Why Are There So Many Cryptocurrency Exchanges?*

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Abstract

The crypto exchange market is simultaneously fragmented and concentrated: there are over 1,000 crypto exchanges, but a small number of large exchanges control a sizable fraction of total market share. How can the long tail of small exchanges coexist with the deep and large core exchanges? We argue that there is a core-periphery structure to the strategic interactions among crypto exchanges, causing smaller peripheral exchanges and large core exchanges to be complements rather than substitutes. In our model, when the core exchange lists a new token, peripheral exchanges experience increased volumes from core-periphery arbitrage trade. Thus, peripheral exchanges tend to follow the token listing decisions of the core exchange. We verify the model's predictions empirically. Our results imply that the proliferation of small crypto exchanges may be detrimental to customers' trading fees, and also that core exchanges' listing decisions may play a systemically important "leader" role in driving trade volumes and listing decisions of the long tail of peripheral exchanges.

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1 Introduction

The cryptocurrency market has increased drammatically since the debut of Bitcoin in 2009. As of December 2022, there are over 20,000 cryptocurrencies with a total market cap close to 1 trillion US dollars. From a market structure perspective, an interesting feature of the crypto exchange market is that it is simultaneously fragmented and concentrated. On the one hand, there are over 1000 crypto exchanges, offering essentially the same few assets to trade.[1] There are over 150 cryptocurrency exchanges in the United States alone, compared to only 16 exchanges for equity trading.[2] On the other hand, a substantial fraction of total industry market share belongs to a small number of very large exchanges. Beginning from this fact, in this paper, we analyze the structure of strategic interactions between crypto exchanges. This paper aims to answer a few questions. From a positive perspective, how can the long tail of small crypto exchanges coexist with the small number of very large exchanges? Why does exchange market structure not consolidate into a monopoly or oligopoly, where all customers trade on a small number of large and liquid exchanges? Moreover, from a normative perspective, is the current fragmented structure of the crypto exchange market beneficial or harmful, from the perspective of reducing the net trading costs paid by cryptocurrency traders?

We argue that the answer to these questions is that there is a core-periphery structure to the nature of strategic interactions among crypto exchanges, which causes the long tail of small peripheral exchanges and the small number of deep and liquid core exchanges to be complements rather than substitutes. We construct a simple model of the structure of competition between exchanges, and empirically test its implications. In our model, a single token is traded on a number of small peripheral exchanges, which have captive customer bases, and possibly a large central exchange. When the central exchange enters a market by listing a new token, it does not cannibalize market share from peripheral exchanges, whose customers are captive. Rather, the entry of the central exchange tends to increase trade volume on peripheral exchanges, by inducing inter-exchange arbitrage trade. As a result, the central exchange and peripheral exchanges are complements, rather than substitutes: peripheral exchanges will tend to follow the central exchange's entry decisions, listing tokens which the central exchange chooses to list a token. Using data on prices, volumes, and listing decisions of a large number of crypto exchanges, we verify the predictions of the model empirically.

Positively, our results provide a solution to the puzzle of why there are so many crypto

[1] For example, a partial list of exchanges can be found on Blockspot.io.

[2] The list of exchanges can be found on the SEC website. Note that 12 of these exchanges are run by three groups: Intercontinental Exchange Inc NYSE, Nasdaq Inc, and Cboe Global Markets.

exchanges: exchanges appear to complement each other, rather than cannibalize each others' market share, as evidenced by the fact that the entry of core exchanges is associated with entry rather than exit of peripheral exchange. Normatively, our results suggest that the structure of exchange competition may be detrimental to consumers, in the sense that their costs of token trading are increased by exchange fragmentation. Moreover, core exchanges appear to play a systemically important "leader" role, in driving the trade volumes and listing decisions of the long tail of peripheral exchanges.

We begin by constructing a simple model of the strategic interactions between a single core exchange and a number of peripheral exchanges. There is a single risky asset, or "token", which can be traded on the a large core exchange, or a number of small peripheral exchanges. The core exchange has infinite market depth. Each peripheral exchange has a captive customer base, which can only trade on the peripheral exchange. Customers receive inventory shocks for the risky asset, motivating them to trade on the peripheral exchange. Inventory shocks have an aggregate and idiosyncratic component. Customers have holding costs for the asset, so aggregate inventory shocks generate pressure on peripheral exchange prices. Each peripheral exchange also has a set of arbitrageurs, who can trade on the peripheral exchange and the central exchange to partially close price gaps for the risky asset. Arbitrageurs have inventory costs, implying that they cannot fully close price gaps induced by inventory shocks. Peripheral exchanges collect fees depending on trade volume, and list the coin if anticipated fees are greater than an exogeneous cost of listing.

We analyze equilibrium outcomes of the model, with and without the presence of the central exchange. In the absence of the central exchange, trade on peripheral exchanges is generated only by the idiosyncratic component of customers' inventory shocks. If customers have positive inventory positions on average, they cannot sell these positions to others, so the token price must decrease significantly to clear the market. Inventory shocks thus have relatively large effects on prices, and trade volumes are relatively low. When the central exchange lists the coin, arbitrageurs trade to partially close the price gaps between the peripheral exchange and the central exchange. This effectively gives peripheral exchange customers partial access to central exchange liquidity, decreasing the price impact of aggregate inventory shocks. Moreover, arbitrage activity generates increased trade volume on the peripheral exchange, which also increases the expected profits of the peripheral exchange.

The model makes a number of predictions which we bring to the data. First, when the core exchange lists a token, trade volumes of the token on existing peripheral exchanges should actually increase. This is because we assumed that peripheral exchanges' customers are fully captive, so the core exchange's entry does not directly cannibalize the peripheral exchange's customers; however, the entry of the central exchange increases volume by allowing arbitrage trade with the peripheral exchange. Second, peripheral exchanges should tend to follow the core exchange's token listing decisions: peripheral exchanges are more likely to list a token after the core exchange has listed it, since peripheral exchange volumes and profits are higher when the central exchange is present.

Third, the structure of price correlations between exchanges should have a core-periphery structure. Peripheral exchange prices consist of the core exchange's price, plus noise generated by inventory shocks of the peripheral exchange's customers; thus, the correlation between a peripheral exchange's price and the core exchange's price should be greater than the correlation between two peripheral exchanges' prices. Fourth, the entry of a central exchange should decrease the volatility of token prices, as well as the dispersion of prices across peripheral exchanges. This is because, once the central exchanges allows trading of the token, arbitrageurs can more effectively trade to equalize prices across peripheral exchanges. Finally, all these phenomena should be correlated with each other: peripheral exchanges which rely more on arbitrage with the central exchange should have larger volume increases when the central exchange lists, stronger price correlations with the central exchange, and also prices more correlated with the central exchange.

We proceed to test the predictions of the model empirically. We use data on top 500 coins' prices, volumes, and listing decisions across 262 exchanges from January 2017 to July 2022.

We find that a coin's trading volume significantly increases after the listing on the central exchange. The results hold general and are not driven by specific countries. Also, we find that other exchanges follow the central exchange's listing decisions. In addition, we show that price correlation with the central exchange and listing following with the central exchange are positively correlated across exchanges, suggesting the structure of price correlations between exchanges should have a core-periphery structure. Moreover, we find that a coin's volatility and price dispersion on peripheral exchanges decrease after it is listed on the central exchange. Finally, we find evidence that peripheral exchanges that have stronger price correlations with the central exchange have larger volume increases when the central exchange lists. All these empirical results are consistent with theoretical predictions.

From a positive perspective, our results help to address the question of why so many crypto exchanges coexist. When peripheral exchanges' customer bases are segmented, but arbitrageurs can trade the peripheral exchange against the central exchange, the presence of the central exchange in a market in fact benefits peripheral exchanges, as it allows them to offer deeper effective liquidity to their captive customer base. Thus, far from competing against each other, peripheral exchanges are economic complements to core exchanges, and proactively enter markets once they observe the core exchange entering. So long as peripheral exchanges' customer bases remain segmented by some force, market structures with a large proliferation of exchanges can be sustained in equilibrium; in fact, entry of large exchanges promotes increased entry of smaller exchanges.

From a normative perspective, our results suggest that the proliferation of crypto exchanges may ultimately result in consumers paying increased fees to peripheral exchanges, and inter-exchange arbitrageurs, to access central exchange liquidity. In our model, customers would on average do better if they traded directly on the deep central exchange; our result suggest that there appear to be barriers to entry to customers doing so. Our results do not pin down the precise nature of these frictions. One possibility is that there are regulatory or jurisdictional barriers, preventing customers from accessing central exchanges directly; peripheral exchanges thus act essentially as regulatory-arbitrage "conduits", giving their customers imperfect access to central exchange liquidity through imperfect arbitrage activity, and collecting fees for this service. Another possibility is that consumers are unsophisticated, are attracted to peripheral exchanges through advertising, and face search frictions for directly trading on central exchanges; peripheral exchanges are thus able to collect spreads from the fact that their customers are not sophisticated enough to switch to the deeper central exchange. Both hypotheses suggest that consumers may be better off if these frictions were eliminated, allowing customers to trade in a large central exchange, disintermediating both peripheral exchanges and the arbitrageurs which profit from the spreads between central and peripheral exchanges.

Another implication of our results is that core crypto exchanges are potentially systematically important players in crypto markets, with substantial power to affect asset prices, volumes, and liquidity. Core exchanges' listings decisions induce peripheral exchanges to list the same token, and also lead to volume increases on peripheral exchanges that have already listed a token. Despite this power, core exchanges currently have a large degree of freedom to decide which assets to list.[3] Given the importance of core exchanges' listing decisions, regulators may wish to monitor the listing decisions of large crypto exchanges, for example requesting that exchanges provide data on tokens they plan to list, and the reasoning for listing these tokens.

This paper relates most closely to a few other papers that study cryptocurrency exchanges. Chan et al. (2020) document 10 stylized facts about cryptocurrency exchanges and cryptocurrency trading, using unique data from a medium-sized cryptocurrency exchange in Asia. Makarov and Schoar (2020) show that there are large price differences in cryptocurrency

[3]Exchanges' ability to list tokens varies by jurisdiction, however; for example, exchanges serving US customers tend not to list tokens which are likely to violate US securities regulations.

across different exchanges, leading to arbitrage opportunities. Our paper also fits into a broader literature on the economics of cryptocurrencies. Several theoretical papers examine the rationale and mechanisms of cryptocurrencies (e.g., Cong and He, 2019; Cong, Li and Wang, 2019; Catalini and Gans, 2018; Sockin and Xiong, 2018). A number of other papers empirically analyze the crypto ecosystem. Liu and Tsyvinski (2018) provide one of the first comprehensive analyses of the risk-return tradeoff of cryptocurrencies. Liu, Tsyvinski and Wu (2019) examine the cross-section of cryptocurrency returns and establish a factor model. A set of empirical papers study factors that contribute to ICO success, including Deng, Lee and Zhong (2018), Lee, Li and Shin (2019), Davydiuk, Gupta and Rosen (2022), and Lyandres, Palazzo and Rabetti (2020). Liu, Sheng and Wang (2021) contruct a tech index from ICO whitepapers and find that cryptocurrencies with higher tech index tend to outperformance in the long-run. Li, Shin and Wang (2021) find that pump-and-dump schemes are pervasive in the cryptocurrency market. Unlike these papers, our paper focuses on the crypto exchanges rather than crypto.

The paper proceeds as follows. Section 2 describes institutional background around cryptocurrency exchanges. Section 3 describes our model and its predictions. Section 4 describes the data that we use. Section 5 contains our empirical results. We conclude in Section 6.

2 Institutional Background

Cryptocurrency exchanges, analogous to exchanges for stocks, bonds, and other financial assets, allow customers to exchange fiat currencies for cryptocurrencies. Crypto exchanges function in a custodial manner: they allow users to "deposit" fiat or cryptocurrencies, hold fiat currencies and cryptocurrencies on behalf of users, and allow users to trade their custodied fiat and crypto with other users of the exchange. For the vast majority of exchanges, trading in each assets is governed through limit-order books.

Like regular financial asset exchanges, users can deposit and withdraw fiat through bank transfers or other means. A unique feature of cryptocurrency exchanges, relative to exchanges for stocks or other traditional financial assets, is that users can also deposit or withdraw cryptocurrencies from the exchange. Users can "withdraw" custodied assets, instructing the exchange to send funds held on her behalf to her own private "wallet" address. Users can also deposit cryptocurrencies, sending it to a designated "deposit" address, and receiving on-exchange custodially-owned crypto in exchange. The ability to deposit and withdraw implies that an important function of crypto exchanges is also to serve as "on/off-ramps" for crypto: allowing users to deposit fiat, exchange fiat for crypto, and withdraw crypto, or vice versa.

As an example of the role cryptocurrency exchanges play in the process of using cryptocurrencies, in Appendix A.1, we describe in detail how a customer would use crypto exchanges and cryptocurrency on-chain transfers to perform an international funds transfer, exchanging, for example, fiat currency in the USA for fiat in the Philippines. In short, a customer would exchange USD fiat for cryptocurrencies using a US crypto exchange, and send the crypto to the funds receipient, who would then exchange the crypto for Phillipine fiat currency. Using cryptocurrencies to perform such transfers is convenient because it allows consumers to partially circumvent capital controls and other restrictions imposed by policymakers, as well as fees charged by intermediary financial institutions who facilitate traditional international remittances. Appendix A.1 also briefly discusses the regulation of crypto exchanges. Crypto exchanges have nontrivial difficulty in expanding across jurisdictions for a number of reasons. First, since crypto exchanges must allow both crypto and fiat deposits and withdrawals, exchanges must be able to integrate with local banking systems for fiat funds transfers. Secondly, due to the necessity of integrating with local banking systems, crypto exchanges logistically must work with local financial regulators, and are subject to varying regulations depending on the jurisdictions they operate within.

There are a number of other uses of cryptocurrencies besides remittances: users in countries with high inflation or low confidence in financial institutions might buy and self-custody cryptocurrencies as a store of value.[4] Cryptocurrencies can also be used to perform a number of simple financial transactions, within the space of "decentralized finance."[5] In addition, many market participants purchase cryptocurrencies on centralized exchanges to speculate on crypto price appreciation.

While we focus on the role of crypto exchanges in facilitating spot trading, crypto

[4]See CNBC and Rest Of World for a discussion of the use of cryptocurrencies as a store of value in Lebanon.

[5]For example, market participants can use stablecoin tokens to purchase other blockchain tokens, such as ETH, MKR, or UNI, using an automated market maker protocol such as Uniswap. Market participants can also lend stablecoin tokens on lending and borrowing protocols, such as Aave and Maker, allowing them to receive positive interest rates, and also to use these assets as collateral to borrow other assets. Market participants can speculate on the prices of assets using derivatives-like contracts, on platforms such as dydx. These functionalities are enabled not by trusted centralized financial intermediaries, or legal contracts, but by pieces of code embedded in the blockchain, which programmatically perform transactions, like exchanging one crypto token for another, in a fully automated manner which does not involve any human discretion. In this way, the blockchain ecosystem allows individuals to engage in a number of simple financial transactions, such as trading assets, borrowing and lending, and speculating, in a way that does not require trust in any legal system, financial institution, or other human entity.

exchanges also offer consumers other products. Some exchanges also offer individuals the ability to short cryptocurrencies or use leverage, as well as various derivative products such as futures and options; see, for example, Bybit and Binance. Some exchanges also pay consumers interest rates on users' custodied cryptocurrencies, in a manner similar to bank deposits or CDs. Two such examples are Binance and Coinbase. Like traditional exchanges, crypto exchanges also offer market data and analytics products; see, for example, Binance.

The primary motivating fact behind our analysis is that, paradoxically, the cryptocurrency exchange market is simultaneously fragmented and concentrated. On the one hand, there are a very large number of crypto exchanges: according to Blockspot.io, as of 2023 there are over 1,000 different exchanges offering fairly similar assets to trade. On the other hand, a small number of very large exchanges account for a sizable fraction of total market share. Figure 1 shows the market share of the top 5 exchanges in our data, and all others, for BTC volume. The market share of the top 5 exchanges is fairly large, reaching 20% in 2022. Moreover, this is likely an underestimate of the top exchanges' market shares, since small exchanges are anecdotally known to falsely overreport or manipulate trade volumes (Cong et al., 2020). This motivates the core question we try to answer in this question, of how large core exchanges and the long tail of smaller peripheral exchanges can coexist.

3 Model

We construct a model where a single token is traded on an infinitely deep "core" exchange, and a number of "peripheral" exchanges with lower depth. The model allows us to analyze how exchanges' prices are related to each other, and how the core exchange's listing decisions affect the peripheral exchanges' trade volumes and listing decisions. Technically, the model builds on the literature on double-auction models with inventory costs (Vayanos, 1999; Vives, 2010; Du and Zhu, 2017; Chen and Duffie, 2021; Zhang, 2022).

There is a single risky asset, which we will call a "token". There is a central exchange, on which the price of the asset is ψ; the central exchange is infinitely deep, in the sense that there are market makers with infinite capacity, offering to buy or sell arbitrary amounts of the asset at price ψ. We assume ψ has mean μ_ψ and standard deviation σ_ψ. There are also N peripheral exchanges, indexed by j. There are two kinds of market participants on the peripheral exchanges: users, who demand liquidity, and arbitrageurs, who trade against price deviations between the peripheral exchange and the central exchange, subject to inventory costs.

Each peripheral exchange has a unit measure of users with some demand to trade the risky asset, in order to reduce inventory costs. Users are constrained to only trade on exchange j. User i has utility ψ per unit of the risky asset, and suffers inventory costs $\frac{\gamma_j}{2}x^2$ if she holds a net position x in the risky asset. User i begins with $x_{i,0}$ units of the risky asset. This position could be thought of as either a literal inventory position, or more generally as a demand shock for the risky asset; for example, i may receive information that induces her to want to take a long or short position in the risky asset. Hence, i's monetary utility for receiving z net units of the risky asset, thus ending with $x = x_{i,0} + z$ units of the risky asset, is:

$$u_i(z) = \psi(z + x_{i,0}) - \frac{\gamma_j}{2}(z + x_{i,0})^2 \tag{1}$$

Users' inventory position has a systematic and an idiosyncratic component. The standard deviation of $x_{i,0}$ across users on exchange j is $\sigma_{I,j}$. The mean of $x_{i,0}$ is η_j, which itself is random with mean μ_j and standard deviation $\sigma_{A,j}$. We assume η_j is uncorrelated with ψ, and $\eta_j, \eta_{j'}$ are uncorrelated for all peripheral exchanges j, j'. η_j can thus be thought of as an aggregate inventory shock which affects all users on exchange j. We assume exchange j charges a quadratic trading fee to users; if the user trades z units of the asset, she pays a fee $\frac{\tau_j}{2}z^2$ to the exchange. The assumption that trading fees are quadratic simplifies the analysis, but can be relaxed without changing the qualitative results. Since users are atomistic, each user's trades have a negligible effect on overall exchange prices, so users ignore their price impact. If a user purchases z units of the asset at price p_j with position $x_{i,0}$, her total value is thus:

$$V_i = \underbrace{\psi(z_i + x_{i,0})}_{\text{Fundamental Value}} - \underbrace{p_j z_i}_{\text{Net Payment}} - \underbrace{\frac{\gamma_j}{2}(z_i + x_{i,0})^2}_{\text{Inventory Costs}} - \underbrace{\frac{\tau_j}{2}z_i^2}_{\text{Exchange Fees}} \tag{2}$$

where we have ignored the agent's initial wealth for simplicity, since it only additively shifts V_i and does not affect any decisions agents make. Differentiating, agents i's marginal utility for purchasing an additional unit of the asset is:

$$\frac{\partial V_i}{\partial z_i} = \psi - p_j - \gamma_j(z_i + x_{i,0}) - \tau_j z_i$$

Setting to 0, agent i's demand for the asset, as a function of the price p_j, is:

$$z_i = \frac{-\gamma_j}{\gamma_j + \tau_j}x_{i,0} + \frac{\psi - p_j}{\gamma_j + \tau_j} \tag{3}$$

Integrating over all users, aggregate demand from users on exchange j at price p is:

$$Z_{user,j}(p_j) = \int_{-\infty}^{\infty} z_i(x)\, dF_{x_{i,0}}(x) = \frac{-\gamma_j}{\gamma_j + \tau_j}\eta_j + \frac{\psi - p_j}{\gamma_j + \tau_j} \tag{4}$$

Each peripheral exchange j has a unit measure of atomistic arbitrageurs, who can trade the risky asset on j as well as the central exchange. We will assume arbitrageurs for exchange j cannot trade on other peripheral exchange. Let k index arbitrageurs. Arbitrageurs have utility linear in money. They cannot hold net inventory, so they must buy on the central exchange as much as they sell on the peripheral exchange. Let z_k be the net amount arbitrageur k buys on j and sell on the central exchange. Arbitrageurs face quadratic inventory costs for arbitrage: they incur a cost $\frac{\zeta_j}{2}z_k^2$ for arbitraging k net units of the asset. Arbitrageurs pay the same fees as users: if they trade a quantity z_k, they pay fee $\frac{\tau_j}{2}z_k^2$. Hence, arbitrageurs' value for buying z_k units at price p_j on exchange j, and selling at price ψ on the central exchange, is:

$$V_k\left(z_k\right) = z_k\left(\psi - p_j\right) - \frac{\zeta_j}{2}z_k^2 - \frac{\tau_j}{2}z_k^2$$

Differentiating, arbitrageurs' marginal utility for purchasing an additional unit of the asset is:

$$\frac{\partial V_k}{\partial z_k} = \psi - p_j - \zeta_j z_k - \tau_j z_k$$

Arbitrageur k's demand for the risky asset at price p_j is thus:

$$z_k = \frac{\psi - p_j}{\zeta_j + \tau_j}$$

Integrating demand over the unit measure of arbitrageurs on exchange j, we have:

$$Z_{arb,j}\left(p_j\right) = \frac{\psi - p_j}{\zeta_j + \tau_j} \tag{5}$$

Peripheral exchange j's profits, if trade volume is z_i for each user, are: $\int_{-\infty}^{\infty} z_i^2\left(x\right) dF_{x_{i,0}}\left(x\right)$. We assume exchange j has some cost C_j of listing tokens. Hence, exchange j will list the risky asset if it anticipates profits greater than C_j from listing. We will think of the central exchange's listing decisions as exogeneous. In practice, the central exchange's listing decisions are driven by

3.1 Equilibrium

In equilibrium, aggregate demand from users and arbitrageurs sums to 0 on each exchange. Thus, adding (4) and (5), market clearing on exchange j requires:

$$Z_{user,j}\left(p_j\right) + Z_{arb,j}\left(p_j\right) = \left(\frac{-\gamma_j}{\gamma_j + \tau_j}\eta_j + \frac{\psi - p_j}{\gamma_j + \tau_j}\right) + \frac{\psi - p_j}{\zeta_j + \tau_j} = 0$$

The following proposition solves for prices, volumes, and exchange profits when the central exchange does not list the token.

Proposition 1. *When the central exchange does not list the token, the equilibrium price on exchange j is:*

$$p^*_{j,0} = \psi - \gamma_j \eta_j \tag{6}$$

Expected squared trade quantity is:

$$\mathbb{E}\left[z^{*2}_{i,0}\right] = \left(\frac{\gamma_j}{\gamma_j + \tau_j}\right)^2 \sigma^2_{I,j} \tag{7}$$

Exchange j's profit from listing the token is:

$$\pi^*_{j,0} = \frac{\tau_j}{2}\left(\frac{\gamma_j}{\gamma_j + \tau_j}\right)^2 \sigma^2_{I,j} \tag{8}$$

Exchange j lists the token if its cost of listing is lower than (8).

The following proposition solves prices, volumes, and exchange profits when the central exchange does list the token.

Proposition 2. *When the central exchange does list the token, the equilibrium price on exchange j is:*

$$p^*_{j,1} = \psi - \frac{\zeta_j + \tau_j}{\gamma_j + \zeta_j + 2\tau_j}\gamma_j \eta_j \tag{9}$$

Expected squared trade quantity is:

$$\mathbb{E}\left[z^{*2}_{i,1}\right] = \left(\frac{\gamma_j}{\gamma_j + \tau_j}\right)^2 \left[\sigma^2_{I,j} + \left(\frac{\gamma_j + \tau_j}{\gamma_j + \zeta_j + 2\tau_j}\right)^2 \eta^2_j\right] \tag{10}$$

Exchange j's profit from listing the token is:

$$\pi^*_{j,1} = \frac{\tau_j}{2}\left(\frac{\gamma_j}{\gamma_j + \tau_j}\right)^2 \left[\sigma^2_{I,j} + \left(\frac{\gamma_j + \tau_j}{\gamma_j + \zeta_j + 2\tau_j}\right)^2 \eta^2_j\right] \tag{11}$$

Exchange j lists the token if its cost of listing is lower than (11).

The intuitions behind Propositions 1 and 2 are as follows.

Prices. Expression (6) states that the price on exchange j, in the absence of the centralized exchange, is the "efficient price" ψ, minus the aggregate inventory shock η_j times users' inventory cost γ_j. If the aggregate component of inventory shocks η_j is positive, there is no other exchange for users to sell their endowments to; exchange j's price must then be higher than ψ in order to clear the market. The gap between exchange j's price and ψ depends on η_j, and users' cost of holding inventory, γ_j.

When the centralized exchange lists the token, arbitrageurs trade against this price gap, buy from the CEX at price ψ and selling to the peripheral exchange. Arbitrage cannot perfectly close the gap, because arbitrageurs also face transaction fees and inventory costs. Comparing (6) and (9), arbitrageurs decrease the effect of inventory shocks on prices by a factor:

$$\frac{\zeta_j + \tau_j}{\gamma_j + \zeta_j + 2\tau_j} \tag{12}$$

When trading costs τ_j are low, and arbitrageurs' inventory costs ζ_j are low relative to users' costs γ_j, prices will tend to converge towards ψ significantly when the centralized exchange lists.

Trade volumes and exchange profits. In the absence of a centralized exchange, trade on peripheral exchanges is generated only by the idiosyncratic component of inventory shocks: (7) states that volume depends on the variance of users' endowments $\sigma^2_{I,j}$, as well as a factor which reflects how large transaction fees τ_j are relative to users' inventory costs γ_j. When a centralized exchange enters, trade is generated by both the idiosyncratic and aggregate components of inventory shocks, since arbitrageurs can buy on the central exchange and sell to the peripheral exchange. (10) shows that expected squared trade volume can be cleanly decomposed into an the sum of (7), and an extra term reflecting the aggregate shock η_j, and the multiplier (12) capturing how active arbitrageurs are. Thus, expected squared trade volume of peripheral exchanges is strictly higher when the central exchange lists the token. Since profits are proportional to squared trade volume, peripheral exchanges' profits are also higher when the central exchange lists.

Next, using these propositions, we derive a number of predictions to bring to the data.

3.2 Comparative Statics and Predictions

Prediction 1. *If peripheral exchange j lists the token before the central exchange, j will experience a volume increase when the central exchange lists the token.*

Prediction 1 follows directly from comparing (7) and (10), and the intuition that the aggregate component of inventory shocks also contributes to trade volume after the CEX lists the token. This is a nontrivial prediction, because it suggests that exchanges are complements rather than substitutes. They are complements due to bridge arbitrage.

Prediction 2. *Listings will tend to follow the central exchange: when the central exchange lists the token, some peripheral exchanges which previously did not list the token will choose to list the token. Formally, peripheral exchanges' profit with the central exchange, (11), is greater than peripheral exchanges' profit without the central exchange, (8), so the set of peripheral exchanges which lists the token is strictly larger after the central exchange enters.*

Prediction 2 follows from (8) and (11). When the central exchange enters, expected profits on all peripheral exchanges increase. Thus, once the central exchange lists the token, all peripheral exchanges which have already listed have no incentive to unlist, even if the listing decision is fully reversible and the cost can be recovered. Moreover, some exchanges which previously did not list the token will find it profitable to list the token. This prediction essentially implies that the core exchange is a complement to peripheral exchanges; in particular, this prediction contrasts with standard models of imperfect competition, in which the entry of a large competitor should cannibalize smaller competitors, and decrease incentives for entry.

The next prediction concerns the structure of prices correlations across exchanges. We first derive expressions for these correlations.

Proposition 3. *The coefficient of determination R^2 between the central exchange's price, and peripheral exchange j's price, is:*

$$R^2_{j,CE} = \frac{Cov^2\left(p_j^*, \psi\right)}{Var\left(p_j^*\right) Var\left(\psi\right)} = \frac{\sigma_\psi^2}{\sigma_\psi^2 + \left(\frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\right)^2 \gamma_j^2 \sigma_{A,j}^2} \tag{13}$$

The R^2 between the prices of exchanges j and j' is:

$$\begin{aligned} R^2_{j,j'} &= \frac{Cov^2\left(p_j^*, p_{j'}^*\right)}{Var\left(p_j^*\right) Var\left(p_{j'}^*\right)} \\ &= \frac{\sigma_\psi^2}{\left[\sigma_\psi^2 + \left(\frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\right)^2 \gamma_j^2 \sigma_{A,j}^2\right]} \frac{\sigma_\psi^2}{\left[\sigma_\psi^2 + \left(\frac{\zeta_{j'}+\tau_{j'}}{\gamma_{j'}+\zeta_{j'}+2\tau_{j'}}\right)^2 \gamma_j^2 \sigma_{A,j'}^2\right]} \end{aligned} \tag{14}$$

Prediction 3. *We always have:*

$$R^2_{j,CE} \geq R^2_{j,j'}$$

That is, the correlation between the central exchange price and the price on any peripheral exchange j is stronger than the correlation between the prices on peripheral exchanges j and j'.

In words, Prediction 3 states that the structure of price correlations between exchanges inherits the core-periphery structure of the exchange network: peripheral exchanges' prices are more correlated with the central exchange than they are with each other. This is because, from expression (9), each peripheral exchange's price is equal to the central exchange's price, plus an error term reflecting aggregate inventory shocks on the peripheral exchange which are imperfectly eliminated by arbitrageurs. Thus, $R^2_{j,CE}$ reflects the correlation of the central exchange price ψ, with a price which is ψ plus a noise term, whereas $R^2_{j,j'}$ reflects the correlation between two prices which are each equal to ψ plus a noise term.

Prediction 4. *Consider all peripheral exchanges j which list the token before the central exchange. The volatility of token prices on these exchanges will fall after the central exchange lists the token. The cross-sectional dispersion of prices across these exchanges will also fall after the central exchange lists the token.*

Prediction 4 follows because, from (6), the variance of j's prices when the centralized exchange does not list is

$$\sigma_\psi^2 + \gamma_j^2 \sigma_{A,j}^2$$

Whereas the variance when the centralized exchange lists is, from (9), the smaller quantity:

$$\sigma_\psi^2 + \left(\frac{\zeta_j + \tau_j}{\gamma_j + \zeta_j + 2\tau_j}\right)^2 \gamma_j^2 \sigma_{A,j}^2$$

Intuitively, arbitrage with the centralized exchange decreases the effect of inventory shocks on peripheral exchanges' prices, limiting volatility. The prediction about dispersion follows similarly. Suppose for simplicity that exchanges are symmetric, so $\sigma_{A,j}^2 = \sigma_A^2$ for all exchanges. The dispersion of peripheral exchange prices around ψ is $\gamma_j^2 \sigma_A^2$ without the central exchange, and the lower quantity

$$\left(\frac{\zeta_j + \tau_j}{\gamma_j + \zeta_j + 2\tau_j}\right)^2 \gamma_j^2 \sigma_A^2$$

with the central exchange. Again, arbitrage with the central exchange causes peripheral exchange prices to cluster more closely around ψ.

Prediction 5. *When peripheral exchanges differ mainly in their arbitrage costs ζ_j, peripheral exchanges whose prices are more correlated with the central exchange, and whose trade volumes tend to increase more when the central exchange lists a token, will also have a stronger tendency to list following the central exchange's listing decisions. Formally, we have:*

$$\frac{\partial R^2_{j,CE}}{\partial \zeta_j} = \frac{-2\sigma_\psi^2 \sigma_{A,j}^2 \gamma_j^2 \left(\zeta_j + \tau_j\right)\left(\gamma_j + \tau_j\right)}{\left[\sigma_\psi^2 + \left(\frac{\zeta_j + \tau_j}{\gamma_j + \zeta_j + 2\tau_j}\right)^2 \gamma_j^2 \sigma_{A,j}^2\right]^2 \left(\gamma_j + \zeta_j + 2\tau_j\right)^3} \leq 0$$

$$\frac{\partial \Delta \mathbb{E}\left[z_{i1}^{*2}\right]}{\partial \zeta_j} = -\frac{2(\gamma_j + \tau_j)^2}{(\gamma_j + \zeta_j + 2\tau_j)^3} \left(\frac{\eta_j}{\sigma_{I,j}}\right)^2 \leq 0$$

$$\frac{\partial \Delta \pi_j^*}{\partial \zeta_j} = -\frac{2(\gamma_j + \tau_j)^2}{(\gamma_j + \zeta_j + 2\tau_j)^3} \left(\frac{\eta_j}{\sigma_{I,j}}\right)^2 \leq 0$$

Prediction 5 follows if there are differences in how "connected" peripheral exchanges are to the central exchange, which in our model corresponds to the arbitrageur inventory cost parameter ζ_j. For a peripheral exchange with lower ζ_j, prices will tend to be more correlated with the central exchange; the central exchange's listings will tend to increase volumes more; and the central exchange's listing decisions will increase the peripheral exchange's profits more, implying that the peripheral exchange has a stronger incentive to "follow" the central exchange's listing decisions. If Prediction 5 holds in the data, this indicates empirically that the three separate phenomena we observe – price correlations, volume increases, and listing following – are statistically associated, increasing our confidence that they are driven by the same underlying economic phenomenon.

3.3 Discussion of Assumptions

Our baseline model assumes a simple model in which users are tied to a single peripheral exchange, and cannot move across exchanges. If users were able to move across peripheral exchanges and the central exchange, perhaps at some cost, this would cause exchanges to become partially substitutes for each other; one exchange's listing decision could potentially cannibalize volume from other exchanges, as users move to the exchange which has newly listed the token. This force would tend to push against the effects that we find, causing exchanges to tend to be substitutes instead of complements. If the user substitution force were strong enough, listings could tend to decrease trade volumes, and the central exchange's decision to list may cannibalize enough volume that it induces peripheral exchanges to unlist. This runs counter to the evidence we find empirically. We thus assume away this effect for expositional simplicity.

Our baseline model also does not feature the "listing pump" effect, that central exchange listings tend to associate with increased token prices, which is emphasized in a number of academic and industry studies. Since the main focus of our paper is to analyze the structure of competition between exchanges, we do not discuss the listing pump effect in detail. However, there are a number of ways to derive the listing pump effect in the context of our model. One approach would be to assume that aggregate inventory shocks η_j have positive means; that is, users on peripheral exchanges have a net positive endowment of the asset. Inventory costs then tend to depress prices on peripheral exchanges, and the entry of the central exchange will tend to alleviate this negative price pressure and raise token prices. The listing pump effect could also be microfounded from a richer multi-period model, in which the entry of the central exchange increases market depth and decreases volatility of the token, thus pushing prices upwards through a "liquidity premium" effect.

A number of other assumptions are made largely for expositional simplicity. We assume the central exchange has infinite depth; it is sufficient for our effects that the central exchange's depth is finite, but much greater than peripheral exchanges' depth. We assume arbitrageurs can only trade the peripheral exchange against the central exchange; it is sufficient that the cost of doing this is lower than the cost of arbitraging two peripheral exchanges against each other. In our conversations with practitioners, most market makers in practice appear to trade smaller exchanges with larger central exchanges. One reason for this is that being a market maker on an exchange often involves direct negotiations with the exchange for special access, and it is potentially difficult to enter into multiple of these agreements at once. We assume there is a single central exchange; in practice, there are a number of bigger exchanges which likely behave more like central exchanges, and smaller exchanges which behave more like peripheral exchanges. In our empirical analysis, we will treat a few of the largest exchanges as central exchanges, and the long tail of smaller exchanges as peripheral.

4 Data

The primary dataset we use in this paper is from cryptotick.com, which collects trade-pair information among cryptocurrencies and fiat currencies from a broad set of cryptocurrency exchanges. Cryptotick obtains this data by querying APIs provided by the exchanges.[6] The dataset contains hourly OHLCV data, that is, open, high, low and close prices, as well as total trade volume, each hour on each exchange. We aggregate the data to daily data for each coin-exchange pair.

In total, there are 264 exchanges for 12,417 coins in the raw dataset. The data spans from January 2017 to July 2022. Many of these coins are not actively traded. Also, many exchanges only have limited trading volume. For the purpose of this paper, we do not need to include all the exchanges and all the coins. In our final sample, we focus on the top 500 coins ranked by by coinmarketcap.com on September 3, 2022. We also focus on 27

[6]We verify the data quality of Cryptotick with other major data sources. For example, existing literature show there is a large volume of wash trading in some exchanges.Our verfication confirms that the data quality of Cryptotick is high. The details can be found in the Internet Appendix.

major fiat currencies.[7] We include two types of transactions: 1) transaction between coins and major fiat currencies, 2) transactions between coins and Bitcoin, Etheruem, and major stablecoins (USDT, USDC, BUSD). For the first type of transaction, we convert the value to US dollar based on the same day exchange rate. For the second type of transactions, we also convert the value to US dollar based on the same day price of these intermediary coins (BTC, ETH, USDT, USDC, BUSD)[8]. As a result, the final sample consists of 500 coins across 262 exchanges. In some of the analysis, we focus on coins that are traded in the top 10 cryptocurrency exchanges based on total trading volume in the sample period.[9] Appendix C contains more details about the data cleaning process. We identify the listing date of a coin on an exchange from observing the first date it appears on an exchange in our price and volume data. Summary statistics of the data are shown in Table 1.

[Table 1 here]

To understand the structure of the cryptocurrency exchange market, we first check which are major exchanges in the sample. Binance is the largest exchange in terms of total trading volume. Further, we examine whether Binance lists coins first relative to other exchanges. The relative listing time ranking of coins i for exchange e $ranking_{i,e}$ is defined as:

$$ranking_{i,e} = \frac{\text{listing ranking of coin } i \text{ for exchange } e - 1}{\text{total listing times of coin } i} \tag{15}$$

Therefore, $ranking_{i,e}$ index takes value from 0 to 1, where 0 means that exchange e is the first to list the coin c among all exchanges and 1 means that exchange is the last. Figure 2 plots the distribution of this above $ranking$ index for ten top exchanges ranked by 2022 total volume. Binance lists coins first relative to other exchanges, and other large exchanges seem not to have a clear listing pattern in terms of listing times.

[Figure 2 here]

5 Empirical Results

We proceed to test our model's predictions empirically. Prediction 1 states that, when the central exchange lists a token, trade volumes of the token on other exchanges which have already listed the token should increase. To test this, we estimate the following difference-in-

[7]These 27 major fiat currencies include: NZD USD KRW JPY CNY IDR SGD VND TWD AUD PKR ZAR TRY MXN BRL CHF ILS PLN GBP RUB EUR CAD HKD INR SAR AED SEK.

[8]Exchange rate data is obtained from the BIS website, and major cryptocurrency conversion rates are obtained from Yahoo Finance.

[9]This sample is comparable to that in the literature. Expanding the sample will not make our results weaker because we expected to see stronger effects among small coins and low-ranked cryptocurrency exchanges.

differences specification:

$$Log(Volume)_{i,t} = \alpha + \beta Listing_{i,t} + \delta_i + \eta_t + \epsilon_{i,t} \tag{16}$$

where i indexes coins and t indexes days. We restrict our sample to those exchange-coin pairs that list coins more than 30 days before major exchange's listings, and $Log(Volume)$ is the total trading volume of those incumbent exchange-coin pairs for coin i at day t. *Listing* is a dummy variable, equal to one for coin i on date t if a major exchange has listed coin i prior to date t. we estimate specifications where we use Binance or Coinbase as the major exchange. δ_i and η_t are respectively coin and date fixed effects. The DID specification essentially compares the change in volume for coins just before and after they are listed by a major exchange, to the volume change for coins that do not experience a listing event.

Before we estimate specification (16), we test for parallel trends between listed and non-listed coins, by estimating a fully flexible period-by-period equation that takes the following form:

$$Log(Volume)_{i,t} = \alpha + \sum_{\tau=-30}^{30} \beta_\tau Listing_{i,\tau} + \delta_i + \eta_t + \epsilon_{i,t} \tag{17}$$

where all variables are defined as in Equation (16). The only difference from Equation (16) is that in Equation (17), we add the one-day dummy variable $Listing_\tau$ rather than the post-listing indicator variable *Listing*, treating observations more than 30 days before the listing as the reference group. The estimated vectors of β_τ reveal the differences between the treated and control coins during each period.

Figure 3 plots the estimates of Equation (17) and their 95% confidence intervals. A clear pattern emerges from this figure. The difference between the treated and control groups is small and not significant in magnitude before listings, suggesting no differential trends between the two groups prior to listings. Furthermore, the coefficients surge and peak at 0 days and start to decrease after that, which follows our expectation that listing has positive effects on coin's volume.

[Figure 3 here]

We now test Equation (16). Table 3 presents the results of this test. Given the central status of Binance, we first examine the effect of listing on Binance on trading volume. Column (1) shows that the coefficient on *Listing* is positive and statistically significant, suggesting that trading volume increases after listings on the central exchange. The results are robust to including control variables and fixed effects. This is consistent with the model prediction. We also examine the listings on Coinbase, another major exchanges, and find similar results. We also find the effect is heterogeneous across two major exchanges. The effect is stronger in

Binance as suggested by the magnitude of the coefficient on *Listing*.

[Table 3 here]

The second prediction we test is whether other exchanges follow the central exchange's listing decision. To test this idea, for each major exchange, we calculate the number of listings on other exchanges 100 days before or after the listing decisions on the major exchange. We then calculate the fraction of these listings within this window [-100,100] and plot them in Figure 4. In the first panel, the x-axis is the absolute distance of the exchange's listing date to Binance coin listing date and y-axis is the fraction of listings on other exchanges over different windows.[10] It shows that other exchanges' coin listings occur exactly after the point when Binance lists the corresponding coin, suggesting that other exchanges follow Binance's listing decisions. Specifically, approximately 15% of all listings in Binance's listing before and after 100-day window happen right within Binance's listing after ten-day window.

[Figure 4 here]

In addition, we examine whether the structure of price correlations between exchanges should have a core-periphery structure. In particular, we test whether price correlation with the central exchange and listing following with the central exchange are positively correlated across exchanges. To test this idea, we run a cross-sectional regression between price correlation distance and listing following distance across exchanges to show whether these two distance variables relative to the major exchanges are positively correlated. The regression takes the following form:

$$PriceCorrelationDistance_i = \alpha + \beta ListingFollowingDistance_i + \epsilon_i \tag{18}$$

where i indexes exchange, and two variables are defined below. Our coefficient of interest, β, indicates the correlation between these two distances. We expect a positive β, suggesting that coin prices of exchanges following central exchange's listings more closely will be more correlated with coin prices of central exchanges.

These distance variables are constructed and defined as follows. We first calculate these distance variables at coin and exchange pair level, meaning that there will be a distance measure for every coin and every exchange pair. For example, the price correlation distance of Bitcoin between Binance and one small exchange will be first calculated using the whole available data, namely their overlapping price data. Then, these measures are aggregated at the exchange pair level by averaging all measures for different coins on the same exchange pair.

[10] We drop all Bitcoin and Ethereum listings and listings that happen on the same day as major exchange's listing

The price correlation distance defined in Equation (19) is proportional to the square root of the correlation distance $1-\rho$,where ρ is the price correlation. This measure ranges from 0 to 1. A smaller distance suggests a more positive price correlation. This metric satisfies all distance properties and is widely used in statistics and other related fields.

$$\text{Price Correlation Distance}_{i,e1,e2} = \sqrt{2(1-\rho_{i,e1,e2})} \tag{19}$$

where i, $e1$, $e2$ indexes coin, one of major exchanges (Binance, Coinbase), and another exchange. ρ denotes the price correlation of coin i between the major exchange $e1$ and another exchange $e2$.

The listing following distance is defined in Euqation (20). This distance transformation guarantees that the listing following effect is properly measured. This measure ranges from 0 to 100. This measure is lowest when exchanges list coins right after the central exchange's listings. Listing before or after 100 days of central exchange's listings will incur a large listing following distance.

$$\text{Listing Following Distance}_{i,e1,e2} = \begin{cases} 100, \ d_{i,e1,e2} < 0 \\ d_{i,e1,e2}, \ 0 \leq d_{i,e1,e2} \leq 100 \\ 100, \ d_{i,e1,e2} > 100 \end{cases} \tag{20}$$

where d denotes the distance between coin i listing on another exchange $e2$ date and listing on the major exchange $e1$ date.

After obtaining these two variables, the average price correlation distance and listing following distance with 10 major exchanges across exchanges are calculated. We plot the correlation between these two distances for all 10 major exchanges. Figure 5 shows that only the correlation for Binance is positive and significant, suggesting those exchanges following Binance's listing decision will have a more significant positive price correlation with Binance.

[Figure 5 here]

Moreover, we examine whether the entry of a central exchange decreases volatility and the dispersion of prices across peripheral exchanges. We first test this idea by looking at the top 3 cryptocurrencies. Figure 6 plots the dispersion of prices around Binance's listings. It shows that a significant decrease in price dispersion after Binance's listings. Also, we formally test this idea using all the cryptocurrencies. The results, presented in Table 4, show that a coin's volatility, intra-day spread, and price dispersion on peripheral exchanges decrease after it is listed on the central exchange.

[Figure 6 here]

Finally, we examine whether peripheral exchanges that have stronger price correlations with the central exchange have larger volume increases when the central exchange lists. We test this idea by adding an interaction term (Listing × Correlation) to Equation (16). Table 5 presents the results. The coefficient on the interaction term is positive and significant, suggesting that peripheral exchanges more correlated with the central exchange have a stronger effect when the central exchange lists.

[Table 5 here]

$$Log(Volume)_{i,t} = \alpha + \sum_{\tau=-30}^{30} \beta_\tau Listing_{i,\tau} + Correlation_{i,t} + \sum_{\tau=-30}^{30} \beta_\tau Listing_{i,\tau} * Correlation_{i,t} + \delta_i + \eta_t + \epsilon_{i,t} \tag{21}$$

5.1 Additional results and robustness

Prior studies show that there is a general listing effect of coin returns (e.g., Ante (2019); Lemmen (2022)). We also examine whether the listing on core exchanges affects coins' returns.The regression specification is similar to Equation (16), except the dependent variable is coins' returns. Table 6 reports the results of this test. The coefficient on Listing is negative and significant, suggesting that the listing on core exchanges have a negative effect on coins returns. This is consistent with the evidence in the existing literature. One concern is that the result might be driven by the differences in countries where exchanges locate, such as regulatry policies. To address the concern, we re-run the test at the coin-exchange level and include country fixed-effects. Table 7 reports the results. Again, the coefficient on the Listing is positive and significant, which is similar to the main results.

6 Conclusion

In this paper, we showed that there is a core-periphery structure to the strategic interactions among cryptocurrency exchanges. A large number of small peripheral exchanges are complementary to a small number of deep and liquid core exchanges. Theoretically, we constructed a model showing how core exchanges can be complementary to peripheral exchanges, by providing a source of deep liquidity which can be accessed through inter-exchange arbitrage. As a result, peripheral exchanges in fact experience increased trading volumes once core exchanges list a token, and thus peripheral exchanges tend to follow the listing decisions of core exchanges. We verify the model's predictions empirically. From a positive perspective, our results help to address the question of why so many crypto exchanges coexist. From a normative perspective, our results suggest that the proliferation of crypto exchanges may result in consumers paying increased fees to peripheral exchanges, and inter-exchange arbitrageurs, to access central exchange liquidity. Our results also suggest that the large core crypto exchanges are potentially systemically important players in crypto markets, since their listing decisions tend to "lead" markets by inducing volume increases across other exchanges. Policymakers may wish to consider monitoring or regulating the listing decisions of large exchanges, given the large impact that these decisions have on crypto market outcomes.

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Figure 1: Market share of the top 5 exchanges for BTC trading over time

This figure shows the market share of the 5 largest exchanges across years of our dataset, for BTC trading volume.

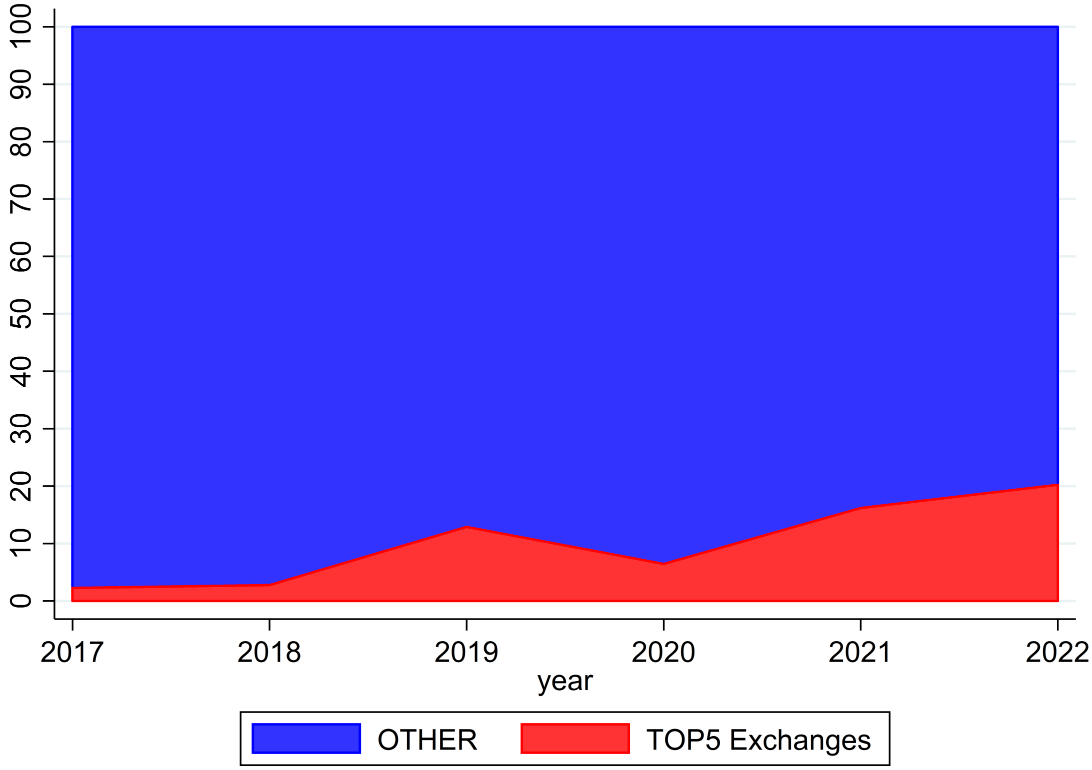

Figure 2: Relative listing time ranking of coin for exchanges

It shows the relative listing time for top 10 exchanges. It plots the ranking, defined in Equation (1).

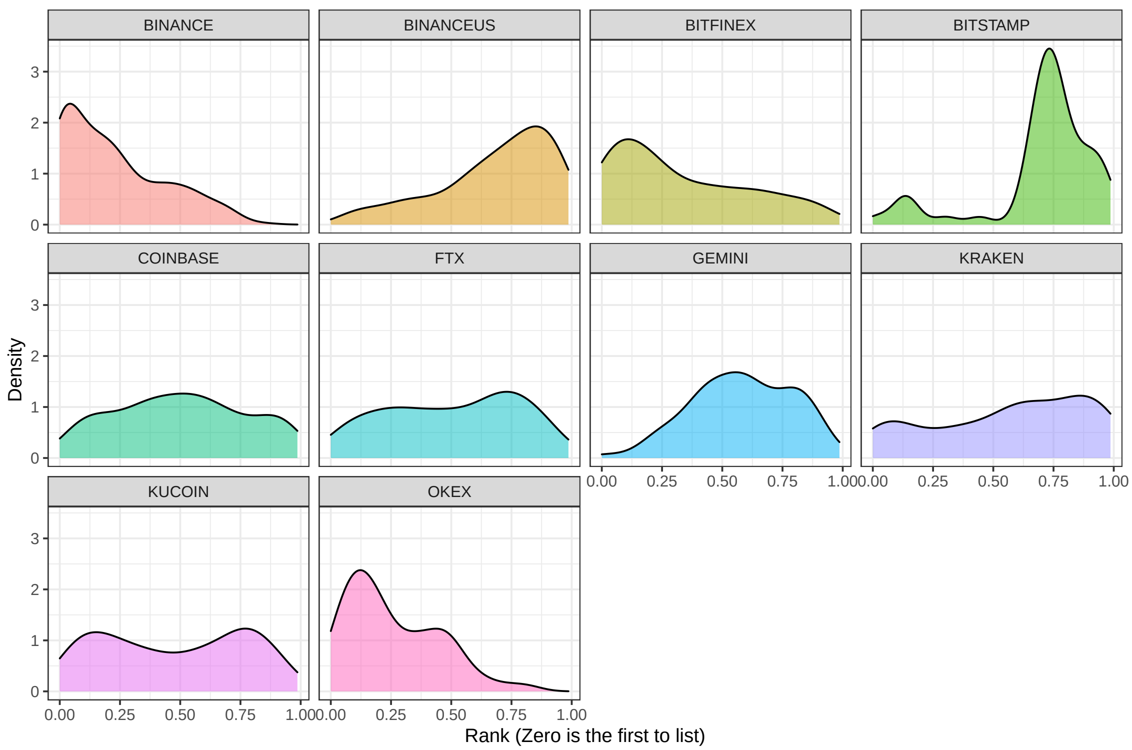

Figure 3: Flexible estimation of the listing effects on log volume by 5 days

This figure tests whether there is a pre-trend in volume for the DID test. It plots the estimates of Equation (17) and their 95% confidence intervals.

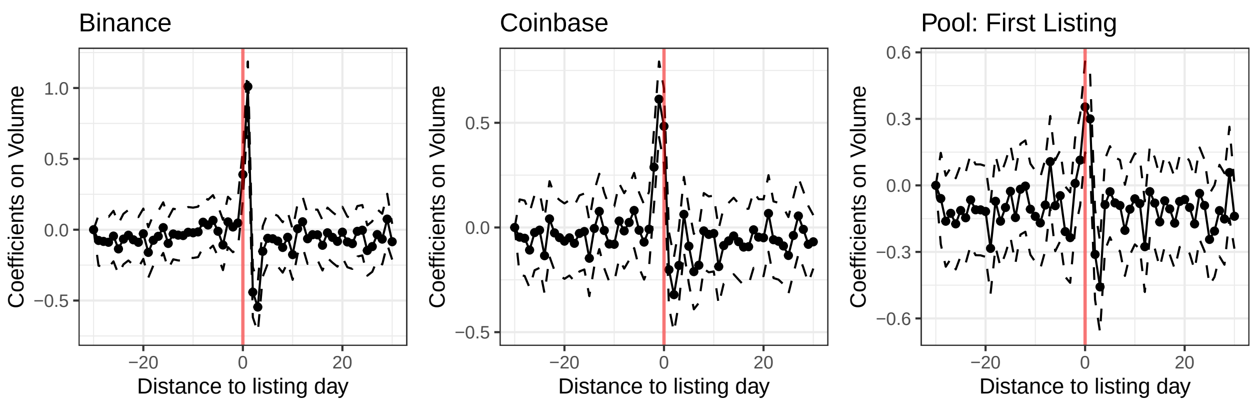

Figure 4: Listing decisions for all exchanges around major exchange's listing date

This figure shows the following pattern of all exchanges relative to the major exchange's listing. The x-axis denotes the time interval between an exchange's listing date and a major exchange's listing date for the same coin. The red vertical line indicates zero time interval with the major exchange listing. The y-axis is the density of each time interval bar. We drop listings whose time interval with the major exchange's listing is zero.

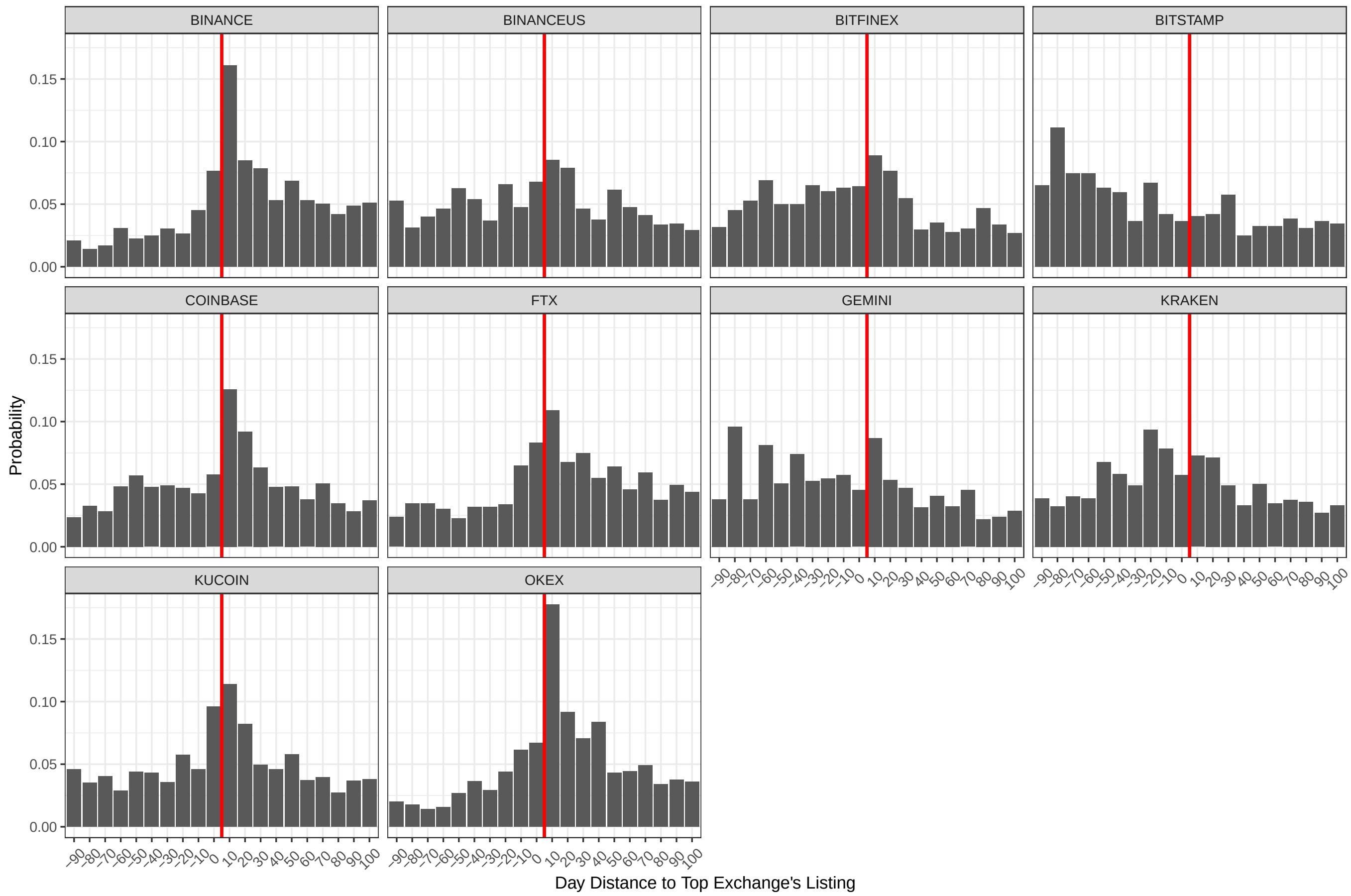

Figure 5: Correlation-listing correlation for main exchanges

This figure displays the relationship between price correlation and listing distance of all exchanges relative to major exchanges. This is a cross-sectional regression at the exchange level, where the dependent variable is the price correlation between an exchange and a major exchange, and the independent variable is the listing distance between an exchange and a major exchange. β coefficient and its 95% confidence interval are reported.

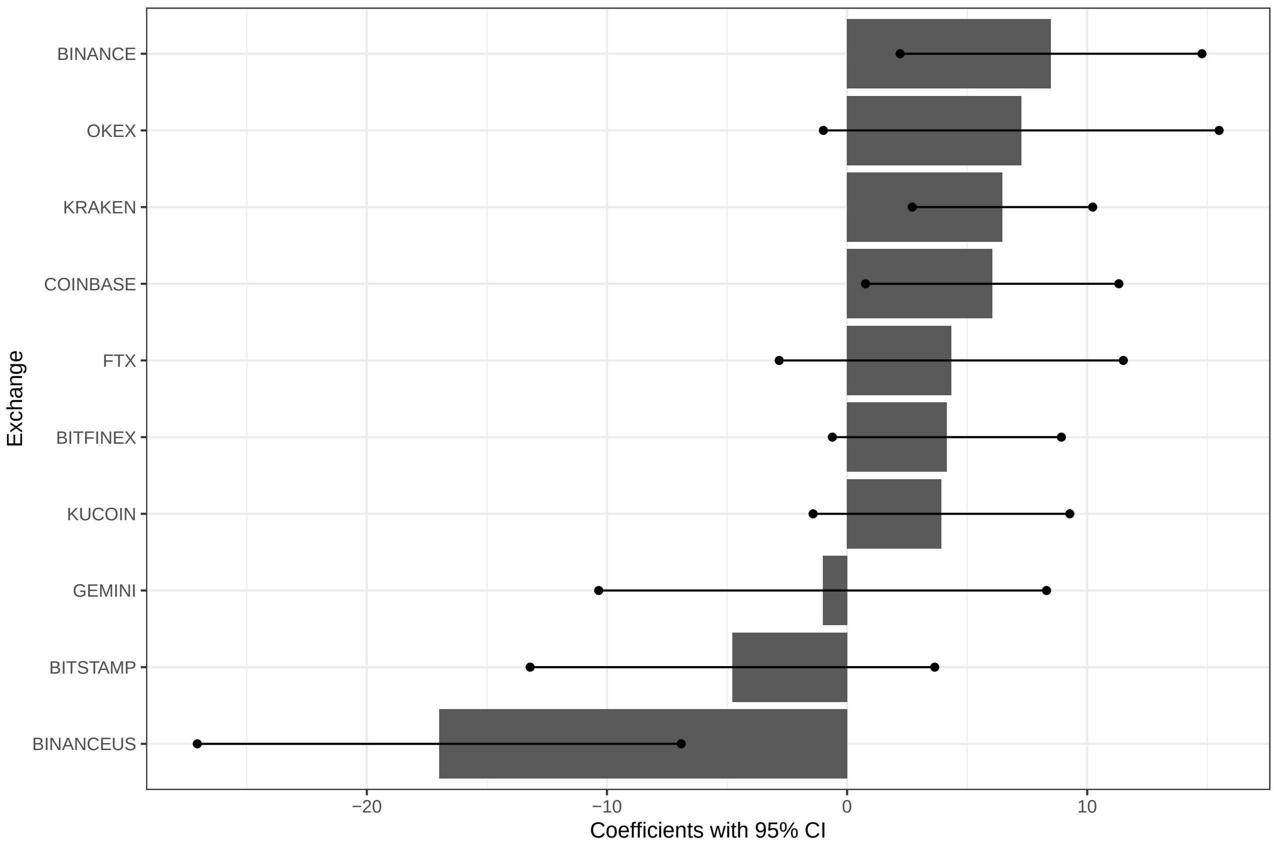

Figure 6: Price dispersion around Binance's listing

This figure plots three coins' price dispersion around Binance's listing. The red vertical line is the listing date of that coin on Binance.

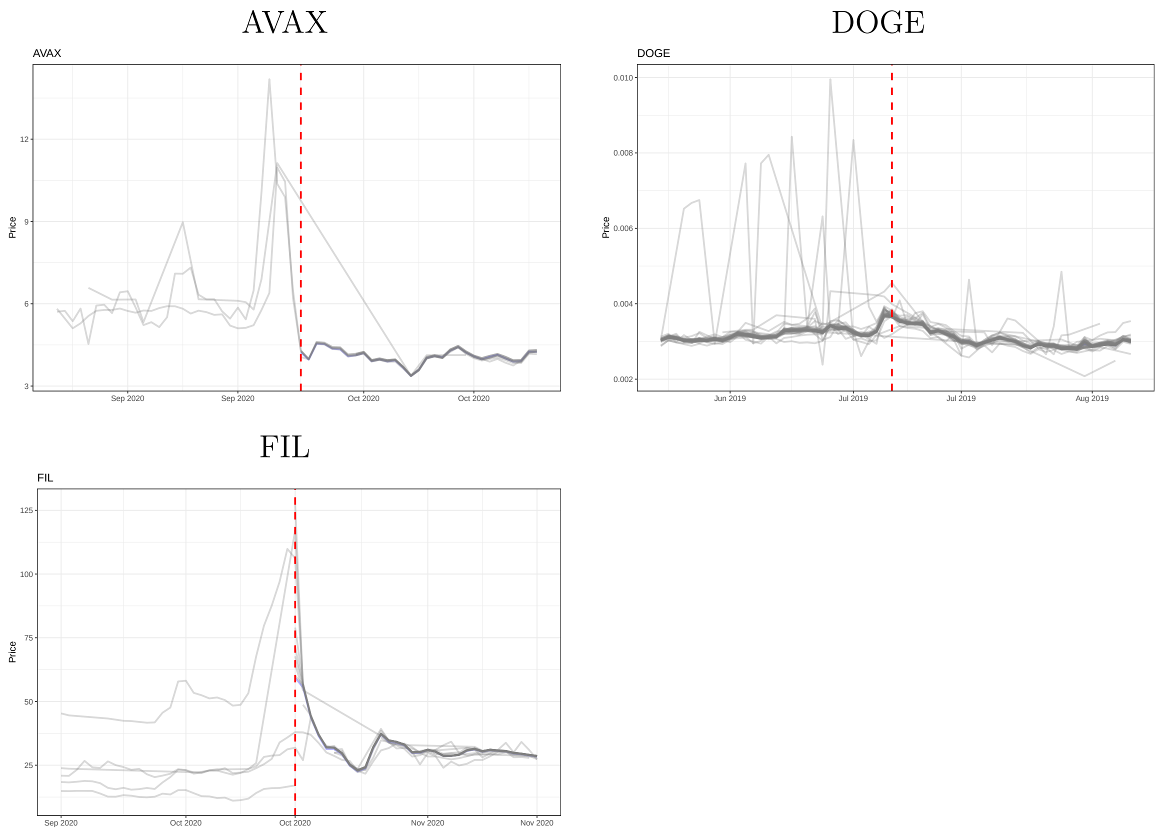

Table 1: Summary Statistics

This table presents summary statistics on variables related to coin outcomes, central exchange's listings, and other exchange's distance to the central exchange. Panel A shows descriptive statistics for exchange's price correlation and listing following distance with regard to the top10 exchanges. Panel B summarizes the coin-level coin outcomes and central exchange's listings, Panel C shows the coin-exchange level variables. For each variable, we show the number of non-missing observations, the mean, the standard deviation and the 10th, 50th and 90th percentile values.

Panel A: Exchange Level

	Obs.	Mean	SD	p10	p50	p90	Obs.	Mean	SD	p10	p50	p90
			BINANCE						*BINANCEUS*			
Price Correlation	252	0.7	0.2	0.4	0.8	1	211	0.7	0.2	0.4	0.8	1
Price Correlation Distance	252	0.7	0.3	0.3	0.7	1.1	211	0.6	0.3	0.2	0.6	1.1
Listing Following Distance	117	85.2	11.2	73.4	87.7	96.2	102	87.8	16.9	76.9	93.2	97.2
			BITFINEX						*BITSTAMP*			
Price Correlation	253	0.7	0.2	0.4	0.8	1	253	0.7	0.2	0.4	0.8	1
Price Correlation Distance	253	0.7	0.3	0.3	0.6	1.1	253	0.7	0.3	0.3	0.6	1.1
Listing Following Distance	111	90.1	7.7	80.5	92.4	96.6	65	90	10.1	77.4	94.1	98.4
			COINBASE						*FTX*			
Price Correlation	253	0.7	0.2	0.4	0.8	1	252	0.7	0.3	0.4	0.8	1
Price Correlation Distance	253	0.7	0.3	0.2	0.6	1.1	252	0.6	0.4	0.2	0.6	1.1
Listing Following Distance	113	86.5	9.3	78	88.2	95.3	117	84.4	11.5	73.2	85.4	96.5
			GEMINI						*KRAKEN*			
Price Correlation	251	0.7	0.2	0.4	0.8	1	253	0.7	0.2	0.3	0.7	0.9
Price Correlation Distance	251	0.7	0.3	0.2	0.76	1.1	253	0.7	0.3	0.3	0.7	1.2
Listing Following Distance	97	84.7	14.2	68.3	88.6	95.7	97	91.2	5.5	86.5	91.9	97.0
			KUCOIN						*OKEX*			
Price Correlation	242	0.7	0.2	0.4	0.8	0.9	242	0.7	0.2	0.4	0.8	1
Price Correlation Distance	242	0.7	0.3	0.3	0.6	1.1	242	0.7	0.3	0.3	0.7	1.1
Listing Following Distance	124	88.6	9.1	80.5	90.5	97.2	120	83.5	14.5	66.5	87	96.7

Panel B: Coin Level

	Obs.	Mean	SD	p10	p50	p90
Log (Volume)	476518	14.37	4.34	8.94	15.02	18.96
Volatility	465823	0.02	0.17	0	0	0.01
Intra-day Spread	476398	0.13	0.16	0.03	0.09	0.25
Return	465823	0.01	0.13	-0.07	0	0.08
Listing Binance	476518	0.48	0.5	0	0	1
Listing Coinbase	476518	0.15	0.36	0	0	1
Listing Pool	476518	0.69	0.46	0	1	1

Panel C: Coin-Exchange Level

	Obs.	Mean	SD	p10	p50	p90
Return	5749870	0	0.1	-0.06	0	0.06
Log (Volume)	5763021	11.99	3.91	6.64	12.35	16.59
Listing Binance	5763021	0.83	0.37	0	1	1
Listing Coinbase	5763021	0.44	0.5	0	0	1
Listing Pool	5763021	0.91	0.29	1	1	1

Table 2: Coin volume and listing: DID estimates

This table presents the listing pumb effect excluding new entrants. We restrict our sample to exchanges that list 30 days before the major exchange, aggregate the volume of these exchanges to the coin level, and run regression as same as Equation (16). The dependent variable is logarithm of trading volume. Columns (1) to (3) are results based on listings on Binance. Columns (4) to (6) are results based on listings on Coinbase. Columns (7) to (9) are results based on listings on the pool of top 10 exchanges. The reported t-statistics are based on robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Dependent Variables:	Log (Volume)								
	Binance			Coinbase			Pool		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Listing	0.048***	0.050***	0.074***	0.135***	0.137***	0.185***	0.047***	0.049***	0.066***
	(0.005)	(0.005)	(0.007)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.009)
Pre Three-day Listing		0.193***	0.250***		0.242***	0.266***		0.181***	0.217***
		(0.043)	(0.041)		(0.035)	(0.033)		(0.057)	(0.056)
One-day Lag Log Volume	0.624***	0.624***	0.594***	0.646***	0.646***	0.620***	0.607***	0.607***	0.570***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Two-day Lag Log Volume	0.351***	0.351***	0.340***	0.326***	0.326***	0.315***	0.365***	0.365***	0.347***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Coin FE	No	No	Yes	No	No	Yes	No	No	Yes
Day FE	No	No	Yes	No	No	Yes	No	No	Yes
R^2	0.932	0.932	0.937	0.948	0.948	0.953	0.921	0.921	0.927
Observations	214,846	214,846	214,307	293,729	293,729	293,193	161,054	161,054	160,497

Table 3: Coin volume and listing: DID Balanced Panel estimates

This table presents the listing pumb effect excluding new entrants. We restrict our sample to exchanges that list 30 days before the major exchange, aggregate the volume of these exchanges to the coin level, and run regression as same as Equation (16). Columns (1) is result based on listings on Binance. Columns (2) is result based on listings on Coinbase. Columns (3) is results based on listings on the pool of top 10 exchanges. The reported t-statistics are based on robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Dependent Variables:	Log (Volume)		
Model:	Binance (1)	Coinbase (2)	Pool (3)
Listing	0.012**	0.001	0.042***
	(0.006)	(0.006)	(0.008)
Pre Three-day Listing	0.220***	0.389***	0.296***
	(0.043)	(0.044)	(0.047)
One-day Lag Log Volume	0.601***	0.615***	0.572***
	(0.002)	(0.001)	(0.002)
Two-day Lag Log Volume	0.338***	0.328***	0.349***
	(0.002)	(0.001)	(0.002)
Coin FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
R^2	0.940	0.950	0.925
Observations	378,824	456,960	289,823

Table 4: Coin volatility and listing: DID estimates

The differential lisitng pump effect of volatility for different major exchanges. The regression model is similar to that in Table 1. The pool here denotes the second listing for a specific coin. The reported t-statistics are based on robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Dependent Variables:	Volatility			Intra-day Spread			Dispersion		
Model:	Binance (1)	Coinbase (2)	Pool (3)	Binance (4)	Coinbase (5)	Pool (6)	Binance (7)	Coinbase (8)	Pool (9)
Listing	-0.002***	-0.001***	-0.002***	-0.012***	-0.013***	-0.015***	-0.037***	0.011***	-0.042***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.002)	(0.003)	(0.002)
Pre Three-day Listing	0.001***	0.002***	0.001***	0.029***	0.050***	0.027***	0.004	0.007	0.031**
	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)	(0.012)	(0.015)	(0.012)
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.279	0.266	0.258	0.306	0.322	0.288	0.311	0.321	0.347
Observations	298,986	165,425	403,201	303,282	168,016	409,626	273,598	149,479	360,997

Table 5: Coin volume, exchange correlation, and listing

This table presents the listing pumb effect excluding new entrants. We restrict our sample to exchanges that list 30 days before the major exchange, and run regression as same as Equation (16) at the exchange-coin-day level. The dependent variable is logarithm of trading volume. Columns (1) to (2) are results based on listings on Binance. Columns (3) to (4) are results based on listings on Coinbase. Columns (5) to (6) are results based on listings the pool of top 10 exchanges. The reported t-statistics are based on robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Dependent Variables:	Log Volume					
	Binance		Coinbase		Pool	
	(1)	(2)	(3)	(4)	(5)	(6)
Listing	0.013***	-0.048***	0.023***	-0.027***	0.014**	-0.199***
	(0.004)	(0.015)	(0.003)	(0.010)	(0.006)	(0.023)
Listing × Correlation		0.062***		0.049***		0.238***
		(0.016)		(0.012)		(0.026)
Pre Three-day Listing	0.118***	0.374***	0.127***	0.251**	0.115***	0.231
	(0.021)	(0.132)	(0.017)	(0.114)	(0.035)	(0.206)
Pre Three-day Listing × Correlation		-0.296**		-0.144		-0.136
		(0.148)		(0.128)		(0.236)
Correlation		0.574***		0.446***		0.684***
		(0.013)		(0.011)		(0.021)
	0.592***	0.586***	0.617***	0.612***	0.580***	0.572***
One-day Lag Log Volume	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
	0.366***	0.359***	0.354***	0.349***	0.366***	0.358***
Two-day Lag Log Volume	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.916	0.917	0.934	0.934	0.909	0.910
Observations	835,336	835,159	3,170,428	3,170,251	375,952	375,798

Table 6: Coin returns and listing: DID estimates

The differential lisitng pump effect of return for different major exchanges. The regression model is similar to that in Table 1. The dependent variable is logarithm of trading volume. Columns (1) to (3) are results based on listings on Binance. Columns (4) to (6) are results based on listings on Coinbase. Columns (7) to (9) are results based on listings on FTX. Columns (10) to (12) are results based on listings on the pool of these three exchanges. The reported t-statistics are based on robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Dependent Variables:	Return								
	Binance			Coinbase			Pool		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Listing	-0.006***	-0.006***	-0.005***	-0.003***	-0.003***	-0.003***	-0.009***	-0.009***	-0.007***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Pre Three-day Listing		0.023***	0.024***		0.034***	0.042***		0.023***	0.025***
		(0.004)	(0.004)		(0.005)	(0.004)		(0.003)	(0.003)
Coin FE	No	No	Yes	No	No	Yes	No	No	Yes
Day FE	No	No	Yes	No	No	Yes	No	No	Yes
R^2	0.00123	0.00128	0.09262	0.00046	0.00052	0.09247	0.00249	0.00256	0.09309
Observations	465,823	465,823	465,823	465,823	465,823	465,823	465,823	465,823	465,823

Table 7: Coin volume, listing and country fixed effects

This table presents the listing pumb effect excluding new entrants. We restrict our sample to exchanges that list 30 days before the major exchange, and run regression as same as Equation (16) at the exchange-coin-day level. The dependent variable is logarithm of trading volume. The dependent variable is logarithm of trading volume. Column (1) is result based on listings on Binance. Column (2) is result based on listings on Coinbase. Column (3) is result based on listings the pool of top 10 exchanges. The reported t-statistics are based on robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

Dependent Variables:	Log Volume		
	Binance	Coinbase	Pool
	(1)	(2)	(3)
Listing	0.017***	0.005*	0.025***
	(0.004)	(0.003)	(0.006)
Pre Three-day Listing	0.122***	0.124***	0.124***
	(0.021)	(0.018)	(0.035)
One-day Lag Log Volume	0.584***	0.611***	0.569***
	(0.001)	(0.001)	(0.002)
Two-day Lag Log Volume	0.358***	0.346***	0.350***
	(0.001)	(0.001)	(0.002)
Coin FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
R^2	0.917	0.933	0.912
Observations	780,259	2,884,134	364,253

Appendix

A Supplementary Material for Section A

A.1 Logistics of International Remittances using Cryptocurrencies

As an extended example which illustrates the role of cryptocurrency exchanges in the usage of crypto, we describe the process of transferring funds internationally using cryptocurrencies. Suppose, for example, an individual in the USA who wished to transfer funds to a individual in the Philippines using cryptocurrencies. Such a transfer would follow the following steps:

1. The US-based individual would deposit fiat, using a bank transfer or other means, into a crypto exchange operating in the USA, and use these funds to purchase cryptocurrencies custodied on the exchange.

2. The US-based individual would “withdraw” her crypto to her private blockchain wallet.

3. The US-based individual could then send her cryptocurrencies to the wallet address of the individual in the Philippines.

4. The Philippines-based individual would “deposit” her crypto into a crypto exchange.

5. The Philippines-based individual would sell her crypto on the exchange for Philippines fiat currency, and then withdraw this, using a bank transfer or other means, to regular Philippines fiat currency.

The total fees charged in the course of this transaction include fees charged by exchanges for depositing, trading, and withdrawing in steps 1, 2, 4, and 5, as well as transaction fees charged for the blockchain transfer in step 3. The fees charged by exchanges vary. For the largest exchange, Binance, deposits and withdrawals are free, and purchases are charged around 0.1%, with discounts for very large trades and traders. Some smaller exchanges charge higher fees. The crypto transfer in step 3 has fees ranging from fractions of a cent to a few US dollars. Fees vary based on the degree of blockchain network congestion, but fees are generally independent of the value of the transaction. These transfers thus have competitive pricing, relative to some countries with inefficient traditional financial infrastructure.

An important benefit of crypto transfers is that they allow users to circumvent various regulations, such as capital controls as well as know-your-customer and anti-money-laundering provisions, imposed by national financial regulators. Crypto wallets are pieces of software or hardware, in which the security of funds is guaranteed through private-key cryptography. Self-custodied cryptocurrencies are not stored with any trusted intermediary: rather, a "private key" – a long numeric code, kept only on the user's hardware device – is used to prove to the blockchain network that the user owns her tokens, and to direct the network to take actions such as transfer tokens to other wallets. Crypto "miners", which build the blockchain by inserting proposed transactions in new "blocks", are incentivized to mine by newly minted crypto tokens they are given, and transaction fees which are paid by users for each transaction that they "mine". Since miners have no access to individuals' private keys, they have no ability to take funds from individuals' wallets.

It is logistically very difficult for regulators to enforce capital controls and other transfer restrictions directly on crypto transfers at the blockchain level, that is, step 3. of the process above. Firstly, there is no public mapping from addresses to individuals, so regulators cannot easily tell who owns a wallet, or even what country a wallet's owner resides in. Secondly, even if regulators were able to identify a set of wallets to impose potential transfer limitations on, enforcing transfer restrictions is difficult to to the structure of blockchain mining, because transactions are processed by geographically dispersed miners in an essentially discretion-free manner. Hypothetically, for example, if US-based Ethereum miners were instructed by US regulators to stop processing transactions from certain wallets, these transactions would only have to wait in the "mempool" of proposed transactions until a non-US miner not subject to the restriction mined a block and included the transaction.[11]

Crypto exchanges play a critical role in the process of sending funds due to their role in steps 1, 2, 4, and 5 of the funds transfer process. They serving as "on/off-ramps", by allowing deposits and withdrawals of crypto or fiat, and the trading of fiat for crypto. Since on-blockchain crypto transfers cannot easily be restricted, regulators have instead focused on imposing financial regulations through exchanges. For example, in the USA, a 2019 joint statement by the CFTC, FinCEN, and the SEC announced that crypto exchanges were classified as money services businesses, and thus are subject to KYC and AML rules under the Bank Secrecy Act of 1970. US-based crypto exchanges thus must gather identifying information about their customers to comply with these requirements. Crypto exchanges in many other countries with strict financial regulations are subject to similar requirements.

[11] One class of exceptions to this rule is that the administrators of certain tokens, such as the Circle (USDC) and Tether (USDT) USD stablecoins, include code in the "smart contracts" governing their tokens which allows them to freeze the funds of certain "blacklisted" wallets. These token administrators cooperate with regulators to freeze the funds of wallet addresses identified as being involved in hacks or other criminal activity. See, for example, Coindesk and Cointelegraph. However, freezing funds is only possible if, at the creation of the token, administrators include the capability to blacklist tokens, and the majority of crypto tokens do not have built-in blacklist functionality.

There are other ways to exchange fiat for cryptocurrencies besides custodial crypto exchanges. Users can simply exchange cryptocurrencies for fiat informally in social networks. Peer-to-peer exchanges, such as LocalBitcoins, also exist, which pair buyers and sellers of crypto in a manner that does not involve exchange custody of assets. Various institutions existing in legal gray areas also offer to exchange fiat for crypto across countries; for example, black market exchanges in Argentina allow individuals to exchange Argentinian pesos for USD, as well as various cryptocurrencies.[12]

B Proofs

B.1 Proof of Proposition 1

Prices. When the CEX does not list the token, arbitrageurs have no activity. Market clearing requires aggregate demand from all users on exchange j to equal 0. Hence, from (4), we need:

$$Z_{user,j}\left(p_j\right)=\int_{-\infty}^{\infty} z_i\left(x\right)dF_{x_{i,0}}\left(x\right)=\frac{-\gamma_j}{\gamma_j+\tau_j}\eta_j+\frac{\psi-p_j}{\gamma_j+\tau_j}=0$$

Solving for p_j, we have:

$$p^*_{j,0}=\psi-\gamma_j\eta_j \tag{22}$$

This is (6).

Trade quantities. To solve for expected squared trade quantity, note that user i's trade quantity is (3). Plugging in for $\psi-p_j$ using (22), we have:

$$z^*_{i,0}=\frac{-\gamma_j}{\gamma_j+\tau_j}x_{i,0}+\frac{\gamma_j\eta_j}{\gamma_j+\tau_j}$$

Thus, we have:

$$\mathbb{E}\left[z^{*2}_{i,0}\right]=\int_{-\infty}^{\infty}\left(\frac{-\gamma_j}{\gamma_j+\tau_j}x_{i,0}+\frac{\psi-p^*_{j0}}{\gamma_j+\tau_j}\right)^2 dF_{x_{i,0}}\left(x\right)$$

Plugging in for p^*_{j0} using (22) and simplifying, we have:

$$=\left(\frac{\gamma_j}{\gamma_j+\tau_j}\right)^2\int_{-\infty}^{\infty}\left(\eta_j-x_{i,0}\right)^2 dF_{x_{i,0}}\left(x\right)$$

$$=\left(\frac{\gamma_j}{\gamma_j+\tau_j}\right)^2\sigma^2_{I,j}$$

[12]See Devon Zuegel.

Exchange profits. The exchange's profit from user i is simply $\frac{\tau_j}{2}z_i^2$; hence, the exchange's profit over all users is:

$$\pi_{j,0}^{*} = \int_{-\infty}^{\infty} \frac{\tau_j}{2} z_i^{*2}\left(x\right) dF_{x_{i,0}}\left(x\right) = \frac{\tau_j}{2}\left(\frac{\gamma_j}{\gamma_j+\tau_j}\right)^2 \sigma_{I,j}^2$$

B.2 Proof of Proposition 2

Prices. When the CEX lists the token, arbitrageurs can trade the risky asset on j as well as the central exchange. Market clearing requires aggregate demand from all users and arbitrageurs on exchange j to equal 0. Hence, from (4) and (5), we need:

$$Z_{user,j}\left(p_j\right) + Z_{arb,j}\left(p_j\right) = \left(\frac{-\gamma_j}{\gamma_j+\tau_j}\eta_j + \frac{\psi - p_j}{\gamma_j+\tau_j}\right) + \frac{\psi - p_j}{\zeta_j+\tau_j} = 0$$

Solving for p_j, we have:

$$p_{j,1}^{*} = \psi - \frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\gamma_j\eta_j \tag{23}$$

This is (9).

Trade quantities. To solve for expected squared trade quantity, note that user i's trade quantity is (3). Plugging in for $\psi - p_j$ using (23), we have:

$$z_{i1}^{*} = \frac{-\gamma_j}{\gamma_j+\tau_j}x_{i,0} + \frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\frac{\gamma_j\eta_j}{\gamma_j+\tau_j}$$

Taking the expectation over all users, we have:

$$\mathbb{E}\left[z_{i1}^{*2}\right] = \int_{-\infty}^{\infty}\left(\frac{-\gamma_j}{\gamma_j+\tau_j}x_{i,0} + \frac{\psi - p_{j,1}^{*}}{\gamma_j+\tau_j}\right)^2 dF_{x_{i,0}}\left(x\right)$$

Plugging in for prices using (23), we have: Algebra:

$$= \int_{-\infty}^{\infty}\left[\frac{-\gamma_j}{\gamma_j+\tau_j}x_{i,0} + \frac{\psi - \left(\psi - \frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\gamma_j\eta_j\right)}{\gamma_j+\tau_j}\right]^2 dF_{x_{i,0}}\left(x\right)$$

$$= \left(\frac{\gamma_j}{\gamma_j+\tau_j}\right)^2 \int_{-\infty}^{\infty}\left(-x_{i,0} + \frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\eta_j\right)^2 dF_{x_{i,0}}\left(x\right)$$

$$= \left(\frac{\gamma_j}{\gamma_j+\tau_j}\right)^2 \int_{-\infty}^{\infty}\left[x_{i,0}^2 - 2\frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\eta_j x_{i,0} + \left(\frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\right)^2\eta_j^2\right] dF_{x_{i,0}}\left(x\right)$$

$$= \left(\frac{\gamma_j}{\gamma_j+\tau_j}\right)^2 \left[\left(\sigma_{I,j}^2+\eta_j^2\right) - 2\frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\eta_j^2 + \left(\frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\right)^2 \eta_j^2\right]$$

$$= \left(\frac{\gamma_j}{\gamma_j+\tau_j}\right)^2 \left[\sigma_{I,j}^2 + \left(\frac{\gamma_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\right)^2 \eta_j^2\right]$$

Exchange profits. The exchange's profit from user i is simply $\frac{\tau_j}{2}z_i^2$; hence, the exchange's profit over all users is:

$$\pi_{j,1}^* = \int_{-\infty}^{\infty} \frac{\tau_j}{2} z_i^{*2}(x)\, dF_{x_{i,0}}(x) = \frac{\tau_j}{2}\left(\frac{\gamma_j}{\gamma_j+\tau_j}\right)^2 \left[\sigma_{I,j}^2 + \left(\frac{\gamma_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\right)^2 \eta_j^2\right]$$

B.3 Proof of Proposition 3

Here we assume the aggregate inventory shock at peripheral exchange η_j is independent of the efficient price ψ and aggregate inventory shock at other peripheral exchanges. The coefficient of determination R^2 between the central exchange's price, and peripheral exchange j's price, is:

$$\begin{aligned}
R_{j,CE}^2 &= \frac{Cov^2\left(p_j^*, \psi\right)}{Var\left(p_j^*\right) Var(\psi)} \\
&= \frac{Cov^2\left(\psi - \frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\gamma_j\eta_j, \psi\right)}{Var\left(\psi - \frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\gamma_j\eta_j\right) Var(\psi)} \\
&= \frac{Cov^2(\psi,\psi)}{\left[Var(\psi) + Var\left(-\frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\gamma_j\eta_j\right)\right] Var(\psi)} \\
&= \frac{\sigma_\psi^2}{\sigma_\psi^2 + \left(\frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\right)^2 \gamma_j^2 \sigma_{A,j}^2}
\end{aligned} \tag{24}$$

The R^2 between the prices of exchanges j and j' is:

$$
\begin{aligned}
R^2_{j,j'} &= \frac{Cov^2\left(p^*_j, p^*_{j'}\right)}{Var\left(p^*_j\right)Var\left(p^*_{j'}\right)} \\
&= \frac{Cov^2\left(\psi - \frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\gamma_j\eta_j, \psi - \frac{\zeta_{j'}+\tau_{j'}}{\gamma_{j'}+\zeta_{j'}+2\tau_{j'}}\gamma_{j'}\eta_{j'}\right)}{Var\left(\psi - \frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\gamma_j\eta_j\right)Var\left(\psi - \frac{\zeta_{j'}+\tau_{j'}}{\gamma_{j'}+\zeta_{j'}+2\tau_{j'}}\gamma_{j'}\eta_{j'}\right)} \\
&= \frac{Cov^2\left(\psi,\psi\right)}{\left[Var\left(\psi\right)+Var\left(-\frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\gamma_j\eta_j\right)\right]\left[Var\left(\psi\right)+Var\left(-\frac{\zeta_{j'}+\tau_{j'}}{\gamma_{j'}+\zeta_{j'}+2\tau_{j'}}\gamma_{j'}\eta_{j'}\right)\right]} \\
&= \frac{\sigma^2_\psi}{\left[\sigma^2_\psi + \left(\frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\right)^2\gamma_j^2\sigma^2_{A,j}\right]}\frac{\sigma^2_\psi}{\left[\sigma^2_\psi + \left(\frac{\zeta_{j'}+\tau_{j'}}{\gamma_{j'}+\zeta_{j'}+2\tau_{j'}}\right)^2\gamma_j^2\sigma^2_{A,j'}\right]}
\end{aligned} \tag{25}
$$

The R^2 between the prices of exchanges j and j' is simply the product of the R^2 between the prices of exchanges j and the central exchange, and the R^2 between the prices of exchanges j' and the central exchange. Therefore, we always have:

$$
R^2_{j,CE} \geq R^2_{j,j'}
$$

B.4 Proof of Prediction 5

The prediction that the correlation between the central exchange's price and peripheral exchange j's price is decreasing in the arbitrage costs ζ_j follows directly from (24):

$$
\frac{\partial R^2_{j,CE}}{\partial \zeta_j} = \frac{-2\sigma^2_\psi\sigma^2_{A,j}\gamma_j^2\left(\zeta_j+\tau_j\right)\left(\gamma_j+\tau_j\right)}{\left[\sigma^2_\psi + \left(\frac{\zeta_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\right)^2\gamma_j^2\sigma^2_{A,j}\right]^2\left(\gamma_j+\zeta_j+2\tau_j\right)^3} \leq 0 \tag{26}
$$

The volume increase of peripheral exchanges after the central exchange lists is defined as:

$$
\begin{aligned}
\Delta\mathbb{E}\left[z^{*2}_{i,1}\right] &= \frac{\mathbb{E}\left[z^{*2}_{i1}\right]-\mathbb{E}\left[z^{*2}_{i0}\right]}{\mathbb{E}\left[z^{*2}_{i0}\right]} \\
&= \frac{\left(\frac{\gamma_j}{\gamma_j+\tau_j}\right)^2\left[\sigma^2_{I,j}+\left(\frac{\gamma_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\right)^2\eta_j^2\right]-\left(\frac{\gamma_j}{\gamma_j+\tau_j}\right)^2\sigma^2_{I,j}}{\left(\frac{\gamma_j}{\gamma_j+\tau_j}\right)^2\sigma^2_{I,j}} \\
&= \left(\frac{\gamma_j+\tau_j}{\gamma_j+\zeta_j+2\tau_j}\right)^2\left(\frac{\eta_j}{\sigma_{I,j}}\right)^2
\end{aligned} \tag{27}
$$

The volume increase of peripheral exchanges is also decreasing in the arbitrage costs ζ_j from (27):

$$\frac{\partial \Delta \mathbb{E}\left[z_{i,1}^{*2}\right]}{\partial \zeta_j} = -\frac{2(\gamma_j + \tau_j)^2}{(\gamma_j + \zeta_j + 2\tau_j)^3}\left(\frac{\eta_j}{\sigma_{I,j}}\right)^2 \leq 0 \tag{28}$$

Similarly, the exchange's profit from user i is simply $\frac{\tau_j}{2} z_i^2$. Therefore, the profits increase of peripheral exchanges is also decreasing in the arbitrage costs ζ_j.

C Details of Data Cleaning

This part introduces our data cleaning process. The raw dataset is at the hourly trade-pair level. There are mainly four steps:

1. Aggregate the data at the daily level for each coin at each exchange.
2. Keep trade-pairs if both coins belong to the top 500 coins ranked by CoinMarketCap.com.
3. Since the prices in the raw dataset are denominated in the second coin of the trade-pair, we first construct coin price conversion series. Conversion prices are same across exchanges. For example, trade-pair
4. We split each trade-pair level observation into two coin level observations. The prices of the coin level data are converted, respectively.
5. We aggregate the previous data by exchanges and coins.
6. We aggregate the data by coins.

Finally, for each coin listed on exchanges, we can observe daily prices and volume. For most analysis, we focus on coin-level data. For some analysis, we use data at coin-exchange level from step 5.

D Additional Empirical Results

We also test the validity of parallel trend for the returns listing effects in Figure A.1. The flexible estimation also shows that the dynamic listing effects of returns for major exchanges are similar.

[Figure A.1 here]

Figure A.1: Flexible estimation of the listing effects on returns by 5 days

This figure tests whether there is a pre-trend in returns for the DID test. It plots the estimates of Equation (17) and their 95% confidence intervals.