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Exchange warnings and crypto prices: Evidence from monitoring tags

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Research Article

Keywords: Cryptocurrency, Delisting, Exchange regulation, Perpetual futures, Price discovery, Short selling

Posted Date: November 3rd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11588547/v1

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Additional Declarations: The authors declare no competing interests.

Exchange warnings and crypto prices: Evidence from monitoring tags

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Abstract
Crypto exchanges decide which tokens the public can trade, and they also warn investors when a token may be removed. This study examines how prices respond to such warnings, using the monitoring tag of Binance, the largest crypto exchange. We time each tag announcement to the second and compare tagged tokens with untagged tokens of similar risk in the same announcement, with tokens that the exchange tags later, and with untagged tokens that a model estimated on earlier announcements ranks as most likely to be tagged. Tagged tokens fall within seconds of the announcement and keep falling through the first day, whereas the comparison tokens barely move. The decline appears on other large exchanges in the same minute, and prices do not recover over the following month. The tag predicts later delisting well beyond observable risk, but the size of the price response says little about which tagged tokens the exchange will remove. Tokens with perpetual futures absorb more of the warning in the first minute and lose less over the first day. The evidence suggests that a private gatekeeper produces information that prices absorb almost at once, and that the ease of betting against a token may shape how its price absorbs this information.
Keywords: Cryptocurrency; Delisting; Exchange regulation; Perpetual futures; Price discovery; Short selling
JEL classification: G12; G14; G15; G18

1. Introduction
Research on crypto markets documents the risk factors that price tokens (Liu et al., 2022), the arbitrage gaps between exchanges (Makarov and Schoar, 2020), and price manipulation through stablecoin issuance (Griffin and Shams, 2020). In this market, the exchange is often the only gatekeeper. No securities regulator reviews most tokens before they trade, so the listing rules of an exchange are the closest substitute for public oversight. Studies of exchange listings show that admission to a large exchange raises token prices (Benedetti and Nikbakht, 2021). Yet we know little about the opposite signal, the warnings that an exchange issues about individual tokens before it removes them. This study provides evidence on such warnings at the level of single minutes.

A simple example shows what is at stake. Suppose that an exchange announces that token A now carries a warning tag because it may no longer meet the listing standards, and token A trades at 1.00 dollar just before the announcement. If investors already knew that token A was weak, the tag tells them nothing new, and the price stays near 1.00. If the tag reveals what the exchange has learned from its own reviews of the project, the price falls to, say, 0.90 and stays there. A third possibility is that holders on the tagging exchange sell because the tag makes trading harder for them. In that case, the price falls to 0.90 on the tagging exchange, other exchanges trade near 1.00, and the price returns to 1.00 once the selling ends.

We study the monitoring tag of Binance, the largest crypto exchange by trading volume. We time each first-time tag to the official announcement and measure returns from one-minute prices. We compare tagged tokens with three benchmarks. The first is a set of untagged tokens in the same announcement with similar risk. The second is the tokens that the exchange tags later. The third is the untagged tokens that a model estimated on earlier announcements ranks as most likely to be tagged. We also follow tagged tokens on other exchanges and in the perpetual futures market, and we track whether they are delisted later. Tagged tokens fall within ten seconds of the announcement and keep falling over the first day, whereas the untagged benchmarks barely move. The decline appears on other exchanges in the same minute. After the first day, tagged tokens that keep trading do not fall further. Averaged over all tags, however, prices keep falling over the next three months, and this further loss arrives with and after the announcements of delisting. The tag predicts later delisting by a wide margin. Tokens with perpetual futures fall more in the first minute and less over the rest of the day.

This study contributes to three strands of research. First, it is closest to studies of how rules shape crypto prices. Karau (2023) and Dufouleur (2026) examine announcements by central banks and national regulators, and Benedetti and Nikbakht (2021) examine admission to exchanges, whereas this study shows that a warning by the exchange itself moves prices and predicts removal. Second, it adds to research on the quality and efficiency of crypto markets, which documents fake volume, thin liquidity, and slow incorporation of information on many venues (Brauneis et al., 2021; Aspris et al., 2021; Cong et al., 2023; Nimalendran et al., 2025). This study shows that the main exchange also produces information about the tokens it lists, and that prices absorb the tag within a day but not which tagged tokens the exchange will remove. Third, the faster and smaller response of tokens with perpetual futures adds to evidence that short sales and derivatives shape price discovery (Saffi and Sigurdsson, 2011; Beber and Pagano, 2013; Alexander et al., 2020; Augustin et al., 2023). The small price slide in the hours before the announcement also relates to evidence on private information and manipulation ahead of public news (Ahern, 2017; Kacperczyk and Pagnotta, 2019; Dhawan and Putniņš, 2023).

The remainder of this study is organized as follows. Section 2 describes the monitoring tag and develops our conjectures, Section 3 describes the data, Section 4 presents the empirical design, Section 5 reports the results, and Section 6 concludes.

2. Institutional Background and Conjectures

Binance introduced the monitoring tag on 26 July 2023.[1] The exchange attaches the tag to

[1] The first announcement was published on 26 July 2023 at 03:00 UTC on the official

tokens that it considers at risk of no longer meeting its listing criteria. The criteria cover the commitment of the team, development activity, trading volume and liquidity, network and contract security, public communication, responses to due diligence requests, evidence of misconduct, and contribution to the crypto ecosystem. Binance reviews tagged tokens regularly and may delist them, and users must pass a risk quiz every 90 days before they can trade tagged tokens on the spot and margin markets. The exchange announces new tags in batches, usually on a weekday morning in Coordinated Universal Time (UTC). Each announcement carries an official time stamp to the millisecond.

The exchange knows more about a token than outside investors do. It talks to project teams, reviews on-chain and trading activity, and knows how close a token is to its internal removal thresholds. A tag therefore may signal that the private assessment of the exchange has worsened. Delisting removes the main trading venue of a token and lowers its liquidity and value, as delisting from stock exchanges does (Macey et al., 2008). If the tag raises the chance of delisting by more than investors expected, the price should fall when the tag is announced and should not recover. We conjecture that tagged tokens fall at the announcement relative to equally risky untagged tokens, and that the decline does not reverse.

Negative news reaches prices faster when short selling is cheap, and prices adjust more slowly when shorting is restricted (Boehmer et al., 2013). In crypto markets, perpetual futures give investors a cheap way to bet against a token, whereas borrowing the spot token is often costly or impossible. Investors who can short through perpetual futures can act on the tag at once, whereas holders of tokens without perpetual futures can only sell what they own. We expect that tokens with perpetual futures incorporate the tag faster.

3. Data

We collect all monitoring tag announcements and all delisting announcements from the official announcement archive of Binance.[2] Binance added 167 monitoring tags in 26 announcements from July 2023 to October 2026. We keep the first tag of each token, which removes 1 repeat tag, and drop 11 tokens that have no daily trading data before the announcement, have traded for less than 30 days, or are stablecoins or leveraged tokens. This leaves 155 first-time tags. For each tagged token, we record whether Binance announces its delisting within 90 or 180 days. We use one-minute spot prices and trading values of the pairs quoted against Tether (USDT) on Binance, and individual trades in the announcement minute. We also use one-minute or hourly prices of the same tokens on Bybit, Coinbase, and KuCoin, and the open interest and funding rates of the Binance perpetual futures.

Except in the daily liquidity panel, each observation in our analysis is a token in one announcement. For each such pair, we combine the one-minute prices and the individual trades into one return for each window, so the number of independent observations is the number of tags and matched tokens, not the number of minutes or trades. The estimation windows contain

announcement page of Binance. A rule update on 4 March 2025 states that tagged tokens are reviewed monthly and that removals are reviewed quarterly.

[2] Announcements come from the public announcement archive of Binance. One-minute spot prices, perpetual futures prices, open interest, and funding rates come from the public data archive of Binance (data.binance.vision). Prices on other exchanges come from the public market data interfaces of Bybit, Coinbase, and KuCoin.

about 35 million one-minute prices. In the announcement minute, a tagged token has a median of 368 trades, against 5 for a matched token, which allows us to split this minute at the release time. Table S1 in Online Resource 1 defines all variables and reports the one-minute data around each announcement, with 204,480 token-minutes of tagged tokens in each of the day before and the day after the announcement.

For each announcement, the risk set contains all USDT pairs on Binance that are neither tagged nor delisted at the announcement. For each token, we measure past returns over 1, 5, 10, and 30 days (*Ret*1, *Ret*5, *Ret*10, and *Ret*30), the volatility and the mean daily range over 30 days (*Vol*30 and *Range*30), trading value (*Volume*), listing age (*Age*), and whether the token has a perpetual futures contract on Binance (*Perp*). All characteristics end before the announcement day. We winsorize each continuous characteristic at the 1st and 99th percentiles of the risk set of each announcement. We winsorize each return at the 1st and 99th percentiles of its estimation sample, separately for tagged tokens, matched tokens, and peers. We do not winsorize indicators or price levels. Repeating the matching and estimation without winsorizing, or with cutoffs at the 0.5th and 99.5th percentiles, gives nearly the same results (Table S2 in Online Resource 1).

Table 1 describes the sample and reports summary statistics. Panel A shows that the exchange tags a few tokens at a time, a median of 5 per announcement against a risk set of about 370 tokens, and that announcements become more frequent over time. Panel D shows that tagged tokens and their matched tokens have nearly the same past returns, volatility, range, trading value, and age, and the same share of them has perpetual futures. The only significant gap is in *Ret*10, where tagged tokens lost 1.9 percentage points less over the ten days before the tag, a gap of 0.17 standard deviations. The peers less often have perpetual futures because they are ranked without regard to *Perp*. The tagged tokens lose far more around the announcement, whereas the matched tokens barely move. Panel E shows that tagged tokens trade more than matched tokens over the days around the tag and have wider daily ranges. Close to half of the tagged tokens are delisted within 90 days, against 2% of the matched tokens.

Table 1. Sample and summary statistics

Panel A. Sample

	Events	Tags	Matched	WithPeers	RiskSet
2023	2	23	17	4	334
2024	4	30	28	30	336
2025	8	41	37	41	364
2026	12	61	60	61	396
All	26	155	142	136	372

Panel B. Tagged tokens

	Obs	Mean	SD	Min	P25	Med	P75	Max
Dependent variables								
Ann	142	-3.162	4.319	-19.90	-4.691	-1.485	-0.040	0.842
PreRel	79	-0.073	0.258	-1.049	-0.049	0.000	0.000	0.575
PostRel	132	-3.340	4.355	-20.03	-5.050	-1.742	-0.079	0.284
Post10	119	-3.104	3.945	-14.80	-4.791	-1.239	0.000	0.146
Post30	134	-3.184	4.177	-18.40	-5.229	-1.490	-0.038	1.227
Jump5	142	-1.920	5.612	-34.57	-2.526	-0.355	0.203	6.265

To5	142	-5.111	6.179	-34.81	-6.789	-3.845	-0.398	3.435
Hour1	142	-5.524	9.600	-39.89	-9.303	-3.246	0.358	15.31
Day1	142	-9.593	11.58	-47.38	-16.80	-7.997	-1.083	10.60
Pre1	142	-0.212	1.116	-4.239	-0.661	-0.063	0.405	2.613
Pre3	142	-0.539	1.642	-5.778	-1.131	-0.385	0.319	2.658
Pre6	142	-0.900	2.970	-11.08	-1.639	-0.355	0.697	5.588
CAR30	140	-14.87	38.94	-127.0	-32.69	-16.95	-1.820	156.8
CAR60	136	-18.46	60.00	-122.4	-52.66	-22.39	1.934	298.5
CAR90	131	-24.63	54.39	-200.5	-54.76	-25.18	1.214	143.1
Delist90	131	0.443	0.499	0.000	0.000	0.000	1.000	1.000
Delist180	114	0.579	0.496	0.000	0.000	1.000	1.000	1.000
Explanatory variables								
Perp	142	0.676	0.470	0.000	0.000	1.000	1.000	1.000
Control variables								
Ret1	142	-2.211	6.276	-21.61	-5.403	-1.290	1.645	14.19
Ret5	142	-3.569	9.926	-28.62	-8.665	-2.613	1.088	27.74
Ret10	142	-4.511	12.22	-36.08	-12.39	-3.454	3.555	39.14
Ret30	142	-9.068	20.46	-54.27	-22.32	-10.16	4.639	48.53
Vol30	142	4.734	2.162	1.662	3.361	4.339	5.324	16.89
Range30	142	8.040	2.769	3.028	6.372	7.495	9.225	18.39
Volume	142	13.82	1.262	11.28	12.96	13.69	14.61	17.36
Age	142	7.026	0.618	4.828	6.744	7.166	7.462	8.000

Panel C. Matched tokens

	Obs	Mean	SD	Min	P25	Med	P75	Max
Dependent variables								
Ann	426	-0.021	0.140	-0.616	-0.032	0.000	0.000	0.338
PreRel	195	0.014	0.082	-0.176	0.000	0.000	0.000	0.342
PostRel	299	-0.024	0.148	-0.573	-0.069	0.000	0.000	0.321
Post10	197	-0.013	0.076	-0.287	0.000	0.000	0.000	0.199
Post30	303	-0.025	0.122	-0.471	-0.062	0.000	0.000	0.277
Jump5	426	-0.008	0.271	-0.786	-0.160	0.000	0.125	0.813
To5	426	-0.045	0.311	-1.066	-0.191	0.000	0.128	0.790
Hour1	426	-0.192	1.061	-3.672	-0.713	0.000	0.449	2.435
Day1	426	-0.985	3.648	-13.07	-2.944	-0.888	1.255	7.018
Pre1	426	0.008	0.722	-2.347	-0.398	0.000	0.433	1.753
Pre3	426	-0.089	1.220	-4.259	-0.794	-0.036	0.623	2.881
Pre6	426	-0.181	2.547	-11.69	-0.809	0.000	1.018	5.821
Delist90	393	0.020	0.141	0.000	0.000	0.000	0.000	1.000
Delist180	342	0.056	0.229	0.000	0.000	0.000	0.000	1.000
Explanatory variables								
Perp	426	0.676	0.469	0.000	0.000	1.000	1.000	1.000
Control variables								
Ret1	426	-1.793	5.895	-22.23	-4.349	-1.027	1.995	21.66
Ret5	426	-3.478	7.893	-36.29	-8.515	-2.756	1.782	26.44
Ret10	426	-6.378	10.64	-51.09	-13.76	-5.167	1.023	42.18

Ret30	426	-9.398	19.21	-64.53	-23.44	-8.433	3.262	71.06
Vol30	426	4.507	1.986	1.430	3.133	4.121	5.281	13.66
Range30	426	7.844	2.623	3.303	5.960	7.372	9.343	20.81
Volume	426	13.86	1.176	11.31	12.98	13.79	14.53	17.53
Age	426	7.092	0.609	4.278	6.838	7.221	7.524	8.060

Panel D. Balance

	Tagged	Matched tokens				Peers		
	Mean	Mean	Diff	t	SMD	Mean	Diff	t
Ret1	-2.211	-1.793	-0.418	-1.25	-0.07	-1.735	-0.477	-0.67
Ret5	-3.569	-3.478	-0.091	-0.12	-0.01	-3.622	0.052	0.05
Ret10	-4.511	-6.378	1.867	2.85	0.17	-6.758	2.247	1.67
Ret30	-9.068	-9.398	0.330	0.21	0.02	-9.712	0.645	0.31
Vol30	4.734	4.507	0.227	1.25	0.11	5.064	-0.330	-0.80
Range30	8.040	7.844	0.196	0.69	0.07	8.713	-0.673	-1.19
Volume	13.82	13.86	-0.042	-0.59	-0.03	13.66	0.158	0.85
Age	7.026	7.092	-0.065	-1.17	-0.11	7.190	-0.164	-1.94
Perp	0.676	0.676	0.000	0.00	0.00	0.274	0.402	5.21

Panel E. Daily liquidity panel

	Obs	Mean	SD	Min	P25	Med	P75	Max
Tagged tokens								
Value	5,682	2.848	5.658	0.030	0.388	0.945	2.548	82.32
Idle	5,664	26.09	24.31	0.000	4.444	18.54	43.89	89.88
Range	5,682	11.05	10.48	0.904	5.020	7.626	12.68	94.70
Spread	5,682	2.566	3.464	0.000	0.000	1.506	3.689	29.83
Impact	5,682	5.818	8.702	0.000	0.936	2.685	6.867	86.64
Matched tokens								
Value	17,366	1.624	3.098	0.045	0.289	0.623	1.462	35.09
Idle	17,364	30.61	24.82	0.000	8.194	24.79	50.97	88.47
Range	17,366	7.267	5.007	1.281	4.214	5.909	8.544	55.11
Spread	17,366	1.860	2.209	0.000	0.000	1.269	2.963	16.38
Impact	17,366	5.862	7.438	0.000	1.142	3.172	7.505	53.45

Notes. In Panels B to D, each observation is a token in one announcement, covering the 142 matched tags and their 426 matched tokens, which are 228 distinct tokens, and in Panel E, each observation is a token-day from day -10 to day 30 around the announcement. Panel A reports, by year, the number of announcements (*Events*), first-time tags (*Tags*), tags with three matched tokens (*Matched*), and tags with peers (*WithPeers*), and the mean number of tokens in the risk set (*RiskSet*). In Panel D, *Diff* is the tagged mean minus the mean of the matched tokens or the peers, *t* is the *t*-statistic of *Diff* from standard errors clustered by token and announcement date, and *SMD* is *Diff* divided by the pooled standard deviation. Panel E has 5,822 token-days of tagged tokens and 17,466 of matched tokens, and each of its variables is winsorized at the 1st and 99th percentiles within each group and event day.

4. Empirical Design

We measure returns in event time. Let t_0 denote the first full minute that starts after the official announcement time. For token *i*, the log return from minute *a* to minute *b* is

$$R_i(a,b) = 100 \cdot \ln\left(\frac{P_{i,b}}{P_{i,a}}\right), \tag{1}$$

where $P_{i,b}$ is the closing price of token *i* in minute *b*, and $P_{i,a}$ is the closing price in the minute before *a*. *Ann* is the return over the minute that contains the official time stamp. The release falls a median of 12 seconds into this minute. To separate the seconds before and after the release, we use individual trades. *PreRel* runs from the first trade of the minute to the last trade before the release, and *PostRel* from the first trade after the release to the last trade of the minute. *Post*10 and *Post*30 run from the first trade after the release to the last trade within 10 and 30 seconds after it. *Jump*5 is the return over the next five full minutes, and *To*5 is the sum of the two. *Day*1 runs from t_0 to one day later, so it excludes the announcement minute.

We compare each tagged token with three untagged tokens from the risk set of the same announcement. For announcement *g*, we estimate the probability of a tag with a logit model on the risk sets of announcement *g* and all earlier announcements,

$$Pr(Tag_{i,g} = 1) = \Lambda(\alpha + \delta \cdot X_{i,g}), \tag{2}$$

where $Tag_{i,g}$ is one if token *i* is tagged in announcement *g*, Λ is the logistic function, and $X_{i,g}$ contains *Ret*1, *Ret*5, *Ret*10, *Ret*30, *Vol*30, *Range*30, *Volume*, *Age*, and *Perp*. The model never uses later announcements, so the matching uses no information from later tags. Because the matching compares tokens within one announcement, using its tags in the model changes only which untagged tokens serve as matches. The peers in Table 4, in contrast, are ranked with a model estimated on earlier announcements only, so that their ranking uses no information from the current tags, and they give a similar decline. Within each announcement, we match each tagged token to the three untagged tokens with the same *Perp* status and the nearest log odds of the tag, within 0.2 standard deviations of the log odds. A token can serve as a match once per announcement. We keep the 142 tags that have three matches. Of the other 13 tags, 4 lack three matches with the same *Perp* status within the caliper, and 9 lack three matches within the caliper even when *Perp* status may differ. The matched difference of tagged token *i* is

$$D_i = R_i - \frac{1}{3}\sum_{j \in C(i)} R_j, \tag{3}$$

where *C*(*i*) is the set of three matched tokens of tagged token *i*. We test whether the mean of R_i or D_i is zero with standard errors clustered by token and announcement date. Because the sample has only 26 announcement dates, we also compute p-values from a wild cluster bootstrap by announcement date with 999 draws. Stars use the larger of the clustered and bootstrap p-values.

To trace prices over several days, we use a staggered event study with tokens that the exchange tags later as controls. The effect on event day τ is

$$ATT(\tau) = \sum_g w_g \cdot \left[\left(\overline{Y}^{tag}_{g,\tau} - \overline{Y}^{tag}_{g,-1}\right) - \left(\overline{Y}^{later}_{g,\tau} - \overline{Y}^{later}_{g,-1}\right)\right], \tag{4}$$

where g indexes announcements, w_g is the share of tags in announcement g, $\overline{Y}^{tag}_{g,\tau}$ is the mean cumulative log price of the tokens tagged in announcement g on event day τ, and $\overline{Y}^{later}_{g,\tau}$ is the same mean for tokens that are still untagged on event day τ and are tagged later. Day -1 is the base day. When a token is delisted, we carry its last traded price forward.

We relate later delisting to the tag in the pooled sample of tagged and matched tokens,

$$Delist_i = \alpha + \beta \cdot Tag_i + \gamma \cdot X_i + \varepsilon_i, \tag{5}$$

where $Delist_i$ is *Delist*90 or *Delist*180, Tag_i is one for tagged tokens and zero for matched tokens, and X_i contains *Ret*30, *Vol*30, *Range*30, *Volume*, *Age*, and *Perp*. Within the tagged tokens, we estimate

$$Delist_i = \alpha + \lambda \cdot Resp_i + \gamma \cdot X_i + \varepsilon_i, \tag{6}$$

where $Resp_i$ is *To*5 or *Day*1 divided by 100. Finally, we relate the matched response to perpetual futures,

$$D_i = \alpha + \theta \cdot Perp_i + \gamma \cdot Z_i + \mu_g + \varepsilon_i, \tag{7}$$

where Z_i contains *Ret*30, *Vol*30, *Range*30, *Volume*, and *Age*, and μ_g is an announcement fixed effect. In Eqs. (5) to (7), standard errors are clustered by token and announcement date.

5. Results

Table 2 shows that tagged tokens fall at once. The decline in the announcement minute is significant at the 1% level. Over the next five full minutes, prices fall further, and this step is significant at the 5% level. Over the following day, tagged tokens lose much more, and the matched differences in Panel B are almost the same size as the raw returns because matched tokens barely move. A tagged token loses 3.2% in the announcement minute and another 9.6% over the following day, so the loss in the first minute is about a third as large as the loss over the following day. The market therefore absorbs part of the tag within the first minute and the rest over the following hours. Table S5 in Online Resource 1 shows that relating these returns to the tag in the pooled sample of tagged and matched tokens, with all characteristics measured before the announcement and with announcement fixed effects, gives nearly the same estimates.

Table 2. Announcement returns

	Ann	Jump5	To5	Day1
	(1)	(2)	(3)	(4)
Panel A. Tagged tokens				
Mean	-3.162***	-1.920**	-5.111***	-9.593***
	(-4.34)	(-2.15)	(-4.80)	(-4.52)
Panel B. Matched differences				
Mean	-3.141***	-1.912**	-5.066***	-8.608***
	(-4.36)	(-2.16)	(-4.83)	(-4.40)

Obs	142	142	142	142

Notes. Each observation is a tagged token in one announcement, with 142 tags in 26 announcements. Panel A reports the mean return of tagged tokens, and Panel B reports the mean of the tagged return minus the mean return of its three matched tokens, both in percent. Each return is winsorized separately, so *To*5 differs slightly from the sum of *Ann* and *Jump*5. Values in parentheses are *t*-statistics from standard errors clustered by token and announcement date, and *** and ** denote significance at the 1% and 5% levels.

Table 3 splits the announcement minute at the official release time. Before the release, tagged tokens move very little, and the change is significant only at the 10% level. After the release, tagged tokens fall sharply, and among tags with trades in these windows most of the decline already appears within the first ten seconds. Matched tokens that trade in the same seconds move very little, although their small rise before the release is significant. The drop in Table 2 thus starts with the release itself and not with trading just before it.

Table 3. Trades around the release

	PreRel	PostRel	Post10	Post30
	(1)	(2)	(3)	(4)
Tagged	-0.073*	-3.340***	-3.104***	-3.184***
	(-1.95)	(-4.60)	(-4.58)	(-4.64)
Controls	0.014**	-0.024	-0.013	-0.025*
	(2.91)	(-1.58)	(-1.86)	(-1.99)
TaggedObs	79	132	119	134
ControlObs	195	299	197	303

Notes. Each observation is a tagged or matched token in one announcement, and a return enters only when its window contains trades. *Tagged* is the mean return of tagged tokens, and *Controls* is the mean return of matched tokens, both in percent. *TaggedObs* is the number of tagged tokens in each column, 79, 132, 119, and 134 in columns (1) to (4), and *ControlObs* is the number of matched tokens, 195, 299, 197, and 303. Values in parentheses are *t*-statistics from standard errors clustered by token and announcement date, and ***, **, and * denote significance at the 1%, 5%, and 10% levels.

One concern is that the exchange tags tokens that are about to fall anyway. Table 4 addresses this concern with the untagged tokens that look most like tagged tokens in the same announcement. We rank them by the tag probability from a model estimated only on earlier announcements, so the 13 matched tags of the first announcement have no peers, and in columns (3) and (4) we keep peers with the same *Perp* status. All returns start at the first full minute after the announcement, so they exclude the announcement minute. The peers barely move over the next hour or the next day, whereas the tagged tokens fall sharply. The difference is significant at the 1% level over both the hour and the day. The decline thus may reflect the tag itself rather than the observable risk profile that leads to it. The tag may also reflect problems that only the exchange observes, and the response then measures how much news the tag carries about them.

Table 4. Tagged tokens and untagged peers

	Top20	SamePerp

	Hour1	Day1	Hour1	Day1
	(1)	(2)	(3)	(4)
Tagged	-6.131***	-10.79***	-6.131***	-10.79***
	(-2.88)	(-5.56)	(-2.88)	(-5.56)
Peers	-0.324	-0.989	-0.248	-0.991
	(-1.70)	(-1.81)	(-1.33)	(-1.82)
Difference	-5.807***	-9.798***	-5.884***	-9.796***
	(-2.95)	(-5.82)	(-2.94)	(-5.40)
Obs	129	129	129	129

Notes. Each observation is a tagged token in one announcement, and all rows use the 129 matched tags with peers, in 25 announcements. *Tagged* is the mean return of tagged tokens, *Peers* is the mean return of the 20 untagged tokens with the highest tag probability from Eq. (2) estimated on earlier announcements only, and *Difference* is *Tagged* minus *Peers*, all in percent. *Top20* ranks all untagged tokens, and *SamePerp* ranks only those with the same *Perp* status as each tagged token. Values in parentheses are *t*-statistics from standard errors clustered by token and announcement date, and *** denotes significance at the 1% level.

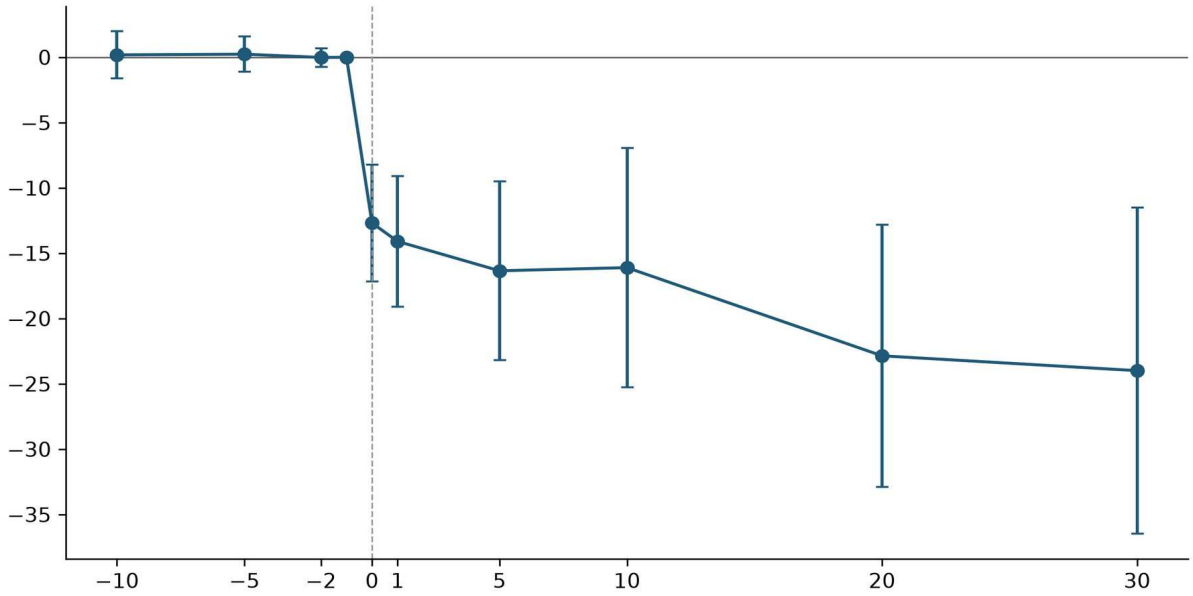
Table 5 and Fig. 1 trace prices over the following month with tokens that the exchange tags later as controls. Before the announcement, tagged tokens move with the controls. None of the daily estimates from day -10 to day -2 is significant, and a joint test does not reject that all nine are zero. On the announcement day and the next day, the cumulative price drops sharply. Losses on later days are larger than on day 1. Table 8, which uses matched tokens and simple returns, shows that the further loss after the first day becomes significant only over 90 days and comes from tokens that the exchange later removes. In log returns, which give more weight to the tokens that lose most, Table S6 in Online Resource 1 shows that the matched loss from day 1 to day 30 is already about 13 percentage points and significant at the 5% level. Prices do not recover after the first day, which fits the information view better than temporary selling pressure. A lasting drop in demand on Binance, for example because of the risk quiz, would also lower prices without a reversal, but it should move trading away from Binance, and Table S3 in Online Resource 1 shows no such shift.

Table 5. Event-time effects

	Event day								
	-10	-5	-2	0	1	5	10	20	30
ATT	0.184	0.236	-0.011	-12.68***	-14.09***	-16.34***	-16.10***	-22.85***	-23.99***
	(0.21)	(0.36)	(-0.03)	(-5.86)	(-5.84)	(-4.94)	(-3.63)	(-4.71)	(-3.99)
Obs	136	136	136	136	136	136	136	136	131

Notes. Each observation is a tagged token in one announcement, and tags with fewer than three controls on a day are dropped for that day, which removes the six tags of the last two announcements from day 0 on and the five tags of the 11 August 2026 announcement by day 30 and leaves 136 tags, and 131 on day 30. *ATT* is the effect of the tag on the cumulative log price from Eq. (4), in percent, where day -1 is the base day, the controls on each event day are tokens that are still untagged on that day and are tagged later, and delisted tokens keep their last traded price. The p-value of a joint test that the estimates on days -10 to -2 are zero is 0.70. Values in parentheses are *t*-statistics from standard errors clustered by token and announcement date, and *** denotes significance at the 1% level.

Fig. 1 Event-time effects



The figure plots the effect of the tag on the cumulative log price in percent (vertical axis) against the event day (horizontal axis), with day -1 as the base day. The vertical bars are 95% confidence intervals from standard errors clustered by token and announcement date.

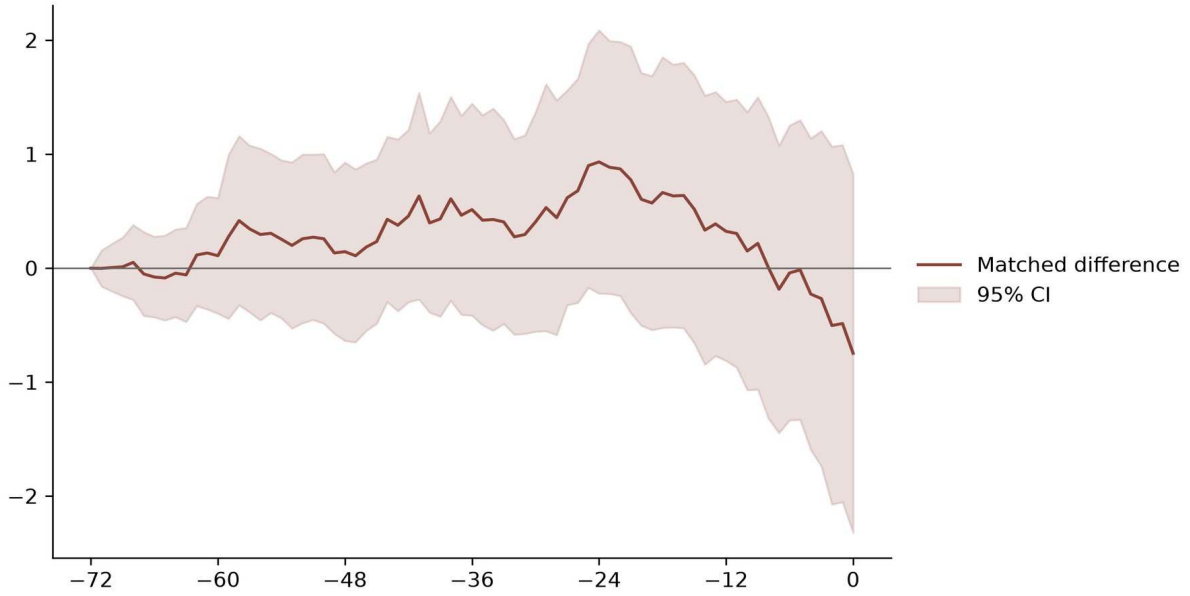
Table 6 shows that a small part of the news reaches prices before the announcement. Over the last one, three, and six hours, tagged tokens lose slightly more than matched tokens. The gap is significant at the 5% level over three and six hours and at the 10% level over one hour. Against bitcoin, the gap is similar in size and significant at the 5% level or better for the last three and six hours. The gap is under 1% even over six hours, a small fraction of the announcement response. Fig. 2 shows that the cumulative gap is small and not significant over the three days before the announcement and turns down only in the last 15 hours. Net selling on Binance does not rise significantly in these hours, so the early decline does not come with steady informed selling.

Table 6. Returns before the announcement

	Last hours		
	1	3	6
Matched	-0.221*	-0.450**	-0.719**
	(-2.05)	(-2.70)	(-2.70)
Bitcoin	-0.225*	-0.542**	-0.916***
	(-1.82)	(-2.69)	(-2.84)
NetSell	2.764	2.813	-3.354
	(1.05)	(0.60)	(-0.47)

Notes. Each observation is a tagged token in one announcement, with 142 tags, and 140 for *NetSell*. *Matched* is the matched difference in log returns over the last one, three, and six hours before the announcement minute, and *Bitcoin* is the log return of tagged tokens minus that of bitcoin over the same hours, both in percent. *NetSell* is the hourly share of seller-initiated minus buyer-initiated trading value on Binance, summed over the last hours, minus its earlier hourly mean from 72 to 6 hours before the announcement, in excess of matched tokens, in percentage points. Values in parentheses are *t*-statistics from standard errors clustered by token and announcement date, and ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Fig. 2 Matched difference before the announcement



The figure plots the cumulative matched difference in log returns in percent (vertical axis) against the hour before the announcement minute (horizontal axis), starting from zero 72 hours before it. The shaded area is the 95% confidence interval from standard errors clustered by token and announcement date.

If the tag caused forced selling on Binance only, prices on other exchanges should fall less. Table 7 shows that tagged tokens fall on Bybit, Coinbase, and KuCoin in the same minute and by a similar amount. On Bybit, the gap between Binance and the other exchange is small and not significant in the announcement minute, and Binance falls only slightly more over the first hour. On Coinbase and KuCoin, Binance falls more in the announcement minute, and the gap narrows over the next five minutes. Table S3 in Online Resource 1 shows that the share of Binance in trading across these exchanges does not change after the tag. Arbitrage would spread a price drop across exchanges in any case, so this test alone does not separate news from selling pressure. Together with the absence of a reversal and of a shift in trading away from the tagging exchange, however, it may point to news that reaches all exchanges at about the same time.

Table 7. Returns on other exchanges

	Bybit	Coinbase	KuCoin
	(1)	(2)	(3)
Other	-4.396***	-3.150***	-4.413***
	(-4.96)	(-5.05)	(-5.60)
Gap	0.167	-1.447**	-0.587**
	(1.52)	(-2.40)	(-3.15)
Gap5	-0.138	0.555	0.383*
	(-1.18)	(1.11)	(2.08)
Gap60	-0.324**	0.236	0.353
	(-2.43)	(0.46)	(1.75)
Obs	32	32	51

Notes. Each observation is a tagged token in one announcement, and a matched tag enters when the token trades on the other exchange in the announcement minute, which gives 32 tags on Bybit, 32 on Coinbase, and 51 on KuCoin. *Other* is the log return of tagged tokens on the other exchange in the announcement minute, and *Gap* is the log return on Binance minus that on the other exchange in the same minute, both in percent. *Gap*5 and *Gap*60 are the same gap over the first 5 and 60 minutes, starting at the first full minute after the announcement, and on Coinbase, each uses 22 tags with complete minute prices, which are not the same tags in the two windows. Values in parentheses are *t*-statistics from standard errors clustered by token and announcement date, and ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table 8 follows prices for up to 90 days and shows where the longer losses come from. Delisted tokens stop trading, so Panel A values them in two ways: at their last traded price (*Last*) and at zero (*Zero*), which treats the token as lost. Under both, tagged tokens lose much more than matched tokens over 30, 60, and 90 days. Panel B starts at the close of the announcement day (*After*1). Over 30 and 60 days, the further loss is not significant, but over 90 days it is significant at the 5% level, so the first-day response understates the eventual loss. Panel B also splits this further loss at the delisting announcements of the tagged and matched tokens. Before any delisting is announced (*PreDel*), tagged tokens do not fall relative to matched tokens. The further loss arrives in the three days around the delisting announcement (*DelWin*) and afterwards (*PostDel*), when trading winds down. Panel C splits the tags by whether the exchange announces their delisting within the window. This split conditions on a later outcome and is only descriptive. Tokens that are later removed lose about half of their value after the announcement day, whereas the others do not fall further and recover somewhat over 60 days, a recovery that is significant only at the 10% level. The tag thus moves prices at once, but the market learns which tagged tokens the exchange will remove mainly around and after the removal announcement, much as delisting losses in stock markets arrive at the delisting itself (Shumway, 1997).

Table 8. Returns over the following months

	Days		
	30	60	90
Panel A. From the day before the tag			
Last	-14.87***	-18.46**	-24.63***
	(-3.48)	(-2.72)	(-4.14)
Zero	-19.81***	-28.97***	-39.31***
	(-4.03)	(-3.40)	(-5.12)
Panel B. After the announcement day			
After1	-3.777	-8.838	-17.39**
	(-0.78)	(-1.25)	(-2.83)
PreDel	3.186	5.263	2.472
	(0.72)	(0.96)	(0.47)
DelWin	-3.502***	-6.111***	-8.384***
	(-3.16)	(-3.19)	(-4.28)
PostDel	-3.462**	-7.990***	-11.48***
	(-2.98)	(-3.61)	(-4.57)
Panel C. After the announcement day, by later delisting			

Removed	-58.34***	-56.31***	-52.98***
	(-9.38)	(-10.19)	(-8.17)
Kept	5.975	15.39*	11.41
	(1.06)	(2.07)	(1.48)

Notes. Each observation is a tagged token in one announcement, with 140, 136, and 131 tags over 30, 60, and 90 days, and each cell is the mean matched difference in simple returns, in percent. In Panel A, returns run from the close of the day before the announcement to the close of day 29, 59, or 89, and delisted tokens are valued at their last traded price (*Last*) or at zero (*Zero*), whereas in Panels B and C, returns run from the close of the announcement day to the close of day 30, 60, or 90, and delisted tokens keep their last traded price. *PreDel*, *DelWin*, and *PostDel* split the full return (*After*1) into the part before the day preceding the delisting announcement of each token, the part from that day to the day after the announcement, and the rest, and *Removed* (21, 46, and 59 tags) and *Kept* (119, 90, and 72 tags) are tags whose delisting is and is not announced within the window, each winsorized separately. Values in parentheses are *t*-statistics from standard errors clustered by token and announcement date, and ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table 9 shows how trading on Binance changes. Trading value jumps on the announcement day and the next day and then mostly returns to normal. The share of minutes without trades falls and stays lower for a month. The daily price range widens and stays wider for a month, and the spread estimate is higher after ten days and after a month. The price impact per million USDT falls on the day after the announcement, when trading is heavy. The tag thus brings a burst of trading and leaves the token more volatile, which may reflect more uncertain prospects for the token. From day -5 to day -2, none of these measures differs between tagged and matched tokens. Ten to six days before, however, tagged tokens trade slightly less and have more minutes without trades, and this early gap in *Idle* is jointly significant. Measured against the mean of days -10 to -6 instead of day -1, the decline in Idle on the announcement day is larger, at 13.68 percentage points, so the early gap does not explain it.

Table 9. Trading activity and liquidity

	Event day							
	-10	-5	-2	0	1	5	10	30
Value	-0.810**	0.130	-0.223	2.189***	1.438***	0.598	1.216*	-0.034
	(-2.11)	(0.30)	(-0.83)	(5.09)	(5.00)	(1.05)	(1.95)	(-0.05)
Idle	3.446**	0.702	1.046	-10.89***	-10.18***	-5.217**	-5.336**	-7.419***
	(2.08)	(0.69)	(1.03)	(-5.77)	(-5.40)	(-2.57)	(-2.52)	(-3.29)
Range	-1.072*	0.402	0.125	13.52***	4.840***	3.152**	4.021***	3.336**
	(-1.73)	(0.61)	(0.23)	(5.27)	(4.07)	(2.51)	(3.20)	(2.55)
Spread	0.072	-0.135	-0.146	-0.258	1.072	0.363	0.872**	1.786***
	(0.30)	(-0.55)	(-0.53)	(-0.69)	(1.37)	(0.99)	(2.46)	(3.15)
Impact	1.039	0.617	0.698	-0.790	-3.520***	-0.954	-1.279	-1.950**
	(1.12)	(0.85)	(1.02)	(-0.80)	(-3.62)	(-1.25)	(-1.30)	(-2.06)

Notes. Each observation is a token-day of a tagged or matched token from day -10 to day 30 in a stacked panel with stacked token fixed effects and calendar date fixed effects, which has 23,048 of the 23,288 possible token-days, 23,028 for *Idle*, and an R^2 from 0.24 to 0.78. Each cell is the coefficient on the tag indicator interacted with the event day, relative to day -1, for daily trading value in millions of USDT (*Value*), the percentage of minutes without trades (*Idle*), the daily

log high minus log low price in percent (*Range*), the two-day high-low spread estimate in percent (*Spread*), and the absolute daily log return in percent per million USDT of trading value (*Impact*). The p-values of joint tests that the coefficients on days -10 to -2 are zero are 0.09 for *Value*, 0.05 for *Idle*, 0.13 for *Range*, 0.98 for *Spread*, and 0.33 for *Impact* after the negative eigenvalues of its clustered covariance matrix are set to zero, and for *Idle*, they are 0.002 for days -10 to -6 and 0.76 for days -5 to -2. Values in parentheses are *t*-statistics from standard errors clustered by token and announcement date, and ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table 10 links the tag to later delisting. In Panel A, tagged tokens are far more likely to be delisted within 90 and 180 days than matched tokens with the same observable risk, and controls barely change the estimate. Tagged tokens have a probability of delisting within 90 days that is higher by 42 percentage points, against a rate of 2% among matched tokens. Among the controls, tokens with lower trading value and a wider daily range are delisted more often. Because the exchange usually removes tokens from the tagged pool, part of this gap reflects the procedure itself. The tag still carries information that the characteristics of a token do not, since the market cannot observe in advance which tokens the exchange will tag. If the announcement response reflects this news, tokens that fall more should be delisted more often. In Panel B, tagged tokens that fall more in the first five minutes are delisted more often, but the estimates are not significant. The return over the first day does not predict delisting either. Within tagged tokens, the size of the response is thus a noisy guide to later removal, whereas the tag itself is a strong one.

Table 10. Tags, announcement responses, and later delisting

	Delist90		Delist180	
	(1)	(2)	(3)	(4)
Panel A. Tag				
Tag	42.24***	42.28***	52.34***	52.36***
	(7.15)	(7.25)	(7.98)	(7.96)
Ret30		-2.837***		-2.106**
		(-2.87)		(-2.38)
Vol30		-4.385		-9.101*
		(-1.36)		(-2.12)
Range30		9.680**		17.97***
		(2.18)		(3.48)
Volume		-6.431**		-11.67***
		(-2.46)		(-4.64)
Age		2.853*		4.182**
		(2.36)		(2.45)
Perp		0.073		1.352
		(0.07)		(0.86)
Obs	524	524	456	456
R^2	0.304	0.344	0.339	0.417
Panel B. Announcement response				
To5	-88.35		-75.94	
	(-1.49)		(-1.19)	
Day1		35.77		-25.03

		(0.91)		(-0.50)
Ret30	-9.072*	-10.13**	-2.497	-2.163
	(-2.02)	(-2.38)	(-0.53)	(-0.46)
Vol30	-6.148	-9.679	-9.394	-10.26
	(-0.76)	(-1.19)	(-1.41)	(-1.44)
Range30	16.15	22.80*	25.53**	26.93**
	(1.37)	(1.97)	(2.59)	(2.72)
Volume	-10.75	-13.51**	-17.53**	-19.17***
	(-1.72)	(-2.36)	(-2.99)	(-3.82)
Age	9.392	10.84*	11.10*	10.87*
	(1.85)	(2.09)	(2.14)	(2.11)
Perp	-0.434	-0.959	1.324	2.463
	(-0.10)	(-0.19)	(0.28)	(0.42)
Obs	131	131	114	114
R^2	0.129	0.123	0.198	0.190

Notes. Each observation is a token in one announcement, and observations enter only when the window is complete. Panel A reports estimates of Eq. (5) in percentage points for tagged tokens and their matched tokens, and Panel B reports estimates of Eq. (6) for tagged tokens, in which *To*5 and *Day*1 enter as log returns, so a coefficient of -100 means that a return lower by 0.10 goes with a delisting probability higher by 10 percentage points. *Ret*30, *Vol*30, *Range*30, *Volume*, *Age*, and *Perp* are standardized to a mean of zero and a standard deviation of one in the pooled sample, so their coefficients are the change in the delisting probability, in percentage points, for an increase of one standard deviation. Values in parentheses are *t*-statistics from standard errors clustered by token and announcement date, and ***, **, and * denote significance at the 1%, 5%, and 10% levels.

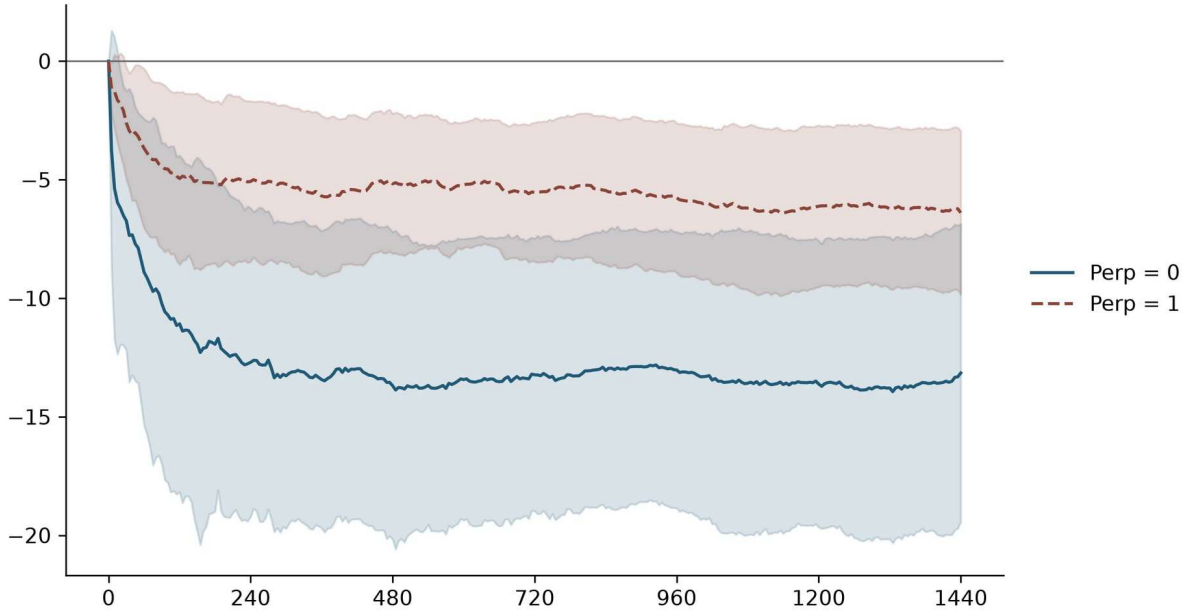
Table 11 relates the response to perpetual futures. Tagged tokens with perpetual futures fall more in the announcement minute, and the difference is significant at the 1% level without and at the 5% level with announcement fixed effects. Over the rest of the first day, tokens with perpetual futures fall less, and this difference is significant at the 5% level. With announcement fixed effects, a tagged token with perpetual futures loses 2.3 percentage points more in the announcement minute and 5.7 percentage points less over the rest of the day. Tokens with perpetual futures thus absorb more of the news in the first minute, whereas the prices of tokens without them keep falling through the day. Table S3 in Online Resource 1 shows that, over the next day, the funding rate of the perpetual futures of tagged tokens falls while open interest rises, which is consistent with new short positions. This pattern may reflect short sellers who act on the tag at once when shorting is cheap. The smaller loss over the whole day has two readings. The tag may carry less news for tokens that are liquid enough to have perpetual futures, or tokens without perpetual futures may face selling by holders who exit, which their thinner markets absorb at a larger price discount. The data do not separate the two. Fig. 3 shows the timing. Over the first day, tokens without perpetual futures lose more, most of their extra loss accrues in the first few hours, and the gap does not close within the day. Tokens with perpetual futures thus absorb more of the news at once and lose less over the day as a whole. Perpetual futures are not assigned at random, but the comparison holds within announcements and with controls for past returns, volatility, trading value, and age.

Table 11. Perpetual futures and the response

	Ann		Day1	
	(1)	(2)	(3)	(4)
Perp	-3.813***	-2.342**	7.124**	5.678**
	(-4.86)	(-2.57)	(3.58)	(2.47)
Ret30	-0.041	-0.017	0.113	0.006
	(-1.80)	(-0.82)	(1.34)	(0.07)
Vol30	0.358	0.185	2.026**	1.424***
	(1.71)	(0.57)	(2.75)	(2.97)
Range30	-0.446*	-0.007	-2.970**	-2.042**
	(-1.94)	(-0.02)	(-3.14)	(-2.21)
Volume	1.200**	0.421	0.432	-0.026
	(3.59)	(1.13)	(0.49)	(-0.02)
Age	1.021*	0.117	-3.593*	-0.837
	(2.04)	(0.29)	(-2.44)	(-0.54)
Event_FE	No	Yes	No	Yes
Obs	142	142	142	142
R^2	0.289	0.682	0.242	0.595

Notes. Each observation is a tagged token in one announcement, and the estimates come from Eq. (7). The dependent variable is the matched difference in *Ann* in columns (1) and (2) and in *Day*1 in columns (3) and (4), in percent, and *Event_FE* denotes announcement fixed effects, which R^2 includes. *Ret*30, *Vol*30, and *Range*30 are in percent, so their coefficients are the change in the dependent variable, in percentage points, for an increase of one percentage point, and *Volume* and *Age* are in natural logarithms. Values in parentheses are *t*-statistics from standard errors clustered by token and announcement date, and ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Fig. 3 First-day path by perpetual futures



The figure plots the cumulative matched difference in log returns in percent (vertical axis) against the minutes after the first full minute after the announcement (horizontal axis), separately for tagged tokens with and without perpetual futures. The shaded areas are pointwise 95% confidence intervals from standard errors clustered by token and announcement date.

The main estimates hold under several other choices. Table S4 in Online Resource 1 reports randomization tests that reassign the tag within each announcement among tokens in the same quintile of the tag probability, and no reassignment out of 5,000 produces responses as large as the actual ones. Dropping one announcement or one calendar month at a time never changes the sign of the main estimates, and *Ann*, *To*5, and *Day*1 stay significant at the 1% level in every case. Table S2 in Online Resource 1 shows that matching and estimating without winsorizing or with cutoffs at the 0.5^{th} and 99.5^{th} percentiles, five matched tokens instead of three, and matching on the distance in characteristics instead of the tag probability give nearly the same estimates as Table 2, although the step over the five minutes after the announcement is significant only at the 10% level without winsorizing or with the wider cutoffs. With a Holm adjustment across the 28 return estimates in Tables 2, 3, and 6 and Table S4 in Online Resource 1, the declines in *Ann*, *To*5, *Day*1, *PostRel*, *Post*10, and *Post*30 remain significant at the 5% level, and so do the declines on Bybit, Coinbase, and KuCoin among the 12 estimates in Table 7. The drift in the hours before the announcement and the separate five-minute step do not survive this adjustment. Table S6 in Online Resource 1 reports three further checks. At the first announcement, when Binance introduced the tag, the 13 matched tags do not fall, perhaps because investors had yet to learn what the tag implies. Excluding this announcement, the declines in the announcement minute and over the first day are slightly larger, and the estimates for perpetual futures keep their signs and significance. Tokens with perpetual futures have a lower tag probability before the announcement, and adding the tag probability and the shorter past returns to Eq. (7) leaves these estimates significant at the 5% level.

6. Conclusion

This study shows that a warning from a crypto exchange moves prices at once and predicts removal. When Binance attaches its monitoring tag to a token, the price falls within seconds on Binance and in the same minute on other large exchanges and keeps falling through the first day, whereas similar tokens that the exchange leaves untagged barely move. After the first day, prices of tokens that keep trading do not fall further, whereas tokens that the exchange later removes keep losing around and after the removal announcement. The tag predicts delisting well beyond observable risk, and tokens with perpetual futures react faster and lose less over the first day. These patterns suggest that the warnings reveal how the exchange assesses a token, that the market prices the average risk of removal at once but learns which tokens will be removed mainly when the exchange says so, and that the ease of betting against a token, or the liquidity that comes with it, shapes how its price absorbs this assessment. Because a large exchange acts as a private regulator in this market, the timing and disclosure of its warnings matter for which investors trade on this information first. The evidence comes from 26 announcements of one exchange, so differences across tokens within the sample rest on a modest number of independent events.

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