						(-3.53)
ILLIQ					0.000					-0.000
					(0.37)					(-1.07)
IVOL						-0.003				-0.002
						(-1.42)				(-0.18)
ASVI							-0.001			-0.000
							(-0.29)			(-0.11)
MAX								-0.001**		-0.000
								(-2.23)		(-0.02)
BM									0.062**	0.066***
									(2.56)	(2.61)
Intercept	0.031	0.014	0.068	0.543**	0.030	0.036	0.031	0.036	0.068*	0.946***
	(0.76)	(0.28)	(1.06)	(2.20)	(0.71)	(0.86)	(0.76)	(0.87)	(1.71)	(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 6. 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_{t+1}	CAPM α_{t+1}	3-factor α_{t+1}	DGTW α_{t+1}	RET_{t+1}	CAPM α_{t+1}	3-factor α_{t+1}	DGTW α_{t+1}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ABVOL_t	-0.079***	-0.065**	-0.097**	-0.049**	0.004	0.004	0.006	-0.001
	(-2.97)	(-2.61)	(-2.24)	(-2.39)	(0.78)	(0.72)	(1.06)	(-0.15)
MCAP_t	-0.566***	-0.554***	-0.268	-0.352***	-0.584***	-0.601***	-0.448***	-0.500***
	(-3.66)	(-4.00)	(-1.41)	(-2.74)	(-5.63)	(-5.10)	(-3.06)	(-5.43)
REV_t	-0.009	-0.015	-0.023	-0.022	-0.020	-0.021	-0.016	-0.023
	(-1.17)	(-0.95)	(-1.23)	(-1.40)	(-1.32)	(-1.50)	(-1.06)	(-1.59)
MOM_t	-0.004*	-0.003	-0.005	-0.006**	-0.002	-0.003	-0.002	-0.007***
	(-1.80)	(-1.27)	(-1.24)	(-2.18)	(-0.76)	(-1.14)	(-0.70)	(-2.83)
ILLIQ_t	0.001	-0.000	0.000	0.000	0.001	0.001	0.001	-0.001
	(0.94)	(-0.37)	(0.33)	(0.45)	(0.96)	(0.71)	(0.80)	(-0.56)
IVOL_t	0.296*	0.125	0.379	0.149	0.054	0.041	0.068	0.035
	(1.67)	(1.10)	(1.54)	(1.19)	(0.45)	(0.34)	(0.48)	(0.31)
ASVI_t	-0.000	0.006	-0.004	0.001	0.016***	0.017***	0.017***	0.016***
	(-0.06)	(0.81)	(-0.36)	(0.10)	(3.71)	(3.68)	(3.59)	(3.84)
MAX_t	-0.085**	-0.050*	-0.081**	-0.063**	-0.068**	-0.072**	-0.095***	-0.049*
	(-2.53)	(-1.77)	(-2.11)	(-2.24)	(-2.24)	(-2.37)	(-3.01)	(-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^2	0.696	0.783	0.769	0.585	0.586	0.476	0.466	0.371

Table 6. The Volume-Return Relation: Movers. (continued)

Panel B: A single setting with dummies and interactive	RET_{t+1}		CAPM α_{t+1}		3-factor α_{t+1}		DGTW α_{t+1}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ABVOL_t$	-0.005	-0.000	-0.007	0.000	-0.007	0.002	-0.010	-0.003
	(-0.44)	(-0.02)	(-0.55)	(0.04)	(-0.48)	(0.19)	(-0.84)	(-0.37)
$CONSTRAINT_t$	0.227***	0.100	0.262***	0.144	0.278**	0.204	0.142	0.055
	(2.75)	(1.15)	(2.74)	(1.44)	(2.15)	(1.57)	(1.35)	(0.52)
$ABVOL_t \times CONSTRAINT_t$	-0.080***	-0.056**	-0.073***	-0.042**	-0.095***	-0.062**	-0.071***	-0.040**
	(-3.27)	(-2.59)	(-2.96)	(-2.23)	(-2.72)	(-2.07)	(-2.93)	(-2.18)
$MCAP_t$		-0.323***		-0.373***		-0.226***		-0.253***
		(-6.21)		(-6.08)		(-3.14)		(-5.17)
REV_t		-0.010		-0.017		-0.017		-0.021*
		(-1.18)		(-1.45)		(-1.30)		(-1.81)
MOM_t		-0.001		-0.001		-0.001		-0.006***
		(-0.70)		(-0.85)		(-0.60)		(-2.98)
$ILLIQ_t$		0.001		-0.000		0.000		0.000
		(0.90)		(-0.73)		(0.22)		(0.17)
$IVOL_t$		0.191		0.084		0.128		0.105
		(1.44)		(0.98)		(1.18)		(1.32)
$ASVI_t$		0.011***		0.014***		0.011**		0.011***
		(3.39)		(3.81)		(2.53)		(3.38)
MAX_t		-0.084***		-0.064***		-0.078***		-0.058***
		(-2.87)		(-3.04)		(-3.39)		(-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^2	0.657	0.657	0.660	0.661	0.650	0.651	0.511	0.511

Table 7. 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:

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

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_t		OIBTRD_t	
	(1)	(2)	(3)	(4)
ABVOL_t	0.087	0.094	0.071	0.077
	(1.07)	(1.08)	(1.03)	(1.04)
$\mathrm{CONSTRAINT}_t$	0.103	0.449	0.596*	0.530
	(0.32)	(1.31)	(1.72)	(1.53)
$\mathrm{ABVOL}_t \times \mathrm{CONSTRAINT}_t$	0.436***	0.448***	0.307***	0.313***
	(3.18)	(3.11)	(2.97)	(2.90)
OIBVOL_{t-1}	0.159***	0.162***		
	(10.90)	(11.03)		
OIBTRD_{t-1}			0.351***	0.356***
			(19.25)	(18.92)
MCAP_{t-1}		1.081***		-0.021
		(3.92)		(-0.10)
REV_{t-1}		-0.078***		-0.098***
		(-2.83)		(-3.50)
MOM_{t-1}		0.004		-0.000
		(1.35)		(-0.19)
ILLIQ_{t-1}		-0.001		-0.001
		(-1.36)		(-1.41)
IVOL_{t-1}		0.687***		0.874***
		(4.08)		(4.93)
ASVI_{t-1}		0.007		-0.000
		(1.59)		(-0.08)
MAX_{t-1}		-0.142***		-0.131***
		(-3.75)		(-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^2	0.124	0.127	0.229	0.231

Table 8. 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 (ΔVOL_{t+1}) measures: ΔBVOL_{t+1} (percentage change in buyer-initiated volume from t to $t+1$), ΔSVOL_{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 (ΔTRD_{t+1}) measures: ΔBTRD_{t+1} (percentage change in number of buyer-initiated trades from t to $t+1$), ΔSTRD_{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

	ΔBVOL_{t+1}		ΔSVOL_{t+1}		$\Delta\text{BVOL}_{t+1} - \Delta\text{SVOL}_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
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)
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)
ΔBVOL_t	0.000** (2.00)	0.000** (2.57)				
ΔSVOL_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)
MCAP_t		-10.016*** (-3.48)		-11.561*** (-6.46)		-2.075 (-1.20)
REV_t		1.532*** (3.13)		1.602*** (5.59)		-0.845*** (-2.93)
MOM_t		-0.232*** (-3.18)		-0.126*** (-3.00)		-0.121*** (-2.85)
ILLIQ_t		0.217*** (3.55)		0.078*** (6.05)		0.144** (2.54)
IVOL_t		-3.110 (-0.32)		-12.852** (-2.05)		9.345* (1.82)
ASVI_t		0.088 (0.85)		0.008 (0.18)		0.080 (0.88)
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^2	0.022	0.030	0.042	0.048	0.007	0.013

Table 8. Trading Activities (Volume and Number of Trades) following Abnormal Trading Volume. (continued)

Panel B: Number of trades following abnormal trading volume

	ΔBTRD$_{t+1}$		ΔSTRD$_{t+1}$		ΔBTRD$_{t+1} - \Delta$STRD$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
ABVOL$_t$	-0.974	-0.645	-0.795	-0.540	-0.189	-0.110
	(-1.07)	(-0.97)	(-1.11)	(-1.04)	(-0.90)	(-0.65)
CONSTRAINT$_t$	12.002***	8.962**	6.724***	4.839**	5.244***	4.101**
	(3.77)	(2.57)	(3.32)	(2.12)	(2.96)	(2.33)
ABVOL$_t$ $\times$ CONSTRAINT$_t$	-4.211***	-2.652**	-3.325***	-2.008**	-0.933***	-0.670**
	(-3.06)	(-2.42)	(-3.09)	(-2.28)	(-2.78)	(-2.08)
ΔBTRD$_t$	-0.001	-0.001				
	(-1.00)	(-1.00)				
ΔSTRD$_t$			-0.000	-0.000		
			(-1.14)	(-1.01)		
ΔBTRD$_t - \Delta$STRD$_t$					-0.000	-0.000
					(-1.17)	(-1.42)
MCAP$_t$		-11.129***		-8.911***		-2.213*
		(-5.31)		(-6.94)		(-1.90)
REV$_t$		1.171***		1.645***		-0.480***
		(3.73)		(6.22)		(-2.79)
MOM$_t$		-0.118***		-0.061***		-0.057***
		(-3.66)		(-2.97)		(-3.22)
ILLIQ$_t$		0.053***		0.045***		0.008
		(6.31)		(8.07)		(0.92)
IVOL$_t$		-12.790***		-16.106***		3.313
		(-3.38)		(-5.53)		(1.49)
ASVI$_t$		0.061		0.048		0.014
		(0.98)		(1.05)		(0.40)
MAX$_t$		-1.523**		-0.889		-0.651*
		(-2.55)		(-1.63)		(-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 9: Is the Volume-Return Relation Driven by Public News? This table reports estimation results on a decomposition of the predictive power of ABVOL for the cross-section of future coin returns. We estimate two-stage Fama and MacBeth (1973) regressions as described in equations (17) to (20). The variable ABVOL(news) is estimated in the first stage using NEWS = log (1+ number of news releases), which proxies for ABVOL that predicts returns associated with contemporaneous news arrival. The residual part of the previous-day ABVOL from first-stage estimation is denoted as "other," which proxies for ABVOL that predicts returns but is not associated with contemporaneous news arrival. We report the results for the full sample period (2018Q3-2021Q4), 2018Q3-2020Q2, and 2020Q3-2021Q4 in panels A, B, and C, respectively. Newey and 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: Full sample period				Panel B: 2018Q3 - 2020Q2				Panel C: 2020Q3 - 2021Q4			
First Stage: Projecting ABVOL on Public News		Second Stage: Decomposing ABVOL's Return Predicting Power		First Stage: Projecting ABVOL on Public News		Second Stage: Decomposing ABVOL's Return Predicting Power		First Stage: Projecting ABVOL on Public News		Second Stage: Decomposing ABVOL's Return Predicting Power	
	$ABVOL_t$		RET_{t+1}		$ABVOL_t$		RET_{t+1}		$ABVOL_t$		RET_{t+1}
$NEWS_t$	0.187***	$ABVOL_t$	-0.322	$NEWS_t$	0.158***	$ABVOL_t$	0.238	$NEWS_t$	0.223***	$ABVOL_t$	-1.040
	(8.44)	(news)	(-0.17)		(5.66)	(news)	(0.21)		(6.36)	(news)	(-0.26)
		$ABVOL_t$	-0.109***			$ABVOL_t$	-0.156***			$ABVOL_t$	-0.049
		(other)	(-4.11)			(other)	(-5.69)			(other)	(-1.02)
REV_{t-1}	0.060***	REV_t	-0.060***	REV_{t-1}	0.068***	REV_t	-0.073***	REV_{t-1}	0.050***	REV_t	-0.043**
	(22.42)		(-5.90)		(16.46)		(-8.51)		(20.02)		(-2.14)
$MCAP_{t-1}$	-0.037***	$MCAP_t$	-0.055**	$MCAP_{t-1}$	-0.029	$MCAP_t$	-0.034	$MCAP_{t-1}$	-0.047***	$MCAP_t$	-0.082**
	(-2.97)		(-2.16)		(-1.45)		(-1.08)		(-3.90)		(-1.99)
MOM_{t-1}	0.002***	MOM_t	-0.000	MOM_{t-1}	0.003**	MOM_t	0.001	MOM_{t-1}	0.001**	MOM_t	-0.002
	(3.24)		(-0.16)		(2.57)		(0.37)		(2.53)		(-0.73)
$ILLIQ_{t-1}$	0.032*	$ILLIQ_t$	0.079***	$ILLIQ_{t-1}$	0.057*	$ILLIQ_t$	0.074***	$ILLIQ_{t-1}$	-0.000	$ILLIQ_t$	0.087**
	(1.70)		(3.68)		(1.80)		(3.58)		(-0.03)		(2.08)
$IVOL_{t-1}$	0.022	$IVOL_t$	-0.043	$IVOL_{t-1}$	0.003	$IVOL_t$	-0.064	$IVOL_{t-1}$	0.047*	$IVOL_t$	-0.016
	(0.98)		(-0.70)		(0.10)		(-1.13)		(1.75)		(-0.013)
$ASVI_{t-1}$	0.002	$ASVI_t$	0.023	$ASVI_{t-1}$	0.001	$ASVI_t$	0.004	$ASVI_{t-1}$	0.003***	$ASVI_t$	0.047
	(0.98)		(1.29)		(0.49)		(0.78)		(2.67)		(1.18)
MAX_{t-1}	0.025***	MAX_t	0.015	MAX_{t-1}	0.036***	MAX_t	0.029	MAX_{t-1}	0.010	MAX_t	-0.003
	(3.45)		(0.65)		(3.42)		(1.61)		(1.12)		(-0.06)
Intercept	0.713***	Intercept	1.207**	Intercept	0.582	Intercept	0.769	Intercept	0.884***	Intercept	1.778**
	(3.18)		(2.30)		(1.63)		(1.22)		(3.83)		(2.03)
Observations	223,476	Observations	223,476	Observations	100,112	Observations	100,112	Observations	123,364	Observations	123,364
Adjusted R^2	0.098	Adjusted R^2	0.123	Adjusted R^2	0.098	Adjusted R^2	0.136	Adjusted R^2	0.097	Adjusted R^2	0.105

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 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 10×10 coin size/momentum portfolio following the approach of Daniel et al. (1997). Newey and 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 α	t-value	3-factor α	t-value	DGTW α	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)