Short-Sale Constraints and the Return Predictability of Idiosyncratic Variance: Evidence from Crypto Perpetuals *

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Abstract

High idiosyncratic variance predicts low future returns in cryptocurrency markets, and the relation comes mainly from large, recent upside price shocks in coins that cannot be shorted. To test whether short-sale constraints drive this relation, we use the staggered expansion of access to short selling across coins and compare the same coin's returns after shocks before and after it can be shorted. After upside shocks, prices reverse over the following week, and access to short selling reduces this reversal by 2.55 percentage points, about three quarters of its size. After downside shocks, by contrast, access matters mainly when the decline follows an upside shock. Consistent with these results, access also weakens the return predictability of recent upside shocks, by an amount similar to the reduction in the reversal. Idiosyncratic variance thus predicts low returns in part because, when pessimistic investors cannot sell short, prices stay above the level implied by the average belief after a shock and fall back as disagreement fades.

JEL: G12, G14, G15. **Keywords:** short-sale constraints, idiosyncratic variance, idiosyncratic volatility puzzle, return predictability, idiosyncratic shocks, disagreement, perpetual futures, cryptocurrency.

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1 Introduction

High idiosyncratic volatility predicts low future returns (Ang et al., 2006, 2009). One explanation combines investor disagreement with short-sale constraints. When pessimistic investors cannot sell short, prices reflect optimistic beliefs and exceed the level implied by the average belief (Miller, 1977; Chen et al., 2002). As disagreement fades, prices fall back, generating negative subsequent returns. This explanation implies that relaxing short-sale constraints should change how prices adjust after shocks. However, testing this implication in equities is difficult: short-sale constraints rarely change for the same stock, mostly through regulation such as the Regulation SHO pilot (Diether et al., 2009)[1] or the 2008 short-sale ban (Beber and Pagano, 2013), and lending fees reflect short sellers' demand as well as the supply of shares (D'Avolio, 2002).

We study this mechanism in cryptocurrency markets, where access to short selling expanded coin by coin. The staggered introduction of margin borrowing and perpetual futures allows us to compare the price response to idiosyncratic shocks within the same asset before and after access. Combining hourly returns for more than 400 cryptocurrencies with their earliest documented dates of access across exchanges and instruments, we examine how access to short selling changes the subsequent price adjustment after large shocks. We also investigate how these price dynamics relate to the negative return predictability of idiosyncratic variance.

Our hypothesis is that idiosyncratic variance predicts low returns because it captures recent shocks after which short-sale constraints keep prices above the level implied by the average belief. We formalize this idea in a model in which shocks raise disagreement based on Miller (1977). When some investors cannot sell short, the price after a shock reflects the more optimistic investors. The difference between this price and the level implied by the average belief, the constraint wedge, disappears as disagreement fades, so the price falls after the shock: it reverses after upside shocks and continues to decline after downside shocks. Because idiosyncratic variance records these shocks, it predicts the low returns that follow them. The model yields three predictions: when short selling is constrained, prices reverse more after upside shocks and continue to decline more after downside shocks (P1); access to short selling reduces the reversal and the continuation (P2); and access weakens the return predictability of idiosyncratic variance (P3).

We first show that the negative relation between idiosyncratic variance and returns is con-

[1] The Regulation SHO pilot suspended the price tests for short sales, the uptick rule, for one third of the stocks in the Russell 3000 from May 2005 until the SEC removed the tests for all stocks in July 2007. Short sellers in pilot stocks still had to borrow shares, so the pilot relaxed a mild trading restriction rather than the ability to sell short, and its effects on prices were small (Diether et al., 2009). The 2008 ban prohibited short selling in financial stocks for about three weeks during the financial crisis, so its effects are difficult to separate from the crisis (Beber and Pagano, 2013). In cryptocurrencies, by contrast, access changes from no shorting instrument to a perpetual or margin account, coin by coin, at different dates.

centrated among coins without access and comes primarily from large, recent shocks. A one-standard-deviation increase in upside idiosyncratic variance predicts a next-day return 53.4 basis points lower ($t = -8.1$). Sorting coins on total idiosyncratic variance produces a high-minus-low return of −56.6 basis points per day among coins without access, compared with approximately zero among coins with access, and the difference remains within size and liquidity groups. Decomposing variance into the contributions of shock hours and other hours shows that the predictability comes from shocks: the upside and downside shock components predict next-day returns of −9.2 ($t = -3.3$) and −7.9 ($t = -3.4$) basis points per standard deviation. Giving greater weight to recent shocks strengthens the upside coefficient to −22.7 basis points ($t = -7.4$).

Our central finding is that access to short selling substantially changes how prices adjust after idiosyncratic shocks. Upside shocks average 6.2% and are followed by abnormal returns of −3.4% over the following week, reversing more than half of the initial increase. Downside shocks are followed by further declines rather than reversals. We compare the returns after shocks within the same coin before and after access, excluding shocks within 91 days of the access date.

Under the earliest documented access date, the same coin's weekly return after an upside shock increases by 2.55 percentage points after access ($t = 3.3$; wild cluster bootstrap $p = 0.002$), approximately three quarters of the average reversal, and most of this change occurs after the first day. The estimate is similar in a stacked design that uses coins gaining access later as controls, under the heterogeneity-robust estimator of Sun and Abraham (2021) (2.84 percentage points, $t = 2.7$), and among the 35 coins whose documented access dates coincide (2.67 percentage points). A placebo that dates access one year early shows no effect.

The response to downside shocks further refines this evidence. The effect of access is concentrated in downside shocks that follow an upside shock in the same coin within 48 hours. For these shocks, access increases the subsequent weekly return by 3.51 percentage points ($t = 2.62$), compared with 0.60 percentage points ($t = 0.59$) after isolated downside shocks; the difference is 2.91 percentage points ($t = 1.98$; wild cluster bootstrap $p = 0.05$). This pattern is consistent with short-sale constraints that keep prices too high after upward price movements, whether the subsequent decline is gradual or begins with a sharp drop (Miller, 1977; Hong and Stein, 2003).

The main alternative explanation is that access coincides with better liquidity. Controlling for liquidity before the shock does not weaken the within-coin estimates: the effect after upside shocks rises from approximately 2.6 to between 4.6 and 4.9 percentage points when we control for dollar volume or Amihud illiquidity. Binance USDT spot listings, which raise trading volume without introducing short selling, raise measured volume by more than access does, yet their effect on the weekly return after upside shocks is small and insignificant (−0.54 percentage points, $t = -0.6$). Improved liquidity alone is therefore difficult to reconcile with the results.

We then connect these price dynamics to the return predictability of idiosyncratic variance.

Coin-days within 48 hours of a shock account for 46% of observations but 69% of the slope on upside idiosyncratic variance. Access weakens the predictive power of a recent upside shock for next-day returns by 37.5 basis points under the earliest documented date ($t = 4.1$) and 46.8 basis points under the Binance perpetual date ($t = 5.3$), and by 44.8 basis points under both dates when baseline slopes differ across groups of coins defined by access ($t = 2.3$ and 2.6). Over the following week, the reduction amounts to approximately 2.3 percentage points under the earliest date, comparable to the 2.55 percentage points by which access reduces the reversal after upside shocks. Although the two estimates use different samples and outcomes, their magnitudes are consistent with a common adjustment after shocks. These results link the return predictability of idiosyncratic variance to the effect of short-sale constraints on price adjustment after shocks.

Beyond liquidity, access is not randomly assigned and may coincide with changes in leverage and attention. The stacked design, the placebo and the absence of pre-access trends after upside shocks support a causal interpretation but do not rule out every concurrent change. The within-coin estimates draw mainly on shocks in the year before access. In addition, shocks are large abnormal returns relative to a value-weighted cryptocurrency market, as in the market factor of Liu et al. (2022), so we observe large price moves but not the information behind them.

Our paper contributes to three strands of literature.

First, we contribute to research on how short-sale constraints affect the way prices incorporate disagreement and information after shocks. Jiang et al. (2014) examine the price responses of high-volatility stocks around changes in short-sale constraints, including IPO lockup expirations, option introductions and the 2008 short-sale ban. We instead examine how access changes the response to subsequent idiosyncratic shocks within the same asset, rather than the price response to the change in constraints itself. Our analysis complements evidence that short-sale restrictions, regulation and the supply of lendable shares affect prices and anomaly returns (Jones and Lamont, 2002; Chang et al., 2007; Diether et al., 2009; Beber and Pagano, 2013; Boehmer et al., 2013; Chu et al., 2020).

Second, we contribute to research on the idiosyncratic volatility puzzle. Previous studies find stronger negative relations between volatility and returns among stocks with higher shorting costs and greater disagreement (Boehme et al., 2009) and on the short side of equity anomalies (Stambaugh et al., 2015). Other explanations emphasize expected volatility, return reversals, skewness and preferences for lottery-like payoffs (Fu, 2009; Huang et al., 2010; Boyer et al., 2010; Han and Kumar, 2013; Hou and Loh, 2016). We show that the negative relation is concentrated in recent idiosyncratic shocks and that this predictability weakens after the same asset gains access to short selling, by an amount consistent with the smaller reversal after upside shocks. This evidence links the return predictability of idiosyncratic variance to the effect of short-sale constraints on prices after shocks.

Third, we contribute to research on cryptocurrency return predictability and market structure. Lee and Wang (2025) show that positive jump variation predicts low cryptocurrency returns and interpret this relation as evidence of lottery demand. We find that this predictability depends on access to short selling: the coefficient on positive jump variation is −6.8 basis points, while its interaction with access is 19.8 basis points ($t = 3.1$; Appendix Table 37). Recent shocks also predict returns more strongly than older shocks. These results do not rule out lottery preferences as a source of optimistic demand; rather, they suggest that short-sale constraints determine how much this demand affects prices. More broadly, our findings relate to research on cryptocurrency asset pricing and market structure (Liu and Tsyvinski, 2021; Liu et al., 2022; Makarov and Schoar, 2020; Augustin et al., 2023).

The remainder of the paper proceeds as follows. Section 2 presents the model, and Section 3 describes the data. Section 4 examines the return predictability of idiosyncratic variance and its shock components. Section 5 studies price adjustment after shocks and access to short selling. Section 6 links this adjustment to the return predictability of idiosyncratic variance. Section 7 examines alternative explanations, and Section 8 concludes.

2 Short-Sale Constraints, Price Adjustment after Shocks, and Idiosyncratic Variance

Miller (1977) argues that when investors disagree and pessimistic investors cannot sell short, the price reflects the more optimistic investors and exceeds the level implied by the average belief. This difference rises with disagreement, implies low subsequent returns, and disappears when the constraint is relaxed. This section develops a dynamic version of this argument, building on Chen et al. (2002). Disagreement rises with shocks and fades over time, so the constraint creates a temporary wedge between the price and the level implied by the average belief, rather than a permanent difference. Appendix A gives the derivations, the proofs and extensions.

2.1 Investors and Equilibrium Prices

A coin in positive net supply Q is held by investors with CARA preferences, common risk tolerance τ and subjective normally distributed payoffs with common variance σ^2. Investors differ in their expected payoff,

$$\mu_{i,t} = \bar{\mu}_t + \delta_{i,t}, \qquad \delta_{i,t} \sim U[-d_t, d_t], \tag{1}$$

where $\bar{\mu}_t$ is the average valuation and d_t measures disagreement. A fraction $\phi \in [0, 1]$ of investors can sell short; the others cannot take negative positions. With $\lambda = \sigma^2/\tau$, the demand of an

investor who can sell short is $(\mu_{i,t} - p_t)/\lambda$, and the demand of an investor who cannot is $\max\{(\mu_{i,t} - p_t)/\lambda, 0\}$. When all investors can sell short, the price is $\bar{\mu}_t - \lambda Q$. In general,

$$p_t = \bar{\mu}_t - \lambda Q + \Delta(d_t, \phi), \tag{2}$$

where the constraint wedge $\Delta(d_t, \phi)$ is the amount by which the price exceeds $\bar{\mu}_t - \lambda Q$, the level implied by the average belief.

Lemma 1 (the constraint wedge). *The wedge is zero when $d \leq \lambda Q$ or $\phi = 1$. When $d > \lambda Q$ and $\phi < 1$, it is positive, increasing in disagreement and decreasing in access to short selling.*
When disagreement is large, pessimistic investors would sell short at the unconstrained price but cannot do so, and the price reflects the more optimistic investors (Miller, 1977).

2.2 Price Adjustment after Shocks

Initially, $d_0 < \lambda Q$. At time 1, an idiosyncratic shock s changes the average valuation to $\bar{\mu}_0 + s$ and raises disagreement to

$$d_1 = d_0 + \kappa_{\text{sgn}(s)}|s|, \qquad 0 \leq \kappa_-, \kappa_+ \leq 1. \tag{3}$$

Heterogeneous interpretations of information can generate disagreement (Harris and Raviv, 1993; Kandel and Pearson, 1995). Upside and downside shocks may raise disagreement by different amounts; the model does not require $\kappa_+ = \kappa_-$. The additional disagreement disappears by time 2, while the change in the average valuation remains. With $D(s, \phi) = \Delta(d_0 + \kappa_{\text{sgn}(s)}|s|, \phi)$,

$$p_1 - p_0 = s + D(s, \phi), \qquad p_2 - p_1 = -D(s, \phi). \tag{4}$$

Proposition 1 (price adjustment after shocks). *Suppose $\phi < 1$ and $d_1 > \lambda Q$. After a positive shock, the price rises by $s + D$ and then falls by D. After a negative shock, the price falls by $|s| - D$ and then falls by another D. For shocks of a given sign, the subsequent decline increases with the size of the shock.*

Proposition 2 (access to short selling). *The subsequent price change $-D(s, \phi)$ increases with ϕ and is zero when $\phi = 1$. Access to short selling therefore reduces the reversal after upside shocks and the continuation after downside shocks.*
Figure 1 illustrates the adjustment. The effect of access is larger after shocks that create more disagreement. It also applies to a downside shock that follows an upside shock before the wedge from the upward move has disappeared: the decline then continues the correction of that wedge,

which keeps the views of pessimistic investors out of the price as it rises (Hong and Stein, 2003), and access to short selling reduces it.

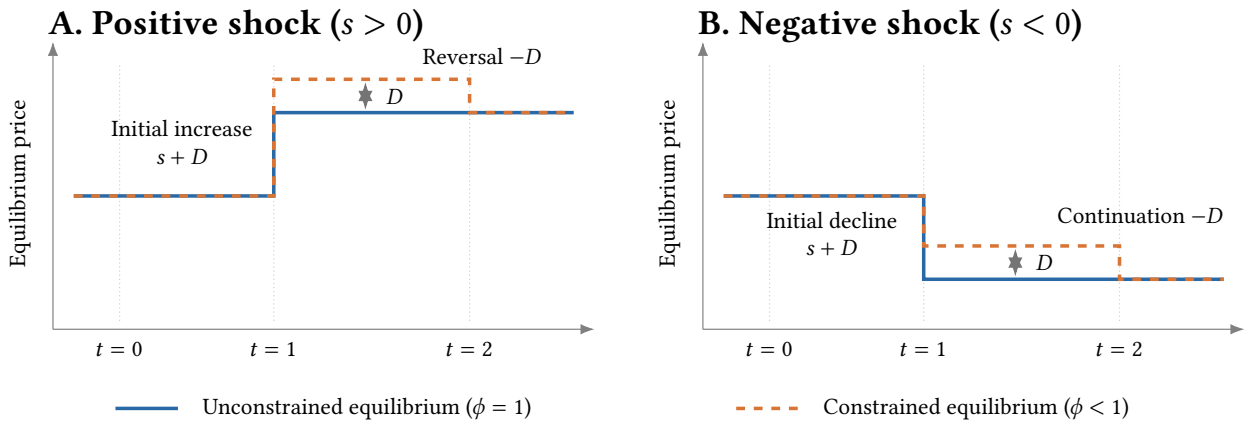


Figure 1: Short-sale constraints and price adjustment after idiosyncratic shocks. The solid line is the equilibrium price when all investors can sell short ($\phi = 1$); the dashed line is the equilibrium price under binding short-sale constraints ($\phi < 1$). At time 1, the shock raises disagreement and creates the constraint wedge D. At time 2, disagreement returns to its initial level, the wedge disappears and the price falls by D: a reversal after a positive shock (Panel A) and a continuation after a negative shock (Panel B). The figure shows equal wedges for both signs. Price levels are illustrative.

2.3 From Shocks to Idiosyncratic Variance

Suppose disagreement accumulates from successive shocks and fades over time,

$$d_t = d_0 + g_t, \qquad g_t = \psi g_{t-1} + \kappa_{\mathrm{sgn}(s_t)}|s_t|, \qquad 0 \le \psi < 1. \tag{5}$$

Without a new shock, the decay of g_t produces the price change

$$p_{t+1} - p_t = -C(g_t, \phi), \qquad C(g, \phi) = \Delta(d_0 + g, \phi) - \Delta(d_0 + \psi g, \phi) \ge 0. \tag{6}$$

The expected return is negative when the remaining disagreement $d_0 + g_t$ exceeds λQ and some investors cannot sell short, and it is zero when $\phi = 1$. When the wedge is convex in disagreement, as in the case $\phi = 0$, the expected decline is larger after larger shocks and after more recent shocks, whose disagreement has decayed less. Disagreement is not observed. The empirical analysis uses the realized upside and downside semivariances of hourly abnormal returns over the previous seven days (Section 3.2). Each semivariance has a shock component, the hours with large moves, and an ordinary component, the remaining hours. Only the shock component is related to g_t.

Predictions. The model implies three predictions.

P1 *Price adjustment after shocks.* When short selling is constrained, prices reverse more after upside shocks and continue to decline more after downside shocks (Proposition 1). Section 5.

P2 *Access to short selling.* Access to short selling reduces the reversal after upside shocks and the continuation after downside shocks (Proposition 2). Section 5.

P3 *Access and predictability.* Idiosyncratic variance predicts low returns through its recent shock component, and access to short selling weakens this predictability (equation (6)). Sections 4.4 and 6.

For total downside variance, which combines a shock component with an ordinary component that the model does not restrict, the model makes no prediction (Appendix A.4).

3 Data and Measurement

3.1 Hourly Returns and the Universe

We obtain hourly candlestick data for Binance spot pairs quoted in USDT or BTC, including subsequently delisted pairs, from July 2017 to September 2023. Returns use the USDT pair when available and otherwise the BTC pair converted at the BTC/USDT rate. Each return is computed within a single pair, avoiding changes caused by switching price levels across pairs. BTC pairs account for 79% of coin-hours in 2017–2019 and 14% from 2020 onward, declining from 38% in 2020 to 2% in 2023.

If no trade occurs during an hour, the price change is assigned to the next hour with a trade, so that the return covers the hours since the last trade. We discard such returns when they cover more than 72 hours. We exclude stablecoins, fiat currencies, wrapped and commodity-backed tokens, and leveraged tokens. A cleaning rule combines price moves exceeding 50 log points that reverse by at least 80% in the next hour into a two-hour return. The rule affects five coin-hours; Appendix B reports the data checks. Market capitalization comes from CoinMarketCap. A coin enters the daily universe if its capitalization is at least $1 million, valid returns cover at least 90% of Binance trading hours in the preceding week, and it traded within the last 24 hours. Characteristics are measured through 22:00 UTC, the final hour is skipped, and outcomes are measured on the following day. The resulting sample contains 447,370 coin-days for 412 coins over 2,188 days from August 2017 to September 2023. Table 1 summarizes the sample.

Coin-days with a Binance perpetual have a median capitalization of $420 million, compared with $48 million without one, and exhibit higher volume and lower annualized idiosyncratic volatility (65% versus 94%). The composition of variance is similar: upside movements account

for about 55% in both groups. These differences in size and liquidity motivate the within-coin designs.

Table 1: Summary statistics

	Aug. 2017 to Aug. 2019	From Sep. 2019, not shortable	From Sep. 2019, shortable	Full sample
Coin-days	68,678	228,769	149,923	447,370
Coins	134	359	206	412
Market cap, median ($ million)	74.5	48.1	420.3	95.7
Log dollar volume, median	15.89	16.09	18.20	16.75
Total volatility, median (% p.a.)	136.4	117.5	102.6	114.9
Idiosyncratic volatility, median (% p.a.)	99.9	93.9	64.8	84.6
Upside share of idiosyncratic variance, mean (%)	54.9	55.9	54.7	55.3
Next-day return, mean (%)	−0.04	0.21	0.09	0.13
Next-day return, standard deviation (%)	7.96	8.17	7.02	7.77
Upside shocks per coin-year (from 2020)		35.8	31.8	
Downside shocks per coin-year (from 2020)		20.2	19.6	

Coin-days of the universe with variance components. Shortable: the coin has a Binance perpetual on that day. Volatilities annualized from the seven-day hourly semivariances. Upside share: idiosyncratic upside semivariance over total idiosyncratic variance. Shocks per coin-year: idiosyncratic shocks (Section 3.2) from 2020, per coin-year of the group.

The principal access tests begin in January 2020 and draw from a common base universe of 361,133 coin-days for 405 coins. Actual estimation samples differ with the access date, exclusion window, available controls, and outcome. Binance introduced its first perpetual in September 2019, but only BTC, ETH, and BCH had contracts before 2020. Descriptive shock statistics use the longer sample beginning in 2017; position data are available only from December 2021.

3.2 Idiosyncratic Variance and Shocks

For each coin i on day d, we estimate over the previous seven days of hourly returns

$$r_{i,h} = a_i + b_{0,i}\, m_h + b_{1,i}\, m_{h-1} + e_{i,h}, \tag{7}$$

where m_h denotes the hourly return of the value-weighted market of all coins in the universe, and the lagged market return accounts for asynchronous trading. The systematic component is $s_{i,h} = b_{0,i} m_h + b_{1,i} m_{h-1}$, whereas the idiosyncratic component is $e_{i,h}$, which we refer to as the abnormal return. The upside and downside semivariances (Barndorff-Nielsen et al., 2010) of each component are

$$SV^{+}_{i,d} = \tfrac{1}{7}\textstyle\sum_h s^2_{i,h}\, \mathbf{1}\{s_{i,h} > 0\}, \qquad SV^{-}_{i,d} = \tfrac{1}{7}\textstyle\sum_h s^2_{i,h}\, \mathbf{1}\{s_{i,h} < 0\}, \tag{8}$$

$$IV^{+}_{i,d} = \tfrac{1}{7}\textstyle\sum_h e^2_{i,h}\, \mathbf{1}\{e_{i,h} > 0\}, \qquad IV^{-}_{i,d} = \tfrac{1}{7}\textstyle\sum_h e^2_{i,h}\, \mathbf{1}\{e_{i,h} < 0\}. \tag{9}$$

Total idiosyncratic variance is $IV_{i,d} = IV^{+}_{i,d} + IV^{-}_{i,d} = \frac{1}{7}\sum_h e^2_{i,h}$, the average daily residual variance over the preceding week. The regressions use logged measures standardized over the sample, so coefficients describe return differences per standard deviation of the transformed variable.

We identify an idiosyncratic shock when the absolute abnormal return in an hour exceeds four times its standard deviation over the preceding 168 hours. For event identification, abnormal returns are calculated using the market exposure estimated on the previous day. This threshold identifies unusually large realized price movements; it does not identify the type or magnitude of the underlying news.

A shock enters the event sample only if the coin belongs to the universe on the event day. We retain the following week even if the coin subsequently leaves the universe, avoiding selection based on future capitalization. To limit event overlap, we retain at most one shock per coin within any 48-hour window and follow abnormal returns from 24 hours before to 168 hours after the event. Standard errors are clustered by coin to account for dependence across events from the same coin. From January 2020, the sample contains 33,895 upside and 19,785 downside shocks to 403 coins. These shocks are statistical classifications of large price movements, not identified news events. Appendix Table 9 provides selected examples matched to contemporaneous news. The distinction between shock hours and other hours also allows us to decompose idiosyncratic variance into the contributions of unusually large movements and the remaining hours.

3.3 Access to Short Selling

Perpetual futures allow traders to take short positions without borrowing the underlying cryptocurrency. Unlike conventional futures, these contracts have no expiration date and use periodic funding payments to keep their prices close to spot prices (He et al., 2022). When funding rates are positive, long positions pay short positions; when negative, the payments are reversed. Although perpetual futures eliminate the need to borrow the underlying asset, traders still face margin requirements and liquidation risk. Appendix B.2 provides further details.

We identify the first trading date of each Binance perpetual contract from Binance's historical futures archive. However, Binance perpetual listings do not necessarily mark the first opportunity to short a coin. Short exposure may have been available earlier through margin trading on Binance or through derivatives and margin trading on other exchanges. To account for this, we construct three access dates: (i) the *perpetual date*, when Binance perpetual trading begins; (ii) the *margin date*, the earlier of Binance margin and perpetual availability; and (iii) the *earliest documented date*, which incorporates earlier access to short selling through perpetual futures, conventional futures, and margin trading across exchanges. When no earlier access is documented,

we retain the Binance perpetual date.

Earlier access is common. Among the 50 largest coins, 49 have a documented access date. Of these, 41 could be shorted before their Binance perpetual listing, including 26 more than three months earlier. Similarly, among 63 mid-sized coins selected for frequent pre-listing shocks, 60 have documented access dates, and 59 had earlier margin access, with a median lead of 214 days. These samples are selected rather than representative, and historical records do not always establish the exact date when short selling first became possible. We therefore treat the earliest documented date as evidence that short selling was available by that date, rather than as the true date of first access. Appendix B.3 describes the underlying sources and date construction.

Let L_i denote the date from which coin i can be shorted, and define $Short_{i,t} = \mathbf{1}\{t \geq L_i\}$, which equals zero before this date and one from this date onward. A coin is shortable, or has access, on a day if $Short_{i,t} = 1$, and non-shortable otherwise. The earliest documented date is the principal definition of L_i; the perpetual and margin dates provide alternative classifications. Access expands substantially during the sample (Figure 2): the share of coins with a Binance perpetual rises from 21% in 2020 to 53% in 2023, and access measured by the earliest documented date is broader.

We exploit variation in access both across and within cryptocurrencies. The cross-sectional analysis compares coins with and without access on the same day. The sample begins in January 2020 and covers 405 coins, with a median of 301 coins observed per day. The within-coin analysis compares each coin before and after it gains access, excluding a 91-day window around the access date, L_i. Under the earliest documented date, the daily panel contains 399 coins: 196 never have access during the sample, 129 have access when the sample begins, and 74 gain access during the sample. These 74 coins provide the within-coin variation used to estimate the effect of access, while the remaining coins contribute to the estimation of fixed effects and baseline relationships. Using perpetual futures listings instead, the corresponding groups contain 206, 103, and 90 coins. For the shock-event analysis, we additionally require each coin that gains access to experience at least one shock both before and after access. This restriction leaves 73 coins that gain access under the earliest-access definition and 88 under the perpetual-listing definition. Finally, Binance perpetual position data, including open interest and long/short account ratios, are available from December 2021 and are used in Section 5.4.

4 Idiosyncratic Variance and Future Returns

This section documents the return predictability of idiosyncratic variance and examines its sources. Coins with higher idiosyncratic variance earn lower subsequent returns, a relation driven primarily by upside variance and concentrated among coins without access. Decomposing variance

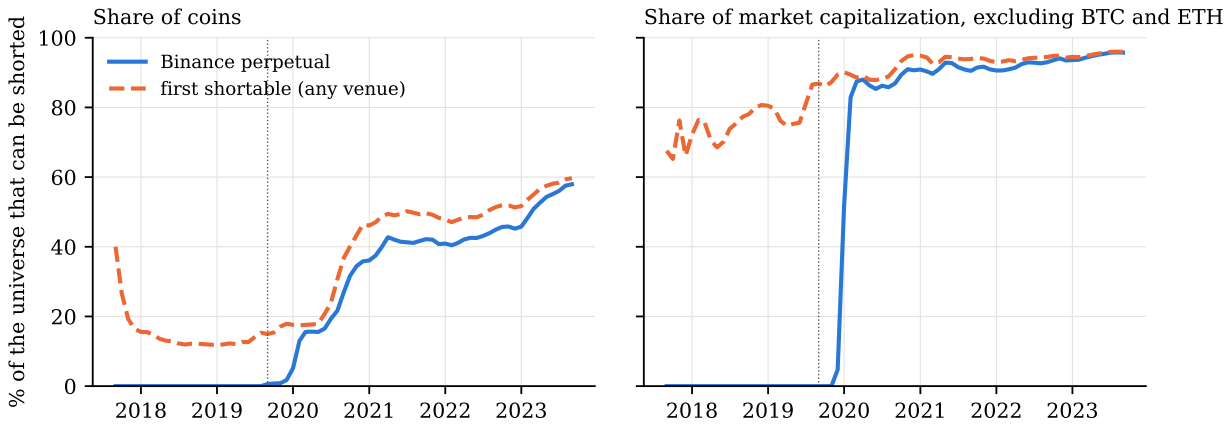


Figure 2: Access to short selling in the universe. The figure shows the share of coins (left) and of market capitalization excluding BTC and ETH (right) in the universe that can be shorted, computed as monthly averages of daily shares, with access dated by the Binance perpetual listing (solid) and by the earliest perpetual, futures or margin listing on any venue (dashed). BTC and ETH, which account for most of the market capitalization of the universe, are excluded from the right panel because they were shortable on other venues throughout the sample. The dotted line marks September 2019, when Binance listed its first perpetual.

further, we find that the predictability comes mainly from hours with large idiosyncratic shocks and is stronger for recent shocks than for more distant ones, consistent with Prediction P3.

4.1 Idiosyncratic Variance and Next-Day Returns

Coins with high idiosyncratic variance earn lower subsequent returns than coins with low idiosyncratic variance. In Panel A of Table 2, the equal-weighted high-minus-low spread is −21.9 basis points per day for total idiosyncratic variance ($t = -2.9$) and −24.0 for upside idiosyncratic variance ($t = -3.2$). Returns are not monotonic across quintiles, but the portfolio with the highest idiosyncratic variance underperforms the one with the lowest under both measures. The value-weighted spread on total idiosyncratic variance is smaller and insignificant, at −13.4 basis points ($t = -1.1$). Alphas relative to the cryptocurrency market, size, and momentum factors of Liu et al. (2022) are negative for both weighting schemes; for total idiosyncratic variance they are −33.3 and −28.7 basis points.

Table 3, Panel A, shows that the negative relation between idiosyncratic variance and future returns is driven by upside variance. Without controls, a one-standard-deviation increase in total idiosyncratic variance predicts 12.5 basis points lower next-day returns ($t = -3.7$; column 1). Separating upside and downside variance reveals larger coefficients of opposite signs: a one-standard-deviation increase in upside variance predicts 53.4 basis points lower returns ($t = -8.1$), whereas the same increase in downside variance predicts 43.1 basis points higher returns ($t = 6.4$;

column 2). The positive downside coefficient is conditional on upside variance, with which it is strongly correlated. It does not imply that downside shocks predict higher returns: Section 4.4 shows that variance attributable to downside shocks predicts lower subsequent returns, consistent with price continuation following negative shocks. Systematic upside and downside semivariances have no significant predictive power across coins (not tabulated). Controlling for these components and other coin characteristics, the coefficient on upside idiosyncratic variance remains strongly negative among coins without access, at −70.5 basis points ($t = -5.8$; column 4), using the earliest documented access date. The negative variance–return relation resembles the idiosyncratic volatility puzzle in equities (Ang et al., 2006), while the asymmetry between upside and downside variance is consistent with evidence that the two have different return implications (Barndorff-Nielsen et al., 2010; Patton and Sheppard, 2015; Bollerslev et al., 2020).

4.2 Access to Short Selling and Return Predictability

The negative spread is concentrated among coins that cannot be shorted (Table 2, Panel C). Under the earliest date, the equal-weighted high-minus-low spread on total idiosyncratic variance is −56.6 basis points per day among coins that cannot be shorted ($t = -6.9$) and 0.1 among shortable coins. The difference of 56.7 basis points ($t = 5.4$) remains after adjusting for the crypto market, size, and momentum factors (54.0, $t = 5.4$). Value weighting gives a difference of 77.8 basis points ($t = 5.5$), sorts on upside idiosyncratic variance give 54.5 and 75.8, and dating access by the Binance perpetual gives similar differences (Panel B). Both groups contain at least 25 coins on every day used, and coin-days within 91 days of access are excluded.

The regressions show the same difference in slopes (Table 3, Panel A). With controls for the systematic semivariances, past returns, MAX, realized skewness, and size, the slope on upside idiosyncratic variance is 36.2 basis points less negative for shortable coins under the earliest date and 34.8 under the perpetual date ($t = 3.1$ in both cases). These are comparisons between coins, which may differ in other ways than access; Section 6 examines whether the slope changes within coins after access.

4.3 Size

Size may confound the relation between access to short selling and return predictability, because shortable coins tend to be larger. We first compare coins within daily size terciles (Appendix Table 12, Panel A). Among coins that cannot be shorted, high idiosyncratic variance predicts lower returns in all three terciles, with high-minus-low spreads of −37.6, −64.8, and −39.3 basis points per day for small, medium, and large coins. Among shortable coins, the spread is smaller in absolute value for medium-sized coins (−27.9 basis points, $t = -3.3$) and insignificant for large

Table 2: Portfolios sorted on idiosyncratic variance

	IV, EW	IV, VW	IV^+, EW	IV^+, VW
Panel A. All coins				
Q1 (low)	28.5**	18.5*	29.8**	18.4*
	(2.31)	(1.86)	(2.39)	(1.85)
Q2	39.0***	9.4	40.3***	17.5
	(2.92)	(0.73)	(3.02)	(1.30)
Q3	37.8***	16.9	37.5***	7.5
	(2.79)	(1.26)	(2.75)	(0.57)
Q4	21.5	16.1	20.2	11.9
	(1.58)	(1.12)	(1.50)	(0.84)
Q5 (high)	6.7	5.1	5.8	7.8
	(0.49)	(0.32)	(0.42)	(0.49)
High minus low	−21.9***	−13.4	−24.0***	−10.6
	(−2.93)	(−1.07)	(−3.19)	(−0.85)
High minus low, alpha	−33.3***	−28.7***	−35.3***	−26.3**
	(−5.77)	(−2.58)	(−6.07)	(−2.42)
Days	1,342	1,342	1,342	1,342
Coins	405	405	405	405
Panel B. By shortability, Binance perpetual date				
High minus low, not shortable	−62.7***	−79.8***	−65.4***	−76.6***
	(−6.99)	(−8.96)	(−7.47)	(−8.95)
High minus low, shortable	−5.5	−10.1	−5.3	−11.2
	(−0.66)	(−0.81)	(−0.66)	(−0.89)
Difference	57.2***	69.6***	60.0***	65.4***
	(5.47)	(4.95)	(5.89)	(4.53)
Difference, alpha	53.6***	64.0***	56.8***	60.6***
	(5.52)	(4.81)	(5.96)	(4.47)
Days	1,091	1,091	1,091	1,091
Coins, not shortable / shortable	270 / 193	270 / 193	270 / 193	270 / 193
Panel C. By shortability, earliest date				
High minus low, not shortable	−56.6***	−75.3***	−58.7***	−73.2***
	(−6.94)	(−8.26)	(−7.39)	(−8.37)
High minus low, shortable	0.1	2.4	−4.2	2.5
	(0.02)	(0.21)	(−0.48)	(0.21)
Difference	56.7***	77.8***	54.5***	75.8***
	(5.39)	(5.47)	(5.20)	(5.47)
Difference, alpha	54.0***	72.2***	52.0***	71.3***
	(5.40)	(5.37)	(5.19)	(5.39)
Days	1,294	1,294	1,294	1,294
Coins, not shortable / shortable	268 / 203	268 / 203	268 / 203	268 / 203

Each day from January 2020, coins are sorted into quintiles of total idiosyncratic variance (IV) or upside idiosyncratic variance (IV^+) over the previous seven days. Average next-day excess returns in basis points per day, equal-weighted (EW) or weighted by market capitalization (VW). Alpha: intercept from a regression on the crypto market, size and momentum factors. Panels B and C form quintiles separately among coins that can and cannot be shorted on the formation day, excluding coin-days within 91 days of the shortability date, and report the high-minus-low return in each group and their difference, all on the days on which both groups have at least 25 coins. Newey-West t-statistics with five lags in parentheses. *, **, *** denote significance at 10%, 5%, 1%.

coins (-6.6, $t = -1.0$). The positive spread for small shortable coins rests on only 53 coins and is significant only at the 10% level. Size is matched only approximately in the large tercile, where the median market capitalization is $257 million among coins that cannot be shorted and $1.1 billion among shortable coins. Panel B addresses size in the regressions. Allowing the slope on upside idiosyncratic variance to vary with log market capitalization leaves an interaction with access of 28.3 basis points ($t = 1.9$), and restricting each day to the common support of the two size distributions gives 39.2 basis points ($t = 1.8$). Across coins, the comparison therefore remains positive but only marginally significant once size is taken into account. Within coins, where coin fixed effects absorb time-invariant differences in size, the slope on upside idiosyncratic variance is more negative for larger coins (-19.5 basis points per standard deviation of log capitalization, $t = -2.6$), and allowing for this raises the change in the slope at access from 49.2 to 62.3 basis points ($t = 2.4$). Size therefore does not explain the weaker predictability among shortable coins, but size matching across coins is imperfect, and the two groups may differ in other ways. Section 5 therefore compares the same coin before and after access.

4.4 The Shock Component of Idiosyncratic Variance

Prediction P3 states that the negative relation between idiosyncratic variance and future returns arises from large idiosyncratic shocks of either sign, and that recent shocks predict more strongly than older ones. To test this prediction, Table 4 decomposes upside and downside idiosyncratic variance into shock and ordinary components. The shock component sums the squared abnormal returns of the hours in which the absolute abnormal return exceeds four robust standard deviations of the coin's abnormal returns over the same seven days, a definition close to that of shocks in Section 3.2. The ordinary component sums the remaining hours. Shock hours account for 59% of upside idiosyncratic variance.

The results support Prediction P3. Across coins, a one-standard-deviation increase in the upside shock component predicts next-day returns that are 9.2 basis points lower ($t = -3.3$), and the downside shock component predicts returns that are 7.9 basis points lower ($t = -3.4$). The ordinary components have small and statistically insignificant coefficients. Within coins, the upside shock component predicts returns that are 13.2 basis points lower ($t = -4.0$) and the downside shock component 5.1 basis points lower ($t = -1.7$). The predictability is therefore concentrated in large idiosyncratic shocks rather than ordinary fluctuations, although the within-coin evidence for downside shocks is weaker.

Recent shocks predict more strongly than older ones. We weight each shock hour's squared abnormal return by a factor of 0.7 per day of age, a half-life of about two days, as the decay of disagreement in equation (6) implies. The decayed upside shock component predicts next-day

Table 3: Access to short selling and the return predictability of idiosyncratic variance

Panel A. Across coins: Fama-MacBeth

Shortability date	(1)	(2)	(3) Binance perpetual	(4) Earliest	(5) Placebo
IV	-12.5^{***}				
	(-3.67)				
IV^{+}		-53.4^{***}	-65.2^{***}	-70.5^{***}	-64.7^{***}
		(-8.12)	(-5.52)	(-5.79)	(-6.59)
IV^{-}		43.1^{***}	39.7^{***}	43.4^{***}	49.9^{***}
		(6.38)	(3.40)	(3.56)	(4.72)
$IV^{+} \times$ *Short*			34.8^{***}	36.2^{***}	-28.8
			(3.06)	(3.13)	(-1.63)
$IV^{-} \times$ *Short*			-26.6^{**}	-25.3^{**}	31.1
			(-2.34)	(-2.10)	(1.58)
Days	1,342	1,342	1,330	1,342	938
Coins	405	405	405	405	291

Panel B. Within coins: coin and day fixed effects

Shortability date	(1)	(2) Binance perpetual	(3)	(4)	(5) Earliest	(6)	(7) Placebo
Group-specific slopes	No	Yes	Yes	No	Yes	Yes	Yes
Year-specific slopes	No	No	Yes	No	No	Yes	No
IV^{+}	-64.5^{***}	-68.4^{***}	-71.5^{***}	-66.8^{***}	-65.5^{***}	-55.9^{***}	-47.1^{***}
	(-5.84)	(-5.89)	(-3.92)	(-5.81)	(-5.56)	(-3.20)	(-3.41)
$IV^{+} \times$ switching coin		28.5	28.1		-11.9	-16.5	22.8
		(1.12)	(1.07)		(-0.50)	(-0.68)	(0.96)
$IV^{+} \times$ always shortable		51.0^{*}	51.4^{*}		-4.9	-10.4	47.9
		(1.70)	(1.67)		(-0.17)	(-0.37)	(1.10)
$IV^{+} \times$ *Short*	41.0^{***}	1.7	1.0	43.3^{***}	49.2^{*}	54.6^{**}	-44.1
	(3.59)	(0.06)	(0.04)	(3.79)	(1.91)	(2.08)	(-1.33)
$IV^{-} \times$ *Short*	-23.8^{*}	19.0	21.0	-26.8^{**}	-22.7	-26.1	53.2
	(-1.82)	(0.72)	(0.77)	(-2.06)	(-0.88)	(-1.00)	(1.61)
Sum of the interactions	17.2^{***}	20.7^{**}	22.1^{**}	16.5^{***}	26.4^{***}	28.5^{***}	9.1
	(3.37)	(2.35)	(2.37)	(3.51)	(3.01)	(3.25)	(0.69)
Post-access IV^{+} slope, switching coins		-38.2^{***}	-42.3^{*}		-28.2^{*}	-17.8	
		(-2.59)	(-1.91)		(-1.96)	(-0.84)	
Coin-days	331,896	331,896	331,896	335,690	335,690	335,690	183,320
Coins	399	399	399	399	399	399	296
Switching coins	90	90	90	74	74	74	59

Next-day returns on standardized log idiosyncratic variance (IV) or its upside and downside parts (IV^{+}, IV^{-}) over the previous seven days, an indicator that the coin can be shorted (*Short*) and their interactions, from January 2020. Panel A: daily cross-sectional regressions with at least 30 coins (and 10 in each shortability group in columns 3 to 5), Newey-West t-statistics; columns 3 and 4 include the controls (systematic upside and downside variance, past abnormal and total returns, MAX, realized skewness and log market capitalization). Panel B: coin and day fixed effects and the controls, excluding coin-days within 91 days of the (placebo) shortability date, Driscoll-Kraay t-statistics. Coins are classified as never shortable, always shortable or switching within the retained sample. Columns 2, 3, 5, 6 and 7 allow the slopes on IV^{+} and IV^{-} to differ between the three groups, so that the interactions with *Short* are identified only from the change in the slopes of switching coins; columns 3 and 6 also allow the slopes to differ by calendar year. The last row is the upside slope of switching coins after access, the sum of the coefficients on IV^{+}, $IV^{+} \times$ switching coin and $IV^{+} \times$ *Short*. Column 5 of Panel A and column 7 of Panel B date each Binance perpetual listing one year early and use only days more than 91 days before the true listing and coins never listed. Coefficients in basis points per standard deviation. *, **, *** denote significance at 10%, 5%, 1%.

returns that are 22.7 basis points lower per standard deviation across coins ($t = -7.4$) and 25.3 basis points lower within coins ($t = -6.4$), more than twice the coefficient on the undecayed component. When total upside idiosyncratic variance and the decayed shock component enter jointly, both remain predictive, with a coefficient of −18.4 basis points on the decayed component across coins ($t = -4.7$). The predictive relation of the decayed upside shock component is also weaker among shortable coins, by 13.0 basis points ($t = 2.9$; column 3). The results hold at shock thresholds of three, four, and five robust standard deviations, at which the interaction with access is 11.7, 13.0, and 15.6 basis points ($t = 2.0$, 2.9, and 4.1; Appendix Table 13).

The negative relation between idiosyncratic variance and future returns is therefore concentrated in large, recent idiosyncratic shocks, and it is weaker among coins that can be shorted. Section 5 examines how prices adjust after these shocks and whether access to short selling changes that adjustment.

5 Price Adjustment after Shocks and Access to Short Selling

Section 4 shows that the negative relation between idiosyncratic variance and future returns is concentrated in recent shocks. This section examines the price adjustment behind this predictability. When short selling is constrained, prices should reverse more after upside shocks and continue to decline more after downside shocks (P1), and access to short selling should reduce both the reversal and the continuation (P2). We first compare coins with and without access, then compare the same coin before and after access, and finally examine short positions and funding around shocks.

5.1 Price Adjustment across Coins

An upside shock averages 6.2% and is followed by abnormal returns of −1.7% over 24 hours, −2.9% over 72 hours, and −3.4% over the week ($t = -9.9$), so more than half of the initial increase reverses. A downside shock averages −5.2% and is followed by little change in the first day and a further decline of −1.4% over the week ($t = -3.1$; Appendix Table 14 and Appendix Figure 8). Abnormal returns are thus negative after shocks of either sign, as P1 predicts, whereas a reversal of temporary price pressure would imply positive returns after downside shocks. Among coins without a Binance perpetual, the first four hours account for about 45% of the weekly reversal after upside shocks and may partly reflect bid–ask bounce or temporary price pressure, so we focus on the adjustment over the following days.

Both the reversal after upside shocks and the continuation after downside shocks are larger

Table 4: Shock hours and the return predictability of idiosyncratic variance

Panel A. Across coins: Fama-MacBeth	(1)	(2)	(3)	(4)
IV^+	−70.5***			−39.7**
	(−5.79)			(−2.49)
IV^+, shock hours		−9.2***		
		(−3.29)		
IV^+, shock hours, decayed			−22.7***	−18.4***
			(−7.36)	(−4.66)
IV^+, other hours		8.0	−8.9	
		(0.76)	(−0.86)	
IV^-	43.4***			36.8**
	(3.56)			(2.53)
IV^-, shock hours		−7.9***		
		(−3.42)		
IV^-, shock hours, decayed			−6.3**	−10.4***
			(−2.42)	(−3.69)
IV^-, other hours		−9.6	10.3	
		(−0.84)	(0.91)	
IV^+ ×*Short*	36.2***			15.0
	(3.13)			(1.02)
IV^+, shock hours ×*Short*		4.4		
		(1.10)		
IV^+, shock hours, decayed ×*Short*			13.0***	10.7*
			(2.89)	(1.93)
IV^+, other hours ×*Short*		−3.3	9.9	
		(−0.20)	(0.61)	
IV^- ×*Short*	−25.3**			−20.4
	(−2.10)			(−1.44)
Days	1,342	1,342	1,342	1,342
Coins	405	405	405	405

Panel B. Within coins: coin and day fixed effects, group-specific slopes	(1)	(2)	(3)	(4)
IV^+	−65.5***			−33.7**
	(−5.56)			(−2.03)
IV^+, shock hours		−13.2***		
		(−4.00)		
IV^+, shock hours, decayed			−25.3***	−18.6***
			(−6.42)	(−3.68)
IV^+, other hours		6.6	−7.2	
		(0.58)	(−0.63)	
IV^-	42.9***			36.9**
	(3.95)			(2.56)
IV^-, shock hours		−5.1*		
		(−1.71)		
IV^-, shock hours, decayed			−5.0	−10.9***
			(−1.45)	(−2.82)
IV^-, other hours		0.6	17.1	
		(0.05)	(1.43)	
IV^+ ×*Short*	49.2*			21.6
	(1.91)			(0.59)
IV^+, shock hours ×*Short*		12.4		
		(1.39)		
IV^+, shock hours, decayed ×*Short*			16.6*	10.5
			(1.66)	(0.87)
IV^+, other hours ×*Short*		15.8	23.1	
		(0.44)	(0.65)	
IV^- ×*Short*	−22.7			−0.4
	(−0.88)			(−0.01)
Coin-days	335,690	335,690	335,690	335,690
Coins	399	399	399	399

Earliest date; coin-days from January 2020. Shock hours: hours of the previous seven days with an abnormal return beyond four robust standard deviations; other hours: the rest. Decayed: each shock hour's squared abnormal return is multiplied by $0.7^{a/24}$, with a the hours since that hour, a half-life of about two days. Components in logs, standardized. Column 1 reproduces Table 3, Panel A, column 4, and Panel B, column 5. All regressions include *Short*, the controls of Table 3 and, in Panel B, group-specific slopes on each component. Interactions of the downside components with *Short* are included but not reported; none is significant at the 10% level. Basis points per standard deviation; Newey-West (A) and Driscoll-Kraay (B) t-statistics. *, **, *** denote significance at 10%, 5%, 1%.

among coins without a Binance perpetual (Figure 3). To account for observable differences, we estimate for each shock sign

$$CAR_e(h) = \alpha_{m(e)} + \beta\, Short_{i(e),\tau(e)} + \gamma' X_e + \varepsilon_e, \tag{10}$$

where e indexes shocks, $i(e)$ is the coin, $\tau(e)$ the shock hour, and $m(e)$ the calendar month. $CAR_e(h)$ is the cumulative abnormal return, in %, from the end of the shock hour to hour $h \in \{24, 72, 168\}$, *Short* equals one if the coin can be shorted at the time of the shock, and X_e contains log market capitalization, log dollar volume, and log absolute shock size. Standard errors are clustered by coin. A positive β indicates a smaller reversal after an upside shock or a weaker continuation after a downside shock. The weekly return is 2.5 percentage points higher after upside shocks ($t = 8.4$) and 2.1 percentage points higher after downside shocks ($t = 7.3$) for coins with a perpetual, and both estimates remain significant with clustering by coin and week ($t = 5.5$ and 4.8; Appendix Table 15). More than 80% of the difference after upside shocks accrues over days two through seven (Appendix Table 16). Because coins with a perpetual are larger, more liquid, and may attract more attention, these comparisons do not identify the effect of access, and we turn to the same coin before and after access.

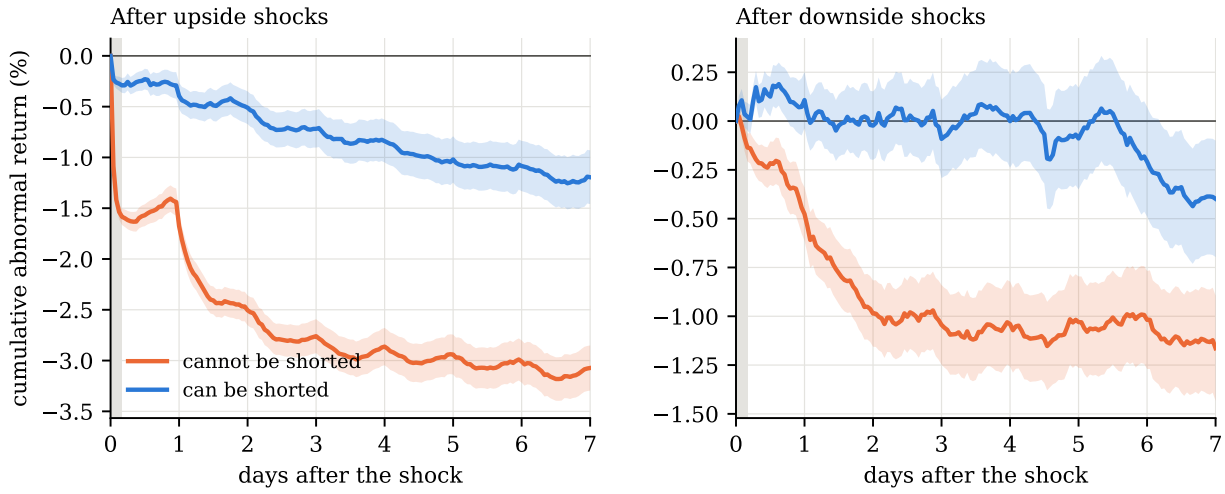


Figure 3: Post-shock returns and access to short selling. Cumulative abnormal returns from the end of the shock hour, in %, for coins with and without a Binance perpetual at the time of the shock, September 2019 to September 2023. Upside shocks: 22,243 without and 13,029 with a perpetual; downside shocks: 12,731 and 8,030. The shaded region marks the first four hours. Means with 95% confidence bands.

5.2 Price Adjustment within Coins

Empirical design. We estimate

$$CAR_e(h) = \alpha_{i(e)} + \alpha_{m(e)} + \beta\, Short_{i(e),\tau(e)} + \varepsilon_e, \tag{11}$$

so that β compares the same coin's post-shock returns before and after access, relative to other coins' shocks in the same month. Because access is staggered, this regression also uses coins with earlier access as controls (Goodman-Bacon, 2021; Baker et al., 2022). We therefore also estimate a stacked design (Gormley and Matsa, 2011; Cengiz et al., 2019). For each access month c, a stack contains the coins that gain access in that month and, as controls, coins whose access begins more than a year later, with shocks within 365 days of month c:

$$CAR_e(h) = \alpha_{c,i(e)} + \alpha_{c,m(e),k(e)} + \beta\, Post_{c,i(e),\tau(e)} + \varepsilon_e, \tag{12}$$

where *Post* marks shocks to coins that gain access after the access date and $k(e)$ is the shock-size quintile within the month. We also report the heterogeneity-robust estimator of Sun and Abraham (2021), with cohorts defined by the half-year of access, and a placebo that dates access one year early and uses only pre-access shocks. All designs exclude shocks within 91 days of access, which removes the listing episode, and cluster standard errors by coin. Under the earliest documented date, 73 coins gain access with shocks on both sides of the date; the stacked design adds 125 control coins for upside shocks and 122 for downside shocks.

Upside shocks. Access reduces the reversal after upside shocks (Table 5). Under the earliest date, the same coin's weekly post-shock return increases by 2.55 percentage points ($t = 3.3$), about three quarters of the average reversal, and 1.74 percentage points of this increase occur over days two through seven ($t = 2.7$). The stacked design gives 2.19 percentage points ($t = 1.9$), the estimator of Sun and Abraham (2021) 2.84 ($t = 2.7$; Appendix Table 17), and the placebo −0.48 ($t = -0.6$). The Binance perpetual and margin dates give 2.36 and 2.59 percentage points in the same-coin design and 2.09 and 2.36 in the stacked design.

Downside shocks. The model implies that access has a larger effect after shocks that create more disagreement, including declines that continue the correction of an earlier upward move (Section 2). We therefore distinguish downside shocks after an upside shock, which follow an upside shock in the same coin within 48 hours, from isolated downside shocks, which do not. The distinction uses only information available at the time of the shock, and both groups use the same shock definition and fixed effects. For downside shocks after an upside shock, access

reduces the subsequent decline by 3.51 percentage points ($t = 2.62$) within the same coin. For isolated downside shocks, the change is 0.60 percentage points ($t = 0.59$). The same-coin estimate for all downside shocks is therefore smaller than the estimate across coins, because it averages over two groups that respond differently to access. At the Binance perpetual date, the pattern is the same but weaker: 2.02 percentage points ($t = 1.50$) for downside shocks after an upside shock and 0.14 ($t = 0.14$) for isolated downside shocks.[2]

Return paths and dynamics. Among the 73 coins that gain access, the weekly return after an upside shock is −2.7% before access and −1.1% after, compared with −4.1% for coins that never gain access (Figure 4). The estimated effect of access grows from 0.5 percentage points in the first hour to 2.55 by the end of the week after upside shocks, and to 2.22 after all downside shocks, which average the two groups distinguished above; the raw downside paths are less informative, because they rest on fewer shocks and mix calendar years with different market-wide declines. In half-year event studies for upside shocks, the pre-access coefficients are jointly insignificant ($p = 0.10$ under the earliest date and 0.30 under the perpetual date), and all four post-access coefficients are positive, averaging 2.28 ($t = 2.2$) and 1.70 percentage points ($t = 1.5$; Figure 5).

Identification. A causal interpretation requires that, absent access, the response to shocks of coins that gain access would have evolved like that of the comparison coins. The stacked and Sun–Abraham estimates, the placebo and the absence of pre-access trends after upside shocks support this assumption. The estimates draw mainly on shocks in the year before access (Appendix Table 18), and access may coincide with changes in leverage and attention; Section 5.3 tests liquidity, the most prominent of these.

5.3 Robustness

Table 6 reports the robustness checks. Because relatively few coins gain access, we report wild cluster bootstrap p-values: 0.002 after upside shocks and 0.016 after downside shocks (Panel A). Pooling both signs gives 2.42 percentage points ($t = 3.4$; bootstrap $p = 0.002$). For 35 coins we find no documented means of short selling before the Binance perpetual, so all three access dates coincide. Among these coins, access raises the weekly return by 2.67 percentage points after

[2]The results are robust to the window that defines a preceding upside shock. For windows of 24, 72 and 168 hours, access reduces the decline after downside shocks after an upside shock by 4.41, 3.50 and 2.85 percentage points ($t = 3.18$, 2.39 and 2.21), and changes the return after isolated downside shocks by less than 0.9 percentage points in absolute value. At the perpetual date, the estimate for the 24-hour window is 2.90 percentage points ($t = 2.70$). In a pooled regression with group-specific fixed effects, the difference between the two groups is 2.91 percentage points ($t = 1.98$; wild cluster bootstrap $p = 0.05$) for the 48-hour window and 3.59 ($t = 2.43$) for the 24-hour window.

Table 5: Access to short selling and the return after shocks: difference-in-differences

	Upside shocks		Downside shocks	
	Same coin	Stacked	Same coin	Stacked
Panel A. Binance perpetual date				
Days 0–7	2.36***	2.09**	1.04	1.75
	(3.16)	(2.12)	(1.03)	(1.38)
Days 2–7	1.87***	1.72**	1.09	1.67
	(2.86)	(2.01)	(1.24)	(1.44)
Hours 1–4	0.35	0.11	−0.15	−0.40*
	(1.49)	(0.38)	(−0.91)	(−1.75)
Days 0–7: Post × shock size		2.28*		2.91**
		(1.81)		(2.35)
Placebo, 12 months early		−0.44		0.00
		(−0.63)		(0.00)
Treated coins	88	88	88	88
Control coins, stacked		145		143
Coins, same coin	396		397	
Panel B. Earliest date on any venue				
Days 0–7	2.55***	2.19*	2.22**	2.85***
	(3.25)	(1.94)	(2.50)	(2.89)
Days 2–7	1.74***	1.53	2.00***	2.76***
	(2.72)	(1.50)	(2.67)	(2.94)
Hours 1–4	0.65***	0.42	−0.16	−0.66***
	(3.12)	(1.45)	(−0.81)	(−2.93)
Days 0–7: Post × shock size		2.77**		2.26
		(2.33)		(1.59)
Placebo, 12 months early		−0.48		0.46
		(−0.60)		(0.52)
Treated coins	73	73	73	73
Control coins, stacked		125		122
Coins, same coin	396		397	
Panel C. First margin or perpetual date				
Days 0–7	2.59***	2.36**	2.34***	2.94***
	(3.34)	(2.09)	(2.66)	(3.00)
Days 2–7	1.78***	1.63	2.07***	2.82***
	(2.83)	(1.60)	(2.79)	(3.01)
Hours 1–4	0.64***	0.43	−0.14	−0.67***
	(3.09)	(1.50)	(−0.75)	(−2.95)
Days 0–7: Post × shock size		3.34***		2.50*
		(2.84)		(1.75)
Placebo, 12 months early		−0.48		0.46
		(−0.60)		(0.52)
Treated coins	75	75	75	75
Control coins, stacked		117		115
Coins, same coin	396		397	

The outcome is the cumulative abnormal return (percent) after a shock. Same coin: regression on an indicator that the coin is shortable, with coin and calendar-month fixed effects and no other controls. Stacked: one sub-sample per calendar month of first shortability, containing the coins that become shortable in that month and, as controls, coins that become shortable only more than a year later; Post equals one for treated coins after the date; fixed effects for coin by sub-sample and for calendar month by shock-size quintile by sub-sample. Post × shock size adds the treated coins' own slope on shock size and year-specific slopes. The placebo dates shortability one year early and uses only shocks before the true date. All specifications exclude shocks within 91 days of the date, which removes the run-up before and the reversal after the listing. Treated coins: coins that become shortable during the sample with shocks both before and after access; in the same-coin design all other coins serve as controls through the month fixed effects, and in the stacked design the controls are coins whose access begins after the stack window. t-statistics clustered by coin in parentheses. *, **, *** denote significance at 10%, 5%, 1%.

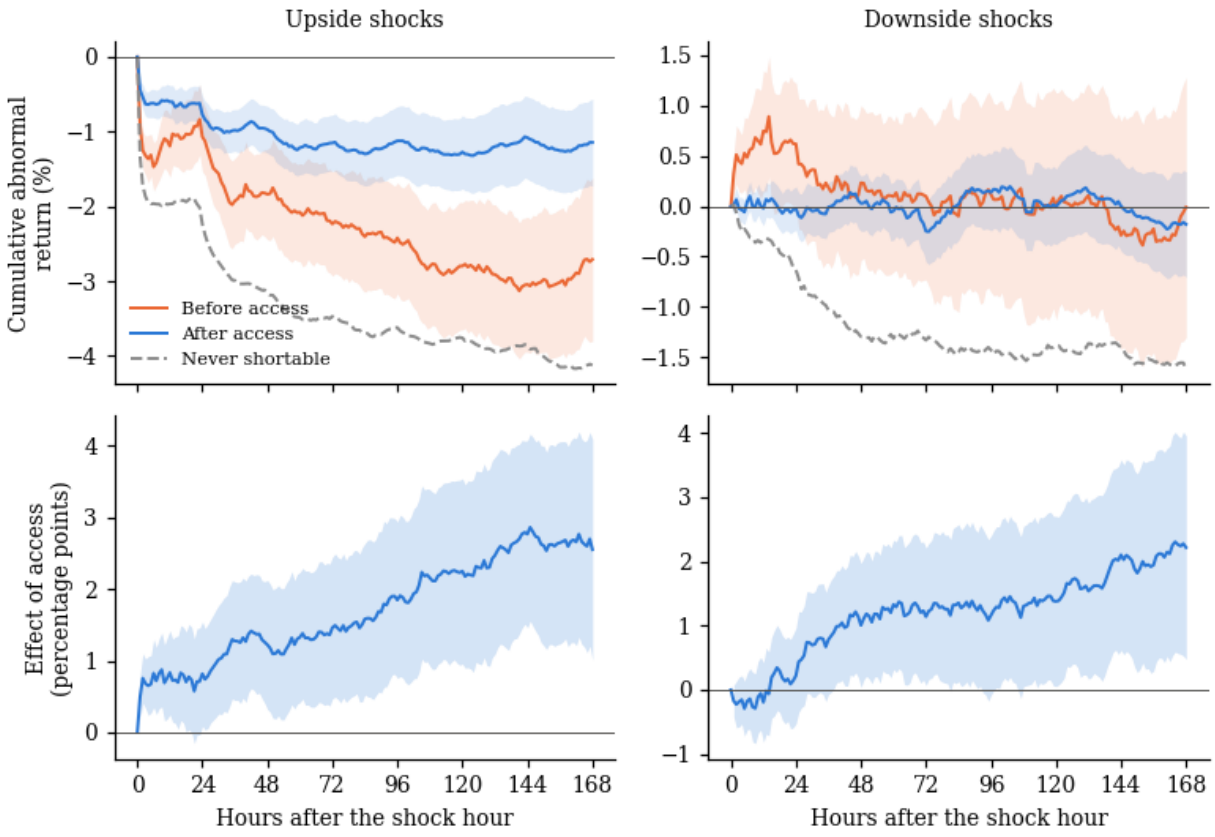


Figure 4: Post-shock returns within the same coins before and after access to short selling. Upper panels: cumulative abnormal returns, in %, after shocks to the 73 coins that gain access during the sample and have shocks on both sides of the earliest documented access date, and to coins that never gain access; shocks from 2020, excluding shocks within 91 days of access. Upside shocks: 1,644 before and 4,712 after access; downside shocks: 916 and 2,844. Lower panels: estimated effect of access at each hour after the shock, from regressions with coin and calendar-month fixed effects, as in Table 5. 95% confidence bands clustered by coin.

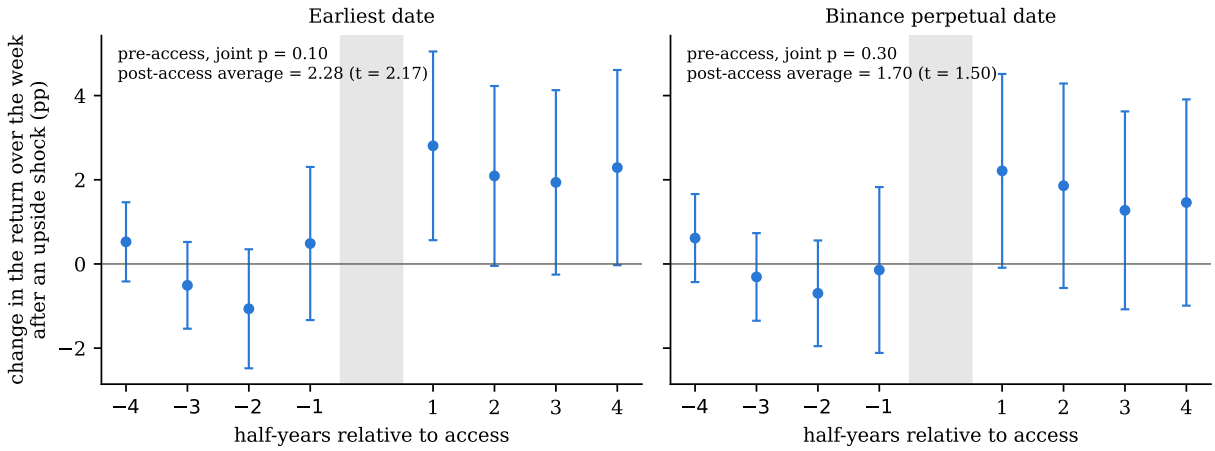


Figure 5: Event study within coins. Change in the return over the week after upside shocks to coins that gain access, by half-year relative to the access date, with coin and calendar-month fixed effects. Reference: shocks more than two years before access and coins that never gain access. Half-year −1 covers days −182 to −92 and half-year 1 days 92 to 182, because shocks within 91 days of access are excluded (shaded). Each panel reports the joint pre-trend p-value and the average post-access effect. 95% confidence intervals clustered by coin.

upside shocks ($t = 2.7$; $p = 0.010$) and by 2.56 after downside shocks ($t = 2.6$; $p = 0.016$; Panel B), so the results do not depend on the hand-collected dates.

A Binance USDT spot pair for coins previously traded only against bitcoin raises trading volume without allowing short selling. Its effect on the weekly return after upside shocks is −0.54 percentage points ($t = -0.6$), while the effect of access remains 2.60; after downside shocks, the USDT effect is 0.83 ($t = 0.7$; Panel C). Controlling for liquidity before the shock raises rather than lowers the effect of access: after upside shocks, it is 2.75 percentage points with turnover, 4.64 with dollar volume, 4.88 with Amihud illiquidity, and 5.17 with turnover and illiquidity together; after downside shocks, it rises from 2.31 to between 3.47 and 3.96 (Panel D). Improved liquidity alone therefore does not explain the results.

5.4 Short Positions and Shorting Costs around Shocks

If access works through short selling, short positions should respond to shocks, and the decline after shocks should be smaller when holding a short position is cheaper. We examine both implications with Binance perpetual position and funding data from December 2021.

Short positions. We follow the share of accounts with net-short positions and open interest from 24 hours before to 72 hours after the 1,500 largest upside and downside shocks (173 and 186 coins; Figure 6 and Appendix Table 21). Neither measure separates directional positions from

Table 6: Robustness of the effect of access on the return after shocks

	Upside shocks	Downside shocks	Pooled
Panel A. Same coin, earliest date			
Short	2.55***	2.22**	2.42***
	(3.25)	(2.50)	(3.39)
Wild bootstrap p-value	0.002	0.016	0.002
Short, days 2–7	1.74***	2.00***	1.83***
	(2.72)	(2.67)	(3.25)
Shocks	31,704	18,565	50,269
Coins	396	397	397
Panel B. Coins with no means of shorting before the Binance perpetual			
Short	2.67***	2.56***	
	(2.70)	(2.58)	
Wild bootstrap p-value	0.010	0.016	
Coins that become shortable	35	35	
Coins	297	298	
Panel C. Listing of a USDT spot pair, without a change in access			
Short	2.60***	2.09**	
	(3.15)	(2.20)	
After USDT listing	−0.54	0.83	
	(−0.57)	(0.69)	
Wild bootstrap p-value, after USDT listing	0.600	0.504	
Change in log dollar volume: access / USDT listing	0.94 / 1.17	1.00 / 1.19	
Coins with a USDT listing	85	85	
Coins in the sample	396	397	
Panel D. Liquidity before the shock			
Short, same sample without controls	2.57***	2.31**	
	(3.26)	(2.55)	
Short, controlling for volume before the shock	4.64***	3.47***	
	(5.16)	(3.53)	
Short, controlling for illiquidity before the shock	4.88***	3.74***	
	(5.32)	(3.74)	
Short, controlling for turnover before the shock	2.75***	2.33**	
	(3.42)	(2.53)	
Short, controlling for turnover and illiquidity before the shock	5.17***	3.96***	
	(5.46)	(3.95)	
Shocks	31,542	18,494	
Coins	396	397	

The outcome is the cumulative abnormal return in percent over the week after the shock (Panel A also reports days 2 to 7). All regressions include coin and calendar-month fixed effects and exclude shocks within 91 days of the date of access. Panel A: access dated by the earliest documented date; the pooled column stacks upside and downside shocks with coin and month fixed effects specific to the sign of the shock, since the model predicts a less negative return after access for both. Panel B: coins for which we find no means of shorting before their Binance perpetual, so that all three access dates coincide, and coins never shortable; access dated by the perpetual listing. Panel C: adds an indicator for shocks more than 91 days after the coin received a USDT spot pair on Binance, for coins that first traded only against BTC, excluding shocks within 91 days of that listing; the last rows report the change in the coin's log dollar volume at access and at the USDT listing from the same regression with log dollar volume as the outcome; after the USDT listing, volume is measured on the USDT pair. Panel D: each row controls for the coin's average log dollar volume, log Amihud illiquidity or log turnover over days −30 to −2 before the shock, standardized; the last row controls for turnover and illiquidity together. Volume and illiquidity are highly correlated (about −0.9 within coins and months) and therefore enter separately. t-statistics clustered by coin in parentheses; wild cluster bootstrap p-values with Rademacher weights, 499 replications and the null imposed. *, **, *** denote significance at 10%, 5%, 1%.

hedges. During upside shocks, the net-short account share rises by 5.3 percentage points ($t = 31$) and open interest by 24 log points ($t = 43$), while the gap between the perpetual and spot prices falls by 0.44 percentage points ($t = -9.1$) and annualized funding falls by 48 percentage points over the following six hours ($t = -9.5$). Both position measures remain above their pre-shock levels three days later. Before downside shocks, positions build up: over the preceding 24 hours, the net-short account share rises by 4.6 percentage points and open interest by 16 log points, compared with 1.3 percentage points and 4 log points before upside shocks, and the difference remains 1.6 percentage points ($t = 5.0$) and 4.1 log points ($t = 3.8$) after controls. This build-up is consistent with traders positioning before large declines (Diamond and Verrecchia, 1987). The position data document trading consistent with the mechanism but do not identify its effect on prices.

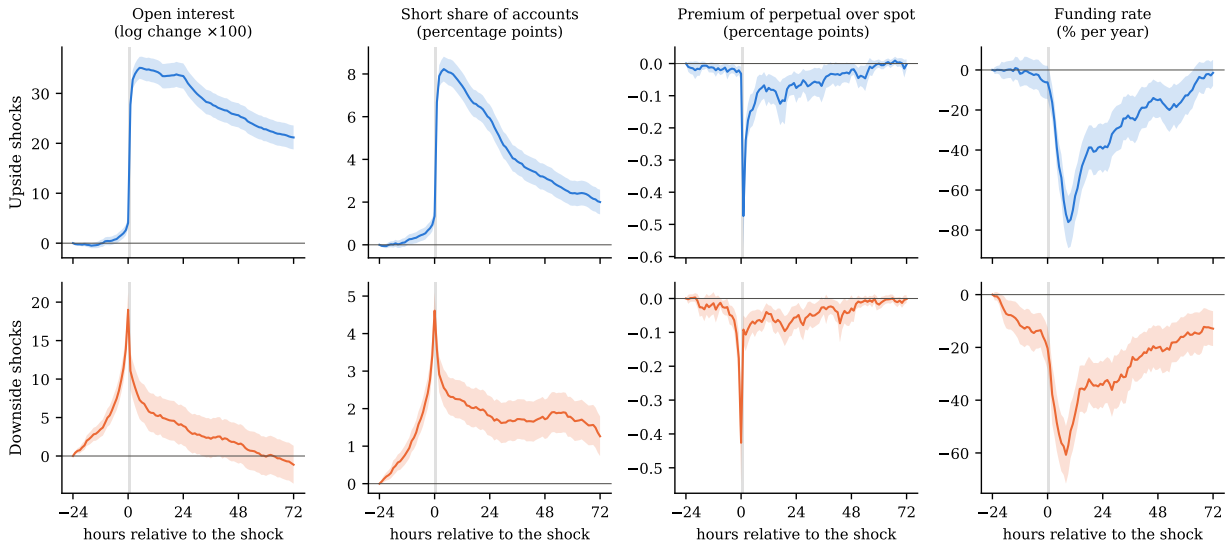


Figure 6: Perpetual-market positions and funding around shocks. Changes relative to 24 hours before the shock in open interest (log change ×100), the share of accounts with net-short positions (percentage points), the gap between the perpetual and spot prices (percentage points), and the annualized funding rate (% per year). Upper panels: upside shocks; lower panels: downside shocks. Hour zero marks the start of the shaded shock hour. The 1,500 largest upside and downside shocks to coins with a Binance perpetual, December 2021 to September 2023, excluding observations within 91 days of the listing. Open interest is winsorized at the 1st and 99th percentiles. Means with 95% confidence bands.

Funding. Funding is income to shorts when positive and a payment by shorts when negative. After downside shocks, higher funding over the preceding week, which makes holding a short position cheaper, predicts less negative returns: 100 percentage points of annualized funding are associated with returns 1.15 percentage points higher over 24 hours ($t = 2.5$), 1.67 over 72 hours ($t = 3.9$), and 1.50 over the week ($t = 2.2$; Appendix Table 22), and negative funding with a

next-day return 0.42 percentage points lower ($t = -2.1$). After upside shocks, funding and open interest have no detectable relation to subsequent returns (Appendix Table 23). Because funding reflects demand on both sides of the market, these associations do not identify a causal effect of shorting costs.

Summary. Abnormal returns are negative after shocks of either sign. Within the same coin, access to short selling reduces the reversal after upside shocks by about 2.5 percentage points, mostly after the first day. After downside shocks, access reduces the subsequent decline by 3.51 percentage points for downside shocks after an upside shock, and changes it little for isolated downside shocks. The results after upside shocks hold across designs, among coins with an unambiguous access date, and with controls for liquidity, and an increase in liquidity without access has no comparable effect. Short positions respond to shocks, and the decline after downside shocks is smaller when holding a short position is cheaper. The next section asks whether this change in price adjustment also weakens the return predictability of idiosyncratic variance.

6 Access to Short Selling and the Return Predictability of Idiosyncratic Variance

Sections 4 and 5 show that the negative relation between idiosyncratic variance and future returns is concentrated in recent shocks, and that post-shock returns become less negative after the same coin gains access to short selling. Prediction P3 connects these findings: if idiosyncratic variance predicts low returns because it records shocks whose adjustment is incomplete, access should weaken this predictability, mainly on days following recent shocks. We test this prediction in the daily panel, with the next-day return as the dependent variable.

Sections 4 and 5 establish two related findings: idiosyncratic variance predicts low future returns primarily through recent shocks, and access to short selling reduces the subsequent price decline after these shocks. This section brings the two findings together by examining whether access also weakens the return predictability of idiosyncratic variance. If the predictability reflects incomplete price adjustment after shocks, as the model suggests, it should weaken when short selling becomes available, particularly on days following recent shocks.

6.1 The Variance-Return Slope within Coins

Using daily observations from January 2020 onward, we estimate

$$\begin{aligned} r_{i,d+1} = a_i + b_d + \sum_g \mathbf{1}\{i \in g\}\left(\beta_g^+ IV_{i,d}^+ + \beta_g^- IV_{i,d}^-\right) \\ + \delta^+ IV_{i,d}^+ Short_{i,d} + \delta^- IV_{i,d}^- Short_{i,d} \\ + \theta Short_{i,d} + \gamma' Z_{i,d} + u_{i,d+1}, \end{aligned} \tag{13}$$

where a_i and b_d are coin and day fixed effects, the semivariances are logged and standardized, and $Z_{i,d}$ contains systematic semivariances, past abnormal and total returns, MAX, realized skewness, and log market capitalization. Baseline slopes differ across coins that can always be shorted, coins that can never be shorted, and coins that gain access, so that δ^+ and δ^- measure changes in the slopes among coins that gain access: 74 of 399 coins under the earliest date and 90 under the Binance perpetual date. We exclude observations within 91 days of access and use Driscoll–Kraay standard errors (Driscoll and Kraay, 1998).

Changes in the slope. The negative slope on upside idiosyncratic variance weakens after access (Table 3, Panel B). Under the earliest date, δ^+ is 49.2 basis points per standard deviation ($t = 1.9$): the slope rises from −77.4 to −28.2 basis points, about two thirds smaller, but remains negative ($t = -2.0$). The estimate is 54.6 basis points ($t = 2.1$) with year-specific baseline slopes, 62.3 ($t = 2.4$) when the slope varies with size (Appendix Table 12), 42.3 ($t = 2.0$) in a stacked comparison with coins that have not yet gained access (Appendix Table 25), and 43.3 ($t = 3.8$) with common baseline slopes. Pre-access dynamic coefficients are close to zero (Appendix Figure 9), and the weakening extends over days two through eight (30.8 basis points per day, $t = 2.3$; Appendix Table 26).

Sensitivity to the access date. The overall change depends on how access is dated. It is 44.9 basis points ($t = 1.8$) under the margin date but 1.7 basis points ($t = 0.1$) under the Binance perpetual date with group-specific slopes (41.0, $t = 3.6$, with common slopes; Appendix Table 24), possibly because many coins could be shorted through margin borrowing before their perpetual listing (Section 3). For downside idiosyncratic variance, the interaction is imprecise (−22.7 basis points, $t = -0.9$). The model does not restrict this slope, because total downside variance combines a shock component that predicts low returns with an ordinary component. Section 6.2 therefore evaluates both signs with the recent-shock part of variance.

6.2 Recent Shocks and Variance Predictability

The overall slope averages over days with and without recent shocks, whereas the mechanism predicts low returns when recent shocks have not yet been incorporated. An upside shock occurs in the preceding week on 78% of coin-days in the top quintile of upside idiosyncratic variance, compared with 31% in the bottom quintile (not tabulated). Because variance rises mechanically after shocks, the informative test is whether access weakens predictability mainly on post-shock days.

Where the slope and its change arise. Coin-days within 48 hours of a shock account for 46% of observations but 69% of the slope on upside idiosyncratic variance (Table 7, Panel A). The change after access is concentrated on the same days. Under the earliest date, the interaction is 69.2 basis points within 48 hours of an upside shock and 34.7 on other days, a difference of 34.5 basis points ($t = 3.2$); under the perpetual date, the difference is 32.4 ($t = 2.9$; Appendix Tables 27 and 28). Unlike the overall change, this difference is similar under both access dates.

Predictability from recent shocks. We next measure recent shocks directly. For each sign, the measure equals one immediately after a shock, declines by a factor of 0.7 per day, and is zero after seven days or without a shock in the preceding week. Unlike the shock component in Section 4.4, it captures the occurrence and recency of a shock rather than its size. Among coins without access, a recent upside shock predicts a next-day return 55.4 basis points lower ($t = -8.0$), and a recent downside shock 35.2 basis points lower ($t = -5.2$; Table 7, Panel B). Access weakens the upside coefficient by 37.5 basis points under the earliest date ($t = 4.1$) and 46.8 under the perpetual date ($t = 5.3$), by 38.3 ($t = 3.5$) among the 35 coins whose access dates coincide, and by 44.8 under both dates with group-specific baseline slopes ($t = 2.3$ and 2.6). A USDT listing in the same regression has no effect (3.7 basis points, $t = 0.4$).

Downside shocks. Access also weakens the predictive power of recent downside shocks: by 23.9 basis points under the earliest date ($t = 2.5$) and 22.3 under the perpetual date ($t = 2.2$) with common baseline slopes, and by 32.6 ($t = 2.4$) among the 35 coins whose access dates coincide. This reduction does not come from downside shocks that follow an upside shock: for recent isolated downside shocks, it is 29.3 basis points. With group-specific baseline slopes, the downside reductions are small (5.3 and 2.4 basis points), so this evidence rests mainly on comparisons that include coins without a change in access. Within the same coin, the effect of access after downside shocks appears after downside shocks after an upside shock (Section 5.2).

Consistency with post-shock price adjustment. Over the following week, access reduces the predictive power of a recent upside shock by 32.7 basis points per day under the earliest date ($t = 3.0$) and 25.0 under the perpetual date ($t = 2.6$), about 2.3 and 1.8 percentage points in total (Table 7, Panel C). These magnitudes are close to the event-level reductions in the reversal after upside shocks, 2.55 and 2.36 percentage points (Table 5). The comparison is informative because, summed over the week, the predictive coefficient on a recent upside shock is the average return after such a shock, so access should reduce it by about as much as it reduces the reversal in the event sample. That the two estimates are close, although they use different samples and dependent variables, indicates that the predictability that access removes is the reversal after upside shocks.

Summary. The overall slope on upside idiosyncratic variance weakens after access under the earliest date but depends on the access definition. Once we focus on recent shocks, the evidence is consistent across access dates: the slope and its weakening are concentrated after upside shocks, access weakens the predictive power of recent upside shocks within coins and of recent downside shocks across coins, and the reduction over the week is comparable to the reduction in the reversal after upside shocks documented in Section 5. These results connect the return predictability of idiosyncratic variance to the effect of short-sale constraints on prices after shocks.

7 Alternative Explanations

Liquidity. Access to short selling often coincides with improvements in liquidity, which may independently affect returns after shocks. Three results indicate that liquidity alone does not explain the change in returns after shocks. First, trading volume rises in the two quarters before access (Figure 7), whereas the response to upside shocks shows no trend before access (Figure 5). Second, controlling for liquidity raises rather than lowers the effect of access after upside shocks, to between 4.64 and 5.17 percentage points (Table 6, Panel D). Third, Binance USDT listings raise trading volume without allowing short selling and leave the return after upside shocks unchanged (Table 6, Panel C). The daily regressions give the same result: the USDT listing does not weaken the predictive power of recent upside shocks, whereas access does (Section 6.2). Further liquidity tests are in Appendix F.

Selection into access. Exchanges introduce shorting instruments for coins that have risen in price and attracted attention. Consistent with this selection, coins with high upside idiosyncratic variance before access outperform comparison coins by 39% to 53% in the month before access (Appendix Table 35). Selection of this kind affects price levels around the listing. Our designs

Table 7: Recent shocks and the return predictability of idiosyncratic variance

Panel A. Days after shocks: share of the slope on upside idiosyncratic variance, earliest date

	Share of coin-days	Slope on IV^+	Share of the slope
Within 24 hours after an upside shock	22%	−30.8***	47%
		(−3.59)	
Within 48 hours after a shock	46%	−45.2***	69%
		(−4.41)	
Within 72 hours after a shock	59%	−40.6***	62%
		(−3.81)	
Within 7 days after an upside shock	80%	−40.9***	62%
		(−2.80)	
All days	100%	−65.5***	100%
		(−5.56)	

Panel B. Next-day return on recent shocks

	(1)	(2)	(3)	(4)	(5)	(6)
Access date	Earliest	Earliest	Perpetual	Perpetual	Perpetual	Earliest
Sample	All	All	All	All	Perpetual first	All
Group-specific slopes	No	Yes	No	Yes	No	No
Recent upside shock	−55.4***	−54.1***	−58.1***	−57.4***	−50.9***	−56.2***
	(−7.98)	(−7.31)	(−8.99)	(−8.02)	(−7.18)	(−7.69)
Recent downside shock	−35.2***	−36.7***	−32.1***	−34.1***	−37.4***	−36.0***
	(−5.16)	(−4.99)	(−4.96)	(−4.80)	(−5.46)	(−5.11)
Recent upside shock × *Short*	37.5***	44.8**	46.8***	44.8***	38.3***	38.1***
	(4.12)	(2.30)	(5.33)	(2.63)	(3.50)	(4.18)
Recent downside shock × *Short*	23.9**	5.3	22.3**	2.4	32.6**	25.9***
	(2.48)	(0.26)	(2.23)	(0.12)	(2.43)	(2.66)
Recent upside shock × USDT listing						3.7
						(0.40)
Recent downside shock × USDT listing						−3.6
						(−0.37)
Coins	399	399	399	399	300	399
Switching coins	74	74	90	90	35	74

Panel C. Average daily return over the following week on recent shocks

	(1)	(2)	(3)	(4)
Access date	Earliest	Earliest	Perpetual	Perpetual
Group-specific slopes	No	Yes	No	Yes
Recent upside shock	−17.4***	−16.3***	−17.7***	−16.8***
	(−5.02)	(−4.59)	(−5.38)	(−5.07)
Recent downside shock	−3.1	−2.3	−3.5	−2.2
	(−0.77)	(−0.56)	(−0.91)	(−0.56)
Recent upside shock × *Short*	15.5***	32.7***	16.3***	25.0***
	(3.69)	(3.01)	(4.07)	(2.64)
Recent downside shock × *Short*	−3.9	−0.1	−2.8	0.8
	(−0.71)	(−0.01)	(−0.48)	(0.08)
Coins	399	399	399	399
Switching coins	74	74	90	90

Panel D. Change in the slope on upside idiosyncratic variance after access

	Earliest	Perpetual
Estimated	49.2*	1.7
	(1.91)	(0.06)
Implied by the recent-shock effect	20.4	25.5

Daily panel from January 2020, excluding 91 days on either side of access, with coin and day fixed effects, the controls of Table 3 and Driscoll–Kraay standard errors; coefficients in basis points of the next-day return, t-statistics in parentheses. Panel A splits the next-day return into its value on days in each window and on all other days and estimates the main specification (group-specific slopes) for each part; the parts add up to the full-sample slope; 335,690 coin-days of 399 coins. Panel B: a recent shock is an age-discounted indicator that equals one in the hour after the most recent shock of that sign, is multiplied by 0.7 each day, and is zero after seven days or when the coin had no shock of that sign in the past week. Column (5) keeps coins with no means of shorting before the Binance perpetual and coins never shortable; column (6) adds the indicator of the 91-day-excluded period after a coin's USDT pair listing and its interactions. Panel C: as Panel B, columns (1) to (4), with the average daily return over the following seven days as the outcome (basis points per day) and Driscoll–Kraay standard errors with ten lags. Panel D: the implied change is the coefficient of the recent-upside-shock indicator on upside idiosyncratic variance (same fixed effects and controls) times the coefficient on Recent upside shock × *Short* in Panel B, column (1) or (3). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

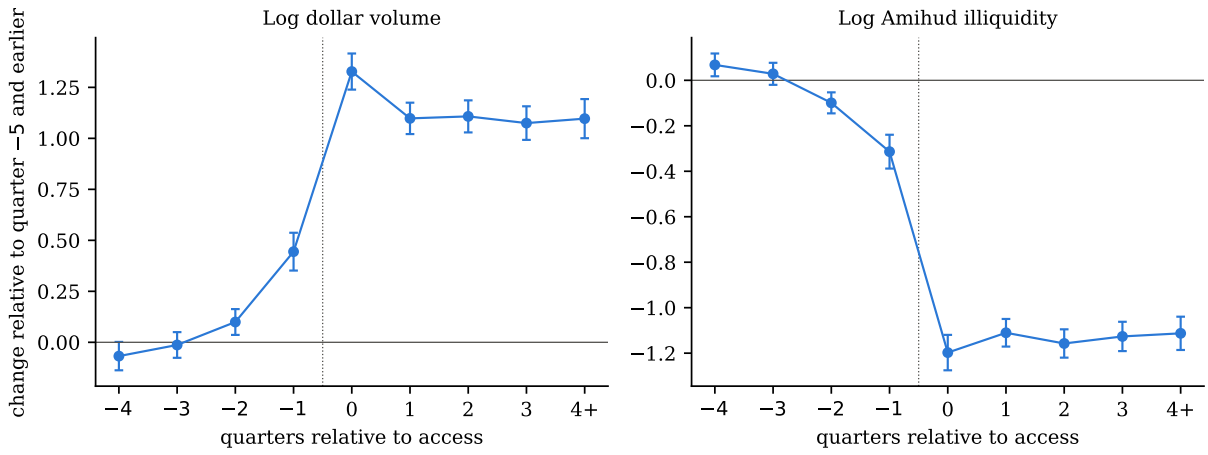


Figure 7: Liquidity around access to short selling. Coefficients from regressions of log dollar volume (left) and log Amihud illiquidity (right) on quarters relative to the earliest documented access date, with coin and day fixed effects, beginning in January 2020. The reference is quarter −5 and earlier and coins that never gain access. The dotted line marks access. Bars show 95% confidence intervals based on Driscoll–Kraay standard errors.

instead compare the same coin's returns after shocks, excluding the 91 days around access, so a confounding explanation must change how the coin's price responds to shocks at the access date for reasons other than short selling. Three results argue against such an explanation. First, the stacked design compares coins that gain access with coins that also gain access, but more than a year later, so both groups pass the exchanges' selection for listing; it gives estimates similar to the baseline (Table 17). Second, the response to upside shocks shows no trend before access, and a placebo that dates access one year early shows no effect (Figure 5 and Table 17). Third, Binance grants USDT listings to coins that attract trading activity and attention, but these listings do not allow short selling and leave the return after upside shocks unchanged (Table 6, Panel C).

Manipulation. Manipulation in thin markets could produce temporary price increases followed by reversals. Reversals after upside shocks also occur among the 20 largest coins, where trading is deep, and the effect of access after downside shocks survives controls for the return before the shock (Appendix F).

Lottery demand. Turnover, size, MAX and realized skewness statistically account for most of the slope on idiosyncratic variance among coins without access (Appendix F). These characteristics are correlated with recent shocks, so this attribution does not distinguish lottery demand from the effect of short-sale constraints. The two explanations are complementary: lottery preferences can generate optimistic demand, and short-sale constraints determine how much this demand affects prices.

8 Conclusion

This paper studies why idiosyncratic variance predicts low future returns in cryptocurrency markets. We propose that it captures recent shocks after which, when pessimistic investors cannot sell short, prices rise above the level implied by the average belief and then fall back as disagreement fades, generating predictable negative returns.

We test this mechanism using the staggered expansion of access to short selling across cryptocurrencies. The negative relation between idiosyncratic variance and returns is concentrated among coins without access to short selling and comes primarily from large, recent shocks. Within the same coin, access reduces the weekly reversal after upside shocks by 2.55 percentage points, approximately three quarters of the average reversal. This result is similar across alternative empirical designs, including the estimator of Sun and Abraham (2021), and among coins whose documented access dates coincide. It is robust to controls for liquidity before the shock, while an increase in liquidity without access to short selling produces no comparable change. After downside shocks, the reduction in the subsequent decline is concentrated in downside shocks after an upside shock, with an estimated effect of 3.51 percentage points. These findings are consistent with short-sale constraints that keep prices too high after upward price movements, whether the subsequent decline is a gradual reversal or begins with a sharp drop. Access also weakens the return predictability of recent upside shocks under both access dates, by an amount over the following week comparable to the reduction in the reversal after upside shocks.

The evidence has several limitations. Access to short selling is not randomly assigned, the within-coin estimates rely mainly on shocks in the year before access, and the change in the overall slope of returns on idiosyncratic variance is sensitive to how access is dated. Neither the information behind shocks nor investor disagreement is directly observed.

The negative relation between idiosyncratic variance and future returns therefore does not have to reflect risk or a preference for lottery-like payoffs. When pessimistic investors cannot sell short, prices rise too far after upward moves and fall back as disagreement fades, and idiosyncratic variance records these moves. More generally, this predictability should be strongest in assets that are hard to short and should weaken as shorting becomes easier, a prediction that equity lending data can test.

A Model Derivations and Extensions

This appendix derives the equilibrium wedge, proves Lemma 1 and Propositions 1 and 2, presents an extension to short positions around shocks (Proposition 3), and discusses the conditions behind Prediction P3.

A.1 Equilibrium and Proof of Lemma 1

Let $z = \bar{\mu} - p$. Since $\delta_i \sim U[-d, d]$, market clearing requires

$$\lambda Q = \phi z + (1-\phi)H(z,d), \qquad H(z,d) = \begin{cases} z, & z \geq d, \\ (z+d)^2/(4d), & -d < z < d, \\ 0, & z \leq -d, \end{cases} \tag{14}$$

where $H(z,d) = E[(z+\delta_i)_+]$ is the average demand of investors who cannot sell short. Aggregate demand is continuous and strictly increasing in z at the solution, so the equilibrium is unique. For $d \leq \lambda Q$, $z = \lambda Q$ clears the market and the constraint does not bind. For $d > \lambda Q$ and $\phi < 1$, the solution satisfies $-d < z < d$. The wedge is $\Delta(d,\phi) = \lambda Q - z$. When $\phi = 0$, $z = 2\sqrt{\lambda Q d} - d$ and

$$\Delta(d,0) = \begin{cases} 0, & d \leq \lambda Q, \\ (\sqrt{d} - \sqrt{\lambda Q})^2, & d > \lambda Q, \end{cases} \tag{15}$$

which is convex in d.

Proof of Lemma 1. For $d > \lambda Q$, let $F(z,d,\phi) = \phi z + (1-\phi)H(z,d) - \lambda Q$. In the interior region, $H_z = (z+d)/(2d) > 0$ and $H_d = (d^2 - z^2)/(4d^2) > 0$. Implicit differentiation gives

$$\Delta_d = \frac{(1-\phi)H_d}{\phi + (1-\phi)H_z} > 0, \tag{16}$$

$$\Delta_\phi = -\frac{H - z}{\phi + (1-\phi)H_z} < 0, \tag{17}$$

where $H - z = (d-z)^2/(4d) > 0$. The wedge is zero for $d \leq \lambda Q$ or $\phi = 1$. □

A.2 Proofs of Propositions 1 and 2

Initially $d_0 < \lambda Q$, so $p_0 = \bar{\mu}_0 - \lambda Q$. After a shock s, $d_1 = d_0 + \kappa_{\mathrm{sgn}(s)}|s|$ and $p_1 = \bar{\mu}_0 + s - \lambda Q + D(s,\phi)$. Once the additional disagreement has faded, $p_2 = \bar{\mu}_0 + s - \lambda Q$, which gives equation (4).

Proof of Proposition 1. The wedge is positive if $\kappa_{\text{sgn}(s)}|s| > \lambda Q - d_0$ and $\phi < 1$. For $s > 0$, the price rises by $s + D$ and then falls by D, a reversal. For $s < 0$, it changes by $s + D$ and then falls by D, a continuation. Since $0 \leq \partial D/\partial|s| = \kappa_{\text{sgn}(s)}\Delta_d \leq 1$ and D is zero below a strictly positive threshold, $D < |s|$, so the initial response to a negative shock is negative. Above the threshold, D increases with $|s|$. □

Proof of Proposition 2. By Lemma 1, $\Delta_\phi < 0$ where the constraint binds, so $\partial(p_2 - p_1)/\partial\phi = -D_\phi > 0$ for either sign of the shock: access reduces the reversal after upside shocks and the continuation after downside shocks. When $\phi = 1$, the wedge and the subsequent price change are zero. □

A.3 Short Positions around Shocks

The same equilibrium determines the positions of investors who can sell short. Such an investor holds a negative position when the price exceeds her valuation, so aggregate short positions are

$$B_t = \frac{\phi}{\lambda} E[(p_t - \mu_{i,t})_+] = \frac{\phi}{4\lambda d_t}[d_t - (\bar{\mu}_t - p_t)]^2 \tag{18}$$

when the constraint binds. Short positions before downside shocks require an additional informational mechanism. Suppose a small mass of investors who can sell short observes private signals z_i before public disclosure, with $E[s \mid z_i] = \rho z_i$ and $\rho > 0$. At the prevailing price p^-, an informed investor's desired short position is

$$b_i^- = \frac{[p^- - \bar{\mu}_0 - \delta_i - \rho z_i - c]_+}{\lambda}, \tag{19}$$

where c is the marginal cost of shorting.

Proposition 3 (short positions around shocks). *(i) For fixed $0 < \phi < 1$, greater disagreement increases aggregate short positions, including after sufficiently large positive shocks. (ii) Before public disclosure, informed investors take larger short positions after more negative private signals; if these signals predict downside shocks, short positions accumulate before such shocks. (iii) Higher shorting costs reduce informed investors' desired short positions. The change in positions after disclosure is ambiguous without additional assumptions about posterior valuations and covering.*

The proposition distinguishes short selling against elevated prices after positive shocks from informed short selling before negative shocks, which relates to how short-sale constraints affect the incorporation of negative beliefs into prices (Diamond and Verrecchia, 1987).

Proof of Proposition 3. (i) For $-d < z < d$, $B(d,\phi) = \phi(d-z)^2/(4\lambda d) = \phi(H-z)/\lambda$. Along the equilibrium, $dB/dd = (\phi/\lambda)[H_d + (H_z - 1)z_d] > 0$, since $H_d > 0$, $H_z < 1$ and $z_d < 0$. When $d \leq \lambda Q$, $B = 0$. (ii)–(iii) Conditional on an active short position, $\partial b_i^- / \partial z_i = -\rho/\lambda < 0$ and $\partial b_i^- / \partial c = -1/\lambda < 0$. The infinitesimal informed mass leaves the price unchanged. □

A.4 Accumulated Disagreement and Realized Semivariance

Accumulated disagreement. Under equation (5), $C_g = \Delta_d(d_0 + g, \phi) - \psi\Delta_d(d_0 + \psi g, \phi)$. When Δ is convex in d, as for $\phi = 0$, $\Delta_d(d_0 + g, \phi) \geq \Delta_d(d_0 + \psi g, \phi) \geq \psi\Delta_d(d_0 + \psi g, \phi)$, so $C_g \geq 0$: larger shocks and more recent shocks, which leave more disagreement, are followed by larger declines. The sign of C_ϕ requires further restrictions; Prediction P3 relies only on $C \geq 0$ for $\phi < 1$ and $C = 0$ for $\phi = 1$.

Shocks and realized semivariance. For an isolated shock of size a and $\kappa_+ = \kappa_-$, the shock-hour price changes are $a + D(a,\phi)$ and $-a + D(a,\phi)$, with squared contributions $[a + D]^2$ and $[a - D]^2$ to the upside and downside semivariance. Since $0 \leq D_a \leq 1$, both increase with a, and the subsequent price change $-D$ decreases with a and increases with ϕ. Larger shocks thus raise realized semivariance and are followed by larger declines, which access reduces.

Total downside variance. Total downside variance combines the shock component, which records shocks followed by a decline, with an ordinary component, which records hours that do not change disagreement. The model does not restrict the relation between the ordinary component and future returns, so it makes no prediction for total downside variance.

Cross-sectional interpretation. Remaining disagreement depends on the weighted history of absolute shocks, $g_t = \psi^k g_{t-k} + \kappa \sum_{\ell=0}^{k-1} \psi^\ell |s_{t-\ell}|$, whereas realized semivariance sums squared returns. Semivariance is therefore not a sufficient statistic for g_t. Prediction P3 requires that measured shocks be informative about remaining disagreement, that other predictable components of returns do not offset the decay of the wedge, and that this mapping be comparable before and after access.

Ordinary movements and liquidity. For an ordinary innovation η_t that does not change disagreement, suppose a fraction θ is temporary price pressure, so that its subsequent correction is $-\theta\eta_t$. Ordinary moves then generate corrections of opposite sign, whereas shocks that raise disagreement are followed by declines of either sign.

Empirical interpretation. The model concerns price differences, while the empirical analysis uses log returns; their signs agree, but magnitudes and semivariances require normalization. The terminal payoff is a modeling device, and the unconstrained price is not an observable fundamental value. Access to short selling may also affect liquidity and information production, and perpetual open interest and account-level short shares are not identical to the model's aggregate short positions.

B Data

B.1 Data Checks

The cleaning rule combines one-hour moves above 50 log points that reverse by at least 80% in the following hour into a two-hour return. It affects five of 12.96 million coin-hours, four of them from 2020 onward.

Access histories are uncertain for two coins. LOOM had isolated-margin access from November 2020; cross-margin borrowing was suspended from February to October 2023, and its perpetual began in October 2023. FRONT had isolated-margin access from February 2021, but its continuity through 2023 is not documented. Both coins are coded as having access from their earliest recorded date and together contribute 2,271 coin-days.

Table 8: Shortability of the sample

Year	Coin-days	New perpetuals	Coins, perpetual	Coins, any venue	Market cap ex BTC/ETH, perpetual	Market cap, perpetual
2017	3,678	0	0.0	22.7	0.0	0.0
2018	36,259	0	0.0	13.1	0.0	0.0
2019	45,098	3	0.3	14.0	0.4	24.2
2020	60,525	78	21.0	27.5	84.3	97.0
2021	96,570	59	40.7	48.8	91.2	97.6
2022	120,860	26	43.2	49.5	92.4	97.8
2023	84,380	99	52.9	56.4	94.8	98.7

Shares in % of the universe that can be shorted, averages of daily shares. Coins: equal-weighted. Market cap: weighted by market capitalization, with and without BTC and ETH, which account for most of the market capitalization of the universe and could be shorted on other venues long before 2019. Perpetual: shortability dated by the first trading day of the Binance USDT-margined perpetual (BTC 8 September, ETH 27 November and BCH 19 December 2019). Any venue: the earliest perpetual, futures or margin listing on Binance or another exchange, where collected (Appendix B.3). New perpetuals: contracts first listed in that year, including coins outside the universe.

Table 9: Examples of idiosyncratic shocks

							CAR after the shock	
Date	Hour	Coin	Event	Type	Shortable	Shock	24 hours	168 hours
Upside shocks followed by a reversal								
2 Nov 2021	00:00	SAND	The Sandbox announces a $93 million funding round led by SoftBank	Funding	Yes	24.9	5.4	−21.3
3 Apr 2023	17:00	DOGE	Twitter replaces its bird logo with the Dogecoin image	Attention	Yes	19.9	−0.2	−17.4
8 Nov 2022	16:00	FTT	Binance announces a non-binding agreement to acquire FTX	Corporate	Yes	16.9	−73.9	−178.7
Downside shocks followed by a continuation								
22 Dec 2020	01:00	XRP	Ripple discloses that the SEC will sue it over sales of XRP	Regulation	Yes	−4.9	−20.5	−103.4
9 May 2022	18:00	MIR	The UST stablecoin loses its peg and the Terra ecosystem collapses	Ecosystem	No	−7.3	−9.4	−92.8
8 Nov 2022	16:00	SOL	Binance announces the agreement to acquire FTX, revealing the distress of FTX and Alameda, large holders of SOL	Exposure	Yes	−5.1	−20.3	−36.8
5 Jun 2023	15:00	BNB	The SEC sues Binance and its founder	Regulation	Yes	−5.6	−0.2	−12.3
1 Feb 2021	11:00	XRP	Collapse of a pump coordinated on social media; the price had risen by 37.4% over the preceding 23 hours	Pump	Yes	−16.2	−47.5	−56.3

Examples of idiosyncratic shocks for which the event behind the shock can be identified from contemporaneous news reports, selected to illustrate the range of events behind shocks; individual price paths need not follow the average pattern. Hour: start of the shock hour in UTC. Shortable: whether the coin had a Binance perpetual at the time of the shock. Shock: abnormal return in the shock hour. CAR: cumulative abnormal return from the end of the shock hour over the following 24 and 168 hours. All returns are log returns in percent. The FTT return after the shock reflects Binance's withdrawal from the agreement on the following day and the collapse of FTX.

B.2 How Perpetual Futures Allow Short Selling

This subsection describes how a short position is taken in a perpetual futures contract and how it differs from shorting through margin borrowing. The description follows the USDT-margined contracts on Binance that define the perpetual date; contract parameters such as margin tiers and funding caps differ across coins and have changed over time.

The contract. A linear USDT-margined perpetual provides exposure to changes in the price of the underlying coin without a fixed expiry. A short position gains when the price falls and loses when it rises, before funding and fees. The exchange matches a long and a short for each open contract. The short seller does not borrow or deliver the underlying coin, although positions remain subject to exchange and collateral limits.

Funding. Periodic payments keep perpetual and spot prices close in the absence of expiry (He et al., 2022). For most contracts in the sample, payments occur every eight hours and equal the funding rate times the notional of the position. Positive funding is paid by longs to shorts, and negative funding by shorts to longs, so funding is either income or a carrying cost for a short.

Margin and liquidation. Traders post collateral rather than borrowing the coin. Losses can trigger liquidation when account equity no longer meets maintenance requirements. For a short, an upward price move therefore creates a risk of forced closure, even though there is no lender recall.

Comparison with borrowing. A margin short requires borrowing the coin, selling it, and later buying it back to repay the loan, so its feasibility depends on lending supply, interest charges and borrowing limits. A perpetual short requires no loan but remains subject to collateral, liquidation, trading costs, funding and exchange limits. In the model, greater access corresponds to a higher fraction ϕ of investors who can sell short, not to a lower shorting cost; the cost c in the extension of Appendix A.3 is a separate object.

Transmission to spot prices. Trading across spot and derivatives markets transmits changes in demand. When selling pressure makes a perpetual relatively cheap, investors holding the coin can substitute perpetual exposure for spot holdings, selling spot and buying the contract. Neither the premium nor funding isolates short demand, because both respond to positions on both sides and to arbitrage constraints.

Data. For every perpetual we observe the first trading day, the funding rate at each funding time, the hourly premium of the perpetual over the index, and, from December 2021, five-minute snapshots of open interest and of the long/short account ratios, all from Binance's public data archive (data.binance.vision). Because every open contract has both a long and a short side, neither measure equals the aggregate short positions of the model.

B.3 Dates of First Access to Short Selling

For the 50 largest coins we collect the earliest documented date on which each coin could be shorted through a perpetual, futures or margin account on BitMEX, OKX, Bybit, FTX, Huobi, Bitfinex, Poloniex or Binance, from exchange announcements, support pages and news reports (Table 10). Confidence is high for dates from an official announcement, medium for dates from news reports, and low when the source only shows that the instrument existed by that date, so that the true date may be earlier. For 49 of the 50 coins a date is documented; 28 have high, 12 medium and 9 low confidence. The earliest instrument is margin trading for 30 coins, futures for 10 and a perpetual for 9.

For the 63 coins with the most upside shocks in the quarter before their perpetual listing, we collect the date on which each became borrowable on Binance cross or isolated margin from Binance's margin announcements. The date is the announcement date, on which borrowing typically opened. Table 11 lists the dates for the 60 coins with a documented announcement; for three coins (HIGH, SSV, SLP) no announcement was found.

C Idiosyncratic Variance and Future Returns

Table 12 reports the comparisons within size terciles and the regressions that account for size discussed in Section 4. Table 13 reports the decomposition of Section 4.4 for shock thresholds of three, four and five robust standard deviations.

D Price Adjustment after Shocks

D.1 Price Adjustment across Coins

Table 14 reports the returns after shocks, and Figure 8 shows the average path around all shocks from 2017. Table 15 reports the comparison of coins with and without a Binance perpetual, and Table 16 the timing of the difference: after upside shocks, more than 80% of it falls on days two to seven.

Table 10: Dates of first access to short selling: the largest coins

Coin	Earliest date	Venue	Instrument	Confidence	Binance margin	Binance perpetual
BTC	2014-08-12	Bitfinex	margin	low	2019-07-11	2019-09-08
DOGE	2015-05-26	Poloniex	margin	medium	2020-07-14	2020-07-10
XLM	2015-05-29	Poloniex	margin	low	2019-08-22	2020-01-20
ETH	2015-08-07	BitMEX	futures	low	2019-07-11	2019-11-27
ETC	2016-07-28	Bitfinex	margin	high	2019-08-08	2020-01-16
ZEC	2016-10-28	BitMEX	futures	low	2019-09-18	2020-02-05
XMR	2017-01-06	BitMEX	futures	low		2020-02-03
DASH	2017-02-14	BitMEX	futures	medium	2019-09-18	2020-02-04
LTC	2017-03-31	BitMEX	futures	low	2019-08-08	2020-01-09
XRP	2017-03-31	BitMEX	futures	low	2019-07-11	2020-01-06
BCH	2017-08-03	Bitfinex	margin	medium	2019-08-22	2019-12-19
NEO	2017-09-18	Bitfinex	margin	high		2020-02-17
ADA	2018-01-08	BitMEX	futures	medium	2019-07-26	2020-01-31
EOS	2018-01-20	OKX	futures	high	2019-07-18	2020-01-08
TRX	2018-06-26	BitMEX	futures	medium	2019-07-11	2020-01-15
OMG	2018-08-20	Bitfinex	margin	low	2020-06-09	2020-07-02
IOTA	2018-08-20	Bitfinex	margin	low	2019-11-14	2020-02-12
ATOM	2019-05-03	Poloniex	margin	medium	2019-09-17	2020-02-07
BNB	2019-07-11	Binance	margin	medium	2019-07-11	2020-02-10
LINK	2019-07-18	Binance	margin	medium	2019-07-18	2020-01-17
ONT	2019-07-26	Binance	margin	high	2019-07-26	2020-02-11
MATIC	2019-09-24	Binance	margin	high	2019-09-24	2020-10-22
BAT	2019-10-22	Binance	margin	high	2019-10-22	2020-02-13
VET	2019-10-29	Binance	margin	high	2019-10-29	2020-02-14
QTUM	2019-10-31	Binance	margin	high	2019-10-31	2020-02-20
XTZ	2019-11-26	Binance	margin	high	2019-11-26	2020-02-06
ALGO	2020-05-13	OKX	perpetual	high	2020-06-11	2020-06-16
THETA	2020-06-02	Binance	margin	high	2020-06-02	2020-05-26
ZIL	2020-06-09	Binance	margin	high	2020-06-09	2020-06-18
KNC	2020-06-16	Binance	margin	high	2020-06-16	2020-06-22
COMP	2020-06-18	FTX	futures	medium	2020-07-09	2020-06-30
SNX	2020-07-21	Binance	margin	medium	2020-07-21	2020-08-14
WAVES	2020-07-21	Binance	margin	medium	2020-07-21	2020-08-12
FIL	2020-07-22	OKX	perpetual	high		2020-10-16
DOT	2020-07-22	OKX	perpetual	high	2020-08-27	2020-08-20
SXP	2020-07-23	Binance	margin	high	2020-07-23	2020-07-21
FTT	2020-07-23	Binance	margin	high	2020-07-23	2022-04-15
MKR	2020-08-04	Binance	margin	high	2020-08-04	2020-08-13
SOL	2020-08-18	Binance	margin	high	2020-08-18	2020-09-14
CRV	2020-09-01	Binance	margin	high	2020-09-01	2020-09-01
YFI	2020-09-01	Binance	margin	high	2020-09-01	2020-08-31
SUSHI	2020-09-03	OKX	perpetual	high	2020-09-05	2020-09-04
UNI	2020-09-17	OKX	perpetual	high	2020-09-18	2020-09-18
AVAX	2020-09-24	Binance	margin	high	2020-09-24	2020-09-23
AAVE	2020-10-20	Binance	margin	high	2020-10-20	
NEAR	2020-12-21	OKX	perpetual	high		2020-10-15
LUNA	2021-03-18	OKX	perpetual	high		2021-01-28
ICP	2021-05-06	FTX	perpetual	medium		2021-05-11
SHIB	2021-05-09	OKX	perpetual	high		2021-05-10

Earliest documented date on which the coin could be shorted through a perpetual, futures or margin account on a venue other than the Binance perpetual, with the venue, instrument and confidence of the source (high: official announcement; medium: news report; low: the instrument existed by that date). Binance margin: first addition to Binance cross or isolated margin. Sources in the data file.

Table 11: Binance margin dates of mid-sized coins

Coin	Binance margin	Binance perpetual	Coin	Binance margin	Binance perpetual
ACH	2022-07-29	2023-02-22	JOE	2023-03-23	2023-03-29
AGIX	2023-02-02	2023-02-16	KAVA	2020-06-09	2020-07-28
AGLD	2021-10-13	2023-07-29	KLAY	2021-07-02	2021-10-12
ANKR	2020-07-23	2021-01-26	LDO	2022-07-25	2022-09-22
ANT	2020-09-01	2021-12-27	LOOM	2020-11-12	2023-10-11
AR	2021-05-21	2021-09-28	MANA	2020-08-11	2021-03-15
ARPA	2020-08-25	2021-10-19	MASK	2021-05-26	2021-08-27
ASTR	2022-04-22	2023-02-14	MDT	2020-11-25	2023-06-30
ATA	2021-06-08	2021-08-31	MINA	2021-08-20	2023-02-07
AUDIO	2021-03-09	2021-08-19	MTL	2020-12-09	2021-03-31
BAND	2020-07-30	2020-07-29	NKN	2020-09-24	2021-04-09
BICO	2021-12-20	2023-09-28	NU	2021-06-24	2021-10-21
BNX	2021-11-05	2022-04-01	ONE	2020-07-21	2021-03-18
CFX	2021-05-07	2023-02-20	PHB	2022-09-13	2023-02-16
CHR	2020-08-04	2021-03-12	POWR	2021-12-09	2023-10-27
CHZ	2020-08-18	2021-01-21	QNT	2021-08-06	2022-10-20
CKB	2021-03-01	2023-02-28	RAD	2021-10-20	2023-05-10
CTSI	2020-08-25	2021-10-26	RIF	2023-03-23	2023-10-21
DAR	2021-12-03	2022-04-29	RLC	2020-07-28	2020-07-31
DUSK	2020-11-03	2022-01-07	ROSE	2020-11-25	2021-12-31
FET	2020-06-11	2023-01-17	SPELL	2022-08-19	2022-09-06
FRONT	2021-02-20	2023-09-22	STMX	2021-02-04	2021-03-22
FTM	2020-07-28	2020-09-24	STORJ	2020-07-30	2020-09-16
FXS	2021-07-02	2023-01-20	STRAX	2021-05-18	2023-10-11
HBAR	2020-06-18	2021-03-17	TOMO	2020-07-21	2020-10-12
HFT	2023-02-10	2023-04-06	UMA	2020-09-15	2023-05-10
ICX	2020-07-07	2020-09-15	XEM	2020-09-10	2021-03-03
IDEX	2021-10-13	2023-05-03	XVG	2020-11-26	2023-07-05
INJ	2020-11-10	2022-08-17	YGG	2021-09-28	2023-08-05
IOTX	2020-08-04	2021-08-12	ZRX	2020-06-02	2020-06-24

Date on which the coin became borrowable on Binance cross or isolated margin, from Binance announcements, for the mid-sized coins with the most upside shocks in the quarter before their perpetual listing. Coins for which no announcement was found are omitted. Announcement URLs, margin type and confidence are in the data file.

Table 12: Size and the return predictability of idiosyncratic variance

Panel A. High-minus-low idiosyncratic variance tercile, within size terciles (bp per day)

	Small	Mid	Large
Not shortable	−37.6***	−64.8***	−39.3***
	(−4.65)	(−9.13)	(−3.34)
Shortable	37.3*	−27.9***	−6.6
	(1.95)	(−3.27)	(−1.00)
Median market capitalization ($m), not shortable / shortable	22 / 34	90 / 124	257 / 1111
Days, not shortable / shortable	1,342 / 632	1,342 / 1,012	607 / 1,342
Coins, not shortable / shortable	183 / 53	204 / 134	86 / 147

Panel B. Regressions

	Across coins (Fama-MacBeth)			Within coins	
	Baseline	Size-dependent slope	Common size support	Baseline	Size-dependent slope
$IV^+ \times$ *Short*	36.2***	28.3*	39.2*	49.2*	62.3**
	(3.13)	(1.89)	(1.83)	(1.91)	(2.42)
$IV^+ \times$ log market capitalization		3.4			−19.5***
		(0.44)			(−2.61)
Days / coin-days	1,342	1,342	1,012	335,690	335,690
Coins	405	405	281	399	399

Shortability dated by the earliest documented date; coin-days from January 2020. Panel A excludes coin-days within 91 days of the date, as do the within-coin regressions in Panel B; the cross-coin regressions use all coin-days, as in Table 3, Panel A. Panel A: each day, coins are sorted into terciles of market capitalization and, within each size tercile and shortability group with at least 15 coins, into terciles of idiosyncratic variance; the entry is the average next-day return of the top minus the bottom variance tercile, with Newey-West t-statistics. Panel B: the regressions of Table 3, Panel A, column 4 (across coins) and Panel B, column 5 (within coins), adding the interactions of IV^+ and IV^- with standardized log market capitalization, or, across coins, restricting each day to the common support of the two size distributions (above the 10th percentile of shortable coins and below the 90th percentile of non-shortable coins). Coefficients in basis points per standard deviation. *, **, *** denote significance at 10%, 5%, 1%.

Table 13: Shock hours and other hours: alternative shock thresholds

	3 standard deviations		4 standard deviations		5 standard deviations	
Panel A. Across coins: Fama-MacBeth						
	(1)	(2)	(3)	(4)	(5)	(6)
IV^+, shock hours	−8.1**		−9.2***		−11.6***	
	(−2.30)		(−3.29)		(−4.30)	
IV^+, shock hours, decayed		−25.6***		−22.7***		−22.4***
		(−6.67)		(−7.36)		(−8.04)
IV^+, other hours	33.3***	16.6	8.0	−8.9	−4.9	−18.2*
	(2.92)	(1.43)	(0.76)	(−0.86)	(−0.50)	(−1.93)
IV^-, shock hours	−6.9**		−7.9***		−5.8***	
	(−2.35)		(−3.42)		(−2.77)	
IV^-, shock hours, decayed		−3.2		−6.3**		−4.6*
		(−0.99)		(−2.42)		(−1.93)
IV^-, other hours	−33.1***	−12.1	−9.6	10.3	2.3	17.8
	(−2.95)	(−1.06)	(−0.84)	(0.91)	(0.20)	(1.63)
IV^+, shock hours ×*Short*	1.5		4.4		7.6**	
	(0.24)		(1.10)		(2.27)	
IV^+, shock hours, decayed ×*Short*		11.7*		13.0***		15.6***
		(1.95)		(2.89)		(4.06)
IV^+, other hours ×*Short*	−21.9	−10.4	−3.3	9.9	10.3	22.9*
	(−1.24)	(−0.59)	(−0.20)	(0.61)	(0.73)	(1.67)
Days	1,342	1,342	1,342	1,342	1,342	1,342
Coins	405	405	405	405	405	405

	3 standard deviations		4 standard deviations		5 standard deviations	
Panel B. Within coins: coin and day fixed effects, group-specific slopes						
	(1)	(2)	(3)	(4)	(5)	(6)
IV^+, shock hours	−13.5***		−13.2***		−14.3***	
	(−2.75)		(−4.00)		(−4.37)	
IV^+, shock hours, decayed		−29.9***		−25.3***		−24.5***
		(−5.61)		(−6.42)		(−6.82)
IV^+, other hours	31.4**	15.8	6.6	−7.2	−2.4	−15.5
	(2.49)	(1.25)	(0.58)	(−0.63)	(−0.21)	(−1.39)
IV^-, shock hours	−2.9		−5.1*		−4.6	
	(−0.80)		(−1.71)		(−1.63)	
IV^-, shock hours, decayed		−0.3		−5.0		−4.7
		(−0.08)		(−1.45)		(−1.46)
IV^-, other hours	−23.9*	−4.5	0.6	17.1	8.0	23.1*
	(−1.78)	(−0.34)	(0.05)	(1.43)	(0.66)	(1.95)
IV^+, shock hours ×*Short*	2.3		12.4		8.7	
	(0.21)		(1.39)		(1.01)	
IV^+, shock hours, decayed ×*Short*		2.6		16.6*		10.9
		(0.20)		(1.66)		(1.17)
IV^+, other hours ×*Short*	−34.8	−35.8	15.8	23.1	13.2	16.6
	(−0.87)	(−0.90)	(0.44)	(0.65)	(0.39)	(0.51)
Coin-days	335,690	335,690	335,690	335,690	335,690	335,690
Coins	399	399	399	399	399	399

As Table 4, columns 2 and 3, with shock hours defined by an abnormal return beyond 3, 4 or 5 robust standard deviations. Odd columns: shock hours and other hours; even columns: decayed shock hours and other hours. Shock hours account for 68%, 59% and 51% of upside idiosyncratic variance at the three thresholds, and 95%, 80% and 63% of coin-days contain at least one upside shock hour in the previous week. Interactions of the downside components with *Short* are included but not reported. Basis points per standard deviation; Newey-West (A) and Driscoll-Kraay (B) t-statistics. *, **, *** denote significance at 10%, 5%, 1%.

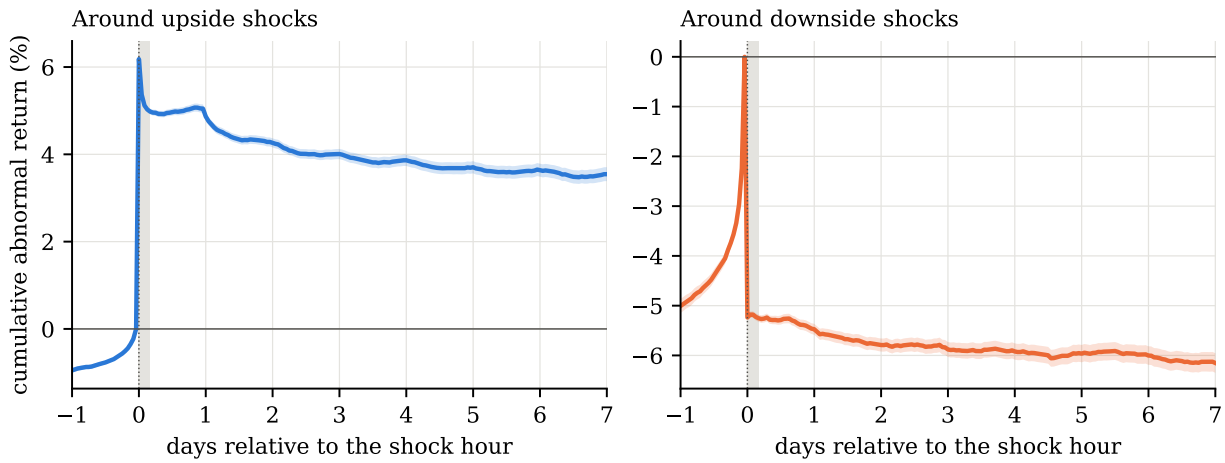


Figure 8: Cumulative abnormal return around shocks, all events, 2017 to 2023. Day 0 is the shock hour, and the return is normalized to zero at the start of the shock hour. The shaded area marks the first four hours after the shock. Means with 95% confidence bands.

Table 14: The response of prices to coin-specific shocks

	24 hours	72 hours	168 hours
Panel A. Cumulative abnormal return after the shock, all events, 2017–2023			
Upside shocks (41,318 events, 411 coins, mean shock 6.18%)	−1.71	−2.92	−3.43
	(−18.42)	(−16.46)	(−9.85)
Downside shocks (24,529 events, 411 coins, mean shock −5.24%)	−0.17	−0.98	−1.43
	(−1.49)	(−3.98)	(−3.08)

Panel B. Return by window after the shock, coins without a perpetual, 2020–2023 (%)	Hour 1	Hours 2–4	Hours 5–24	Days 2–7
Upside shocks	−1.14	−0.53	−0.19	−1.85
Downside shocks	0.02	−0.17	−0.38	−0.94

Shocks: hours in which a coin's abnormal return exceeds four times its idiosyncratic volatility over the previous 168 hours in absolute value; one event per coin per 48 hours. Abnormal return: coin return minus beta times the market return, beta from the previous seven days of hourly data. Panel A: mean cumulative abnormal return from the end of the shock hour, in %; t-statistics from daily averages with Newey-West (5 lags) in parentheses. Panel B: events from 2020, excluding ±91 days around a perpetual listing, coins without a perpetual at the event. These are 19,653 upside and 11,182 downside shocks to 293 coins.

Table 15: The perpetual listing and the response to idiosyncratic shocks

	Cumulative abnormal return (pp)			
	24 hours	72 hours	168 hours	Events
Upside shocks	0.43	1.49	2.54	31,176
	(2.19)	(6.15)	(8.35)	
Downside shocks	0.63	1.35	2.11	18,341
	(4.23)	(6.95)	(7.27)	

Coefficients on a dummy for a Binance perpetual at the time of the shock, in regressions of the cumulative abnormal return after each shock on this dummy, log market capitalization, log dollar volume, log shock size and month fixed effects. Events from 2020, excluding shocks within 91 days of the listing: 396 coins with upside shocks (293 with shocks without a perpetual and 191 with shocks with one) and 397 coins with downside shocks (293 and 192). t-statistics clustered by coin in parentheses. The daily cross-sectional tests are in Table 3.

Table 16: When does the reversal happen?

	Hour 1	Hours 2–4	Hours 5–24	Days 2–3	Days 4–7
Upside shocks (31,176 events, 396 coins)					
Mean, not shortable (%)	−1.14	−0.53	−0.19	−1.24	−0.61
Mean, shortable (%)	−0.23	−0.06	−0.10	−0.26	−0.33
Shortable effect (pp)	0.31	0.17	−0.05	1.06	1.05
	(3.07)	(2.36)	(−0.40)	(7.73)	(6.27)
Downside shocks (18,341 events, 397 coins)					
Mean, not shortable (%)	0.02	−0.17	−0.38	−0.75	−0.19
Mean, shortable (%)	0.05	−0.07	0.13	−0.18	−0.21
Shortable effect (pp)	−0.05	−0.03	0.70	0.72	0.75
	(−0.80)	(−0.44)	(5.64)	(5.10)	(3.46)

Cumulative abnormal return over each window after the shock hour. Shortable effect: coefficient on the shortable dummy with log market cap, log dollar volume, log Amihud illiquidity, log shock size and month fixed effects; events from 2020 excluding ±91 days around the listing; t-statistics clustered by coin.

D.2 Heterogeneity-Robust Estimates

Under staggered access, two-way fixed-effects estimates can be biased when the effect of access differs across cohorts or with time since access (Goodman-Bacon, 2021; Sun and Abraham, 2021). Table 17 reports the interaction-weighted estimator of Sun and Abraham (2021), which estimates a separate effect for each cohort of coins that gain access in the same half-year, relative to coins without access during the sample, and averages these effects with weights equal to the number of shocks. After upside shocks, the estimate under the earliest date is 2.84 percentage points ($t = 2.7$) relative to the half-year before access and 2.88 ($t = 3.2$) relative to all half-years before access. After downside shocks, the corresponding estimates are 2.72 ($t = 2.2$) and 3.27 ($t = 2.9$). The estimates under the margin date are almost identical, and those under the perpetual date are 2.32 and 1.97 after upside shocks and imprecise after downside shocks. The earlier pre-access half-years differ from the half-year before access by 1.26 percentage points after upside shocks ($t = 1.5$) and by −0.58 after downside shocks ($t = -0.5$), so we do not detect differences in trends before access.

Table 17: The effect of access to short selling across difference-in-differences designs

	Upside shocks			Downside shocks		
	Earliest	Perpetual	Margin	Earliest	Perpetual	Margin
Same coin	2.55***	2.36***	2.59***	2.22**	1.04	2.34***
	(3.25)	(3.16)	(3.34)	(2.50)	(1.03)	(2.66)
Stacked	2.19*	2.09**	2.36**	2.85***	1.75	2.94***
	(1.94)	(2.12)	(2.09)	(2.89)	(1.38)	(3.00)
Sun–Abraham, reference: half-year before access	2.84***	2.32***	2.84***	2.72**	1.24	2.71**
	(2.72)	(2.60)	(2.73)	(2.24)	(1.01)	(2.24)
Sun–Abraham, reference: all half-years before access	2.88***	1.97**	2.87***	3.27***	1.15	3.26***
	(3.21)	(2.29)	(3.21)	(2.88)	(1.05)	(2.87)
Sun–Abraham, earlier half-years before access	1.26	0.78	1.27	−0.58	0.03	−0.58
	(1.46)	(0.99)	(1.46)	(−0.49)	(0.03)	(−0.48)
Placebo, one year early (stacked)	−0.48	−0.44	−0.48	0.46	0.00	0.46
	(−0.60)	(−0.63)	(−0.60)	(0.52)	(0.00)	(0.52)
Coins gaining access: same coin and stacked	73	88	75	73	88	75
Coins gaining access: Sun–Abraham	128	140	129	129	141	130

Effect of access to short selling on the cumulative abnormal return over the week after the shock, in percentage points. Earliest: earliest documented date; Perpetual: Binance perpetual listing; Margin: the earlier of Binance margin and the Binance perpetual. Same coin: coin and calendar-month fixed effects (Table 5). Stacked: one sub-sample per month of access with coins that gain access more than a year later as controls (Table 5). Sun–Abraham: interaction-weighted estimator of Sun and Abraham (2021) with cohorts defined by the half-year of access, relative-time bins of 182 days outside the 91 days around access, coins without access during the sample as controls, and coin and calendar-month fixed effects; post-access bins are averaged with weights equal to the number of shocks. The reference is either the half-year before the excluded window or all half-years before access. The row for earlier half-years averages the pre-access bins relative to the half-year before access and tests for differences in trends. Coins that can be shorted from the start of the sample are dropped. t-statistics clustered by coin in parentheses. *, **, *** denote significance at 10%, 5%, 1%.

D.3 Shocks by Time to Access

Table 18 reports the within-coin estimates by the distance of shocks from the access date, which Section 5.2 discusses.

Table 18: The effect of access: excluded window, coin age and shock size

	Upside shocks	Downside shocks	Pooled
Panel A. Earliest date			
Excluding days −91 to 91 (baseline)	2.55***	2.22**	2.42***
	(3.25)	(2.50)	(3.39)
Excluding days −182 to 91	3.83***	3.71***	3.78***
	(4.89)	(3.69)	(4.98)
Excluding days −365 to 91	1.43	0.77	1.17
	(0.93)	(0.45)	(0.87)
Coin-age fixed effects	2.44***	2.13**	2.32***
	(3.13)	(2.41)	(3.26)
Control for log shock size	1.92**	1.80**	
	(2.42)	(2.03)	
Month by shock-size quintile fixed effects	2.14***	2.01**	
	(2.71)	(2.37)	
Panel B. Binance perpetual date			
Excluding days −91 to 91 (baseline)	2.36***	1.04	1.86**
	(3.16)	(1.03)	(2.46)
Excluding days −182 to 91	2.10**	0.81	1.61*
	(2.37)	(0.61)	(1.70)
Excluding days −365 to 91	0.36	−0.96	−0.16
	(0.21)	(−0.43)	(−0.09)
Coin-age fixed effects	2.31***	0.95	1.79**
	(3.10)	(0.96)	(2.41)
Control for log shock size	1.62**	0.64	
	(2.08)	(0.62)	
Month by shock-size quintile fixed effects	1.91**	0.82	
	(2.43)	(0.80)	

The outcome is the cumulative abnormal return in percent over the week after the shock; same-coin regressions with coin and calendar-month fixed effects (by sign of the shock in the pooled column), as in Table 6, Panel A. The first three rows vary the window of excluded shocks before access; the coins with shocks both before and after access (upside / downside) number 73 / 73, 56 / 55 and 21 / 19 under the earliest date and 88 / 88, 73 / 69 and 44 / 42 under the Binance perpetual date, out of 396 coins with upside and 397 with downside shocks. Coin-age fixed effects: indicators for half-years since the coin's first trade on Binance. Log shock size: the logarithm of the absolute abnormal return in the shock hour. Size quintiles are formed within calendar month. t-statistics clustered by coin in parentheses. *, **, *** denote significance at 10%, 5%, 1%.

Table 19: Width of the excluded listing window

Days excluded on each side of the date	0	30	60	91	120	180
Binance perpetual date						
Upside, same coin	-1.92***	1.22**	2.15***	2.36***	2.25***	2.00*
	(-3.58)	(2.29)	(3.33)	(3.16)	(2.83)	(1.95)
Upside, stacked	-2.60***	0.64	1.71**	2.09**	1.86*	0.96
	(-3.72)	(0.87)	(2.01)	(2.12)	(1.74)	(0.67)
Upside, placebo	0.14	-0.42	-0.43	-0.44	-0.69	-2.21
	(0.27)	(-0.75)	(-0.73)	(-0.63)	(-0.83)	(-0.89)
Downside, same coin	-0.30	0.79	1.10	1.04	0.71	-0.14
	(-0.43)	(1.00)	(1.21)	(1.03)	(0.59)	(-0.07)
Downside, stacked	0.12	1.08	1.66	1.75	1.15	-0.26
	(0.14)	(1.13)	(1.45)	(1.38)	(0.74)	(-0.09)
Downside, placebo	0.52	-0.25	-0.46	-0.00	-0.53	-2.41
	(0.95)	(-0.39)	(-0.66)	(-0.00)	(-0.58)	(-1.00)
Coins, same coin, upside / downside	403 / 403	400 / 401	398 / 398	396 / 397	395 / 395	387 / 386
Treated coins, upside / downside	145 / 138	113 / 104	97 / 94	88 / 88	79 / 81	64 / 62
Control coins, stacked, upside / downside	176 / 171	158 / 157	152 / 149	145 / 143	141 / 140	131 / 131
First margin or perpetual date						
Upside, same coin	-0.51	2.04***	2.73***	2.59***	3.16***	3.81***
	(-0.88)	(3.35)	(3.93)	(3.34)	(4.00)	(4.59)
Upside, stacked	-1.21	1.60*	2.50**	2.36**	2.89**	3.27**
	(-1.48)	(1.79)	(2.52)	(2.09)	(2.38)	(2.47)
Upside, placebo	-0.02	-0.53	-0.63	-0.48	-0.87	0.69
	(-0.03)	(-0.89)	(-0.95)	(-0.60)	(-0.84)	(0.26)
Downside, same coin	0.15	1.89***	2.26***	2.34***	2.73***	3.65***
	(0.20)	(2.60)	(2.96)	(2.66)	(2.79)	(2.80)
Downside, stacked	0.35	2.14**	2.71***	2.94***	3.27***	4.12***
	(0.41)	(2.57)	(3.08)	(3.00)	(3.05)	(2.66)
Downside, placebo	0.45	-0.34	-0.21	0.46	-0.06	-2.38
	(0.69)	(-0.47)	(-0.27)	(0.52)	(-0.06)	(-0.81)
Coins, same coin, upside / downside	403 / 403	400 / 401	398 / 398	396 / 397	395 / 396	389 / 388
Treated coins, upside / downside	117 / 109	92 / 84	81 / 79	75 / 75	70 / 69	51 / 49
Control coins, stacked, upside / downside	159 / 152	134 / 132	123 / 122	117 / 115	111 / 109	99 / 99

Effect of shortability on the cumulative abnormal return (percent) over the week after the shock, excluding shocks within the stated number of days on each side of the date the coin first becomes shortable. Same coin: coin and calendar-month fixed effects, no other controls. Stacked: one sub-sample per calendar month of first shortability, with coins that become shortable only later as controls, fixed effects for coin by sub-sample and for calendar month by shock-size quintile by sub-sample. Placebo: the stacked design with shortability dated one year early, using only shocks before the true date. Treated coins: coins that become shortable with shocks both before and after the excluded window; control coins: coins first shortable after the stack window. t-statistics clustered by coin in parentheses. *, **, *** denote significance at 10%, 5%, 1%.

D.4 Shocks in Hours in Which Many Coins Move Together

Shocks to different coins in the same hour may reflect market-wide news that the market model does not remove. Table 20 excludes hours in which more than 10% of the coins in the universe have a shock of the same sign, using shocks from January 2020. The exclusion leaves the results for upside shocks unchanged and strengthens the continuation after downside shocks, from −0.89% to −1.79% over the week. The table uses a stacked design whose controls are coins that gain access more than 456 days after the cohort month, so its event counts and estimates differ slightly from those in Table 5.

Table 20: Returns after shocks and access to short selling, with and without clustered hours

	Upside shocks		Downside shocks	
	All	No clustered hours	All	No clustered hours
Mean CAR, 24 hours	−1.20***	−1.23***	−0.22	−0.66***
	(−12.07)	(−14.05)	(−1.38)	(−4.22)
Mean CAR, 168 hours	−2.42***	−2.44***	−0.89**	−1.79***
	(−11.20)	(−11.57)	(−2.49)	(−6.89)
Across coins: *Short*	1.60***	1.62***	1.74***	1.08***
	(5.32)	(5.25)	(5.91)	(2.83)
Within coin, Binance perpetual	2.36***	2.42***	1.04	0.71
	(3.16)	(3.17)	(1.03)	(0.51)
Within coin, earliest date	2.55***	2.71***	2.22**	2.44***
	(3.25)	(3.54)	(2.50)	(2.63)
Stacked, Binance perpetual	2.58***	2.60***	2.31*	1.21
	(2.75)	(2.74)	(1.92)	(0.75)
Stacked, earliest date	2.46**	2.44**	3.09***	3.23***
	(2.45)	(2.51)	(3.14)	(2.94)
Shocks	33,895	32,648	19,785	14,830
Coins	403	403	403	403
Treated coins, perpetual / earliest date	88 / 73	88 / 73	88 / 73	87 / 71

Cumulative abnormal returns in percent after upside and downside shocks from January 2020. Clustered hours are hours in which more than 10% of the coins in the universe have a shock of the same sign. Mean CAR: t-statistics clustered by calendar day. Across coins: regression of the 168-hour CAR on an indicator for a Binance perpetual at the time of the shock, with log market capitalization, log dollar volume, log shock size and month fixed effects. Within coin: coin and month fixed effects, shocks within 91 days of the shortability date excluded. Stacked: monthly cohorts with controls first shortable more than 365 days later or never, stack-by-coin and stack-by-month-by-shock-size-quintile fixed effects. Treated coins: coins with shocks both before and after access, under the Binance perpetual and the earliest date. Standard errors clustered by coin unless stated otherwise. *, **, *** denote significance at 10%, 5%, 1%.

D.5 Funding and Open Interest

Table 21 reports the changes in positions and funding around shocks shown in Figure 6, Table 22 the relation between funding before the shock and the return after shocks, and Table 23 returns

after shocks by terciles of open interest relative to market capitalization (Section 5.4).

Table 21: The perpetual market around shocks

Hours relative to the shock	−24	+1	+6	+24	+72
Upside shocks					
Open interest (log change ×100)	−3.89	23.72	30.66	28.86	16.69
	(−6.75)	(42.64)	(32.39)	(25.82)	(15.09)
Short share of accounts (pp)	−1.34	5.33	6.73	4.58	0.66
	(−8.01)	(31.32)	(23.56)	(14.72)	(2.27)
Short share of top-trader accounts (pp)	−1.28	4.80	5.57	3.74	0.20
	(−5.79)	(25.78)	(17.14)	(9.66)	(0.54)
Premium, perpetual minus spot (pp)	0.03	−0.44	−0.09	−0.04	0.03
	(2.84)	(−9.09)	(−3.58)	(−1.77)	(2.14)
Funding (% p.a.)	6.18	−4.30	−47.64	−33.15	4.75
	(1.47)	(−2.84)	(−9.52)	(−5.21)	(1.25)
Downside shocks					
Open interest (log change ×100)	−16.19	−8.12	−12.00	−15.27	−20.45
	(−16.69)	(−23.19)	(−23.26)	(−19.76)	(−20.75)
Short share of accounts (pp)	−4.61	−1.05	−2.28	−2.83	−3.36
	(−18.32)	(−8.85)	(−11.91)	(−10.83)	(−10.67)
Short share of top-trader accounts (pp)	−4.06	−1.59	−2.29	−2.49	−3.14
	(−13.07)	(−10.88)	(−9.73)	(−7.94)	(−8.05)
Premium, perpetual minus spot (pp)	0.43	0.34	0.35	0.37	0.43
	(6.92)	(6.25)	(6.26)	(5.97)	(6.82)
Funding (% p.a.)	20.33	−6.23	−35.92	−13.93	7.43
	(5.00)	(−3.68)	(−7.29)	(−2.67)	(1.59)
Before the shock: change from hour −24 to 0, downside minus upside shocks					
Short share of accounts (pp)	1.57				
	(5.04)				
Open interest (log change ×100)	4.14				
	(3.84)				

Events: idiosyncratic shocks in coins with a Binance perpetual (excluding ±91 days around the listing), December 2021 to September 2023, the 1,500 largest per sign (173 coins with upside and 186 coins with downside shocks). Each variable is measured relative to hour 0, the start of the shock hour; means across events with t-statistics in parentheses. Short share of accounts: 1/(1 + long/short account ratio). At hour −24 the entry is the value at hour −24 minus the value at hour 0, so a negative number means the variable rose over the 24 hours before the shock. Last panel: regressions of the change from hour −24 to 0 on a downside-shock dummy (upside shocks as comparison), with the abnormal return over hours −23 to −1, log market cap and log dollar volume; clustered by coin.

E Access to Short Selling and Variance Predictability

Table 24 re-estimates the within-coin regression of Table 3, Panel B, under the three definitions of access. The interaction of upside variance with access is 1.7 basis points under the Binance perpetual date ($t = 0.1$), 44.9 under the margin date ($t = 1.8$) and 49.2 under the earliest date ($t = 1.9$). Figure 9 shows the change in the slope by quarter relative to access. Table 25 reports the

Table 22: The cost of shorting

	24 hours	72 hours	168 hours
Panel A. Upside shocks			
Negative funding dummy	0.20	0.12	0.11
	(1.07)	(0.45)	(0.30)
Funding (annualized)	0.17	0.25	−0.28
	(0.54)	(0.52)	(−0.39)
Events		11,189	
Coins		189	
Panel B. Downside shocks			
Negative funding dummy	−0.42	−0.32	0.34
	(−2.11)	(−1.10)	(0.87)
Funding (annualized)	1.15	1.67	1.50
	(2.46)	(3.94)	(2.16)
Events		6,946	
Coins		190	

Shortable coins only, excluding ±91 days around the listing. Post-shock cumulative abnormal return (pp) on the mean funding rate over the 168 hours before the shock (annualized; positive: longs pay shorts, so shorting is cheap) or a dummy for negative mean funding (shorts pay), with the event-level controls and month fixed effects; clustered by coin. Funding is measured as an annualized fraction, so the continuous coefficient is the effect of 100 percentage points of annualized funding.

Table 23: The amount of short capital before the shock

Open interest / market cap	Median (%)	168 hours	72 hours	Hours 1–4	Days 2–7
Upside shocks (600 per tercile)					
Low tercile	1.32	−1.64	−1.20	−0.83	−0.79
Middle tercile	3.61	−2.22	−1.25	−0.75	−1.32
High tercile	10.22	−0.61	−0.82	−0.37	0.18
Downside shocks (455 to 456 per tercile)					
Low tercile	1.42	0.33	0.25	0.42	−0.40
Middle tercile	4.09	−0.05	0.10	0.04	−0.47
High tercile	12.00	−0.14	−0.59	−0.36	0.53

Shocks to coins with a Binance perpetual from December 2021, excluding 91 days around the listing, sorted into terciles of perpetual open interest in % of the coin's market capitalization, averaged over the 24 hours before the shock. Mean cumulative abnormal return after the shock, in %, by window.

stacked design and Table 26 longer horizons. Tables 27 and 28 complement Section 6.2: Table 28, Panel A, lets the interaction of upside variance with access differ on coin-days with a recent upside shock, and Panel B reports the shock index and its interaction with access, alone and together with the semivariances.

Table 24: Three definitions of access to shorting

Within coins, group-specific slopes	Binance perpetual	First margin or perpetual	Earliest
$IV^{+} \times Short$	1.7	44.9*	49.2*
	(0.06)	(1.75)	(1.91)
$IV^{-} \times Short$	19.0	−18.6	−22.7
	(0.72)	(−0.73)	(−0.88)
Sum of the interactions	20.7**	26.3***	26.4***
	(2.35)	(3.02)	(3.01)
Post-access IV^{+} slope, switching coins	−38.2***	−32.8**	−28.2*
	(−2.59)	(−2.22)	(−1.96)
Coin-days	331,896	334,938	335,690
Coins	399	399	399
Switching coins	90	76	74

Specification of Table 3, Panel B, column 5, with access dated by the Binance perpetual listing, by the earlier of the perpetual and Binance margin borrowing, and by the earliest documented perpetual, futures or margin listing on any venue. Coin-days from January 2020, excluding those within 91 days of the date. Coefficients in basis points per standard deviation; Driscoll-Kraay t-statistics. *, **, *** denote significance at 10%, 5%, 1%.

F Alternative Explanations

This appendix complements Section 7. It reports the liquidity tests for the daily slope, the price paths around access, and the evidence on manipulation and lottery demand.

F.1 Liquidity

Table 29 reports the event-level regressions with contemporaneous volume and its interactions with access discussed in Section 7.

Portfolio comparisons within liquidity terciles show the difference between coins with and without access (Table 31, Panel A). The high-minus-low spread on idiosyncratic variance is −50.3, −40.9 and −35.9 basis points among coins without access, compared with −4.4, −7.4 and 1.7 among coins with access. Regressions across coins separate access from liquidity less clearly: allowing the upside slope to vary with Amihud illiquidity reduces the access interaction to 10.6 basis points ($t = 0.6$; Panel B).

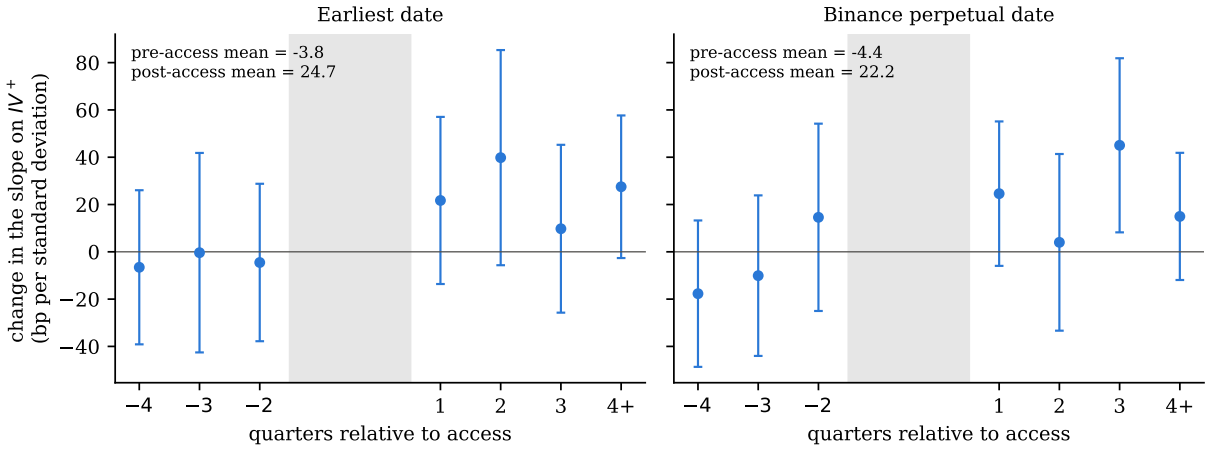


Figure 9: Dynamics of the return predictability of upside idiosyncratic variance. Change in the slope of next-day returns on upside idiosyncratic variance for coins that gain access during the sample, by quarter relative to the earliest documented access date (left) and the Binance perpetual date (right); the text in each panel reports the mean of the pre-access and of the post-access coefficients. The specification includes separate slopes for coins that always have access and coins that gain access, the controls of Table 3, and coin and day fixed effects; the reference is quarter −5 and earlier of the same coins. Quarters −1 and 0 (shaded) are excluded. Bars denote 95% confidence intervals based on Driscoll–Kraay standard errors.

Table 25: Stacked within-coin design

Stacked within-coin design	Binance perpetual		Earliest	
	360 days	180 days	360 days	180 days
IV^+	−49.1***	−53.0***	−44.1***	−44.7***
	(−3.75)	(−4.21)	(−3.22)	(−3.37)
$IV^+ \times$ treated coin	−3.6	−2.7	−12.9	−12.1
	(−0.20)	(−0.12)	(−0.74)	(−0.51)
$IV^+ \times Post$	34.4*	19.8	42.3**	36.8
	(1.66)	(0.66)	(1.97)	(1.09)
$IV^- \times Post$	−5.9	9.4	−1.7	11.3
	(−0.28)	(0.31)	(−0.07)	(0.32)
Stacked coin-days	1,474,966	913,456	1,398,705	841,260
Cohorts	20	19	21	19
Treated coins	249	225	233	208
Control coins	271	287	244	260

Stacked regressions of next-day returns on standardized log upside and downside idiosyncratic variance, their interactions with an indicator for treated coins and with *Post*, which equals one for treated coins more than 91 days after first shortability, and the level of *Post*. Each stack contains the coins first shortable in one calendar quarter and, as controls, coins first shortable only more than the stated window plus 91 days after the end of the quarter, or never, over the stated window on each side of the quarter. Treated coin-days within 91 days of the date are excluded. Coin and day fixed effects specific to each stack and the controls of Table 3; Driscoll-Kraay t-statistics. Control coins can enter several stacks. Coefficients in basis points per standard deviation. *, **, *** denote significance at 10%, 5%, 1%.

Table 26: Return horizons

Panel A. Shortability: Binance perpetual date	1 day	day 2	7 days	days 2-8	30 days
$IV \times Short$	18.5**	16.0**	8.4	6.2	2.3
	(2.08)	(2.08)	(1.44)	(1.04)	(0.51)
$IV^+ \times Short$, per day	1.7	30.3	12.3	12.0	−6.7
	(0.06)	(1.27)	(0.86)	(0.88)	(−0.84)
$IV^+ \times Short$, cumulative	1.7	30.3	85.9	84.1	−201.8
	(0.06)	(1.27)	(0.86)	(0.88)	(−0.84)
$IV^- \times Short$, per day	19.0	−13.9	−3.4	−5.6	9.6
	(0.72)	(−0.60)	(−0.23)	(−0.39)	(1.03)
Coin-days	331,896	331,368	329,916	329,520	323,293
Coins	399	399	398	398	397

Panel B. Shortability: earliest date	1 day	day 2	7 days	days 2-8	30 days
$IV \times Short$	26.2***	20.2**	12.9**	9.6	6.0
	(3.01)	(2.47)	(1.99)	(1.44)	(1.42)
$IV^+ \times Short$, per day	49.2*	53.3**	35.3***	30.8**	12.6
	(1.91)	(2.39)	(2.65)	(2.31)	(1.46)
$IV^+ \times Short$, cumulative	49.2*	53.3**	246.8***	215.3**	376.7
	(1.91)	(2.39)	(2.65)	(2.31)	(1.46)
$IV^- \times Short$, per day	−22.7	−33.6	−22.7	−21.5	−6.8
	(−0.88)	(−1.46)	(−1.63)	(−1.55)	(−0.80)
Coin-days	335,690	335,134	333,665	333,260	326,857

Average daily excess returns over the stated horizon after the formation day, in basis points, on standardized log idiosyncratic variance and its interaction with *Short* (first row, separate regression) or on upside and downside idiosyncratic variance and their interactions, with *Short*, the controls of Table 3, group-specific slopes as in Table 3, column 2, and coin and day fixed effects, excluding coin-days within 91 days of the shortability date. The cumulative row multiplies the per-day coefficient by the number of days in the horizon. "Day 2" and "days 2–8" skip the first day after formation. Driscoll-Kraay t-statistics with lags equal to the horizon length plus the skipped day (at least five). *, **, *** denote significance at 10%, 5%, 1%.

Table 27: Idiosyncratic shocks and the return predictability of idiosyncratic variance

Panel A. Coin-days with and without a recent shock

	Binance perpetual			Earliest		
	All	Recent shock	No recent shock	All	Recent shock	No recent shock
$IV^+ \times Short$	1.7	−21.5	54.5	49.2*	43.2	8.2
	(0.06)	(−0.65)	(1.10)	(1.91)	(1.39)	(0.16)
$IV^- \times Short$	19.0	46.5	−42.9	−22.7	−5.3	−7.2
	(0.72)	(1.49)	(−0.91)	(−0.88)	(−0.17)	(−0.15)
Coin-days	331,896	219,053	112,843	335,690	222,110	113,580
Coins	399	397	399	399	397	399

Panel B. $IV^+ \times Short$ by time since the most recent upside shock

	Binance perpetual	Earliest
No upside shock in the previous 168 hours	−12.6	34.7
	(−0.44)	(1.27)
Upside shock in the previous 48 hours	19.8	69.2**
	(0.67)	(2.45)
Upside shock 48 to 168 hours earlier	−15.7	34.4
	(−0.56)	(1.29)
Difference: previous 48 hours minus no shock	32.4***	34.5***
	(2.86)	(3.17)
Coin-days	331,896	335,690
Coins	399	399

Specification of Table 3, Panel B, column 2 (group-specific slopes) or column 5, from January 2020. A recent shock is a shock of either sign in the 168 hours before the end of the measurement window. Panel A estimates the regression on all coin-days and separately on coin-days with and without a recent shock. Panel B allows the interaction of IV^+ with *Short* to differ by the time since the most recent upside shock and includes the corresponding indicators and their interactions with IV^+ and *Short*; the last row tests the difference between the first two rows. Coefficients in basis points per standard deviation; Driscoll-Kraay t-statistics in parentheses. *, **, *** denote significance at 10%, 5%, 1%.

Table 28: Idiosyncratic shocks and the return predictability of idiosyncratic variance: further tests

Panel A. Interaction with a recent upside shock		
	Binance perpetual	Earliest
$IV^+ \times Short$	−8.5	37.2
	(−0.30)	(1.36)
$IV^+ \times Short \times$ recent upside shock	7.1	9.9
	(1.12)	(1.61)
Coin-days	331,896	335,690
Coins	399	399

Panel B. Shock index				
	Binance perpetual: G only	Binance perpetual: G and IV	Earliest: G only	Earliest: G and IV
G^+	−14.9***	−9.1***	−14.7***	−9.2***
	(−6.25)	(−3.64)	(−6.13)	(−3.65)
$G^+ \times Short$	11.4*	9.3	17.1***	6.9
	(1.95)	(1.30)	(2.80)	(0.89)
$IV^+ \times Short$		−16.5		36.0
		(−0.49)		(1.13)
Coin-days	331,896	331,896	335,690	335,690
Coins	399	399	399	399

Specifications as in Table 27, with group-specific slopes. Panel A estimates one regression in which the interaction of IV^+ with *Short* differs on coin-days with an upside shock in the previous 168 hours, with the corresponding lower-order terms. Panel B: G^+ (G^-, included but not reported) is the sum of the absolute abnormal returns of upside (downside) shocks in the previous 14 days, each weighted by 0.7 raised to its age in days, in logs and standardized, with separate slopes for always-shortable and switching coins. Coefficients in basis points per standard deviation; Driscoll-Kraay t-statistics in parentheses. *, **, *** denote significance at 10%, 5%, 1%.

Table 29: Liquidity and the effect of access on the return after shocks

	Upside shocks		Downside shocks	
	Post	Interaction	Post	Interaction
Binance perpetual date				
Baseline	2.09**		1.75	
	(2.12)		(1.38)	
Log volume	5.29***		3.89***	
	(4.67)		(2.83)	
Log volume and volume × size	5.34***		4.07***	
	(4.57)		(2.80)	
Post × volume	5.57***	-0.17	4.33***	-0.29
	(4.80)	(-0.28)	(3.56)	(-0.51)
Post × change in volume	1.98**	0.46	1.74	0.96
	(1.98)	(0.69)	(1.44)	(0.96)
Treated coins	88		88	
Control coins	145		143	
First margin or perpetual date				
Baseline	2.36**		2.94***	
	(2.09)		(3.00)	
Log volume	5.56***		4.97***	
	(4.29)		(4.50)	
Log volume and volume × size	5.55***		4.98***	
	(4.25)		(4.30)	
Post × volume	5.93***	-0.26	5.05***	-0.05
	(4.66)	(-0.47)	(4.16)	(-0.10)
Post × change in volume	2.32**	0.19	3.04***	0.12
	(2.08)	(0.31)	(3.04)	(0.24)
Treated coins	75		75	
Control coins	117		115	

Stacked difference-in-differences of Table 5 for the return over the week after the shock, with liquidity controls. Log volume: the coin's log dollar volume at the time of the shock. Volume × size: the slope on shock size varies with volume. Post × volume: the effect of shortability varies with volume (centred, so Post is the effect at average volume); the interaction column reports this coefficient. Post × change in volume: the effect varies with the treated coin's change in median log volume from the pre-period to the post-period (centred); the interaction column reports this coefficient. Treated coins: coins that become shortable with shocks both before and after access; control coins: coins whose access begins after the stack window. t-statistics clustered by coin in parentheses.

Within coins, the access estimate ranges from 39.3 basis points with Amihud illiquidity to 55.7 with dollar volume when the measures enter one at a time, compared with 49.2 without them (Table 30). Because contemporaneous liquidity may respond to access, we also interact upside variance with liquidity before access, which gives access estimates of 44.8 and 45.1 basis points, compared with 45.8 in the same sample without these interactions (Table 31, Panel C).

A placebo uses 77 coins without access that experience large volume increases (Table 32). The interaction of upside idiosyncratic variance with the placebo event is 31.2 basis points ($t = 1.2$), compared with 49.2 at access. Liquidity may therefore contribute to the change in the overall daily slope, although it does not explain the effect of access on the return after shocks (Section 5.3).

Table 30: Liquidity and the effect of access on the slope on idiosyncratic variance

Within coins, group-specific slopes, earliest date	Baseline	Dollar volume	Turnover	Amihud illiquidity	Age	Turnover and Amihud
$IV^+ \times$ *Short*	49.2*	55.7**	44.3*	39.3	49.3*	39.8
	(1.91)	(2.15)	(1.71)	(1.50)	(1.89)	(1.51)
$IV^+ \times$ liquidity measure		−17.9**	2.8	−5.4	−0.6	
		(−2.53)	(0.49)	(−0.72)	(−0.08)	
Coin-days	335,690	335,690	335,690	335,690	335,690	335,690
Coins	399	399	399	399	399	399

Specification of Table 3, Panel B, column 5 (group-specific slopes, earliest date), on coin-days with all four liquidity measures, adding each measure, its interactions with IV^+ and IV^-, and, in the last column, turnover and Amihud illiquidity together with their interactions. Dollar volume and Amihud illiquidity are highly correlated and therefore enter separately. Liquidity measures: log dollar volume, log turnover, log Amihud illiquidity and log coin age, winsorized at 1% and 99% and standardized. The second row reports the interaction of IV^+ with the measure in the columns with a single measure. Coefficients in basis points per standard deviation; Driscoll-Kraay t-statistics. *, **, *** denote significance at 10%, 5%, 1%.

F.2 Manipulation

Upside reversals are present among the 20 largest coins. Shocks average 3.9% and are followed by weekly returns of −1.1% ($t = -3.2$), almost entirely after the first day (Table 33), so the pattern is not confined to small, thinly traded coins. For these coins, the Binance perpetual often followed earlier access elsewhere, and its interaction with the return after shocks is insignificant.

Declines after downside shocks may partly reflect the unwinding of manipulation. Table 34 controls for the return before the shock and separates events by its size. Adding the control reduces the difference between coins with and without a perpetual over the week after downside shocks from 2.1 to 1.8 percentage points ($t = 6.1$), and among events with the smallest prior returns, the difference is still 1.8 percentage points ($t = 3.9$). These checks do not identify which events were manipulated.

F.3 Selection into Listing

Table 35 reports the cumulative abnormal return around access for coins with low and high upside idiosyncratic variance before access, and at a placebo date one year earlier. Coins with high upside

Table 31: Liquidity and the return predictability of idiosyncratic variance

Panel A. High-minus-low idiosyncratic variance tercile, within terciles of Amihud illiquidity (bp per day)

	Liquid	Mid	Illiquid
Not shortable	−50.3***	−40.9***	−35.9***
	(−3.21)	(−5.86)	(−4.92)
Shortable	−4.4	−7.4	1.7
	(−0.61)	(−0.72)	(0.15)
Days, not shortable / shortable	494 / 1,342	1,342 / 1,003	1,342 / 460
Coins, not shortable / shortable	189 / 198	252 / 161	236 / 90

Panel B. Across coins: slope on IV^+ varying with liquidity (Fama-MacBeth)

	None	Dollar volume	Turnover	Amihud	Turnover and Amihud
$IV^+ \times$ *Short*	36.2***	26.2	32.6***	10.6	10.0
	(3.13)	(1.54)	(2.70)	(0.60)	(0.55)
$IV^+ \times$ liquidity measure		−3.3	−5.3	−12.9	
		(−0.38)	(−0.84)	(−1.59)	
Days	1,342	1,342	1,342	1,342	1,342
Coins	405	405	405	405	405

Panel C. Within coins: slope on IV^+ varying with liquidity before access

	Amihud illiquidity		Dollar volume	
	Without	With	Without	With
$IV^+ \times$ *Short*	45.8*	44.8*	45.8*	45.1*
	(1.78)	(1.76)	(1.78)	(1.78)
$IV^+ \times$ liquidity before access		7.1		−4.5
		(0.47)		(−0.29)
Coin-days	232,315	232,315	232,315	232,315
Coins	270	270	270	270

Panel D. Across coins within cells of similar liquidity and size

	Same day, Amihud and size quintile
IV^+	−49.2***
	(−2.91)
$IV^+ \times$ *Short*	21.3
	(1.21)
$IV^- \times$ *Short*	−3.0
	(−0.18)
Days	1,300
Coins	401

Panel E. Within coins: change in the slope by the coin's change in liquidity at access

	Amihud	Dollar volume
$IV^+ \times$ *Short*	42.9	44.6*
	(1.63)	(1.75)
$IV^+ \times$ *Short* $\times$ change in liquidity	−13.5	17.1
	(−0.62)	(0.79)
Coin-days	335,690	335,690
Coins	399	399

Shortability dated by the earliest documented date; coin-days from January 2020. Panel A: each day, coins are sorted into terciles of log Amihud illiquidity and, within each tercile and shortability group with at least 15 coins, into terciles of idiosyncratic variance; the entry is the average next-day return of the top minus the bottom variance tercile, excluding coin-days within 91 days of the date, with Newey-West t-statistics. Panel B: the regression of Table 3, Panel A, column 4, adding log dollar volume, log turnover or log Amihud illiquidity (winsorized and standardized) and its interactions with IV^+ and IV^-, or turnover and Amihud illiquidity together; dollar volume and Amihud illiquidity are not entered together because their within-coin correlation is −0.91. Panel C: the regression of Table 3, Panel B, column 5, adding the interactions of IV^+ and IV^- with the coin's average liquidity on days more than 91 days before access, on coins with such days. Panel D: daily cross-sectional regressions within cells defined by the day and quintiles of log Amihud illiquidity and log market capitalization, using only cells that contain both shortable and non-shortable coins (77% of coin-days), with the controls except size; Newey-West t-statistics. Panel E: the regression of Panel C without the liquidity interaction, adding the interaction of $IV^+ \times$ *Short*, $IV^- \times$ *Short*, *Short*, IV^+ and IV^- with the switching coin's change in average liquidity from before to after access (standardized; zero for other coins). Coefficients in basis points per standard deviation. *, **, *** denote significance at 10%, 5%, 1%.

Table 32: Liquidity increases without a change in access

Change in the slope after a large increase in liquidity	Placebo: liquidity increase	Actual access
$IV^{+} \times After$	31.2	49.2*
	(1.23)	(1.91)
$IV^{-} \times After$	−37.7	−22.7
	(−1.50)	(−0.88)
Coin-days	148,852	335,690
Coins	196	399
Coins with an event	77	63
Mean increase in log dollar volume	2.70	1.65

Shortability dated by the earliest documented date; coin-days from January 2020. For each coin, the increase in liquidity at a date is the mean log dollar volume over days 92 to 182 after it minus the mean over days 182 to 92 before it. The placebo event is the date with the largest increase, for coins that cannot be shorted during the sample, retained if the increase is at least the median increase at actual access. *After* equals one after the placebo event. The regression is that of Table 3, Panel B, with *After* in place of *Short*, slopes on IV^{+} and IV^{-} specific to coins with an event, coin and day fixed effects, and excluding the 91 days on each side of the event. Column 2 repeats the main specification with actual access, and its last row is the increase in log dollar volume at access. Coefficients in basis points per standard deviation; Driscoll-Kraay *t*-statistics in parentheses. *, **, *** denote significance at 10%, 5%, 1%.

Table 33: The 20 largest coins

	Events	Shock (%)	Days 2–7 (%)	0–7 days (%)
Panel A. Upside shocks: mean return (%) after the shock				
Top 20, all	3,884	3.89	−0.95	−1.11
				(−3.23)
Top 20, not shortable	1,535	4.66	−1.16	−1.41
				(−2.67)
Top 20, shortable	2,349	3.40	−0.88	−0.93
				(−2.13)
Outside top 20, all	37,434	6.42	−1.72	−3.70
				(−9.45)

Panel B. Top-20 coin-days: 7-day return after shock days vs other days (pp), coin and day fixed effects	Upside-shock day	× PERP	PERP	Coin-days
All days	−0.55	0.25	−3.48	43,308
	(−2.03)	(0.70)	(−3.28)	
Excl. ±30 days	−0.64	0.35	−2.28	41,937
	(−2.31)	(0.96)	(−1.73)	
Excl. ±90 days	−0.65	0.39	−3.79	39,316
	(−2.21)	(1.02)	(−1.98)	

Top 20: the 20 largest coins by market capitalization on the day before the event. Panel A: upside shocks to 69 coins while in the top 20 (48 while not shortable and 44 while shortable) and to 405 coins outside it; Panel B: 88, 88 and 85 coins. Events from 2017 (shock threshold 4). Panel A: t-statistics from daily averages (Newey-West) in parentheses. Panel B: daily panel of top-20 coin-days, abnormal return over the next seven days on dummies for upside and downside shock days, *PERP* and their interactions, with coin and day fixed effects; Driscoll-Kraay t-statistics. The *PERP* level coefficient reflects selection into the top 20 and near-simultaneous listing dates and is not interpreted.

Table 34: Downside shocks: continuation or unwinding of pumps?

	72 hours	168 hours	Days 2–7
Downside shocks			
All	1.35	2.11	1.48
	(6.95)	(7.27)	(5.41)
All, + pre-shock return	1.09	1.83	1.35
	(5.92)	(6.06)	(4.65)
Run-up tercile low	0.69	1.78	1.61
	(2.19)	(3.88)	(4.01)
Run-up tercile mid	0.70	1.25	1.06
	(3.29)	(3.07)	(2.64)
Run-up tercile high	2.10	3.02	2.05
	(4.55)	(4.88)	(3.64)
Upside shocks			
All	1.49	2.54	2.11
	(6.15)	(8.35)	(8.96)
All, + pre-shock return	1.47	2.52	2.10
	(6.11)	(8.30)	(8.88)
Run-up tercile low	1.14	2.06	2.03
	(3.77)	(4.63)	(5.48)
Run-up tercile mid	1.18	1.85	1.46
	(4.08)	(5.29)	(4.63)
Run-up tercile high	1.77	3.40	2.76
	(4.07)	(5.94)	(6.07)

Shortable effect (pp) on the post-shock abnormal return, with log market cap, log dollar volume, log shock size and month fixed effects, excluding ±91 days around the listing; t-statistics clustered by coin. Pre-shock return: abnormal return over the 23 hours before the shock hour. Run-up terciles: terciles of the pre-shock return.

idiosyncratic variance before access outperform comparison coins by 39% to 53% in the preceding month and by another 13% to 25% around access. Section 7 discusses why this selection in price levels does not explain the within-coin estimates.

Table 35: Price reaction at first access to short selling

	Terciles of pre-listing IV^+			Regression (pp per sd)		Placebo
Event days	Low	High	High − low	IV^+	IV^-	High − low
Panel A: Binance perpetual date (76 coins)						
Pre [-30,-4]	20.93	53.18	32.25	−39.98	38.58	16.84
			(2.33)	(−0.77)	(0.71)	(2.18)
[-3,+3]	17.41	13.38	−4.03	14.67	−24.78	−2.86
			(−0.60)	(0.63)	(−1.05)	(−1.23)
[-10,+10]	27.89	49.29	21.41	−15.19	3.32	−7.58
			(1.55)	(−0.33)	(0.07)	(−1.20)
[0,+30]	−14.54	3.13	17.68	35.95	−29.77	4.64
			(2.45)	(1.49)	(−1.32)	(0.58)
[+1,+60]	−8.47	1.44	9.91	34.16	−30.67	−0.20
			(0.73)	(1.07)	(−0.98)	(−0.02)
[+1,+90]	−10.04	−1.70	8.34	31.73	−25.97	4.29
			(0.58)	(0.94)	(−0.77)	(0.43)
Panel B: Earliest shortability date (56 coins)						
Pre [-30,-4]	31.44	38.71	7.27	57.00	−56.80	13.80
			(0.55)	(1.66)	(−1.62)	(1.80)
[-3,+3]	20.52	25.46	4.95	8.42	−6.06	−3.32
			(0.42)	(0.36)	(−0.27)	(−0.98)
[-10,+10]	39.81	49.02	9.21	49.69	−52.16	0.85
			(0.63)	(1.68)	(−1.81)	(0.10)
[0,+30]	−0.84	14.94	15.78	42.66	−30.75	3.85
			(1.47)	(1.68)	(−1.27)	(0.40)
[+1,+60]	10.81	12.43	1.62	−43.13	46.01	−2.02
			(0.10)	(−1.17)	(1.33)	(−0.18)
[+1,+90]	12.78	9.09	−3.69	−50.61	53.87	2.52
			(−0.24)	(−1.40)	(1.53)	(0.22)

Cumulative abnormal returns (%) around the date a coin first becomes shortable, by terciles of its idiosyncratic upside variance over days −120 to −31 (average daily cross-sectional percentile). Abnormal return: return minus the mean return of benchmark coins on the same day in the same daily tercile of IV^+, among coins with no first shortability within ±180 days. Regression: CAR on standardized pre-listing percentiles of IV^+ and IV^-, log market capitalization, log dollar volume and listing-year fixed effects, heteroskedasticity-robust t-statistics. Placebo: the same high − low difference one year before the date. The test follows Jiang et al. (2014).

F.4 Lottery Demand

The decomposition of Hou and Loh (2016) attributes 89% of the slope on total idiosyncratic variance among coins without access to the included characteristics, mainly turnover, size, realized

skewness and MAX (Table 36). The decomposition is a statistical attribution and does not identify the mechanism.

Positive jump variation (Lee and Wang, 2025) has been interpreted as a measure of lottery demand. In the within-coin specification with group-specific slopes, its slope is −6.8 basis points ($t = -2.4$) and its interaction with access 19.8 ($t = 3.1$; Table 37). When upside idiosyncratic variance enters jointly, the slope on jump variation is 0.6 basis points ($t = 0.2$), while the slope on upside variance remains −62.7 ($t = -4.9$). Lottery demand and short-sale constraints can be complementary: demand can raise prices, and constraints limit trading against them.

Table 36: Decomposition of the slope on idiosyncratic variance

Components of the slope on idiosyncratic risk						
	IV			IV^+		
	All	Not shortable	Shortable	All	Not shortable	Shortable
Total slope $\bar{\gamma}$	−14.9***	−29.1***	−0.9	−15.9***	−29.8***	−2.0
	(−4.82)	(−7.39)	(−0.23)	(−5.19)	(−7.79)	(−0.52)
MAX	−2.9***	−4.5***	1.8	−2.5***	−3.7***	1.9
	(−3.38)	(−4.44)	(1.13)	(−3.15)	(−3.98)	(1.24)
Realized skewness	−4.2***	−7.0***	−0.7	−5.7***	−9.5***	−0.7
	(−6.95)	(−7.99)	(−0.81)	(−7.20)	(−8.19)	(−0.64)
Past abnormal return	−0.8	−1.2	0.7	−1.1**	−1.8***	0.4
	(−1.61)	(−1.52)	(0.81)	(−2.33)	(−2.58)	(0.48)
Size	−3.6	−12.5***	6.1**	−3.3	−11.5***	6.1**
	(−1.56)	(−4.18)	(1.97)	(−1.61)	(−4.25)	(2.00)
Illiquidity	6.0***	15.4***	−2.8	5.5***	13.7***	−3.1
	(2.62)	(6.40)	(−1.41)	(2.59)	(6.34)	(−1.57)
Turnover	−5.7***	−17.4***	−1.5	−5.2***	−15.6***	−1.5
	(−2.64)	(−4.18)	(−0.62)	(−2.62)	(−4.12)	(−0.64)
Beta	0.9**	1.1**	0.8	0.8**	1.1**	0.5
	(2.08)	(2.25)	(1.02)	(2.00)	(2.17)	(0.67)
Short	−0.6**			−0.5*		
	(−2.02)			(−1.91)		
Unexplained	−4.1***	−3.2*	−5.2***	−3.9***	−2.5*	−5.6***
	(−3.64)	(−1.95)	(−3.79)	(−3.67)	(−1.72)	(−4.24)
Days	1,342	1,342	1,294	1,342	1,342	1,294
Coins	399	270	203	399	270	203
Share explained	72%	89%	–	76%	92%	–

Following Hou and Loh (2016), the average daily cross-sectional slope of next-day returns on standardized log idiosyncratic variance (*IV*) or upside idiosyncratic variance (IV^+), $\bar{\gamma}$, is decomposed into the parts associated with each candidate explanation and an unexplained part. Each day, idiosyncratic variance is regressed on all candidates; the component of candidate k is $\mathrm{Cov}(r, \hat{\delta}_k Z_k)/\mathrm{Var}(IV)$, and the components sum to γ. Candidates: MAX, realized skewness, past seven-day abnormal return, log market capitalization, log Amihud illiquidity, turnover, market beta and, in the full sample, *Short* (earliest date). Shares are not reported where the total slope is insignificant. Not shortable and shortable: separate daily cross-sections of coins that cannot and can be shorted, excluding coin-days within 91 days of the shortability date. Basis points per standard deviation; Newey-West t-statistics in parentheses. *, **, *** denote significance at 10%, 5%, 1%.

Table 37: Positive jump variance and access to short selling

Positive and negative jump variance	Within coins		Across coins (Fama-MacBeth)	
	Jump variance	With semivariances	Jump variance	With semivariances
Positive jump variance	−6.8**	0.6	−2.1	1.0
	(−2.35)	(0.19)	(−1.02)	(0.47)
Positive jump variance ×*Short*	19.8***	10.0		
	(3.09)	(1.22)		
Positive jump variance, switching coins after access	8.0*			
	(1.88)			
Negative jump variance	−6.4**	−7.4**	−11.8***	−12.1***
	(−2.24)	(−2.51)	(−4.43)	(−3.66)
IV^+		−62.7***		−49.4***
		(−4.86)		(−4.96)
$IV^+ \times$ *Short*		28.1		
		(0.89)		
Observations	335,690	335,690	1,342	1,342
Coins	399	399	405	405

Positive (negative) jump variance: the sum of squared hourly total returns above (below) four (minus four) times the coin's return volatility over the previous 168 hours, over the seven-day window, in logs and standardized. Within coins: specification of Table 3, Panel B, column 5, with group-specific slopes on every risk measure and access dated by the earliest date; Driscoll-Kraay t-statistics. Across coins: daily cross-sectional regressions with the controls, Newey-West t-statistics. Observations: coin-days (within) or days (across). Coefficients in basis points per standard deviation. *, **, *** denote significance at 10%, 5%, 1%.

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