Disagreement and Returns: The Case of Cryptocurrencies

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Abstract

We present the first evidence of investor-trading-based disagreement's influence on cross-sectional cryptocurrency daily returns. 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. We conclude that price optimism models explain the disagreement-returns relationship when opinion divergence is likely the dominant determinant of returns.

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1 Introduction

The relationship between investor disagreement and returns is well-debated and without consensus. Theoretical work offers two broadly opposing views. Miller (1977) along with other price-optimism models[1] posit 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, resulting in lower future returns. On the other hand, Varian (1985), Merton (1987) and others[2] all consider disagreement as a source of risk and predict a positive relation between disagreement and expected asset returns.

Empirical work is equally divided. A negative relationship between disagreement and returns is found in Chen et al. (2002), Diether et al. (2002), Anderson et al. (2005), Ang et al. (2006), Berkman et al. (2009), Yu (2011), Hong et al. (2017), Ma et al. (2022), and Hameed & Jeon (2024). On the other hand, Garfinkel & Sokobin (2006), Boehme et al. (2009), Carlin et al. (2014), Ehling et al. (2018), and Cookson et al. (2022) all document positive relationships between heterogeneous investor opinions and ex-post returns. One potential explanation for the disparity in conclusions is that empirical study is compromised by difficulty isolating the role of investor opinion divergence, from among the many other factors known to influence asset prices. In particular, cash flows and (expert) expectations of their future amounts would seem equally important to asset values, as opinion divergence. But controls for these factors are also likely to overlap with opinion divergence.

We offer a work-around by studying cryptocurrencies. Even though cryptocurrency

[1] See Mayshar (1983), Harrison & Kreps (1978), Morris (1996), Chen et al. (2002), Scheinkman & Xiong (2003), and Hong et al. (2006).

[2] See Johnson (2004), David (2008), Banerjee (2011), and Gao et al. (2019).

valuation is known to be difficult (X. Jiang et al., 2023), it is precisely because of the lack of two characteristics common to other asset categories: cash flows and information about their future expected amounts. Most cryptocurrencies do not offer rights on dividends, provide no earnings to project, and receive few professional forecasts from analysts on a regular basis (Cong et al., 2021). Combined, this absence of relatively hard information is simultaneously likely to increase both investors' disagreement about a crypto asset's value and the relative importance of disagreement for said value.[3]

We rely on this to explore the influence of investor opinion divergence on ex-post returns, in a setting where disagreement likely plays a uniquely pronounced role. Our analysis centers on a cryptocurrency's abnormal trading volume as *primarily* reflecting differences of opinion on its value.[4] Trading volume is one of the most widely used market-based measures for differences of opinion in the prior accounting literature (e.g., Beaver, 1968; L. S. Bamber, 1987; L. Bamber et al., 2011).[5] 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.[6] Cookson & Niessner (2020) and Cookson et al. (2021) provide more targeted finance evidence:

[3]Recent work by Biais et al. (2023) highlights this. They construct a model in which a crypto'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.

[4]We actually use abnormal turnover to control for float variation, consistent with the literature linking trading volume with returns. But we defer to the literature's norm of labeling it "abnormal volume". See discussion in Section 2.2.

[5]See also Ajinkya et al. (1991), L. S. Bamber et al. (1997), and Garfinkel & Sokobin (2006) in accounting. Finance work in this line includes Karpoff (1987), Harris & Raviv (1993), Kandel & Pearson (1995), Bessembinder et al. (1996), Garfinkel (2009), and Berkman et al. (2009)

[6]He also shows it dominates other disagreement measures including return variation, bid-ask spread, and analyst forecast dispersion. In particular, stock return volatility and analyst forecast dispersion are negatively related to his direct disagreement measure.

a direct measure of disagreement constructed from StockTwits is an important determinant of abnormal trading volume. Importantly, none of these papers study disagreement's influence on cryptocurrency returns.

Using Binance data[7] we document a *negative* relation between abnormal trading volume and expected cryptocurrency returns in the cross section, supporting the price-optimism models represented by Miller (1977). In particular, when we form daily quintile portfolios of crypto assets on the basis of abnormal volume, the difference between the highest and lowest quintile portfolios' next-day returns is always negative and significant. In excess returns it is -0.498%; when risk-adjusted, the CAPM alpha is -0.491%, the three-factor alpha is -0.464%, and the DGTW alpha is -0.459%.[8] This negative high-volume return relation persists after controlling via Fama & MacBeth (1973) regressions for liquidity, investor attention, trading activity variation (Babiak & Erdis, 2022), and other individual crypto characteristics.[9]

However, Miller (1977) is predicated on the existence of short sale constraints to generate the negative disagreement-returns relationship. Without short sale constraints, both optimists' and pessimists' beliefs will be incorporated into stock prices, and thus no overpricing (with subsequent negative returns) of assets will occur. Hence, when frictions that prevent the reflection of negative opinions are removed, the negative relation between expected returns and disagreement should become less pronounced. We explore this dichotomy by relying on Binance's mechanism for allowing short selling. Specifically, shorting a cryptocurrency on

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

[8]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).

[9]In addition, our results using portfolio sorts and cross-sectional regressions are robust to subsample analysis.

the platform is not feasible until Binance publicly announces the activation of the currency's margin trading services.[10]

We continue to find support for Miller (1977). When a cryptocurrency is short-constrained (i.e. margin trading is not allowed on it), we observe the negative relation between abnormal volume and ex-post returns. By contrast, when Binance has allowed margin trading services on a cryptocurrency, the relationship between abnormal volume and ex-post returns is zero.

The above results are largely cross-sectional in nature. We also conduct event-study (time-series diff) tests, focusing on cryptocurrencies that transition from "not shortable" to "shortable" in our sample period. This subsample allows us to focus on crypto assets with a natural counterpart (itself), with the only difference being whether it is constrained from being sold short or not.[11] Given the necessity of the Binance exchange's decision, we simply construct a dummy variable for short-ability of the crypto (prior to margin trading activation versus after margin trading activation of the crypto). We expect the negative relation between high disagreement and expected crypto returns to present only when the cryptocurrency is subject to short sale constraints, and to disappear once a crypto 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 crypto

[10]Binance does not mention their criteria for initiating a crypto asset'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 crypto asset's margin interest rates are typically fixed except for few occasional adjustments after the crypto becomes shortable on Binance. It is possible that shorting interest rates are more endogenous recently, since Binance announced a dynamic margin interest rate system "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..." However, recent changes at Binance removed researchers' ability to identify the date upon which margin trading became allowed (unless it was upon listing). This discourages extension of our sample. We discuss further in section 2.

[11]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 later.

characteristics. By contrast, when a crypto asset's margin trading is available, high abnormal trading volume does not result in lower future returns.

We provide two other perspectives to support Miller (1977).[12] 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 crypto. We find this too. Before the release of short selling constraints, cryptocurrencies 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 crypto 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 crypto returns: the lower expected return following high disagreement is achieved via resolution of disagreement. When high disagreement subsides, the proportion of investors with extreme valuations of the asset decreases, reducing both buying and selling activities. However, we should see a smaller decrease in selling activities since pessimists with the lowest valuations of the asset were previously restrained from selling (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]

[12]These tests utilize the sample of crypto assets that migrate from short-constrained to shortable. We do so for the tighter comparison benefits noted above.

[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 (Gervais et al., 2001) in stock

On the other hand, when margin trading is activated, we do not observe diminutions of buying and selling activities following high disagreement.

We conduct several robustness checks on the disagreement-return relation. First, our results are robust to different-length windows (7, 15, 30, and 45 days) for the calculation of the first and second moments of cryptocurrency turnover. Second, they are also robust to using unscaled volume - instead of turnover - to construct disagreement. Third, the lower subsequent returns following high abnormal trading volume persist in longer windows, mitigating the concern that our results are caused by a statistical fluke or bid-ask bounce. Fourth, the negative disagreement-return relation remains during both periods of high and (separately) low Bitcoin trading volume, suggesting that the significant cross-asset effects of Bitcoin (e.g. Yarovaya & Zięba, 2022) do not drive our results. Lastly, whether the crypto (or the protocol behind it) enables creating decentralized applications (dApps) or smart contracts, whether the crypto operates on its own blockchain, and whether the crypto is primarily designed as a transaction-focused crypto, does not affect the negative disagreement-return relation.[14]

Our paper makes several contributions. Most broadly, we add to the literature on investor disagreement and testing of disagreement models (Chang et al., 2022), by providing unique supporting evidence for Miller (1977). We emphasize the equally important roles of high disagreement and the presence of short sale constraints to produce overpricing, and provide layers of evidence on contemporaneous order imbalance and subsequent trading activities consistent with his implications, using directional trade information. Testing

markets that unusually high volume increases visibility and investor base.

[14]In untabulated tests, we also classify crypto assets according to the blockchain layer they reside in. Based on our findings, we are reticent to conclude that there is a clear difference between some crypto assets and others, in terms of the disagreement-return relation. See Section 4.4 for more details.

these implications, which is often ignored, helps pin down the underlying mechanism of a disagreement model. For example, if a disagreement measure is negatively related to future returns, one may conjecture Miller (1977)'s hypothesis to be valid, whereas the negative relation may stem from other channels. The speculative nature of cryptocurrencies, the gradual relaxation of margin trading service on Binance, and the availability of directional trade information allow us to fully test Miller (1977)'s hypothesis. Overall, our paper complements the disagreement studies that support Miller (1977) in other asset classes[15], while casting some doubts on opposite conclusions (Garfinkel & Sokobin, 2006; Boehme et al., 2009; Carlin et al., 2014; Ehling et al., 2018; Cookson et al., 2022) represented by Varian (1985).

Second, we contribute to the burgeoning literature studying cross-sectional returns of cryptocurrencies. For example, Liu & Tsyvinski (2021) and Liu et al. (2022) study size and momentum factors' influences, while Babiak & Erdis (2022) explore the role of costly arbitrage. Following Baker & Wurgler (2006), sentiment proxies such as direct Bitcoin sentiment (from Sentix) or even general (Twitter) happiness, have also been linked to cryptocurrency returns (Naeem et al., 2021; Anamika et al., 2023). But while prior 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. To the best of our knowledge, we are the first to investigate the role of investor disagreement in the cross-sectional pricing of crypto assets where investor opinion divergence is likely to carry

[15]For example, Chen et al. (2002), Diether et al. (2002), Anderson et al. (2005), Ang et al. (2006), and Berkman et al. (2009), among others, document a negative relation between disagreement and stock returns in the cross section. Yu (2011) documents that greater stock portfolio disagreement from the bottom-up is associated with lower subsequent stock portfolio return. Hong et al. (2017) find that disagreement on future inflation lowers expected excess bond returns in the presence of short-sale constraints in the U.S. Treasury bond market.

outsize importance.

Lastly, we contribute to the literature studying the volume-return relation. In contrast to the high-volume return premium (Gervais et al., 2001; G. Jiang et al., 2005; Garfinkel & Sokobin, 2006; Schneider, 2009; Banerjee & Kremer, 2010; Lerman et al., 2010; Kaniel et al., 2012; Wang, 2021; Israeli et al., 2022) in stocks[16], we instead document a negative relation between high-volume and return in the cross section of cryptocurrencies. While Liu et al. (2022) document that high *dollar trading volume* crypto assets earn lower returns compared to low dollar trading volume crypto assets, 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. We find that the negative relation persists after controlling for Liu et al. (2022)'s three-factor model, as well as crypto characteristics that are known to predict returns.

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 crypto volatility, liquidity, and demand for lottery-like

[16] On the other hand, Han et al. (2022) document that among overpriced (underpriced) stocks, the volume-return relation is negative (positive). They interpret trading volume as investor disagreement and argue that the findings are consistent with an implication of Atmaz & Basak (2018): investor disagreement has an amplification effect on the average expectation bias.

crypto assets (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.[17] We also note here the benefit of Binance's (previously provided) precise dating of margin-trading allowance, and its provision of directional trade data.

We admit potential limitations related to our data. One is that we sample from Binance.[18] The recent SEC suit against the Binance.US platform expresses concern with "wash trading". And while our sample comes from the Binance.com[19] platform (Binance, hereafter), any lingering concern that Binance.com is susceptible to wash trading is addressed by our findings in Section 3.6.1. There we provide evidence that the volume-return relation is unlikely to be explained by the wash-trade effect.

Another potential concern is the phenomenon of pump and dump in cryptocurrencies. As Li et al. (2023) show, these schemes associate with volume spikes, potentially influencing our measure of disagreement. However, the returns associated with pump and dump are especially short-lived, usually dissipating within an hour. Our main test links disagreement (abnormal volume) with *next-day* returns, likely avoiding concern about alternative interpretation of our results.

[17]Easley et al. (2024) also obtain data from Binance for similar reasons. 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.

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

[19]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.

The sample period is from July 1, 2018 through December 31, 2021.[20] Each cryptocurrency trading pair (X/Y) consists of a base asset (X) and a quote asset (Y). The trading volume and price of the pair are measured in X and denominated in Y, respectively. For a given base asset, there can be more than one quote asset. For example, "ETH/BTC" and "ETH/USDT" are both active trading pairs on Binance.

Since trading pairs with the same base asset have almost perfect return comovement due to market efficiency, we treat such cryptocurrencies as the same. We thus only focus on trading pairs with BTC as the quote asset. The main advantage of this approach is that the number of trading pairs quoted in BTC is the largest on Binance. This allows us to maximize the number of base assets in the cross section that we examine. For simplicity, we refer to base assets as crypto assets throughout the paper. Since crypto 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 crypto assets also comes from CoinAPI.io. The advantage of our collected trade data is that volume and the direction of each trade (buyer-initiated or seller-initiated) are recorded. This enables us to examine trading activity in greater depth with more clarity than usual. In particular, we do not have to rely on an algorithm to classify trades, such as the commonly used one by Lee & Ready (1991).

We require that crypto assets 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

[20] Extending the sample is compromised in two ways. First, Binance no longer indicates the precise date of margin-trading allowance, unless a crypto asset has allowed margin trading at first listing. Second, over 90% of crypto assets listed from January 2022 through October 2024 have margin trading allowed at first listing. This implies little-to-no cross-sectional variation in the short constraint indicator for this time period, limiting our ability to test Miller (1977).

December 31st, 2021. We further exclude leverage crypto assets, and also crypto assets with missing price or volume data.[21] Market capitalization information and circulating supply data comes from CoinMarketCap. To ensure our results are not driven by small crypto we eliminate those with market capitalization less than \$1 million at the end of the previous months following Liu & Tsyvinski (2021) and Liu et al. (2022). Our final sample consists of 356 crypto assets.[22]

To construct common risk factors for the whole crypto 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). Details are provided in the Appendix.

2.2 Disagreement Measure: Abnormal Trading Volume

In this section, we construct our measure of market-based investor disagreement, abnormal trading volume. First, we note that our calculations use turnover instead of raw volume to account for cross-sectional variation in crypto trading. Second, we subtract from our daily turnover, the same crypto asset's turnover measured over a reference period ($[t-30, t-1]$), to remove likely liquidity-oriented turnover.[23] The specific calculation of a crypto's daily abnormal turnover is:

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

[21] Our empirical results are robust to the exclusion of stablecoins.

[22] We have provided the list at https://sites.google.com/view/lawrencehsiao/research.

[23] Raw trading activity may largely capture liquidity trading needs, as discussed in Benston & Hagerman (1974), Branch & Freed (1977), and Petersen & Fialkowski (1994).

where i refers to the crypto and t refers to the day. Change in turnover is thus a crypto asset's daily turnover minus the prior 30-day average turnover (as proxy for liquidity). This netting approach recognizes that crypto assets with high trading volume are reasonably more liquid[24] and that some research ties liquidity fluctuations to asset returns.[25] 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 crypto trading volatility.[26] Hence, abnormal trading volume (DISAGREE) for crypto i on day t is defined as follows:

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

2.2.1 Alternative Interpretation of Abnormal Trading Activity

Prior literature using data on StockTwits, as well as the literature using proprietary investors' orders, provide ample support for interpreting abnormal trading volume as a proxy for disagreement. However, Han et al. (2022) provides an alternative interpretation that treats abnormal volume as a proxy for attention. This difference in our interpretation vs. theirs is due to differences in construction.

The construction of Han et al. (2022)'s measure of abnormal volume follows Gervais et al. (2001); it is cross-sectional in nature. Specifically, they categorize abnormal volume as high or "other" based on whether the volume is in the top 10 percent of volume *from the cross-section* using 50-day averages. In other words, it measures whether the asset is traded

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

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

[26] Our results are robust to different-length windows (7 days, 15 days, 45 days) for the calculation of the first and second moments of crypto turnover, or using volume instead of turnover to define DISAGREE. See Section 4.1 for more details.

a lot relative to different assets. Such an approach is less likely to pick up day-specific trading activity spikes that are uniquely measured against the focal asset (not peers). Our measure of DISAGREE is a time-series measure of trading activity spikes in an asset relative to its own recent trading activity; i.e. it's focal-asset oriented.

Put differently, the Han et al. (2022) (Gervais et al., 2001) abnormal volume measures carry a wholly different meaning – much closer to their intended attention proxy – than our abnormal trading focal-firm-specific measures do. That is the reason why we construct and interpret our abnormal trading volume as measure of DISAGREE, different from their construct aiming to capture attention. Nonetheless, to further differentiate our explanation from the attention explanation, we retain a couple of measures of retail investor attention (ASVI and |REV|) as controls in our main tests, and our results are robust.

2.3 Defining Crypto Characteristics

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

Following Babiak & Erdis (2022), we construct coefficient of variation of turnover (CV), a measure of trading activity variation. It is defined as the ratio of the standard deviation to the mean of turnover over the past 30 days.[27] Following Jegadeesh (1990), short-term reversal (REV) is defined as the crypto return in the previous day - i.e. the day prior to the portfolio formation day. We also define the absolute short-term reversal (|REV|) as the

[27]Our empirical results are robust to controlling for their alternative measure of trading activity variation, coefficient of variation of *dollar* trading volume. Using different-length window (7 days, 15 days, 45 days) for the calculation of CV also leads to qualitatively similar results.

absolute crypto return in the previous day, to proxy for retail investor attention. Following Jegadeesh & Titman (1993), momentum (MOM) is the cumulative return of a crypto over a period of 11 days ending one day prior to the portfolio formation day. MCAP is a crypto asset's market capitalization at the end of the 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 crypto asset 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 crypto asset 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 crypto i and the crypto 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 crypto asset, we specifically compute daily abnormal Google search volume index (ASVI) as the Google search volume index on that day minus its median search volume index during the prior week.[28] We set ASVI for a crypto to zero if its is missing.

[28]We use the crypto symbol found on Binance as the Google search term. The results are robust to using

Finally, we follow Bali et al. (2011) to measure demand for lottery-like crypto assets using MAX, calculated as a crypto asset'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 crypto characteristics. Notably, DISAGREE has a time-series mean of 0.168 and median of −0.279, clearly indicating right-skewed distribution of DISAGREE.[29] Panel B shows the quarterly time series of the count of crypto assets we study, their average and median market caps, as well as similar information at the crypto market level.

Panel B shows our growing cross-section of crypto assets throughout the sample period. We start with 138 crypto assets in the third quarter of 2018 and end with 301 crypto assets in the fourth quarter of 2021. The number of crypto assets and mean/median market capitalization of the crypto market, are generally within norms from other studies (e.g., Liu & Tsyvinski, 2021; Liu et al., 2022). While our sample on average captures about 14% of the crypto assets in the market, the mean/median market capitalization of our sample crypto assets is relatively larger than that of the overall market's. This is due to the listing requirements on Binance[30], which essentially rule out crypto assets with smaller size and lower user adoption. Overall, the total market capitalization in our sample on average accounts for about 34% of the total market capitalization of the crypto market.

the crypto symbol along with BTC (the quote asset) as the search term.

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

[30] "...We want good crypto assets listed on Binance, such as crypto assets with a proven team, a useful product, and a large user base..." See the "How to Get Your crypto Listed on Binance.com" section in https://www.binance.com/en/support/faq/ for more details.

3 Empirical Results

3.1 Portfolio Analysis: Univariate Sort

First, we examine the predictive power of abnormal trading volume (DISAGREE) over future excess crypto returns using portfolio sorts. For each day, we form quintile portfolios by sorting individual crypto assets based on their abnormal trading volume (DISAGREE) in the previous day. Quintile 1 contains crypto assets with the lowest 20% of DISAGREE and quintile 5 contains crypto assets with the highest 20% of DISAGREE. Then, we examine the average portfolio returns within each DISAGREE quintile.[31]

Panel A of Table 2 reports the results, and Newey & West (1987) t-statistics with eight lags are reported in parentheses.[32] The first column shows that moving from the lowest to the highest DISAGREE quintile, decreases the average excess return significantly. crypto assets in the lowest DISAGREE quintile generate an average excess return of 0.542% per day, whereas crypto assets in the highest DISAGREE quintile generate an average excess return of 0.044% per day. The average return difference between the highest and the lowest DISAGREE quintile is −0.498% per day with a t-statistic of −7.20.

In addition to excess returns, we compute three types of risk-adjusted returns. CAPM alpha is the intercept from the regression of excess portfolio returns on a constant and the cryptocurrency excess market return (CMKT). Three-factor alpha is the intercept from the regression of excess portfolio returns on a constant, the cryptocurrency excess market

[31]The effect of delisting is minor, since Binance publicly announces a crypto asset'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.

[32]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.

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 DISAGREE portfolio. In particular, each day we sort crypto assets in the crypto market into $10 \times 10 = 100$ portfolios based on their crypto size and momentum measured at the end of previous day.[33] Each crypto is assigned to a benchmark portfolio according to its crypto size and momentum rank. We compute the DGTW alpha for a crypto 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 crypto assets 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 all show significantly lower returns in the highest vs. lowest DISAGREE quintile.[34] Specifically, the average daily return differential between the two DISAGREE quintiles is -0.491% (t-statistic = -7.21), -0.464% (t-statistic = -7.00), and -0.459% (t-statistic = -7.29), respectively. Overall, these results support the negative disagreement-return relation and are not driven by common risk factors in the cryptocurrency market.

[33] Here we follow Daniel et al. (1997) and use sequential sorts (first crypto size, then momentum). Using an independent sort does not qualitatively affect the results in the paper.

[34] Note that the average three-factor alphas of all DISAGREE quintiles are negative. This is due to the size effect in cryptocurrency (Liu & Tsyvinski, 2021 and Liu et al., 2022) that larger crypto assets earn significantly lower returns compared to smaller crypto assets. As documented in Panel B of Table 1, the crypto assets in our Binance sample have relatively larger crypto size compared to the crypto market and thus have lower returns.

3.2 Average Crypto Characteristics

In addition to our univariate portfolio analysis, in this section we consider more controls known to influence returns. We choose the controls based on past research linking them with either crypto or stock returns. For example, Babiak & Erdis (2022) document a negative relation between trading activity variation and subsequent crypto returns. Liu & Tsyvinski (2021) and Liu et al. (2022) find qualitatively similar size (e.g, Fama & French, 1992, 1993), momentum (e.g., Jegadeesh & Titman, 1993, 2001, 2002), and investor attention (e.g., Da et al., 2011) effects in the crypto market. Bianchi et al. (2022) find that crypto assets exhibit return reversals (e.g., like in equity in Jegadeesh, 1990; Lehmann, 1990) over short horizons. Other commonly-known return predictors in the stock market appear to possess insignificant return predicting power in the cross section of crypto assets. 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 crypto returns.

It is useful to understand how these variables may be correlated with our key metric of DISAGREE before we proceed to the two-way sorting analysis. Thus, we examine average values of crypto characteristics within each DISAGREE quintile. Panel B of Table 2 presents these relationships.

First, we note that most of our crypto characteristic controls appear to be monotonic in relation to DISAGREE. For example, moving from the lowest to the highest DISAGREE 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, absolute short-term reversal (|REV|), momentum (MOM), idiosyncratic volatility (IVOL), abnormal google search volume index (ASVI), and demand for lottery-like crypto assets (MAX) all increase monotonically with abnormal volume (DISAGREE). The fact that REV, IVOL, and MAX all increase with DISAGREE is somewhat expected since past studies document that stock trading volume is contemporaneously related to return (Ying, 1966; Westerfield, 1977) and volatility (Clark, 1973; Tauchen & Pitts, 1983; Karpoff, 1987; Gallant et al., 1992; Andersen, 1996). In the opposite direction, average illiquidity (ILLIQ) decreases monotonically with DISAGREE. Finally, we note a U-shape between average coefficient of variation of turnover (CV) and market capitalization (MCAP) and the DISAGREE quintile. In particular, average MCAP is largest (1.643 billions) within the lowest DISAGREE quintile, and second largest (1.244 billions) within the highest DISAGREE quintile.

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

3.3 Portfolio Analysis: Two-Way Sorting

In this section we examine the relation between DISAGREE and future returns after (separately) controlling for coefficient of variation of turnover (CV), short-term reversal (REV), absolute short-term reversal (|REV|), market capitalization (MCAP), momentum (MOM), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), abnormal google search volume index (ASVI), and demand for lottery-like crypto assets (MAX). To do this, we first sort the crypto assets into terciles using the control variable, then within each tercile, we sort crypto assets into quintile portfolios based on DISAGREE in the previous day, where quintile 1 contains crypto assets with the lowest 20% DISAGREE and quintile 5 contains crypto assets with the highest 20% DISAGREE.[35] Table 3 presents average excess daily returns across the three control terciles to produce quintile portfolios with dispersion in DISAGREE but with similar levels of the control variable.

In column 1 we see that after controlling for CV, the average return difference between the high and low DISAGREE quintiles is −0.473% per day (t-statistic = −6.98). The corresponding CAPM alpha, three-factor alpha, and DGTW alpha are −0.473% (t-statistic = −7.03), −0.455% (t-statistic = −6.95), and −0.389% (t-statistic = −4.55) per day, respectively. Hence, trading activity variation proxied by CV does not explain the negative relation between DISAGREE and subsequent returns.

When controlling for the other crypto characteristics in columns 2 to 9, the effect of DISAGREE on future returns is preserved as the return differential between the high and low DISAGREE quintile is economically large, ranging from −0.359% to −0.573% per day,

[35]The number of crypto assets in the cross section is too few to perform a 5×5 double sort, so we perform a 3×5 double sort instead.

and statistically significant at the 1% level. The corresponding risk-adjusted returns are all positive and highly significant, mitigating the concern of insufficient risk controls. Overall, the results in Table 3 indicate that the well-known cross-sectional return predictors in cryptocurrency cannot explain the negative DISAGREE-return relation.

3.4 Fama-Macbeth Cross-Sectional Regressions

In this section, we examine whether the underperformance of high DISAGREE crypto assets in the cross section is simply capturing the joint effect of other crypto characteristics on returns. We maintain the same control variables that were in Table 3: coefficient of variation of turnover (CV); short-term reversal (REV); absolute short-term reversal (|REV|); market capitalization (MCAP); momentum (MOM); illiquidity (ILLIQ); idiosyncratic volatility (IVOL); abnormal google search volume index (ASVI); and demand for lottery-like crypto assets (MAX).

We run Fama & MacBeth (1973) regressions of excess crypto returns on DISAGREE along with those crypto characteristics. For every day, we perform the following cross-sectional (i.e. across crypto assets) regressions:

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

where i refers to the crypto asset, 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 10, and then all controls in column 11. The former helps us assess comparability with extant crypto research. The latter asks whether DISAGREE is incrementally important. In all regressions, the main variable of interest is DISAGREE. The coefficient on this variable captures the difference in next-day excess crypto returns based on the level of DISAGREE, after controlling for various crypto characteristics.

Table 4 reports the time-series averages of the slope coefficients, with the Newey & West (1987) adjusted t-statistics reported in parentheses. In column 1, the average slope, β, from the daily regressions of next-day excess returns on DISAGREE alone is -0.179 with a t-statistic of -9.72. Next, the relation between DISAGREE and future crypto returns is examined jointly with each of the nine crypto (control) characteristics. In each specification, the coefficients on DISAGREE remain negative (ranging from -0.184 to -0.108) and are all statistically significant at the 1% level. The other significant controls are: CV, REV, and |REV|. The cofficient on CV is significantly negative (-0.097 with a t-statistic of -2.42), suggesting that fluctuations in crypto trading activity negatively affects future returns.[36] The coefficient on REV is significantly negative (-0.057 with a t-statistic of -8.39), indicating that crypto assets exhibit strong short-term reversals.[37] The coefficient on |REV| is significantly negative, indicating high current absolute returns associate with lower future returns. The coefficient on ASVI is significantly positive (0.007 with a t-statistic of 2.10), suggesting that crypto assets 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 4, which reports the results for the full

[36] In column 2, we see that the coefficient on DISAGREE barely changes when including CV as a control. This result provides evidence that our DISAGREE contains incremental explanatory power for ex-post returns after controlling for the effects of variability in trading (Babiak & Erdis, 2022). Also, a VIF test (untabulated) shows average and median values (across days) of 1.02 to 1.05. These are so close to 1 (which is the minimum value of VIF by construction), that the two variables appear essentially uncorrelated in their influence on returns.

[37] We revisit the importance of reversals below in section 3.4, as we explore alternative interpretations of our results.

specification with DISAGREE and all nine crypto control characteristics. The average slope coefficient on DISAGREE is -0.102 with a t-statistic of -4.50, indicating that DISAGREE significantly and negatively predicts next-day crypto returns even after controlling for all crypto characteristics simultaneously. Among these controls, only the coefficients on CV and ILLIQ are statistically significant. Overall, the Fama & MacBeth (1973) cross-sectional regressions in Table 4 provide strong evidence for a significantly negative relation between DISAGREE and future crypto returns.[38]

3.5 The Role of Short Sale Constraints

3.5.1 Short selling on Binance

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

One can sell short a crypto asset via the margin trading services on Binance. The activation timing of a crypto asset's margin trading services is determined by Binance. In order to borrow crypto assets from a third party on Binance, one must first provide collateral, and then pay back those crypto assets 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

[38] Introducing a quadratic term to the regression appears to add little explanatory power and does not change the significantly negative coefficient on DISAGREE.

spot trading volume, futures trading volume, and BNB balance.[39]

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 crypto asset) for two reasons. First, the historical data of tier composition, maximum borrowing limits, and shorting volume (demand or supply) for each crypto asset is not available. Second, most shortable crypto assets' borrowing interest rates are fixed except for an occasional adjustment, and thus do not exhibit much time-series variation.[40] Instead, we define a crypto asset as "constrained" on a given day as a simple dummy (equal to one) if the crypto asset's borrowing interest rate is not available on Binance (one cannot borrow on Binance to sell short the crypto asset) 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 crypto assets in the cross section (the number of constrained crypto assets divided by the number of all crypto assets in our sample) to measure the level of short-selling difficulty in the market as a whole. We then examine whether this "market-wide short sale constraint average" appears related to underperformance of high disagreement crypto assets through time.

To analyze the underperformance of high disagreement crypto assets through time, we calculate the average return differences between the highest and the lowest DISAGREE 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

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

[40] 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.

30 observations. Then, we adjust crypto 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 DISAGREE quintile and daily proportion of constrained crypto assets. We find that both the underperformance of high DISAGREE crypto assets and the proportion of constrained crypto assets have a decreasing trend, thus providing preliminary support for an implication of Miller (1977) that the underperformance of high disagreement crypto assets gets weaker when short sale constraints are removed. In particular, about 85% of crypto assets in our sample are short sale constrained until mid-2020, and the underperformance of high (relative to low) DISAGREE crypto assets 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 crypto assets climbs rapidly and the underperformance dissipates by at least half.

3.5.2 Short-constrained crypto assets

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

To examine this hypothesis, we restrict our sample to constrained crypto-day observations (around 60% of the full sample), re-run the regressions in equation (5), and report the results in Table 5. First, the coefficients on DISAGREE are negative (ranging from −0.228 to −0.111) and statistically significant at the 1% level across all model specifications. In addition, they are larger in magnitude compared to the corresponding specifications in Table 4. This is because Table 4 also contains observations with no impediments to short sales, which according to Miller (1977) should not result in lower future crypto returns. As a result, the negative relation between DISAGREE and future crypto returns is weaker in Table 4 due to the averaging across samples.[41]

3.6 The Movers Subsample - Deeper Exploration

Miller (1977)'s hypothesis indicates that high disagreement associates with overpricing only when short sale constraints are present. In this section we examine this implication in more detail by focusing on the "movers" subsample. Movers are crypto assets that experience a transition stage (their margin trading services are activated some time during the sample period). Among the 356 crypto assets in our sample, 153 crypto assets are movers and they account for around 57% of crypto-day observations in our sample. This allows us to use the same crypto as a benchmark when evaluating the effect of investor disagreement on certain characteristics from pre- to post-relaxation of short sale constraints.[42] This facilitates our event-study analysis.

[41]In untabulated analyses, we limit our sample to shortable crypto assets and re-run the regressions in equation (5). As expected, the relation between DISAGREE and future crypto returns is statistically indistinguishable from zero.

[42]Notably, in the movers subsample the number of constrained crypto-day observations is about the same as the number of shortable crypto-day observations. Hence, for each crypto asset we have on average the same number of observations before and after the activation of its margin trading. In addition, the activation of a crypto asset'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).

3.6.1 Disagreement, short-selling restrictions, and overpricing

We first examine the relation between disagreement and future crypto returns by running separate regressions for the movers; one regression on the sample of crypto assets on days prior to the allowance of margin trading, and the other on the same (movers) sample but on days after allowance of margin trading:

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

where i refers to the crypto asset and t refers to the day. We study the usual four measures of returns: the excess return (RET), the CAPM alpha, the three-factor alpha, and the DGTW alpha. Control variables are also the usual, and include short-term reversal, market capitalization, momentum, illiquidity, idiosyncratic volatility, abnormal google search volume index, and demand for lottery-like crypto assets. We include both crypto and day fixed effects, and standard errors are double-clustered by crypto 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 DISAGREE are negative (ranging from -0.098 to -0.053) and statistically significant (t-statistics ranging from -2.99 to -2.32) prior to the allowance of margin trading services. They also become indistinguishable from zero after the relaxation of short sale constraints.

For Panel B, we use a single panel. We construct the dummy variable, CONSTRAINT, to be one if the crypto asset is short sale constrained (i.e. before Binance activates margin trading services on the crypto asset), and zero otherwise. Then we further create an interactive of CONSTRAINT with DISAGREE to measure the influence of investor disagreement when the crypto asset is constrained, on ex-post returns. We run the following regression:

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

where i refers to the crypto asset and t refers to the day. We use the same four measures of returns: the excess return (RET), the CAPM alpha, the three-factor alpha, and the DGTW alpha. The control variables are also the same; coefficient of variation of turnover, short-term reversal, absolute short-term reversal, market capitalization, momentum, illiquidity, idiosyncratic volatility, abnormal google search volume index, and demand for lottery-like crypto assets. We include both crypto and day fixed effects, and standard errors are double-clustered by crypto and day.[43]

Again, our expectation is that when short-selling restrictions are present (CONSTRAINT = 1), high disagreement crypto assets 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 crypto returns will disappear. Therefore, the coefficient β_3 on the interaction term, DISAGREE $\times$ CONSTRAINT, should

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

be negative and statistically significant, while the coefficient on DISAGREE 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 DISAGREE is indistinguishable from zero. To calibrate the economic significance, the standard deviation of DISAGREE for the models in Table 6 is 3.99. Hence, when short-selling restrictions are present, a one-standard-deviation increase in DISAGREE 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 DISAGREE 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 -0.063 to -0.042) and are all statistically significant at the 5% level (t-statistics ranging from -2.61 to -2.13). On the other hand, both the coefficients on DISAGREE and CONSTRAINT are indistinguishable from zero, indicating that neither high disagreement nor the presence of short-selling restrictions is *independently* sufficient to generate overpricing.[44]

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

[44]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 & 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-crypto observations as the benchmark/control in the volume-return relation. The results are qualitatively the same.

on wash-trading. One might initially think that unusually high volume due to wash trades (Amiram et al., 2021; Le Pennec et al., 2021; Chen et al., 2022; Cong et al., 2023) drives up the contemporaneous price, which is followed by a reversal as arbitrageurs take advantage of price differences across various exchanges. However, the striking sensitivity of the abnormal volume-return relation to the activation of margin trading services on Binance cannot be explained, at least without further assumptions, by the cross-exchange arbitrage hypothesis. In fact, if the lower expected returns of crypto assets 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 crypto asset's margin trading has been activated on Binance.

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

Key to Miller (1977)'s arguments linking disagreement, short sales constraints, and overpricing at time "t", are two factors. First, higher disagreement associates with more extreme evaluations of an asset.[45] Second, in the presence of short-sale constraints, pessimists are restrained from selling short while optimists can freely trade on their positive beliefs.[46] Combined, the overpricing of high disagreement assets (at time "t") stems from a surfeit of

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

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

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 DISAGREE and disagreement.

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

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

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

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:

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

where i refers to the crypto asset 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 are again the usual; coefficient of variation of turnover, short-term reversal, market capitalization, momentum, illiquidity, idiosyncratic volatility, abnormal google search volume index, and demand for lottery-like crypto assets. We include both crypto and day fixed effects, and standard errors are double-clustered by crypto 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, DISAGREE $\times$ CONSTRAINT, are 0.436 (t-statistic = 3.18) and 0.446 (t-statistic = 3.11) with and without control variables respectively. This indicates a positive and statistically significant relation between DISAGREE and OIBVOL in the presence of short-selling restrictions (CONSTRAINT = 1). High disagreement associates with greater order imbalance when a crypto asset 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 0.316) and statistically significant at the 1% level (t-statistics = 2.97 and 2.91).

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.[47] On the other hand, the coefficients on DISAGREE 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.

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

The results of Table 7 indicate that high investor disagreement, as measured by high DISAGREE, is associated with more positive gap between buying and selling in the presence of suppressed short sales. This provides further support for the model by Miller (1977).

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

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

Following this logic, we examine whether - in the presence of short sale constraints - high disagreement crypto assets exhibit subsequent decreases in both buyer-initiated and seller-initiated trades, with the decrease in the former being larger in magnitude.[48] To test this implication, we first construct the following four variables for crypto asset i at any day

[48] On the other hand, if the lower expected returns of high volume crypto assets are driven by cross-exchange arbitrage activities rather than Miller (1977)'s mechanism, we'd expect subsequent selling activities to increase instead of decreasing.

$t+1$, 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 crypto asset 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 crypto asset i from day t to $t+1$.[49] Then we run the following two regressions:

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

and

$$\begin{aligned}\Delta\text{TRD}_{i,t+1} = \beta_0 + \beta_1\text{DISAGREE}_{i,t} + \beta_2\text{CONSTRAINT}_{i,t} + \beta_3\text{DISAGREE}_{i,t} \times \text{CONSTRAINT}_{i,t} \\ + \beta_4\Delta\text{TRD}_{i,t} + \beta_c\text{Controls}_{i,t} + c_i + c_t + \epsilon_{i,t+1},\end{aligned} \tag{16}$$

where i refers to the crypto asset and t refers to the day. We use three change in trading

[49] 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.

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 the usual; coefficient of variation of turnover, short-term reversal, market capitalization, momentum, illiquidity, idiosyncratic volatility, abnormal google search volume index, and demand for lottery-like crypto assets. We include both crypto and day fixed effects, and standard errors are double-clustered by crypto and day.

Panel A of Table 8 reports the regression results of equation (20). In columns 1 to 4, the coefficients on the interaction term, DISAGREE $\times$ CONSTRAINT, are negative and statistically significant, both with and without control variables. This indicates that when short-selling restrictions are binding (CONSTRAINT $= 1$), DISAGREE decreases subsequent buyer-initiated and seller-initiated trading volume. In particular, using columns 1 and 3, a one-standard-deviation increase in DISAGREE results in a $|3.99 \times (-6.465)| = 25.795\%$ 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.[50] When we further include the control variables in the last column, the coefficient on the interaction term remains negative (-1.604) and statistically significant at the 5% level (t-statistic $= -2.41$). In contrast, the coefficients on DISAGREE alone in all specifications are insignificantly different from zero, again stressing the role of short-selling restrictions in Miller (1977)'s model.[51]

[50]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.

[51]Unreported tests exploring change in order imbalance from t to t+1 confirm that during a crypto asset's constrained window, when DISAGREE is higher on day t, there is more convergence (shrinking OIB) *the*

Panel B of Table 8 reports the regression results of equation (21). Consistent with the results in Panel A, we find that in the presence of short-selling restrictions, a one-standard-deviation increase in DISAGREE 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.

4 Robustness Checks

4.1 Alternative Definitions of DISAGREE

In this section, we examine whether our main results in Panel A of Table 2 are robust to different-length windows for the calculation of the first and second moments of crypto turnover, or using volume instead of turnover to define DISAGREE. We begin by computing the first and second moments of turnover in the past 7, 15, and 45 days (as opposed to 30 days in Section 2.2) and define DISAGREE as in equation (2). Next, we calculate the first and second moments of crypto trading volume in the past 7, 15, 30, and 45 days and define DISAGREE as "Change in volume" divided by the standard deviation.[52] We then follow the

next day. This supports our study of next-day returns after measuring DISAGREE, in our main tests.

[52]We thank one of our referees for this suggestion.

approach in Section 3.1 to sort crypto assets into quintiles based on these alternative measures of DISAGREE and examine the average next-day excess returns in each DISAGREE quintile portfolio.

Table A1 reports the results. To conserve space, we only report the results for excess returns, but the results for CAPM alphas, three-factor alpha, and DGTW alpha are similar. In columns 1 to 3 (the first and second moments of crypto turnover are computed in the past 7, 15, and 45 days when defining DISAGREE), the average return difference between the highest and the lowest DISAGREE quintile ranges from -0.478% to -0.397%, all statistically significant at the 1% level. In columns 4 to 7 (the first and second moments of crypto turnover are computed in the past 7, 15, and 45 days when defining DISAGREE), the average return difference between the highest and the lowest DISAGREE quintile ranges from -0.497% to -0.397% and remains highly significant. We thus conclude that the negative relation between DISAGREE and the next-day return is robust to alternative definitions of DISAGREE. In untabulated tests, we find the other results in the paper are qualitatively the same when using alternative definitions of DISAGREE.

4.2 Different Portfolio Holding Periods

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 DISAGREE quintiles persists under longer holding periods, following the approach of Jegadeesh & Titman (1993).[53] Table A2 shows that for holding periods up

[53] In particular, we vary the number of holding days for each DISAGREE 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

to 19 days, the differences in average returns (excess return, CAPM alpha, three-factor alpha, and DGTW alpha) between the highest and lowest DISAGREE quintile remain negative and statistically significant. The result suggests that the negative relation between DISAGREE and expected crypto 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 DISAGREE. Thus, our main tests conservatively fixate on the day after DISAGREE calculation.

4.3 The Effect of Bitcoin's Trading Volume

Yarovaya & Zięba (2022) document a significant relationship between Bitcoin trading volume, and the returns and volume of other crypto assets. We therefore examine whether the negative DISAGREE-return relation presents *only* during periods of high (or low) Bitcoin trading volume. We first follow the previous approach in Section 2.2 to define DISAGREE for Bitcoin. Then we classify days in our sample into three non-consecutive time periods based on the daily ranking of Bitcoin's DISAGREE in the cross section of crypto assets' DISAGREE. Specifically, days when the Bitcoin's DISAGREE is among the lowest 30%, the middle 40%, and the highest 30% - respectively - of the full-sample distribution of crypto assets' DISAGREE, are classified as "Low", "Medium", and "High", days. We then run equation (5) separately on each of the three groupings, and report the results in Table A3. The coefficients on DISAGREE remain negative and statistically significant at the 1% level when all control variables are included, indicating that the negative relation between DISAGREE and future returns cannot be explained by fluctuations in Bitcoin trading volume.

one-third of its composition each day.

4.4 The Effect of Crypto Classifications

Lastly, we examine whether the negative relation between DISAGREE and future returns persists in different types of crypto assets. While there is no universal approach to classify crypto assets, in Table A4 we use three classification questions to sort the crypto assets in our sample broadly into two groups for each of the following questions.[54] First, Panel A classifies crypto assets into two groups based on whether the crypto asset or the protocol behind it enables creating decentralized applications (dApps) or smart contracts. Second, Panel B classifies crypto assets into two groups based on whether the crypto asset operates on its own blockchain (i.e., a coin) or not (i.e., a token). Third, Panel C classifies crypto assets into two groups based on whether the crypto asset is primarily designed for borderless trading (i.e., the main purpose of the crypto asset is to facilitate decentralized payments and transactions).

Among the 356 crypto assets in our sample, 177 crypto assets have an answer of "Yes" to Panel A's classification question, 117 crypto assets have an answer of "Yes" to Panel B's classification question, and 121 crypto assets have an answer of "Yes" to Panel C's classification question.[55] We re-run the Fama & MacBeth (1973) regression in equation (5) for each of the subsamples and report the coefficients. We find that the coefficients on DISAGREE are all significantly negative when all the control variables are included.

We also explored classifications of crypto assets by "blockchain layer". We classified crypto assets into a lower layer and an upper layer.[56] The lower layer (layer-0 and layer-1)

[54]The first two classifications questions are proposed by Yarovaya & Zięba (2022).

[55]We do not use the other classification questions in Yarovaya & Zięba (2022), as they result in extremely unbalanced groups of crypto assets in our sample. For example, 43 crypto assets (313 crypto assets) are mineable (not mineable), and 64 crypto assets (292 crypto assets) have unlimited (limited supply).

[56]See for example: https://tatianarevoredo.medium.com/; https://zebpay.com/; https://medium.com/;

is essentially foundational, with Bitcoin and Ethereum as examples. Crucial among their characteristics is their well-established consensus mechanism (such as Proof of Work for Bitcoin or Proof of Stake for Ethereum after September 2022).[57] Next, the upper layer contains layer-2 and layer-3 blockchains. Layer-2 focuses on scalability, extending blockchain by processing transactions off-chain or in batches, then settling them on layer-1. In other words, these cryptocurrencies run alongside the layer-1 cryptocurrencies. Layer-3 acts as an application layer and provides the user interface.

In our sample, 99 crypto assets belong to the lower layer (4 for layer-0 and 95 for layer-1) and 257 crypto assets belong to the upper layer (147 for layer-2 and 110 for layer-3). We conjectured that crypto assets in the lower layer are likely to be more stable than those in the upper layer due to their foundational nature and established consensus mechanisms. However, our analysis results were quite noisy and provide mixed indications of differences in the DISAGREE-return relation.[58]

When running the Fama & MacBeth (1973) regression in equation (5) for each of the subsamples, we find that only the upper layer sample continues to show a significantly negative relationship between DISAGREE and future returns; the lower layer does not. However, the coefficients on DISAGREE are negative in both samples and they are not statistically different from each other. Our concern with noisiness in the estimation is driven by the following further results. When we further disaggregate, we find that for both layer-2 and layer-3, crypto assets experience a negative relation between DISAGREE and future returns. The coefficient in layer-2, however, is larger in apparent magnitude - though not

https://chain.link/education-hub/

[57]Specifically, the lower layer includes layer-0 and layer-1, with layer-0 consisting of the foundational infrastructure and layer-1 consisting of the decentralized ledger and consensus mechanisms.

[58]Therefore we conserve space by not tabulating. We simply describe the results (briefly), next.

statistically so - compared to the coefficient in layer-3. This leans against our instincts that 'higher' layers associate with higher disagreement. Then we also find that the coefficient in layer-3 closely resembles the coefficient in the *lower layer* sample. Overall, we have a difficult time supporting the notion that there can be different groupings of crypto assets that evince varying DISAGREE-return relations. Perhaps further understanding is best left for future work, potentially incorporating new theory.

5 Conclusion

Using price and directional trades data from Binance, we find that investor disagreement, as measured by abnormal trading volume (DISAGREE), is negatively related to cross-sectional cryptocurrency expected returns. This negative relation cannot be explained by common risk factors nor various crypto characteristics including variations in trading activity, short-term reversal, absolute short-term reversal, size, momentum, illiquidity, investor attention, idiosyncratic volatility, and demand for lottery-like crypto assets.

This significantly negative relation refutes an interpretation of DISAGREE as risk or uncertainty. Instead, the evidence supports Miller (1977)'s hypothesis: when disagreement is high, the opinions of pessimists will fail to be incorporated into asset prices due to short-sale constraints, resulting in overpricing and lower subsequent returns of those assets.

Miller (1977)'s hypothesis also implies that when frictions that prevent pessimists from selling short are relaxed, the underperformance of high disagreement assets should subside. Consistent with this, we find that the negative DISAGREE-return relation is concentrated in the crypto-day observations when margin trading is not allowed. By contrast, the crypto-day observations where margin trading is allowed do not exhibit this relation.

To examine the role of short-selling restrictions at a finer level, we study crypto assets that transition from "not shortable" to "shortable" in our sample. We find that the negative DISAGREE-return relation exists only when both high disagreement and short-selling restrictions are present, while neither of the two is independently sufficient to produce the result. This sample also enables utilization of directional trades data to test whether trading activities are linked to disagreement in a manner consistent with Miller (1977). First, in the presence of short sale constraints, high disagreement is *contemporaneously* associated with more asymmetric trading activities, since pessimists cannot freely trade on their negative beliefs. We find that when short-selling restrictions are present, order imbalance for volume and trade are increasing in DISAGREE, even after controlling for order imbalance persistence. Second, the lower ex-post returns of high disagreement assets imply resolution of disagreement. Miller (1977) indicates that increased disagreement leads to a larger increase in buying activities relative to selling activities due to short sale constraints. Therefore, ex-post we should observe a larger decrease in buying activities relative to selling activities (i.e. convergence of beliefs), to align with this condition. We find that in the presence of short-selling restrictions, both buying and selling activities of crypto assets decline following high DISAGREE, but with the decrease in former showing much larger magnitude than the decrease in latter.

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

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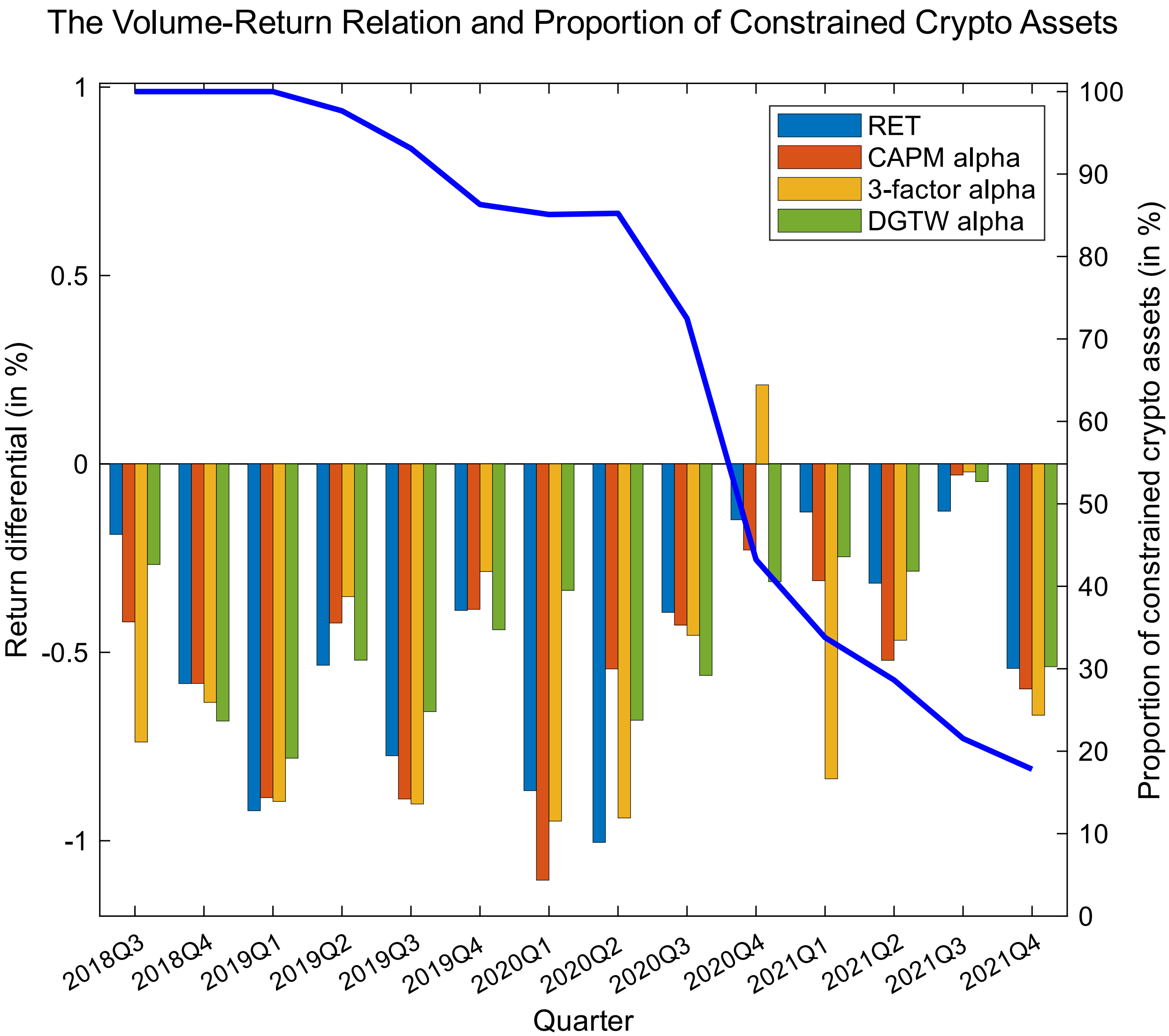

Figure 1. The Volume-Return Relation and Proportion of Constrained Crypto Assets. For each day, quintile portfolios are formed by sorting individual crypto assets based on their abnormal trading volume (DISAGREE) in the previous day. DISAGREE is defined as the daily turnover ratio minus the average turnover 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%) DISAGREE crypto assets as well as the proportion of constrained crypto assets (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 crypto asset is constrained if its margin trading is not available on Binance (one cannot borrow on Binance to sell short the crypto asset). The sample period is 2018Q3 to December 2021Q4.

Table 1. Summary Statistics. Panel A presents the time-series averages of summary statistics for various crypto characteristics, including abnormal trading volume (DISAGREE), coefficient of variation of turnover (CV), short-term reversal (REV, in %), absolute 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-like crypto assets (MAX, in %). DISAGREE 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 crypto characteristics are defined in Section 2.1. Panel B presents the number of individual crypto assets and mean/median market capitalization (MCAP, in billions) at the end of each quarter for the sample and the crypto market. The sample period is August 1st, 2018 to December 31st, 2021.

Panel A: Crypto characteristics

	Mean	SD	P25	Median	P75
DISAGREE	0.168	2.116	−0.590	−0.279	0.247
CV	0.896	0.441	0.589	0.782	1.088
REV	0.479	5.728	−2.345	−0.329	2.182
|REV|	5.424	4.757	2.828	4.437	6.637
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 crypto assets and crypto size by quarter

		Sample		crypto 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 Crypto Assets Sorted by Abnormal Trading Volume. For each day, quintile portfolios are formed by sorting individual crypto assets based on their abnormal trading volume (DISAGREE) in the previous day, where quintile 1 contains crypto assets with the lowest 20% DISAGREE and quintile 5 contains crypto assets with the highest 20% DISAGREE. DISAGREE 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 DISAGREE 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 crypto asset's DGTW alpha is the difference between a crypto asset's return and the value-weighted return of its matching 10 × 10 crypto size/momentum portfolio following the approach of Daniel et al. (1997). Panel B reports for each DISAGREE quintile the time-series averages of crypto characteristics, including DISAGREE, coefficient of variation of turnover (CV), short-term reversal (REV, in %), absolute 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-like crypto assets (MAX, in %). Newey & West (1987) adjusted t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The sample is all crypto assets meeting the requirements in Section 2.1 and the sample period is August 1st, 2018 to December 31st, 2021.

Panel A: Average returns across DISAGREE quintiles

DISAGREE 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 crypto characteristics across DISAGREE quintiles

DISAGREE quintiles	DISAGREE	CV	REV	|REV|	MCAP	MOM	ILLIQ	IVOL	ASVI	MAX
Q1 (Low)	−0.884	0.701	−0.770	4.154	1.643	−1.186	28.993	0.988	1.022	2.746
Q2	−0.531	0.920	−0.590	4.469	1.038	0.670	27.450	1.098	1.037	3.010
Q3	−0.275	1.022	−0.327	4.786	0.851	2.910	23.196	1.174	1.046	3.269
Q4	0.121	0.964	0.334	5.441	1.159	5.259	18.451	1.319	1.181	3.771
Q5 (High)	2.421	0.867	3.763	8.292	1.244	8.204	14.171	1.939	1.579	6.045

Table 3. Returns on Portfolios of Crypto Assets Double-Sorted by Abnormal Trading Volume and Other Crypto Characteristics. Double-sorted quintile portfolios are formed every day by sorting crypto assets based on their abnormal trading volume (DISAGREE) after controlling for the crypto characteristics in Table 2. DISAGREE 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. In each case, we first sort the crypto assets into terciles using the control variable, then within each tercile, we sort crypto assets into quintile portfolios based on DISAGREE in the previous day where quintile 1 contains crypto assets with the lowest 20% DISAGREE and quintile 5 contains crypto assets with the highest 20% DISAGREE. The table presents average excess daily returns across the three control terciles to produce quintile portfolios with dispersion in DISAGREE but with similar levels of the control variable. Portfolio returns are equal-weighted. The control variables include coefficient of variation of turnover (CV), short-term reversal (REV), absolute short-term reversal (|REV|), market capitalization (MCAP), momentum (MOM), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), abnormal google search volume index (ASVI), and demand for lottery-like crypto assets (MAX). Newey & West (1987) adjusted t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The sample is all crypto assets meeting the requirements in Section 2.1 and the sample period is August 1st, 2018 to December 31st, 2021.

	Control crypto characteristics								
DISAGREE quintiles	CV	REV	|REV|	MCAP	MOM	ILLIQ	IVOL	ASVI	MAX
Q1(Low)	0.543**	0.493*	0.516**	0.599**	0.555**	0.559**	0.584**	0.898**	0.551**
	(2.13)	(1.91)	(1.98)	(2.29)	(2.16)	(2.16)	(2.23)	(2.38)	(2.11)
Q2	0.536**	0.523**	0.560**	0.523**	0.537**	0.496**	0.503**	0.483**	0.505**
	(2.35)	(2.31)	(2.45)	(2.32)	(2.36)	(2.18)	(2.21)	(2.13)	(2.21)
Q3	0.542**	0.509**	0.483**	0.519**	0.527**	0.556**	0.509**	0.627**	0.503**
	(2.37)	(2.24)	(2.11)	(2.29)	(2.33)	(2.45)	(2.23)	(2.51)	(2.22)
Q4	0.458**	0.487**	0.420*	0.478**	0.476**	0.455**	0.396*	0.565**	0.459**
	(1.99)	(2.12)	(1.85)	(2.09)	(2.07)	(1.98)	(1.74)	(2.33)	(1.99)
Q5(High)	0.070	0.134	0.176	0.026	0.055	0.086	0.168	0.268	0.140
	(0.30)	(0.58)	(0.76)	(0.11)	(0.23)	(0.37)	(0.73)	(0.91)	(0.61)
Q5-Q1	−0.473***	−0.359***	−0.340***	−0.573***	−0.500***	−0.474***	−0.416***	−0.458***	−0.411***
	(−6.98)	(−5.40)	(−5.04)	(−8.78)	(−7.59)	(−6.91)	(−6.59)	(−2.86)	(−6.18)
CAPM alpha	−0.473***	−0.353***	−0.332***	−0.563***	−0.491***	−0.462***	−0.407***	−0.394***	−0.403***
	(−7.03)	(−5.41)	(−4.97)	(−8.80)	(−7.60)	(−6.80)	(−6.56)	(−3.21)	(−6.16)
3-factor alpha	−0.455***	−0.332***	−0.297***	−0.521***	−0.442***	−0.447***	−0.322***	−0.317**	−0.338***
	(−6.95)	(−5.22)	(−4.63)	(−8.68)	(−6.88)	(−6.94)	(−5.41)	(−2.40)	(−5.60)
DGTW alpha	−0.389***	−0.363***	−0.347***	−0.455***	−0.447***	−0.428***	−0.353***	−0.365**	−0.408***
	(−4.55)	(−5.45)	(−6.16)	(−6.48)	(−6.50)	(−6.33)	(−6.66)	(−2.54)	(−7.03)

Table 4. Fama-Macbeth Cross-Sectional Regressions. This table reports the time-series averages of the slope coefficients obtained from

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

where i refers to crypto asset i and t refers to day t. The dependent variable is excess return (RET, in %). Abnormal trading volume (DISAGREE) 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 coefficient of variation of turnover (CV), short-term reversal (REV, in %), absolute 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-like crypto assets (MAX, in %). Newey & West (1987) adjusted t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The sample is all crypto assets 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)	(10)	(11)
DISAGREE	−0.179***	−0.175***	−0.108***	−0.139***	−0.183***	−0.184***	−0.175***	−0.175***	−0.181***	−0.163***	−0.102***
	(−9.72)	(−9.72)	(−5.44)	(−7.16)	(−10.74)	(−10.44)	(−9.38)	(−9.42)	(−9.80)	(−6.69)	(−4.50)
CV		−0.097**									−0.182***
		(−2.42)									(−3.24)
REV			−0.057***								0.101
			(−8.39)								(0.67)
|REV|				−0.018**							−0.102
				(−2.54)							(−0.67)
MCAP					−0.025						−0.015
					(−1.36)						(−0.76)
MOM						0.002					0.001
						(0.98)					(0.38)
ILLIQ							0.030				0.093***
							(1.05)				(3.72)
IVOL								−0.007			0.033
								(−0.17)			(0.59)
ASVI									0.007**		0.005
									(2.10)		(1.46)
MAX										−0.012	0.000
										(−0.83)	(0.02)
Intercept	0.439*	0.518**	0.347	0.464*	0.887*	0.354	0.395*	0.443**	0.431*	0.491**	0.625
	(1.88)	(2.17)	(1.37)	(1.84)	(1.89)	(1.52)	(1.80)	(2.06)	(1.83)	(2.36)	(1.35)
Obs.	223,476	223,476	223,476	223,476	223,476	223,476	223,476	223,476	223,476	223,476	223,476
Adj. R^2	0.020	0.026	0.049	0.044	0.038	0.045	0.026	0.048	0.023	0.044	0.133

Table 5. Fama-Macbeth Cross-Sectional Regressions: Short-Constrained Crypto Assets. 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

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

where i refers to crypto asset i and t refers to day t. The dependent variable is excess return (RET, in %). Abnormal trading volume (DISAGREE) 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 coefficient of variation of turnover (CV), short-term reversal (REV, in %), absolute 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-like crypto assets (MAX, in %). Newey & West (1987) adjusted t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The sample period is August 1st, 2018 to December 31st, 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
DISAGREE	−0.224***	−0.219***	−0.127***	−0.159***	−0.228***	−0.240***	−0.226***	−0.216***	−0.228***	−0.200***	−0.111***
	(−8.00)	(−7.73)	(−4.52)	(−6.01)	(−8.24)	(−7.60)	(−7.95)	(−6.62)	(−7.93)	(−6.08)	(−3.65)
CV		−0.135***									−0.165***
		(−2.61)									(−2.88)
REV			−0.076***								0.039
			(−8.32)								(0.26)
|REV|				−0.026**							−0.100
				(−2.46)							(−0.65)
MCAP					−0.025						−0.015
					(−1.36)						(−0.57)
MOM						0.002					−0.002
						(0.85)					(−1.05)
ILLIQ							0.091*				−0.008
							(1.89)				(−0.20)
IVOL								0.011			0.045
								(0.23)			(0.80)
ASVI									0.001		0.005
									(0.17)		(0.97)
MAX										−0.008	0.011
										(−0.51)	(0.53)
Intercept	0.403*	0.528**	0.302	0.437*	0.775	0.328	0.342	0.401*	0.402*	0.449**	0.648
	(1.71)	(2.10)	(1.16)	(1.67)	(1.38)	(1.38)	(1.55)	(1.88)	(1.69)	(2.15)	(1.18)
Obs.	133,596	133,596	133,596	133,596	133,596	133,596	133,596	133,596	133,596	133,596	133,596
Adj. R^2	0.026	0.029	0.063	0.057	0.041	0.056	0.031	0.061	0.031	0.057	0.158

Table 6. The Volume-Return Relation: Movers. In this table, the sample is all crypto assets 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 crypto-day observations into two groups (those prior to and after the relaxations of margin trading) and presents coefficient estimates from the following regression:

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

Panel B presents coefficient estimates from the following regression:

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

In both panels, i refers to crypto asset 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. DISAGREE and the control variables are defined as before. The existence of short sale constraint (CONSTRAINT) is a dummy variable that equals one if the crypto asset's margin trading is not available on Binance (one cannot borrow on Binance to sell short the crypto asset) and zero otherwise. We include both crypto and day fixed effects. Standard errors are double-clustered by crypto 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)
DISAGREE	−0.073***	−0.069**	−0.098**	−0.053**	0.004	0.004	0.005	−0.001
	(−2.99)	(−2.53)	(−2.32)	(−2.32)	(0.75)	(0.77)	(0.89)	(−0.25)
CV	−0.267**	−0.235***	−0.271**	−0.271**	−0.043	−0.101	0.046	0.036
	(−2.37)	(−2.66)	(−2.36)	(−2.51)	(−0.28)	(−0.66)	(0.23)	(0.24)
REV	−0.036***	−0.038***	−0.038***	−0.042***	−0.026*	−0.025*	−0.024*	−0.030**
	(−3.30)	(−2.88)	(−2.68)	(−3.13)	(−1.97)	(−1.97)	(−1.92)	(−2.48)
|REV|	0.038***	0.048***	0.030	0.044**	0.012	0.007	0.016	0.014
	(2.80)	(2.79)	(1.17)	(2.58)	(0.62)	(0.37)	(0.84)	(0.76)
MCAP	−0.608***	−0.592***	−0.306	−0.393***	−0.587***	−0.603***	−0.451***	−0.503***
	(−3.85)	(−4.28)	(−1.61)	(−3.07)	(−5.59)	(−5.07)	(−3.04)	(−5.37)
MOM	−0.004**	−0.004	−0.005	−0.007**	−0.002	−0.003	−0.002	−0.008***
	(−2.03)	(−1.51)	(−1.44)	(−2.32)	(−0.83)	(−1.10)	(−0.80)	(−2.98)
ILLIQ	0.001	−0.000	0.000	0.000	0.001	0.001	0.001	−0.001
	(0.97)	(−0.27)	(0.37)	(0.53)	(1.00)	(0.72)	(0.86)	(−0.53)
IVOL	0.227	0.076	0.355	0.102	0.038	0.037	0.039	0.011
	(1.24)	(0.75)	(1.33)	(0.90)	(0.31)	(0.31)	(0.27)	(0.09)
ASVI	−0.000	0.006	−0.004	0.001	0.016***	0.017***	0.016***	0.016***
	(−0.01)	(0.82)	(−0.35)	(0.12)	(3.71)	(3.69)	(3.57)	(3.83)
MAX	−0.074**	−0.049*	−0.080**	−0.061**	−0.068**	−0.071**	−0.095***	−0.048*
	(−2.30)	(−1.77)	(−2.10)	(−2.19)	(−2.24)	(−2.38)	(−3.00)	(−1.71)
Constant	11.466***	10.907***	4.280	7.468***	12.347***	12.333***	8.272***	10.215***
	(4.09)	(4.44)	(1.26)	(3.27)	(6.00)	(5.26)	(2.81)	(5.57)
Obs.	62,488	56,964	56,964	61,304	65,204	64,853	64,853	64,733
Adj. R^2	0.697	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)
DISAGREE	−0.005	0.000	−0.007	0.000	−0.007	0.001	−0.010	−0.003
	(−0.44)	(0.03)	(−0.55)	(0.02)	(−0.48)	(0.14)	(−0.84)	(−0.40)
$CONSTRAINT_t$	0.227***	0.100	0.262***	0.145	0.278**	0.204	0.142	0.053
	(2.75)	(1.14)	(2.74)	(1.44)	(2.15)	(1.58)	(1.35)	(0.50)
$DISAGREE_t \times CONSTRAINT_t$	−0.080***	−0.054**	−0.073***	−0.042**	−0.095***	−0.063**	−0.071***	−0.042**
	(−3.27)	(−2.61)	(−2.96)	(−2.22)	(−2.72)	(−2.13)	(−2.93)	(−2.19)
CV		−0.167*		−0.174**		−0.125		−0.124
		(−1.80)		(−2.10)		(−1.05)		(−1.38)
REV		−0.028***		−0.030***		−0.030***		−0.035***
		(−2.83)		(−2.84)		(−2.74)		(−3.41)
|REV|		0.028**		0.026*		0.025		0.028**
		(2.47)		(1.85)		(1.61)		(2.10)
MCAP		−0.338***		−0.387***		−0.237***		−0.265***
		(−6.46)		(−6.21)		(−3.24)		(−5.34)
MOM		−0.001		−0.002		−0.002		−0.006***
		(−0.87)		(−0.95)		(−0.74)		(−3.24)
ILLIQ		0.001		−0.000		0.000		0.000
		(0.92)		(−0.60)		(0.32)		(0.29)
IVOL		0.151		0.059		0.101		0.072
		(1.13)		(0.71)		(0.90)		(0.90)
ASVI		0.011***		0.013***		0.011**		0.011***
		(3.41)		(3.79)		(2.51)		(3.35)
MAX		−0.079***		−0.063***		−0.078***		−0.057***
		(−2.88)		(−3.03)		(−3.38)		(−2.93)
Constant	0.431***	6.975***	0.063	7.600***	−1.129***	3.527**	0.144***	5.296***
	(11.88)	(6.87)	(1.48)	(6.32)	(−19.54)	(2.46)	(2.97)	(5.55)
Obs.	127,693	127,693	121,819	121,819	121,819	121,819	126,038	126,038
Adj. 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 crypto assets that meet the requirements in Section 2.1 and whose margin trading transitions from unavailable to available on Binance in our sample period (August 1st, 2018 to December 31st, 2021). This table presents coefficient estimates from the following regression:

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

where i refers to crypto asset 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 (DISAGREE) 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 crypto asset's margin trading is not available on Binance (one cannot borrow on Binance to sell short the crypto asset) and zero otherwise. The control variables are defined as before. We include both crypto and day fixed effects. Standard errors are double-clustered by crypto 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)
DISAGREE_t	0.087	0.093	0.071	0.078
	(1.07)	(1.08)	(1.03)	(1.05)
CONSTRAINT_t	0.103	0.449	0.596*	0.541
	(0.32)	(1.31)	(1.72)	(1.57)
$\text{DISAGREE}_t \times \text{CONSTRAINT}_t$	0.436***	0.446***	0.307***	0.316***
	(3.18)	(3.11)	(2.97)	(2.91)
$\Delta\text{OIBVOL}_{t-1}$	0.159***	0.167***		
	(10.90)	(11.46)		
$\Delta\text{OIBTRD}_{t-1}$			0.351***	0.360***
			(19.25)	(19.48)
CV_{t-1}		−0.551**		0.337*
		(−2.18)		(1.77)
REV_{t-1}		−0.157***		−0.176***
		(−8.97)		(−11.16)
$\lvert\text{REV}_{t-1}\rvert$		0.122***		0.123***
		(7.28)		(7.95)
MCAP_{t-1}		1.012***		−0.030
		(3.76)		(−0.14)
MOM_{t-1}		0.003		−0.004
		(0.93)		(−1.59)
ILLIQ_{t-1}		−0.001		−0.001
		(−1.27)		(−1.27)
IVOL_{t-1}		0.502***		0.626***
		(2.93)		(3.80)
ASVI_{t-1}		0.007		−0.001
		(1.62)		(−0.13)
MAX_{t-1}		−0.123***		−0.115***
		(−4.05)		(−3.18)
Constant	−3.491***	−23.004***	0.373**	−0.191
	(−21.72)	(−4.50)	(2.17)	(−0.05)
Obs.	128,385	128,233	128,385	128,233
Adj. R^2	0.124	0.128	0.229	0.232

Table 8. Trading Activities (Volume and Number of Trades) following Abnormal Trading Volume. In this table, the sample is all crypto assets 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:

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

and Panel B presents coefficient estimates from the following regression:

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

In both panels, i refers to crypto asset 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 (DISAGREE) 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 crypto asset's margin trading is not available on Binance (one cannot borrow on Binance to sell short the crypto asset) and zero otherwise. The control variables are defined as before. We include both crypto and day fixed effects. Standard errors are double-clustered by crypto 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)
DISAGREE_t	−1.415	−1.103	−1.122	−0.844	−0.293	−0.259
	(−1.11)	(−1.09)	(−1.13)	(−1.09)	(−1.02)	(−0.99)
CONSTRAINT_t	19.485***	11.728**	9.162***	5.473**	10.322**	6.254**
	(3.14)	(2.34)	(3.26)	(2.11)	(2.48)	(1.99)
$\text{DISAGREE}_t \times \text{CONSTRAINT}_t$	−6.465***	−4.846***	−4.670***	−3.243**	−1.795***	−1.604**
	(−3.25)	(−2.74)	(−3.16)	(−2.59)	(−3.12)	(−2.41)
ΔBVOL_t	0.000**	0.000				
	(2.00)	(0.91)				
ΔSVOL_t			−0.000	−0.000		
			(−0.90)	(−1.52)		
$\Delta\text{BVOL}_t - \Delta\text{SVOL}_t$					−0.000*	−0.000***
					(−1.88)	(−3.52)
CV_t		10.737***		3.575*		7.161***
		(3.04)		(1.72)		(3.26)
REV_t		0.604*		2.332***		−1.728***
		(1.68)		(10.86)		(−6.98)
$\lvert\text{REV}_t\rvert$		0.285		−1.139***		1.424***
		(0.91)		(−6.00)		(4.69)
MCAP_t		−13.098***		−11.111***		−1.987
		(−5.00)		(−6.36)		(−1.18)
MOM_t		−0.272***		−0.109***		−0.163***
		(−3.59)		(−2.74)		(−3.46)
ILLIQ_t		0.223***		0.078***		0.145**
		(3.68)		(6.03)		(2.55)
IVOL_t		−4.589		−11.042*		6.453
		(−0.47)		(−1.74)		(1.35)
ASVI_t		0.084		0.008		0.076
		(0.77)		(0.17)		(0.85)
MAX_t		−3.456**		−2.025**		−1.432**
		(−2.57)		(−2.14)		(−2.06)
Constant	33.366***	290.449***	27.527***	260.751***	5.840***	29.709
	(10.81)	(5.43)	(21.01)	(7.63)	(2.77)	(0.85)
Obs.	128,125	128,125	128,124	128,124	128,124	128,124
Adj. 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$_{t+1}$ − ΔSTRD$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
DISAGREE$_t$	−0.974	−0.682	−0.795	−0.549	−0.189	−0.137
	(−1.07)	(−1.02)	(−1.11)	(−1.07)	(−0.90)	(−0.77)
CONSTRAINT$_t$	12.002***	9.042***	6.724***	4.822**	5.244***	4.198**
	(3.77)	(2.61)	(3.32)	(2.16)	(2.96)	(2.34)
DISAGREE$_t$ × CONSTRAINT$_t$	−4.211***	−2.744**	−3.325***	−2.035**	−0.933***	−0.734**
	(−3.06)	(−2.47)	(−3.09)	(−2.35)	(−2.78)	(−2.29)
ΔBTRD$_t$	−0.001	−0.001				
	(−1.00)	(−1.00)				
ΔSTRD$_t$			−0.000	−0.000		
			(−1.14)	(−1.42)		
ΔBTRD$_t$ − ΔSTRD$_t$					−0.000	−0.000*
					(−1.17)	(−1.76)
CV$_t$		7.665***		4.062**		3.592***
		(2.84)		(2.26)		(3.06)
REV$_t$		1.229***		2.181***		−0.960***
		(6.12)		(17.37)		(−7.43)
|REV$_t$|		−0.061		−0.831***		0.773***
		(−0.22)		(−3.89)		(4.12)
MCAP$_t$		−10.686***		−8.501***		−2.182*
		(−5.22)		(−6.86)		(−1.91)
MOM$_t$		−0.131***		−0.051***		−0.079***
		(−3.91)		(−2.67)		(−3.73)
ILLIQ$_t$		0.053***		0.045***		0.008
		(6.31)		(7.90)		(0.97)
IVOL$_t$		−13.095***		−14.863***		1.759
		(−3.43)		(−5.09)		(0.93)
ASVI$_t$		0.059		0.047		0.012
		(0.94)		(1.03)		(0.35)
MAX$_t$		−1.556**		−1.023*		−0.551*
		(−2.53)		(−1.95)		(−1.72)
Constant	123.777***	341.023***	120.067***	302.063***	3.574***	38.837
	(72.05)	(8.18)	(116.41)	(12.44)	(3.65)	(1.61)
Obs.	128,125	128,125	128,124	128,124	128,124	128,124
Adj. R^2	0.020	0.022	0.044	0.051	0.007	0.008

Appendix

We construct daily common risk factors in the cryptocurrency market following the approach of Liu et al. (2022). We require that the crypto assets have information on price, volume, and market capitalization. We further exclude crypto assets with market capitalization of less than $1 million. The cryptocurrency excess market return factor (CMKT) is the difference between the value-weighted crypto 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 crypto assets, where the portfolios are formed daily based on crypto market capitalization, into the smallest 30%, the middle 40%, and largest 30% of crypto assets 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 crypto assets into two size portfolios (small 50% and big 50%) and then within each size portfolio we form three prior return portfolios (the lowest 30%, middle 40% and highest 30%). The momentum factor is constructed as the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. In particular, CMOM = 1/2(Small High + Big High) − 1/2(Small Low + Big Low).

Table A1. Alternative Definitions of DISAGREE. For columns 1 to 3, we compute the first and second moments of turnover in the past 7, 15, and 45 days (as opposed to 30 days in Section 2.2) and define DISAGREE as in equation (2). For columns 4 to 7, we calculate the first and second moments of crypto trading volume in the past 7, 15, 30, and 45 days and define DISAGREE as "Change in volume" divided by the standard deviation. Next, for each day, quintile portfolios are formed by sorting individual crypto assets based on their DISAGREE in the previous day, where quintile 1 contains crypto assets with the lowest 20% DISAGREE and quintile 5 contains crypto assets with the highest 20% DISAGREE. This table presents the average excess daily return (RET) for each DISAGREE quintile portfolio. Portfolio returns are equal-weighted. Newey & West (1987) adjusted t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The sample is all crypto assets meeting the requirements in Section 2.1 and the sample period is August 1st, 2018 to December 31st, 2021.

	Turnover			Volume			
	7 days	15 days	45 days	7 days	15 days	30 days	45 days
DISAGREE quintiles	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Q1(Low)	0.520**	0.489*	0.537**	0.519**	0.487*	0.536**	0.522**
	(2.05)	(1.92)	(2.09)	(2.04)	(1.91)	(2.07)	(2.02)
Q2	0.548**	0.602***	0.539**	0.550**	0.595***	0.534**	0.553**
	(2.39)	(2.62)	(2.37)	(2.40)	(2.59)	(2.35)	(2.43)
Q3	0.514**	0.514**	0.563**	0.508**	0.525**	0.570**	0.567**
	(2.24)	(2.27)	(2.45)	(2.22)	(2.31)	(2.50)	(2.49)
Q4	0.452**	0.486**	0.475**	0.459**	0.477**	0.479**	0.462**
	(1.99)	(2.11)	(2.09)	(2.02)	(2.08)	(2.09)	(2.03)
Q5(High)	0.123	0.065	0.058	0.121	0.072	0.039	0.066
	(0.52)	(0.28)	(0.25)	(0.52)	(0.31)	(0.17)	(0.28)
Q5-Q1	−0.397***	−0.425***	−0.478***	−0.397***	−0.416***	−0.497***	−0.456***
	(−6.52)	(−6.81)	(−6.96)	(−6.48)	(−6.62)	(−7.07)	(−6.49)

Table A2. Different Holding Periods. For each day, quintile portfolios are formed by sorting individual crypto assets based on their abnormal trading volume (DISAGREE) in the previous day, where quintile 1 contains crypto assets with the lowest 20% DISAGREE and quintile 5 contains crypto assets with the highest 20% DISAGREE. DISAGREE 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 crypto assets 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 crypto asset's DGTW alpha is the difference between a crypto asset's return and the value-weighted return of its matching 10 × 10 crypto size/momentum portfolio following the approach of Daniel et al. (1997). Newey & West (1987) adjusted t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The sample is all crypto assets 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)

Table A3. Fama-Macbeth Regression: Different Bitcoin Volume Periods. Days are classified into three non-consecutive time periods based on the daily ranking of Bitcoin's abnormal trading volume (DISAGREE) among the cross section of all crypto assets' DISAGREE in the sample. Specifically, days when the Bitcoin's DISAGREE is among the lowest 30%, the middle 40%, and the highest 30% of the crypto assets' DISAGREE are labeled "Low", "Medium", and "High", respectively. Then, we re-run the Fama & MacBeth (1973) regression in equation (5) for each of the three subperiods and report the coefficients. Newey & West (1987) adjusted t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The sample is all crypto assets meeting the requirements in Section 2.1 and the sample period is August 1st, 2018 to December 31st, 2021.

	Cross-sectional DISAGREE rank of Bitcoin		
	Low (1)	Medium (2)	High (3)
DISAGREE	−0.070***	−0.121***	−0.116***
	(−2.65)	(−2.84)	(−2.86)
CV	−0.215***	−0.253***	−0.096
	(−3.25)	(−3.30)	(−0.84)
REV	−0.037	−0.055***	0.346
	(−1.60)	(−3.06)	(0.87)
|REV|	−0.015	−0.017	−0.246
	(−0.82)	(−0.86)	(−0.61)
MCAP	−0.060**	−0.015	0.026
	(−2.21)	(−0.43)	(0.87)
MOM	−0.002	0.005	−0.001
	(−0.73)	(1.40)	(−0.16)
ILLIQ	0.135**	0.110**	0.042**
	(2.18)	(2.29)	(2.04)
IVOL	−0.052	−0.087	0.199**
	(−0.65)	(−0.60)	(2.38)
ASVI	0.008	0.005	0.001
	(1.12)	(1.05)	(0.33)
MAX	−0.008	0.023	−0.010
	(−0.30)	(0.70)	(−0.47)
Intercept	1.283**	0.755	−0.089
	(2.29)	(0.97)	(−0.11)
Obs.	71,750	66,959	84,616
Adj. R^2	0.127	0.142	0.131

Table A4. Fama-Macbeth Regression: Crypto Classifications. In Panel A, we classify crypto assets into two groups based on whether the crypto asset or the protocol behind it enables creating decentralized applications (dApps) or smart contracts. In Panel B, we classify crypto assets into two groups based on whether the crypto asset operates on its own blockchain or not. In Panel C, we classify crypto assets into two groups based on whether the crypto asset is primarily designed for borderless trading. Then, we re-run the Fama & MacBeth (1973) regression in equation (5) for each of the subsamples and report the coefficients. Newey & West (1987) adjusted t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The sample is all crypto assets meeting the requirements in Section 2.1 and the sample period is August 1st, 2018 to December 31st, 2021.

	Panel A: dApps or smart contracts?		Panel B: Own blockchain?		Panel C: Borderless trading?	
	Yes	No	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
DISAGREE	−0.116***	−0.111***	−0.085**	−0.137***	−0.105**	−0.144***
	(−3.68)	(−3.89)	(−2.13)	(−3.75)	(−2.55)	(−3.94)
CV	−0.196***	−0.038	−0.102	−0.148**	−0.130	−0.105*
	(−3.26)	(−0.61)	(−1.23)	(−2.23)	(−1.51)	(−1.74)
REV	0.055	0.026	0.001	0.193	−0.011	0.121
	(0.65)	(0.17)	(0.02)	(1.09)	(−0.12)	(1.06)
|REV|	−0.000	−0.177	−0.059*	−0.275	0.018	−0.216*
	(−0.00)	(−1.09)	(−1.91)	(−1.54)	(0.21)	(−1.85)
MCAP	−0.019	−0.014	−0.024	−0.025	−0.031	−0.024
	(−1.00)	(−0.64)	(−1.16)	(−0.76)	(−1.51)	(−0.76)
MOM	0.001	−0.002	0.004	−0.003	0.003	0.000
	(0.44)	(−0.71)	(1.37)	(−1.17)	(0.91)	(0.19)
ILLIQ	0.167***	−0.011	0.072	0.140*	0.036	0.154**
	(2.92)	(−0.12)	(0.85)	(1.66)	(1.26)	(2.22)
IVOL	0.016	−0.026	−0.008	0.012	0.026	−0.012
	(0.17)	(−0.40)	(−0.09)	(0.17)	(0.33)	(−0.13)
ASVI	0.004	0.008	0.004	−0.003	0.005	0.002
	(0.57)	(1.33)	(0.55)	(−0.60)	(0.84)	(0.46)
MAX	0.002	0.051**	−0.005	0.026	0.012	0.004
	(0.10)	(2.06)	(−0.19)	(1.15)	(0.48)	(0.16)
Intercept	0.841*	0.350	0.846	0.737	0.964*	0.687
	(1.71)	(0.67)	(1.62)	(1.24)	(1.84)	(1.13)
Obs.	117,454	106,022	95,495	127,981	96,875	126,601
Adj. R^2	0.144	0.188	0.153	0.164	0.191	0.144