Trading volume and liquidity provision in cryptocurrency markets*

Daniele Bianchi† Mykola Babiak‡ Alexander Dickerson§

Abstract

We provide empirical evidence within the context of cryptocurrency markets that the returns from liquidity provision, proxied by the returns of a short-term reversal strategy, are primarily concentrated in trading pairs with lower levels of market activity. Empirically, we focus on a moderately large cross section of cryptocurrency pairs traded against the U.S. Dollar from March 1, 2017 to March 1, 2022 on multiple centralised exchanges. Our findings suggest that expected returns from liquidity provision are amplified in smaller, more volatile, and less liquid cryptocurrency pairs, where fear of adverse selection might be higher. A panel regression analysis confirms that the interaction between lagged returns and trading volume contains significant predictive information about the dynamics of cryptocurrency returns. This is consistent with theories that highlight the roles of inventory risk and adverse selection for liquidity provision.

Keywords: Liquidity provision, short-term reversal, trading volume, empirical asset pricing, adverse selection.

JEL codes: G12, G17, E44, C58

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†School of Economics and Finance, Queen Mary University of London, Mile End Rd, London E1 4NS, UK. E-mail: d.bianchi@qmul.ac.uk Web: whitesphd.com

‡Department of Accounting and Finance, Lancaster University Management School, Lancaster. E-mail: m.babiak@lancaster.ac.uk Web: sites.google.com/site/mykolababiak

§Warwick Business School, University of Warwick, Scarman Road, Coventry CV4 7AL, UK. E-mail: a.dickerson@warwick.ac.uk

1 Introduction

Liquidity refers to the ability to trade an asset quickly without a large impact on its price. That is, liquid markets operate in settings where there is execution immediacy with minimal price impact. Due to their relatively low market capitalization, concentrated ownership structure, and a highly fragmented, multi-platform market structure, cryptocurrency markets are typically considered much less liquid than more traditional asset classes (see, e.g., Makarov and Schoar, 2021). However, there are only a handful of cryptocurrency exchanges that generate enough liquidity to function as reliable designated market makers. As a result, liquidity provision is often performed by large investors and algorithmic traders, which may sustain trading activity across different exchanges. The presence of extreme volatility, frequent crashes, and relatively low transparency in cryptocurrency markets could exacerbate cross sectional variation in risk and rewards from liquidity provision. This paper aims to examine this variation.

We assume that the extent to which liquidity provision is profitable can be proxied by the returns of short-term reversal strategies. Similar to more traditional asset classes, the pattern of buying and selling cryptocurrencies contrary to their most recent performance resembles market maker behavior (see, e.g., Nagel, 2012; Blitz et al., 2013; Da et al., 2014). This entails selling when the public is buying (when prices increase) and buying when the public is selling (when prices decrease), providing immediacy to less patient investors. The presence of inventory risks, financing constraints, and limited risk capacity imply that the provision of liquidity should be compensated by positive expected returns (see, e.g., Hendershott and Seasholes, 2007). Given the extreme cross-sectional variation in cryptocurrency returns, we extend a conventional short-term reversal strategy by further conditioning on the level of individual trading activity. Our idea is that compensation from liquidity provision is possibly a decreasing function of adverse selection between buyers and sellers; that is, specialists are more willing to supply liquidity for pairs in which inventory risk is relatively more manageable (see, e.g, Wang, 1994; Llorente et al., 2002; Easley and O'Hara, 2004).

Empirically, we study the interplay between the expected returns from liquidity provision and adverse selection by investigating the intersection between the returns from a short-term reversal strategy and de-trended trading volume on a daily basis. Our main objective is to estimate the extent to which the interaction between past returns and volume shocks can explain the risk-reward trade-off embedded in liquidity supply. We focus on a moderately large cross section of cryptocurrency pairs traded against the U.S. Dollar (USD) from March 1, 2017 to March 1, 2022. We aggregate market prices and trading volume across multiple centralized exchanges. This allows us to adopt a broad definition of what constitutes a *liquidity provider*, including automated liquidity provision algorithms, liquidity pools, algorithmic traders, large individual investors, miners, and other quantitative investors who play market making roles.

Cryptocurrency markets constitute a fascinating playground for examining the information content of trading volume and its relationship with returns from liquidity provision. The reasons are threefold. First, unlike traditional asset classes, there are only a handful of exchanges that generate large enough liquidity to act as market makers in a traditional sense. Yet, trading in cryptocurrencies is inherently plagued by opaque information, pervasive asymmetric information, and larger-than-usual trading frictions (see, e.g., Makarov and Schoar, 2020). Second, until recently, the lack of comprehensive regulatory oversight has prevented the inflow of capital from traditional institutional investors such as mutual and pension funds. As a result, the majority of trading volume is initiated by small- and large-scale retail investors, while participation from institutional investors and professional market makers is still relatively limited compared to activities in traditional asset classes (see, e.g., Dyhrberg et al., 2018; Bianchi and Babiak, 2022b). Third, an extremely high volatility of the returns is coupled with moderately low market activity. The interplay between high volatility and low aggregate liquidity can potentially exacerbate the fear of adverse selection compared to the same fear when dealing with more active asset classes and also impacts the cross-sectional and time-series variation in the risk-reward trade-off in liquidity provision.

1.1 Findings

Our main empirical results are fourfold. First, we show that the returns from liquidity provision, proxied by the returns from a short-term reversal strategy, are primarily concentrated in pairs with lower levels of trading activity as measured by de-trended trading volume. Specifically, a simple equal-weighted reversal strategy conditional on low trading volume generates a daily average return of 1.26% (p-value: 0.001) against an average of 0.54% (p-value: 0.002) when conditioned on high trading volume. Similarly, the performance from a value-weighted reversal strategy confirms that a larger premium is concentrated within low volume assets. Specifically, the average returns from a value-weighted reversal strategy conditional on low volume is 0.65% (p-value: 0.002) against -0.19% (p-value: 0.251) obtained by focusing on high volume pairs. The results are robust to using different windows to calculate the volume trend and to the inclusion of linear transaction costs. In addition, we show that returns from the reversal strategy conditional on low volume cannot be explained by exposures to sources of systematic risk, proxied by the returns on the market portfolio and long-short portfolios in which cryptocurrency pairs are sorted based on liquidity, volatility, past performance, or market capitalization (see, e.g., Liu et al., 2022; Bianchi and Babiak, 2022a).

Second, we provide empirical evidence that the returns from liquidity provision conditional on different levels of de-trended trading volume are predictable. Specifically, predictive regressions confirm that the correlation between the returns from liquidity provision and several proxies for liquidity supply, including idiosyncratic volatility, the aggregate bid-ask spread, and the Treasury-Eurodollar spread, is stronger when the level of trading activity is lower than average. This is confirmed for both equal- and value-weighted portfolio constructions and is consistent with the dynamics of portfolio returns with and without transaction costs. Such predictive correlations persist when the returns from the conditional reversal strategies are standardized by their conditional volatility. This effectively shows that the conditional Sharpe ratio from liquidity provision is concentrated in low volume cryptocurrency pairs and is also predictable with both traditional and cryptocurrency-specific proxies for liquidity supply.

Third, we delve deeper into the origins of the returns from a short-term reversal strategy conditional on low volume. We show that "lower quality" assets, which are smaller, less liquid, and more volatile, tend to offer higher reversal strategy returns, consistent with Avramov et al. (2006). In contrast, for larger, more liquid, and less volatile assets, the reversal strategy returns tend to be close to zero and are not statistically significant. This monotonic relationship is preserved for different levels of market activity, as proxied by de-trended trading volume. However, when we conduct a univariate portfolio sort on past returns alone, that is, when we examine the composition of portfolios sorted only on short-term reversal, the average characteristics no longer show a clear pattern. For instance, the relationship between volatility, market capitalization, and liquidity is no longer monotonic, but becomes U-shaped. This suggests that, by further conditioning on de-trended volume, one can more effectively isolate the risk premium of a short-term reversal strategy and the associated returns from liquidity provision.

Finally, a cross-sectional regression á la Fama and MacBeth (1973) provides evidence that the strength of the relationship between returns and the interaction of lagged returns and volume positively and significantly correlates with a series of proxies for information asymmetry including average liquidity, volatility, and market capitalization. Overall, these results seem to suggest that the returns from liquidity provision tend to be positively correlated with the intensity of adverse selection. This is consistent with theories of liquidity provision by financially constrained investors (see, e.g., Gromb and Vayanos, 2002 and Brunnermeier and Pedersen, 2008) and the role of information in affecting the cost of capital with investors demanding a higher return for stocks in which the fear of adverse selection could be higher (see, e.g., Wang, 1994; Llorente et al., 2002; Easley and O'Hara, 2004; Gorton and Metrick, 2009).

1.2 Related literature

This paper is connected to a growing literature that aims to understand the trade-off between risks and rewards within the context of cryptocurrency markets. A subset of the existing research seeks to understand the pricing performance of specific observable risk factors by sorting cryptocurrency pairs into portfolios based on a small set of characteristics including size, momentum, liquidity, and reversal. Examples can be found in Bianchi and Babiak (2022a), Liu et al. (2022), and Dobrynskaya (2021), among others. Our paper expands this literature by providing empirical evidence that negative liquidity supply and an associated increase in expected returns from liquidity provision represent a key component in the dynamics of cryptocurrency returns. More generally, this paper adds to recent literature that aims to understand the economics of cryptocurrency trading. Notable examples include Brandvold et al. (2015), Gandal et al. (2018), Makarov and Schoar (2020), Sockin and Xiong (2018), and Li et al. (2018). For instance, Sockin and Xiong (2018) provide a theoretical framework to assess the fundamental value of a cryptocurrency. They show that, when aggregate demand is unobservable, the trading price and volume of cryptocurrencies could theoretically serve as important channels for aggregating private information and facilitating coordination on equilibrium prices. Taking a different approach, we contribute to this literature by showing that there are significant cross-sectional differences in the information content of trading volumes for the dynamics of future returns. At a very general level, we believe that the results of this paper could be relevant to a broad audience, due to the inherent differences of cryptocurrencies compared to traditional asset classes, and their novel and emergent status as a form of investment. In particular, our findings could be interesting to market participants seeking different sources of returns and diversification, to regulators wishing to understand the risks embedded in cryptocurrency markets, and to academics searching for new insights into the market structure of digital assets.

2 Research design

2.1 Data

We collect OHLC prices and trading volume from CryptoCompare.com and the data on market capitalization from CoinGecko.com. We sample the data daily from March 1, 2017 to March 1, 2022, and define a day as starting at 00:00:00 UTC. Daily prices and volume are aggregated across more than 80 different centralised exchanges which CryptoCompare deems to be sufficiently reliable trading platforms.[1] The aggregation across different exchanges is volume-weighted, that is, prices and trading volume are aggregated based on the exchange-specific trading activity. Larger exchanges tend to have relatively more weight in the aggregation of the price and volume of a given pair than smaller exchanges. All cryptocurrency pairs in the sample use USD as the quote currency, that is, USD represents the "domestic" currency in the sample. We only retain cryptocurrency pairs if they have all available data from CryptoCompare and CoinGecko after we merge the data. We introduce a variety of filters in each

[1]The exchanges included in the aggregation are those that are ranked from AA to B by CryptoCompare. The precise ranking of all exchanges can be found on the company website at https://www.cryptocompare.com/exchanges//overview.

cryptocurrency pair to mitigate the effect of erratic trading activity. First, we exclude any pair that had zero traded volume or a zero price for any day t. Second, for each pair and day t we compute the ratio of traded volume to market capitalization of a particular cryptocurrency, and exclude any pair with a ratio greater than 1. This is a simple filter to screen out pairs with "erroneous" or "fake" volume. The measure is conservative, because the median of the ratio is 0.001. Third, we screen out (1) all cryptocurrencies that are backed by or track the price of gold, or any precious metal, (2) so-called "wrapped" coins, e.g., Wrapped Bitcoin (WBTC), (3) stablecoins, including those that are centralized (e.g., USDT, USDC) and algorithmically stabilized (DAI, UST) for all fiat currencies, and (4) coins that are actually derivatives. This screening is based on the classification provided by CoinMarketCap.com. Section A in the online appendix provides more detailed description of the additional filters implemented in the aggregation step by CryptoCompare to mitigate the impact of suspicious and fraudulent trading activity. We are left with an unbalanced panel of more than 300 cryptocurrency pairs after applying all filters.

The final panel of cryptocurrency pairs is used differently to construct the portfolios vis-á-vis to estimate the panel regressions. In our main portfolio analysis, for a given month, we select the top 100 most liquid cryptocurrency pairs based on the previous within-month mean of the Amihud (2002) ratio. This means that the assets employed in portfolio construction are dynamically adjusted to exclude the least liquid cryptocurrency pairs. For the panel regression analysis, instead, the selection of the top 100 most liquid assets does not change over time and is based on the sample average of the Amihud (2002) illiquidity measure. This facilitates the use of individual and time fixed effects in the dynamic panel regression. For both the portfolio allocation and the panel regression analysis, a cryptocurrency pair must have been traded for at least a year (365 trading days), although they do not necessarily have to be traded at the end of the sample. This excludes short-lived coins and mitigates potential survivorship biases. The fixed selection of the cross section implies that there are at most 100 individual cryptocurrencies that have been traded for at least 365 trading days. This should mitigate potential concerns of biases in the dynamic panel regression implementation (see, e.g., Nickell, 1981).

The top-left panel of Figure 1 suggests that our dynamically adjusted cross section is a good proxy for the entire market. Although we cap the size of the cross section to include the top 100 most liquid assets as per the Amihud (2002) measure, our sample is fairly representative of the total market size. The market capitalization of the cryptocurrency pairs selected on a given day (the solid red line) is fairly close to the total market capitalization (the blue dashed line), with the gap between the two lines being as close as a few billion dollars until early 2021. The dynamics of market capitalization also shows that, although the time period of our sample is limited, it is fairly representative of different market phases and situations. For instance, the sample includes the ICO mania of late 2017, the so-called 'crypto-winter' of 2018-2019, and the COVID-19 crash in March 2020, which resulted in a 40% loss in Bitcoin (BTC), and even greater losses in the altcoin market. In addition, our sample includes major regulatory and institutional changes, including the Chinese government ban on crypto exchanges, the introduction of tradable Bitcoin futures contracts on the Chicago Mercantile Exchange (CME) in December 2017, CME Ethereum contracts in February 2021, and the launch of the first traded Bitcoin Futures ETFs in October 2021.

As a result, the sample under investigation ensures there is enough time series variation covering major market phases and situations. This is important not only to draw more reliable conclusions about the functioning of the cryptocurrency market based on the statistical evidence, but also to assess its economic value in a portfolio strategy that covers a representative sample of the aggregate market dynamics. The top-right panel of Figure 1 shows the corresponding daily trading volume of the cryptocurrency pairs selected on a given day, expressed in millions of USD. As expected, there is a tight link, at least in levels, between the market value and aggregate trading activity. The dynamics of the trading volume shows a substantial variation over the sample period, with a clear spike in trading activity between the end of 2017 and the beginning of 2018, the COVID-19 crash, and the cascading liquidation crash of April 2021.

Our final sample includes a total of 179,023 pair-day return observations during the sample period of March 1, 2017 to March 1, 2022. Panel A of Table 1 reports the time-series average of the cross-sectional return distribution and additional characteristics. In addition to the daily returns and trading volume (in $mln), the table reports the cross-sectional distribution of the average market capitalization (in $mln), the realised volatility as calculated by Yang and Zhang (2000), and the Amihud (2002) ratio. The average daily return is 0.085%. The sample contains cryptocurrency pairs with a cross-sectional daily average trading volume of $37 mln and an average market capitalization of $5 billion. Interestingly, one can notice a few key features of the cross-sectional distribution of the time series averages. While volatilities are somewhat evenly distributed in the cross section, the returns, volume, market capitalization, and illiquidity measures are not. For instance, daily returns are positively skewed, as suggested by the mean returns, which are significantly higher than the median returns. This is possibly due to the dramatic increase in prices towards the end of 2017 (the ICO mania) and 2020 (the post COVID bull market). In addition, both trading volume and market capitalization are heavily skewed towards a handful of widely traded cryptocurrency pairs such as BTC, Ethereum (ETH), Cardano (ADA), among others. This is somewhat expected, given that these assets are more visible in the media and have relatively higher market capitalization. Similarly to volume and market capitalization, liquidity is also particularly skewed towards a handful of relatively more liquid assets.

This imbalance in the cross-sectional distribution of trading activity is quite visible in the bottom-right panel of Figure 1. The figure shows the Lorenz curve, a visual representation of the Gini concentration index, for the average daily raw trading volume for the cryptocurrency pairs used to construct the conditional reversal strategies. The top 10% of assets correspond to roughly 90% of trading volume; that is, the bottom 90% of cryptocurrencies in our sample effectively represent only 10% of the trading activity in the cross section. Further, this maps into the concentration of the market capitalization as shown in the bottom-left panel of Figure 1. The market capitalization for the same set of cryptocurrency pairs is perhaps even more concentrated, with a Gini index of 0.96 against 0.91 for the trading volume. This suggests that trading activity in cryptocurrency markets is far from being perfectly even across pairs, as perfect equality would correspond to the Lorenz curve having a 45-degree slope. Interestingly, the most traded pairs in our sample prove to have the highest volume volatility, as shown by the unconditional standard deviation of traded volumes in Table 1. In the next section, we exploit this substantial heterogeneity in trading volume and returns to investigate the cross-sectional and time-series dynamics of expected returns from liquidity provision.

2.2 Empirical implementation

Trading volume. Empirical implementation of the conditional reversal strategies is based on a de-trended version of trading volume. We build on existing research and define a volume shock as the log deviation of trading volume from its trend, estimated over a rolling period for a cryptocurrency pair i at time t (see, e.g., Campbell et al., 1993, Llorente et al., 2002, Cespa et al., 2021):

$$v_{i,t} = log(\text{Volume}_{i,t}) - log\left(\frac{\sum_{s=1}^{m} \text{Volume}_{i,t-s}}{m}\right), \tag{1}$$

where m is the number of periods we use to estimate each volume shock. The transformation in Eq.(1) ensures stationarity and measures trading volume relative to the market capacity for each cryptocurrency pair i. Table 1 and Figure 1 show that trading volume is strongly concentrated within the top pairs. This concentration may skew the results towards the least traded pairs. Indeed, very high volume pairs possibly never appear in the low volume sub-portfolio because their trading activity is much higher (in levels) relative to the other pairs for each time t. To mitigate this issue, we standardise $v_{i,t}$ in Eq.(1) by the log standard deviation computed over the same rolling window of the size m. In this case, we treat each cryptocurrency pair equally when we determine whether it has experienced a positive or a negative volume change compared to the trend. Two comments are in order. First, in the main empirical analysis we refer to "volume" as the volume shock $v_{i,t}$ instead of the raw trading volume expressed in \$ mln, unless specified otherwise. Second, in the main empirical analysis, the trailing period is assumed to be $m = 30$ days. Section B in the online appendix replicates the set of main results for a trailing period with $m = 60$ days. The empirical evidence is qualitatively the same.

Portfolio construction. Most of our empirical analysis employs both single- and double-sorted strategies based on (de-trended) volume, lagged returns, and a combination of the two quantities. It is not obvious what the optimal horizon would be for such investment strategies. The relatively recent history that characterizes cryptocurrency markets limits the usefulness of using monthly returns. As highlighted by Nagel (2012), data at a daily frequency may be the most suitable choice to capture much of the effect of imperfect liquidity provision. Thus, our approach is to construct the weights of the short-term reversal strategy at time t based only on returns at time $t-1$. One comment is in order. Adding lags beyond the first could mitigate the effect of continuation of the returns and delayed reversal. In this respect, by considering only the returns of the prior day, we believe our approach represents a conservative estimate of the returns to liquidity provision.

For the univariate portfolio sort, we follow the existing literature (see, e.g., Jegadeesh, 1990, Lehmann, 1990, Lo and MacKinlay, 1990, and Jegadeesh and Titman, 1995) and sort cryptocurrency pairs at each day t based on lagged values of a given characteristic, such as the standardized volume or previous-day return. For each sort, we form a total of 10 sub-portfolios (deciles) based on the information available at time t. For instance, we measure the returns from liquidity provision as the returns at time $t + 1$ of a long-short strategy that initiates at time t a long position in low return pairs and a short position in high return pairs, where we calculate the returns at $t - 1$. For the double-sorted strategies, the cryptocurrency pairs are first allocated at time t into $n = 3$ groups from low to high based on their return at time $t - 1$. Then, each pair is further allocated into $p = 3$ sub-groups from low to high based on standardized volume at time t (contemporaneous to the lagged return). This yields 3×3 sub-portfolios, which are rebalanced each day. For the single- and double-sorted strategies, we construct the equal- and value-weighted portfolios by using the market capitalization of each pair at time t.

Transaction costs. If a short-term reversal strategy is calculated based on end-of-day transaction prices, its returns summarize the returns of a hypothetical representative liquidity provider whose limit orders are always executed at the closing transaction price without fees or slippage. While the goal of this paper is not to provide a recipe for a real-time trading strategy, it is instructive to investigate to the extent to which the long-short portfolio returns would survive very simplistic transaction costs. However, obtaining aggregated data on a large cross section of cryptocurrency spreads and daily slippage rates with data extending back to 2017 is a challenging task. In addition, market-making fees are different across exchanges.

Order making fees are zero for the cheapest exchanges, such as *CoinbasePro*, *itBit* and *Luno*, and increase to 0.43% for more expensive exchanges such as *BitBay*. For this reason, we apply a fixed cost of 30 (40) basis points for the long (short) side of the strategy to approximate trading frictions in liquidity provision. Given the average trading fees on major exchanges, our approximation somewhat represents a set of fairly conservative transaction costs for a market maker.

Common factors in cryptocurrency returns. The standard short-term reversal and conditional reversal strategy based on past volume has a rather mechanical exposure to sources of systematic risk and common factors. For example, consider a pure reversal strategy that buys (sells) assets with negative (positive) returns on day $t-1$. If the market index increased in value the same day, this simple strategy tends to be long on low-beta assets and short on high-beta assets. This yields a negative and possibly significant exposure to aggregate market risk. Similarly, the returns of the strategies can be exposed to other risk factors. For this reason, we also investigate risk-adjusted returns from liquidity provision. We consider five risk factors: the aggregate market (`mkt`) and long-short portfolios formed on the Amihud (2002) ratio (`illiq`), the Yang and Zhang (2000) volatility estimate (`rvol`), market capitalization (`size`) and the three-week momentum (`mom`) as in Liu et al. (2022). Except for the market portfolio and the three-week momentum strategy, which has a one-day holding period, other risk factors are obtained from decile portfolios sorted on the relevant characteristic observed at time $t-1$.

3 Short-term reversal strategy returns

Panel A of Table 2 reports a set of summary statistics of the short-term reversal strategy returns. The top (bottom) sub-panel reports the results for the equal-weighted (value-weighted) decile portfolios and the long-short strategy. When we compare the results, we find substantially lower returns on the strategy when a value-weighed scheme is considered. The average gross daily return on the equal-weighted short-term reversal is as high as 2.2% daily (p-value: 0.000), while it falls to only 0.6% (p-value: 0.001) when assets in the portfolios are weighted based on their market capitalization (see Section 2.2). In risk-adjusted terms, returns are also lower for the value-weighting scheme. The Sharpe ratio for the equal-weighted portfolio is 0.37, whereas for the value-weighted portfolio, it is as low as 0.06, daily. The discrepancy between the performance of the equal-weighted and value-weighted implementation reflects the fact that the unconditional returns on liquidity provision are possibly due to smaller cryptocurrency pairs.

Panel B of Table 2 reports summary statistics for the decile portfolios sorted on (de-trended) volume. The table reports the results for ten sub-portfolios (deciles) formed from low volume to high volume pairs. For the equal-weighted and the value-weighted deciles, the sub-portfolio return pattern is not monotonic. In fact, only the sub-portfolio with the highest trading activity compared to the recent trend shows a negative and significant return. Nevertheless, the performance of the low-minus-high de-trended volume portfolio yields average portfolio returns that are statistically different from zero only for the equal-weighted portfolio composition. When a value-weighted scheme is used, neither the sub-portfolios nor the long-short strategy deliver significant returns. In fact, the latter generates a mildly negative Sharpe ratio. This provides evidence against the idea that high volume assets pay higher returns (see, e.g., Gervais et al., 2001, Kaniel et al., 2012, Wang, 2020). Panel B of Table 2 shows that lower trading activity might be linked to cryptocurrencies that exhibit lower liquidity and smaller market capitalization. This is confirmed by the value-weighted portfolio sorts in which the returns of low de-trended volume sub-portfolio (Q1) are significantly lower (and negative) relative to those of the equal-weighted sub-portfolio (Q1). Overall, Table 2 provides evidence of a significant short-term reversal, whilst a low volume premium is only captured by an equal-weighted scheme. This suggests that a significant fraction of the compensation for liquidity provision may be concentrated in relatively small cryptocurrencies.

3.1 A conditional reversal strategy

Table 2 shows that a standard reversal strategy delivers positive and significant returns. On the other hand, the information content of de-trended volume does not seem to have strong economic significance, especially within the context of a value-weighted portfolio composition. We now combine the information content of short-term reversal and deviations from the volume trend, and construct a double-sorted strategy based on lagged returns and lagged de-trended volume (see Section 2.2 for a detailed description). Our underlying hypothesis is that the returns from liquidity provision could be concentrated in less liquid assets, where fears of adverse selection and inventory risk could be higher. This is in line with the existing research on the impact of adverse selection on asset prices. For instance, Wang (1994) and Llorente et al. (2002) show that the strength of future return reversals can be predicted by the interaction between past volume and returns. Similarly, Easley and O'Hara (2004) and Hendershott and Seasholes (2007) show that inventory risk and adverse selection are primarily concentrated in "low-quality" assets, meaning smaller, less liquid, and more volatile stocks. We now exploit these theoretical underpinnings and show the cross-sectional variation of the returns from liquidity provision for different levels of trading volume.

Table 3 presents our results. The evidence shows that the returns from liquidity provision are primarily concentrated in pairs with lower trading volume. A simple equal-weighted reversal strategy conditional on low volume delivers a 1.22% (p-value: 0.002) average daily return against a 0.54% (p-value: 0.003) daily average return when we condition on high volume pairs. Higher average returns are not obtained at the expense of higher volatility; the Sharpe ratio of the reversal low volume strategy is twice as large as the Sharpe ratio produced by reversal strategy conditional on high volume. The results for the value-weighted portfolio composition provide stronger evidence of the interplay between reversal and trading volume. There is a profitable reversal, i.e., 0.6% daily return (p-value: 0.001), in the return dynamics, conditional on low levels of abnormal market activity even when we weight assets by their market capitalization. Instead, when the level of trading activity is higher, a reversal strategy does not generate any level of significant performance, i.e., -0.18% (p-value: 0.543).

Figure 2 shows the cumulative log returns for three conditional reversal strategies. We compare the cumulative performance of all strategies with a simple buy-and-hold return on BTC. The left panel shows the returns for the equal-weighted portfolios, while the right panel shows the returns for the value-weighted portfolio composition. Two facts emerge. First, the performance of the equal-weighted conditional reversal strategy flattens after early 2021, but does not deteriorate and remains largely above the cumulative returns of BTC/USD throughout the sample. This shows that the performance is not significantly affected by the substantial market volatility that occurred from early 2021 (see Figure 1). Second, a value-weighted conditional reversal strategy performs substantially weaker than its equal-weighted counterpart, consistent with the results in Table 3. This finding implies that a substantial fraction of the returns from the long-short portfolio is driven by small-cap pairs. Nevertheless, when looking at the short-term reversal conditional on low trading volume, the performance of the portfolio is still stronger than for a buy-and-hold return in BTC/USD. In fact, cumulative log returns from liquidity provision in low volume assets is still almost four times higher than those for BTC/USD. In sum, the results in Table 3 and Figure 2 indicate that, to the extent that the returns from a short-term reversal strategy proxy the returns from liquidity provision, expected returns for providing liquidity tend to be concentrated in low volume pairs. This is consistent with existing studies linking liquidity provision and asset prices (see, e.g., Lehmann, 1990; Wang, 1994; Llorente et al., 2002; Easley and O'Hara, 2004; Hendershott and Seasholes, 2007).

Table 4 provides a further breakdown of the characteristics of the average cryptocurrency in each of the 3×3 sub-portfolios of digital assets sorted by lagged returns and de-trended volume, as in Eq.(1). The table reports the statistics of the raw trading volume (`volume`), the realised volatility (`rvol`), the market capitalization (`size`), and the Amihud (2002) ratio (`illiq`). Further, for each asset, we calculate two alternative bid-ask spread measures. The first measure is the bid-ask spread approximation proposed by Corwin and Schultz (2012) (`bid-ask cs`). We compute this based on the daily high and low prices. Intuitively, the highest price observed on a trading day typically results from a transaction at the ask price and the lowest price from a transaction at the bid price. The second measure of liquidity is the bid-ask spread approximation proposed by Abdi and Ranaldo (2017) (`bid-ask ar`), which is also based on daily high and low prices.

A few interesting patterns emerge. First, the average values of `illiq` is higher for those assets with trading activity below the short-term trend, independently of the magnitude of lagged returns. For instance, within the context of low-return assets, the `illiq` measure is equal to 0.36 for low volume and 0.24 for high volume assets. Although this seems quite intuitive, there should be no reason a priori that low values of de-trended volume should correspond to lower liquidity. The average values of `volume` seem to confirm this intuition. De-trended volume is in fact highly correlated with the level of trading activity in a given asset. Both the level of realised volatility and market capitalization seem to be correlated with liquidity across sub-portfolios, that is, the average `rvol` (`size`) is higher (lower) for those assets with lower trading activity. The pattern is much less clear when we look at both approximations of the bid-ask spread. The difference between the average spreads is rather small, perhaps with the single exception of the `bid-ask ar` for the high-returns sub-portfolios. Overall, our empirical results clearly support the intuition that "lower-quality" assets – smaller, less liquid, and more volatile – generally offer higher reversal strategy returns, consistent with Avramov et al. (2006).

Transaction costs and risk-adjusted returns. The empirical evidence in Tables 3 and 4 suggests that the expected returns from liquidity provision seem to be concentrated in cryptocurrency pairs with lower market activity. Those pairs tend to be smaller, less liquid, and more volatile. In this section, we investigate the extent to which portfolio returns would survive transaction costs. Because aggregate proxies of fees and slippage costs across exchanges are hard to obtain, we approximate trading frictions from liquidity provision by applying a conservative fixed cost of 30 (40) basis points for the long (short) side of the long-short strategy. This is a conservative value, considering that market making fees are very low, if not zero, on major centralised exchanges.

Table 5 reports the fee-adjusted portfolio returns for both the single-sorted long-short strategies based on short-term reversal and de-trended volume, and for the double-sorted strategies. The first five columns report the results for the equal-weighted portfolio compositions. The returns of the standard short-term reversal strategy decrease slightly, but remain positive and significant, with an average daily return of 1.68% (p-value= 0.001). Meanwhile, the returns of the equal-weighted long-short strategy formed on de-trended volume are not different from zero after we account for transaction costs. The net-of-fees returns of the reversal strategy conditional on low volume (`lvr`) confirm that expected returns from liquidity provision tend to be more concentrated in digital assets with lower trading activity. For the value-weighted sorts, none of the strategies generate positive and statistically significant returns. In fact, the average return of the single-sorted strategy based on volume becomes negative and statistically significant. The same holds for returns on the double-sorted long-short portfolios formed on lagged returns conditional on medium (`mvr`) or high (`hvr`) volume.

Our main empirical results suggest that the returns from liquidity provision could have a mechanical exposure to sources of systematic risk and common factors. For instance, smaller, more volatile, and less liquid assets tend to be concentrated in low volume sub-portfolios. For this reason, we explore the significance of the returns of the conditional reversal strategies when we control for a variety of proxies for sources of systematic risk. Section 2.2 offers a detailed description of the risk factors. Table 6 presents the alphas (in decimal form) estimated from gross or net returns of the conditional volume reversal strategies that ignore or include transaction costs. The first and last four columns report the results for the equal- and value-weighted portfolios, respectively.

Focusing on the equal-weighted portfolios, the market beta is small, but it indicates a positive and significant correlation between the strategy returns and the aggregate market portfolio. Similarly, there is a positive and significant relationship between the strategy returns with volatility risk, proxied by the long-short portfolio returns sorted on volatility (`vol`). Interestingly, none of the liquidity (`illiq`), momentum (`mom`), or size (`size`) factors is significantly correlated with the equal-weighted conditional reversal returns. This result holds for the strategy returns with and without transaction fees. The estimated alphas of gross returns of the value-weighted portfolio are half those of the equal-weighted strategy, however, they remain positive and significant. When we account for transaction costs, the alphas drastically decrease and are no longer statistically significant. The positive and significant correlation with the market portfolio suggests that the average returns may be absorbed by trading frictions and other costs. Overall, despite the significant betas on the `mkt` and `vol` factors, the adjusted R^2 is quite low for all factor models. This implies that the risk factors we consider do not fully explain the returns of the conditional reversal strategy.

Implementation on individual exchanges. A drawback of using aggregated prices and volumes from different exchanges is that the returns from liquidity provision are not necessarily reflective of an actual, implementable trading strategy. For instance, Makarov and Schoar (2020) show substantial frictions and costs that are incurred when trading across different exchanges and jurisdictions, which significantly mitigate investment returns and arbitrage opportunities. In this section, we address this issue by replicating the conditional reversal strategy for a variety of individual centralised exchanges including *Poloniex*, *HitBTC*, *GateIO*, *BitTrex*, and *Binance*. These exchanges rank among the largest in terms of both reputation and average trading volume, according to CryptoCompare.com.

We deviate from the main portfolio implementation in two directions to make the strategy more realistic in practice. First, we assume that the base currency is Tether USD (USDT) instead of the U.S. dollar. This is because a non trivial fraction of the assets used in the core empirical analysis are traded against USDT and not USD on some exchanges we consider. Because USDT is a stablecoin pegged 1:1 to the USD, using the pairs traded against USDT seems to be a minor change. Second, the size of the cross section on individual exchanges differs slightly from the number of cryptocurrencies used in our main analysis based on the aggregation of multiple exchanges. In particular, the number of pairs traded against the USDT was small until early 2018 and, hence, the sample now starts from January 1st 2018 for *Poloniex*, *HitBTC* and *GateIO* and from October 2018 for *BitTrex* and *Binance*. As with our main empirical results, the end of the sample is March 1, 2022 across all exchanges.

Table 7 reports summary statistics of gross and net returns of the conditional reversal strategy implemented on the individual exchanges. So far as the equal-weighted portfolios are concerned, the gross returns from liquidity provision are largely consistent with those from our main empirical analysis. For instance, the average gross returns of the reversal strategy conditional on low volume are positive and significant across all exchanges we consider, although they are significantly smaller for the *Binance* exchange. When transaction fees are omitted, the strategy performance becomes significantly weaker, especially for the *Binance* exchange predicting the negative average returns of the strategy. Similarly to aggregate results, an equal-weighted composition, which tends to overweight smaller assets, delivers higher returns than the value-weighted implementation.

In sum, the results for individual exchanges reported in Table 7 largely confirm substantial cross-sectional variation in the returns from liquidity provision: assuming the returns of a short-term reversal strategy proxy the returns from liquidity provision, the strategy expected returns tend to be concentrated in low volume pairs.

4 Dissecting the reversal strategy returns

Table 3 reports summary statistics of the returns from liquidity provision conditional on different levels of (de-trended) volume. Focusing on the long-short portfolios, the reversal strategy conditional on low trading activity generates the largest average returns, while the volatility remains comparable between the strategies with different volumes. This leads to higher Sharpe ratios for the conditional reversal strategy with low volume. This observation holds for equal- and value-weighted portfolio implementations. Thus, it is possible that the dynamics of the returns from liquidity provision, proxied by the returns of the short-term reversal strategy, are driven by this interplay between past returns and volume. Table 6 shows that there is a mild exposure of conditional reversal strategies to the aggregate market trend. This suggests that market risk does not necessarily play an economically large role in the expected returns from liquidity provision. In this section, we delve deeper into the nature of the risk-volume relationship and its implications for the raw and risk-adjusted returns from liquidity provision.

4.1 Predicting returns from liquidity provision

We focus on the time-series variation in returns from liquidity provision. We examine the role of a variety of "state variables" capturing aggregate and market-specific conditions in predicting the returns of the conditional reversal strategy. We estimate a number of predictive regressions of the form $y_t = a + bz_{t-1} + cr_{m,t-1} + \epsilon_t$ where y_t is the return of the short-term reversal strategy conditional on low (`lvr`), mid (`mvr`), or high (`hvr`) volume. Motivated by Hameed et al. (2010), we include the lagged returns of the value-weighted market portfolio $r_{m,t-1}$ into the regression to capture the dependence of the reversal strategy on past market performance. Our main goal is to investigate the predictive content of a state variable z_{t-1}. We study three state variables. These include: (1) the level of idiosyncratic volatility (`ivol`) – measured as the cross-sectional standard deviation of individual cryptocurrency returns during the previous day – as a proxy for the level of risk faced by imperfectly diversified liquidity providers, (2) the TED spread (`ted`) – measured as the three-month Eurodollar deposit rate minus the three-month T-bill rate – as a proxy for funding costs of financial intermediaries, and (3) the average between the Abdi and Ranaldo (2017) and Corwin and Schultz (2012) synthetic bid-ask spread (`bid-ask`), as a measure of tightening trading constraints.[2]

Table 8 reports the results of the predictive regressions in which the dependent variable is the short-term reversal strategy or conditional reversal portfolios based on low `lvr` or high `hvr` volume. Panel A shows that `ivol` does indeed capture some of the predictable variation of the returns from liquidity provision. Intuitively, high idiosyncratic volatility should be associated with lower liquidity supply and, therefore, higher expected returns from liquidity provision, which is consistent with the results of all model specifications in Panel A. Focusing on the equal-weighted conditional reversal strategies, the impact of idiosyncratic volatility on expected returns are decreasing in the magnitude of de-trended volume. For instance, the coefficient on `ivol` is almost twice as large for `lvr` as it is for `hvr`. The corresponding adjusted R^2 for the `lvr` portfolio is almost twice as large as that of the `hvr` portfolio. Consistent with the performance of equal- and value-weighted portfolios reported in Section 3.1, the predictive power of `ivol` weakens for the value-weighted strategies. Panels B and C in Table 8 replace idiosyncratic volatility with the bid-ask `bid-ask` and TED `ted` spreads. High `bid-ask` and `ted` spreads are associated with lower liquidity supply and therefore should predict higher expected returns from liquidity provision. Panels B and C support this view, particularly for the equal-weighted portfolio returns. Interestingly, the significance of the coefficients of `bid-ask` and

[2] Section B in the online appendix reports a set of additional results using the VIX index and the realised market returns variance as alternative state variables.

`ted` are primarily concentrated in the `lvr` strategy. These results lead to the conclusion that the reversal returns are in part driven by liquidity supply factors and such predictability is primarily concentrated in cryptocurrency pairs with a relatively lower level of trading activity.

Table 3 shows that the volatility of short-term reversal strategies is generally low compared to their mean returns, yielding high unconditional Sharpe ratios. Nevertheless, the extreme volatility that characterizes cryptocurrency markets could also produce bursts of extremely low compensation for risk. To illustrate the time variation in the magnitude of the expected returns from liquidity provision, Figure 3 plots the fitted values from the regressions in Table 8 for the short-term reversal strategy conditional on low volume. The plots clearly show a significant time variation in expected returns from liquidity provision with a common trend depending on the predictors used. For instance, the expected returns implied by `ted` and `bid-ask` surged during the beginning of the COVID-19 pandemic. While aggregate financing conditions remained fairly stable throughout 2021, the average market liquidity in cryptocurrencies deteriorated in early 2021, as indicated by higher expected returns based on `bid-ask`. The plots also show a clear separation between cryptocurrency-specific measures (`ivol` and `bid-ask`) and aggregate financing conditions (`ted`). The highest expected returns from liquidity provision are actually concentrated around the buildup and burst of the so-called ICO bubble around the end of 2017 and the beginning of 2018.

The significant time variation in expected returns of the conditional reversal strategy suggests that, in order to obtain a clearer interpretation of the predictability of the returns from liquidity provision, it would be instructive to know whether a rise in expected returns with `ivol`, `bid-ask` and `ted` is commensurate with a rise in conditional volatility. To answer this question, we investigate the extent to which the conditional Sharpe ratio of the conditional reversal strategies varies with the measures of liquidity supply. For each predictive regression, the expected compensation for unit of risk is calculated as $y_t^* = y_t/\sigma_t$, where y_t denotes the original returns of a given strategy, and σ_t is the conditional volatility estimated from an asymmetric GARCH(1,1) model as in Glosten and Milgrom (1985).

Table 9 presents the predictive regression results in which the dependent variable is the conditional Sharpe ratio. It shows that `ivol`, `bid-ask`, and `ted` still have strong explanatory power after scaling the returns with the reciprocal of their conditional volatility. The point estimates of the reversal strategy conditional on low volume are larger than those that are conditional on high volume. This is true for equal- and value-weighted portfolios. Similarly to Table 8, the results for the value-weighted portfolios are less significant in statistical terms. The fact that the compensation from liquidity provision for a unit of risk increases as a function of supply changes indicates that additional impediments to liquidity provision, such as market-wide funding constraints, may play a relevant role (see, e.g., Gromb and Vayanos, 2002 and Brunnermeier and Pedersen, 2008). For instance, Grossman and Miller (1988) suggest that a rise in the conditional Sharpe ratio from liquidity provision could be the result of higher participation costs or of higher risk aversion in times of lower liquidity supply. Table 9 supports this view, particularly for cryptocurrency pairs with a relatively low level of trading activity.

4.2 Returns, volume and proxies for adverse selection

The main empirical results reported in Tables 3-7 suggest that, to the extent that the returns from a short-term reversal strategy proxies for the returns from liquidity provision, expected returns for providing liquidity tend to be concentrated within low volume pairs. Table 4 expands this result and shows that these pairs tend to coincide with "lower-quality" cryptocurrencies, which are smaller, less liquid, and more volatile. Intuitively, these are pairs for which the ability of investors to trade without fear of adverse selection might be lower (see, e.g., Gorton and Metrick, 2009). To more formally test the relationship between portfolio returns and adverse selection, we adopt a two-step approach in the spirit of Wang (1994) and Llorente et al. (2002). In the first step, we estimate the predictive content of the interaction between lagged returns and (de-trended) volume on future returns by implementing a fixed-effects panel regression to test (1) whether past volume itself has any in-sample correlation with future returns and, (2) whether the interaction between past volumes and lagged returns contains predictive information about future cryptocurrency returns. The baseline regression model is specified as follows,

$$y_{i,t+1} = \alpha_i + \tau_t + \beta_1 y_{i,t} + \beta_2 v_{i,t} + \beta_3 \left(y_{i,t} \times v_{i,t}\right) + \boldsymbol{\gamma}' \boldsymbol{x}_{i,t} + \epsilon_{i,t+1}, \tag{2}$$

where η_i and τ_t are the cryptocurrency pair and time effects, and $y_{i,t}$ and $v_{i,t}$ are the log returns and volume shock as in Eq.(1), calculated for each pair i at time t. The vector of control variables $\boldsymbol{x}_{i,t}$ contains a set of additional predictors; these include the aggregate returns on the cryptocurrency market portfolio, the Amihud (2002) ratio, the average bid-ask spread obtained from Corwin and Schultz (2012) and Abdi and Ranaldo (2017), and the realised volatility of returns computed according to Yang and Zhang (2000).

Panel A of Table 10 reports the estimates produced by Eq.(2).[3] For ease of exposition, we report the results for $m = 30$ days of a rolling window when we calculate the de-trended volume from Eq.(1). The results for an $m = 60$ rolling window are qualitatively similar and are reported in Section B. A few interesting facts emerge. First, there is substantial evidence of short-term reversal; that is, returns on cryptocurrency pairs are negatively autocorrelated on a daily basis. This negative autocorrelation holds regardless of whether a pair- and a time-fixed effect are included. The evidence on the lagged value of volume shock is somewhat mixed.

[3] Robust standard errors are reported in parenthesis and calculated by double clustering for pairs and time to account for both cross-sectional and autocorrelation in the residuals (see, e.g., Thompson, 2011 and Cameron et al., 2011).

When a time fixed effect is not included, there seems to be a positive and significant correlation between lagged volume shocks and current returns. This is consistent with the prediction in Llorente et al. (2002) and Gervais et al. (2001). On the other hand, when a time fixed effect is included, the correlation between volume shocks and current returns remain positive but weakly significant (at the 10% level).

Turning to the interaction terms β_3, there is strong evidence of a positive and significant correlation between the interaction between past returns and volume shocks with current returns. This result is consistent with existing theoretical predictions, such as Miller (1977), Merton (1987), Wang (1994) and Llorente et al. (2002), outlined for more traditional markets. For instance, Miller (1977) observes that, in theory, high volume does not necessarily indicate that the stock price will rise (the volume could have been caused by selling), and that heavy volume alone should not be seen as a signal to increase buying activity. Volume does, however, induce more people to investigate the asset, which, in the presence of short sale constraints, will result in increased buying pressure driving up future prices. In a similar vein, Merton (1987) developed a general equilibrium model in which positive shocks to investor interest are shown to increase the price of a stock.

Our estimates of the interaction term in Table 10 suggest that the interplay between past de-trended volume and returns may have some correlation with future returns. We test the relationship between this interaction and proxies for adverse selection based on a Fama and MacBeth (1973)-style cross-sectional regression of the form,

$$\widehat{\beta}_{3,i,t} = \lambda_0 + \lambda_1 \text{Adv. Selection}_{i,t} + \epsilon_{i,t}. \tag{3}$$

where $\widehat{\beta}_{3,i,t}$ is the interaction term of lagged returns and volume shocks recursively estimated using the past 30-days for each cryptocurrency pair $i = 1, \ldots, n$ in our sample, and Adv. $\text{Selection}_{i,t}$ an observable proxy for latent adverse selection. The assumption is that the interaction term $\widehat{\beta}_{3,i,t}$ may possibly capture the degree of adverse selection.[4] This is consistent with theories of asymmetric information in asset pricing. For instance, Easley and O'Hara (2004) shows that the interplay between trading volume and returns reflects adverse selection costs for which investors command a premium. By looking at the estimates $\widehat{\lambda}_1$ we can formally test this assumption. We follow Llorente et al. (2002) and use measures of liquidity and volatility to proxy for information asymmetry and adverse selection costs. In addition to the Amihud (2002) measure (`illiq`), the Corwin and Schultz (2012) bid-ask spread (`bid-ask cs`),the Abdi and Ranaldo (2017) bid-ask spread (`bid-ask ar`), we consider both the return volatility estimate based on Yang and Zhang (2000) (`rvol`) ands the log of market capitalization (`size`).

[4]Notice that the scope of this regression is not to isolate risk premiums related to the interaction terms, but rather to infer the correlation between observable proxies of adverse selection and information asymmetry and the interacting effect of returns and volume.

We standardize each measure to have a zero mean and unit standard deviation to enable comparability across the regression coefficients. One comment is in order. Return volatility is not often used to proxy for the presence of information asymmetry; in fact, the volatility of the dividend component of the returns process on which investors may have private information is a more natural measure. However, unlike other asset classes, most cryptocurrencies do not pay dividends, meaning that returns are primarily, if not exclusively, driven by shocks to discount rates. As a result, unconditional risk is primarily given by uncertainty in future price changes resulting from increasing or decreasing adoption.

Panel B of Table 10 reports the slope coefficients estimated in Eq.(3). The results indicate that, on average, lower liquidity corresponds to a larger beta on the interaction term between returns and volume. Assuming lower liquidity proxies for higher adverse selection and costs of asymmetric information, results are consistent with those of Wang (1994), Llorente et al. (2002), and Easley and O'Hara (2004): the interaction between returns and past volume ultimately captures the effect of adverse selection on future returns. A similar finding is shown for the volatility of returns; higher return volatility, which is associated with higher levels of information asymmetry, corresponds to higher interaction between returns and volume shocks, on average. In the multivariate model in which we consider all measures jointly, the price impact measure is subsumed by `bid-ask ar`, `rvol`, and `size`. This suggests that smaller cryptocurrencies with relatively higher levels of volatility are prone to higher levels of adverse selection. Overall, the results in Table 10 expand Proposition 3 in Llorente et al. (2002) to the cross-section of the returns from liquidity provision: conditional on heightened levels of adverse selection, noise trades cause larger price changes, which leads to higher returns from liquidity provision.

5 Conclusion

We provide empirical evidence within the context of cryptocurrency markets that the returns of a short-term reversal strategy are primarily concentrated within smaller, less liquid and more volatile assets. To the extent that the returns of the short-term reversal strategy proxy for the returns from liquidity provision, our results suggest that the expected returns earned by market makers tend to be higher when fears of adverse selection on either side of the transaction are higher. For instance, when the liquidity supply is low, as indicated by higher idiosyncratic volatility and wider TED and bid-ask spreads, the expected returns from reversal strategies tend to be higher. We further show that the strength of the interaction between past returns and volume and its role in forecasting future cryptocurrency returns is directly linked to the level of adverse selection costs. These findings support our motivation for considering the conditional reversal strategy, and suggest that the expected returns and risk premiums required by liquidity providers are concentrated within "lower quality" assets. Thus, at least part of the reason market liquidity tends to evaporate during periods of high volatility seems to be related to the increasing risk premiums required to supply liquidity. This observation is more pronounced for those assets with lower levels of market activity relative to the average cryptocurrency against the U.S Dollar. Due to institutional differences, we view this paper as an out-of-sample test of existing theories on the asset pricing implications of limited risk capacity, liquidity constraints, and adverse selection developed in more traditional financial markets.

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Table 1: **Descriptive statistics**

This table reports a set of descriptive statistics for the sample of cryptocurrency pairs used for the single- and double-sorting strategies. Each month we select the top 100 most liquid cryptocurrency pairs based on the lagged within-month mean of the Amihud (2002) ratio. The table reports the time-series average of the cross-sectional distribution of the returns, raw trading volume (in \$mln), market capitalization (in \$mln), realised volatility, and the Amihud (2002) ratio. The sample period is from March 1, 2017 to March 1, 2022.

					Percentiles					
	Obs.	Mean	Median	SD	1	5	25	75	95	99
Return (%)	179,023	0.085	-0.611	6.889	-13.800	-7.694	-3.012	2.314	10.249	20.184
Volume (\$mln)	179,023	37.474	6.180	125.445	0.464	0.870	2.390	19.449	136.952	592.275
Market Cap (\$mln)	179,023	5435.12	297.46	32698.43	13.66	22.56	74.41	1104.44	9877.81	102657.81
Volatility (%)	179,023	11.232	8.849	11.217	3.910	5.044	7.057	11.64	22.017	50.146
Amihud	179,023	0.192	0.019	0.473	0.000	0.000	0.004	0.084	1.32	1.746

Table 2: **Single-sorted portfolio strategies**

This table reports a set of descriptive statistics for the daily returns of the univariate portfolio sorts. We report the mean (%), the standard deviation (%), the Sharpe ratio, and the skewness of the returns. Panel A reports the returns of the decile and long-short portfolios formed on past returns. Panel B reports the returns of decile and long-short portfolios formed on de-trended volume, as in Eq.(1). The upper and lower sections of each panel report the results for equal- and value-weighted portfolios. The sample period is from March 1, 2017 to March 1, 2022. We compute Newey and West (1986) standard errors using 20 lags for the statistical significance of the mean returns. We distinguish statistical significance with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Sorting based on lagged returns

Equal-weighted portfolios

	Q1 (Low Ret.)	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10 (High Ret.)	Q1-Q10
Mean (%)	0.908***	0.28*	0.14	0.245	0.159	0.201	0.106	0.078	-0.016	-1.28***	2.187***
StdDev (%)	6.607	5.961	5.833	5.761	5.667	5.779	5.761	5.738	5.997	6.736	5.918
Sharpe Ratio	0.137	0.047	0.024	0.042	0.028	0.035	0.018	0.014	-0.003	-0.19	0.37
Skewness	-0.381	-1.149	-1.331	-1.12	-1.124	-1.209	-1.201	-1.246	-0.822	-0.606	0.784

Value-weighted portfolios

	Q1 (Low Ret.)	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10 (High Ret.)	Q1-Q10
Mean (%)	0.297*	0.056	-0.081	0.284	0.191	0.111	0.155	0.185	0.151	-0.261	0.558***
StdDev (%)	8.262	6.189	5.942	5.865	5.913	5.745	5.839	5.931	6.679	8.776	9.212
Sharpe Ratio	0.036	0.009	-0.014	0.048	0.032	0.019	0.027	0.031	0.023	-0.03	0.061
Skewness	0.218	-0.653	-1.123	-0.554	-0.021	-0.844	-0.405	-0.316	0.254	0.892	-0.175

Panel B: Sorting based on de-trended volume

Equal-weighted portfolios

	Q1 (Low Vol.)	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10 (High Vol.)	Q1-Q10
Mean (%)	0.198	0.065	0.186	0.077	0.233	0.174	0.139	0.124	0.108	-0.476***	0.674***
StdDev (%)	6.338	5.861	5.81	5.84	5.64	5.841	5.888	6.033	5.929	6.51	5.339
Sharpe Ratio	0.031	0.011	0.032	0.013	0.041	0.03	0.024	0.021	0.018	-0.073	0.126
Skewness	-0.25	-1.41	-1.304	-1.242	-1.078	-1.186	-0.854	-1.026	-0.809	-0.964	1.118

Value-weighted portfolios

	Q1 (Low Vol.)	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10 (High Vol.)	Q1-Q10
Mean (%)	-0.064	-0.128	0.056	-0.045	0.23	0.218	0.223	0.228	0.164	-0.04	-0.025
StdDev (%)	7.416	6.627	6.031	5.944	5.815	6.027	5.773	6.029	6.426	7.867	8.074
Sharpe Ratio	-0.009	-0.019	0.009	-0.008	0.039	0.036	0.039	0.038	0.026	-0.005	-0.003
Skewness	-0.219	-0.134	-0.597	-0.549	-0.603	-0.225	-0.536	0.057	-0.513	1.122	-1.675

Table 3: **Double-sorted portfolio strategies**

This table reports a set of descriptive statistics for the daily returns of double-sorted portfolios formed on past returns and past de-trended volume as in Eq.(1). We report the mean (%), the standard deviation (%), the Sharpe ratio, and the skewness of the returns. The upper and lower panels report the results for equal- and value-weighted portfolios. The sample period is from March 1, 2017 to March 1, 2022. We compute Newey and West (1986) standard errors using 20 lags for the statistical significance of the mean returns. We distinguish statistical significance with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Equal-weighted portfolios												
	Low returns			Mid. returns			High returns			Long-short strategy		
	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.
Mean (%)	0.722***	0.367***	0.127	0.152	0.188	0.209	-0.504***	-0.153	-0.417***	1.226***	0.52***	0.543***
StdDev (%)	6.185	5.845	6.091	5.697	5.634	5.833	5.981	5.955	6.333	4.103	3.48	4.525
Sharpe ratio	0.117	0.063	0.021	0.027	0.033	0.036	-0.084	-0.026	-0.066	0.299	0.149	0.12
Skewness	-1.018	-1.114	-0.961	-1.306	-1.332	-0.84	-0.886	-0.936	-0.812	0.463	-0.338	0.254
Value-weighted portfolios												
	Low returns			Mid. returns			High returns			Long-short strategy		
	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.
Mean (%)	0.298*	0.14	-0.088	0.19	0.138	0.204	-0.327*	0.21	0.099	0.625***	-0.07	-0.187
StdDev (%)	7.068	5.999	6.472	5.931	5.562	5.625	6.719	6.362	7.271	6.349	4.8	6.681
Sharpe ratio	0.042	0.023	-0.014	0.032	0.025	0.036	-0.049	0.033	0.014	0.098	-0.015	-0.028
Skewness	0.94	-0.794	-0.99	-0.268	-0.873	-0.45	-0.405	-0.391	0.588	2.021	-0.775	-1.037

Table 4: **Characteristics of the cryptocurrency pairs in each sub-portfolio**

This table reports the breakdown of the characteristics of the average cryptocurrency in each of the 3 × 3 sub-portfolios formed on past returns and past volume shocks as in Eq.(1). For each sub-portfolio, we report the average of the raw trading volume (`volume`) in $mln, the realised volatility (`rvol`) in %, the market capitalization (`size`) in $mln, the Amihud (2002) ratio (`illiq`), the Corwin and Schultz (2012) (`bid-ask cs`), and Abdi and Ranaldo (2017) (`bid-ask ar`) bid-ask spread approximations in %. The sample period is from March 1, 2017 to March 1, 2022.

	Low returns			Mid. returns			High returns		
	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.
`volume`	10.743	28.087	45.499	11.372	36.405	67.842	17.152	50.345	72.263
`bid-ask ar`	9.866	9.031	10.557	6.893	6.515	7.115	9.627	9.532	14.141
`bid-ask cs`	4.589	4.345	5.334	3.394	3.206	3.641	4.649	4.398	4.702
`illiq`	0.359	0.12	0.24	0.256	0.068	0.141	0.386	0.135	0.272
`rvol`	13.005	10.821	11.821	11.143	9.089	9.399	12.762	10.868	11.987
`size`	1720.3	4525.9	4253.7	2808.6	7562.6	11470.5	3158.8	7696.8	6059.5

Table 5: **The conditional reversal strategy and transaction costs**

This table reports a set of descriptive statistics for the daily returns of double-sorting portfolios formed on past returns and past volume shocks as in Eq.(1). We report the mean (%), the standard deviation (%), the Sharpe ratio, and the skewness of the returns. Returns are net of transaction costs. We apply a constant cost of 20bps to the long side and 30bps to the short side of the portfolio. These costs are applied each day t that the portfolio is rebalanced (every 24-hours at 00:00:00 UTC time). We report the results for a standard short-term reversal strategy, a long-short strategy based on single-sorting on past volume shocks, and a short-term reversal strategy conditional on low (`lvr`), mid (`mvr`) or high (`hvr`) volume. We report the results for equal- and value-weighted portfolios. The sample period is from March 1, 2017 to March 1, 2022. We compute Newey and West (1986) standard errors using 20 lags for the statistical significance of the mean returns. We distinguish statistical significance with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Equal-weighted portfolios					Value-weighted portfolios				
	Single sorts		Double sorts			Single sorts		Double sorts		
	Reversal	Volume	`lvr`	`mvr`	`hvr`	Reversal	Volume	`lvr`	`mvr`	`hvr`
Mean (%)	1.687***	0.174	0.726***	0.02	0.043	0.058	-0.525***	0.125	-0.57***	-0.687***
StdDev (%)	5.918	5.339	4.103	3.48	4.525	9.212	8.074	6.349	4.8	6.681
Sharpe Ratio	0.285	0.033	0.177	0.006	0.01	0.006	-0.065	0.02	-0.119	-0.103
Skewness	0.784	1.118	0.463	-0.338	0.254	-0.175	-1.675	2.021	-0.775	-1.037

Table 6: **The risk-adjusted returns of the conditional reversal strategies**

This table reports the results from a regression analysis in which the returns of the conditional low volume reversal strategy are regressed onto a set of risk factors including the cryptocurrency market (`mkt`), liquidity (`illiq`), volatility (`vol`), momentum (`mom`), and size (`size`) factors. A full description of all portfolios is outlined in the main text. We report the gross (α_{Gross}) and net (α_{Net}) alphas of the conditional low volume reversal strategy using gross and net returns. We report the risk-adjusted returns (expressed in decimals) for the equal- and value-weighted portfolios. The sample period is from March 1, 2017 to March 1, 2022. We compute Newey and West (1986) standard errors using 20 lags for the statistical significance of the mean returns. We distinguish statistical significance with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Equal-weighted				Value-weighted			
	Gross		Net		Gross		Net	
α	0.012***	0.013***	0.007***	0.008***	0.006***	0.006***	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
`mkt`	0.064**	0.057**	0.066**	0.063**	0.124**	0.113**	0.132**	0.121**
	(0.026)	(0.026)	(0.026)	(0.026)	(0.053)	(0.051)	(0.056)	(0.052)
`liq`		-0.027		-0.006		-0.027		-0.007
		(0.036)		(0.036)		(0.041)		(0.035)
`vol`		0.069***		0.049*		0.076		0.072
		(0.026)		(0.025)		(0.053)		(0.055)
`mom`		0.029		0.033		-0.036		-0.011
		(0.036)		(0.032)		(0.077)		(0.080)
`size`		-0.025		-0.043		-0.032		-0.031
		(0.039)		(0.039)		(0.060)		(0.067)
Obs.	1,827	1,827	1,827	1,827	1,827	1,827	1,827	1,827
Adj. R^2	0.007	0.017	0.008	0.017	0.008	0.020	0.009	0.018

Table 7: **The returns from liquidity provision: individual exchanges**

This table reports a set of descriptive statistics for the daily returns of the conditional low volume reversal strategy. We report the mean (%), the standard deviation (%), the Sharpe ratio, and the skewness of the gross and net returns. The conditional reversal strategy is implemented on five different exchanges: Poloniex, HitBTC, GateIO, BitTrex, and Binance. The top and bottom panels present the results for the equal- and value-weighted portfolios. The sample period is from January 1, 2018 to March 1, 2022 for Poloniex, HitBTC, and GateIO, and from October 1, 2018 to March 1, 2022 for BitTrex and Binance. We compute Newey and West (1986) standard errors using 20 lags for the statistical significance of the mean returns. We distinguish statistical significance with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Equal-weighted	Poloniex		HitBTC		GateIO		BitTrex		Binance	
	Gross	Net	Gross	Net	Gross	Net	Gross	Net	Gross	Net
Mean (%)	0.716***	0.316***	2.518***	2.118***	1.211***	0.811***	1.365***	0.965***	0.187***	-0.213***
StdDev (%)	3.725	3.725	4.519	4.519	3.393	3.393	4.961	4.961	2.68	2.68
Sharpe ratio	0.192	0.085	0.557	0.469	0.357	0.239	0.275	0.194	0.07	-0.08
Skewness	0.007	0.007	0.711	0.711	-0.178	-0.178	0.123	0.123	0.033	0.033

Value-weighted	Poloniex		HitBTC		GateIO		BitTrex		Binance	
	Gross	Net	Gross	Net	Gross	Net	Gross	Net	Gross	Net
Mean (%)	0.482***	0.082	1.261***	0.861***	0.729***	0.329**	0.682***	0.282*	0.059	-0.341***
StdDev (%)	4.374	4.374	5.234	5.234	4.387	4.387	4.994	4.994	3.5	3.5
Sharpe ratio	0.11	0.019	0.241	0.165	0.166	0.075	0.137	0.056	0.017	-0.097
Skewness	0.328	0.328	0.326	0.326	-0.328	-0.328	0.444	0.444	-0.442	-0.442

Table 8: **Predicting the returns from liquidity provision**

This table reports the regression results from a set of predictive regressions in which the dependent variable is the returns of a short-term reversal strategy (`rev`) or a conditional reversal strategy based on low (`lvr`) or high (`hvr`) volume. The predictors include a few proxies of liquidity supply issues, including the level of idiosyncratic volatility (`ivol`), the TED spread (`ted`), and the average between the Abdi and Ranaldo (2017) and Corwin and Schultz (2012) synthetic bid-ask spreads (`bid-ask`). A detailed description of the variables is provided in the main text. The sample period is from March 1, 2017 to March 1, 2022. We distinguish statistical significance with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Idiosyncratic volatility

	Equal-weighted portfolios						Value-weighted portfolios					
	`lvr`		`hvr`		`rev`		`lvr`		`hvr`		`rev`	
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.007**	-0.007**	-0.007*	-0.007*	-0.015***	-0.015***	-0.004	-0.004	-0.014**	-0.015**	-0.016***	-0.016***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
`ivol`	0.280***	0.284***	0.168**	0.172**	0.508***	0.513***	0.155*	0.160*	0.169*	0.176*	0.291***	0.303***
	(0.056)	(0.055)	(0.072)	(0.071)	(0.094)	(0.093)	(0.093)	(0.091)	(0.102)	(0.102)	(0.096)	(0.093)
`mkt`		-0.069***		-0.069***		-0.093***		-0.112***		-0.134***		-0.237***
		(0.021)		(0.026)		(0.034)		(0.042)		(0.041)		(0.041)
Adj R^2	0.049	0.054	0.014	0.018	0.092	0.097	0.006	0.013	0.005	0.012	0.011	0.027

Panel B: Bid-ask spread

	Equal-weighted portfolios						Value-weighted portfolios					
	`lvr`		`hvr`		`rev`		`lvr`		`hvr`		`rev`	
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.007***	0.007***	0.002	0.002	0.013***	0.013***	-0.001	0.001	-0.004	-0.004	-0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
`bid-ask`	0.085**	0.082**	0.063**	0.059**	0.119***	0.114***	0.114**	0.106**	0.042	0.034	0.087	0.070
	(0.033)	(0.033)	(0.031)	(0.029)	(0.043)	(0.041)	(0.051)	(0.052)	(0.052)	(0.046)	(0.073)	(0.060)
		-0.054***		-0.049**		-0.074**		-0.118**		-0.117***		-0.250***
`mkt`		(0.020)		(0.024)		(0.032)		(0.049)		(0.035)		(0.045)
Adj R^2	0.006	0.009	0.002	0.004	0.007	0.010	0.004	0.011	0.001	0.006	0.001	0.017

Panel C: TED spread

	Equal-weighted portfolios						Value-weighted portfolios					
	`lvr`		`hvr`		`rev`		`lvr`		`hvr`		`rev`	
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.007***	0.007***	0.002	0.002	0.014***	0.014***	0.004	0.004	-0.005*	-0.005*	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
`ted`	0.022***	0.022***	0.009	0.001	0.024***	0.024***	0.011	0.011*	0.009	0.009	0.016*	0.017*
	(0.007)	(0.007)	(0.006)	(0.006)	(0.008)	(0.008)	(0.006)	(0.006)	(0.007)	(0.007)	(0.009)	(0.009)
`mkt`		-0.056***		-0.081***		-0.092***		-0.108**		-0.129***		-0.230***
		(0.019)		(0.027)		(0.031)		(0.042)		(0.043)		(0.044)
Adj R^2	0.008	0.013	0.001	0.010	0.005	0.013	0.001	0.006	-0.001	0.006	0.001	0.015

Table 9: **Predicting the conditional Sharpe ratio from liquidity provision**

This table reports regression results from a set of predictive regressions in which the dependent variable is the conditional Sharpe ratio of a short-term reversal strategy (`rev`) or a conditional reversal strategy based on low (`lvr`) or high (`hvr`) volume. The predictors include a few proxies of liquidity supply issues, including the level of idiosyncratic volatility (`ivol`), the TED spread (`ted`), and the average between the Abdi and Ranaldo (2017) and Corwin and Schultz (2012) synthetic bid-ask spreads (`bid-ask`). A detailed description of the variables is provided in the main text. The sample period is from March 1, 2017 to March 1, 2022. We distinguish statistical significance with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Idiosyncratic volatility

	Equal-weighted portfolios						Value-weighted portfolios					
	`lvr`		`hvr`		`rev`		`lvr`		`hvr`		`rev`	
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.027	-0.033	0.003	0.001	-0.057	-0.063	-0.057	-0.063	-0.167**	-0.172***	-0.162***	-0.169***
	(0.074)	(0.072)	(0.052)	(0.052)	(0.083)	(0.082)	(0.071)	(0.069)	(0.066)	(0.066)	(0.054)	(0.052)
`ivol`	4.568***	4.669***	1.842**	1.887***	6.132***	6.237***	2.351**	2.448**	1.892*	1.987*	2.977***	3.107***
	(1.176)	(1.147)	(0.728)	(0.713)	(1.325)	(1.296)	(1.167)	(1.136)	(1.062)	(1.061)	(0.827)	(0.792)
`mkt`		-1.944***		-0.787*		-2.032***		-1.858***		-1.836***		-2.506***
		(0.519)		(0.465)		(0.656)		(0.545)		(0.591)		(0.4932)
Adj R^2	0.024	0.032	0.005	0.007	0.043	0.0512	0.0062	0.0140	0.0037	0.0112	0.0109	0.0265

Panel B: Bid-ask spread

	Equal-weighted portfolios						Value-weighted portfolios					
	`lvr`		`hvr`		`rev`		`lvr`		`hvr`		`rev`	
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.158***	0.170***	0.077*	0.082**	0.197***	0.209***	0.032	0.045	-0.144***	-0.132***	-0.063	-0.046
	(0.057)	(0.052)	(0.040)	(0.041)	(0.058)	(0.054)	(0.053)	(0.055)	(0.049)	(0.045)	(0.054)	(0.045)
`bid-ask`	2.231***	2.045**	0.915	0.840	2.914***	2.730***	1.848**	1.663***	1.245*	1.053	1.836**	1.578**
	(0.847)	(0.843)	(0.589)	(0.605)	(0.898)	(0.798)	(0.744)	(0.691)	(0.722)	(0.624)	(0.863)	(0.678)
`mkt`		-1.648***		-0.665		-1.636***		-1.704***		-1.642***		-2.289***
		(0.529)		(0.490)		(0.580)		(0.566)		(0.548)		(0.477)
Adj R^2	0.008	0.013	0.001	0.002	0.014	0.019	0.002	0.008	0.006	0.011	0.005	0.0186

Panel C: TED spread

	Equal-weighted portfolios						Value-weighted portfolios					
	`lvr`		`hvr`		`rev`		`lvr`		`hvr`		`rev`	
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.173***	0.172***	0.055	0.056	0.277***	0.276***	0.055	0.056	-0.074**	-0.075**	-0.010	-0.011
	(0.057)	(0.057)	(0.039)	(0.039)	(0.050)	(0.051)	(0.044)	(0.045)	(0.035)	(0.036)	(0.039)	(0.039)
`ted`	0.440***	0.448***	0.286**	0.289***	0.349**	0.357**	0.189	0.196*	0.145	0.152	0.208*	0.219**
	(0.152)	(0.150)	(0.111)	(0.109)	(0.136)	(0.139)	(0.116)	(0.115)	(0.089)	(0.094)	(0.112)	(0.109)
`mkt`		-1.849***		-0.755		-1.890***		-1.806***		-1.793***		-2.437***
		(0.541)		(0.469)		(0.715)		(0.534)		(0.613)		(0.5296)
Adj R^2	0.006	0.013	0.003	0.005	0.003	0.011	0.001	0.008	-0.001	0.007	0.001	0.015

Table 10: **Volume, returns, and proxies for adverse selection**

Panel A of this table reports the estimates from the panel regression outlined in Eq.(2). Panel B of this table reports the results for the cross-sectional regression outlined in Eq.(3). Double-clustered robust standard errors are reported in parenthesis. The sample period is from March 1, 2017 to March 1, 2022. We distinguish statistical significance with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: The interaction between volume and returns

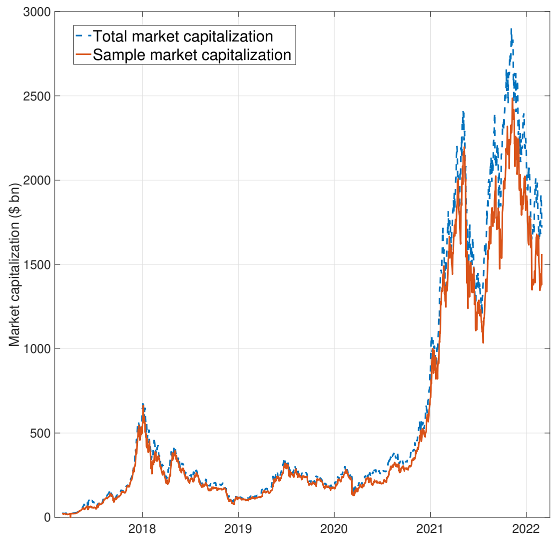
	(1)	(2)	(3)	(4)	(5)	(6)
Ret_t	-0.090***	-0.097***	-0.103***	-0.073***	-0.076***	-0.088***
	(0.021)	(0.021)	(0.020)	(0.016)	(0.017)	(0.013)
v_t		0.054***	0.047***		0.017*	0.010
		(0.015)	(0.014)		(0.009)	(0.006)
$Ret_t * v_t$			0.509***			0.524***
			(0.140)			(0.119)
Obs.	82,027	82,027	82,027	82,027	82,027	82,027
Adj. R^2	0.011	0.013	0.015	0.483	0.483	0.486
Crypto FE	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	YES	YES	YES

Panel B: Interaction terms and proxies for adverse selection

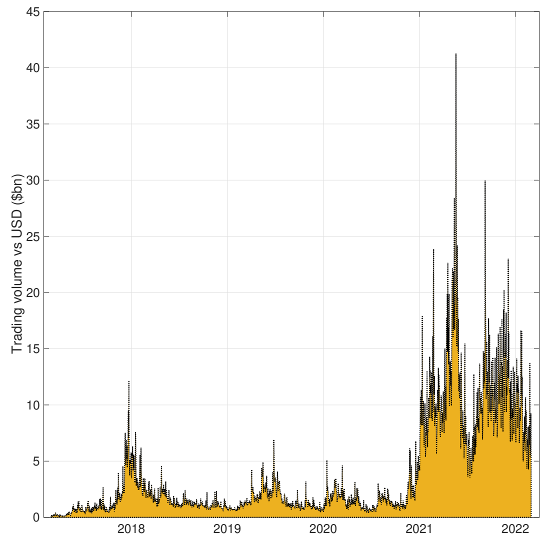
	(1)	(2)	(3)	(4)	(5)	(6)
`bid-ask ar`	0.155***					0.209**
	(0.049)					(0.081)
`bid-ask cs`		0.187***				
		(0.055)				
`illiq`			0.625***			-0.075
			(0.062)			(0.093)
`rvol`				0.277***		0.156**
				(0.054)		(0.071)
`size`					-0.446***	-0.503***
					(0.052)	(0.071)
Obs.	82,027	82,027	82,027	82,027	82,027	82,027
Adj. R^2	0.039	0.039	0.036	0.049	0.076	0.186

Figure 1: **A snapshot of the sample of cryptocurrency pairs**

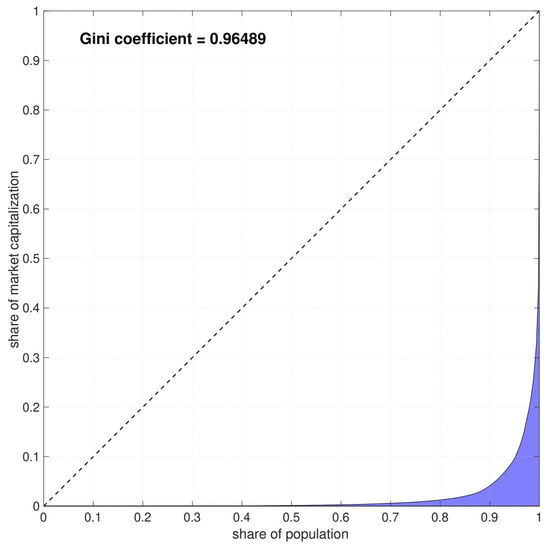
The top-left panel of the figure shows the market capitalization (in \$bn) of the cryptocurrency pairs selected on a given day (a solid red line) vis-á-vis the total market capitalization (a blue dashed line). The top-right panel of the figure shows the corresponding daily trading volume (in \$mln) of the cryptocurrency pairs selected on a given day. The bottom panels show the Lorenz curve, a visual representation of the Gini concentration index, for the average market capitalization (the bottom-left panel) and the average daily trading volume (the bottom-right panel) for the set of cryptocurrency pairs used in the portfolio analysis. The sample period is from March 1, 2017 to March 1, 2022.



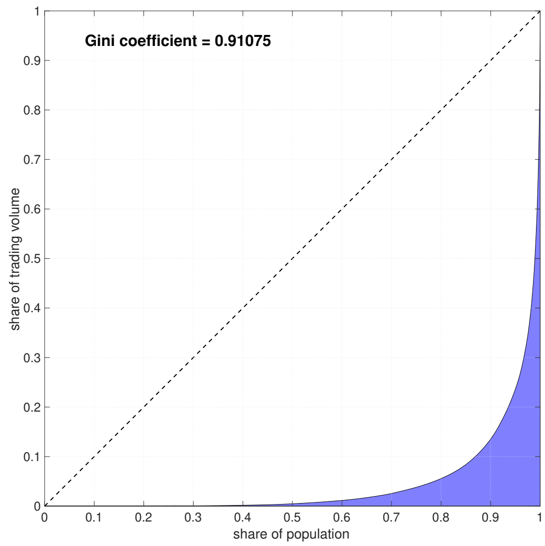
(a) Market capitalization



(b) Trading volume



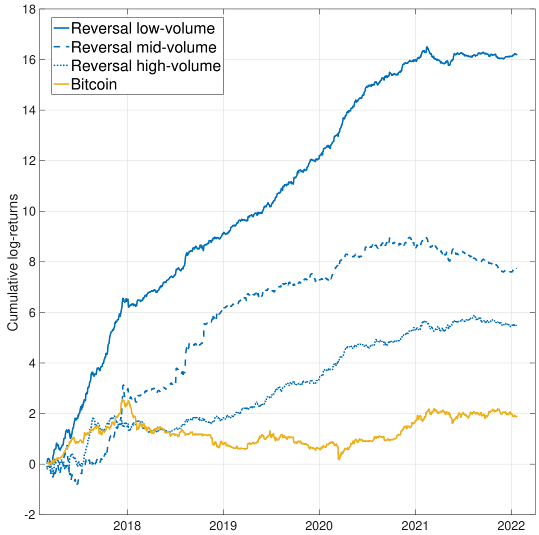
(c) Size concentration



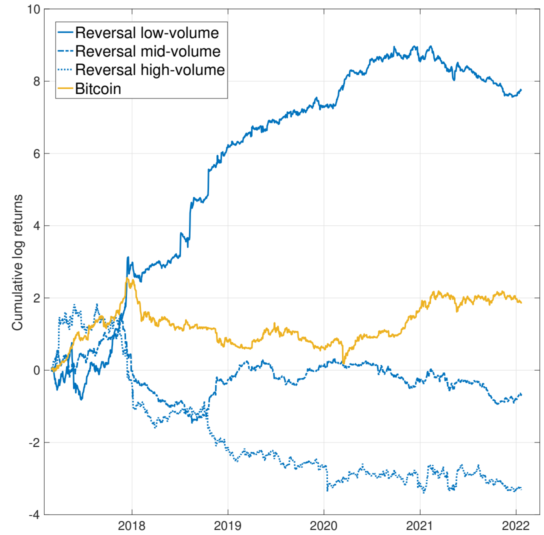
(d) Volume concentration

Figure 2: **Cumulative returns of the conditional reversal strategies**

This figure shows the cumulative log returns of an equal-weighted (the left panel) and value-weighted (the right panel) portfolios of a conditional reversal strategy based on low, mid, or high volume. We compare the performance of these portfolios with the cumulative log returns of a buy-and-hold strategy in BTC. The sample period is from March 1, 2017 to March 1, 2022.



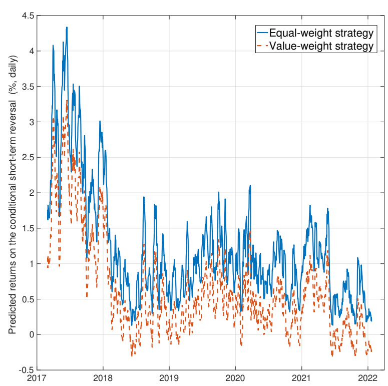
(a) Equal-weighted



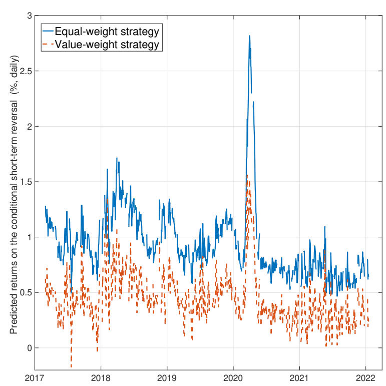
(b) Value-weighted

Figure 3: **Predicted returns of conditional reversal strategies**

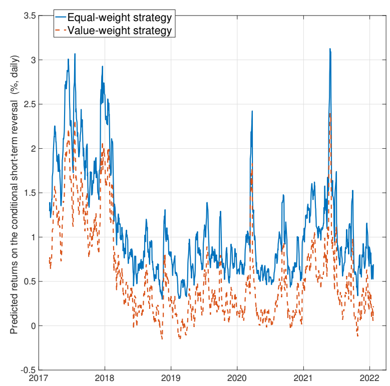
This figure shows the expected returns from a predictive regression in which the dependent variable is the returns of the conditional low volume reversal strategy and the independent variable is the level of idiosyncratic volatility (the left panel), the TED spread (the middle panel), and a measure of bid-ask spread (the right panel). We report the results for the equal- and the value-weighted returns of the conditional reversal strategy. The sample is from March 1, 2017 to March 1, 2022.



(a) Idiosyncratic volatility



(b) TED spread



(c) Bid-ask spread

Internet Appendix to

Trading volume and liquidity provision in cryptocurrency markets

A Data construction

This Appendix describes the procedures we used for sourcing, cleaning, and preparing the cryptocurrency database. The main results of this paper rely on two cryptocurrency databases. We source all price and volume data from the CryptoCompare API and market capitalization data from the CoinGecko API.

A.1 Cryptocurrency databases

1. We used the CryptoCompare database to download aggregated and exchange level OHLC pricing and volume cryptocurrency data each day, where a day starts at 00:00:00 UTC. We set tryConversion to 'true' and the tsym parameter to 'USD' for the regression and then aggregated data-based portfolio sorts. We set tsym to 'USDT' and tryConversion to 'false' to produce the exchange-level portfolio sort robustness results.
2. We used the CoinGecko database to source all cryptocurrency market capitalization data. The day 'start time' is also set at exactly 00:00:00 UTC.

A.2 Data cleaning and pre-processing

We only retain cryptocurrency pairs if they have all available data from CryptoCompare and CoinGecko after merging. We consider a variety of pre-processing steps to include a cryptocurrency in our sample:

1. `Non-zero price and volume`: we exclude any pair that had zero traded volume or a zero price for any day t.
2. `Volume-to-market-capitalization`: we compute, for each pair and day t, the ratio of cryptocurrency traded volume to market capitalization, and exclude any pair with a ratio > 1. This is a simple filter to screen out pairs with 'erroneous' or 'fake' volume. The measure is conservative - the median of the ratio is 0.001. This allows us to exclude any data points that are clearly erroneous.
3. `Cryptocurrency type`: We utilize cryptocurrency classification data from CoinMarketCap and screen out all cryptocurrencies that:

– Are linked, are buy-backed, or track the price of gold or any precious metal.
– So-called 'wrapped' coins - i.e., WBTC.
– Stablecoins, including those which are centralized (USDT, USDC), or algorithmically stabilized (DAI, UST) for all fiat currencies.
– Centralized exchange based coins that are derivatives.

So far as suspicious trading activity is concerned, a series of filters are implemented by CryptoCompare.com to mitigate the effects of suspicious trading activity: first, trade outliers are automatically excluded from the calculation of trading volume and therefore from the volume-weighting scheme. For a trade to be considered an outlier, it must deviate significantly either from the median of the set of exchanges, or from the previous aggregate price.[5] Second, exchanges are reviewed on a regular basis for each given cryptocurrency pair. Constituent exchanges are excluded if (1) posted prices are too volatile compared to the market average of a given pair, (2) trading has been suspended by the exchange on a given day, (3) a verified user or social media report postings of false data, or (4) malfunctioning of their public API. These steps mitigate the effects of fake volume and substantially reduce the exposure of our empirical analysis to concerns of misreporting of trading activity for some exchanges.[6]

A.3 Construction of the data for the portfolios

To ensure that our results are out-of-sample and free of look-ahead bias, and to ensure that very illiquid coins are excluded, our tradable sample of cryptocurrencies is rebalanced each month. We do this by selecting the top 100 most liquid cryptocurrency pairs based on the within-month mean of the Amihud (2002) ratio. For any month $t+1$, the tradable sample includes daily data for the top 100 most liquid pairs based on the ranking conducted in month t. This means that, month-to-month, the sample is dynamically adjusted to exclude least liquid cryptocurrency pairs.

[5] Such deviations can occur for a number of reasons, including extremely low liquidity of a particular pair, erroneous data from an exchange, and the incorrect mapping of a pair in the API.

[6] Two additional comments are in order. First, notice that "fake" trading typically takes place on crypto-to-crypto trading on single, likely small exchanges, which inflates trading volume to attract Initial Coin Offering (ICO) listings and/or to manipulate the market (see, e.g., Li et al., 2018). By considering trading against a fiat currency and an aggregation over a large cross-section of exchanges, the risk that manipulation on a single exchange could affect overall market activity is substantially mitigated. Second, the fact that we focus on transactions that take place on regular trading exchanges should mitigate the concern that market activity is primarily driven by illegal activities. The latter typically do not take place on registered centralised or decentralised exchanges, but are more common through peer-to-peer transactions on the blockchain (see Foley et al., 2019 and Griffin and Shams, 2020).

A.4 Construction of the data for regression analysis

To facilitate the use of firm and time fixed effects in the regression analysis, we select, unconditionally, the top 100 most liquid cryptocurrency pairs based on the Amihud (2002) ratio. The ratio is computed using a rolling window with 30 days of data. The ranking is based simply on the overall mean of the ratio, i.e., we select the 100 cryptocurrency pairs with the lowest unconditional Amihud (2002) ratio.

B Additional empirical results

This section contains a set of additional results from our use of an alternative trailing period for the calculation of the de-trended volume. We replicate the main empirical analysis for the conditional reversal strategy, considering $m = 60$ days as our trailing period in Eq.(1). In addition, we report the results from a set of additional predictive regressions, in which we investigate the predictive content of the VIX and the realised volatility for the dynamics of the returns on our conditional reversal strategy.

B.1 The returns on the conditional reversal strategy

Table 3 in the main paper shows that returns from liquidity provision primarily are concentrated in pairs with lower trading volume. This is based on the assumption that trading volume is de-trended by using an $m = 30$ days trailing mean. Table B.1 shows that the same result holds when we use a longer trailing period of $m = 60$ days. The evidence confirms that a simple equal-weight reversal strategy conditional on low volume delivers a 1.23% (p-value: 0.001) average daily return against a 0.50% (p-value: 0.003) daily average return when we condition on high volume pairs. The results for the value-weighted portfolio composition provide stronger evidence of the interplay between reversal and trading volume. There is a profitable reversal, i.e., 0.63% daily return (p-value: 0.003), in the return dynamics, conditional on low levels of abnormal market activity as proxied by the volume shock, even when assets are weighted by their market capitalization. On the other hand, when the level of trading activity is higher than the 60-day trend, a reversal strategy generates a negative and significant performance, i.e., -0.24% (p-value: 0.09).

Table B.2 provides a breakdown of the characteristics of the average firm in each of the 3×3 sub-portfolios of assets sorted by lagged returns and past de-trended volume with $m = 60$. The properties of the assets in each sub-portfolio are very similar to those in the main empirical analysis in Table 4. That is, the average values of the Amihud (2002) illiquidity ratio `illiq` is higher for those assets with trading activity below the short-term trend, independently of the magnitude of lagged returns. For instance, within the context of the low-return assets, the

Table B.1: **Double-sorted portfolio strategies**

This table reports a set of descriptive statistics for the daily returns of double-sorting portfolios formed on past returns and past volume shocks as in Eq.(1). We report the mean (%), the standard deviation (%), the Sharpe ratio, and the skewness of the returns. The volume shocks are now calculated based on a rolling window with $m = 60$ days. The upper and lower panels report the results for equal- and value-weighted portfolios. The sample period is from March 1, 2017 to March 1, 2022. We compute Newey and West (1986) standard errors using 20 lags for the statistical significance of the mean returns. We distinguish statistical significance with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Equal-weighted portfolios												
	Low returns			Mid. returns			High returns			Long-short strategy		
	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.
Mean (%)	0.718***	0.446***	0.054	0.154	0.220	0.178	-0.515***	-0.113	-0.446***	1.233***	0.559***	0.500***
StdDev (%)	6.152	5.910	6.071	5.651	5.702	5.844	5.965	5.971	6.370	4.000	3.531	4.472
Sharpe ratio	0.117	0.075	0.009	0.027	0.039	0.030	-0.086	-0.019	-0.070	0.308	0.158	0.112
Skewness	-0.965	-1.177	-0.953	-1.211	-1.361	-0.926	-0.843	-0.854	-0.872	0.321	-0.252	0.119

Value-weighted portfolios												
	Low returns			Mid. returns			High returns			Long-short strategy		
	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.
Mean (%)	0.313***	0.124	-0.081	0.216	0.122	0.213*	-0.34*	0.228	0.158	0.653***	-0.105	-0.239*
StdDev (%)	7.054	5.994	6.482	5.963	5.588	5.588	6.699	6.495	7.213	6.244	4.966	6.596
Sharpe ratio	0.044	0.021	-0.012	0.036	0.022	0.038	-0.051	0.035	0.022	0.105	-0.021	-0.036
Skewness	0.656	-0.901	-0.935	0.386	-0.955	-0.463	-0.45	0.249	0.329	1.718	-1.552	-0.877

`illiq` ratio is equal to 0.38 for low volume and 0.21 for high volume assets. Both the level of realised volatility and market capitalization seem to be correlated with liquidity across subportfolios, that is, the average `rvol` (`size`) is higher (lower) for those assets with lower trading activity. Overall, even when we consider a longer term trailing period, the empirical results support the idea that the returns to liquidity provision tend to be higher for "lower quality" assets – those that are smaller, less liquid, and more volatile. This is consistent with Avramov et al. (2006) and the intuition in Easley and O'Hara (2004); Hendershott and Seasholes (2007), where inventory risk and adverse selection tend to be concentrated in less active stocks, so that specialists and market makers might have fewer incentives, or, to state it differently, require a higher premium to support trading in these assets.

B.2 Expected returns and volatility proxies

Table 8 in the main text shows that idiosyncratic volatility, liquidity, and financing conditions are positively correlated with the returns on the conditional reversal strategy based on low volume assets. This result supports the notion that the time variation in expected reversal returns is significantly driven, at least in part, by liquidity supply factors and that such predictability is more concentrated in assets with a lower level of trading activity (see, e.g., Nagel, 2012). In this section, we provide a set of additional predictive regressions using two other popular measures of market uncertainty and, more generally, liquidity supply: the VIX index

Table B.2: **Characteristics of the cryptocurrency pairs in each sub-portfolio**

This table reports the breakdown of the characteristics of the average cryptocurrency in each of the 3×3 sub-portfolios formed on past returns and past volume shocks, as in Eq.(1). The volume shocks are now calculated based on the rolling window with $m = 60$ days. For each sub-portfolio, we report the average raw trading volume (`volume`) in \$mln, the realised volatility (`rvol`) in %, the market capitalization (`size`) in \$mln, the Amihud (2002) ratio (`illiq`), and the Corwin and Schultz (2012) (`bid-ask cs`) and Abdi and Ranaldo (2017) (`bid-ask ar`) bid-ask spread approximations in %. The sample period is from March 1, 2017 to March 1, 2022.

	Low returns			Mid. returns			High returns		
	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.	Low vol.	Mid. vol.	High vol.
`volume`	9.673	27.249	47.514	10.317	34.869	70.438	14.796	47.652	77.316
`bid-ask ar`	9.737	9.135	10.592	6.829	6.506	7.189	9.675	9.482	14.145
`bid-ask cs`	4.569	4.358	5.342	3.36	3.216	3.667	4.612	4.331	4.806
`illiq`	0.387	0.124	0.206	0.275	0.06	0.129	0.423	0.121	0.249
`rvol`	12.547	10.989	12.149	10.843	9.098	9.695	12.394	10.986	12.238
`size`	1660.9	4542.3	4303.9	2360.1	7669.1	11813.7	2660.2	7330.7	6924.2

(`vix`) and the market realised volatility (`mkt vol`). Table B.3 shows the results. Panel A shows that (`mkt vol`) is positively and significantly correlated with the returns on the reversal strategy conditional on low volume. On the other hand, when we condition on high volume – compared to its short-term trend – aggregate market volatility does not correlate with the returns on a reversal strategy. The same result holds for a single-sorting strategy based on past returns. The fact that the compensation from liquidity provision increases as a function of market volatility is consistent with theories of limited risk capacity under financing constraints (see, e.g., Gromb and Vayanos, 2002 and Brunnermeier and Pedersen, 2008): higher volatility tightens the funding constraints of market makers and thereby reduces their liquidity-provision capacity. Interestingly, Panel B shows that the same positive relationship does not hold for the VIX index. This contradicts some of the findings in the existing literature (see, e.g., Nagel, 2012). As a matter of fact, the VIX index is often thought to be related to various asset-pricing phenomena in which risk taking by financial intermediaries may play a role. The fact that the VIX is not correlated with the returns from liquidity provision in cryptocurrency markets does not necessarily mean that volatility does not play a role, as shown in Panel A. This could be due to a de-coupling of the pricing kernel of cryptocurrencies vs equity markets, as suggested by Bianchi and Babiak (2022a) and Liu and Tsyvinski (2020), among others. In other words, there is indeed some peculiarity in the driving liquidity supply forces within the context of cryptocurrency markets that do not necessarily overlap with traditional asset classes.

Table B.3: **Predicting the returns from liquidity provision**

This table reports the regression results from a set of predictive regressions in which the dependent variable is the returns of a short-term reversal strategy (`rev`) or a conditional reversal strategy based on low (`lvr`) or high (`hvr`) volume. The volume shocks are calculated on the rolling window with $m = 30$ days as in the main text. The predictors include the VIX index (`vix`) and the realised volatility of the market portfolio calculated from Yang and Zhang (2000) (`mkt vol`). A detailed description of the variables appears in the main text. The sample period is from March 1, 2017 to March 1, 2022. We distinguish statistical significance with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Realised market volatility

	Equal-weighted portfolios						Value-weighted portfolios					
	`lvr`		`hvr`		`rev`		`lvr`		`hvr`		`rev`	
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.008***	0.008***	0.002	0.003	0.017***	0.017***	-0.001	0.004	-0.003	-0.002	0.003	0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
`mkt vol`	0.113**	0.101*	0.084	0.073	0.089	0.071	0.196**	0.168**	0.036	0.007	0.064	0.001
	(0.055)	(0.057)	(0.051)	(0.054)	(0.069)	(0.069)	(0.084)	(0.084)	(0.057)	(0.055)	(0.102)	(0.096)
`mkt`		-0.049**		-0.046**		-0.074**		-0.110**		-0.118***		-0.254***
		(0.021)		(0.023)		(0.033)		(0.048)		(0.036)		(0.046)
Adj R^2	0.004	0.007	0.002	0.003	0.001	0.004	0.006	0.011	-0.001	0.005	-0.001	0.016

Panel B: VIX

	Equal-weighted portfolios						Value-weighted portfolios					
	`lvr`		`hvr`		`rev`		`lvr`		`hvr`		`rev`	
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.012**	0.012**	0.003	0.003	0.022***	0.0226***	0.005	0.006	-0.008	-0.007	-0.002	-0.008
	(0.005)	(0.005)	(0.004)	(0.004)	(0.008)	(0.0080)	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)	(0.007)
`vix`	0.001	0.000	0.001	0.000	-0.001	-0.0001	0.001	0.000	0.001	0.002	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.0004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
`mkt`		-0.062***		-0.064**		-0.0811**		-0.107**		-0.127***		-0.227***
		(0.023)		(0.026)		(0.0366)		(0.042)		(0.042)		(0.042)
Adj R^2	-0.007	0.003	-0.004	0.003	-0.006	0.0032	-0.007	0.005	0.001	0.006	0.004	0.014

B.3 The role of adverse selection

Table 10 provides empirical evidence that the interaction between lagged volume and returns positively and significantly affects the dynamics of future returns. Assuming lower liquidity proxies for higher adverse selection and costs of asymmetric information, the results are consistent with Wang (1994) and Llorente et al. (2002): the interaction between returns and past volume ultimately capture the effects of adverse selection on future returns. The results in the main paper are based on $m = 30$ days as the trailing period to calculate the de-trended volume. Table B.4 reports the results for the same analysis based on $m = 60$ in Eq.(1). The results are largely consistent with those in the main empirical analysis. On average, lower liquidity corresponds to a larger beta on the interaction term between returns and volume. We find similar results when we look at the volatility of returns; higher return volatility, which is assumed to be associated with higher levels of information asymmetry, corresponds to higher interaction between returns and volume shocks, on average. In the multivariate model in which all measures are considered jointly, the price impact measure is subsumed by `bid-ask ar`, `rvol` and `size`. This suggests that smaller cryptocurrencies with relatively higher levels of volatility are prone to higher degrees of adverse selection. Overall, the results in Table B.4 are consistent with Proposition 3 in Llorente et al. (2002): conditional on heightened levels of information asymmetry, noise trades cause larger price changes, which leads to more significant return reversals.

Table B.4: **Volume, returns, and proxies for adverse selection**

Panel A of this table reports the estimates from the panel regression outlined in Eq.(2). Panel B of this table reports the results for the cross-sectional regression outlined in Eq.(3). The volume shocks for the conditional reversal strategy are now calculated on the rolling window with $m = 60$ days. The sample period is from March 1, 2017 to March 1, 2022. We report double-clustered robust standard errors in parenthesis. We distinguish statistical significance with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: The interaction between volume and returns

	(1)	(2)	(3)	(4)	(5)	(6)
Ret_t	-0.090***	-0.096***	-0.103***	-0.073***	-0.076***	-0.089***
	(0.021)	(0.021)	(0.021)	(0.016)	(0.017)	(0.013)
v_t		0.051***	0.046***			0.008
		(0.015)	(0.014)		0.013	(0.006)
$Ret_t * v_t$			0.454***			0.492***
			(0.148)			(0.125)
Obs.	82,027	82,027	82,027	82,027	82,027	82,027
Adj. R^2	0.011	0.013	0.015	0.483	0.483	0.485
Crypto FE	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	YES	YES	YES

Panel B: Interaction terms and proxies for adverse selection

	(1)	(2)	(3)	(4)	(5)	(6)
`bid-ask ar`	0.230***					0.149*
	(0.053)					(0.080)
`bid-ask cs`		0.235***				
		(0.059)				
`illiq`			0.290***			0.558***
			(0.076)			(0.124)
`rvol`				0.313***		0.220***
				(0.056)		(0.074)
`size`					-0.400***	-0.564***
					(0.056)	(0.076)
Obs.	82,027	82,027	82,027	82,027	82,027	82,027
Adj. R^2	0.039	0.040	0.038	0.047	0.078	0.192