Correlated Signals and Certification Value: Evidence from Crypto Listings*

Te Bao† Lin William Cong‡ Mengzhong Ma§

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Abstract

When multiple certifiers of different quality evaluate the same asset, their assessments reveal overlapping information. We study how markets process such certification signals utilizing the setting of cryptocurrency exchange listings, where tokens list on multiple exchanges across the quality spectrum. Top-tier listings generate average cumulative abnormal returns of 7.2%, compared with 0.1% for bottom-tier listings. To separate exchange-specific information from information already revealed by prior or concurrent listings, we develop: (i) a Heckman two-stage framework for sequential listings and (ii) an extension of the conditional event-study framework of Nayak and Prabhala (2001) to a multivariate setting for simultaneous listings on multiple exchanges. (i) shows that prior certifications attenuate subsequent listing premia through reduced surprise and asymmetric informational substitution: prior mid-tier listings substitute for top-tier listings, whereas prior bottom-tier listings do not. (ii) decomposes listing premia into exchange-specific component, interpreted as an informational complement, and implied-uplisting component, interpreted as an informational substitute. Between 42.9% and 94.4% of the reaction to sub-top-tier listings reflects implied uplisting rather than exchange-specific information. Natural-experiment evidence from the November 2022 FTX collapse, together with post-listing return predictability, validate these certification results and interpretation. Our findings imply that whenever multiple certifiers of different quality evaluate the same asset, ignoring the overlapping information in their assessments overstates any single certifier's marginal value.

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†Email: baote@ntu.edu.sg, School of Social Sciences, Nanyang Technological University, Singapore.

‡Email: will.cong@ntu.edu.sg, Nanyang Business School, Nanyang Technological University, Singapore.

§Email: mengzhon001@e.ntu.edu.sg, Interdisciplinary Graduate School, Nanyang Technological University, Singapore.

1 Introduction

In many markets, the value of an asset, a firm, or an institution is determined not by a single assessment but by multiple certifications from intermediaries that are of varying quality. Bond issuers are rated by agencies of different methodologies. Firms list securities on exchanges of different prestige. Products receive safety approvals from regulators of different stringency. In each case, the certifiers are screening the same underlying quality—creditworthiness, firm fundamentals, product safety—but with different precision, different thresholds, and different reputational stakes. The resulting certifications are not independent: an entity that passes a stringent screen is likely, though not certain, to pass a lenient one, and vice versa. This overlap in the information revealed by different certifiers creates a fundamental question in information economics: how do markets process correlated certification signals?

This question has two dimensions. First, when certifications accumulate over time, how does the informational content of a new certification depend on the existing certification history? If a firm has already been rated by one agency, a subsequent rating by a different agency reveals less incremental information because the two signals overlap. Second, for any given certification, how much of the market's reaction reflects information specific to that certifier—its unique methodology, its particular screening criteria—versus information that is common across certifiers and thus implies assessments by other certifiers? We term these two components *informational complement* and *informational substitute*, respectively. Whether markets apply the Bayesian discount that overlap implies or instead overweight redundant signals—as a large literature on correlation neglect documents (DeMarzo et al., 2003; Enke & Zimmermann, 2019; Levy & Razin, 2015)—is itself an open question that a clean decomposition can address.

These questions have been studied in specific domains—IPO underpricing (Beatty & Ritter, 1986; Rock, 1986), cross-listing premia (Doidge et al., 2004; Miller, 1999), and credit rating splits (Bongaerts et al., 2012)—but always within the constraints of a particular market's institutional structure. Across these literatures, two empirical challenges have prevented a complete characterization of how markets process correlated certification signals.

The first challenge is *path variation*. To measure how prior certifications attenuate subsequent ones, the researcher needs sufficient variation in certification histories—different entities taking different routes through the certifier hierarchy. In most markets, the certification path is narrow. Equity issuers face a near-linear progression: OTC to NASDAQ to NYSE, or home exchange to depositary receipt. Bond issuers typically obtain all major ratings at issuance, with little variation in the sequence. This limited path structure prevents estimation of how informational substitution varies across certifier pairs and across different prior histories.

The second challenge is *decomposition*. To separate the informational complement from the informational substitute within a single certification, the researcher must identify the covariance structure of private information across certifiers. Identification of this covariance requires observing the market's joint reaction to certifications across different tiers for the same entity. While some certification markets feature simultaneous assessments—credit agencies often rate bond issuers concurrently, ESG raters maintain parallel ratings for the same firms—these settings face other limitations: infrequent rating changes, confounding from public information, or imprecise price measurement. Many other certification markets are sequential by institutional design, with months or years between assessments, making the decomposition infeasible.

We overcome both challenges in the setting of cryptocurrency exchange listings, which offers three identification advantages. First, *path richness*: with 87 exchanges rated across eight quality tiers by CoinDesk, tokens traverse a rich lattice of certification paths—from direct listing on top-tier exchanges to gradual ascent through multiple tiers—providing cross-sectional variation in certification histories that far exceeds what is available in equity, credit, or other certification markets. Our sample contains 8,365 tokens and 6,717 single-exchange listing events distributed across five types of listing histories, enabling estimation of informational substitution for each tier pair separately. Second, *frequent simultaneous multi-tier certification*: tokens regularly list on exchanges spanning the full quality spectrum within a 72-hour window, with 353 events of simultaneous listings on exchanges in at least two distinct rating categories in our sample. While simultaneous certification exists in some other markets (e.g., credit ratings at bond issuance), crypto markets generate it at a scale

and frequency that enables precise estimation of the cross-tier covariance structure. Third, *clean price measurement*: liquid trading on decentralized exchanges provides a continuous benchmark price that is not mechanically affected by the centralized exchange listing event, enabling precise measurement of abnormal returns at half-day frequency.

We formalize the multi-certifier problem with a model of hierarchically ranked exchanges that screen the same latent token quality with different precision. Each exchange's listing decision is an endogenous threshold rule derived from the tradeoff between fee revenue and reputational cost. Because all exchanges screen the same underlying quality, their listing signals are correlated, and this correlation is determined by the signal structure rather than assumed as a free parameter.

Empirically, our results proceed in three stages. In the first stage, we document the unconditional listing premium across exchange tiers: the average cumulative abnormal return (CAR) is 7.2% for top-tier (AA–A) exchanges and 0.1% for bottom-tier (E–F) exchanges.

In the second stage, we disentangle the effects of informational overlap through two complementary analyses. For sequential listings, we employ a Heckman (1979) two-stage framework and show that prior certifications attenuate subsequent listing premia through two channels: investors form higher ex ante listing expectations for previously certified tokens (the surprise channel), and each unit of newly revealed private information generates a smaller price reaction when prior certifications have already absorbed part of the informational content (the substitution channel). For simultaneous listings, we extend the bivariate conditional event-study framework of Nayak and Prabhala (2001) to a multivariate setting, enabling decomposition of listing premia into informational complement and informational substitute. We find that 42.9% to 94.4% of the market reaction to sub-top-tier listings is attributable to informational substitute, the implied signal about potential listing on higher-tier exchanges, with the remainder reflecting exchange-specific information.

In the third stage, two further tests corroborate the mechanism. The listing premium increases in the information distance between the current and prior tiers, consistent with the model's structural prediction; and two exchange-failure natural experiments—the November 2022 FTX collapse and the April 2023 SEC complaint against Bittrex—show that tokens losing their only high-tier certifier suffer larger negative reactions than tokens that retain

higher-tier listings, with the differential sharper for the higher-rated removal.

Our findings contribute to three literatures. First, we contribute to the literature on IPO underpricing and cross-listing premia by providing the first empirical decomposition of certification premia into certifier-specific and cross-certifier components, and by quantifying the informational substitution that occurs when certifications accumulate over time. Our results suggest that studies of cross-listing premia that treat each listing as an isolated event may substantially overstate the exchange-specific effect by not accounting for implied information about other venues. Second, we contribute to the methodology of event studies by extending the conditional event-study framework of Nayak and Prabhala (2001) to a multivariate setting, providing a general tool for analyzing simultaneous multiple announcements. Third, we contribute to the cryptocurrency literature by offering the first systematic characterization of listing premia across exchange tiers, complementing work on crypto asset pricing (Cong et al., 2021, 2022; Liu & Tsyvinski, 2021; Liu et al., 2022) and cross-listing effects (Benedetti & Nikbakht, 2021).

Our results also relate to the literature on correlation neglect (Cong & Yang, 2025; DeMarzo et al., 2003; Enke & Zimmermann, 2019; Guo & Wachter, 2025; Levy & Razin, 2015), which documents that agents systematically fail to discount overlapping signals. Our decomposition delivers, for the first time in a field certification market, a market-based estimate of the rational Bayesian discount: the substitute share of 42.9% to 94.4% serves as a benchmark against which behavioral correlation neglect can be evaluated. Most directly, Chen et al. (2025) microfound correlation neglect when sources are not authenticated, suggesting an extension to settings in which certifiers themselves are strategically misaligned.

More broadly, our framework and results carry implications for any market in which hierarchically ranked certifiers screen the same underlying quality. In Online Appendix A, we discuss these implications for credit ratings, ESG assessments, equity cross-listings, and other certification markets, identifying which of our predictions are testable in each setting and what our estimates suggest about the magnitude of informational overlap in those markets.

We structure the rest of the paper as follows. Section 2 reviews the institutional background. Section 3 develops the model. Section 4 describes the data and unconditional event studies. Sections 5 and 6 present the conditional event-study methods and results for se-

quential and simultaneous listings. Section 7 tests the information-distance prediction, and Section 8 exploits the FTX and Bittrex shocks as natural experiments. Section 9 examines post-listing dynamics, and Section 10 reports robustness and placebo tests. Section 11 concludes.

2 Institutional Background

There are two types of exchanges in the crypto market distinguished by their nature of operation: decentralized exchanges (DEXs) and centralized exchanges (CEXs). DEXs are based on smart contracts on blockchains, allowing deployments of trading pairs permissionlessly, while CEXs are operated by centralized entities and run in a similar manner with traditional stock exchanges, to which assets need to be evaluated and approved before being listed. This study is mainly focusing on the second type, CEXs. [1] However, not all exchanges are created equal. While some top-tier platforms like Binance and Coinbase maintain robust regulatory compliance, deep liquidity, and high security standards, many others operate with limited oversight, poor transparency, or lower user trust. This heterogeneity in exchange quality is reflected in the crypto exchange rankings or ratings maintained by some third-party organizations, such as CoinDesk and CoinGecko.[2] In this study, we adopt the ratings from CoinDesk, which grades exchanges with 8 ratings, i.e., AA, A, BB, B, C, D, E, and F. To ensure the ratings are generally agreed, we check the consistency of the ratings from CoinDesk and CoinGecko, and find that they are highly consistent, with Spearman rank correlation of 0.618, p-value < 0.001.

CoinDesk assigns ratings to exchanges based on 8 components: market quality, security, legal/regulation, KYC/transaction risk, data provision, transparency, management team, and negative events penalty. Exchanges with higher ratings generally are more reputable, better regulated, and more secure, while they also adopt more stringent listing requirements.[3]

[1] In this study, we will use the term "exchange" to refer to CEXs unless otherwise specified.

[2] Readers can find the exchange rating by CoinDesk on https://data.coindesk.com/exchange-benchmark-rankings, and the rating by CoinGecko on https://www.coingecko.com/en/exchanges. Also, they published benchmark methodology, based on which the ratings are assigned, on their websites.

[3] Exchanges under more stringent regulation usually require higher standard for the listed assets to comply with the regulations. Some media reports summarizes the different listing requirements and difficulties among exchanges in different tiers, i.e., "How to Choose an Exchange for Your Token Debut" and "Increase Token

With exchanges graded with ordinal ratings, listings of crypto assets follow unique patterns. This issue involves two dimensions. First, a crypto asset can be listed on multiple exchanges across time, i.e., "sequential listings". For example, the asset $BLUR was listed on the C-rated exchange Bitkub on 26 June 2023, despite having already been listed on the AA-rated exchange Binance on 24 May 2023. Given its prior listing on a top-tier exchange, investors would not find a subsequent listing on a lower-tier exchange surprising. Second, a crypto asset can be listed on multiple exchanges simultaneously, i.e., "simultaneous listings". As shown in Figure 1, $BLUR was listed on 10 exchanges on 14 February 2023, with ratings ranging from AA to E. If we fail to account for these simultaneous listings, the effect of listing on an E-rated exchange may be overstated, as market reactions to AA-rated listings could be mistakenly attributed to the E-rated one.

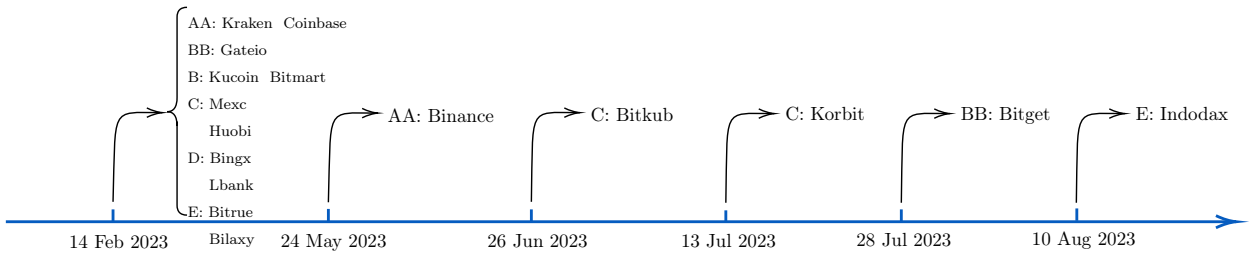


Figure 1: Timeline of exchange listings for $BLUR. This figure illurstrates the timeline of exchange listing events for the asset $BLUE (Ethereum address: 0x5283d291dbcf85356a21ba090e6 db59121208b44) from Feb 2023 to Aug 2023. On 14 Feb 2023, this asset was listed simultaneously on multiple exchanges with various ratings, including AA-rated Kraken and Coinbase, BB-rated Gateio, B-rated Kucoin and Bitmart, C-rated Mexc and Huobi, D-rated Bingx and Lbank, E-rated Bitrue and Bilaxy.

3 A Stylized Model of Multi-Venue Certification

This section develops a stylized model of listing premia in a market where multiple exchanges screen the same underlying token quality. Exchanges independently evaluate a token within one period and decide whether to list, generating predictions about listing premia, informational substitution, simultaneous listings, and the cross-sectional prediction based on information distance. Within a single period, multiple exchanges may list the same token—these are *simultaneous listings*. Listings occurring in different periods constitute *sequential*

Listing Chances on Major Exchanges".

listings. Proofs and derivations are in Online Appendix B.

3.1 Environment

Asset quality. A continuum of tokens is indexed by i. Each token has a latent quality $z_i \sim \mathcal{N}(\mu_0, \tau_0^2)$, which captures the token's crypto-specific fundamentals: platform productivity, user adoption, network effects, and convenience yield. The terminal value of token i is

$$v_i = \bar{v} + \delta\, z_i, \qquad \delta > 0, \tag{1}$$

where $\bar{v}$ is a baseline value and δ translates quality into value. Investors are risk-neutral with a zero discount rate. The market price at any information set $\mathcal{I}$ is

$$P(\mathcal{I}) = \mathbb{E}[v_i \mid \mathcal{I}] = \bar{v} + \delta \mathbb{E}[z_i \mid \mathcal{I}].$$

Before any listing, the price is $P_0 = \bar{v} + \delta\mu_0$.

Exchanges. There are J centralized exchanges, ordered by tier $j \in \{1, 2, \ldots, J\}$, where $j = J$ denotes the highest-tier exchange. Each exchange j evaluates a token by observing a noisy signal about its latent quality:

$$X_{ij} = \alpha_j z_i + \phi_{ij}, \qquad \phi_{ij} \sim \mathcal{N}(0, \sigma_j^2), \tag{2}$$

where $\alpha_j > 0$ is the screening intensity and ϕ_{ij} is an idiosyncratic exchange-specific component capturing venue-specific frictions (trading infrastructure, investor base, regulatory quirks). The noise terms $\{\phi_{ij}\}$ are mutually independent and independent of z. We order exchanges so that higher tiers screen more precisely:

$$\frac{\alpha_1^2}{\sigma_1^2} < \frac{\alpha_2^2}{\sigma_2^2} < \cdots < \frac{\alpha_J^2}{\sigma_J^2}. \tag{3}$$

All signals load on the same latent quality z, creating overlapping private information across exchanges. Define the precision of exchange j's signal as $\pi_j \equiv \frac{\alpha_j^2}{\sigma_j^2}$, and the prior precision as

$\pi_0 \equiv 1/\tau_0^2$. The precision ordering condition (3) becomes $\pi_1 < \pi_2 < \cdots < \pi_J$.

3.2 Endogenous Listing Decisions

Exchange j observes $X_{ij} = x$ before deciding whether to list token i. By normal conjugacy,

$$z_i \mid X_{ij} = x \sim \mathcal{N}\big(m_j(x), s_j^2\big),$$

where

$$m_j(x) = \mu_0 + \frac{\alpha_j \tau_0^2}{\alpha_j^2 \tau_0^2 + \sigma_j^2}\big(x - \alpha_j \mu_0\big), \qquad s_j^2 = (\pi_0 + \pi_j)^{-1}. \tag{4}$$

Let $\underline{z}$ denote a failure threshold below which the token's quality is deemed unacceptable. Conditional on its signal, exchange j's perceived failure probability is

$$p_j(x) \equiv \Pr(z_i < \underline{z} \mid X_{ij} = x) = \Phi\left(\frac{\underline{z} - m_j(x)}{s_j}\right). \tag{5}$$

Here and below, Φ and ϕ denote the standard normal CDF and PDF. Listing generates expected revenue $B_j(m_j(x))$, where $B_j(\cdot)$ is continuously differentiable and strictly increasing. This revenue can be interpreted as listing fees, expected trading-fee revenue, and reputational benefits from attracting valuable tokens. Listing also exposes the exchange to reputational loss $R_j > 0$ if the token later fails. The exchange's net payoff from listing is

$$\Pi_j(x) = B_j(m_j(x)) - R_j p_j(x) - c_j, \tag{6}$$

where c_j is a fixed operational cost. We assume the crossing condition

$$\lim_{x \to -\infty} \Pi_j(x) < 0, \qquad \lim_{x \to +\infty} \Pi_j(x) > 0, \tag{7}$$

which rules out the degenerate cases in which an exchange lists all tokens or no tokens.

Proposition 1 (Optimality of threshold listing rules) *For each exchange j, the unique*

optimal listing policy is a threshold rule:

$$\textit{List token } i \textit{ on exchange } j \quad \Longleftrightarrow \quad X_{ij} \geq \bar{X}_j.$$

where $\bar{X}_j$ is the unique signal realization at which the exchange breaks even: $\Pi_j(\bar{X}_j) = 0$.

Threshold ordering. Under the additional condition that higher-tier exchanges have sufficiently more reputational capital at stake, the endogenous thresholds are ordered across tiers:

$$\bar{X}_1 < \bar{X}_2 < \cdots < \bar{X}_J.$$

A higher R_j increases the marginal reputational cost of listing a token that subsequently fails, raising the break-even signal $\bar{X}_j$. Formally, applying the implicit function theorem to $\Pi_j(\bar{X}_j) = 0$:

$$\frac{\partial \bar{X}_j}{\partial R_j} = \frac{p_j(\bar{X}_j)}{\Pi_j'(\bar{X}_j)} > 0, \tag{8}$$

since $p_j(\bar{X}_j) > 0$ and $\Pi_j'(\bar{X}_j) > 0$.

Simultaneous listings in the single-period model. Within a single period, all J exchanges independently observe their signals and apply their threshold rules. Because signals are correlated through the common latent quality z, a high-quality token is likely to cross multiple thresholds simultaneously. The probability of simultaneous listing on exchanges j and k is

$$\Pr(X_{ij} > \bar{X}_j,\, X_{ik} > \bar{X}_k) = \Phi_2(-\kappa_j, -\kappa_k; \rho_{jk})\,, \tag{9}$$

where $\kappa_j = (\bar{X}_j - \alpha_j \mu_0)/\nu_j$, $\nu_j^2 = \alpha_j^2 \tau_0^2 + \sigma_j^2$, and ρ_{jk} is the unconditional correlation between X_{ij} and X_{ik}. The function Φ_2 denotes the bivariate normal CDF. The probability in (9) is positive, increasing in the signal correlation ρ_{jk}, and decreasing in the thresholds $\bar{X}_j, \bar{X}_k$. Simultaneous listings are a generic feature of the single-period model, not a knife-edge outcome.

Endogenous correlation structure. The correlation in listing decisions is *not a free parameter*—it is pinned down by the signal structure (α_j, σ_j) and the prior on z:

$$\rho_{jk} = \frac{\alpha_j \alpha_k \tau_0^2}{\sqrt{(\alpha_j^2 \tau_0^2 + \sigma_j^2)(\alpha_k^2 \tau_0^2 + \sigma_k^2)}}. \tag{10}$$

Higher screening intensities α_j, α_k and lower idiosyncratic noise σ_j, σ_k produce higher correlation. The correlation approaches 1 when both exchanges screen very precisely (idiosyncratic noise vanishes) and approaches 0 when exchange-specific noise dominates.

3.3 Price Reaction to Listings

The market does not observe the exchange's exact private signal. Instead, a listing announcement reveals the event $L_{ij} \equiv \{X_{ij} \geq \bar{X}_j\}$. The posterior mean of quality after a first listing on exchange j is

$$\mathbb{E}[z_i \mid L_{ij}] = \mu_0 + \frac{\alpha_j \tau_0^2}{\nu_j} \lambda(\kappa_j), \tag{11}$$

where $\nu_j^2 \equiv \mathrm{Var}(X_{ij}) = \alpha_j^2 \tau_0^2 + \sigma_j^2$ is the unconditional variance of X_{ij}, $\kappa_j \equiv \frac{\bar{X}_j - \alpha_j \mu_0}{\nu_j}$, and $\lambda(\kappa) = \frac{\phi(\kappa)}{1-\Phi(\kappa)}$ is the upper-tail inverse Mills ratio. Therefore, the first-time listing premium is

$$\mathrm{CAR}_{ij} \equiv P(L_{ij}) - P_0 = \delta \frac{\alpha_j \tau_0^2}{\nu_j} \lambda(\kappa_j) > 0. \tag{12}$$

Proposition 2 (First-time listing premium increases with exchange tier) *Suppose exchange tiers are ordered by signal precision as in ordering condition* (3) *and by standardized listing selectivity,*

$$\kappa_1 \leq \kappa_2 \leq \cdots \leq \kappa_J. \tag{13}$$

Then the first-time listing premium is increasing in tier:

$$\mathrm{CAR}_{i1} < \mathrm{CAR}_{i2} < \cdots < \mathrm{CAR}_{iJ}\,.$$

To consider the case when token i is listed on multiple exchanges sequentially, let $m_{\mathcal{A}} \equiv \mathbb{E}[z_i \mid \mathcal{A}]$ be the posterior mean of quality under information set $\mathcal{A}$. Because prices are affine

in posterior means, the price reaction to new information equals δ times the corresponding change in $m_{\mathcal{A}}$.

If exchange j's signal is observed as a first signal, posterior precision increases from π_0 to $\pi_0 + \pi_j$, and the expected squared belief revision is

$$Q_j \equiv \mathbb{E}\big[(P_j - P_0)^2\big] = \delta^2 \left[\frac{1}{\pi_0} - \frac{1}{\pi_0 + \pi_j}\right] = \delta^2 \frac{\pi_j}{\pi_0(\pi_0 + \pi_j)}. \tag{14}$$

If the token has already been certified by exchange h, then observing exchange j's signal raises precision from $\pi_0 + \pi_h$ to $\pi_0 + \pi_h + \pi_j$, so the expected squared incremental reaction is

$$Q_{j|h} \equiv \mathbb{E}\big[(P_{hj} - P_h)^2\big] = \delta^2 \left[\frac{1}{\pi_0 + \pi_h} - \frac{1}{\pi_0 + \pi_h + \pi_j}\right] = \delta^2 \frac{\pi_j}{(\pi_0 + \pi_h)(\pi_0 + \pi_h + \pi_j)}.$$

Proposition 3 (Informational substitution in sequential listings) *For any $\pi_h > 0$ and $\pi_j > 0$,*

$$Q_{j|h} < Q_j.$$

More generally, if a prior listing history $\mathcal{H}$ has total precision $\Pi_{\mathcal{H}} \equiv \sum_{h \in \mathcal{H}} \pi_h > 0$, then

$$Q_{j|\mathcal{H}} = \delta^2 \frac{\pi_j}{(\pi_0 + \Pi_{\mathcal{H}})(\pi_0 + \Pi_{\mathcal{H}} + \pi_j)} < Q_j. \tag{15}$$

Intuitively, previous listings reveal part of the same underlying quality. A subsequent listing may still be good news, but its incremental informational content is smaller because some overlapping private information (i.e., *informational substitute*) has already been incorporated into price.

Sequential listings show that prior certifications can be partial substitutes for later certifications. Simultaneous listings allow the researcher to measure how much of one exchange's information overlaps with another exchange's information.

Consider a lower-tier exchange j and a higher-tier exchange $k > j$. The linear projection of X_{ij} on X_{ik} is

$$X_{ij} - \mathbb{E}[X_{ij}] = \gamma_{jk}\big(X_{ik} - \mathbb{E}[X_{ik}]\big) + \eta_{ij|k}, \qquad \gamma_{jk} = \frac{\mathrm{Cov}(X_{ij}, X_{ik})}{\mathrm{Var}(X_{ik})},$$

where $\mathrm{Cov}(\eta_{ij|k}, X_{ik}) = 0$. The projected component is the part of exchange j's information aligned with the higher-tier signal, and the residual component is the part specific to exchange j.

Proposition 4 (Informational decomposition via simultaneous listings) *Under the jointly Gaussian signal structure, the price reaction to exchange j's certification can be written as*

$$P_j(X_{ij}) - P_0 = a_j + b_j \gamma_{jk}\big(X_{ik} - \mathbb{E}[X_{ik}]\big) + b_j \eta_{ij|k}, \tag{16}$$

for constants a_j and $b_j > 0$. The term involving X_{ik} is the informational-substitute component: the part of the lower-tier listing that is informative about potential higher-tier certification. The residual term $\eta_{ij|k}$ is the informational-complement component: the information specific to exchange j after removing the higher-tier component.

For multiple higher tiers $\mathcal{H}_j \equiv \{k : k > j\}$, the same decomposition is

$$X_{ij} - \mathbb{E}[X_{ij}] = \boldsymbol{\gamma}_j'\big(\boldsymbol{X}_{i\mathcal{H}_j} - \mathbb{E}[\boldsymbol{X}_{i\mathcal{H}_j}]\big) + \eta_{ij|\mathcal{H}_j}, \qquad \boldsymbol{\gamma}_j' = \Sigma_{j\mathcal{H}_j}\Sigma_{\mathcal{H}_j\mathcal{H}_j}^{-1}, \tag{17}$$

where $\eta_{ij|\mathcal{H}_j}$ is orthogonal to all higher-tier signals. Simultaneous listings enable the identification of the covariance structure needed for this projection because listing outcomes across tiers are observed in the same event window.

3.4 Information Distance

The projection above suggests a cross-sectional measure of how much new information a current listing contributes relative to information already absorbed from prior listings.

Definition 1 (Information distance) *For a token with highest prior listing on exchange tier h (in some earlier period) that is subsequently listed on exchange tier j (in the current period), the information distance is*

$$\begin{aligned} d_{jh} &\equiv 1 - R_{jh}^2, \\ R_{jh}^2 \equiv \rho_{jh}^2 &= \frac{(\alpha_j \alpha_h \tau_0^2)^2}{(\alpha_j^2\tau_0^2 + \sigma_j^2)(\alpha_h^2\tau_0^2 + \sigma_h^2)} = \frac{\pi_j \pi_h}{(\pi_0 + \pi_j)(\pi_0 + \pi_h)}. \end{aligned} \tag{18}$$

For first-time listings (no prior listing), $d_{j0} = 1$.

The information distance d_{jh} measures the fraction of exchange j's signal variance that is *not* linearly explained by exchange h's signal. When d_{jh} is large, the current exchange's signal has a large residual component relative to the prior exchange's signal, so a listing on j after a prior listing on h conveys substantial new information. When d_{jh} is small, the signals overlap heavily and most of the information has already been absorbed.

Proposition 5 (Reaction magnitude increases with information distance) *Fix the current listing exchange* j*. Compare prior listing histories summarized by the precision* π_h *of the information already absorbed by the market. The expected squared incremental reaction*

$$Q_{j|h} = \delta^2 \frac{\pi_j}{(\pi_0 + \pi_h)(\pi_0 + \pi_h + \pi_j)} \tag{19}$$

is strictly increasing in the information distance d_{jh} *defined in* (18).

This proposition gives a sharper empirical prediction than a comparison of average CARs by different prior listing histories. Conditional on the current listing tier, the reaction should be larger when the current exchange's information is farther from the information that the market has already absorbed through earlier listings.

4 Data Description and Listing Premium based on Unconditional Event Study

As the first part of our empirical study, we provide an overview of how the market responds to listings on exchanges with different ratings. To obtain preliminary evidence, we conduct an unconditional event study and find that market reactions generally align with the ordinal rating of the exchanges. Our sample includes assets deployed on five major blockchains, i.e., Ethereum, Solana, Binance Smart Chain (BSC), Arbitrum, and Avalanche, a subset of which were subsequently listed on centralized exchanges (CEXs). Upon creation, these assets can be traded on-chain via decentralized exchanges (DEXs). Even if they are later listed on

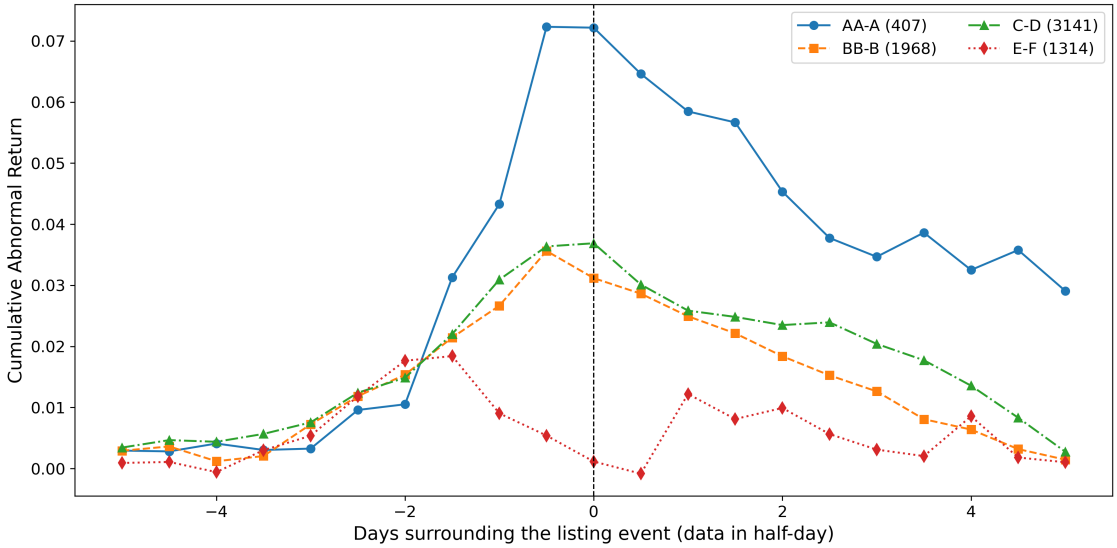


Figure 2: Cumulative Abnormal Returns (CARs) around exchange listing events by exchange rating categories. We indicate the number of listing events for each exchange rating category in parentheses.

CEXs, arbitrageurs are expected to quickly eliminate any price discrepancies between the on-chain and CEX markets. Therefore, we use the on-chain price as a consistent benchmark to measure potential abnormal returns around CEX listing events. [4]

Our sample consists of 8365 assets, of which 2695 are listed on the 87 CEXs rated by CoinDesk, with the sample period from 1st September 2021 to 31st March 2025. We adopt the market model to calculate abnormal returns, with the event window set to be $[-5, +5]$ days around the listing event and the estimation window set to be $[-125, -5]$ days relative to the event time. The cumulative abnormal return (CAR) is obtained by adding up the corresponding abnormal returns, $\mathrm{CAR}_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \mathrm{AR}_{i\tau}$. Detailed data construction (multi-chain asset merging, pricing and market-capitalization sources, half-day frequency alignment) and the event-study methodology, including the choice of the first-trade time as the event time, are reported in Online Appendix C.

To ensure sufficient sample size when evaluating, we group listing events to 4 categories of exchange ratings: AA to A rated exchanges (AA-A), BB to B (BB-B), C to D (C-D), and E to F (E-F).

[4] According to Heimbach et al. (2024) and Wu et al. (2025), as arbitragers are competing for CEX-DEX arbitrage opportunities, any price gap between CEX and DEX would be closed almost instantly.

Figure 2 plots the CARs 10 days around the listing events on exchanges in different rating categories. At the time of listing, assets listed on the top-tier exchanges (AA-A) experience considerable positive price drift, with average CAR of 7.2% (t-stats=20.88). The market reacts moderately to listings on mid-tier exchanges (BB-B and C-D), with average CAR of 3.1% (t-stats=16.52) and 3.7% (t-stats=18.91) for BB-B and C-D respectively. By contrast, listings on bottom-tier exchanges (E–F) elicit a trivial market response, with an average CAR of 0.1% (t-stats = 0.47), which is not statistically significant. The result is consistent with Proposition 2 that higher-tier exchange listings should elicit greater market response for the more informative signals they contain. We can summarize the results as Finding 1:

Finding 1 *We find strong supportive evidence for Proposition 2. The estimated simple listing premium is averagely 7.2% for top-tier crypto exchanges but only 0.1% for bottom-tier exchanges.*

Since in this event study we pool together all the listing events while have not distinguished either case with different listing histories, i.e., due to "sequential listings", or the issue of simultaneous listings, CAR estimates for the listings are potentially biased, although it already shows a clear trend that the magnitude of market response to listings follows the ordinal ratings of the targeted exchanges. To have a preliminary check on whether the market reacts differently to listings with different listing histories, we perform sets of event studies focusing on assets with the same listing background, defining an asset's listing history by the highest-rated exchange it was previously listed on. Detailed results are reported in Online Appendix C and reveal two patterns of interest. First, the effects of listings are more pronounced when the asset has never been listed on any exchange before, and this distinction is most evident for listings on AA–A rated exchanges: the market reaction to a first-time listing on an AA–A exchange is 44.5% in CAR (t-stats=16.16), while the reaction to a subsequent AA–A listing is only 4.3% (t-stats=11.95) when the asset has already been listed on an AA–A exchange. Second, the market reaction to a given rated exchange decreases as the rating of the asset's prior listing increases, and the same pattern holds for listings on all four rating categories. We summarize these findings as:

Finding 2 *The estimated listing premium for a given exchange tier declines as the asset is listed on more exchanges elsewhere, consistent with Proposition 3.*

Our evidence suggests that the market does react differently to listings with different listing histories. However, although the results from these event studies appear consistent with Proposition 3, we must account for the exchanges' inherent self-selection problem: exchanges tend to list trending assets to attract users and increase trading activity. In this sense, investors respond not only to the private information revealed through listings but also public information, e.g., good news and technological improvement, about the assets around the listing days. Also, we need to address the issue of simultaneous listings, which is explored together with the issue of listing history in the later sections. Details of data and event-study results, as well as robustness check based on the original 8 ratings, are reported in Online Appendix C.

5 Premium for Multiple Listings and Methods for Conditional Event Study

Our model generates two key implications: (i) in sequential listings the marginal informativeness of additional listings declines once some of the private information (*information substitute*) has already been revealed in prior listings, i.e., Proposition 3; and (ii) any listing bundles two components of information, *informational substitute* and *informational complement*, the effect of which can be disentangled via simultaneous listings, i.e., Proposition 4. The first implication shows how *informational substitute* is subsumed over time, while the second illustrates the presentation of *informational substitute* at certain time point.

To examine empirical support for these two model implications, arising respectively from sequential and simultaneous listings, we conduct primarily two sets of analyses. The first investigates why market reactions, measured by cumulative abnormal returns (CARs), to listings on the same exchange vary with an asset's prior listing history (due to sequential listings). The second disentangles the market reaction to those two informational components via simultaneous listings across exchanges with different ratings.

5.1 Listing premium under sequential listings

Because of self-selection, exchanges tend to list assets that are already trending, so investors' reactions around listing dates reflect both public information about the asset and private information revealed through the listing decision. To control the effect of public news and isolate the market response to the private information, we propose methods based on conditional event studies.

We begin by modeling the exchange's listing decision. Exchanges are grouped into four ordered rating categories

$$\{\text{E–F},\ \text{C–D},\ \text{BB–B},\ \text{AA–A}\} \equiv \{1, 2, 3, 4\},$$

where $j = 4$ denotes AA–A exchanges (highest tier) and $j = 1$ denotes E–F exchanges (lowest tier), as in Section 4. For asset i and exchange tier j, let a latent variable $LIST^*_{ij}$ represent the listing prospect or perceived project quality at tier j, capturing the joint benefit of listing for both the project and the exchange. We assume

$$LIST^*_{ij} = X'_{ij}\theta_j + \epsilon_{ij}, \qquad \epsilon_{ij} \sim \mathcal{N}(0, \sigma^2), \tag{20}$$

where X_{ij} collects observable pre-listing characteristics (e.g., market capitalization, liquidity, trading volume, and price run-up) and ϵ_{ij} captures private information known to the project team and the exchange but not to the market. Asset i is listed on an exchange in tier j if and only if

$$LIST^*_{ij} > 0 \iff \epsilon_{ij} > -X'_{ij}\theta_j. \tag{21}$$

Ex ante, $\mathbb{E}[\epsilon_{ij}] = 0$; ex post, conditional on $LIST^*_{ij} > 0$, the listing decision reveals private information summarized by $\mathbb{E}[\epsilon_{ij} \mid LIST^*_{ij} > 0]$.

We link this learning to price reactions via

$$\mathbb{E}[\text{CAR}_{ij} \mid LIST_i = j] = \alpha_j + \beta_j\, \mathbb{E}[\epsilon_{ij} \mid LIST^*_{ij} > 0], \tag{22}$$

where $LIST_i = j$ denotes that asset i is listed on tier j, and $\mathbb{E}[\epsilon_{ij} \mid LIST^*_{ij} > 0]$ is the inverse

Mills ratio implied by (20). If listing on tier j has positive valuation effects, we expect $\beta_j > 0$.

We estimate (20) and (22) separately for listings with different prior listing histories (first-time listings and listings on AA–A, BB–B, C–D, and E–F exchanges). To test if private information revealed through previous listings contain *informational substitute* for subsequent listings, we compare β_j across listing histories. Because β_j measures the market reaction to each unit of new private information revealed by the listing, informational substitution implies that β_j is smaller when a listing follows prior listings elsewhere. For example, for AA–A listings, we expect $\beta_{4,3} < \beta_{4,0}$, where $\beta_{4,0}$ is the coefficient for first-time AA–A listings and $\beta_{4,3}$ is that for AA–A listings preceded by BB–B listings. Similarly, for BB–B listings we expect $\beta_{3,4} < \beta_{3,0}$ when the BB–B listing follows an AA–A listing.

In addition to the effect from *informational substitute* component of private information, the pattern in Finding 2 may also be ascribed to investors' reaction to assets' publicly known information: investors form different ex ante belief about the listing likelihood based on different listing history. Exchanges with different ratings attract assets with systematically different characteristics, so investors form different priors about the probability of further listings. For example, projects whose assets have never been listed on any exchange are typically younger, less mature, and more volatile than those already listed on BB–B rated exchanges.[5] Such assets are ex ante less likely to pass the scrutiny required for an AA–A listing. Consequently, when an AA–A exchange lists an asset with no prior listings, the event is more surprising and generates a stronger reaction (higher CAR) than when the same AA–A listing follows a prior BB–B listing.

To control for investors' reactions to public information about the asset, we also test whether differences in investors' ex ante beliefs contribute to the variation in listing premium over time. We test such difference in listing expectation by comparing the fitted latent scores $X'_{ij}\theta_j$ across histories. For AA–A listings ($j = 4$), denote the expected latent score for first-time listings by $\mathbb{E}[X'_4\theta_4]_0$ and for assets previously listed on BB–B exchanges by $\mathbb{E}[X'_4\theta_4]_3$. If $\mathbb{E}[X'_4\theta_4]_3 > \mathbb{E}[X'_4\theta_4]_0$, assets with prior BB–B listings are ex ante perceived as more likely AA–A candidates than first-time listings. Moreover, a higher $X'_{ij}\theta_j$ implies less remaining

[5] In the crypto market, assets/coins are issued by projects, whose fundamentals determine the value of the associated tokens.

private information and therefore a smaller surprise when the listing occurs.

Finally, if differences in CARs across listing histories remain even after controlling for $\mathbb{E}[\epsilon_{ij} \mid LIST^*_{ij} > 0]$, they will show up in the intercepts α_j of (22), indicating additional channels beyond the two considered above.

5.2 Listing premium under simultaneous listings

As shown in Proposition 4, for any given listing on the sub-top tier exchange, market reaction to the revealed private information can be split into two parts: the part due to *informational substitute* and the part due to *information complement*. We can also interpret such disentangling as investors' inferring any potential uplisting on higher-tier exchanges implied by the current listing (i.e., *informational substitute*), which confounds the measured impact. Regardless of whether the asset is listed on a single exchange or multiple exchanges simultaneously, effects of listing derive from those two components. However, only with simultaneous events, we can measure the correlation of private information revealed by exchanges in different tiers. Otherwise, we cannot disentangle these two information components, making it impossible to quantify investors' reaction to any part of them. Therefore, simultaneous listings provide a unique opportunity to separate and precisely quantify market reactions to the *informational substitute* and *informational complement* components for any given listing on a sub–top-tier exchange.

We model the listing decision in a multivariate latent-index framework, extending (20):

$$LIST^*_{ij} = X'_{ij}\theta_j + \epsilon_{ij}, \qquad \epsilon_i \sim \mathcal{N}(0, \Sigma), \tag{23}$$

where $j \in \mathcal{J} = \{1, 2, 3, 4\}$ indexes rating categories (E–F, C–D, BB–B, AA–A), X_{ij} collects observable characteristics, and the covariance matrix Σ captures the correlation in private information across tiers. As before, asset i is listed on tier j if $LIST^*_{ij} > 0$.

When an asset is listed on a set of tiers $\mathcal{J} \subseteq \{1, 2, 3, 4\}$, the listing decisions jointly reveal the vector of private signals $\{\epsilon_{ik}\}_{k \in \mathcal{J}}$. We summarize the corresponding price reaction as

$$\mathbb{E}[\text{CAR}_{ij} \mid j \in \mathcal{J}] = \alpha_{\mathcal{J}} + \sum_{j \in \mathcal{J}} \beta_j \, \mathbb{E}\big[\epsilon_{ij} \mid \epsilon_{ik} > -X'_{ik}\theta_k, \ \forall k \in \mathcal{J}\big], \tag{24}$$

where the multivariate inverse Mills ratios $\mathbb{E}[\epsilon_{ij} \mid \epsilon_{ik} > -X'_{ik}\theta_k,\ \forall k \in \mathcal{J}]$ represent the private information about listing on tier j revealed by the entire set of simultaneous listing decisions. The coefficient β_j measures the marginal valuation effect of information specific to tier j, controlling for information revealed by listings on other tiers in $\mathcal{J}$; $\beta_j > 0$ indicates that the market reacts positively to private information about listing on tier j.

For a listing on tier j, we ask: how much of the reaction reflects (i) information purely about listing on tier j (i.e., *informational complement*), and how much reflects (ii) implied information about being listed on higher-tier tiers $k > j$ (i.e., *informational substitute* to tier-k)? Following Proposition 4, we linearly decompose the latent information as

$$\epsilon_{ij} = \sum_{k=j+1}^{4} \gamma_{jk}\, \epsilon_{ik} + \epsilon_{ij}^{\perp}, \tag{25}$$

where ϵ_{ik} is the private information relevant for listing on higher-tier $k > j$ and $\gamma_{jk}\epsilon_{ik}$ captures the component of ϵ_{ij} that is aligned with higher-tier signals (i.e., *informational substitute*). $\epsilon_{ij}^{\perp}$ is orthogonal to all $\{\epsilon_{ik}\}_{k>j}$ and represents *informational complement* about tier j. In terms of linear projections, γ_{jk} is the coefficient on ϵ_{ik} in the multiple regression of ϵ_{ij} on $\{\epsilon_{ik}\}_{k>j}$. The derivations are provided in Online Appendix D.

When the listing on tier j occurs, the market responds to both components of ϵ_{ij}. Under the multivariate normality assumption, we can write

$$\mathbb{E}[\text{CAR}_{ij} \mid \epsilon_{ij}] = \alpha_j^{\perp}\, \mathbb{E}\big[\epsilon_{ij}^{\perp} \mid \epsilon_{ij}\big] + \sum_{k=j+1}^{4} \alpha_k\, \mathbb{E}[\epsilon_{ik} \mid \epsilon_{ij}]\,, \tag{26}$$

$$= \left\{ \underbrace{\alpha_j^{\perp}\left[1 - \sum_{k=j+1}^{4} \gamma_{jk}\rho_{ik,j}\right]}_{\textit{Informational complement}\text{ effect}} + \underbrace{\sum_{k=j+1}^{4} \alpha_k \rho_{ik,j}}_{\textit{Informational substitute}\text{ effect}} \right\} \epsilon_{ij}. \tag{27}$$

where $\alpha_j^{\perp}$ measures the market's sensitivity to *informational complement* about tier j, and α_k captures the sensitivity to *informational substitute* to tier-k exchanges implied by the tier-j listing (Online Appendix E provides the derivations). Therefore, with (27), we disentangle the private-information-driven component of CAR_{ij} into two parts, corresponding to the

marginal reaction to each unit of private information:

- *Informational complement* effect: the component due to private information solely about listing on exchange j, *informational complement* for tier j exchanges;
- *Informational substitute* effect: the component due to implied private information about asset i to be listed on higher-tier exchanges $k > j$, *informational substitute* to exchange k implied by exchange j (the overlapping information). [6]

In this way, we can control reaction to listings on other exchanges when focusing on a certain tier, for simultaneous listings. We conduct the two-stage estimation with (23) and (24) to recover $\alpha_j^{\perp}$ and α_j, as well as reconstructing the two types of effects. Procedure of the estimation can be found in Online Appendix F.

6 Empirical Results for Conditional Event Study

6.1 Data and pre-listing characteristics

We adopt the same dataset as described in Section 4 and the same definition for simultaneous listings, i.e., listings of the same assets across differently rated exchanges within the same 72-hour window. As a result, we have two sorts of listing events: 6717 (90%) listing events on a single exchange and 742 (10%) events involving simultaneous listings across multiple exchange. [7] After aggregating the 742 listings overlapped in the same 72-hour window on multiple exchanges, we identify 353 unique events of simultaneous listing on multiple exchange tiers. In each of the 353 events, an asset is listed on multiple exchanges spanning at least two distinct rating categories. We use cumulative abnormal return (CAR) from day -5 to day 0 relative to the event date as the measure of market reaction to the listing

[6] (27) highlights that both components depend on the correlation structure $\{\rho_{ik,j}\}_{k>j}$ and the sensitivities $\alpha_j^{\perp}$ and $\{\alpha_k\}_{k>j}$. If ϵ_{ij} is perfectly correlated with higher-tier signals $\{\epsilon_{ik}\}_{k>j}$, then $\epsilon_{ij}^{\perp}$ vanishes and the reaction is entirely driven by *informational substitute*. If, instead, ϵ_{ij} is independent of $\{\epsilon_{ik}\}_{k>j}$, then $\epsilon_{ij} = \epsilon_{ij}^{\perp}$ and the *informational substitute* effect disappears: the reaction reflects purely tier-j information (*information complement*). The magnitude and sign of $\alpha_j^{\perp}$ determine whether listing on tier j is, on net, good or bad news. For example, a negative $\alpha_j^{\perp}$ would arise if the market interprets a listing on a low-rated exchange as a signal that the project is unlikely to qualify for higher-rated venues.

[7] In our sample, 155 out of 7459 (2%) listing events are simultaneous listings on multiple exchanges with the same rating, which we regard as single-exchange listing events in our analysis. Therefore, precisely speaking, we are analyzing events of listing on exchange (s) in the same rating category and the events of simultaneous listings on multiple exchanges with different ratings.

events, i.e., $CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau}$, where we adopt $\tau_1 = -5$, the beginning of the event window, and $\tau_2 = 0$, the event time.

In the last section, we include a set of variables X_{ij} in our latent decision equations to capture the publicly known characteristics of asset i before the listing on exchange tier j. To this end, we specify the following characteristics for asset i in X_{ij} upon its listing on exchange tier j in our sample:

- VOLUME: the trading volume calculated as the average number of tokens traded over the 15 days prior to the listing event, divided by the total circulating token supply 5 days before the listing event.

- NO_CHAIN: the number of chains on which the coin has been launched upon the time of listing events, i.e., among the 5 blockchains examined in this study, Ethereum, Solana, Binance Smart Chain (BSC), Arbitrum, and Avalanche. Being launched on multiple chains indicates broader adoption and usage.

- VOLATL: crypto asset return volatility, defined as the standard deviation of daily returns over the 120-day period ending five trading days before the listing.

- RUNUP: the price run-up, calculated as the ratio of the price of the asset five trading days prior to the listing event to the price 120 days before the listing.

- SIZE: the natural logarithm of the asset's market capitalization measured five trading days before the listing event.

- PR_FUT_RATE: a sort of dummy variables indicating the listing status of the asset on the perpetual futures market of exchanges with different ratings before the listing event. [8] We define 4 dummy variables to indicate whether the asset has been listed on the perpetual futures market of exchanges with ratings AA-A, BB-B, C-D, and E-F, respectively, before the listing event: PR_FUT_RATE_4, PR_FUT_RATE_3,

[8] Perpetual futures are future contracts without expiry date, allowing traders to hold positions indefinitely. Readers can refer to Ackerer et al. (2024) and He et al. (2022) for more details about perpetual futures. For the 87 exchanges in our sample, 41 of them have perpetual futures markets together with spot markets. An asset can usually be listed on both the spot and perpetual future markets of the same exchange if it passes the exchange's listing review, but not necessarily at the same time. Therefore, solely being listed on the perpetual futures market of an exchange can also be a signal of the asset's quality.

PR_FUT_RATE_2, and PR_FUT_RATE_1. If the asset has been listed on the perpetual market of exchanges with certain rating, the corresponding dummy variable equals 1, and 0 otherwise. The benchmark case is that the asset has never been listed on the perpetual futures market of any exchange before the listing event, i.e., all the 4 dummy variables equal 0.

We select the characteristic variables based on token characteristics correlate with cross-listing probability documented by Benedetti and Nikbakht (2021), i.e., trading volume, network growth, and on-chain activity. Asset characteristics for those never been listed during our sampling period are obtained as of the end of our sample period, i.e., 31st March, 2025. Then we specify the decision by latent listing equation (20) and (23) as the market expectations of the listing, based on the upper mentioned asset characteristics:

$$\begin{aligned} LIST_{ij}^{*} = \; & \theta_{j0} + \theta_{j1} * \text{VOLUME}_i + \theta_{j2} * \text{NO_CHAIN}_i + \; \theta_{j3} * \text{VOLATL}_i \\ & + \theta_{j4} * \text{RUNUP}_i + \theta_{j5} * \text{RUNUP}_i + \theta_{j6} * \text{SIZE}_i + \theta_{j7} * \text{PR_FUT_RATE_1}_i \\ & + \theta_{j8} * \text{PR_FUT_RATE_2}_i + \theta_{j9} * \text{PR_FUT_RATE_3}_i \\ & + \theta_{j10} * \text{PR_FUT_RATE_4}_i + \epsilon_{ij}, \end{aligned} \tag{28}$$

where ϵ_{ij} is assumed to follow a standard normal distribution in (20) and a multivariate normal distribution in (23). As it is expected that more matured assets with larger market capitalization, higher trading volume, and broader adoption (being launched on multiple chains) are more likely to be listed on exchanges, we include the variables SIZE, VOLUME, and NO_CHAIN. Also, matured assets are less risky, shown by lower volatility and smaller price run-up, so we include VOLATL and RUNUP. In addition, being listed on the perpetual futures market of exchanges with different ratings before the listing event can also be a signal of the asset's quality, so we include the sort of dummy variables under PR_FUT_RATE.

Our analysis uses the 6717 single-exchange listings and the 353 simultaneous-listing events introduced above. Across both samples, assets previously listed on higher-rated exchanges tend to be more matured, with larger SIZE, lower VOLUME, lower VOLATL, and a higher probability of having been listed on the perpetual futures market of higher-rated exchanges. Detailed descriptive statistics for characteristics in X_{ij} are reported in Online Appendix G.

To estimate the two-stage model for simultaneous listings, our sample must include at least one listing on each of the 4 rating categories (AA–A, BB–B, C–D, and E–F). However, only the groups with prior AA–A (Panel A, $n = 253$) and BB–B (Panel B, $n = 53$) listings have sufficient observations, while the other three groups contain no AA–A listings, so we cannot identify the correlation between the AA–A private shock (ϵ_{i4}) and those of the other tiers (ϵ_{ik}, $k \in \{1, 2, 3\}$). Therefore, we perform the two-stage estimation, as well as the disentangling, only for events with listing histories on AA–A and BB–B exchanges, following the procedure in Online Appendix F.

6.2 Results for sequential listings

How the *informational substitute* play out in the market reactions to listings on exchanges with different listing history? Is there any statistical evidence supporting the conjectures to explain the phenomenon predicted by Proposition 3? We conduct the two-stage estimation for the conditional event studies, while results from the first-stage are used to test if investors form different ex ante expectation of listings for the asset with different listing history. With estimation of the second-stage, we test if prior listings contain *informational substitute* to subsequent listings.

We conduct the first-stage estimation based on (28) for each condition of listing history, results of which are presented in Table 1. Before formally testing the difference in ex ante listing probability, a clear distinction already emerges in the listing potential between first-time listings and those with prior listings. For assets already listed elsewhere (Columns (1)–(4) in each panel), the estimated coefficients on subsequent listing decisions across exchanges of different tiers vary substantially. For listing decisions on AA-A rated exchanges (Panel A), the coefficients for SIZE are estimated to be significantly positive across all listing history conditions: assets with larger market capitalization are more likely to be listed on the top-tier (AA-A) exchanges no matter what their listing history is, controlling for other characteristics. In contrast, estimated coefficients on SIZE for listing decision on lower-tier exchanges (Panel B, C, and D) are negative. This pattern reveals that exchanges with different ratings may prefer assets in different size when the assets has already been listed on other exchanges: top-tier exchanges prefer more matured assets with larger market capitalization, while lower-

tier exchanges tend to list relatively smaller and less matured assets. However, if we only consider first-time listing events, reported in Column (5) of each panel, how exchanges in different tiers choose assets do not differ much. They all prefer relatively matured assets with larger market capitalization, lower volatility, and broader adoption (being launched on multiple chains). This suggests that medium- to bottom-tier exchanges would loosen their listing scrutinization when the asset has already been listed on other exchanges.

To formally test if the market expects different ex ante listing probabilities based on an asset's history, we calculate

$$\mathbb{E}[X_4'\theta_4]_h \; - \; \mathbb{E}[X_4'\theta_4]_0,$$

the difference in expected listing probability between assets with different listing history $h \in \{1, 2, 3, 4\}$ and those never listed ($h = 0$), reported in the left column of Panel A in Table 3. Based on observable characteristics of assets, the market expects assets with prior AA–A listings to be more likely to get listed on other AA–A rated exchanges than assets never been listed before, evidenced by the positive and significant differences in expectation, i.e., $\mathbb{E}[X_4'\theta_4]_4 - \mathbb{E}[X_4'\theta_4]_0 = 1.455$ and p-value < 0.001. Similarly, prior listings on BB-B exchanges also increase the market's subsequent expectation towards being listed on AA-A rated exchanges, with $\mathbb{E}[X_4'\theta_4]_3 - \mathbb{E}[X_4'\theta_4]_0 = 1.075$ and p-value $= 0.015$. In contrast, prior listings on C-D and E-F exchanges do not significantly affect the market's expectation towards being listed on AA-A rated exchanges, with t-statistics of the difference being -0.46 and -0.93, respectively. Therefore, assets that have already been listed on top-tier or sub-top-tier exchanges (AA–A or BB–B) have a higher ex ante likelihood of being listed on another top-tier venues, supporting our conjecture that investors form different ex ante expectation towards listing beased on different listing history.

In addition to listing on AA-A rated exchanges, we find that prior listings, even on bottom-tier exchanges, also changes the market's perceived likelihood of being listed on medium- and lower-tier exchanges, i.e., BB-B, C-D, and E-F rated exchanges, so investors also have different ex ante expectation towards listing on lower-tier exchanges for different listing history. If an asset has been listed before, the market expects it to be more likely to be listed on BB-B rated exchanges, regardless of the rating of the previously listed exchange,

indicated by the positive and significant expected differences of the latent score $X_3'\theta_3$ for all types of listing history as reported in Panel B of Table 3. Similar patterns exist for listings on both C-D and E-F rated exchanges, shown in Panel C and D of Table 3.

As discussed in Section 5.1, private information revealed ex post after listing can be represented by the inverse Mills ratio, so large expected latent score $X_j'\theta_j$ implies small expected inverse Mills ratio, i.e., less private information revealed. Our results suggest that the latent score, market expectation of listing, is higher for assets with prior listings. As a result, listings with prior listings reveal less private information and thus are less surprising, resulting in weaker price reaction.

To test if prior listings contain *informational substitute* to subsequent listings, we estimate the second-stage equation (22) for different listing history conditions, with IMRs calculated based on the first-stage probit estimates reported in Table 1. Table 2 reports the estimation results, while we adjust standard errors according to Heckman (1979).

Panel A of Table 2 presents the estimation results for listings on AA-A rated exchanges. The slope coefficients $\beta_{4,h}$ for IMRs are significantly positive for cases with prior listings on AA-A ($h = 4$) and of first-time-listing ($h = 0$) (Column (1) and (5)). The coefficient for the case of first-time-listing ($\beta_{4,0} = 0.129$) is substantially larger than that previously listed on AA-A rated exchanges ($\beta_{4,4} = 0.019$), with $\beta_{4,0} \approx 6\beta_{4,4}$. The difference in slope coefficients is both statistically and economically significant, evidenced by negative $\beta_{4,4} - \beta_{4,0} = -0.113$ with p-value < 0.1, as reported in Column (2) of Panel A in Table 3. This result is consistent with our conjecture that the component of *informational substitute* revealed in earlier listings has already been absorbed by the market, and thus the market muted in reaction to this component of information in later listings. It can be expected that listing quality standards for AA–A-rated exchanges are broadly consistent across all such venues. Previous listings on any of the AA–A rated exchanges have already established a signaling channel indicating that the asset meets those standards. Consequently, because the market has already absorbed this signal, it reacts less to each additional unit of private information revealed by further listings on other AA–A rated exchanges. Similar pattern can be observed for AA-A and BB-B pair, evidenced by the significant negative difference $\beta_{4,3} - \beta_{4,0} = -0.136$, so private information revealed by BB-B listings and that by AA-A listings also amounts to partial

informational substitute to each other.

In contrast, when an asset with prior E–F listings is subsequently listed on AA–A rated exchanges (Column (3), Panel A of Table 2), the IMR slope remains significantly positive ($\beta_{4,1} = 0.098, p < 0.10$), only marginally below the first-time-listing coefficient ($\beta_{4,0} = 0.129$). As shown in Column (2) of Panel A in Table 3, this difference is not statistically significant, with $\beta_{4,1} - \beta_{4,0} = -0.108$ and t-statistics = -0.33. This pattern suggests the systematic differences in listing assessment and standards between top-tier (AA-A) and bottom-tier (E-F) exchanges. Although prior E-F listings convey some information about the asset, the information does not align much with the quality criteria of AA-A rated exchanges. Information revealed by the subsequent AA-A listing is still new and largely unexpected to the market, eliciting a strong reaction similar to that observed for first-time listings.

Together with the testing on investors' different ex ante expectation towards listing, we can summarize our finding as following:

Finding 3 *If the asset to be listed has already been listed elsewhere, the new listing conveys less incremental private information. Moreover, investors respond less to each unit of newly revealed information because the informational-substitute component has been partially absorbed through prior listings. These results help authenticate the mechanism underlying Proposition 3.*

We observe systematic differences in IMR slopes between first-time listings and those with prior listings only for listings on AA–A rated exchanges (i.e., conjecture about *informational substitute* holds only in this case while is rejected when the asset is listed on other lower-tier exchanges). Most of the slope coefficients are estimated to be insignificant for listings on lower-tier exchanges, especially for cases when the asset has been previously listed on medium-tier exchanges. Two possible reasons may underlie this pattern. Firstly, it may be that both of our two channels are unable to explain differences in market reactions with different listings history for the cases of lower-tier listings. As we discussed earlier, in such cases we would observe significant differences in estimated intercepts of (22) among different listing history conditions, a signal of no substantial selection bias.

Another potential reason is that the market reacts to the information related to higher-

tier listings (i.e., *information substitute*) in opposite direction with that solely related to the listing itself (i.e, *informational complement*). Our evidence already suggests that even listings on bottom-tier exchanges can reveal information about the asset assessed by the top-tier exchanges. If the market perceive the component of *informational substitute* positively, while the component of *inoformational complement* negatively, the two effects may offset each other, leading to insignificant slope coefficients for IMRs.

As shown in Proposition 4, it is impossible to disentangle the pricing effect due to components of *information substitute* and *informational complement* when only single-exchange listings data are available. However, using data on simultaneous listings across multiple venues allows us to separate these two effects. In the next section, we will present empirical results based on simultaneous listings, which provide evidence supporting the second reason.

Table 1: First-Stage Probit Estimations by Listing History

Notes: This table presents the first-stage probit estimates with (20), i.e., specified by (28), for each condition of listing history. Each pf the 5 panels illustrates estimated coefficients for the listing decision on exchanges with certain rating, i.e., AA-A in Panel A, BB-B in Panel B, C-D in Panel C, and E-F in Panel D. Each column in a panel represents the listing events with certain listing history, i.e., previously highest listed exchange in rating AA-A, BB-B, C-D, E-F, and first-time-listing. t-statistics are shown in parentheses. ***/**/* denote p<0.01/0.05/0.10.

Condition	AA-A (1)	BB-B (2)	C-D (3)	E-F (3)	first-time -listing (5)
Panel A: Listing on AA-A rated exchanges					
Dependent variable: $LIST_{AA-A}$					
Independent variable:					
Intercept	-4.174*** (-11.99)	-5.060*** (-9.59)	-4.627*** (-7.88)	-3.883*** (-3.01)	-4.299*** (-21.62)
VOLUME	14.624*** (2.74)	0.415 (0.21)	3.427 (0.64)	5.391 (0.39)	-0.101 (-0.08)
NO_CHAIN	0.016 (0.35)	0.024 (0.20)	0.629*** (3.45)	0.244 (0.76)	0.327*** (3.51)
VOLATL	1.283** (2.40)	0.194 (0.11)	-1.285 (-0.27)	2.363 (0.72)	-0.278 (-0.29)
RUNUP	-0.000** (-2.05)	-0.006 (-1.06)	-0.027 (-0.91)	-0.180 (-1.25)	0.000 (0.56)
SIZE	0.139*** (7.30)	0.186*** (6.52)	0.107*** (3.53)	0.127** (2.17)	0.072*** (6.03)
PR_FUT_RATE_2	-6.295*** (-28.68)	-4.874*** (-10.84)	-	-	-

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Table 1: First-Stage Probit Coefficients by Listing History (continued)

Condition	AA-A (1)	BB-B (2)	C-D (3)	E-F (3)	first-time -listing (5)
PR_FUT_RATE_4	-0.202*** (-2.75)	0.284 (0.91)	-4.515*** (-20.72)	-	-4.618*** (-21.70)
Panel B: Listing on BB-B rated exchanges					
Dependent variable: $LIST_{BB-B}$					
Independent variable:					
Intercept	-0.126 (-0.47)	-0.234 (-0.71)	0.144 (0.31)	1.385 (1.39)	-2.844*** (-19.89)
VOLUME	7.138 (1.42)	-6.712* (-1.88)	-5.394 (-1.16)	9.269 (0.92)	1.035* (1.75)
NO_CHAIN	-0.002 (-0.05)	-0.101 (-1.40)	0.077 (0.63)	-0.068 (-0.27)	0.174** (2.39)
VOLATL	-0.327 (-0.53)	-0.572 (-0.57)	-3.017* (-1.90)	-5.088* (-1.77)	-3.353*** (-5.08)
RUNUP	-0.004 (-1.31)	0.000** (2.01)	-0.000 (-0.63)	-0.001 (-0.83)	0.002*** (2.64)
SIZE	-0.036** (-2.45)	-0.019 (-1.04)	-0.027 (-1.01)	-0.107* (-1.74)	0.062*** (6.54)
PR_FUT_RATE_2	-0.397 (-0.98)	-3.725*** (-5.44)	-	-	-
PR_FUT_RATE_4	0.054 (1.10)	-0.061 (-0.23)	0.247 (0.28)	-	-8.157*** (-56.70)
Panel C: Listing on C-D rated exchanges					
Dependent variable: $LIST_{C-D}$					
Independent variable:					
Intercept	0.239 (1.00)	0.918*** (3.06)	-0.663 (-1.62)	-2.186** (-2.12)	-3.588*** (-18.24)
VOLUME	-0.792 (-0.16)	4.106* (1.67)	0.404 (0.10)	-6.981 (-0.56)	0.479 (1.21)
NO_CHAIN	-0.053* (-1.71)	0.003 (0.05)	-0.069 (-0.57)	-0.021 (-0.08)	0.165** (2.29)
VOLATL	0.411 (0.83)	0.457 (0.50)	3.770** (2.52)	6.967** (2.30)	-1.101*** (-2.64)
RUNUP	-0.000*** (-3.07)	-0.000 (-0.40)	0.000 (1.62)	-0.001*** (-2.84)	0.003*** (3.53)
SIZE	-0.023* (-1.77)	-0.059*** (-3.49)	0.016 (0.70)	0.100 (1.59)	0.115*** (7.94)
PR_FUT_RATE_2	-0.527 (-1.57)	6.594*** (13.81)	-	-	-
PR_FUT_RATE_4	-0.109** (-2.43)	0.068 (0.30)	0.397 (0.45)	-	1.084* (1.78)
Panel D: Listing on E-F rated exchanges					
Dependent variable: $LIST_{E-F}$					
Independent variable:					

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Table 1: First-Stage Probit Coefficients by Listing History (continued)

Condition	AA-A (1)	BB-B (2)	C-D (3)	E-F (3)	first-time -listing (5)
Intercept	-0.655** (-2.46)	-1.450*** (-3.76)	0.001 (0.00)	0.047 (0.04)	-3.262*** (-16.46)
VOLUME	6.064 (1.11)	-9.734 (-1.54)	6.668 (1.58)	-15.679 (-1.44)	1.370* (1.92)
NO_CHAIN	0.021 (0.59)	0.054 (0.71)	-0.241 (-1.50)	0.062 (0.24)	0.150 (1.63)
VOLATL	-1.267* (-1.70)	-0.515 (-0.34)	-3.970** (-2.01)	-5.376 (-1.10)	-2.170** (-2.06)
RUNUP	-0.005 (-0.90)	-0.029 (-1.29)	-0.000 (-0.64)	-0.056 (-1.15)	0.000 (0.35)
SIZE	-0.018 (-1.22)	0.022 (1.01)	-0.033 (-1.25)	-0.026 (-0.36)	0.071*** (6.13)
PR_FUT_RATE_2	0.483 (1.49)	-4.982*** (-4.21)	-	-	-
PR_FUT_RATE_4	0.063 (1.19)	0.256 (0.92)	-8.304*** (-63.72)	-	-4.872*** (-25.89)

Table 2: Second-Stage Estimations by Listing History

Notes: This table presents the second-stage estimates with (22) for each condition of listing history. Each pf the 5 panels illustrates estimated coefficients for the effects of listing on exchanges with certain rating, i.e., AA-A in Panel A, BB-B in Panel B, C-D in Panel C, and E-F in Panel D. Each column in a panel represents the listing events with certain listing history, i.e., previously highest listed exchange in rating AA-A, BB-B, C-D, E-F, and first-time-listing. We adjust standard errors according to Heckman (1979) to account for variability generated by the first-stage estimation. t-statistics are shown in parentheses. ***/**/* denote p<0.01/0.05/0.10.

Condition	AA-A (1)	BB-B (2)	C-D (3)	E-F (3)	first-time -listing (5)
Panel A: Listing on AA-A rated exchanges Dependent variable: CAR Independent variable:					
Intercept	0.010*** (3.98)	0.019*** (2.99)	-0.009 (-0.56)	0.060*** (2.58)	0.072*** (3.90)
λ_{AA-A}	0.019*** (3.54)	-0.004 (-0.28)	0.026 (1.03)	0.098* (1.95)	0.129** (2.05)
Panel B: Listing on BB-B rated exchanges Dependent variable: CAR Independent variable:					

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Table 2: Second-Stage Estimations by Listing History (continued)

Condition	AA-A (1)	BB-B (2)	C-D (3)	E-F (3)	first-time -listing (5)
Intercept	0.010*** (3.97)	0.019*** (2.99)	-0.009 (-0.58)	0.045* (1.84)	0.091*** (3.71)
λ_{BB-B}	0.007* (1.77)	-0.001 (-0.19)	0.012 (0.67)	0.026 (0.85)	-0.013 (-0.84)
Panel C: Listing on C-D rated exchanges					
Dependent variable: CAR					
Independent variable:					
Intercept	0.010*** (3.97)	0.019*** (3.00)	-0.009 (-0.58)	0.045* (1.84)	0.073*** (3.27)
λ_{C-D}	0.001 (0.20)	0.006 (0.67)	-0.011 (-0.51)	-0.024 (-0.72)	0.010 (0.57)
Panel D: Listing on E-F rated exchanges					
Dependent variable: CAR					
Independent variable:					
Intercept	0.010*** (3.97)	0.019*** (2.99)	-0.009 (-0.56)	0.045* (1.84)	0.092*** (4.27)
λ_{E-F}	-0.019*** (-6.07)	-0.008 (-1.10)	-0.043 (-1.35)	0.001 (0.03)	-0.025 (-1.47)

Table 3: Test of Differences: First- and Second-Stage

Notes: Columns 1 and 2 report the estimated difference and z-statistic for the first- and second-stage tests, respectively. In each panel, Column (1) reports estimations of $\mathbb{E}[X_j'\theta_j]_h - \mathbb{E}[X_j'\theta_j]_0$, the difference in expected probability of listing on j-rated exchange between assets with different listing history $h \in \{1,2,3,4\}$ and those never listed ($h = 0$). Column (2) reports the difference in estimated slope coefficients of IMRs, i.e., $\beta_{j,h} - \beta_{j,0}$, between assets with different listing history $h \in \{1,2,3,4\}$ and those never listed ($h = 0$). Differences for listings on AA-A rated exchanges are reported in Panel A, those on BB-B rated exchanges are in Panel B, those on C-D rated exchanges are in Panel C, and those on E-F rated exchanges are in Panel D. We use numerical levels 4, 3, 2, and 1 to denote listing on AA-A, BB-B, C-D, and E-F rated exchanges respectively for readability, as mentioned in Section 5.1. t-statistics are shown in parentheses. ***/**/* denote p<0.01/0.05/0.10.

$\mathbb{E}[X_j'\theta_j]_h - \mathbb{E}[X_j'\theta_j]_0$	First-stage diff (1)	$\beta_{j,h} - \beta_{j,0}$	Second-stage diff (2)
Panel A: Listing on AA-A rated exchanges (with numerical level of 4)			
$\mathbb{E}[X_4'\theta_4]_4 - \mathbb{E}[X_4'\theta_4]_0$	1.455*** (14.37)	$\beta_{4,4} - \beta_{4,0}$	-0.113* (-1.70)
$\mathbb{E}[X_4'\theta_4]_3 - \mathbb{E}[X_4'\theta_4]_0$	1.075*** (8.31)	$\beta_{4,3} - \beta_{4,0}$	-0.136** (-2.02)

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Table 3: Test of Differences: First- and Second-Stage (continued)

$\mathbb{E}[X_j'\theta_j]_h - \mathbb{E}[X_j'\theta_j]_0$	First-stage diff (1)	$\beta_{j,h} - \beta_{j,0}$	Second-stage diff (2)
$\mathbb{E}[X_4'\theta_4]_2 - \mathbb{E}[X_4'\theta_4]_0$	-0.871	$\beta_{4,2} - \beta_{4,0}$	-0.108
	(-0.46)		(-1.64)
$\mathbb{E}[X_4'\theta_4]_1 - \mathbb{E}[X_4'\theta_4]_0$	-3.895	$\beta_{4,1} - \beta_{4,0}$	-0.037
	(-0.93)		(-0.33)
Panel B: Listing on BB-B rated exchanges (with numerical level of 3)			
$\mathbb{E}[X_3'\theta_3]_4 - \mathbb{E}[X_3'\theta_3]_0$	1.396***	$\beta_{3,4} - \beta_{3,0}$	0.020
	(28.93)		(1.26)
$\mathbb{E}[X_3'\theta_3]_3 - \mathbb{E}[X_3'\theta_3]_0$	1.438***	$\beta_{3,3} - \beta_{3,0}$	0.011
	(25.34)		(0.64)
$\mathbb{E}[X_3'\theta_3]_2 - \mathbb{E}[X_3'\theta_3]_0$	1.760***	$\beta_{3,2} - \beta_{3,0}$	0.025
	(24.37)		(1.03)
$\mathbb{E}[X_3'\theta_3]_1 - \mathbb{E}[X_3'\theta_3]_0$	1.604***	$\beta_{3,1} - \beta_{3,0}$	0.040
	(11.73)		(1.13)
Panel C: Listing on C-D rated exchanges (with numerical level of 2)			
$\mathbb{E}[X_2'\theta_2]_4 - \mathbb{E}[X_2'\theta_2]_0$	1.778***	$\beta_{2,4} - \beta_{2,0}$	-0.010
	(41.40)		(-0.58)
$\mathbb{E}[X_2'\theta_2]_3 - \mathbb{E}[X_2'\theta_2]_0$	2.095***	$\beta_{2,3} - \beta_{2,0}$	-0.007
	(40.90)		(-0.36)
$\mathbb{E}[X_2'\theta_2]_2 - \mathbb{E}[X_2'\theta_2]_0$	1.849***	$\beta_{2,2} - \beta_{2,0}$	-0.022
	(26.92)		(-0.77)
$\mathbb{E}[X_2'\theta_2]_1 - \mathbb{E}[X_2'\theta_2]_0$	1.727***	$\beta_{2,1} - \beta_{2,0}$	-0.037
	(13.09)		(-1.04)
Panel D: Listing on E-F rated exchanges (with numerical level of 1)			
$\mathbb{E}[X_1'\theta_1]_4 - \mathbb{E}[X_1'\theta_1]_0$	1.426***	$\beta_{1,4} - \beta_{1,0}$	0.007
	(23.31)		(0.38)
$\mathbb{E}[X_1'\theta_1]_3 - \mathbb{E}[X_1'\theta_1]_0$	1.037***	$\beta_{1,3} - \beta_{1,0}$	0.019
	(5.15)		(0.98)
$\mathbb{E}[X_1'\theta_1]_2 - \mathbb{E}[X_1'\theta_1]_0$	1.372***	$\beta_{1,2} - \beta_{1,0}$	-0.019
	(15.49)		(-0.49)
$\mathbb{E}[X_1'\theta_1]_1 - \mathbb{E}[X_1'\theta_1]_0$	0.038	$\beta_{1,1} - \beta_{1,0}$	0.029
	(0.03)		(0.90)

6.3 Results for simultaneous listings

How much the market response to the implied information of higher-tier exchange evaluation in a listing (i.e., *informational substitute* effect)? How much of the listing effects can be attributed to the information purely about the listed exchange itself (i.e., *informational complement* effect)? In this section, we firstly present results for the two-stage estimation necessary for recovering parameters and then the disentangling of how the market reacts to

such two types of effects in simultaneous listings.

Panel A of Table 4 reports the first-stage multivariate probit estimates for the simultaneous listings with previously highest listed exchanges in the AA–A category. The results largely resemble those in single-exchange listings illustrated in Panel A of Table 1, except the coefficient sign for PR_FUT_RATE_4. It shows that for simultaneous listings with prior AA-A listings, matured assets with larger SIZE and lower VOLATL are preferred by not only AA–A exchanges but also those in lower rating categories, unlike in single-exchange listings where only AA–A exchanges prefer larger SIZE and lower VOLATL. Because in simultaneous listings, assets' features preferred by exchanges in multiple tiers are involved, this pattern suggests that qualities favored by higher-tier exchanges dominate those by lower-tier ones.

Panel B of Table 4 reports the estimated correlations among the private information. All pairwise correlations are significantly positive, ranging from 0.258 for $(\epsilon_{i3}, \epsilon_{i4})$ to 0.599 for $(\epsilon_{i1}, \epsilon_{i3})$. Among listings on sub–top-tier categories, their correlation with the AA–A listing is always the smallest. For instance, the private information correlation between AA-A and C-D listings ($\rho_{2,4} = 0.338$) is lower than that for pair of BB-B and C-D ($\rho_{2,3} = 0.540$). Similarly, the correlation of private information between AA-A and E-F listings ($\rho_{1,4} = 0.269$) is lower than that for both the pairs BB-B&E-F ($\rho_{1,3} = 0.599$) and C-D&E-F ($\rho_{1,2} = 0.381$).

Panel C of Table 4 represents both the univariate estimates with (22) (Column (1) to Column (4)) and the estimates of the multivariate specification in (24) (Column (5)). Estimation results for the univariate and multivariate cases are highly consistent: slope coefficients for AA-A (β_4), BB-B (β_3), and C-D (β_2) listing are positive while that for E-F listing (β_1) is negative. However, only the estimate for AA-A listing is statistically significant. This pattern mirrors the unconditional event-study findings in Section 4 that market reactions diminish as the rating of the listing exchange declines, even becoming negative for E-F listings.

Results of the decomposing (*informational substitute* effect versus *informational complement* effect) are summarized in Table 5. For E-F listings, the part of marginal CAR from the market's reaction to the potential uplings (*informational substitute* effect) is 0.078, which largely offsets the *informational complement* effect) calculated as -0.105, resulting in minor negative total effect -0.026, i.e., β_4 estimated in Table 4 and the one reconstructed by our decomposition. Similarly for C-D listings, the *informational substitute* effect is calculated as

0.089, which more than offsets the *informational complement* effect of -0.027, so the total effect captured by the slope coefficient β_2 is positive, estimated as 0.007 while reconstructed as 0.062. Therefore for listings on medium-to-bottom tier exchanges, as large as 76.9% (C-D listing) of the valuation effects reflects investor reactions to the features related to other higher-tier exchanges (*informational substitute* effect), while their signs are opposite to the effects purely coming from the listed exchange itself (*informational complement* effect).

For BB-B listings, the decomposed *informational substitute* effect has the same sign as the *informational complement* effect, and former accounts for more than half of the total impact (68.2 %). Since there is no exchange rated above AA-A, the *informational complement* effect alone explains the entire market reaction to AA-A listings.

Thus, we observe that the decomposition of listing effects varies across exchanges of different rating tiers. The sign and magnitude of both the *informational substitute* effect and the *informational complement* effect depend on two factors: the market's sensitivity to each component of the decomposed information (i.e., $\alpha_j^{\perp}$ versus α_j); and the correlation between those components. Although listings on E–F exchanges invoke market reactions to potential listings on all three higher tiers (C–D, BB–B, and AA–A), the aggregate implied effect not necessarily exceed that of C–D listings, which only imply two upper-tier listings (BB–B and AA–A). One reason is that the market reacts negatively to the implied C–D listing, i.e., α_2 is –0.032, thereby dampening the *informational substitute* effect for E–F listings. Another reason is that the projection parameter from C–D to AA–A listings ($\gamma_{24} = 0.213$) exceeds the corresponding projection from E–F to AA–A ($\gamma_{14} = 0.112$), so C–D listings reveal more AA–A–related information and thus elicit stronger market response.

Notably, the market's sensitivity to implied information from a listing on exchange k ($\alpha_k^{\perp}$) and to revealed information from an actual listing on this exchange k (α_k) share the same sign, while the calculated value of α_4 (0.071) and α_3 (0.119) are even larger than $\alpha_4^{\perp}$ (0.046) and $\alpha_3^{\perp}$ (0.009). This indicates that although some information overlaps between listings on tier j and higher-tier k exchanges, the market interprets such *informational substitute* as a signal of a listing on the higher-tier exchange k rather than on exchange j. Investors treat the implied signal as if they are partially observing a listing on the higher-tier exchange k.

We also perform the two-stage estimation for simultaneous listings whose highest prior

listing was in the BB–B category, results of which are summarized in Online Appendix G. Unlike the AA–A case, the estimated slope coefficients for listings in all 4 tiers are positive. However, the *informational complement* effect still declines as the exchange rating falls, resembling the AA–A results. Although the pre-decomposition market reactions for C–D ($\beta_2 = 0.148$) and E–F ($\beta_1 = 0.149$) listings are positive, their *informational complement* effect remain negative (–0.011 for C–D and –0.018 for E–F), consistent with findings in AA–A case. Moreover, larger projection coefficients (γ_{jk}) amplify the *informational substitute* effect, accounting for up to 94.4 % (C-D listing) of the total impact in our estimation. The different results of disentangling for those previously listed on AA-A and BB-B rated exchanges also resonate with the informational substitute hypothesis discussed in Section 6.2. When an asset has already been listed on AA–A exchanges, established information channels reduce the market's sensitivity to additional implied signals from higher-tier listings. In contrast, prior BB–B listings convey less top-tier information, so the market reacts more strongly to implied higher-tier listings in that case (larger $\alpha_4^{\perp}/\alpha_3^{\perp}$ and α_4/α_3 in magnitude).

Our results can be summarized as:

Finding 4 *Following the way of linear information decomposing in proposition 4, a substantial share of the market reaction to private information revealed by listings on sub-top-tier exchanges is attributable to the response to informational substitute, ranging from 42.9% to 94.4% (with the remainder attributable to informational complement), depending on the tier of the listing exchange and the tiers of exchanges on which the asset was previously listed.*

Therefore, it is hasty to draw any conclusion on the valuation effects of the listing on certain exchange without considering effects from other potential listing mixed.

Table 4: Two-stage estimation for simultaneous listings with previous listing on exchanges in AA-A group

Notes: This table represents the two-stage estimation results based on simultaneous listings with prior highest rated exchanges in AA-A group, following the procedure illustrated in Online Appendix F. Panel A reports the first-stage multivariate probit estimates based on (28) with ϵ_{ij} following multivariate normal distribution. Results for listings on AA-A rated exchanges are in Column (1), those of BB-B listings are in Column (2), C-D in Column (3), and E-F in Column (4). Panel B shows the private-information correlations. The pairwise correlations are shown in the off-diagonal cells in Panel B. For example, the correlation between BB-B and AA-A listings is recorded at the second row under Column (1). Panel C shows the second-stage IMR estimates, while Column (1) to (4) for univariate and Column (5) for multivariate estimation. For the univariate ones we adopt (22) while for the multivariate one we use (24), but both cases are based on the IMRs from the multivariate probit estimation. t-statistics are shown in parentheses. ***/**/* denote p<0.01/0.05/0.10.

Listing	AA-A (1)	BB-B (2)	C-D (3)	E-F (4)	(5)
Panel A: First-stage estimation					
Dependent variable: $LIST_j$					
Independent variables:					
Intercept	-4.826***	-4.356***	-4.550***	-4.305***	
	(-14.01)	(-17.91)	(-17.57)	(-16.57)	
VOLUME	-5.260	-2.679	-6.022	-13.614	
	(-0.47)	(-0.40)	(-0.60)	(-1.06)	
NO_CHAIN	0.122	0.060	0.134	0.105	
	(1.05)	(0.67)	(1.49)	(1.16)	
VOLATL	0.577	-2.554***	-1.610*	-0.834	
	(0.84)	(-2.64)	(-1.72)	(-0.98)	
RUNUP	-0.000	-0.000	0.000	0.000	
	(-0.59)	(-0.77)	(0.71)	(0.69)	
SIZE	0.130***	0.149***	0.147***	0.131***	
	(7.90)	(12.08)	(11.41)	(9.87)	
PR_FUT_RATE_4	1.377***	1.903***	1.766***	1.815***	
	(9.16)	(16.14)	(14.89)	(15.13)	
Panel B: Private-information correlations					
AA-A	-	0.258***	0.338***	0.269***	
		(3.73)	(5.26)	(3.67)	
BB-B	0.258***	-	0.540***	0.599***	
	(3.73)		(10.62)	(12.54)	
C-D	0.338***	0.540***	-	0.381***	
	(5.26)	(10.62)		(6.54)	
E-F	0.269***	0.599***	0.381***	-	
	(3.67)	(12.54)	(6.54)		
Panel C: Second-stage estimation					
Dependent variable: CAR					
Independent variable: IMR terms					
Intercept	0.019	0.024	0.027	0.057***	0.017
	(1.12)	(1.05)	(1.30)	(2.77)	(0.15)

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Table 4: Two-stage estimation for simultaneous listings with previous listing on exchanges in AA-A group (continued)

Listing	AA-A (1)	BB-B (2)	C-D (3)	E-F (4)	(5)
λ_{AA-A}	0.050**	-	-	-	0.046*
	(2.50)	-	-	-	(1.93)
λ_{BB-B}	-	0.015	-	-	0.020
	-	(0.87)	-	-	(0.50)
λ_{C-D}	-	-	0.014	-	0.007
	-	-	(0.76)	-	(0.18)
λ_{E-F}	-	-	-	-0.025	-0.026
	-	-	-	(-1.43)	(-0.82)

Table 5: Disentangling effects for simultaneous listings with highest previous listed exchanges in AA-A group

Notes: This table summarizes results of disentangling the listing effects into the two components illustrated by (27): the *informational complement* effect and *informational substitute* effect. Results in this table are calculated with data of simultaneous listings with highest previous listed exchanges in AA-A group Panel A reports the calculated projection parameters, γ_{jk}, using (F1) and estimated covariance summarized in Panel B of Table 4. Panel B shows the constructed $\alpha_j^{\perp}$ and α_j solved from (F5) and (F2) with estimated slope coefficients, β_j, in Panel C of Table 4. Panel C summarizes the estimated slope coefficients, β_j, as well as the reconstructed ones based on the decomposition. The slope coefficient for each rating category listing is decomposed into two parts, which are shown in the two rows *informational complement* effect and *informational substitute* effect separately. We also report the percentage of effect of each component to the total.

Listing	AA-A	BB-B	C-D	E-F
Panel A: Estimation of γ_{jk}				
E-F ($j=1$)	0.112 (γ_{14})	0.543 (γ_{13})	0.050 (γ_{12})	—
C-D ($j=2$)	0.213 (γ_{24})	0.485 (γ_{23})	—	—
BB-B ($j=3$)	0.258 (γ_{34})	—	—	—
AA-A ($j=4$)	—	—	—	—
Panel B: Calculated $\alpha_j^{\perp}$ and α_j				
$\alpha_j^{\perp}$	0.046($\alpha_4^{\perp}$)	0.009($\alpha_3^{\perp}$)	-0.040($\alpha_2^{\perp}$)	-0.167($\alpha_1^{\perp}$)
α_j	0.071(α_4)	0.119(α_3)	-0.032(α_2)	-0.167(α_1)
Panel C: Disentangling effects for simultaneous listings				
β_j	0.046	0.020	0.007	-0.026
Informational complement effect	0.046	0.009	-0.027	-0.105
Informational substitute effect	0.000	0.018	0.089	0.078
Reconstructed β_j	0.046	0.027	0.062	-0.026
Informational complement effect %	100.0%	31.8%	23.1%	57.1%
Informational substitute effect %	0.0%	68.2%	76.9%	42.9%

7 Information distance and the listing premia

Proposition 5 predicts increasing price reaction magnitude with information distance. It implies that with fixed listing exchange j, the expected listing premium for a token with highest prior listing on exchange h is increasing in the information distance d_{jh} between the current tier j and the highest prior tier h. Moreover, the marginal sensitivity of CAR to each unit of private information (the IMR slope β_j) is also increasing in d_{jh}. The first claim is a conditional-mean prediction on the level of the CAR. The second is a structural prediction on the slope of the inverse Mills ratio (IMR) term in the second-stage regression. Both claims can be tested within a single per-tier regression of CAR on the empirical distance, the IMR, and their interaction.

The theoretical distance is $d_{jh} \equiv 1 - R^2_{jh}$, where R^2_{jh} measures the share of tier-j private information already contained in the tier-h signal observed at the prior listing. We construct an empirical analog at the token level using the first-stage probit estimates. For asset i, let $\hat{\theta}_j$ denote the pooled probit coefficient vector for current tier j (estimated on the full single-listing sample, unconditional on prior-listing state). The characteristic-based distance between current tier j and prior tier h for asset i is

$$\mathrm{DIST}_i = \left|\Phi(X'_{ij}\hat{\theta}_j) - \Phi(X'_{ij}\hat{\theta}_h)\right|,$$

where X_{ij} is the asset-characteristic vector at the time of the listing and Φ is the standard normal CDF. By construction, $\mathrm{DIST}_i = 1$ when the listing has no prior ($h = 0$), reflecting the maximum informational distance between a first-time listing and the empty prior history. The pooled-per-tier specification of the first-stage probits and the resulting $\hat{\theta}_j$ vectors are documented in Online Appendix H.

For each current tier $j \in \{\text{AA-A}, \text{BB-B}, \text{C-D}, \text{E-F}\}$ we estimate

$$\mathrm{CAR}_i = \alpha + \beta_1 \,\mathrm{DIST}_i + \beta_2 \,\mathrm{IMR}_i + \beta_3 \,(\mathrm{DIST}_i \times \mathrm{IMR}_i) + \varepsilon_i, \tag{29}$$

on the same single-listing sample used in Section 6.2. The IMR term is estimated in the same manner with that in Section 5. The conditional-mean prediction of Proposition 5 implies

$\beta_1 > 0$. The structural prediction implies $\beta_3 > 0$, since the IMR slope itself scales with d_{jh} and an interaction with the empirical distance is the regression-form analog of that scaling. The conditional-mean prediction is the broader claim and the structural prediction is the sharper one, since its identification also depends on per-tier IMR slopes.

Table 6: Information distance regression with DIST_i, per current tier

Notes: OLS estimates of (29) per current tier j. The sample of 5,710 events is the subset of single-listing events with complete first-stage covariates, as detailed in Online Appendix H. Heteroskedasticity-robust t-statistics in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Variable	AA-A ($j = 4$)	BB-B ($j = 3$)	C-D ($j = 2$)	E-F ($j = 1$)
Intercept	0.0082***	0.0009	-0.0151*	0.0024
	(2.86)	(0.20)	(-1.79)	(0.58)
DIST	0.0467***	0.0677***	0.0840***	0.0657***
	(2.76)	(3.27)	(3.74)	(3.00)
IMR	0.0148**	0.0052	0.0012	-0.0151***
	(2.52)	(0.93)	(0.11)	(-2.83)
DIST × IMR	0.1233*	-0.0060	0.0055	-0.0232
	(1.91)	(-0.25)	(0.20)	(-0.78)
N	5710	5710	5710	5710
Adj. R^2	0.0082	0.0042	0.0056	0.0072

Table 6 reports the per-tier estimates of (29). The coefficient on information distance, β_1, is positive and statistically significant at the 1% level for every current tier, ranging from 0.047 for AA–A to 0.084 for C–D. This evidence supports the conditional-mean prediction of Proposition 5 across the full tier ladder. The interaction coefficient, β_3, is positive and significant for AA–A listings (0.123, $t = 1.91$), but is not for BB–B, C–D, or E–F listings. The AA–A estimate supports the structural prediction of Proposition 5 in the tier where the IMR slope is itself estimated to be significantly positive. By contrast, the lack of significant interaction effects in the lower tiers is consistent with the pattern documented in Section 6.2, where the second-stage IMR coefficients for BB–B, C–D, and E–F are less statistically significant, making it unlikely that an interaction term scaled by the IMR would be estimated with sufficient significance in those tiers.[9]

[9]As a robustness check, we replace the characteristic-based distance with the exchange-rating difference $\text{DIST_ord}_i = j - h$. The qualitative pattern preserves and detailed estimates are reported in Online Appendix H.

Finding 5 *The listing premium increases with on the characteristic-based distance between the current and prior tiers across all four current tiers, and at the AA–A tier the per-unit sensitivity of CAR to private information itself increases in distance. These results support both the conditional-mean and structural-slope predictions of Proposition 5.*

8 Exchange-Failure Natural Experiments

Our model characterizes an exchange listing as a noisy certification of token quality, with two main implications. First, the price reaction to a listing is increasing in the precision of the certifier's signal, and hence in the tier of the listing exchange, because higher-tier exchanges screen tokens more accurately. Second, when a token has already been listed on other exchanges, those listings serve as partial *informational substitutes* for one another, leading to a market reaction that is smaller in magnitude than it would be if the token had no prior listings. The same implications extend to the *removal* of a certifier. If a listing represents certification information, and if listings on different exchanges are partial substitutes, then the price reaction to an exchange failure or collapse should be smaller for tokens that retain listings on other exchanges than for tokens whose only certification venue was the failed exchange. In addition, price reactions to an exchange failure should be larger in magnitude when the failed exchange has a higher rating, since the lost informational content is greater.

We test these two predictions using two unrelated quasi-experimental shocks to the availability of exchange certifiers: the November 2022 collapse of FTX, an A-rated exchange, and the April 2023 SEC complaint against Bittrex, a B-rated exchange. Both events removed an exchange from the certification pool in a manner plausibly orthogonal to the quality of most individual listed tokens. The two shocks differ in the tier of the removed certifier: FTX was A-rated, whereas Bittrex was B-rated, two tiers below.

8.1 Identification strategy and methodology

For each event, the affected tokens are those listed on the failed exchange as of the day before the event. Within such set of tokens, we define $\text{TREATED}_i = 1$ for tokens with no contemporaneous listing on any other higher-tier exchange, and $\text{TREATED}_i = 0$ for tokens

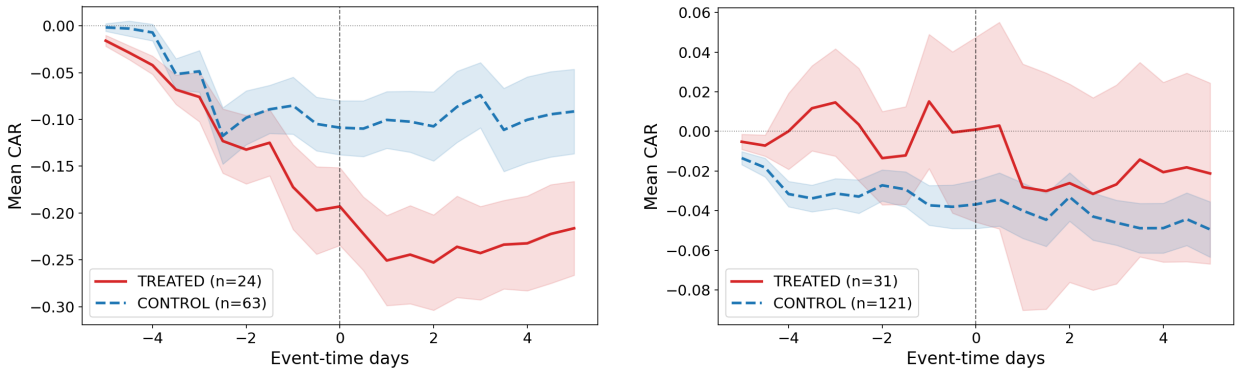
with at least one such listing. The substitute effect predicts more negative event-window CARs for treated tokens than for control tokens. Tokens that retain a higher-tier listing are partially insulated from the loss of the failed certifier because their remaining listings provide informational redundancy. It also predicts larger absolute event-window CARs when the failed exchange has a higher rating, since the loss entails greater informational content. Taken together, these mechanisms imply that the treated-control differential should be strongest when the failed exchange sits at or near the top of a token's certification pool, as in the case of FTX, an A-rated exchange. By contrast, the differential should be small or negligible when the failed exchange sits at the lower tier of the pool, as in the case of Bittrex, a B-rated exchange. In that case, the overall reaction to losing the certifier is bounded by the relatively modest informational content of a B-tier certification, leaving little scope for a treated-control differential to emerge.

For each event, the higher-tier substitute set comprises all exchanges rated above the failed exchange that were active on the event date. Abnormal returns and CARs are computed using the market-model specification described in Section 4. Event time is defined as November 11, 2022, for the FTX collapse and April 17, 2023, for the Bittrex SEC complaint. Online Appendix I reports the exchange composition of each higher-tier set, the calibration of the estimation window for the FTX event, and the timeline of public milestones surrounding each event.

For event window (τ_1, τ_2) we estimate

$$\mathrm{CAR}_i(\tau_1, \tau_2) = \alpha + \beta_{\mathrm{TREATED}}\,\mathrm{TREATED}_i + \gamma' Z_i + \delta_{c(i)} + \varepsilon_i, \tag{30}$$

where Z_i is a vector of asset characteristics measured at the event date that includes the controls used in Section 6 and $\mathrm{NO_HIGHER}_i$, the count of higher-tier exchanges on which asset i is listed at the event date. $\mathrm{NO_HIGHER}_i$ is included as a continuous control so the binary TREATED indicator isolates the discrete at least one higher-tier substitute distinction rather than conflating it with breadth of higher-tier coverage. $\delta_{c(i)}$ are blockchain fixed effects, and standard errors are heteroskedasticity-robust. Detailed definitions of variables in Z_i are in Online Appendix I.



(a) FTX collapse

(b) Bittrex SEC complaint

Figure 3: CAR paths by group around the FTX collapse (Panel a) and the Bittrex SEC complaint (Panel b). TREATED and CONTROL groups are defined in Section 8.1. Shaded bands are ±1 standard error of the cross-sectional mean.

It is expected that $\beta_{\text{TREATED}} < 0$ for the FTX collapse.[10] For tokens in the control group ($\text{TREATED}_i = 0$), the retained AA listings serve as partial informational substitutes for the certification information lost when FTX fails, attenuating the negative price reaction. Tokens in the treated group ($\text{TREATED}_i = 1$) hold no such higher-tier substitute, and the absence of attenuation implies a more negative price reaction than for the control group. For the Bittrex SEC complaint it is expected that β_{TREATED} to be negative but small in magnitude or even negligible. The modest informational content of a B-rated certification bounds the absolute price reaction in both groups, so the between-group differential is expected to be correspondingly small.

8.2 Results

Figure 3 plots the daily mean CAR of tokens in the CONTROL and TREATED groups over the $[-5, +5]$ event window for each event. Panel (a) shows the case of FTX collapse, in which the TREATED average CAR drops to roughly -0.22 over the eleven-day window, while the CONTROL average lands near -0.09, a separation of about thirteen percentage points. For Bittrex SEC complaint in Panel (b), TREATED and CONTROL paths overlap throughout the event window, with no visible separation around $t = 0$. Table 7 reports group-level

[10]The FTX main specification excludes seven FTX-affiliated tokens that faced direct Alameda-holdings liquidation shocks. The list of excluded tokens are reported in Online Appendix I. The Bittrex test applies no analogous exclusion.

average CARs across five event windows. Panel A documents the substitute effect for the FTX collapse. Tokens in the TREATED group, which retained no AA listing to absorb the loss of FTX certification, experienced large and statistically significant negative CARs, ranging from -0.09 to -0.22. By contrast, CONTROL tokens, which retained at least one AA listing, exhibited CARs close to zero. The TREATED $-$ CONTROL differential ranges from nine to thirteen percentage points, with the strongest statistical evidence concentrated in the main short-window specifications. This pattern indicates the price-protection value of retaining an AA substitute when an A-rated certifier fails. Panel B reports the estimates for the Bittrex SEC complaint. In contrast to the FTX results, the CARs are small for both TREATED and CONTROL tokens, and the TREATED $-$ CONTROL differences remain economically modest across all event windows, the pattern consistent with our prediction.

Table 8 reports the estimated β_{TREATED} from the cross-sectional regression in (30). In Panel A for FTX collapse, the coefficient remains negative across all event windows after controlling for asset characteristics and blockchain fixed effects, with magnitudes ranging from -0.13 for the $[-1,+1]$ window to -0.34 for the $[-1,+10]$ window. The effects are economically large. An FTX-listed token with no AA substitute underperformed an FTX-listed token with at least one AA substitute by approximately 22% over the $[-1,+5]$ window and 34% over the $[-1,+10]$ window. In contrast, the Bittrex estimates are small in magnitude (alsostatistically insignificant) across all event windows. This pattern is consistent with the view that the loss of a B-rated certifier generated little incremental price response for tokens without a higher-tier substitute.

Table 7: CARs around exchange-failure events by group and event window

Notes: Panel A reports group means of cumulative abnormal returns (CARs) for FTX-listed tokens around the 2022-11-11 FTX collapse. Panel B reports the analogous statistics for Bittrex-listed tokens around the 2023-04-17 SEC complaint. TREATED and CONTROL groups, sample exclusions, and per-event higher-tier substitute sets are defined in Section 8.1 and Online Appendix I. The TREATED and CONTROL rows report the group mean CAR with the t-statistic in parentheses. The TREATED $-$ CONTROL row reports the difference in means with the Welch t-statistic in parentheses. ***/**/* denote significance at the 1%/5%/10% levels (Welch test for the difference row).

Event window of CAR	$[-5,+5]$	$[-1,+1]$	$[-1,+3]$	$[-1,+5]$	$[-1,+10]$
Panel A: FTX collapse ($N_{\text{TREATED}}=24$, $N_{\text{CONTROL}}=63$)					

Continued on next page

Table 7: CARs around exchange-failure events by group and event window (continued)

Event window of CAR	$[-5,+5]$	$[-1,+1]$	$[-1,+3]$	$[-1,+5]$	$[-1,+10]$
TREATED	-0.216 (-4.31)	-0.126 (-2.69)	-0.118 (-2.60)	-0.091 (-2.07)	-0.091 (-1.54)
CONTROL	-0.091 (-2.03)	-0.011 (-0.71)	0.015 (0.73)	-0.002 (-0.06)	0.040 (1.32)
TREATED − CONTROL	-0.125^{*} (-1.85)	-0.114^{**} (-2.32)	-0.133^{**} (-2.67)	-0.089 (-1.55)	-0.130^{*} (-1.97)
Panel B: Bittrex SEC complaint ($N_{\text{TREATED}} = 31$, $N_{\text{CONTROL}} = 121$)					
TREATED	-0.021 (-0.46)	-0.016 (-0.31)	-0.015 (-0.37)	-0.009 (-0.27)	-0.001 (-0.02)
CONTROL	-0.049 (-3.53)	-0.011 (-1.13)	-0.017 (-1.95)	-0.020 (-1.79)	-0.007 (-0.29)
TREATED − CONTROL	0.028 (0.59)	-0.005 (-0.10)	0.002 (0.05)	0.011 (0.31)	0.006 (0.10)

Table 8: Cross-sectional regression results for (30)

Notes: The table reports OLS estimates of β_{TREATED} from (30), separately for the FTX collapse (Panel A) and the Bittrex SEC complaint (Panel B, anchor 2023-04-17). Heteroskedasticity-robust standard errors in parentheses. $^{***}/^{**}/^{*}$ denote significance at the 1%/5%/10% levels.

Event window of CAR	$[-5,+5]$	$[-1,+1]$	$[-1,+3]$	$[-1,+5]$	$[-1,+10]$
Panel A: FTX collapse ($N = 84$)					
β_{TREATED}	-0.182 (0.164)	-0.127^{*} (0.067)	-0.176^{**} (0.077)	-0.217^{**} (0.108)	-0.343^{***} (0.130)
Controls Z_i	Yes	Yes	Yes	Yes	Yes
Chain FE	Yes	Yes	Yes	Yes	Yes
Panel B: Bittrex SEC complaint ($N = 135$)					
β_{TREATED}	0.054 (0.077)	0.057 (0.073)	0.001 (0.060)	0.015 (0.052)	-0.018 (0.111)
Controls Z_i	Yes	Yes	Yes	Yes	Yes
Chain FE	Yes	Yes	Yes	Yes	Yes

9 Post-listing Evaluation

Results in the previous sections show that listings on lower-tier exchanges reveal information about potential uplistings (i.e., *informational substitute*), but how such information changes investors' perception about future listings? Do investors expect such information to be

confirmed by actual listings in the near future? In this section we examine the role of current listings in predicting future listings and the post-listing performance of assets with different future listing outcomes.

9.1 The Role of Current Listing in Predicting Future Listings

Listings on lower-tier exchanges reveal qualities favored by both higher- and lower-tier exchanges, which may be a signal that the asset is more likely to be listed on higher-tier exchanges than usual later in time. To examine this possibility, we examine if current listings have any power to predict future listings within certain post-listing windows.

Table 9 summarizes the preliminary evidence on the ability of current listings to predict 1-month and 4-month ahead future listings. When examining one type of the post-listing window (i.e., 1-month or 4-month), we classify events of listing asset i on exchanges of certain rating category ($\text{LIST}_{it} \in \{\text{AA-A}, \text{BB-B}, \text{C-D}, \text{E-F}\}$) into 4 groups: assets that were later listed on exchanges with increased rating tier (e.g., from C-D to BB-B), those that were later listed on exchanges with unchanged rating tier (e.g., from BB-B to BB-B), those that were later listed on exchanges with decreased rating tier (e.g., from BB-B to C-D), and ones that were not listed on any exchange later in the window. Within events of listing on certain tiered exchanges, we calculate the percentage of each of the 4 groups. To estimate the general likelihood of future listings, we select the characteristic-controlled benchmark asset for each listing event based on the procedure by Barber and Lyon (1997). For listing event of asset i at time t, we sort all other assets in the same asset category by the absolute difference in SIZE, VOLUME, VOLATL at time t with those of asset i, and select the one with the smallest difference as the benchmark. [11]

Results in Table 9 suggest that current listings do have power in predicting future listings. Within the benchmark group, only about 1% (100/7678) and 3% (264/7678) of assets were later listed on exchanges with increased rating tier within 1-month and 4-month windows respectively. However, once controlling for the tiers of current listings, it is more likely to see future listings on exchanges with increased rating tier. For example, among assets listed on

[11] Asset category is defined and given by CoinGecko, which classifies cryptocurrencies into categories such as "DeFi", "NFT", etc.

Table 9: Future listings in the post-listing window.

Notes: This table presents the the number of assets that were listed on exchanges with increased tier, unchanged tier, decreased tier, or not listed on any exchange within the post-listing windows after events of listing on exchanges in 4 rating categories (AA-A, BB-B, C-D, E-F) separately. Panel A reports the results for future listings within post-listing window of 1 month (30 days), while Panel B reports those within 4 months (120 days). For each rating category of current listing, we also report the results for characteristic-controlled benchmark assets selected based on the procedure by Barber and Lyon (1997). We select asset with smallest absolute difference in SIZE, VOLUME, VOLATL at the time of the listing event within the same asset category as the benchmark. We examine the 6717 events of listing on single exchanges, 1007 of which are listings on exchanges that have not been rated by CoinGecko yet and thus are treated as benchmarks. The percentages in parentheses denote the fraction of assets that were further listed on exchanges with increased tier, unchanged tier, decreased tier, or not listed on any exchange within the post-listing window among all listing events in the same rating category.

Current Exchange Listed	Rating tier increased	Rating tier unchanged	Rating tier decreased	No listing	All
Panel A: future listings within 1 month (30 days) after the current listing					
AA-A	0 (0%)	29 (9%)	116 (36%)	177 (55%)	322
BB-B	52 (3%)	116 (7%)	359 (22%)	1071 (67%)	1598
C-D	270 (10%)	241 (9%)	92 (3%)	2116 (78%)	2719
E-F	275 (26%)	29 (3%)	0 (0%)	767 (72%)	1071
Benchmark	100 (1%)	243 (3%)	1166 (15%)	6169 (80%)	7678
Panel B: future listings within 4 months (120 days) after the current listing					
AA-A	0 (0%)	81 (25%)	184 (57%)	57 (18%)	322
BB-B	131 (8%)	280 (18%)	583 (36%)	604 (38%)	1598
C-D	1034 (38%)	439 (16%)	152 (6%)	1094 (40%)	2719
E-F	584 (55%)	47 (4%)	0 (0%)	440 (41%)	1071
Benchmark	264 (3%)	535 (7%)	2057 (27%)	4822 (63%)	7678

E-F rated exchanges, 26% (275/1071) were later listed on exchanges with increased rating tier within 1-month window, while 55% (584/1071) in the 4-month window. Similar patterns can also be observed for assets listed on C-D and BB-B rated exchanges.

Table 10: Probit model estimation for future listings

Notes: This table represents the estimates of the probit model specified in (31) for future listings within two post-listing windows: 1 month (30 days) in Panel A and 4 months (120 days) in Panel B. The dependent variable is an indicator variable, representing the actualized status of future listing, that equals one if asset i was listed on exchanges with increased or unchanged rating tier within the post-listing window after being listed on exchange j. In addition to the specification in (31), we also estimate a simpler model without asset characteristic variables, i.e., Y'_{ij}, the results of which are reported in the first column of each panel. t-statistics are shown in parentheses. ***/**/* denote p<0.01/0.05/0.10.

Model Specification	Without Characteristics Variables Y'_{ij}	With Characteristics Variables Y'_{ij}
Panel A: future listings within 1 month (30 days) after the current listing		
Dependent variable: UP_EQUAL_30$_{ij}$		
Independent variables:		
Intercept	-1.699*** (-67.90)	-3.026*** (-20.52)
LIST_AA_A	0.358*** (3.54)	0.270*** (2.70)
LIST_BB_B	0.446*** (9.10)	0.447*** (9.05)
LIST_C_D	0.813*** (21.75)	0.809*** (21.21)
LIST_E_F	1.127*** (23.62)	1.132*** (23.30)
VOLUME	-	3.235** (2.12)
SIZE	-	0.070*** (9.31)
VOLATL	-	0.974*** (2.71)
RUNUP	-	-0.000 (-0.28)
NO_CHAIN	-	0.017 (0.72)
Panel B: future listings within 4 months (120 days) after the current listing		
Dependent variable: UP_EQUAL_120$_{ij}$		
Independent variables:		
Intercept	-1.259*** (-65.26)	-2.737*** (-22.53)
LIST_AA_A	0.589*** (7.53)	0.499*** (6.44)
LIST_BB_B	0.607*** (15.56)	0.620*** (15.83)
LIST_C_D	1.364*** (44.19)	1.385*** (43.64)
LIST_E_F	1.484*** (34.36)	1.501*** (34.40)
VOLUME	-	2.029 (1.28)
SIZE	-	0.082*** (13.08)
VOLATL	-	0.588* (1.74)
RUNUP	-	-0.000 (-0.75)
NO_CHAIN	-	-0.020 (-1.01)

To statistically test the power of current listings in predicting future listings, we estimate a probit specification with the following underlying latent variable for future listings on

exchanges of increased or unchanged rating tier after asset i has been listed on exchange j:

$$\begin{aligned} \text{UP_EQUAL_DAYS}^*_{ij} = \alpha_0 &+ \alpha_1 * \text{LIST_AA_A}_{ij} + \alpha_2 * \text{LIST_BB_B}_{ij} \\ &+ \alpha_3 * \text{LIST_C_D}_{ij} + \alpha_4 * \text{LIST_E_F}_{ij} \\ &+ Y'_{ij}\alpha_{\mathbf{5}} + \epsilon_{ij}, \end{aligned} \tag{31}$$

where LIST_AA_A_{ij}, LIST_BB_B_{ij}, LIST_C_D_{ij}, and LIST_E_F_{ij} are indicator variables for whether asset i is listed on exchange j with corresponding rating category respectively. Y'_{ij} is a vector of asset characteristic variables at the time of listing, including VOLUME, SIZE, VOLATL, RUNUP, and NO_CHAIN, as defined in Section 6.

Table 10 reports the estimation results of the probit model specified by (31) for future listings within two post-listing windows: 1 month (30 days) in Panel A and 4 months (120 days) in Panel B. In addition to the original specification, we also estimate a simpler model without asset characteristic variables, i.e., Y'_{ij}, the results of which are reported in the first column of each panel. As expected, current listings have power to predict future listings on exchanges with increased or same rating tier, evidenced by the positive and significant coefficients of listing tier indicators, i.e., LIST_AA_A_{ij}, LIST_BB_B_{ij}, LIST_C_D_{ij}, and LIST_E_F_{ij}, in both panels and both specifications. Moreover, it is shown that coefficients for the listing tier indicators are more significant both statistically and economically in the 4-month window than those in the 1-month window, indicating that the role of current listings in predicting future listings is more pronounced over a longer horizon.

9.2 Post-listing Valuation Effects

Investors may revise their beliefs about asset quality based on current listings and expectations of future listings. These beliefs could be further adjusted when anticipated signals are confirmed by actual future listings, resulting in differential post-listing performance across assets depending on their subsequent listing outcomes. We test our conjecture by comparing risk-adjusted performance measures for assets in different groups based on their future listing outcomes, constructing buy-and-hold abnormal returns (BHAR) over post-listing windows of 1 month (30 days) and 4 months (120 days) respectively.

We apply the the characteristic-based matching approach (Barber & Lyon, 1997; Lyon et al., 1999) to construct the reference portfolio for each asset i at the time of its listing on exchange j. Specifically, we sort all other assets in the same asset category by the absolute difference in SIZE, VOLUME, VOLATL at the time of listing with those of asset i (i.e., Euclidean distance in the size–volume–volatility space), and then select the closest 10 assets to construct the equally-weighted reference portfolio. In this way, assets in the reference portfolio are in the same asset category while having similar characteristics as the listed asset at the time of listing.

With the constructed reference portfolio, we calculate the BHAR for listing asset i on exchange j over the post-listing window of τ days as:

$$\text{BHAR}_{i,j,[6,\tau]} = \prod_{t=6}^{\tau}(1 + r_{it}) - \prod_{t=6}^{\tau}(1 + r_{bt}), \tag{32}$$

where r_{it} is the daily return of asset i at day t after the listing event window (our event window is defined to be $[-5, 5]$ days around the listing event), and r_{bt} is the daily return of the reference portfolio at day t. We use $\tau = 30$ and $\tau = 120$ to capture the 1- and 4-month post-listing drifts.

Table 11 reports the cross-sectional average BHARs for assets grouped by their current listing exchange rating category and future listing outcomes within the post-listing windows. According to Lyon et al. (1999), we adopt skewness-adjusted t-statistics. For cases of shorter post-listing window (i.e., 1 month) in Panel A, we find that assets with equal or increased tier for future listings, which confirms the information implied from the current listing, experience significant positive post-listing abnormal returns, while those with decreased tier for future listings even elicit negative post-listing market reaction, although not statistically significant. For example, if assets listed on BB-B or C-D rated exchanges were later listed on higher- or equally-tier exchanges, they would experience positive abnormal returns of around 9.6% and 14.0% respectively, but if they were later listed on lower-tier exchanges, we observe negative average post-listing performance of -0.1% and -0.7% respectively.

For the longer post-listing window (i.e., 4 months) in Panel B, positive abnormal returns are more pronounced while the pattern in differences across future listing outcomes weakens.

It shows that the 4-month post-listing average abnormal returns are positive for all groups of current listings regardless of future listing outcomes, while all are statistically significant except for assets listed on E-F rated exchanges with unchanged tier for future listings. However, the magnitude of abnormal returns still varies across different future listing outcomes. Assets later listed on exchanges with increased tier generally experience the highest 4-month post-listing abnormal returns among all the future listing outcomes. Moreover, we observe that the magnitude of the overall average abnormal returns (the 5th column of Table 11) follows the pattern opposite to what we find for their CARs in the current listing event-windows, that assets listed on lower-tier exchanges tend to have higher average abnormal returns in the 4-month post-listing window. The overall post-listing average abnormal return for assets listed on E-F rated exchanges reaches 18.0%, while that for assets listed on AA-A rated exchanges is only 10.7%.

Together with results in the previous sections, our findings suggest that the listings not only generated positive immediate abnormal returns captured by CARs in the event windows, but triggered a sustained price outperformance over the subsequent periods. The outperformance reflects not only a one-shot jump, but rather a gradual price discovery process as investors update their beliefs about the asset quality when anticipated signals are confirmed by actual future listings.

Table 11: Average abnormal returns based on BHAR in post-listing periods

Notes: This table represents the average abnormal returns based on BHAR for assets grouped by their current listing exchange rating category and future listing outcomes within the post-listing windows: 1 month (30 days) in Panel A and 4 months (120 days) in Panel B. For each event of listing asset i on exchange j, we construct the reference portfolio using the characteristic-based matching approach (Barber & Lyon, 1997; Lyon et al., 1999). The buy-and-hold abnormal return (BHAR) over the post-listing window of τ days is calculated as the difference between the buy-and-hold return of asset i and that of its reference portfolio from day 6 to day τ after the listing event as defined by (32). We report the cross-sectional average BHARs with the corresponding skewness-adjusted t-statistics in parentheses (Lyon et al., 1999). t-statistics are shown in parentheses. ***/**/* denote p<0.01/0.05/0.10.

Current Exchange Listed	Rating tier increased	Rating tier unchanged	Rating tier decreased	No listing	All
Panel A: future listings within 1 month (30 days) after the current listing					
AA-A	-	0.086 (1.52)	0.096* (1.94)	0.041*** (3.53)	0.048*** (4.21)

Continued on next page

Table 11: Average abnormal returns based on BHAR in post-listing periods (continued)

Current Exchange Listed	Rating tier increased	Rating tier unchanged	Rating tier decreased	No listing	All
BB-B	0.096 (1.67)	0.054* (1.73)	-0.001 (-0.04)	0.014 (1.00)	0.016 (1.62)
C-D	0.140*** (4.79)	0.100*** (3.88)	-0.007 (-0.29)	0.058*** (4.91)	0.068*** (7.17)
E-F	0.032** (2.17)	0.067 (1.58)	-	0.030 (1.60)	0.032** (2.33)
Panel B: future listings within 4 months (120 days) after the current listing					
AA-A	-	0.275*** (3.95)	0.168*** (3.30)	0.054** (2.47)	0.107*** (5.25)
BB-B	0.136*** (3.22)	0.099*** (3.18)	0.143*** (5.67)	0.116*** (3.80)	0.125*** (8.01)
C-D	0.235*** (10.38)	0.072*** (3.28)	0.189** (2.12)	0.083*** (3.07)	0.145*** (10.18)
E-F	0.237*** (6.82)	0.195 (0.97)	-	0.093*** (2.78)	0.176*** (7.08)

10 Robustness checks

Our findings for informational substitution in Section 6.2 and the decomposition for simultaneous listings in Section 6.3 both rest on the market-model benchmark for abnormal returns, the 72-hour detection window for simultaneous listings, and cumulative abnormal return as the dependent variable. We perform three robustness exercises that vary these choices one at a time, namely (i) the abnormal-return benchmark, (ii) the simultaneous-listing detection window, and (iii) the dependent variable, together with placebo tests that replace the actual CEX listing dates with randomly assigned within-token dates and with DEX listing dates. Online Appendix J reports the underlying detailed results.

10.1 Market model alternatives

The two-stage Heckman specification of Section 6.2 and the simultaneous-listing decomposition of Section 6.3 are re-estimated under two alternative abnormal-return benchmarks. The first is the Liu-Tsyvinski-Wu three-factor model (LTW3), under which the abnormal return is the residual from a daily time-series regression of token returns on a crypto market fac-

tor, a size factor, and a momentum factor. The second is a characteristic-matched portfolio benchmark, under which abnormal returns are defined as the difference between the realized token return and the mean return on a portfolio of tokens matched using the same criteria as in Section 9. Table 12 reports main estimates across the three benchmarks.

Table 12: Single-listing and simultaneous-listing results across abnormal-return benchmarks

Notes: Panel A reports the second-stage IMR slope $\beta_{4,h}$ at AA-A current tier ($j = 4$) for each prior-tier condition h, sourced from the λ_{AA-A} row of Panel A of Table 2 for the main spec and from the analogous panels in Online Appendix J for the two alternatives. Panel B reports the informational-substitute effect share for simultaneous listings with AA-A prior history, sourced from the substitute-effect-share row of Panel C of 5 for the main spec and from the analogous rows in the corresponding appendix decomposition tables for the two alternatives. Heteroskedasticity-robust t-statistics are reported in parentheses below the point estimates in Panel A. ***/**/* denote significance at the 1%/5%/10% levels.

	Main spec (market model)	LTW3 three-factor	Char-matched portfolio
Panel A: Second-stage IMR slope $\beta_{4,h}$ at AA-A current tier, by prior tier h			
$\beta_{4,0}$ (first-time)	0.129**	0.130**	0.141
	(2.05)	(2.06)	(0.40)
$\beta_{4,1}$ (prior E-F)	0.098*	0.106**	0.149**
	(1.95)	(2.14)	(2.10)
$\beta_{4,2}$ (prior C-D)	0.026	0.015	0.055
	(1.03)	(0.44)	(1.53)
$\beta_{4,3}$ (prior BB-B)	-0.004	0.000	0.002
	(-0.28)	(0.00)	(0.14)
$\beta_{4,4}$ (prior AA-A)	0.019***	0.016***	0.016***
	(3.54)	(2.90)	(3.09)
Panel B: Informational-substitute effect share at AA-A prior, by listed tier j			
j = BB-B	68.2%	70.5%	77.9%
j = C-D	76.9%	75.9%	94.4%
j = E-F	42.9%	42.4%	41.2%

The information-substitution pattern is robust to both alternative benchmarks, as shown in Panel A. Across all three specifications, the differential $\beta_{4,h} - \beta_{4,0}$ is large and negative for $h \in \{3, 4\}$ and small or close to zero for $h \in \{1, 2\}$, consistent with the asymmetric interpretation in Section 6.2.[12] Panel B shows that the decomposition for simultaneous listings is similarly robust. The informational-substitute share remains substantial for simultaneous listings on the three lower tiers, exceeding 40% for E–F and 70% for BB–B and C–D under every benchmark. The matched-portfolio benchmark produces the largest substitute share

[12]Statistics of the differentials can be found in Online Appendix J.

for j = C–D, at 94.4%. The corresponding results for BB–B current-tier and BB–B prior-tier listings exhibit the same qualitative pattern and are reported in Online Appendix J.

10.2 Simultaneous-listing window robustness

The simultaneous-listing decomposition of Section 6.3 is identified off the events in which a token receives listings on exchanges across multiple tiers within a 72-hour detection window. We re-run the decomposition with three alternative windows, namely 24, 48, and 96 hours, and report the resulting β_j and the share of informational-substitute effect for each prior-history in Table 13.

Table 13: Simultaneous-listing decomposition across detection windows

Notes: Each cell reports β_j followed by the informational-substitute effect share (Sub.%). The 72-hour row is the baseline-window results in Table 5 and Table G.4 in Online Appendix G.

Prior history	Window	AA-A β_j / Sub.%	BB-B β_j / Sub.%	C-D β_j / Sub.%	E-F β_j / Sub.%
AA-A	24h	0.058 0.0%	0.012 96.8%	0.048 48.9%	-0.016 51.3%
AA-A	48h	0.076 0.0%	0.033 79.5%	0.009 60.7%	-0.016 43.4%
AA-A	72h	0.046 0.0%	0.020 68.2%	0.007 76.9%	-0.026 42.9%
AA-A	96h	0.047 0.0%	0.013 91.9%	-0.007 53.5%	-0.012 39.4%
BB-B	24h	0.235 0.0%	0.032 50.1%	0.147 66.8%	0.020 59.7%
BB-B	48h	0.179 0.0%	0.078 54.5%	0.163 77.0%	0.166 70.9%
BB-B	72h	0.153 0.0%	0.114 57.7%	0.148 94.4%	0.149 90.2%
BB-B	96h	0.151 0.0%	0.104 45.9%	0.137 95.2%	0.137 88.0%

The informational-substitute share varies by roughly 10% to 30% across detection windows for any given prior-tier-by-listed-tier cell. The qualitative pattern documented in Section 6.3, in which the substitute share is non-trivial at every lower-tier listing for both AA-A and BB-B prior-history groups, is preserved under every alternative window. The 72-hour baseline is therefore validated against tighter and looser definitions of co-listing.

10.3 Volume as a second dependent variable

We also re-estimate the simultaneous-listing decomposition using cumulative abnormal volume (CAV) in place of CAR as the second-stage outcome. The event-study literature on trading volume typically measures abnormal volume relative to a benchmark period and then tests whether event-period volume contains incremental information (Ajinkya & Jain, 1989; Campbell & Wasley, 1996). Following Karafiath (2009), we use the cumulative version of this benchmark-adjusted volume measure. The decomposition framework in Section 6.3 requires only that the second-stage outcome be linear in the multivariate-probit IMR vector and is not otherwise restricted to returns. Accordingly, the substitute-share decomposition can be applied to CAV as an alternative outcome. Because the model in Section 3 is formulated in terms of price reactions rather than trading volume, we conduct the CAV examiniation as a robustness check based on a second dependent variable.

Table 14: CAV slope coefficients and informational-substitute shares from the simultaneous-listing decomposition

Notes: Panel A reports the CAV slope coefficient β_j from the simultaneous-listing two-stage estimation under each prior history (simultaneous listings with prior highest rated exchanges in AA-A group, i.e., AA-A prior, and BB-B group, i.e., BB-B prior), with heteroskedasticity-robust t-statistics in parentheses. ***/**/* denote significance at the 1%/5%/10% levels. Panel B reports the informational-substitute effect share (Sub.%) at each lower-tier listing under each prior history. Details of the estimations can be found in Online Appendix J.

Prior history	AA-A	BB-B	C-D	E-F
Panel A: CAV slope coefficient β_j				
AA-A prior	4.734***	2.293	1.103	-2.157
	(2.95)	(1.58)	(0.77)	(-1.50)
BB-B prior	10.544***	-0.978	5.820*	-0.574
	(3.10)	(-0.29)	(1.85)	(-0.19)
Panel B: Informational-substitute effect share (Sub.%)				
AA-A prior	0.0%	60.5%	79.9%	43.9%
BB-B prior	0.0%	52.3%	73.7%	47.7%

Table 14 reports the simultaneous-listing decomposition using CAV as the second-stage outcome. Panel A shows that the CAV slope coefficient β_j is statistically significant only for AA–A current-tier listings under both prior-history specifications, while the estimates for the lower current tiers are not statistically significant. This pattern is consistent with the corresponding CAR estimates in Tables 4 and G.3 (in Online Appendix G). The AA–

A current-tier estimate is larger under a BB–B prior history than under an AA–A prior history, consistent with the informational-substitution interpretation: a prior AA–A listing has already incorporated part of the higher-tier certification signal, thereby attenuating the incremental information conveyed by a subsequent simultaneous AA–A listing. Panel B shows that, under an AA–A prior history, the CAV substitute share closely follows the CAR substitute share reported in Table 5. Under a BB–B prior history, the CAV substitute share remains substantial for each lower-tier listing, although it is smaller than the corresponding CAR share in Table G.4 (in Online Appendix G). Overall, the CAV results indicate that the substitute interpretation of the listing premium extends beyond price reactions to trading activity, supporting the robustness of the main decomposition to an alternative outcome variable.

10.4 Placebo tests

Random-date placebo within token. The first placebo replaces each actual listing date with a randomly drawn date from the same token's price history, excluding a 30-day window around real CEX listings to avoid contamination from listing-related price effects. We then recompute event-window CARs using the market-model specification in Section 4 and construct the distribution of mean placebo CARs by current tier across random draws. The mean placebo CAR is close to zero at every current tier with a placebo standard deviation below 1% at every tier. By contrast, the mean actual CAR documented in Finding 1 ranges from 7.2% for AA–A to 0.1% for E–F. The actual-placebo difference is significant at the 1% level for AA–A, BB–B, and C–D listings under both one-sided and two-sided empirical p-values. These results indicate that the listing premium documented in Section 4 is concentrated around the actual listing date and is not driven by baseline token returns.

DEX listing placebo. The second placebo uses DEX listing dates as event dates. The rationale is that decentralized venues do not conduct centralized screening and therefore should not generate a certification premium under the mechanism in Section 3. The first-pool DEX launch, which marks the token's initial appearance on any decentralized venue, yields no significant price response (-0.740, $t = -0.88$), consistent with the absence of a screening signal. Secondary or multichain DEX launches generate a small positive CAR

(0.052, $t = 3.43$). This response is substantially smaller than the AA–A CEX listing CAR documented in Section 4, consistent with the interpretation that multichain expansion carries only limited certification content relative to a centralized exchange listing.

11 Conclusion

This paper studies how markets process correlated certification signals when hierarchically ranked intermediaries screen the same latent quality—a question central to information economics that has resisted full empirical characterization in equity, credit, and ESG markets because of limited variation in certification histories and the infeasibility of decomposing a single certification into its certifier-specific and cross-certifier components. We address both obstacles in cryptocurrency exchange listings, which combine a rich lattice of certification paths (87 exchanges across 8 tiers), frequent simultaneous multi-tier listings, and a continuous decentralized-exchange benchmark for clean price measurement. A stylized model in which exchanges of heterogeneous precision endogenously choose listing thresholds yields testable predictions on premium magnitudes, sequential substitution, simultaneous-listing decomposition, and the role of information distance.

The unconditional listing premium ranges from 7.2% for AA–A exchanges to 0.1% for E–F exchanges, but those numbers are misleading once correlated signals are accounted for. Our two-channel Heckman framework shows that prior certifications attenuate subsequent premia through both a surprise channel and a substitution channel, concentrated in tier pairs whose screens overlap. Extending Nayak and Prabhala (2001) to a multivariate setting, we decompose simultaneous-listing premia and find that 42.9% to 94.4% of the reaction to sub-top-tier listings reflects the implied signal about higher-tier venues rather than the certifying exchange itself. A cross-sectional test confirms that premia rise with the characteristic-based distance between listed and prior tiers, and two natural experiments—the FTX collapse and the SEC complaint against Bittrex—show that tokens losing their only high-tier certifier suffer larger negative reactions than tokens retaining substitute listings. These findings survive alternative abnormal-return benchmarks, detection windows, an abnormal-volume outcome, and within-token and DEX placebo tests.

Our framework applies to any market in which hierarchically ranked certifiers screen the same quality. In Online Appendix A we map the model to credit ratings, equity cross-listings, ESG, and product safety: split credit ratings can be reinterpreted as direct measurements of the informational-complement component, existing cross-listing premium estimates likely overstate the exchange-specific effect once implied information about higher-tier venues is netted out, and the documented divergence among ESG raters should translate into unusually large complement shares. More methodologically, the multivariate conditional event study and two-channel Heckman decomposition extend to any setting with multiple correlated announcements. The crypto-specific takeaway is that the "Binance effect"[13] arises jointly from top-tier certification precision and the substitute content of correlated listings, and the consistency between third-party exchange ratings and observed market reactions indicates that the rating system aggregates exchange quality efficiently—a useful map for investors and regulators alike.

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[13] See media posts, for example, "The Binance Listing Effect: Why It Matters for Altcoins" and "'Binance Effect' Means 41% Price Spike for Newly Listed Tokens".

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Online Appendix

to "Correlated Signals and Certification Value: Evidence from Crypto Listings"

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A Broader Applications: Mapping to Other Certification Markets

Our model and empirical framework apply to any setting in which multiple certifiers of different quality screen the same latent attribute. In this section, we map our results to several prominent certification markets, assess which of our predictions are testable in each, and identify which implications are genuinely new to those literatures. Table A.1 provides an overview; we discuss each application in detail below.

A.1 Credit Ratings

Setting. Bond issuers are rated by Moody's, S&P, and Fitch, which screen the same underlying creditworthiness with different methodologies. At bond issuance, issuers typically obtain two or three ratings simultaneously, providing a direct analogue to our simultaneous listings. Rating changes subsequent to issuance occur asynchronously, creating sequential certification events analogous to our sequential listings.

What our framework predicts. When Moody's downgrades a bond issuer, the bond price reaction consists of two components: a Moody's-specific component (reflecting Moody's particular methodology and information set—the informational complement) and an implied-S&P component (the portion of Moody's signal that is correlated with S&P's assessment—the informational substitute). Our model predicts that a substantial fraction of the market reaction to a Moody's downgrade reflects the implied information about S&P's likely future action. If S&P subsequently confirms the downgrade, the market reaction to S&P's action should be attenuated—the informational substitute has already been absorbed.

What is genuinely new for this literature. The credit rating literature has extensively studied "split ratings"—cases where agencies assign different ratings to the same issuer—and documented that bond yields are higher when ratings disagree (Bongaerts et al., 2012). The literature interprets disagreement as reflecting either differences in rating criteria or private information. Our framework provides a structural interpretation: disagreement measures

Table A.1: Mapping the Framework to Other Certification Markets

Feature	**Crypto Exchanges**	**Credit Ratings**	**Equity Cross-Listings**	**ESG Ratings**	**Product Safety**
Simultaneous certification	Frequent (353 events)	At issuance (common)	Rare	Ongoing (parallel ratings)	Varies by jurisdiction
Path variation	Very rich (87 exchanges, 8 tiers)	Limited (3 major agencies)	Narrow (OTC to NYSE)	Moderate (growing rater count)	Limited
Clean price measure	Yes (DEX benchmark)	Yes (bond spreads)	Yes (stock returns)	Yes (stock returns)	Weak (product sales)
Sample size	More than 6,717 events	Large (bond issuances)	Moderate (hundreds of firms)	Growing	Small
Decomposition feasible?	**Yes**	**Feasible in principle**	No (insufficient simultaneous)	**Feasible in principle**	No
Sequential substitution testable?	**Yes**	Limited (little path variation)	Partially (limited paths)	**Yes** (rating changes)	No

the informational-complement component, while agreement measures the informational substitute. This reinterpretation is new. Specifically:

- The decomposition of bond price reactions to a single agency's rating action into agency-specific and cross-agency components has not been performed. Our multivariate conditional event-study framework is directly applicable to simultaneous ratings at issuance, where the joint observation of Moody's, S&P, and Fitch ratings identifies the covariance structure.
- The prediction that the market's reaction to a Moody's downgrade is attenuated when S&P has recently downgraded (sequential informational substitution) has been informally discussed but never tested with the two-channel decomposition (surprise channel versus substitution channel) that our Heckman framework provides.
- Our information-distance measure d_{jh} provides a new way to predict the magnitude of rating-change spillovers across agencies: the market reaction to a Moody's action should be larger for issuers whose Moody's and S&P ratings are far apart (high information distance, implying less overlap in the signals).

Feasibility and limitations. The decomposition is feasible at bond issuance, where simultaneous ratings are common and the bond market provides clean price measures (yield spreads or CDS spreads). The main limitation is path variation: most investment-grade issuers obtain all three major ratings, so there is limited cross-sectional variation in rating history. Our sequential-substitution analysis (which requires comparing issuers with different prior rating histories) is harder to implement because the rating path is relatively uniform. However, the growing number of smaller rating agencies (DBRS, Kroll, Egan-Jones) and the post-2008 regulatory push to reduce reliance on the Big Three are creating more variation in rating paths, making our sequential analysis increasingly feasible.

A.2 Equity Cross-Listings and IPO Underpricing

Setting. Firms seeking equity listings progress through a loose hierarchy of venues: OTC Bulletin Board, NASDAQ, NYSE in the U.S.; AIM, Main Market in the U.K.; SME boards to main boards in Asia. Foreign firms follow a similar progression through ADR levels. Each

venue screens firm quality with different stringency, analogous to our exchange tiers.

What our framework predicts. When a firm cross-lists from OTC to NYSE, the price reaction contains an exchange-specific component (NYSE's particular governance, liquidity, and visibility benefits—the informational complement) and an implied component (the portion of OTC's prior listing signal that already conveyed information about NYSE-level quality—the informational substitute). Our estimates from crypto markets, where the informational-substitute share ranges from 42.9% to 94.4% for sub-top-tier listings, suggest that a substantial fraction of the cross-listing premium documented in the equity literature may reflect implied information about higher-tier venues rather than the pure effect of the listing exchange itself.

What is genuinely new for this literature.

- The equity cross-listing literature (Doidge et al., 2004; Miller, 1999; Sarkissian & Schill, 2012) has documented that cross-listing premia are larger for firms from weaker home markets, but has not decomposed this pattern into the surprise channel (firms from weaker markets are less expected to cross-list, so the event is more surprising) and the substitution channel (firms from weaker markets have less prior informational overlap with the listing exchange). Our two-channel Heckman framework provides this decomposition for the first time, albeit in the crypto setting. The framework is directly portable to equity data.
- Our finding that informational substitution is asymmetric—prior bottom-tier listings do not substitute for top-tier listings ($\beta_{4,1} - \beta_{4,0}$ insignificant) while prior mid-tier listings do ($\beta_{4,3} - \beta_{4,0}$ significant)—generates a new prediction for equity markets: an OTC listing should not meaningfully attenuate the subsequent NYSE listing premium (the quality screens are too different), but a NASDAQ listing should (the quality screens overlap substantially). This prediction has not been tested in the equity literature.
- The information-decay prediction (Proposition 11 in the theory section) implies that the cross-listing premium should be larger when more time has elapsed since the prior listing, because the prior signal has become stale. This prediction is testable in equity

data and, to our knowledge, has not been examined.

Feasibility and limitations. The sequential-substitution analysis is feasible in equity markets: there are enough firms with different prior listing histories (OTC only, NASDAQ only, foreign exchange only) to compare listing premia across history types. The key limitation is that the *decomposition* into informational complement and substitute is not feasible because simultaneous multi-venue equity listings essentially do not occur—a firm cannot list on OTC and NYSE on the same day. Our crypto-based estimates can be used to provide a back-of-the-envelope calibration: if the informational-substitute share for sub-top crypto listings (42.9–94.4%) is broadly representative of the general certification problem, then existing estimates of NYSE cross-listing premia may overstate the exchange-specific effect by a factor of two to twenty. We emphasize that this extrapolation is illustrative, not definitive—the correlation structure may differ across markets. Nevertheless, it provides the first quantitative benchmark for the bias in cross-listing premium estimates.

A.3 ESG Ratings

Setting. Firms are rated on environmental, social, and governance criteria by MSCI, Sustainalytics, CDP, ISS, and a growing number of other providers. Unlike credit ratings, ESG ratings exhibit notoriously low cross-rater correlations—Berg et al. (2022) document correlations as low as 0.38 between major providers. Firms carry multiple simultaneous ESG ratings that are updated at different frequencies.

What our framework predicts. Low cross-rater correlation implies large informational-complement components: each rater's assessment is largely orthogonal to the others, reflecting genuinely different screening criteria rather than correlated signals about the same quality. Our model predicts that when MSCI upgrades a firm's ESG rating, the market reaction should be almost entirely attributable to MSCI-specific information (informational complement), with little implied Sustainalytics content (informational substitute). This contrasts sharply with credit ratings, where cross-agency correlation is high and the informational-substitute share should be large.

What is genuinely new for this literature.

- Berg et al. (2022) decompose ESG rating *disagreement* into scope, measurement, and weight divergence. Our framework provides a complementary decomposition of *market reactions*: how much of the stock price response to an MSCI ESG upgrade reflects MSCI-specific information versus implied information about other raters' likely assessments? This market-reaction decomposition has not been performed in the ESG literature.
- Our information-distance measure provides a firm-specific prediction: firms for which MSCI and Sustainalytics ratings are far apart (high d_{jh}) should exhibit larger stock price reactions to either rater's upgrade, because less of the information overlaps. Firms with closely aligned ratings across raters should exhibit smaller reactions, as each individual rating is more redundant. This cross-sectional prediction is testable and new.
- The sequential-substitution analysis is feasible for ESG ratings because rating changes occur at different times across providers: when MSCI upgrades a firm, the subsequent Sustainalytics upgrade (if it occurs) should elicit a muted market reaction. The magnitude of attenuation should be predictable from the cross-rater correlation.

Feasibility and limitations. Both the decomposition and the sequential-substitution analysis are feasible in the ESG setting. Firms carry multiple simultaneous ratings (enabling the decomposition), and rating changes occur asynchronously across providers (enabling the sequential analysis). The main challenges are (i) ESG rating changes are less frequent than crypto listings, yielding smaller samples; (ii) the "price" response to ESG rating changes is often small and noisy, making precise estimation difficult; and (iii) the tier structure among ESG raters is less clearly defined than among crypto exchanges or credit agencies, complicating the mapping to our hierarchical framework.

A.4 Other Applications

Product safety and regulatory approval. Pharmaceutical drugs, medical devices, and consumer products receive safety certifications from regulators of different stringency across

jurisdictions (e.g., FDA in the U.S., EMA in Europe, PMDA in Japan). Our model predicts that a drug approved by EMA carries an implied FDA signal: if EMA approval reveals quality information correlated with FDA criteria, the market should partially price in the expected FDA decision. The subsequent FDA approval should then generate a smaller price reaction than if EMA had not approved first. This prediction is testable using pharmaceutical stock returns around regulatory announcements. However, the institutional structure differs from our model in that regulators often explicitly condition on each other's decisions (the FDA reviews EMA data), violating the independence assumption in our signal structure. Our framework applies most cleanly to jurisdictions with independent regulatory processes.

Academic journal peer review. Manuscripts are reviewed by multiple referees who independently screen the same paper quality with different expertise. The editor observes correlated signals and makes an accept/reject decision. Our model predicts that the marginal informativeness of each additional referee report declines—the third referee adds less than the second, because more of the paper's quality has already been assessed. While the "price" (publication decision) is binary rather than continuous, the model's insight about correlated screening applies to editorial decision-making. This application is conceptual rather than empirically testable.

University rankings. QS, Times Higher Education, and US News rank universities annually on overlapping quality dimensions. The rankings are effectively simultaneous (published within a single year). Our model predicts that a university's "price response" (applications, yield, donations) to a QS improvement consists of a QS-specific component and an implied component about the university's likely Times or US News ranking. While the model structure maps directly, the absence of clean, high-frequency price data makes empirical implementation impractical with current data. This remains an illustrative application.

B Proofs for the Multi-Venue Certification Model

B.1 Proof of Proposition 1

From (4),

$$m_j'(x) = \frac{\alpha_j \tau_0^2}{\alpha_j^2 \tau_0^2 + \sigma_j^2} > 0.$$

The failure probability in (5) is

$$p_j(x) = \Phi\left(\frac{\underline{z} - m_j(x)}{s_j}\right).$$

Differentiating gives

$$p_j'(x) = -\phi\left(\frac{\underline{z} - m_j(x)}{s_j}\right)\frac{m_j'(x)}{s_j} < 0.$$

Using (6),

$$\Pi_j'(x) = B_j'(m_j(x))m_j'(x) - R_j p_j'(x) > 0,$$

because $B_j'(\cdot) > 0$, $m_j'(x) > 0$, $R_j > 0$, and $p_j'(x) < 0$. Hence $\Pi_j(x)$ is strictly increasing in x. The crossing condition in (7) then implies that there exists a unique $\bar{X}_j$ satisfying $\Pi_j(\bar{X}_j) = 0$. Since listing yields payoff $\Pi_j(x)$ and non-listing yields zero, the exchange lists if and only if $\Pi_j(x) \geq 0$, which is equivalent to $x \geq \bar{X}_j$.

To obtain the comparative static with respect to R_j, define

$$F(x, R_j) = B_j(m_j(x)) - R_j p_j(x) - c_j.$$

At the cutoff, $F(\bar{X}_j, R_j) = 0$. The implicit function theorem gives

$$\frac{\partial \bar{X}_j}{\partial R_j} = -\frac{F_{R_j}(\bar{X}_j, R_j)}{F_x(\bar{X}_j, R_j)} = \frac{p_j(\bar{X}_j)}{\Pi_j'(\bar{X}_j)} > 0,$$

which proves (8).

B.2 Proof of Proposition 2

Let $\nu_j^2 = \mathrm{Var}(X_{ij}) = \alpha_j^2 \tau_0^2 + \sigma_j^2$. Since (z_i, X_{ij}) is jointly normal,

$$\mathbb{E}[z_i \mid X_{ij}] = \mu_0 + \frac{\mathrm{Cov}(z_i, X_{ij})}{\mathrm{Var}(X_{ij})}\big(X_{ij} - \mathbb{E}[X_{ij}]\big).$$

Taking expectations conditional on $X_{ij} \geq \bar{X}_j$ gives

$$\begin{aligned}
\mathbb{E}[z_i \mid X_{ij} \geq \bar{X}_j] &= \mu_0 + \frac{\alpha_j \tau_0^2}{\nu_j^2} \mathbb{E}\big[X_{ij} - \alpha_j \mu_0 \mid X_{ij} \geq \bar{X}_j\big] \\
&= \mu_0 + \frac{\alpha_j \tau_0^2}{\nu_j^2} \nu_j \lambda(\kappa_j) \\
&= \mu_0 + \frac{\alpha_j \tau_0^2}{\nu_j} \lambda(\kappa_j),
\end{aligned}$$

which proves (11) and (12).

It remains to show monotonicity. Write $r_j = \alpha_j / \sigma_j$. Then

$$\frac{\alpha_j \tau_0^2}{\nu_j} = \frac{\tau_0^2 r_j}{\sqrt{1 + \tau_0^2 r_j^2}}.$$

The derivative of this expression with respect to r_j is

$$\frac{\tau_0^2}{(1 + \tau_0^2 r_j^2)^{3/2}} > 0.$$

Thus the Bayesian updating coefficient is increasing in signal precision. Also, for the upper-tail inverse Mills ratio,

$$\lambda'(\kappa) = \lambda(\kappa)\big[\lambda(\kappa) - \kappa\big] > 0.$$

Therefore, under the precision ordering condition (3) and the standardized threshold ordering condition (13), both multiplicative terms in (12) are increasing in exchange tier. Since $\delta > 0$, the first-listing premium is increasing in tier.

B.3 Derivation of the Endogenous Correlation Structure

From (2),

$$\mathrm{Cov}(X_{ij}, X_{ih}) = \mathrm{Cov}(\alpha_j z_i + \phi_{ij}, \alpha_h z_i + \phi_{ih}) = \alpha_j \alpha_h \tau_0^2,$$

because the idiosyncratic errors are independent of each other and of z_i. Also,

$$\mathrm{Var}(X_{ij}) = \alpha_j^2 \tau_0^2 + \sigma_j^2.$$

This gives (10). Since $\sigma_j^2 = \alpha_j^2/\pi_j$ and $\tau_0^2 = 1/\pi_0$,

$$\alpha_j^2 \tau_0^2 + \sigma_j^2 = \alpha_j^2 \left(\frac{1}{\pi_0} + \frac{1}{\pi_j} \right),$$

so

$$\rho_{jh}^2 = \frac{\pi_j \pi_h}{(\pi_0 + \pi_j)(\pi_0 + \pi_h)}.$$

Taking logs,

$$\log \rho_{jh} = \frac{1}{2} \log \pi_j + \frac{1}{2} \log \pi_h - \frac{1}{2} \log(\pi_0 + \pi_j) - \frac{1}{2} \log(\pi_0 + \pi_h).$$

Therefore,

$$\frac{\partial \log \rho_{jh}}{\partial \pi_j} = \frac{1}{2\pi_j} - \frac{1}{2(\pi_0 + \pi_j)} = \frac{\pi_0}{2\pi_j(\pi_0 + \pi_j)} > 0,$$

and similarly $\partial \log \rho_{jh}/\partial \pi_h > 0$. Finally,

$$\frac{\partial \log \rho_{jh}}{\partial \pi_0} = -\frac{1}{2(\pi_0 + \pi_j)} - \frac{1}{2(\pi_0 + \pi_h)} < 0.$$

Since $\pi_0 = 1/\tau_0^2$, an increase in prior uncertainty τ_0^2 lowers π_0 and therefore raises ρ_{jh}.

B.4 Proof of Proposition 3

For a normal prior and a normal signal, observing signal j changes posterior precision from π_0 to $\pi_0 + \pi_j$. Hence the posterior variance changes from $1/\pi_0$ to $1/(\pi_0 + \pi_j)$. The variance

of the change in the posterior mean equals the reduction in posterior variance:

$$\mathrm{Var}(\mathbb{E}[z_i \mid X_{ij}] - \mathbb{E}[z_i]) = \frac{1}{\pi_0} - \frac{1}{\pi_0 + \pi_j}.$$

Since price is affine in the posterior mean by (1), the expected squared first reaction is Q_j in (14).

Now suppose signal h has already been observed. The posterior precision before observing signal j is $\pi_0+\pi_h$, and the posterior precision after observing signal j is $\pi_0+\pi_h+\pi_j$. Therefore

$$Q_{j|h} = \delta^2 \left[\frac{1}{\pi_0 + \pi_h} - \frac{1}{\pi_0 + \pi_h + \pi_j} \right] = \delta^2 \frac{\pi_j}{(\pi_0 + \pi_h)(\pi_0 + \pi_h + \pi_j)}.$$

Comparing with (14),

$$\frac{Q_{j|h}}{Q_j} = \frac{\pi_0(\pi_0 + \pi_j)}{(\pi_0 + \pi_h)(\pi_0 + \pi_h + \pi_j)} < 1,$$

because $\pi_h > 0$. Thus $Q_{j|h} < Q_j$. Replacing π_h by the total prior-history precision $\Pi_{\mathcal{H}} = \sum_{h \in \mathcal{H}} \pi_h$ yields (15).

B.5 Proof of Proposition 4

Because (X_{ij}, X_{ik}) is jointly Gaussian, the linear projection of X_{ij} on X_{ik} is

$$X_{ij} - \mathbb{E}[X_{ij}] = \gamma_{jk}\big(X_{ik} - \mathbb{E}[X_{ik}]\big) + \eta_{ij|k},$$

where

$$\gamma_{jk} = \frac{\mathrm{Cov}(X_{ij}, X_{ik})}{\mathrm{Var}(X_{ik})}, \qquad \mathrm{Cov}(\eta_{ij|k}, X_{ik}) = 0.$$

Under joint normality, the residual is not only uncorrelated with X_{ik} but independent of it.

The price conditional on X_{ij} is affine in X_{ij}:

$$P_j(X_{ij}) = \mathbb{E}[v_i \mid X_{ij}] = a_j + b_j\big(X_{ij} - \mathbb{E}[X_{ij}]\big) + P_0,$$

where

$$b_j = \delta \frac{\mathrm{Cov}(z_i, X_{ij})}{\mathrm{Var}(X_{ij})} > 0.$$

Substituting this projection gives

$$P_j(X_{ij}) - P_0 = a_j + b_j\gamma_{jk}\big(X_{ik} - \mathbb{E}[X_{ik}]\big) + b_j\eta_{ij|k},$$

which proves (16). The multivariate expression in (17) follows from the standard multivariate linear projection formula.

B.6 Proof of Proposition 5

Fix the current listing exchange j. From (19), define

$$Q(\pi_h) = \delta^2 \frac{\pi_j}{(\pi_0 + \pi_h)(\pi_0 + \pi_h + \pi_j)}.$$

Differentiating with respect to π_h gives

$$\frac{\partial Q(\pi_h)}{\partial \pi_h} = -\delta^2 \pi_j \frac{2(\pi_0 + \pi_h) + \pi_j}{(\pi_0 + \pi_h)^2(\pi_0 + \pi_h + \pi_j)^2} < 0.$$

Thus, the incremental reaction becomes smaller as the prior listing history becomes more informative.

From (18),

$$d(\pi_h) = 1 - \frac{\pi_j \pi_h}{(\pi_0 + \pi_j)(\pi_0 + \pi_h)}.$$

Differentiating gives

$$\frac{\partial d(\pi_h)}{\partial \pi_h} = -\frac{\pi_j}{\pi_0 + \pi_j} \frac{\pi_0}{(\pi_0 + \pi_h)^2} < 0.$$

Both $Q(\pi_h)$ and $d(\pi_h)$ are strictly decreasing functions of π_h. Since $d(\pi_h)$ is one-to-one in π_h, Q can be written as a function of d, and

$$\frac{dQ}{dd} = \frac{\partial Q / \partial \pi_h}{\partial d / \partial \pi_h} > 0.$$

Therefore the expected squared incremental reaction is strictly increasing in information distance.

C Data Construction and Unconditional Event-Study Details

This appendix collects the data sources, sample construction, event-study methodology, and full result tables underlying the unconditional event study reported in Section 4, together with a robustness check based on the original eight CoinDesk exchange ratings.

C.1 Data sources and sample construction

We stick to the coins list for each blockchain from Coingecko API, based on which we merge the assets existing on multiple chains and adopt data of the chain with the longest pricing history. [14] After unifying multi-chain assets, our sample consists of 8365 assets, of which 2695 assets were listed on the 87 CEXs rated by CoinDesk, with the sample period from 1st September 2021 to 31st March 2025. For each asset, we fetch the pricing history of the largest DEX pool on the chain under examining using Coingecko on-chain DEX API. In addition to pricing data, we fetch series of half-day market capitalization data via three sources and then average them to form the usable values. Coinranking provides API endpoint for market capitalization, which we use as the supplement for the data from Coingecko. We also use the series of circulating supply fetched from CoinDesk API and asset price to calculate as for the third source of market capitalization. Considering that the crypto market is in operating 24/7 but its intraday volume and volatility are highly correlated with traders working business hours, represented by the major stock market opening and close time (De Blasis & Webb, 2022), we adjust our data, i.e., asset price and market capitalization, to half-day frequency in UTC time. In this way our data can include more information revealed by intraday trading.

C.2 Event-time choice and market-model methodology

We calculate the price reaction around the time of the first trade for assets listed, as recorded by CoinDesk. Rather than using announcement time of the listings, we use the time of the

[14] The same asset may exist on multiple chains, .e.g, the token issued by Chainlink (https://chain.link) was initially on Ethereum with the address of 0x514910771af9ca656af840dff83e8264ecf986ca, while later was bridged to BSC as 0xf8a0bf9cf54bb92f17374d9e9a321e6a111a51bd.

first trade as the event time for two reasons. One is that most of the exchanges announce the listing 24 to 72 hours before the actual listing, the variability adding noise to identifying simultaneous listings. Secondly, exchanges usually announce the incoming listing via multiple channels at different time points, e.g., Twitter, Telegram, and their own websites, making it hard to determine the exact announcement time.

We adopt the market model to calculate abnormal returns. For each listing event, the event window is set to be $[-5, +5]$ days around the listing event, and we estimate the market model with data of the estimation window $[-125, -5]$ days relative to the event time. The abnormal return of asset i on half-day t is calculated by, $AR_{it} = R_{it} - \hat{R}_{it}$, where $\hat{R}_{it}$ denotes the return predicted by the estimated market model and R_{it} denotes the realized return. We obtain cumulative abnormal return (CAR) by adding up the corresponding ARs, $\text{CAR}_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \text{AR}_{i\tau}$. [15]

C.3 Cumulative abnormal returns by four rating categories

Table C.1 reports the full time path of CARs around CEX listing events grouped by the four exchange rating categories used in Section 4 (AA-A, BB-B, C-D, E-F), from day -5 to day $+5$ at half-day frequency.

Table C.1: Cumulative Abnormal Returns (CARs) Analysis by Exchange Rating Categories

Notes: This table presents the Cumulative Abnormal Returns (CARs) around exchange listing events, grouped by exchange rating categories, i.e., AA to A rated exchanges (AA-A), BB to B (BB-B), C to D (C-D), and E to F (E-F). The event window is set to be $[-5, +5]$ days around the listing event, and the estimation window is $[-125, -5]$ days relative to the event time. Cumulative abnormal returns (CARs) are calculated by adding up the corresponding ARs, $CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau}$. Each row represents the average CARs by cumulating the abnormal returns from day -5 to the corresponding day indicated in the first column. t-statistics are shown in parentheses below each coefficient.
***/**/* denote significance at 1%/5%/10% levels respectively.

Day	AA-A	BB-B	C-D	E-F
-5	0.003 (0.35)	0.003 (0.63)	0.003 (0.72)	0.001 (0.15)
-4.5	0.003 (0.35)	0.004 (0.82)	0.005 (1.02)	0.001 (0.19)

Continued on next page

[15] As clustering problem incurs in our case, i.e., the event windows in the same event group overlap so that the covariances between the abnormal returns will not be zero, we address this issue by aggregating returns of individual assets into portfolios dated using event time, as suggested by MacKinlay (1997).

Table C.1: Cumulative Abnormal Returns (CARs) Analysis by Exchange Rating Categories (continued)

Day	AA-A	BB-B	C-D	E-F
-4	0.004 (0.53)	0.001 (0.28)	0.004 (1.01)	-0.001 (-0.11)
-3.5	0.003 (0.41)	0.002 (0.51)	0.006 (1.37)	0.003 (0.58)
-3	0.003 (0.47)	0.007* (1.92)	0.008* (1.94)	0.005 (1.10)
-2.5	0.010 (1.48)	0.012*** (3.35)	0.012*** (3.40)	0.012** (2.59)
-2	0.011* (1.76)	0.015*** (4.70)	0.015*** (4.40)	0.018*** (4.17)
-1.5	0.031*** (5.73)	0.021*** (7.19)	0.022*** (7.14)	0.018*** (4.77)
-1	0.043*** (8.86)	0.027*** (9.99)	0.031*** (11.21)	0.009*** (2.62)
-0.5	0.072*** (17.08)	0.036*** (15.41)	0.036*** (15.23)	0.005* (1.81)
0	0.072*** (20.88)	0.031*** (16.52)	0.037*** (18.91)	0.001 (0.47)
0.5	0.065*** (15.26)	0.029*** (12.39)	0.030*** (12.61)	-0.001 (-0.28)
1	0.059*** (11.96)	0.025*** (9.34)	0.026*** (9.37)	0.012*** (3.53)
1.5	0.057*** (10.37)	0.022*** (7.42)	0.025*** (8.05)	0.008** (2.10)
2	0.045*** (7.57)	0.018*** (5.63)	0.024*** (6.95)	0.010** (2.34)
2.5	0.038*** (5.84)	0.015*** (4.32)	0.024*** (6.56)	0.006 (1.24)
3	0.035*** (5.01)	0.013*** (3.35)	0.020*** (5.23)	0.003 (0.63)
3.5	0.039*** (5.27)	0.008** (2.02)	0.018*** (4.29)	0.002 (0.39)
4	0.033*** (4.21)	0.006 (1.51)	0.014*** (3.11)	0.009 (1.57)
4.5	0.036*** (4.41)	0.003 (0.72)	0.008* (1.82)	0.002 (0.32)
5	0.029*** (3.43)	0.002 (0.31)	0.003 (0.57)	0.001 (0.17)

C.4 Cumulative abnormal returns by listing history

This subsection reports the full results for the conditional event study referenced by Finding 2 in Section 4. Listing history is defined as the highest-rated exchange the asset was previously listed on. For example, if an asset was already listed on both an AA-rated exchange (e.g.,

Binance) and a C-rated exchange (e.g., Bitkub), we classify its prior listing history as AA–A only. [16] Two patterns are of interest. First, the effects of listings are more pronounced when the asset has never been listed on any exchange before (i.e., first-time listings), as shown in the bottom row of Table C.2. This distinction is most evident for listings on AA–A rated exchanges. If an asset has never been listed before, the market reaction to its listing on an AA–A rated exchange is 44.5% of CAR (CAR 5 days before the listing event) (t-stats=16.16), while if the asset has already been listed on an AA–A rated exchange, the market reaction to its listing on another AA–A rated exchange is only 4.3% in CAR (t-stats=11.95). We also plot the CARs surrounding the listing events for assets that have never been listed before in Figure C.1 and that have been listed on an AA–A rated exchange before in Figure C.2. It shows that, for first-time-listing, effects of listing on AA-A rated exchanges are not only larger in magnitude but also more persistent, with CARs of more than 40% even at the end of the event window.

Secondly, it reveals that the market reaction to the same rated exchange decreases with the rating of the exchange that the asset has been listed on before. If an asset has been listed on an E-F rated exchange before, the average CAR for its listing on an AA–A rated exchange is 28.2% (t-stats=10.55), while if the asset has been listed on an C-D rated exchange before, the average CAR for its listing on an AA–A rated exchange decreases to 4.9% (t-stats=2.66). The same pattern exists for listings on all the 4 categories of exchanges.

[16] We exclude cases of simultaneous listings in this set of event studies. In this paper, we define simultaneous listings as cases when an asset is listed on multiple exchanges within 72 hours, with at least one of them being a different rating than the others.

Table C.2: Cumulative Abnormal Returns (CARs) by Exchange Rating Categories with Different Listing Histories

Notes: This table presents the Cumulative Abnormal Returns (CARs) by exchange rating categories with different listing histories. We conduct 4 event studies for listings with the same listing history, which is defined by the highest-rated (in category) exchange the asset was previously listed on, i.e., the first-time-listing (never listed before), previously listed on AA-A rated exchanges, on BB-B rated exchanges, on C-D rated exchanges, and on E-F rated exchanges respectively. Therefore, we conduct 5 sets of event studies depending on the 5 types of listing histories, which are illustrated by the 5 rows in this table respectively. For example, the first row shows the average CARs untill the time of listing on exchanges of the 4 rating categories respectively in the 4 columns, while in Column (1) it shows the average CAR at the time of listing on AA-A rated exchanges for assets that were previously listed on AA-A exchanges. All the CARs are calculated by adding up ARs from day -5 to day 0 relative to the event time, i.e., $CAR_i(-5,0) = \sum_{\tau=-5}^{0} AR_{i\tau}$.
t-statistics are shown in parentheses below each coefficient.
***/**/* denote significance at 1%/5%/10% levels respectively.

Listing History	AA-A (1)	BB-B (2)	C-D (3)	E-F (4)
AA-A	0.043***	0.020***	0.012***	-0.015***
	(11.95)	(7.84)	(4.63)	(-5.32)
BB-B	0.021**	0.010**	0.034***	0.007
	(1.98)	(2.48)	(13.64)	(1.37)
C-D	0.049***	0.012**	0.006	-0.061***
	(2.66)	(2.35)	(1.03)	(-7.93)
E-F	0.282***	0.086***	0.015	0.052***
	(10.55)	(9.41)	(0.99)	(5.15)
first-time-listing	0.445***	0.068***	0.101***	0.027**
	(16.16)	(10.71)	(12.71)	(2.54)

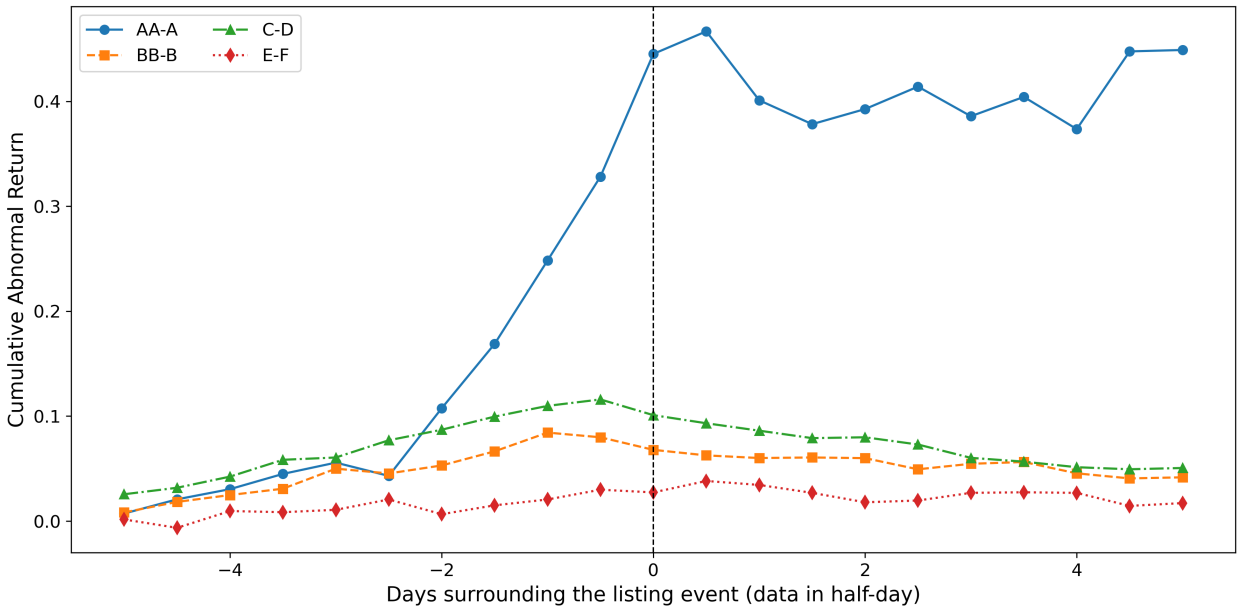


Figure C.1: Cumulative Abnormal Returns (CARs) around exchange listing events for the first-time listing (events grouped by exchange rating categories).

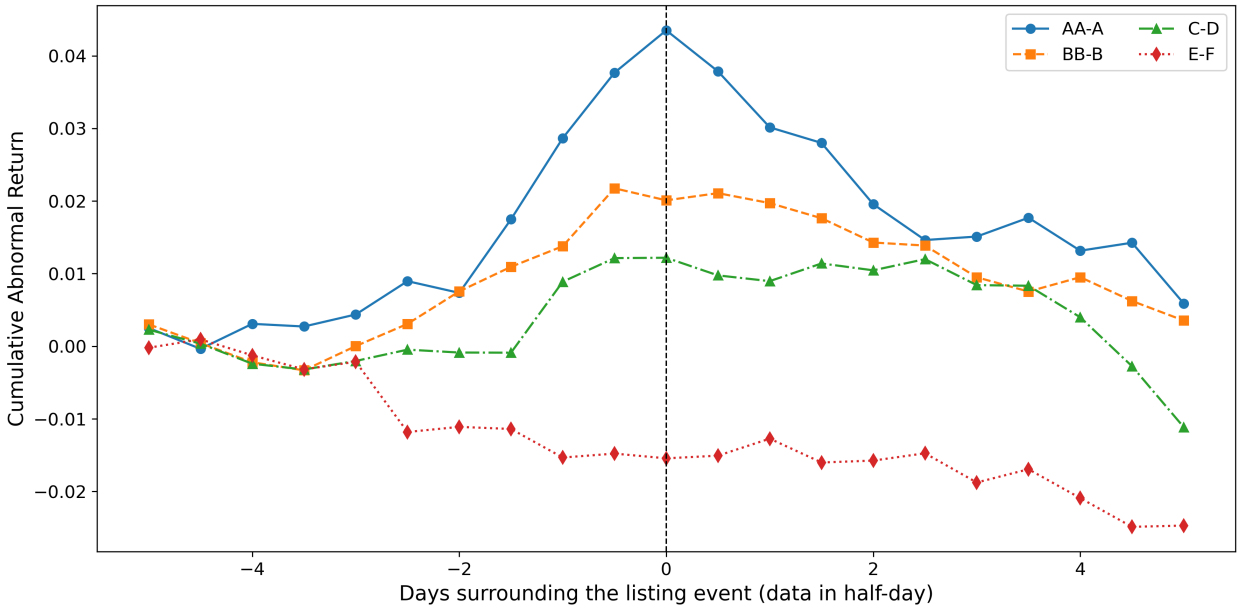


Figure C.2: Cumulative Abnormal Returns (CARs) around exchange listing events for assets previously listed on exchanges in AA-A rating category (events grouped by exchange rating categories).

C.5 Robustness: tests based on the original exchange ratings

In this section, we present results of the unconditional event studies in the similar way as in Section 4, but based on the original exchange ratings by CoinGecko, i.e., AA, A, BB, B, C, D, E, and F. Figure C.3 plots the Cumulative Abnormal Returns (CARs) around exchange listing events grouped by exchange ratings, and detailed results are reported in Table C.3. It reveals a similar pattern as in Section 4 that listings on higher-tier exchanges tend to elicit stronger positive market reactions while those on lower-tier exchanges generate milder or even negative market reactions. The average CARs at the event time (day 0) ranges from 9% for AA-rated exchanges to -2.5% for F-rated exchanges.

Similarly, we conduct sets of unconditional event studies grouping listing events with the same listing history, results of which are reported in Table C.4. We define listing history in the same way as in Section 4: the highest rating of the exchanges where the asset has been listed prior to the current listing event. Similar patterns can be observed. The market reactions to listings on exchanges on the same rating vary depending on the listing history. While the first-time listings generate the strongest response, e.g., as shown in Figure C.4,

assets that have been previously listed on A-rated exchanges tend to have the weakest market reactions if they are further listed, e.g., as shown in Figure C.5.

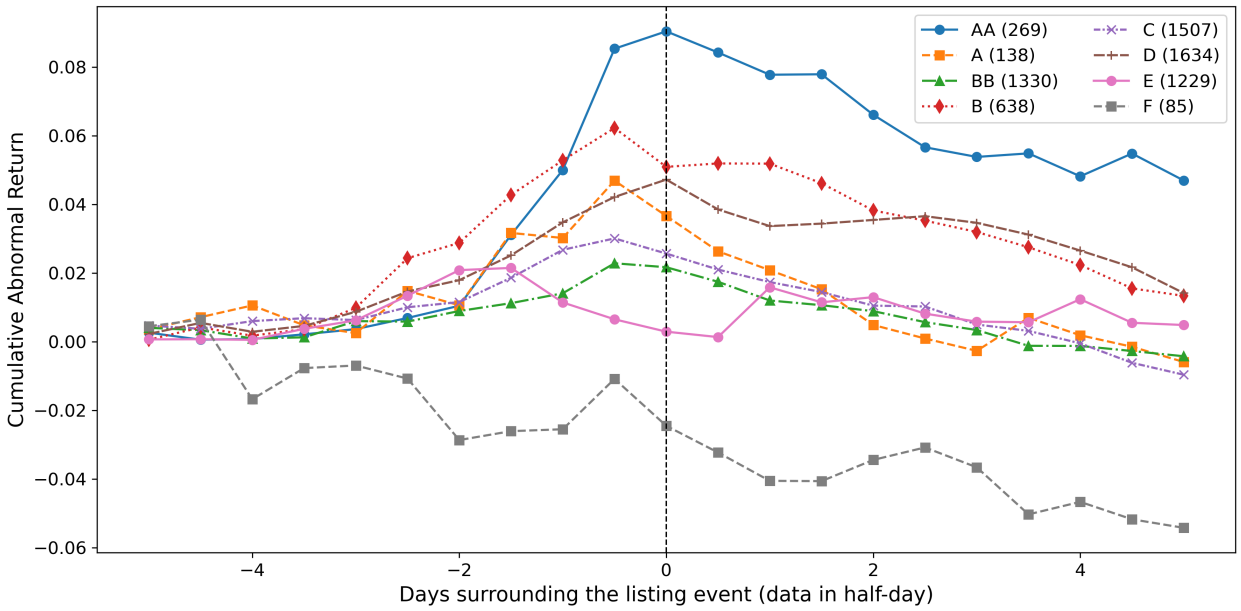


Figure C.3: Cumulative Abnormal Returns (CARs) around exchange listing events by exchange rating. We indicate the number of listing events for each exchange rating in our sample in parentheses.

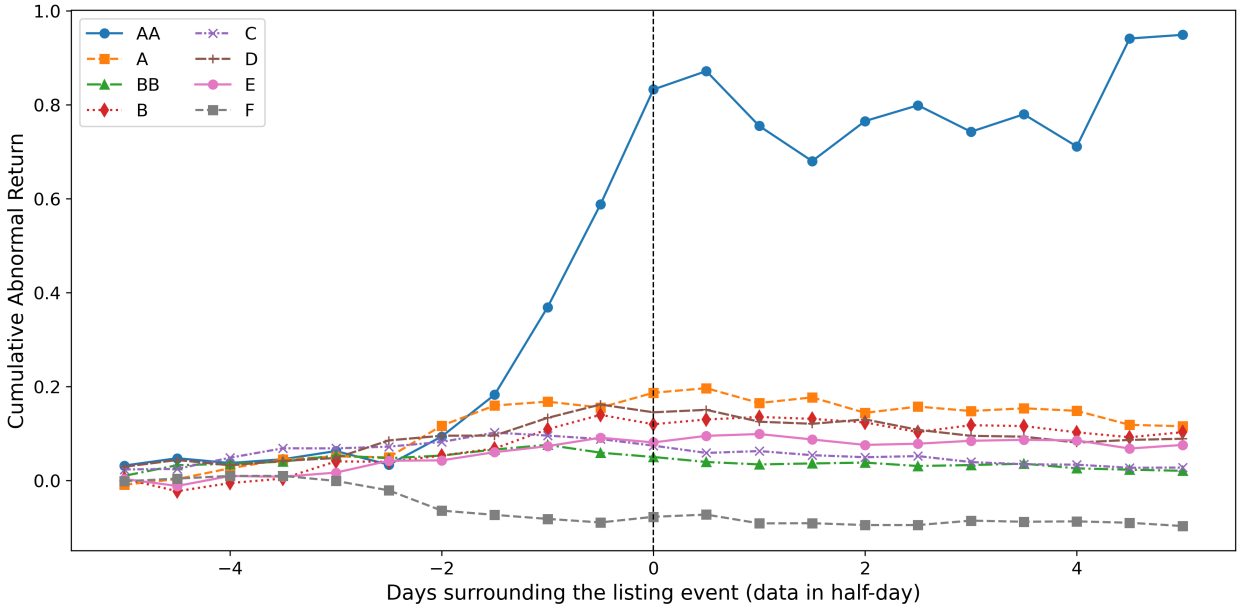


Figure C.4: Cumulative Abnormal Returns (CARs) around exchange listing events for the first-time listing (events grouped by exchange ratings).

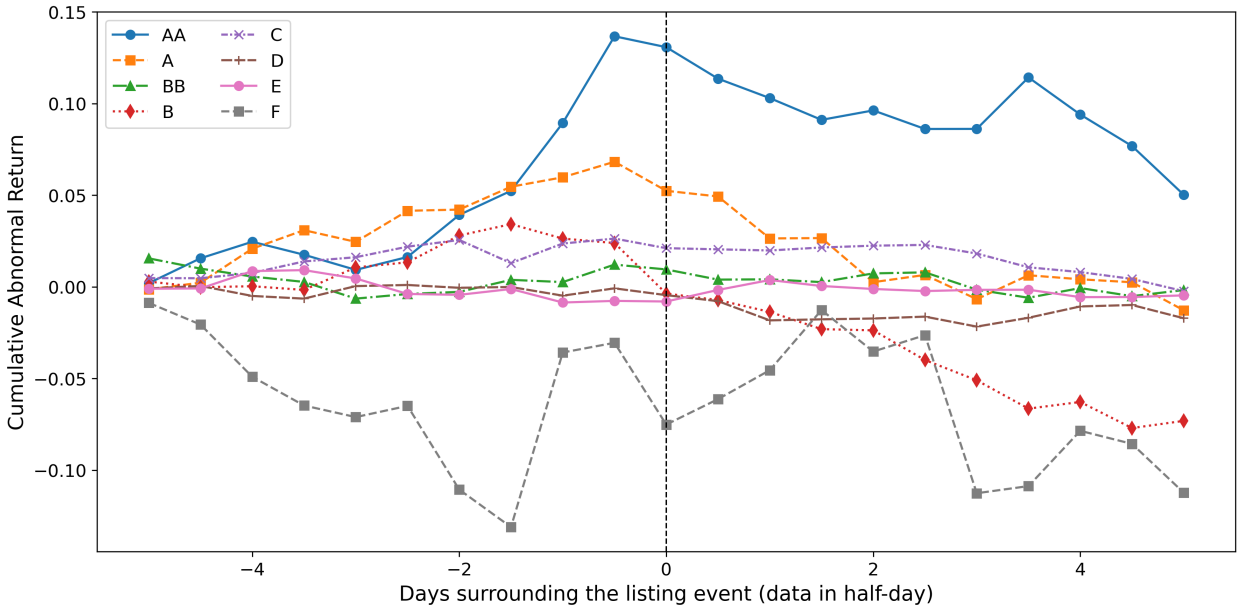


Figure C.5: Cumulative Abnormal Returns (CARs) around exchange listing events for assets previously listed on A-rated exchanges (events grouped by exchange ratings).

Table C.3: Cumulative Abnormal Returns (CARs) Analysis by Exchange Rating

Notes: This table presents the Cumulative Abnormal Returns (CARs) around exchange listing events, categorized by exchange ratings, i.e., AA, A, BB, B, C, D, E, and F. Abnormal returns (AR) are calculated using the market model, estimated from an estimation window. The event window is set to be $[-5, +5]$ days around the listing event, and the estimation window is $[-125, -5]$ days relative to the event time. Cumulative abnormal returns (CARs) are calculated by adding up the corresponding ARs, $CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau}$. Each row represents the CAR by cumulating the abnormal returns from day -5 to the corresponding day indicated in the left-most column.
t-statistics are shown in parentheses below each coefficient.
***/**/* denote significance at 1%/5%/10% levels respectively.

Day	AA	A	BB	B	C	D	E	F
-5	0.003	0.004	0.004	0.001	0.005	0.002	0.001	0.004
	(0.27)	(0.22)	(0.73)	(0.07)	(0.70)	(0.36)	(0.11)	(0.19)
-4.5	0.001	0.007	0.003	0.004	0.004	0.005	0.001	0.006
	(0.06)	(0.46)	(0.63)	(0.56)	(0.59)	(0.91)	(0.13)	(0.28)
-4	0.001	0.011	0.001	0.002	0.006	0.003	0.001	-0.017
	(0.09)	(0.72)	(0.18)	(0.25)	(0.98)	(0.51)	(0.10)	(-0.78)
-3.5	0.002	0.005	0.001	0.004	0.007	0.005	0.004	-0.008
	(0.26)	(0.34)	(0.26)	(0.54)	(1.18)	(0.85)	(0.73)	(-0.38)
-3	0.004	0.003	0.006	0.010	0.006	0.009*	0.006	-0.007
	(0.47)	(0.19)	(1.32)	(1.55)	(1.15)	(1.70)	(1.29)	(-0.36)
-2.5	0.007	0.015	0.006	0.024***	0.010*	0.015***	0.013***	-0.011
	(0.94)	(1.21)	(1.38)	(4.09)	(1.96)	(3.06)	(2.97)	(-0.59)
-2	0.011	0.011	0.009**	0.029***	0.011**	0.018***	0.021***	-0.029*
	(1.54)	(0.93)	(2.27)	(5.23)	(2.43)	(4.05)	(5.00)	(-1.71)
-1.5	0.031***	0.032***	0.011***	0.043***	0.019***	0.025***	0.021***	-0.026*
	(5.00)	(3.05)	(3.13)	(8.50)	(4.30)	(6.22)	(5.64)	(-1.71)
-1	0.050***	0.030***	0.014***	0.053***	0.027***	0.035***	0.011***	-0.025*
	(8.99)	(3.25)	(4.40)	(11.75)	(6.91)	(9.62)	(3.36)	(-1.87)
-0.5	0.085***	0.047***	0.023***	0.062***	0.030***	0.042***	0.006**	-0.011
	(17.72)	(5.83)	(8.22)	(15.99)	(8.97)	(13.46)	(2.21)	(-0.92)
0	0.090***	0.037***	0.022***	0.051***	0.026***	0.047***	0.003	-0.025**
	(22.99)	(5.58)	(9.56)	(16.02)	(9.38)	(18.47)	(1.21)	(-2.54)
0.5	0.084***	0.026***	0.018***	0.052***	0.021***	0.038***	0.001	-0.032***
	(17.50)	(3.27)	(6.28)	(13.34)	(6.27)	(12.30)	(0.46)	(-2.73)

Continued on next page

Table C.3: Cumulative Abnormal Returns (CARs) Analysis by Exchange Rating (continued)

Day	AA	A	BB	B	C	D	E	F
1	0.078***	0.021**	0.012***	0.052***	0.017***	0.034***	0.016***	-0.041***
	(13.99)	(2.24)	(3.74)	(11.54)	(4.49)	(9.31)	(4.66)	(-2.97)
1.5	0.078***	0.015	0.011***	0.046***	0.015***	0.034***	0.011***	-0.041***
	(12.53)	(1.47)	(2.96)	(9.18)	(3.34)	(8.51)	(3.01)	(-2.66)
2	0.066***	0.005	0.009**	0.038***	0.011**	0.035***	0.013***	-0.034**
	(9.71)	(0.43)	(2.26)	(6.94)	(2.21)	(8.01)	(3.11)	(-2.06)
2.5	0.057***	0.001	0.006	0.035***	0.010**	0.037***	0.008*	-0.031*
	(7.70)	(0.08)	(1.34)	(5.93)	(2.00)	(7.64)	(1.81)	(-1.71)
3	0.054***	-0.003	0.003	0.032***	0.005	0.035***	0.006	-0.037*
	(6.84)	(-0.20)	(0.75)	(5.03)	(0.91)	(6.77)	(1.21)	(-1.89)
3.5	0.055***	0.007	-0.001	0.028***	0.003	0.031***	0.006	-0.050**
	(6.58)	(0.50)	(-0.25)	(4.08)	(0.54)	(5.75)	(1.11)	(-2.46)
4	0.048***	0.002	-0.001	0.022***	-0.001	0.026***	0.012**	-0.047**
	(5.48)	(0.13)	(-0.24)	(3.14)	(-0.08)	(4.64)	(2.30)	(-2.16)
4.5	0.055***	-0.002	-0.003	0.015**	-0.006	0.022***	0.005	-0.052**
	(5.95)	(-0.10)	(-0.51)	(2.08)	(-0.96)	(3.62)	(0.98)	(-2.28)
5	0.047***	-0.006	-0.004	0.013*	-0.010	0.014**	0.005	-0.054**
	(4.87)	(-0.37)	(-0.76)	(1.71)	(-1.44)	(2.26)	(0.82)	(-2.29)

Table C.4: Cumulative Abnormal Returns (CARs) by Exchange Ratings with Different Listing Histories

Notes: This table presents the Cumulative Abnormal Returns (CARs) by exchange rating with different listing histories. We conduct 8 studies for listings with the same listing history, which is defined by the highest-rated exchange the asset was previously listed on, i.e., first-time listing (no previous listings), previously listed on AA-A, A, BB, B, C, D, E, and F rated exchanges respectively. Therefore, we conduct 9 sets of event studies depending on the 9 types of listing histories, which are illustrated by the 9 rows in this table respectively. For example, the first row shows CARs until the time of listing on exchanges of the 8 rating respectively in the 8 columns, while in the first column it shows the CAR at the time of listing on AA-rated exchanges for assets that were previously listed on AA exchanges. All the CARs are calculated by adding up ARs from day -5 to day 0 relative to the event time, i.e., $CAR_i(-5,0) = \sum_{\tau=-5}^{0} AR_{i\tau}$. t-statistics are shown in parentheses below each coefficient. ***/**/* denote significance at 1%/5%/10% levels respectively.

Exchange Rating	AA	A	BB	B	C	D	E	F
AA	0.051***	-0.016*	0.025***	0.021***	0.013***	0.014***	-0.018***	0.163***
	(10.56)	(-1.77)	(7.54)	(4.62)	(2.65)	(3.48)	(-5.85)	(2.81)
A	0.131***	0.052***	0.009*	-0.004	0.021***	-0.004	-0.008	-0.075***
	(11.62)	(3.51)	(1.86)	(-0.38)	(4.12)	(-0.97)	(-1.27)	(-3.06)
BB	0.016	0.059***	0.032***	0.031***	0.010*	0.024***	0.004	0.063**
	(0.94)	(2.60)	(4.32)	(2.75)	(1.93)	(6.51)	(0.47)	(2.16)
B	0.062**	-0.042***	-0.025***	0.077***	0.036***	0.097***	0.002	0.066
	(2.31)	(-2.98)	(-4.73)	(5.49)	(6.05)	(12.80)	(0.23)	(1.50)
C	0.162***	-0.064**	0.027***	-0.014	0.016*	-0.006	0.010	-0.029
	(5.73)	(-2.52)	(4.15)	(-1.21)	(1.75)	(-0.52)	(1.06)	(-0.79)
D	–	–	0.025**	-0.052**	0.014	-0.034*	-0.185***	-0.100***
			(2.36)	(-2.39)	(1.12)	(-1.88)	(-13.51)	(-4.79)
E	0.063	0.351***	0.037***	0.168***	0.037**	-0.030	0.028**	0.101***
	(1.39)	(8.61)	(3.30)	(10.14)	(2.48)	(-0.98)	(2.57)	(3.67)
F	0.292***	–	–	-0.032	–	0.099***	0.062***	-
	(11.30)			(-0.60)		(3.02)	(5.18)	
first-time -listing	0.833***	0.187***	0.050***	0.120***	0.074***	0.145***	0.081***	-0.077***
	(13.07)	(9.75)	(7.33)	(8.10)	(7.38)	(11.36)	(5.66)	(-6.15)

D Derivation of Decomposing the Private Information

Let $\boldsymbol{\epsilon}_i = (\epsilon_{i1}, \epsilon_{i2}, \epsilon_{i3}, \epsilon_{i4})^\top \sim \mathcal{N}(0, \Sigma)$.

- For a fixed j, define the set of higher ratings $\mathcal{H}_j = \{k : k > j\}$.
- Let $\Sigma_{j,\mathcal{H}_j}$ be the $1 \times h$ vector of covariances of ϵ_{ij} with each ϵ_{ik}, $k > j$, where $h = 4 - j$.
- Let $\Sigma_{\mathcal{H}_j,\mathcal{H}_j}$ be the $h \times h$ covariance submatrix among $\{\epsilon_{ik}\}_{k>j}$.

We want to write

$$\epsilon_{ij} = \sum_{k=j+1}^{4} \gamma_{jk}\epsilon_{ik} + \epsilon_{ij}^{\perp}, \tag{D1}$$

where $\epsilon_{ij}^{\perp}$ is uncorrelated with all ϵ_{ik} for $k > j$. By the projection theorem (or OLS for multivariate normal), we have

$$\boldsymbol{\gamma}_j = (\gamma_{j,j+1}, \ldots, \gamma_{j,4}) = \Sigma_{j,\mathcal{H}_j} \cdot \Sigma_{\mathcal{H}_j,\mathcal{H}_j}^{-1}, \tag{D2}$$

where $\Sigma_{j,\mathcal{H}_j}$ is a row vector $[\mathrm{Cov}(\epsilon_{ij}, \epsilon_{i,j+1}), \ldots, \mathrm{Cov}(\epsilon_{ij}, \epsilon_{i4})]$, and $\Sigma_{\mathcal{H}_j,\mathcal{H}_j}$ is the covariance matrix for $(\epsilon_{i,j+1}, \ldots, \epsilon_{i4})$.

Proof:

For all $\ell > j$,

$$\begin{aligned}
\mathbb{E}[\epsilon_{ij}^{\perp}\epsilon_{i\ell}] &= \mathbb{E}\left[\left(\epsilon_{ij} - \sum_{k=j+1}^{4} \gamma_{jk}\epsilon_{ik}\right)\epsilon_{i\ell}\right] = 0 \\
\implies \mathrm{Cov}(\epsilon_{ij}, \epsilon_{i\ell}) &= \sum_{k=j+1}^{4} \gamma_{jk}\mathrm{Cov}(\epsilon_{ik}, \epsilon_{i\ell}) \\
\implies \Sigma_{j,\mathcal{H}_j} &= \boldsymbol{\gamma}_j\Sigma_{\mathcal{H}_j,\mathcal{H}_j} \\
\implies \boldsymbol{\gamma}_j &= \Sigma_{j,\mathcal{H}_j} \cdot \Sigma_{\mathcal{H}_j,\mathcal{H}_j}^{-1}.
\end{aligned} \tag{D3}$$

By construction, $\epsilon_{ij}^{\perp}$ is uncorrelated with all ϵ_{ik} for $k > j$.

$$\epsilon_{ij}^{\perp} = \epsilon_{ij} - \sum_{k=j+1}^{4} \gamma_{jk}\epsilon_{ik}. \tag{D4}$$

The variance of $\epsilon_{ij}^{\perp}$ is:

$$\begin{aligned}\mathrm{Var}(\epsilon_{ij}^{\perp}) &= \mathrm{Var}\left(\epsilon_{ij} - \sum_{k=j+1}^{4} \gamma_{jk}\epsilon_{ik}\right) \\ &= \mathrm{Var}(\epsilon_{ij}) + \mathrm{Var}\left(\sum_{k=j+1}^{4} \gamma_{jk}\epsilon_{ik}\right) - 2\mathrm{Cov}\left(\epsilon_{ij}, \sum_{k=j+1}^{4} \gamma_{jk}\epsilon_{ik}\right) \\ &= \Sigma_{jj} + \boldsymbol{\gamma}_j \Sigma_{\mathcal{H}_j,\mathcal{H}_j} \boldsymbol{\gamma}_j^{\top} - 2\boldsymbol{\gamma}_j \Sigma_{j,\mathcal{H}_j}^{\top}. \end{aligned} \tag{D5}$$

From (D3),

$$\boldsymbol{\gamma}_j \Sigma_{\mathcal{H}_j,\mathcal{H}_j} = \Sigma_{j,\mathcal{H}_j}, \tag{D6}$$

so (D5) becomes:

$$\mathrm{Var}(\epsilon_{ij}^{\perp}) = \Sigma_{jj} - \Sigma_{j,\mathcal{H}_j} \Sigma_{\mathcal{H}_j,\mathcal{H}_j}^{-1} \Sigma_{j,\mathcal{H}_j}^{\top}. \tag{D7}$$

For a correlation matrix ($\Sigma_{jj} = 1$), this is:

$$\mathrm{Var}(\epsilon_{ij}^{\perp}) = 1 - \Sigma_{j,\mathcal{H}_j} \Sigma_{\mathcal{H}_j,\mathcal{H}_j}^{-1} \Sigma_{j,\mathcal{H}_j}^{\top}. \tag{D8}$$

E Derivation of Decomposing the Listing Effects

We model cumulative abnormal return (CAR) as:

$$\mathrm{CAR}_{ij} = \alpha_j^{\perp} \epsilon_{ij}^{\perp} + \sum_{k=j+1}^{4} \alpha_k \epsilon_{ik}, \tag{E1}$$

where $\epsilon_{ij}^{\perp} = \epsilon_{ij} - \sum_{k=j+1}^{4} \gamma_{jk}\epsilon_{ik}$ and γ_{jk} are the projection coefficients defined in (D3). Then we decompose the expectation of CAR conditional on the information revealed by the listing on exchange j, $\mathbb{E}\left[\mathrm{CAR}_{ij} \mid \epsilon_{ij}\right]$, as follows:

$$\mathbb{E}\left[\mathrm{CAR}_{ij} \mid \epsilon_{ij}\right] = \alpha_j^{\perp}\, \mathbb{E}\left[\epsilon_{ij}^{\perp} \mid \epsilon_{ij}\right] + \sum_{k=j+1}^{4} \alpha_k\, \mathbb{E}\left[\epsilon_{ik} \mid \epsilon_{ij}\right]. \tag{E2}$$

Since $(\epsilon_{ij}, \epsilon_{ik})$ are jointly standard normal,

$$\mathbb{E}[\epsilon_{ik} \mid \epsilon_{ij}] = \rho_{ik,j}\epsilon_{ij}, \tag{E3}$$

where

$$\rho_{ik,j} = \text{Cov}(\epsilon_{ik}, \epsilon_{ij}), \tag{E4}$$

or

$$\mathbb{E}[\epsilon_{ik} \mid \epsilon_{ij}] = \frac{\Sigma_{ik,j}}{\Sigma_{jj}}\epsilon_{ij}, \tag{E5}$$

but with standardized variables ($\Sigma_{jj} = 1$) we can just use the covariance. For the orthogonal residual,

$$\epsilon_{ij}^{\perp} = \epsilon_{ij} - \sum_{k=j+1}^{4} \gamma_{jk}\epsilon_{ik}, \tag{E6}$$

so,

$$\begin{aligned}
\mathbb{E}[\epsilon_{ij}^{\perp} \mid \epsilon_{ij}] &= \epsilon_{ij} - \sum_{k=j+1}^{4} \gamma_{jk}\mathbb{E}[\epsilon_{ik} \mid \epsilon_{ij}] \\
&= \epsilon_{ij} - \sum_{k=j+1}^{4} \gamma_{jk}\rho_{ik,j}\epsilon_{ij} \\
&= \left(1 - \sum_{k=j+1}^{4} \gamma_{jk}\rho_{ik,j}\right)\epsilon_{ij}.
\end{aligned} \tag{E7}$$

Then replace $\mathbb{E}[\epsilon_{ik} \mid \epsilon_{ij}]$ derived in (E3) and $\mathbb{E}[\epsilon_{ij}^{\perp} \mid \epsilon_{ij}]$ derived in (E7) into (E2), we have the final decomposition of the listing effects:

$$\begin{aligned}
\mathbb{E}\left[AR_{ij} \mid \epsilon_{ij}\right] &= \alpha_j^{\perp}\left(1 - \sum_{k=j+1}^{4} \gamma_{jk}\rho_{ik,j}\right)\epsilon_{ij} + \sum_{k=j+1}^{4} \alpha_k\rho_{ik,j}\epsilon_{ij} \\
&= \left\{\alpha_j^{\perp}\left[1 - \sum_{k=j+1}^{4} \gamma_{jk}\rho_{ik,j}\right] + \sum_{k=j+1}^{4} \alpha_k\rho_{ik,j}.\right\}\epsilon_{ij}
\end{aligned} \tag{E8}$$

F Procedure of Estimating Parameters for Simultaneous Listing Premium

To obtain the listing effects decomposed into two parts as shown in (27), we need the estimates of $\alpha_j^{\perp}$, α_j, γ_{jk}, and ρ_{jk} for all j and $k > j$, across all exchange ratings. To this end, we firstly estimate a multivariate probit model for the listing decisions of assets on exchanges with different ratings, yielding the estimates of the variance-covariance matrix Σ of the private information ϵ_{ij} and θ_j $(j = 1, 2, 3, 4)$ in the latent decision equation (23). With the estimated variance-covariance matrix Σ, we can then obtain the estimates of γ_{jk} using

$$\gamma_{jk} = (\boldsymbol{\gamma}_j)_k = \left[\Sigma_{j,\mathcal{H}_j} \cdot \Sigma_{\mathcal{H}_j,\mathcal{H}_j}^{-1}\right]_k, \tag{F1}$$

where we define the set of higher ratings $\mathcal{H}_j = \{k : k > j\}$ for a fixed j, $\Sigma_{j,\mathcal{H}_j}$ as the $1 \times h$ vector of covariances of ϵ_{ij} with each ϵ_{ik}, $k > j$ $(h = 4 - j)$, and $\Sigma_{\mathcal{H}_j,\mathcal{H}_j}$ is the $h \times h$ covariance sub-matrix among $\{\epsilon_{ik}\}_{k>j}$ [17]. Also, we can retrieve the estimation of ρ_{jk} from Σ as $\rho_{jk} = \Sigma_{jk}$.

Our second stage estimation is based on (24), where the conditional expectations in the right-hand side can be computed using our estimates of Σ and θ_j $(j = 1, 2, 3, 4)$ in the first stage. Note that the conditional expectations $\mathbb{E}[\epsilon_{ij} \mid \epsilon_{ik} > -X_{ij}'\theta_j, \forall k \in \mathcal{J}]$ constitute multivariate inverse Mills ratios (multivariate IMRs), denoted as $\lambda_{ij|\mathcal{J}}$. These IMRs are defined and computed based on the multivariate normal distribution of $\boldsymbol{\epsilon}_i = (\epsilon_{i1}, \epsilon_{i2}, \epsilon_{i3}, \epsilon_{i4})^{\top} \sim \mathcal{N}(0, \Sigma)$, which we estimate in the first stage. With the IMRs, we can estimate the regressors β_j $(j \in \{1, 2, 3, 4\})$ at the righ-hand side of (24).

Now we have the estimates of γ_{jk}, ρ_{jk}, and β_j, the next step is to recover $\alpha_j^{\perp}$ and α_j. According to the Gram–Schmidt orthogonalization process, we have:

$$\alpha_k = \alpha_k^{\perp} - \sum_{m<k} \alpha_m^{\perp} \gamma_{mk}, \tag{F2}$$

the derivation of which is shown in F.1. The expected market reaction conditional on the

[17] (F1) is derived in Appendix D.

observed private information of the listing on exchange j illustrated in (E8) equates to the effects measured by β_j:

$$\beta_j = \alpha_j^{\perp} \left(1 - \sum_{k=j+1}^{4} \gamma_{jk} \rho_{jk} \right) + \sum_{k=j+1}^{4} \alpha_k \rho_{jk}. \tag{F3}$$

The systems constructed by (F2) and (F3) are sufficient to solve for $\alpha_j^{\perp}$ and α_j ($j = 1, 2, 3, 4$), which include 8 unknowns. Substitute (F2) into the second term in the right-hand side of (F3), we have

$$\beta_j = \alpha_j^{\perp} \left(1 - \sum_{k=j+1}^{4} \gamma_{jk} \rho_{jk} \right) + \sum_{k=j+1}^{4} \alpha_k^{\perp} \rho_{jk} - \sum_{k=j+1}^{4} \sum_{m<k} \gamma_{mk} \alpha_m^{\perp} \rho_{jk}, \tag{F4}$$

with which we can form a upper-triangular system for $\boldsymbol{\alpha}^{\perp} = (\alpha_1^{\perp}, \alpha_2^{\perp}, \alpha_3^{\perp}, \alpha_4^{\perp})^{\top}$:

$$\boldsymbol{C}\boldsymbol{\alpha}^{\perp} = \boldsymbol{\beta}, \tag{F5}$$

where $\boldsymbol{\beta} = (\beta_1, \beta_2, \beta_3, \beta_4)^{\top}$ and $\boldsymbol{C}$ follows:

$$C_{j\ell} = \begin{cases} 1 - 2 \sum_{k=j+1}^{4} \gamma_{jk} \rho_{jk}, & \ell = j \\ \rho_{j\ell} - \sum_{k=\ell+1}^{4} \gamma_{\ell k} \rho_{jk}, & \ell > j \end{cases}. \tag{F6}$$

Then we can solve for $\boldsymbol{\alpha}^{\perp}$ by $\boldsymbol{\alpha}^{\perp} = \boldsymbol{C}^{-1}\boldsymbol{\beta}$, and α_k by substituting $\boldsymbol{\alpha}^{\perp}$ into (F2). Detailed derivations can be found in F.2.

F.1 Derivation of the downward recursion

In (D1), we decomposed the private information ϵ_{ij} into a part that is orthogonal to all higher-tier exchanges, $\epsilon_{ij}^{\perp}$, and a part that is correlated with the private information of higher-tier exchanges, $\sum_{k=j+1}^{4} \gamma_{jk} \epsilon_{ik}$. However, if we fully decompose private information by projecting it to all levels of exchanges, the market reaction to the information of asset i can

be expressed as:

$$\text{CAR}_i = \sum_k \alpha_k^{\perp} \epsilon_{ik}^{\perp},\ k \in \{1,2,3,4\}, \tag{F7}$$

by which we sum over all possible listing levels, and at each level, we include the component of the latent shock $\epsilon_{ik}^{\perp}$ that is orthogonal to all other levels. Each $\alpha_k^{\perp}$ gives the sensitivity to the information solely to listing on exchanges rated as k. Substitute (D4) into (F7), we have:

$$\begin{aligned}\text{CAR}_i &= \sum_k \alpha_k^{\perp} \epsilon_{ik}^{\perp} = \sum_k \alpha_k^{\perp} \left(\epsilon_{ik} - \sum_{\ell>k} \gamma_{k\ell} \epsilon_{i\ell} \right) \\ &= \sum_k \alpha_k^{\perp} \epsilon_{ik} - \sum_k \sum_{\ell>k} \alpha_k^{\perp} \gamma_{k\ell} \epsilon_{i\ell}. \end{aligned} \tag{F8}$$

Switch the order of summation for the double sum:

$$\sum_k \sum_{\ell>k} \alpha_k^{\perp} \gamma_{k\ell} \epsilon_{i\ell} = \sum_\ell \left(\sum_{k<\ell} \alpha_k^{\perp} \gamma_{k\ell} \right) \epsilon_{i\ell}, \tag{F9}$$

so

$$\begin{aligned}\text{CAR}_i &= \sum_k \alpha_k^{\perp} \epsilon_{ik} - \sum_\ell \left(\sum_{k<\ell} \alpha_k^{\perp} \gamma_{k\ell} \right) \epsilon_{i\ell} \\ &= \sum_k \left[\alpha_k^{\perp} - \sum_{m<k} \alpha_m^{\perp} \gamma_{mk} \right] \epsilon_{ik}, \end{aligned} \tag{F10}$$

where in the last line, we relabelled $k \to m$ and $\ell \to k$. As without the linear projection, market reaction can be written as

$$\text{CAR}_i = \sum_k \alpha_k \epsilon_{ik}, \tag{F11}$$

and refer to (F10), we have

$$\text{CAR}_i = \sum_k \alpha_k \epsilon_{ik} = \sum_k \left[\alpha_k^{\perp} - \sum_{m<k} \alpha_m^{\perp} \gamma_{mk} \right] \epsilon_{ik}. \tag{F12}$$

Therefore, we can recover the market sensitivity parameters α_k recursively in an increasing order:

$$\alpha_k = \alpha_k^{\perp} - \sum_{m<k} \alpha_m^{\perp} \gamma_{mk}. \tag{F13}$$

F.2 System of equations recovering the market sensitivity parameters

From our conditional expectation regression, for $j = 1, 2, 3, 4$, we have the estimates of β_j:

$$\beta_j = \alpha_j^{\perp} \left(1 - \sum_{k=j+1}^{4} \gamma_{jk} \rho_{jk} \right) + \sum_{k=j+1}^{4} \alpha_k \rho_{jk}, \tag{F14}$$

where we have β_j (estimated from the regression) and all γ_{jk}, ρ_{jk} from first stage estimation. With (F13), we can express every α_k in (F13) entirely in terms of $\alpha_1^{\perp}, \ldots, \alpha_4^{\perp}$:

$$\beta_j = \alpha_j^{\perp} \left(1 - \sum_{k=j+1}^{4} \gamma_{jk} \rho_{jk} \right) + \sum_{k=j+1}^{4} \left[\alpha_k^{\perp} - \sum_{m<k} \gamma_{mk} \alpha_m^{\perp} \right] \rho_{jk}, \tag{F15}$$

the second term of which can be expanded as

$$\sum_{k=j+1}^{4} \left[\alpha_k^{\perp} - \sum_{m<k} \gamma_{mk} \alpha_m^{\perp} \right] \rho_{jk} = \sum_{k=j+1}^{4} \alpha_k^{\perp} \rho_{jk} - \sum_{k=j+1}^{4} \left(\sum_{m<k} \gamma_{mk} \alpha_m^{\perp} \right) \rho_{jk}. \tag{F16}$$

So (F15) can be rewritten as:

$$\beta_j = \alpha_j^{\perp} \left(1 - \sum_{k=j+1}^{4} \gamma_{jk} \rho_{jk} \right) + \sum_{k=j+1}^{4} \alpha_k^{\perp} \rho_{jk} - \sum_{k=j+1}^{4} \sum_{m<k} \gamma_{mk} \alpha_m^{\perp} \rho_{jk}, \tag{F17}$$

which forms a system of equations for $\alpha_j^{\perp}$, $j = 1, 2, 3, 4$. The system of equations can be written as a upper-triangular system for the unknown $\boldsymbol{\alpha}^{\perp} = (\alpha_1^{\perp}, \ldots, \alpha_4^{\perp})^{\top}$:

$$\begin{bmatrix} C_{11} & C_{12} & C_{13} & C_{14} \\ 0 & C_{22} & C_{23} & C_{24} \\ 0 & 0 & C_{33} & C_{34} \\ 0 & 0 & 0 & C_{44} \end{bmatrix} \begin{bmatrix} \alpha_1^{\perp} \\ \alpha_2^{\perp} \\ \alpha_3^{\perp} \\ \alpha_4^{\perp} \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{bmatrix}. \tag{F18}$$

For C_{jl} in the upper-triangular matrix, when $j = l$ the coefficients for $\alpha_j^{\perp}$ appears in the first term of (F17) as $\alpha_j^{\perp}\left(1 - \sum_{k=j+1}^{4} \gamma_{jk}\rho_{jk}\right)$, while it also appears in the double sum whenever $m = j$, i.e., for all $k = j+1, \ldots, 4$, $-\sum_{k=j+1}^{4} \gamma_{jk}\alpha_j^{\perp}\rho_{jk}$. So, the total coefficient for $\alpha_j^{\perp}$ is:

$$C_{jj} = 1 - \sum_{k=j+1}^{4} \gamma_{jk}\rho_{jk} - \sum_{k=j+1}^{4} \gamma_{jk}\rho_{jk} = 1 - 2\sum_{k=j+1}^{4} \gamma_{jk}\rho_{jk}. \tag{F19}$$

When $j < l$, the coefficients for $\alpha_l^{\perp}$ appear in both the second and third terms of (F17):

$$C_{j\ell} = \rho_{j\ell} - \sum_{k=\ell+1}^{4} \gamma_{\ell k}\rho_{jk}. \tag{F20}$$

Thus elements in the upper-triangular matrix $\boldsymbol{C}$ are:

$$C_{j\ell} = \begin{cases} 1 - 2\displaystyle\sum_{k=j+1}^{4} \gamma_{jk}\rho_{jk}, & \ell = j \\ \rho_{j\ell} - \displaystyle\sum_{k=\ell+1}^{4} \gamma_{\ell k}\rho_{jk}, & \ell > j \end{cases}. \tag{F21}$$

Then we can solve the for $\boldsymbol{\alpha}^{\perp}$ by $\boldsymbol{\alpha}^{\perp} = \boldsymbol{C}^{-1}\boldsymbol{\beta}$ with unique solution as long as diagonal entries C_{jj} are non-zero. Finally, with all $\alpha_k^{\perp}$, we can solve α_k using (F13).

G Additional Tables for Conditional Event Study

This appendix collects supplementary tables for the conditional event study reported in Section 6. The first subsection reports the descriptive statistics of observable characteristics for

the single-listing and simultaneous-listing samples used in the first-stage probit estimation in Section 5. The second subsection reports the two-stage estimation and decomposition for simultaneous listings whose highest prior listed exchange was in the BB-B group, complementing the AA-A prior results reported in Section 6.3.

G.1 Descriptive statistics for listings

This subsection reports the per-panel descriptive statistics of the observable-characteristic vector X_{ij} for the single-exchange and simultaneous-listing samples used in the conditional event study in Section 6.

We examine why the premium varies across sequential listings by employing the first sort of listing events: the 6717 listings on a single exchange. Descriptive statistics of assets' characteristics for this sort of events, i.e., X_{ij}, summarized in Table G.1 reveal hints on how assets with different listing histories differ. Consistent with our expectation, assets that have been already listed on high-rated exchanges tend to be more matured, indicated by larger market capitalization (SIZE), lower trading volume to circulating supply (VOLUME), and larger average number of chains launched (NO_CHAIN), especially compared with those have never been listed before (Panel E). Assets with higher-tier listing history tend to be less risky, shown by lower volatility (VOLATL), but the price run-up (RUNUP) does not show a clear monotonous pattern, with assets in Panel C (C-D) having the highest average run-up. Since listings on perpetual market and spot market of the same exchange usually happen together, it is not surprising that assets with higher-tier listing history are more likely to be listed on the perpetual futures market of exchanges with higher ratings (PR_FUT_RATE_2 and PR_FUT_RATE_4 represent the probability of being listed on the perpetual market of the exchange with the according rating).

To investigate premium for simultaneous listings, we adopt the second sort of listing events: the 353 events of simultaneous listings. Table G.2 reports descriptive statistics of observable characteristics for those simultaneous listing events. The patterns are consistent with those seen in single-exchange listings (Table G.1): assets already listed on higher-rated venues tend to be more matured, exhibiting lower VOLUME, lower VOLATL, and larger SIZE.

Table G.1: Descriptive Statistics of Observable Characteristics for Listings on Single Exchange

Notes: This table presents the mean value and standard deviation (Std) of each observable characteristics variable in X_{ij}, which we use to estimate (28) with ϵ_{ij} of standard normal distribution (20). The 5 panels in this table illustrate descriptive statistics of observable characteristics variables for listing events with previously highest rated exchange in AA-A, BB-B, C-D, E-F, and first-time-listing, respectively. Panel E, which we label as first-time-listing, includes all cases that have never been listed on any exchange before, so assets that have never been listed during our sampling period are considered in this panel. Our data do not contain any assets that have been listed on the perpetual futures market of exchanges with rating C-D and E-F before the listing event, so the corresponding variables (PR_FUT_RATE_3 and PR_FUT_RATE_1) are skipped in this table. Characteristics of assets that have never been listed are considered in Panel E, cases without any listing history.

Observable Asset Features	VOLUME	NO_CHAIN	VOLATL	RUNUP	SIZE	PR_FUT _RATE_2	PR_FUT _RATE_4
Panel A: listing of assets with highest previously listed exchange in rating AA-A (No. of observations: 4380)							
Mean	0.0013	1.3808	0.0475	3.8758	18.5722	0.0041	0.6331
Std	0.0040	0.6413	0.0389	164.1214	1.6588	0.0640	0.4820
Panel B: listing of assets with highest previously listed exchange in rating BB-B (No. of observations: 1374)							
Mean	0.0049	1.2817	0.0561	9.7741	16.4746	0.0007	0.0233
Std	0.0207	0.5504	0.0409	165.9051	2.0885	0.0270	0.1509
Panel C: listing of assets with highest previously listed exchange in rating C-D (No. of observations: 500)							
Mean	0.0065	1.2040	0.0596	65.7869	16.1761	-	0.0040
Std	0.0151	0.4805	0.0432	1190.8602	2.5146	-	0.0632
Panel D: listing of assets with highest previously listed exchange in rating E-F (No. of observations: 107)							
Mean	0.0059	1.2336	0.0567	30.5727	15.1818	-	-
Std	0.0128	0.5062	0.0495	280.4030	2.1527	-	-
Panel E: first-time listings (No. of observations: 5882)							
Mean	0.0116	1.0908	0.0905	2.2368	12.1917	-	0.0005
Std	0.0463	0.3556	0.0876	23.9368	2.8460	-	0.0226

Table G.2: Descriptive Statistics of Observable Characteristics for Simultaneous Listings on Multiple Exchanges

Notes: This table presents the mean value and standard deviation (Std) of each observable characteristics variable in X_{ij}, which we use to estimate (28) with ϵ_{ij} of multivariate normal distribution (23). The 5 panels in this table illustrate descriptive statistics of observable characteristics variables for listing events with previously highest rated exchange in AA-A, BB-B, C-D, E-F, and first-time-listing, respectively. Panel E, which we label as first-time-listing, includes all cases that have never been listed on any exchange before, so assets that have never been listed during our sampling period are considered in this panel. Our data do not contain any assets that have been listed on the perpetual futures market of exchanges with rating C-D and E-F before the listing event, so the corresponding variables (PR_FUT_RATE_3 and PR_FUT_RATE_1) are skipped in this table. Characteristics of assets that have never been listed are considered in Panel E, cases without any listing history. In Panel E, 17 out of 5543 observations are listing events in our sampling period, while the rest 5526 observations are assets not listed even at the end of our sampling period.

Observable Asset Features	VOLUME	NO_CHAIN	VOLATL	RUNUP	SIZE	PR_FUT _RATE_2	PR_FUT _RATE_4
Panel A: listing of assets with highest previously listed exchange in rating AA-A (No. of observations: 253)							
Mean	0.0016	1.3439	0.0539	32.5850	18.9097	-	0.6640
Std	0.0030	0.5946	0.0571	461.9435	1.6295	-	0.4733
Panel B: listing of assets with highest previously listed exchange in rating BB-B (No. of observations: 53)							
Mean	0.0054	1.3774	0.0606	3.9145	17.2381	-	0.0566
Std	0.0079	0.6571	0.0317	7.9672	1.7455	-	0.2333
Panel C: listing of assets with highest previously listed exchange in rating C-D (No. of observations: 29)							
Mean	0.0076	1.3448	0.0694	9.8929	16.1933	-	-
Std	0.0183	0.5526	0.0724	35.7604	2.4474	-	-
Panel D: listing of assets with highest previously listed exchange in rating E-F (No. of observations: 1)							
Mean	0.0002	1.0000	0.0857	10.3553	18.6954	-	-
Std	-	-	-	-	-	-	-
Panel E: first-time listings (No. of observations: 5543)							
Mean	0.0720	1.0588	0.0767	19.1326	15.1326	-	-
Std	0.2426	0.2425	0.0544	71.7568	3.3680	-	-

G.2 Simultaneous listings with BB-B prior history

Table G.3: Two-stage estimation for simultaneous listings with previously listing on exchanges in BB-B group

Notes: This table represents the two-stage estimation results based on simultaneous listings with prior highest rated exchanges in BB-B group, following the procedure illustrated in Appendix F. Panel A reports the first-stage multivariate probit estimates based on (28) with ϵ_{ij} following multivariate normal distribution. Results for listings on AA-A rated exchanges are in Column (1), those of BB-B listings are in Column (2), C-D in Column (3), and E-F in Column (4). Panel B shows the private-information correlations. The pairwise correlations are shown in the off-diagonal cells in Panel B. For example, the correlation between BB-B and AA-A listings is recorded at the second row under Column (1). Panel C shows the second-stage IMR estimates, while Column (1) to (4) for univariate and Column (5) for multivariate estimation. For the univariate ones we adopt (22) while for the multivariate one we use (24), but both cases are based on the IMRs from the multivariate probit estimation. t-statistics are shown in parentheses. ***/**/* denote p<0.01/0.05/0.10.

Listing	AA-A (1)	BB-B (2)	C-D (3)	E-F (4)	(5)
Panel A: First-stage estimation					
Dependent variable: $LIST_j$					
Independent variables:					
Intercept	-4.203*** (-5.13)	-4.301*** (-16.56)	-4.579*** (-15.87)	-4.214*** (-13.68)	
VOLUME	0.328 (0.07)	0.058 (0.02)	-0.001 (-0.00)	0.976 (0.49)	
NO_CHAIN	-0.438 (-0.64)	0.292*** (3.08)	0.271** (2.53)	0.256** (2.27)	
VOLATL	-0.663 (-0.27)	-1.676 (-1.41)	-0.467 (-0.46)	-5.155** (-2.48)	
RUNUP	0.001 (0.51)	-0.000 (-0.02)	0.001 (0.15)	0.003 (1.51)	
SIZE	0.112*** (5.22)	0.117*** (8.92)	0.123*** (8.87)	0.113*** (7.43)	
PR_FUT_RATE_4	2.658*** (3.89)	1.049* (1.86)	1.587*** (2.76)	1.821*** (3.15)	
Panel B: Private-information correlations					
AA-A	-	0.609*** (9.10)	0.585*** (7.68)	0.558*** (6.98)	
BB-B	0.609*** (9.10)	-	0.850*** (26.92)	0.815*** (20.47)	
C-D	0.585*** (7.68)	0.850*** (26.92)	-	0.823*** (18.23)	
E-F	0.558*** (6.98)	0.815*** (20.47)	0.823*** (18.23)	-	
Panel C: Second-stage estimation					
Dependent variable: CAR					
Independent variable: IMR terms					

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Table G.3: Two-stage estimation for simultaneous listings with previously listing on exchanges in BB-B group (continued)

Listing	AA-A (1)	BB-B (2)	C-D (3)	E-F (4)	(5)
Intercept	-0.026	-0.031	-0.066	-0.058	-0.704
	(-0.45)	(-0.26)	(-0.72)	(-0.71)	(-1.09)
λ_{AA-A}	0.150***	-	-	-	0.153
	(2.73)	-	-	-	(1.46)
λ_{BB-B}	-	0.031	-	-	0.114
	-	(0.58)	-	-	(1.26)
λ_{C-D}	-	-	0.060	-	0.148
	-	-	(1.35)	-	(1.47)
λ_{E-F}	-	-	-	0.064	0.149*
	-	-	-	(1.51)	(1.68)

Table G.4: Disentangling effects for simultaneous listings with highest previously listed exchanges in BB-B group

Notes: This table summarizes results of disentangling the listing effects into the two components illustrated by (27): the *informational complement* effect and *informational substitute* effect. Results in this table are calculated with data of simultaneous listings with highest previous listed exchanges in AA-A group Panel A reports the calculated projection parameters, γ_{jk}, using (F1) and estimated covariance summarized in Panel B of Table G.3. Panel B shows the constructed $\alpha_j^{\perp}$ and α_j solved from (F5) and (F2) with estimated slope coefficients, β_j, in Panel C of Table G.3. Panel C summarizes the estimated slope coefficients, β_j, as well as the reconstructed ones based on the decomposition. The slope coefficient for each rating category listing is decomposed into two parts, which are shown in the two rows *informational complement* and *informational substitute* effect separately. We also report the percentage of effect of each component to the total.

Listing	AA-A	BB-B	C-D	E-F
Panel A: Estimation of γ_{jk}				
E-F ($j=1$)	0.050 (γ_{14})	0.395 (γ_{13})	0.458 (γ_{12})	—
C-D ($j=2$)	0.107 (γ_{24})	0.785 (γ_{23})	—	—
BB-B ($j=3$)	0.609 (γ_{34})	—	—	—
AA-A ($j=4$)	—	—	—	—
Panel B: Calculated $\alpha_j^{\perp}$ and α_j				
$\alpha_j^{\perp}$	0.153($\alpha_4^{\perp}$)	0.080($\alpha_3^{\perp}$)	-0.040($\alpha_2^{\perp}$)	-0.066($\alpha_1^{\perp}$)
α_j	0.113(α_4)	0.137(α_3)	-0.010(α_2)	-0.066(α_1)
Panel C: Disentangling effects for simultaneous listings				
β_j	0.153	0.114	0.148	0.149
Informational complement effect	0.153	0.050	-0.011	-0.018
Informational substitute effect	0.000	0.068	0.183	0.167
Reconstructed β_j	0.153	0.119	0.172	0.149

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Table G.4: Disentangling effects for simultaneous listings with highest previously listed exchanges in BB-B group (continued)

Listing	AA-A	BB-B	C-D	E-F
Informational complement effect %	100.0%	42.3%	5.6%	9.8%
Informational substitute effect %	0.0%	57.7%	94.4%	90.2%

H Details for the information-distance test

This appendix documents the sample construction, the first-stage probit specification, and an ordinal-distance robustness check for the test reported in Section 7.

Sample construction. The estimation sample starts from the 6,717 single-listing events analyzed in Section 6.2 and retains the 5,710 events with complete data on the asset-characteristic vector required by the first-stage probit (VOLUME, SIZE, VOLATL, RUNUP, PR_FUT_RATE, and NO_CHAIN). Each retained event records X_{ij} at the time of the listing, the current listing tier j, the highest prior listing tier h (with $h = 0$ for first-time listings), and the standardized event-window CAR.

First-stage probits. For each current tier j, the first-stage probit is fit on the full single-listing sample, unconditional on prior-listing state. This pooled-per-tier specification is required for the characteristic-based distance to be a well-defined cross-tier comparison, since slice-conditional probits (one per (j, h) cell) would estimate $\hat{\theta}_{j|h}$ on different sub-samples and the resulting linear indices $X'_{ij}\hat{\theta}_{j|h}$ would not be directly comparable across prior-tier conditions. Table H.1 reports the pooled probit estimates per current tier.

Table H.1: First-stage pooled probits per current tier

Notes: Pooled univariate probit $\Pr(\text{LIST}_j = 1 \mid X_{ij}) = \Phi(X'_{ij}\theta_j)$ per current tier j. The sample of 5,710 events is the subset of single-listing events with complete first-stage covariates, as detailed in the sample-construction paragraph above. The covariate vector X_{ij} matches Section 6.2. The resulting $\hat{\theta}_j$ are used to construct DIST_i and the IMR in (29). Heteroskedasticity-robust z-statistics in parentheses.
***/**/* denote significance at the 1%/5%/10% levels.

Variable	AA-A	BB-B	C-D	E-F
Intercept	-4.3507***	0.2423	-0.1553	-0.8244***
	(-17.62)	(1.44)	(-1.02)	(-4.69)

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Table H.1: First-stage pooled probits per current tier (continued)

Variable	AA-A	BB-B	C-D	E-F
VOLUME	0.9865 (0.79)	-2.1618 (-1.41)	1.0968 (0.87)	0.1814 (0.12)
SIZE	0.1470*** (10.63)	-0.0449*** (-4.65)	0.0054 (0.63)	-0.0038 (-0.38)
VOLATL	1.0213* (1.83)	-0.7621 (-1.51)	1.5143*** (3.26)	-1.6382** (-2.41)
RUNUP	-0.0024 (-1.05)	0.0000 (0.02)	0.0000 (0.83)	-0.0002 (-0.50)
PR_FUT_RATE_2	-6.2067*** (-47.15)	-0.2372 (-0.54)	-0.2744 (-0.76)	0.7781** (2.12)
PR_FUT_RATE_4	-0.0882 (-1.36)	0.0722* (1.65)	-0.1245*** (-3.07)	0.1263*** (2.71)
NO_CHAIN	0.0680 (1.61)	-0.0152 (-0.50)	-0.0239 (-0.85)	0.0247 (0.77)
N	5710	5710	5710	5710
Pseudo-R^2	0.047	0.004	0.004	0.005

Robustness: ordinal distance. The ordinal distance $\text{DIST_ord}_i = j - h$ is a coarser benchmark that uses only the integer tier ranks and ignores asset-level characteristics. We re-estimate (29) with DIST_ord_i in place of DIST_i, holding the sample, the IMR construction, and the standard-error treatment fixed. Table H.2 reports the results, which are qualitatively similar to those in Table 6.

Table H.2: Information distance regression with DIST_ord_i, per current tier

Notes: OLS estimates of (29) per current tier j with $\text{DIST_ord}_i = j - h$ in place of DIST_i. The sample of 5,710 events is the subset of single-listing events with complete first-stage covariates, as detailed in Appendix H. IMR construction and standard-error treatment match Table 6. Heteroskedasticity-robust t-statistics in parentheses.
***/**/* denote significance at the 1%/5%/10% levels.

Variable	AA-A ($j = 4$)	BB-B ($j = 3$)	C-D ($j = 2$)	E-F ($j = 1$)
Intercept	0.0074*** (2.61)	0.0190*** (4.98)	0.0305*** (4.23)	0.0424*** (3.92)
DIST	0.0118*** (3.06)	0.0116*** (2.93)	0.0116*** (2.93)	0.0117*** (3.01)
IMR	0.0135** (2.38)	0.0032 (0.73)	0.0020 (0.23)	-0.0226 (-1.44)
DIST × IMR	0.0274** (2.00)	-0.0023 (-0.52)	-0.0008 (-0.16)	-0.0013 (-0.24)
N	5710	5710	5710	5710
Adj. R^2	0.0087	0.0030	0.0029	0.0063

Table H.2: Information distance regression with DIST_ord$_i$, per current tier (cont.)

Variable	AA-A ($j = 4$)	BB-B ($j = 3$)	C-D ($j = 2$)	E-F ($j = 1$)

The qualitative pattern of Table 6 is preserved under the ordinal distance, with β_1 positive and significant at the 1% level in every tier and β_3 positive and significant at AA-A only.

I Details for the Exchange-Failure Natural Experiments

This appendix documents the timelines of the two events, the explicit higher-tier substitute set used in each test, the rationale for excluding seven FTX-affiliated tokens from the FTX main specification, the FTX-specific estimation-window calibration, and the construction of the control variables.

Timeline of the FTX collapse. On 2022-11-02 a CoinDesk article raised concerns about the balance sheet of Alameda Research, FTX's sister trading firm. On 2022-11-06 Binance CEO Changpeng Zhao tweeted that Binance would liquidate its remaining FTT holdings, and on 2022-11-07 the FTT price crashed and runs on FTX began. On 2022-11-08 Binance announced a non-binding letter of intent to acquire FTX; Binance withdrew the LOI on 2022-11-09 after inspecting FTX's books, and FTX Trading Ltd. filed for Chapter 11 bankruptcy protection on 2022-11-11. We use 2022-11-11 as the event date because only on that date did the loss of certification become irrevocable and mechanical delistings follow.

Timeline of the Bittrex SEC complaint. On 2023-03-31 Bittrex Global announced the cessation of its US operations effective 2023-04-30. On 2023-04-17 the U.S. Securities and Exchange Commission filed a complaint against Bittrex Inc. and Bittrex Global GmbH, alleging that they operated as an unregistered securities exchange, broker, and clearing agency. Bittrex US filed for Chapter 11 bankruptcy protection on 2023-04-28. We use 2023-04-17 as the event date because the SEC complaint is the regulatory shock that triggered the loss of Bittrex's certification function for new tokens. The subsequent Chapter 11 filing was a mechanical follow-on to the complaint and falls inside the $[-5, +5]$ event window. The 2023-03-31 announcement, by contrast, concerned the cessation of US operations rather than

the certification function as a whole.

Higher-tier substitute set. For the FTX event the higher-tier set comprises the six AA-rated exchanges in our sample over 2022: Binance, Bitstamp, Bullish, Coinbase, Crypto.com, and Kraken. For the Bittrex event the higher-tier set comprises (i) these six AA exchanges; (ii) the five A-rated exchanges active on 2023-04-17 (Bitfinex, Bybit, Gemini, LMAX Digital, OKX); and (iii) the twelve BB-rated exchanges active on the same date (Bitget, Bithumb Korea, Bitvavo, CrossTower, Deribit, Cboe Digital/ErisX, Gate.io, itBit, Luno, Okcoin, UPbit, WhiteBIT). Four exchanges with A or BB CryptoCompare ratings are excluded from the higher-tier union for the Bittrex test because they were defunct or in bankruptcy by April 2023: FTX (filed Chapter 11 in November 2022), AAX (defunct from November 2022), FTX US (defunct from November 2022 as a subsidiary of FTX), and Liquid (acquired by FTX in March 2022 and non-operational following the FTX collapse).

FTX-affiliated tokens. Seven tokens (FTT, serum, maps, oxygen, star-atlas, star-atlas-dao, and raydium) had direct affiliations with FTX or its sister trading firm Alameda Research and faced token-specific Alameda-holdings liquidation pressures on top of the certification shock. Because these affiliated tokens are disproportionately in the CONTROL group, including them mechanically pushes CONTROL CARs more negative and biases β_{TREATED} upward.

Estimation window. The estimation window is $[-125, -5]$ days for both events, with one exception: for the FTX event we shorten the cutoff to $[-125, -10]$ to exclude the six-day pre-event rumor regime initiated by the November 2, 2022 CoinDesk article on Alameda Research's balance sheet from the market-model fit. The Bittrex SEC complaint had no analogous pre-event leak.

Control variables. The vector Z_i in (30) contains $\log(\text{SIZE}_i)$, $\log(\text{VOLUME}_i)$, VOLATL_i, RUNUP_i, $\log(\text{AGE}_i)$, $\log(\text{NO_CEX}_i)$, and NO_HIGHER_i. The first six variables are constructed exactly as in Section 6, with the only adaptation that they are computed against the calendar event date rather than against an asset-specific listing date. NO_HIGHER_i is the count of higher-tier exchanges on which asset i is listed at the event date, where the higher-tier set is defined per event as above (six AA exchanges for the FTX event; six AA, five A, and twelve BB exchanges for the Bittrex event).

J Details for the robustness checks

This appendix collects the detailed result tables underlying the four robustness exercises reported in Section 10 and complements the condensed methodology described there. The four subsections of this appendix mirror the four subsections of Section 10 in the same order.

C.1 Market model alternatives

The two alternative abnormal-return benchmarks are constructed as follows. The Liu-Tsyvinski-Wu three-factor model (LTW3) follows Liu et al. (2022) and defines the abnormal return at the daily frequency as the residual from a time-series regression of the realized token return on a crypto market factor (the value-weighted return of the universe of CoinGecko-listed coins on each chain), a size factor (the long-short return on the value-weighted top-decile minus bottom-decile sort on the prior-month market capitalization), and a momentum factor (the long-short return on the prior-month return sort). Factor returns are constructed at the half-day frequency to match the event-study window granularity. The characteristic-matched portfolio benchmark defines the abnormal return as the realized token return minus the mean return on a portfolio of tokens matched on size and momentum quintiles, with the matched portfolio re-formed each day. Cumulative abnormal returns under each benchmark are summed over the same event window used for the market-model baseline. The first-stage probit selection equation is unchanged across all three benchmarks since the selection equation does not depend on the abnormal-return measure. The second-stage IMR regression and the simultaneous-listing decomposition are re-estimated under each benchmark. The remainder of this subsection reports the detailed result tables for the LTW3 specification first and the characteristic-matched specification second, with single-listing first-stage probits, single-listing IMR slopes by current and prior tier, single-listing difference tests, and simultaneous-listing two-stage estimates and decompositions for both AA-A and BB-B prior histories.

Table J.1: First-stage estimates for the single-listing LTW-style CAR robustness study

Notes: This table reports the first-stage probit estimates for each (current tier j, prior tier h) cell on the single-listing sample under the LTW3 benchmark. The probit outcome is the indicator for listing of token i on a tier-j exchange, and the covariate vector includes log(SIZE$_i$), log(VOLUME$_i$), VOLATL$_i$, RUNUP$_i$, NO_CHAIN$_i$, and dummies PR_FUT_RATE$_2$ and PR_FUT_RATE$_4$ for the highest prior futures rating. The estimation sample for each column restricts to listing events whose highest prior spot listing was on the corresponding prior tier, plus never-listed events. The four panels correspond to the four current tiers AA-A, BB-B, C-D, and E-F, and the five columns within each panel correspond to the five prior-tier conditions. Heteroskedasticity-robust t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Condition	AA-A	BB-B	C-D	E-F	first-time -listing
Panel A: Listing on AA-A rated exchanges Dependent variable: $LIST_{AA-A}$					
Intercept	-4.174*** (-11.99)	-5.060*** (-9.59)	-4.627*** (-7.88)	-3.883*** (-3.01)	-4.299*** (-21.62)
VOLUME	14.624*** (2.74)	0.415 (0.21)	3.427 (0.64)	5.391 (0.39)	-0.101 (-0.08)
NO_CHAIN	0.016 (0.35)	0.024 (0.20)	0.629*** (3.45)	0.244 (0.76)	0.327*** (3.51)
VOLATL	1.283** (2.40)	0.194 (0.11)	-1.285 (-0.27)	2.363 (0.72)	-0.278 (-0.29)
RUNUP	-0.000** (-2.05)	-0.006 (-1.06)	-0.027 (-0.91)	-0.180 (-1.25)	0.000 (0.56)
SIZE	0.139*** (7.30)	0.186*** (6.52)	0.107*** (3.53)	0.127** (2.17)	0.072*** (6.03)
PR_FUT_RATE_2	-6.271*** (-28.58)	-4.874*** (-10.84)	-	-	-
PR_FUT_RATE_4	-0.202*** (-2.75)	0.284 (0.91)	-4.516*** (-20.73)	-	-4.618*** (-21.70)
Panel B: Listing on BB-B rated exchanges Dependent variable: $LIST_{BB-B}$					
Intercept	-0.126 (-0.47)	-0.234 (-0.71)	0.144 (0.31)	1.385 (1.39)	-2.844*** (-19.89)
VOLUME	7.138 (1.42)	-6.712* (-1.88)	-5.394 (-1.16)	9.269 (0.92)	1.035* (1.75)
NO_CHAIN	-0.002 (-0.05)	-0.101 (-1.40)	0.077 (0.63)	-0.068 (-0.27)	0.174** (2.39)
VOLATL	-0.327 (-0.53)	-0.572 (-0.57)	-3.017* (-1.90)	-5.088* (-1.77)	-3.353*** (-5.08)
RUNUP	-0.004 (-1.31)	0.000** (2.01)	-0.000 (-0.63)	-0.001 (-0.83)	0.002*** (2.64)
SIZE	-0.036** (-2.45)	-0.019 (-1.04)	-0.027 (-1.01)	-0.107* (-1.74)	0.062*** (6.54)
PR_FUT_RATE_2	-0.397 (-0.98)	-12.915 (-0.00)	-	-	-
PR_FUT_RATE_4	0.054 (1.10)	-0.061 (-0.23)	0.247 (0.28)	-	-8.157 (-0.00)
Panel C: Listing on C-D rated exchanges Dependent variable: $LIST_{C-D}$					

Intercept	0.239 (1.00)	0.918*** (3.06)	-0.663 (-1.62)	-2.186** (-2.12)	-3.588*** (-18.24)
VOLUME	-0.792 (-0.16)	4.106* (1.67)	0.404 (0.10)	-6.981 (-0.56)	0.479 (1.21)
NO_CHAIN	-0.053* (-1.71)	0.003 (0.05)	-0.069 (-0.57)	-0.021 (-0.08)	0.165** (2.29)
VOLATL	0.411 (0.83)	0.457 (0.50)	3.770** (2.52)	6.967** (2.30)	-1.101*** (-2.64)
RUNUP	-0.000*** (-3.07)	-0.000 (-0.40)	0.000 (1.62)	-0.001*** (-2.84)	0.003*** (3.53)
SIZE	-0.023* (-1.77)	-0.059*** (-3.49)	0.016 (0.70)	0.100 (1.59)	0.115*** (7.94)
PR_FUT_RATE_2	-0.527 (-1.57)	18.925 (0.00)	-	-	-
PR_FUT_RATE_4	-0.109** (-2.43)	0.068 (0.30)	0.397 (0.45)	-	1.084* (1.78)
Panel D: Listing on E-F rated exchanges Dependent variable: $LIST_{E-F}$					
Intercept	-0.655** (-2.46)	-1.450*** (-3.76)	0.001 (0.00)	0.047 (0.04)	-3.262*** (-16.46)
VOLUME	6.064 (1.11)	-9.734 (-1.54)	6.668 (1.58)	-15.679 (-1.44)	1.370* (1.92)
NO_CHAIN	0.021 (0.59)	0.054 (0.71)	-0.241 (-1.50)	0.062 (0.24)	0.150 (1.63)
VOLATL	-1.267* (-1.70)	-0.515 (-0.34)	-3.970** (-2.01)	-5.376 (-1.10)	-2.170** (-2.06)
RUNUP	-0.005 (-0.90)	-0.029 (-1.29)	-0.000 (-0.64)	-0.056 (-1.15)	0.000 (0.35)
SIZE	-0.018 (-1.22)	0.022 (1.01)	-0.033 (-1.25)	-0.026 (-0.36)	0.071*** (6.13)
PR_FUT_RATE_2	0.483 (1.49)	-4.982*** (-4.15)	-	-	-
PR_FUT_RATE_4	0.063 (1.19)	0.256 (0.92)	-8.304*** (-63.72)	-	-4.872*** (-25.89)

Table J.2: Second-stage LTW-style CAR estimates for the single-listing study

Notes: This table reports the second-stage IMR slope coefficient $\beta_{j,h}$ for each (current tier j, prior tier h) cell on the single-listing sample, with LTW-style three-factor CAR as the dependent variable. The regressor is the inverse Mills ratio λ_{ij} constructed from the first-stage probit in Table J.1. The four panels correspond to the four current tiers AA-A, BB-B, C-D, and E-F, and the five columns within each panel correspond to the five prior-tier conditions. Standard errors are adjusted following Heckman (1979) to account for variability generated by the first-stage estimation. t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Condition	AA-A	BB-B	C-D	E-F	first-time -listing
Panel A: Listing on AA-A rated exchanges Dependent variable: LTW-style CAR					

Intercept	0.010***	0.018***	-0.003	0.062***	0.072***
	(3.86)	(2.90)	(-0.24)	(2.75)	(3.83)
λ_{AA-A}	0.016***	-0.000	0.015	0.106**	0.130**
	(2.90)	(-0.00)	(0.44)	(2.14)	(2.06)
Panel B: Listing on BB-B rated exchanges					
Dependent variable: LTW-style CAR					
Intercept	0.010***	0.018***	-0.004	0.047*	0.090***
	(3.87)	(2.90)	(-0.25)	(1.94)	(3.62)
λ_{BB-B}	0.008**	-0.002	0.005	0.023	-0.013
	(2.08)	(-0.28)	(0.29)	(0.77)	(-0.80)
Panel C: Listing on C-D rated exchanges					
Dependent variable: LTW-style CAR					
Intercept	0.010***	0.018***	-0.003	0.047*	0.071***
	(3.87)	(2.90)	(-0.24)	(1.94)	(3.17)
λ_{C-D}	-0.001	0.005	-0.018	-0.021	0.012
	(-0.44)	(0.64)	(-0.89)	(-0.66)	(0.70)
Panel D: Listing on E-F rated exchanges					
Dependent variable: LTW-style CAR					
Intercept	0.010***	0.018***	-0.004	0.047*	0.092***
	(3.86)	(2.87)	(-0.26)	(1.94)	(4.24)
λ_{E-F}	-0.019***	-0.008	-0.015	-0.004	-0.027
	(-6.04)	(-1.09)	(-0.84)	(-0.12)	(-1.52)

Table J.3: First-stage versus LTW-style CAR-stage difference tests for single listings

Notes: This table reports the differences between each prior-tier condition $h \in \{1, 2, 3, 4\}$ and the first-time-listing condition $h = 0$ for both the first-stage selection index and the second-stage LTW-style IMR slope, on the single-listing sample. The first-stage diff column reports the difference in the expected probability of listing on the current tier, $\mathbb{E}[X'_{ij}\hat{\theta}_j]_h - \mathbb{E}[X'_{ij}\hat{\theta}_j]_0$, with the corresponding z-statistic in parentheses. The LTW-style CAR-stage diff column reports $\beta_{j,h} - \beta_{j,0}$, with the bootstrap z-statistic in parentheses obtained by repeating the two-stage estimation on $B = 500$ paired bootstrap draws of the underlying sample. The four panels correspond to the four current tiers AA-A through E-F, and the Condition level column encodes the numerical level of the prior tier (4 = AA-A, 3 = BB-B, 2 = C-D, 1 = E-F). ***/**/* denote significance at the 1%/5%/10% levels.

Comparison	First-stage diff (z-stat)	LTW-style CAR-stage diff (z-stat)	Condition level
Panel A: Listing on AA-A rated exchanges (with numerical level of 4)			
AA-A minus first-time	1.475***	-0.117*	4
	(14.57)	(-1.76)	
BB-B minus first-time	1.087***	-0.134**	3
	(8.70)	(-2.12)	
C-D minus first-time	-0.858	-0.118*	2
	(-0.45)	(-1.72)	
E-F minus first-time	-3.897	-0.031	1
	(-0.93)	(-0.28)	

Panel B: Listing on BB-B rated exchanges (with numerical level of 3)			
AA-A minus first-time	1.393***	0.020	4
	(28.87)	(1.24)	
BB-B minus first-time	1.437***	0.011	3
	(25.31)	(0.60)	
C-D minus first-time	1.756***	0.017	2
	(24.31)	(0.73)	
E-F minus first-time	1.600***	0.037	1
	(11.70)	(1.16)	
Panel C: Listing on C-D rated exchanges (with numerical level of 2)			
AA-A minus first-time	1.778***	-0.015	4
	(41.37)	(-0.83)	
BB-B minus first-time	2.091***	-0.010	3
	(40.80)	(-0.49)	
C-D minus first-time	1.849***	-0.032	2
	(26.91)	(-1.17)	
E-F minus first-time	1.727***	-0.037	1
	(13.09)	(-1.03)	
Panel D: Listing on E-F rated exchanges (with numerical level of 1)			
AA-A minus first-time	1.424***	0.008	4
	(23.27)	(0.46)	
BB-B minus first-time	1.038***	0.020	3
	(5.17)	(1.03)	
C-D minus first-time	1.400***	0.011	2
	(15.79)	(0.45)	
E-F minus first-time	0.036	0.026	1
	(0.03)	(0.76)	

Table J.4: Two-stage LTW-style CAR estimation for simultaneous listings with highest previously listed exchanges in AA-A group

Notes: This table reports the two-stage estimation for simultaneous listings within the 72-hour detection window whose highest prior spot listing was on the AA-A tier, with LTW-style three-factor CAR as the second-stage dependent variable. Panel A reports the first-stage multivariate probit estimates, with one column per listed tier $j \in \{\text{AA-A, BB-B, C-D, E-F}\}$ and the same covariate vector as the single-listing first-stage probit. Panel B reports the estimated pairwise correlations among the private-information errors ϵ_{ij} of the four tier-specific probits, with the t-statistic in parentheses. Panel C reports the second-stage IMR slope β_j, with columns 1 through 4 reporting the univariate IMR specification per tier and column 5 reporting the joint multivariate specification that includes all four IMRs simultaneously. Standard errors are adjusted following Heckman (1979). t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Listing	AA-A	BB-B	C-D	E-F	Joint
Panel A: First-stage estimation					
Intercept	-4.826***	-4.356***	-4.550***	-4.305***	
	(-14.01)	(-17.91)	(-17.57)	(-16.57)	
VOLUME	-5.260	-2.679	-6.022	-13.614	
	(-0.47)	(-0.40)	(-0.60)	(-1.06)	

NO_CHAIN	0.122 (1.05)	0.060 (0.67)	0.134 (1.49)	0.105 (1.16)	
VOLATL	0.577 (0.84)	-2.554*** (-2.64)	-1.610* (-1.72)	-0.834 (-0.98)	
RUNUP	-0.000 (-0.59)	-0.000 (-0.77)	0.000 (0.71)	0.000 (0.69)	
SIZE	0.130*** (7.90)	0.149*** (12.08)	0.147*** (11.41)	0.131*** (9.87)	
PR_FUT_RATE_4	1.377*** (9.16)	1.903*** (16.14)	1.766*** (14.89)	1.815*** (15.13)	
Panel B: Private-information correlations					
AA-A	-	0.258*** (3.73)	0.338*** (5.26)	0.269*** (3.67)	
BB-B	0.258*** (3.73)	-	0.540*** (10.62)	0.599*** (12.54)	
C-D	0.338*** (5.26)	0.540*** (10.62)	-	0.381*** (6.54)	
E-F	0.269*** (3.67)	0.599*** (12.54)	0.381*** (6.54)	-	
Panel C: Second-stage estimation Dependent variable: LTW-style CAR					
Intercept	0.023 (1.34)	0.029 (1.27)	0.032 (1.53)	0.062*** (3.04)	0.026 (0.22)
λ_{AA-A}	0.048** (2.44)	-	-	-	0.045* (1.87)
λ_{BB-B}	-	0.013 (0.76)	-	-	0.019 (0.47)
λ_{C-D}	-	-	0.012 (0.65)	-	0.005 (0.13)
λ_{E-F}	-	-	-	-0.028 (-1.59)	-0.029 (-0.90)

Table J.5: Disentangling LTW-style CAR effects for simultaneous listings with highest previously listed exchanges in AA-A group

Notes: This table reports the decomposition of the simultaneous-listing IMR slope β_j into informational-complement and informational-substitute components, for simultaneous listings with AA-A prior history under the LTW3 benchmark. Panel A reports the projection parameters γ_{jk} that map the implied higher-tier signal onto the linear index of the listed tier j, with each cell at row j and column k giving the value of γ_{jk}. Panel B reports the implied valuation sensitivities $\alpha_j^{\perp}$ to the higher-tier-orthogonal residual and α_j to the listing of tier j itself. Panel C reports the reconstruction of β_j as the sum of the pure-rating-j effect (α_j-driven, the informational-complement component) and the higher-rating listing effect ($\alpha_k^{\perp}$-driven through γ_{jk}, the informational-substitute component), reported both in level and as a percentage share of the reconstructed β_j.

Listing	AA-A	BB-B	C-D	E-F
Panel A: Estimation of γ_{jk}				
E-F ($j = 1$)	0.112	0.543	0.050	-
C-D ($j = 2$)	0.213	0.485	-	-

BB-B ($j = 3$)	0.258	-	-	-
AA-A ($j = 4$)	-	-	-	-
Panel B: Calculated $\alpha_j^{\perp}$ and α_j				
$\alpha_j^{\perp}$	0.045	0.008	-0.043	-0.173
α_j	0.071	0.123	-0.035	-0.173
Panel C: Disentangling effects for simultaneous listings				
Dependent variable: LTW-style CAR				
β_j	0.045	0.019	0.005	-0.029
Pure rating j effect	0.045	0.008	-0.029	-0.108
Higher-rating listing effect	0.000	0.018	0.091	0.080
Reconstructed β_j	0.045	0.026	0.062	-0.029
Pure rating j effect (%)	100.0%	29.5%	24.1%	57.6%
Higher-rating listing effect (%)	0.0%	70.5%	75.9%	42.4%

Table J.6: Two-stage LTW-style CAR estimation for simultaneous listings with highest previously listed exchanges in BB-B group

Notes: This table reports the two-stage estimation for simultaneous listings within the 72-hour detection window whose highest prior spot listing was on the BB-B tier, with LTW-style three-factor CAR as the second-stage dependent variable. Panel A reports the first-stage multivariate probit estimates, with one column per listed tier $j \in$ {AA-A, BB-B, C-D, E-F}. Panel B reports the estimated pairwise correlations among the private-information errors of the four tier-specific probits, with the t-statistic in parentheses. Panel C reports the second-stage IMR slope β_j, with columns 1 through 4 reporting the univariate IMR specification per tier and column 5 reporting the joint multivariate specification. Standard errors are adjusted following Heckman (1979). t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Listing	AA-A	BB-B	C-D	E-F	Joint
Panel A: First-stage estimation					
Intercept	-4.203*** (-5.13)	-4.301*** (-16.56)	-4.579*** (-15.87)	-4.214*** (-13.68)	
VOLUME	0.328 (0.07)	0.058 (0.02)	-0.001 (-0.00)	0.976 (0.49)	
NO_CHAIN	-0.438 (-0.64)	0.292*** (3.08)	0.271** (2.53)	0.256** (2.27)	
VOLATL	-0.663 (-0.27)	-1.676 (-1.41)	-0.467 (-0.46)	-5.155** (-2.48)	
RUNUP	0.001 (0.51)	-0.000 (-0.02)	0.001 (0.15)	0.003 (1.51)	
SIZE	0.112*** (5.22)	0.117*** (8.92)	0.123*** (8.87)	0.113*** (7.43)	
PR_FUT_RATE_4	2.658*** (3.89)	1.049* (1.86)	1.587*** (2.76)	1.821*** (3.15)	
Panel B: Private-information correlations					
AA-A	-	0.609*** (9.10)	0.585*** (7.68)	0.558*** (6.98)	
BB-B	0.609*** (9.10)	-	0.850*** (26.92)	0.815*** (20.47)	

C-D	0.585*** (7.68)	0.850*** (26.92)	-	0.823*** (18.23)	
E-F	0.558*** (6.98)	0.815*** (20.47)	0.823*** (18.23)	-	
Panel C: Second-stage estimation					
Dependent variable: LTW-style CAR					
Intercept	-0.018 (-0.31)	-0.033 (-0.27)	-0.058 (-0.63)	-0.055 (-0.68)	-0.706 (-1.09)
λ_{AA-A}	0.141** (2.51)	-	-	-	0.145 (1.37)
λ_{BB-B}	-	0.034 (0.64)	-	-	0.117 (1.29)
λ_{C-D}	-	-	0.058 (1.29)	-	0.148 (1.46)
λ_{E-F}	-	-	-	0.066 (1.54)	0.151* (1.69)

Table J.7: Disentangling LTW-style CAR effects for simultaneous listings with highest previously listed exchanges in BB-B group

Notes: This table reports the decomposition of the simultaneous-listing IMR slope β_j into informational-complement and informational-substitute components, for simultaneous listings with BB-B prior history under the LTW3 benchmark. Panel A reports the projection parameters γ_{jk}, with each cell at row j and column k giving the value of γ_{jk}. Panel B reports the implied valuation sensitivities $\alpha_j^{\perp}$ and α_j. Panel C reports the reconstruction of β_j as the sum of the pure-rating-j effect (informational-complement) and the higher-rating listing effect (informational-substitute), reported both in level and as a percentage share of the reconstructed β_j.

Listing	AA-A	BB-B	C-D	E-F
Panel A: Estimation of γ_{jk}				
E-F ($j = 1$)	0.050	0.395	0.458	-
C-D ($j = 2$)	0.107	0.785	-	-
BB-B ($j = 3$)	0.609	-	-	-
AA-A ($j = 4$)	-	-	-	-
Panel B: Calculated $\alpha_j^{\perp}$ and α_j				
$\alpha_j^{\perp}$	0.145	0.113	-0.016	-0.041
α_j	0.080	0.141	0.003	-0.041
Panel C: Disentangling effects for simultaneous listings				
Dependent variable: LTW-style CAR				
β_j	0.145	0.117	0.148	0.151
Pure rating j effect	0.145	0.071	-0.004	-0.011
Higher-rating listing effect	0.000	0.049	0.167	0.162
Reconstructed β_j	0.145	0.119	0.163	0.151
Pure rating j effect (%)	100.0%	59.3%	2.5%	6.5%
Higher-rating listing effect (%)	0.0%	40.7%	97.5%	93.5%

Table J.8: First-stage estimates for the single-listing matched-portfolio CAR robustness study

Notes: This table reports the first-stage probit estimates for each (current tier j, prior tier h) cell on the single-listing sample under the characteristic-matched portfolio benchmark. The first-stage specification is identical to the LTW3 first-stage in Table J.1 since the selection equation does not depend on the abnormal-return measure. The probit outcome is the indicator for listing of token i on a tier-j exchange, and the covariate vector includes log(SIZE$_i$), log(VOLUME$_i$), VOLATL$_i$, RUNUP$_i$, NO_CHAIN$_i$, and dummies PR_FUT_RATE$_2$ and PR_FUT_RATE$_4$ for the highest prior futures rating. The four panels correspond to the four current tiers AA-A, BB-B, C-D, and E-F, and the five columns within each panel correspond to the five prior-tier conditions. Heteroskedasticity-robust t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Condition	AA-A	BB-B	C-D	E-F	first-time -listing
Panel A: Listing on AA-A rated exchanges Dependent variable: $LIST_{AA-A}$					
Intercept	-4.174*** (-11.99)	-5.060*** (-9.59)	-4.627*** (-7.88)	-3.883*** (-3.01)	-4.299*** (-21.62)
VOLUME	14.624*** (2.74)	0.415 (0.21)	3.427 (0.64)	5.391 (0.39)	-0.101 (-0.08)
NO_CHAIN	0.016 (0.35)	0.024 (0.20)	0.629*** (3.45)	0.244 (0.76)	0.327*** (3.51)
VOLATL	1.283** (2.40)	0.194 (0.11)	-1.285 (-0.27)	2.363 (0.72)	-0.278 (-0.29)
RUNUP	-0.000** (-2.05)	-0.006 (-1.06)	-0.027 (-0.91)	-0.180 (-1.25)	0.000 (0.56)
SIZE	0.139*** (7.30)	0.186*** (6.52)	0.107*** (3.53)	0.127** (2.17)	0.072*** (6.03)
PR_FUT_RATE_2	-6.271*** (-28.58)	-4.874*** (-10.84)	-	-	-
PR_FUT_RATE_4	-0.202*** (-2.75)	0.284 (0.91)	-4.516*** (-20.73)	-	-4.618*** (-21.70)
Panel B: Listing on BB-B rated exchanges Dependent variable: $LIST_{BB-B}$					
Intercept	-0.126 (-0.47)	-0.234 (-0.71)	0.144 (0.31)	1.385 (1.39)	-2.844*** (-19.89)
VOLUME	7.138 (1.42)	-6.712* (-1.88)	-5.394 (-1.16)	9.269 (0.92)	1.035* (1.75)
NO_CHAIN	-0.002 (-0.05)	-0.101 (-1.40)	0.077 (0.63)	-0.068 (-0.27)	0.174** (2.39)
VOLATL	-0.327 (-0.53)	-0.572 (-0.57)	-3.017* (-1.90)	-5.088* (-1.77)	-3.353*** (-5.08)
RUNUP	-0.004 (-1.31)	0.000** (2.01)	-0.000 (-0.63)	-0.001 (-0.83)	0.002*** (2.64)
SIZE	-0.036** (-2.45)	-0.019 (-1.04)	-0.027 (-1.01)	-0.107* (-1.74)	0.062*** (6.54)
PR_FUT_RATE_2	-0.397 (-0.98)	-12.915 (-0.00)	-	-	-

PR_FUT_RATE_4	0.054 (1.10)	-0.061 (-0.23)	0.247 (0.28)	-	-8.157 (-0.00)
Panel C: Listing on C-D rated exchanges Dependent variable: $LIST_{C-D}$					
Intercept	0.239 (1.00)	0.918*** (3.06)	-0.663 (-1.62)	-2.186** (-2.12)	-3.588*** (-18.24)
VOLUME	-0.792 (-0.16)	4.106* (1.67)	0.404 (0.10)	-6.981 (-0.56)	0.479 (1.21)
NO_CHAIN	-0.053* (-1.71)	0.003 (0.05)	-0.069 (-0.57)	-0.021 (-0.08)	0.165** (2.29)
VOLATL	0.411 (0.83)	0.457 (0.50)	3.770** (2.52)	6.967** (2.30)	-1.101*** (-2.64)
RUNUP	-0.000*** (-3.07)	-0.000 (-0.40)	0.000 (1.62)	-0.001*** (-2.84)	0.003*** (3.53)
SIZE	-0.023* (-1.77)	-0.059*** (-3.49)	0.016 (0.70)	0.100 (1.59)	0.115*** (7.94)
PR_FUT_RATE_2	-0.527 (-1.57)	18.925 (0.00)	-	-	-
PR_FUT_RATE_4	-0.109** (-2.43)	0.068 (0.30)	0.397 (0.45)	-	1.084* (1.78)
Panel D: Listing on E-F rated exchanges Dependent variable: $LIST_{E-F}$					
Intercept	-0.655** (-2.46)	-1.450*** (-3.76)	0.001 (0.00)	0.047 (0.04)	-3.262*** (-16.46)
VOLUME	6.064 (1.11)	-9.734 (-1.54)	6.668 (1.58)	-15.679 (-1.44)	1.370* (1.92)
NO_CHAIN	0.021 (0.59)	0.054 (0.71)	-0.241 (-1.50)	0.062 (0.24)	0.150 (1.63)
VOLATL	-1.267* (-1.70)	-0.515 (-0.34)	-3.970** (-2.01)	-5.376 (-1.10)	-2.170** (-2.06)
RUNUP	-0.005 (-0.90)	-0.029 (-1.29)	-0.000 (-0.64)	-0.056 (-1.15)	0.000 (0.35)
SIZE	-0.018 (-1.22)	0.022 (1.01)	-0.033 (-1.25)	-0.026 (-0.36)	0.071*** (6.13)
PR_FUT_RATE_2	0.483 (1.49)	-4.982*** (-4.15)	-	-	-
PR_FUT_RATE_4	0.063 (1.19)	0.256 (0.92)	-8.304*** (-63.72)	-	-4.872*** (-25.89)

Table J.9: Second-stage matched-portfolio CAR estimates for the single-listing study

Notes: This table reports the second-stage IMR slope coefficient $\beta_{j,h}$ for each (current tier j, prior tier h) cell on the single-listing sample, with characteristic-matched portfolio CAR as the dependent variable. The regressor is the inverse Mills ratio λ_{ij} constructed from the first-stage probit in Table J.8. The four panels correspond to the four current tiers AA-A, BB-B, C-D, and E-F, and the five columns within each panel correspond to the five prior-tier conditions. Standard errors are adjusted following Heckman (1979). t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Condition	AA-A	BB-B	C-D	E-F	first-time -listing
Panel A: Listing on AA-A rated exchanges Dependent variable: Matched-portfolio CAR					
Intercept	0.021*** (8.58)	0.045*** (6.62)	0.035*** (2.67)	0.082*** (2.86)	0.148*** (4.49)
λ_{AA-A}	0.016*** (3.09)	0.002 (0.14)	0.055 (1.53)	0.149** (2.10)	0.141 (0.40)
Panel B: Listing on BB-B rated exchanges Dependent variable: Matched-portfolio CAR					
Intercept	0.021*** (8.60)	0.045*** (6.73)	0.037*** (2.77)	0.063* (1.82)	0.184*** (4.60)
λ_{BB-B}	0.011*** (2.79)	-0.010 (-1.26)	0.013 (0.78)	-0.003 (-0.06)	-0.047** (-2.06)
Panel C: Listing on C-D rated exchanges Dependent variable: Matched-portfolio CAR					
Intercept	0.021*** (8.59)	0.045*** (6.67)	0.037*** (2.86)	0.064* (1.80)	0.142*** (3.59)
λ_{C-D}	0.000 (0.04)	0.013 (1.41)	-0.021 (-1.32)	-0.009 (-0.22)	0.018 (0.66)
Panel D: Listing on E-F rated exchanges Dependent variable: Matched-portfolio CAR					
Intercept	0.021*** (8.59)	0.045*** (6.56)	0.036*** (2.72)	0.062* (1.85)	0.170*** (4.70)
λ_{E-F}	-0.016*** (-5.19)	-0.015* (-1.95)	-0.021 (-1.13)	-0.006 (-0.17)	-0.029 (-0.95)

Table J.10: First-stage versus matched-portfolio CAR-stage difference tests for single listings

Notes: This table reports the differences between each prior-tier condition $h \in \{1, 2, 3, 4\}$ and the first-time-listing condition $h = 0$ for both the first-stage selection index and the second-stage matched-portfolio IMR slope, on the single-listing sample. The first-stage diff column reports the difference in the expected probability of listing on the current tier, with the corresponding z-statistic in parentheses. The matched-portfolio CAR-stage diff column reports $\beta_{j,h} - \beta_{j,0}$, with the bootstrap z-statistic in parentheses obtained by repeating the two-stage estimation on $B = 500$ paired bootstrap draws. The four panels correspond to the four current tiers AA-A through E-F, and the Condition level column encodes the numerical level of the prior tier. ***/**/* denote significance at the 1%/5%/10% levels.

Comparison	First-stage diff (z-stat)	Matched-portfolio CAR-stage diff (z-stat)	Condition level
Panel A: Listing on AA-A rated exchanges (with numerical level of 4)			
AA-A minus first-time	1.475*** (14.57)	-0.115* (-1.90)	4
BB-B minus first-time	1.087*** (8.70)	-0.129** (-2.10)	3

C-D minus first-time	-0.858 (-0.45)	-0.076 (-1.08)	2
E-F minus first-time	-3.897 (-0.93)	0.010 (0.08)	1
Panel B: Listing on BB-B rated exchanges (with numerical level of 3)			
AA-A minus first-time	1.393*** (28.87)	0.058** (2.30)	4
BB-B minus first-time	1.437*** (25.31)	0.038 (1.46)	3
C-D minus first-time	1.756*** (24.31)	0.060* (1.95)	2
E-F minus first-time	1.600*** (11.70)	0.048 (0.95)	1
Panel C: Listing on C-D rated exchanges (with numerical level of 2)			
AA-A minus first-time	1.778*** (41.37)	-0.021 (-0.70)	4
BB-B minus first-time	2.091*** (40.80)	-0.009 (-0.30)	3
C-D minus first-time	1.849*** (26.91)	-0.042 (-1.29)	2
E-F minus first-time	1.727*** (13.09)	-0.033 (-0.66)	1
Panel D: Listing on E-F rated exchanges (with numerical level of 1)			
AA-A minus first-time	1.424*** (23.27)	0.014 (0.44)	4
BB-B minus first-time	1.038*** (5.17)	0.015 (0.46)	3
C-D minus first-time	1.400*** (15.79)	0.007 (0.19)	2
E-F minus first-time	0.036 (0.03)	0.022 (0.48)	1

Table J.11: Two-stage matched-portfolio CAR estimation for simultaneous listings with highest previously listed exchanges in AA-A group

Notes: This table reports the two-stage estimation for simultaneous listings within the 72-hour detection window whose highest prior spot listing was on the AA-A tier, with characteristic-matched portfolio CAR as the second-stage dependent variable. Panel A reports the first-stage multivariate probit estimates, with one column per listed tier $j \in \{\text{AA-A, BB-B, C-D, E-F}\}$. Panel B reports the estimated pairwise correlations among the private-information errors of the four tier-specific probits, with the t-statistic in parentheses. Panel C reports the second-stage IMR slope β_j, with columns 1 through 4 reporting the univariate IMR specification per tier and column 5 reporting the joint multivariate specification. Standard errors are adjusted following Heckman (1979). t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Listing	AA-A	BB-B	C-D	E-F	Joint
Panel A: First-stage estimation					
Intercept	-4.826*** (-14.01)	-4.356*** (-17.91)	-4.550*** (-17.57)	-4.305*** (-16.57)	

VOLUME	-5.260 (-0.47)	-2.679 (-0.40)	-6.022 (-0.60)	-13.614 (-1.06)	
NO_CHAIN	0.122 (1.05)	0.060 (0.67)	0.134 (1.49)	0.105 (1.16)	
VOLATL	0.577 (0.84)	-2.554*** (-2.64)	-1.610* (-1.72)	-0.834 (-0.98)	
RUNUP	-0.000 (-0.59)	-0.000 (-0.77)	0.000 (0.71)	0.000 (0.69)	
SIZE	0.130*** (7.90)	0.149*** (12.08)	0.147*** (11.41)	0.131*** (9.87)	
PR_FUT_RATE_4	1.377*** (9.16)	1.903*** (16.14)	1.766*** (14.89)	1.815*** (15.13)	
Panel B: Private-information correlations					
AA-A	-	0.258*** (3.73)	0.338*** (5.26)	0.269*** (3.67)	
BB-B	0.258*** (3.73)	-	0.540*** (10.62)	0.599*** (12.54)	
C-D	0.338*** (5.26)	0.540*** (10.62)	-	0.381*** (6.54)	
E-F	0.269*** (3.67)	0.599*** (12.54)	0.381*** (6.54)	-	
Panel C: Second-stage estimation Dependent variable: Matched-portfolio CAR					
Intercept	0.044** (2.37)	0.055** (2.32)	0.044** (2.00)	0.093*** (4.35)	0.048 (0.41)
λ_{AA-A}	0.049** (2.43)	-	-	-	0.042* (1.77)
λ_{BB-B}	-	0.011 (0.55)	-	-	0.015 (0.37)
λ_{C-D}	-	-	0.026 (1.34)	-	0.019 (0.52)
λ_{E-F}	-	-	-	-0.040** (-2.09)	-0.041 (-1.30)

Table J.12: Disentangling matched-portfolio CAR effects for simultaneous listings with highest previously listed exchanges in AA-A group

Notes: This table reports the decomposition of the simultaneous-listing IMR slope β_j into informational-complement and informational-substitute components, for simultaneous listings with AA-A prior history under the characteristic-matched portfolio benchmark. Panel A reports the projection parameters γ_{jk}, with each cell at row j and column k giving the value of γ_{jk}. Panel B reports the implied valuation sensitivities $\alpha_j^{\perp}$ and α_j. Panel C reports the reconstruction of β_j as the sum of the pure-rating-j effect (informational-complement) and the higher-rating listing effect (informational-substitute), reported both in level and as a percentage share of the reconstructed β_j.

Listing	AA-A	BB-B	C-D	E-F
Panel A: Estimation of γ_{jk}				
E-F ($j = 1$)	0.112	0.543	0.050	-
C-D ($j = 2$)	0.213	0.485	-	-

BB-B ($j = 3$)	0.258	-	-	-
AA-A ($j = 4$)	-	-	-	-
Panel B: Calculated $\alpha_j^{\perp}$ and α_j				
$\alpha_j^{\perp}$	0.042	0.005	0.008	-0.218
α_j	0.063	0.120	0.018	-0.218
Panel C: Disentangling effects for simultaneous listings				
Dependent variable: Matched-portfolio CAR				
β_j	0.042	0.015	0.019	-0.041
Pure rating j effect	0.042	0.005	0.005	-0.136
Higher-rating listing effect	0.000	0.016	0.086	0.096
Reconstructed β_j	0.042	0.021	0.091	-0.041
Pure rating j effect (%)	100.0%	22.1%	5.6%	58.8%
Higher-rating listing effect (%)	0.0%	77.9%	94.4%	41.2%

Table J.13: Two-stage matched-portfolio CAR estimation for simultaneous listings with highest previously listed exchanges in BB-B group

Notes: This table reports the two-stage estimation for simultaneous listings within the 72-hour detection window whose highest prior spot listing was on the BB-B tier, with characteristic-matched portfolio CAR as the second-stage dependent variable. Panel A reports the first-stage multivariate probit estimates, with one column per listed tier $j \in \{$AA-A, BB-B, C-D, E-F$\}$. Panel B reports the estimated pairwise correlations among the private-information errors of the four tier-specific probits, with the t-statistic in parentheses. Panel C reports the second-stage IMR slope β_j, with columns 1 through 4 reporting the univariate IMR specification per tier and column 5 reporting the joint multivariate specification. Standard errors are adjusted following Heckman (1979). t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Listing	AA-A	BB-B	C-D	E-F	Joint
Panel A: First-stage estimation					
Intercept	-4.203***	-4.301***	-4.579***	-4.214***	
	(-5.13)	(-16.56)	(-15.87)	(-13.68)	
VOLUME	0.328	0.058	-0.001	0.976	
	(0.07)	(0.02)	(-0.00)	(0.49)	
NO_CHAIN	-0.438	0.292***	0.271**	0.256**	
	(-0.64)	(3.08)	(2.53)	(2.27)	
VOLATL	-0.663	-1.676	-0.467	-5.155**	
	(-0.27)	(-1.41)	(-0.46)	(-2.48)	
RUNUP	0.001	-0.000	0.001	0.003	
	(0.51)	(-0.02)	(0.15)	(1.51)	
SIZE	0.112***	0.117***	0.123***	0.113***	
	(5.22)	(8.92)	(8.87)	(7.43)	
PR_FUT_RATE_4	2.658***	1.049*	1.587***	1.821***	
	(3.89)	(1.86)	(2.76)	(3.15)	
Panel B: Private-information correlations					
AA-A	-	0.609***	0.585***	0.558***	
		(9.10)	(7.68)	(6.98)	
BB-B	0.609***	-	0.850***	0.815***	
	(9.10)		(26.92)	(20.47)	

C-D	0.585*** (7.68)	0.850*** (26.92)	-	0.823*** (18.23)	
E-F	0.558*** (6.98)	0.815*** (20.47)	0.823*** (18.23)	-	
Panel C: Second-stage estimation					
Dependent variable: Matched-portfolio CAR					
Intercept	-0.006 (-0.08)	0.026 (0.15)	-0.035 (-0.25)	-0.019 (-0.19)	-0.628 (-0.90)
λ_{AA-A}	0.163** (2.58)	-	-	-	0.165 (1.28)
λ_{BB-B}	-	0.028 (0.38)	-	-	0.102 (0.96)
λ_{C-D}	-	-	0.064 (0.98)	-	0.138 (1.28)
λ_{E-F}	-	-	-	0.092 (1.62)	0.141* (1.95)

Table J.14: Disentangling matched-portfolio CAR effects for simultaneous listings with highest previously listed exchanges in BB-B group

Notes: This table reports the decomposition of the simultaneous-listing IMR slope β_j into informational-complement and informational-substitute components, for simultaneous listings with BB-B prior history under the characteristic-matched portfolio benchmark. Panel A reports the projection parameters γ_{jk}, with each cell at row j and column k giving the value of γ_{jk}. Panel B reports the implied valuation sensitivities $\alpha_j^{\perp}$ and α_j. Panel C reports the reconstruction of β_j as the sum of the pure-rating-j effect (informational-complement) and the higher-rating listing effect (informational-substitute), reported both in level and as a percentage share of the reconstructed β_j.

Listing	AA-A	BB-B	C-D	E-F
Panel A: Estimation of γ_{jk}				
E-F ($j = 1$)	0.050	0.395	0.458	-
C-D ($j = 2$)	0.107	0.785	-	-
BB-B ($j = 3$)	0.609	-	-	-
AA-A ($j = 4$)	-	-	-	-
Panel B: Calculated $\alpha_j^{\perp}$ and α_j				
$\alpha_j^{\perp}$	0.165	0.007	-0.081	-0.122
α_j	0.175	0.119	-0.026	-0.122
Panel C: Disentangling effects for simultaneous listings				
Dependent variable: Matched-portfolio CAR				
β_j	0.165	0.102	0.138	0.141
Pure rating j effect	0.165	0.005	-0.022	-0.033
Higher-rating listing effect	0.000	0.107	0.204	0.174
Reconstructed β_j	0.165	0.111	0.182	0.141
Pure rating j effect (%)	100.0%	4.2%	9.7%	16.1%
Higher-rating listing effect (%)	0.0%	95.8%	90.3%	83.9%

C.2 Simultaneous-listing window robustness

The detection-window robustness exercise repeats the simultaneous-listing two-stage estimation and the informational-substitute decomposition of Section 6.3 for each of four candidate detection windows, namely 24, 48, 72, and 96 hours. The detection window defines which combinations of listings on different CEX tiers are treated as a single simultaneous-listing event. For each window, two listings of the same token on different-tier exchanges are aggregated into a simultaneous-listing event when their listing timestamps fall within the window of one another, with the event date set to the earliest of the constituent timestamps. The first-stage multivariate probit, the IMR construction from the probit's predicted index, and the second-stage decomposition into informational-complement and informational-substitute components are otherwise identical to the main specification. The sample-counts table below shows, for each window and prior-history block, the number of listing rows that satisfy the simultaneous-listing detection rule, the number of those rows with non-missing CAR coverage, the number of never-listed events that enter the first-stage probit as the comparison sample, and the total number of estimation rows. The 72-hour window is the baseline used throughout Section 6.3, and its two-stage estimates and decomposition appear in Tables 4, 5, G.3, and G.4 of the main text; they are therefore not reproduced here. The remainder of this subsection reports the two-stage estimates and the decomposition separately for the three alternative windows (24, 48, and 96 hours) crossed with the two prior-history blocks (AA-A and BB-B), in that order, and within each window with AA-A prior first and BB-B prior second.

Table J.15: Sample counts for simultaneous-listing window robustness

Notes: This table reports the sample counts used for the simultaneous-listing window robustness analysis. For each combination of detection window (24h, 48h, 72h, 96h) and prior-history block (AA-A, BB-B), the columns show the number of listing rows that satisfy the simultaneous-listing detection rule (Listed rows), the subset of those rows with non-missing event-window CAR (Listed rows with CAR), the number of never-listed events that enter the first-stage probit as the comparison sample (Never listed), and the total number of estimation rows (Estimation rows). The never-listed sample is held fixed across windows since it is independent of the detection-window definition.

Window	Prior history	Listed rows	Listed rows with CAR	Never listed	Estimation rows
24h	BB-B	26	26	5526	5552

24h	AA-A	134	134	5526	5660
48h	BB-B	43	43	5526	5569
48h	AA-A	206	206	5526	5732
72h	BB-B	53	53	5526	5579
72h	AA-A	254	254	5526	5780
96h	BB-B	61	61	5526	5587
96h	AA-A	286	286	5526	5812

Table J.16: Two-stage market-model CAR estimation for 24h simultaneous listings with highest previously listed exchanges in AA-A group

Notes: This table reports the two-stage estimation for simultaneous listings within the 24-hour detection window whose highest prior spot listing was on the AA-A tier, with market-model CAR as the second-stage dependent variable. Panel A reports the first-stage multivariate probit estimates, with one column per listed tier $j \in \{\text{AA-A, BB-B, C-D, E-F}\}$ and the same covariate vector as the single-listing first-stage probit. Panel B reports the estimated pairwise correlations among the private-information errors of the four tier-specific probits, with the t-statistic in parentheses. Panel C reports the second-stage IMR slope β_j, with columns 1 through 4 reporting the univariate IMR specification per tier and column 5 reporting the joint multivariate specification. Standard errors are adjusted following Heckman (1979). t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Listing	AA-A	BB-B	C-D	E-F	Joint
Panel A: First-stage estimation					
Intercept	-4.805*** (-11.50)	-4.242*** (-13.67)	-4.523*** (-15.90)	-4.399*** (-12.54)	
VOLUME	-6.124 (-0.43)	-18.947 (-1.01)	-1.793 (-0.30)	-15.811 (-0.84)	
NO_CHAIN	0.138 (0.90)	0.130 (1.11)	0.224** (2.20)	0.138 (1.07)	
VOLATL	0.347 (0.39)	-3.012** (-2.13)	-1.669 (-1.63)	0.213 (0.25)	
RUNUP	0.002 (1.12)	0.002 (0.80)	-0.003 (-0.84)	-0.027 (-1.47)	
SIZE	0.115*** (6.12)	0.118*** (7.97)	0.126*** (9.13)	0.105*** (6.15)	
PR_FUT_RATE_4	1.567*** (8.19)	2.339*** (14.73)	1.950*** (13.11)	2.385*** (14.06)	
Panel B: Private-information correlations					
AA-A	-	0.351*** (4.43)	0.528*** (7.17)	0.331*** (3.58)	
BB-B	0.351*** (4.43)	-	0.631*** (11.00)	0.448*** (5.80)	
C-D	0.528*** (7.17)	0.631*** (11.00)	-	0.440*** (5.72)	
E-F	0.331*** (3.58)	0.448*** (5.80)	0.440*** (5.72)	-	
Panel C: Second-stage estimation					
Dependent variable: market-model CAR					

Intercept	0.041 (1.08)	0.041 (0.87)	0.011 (0.23)	0.075* (1.74)	-0.001 (-0.01)
λ_{AA-A}	0.068* (1.72)	-	-	-	0.058 (1.33)
λ_{BB-B}	-	0.032 (0.88)	-	-	0.012 (0.23)
λ_{C-D}	-	-	0.061* (1.77)	-	0.048 (0.85)
λ_{E-F}	-	-	-	-0.008 (-0.20)	-0.016 (-0.34)

Table J.17: Disentangling market-model CAR effects for 24h simultaneous listings with highest previously listed exchanges in AA-A group

Notes: This table reports the decomposition of the simultaneous-listing IMR slope β_j into informational-complement and informational-substitute components, for simultaneous listings detected within the 24-hour window with AA-A prior history. Panel A reports the projection parameters γ_{jk}, with each cell at row j and column k giving the value of γ_{jk}. Panel B reports the implied valuation sensitivities $\alpha_j^{\perp}$ and α_j. Panel C reports the reconstruction of β_j as the sum of the pure-rating-j effect (informational-complement) and the higher-rating listing effect (informational-substitute), reported both in level and as a percentage share of the reconstructed β_j.

Listing	AA-A	BB-B	C-D	E-F
Panel A: Estimation of γ_{jk}				
E-F ($j = 1$)	0.130	0.278	0.196	-
C-D ($j = 2$)	0.349	0.508	-	-
BB-B ($j = 3$)	0.351	-	-	-
AA-A ($j = 4$)	-	-	-	-
Panel B: Calculated $\alpha_j^{\perp}$ and α_j				
$\alpha_j^{\perp}$	0.058	-0.011	-2.358	0.403
α_j	0.833	1.075	-2.437	0.403
Panel C: Disentangling effects for simultaneous listings				
Dependent variable: market-model CAR				
β_j	0.058	0.012	0.048	-0.016
Pure rating j effect	0.058	-0.010	-1.168	0.300
Higher-rating listing effect	0.000	0.293	1.117	-0.316
Reconstructed β_j	0.058	0.283	-0.050	-0.016
Pure rating j effect (%)	100.0%	3.2%	51.1%	48.7%
Higher-rating listing effect (%)	0.0%	96.8%	48.9%	51.3%

Table J.18: Two-stage market-model CAR estimation for 24h simultaneous listings with highest previously listed exchanges in BB-B group

Notes: This table reports the two-stage estimation for simultaneous listings within the 24-hour detection window whose highest prior spot listing was on the BB-B tier, with market-model CAR as the second-stage dependent variable. Panel A reports the first-stage multivariate probit estimates, with one column per listed tier $j \in$ {AA-A, BB-B, C-D, E-F} and the same covariate vector as the single-listing first-stage probit. Panel B reports the estimated pairwise correlations among the private-information errors of the four tier-specific probits, with the t-statistic in parentheses. Panel C reports the second-stage IMR slope β_j, with columns 1 through 4 reporting the univariate IMR specification per tier and column 5 reporting the joint multivariate specification. Standard errors are adjusted following Heckman (1979). t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Listing	AA-A	BB-B	C-D	E-F	Joint
Panel A: First-stage estimation					
Intercept	-4.507***	-4.575***	-4.581***	-4.253***	
	(-6.17)	(-13.13)	(-14.52)	(-11.09)	
VOLUME	1.252	0.100	0.790	2.530	
	(0.37)	(0.03)	(0.42)	(1.02)	
NO_CHAIN	0.015	0.381***	0.248**	0.305**	
	(0.04)	(3.49)	(2.08)	(2.33)	
VOLATL	-1.815	-0.766	-0.281	-8.071**	
	(-0.47)	(-0.51)	(-0.24)	(-2.32)	
RUNUP	0.002	0.000	-0.007	0.004	
	(0.58)	(0.04)	(-0.49)	(1.31)	
SIZE	0.090***	0.101***	0.112***	0.096***	
	(3.55)	(5.91)	(7.66)	(5.24)	
PR_FUT_RATE_4	3.158***	1.419*	1.328*	1.811***	
	(4.54)	(1.94)	(1.88)	(2.65)	
Panel B: Private-information correlations					
AA-A	-	0.523***	0.463***	0.223	
		(4.98)	(4.51)	(1.59)	
BB-B	0.523***	-	0.836***	0.726***	
	(4.98)		(21.66)	(10.50)	
C-D	0.463***	0.836***	-	0.898***	
	(4.51)	(21.66)		(18.24)	
E-F	0.223	0.726***	0.898***	-	
	(1.59)	(10.50)	(18.24)		
Panel C: Second-stage estimation					
Dependent variable: market-model CAR					
Intercept	0.005	0.014	-0.175	0.154	-0.400
	(0.04)	(0.07)	(-0.80)	(0.98)	(-0.65)
λ_{AA-A}	0.234**	-	-	-	0.235*
	(2.39)				(1.77)
λ_{BB-B}	-	0.048	-	-	0.032
		(0.52)			(0.29)
λ_{C-D}	-	-	0.133	-	0.147
			(1.49)		(1.12)
λ_{E-F}	-	-	-	-0.032	0.020
				(-0.42)	(0.19)

Table J.19: Disentangling market-model CAR effects for 24h simultaneous listings with highest previously listed exchanges in BB-B group

Notes: This table reports the decomposition of the simultaneous-listing IMR slope β_j into informational-complement and informational-substitute components, for simultaneous listings detected within the 24-hour window with BB-B prior history. Panel A reports the projection parameters γ_{jk}, with each cell at row j and column k giving the value of γ_{jk}. Panel B reports the implied valuation sensitivities $\alpha_j^{\perp}$ and α_j. Panel C reports the reconstruction of β_j as the sum of the pure-rating-j effect (informational-complement) and the higher-rating listing effect (informational-substitute), reported both in level and as a percentage share of the reconstructed β_j.

Listing	AA-A	BB-B	C-D	E-F
Panel A: Estimation of γ_{jk}				
E-F ($j = 1$)	-0.252	0.032	0.988	-
C-D ($j = 2$)	0.036	0.817	-	-
BB-B ($j = 3$)	0.523	-	-	-
AA-A ($j = 4$)	-	-	-	-
Panel B: Calculated $\alpha_j^{\perp}$ and α_j				
$\alpha_j^{\perp}$	0.235	-0.201	-0.396	-0.294
α_j	0.280	0.132	-0.106	-0.294
Panel C: Disentangling effects for simultaneous listings				
Dependent variable: market-model CAR				
β_j	0.235	0.032	0.147	0.020
Pure rating j effect	0.235	-0.146	-0.119	-0.043
Higher-rating listing effect	0.000	0.147	0.240	0.063
Reconstructed β_j	0.235	0.000	0.121	0.020
Pure rating j effect (%)	100.0%	49.9%	33.2%	40.3%
Higher-rating listing effect (%)	0.0%	50.1%	66.8%	59.7%

Table J.20: Two-stage market-model CAR estimation for 48h simultaneous listings with highest previously listed exchanges in AA-A group

Notes: This table reports the two-stage estimation for simultaneous listings within the 48-hour detection window whose highest prior spot listing was on the AA-A tier, with market-model CAR as the second-stage dependent variable. Panel A reports the first-stage multivariate probit estimates, with one column per listed tier $j \in \{$AA-A, BB-B, C-D, E-F$\}$ and the same covariate vector as the single-listing first-stage probit. Panel B reports the estimated pairwise correlations among the private-information errors of the four tier-specific probits, with the t-statistic in parentheses. Panel C reports the second-stage IMR slope β_j, with columns 1 through 4 reporting the univariate IMR specification per tier and column 5 reporting the joint multivariate specification. Standard errors are adjusted following Heckman (1979). t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Listing	AA-A	BB-B	C-D	E-F	Joint
Panel A: First-stage estimation					
Intercept	-4.996*** (-13.23)	-4.435*** (-16.44)	-4.523*** (-16.82)	-4.330*** (-14.67)	

VOLUME	-1.705 (-0.26)	-4.576 (-0.50)	-8.167 (-0.68)	-41.204* (-1.82)	
NO_CHAIN	0.155 (1.23)	0.121 (1.26)	0.168* (1.82)	0.181* (1.86)	
VOLATL	0.693 (1.03)	-1.636 (-1.63)	-1.439 (-1.52)	-0.269 (-0.31)	
RUNUP	-0.000 (-0.57)	-0.000 (-0.85)	0.000 (0.59)	0.000 (0.50)	
SIZE	0.129*** (7.37)	0.137*** (10.26)	0.139*** (10.49)	0.117*** (7.89)	
PR_FUT_RATE_4	1.467*** (8.90)	2.064*** (15.96)	1.810*** (14.41)	2.117*** (15.81)	
Panel B: Private-information correlations					
AA-A	-	0.324*** (4.41)	0.404*** (5.64)	0.400*** (5.16)	
BB-B	0.324*** (4.41)	-	0.556*** (10.65)	0.456*** (7.47)	
C-D	0.404*** (5.64)	0.556*** (10.65)	-	0.428*** (6.72)	
E-F	0.400*** (5.16)	0.456*** (7.47)	0.428*** (6.72)	-	
Panel C: Second-stage estimation Dependent variable: market-model CAR					
Intercept	0.004 (0.18)	0.003 (0.10)	0.010 (0.37)	0.041 (1.57)	-0.021 (-0.16)
λ_{AA-A}	0.077*** (3.05)	-	-	-	0.076*** (2.63)
λ_{BB-B}	-	0.033 (1.50)	-	-	0.033 (0.79)
λ_{C-D}	-	-	0.025 (1.15)	-	0.009 (0.22)
λ_{E-F}	-	-	-	-0.013 (-0.56)	-0.016 (-0.43)

Table J.21: Disentangling market-model CAR effects for 48h simultaneous listings with highest previously listed exchanges in AA-A group

Notes: This table reports the decomposition of the simultaneous-listing IMR slope β_j into informational-complement and informational-substitute components, for simultaneous listings detected within the 48-hour window with AA-A prior history. Panel A reports the projection parameters γ_{jk}, with each cell at row j and column k giving the value of γ_{jk}. Panel B reports the implied valuation sensitivities $\alpha_j^{\perp}$ and α_j. Panel C reports the reconstruction of β_j as the sum of the pure-rating-j effect (informational-complement) and the higher-rating listing effect (informational-substitute), reported both in level and as a percentage share of the reconstructed β_j.

Listing	AA-A	BB-B	C-D	E-F
Panel A: Estimation of γ_{jk}				
E-F ($j = 1$)	0.238	0.282	0.175	-
C-D ($j = 2$)	0.250	0.476	-	-

BB-B ($j = 3$)	0.324	-	-	-
AA-A ($j = 4$)	-	-	-	-
Panel B: Calculated $\alpha_j^{\perp}$ and α_j				
$\alpha_j^{\perp}$	0.076	0.011	-0.097	-0.097
α_j	0.120	0.085	-0.080	-0.097
Panel C: Disentangling effects for simultaneous listings				
Dependent variable: market-model CAR				
β_j	0.076	0.033	0.009	-0.016
Pure rating j effect	0.076	0.010	-0.062	-0.068
Higher-rating listing effect	0.000	0.039	0.095	0.052
Reconstructed β_j	0.076	0.049	0.034	-0.016
Pure rating j effect (%)	100.0%	20.5%	39.3%	56.6%
Higher-rating listing effect (%)	0.0%	79.5%	60.7%	43.4%

Table J.22: Two-stage market-model CAR estimation for 48h simultaneous listings with highest previously listed exchanges in BB-B group

Notes: This table reports the two-stage estimation for simultaneous listings within the 48-hour detection window whose highest prior spot listing was on the BB-B tier, with market-model CAR as the second-stage dependent variable. Panel A reports the first-stage multivariate probit estimates, with one column per listed tier $j \in$ {AA-A, BB-B, C-D, E-F} and the same covariate vector as the single-listing first-stage probit. Panel B reports the estimated pairwise correlations among the private-information errors of the four tier-specific probits, with the t-statistic in parentheses. Panel C reports the second-stage IMR slope β_j, with columns 1 through 4 reporting the univariate IMR specification per tier and column 5 reporting the joint multivariate specification. Standard errors are adjusted following Heckman (1979). t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Listing	AA-A	BB-B	C-D	E-F	Joint
Panel A: First-stage estimation					
Intercept	-4.311*** (-5.55)	-4.489*** (-15.09)	-4.729*** (-15.29)	-4.225*** (-13.89)	
VOLUME	0.664 (0.17)	-0.267 (-0.08)	0.149 (0.05)	2.296 (1.28)	
NO_CHAIN	-0.250 (-0.44)	0.340*** (3.48)	0.276** (2.54)	0.253** (2.34)	
VOLATL	-1.107 (-0.38)	-0.827 (-0.65)	-0.746 (-0.64)	-6.199*** (-2.90)	
RUNUP	0.002 (0.62)	-0.002 (-0.34)	0.002 (0.75)	0.004** (2.26)	
SIZE	0.103*** (4.30)	0.116*** (7.52)	0.126*** (8.65)	0.112*** (7.52)	
PR_FUT_RATE_4	2.651*** (4.11)	1.210* (1.72)	1.608** (2.40)	1.762*** (2.74)	
Panel B: Private-information correlations					
AA-A	-	0.675*** (10.27)	0.582*** (7.56)	0.538*** (6.33)	
BB-B	0.675*** (10.27)	-	0.871*** (27.48)	0.845*** (21.90)	

C-D	0.582*** (7.56)	0.871*** (27.48)	-	0.890*** (24.07)	
E-F	0.538*** (6.33)	0.845*** (21.90)	0.890*** (24.07)	-	
Panel C: Second-stage estimation					
Dependent variable: market-model CAR					
Intercept	-0.030 (-0.43)	-0.004 (-0.03)	-0.082 (-0.77)	-0.076 (-0.75)	-0.695 (-1.22)
λ_{AA-A}	0.159** (2.50)	-	-	-	0.179* (1.66)
λ_{BB-B}	-	0.020 (0.33)	-	-	0.078 (0.95)
λ_{C-D}	-	-	0.075 (1.42)	-	0.163* (1.80)
λ_{E-F}	-	-	-	0.075 (1.48)	0.166* (1.79)

Table J.23: Disentangling market-model CAR effects for 48h simultaneous listings with highest previously listed exchanges in BB-B group

Notes: This table reports the decomposition of the simultaneous-listing IMR slope β_j into informational-complement and informational-substitute components, for simultaneous listings detected within the 48-hour window with BB-B prior history. Panel A reports the projection parameters γ_{jk}, with each cell at row j and column k giving the value of γ_{jk}. Panel B reports the implied valuation sensitivities $\alpha_j^{\perp}$ and α_j. Panel C reports the reconstruction of β_j as the sum of the pure-rating-j effect (informational-complement) and the higher-rating listing effect (informational-substitute), reported both in level and as a percentage share of the reconstructed β_j.

Listing	AA-A	BB-B	C-D	E-F
Panel A: Estimation of γ_{jk}				
E-F ($j = 1$)	-0.054	0.325	0.638	-
C-D ($j = 2$)	-0.010	0.877	-	-
BB-B ($j = 3$)	0.675	-	-	-
AA-A ($j = 4$)	-	-	-	-
Panel B: Calculated $\alpha_j^{\perp}$ and α_j				
$\alpha_j^{\perp}$	0.179	-0.484	-0.561	-0.620
α_j	0.467	0.210	-0.166	-0.620
Panel C: Disentangling effects for simultaneous listings				
Dependent variable: market-model CAR				
β_j	0.179	0.078	0.163	0.166
Pure rating j effect	0.179	-0.263	-0.136	-0.116
Higher-rating listing effect	0.000	0.315	0.455	0.281
Reconstructed β_j	0.179	0.052	0.319	0.166
Pure rating j effect (%)	100.0%	45.5%	23.0%	29.1%
Higher-rating listing effect (%)	0.0%	54.5%	77.0%	70.9%

Table J.24: Two-stage market-model CAR estimation for 96h simultaneous listings with highest previously listed exchanges in AA-A group

Notes: This table reports the two-stage estimation for simultaneous listings within the 96-hour detection window whose highest prior spot listing was on the AA-A tier, with market-model CAR as the second-stage dependent variable. Panel A reports the first-stage multivariate probit estimates, with one column per listed tier $j \in \{\text{AA-A, BB-B, C-D, E-F}\}$ and the same covariate vector as the single-listing first-stage probit. Panel B reports the estimated pairwise correlations among the private-information errors of the four tier-specific probits, with the t-statistic in parentheses. Panel C reports the second-stage IMR slope β_j, with columns 1 through 4 reporting the univariate IMR specification per tier and column 5 reporting the joint multivariate specification. Standard errors are adjusted following Heckman (1979). t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Listing	AA-A	BB-B	C-D	E-F	Joint
Panel A: First-stage estimation					
Intercept	-4.840*** (-14.10)	-4.462*** (-19.00)	-4.508*** (-18.20)	-4.252*** (-16.88)	
VOLUME	-2.330 (-0.34)	-1.500 (-0.30)	-6.383 (-0.68)	-18.611 (-1.37)	
NO_CHAIN	0.085 (0.73)	0.122 (1.48)	0.143* (1.71)	0.072 (0.82)	
VOLATL	0.494 (0.70)	-2.404** (-2.56)	-1.607* (-1.76)	-0.861 (-1.02)	
RUNUP	-0.000 (-0.58)	-0.000 (-0.76)	0.001 (0.63)	0.000 (0.58)	
SIZE	0.134*** (8.10)	0.154*** (12.89)	0.148*** (11.90)	0.134*** (10.41)	
PR_FUT_RATE_4	1.371*** (9.46)	1.847*** (16.50)	1.724*** (15.32)	1.775*** (15.47)	
Panel B: Private-information correlations					
AA-A	-	0.306*** (4.42)	0.382*** (5.50)	0.233*** (2.96)	
BB-B	0.306*** (4.42)	-	0.500*** (10.17)	0.548*** (11.63)	
C-D	0.382*** (5.50)	0.500*** (10.17)	-	0.337*** (5.87)	
E-F	0.233*** (2.96)	0.548*** (11.63)	0.337*** (5.87)	-	
Panel C: Second-stage estimation					
Dependent variable: market-model CAR					
Intercept	0.012 (0.79)	0.022 (1.09)	0.031 (1.62)	0.039** (2.11)	0.015 (0.13)
λ_{AA-A}	0.048*** (2.61)	-	-	-	0.047** (1.98)
λ_{BB-B}	-	0.008 (0.47)	-	-	0.013 (0.33)
λ_{C-D}	-	-	-0.002 (-0.12)	-	-0.007 (-0.20)
λ_{E-F}	-	-	-	-0.013 (-0.80)	-0.012 (-0.38)

Table J.25: Disentangling market-model CAR effects for 96h simultaneous listings with highest previously listed exchanges in AA-A group

Notes: This table reports the decomposition of the simultaneous-listing IMR slope β_j into informational-complement and informational-substitute components, for simultaneous listings detected within the 96-hour window with AA-A prior history. Panel A reports the projection parameters γ_{jk}, with each cell at row j and column k giving the value of γ_{jk}. Panel B reports the implied valuation sensitivities $\alpha_j^{\perp}$ and α_j. Panel C reports the reconstruction of β_j as the sum of the pure-rating-j effect (informational-complement) and the higher-rating listing effect (informational-substitute), reported both in level and as a percentage share of the reconstructed β_j.

Listing	AA-A	BB-B	C-D	E-F
Panel A: Estimation of γ_{jk}				
E-F ($j = 1$)	0.055	0.498	0.066	-
C-D ($j = 2$)	0.252	0.423	-	-
BB-B ($j = 3$)	0.306	-	-	-
AA-A ($j = 4$)	-	-	-	-
Panel B: Calculated $\alpha_j^{\perp}$ and α_j				
$\alpha_j^{\perp}$	0.047	-0.002	-0.064	-0.051
α_j	0.067	0.050	-0.060	-0.051
Panel C: Disentangling effects for simultaneous listings				
Dependent variable: market-model CAR				
β_j	0.047	0.013	-0.007	-0.012
Pure rating j effect	0.047	-0.002	-0.044	-0.035
Higher-rating listing effect	0.000	0.020	0.051	0.023
Reconstructed β_j	0.047	0.019	0.007	-0.012
Pure rating j effect (%)	100.0%	8.1%	46.5%	60.6%
Higher-rating listing effect (%)	0.0%	91.9%	53.5%	39.4%

Table J.26: Two-stage market-model CAR estimation for 96h simultaneous listings with highest previously listed exchanges in BB-B group

Notes: This table reports the two-stage estimation for simultaneous listings within the 96-hour detection window whose highest prior spot listing was on the BB-B tier, with market-model CAR as the second-stage dependent variable. Panel A reports the first-stage multivariate probit estimates, with one column per listed tier $j \in \{$AA-A, BB-B, C-D, E-F$\}$ and the same covariate vector as the single-listing first-stage probit. Panel B reports the estimated pairwise correlations among the private-information errors of the four tier-specific probits, with the t-statistic in parentheses. Panel C reports the second-stage IMR slope β_j, with columns 1 through 4 reporting the univariate IMR specification per tier and column 5 reporting the joint multivariate specification. Standard errors are adjusted following Heckman (1979). t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Listing	AA-A	BB-B	C-D	E-F	Joint
Panel A: First-stage estimation					
Intercept	-4.354*** (-7.97)	-4.325*** (-16.59)	-4.537*** (-17.15)	-4.278*** (-14.76)	

VOLUME	-0.268 (-0.05)	0.410 (0.15)	0.052 (0.03)	1.513 (0.73)	
NO_CHAIN	-0.146 (-0.43)	0.264*** (2.75)	0.229** (2.30)	0.228** (2.11)	
VOLATL	-0.764 (-0.35)	-1.566 (-1.31)	-0.596 (-0.56)	-4.635** (-2.49)	
RUNUP	0.001 (0.30)	-0.002 (-0.28)	0.000 (0.15)	0.003 (1.38)	
SIZE	0.108*** (5.55)	0.122*** (9.35)	0.130*** (10.22)	0.121*** (8.45)	
PR_FUT_RATE_4	2.671*** (4.76)	1.006* (1.87)	1.295*** (2.58)	1.850*** (3.83)	
Panel B: Private-information correlations					
AA-A	-	0.373*** (4.82)	0.373*** (5.49)	0.345*** (3.91)	
BB-B	0.373*** (4.82)	-	0.900*** (38.88)	0.840*** (22.39)	
C-D	0.373*** (5.49)	0.900*** (38.88)	-	0.845*** (20.61)	
E-F	0.345*** (3.91)	0.840*** (22.39)	0.845*** (20.61)	-	
Panel C: Second-stage estimation Dependent variable: market-model CAR					
Intercept	-0.024 (-0.43)	-0.025 (-0.24)	-0.068 (-0.78)	-0.040 (-0.56)	-0.630* (-1.81)
λ_{AA-A}	0.117** (2.30)	-	-	-	0.151** (2.48)
λ_{BB-B}	-	0.026 (0.57)	-	-	0.104 (1.56)
λ_{C-D}	-	-	0.057 (1.32)	-	0.137* (1.92)
λ_{E-F}	-	-	-	0.053 (1.31)	0.137** (2.20)

Table J.27: Disentangling market-model CAR effects for 96h simultaneous listings with highest previously listed exchanges in BB-B group

Notes: This table reports the decomposition of the simultaneous-listing IMR slope β_j into informational-complement and informational-substitute components, for simultaneous listings detected within the 96-hour window with BB-B prior history. Panel A reports the projection parameters γ_{jk}, with each cell at row j and column k giving the value of γ_{jk}. Panel B reports the implied valuation sensitivities $\alpha_j^{\perp}$ and α_j. Panel C reports the reconstruction of β_j as the sum of the pure-rating-j effect (informational-complement) and the higher-rating listing effect (informational-substitute), reported both in level and as a percentage share of the reconstructed β_j.

Listing	AA-A	BB-B	C-D	E-F
Panel A: Estimation of γ_{jk}				
E-F ($j = 1$)	0.017	0.413	0.467	-
C-D ($j = 2$)	0.043	0.884	-	-

BB-B ($j = 3$)	0.373	-	-	-
AA-A ($j = 4$)	-	-	-	-
Panel B: Calculated $\alpha_j^{\perp}$ and α_j				
$\alpha_j^{\perp}$	0.151	0.066	-0.048	-0.086
α_j	0.130	0.144	-0.008	-0.086
Panel C: Disentangling effects for simultaneous listings				
Dependent variable: market-model CAR				
β_j	0.151	0.104	0.137	0.137
Pure rating j effect	0.151	0.057	-0.009	-0.022
Higher-rating listing effect	0.000	0.048	0.178	0.159
Reconstructed β_j	0.151	0.106	0.169	0.137
Pure rating j effect (%)	100.0%	54.1%	4.8%	12.0%
Higher-rating listing effect (%)	0.0%	45.9%	95.2%	88.0%

C.3 Volume decomposition

The volume robustness exercise repeats the simultaneous-listing two-stage estimation and the informational-substitute decomposition with cumulative abnormal volume (CAV) replacing cumulative abnormal return (CAR) as the second-stage dependent variable. Daily abnormal volume is constructed at the token-day level as the natural-log deviation of the realized trading volume from a token-specific baseline benchmark, where the baseline is the mean log volume over a pre-event estimation window that ends 5 days before the event date, following the convention of Ajinkya and Jain (1989) and Campbell and Wasley (1996). The event-window CAV is the sum of daily abnormal log volume over the same event window used for CAR, as in Karafiath (2009). The first-stage multivariate probit and the IMR construction are unchanged from the CAR specification, since the selection equation does not depend on the outcome variable. The second-stage IMR regression and the decomposition into informational-complement and informational-substitute components are then estimated with CAV in place of CAR, and the substitute share is reported as the share of β_j that loads on the higher-rating implied signal. The remainder of this subsection reports the two-stage estimates and the decomposition for both AA-A and BB-B prior-history blocks.

Table J.28: Two-stage CAV estimation for simultaneous listings with highest previously listed exchanges in AA-A group

Notes: This table reports the two-stage estimation for simultaneous listings within the 72-hour detection window whose highest prior spot listing was on the AA-A tier, with cumulative abnormal volume (CAV) as the second-stage dependent variable. Panel A reports the first-stage multivariate probit estimates, with one column per listed tier $j \in \{\text{AA-A, BB-B, C-D, E-F}\}$ and the same covariate vector as the single-listing first-stage probit. Panel B reports the estimated pairwise correlations among the private-information errors of the four tier-specific probits, with the t-statistic in parentheses. Panel C reports the second-stage IMR slope β_j, with columns 1 through 4 reporting the univariate IMR specification per tier and column 5 reporting the joint multivariate specification. Daily abnormal volume is the natural-log deviation of realized volume from a token-specific pre-event baseline, summed over the event window to obtain CAV. Standard errors are adjusted following Heckman (1979). t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Listing	AA-A (1)	BB-B (2)	C-D (3)	E-F (4)	(5)
Panel A: First-stage estimation Dependent variable: $LIST_j$ Independent variables: probit covariates					
Intercept	-4.826*** (-14.01)	-4.356*** (-17.91)	-4.550*** (-17.57)	-4.305*** (-16.57)	
VOLUME	-5.260 (-0.47)	-2.679 (-0.40)	-6.022 (-0.60)	-13.614 (-1.06)	
NO_CHAIN	0.122 (1.05)	0.060 (0.67)	0.134 (1.49)	0.105 (1.16)	
VOLATL	0.577 (0.84)	-2.554*** (-2.64)	-1.610* (-1.72)	-0.834 (-0.98)	
RUNUP	-0.000 (-0.59)	-0.000 (-0.77)	0.000 (0.71)	0.000 (0.69)	
SIZE	0.130*** (7.90)	0.149*** (12.08)	0.147*** (11.41)	0.131*** (9.87)	
PR_FUT_RATE_4	1.377*** (9.16)	1.903*** (16.14)	1.766*** (14.89)	1.815*** (15.13)	
Panel B: Private-information correlations					
AA-A	-	0.258*** (3.73)	0.338*** (5.26)	0.269*** (3.67)	
BB-B	0.258*** (3.73)	-	0.540*** (10.62)	0.599*** (12.54)	
C-D	0.338*** (5.26)	0.540*** (10.62)	-	0.381*** (6.54)	
E-F	0.269*** (3.67)	0.599*** (12.54)	0.381*** (6.54)	-	
Panel C: Second-stage estimation Dependent variable: CAV Independent variable: IMR terms					
Intercept	3.886*** (2.82)	3.937** (2.16)	4.350** (2.57)	7.359*** (4.40)	2.715 (1.19)

Continued on next page

Table J.28: Two-stage CAV estimation for simultaneous listings with highest previously listed exchanges in AA-A group (continued)

Listing	AA-A (1)	BB-B (2)	C-D (3)	E-F (4)	(5)
λ_{AA-A}	5.093***	-	-	-	4.734***
	(3.19)	-	-	-	(2.95)
λ_{BB-B}	-	2.018	-	-	2.293
	-	(1.41)	-	-	(1.58)
λ_{C-D}	-	-	1.854	-	1.103
	-	-	(1.28)	-	(0.77)
λ_{E-F}	-	-	-	-2.014	-2.157
	-	-	-	(-1.42)	(-1.50)

Table J.29: Disentangling CAV effects for simultaneous listings with highest previously listed exchanges in AA-A group

Notes: This table reports the decomposition of the simultaneous-listing IMR slope β_j into informational-complement and informational-substitute components, for simultaneous listings with AA-A prior history and cumulative abnormal volume (CAV) as the second-stage dependent variable. Panel A reports the projection parameters γ_{jk}, with each cell at row j and column k giving the value of γ_{jk}. Panel B reports the implied valuation sensitivities $\alpha_j^{\perp}$ and α_j, expressed in CAV units. Panel C reports the reconstruction of β_j as the sum of the pure-rating-j effect (informational-complement) and the higher-rating listing effect (informational-substitute), reported both in level and as a percentage share of the reconstructed β_j.

Listing	AA-A	BB-B	C-D	E-F
Panel A: Estimation of γ_{jk}				
E-F ($j=1$)	0.112	0.543	0.050	—
C-D ($j=2$)	0.213	0.485	—	—
BB-B ($j=3$)	0.258	—	—	—
AA-A ($j=4$)	—	—	—	—
Panel B: Calculated $\alpha_j^{\perp}$ and α_j				
$\alpha_j^{\perp}$	$\alpha_4^{\perp}=4.734$	$\alpha_3^{\perp}=1.237$	$\alpha_2^{\perp}=-3.194$	$\alpha_1^{\perp}=-15.826$
α_j	$\alpha_4=6.871$	$\alpha_3=11.382$	$\alpha_2=-2.407$	$\alpha_1=-15.826$
Panel C: Disentangling effects for simultaneous listings Dependent variable: CAV				
β_j	4.734	2.293	1.103	-2.157
Pure rating j effect	4.734	1.155	-2.126	-9.903
Higher-rating listing effect	0.000	1.770	8.473	7.745
Reconstructed β_j	4.734	2.926	6.347	-2.157
Pure rating j effect (%)	100.0%	39.5%	20.1%	56.1%
Higher-rating listing effect (%)	0.0%	60.5%	79.9%	43.9%

Table J.30: Two-stage CAV estimation for simultaneous listings with highest previously listed exchanges in BB-B group

Notes: This table reports the two-stage estimation for simultaneous listings within the 72-hour detection window whose highest prior spot listing was on the BB-B tier, with cumulative abnormal volume (CAV) as the second-stage dependent variable. Panel A reports the first-stage multivariate probit estimates, with one column per listed tier $j \in \{\text{AA-A, BB-B, C-D, E-F}\}$. Panel B reports the estimated pairwise correlations among the private-information errors of the four tier-specific probits, with the t-statistic in parentheses. Panel C reports the second-stage IMR slope β_j, with columns 1 through 4 reporting the univariate IMR specification per tier and column 5 reporting the joint multivariate specification. Daily abnormal volume is the natural-log deviation of realized volume from a token-specific pre-event baseline, summed over the event window to obtain CAV. Standard errors are adjusted following Heckman (1979). t-statistics are reported in parentheses. ***/**/* denote significance at the 1%/5%/10% levels.

Listing	AA-A (1)	BB-B (2)	C-D (3)	E-F (4)	(5)
Panel A: First-stage estimation					
Dependent variable: $LIST_j$					
Independent variables: probit covariates					
Intercept	-4.203***	-4.301***	-4.579***	-4.214***	
	(-5.13)	(-16.56)	(-15.87)	(-13.68)	
VOLUME	0.328	0.058	-0.001	0.976	
	(0.07)	(0.02)	(-0.00)	(0.49)	
NO_CHAIN	-0.438	0.292***	0.271**	0.256**	
	(-0.64)	(3.08)	(2.53)	(2.27)	
VOLATL	-0.663	-1.676	-0.467	-5.155**	
	(-0.27)	(-1.41)	(-0.46)	(-2.48)	
RUNUP	0.001	-0.000	0.001	0.003	
	(0.51)	(-0.02)	(0.15)	(1.51)	
SIZE	0.112***	0.117***	0.123***	0.113***	
	(5.22)	(8.92)	(8.87)	(7.43)	
PR_FUT_RATE_4	2.658***	1.049*	1.587***	1.821***	
	(3.89)	(1.86)	(2.76)	(3.15)	
Panel B: Private-information correlations					
AA-A	-	0.609***	0.585***	0.558***	
		(9.10)	(7.68)	(6.98)	
BB-B	0.609***	-	0.850***	0.815***	
	(9.10)		(26.92)	(20.47)	
C-D	0.585***	0.850***	-	0.823***	
	(7.68)	(26.92)		(18.23)	
E-F	0.558***	0.815***	0.823***	-	
	(6.98)	(20.47)	(18.23)		
Panel C: Second-stage estimation					
Dependent variable: CAV					
Independent variable: IMR terms					
Intercept	9.481**	19.789**	2.992	17.929***	2.996
	(2.62)	(2.53)	(0.52)	(3.38)	(0.23)

Continued on next page

Table J.30: Two-stage CAV estimation for simultaneous listings with highest previously listed exchanges in BB-B group (continued)

Listing	AA-A (1)	BB-B (2)	C-D (3)	E-F (4)	(5)
λ_{AA-A}	10.946***	-	-	-	10.544***
	(3.15)	-	-	-	(3.10)
λ_{BB-B}	-	-3.021	-	-	-0.978
	-	(-0.88)	-	-	(-0.29)
λ_{C-D}	-	-	6.602**	-	5.820*
	-	-	(2.37)	-	(1.85)
λ_{E-F}	-	-	-	-3.050	-0.574
	-	-	-	(-1.10)	(-0.19)

Table J.31: Disentangling CAV effects for simultaneous listings with highest previously listed exchanges in BB-B group

Notes: This table reports the decomposition of the simultaneous-listing IMR slope β_j into informational-complement and informational-substitute components, for simultaneous listings with BB-B prior history and cumulative abnormal volume (CAV) as the second-stage dependent variable. Panel A reports the projection parameters γ_{jk}, with each cell at row j and column k giving the value of γ_{jk}. Panel B reports the implied valuation sensitivities $\alpha_j^{\perp}$ and α_j, expressed in CAV units. Panel C reports the reconstruction of β_j as the sum of the pure-rating-j effect (informational-complement) and the higher-rating listing effect (informational-substitute), reported both in level and as a percentage share of the reconstructed β_j.

Listing	AA-A	BB-B	C-D	E-F
Panel A: Estimation of γ_{jk}				
E-F ($j=1$)	0.050	0.395	0.458	—
C-D ($j=2$)	0.107	0.785	—	—
BB-B ($j=3$)	0.609	—	—	—
AA-A ($j=4$)	—	—	—	—
Panel B: Calculated $\alpha_j^{\perp}$ and α_j				
$\alpha_j^{\perp}$	$\alpha_4^{\perp}=10.544$	$\alpha_3^{\perp}=-28.547$	$\alpha_2^{\perp}=-29.890$	$\alpha_1^{\perp}=-23.819$
α_j	$\alpha_4=32.324$	$\alpha_3=4.317$	$\alpha_2=-18.986$	$\alpha_1=-23.819$
Panel C: Disentangling effects for simultaneous listings Dependent variable: CAV				
β_j	10.544	-0.978	5.820	-0.574
Pure rating j effect	10.544	-17.972	-8.065	-6.519
Higher-rating listing effect	0.000	19.674	22.580	5.945
Reconstructed β_j	10.544	1.702	14.515	-0.574
Pure rating j effect (%)	100.0%	47.7%	26.3%	52.3%
Higher-rating listing effect (%)	0.0%	52.3%	73.7%	47.7%

C.4 Placebo tests

The placebo tests assess whether the listing premium documented in Section 4 is genuinely attributable to the listing event rather than to baseline token return dynamics or to the event-window measurement procedure. Two placebo designs are implemented. The random-date placebo replaces the actual listing date for every real CEX listing event with a randomly drawn date from the same token's price history, excluding a 30-day window around any real CEX listing date of that token to prevent contamination by leaked listing-effect mass. The event-window CAR is recomputed for each placebo draw under the same market-model specification used in Section 4, and the placebo distribution is constructed by replicating the random draw across the full single-listing sample. Empirical p-values are computed from the placebo distribution as the share of placebo draws whose mean CAR is at least as extreme as the actual mean CAR, with one-sided and two-sided variants reported separately. The single-listing conditional version of this exercise mirrors the prior-history slicing used for the second-stage IMR estimates in Section 6.2, holding the first-stage probit fixed and replacing only the CAR observations. The DEX listing placebo uses DEX pool launch dates as the event date, on the rationale that decentralized venues do not screen tokens prior to listing and therefore should not produce a certification premium under the mechanism modeled in Section 3. Two types of DEX events are separated. The first-pool launch (`first_pool`) is the timestamp at which the token's earliest DEX pool launched, sourced from the spot-listing table's `pool_launch_time` column, and represents the token's birth on any decentralized venue. The secondary or multichain launch (`secondary_multichain`) is a subsequent pool launch on a different chain, sourced from the per-chain coin-list files and reclassified as a duplicate of the first pool when its timestamp falls within one hour of the first-pool event. The remainder of this subsection reports the per-tier random-date placebo summary, the per-current-tier-by-prior-history random-date placebo, the DEX placebo CAR estimates, and the DEX placebo feasibility counts.

Table J.32: Random-date placebo test by CEX tier

Notes: This table summarizes the per-tier random-date placebo test for the unconditional CAR. For each CEX rating tier, placebo dates are drawn for every real listing from the same token's price history, excluding a 30-day window around any actual CEX listing of that token to prevent contamination by leaked listing-effect mass. The event-window CAR is recomputed for each placebo draw under the market-model specification used in Section 4, and the placebo distribution is constructed across draws. The Actual CAR column reports the mean realized CAR per tier under the actual listing dates, and the Placebo mean and Placebo SD columns report the mean and standard deviation of the per-tier mean across placebo draws. The Difference column reports the actual mean minus the placebo mean, and the last two columns report the one-sided and two-sided empirical p-values from the placebo distribution. Stars on the Actual CAR and Difference columns use the two-sided empirical p-value. ***/**/* denote significance at the 1%/5%/10% levels.

Tier	N	Actual CAR	Placebo mean	Placebo SD	Difference	p 1-sided	p 2-sided
AA_A	557	0.055***	-0.004	0.007	0.059***	0.000	0.000
BB_B	2265	0.031***	-0.003	0.006	0.034***	0.000	0.001
C_D	3765	0.038***	-0.005	0.004	0.043***	0.000	0.000
E_F	1546	0.001	-0.002	0.004	0.003	0.189	0.399

Table J.33: Single-listing conditional random-date placebo

Notes: This table reports the conditional random-date placebo test for the second-stage IMR slope $\beta_{j,h}$ at each (current tier j, prior tier h) cell. The first-stage probit selection model is fixed from the real single-listing panel, and only the dependent variable (CAR) is replaced by the placebo CAR computed at randomly drawn dates within the same token's price history. The 30-day exclusion window around real CEX listings is enforced as in Table J.32. For each cell, the Actual λ column reports the realized second-stage IMR slope, and the Placebo mean and Placebo SD columns report the mean and standard deviation of the per-cell IMR slope across placebo draws. the last two columns report the one-sided and two-sided empirical p-values. Stars on the Actual λ column use the two-sided empirical p-value. ***/**/* denote significance at the 1%/5%/10% levels.

Target tier	Prior history	N	Actual λ	Placebo mean	Placebo SD	p 1-sided	p 2-sided
AA-A	first-time-listing	356	0.133***	-0.005	0.018	0.000	0.000
AA-A	E-F	107	0.096**	0.006	0.041	0.027	0.039
AA-A	C-D	500	0.025	0.001	0.039	0.182	0.397
AA-A	BB-B	1370	-0.002	-0.002	0.013	0.510	0.996
AA-A	AA-A	4319	0.019***	-0.001	0.005	0.000	0.000
BB-B	first-time-listing	356	-0.013	0.001	0.011	0.908	0.187
BB-B	E-F	107	0.027	-0.001	0.026	0.131	0.244
BB-B	C-D	500	0.012	-0.001	0.013	0.156	0.312
BB-B	BB-B	1370	-0.002	-0.000	0.007	0.600	0.820
BB-B	AA-A	4319	0.007**	0.000	0.003	0.011	0.031
C-D	first-time-listing	356	0.011	-0.002	0.012	0.121	0.239
C-D	E-F	107	-0.025	0.002	0.028	0.857	0.289
C-D	C-D	500	-0.011	-0.001	0.014	0.780	0.445
C-D	BB-B	1370	0.004	-0.001	0.006	0.233	0.451
C-D	AA-A	4319	0.000	-0.001	0.003	0.382	0.736
E-F	first-time-listing	356	-0.025**	0.001	0.011	0.989	0.018

E-F	E-F	107	0.004	-0.002	0.026	0.411	0.829
E-F	C-D	500	-0.044***	0.003	0.018	0.998	0.008
E-F	BB-B	1370	-0.006	0.000	0.007	0.799	0.400
E-F	AA-A	4319	-0.019***	-0.000	0.003	1.000	0.000

Table J.34: DEX placebo CAR estimates

Notes: This table reports the DEX placebo CAR estimates, in which DEX pool launch dates are used as the event date and the event-window CAR is computed under the same market-model specification used in Section 4. Panel A reports estimates for the secondary or multichain DEX launch sample, which excludes the token's first-pool launch and includes only DEX events that satisfy the market-model support rule and fall outside the 30-day window around any real CEX listing. The overall row reports the pooled mean CAR, and the chain and prior_cex rows partition the sample by issuing chain and by whether the token had any prior CEX listing at the event date. Panel B reports the first-pool launch audit, which uses the token's earliest DEX pool as the event date. The market_model_supported row reports the mean CAR for the subset of first-pool events that satisfy the market-model support rule. The aux_post_0_5 row reports the alternative cumulative market-adjusted return $\sum_{t=0}^{5}(r_{it} - r_{mt})$ over the five-day post-event window, computed on the larger first-pool sample that does not require the 60 pre-event daily observations needed by the market model (further details in the notes to Table J.35). Stars on the Mean column use a two-sided one-sample t-test of the null that the mean equals zero, with standard error SD/$\sqrt{N}$. ***/**/* denote significance at the 1%/5%/10% levels.

Sample	N	Mean	Median	SD	t-stat	p-value
Panel A: Primary secondary/multichain DEX launches						
overall	506	0.052***	0.007	0.343	3.430	0.001
chain=arbitrum-one	93	0.099***	0.018	0.349	2.749	0.007
chain=avalanche	32	0.048	0.015	0.251	1.087	0.285
chain=binance-smart-chain	146	0.034*	0.003	0.242	1.698	0.092
chain=ethereum	128	0.049	-0.000	0.435	1.276	0.204
chain=solana	107	0.041	0.012	0.355	1.199	0.233
prior_cex=0	255	0.064**	0.000	0.416	2.475	0.014
prior_cex=1	251	0.040**	0.015	0.248	2.550	0.011
Panel B: First-pool-launch audit						
first_pool_market_model_supported (market_model_car)	72	-0.740	0.010	7.122	-0.882	0.381
first_pool_aux_post_0_5 (aux_post_0_5_market_adjusted)	3189	0.309***	0.089	1.583	11.032	0.000

Table J.35: DEX placebo feasibility counts

Notes: This table reports the feasibility counts for the DEX placebo test, broken down by DEX event type. The first-pool event type captures the timestamp at which the token's earliest DEX pool launched, and the secondary or multichain event type captures subsequent pool launches on different chains. The Candidates column reports the raw number of events per type before any filtering. The Market-model supported column reports the subset of candidates that satisfy the market-model support rule, that is, the token has at least 60 valid daily return observations in the pre-event estimation window so that the market-model intercept $\hat{\alpha}_i$ and slope $\hat{\beta}_i$ can be fit. The Primary eligible column reports the subset of market-model-supported events that additionally fall outside the 30-day window around any real CEX listing of the token. The Auxiliary supported column reports the subset that satisfies the alternative post-event return measure `aux_post_0_5`, which is defined as the cumulative market-adjusted return $\sum_{t=0}^{5}(r_{it} - r_{mt})$ over the five-day post-event window, where r_{it} is the token return on day t relative to the event date and r_{mt} is the contemporaneous market return. The `aux_post_0_5` measure does not estimate $\hat{\alpha}_i$ or $\hat{\beta}_i$ from a pre-event window and therefore admits newly launched tokens that lack the 60 pre-event daily observations required by the market model. The subscript "0_5" in the name refers to the post-event day range $[0, 5]$ over which the cumulative market-adjusted return is taken.

DEX event type	Candidates	Market-model supported	Primary eligible	Auxiliary supported
First-pool	8365	72	62	3189
Secondary-multichain	3509	650	506	988