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Returns and network growth of digital tokens after cross-listings

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A B S T R A C T

This paper examines the role of cross-listings in the digital token marketplace ecosystem. Using a unique set of publicly available and hand-collected data from 3625 tokens traded in 108 marketplaces, we find significant increases in price, trading volume, network growth and on-chain activity around the date of a token's first cross-listing. Tokens earn a 16% crypto-market adjusted return in the two weeks around the cross-listing date. Daily network growth triples on the day of cross-listing. Using the uniquely heterogeneous characteristics of token marketplaces, we identify specific value-creation channels. We provide the first evidence supporting value creation through network externalities proposed by recent token-valuation models. Consistent with equity cross-listing theory, we find higher returns for cross-listings that reduce market segmentation and improve information production. Our reported findings have significant policy implications in terms of more transparent regulations to reduce financial misconduct in the digital marketplace.

1. Introduction and overview

The growth of the ecosystem of digital "*tokens*" (cryptographically secured digital currencies, assets, or securities built using blockchain technology, such as Bitcoin) has been exponential. From the creation of Bitcoin to early 2019, more than 5000 tokens have been actively traded in more than 300 digital marketplaces (digital platforms that enable peer-to-peer trading of tokens). During 2019, the token market cap of tokens fluctuated around USD150 billion, with and average trading volume of over USD 5 trillion, according to data obtained from the website www.cryptocompare.com. During 2019, Binance was the largest marketplace by trading volume with a 20% global market share and earned an estimated trading revenue of $800 million. This figure is roughly equal to the revenues received from equity trading by the Intercontinental Exchange Inc. (ICE, parent company of the NYSE, among others) and five times those of NASDAQ Inc. (the parent company of the Nasdaq and 79 other exchanges in 50 countries). Most importantly, digital marketplaces have developed without any explicit regulatory oversight of the procedures and policies that govern their operations.

The lack of specific regulations provides marketplaces with incomparable flexibility regarding operational strategies on the part of token-issuers and user/investors, resulting in a set of heterogeneous policies and practices. Moreover, this heterogeneity has resulted in user/investor segmentation and significant differences in information production across marketplaces. To date, we still see no evidence supporting fundamental valuation models for digital tokens that, in contrast to common asset-valuation models, incorporate the existence of network externalities on pricing dynamics (such as those proposed by Biais et al., 2018; Cong et al., 2020; Sockin and Xiong,

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2018; and Gandal et al., 2018.)

The primary goal of this paper is to fill this gap in the literature and identify potential sources of value in the digital-token ecosystem, using the setup that precedes a token's first cross-listing. This setting provides control not only for token characteristics but also for changes in the accessible market and information environment that arise from listing in an additional marketplace. The conceptual framework in which we conduct this research is evaluating the significance of changes in four inter-related variables as consequences of cross-listings of digital tokens. The four variables are cross-listings' returns, trading volume, network growth, and on-chain activity. The expected impact on returns is conceptually justified by reduction in market segmentation and improvement of information production. Other variables (trading volume, network growth, and on-chain activities) are justified based on valuation theories that rely on network externalities,[1] implying that the value of the service provided by a network (and therefore the value of the network itself) is driven by increases in the user base and diversity. The absence of multiple platforms or outright blocking of certain users from accessing a given marketplace (or providing services tailored to a specific type of user to the detriment of others) simply increase the level of market segmentation. The theoretical implication would be that cross-listings that reduce market segmentation by allowing new users/investors to access a token would in turn reduce the cost of capital and raise valuations. A complementary interpretation is that new users/investors not only enjoy a lower cost of capital but also directly increase the value of a token by increasing the size and interconnectedness of the users' network.

In particular, we address the following questions:

- How do token characteristics correlate with the probability of cross-listing?
- How do token-related returns, trading and network growth evolve around the date of cross-listing?
- How is each (pricing, trading, and network growth) affected by the characteristics of tokens and marketplaces?
- How well newly proposed token valuation and conventional asset pricing theories explain the findings?

For conducting this research, we build a unique dataset combining publicly available daily prices and volumes from over 3600 tokens traded in over 100 marketplaces and in more than 12,000 unique pricing combinations. Additionally, we hand-collect characteristics for close to 400 cross-listed token-issuers as well as data on applicable jurisdictions, regulations, policies, and practices for 80% of the marketplaces involved in the initial listing and first cross-listing of tokens. Lastly, for tokens issued on the Ethereum blockchain, we compile all the on-chain transactions from all addresses that have ever interacted with each token and create daily measures of network growth and usage. This allows us to identify and track all the addresses that have interacted with each token.

Before getting into details and the tables, we give a brief overview of the findings. We find a significant and positive relationship between token pricing and cross-listing. Tokens earn a raw cumulative return of 49%, measured in US dollars, over the period that runs from two weeks prior to two weeks subsequent to the cross-listing day, with two-thirds of the returns accruing in the pre-cross-listing period. We adjust for potential market-wide token appreciation in three ways: adjusting for the return on Bitcoin (the most actively traded token and the most commonly used pricing denomination for tokens), adjusting by the return on the MVIS CryptoCompare Digital Asset 10 Index (a modified market cap–weighted index that tracks the performance of the ten largest and most liquid digital assets), and calculating abnormal returns based on a crypto-specific three factor model. The Bitcoin-adjusted cumulative return is 27.9% and the index-adjusted cumulative return is 15.5%. Concurrent research by Liu et al. (2019) and Liu et al. (2020) has found the existence of crypto-specific risk premia. In addition to the crypto market risk premium, size and momentum factors are also priced. Adjusting for the expected return of a crypto-specific three factor model, we obtain a cumulative abnormal return of 16.3%.

We also find a significant and positive impact on trading activity. Trading volume in the initial marketplace increases by 200% relative to the pre-cross-listing trading volume and by 180% after controlling for changes in the overall trading volume of all other tokens traded in the same marketplace. The joint trading volume (the sum of the volumes in both the initial and cross-listing marketplaces) is almost 50 times higher than the pre-cross-listing baseline. This increase in trading volume is consistent with market segmentation across marketplaces, as some users/investors seem able to trade a cross-listed token only after being listed on the cross-listing marketplace. Additionally, market presence (measured as a token's having a positive trading volume on a given day) increases from 90% of the pre-cross-listing to almost 100% after cross-listing.

We use heterogeneity in token and marketplace characteristics to identify specific value-creation mechanisms. We find that cross-listings of digital tokens that enable platforms and peer-to-peer networks generate higher returns and higher abnormal trading. This result is consistent with the implications of token valuation theories that rely on network externalities.

Cross-listings also generate higher returns and higher abnormal volume when they involve marketplaces that target multiple user/investor segments. Specifically, we find positive returns when cross-listing to marketplaces that use multiple pricing denominations (provide additional fiat currencies or digital token pricing), or offer services targeting sophisticated investors (margin trading and over-the-counter trading). This result is consistent with creating value by reducing user/investor segmentation, as initially proposed by Merton (1987) and Miller (1999). We find no evidence of higher returns when cross-listing to higher-volume marketplaces (in contrast to the implications of liquidity theories, as in Amihud and Mendelson (1986), reinforcing the notion of segmented markets and network externalities. Higher returns are associated with cross-listings to marketplaces that cater to a different set of user/investors, but not to higher-volume marketplaces that cater to the same set of user/investors.

Cross-listings also generate higher returns and higher abnormal volumes when they lead to a stricter regulatory environment. We

[1] For instance, Bakos and Halaburda (2018), Catalini and Gans (2019), Cong et al. (2020), Li and Mann (2018), Sockin and Xiong (2018), Gandal and Halaburda (2016), and Gans and Halaburda (2015).

find higher returns and higher abnormal volumes when a cross-listing marketplace is under the jurisdiction of countries that have crypto-specific regulations or policies in place, employ "Know Your Customer" (KYC) identification procedures, offer potentially regulated services, employ token-selection procedures, or charge listing fees. This result is consistent with creating value by improving information production by the market and quality-signaling by issuers, as proposed by Baker et al. (2002). We also find evidence of order-flow migration from the initial to the cross-listing marketplace when cross-listings involve marketplaces with stricter internal regulations, hinting at users/investors' preference for a more highly regulated trading environment. These findings are in direct contrast to the popular belief in a "Wild West" (Office of the New York State Attorney General, 2018; House of Commons Treasury Committee, 2018) of unregulated digital token trading leading to higher prices and trading volumes. Our findings also show that stricter policies, whether voluntary or mandatory, generate higher returns as well as higher trading volume. This finding is in line with Huang et al. (2019) indicating that countries that actively support and demonstrate their "intention" for enacting regulations and policies attract more ICOs.

Lastly, we find that around the date of cross-listing, there is a significant increase in the number of on-chain transactions and token transaction volume. More importantly, we find an increase in the size and growth rate of the token's network (number of accounts with positive token balance). The increase in on-chain transactions and on-chain token volume persists for up to three weeks after the date of cross-listing.

The findings, in particular, contribute to the literature on digital tokens, providing empirical evidence of network externalities on crypto-tokens which is consistent with the analysis of Gandal and Halaburda (2016), the model for digital currencies proposed by Gans and Halaburda (2015), models that rely on user-base complementarity as in Cong et al. (2020) and Sockin and Xiong (2018), dynamic pricing as in Catalini and Gans (2019), and coordination as in Bakos and Halaburda (2018) and Li and Mann (2018). Support for external growth effect in the digital marketplace, specifically for cross listings of digital tokens in this paper, is also consistent with the external effects investigated and supported in other areas of business. For example, Chu and Manchanda (2016) find a significant and positive cross-network effect on both sides of digital platforms; sellers and buyers. In the area of crowd financing, Belleflamme et al. (2018) empirically support, among other findings, the network effects from increased usage of the crowdfunding platforms.

This paper also identifies potential sources of value creation around digital asset cross-listings, that are consistent with traditional equity cross-listing theories. In particular, cross-listings lead to higher returns by reducing market segmentation (Alhaj-Yaseen, 2013; Kadlec and McConnell, 1994; Miller, 1999), improving information production by the market and providing quality signals (Baker et al., 2002; Lang et al., 2003; Foucault and Gehrig, 2008; and Fernandes and Ferreira, 2008). Given the considerable heterogeneity observable in the practices and policies of token marketplaces, we identify the specific characteristics that are relevant to value creation within each channel.

The structure of the paper is as follows. In Section 2 we describe the institutional setting of token marketplaces, explain how they differ from traditional equities exchanges, and explore the potential implications for the analysis. In Section 3 we discuss the data and computation algorithm. We present the empirical strategy and results in Section 4 and identify the relationship between token characteristics, marketplace features, and returns around cross-listing as well as the correspondence between current cross-listing and token-valuation theories. We conclude in Section 5.

2. Differences between traditional security exchanges and crypto-marketplaces

The differences between traditional security exchanges and crypto-marketplaces can be attributed primarily to two main sources with possible implications as discussed in 2.3. The main differences are in the regulatory environment and differences in the technological features inherent to blockchain–enabled tokens. We briefly discuss each and illustrate how they could potentially influence the pricing of, and trading behavior associated with tokens.

2.1. Differences in the regulatory environment

The most salient difference in the regulatory environments in which traditional securities and digital tokens are traded is the lack of regulations tailored to token marketplaces. Money transmission laws, KYC (know your customer) and AML (anti money laundering) procedures, reserve requirements, and cybersecurity targeted at tokens have all improved, but up to June 2019 there is no specific enacted regulation to ensure token-marketplace integrity, and transparent, and orderly trading. This, in turn, translates into a considerable degree of freedom for marketplaces when setting up their policies and practices.

The most significant difference in token-issuer operational strategies is the lack of legal and financial disclosure requirements pertaining to token issuers with respect to the marketplace and the general public. None of the sample marketplaces requires any legal or financial documentation from token issuers, either before listing as part as the listing review and selection process or going forward after a token is listed. Some marketplaces require token issuers to disclose material business information to the marketplace, not to the public. The content of and details in this information are not consistent across marketplaces, relating primarily to software issues (upgrades, bugs, hacks, forks, etc.), liquidation (large sales of tokens by an issuer or founding team that could impact prices), and project termination (team dissolution, as most issuers are not legal entities). Some marketplaces do not utilize any selection process and list any token that is compatible with their software protocols.

Some marketplaces, in addition to utilizing some sort of selection process, charge listing fees. These can be publicly disclosed or privately negotiated and vary from a few thousand to a few million US dollars. On top of listing fees, some marketplaces require token issuers to maintain "security deposits" in the form of some quantity of tokens, donate tokens for marketplace giveaways, contract market-maker services and liquidity "insurance" from the marketplace, and maintain a minimum level of daily trading. Another nuance in the selection process is the practice of user-voting systems, whereby a marketplace holds periodic rounds of voting to select new tokens to be listed.

Regarding user/investor operational strategies, in this unique and less-regulated environment, we will focus on user selection and approval, trading practices, and additional services rendered by marketplaces. User selection is based on a marketplace's strategic definitions and applicable regulations. Some marketplaces require comprehensive identification verification with passports or government-issued identification documents (IDs), bank account linkages, physical address and cell phone validation, while others apply no requirements at all (not even user sign-ups). Marketplaces with strict identity verification can ban users from certain jurisdictions, limit users to one transaction per ID, create special users for institutional use, impose temporal bans and de-register non-compliant users, and, if required, disclose trade information to regulators. Some exchanges impose geographic bans by blocking IP addresses, limiting user access in specific locations (common banned locations are the United States, China, and the countries in United States' Office of Foreign Asset Control list).

These user/investor-oriented practices effectively provide market segmentation, by either outright blocking certain users from accessing a given marketplace or providing services tailored to a specific type of user to the detriment of others. The theoretical implication would be that cross-listings that reduce market segmentation by allowing new users/investors to access a token would in turn reduce the cost of capital and raise valuations. A complementary interpretation is that new users/investors not only enjoy a lower cost of capital but also directly increase the value of a token by increasing the size and interconnectedness of the users' network.

As an additional observation, while there is no corporation represented by the token, the issuer and token holders have a vested interest in the appreciation of token value, which is linked to the network value.

The public nature of most blockchain protocols provides universal token access to anyone with an internet connection. However, this access could be limited by factors such as token awareness (difficult to discover and evaluate the universe of available token projects), uncertainty of token quality, technical knowledge on specific blockchain programing language, and more mundane as geographic restrictions, means of payment and currency restrictions, language barriers, and even supply constraints for highly sought ICOs, among others. Exchanges can reduce some of these restrictions, hence become a key element in the ecosystem, by not only creating a market for tokens, but also reducing those access constraints, by providing signals of token quality and serving as an easy on-ramp for users lower technical blockchain knowledge.

2.2. Differences in technological features and processes

The technological features of blockchain–enabled tokens, which provide both benefits and limitations in the shaping of the overall digital token ecosystem, mark an important difference between traditional and token marketplaces. In the absence of a centralized custodian, clearing, or settling entity, the cryto-marketplace becomes the depository and takes the custody of the tokens, meaning that users transfer tokens from their personal "accounts" (blockchain "addresses" or "wallets") to the marketplace's "account." In turn, the marketplace creates an internal and private ledger to keep track of the deposits, trades, and withdrawals of each user. This implies that all transactions that take place in a token marketplace should be fully backed by tokens held in its custody (creating a higher operational risk of hacks, given the large number of tokens held in custody).

As trading in a token marketplace requires digital custody of a token, deposits of the token must be made before trading can begin. For a new listing, this implies that some party (the issuer, a large block investor, a market-maker, a marketplace proprietary account) must acquire tokens elsewhere and deposit them in the marketplace. For initial listings, this does not affect the pricing and trading of the token, as there is no market for it yet. This would not be the case for cross-listings, however, for two main reasons. If the token is withdrawn from the initial listing marketplace, it would result in lower liquidity, potentially affecting the price. If the token is not withdrawn from a marketplace but transferred from a large stakeholder account then, as all account transfers are publicly visible on the blockchain, investors and analysts that monitor for such movements could observe the transfers, infer that a cross-listing is likely, and act accordingly. Hence, even without inside trading by any of the parties directly involved, the market could observe information production before a cross-listing is officially announced.

In most public equity markets, investors do not trade directly with each other, but through intermediaries that interact in a centralized marketplace (the securities exchange). Such a centralized marketplace is itself supported by a centralized custodian and a centralized clearing-and-settlement entity, all of which are overseen by one or more regulatory institutions.

In contrast, blockchain–enabled tokens, by design, do not require a central entity to process and settle transactions. This is the central element that makes it possible to remove intermediaries from peer-to-peer token transactions. Peer-to-peer token transactions are possible, however, only if users/investors already hold tokens to trade (both to buy and to sell).

2.3. Possible implications of the differences in the regulatory environment and technical features

A major implication in the aftermath of cross-listings of digital tokens is the higher risk of exasperated corporate governance and new agency problems as a result of possible transferring of governance from one entity to another and/or sharing surveillance among different settings. There is currently no clear and legally binding set of straightforward and enforceable rules in place as to which jurisdictions are responsible when conflicts arise. Thus, the introduction of multiple channels of trading cross-listed digital tokens may bring incremental risks to market function and investor protection, creating a need for putting these activities into a global and multilateral regulatory framework. Although governance issues are not within the scope of this paper, the findings of attractive returns and more volume and activities, post cross-listings, have policy implications for scrutiny and transparency to reduce financial misconduct in the digital marketplace. Cohney et al. (2019) reveal and deliberate the "failure" of many ICOs in upholding the standards of integrity to protect the rights of the investors. Consistently, Cumming et al. (2019) discusses inadequate regulations, unvetted advisors, and different possible forms of hacking, among other reasons that may all contribute to the returns of digital assets. Despite growing trends in regulations in different countries, it is plausible to infer that the new phase of trading on different platforms (cross-listings of digital tokens) would add another layer of complexity and disclosure requirements that demands a closer attention of the regulators at both domestic and global levels.

Lack of marketplace-specific regulation coupled with technological features of blockchain also may provide- leeway for creativity in trading practices, for example in token-pricing denominations (fiat currency, main tokens, marketplace proprietary tokens, multi-tokens), order types (market, limit, hidden, iceberg, fill or kill, etc.), trading fee policies (fee per trade, percentage of traded amount, volume discounts, maker–taker pricing, payment for order flow, trading mining (payback of trading fees in the form of a marketplace's proprietary token), types of participants (market-makers, proprietary trading desks, institutional only, automated/algorithmic trading support), alternative parallel venues (over-the-counter, dark-pool), and additional non-regulated products (contracts for difference, collateralized and non-collateralized derivatives, margin trading, gambling products).

This ample set of unregulated practices provides an ideal setting for empirical research, not commonly available in traditional equity markets. By including and controlling for each marketplace choice in trading practices, we are able to identify their impact on the pricing of the marketplaces' listed tokens. In the following section we present the data, calculation algorithm and the different samples used in our research.

3. Data

We collect daily prices (open, high, low, and close) and traded volume from cryptocompare.com, using their public API. Data are collected from all reported marketplaces, for each pricing denomination available,[2] allowing for the construction of a global volume-weighted daily average price for each reported token, pricing denomination, and marketplace. If a token is quoted in multiple price denominations, price is converted to US dollars at the global volume weighted price for each denomination. Each marketplace reports all trades and quotes for all listed tokens to cryptocompare.com, which compiles a survivorship-bias-free dataset.[3] We also collect each token-issuer's identifying information, such as token name, ticker, initial coin offering (ICO) information (when applicable), and website.

For the set of tokens that cross-list and fulfill the sampling selection process, we download their whitepapers (technical and business summaries of their projects) and use it to classify each token according to its function, using the taxonomy proposed by the Blockchain Research Institute (crypto-currencies, platform-tokens, utility-tokens, security-tokens, asset-tokens, crypto-collectibles and crypto-fiat-currencies).

To control for market-wide price appreciation, we use the MVIS CryptoCompare Digital Assets 10 Index ("MVIS Index"), a modified market cap–weighted index that tracks the performance of the ten largest and most liquid digital assets, equivalent to 80% of total digital token market valuation. Therefore, a potential limitation of this popular index is the lack of representativeness of smaller tokens. To control for crypto-market specific risks, we use the risk premia for the crypto-market return, size and momentum factors estimated by Liu et al. (2020).

The data collected from marketplaces also include client identification requirements and information disclosure based on the KYC (know your customer), AML (Anti-money laundering) procedures, applicable law as stated in the terms of service, geographical and linguistic segmentation (access forbidden to certain nationalities or residencies, supported languages), token-listing policies (application and evaluation processes, listing fees, user voting, advertising requirements, incentive requirements, listing announcement policies), additional financial services provided (technical analysis and algorithmic trading support, margin trading, unregulated futures trading, unregulated derivatives trading, over-the-counter markets), order types, and trading fee structure; and deposit and withdrawal procedures (fees, limits, and processing time).[4]

For tokens issued on the Ethereum blockchain (also known as ERC-20 tokens), we collect from Aleth.io (an advanced Ethereum blockchain analytics platform, part of Consensys A.G.), a log of all transactions ever recorded for each token. This log includes for each transaction, the token volume transferred, sender address, recipient address and time stamp. With this information, we compile the daily transaction volume (in terms of tokens), number of transactions, the average transaction volume, number of active addresses (addresses with a positive token balance), number of new addresses (addresses that receive the token for the first time) and number of empty addresses (addresses that transferred 100% of token holdings).

The data spans a period running from June 6, 2014 through June 6, 2018.[5] The sample includes 108 reporting marketplaces, trading 3625 tokens in 83 distinct fiat currencies and a total of 12,464 price denominations. For tokens issued on the Ethereum

[2] If token AAA is traded in USD and BTC, there will be a time series of prices and volumes expressed as AAA/USD and another as AAA/BTC. All prices are converted to USD using the volume weighted exchange rates.

[3] Not all marketplaces report their trades to cryptocompare.com. While the dataset is free of survivorship bias, it does not reflect the universe of marketplaces nor tokens. This is, however, the largest and most detailed public dataset available in the market.

[4] The hand collected characteristics of marketplaces was retrieved between May 1 and May 31, 2018 and may not represent the characteristics of some marketplaces throughout the whole sample period.

[5] Data are available from March 11, 2013, but they do not include Mount Gox, the largest marketplace at the time, with an approximately 70% share of global Bitcoin trading. Mount Gox ceased operations on February 7, 2014 and filed for bankruptcy protection in Japan on February 28, 2014 and in the US on March 9, 2014. Additionally, Gandal et al. (2018) found evidence of Bitcoin price manipulation at Mt. Gox in late 2013.

Blockchain, we study over 12 million transactions from over 3 million addresses for 71 tokens. Table 1 shows a breakdown of the various sub-samples used in the paper. Out of the 3625 tokens traded from June 6, 2014 to June 6, 2018, a total of 1248 were listed simultaneously in more than one marketplace ("cross-listed"). 3279 tokens have been listed for at least 28 days. Of these, 1183 were cross-listed and 2096 remained single listed.

We select tokens that listed to a second marketplace at least 28 days after their initial listing, as to reduce the effect of the initial listing return identified in Benedetti and Kostovetsky (2021) and Momtaz (2019),[6] reducing the sample to 645 tokens. Lastly, we select tokens that had an average daily trading volume larger than $100 US dollars in two weeks prior the start of our event study window. Tables 2 and 3 present a summary of token characteristics and of initial and cross-listing marketplaces' characteristics, respectively.

4. Analysis and results

In this section, we explain our analysis in detail and report the empirical results.

4.1. Determinants of cross-listings

To evaluate the characteristics that determine the probability of cross-listing, we follow two empirical approaches based on survival-analysis models. First, we estimate a Cox proportional hazard regression (Cox and Oakes, 1984) with a token's first cross-listing as the risk event. While this method improves on simple logistic probability estimation which corrects for data censoring, it also comes with limitations. The method allows for only a binomial outcome (cross-listed or not cross-listed), while in reality, there are three mutually exclusive outcomes (cross-listed, delisted, and listed). To accommodate for this limitation, we use the Cumulative Incidence Competing Risk (CIRC) method proposed by Han and Hausman (1990). This model allows for interaction not only between risk factors and elapsed time but also between competing events. In this case, the occurrence of delisting will automatically rule out the occurrence of cross-listing (but not vice versa, a cross-listed token might delist in the future). Both models deliver estimates of the factor hazard ratio for the event of interest, and hence estimates greater (lesser) than a value of 1 imply that the factor increases (decreases) the probability the event of interest occurs.

In both models, our data set consists of all tokens that have been listed for at least 28 days. For cross-listed tokens, we include an additional restriction of being cross-listed at least 28 days after the initial listing.

We present the results of the estimation in Table 4, using both static and dynamic models. All model specifications indicate that tokens are more likely to cross-list if, they performed an ICO, or during the [−28,-14] time window had fewer pricing denominations, earned higher returns, and traded at higher volumes. These results are consistent with an economic rationale. For instance, tokens that have performed ICOs have stronger incentives to cross-list to provide greater liquidity to users/investors who purchased the tokens, and potentially had sufficient financial resources to pay for listings. On the contrary, token issuers who do not perform an ICO typically distribute tokens via mining, airdrops (giveaways), or in exchange for services, and do not receive external funds in exchange. Tokens with few trading pairs (pricing denominations) have stronger incentives to cross-list and can be traded in additional denominations and user markets. Marketplaces might be interested in listing tokens with high past returns (higher publicity) and high volume (potentially higher volume in the future).

These results are consistent with token issuers' cross-listing to provide additional liquidity and pricing denominations to early users/investors through the ICO process, after periods of favorable market performance. They are also consistent with marketplaces' deciding to list tokens that have been successful in the past, demonstrating public interest by raising funds via ICOs, thereby sustaining high market presence, trading volume, and positive returns.

We use identical empirical strategies to identify determinants of token de-listings and find that de-listing is more likely for tokens that did not have an ICO, have more pricing denominations, and have earned lower returns, lower market volumes, and lower market presence in the previous two weeks. Results of this analysis are presented in Appendix Table 1.

4.2. Cumulative abnormal returns

We study the overall univariate dynamics of the raw cumulative return in US dollars and the cumulative return adjusted according to returns on BTC (the most actively traded token and the most commonly used pricing denomination for tokens), the returns on the MVIS Index,[7] and the expected return obtained using the pricing model and risk premia developed by Liu et al. (2020).

Summary Exhibit 1 and Table 5 show a significant increase in returns starting two weeks prior to cross-listing. The raw cumulative token return (in terms of US dollars) reaches 32% at cross-listing and continues to increase thereafter. The BTC-adjusted cumulative return is 21% at cross-listing; it continues to increase at a slightly lower rate for around two weeks after cross-listing, to almost 30%. The index-adjusted cumulative return reaches 15.9% at cross-listing and oscillates around that level during the post cross-listing period. The cumulative abnormal return adjusting for the expected return resulting from a crypto-specific three-factor model

[6] Related to the post ICO listing return drift, Benedetti and Kostovetsky (2021) identify a post-listing cumulative abnormal token return over the return of a value weighted token index of 29% over a one-week period and 41% over a one-month period. Momtaz (2019), identifies a post listing buy and hold return of 20% for a one-week period and 25% for a one-month period.

[7] Analogous analysis on abnormal trading volume and market presence around cross-listings leads to similar and consistent results and is available from the authors upon request.

Table 1
Sample selection.

Sample	# Tokens	# Marketplaces
All tokens	3625	108
Cross-listed tokens	1248	53
Single listed tokens	2377	59
Tokens listed for at least 28 days	3279	81
Cross-listed tokens	1183	53
Single listed tokens	2096	45
Cross-listed tokens listed for at least 28 days	1183	53
Cross-listed tokens, cross-listing in fewer than 28 days since initial listing	538	31
Cross-listed tokens, cross-listing in more than 28 days since initial listing	645	40
Daily traded volume > $100 in [−28,-14]	375	40
MVIS Digital Assets 10 Index available	364	40
Hand collected data available for cross-listing marketplace	273	27
Hand collected data available for initial marketplace	288	21
Hand collected data available for both initial and cross-listing marketplaces	215	21

Table 1 provides a breakdown of the sampling process. Out of the 3625 tokens traded from June 6, 2014 to June 6, 2018, a total of 1248 have been cross-listed. 3279 tokens have been listed for at least 28 days. Of these, 1183 have been cross-listed and 2096 remained single listed. Out of the 1183 that cross-listed, 538 are cross-listing that occurred in less than 28 days from the initial listing and 645 are cross-listings that occurred at least 28 days after the initial listing; and of those, 375 had a daily traded volume in the [−28,-14] window of at least $100. Data on the MVIS Digital Assets 10 Index are available for 364 tokens. *Cross-listing* is defined as being listed simultaneously in more than one marketplace. *First cross-listing* occurs when a token that is currently traded on its first listing marketplace begins trading on a second marketplace. The first cross-listing date is the first day a token is traded in the cross-listing exchange. This date coincides with the announcement date for all cross-listing marketplaces that provide a record of announcement dates.

Table 2
Summary of token characteristics around the first cross-listing date.

	# Tokens	Mean	Std Dev	Min	25%	50%	75%	Max
Token characteristics								
Currency	375	23%	42%	0	0	0	0	1
Utility	375	24%	43%	0	0	0	0	1
Plataform	375	11%	31%	0	0	0	0	1
Security	375	2%	14%	0	0	0	0	1
Asset	375	2%	13%	0	0	0	0	1
Unavailable	375	38%	49%	0	0	0	1	1
ICO	375	31%	46%	0	0	0	1	1
Characteristics pre cross-listing (t = −14)								
Days since initial listing	375	165	205	29	46	76	179	1119
Daily return since listing (USD)	375	0.10%	3.11%	−15.53%	−1.08%	0.20%	1.23%	9.66%
Daily return since listing (BTC)	375	−0.23%	3.09%	−16.78%	−1.24%	−0.02%	0.88%	8.96%
Cumulative return [−28,-14]	375	1.37%	35.73%	−99.51%	−18.88%	−3.57%	14.56%	122.52%
Bitcoin adjusted cumulative return [−28,-14]	375	0.25%	33.73%	−99.55%	−17.64%	−4.34%	11.28%	120.15%
Average volume (USD) [−28,-14]	375	383,598	2,893,383	101	523	3580	34,785	46,687,554
Market presence [−28,-14]	375	93%	16%	14%	93%	100%	100%	100%
Characteristics post cross-listing (t = +14)								
CR from price at t-14	375	49.76%	171.95%	−95.16%	−40.39%	−3.73%	57.88%	769.83%
Bitcoin adjusted CAR from price at t-14	375	30.62%	155.25%	−96.22%	45.84%	−15.94%	28.53%	785.67%
Index adjusted CAR from price at t-14	364	16.37%	103.14%	−96.02%	−43.56%	−13.43%	30.16%	411.18%
Crypto-specific 3 factor model adjusted CAR	326	16.26%	124.87%	−228.93%	−40.46%	0.10%	68.79%	277.77%
Volume at initial marketplace (USD)	375	278,522	2,476,574	0	75	1837	22,860	45,521,925
Volume at cross-listing marketplace (USD)	375	387,505	3,332,482	0	1	305	14,931	55,520,595
Total volume (USD)	375	666,028	5,004,607	0	467	7452	86,177	76,935,390
Abnormal volume at initial marketplace	375	205%	983%	−100%	−96%	−69%	33%	5750%
Abnormal volume at cross-listing marketplace	375	1924%	6979%	−100%	−100%	−95%	−4%	37,408%
Abnormal total volume	375	2273%	7260%	−100%	−81%	−15%	304%	37,737%
Market presence at initial marketplace	375	89%	32%	0%	100%	100%	100%	100%
Market presence at cross-listing marketplace	375	81%	39%	0%	100%	100%	100%	100%
Market presence at any marketplace	375	99%	7%	0%	100%	100%	100%	100%

Table 2 reports the descriptive statistics on token characteristic for the sample of cross-listed tokens. The variables are defined as in Appendix Table A.1.

Table 3
Summary of initial and cross-listing marketplaces' characteristics at t − 14.

	Initial Marketplace		Cross-listing Marketplace	
	# tokens	Mean	# tokens	Mean
Decentralized Exchange (DEX)	375	17%	375	12%
Listing process				
Accepts listing proposals	273	95%	288	93%
Charges listing fee	273	56%	288	70%
Requires listing review	273	64%	288	71%
User vote on listings	273	12%	288	25%
Regulations				
Accepts US users	273	92%	288	79%
KYC process required	273	8%	288	13%
KYC process available	273	45%	288	70%
Procedures and Policies				
Maker-taker fees	273	46%	288	38%
Rebates on trading volume	273	23%	288	32%
Margin trading	273	35%	288	38%
OTC trading	273	13%	288	11%
Institutional trading	273	14%	288	14%
Derivatives trading	273	9%	288	13%
Jurisdiction				
Canada	273	1%	288	0%
Cayman Islands	273	1%	288	2%
Gibraltar	273	1%	288	2%
China (Hong Kong)	273	10%	288	18%
Italy	273	0%	288	0%
Japanese	273	0%	288	0%
Malta	273	0%	288	0%
New Zealand	273	10%	288	11%
Russia	273	0%	288	1%
South Korea	273	0%	288	1%
Sweden	273	4%	288	12%
UK	273	1%	288	1%
US	273	4%	288	4%

Table 3 reports the descriptive statistics for the initial and cross-listing marketplaces involved in the first cross-listing of tokens in the sample. Variables are defined as in Appendix Table A.1.

reaches 12.7% at cross-listing and continues to increase to levels near 20%.[8] The difference in magnitude observed in the three measures suggests the existence of a market-wide price increase during the observed period and emphasizes the need to use a market-adjusted return measure to isolate or reduce the impact of such market-wide events in the analysis of return evolution.

An analogous analysis[9] of the cumulative abnormal return around the date of a token's first de-listing yields significant and opposite results. Just as with cross-listings, we observe an effect on the index adjusted CAR as early as two weeks before the de-listing event, pointing out to information leakage. At the de-listing event, the index adjusted CAR reaches −4.8%. Two weeks after de-listing, the index adjusted CAR reaches −9.2% and − 15.9% at 4 weeks after the de-listing. Of the 391 tokens de-listed at one exchange, an additional 122 tokens are de-listed from the surviving exchange in the following 4 weeks.

As presented by Li et al. (2020), pump and dump schemes have occurred rather frequently in the crypto-ecosystem. These events last for only several minutes, with the run-up in price and increased trading volume being quickly reversed. These schemes are not associated with token issuer actions such as software upgrades, news announcements or cross-listings. While we cannot rule out the presence of pump and dump schemes within the period under analysis, their potential effect would be short lived given their documented nature of reversal within the day of the event. Our index adjusted cumulative returns accumulate over a 28-day window (−14, +14), hence the pump price increase would be netted out by the dump price reversal within the observed time window.

4.3. Network growth

At conceptual level, it is reasonable to expect network growth (a positive network externality) arise as more users and participants are enabled to enter the space for trading crypto-assets. Yet, the literature is void of an evidence supporting new valuation models for digital tokens which integrate the existence of network externalities. This section provides the first evidence showing the value creation through network externalities suggested through novel approaches cited in Section 1.

One of the key measures for token adoption and network growth is the number of addresses or "accounts" that hold the token.

[8] The risk premia dataset from Liu et al. (2020) spans from August 1, 2016 to December 31, 2018. Hence, the cumulative abnormal returns obtained from the crypto-specific three-factor model is limited to cross-listings occurring within that timeframe.
[9] Detailed results are available from the authors upon request.

Table 4
Token characteristics and the probability of cross-listing.

	Dependent variable: Cross-listing dummy							
	Time-varying Cox Hazard Model		Static Cox Hazard Model		Time-varying Competing Risk Model		Static Competing Risk Model	
	(1)		(2)		(3)		(4)	
ICO	2.60	***	2.27	***	2.73	***	2.32	***
	(0.26)		(0.23)		(0.27)		(0.23)	
# of current trading pairs	0.94	*	0.74	***	0.94	**	0.74	***
	(0.03)		(0.02)		(0.03)		(0.02)	
Past returns	1.05	**	1.01		1.06	***	1.02	**
	(0.02)		(0.01)		(0.02)		(0.01)	
Past volume	1.13	***	1.06	***	1.14	***	1.09	***
	(0.02)		(0.02)		(0.02)		(0.01)	
Past market presence	0.56	***	1.18		0.8		1.43	**
	(0.09)		(0.19)		(0.13)		(0.24)	
# Tokens	2741		2741		2741		2741	
# Cross-listed	645		645		645		645	
# Censored	2096		2096		950		950	
# Delisted					1146		1146	
# Observations	549,562		2741		549,562		2741	

In all models, the dependent variable is a dummy that equals 1 at the time of cross-listing. *ICO* is a dummy variable that equals 1 if the tokens had an initial coin offering. *# of current trading pairs* is the number of distinct tokens and fiat currencies used as price denominators in the initial marketplace. *Past returns* is the log of (1.01+ the 14-day cumulative return on a token) measured in bitcoin. *Past volume* is the log of (1.01 the 14-day average traded volume) measured in dollars. *Past market presence* is the 14-day average of a dummy variable that equals 1 if the token was traded during that day. All explanatory variables are measured with a 14-day lag from the cross-listing, delisting, or last available date. The results reported in columns (1) and (2) correspond to Cox proportional hazard regressions, where tokens that are not cross-listed (delisted or listed in only one marketplace) are considered censored and the estimated coefficients are equal to the hazard ratio compared with the mean baseline. The results reported in columns (3) and (4) correspond to Cumulative Incidence Competing Risk (CIRC) regressions, where the competing risk is delisting, and observations from tokens listed in only one marketplace are considered censored. The estimated coefficients correspond to the sub-hazard ratios compared with the mean baseline. The results reported in columns (1) and (3) are time-series models that allow for time-varying variables, while models (2) and (4) are static models that use the last available observation for estimation. For models (1) and (3), standard errors are clustered at the token level. Asterisks denote significance levels: one asterisk denotes significance at the 10% level, two asterisks denote significance at the 5% level, and three asterisks denote significance at the 1% level. Heteroskedasticity-consistent standard errors, are shown in brackets.

While it is possible to trade tokens without interacting with an exchange, the trading options are more limited (in terms of available order types, trading fees and execution speed), hence most active traders prefer to store their tokens on an exchange, and long term investors and potential users store tokens using individual addresses.

To account for such users, we compile the totality of peer-to-peer transactions of tokens issued on the Ethereum blockchain. We analyze the evolution of on-chain peer to peer transactions (direct transactions between Ethereum addresses, which exclude trading transactions performed within crypto-exchanges) around the date of a token's first cross-listing and find that the number of transactions and the total transaction volume sharply increase close to the cross-listing date.

We observe that during the week before cross-listing, the number of peer-to-peer transactions is over 150% higher than the number of transactions during the baseline period [−28, −14]. There is a local maximum on the day of cross-listing, with 270% more transactions than the baseline and 6 days after cross-listing, another maxima of 300%. The number of transactions remains significantly higher than the baseline for 3 weeks after cross-listing. In terms of peer to peer transactions, the volume is on average 400% higher during the week before cross-listing than on the baseline [−28,-14]. On the cross-listing day, volume is 600% higher than the baseline, and volume remains significantly higher throughout the following month. Both analyses are consistent with investors preparing for cross-listing by withdrawing funds from the initial exchange into their personal addresses, transferring to the cross-listing exchange upon cross-listing and investors withdrawing from the new exchange once cross-listed.

In order to analyze the user network (the number of users/addresses), we use the full log of peer-to-peer transactions to reconstruct the daily balances of all addresses that have ever interacted with each token. We find that around the date of cross-listing there is an increase in the number of addresses with a zero-token balance (addresses that transfer out the totality of their token balance), an increase in the number of new addresses holding the token and an increase in the total number of addresses holding the token. At cross-listing, the daily growth rate is 5% higher than the baseline. Namely, 8% on the day of cross-listing compared to an average of 3% in the [−28,-14] period. The increase of zero token balance accounts is consistent with users transferring their individual holdings to the cross-listing exchange, while the increase in new addresses is consistent with users from the initial exchange and the new exchange withdrawing tokens to new individual addresses.

Our finding about network growth for crypto-assets is unique and not the same for other common asset valuation models. A plausible explanation for such network growth is the adoption by new users brought forward by the cross-listing marketplace, encouraging investors' participation and attention. The increase in total positive balance addresses is consistent with sustained network growth around the date of cross-listing.

Table 5
Index adjusted cumulative return and test statistics around the date of first cross-listing.

	Index adjusted CAR								Crypto-specific 3 factor model adjusted CAR							
t-event	Mean	N	t-test	p-value	BMP	p-value	Wilcoxon	p-value	Mean	N	T-test	p-value	BMP	p-value	Wilcoxon	p-value
-14	1.6%	364	0.80	21.3%	0.99	16.0%	33,872	9.6%	0.2%	326	0.18	42.9%	0.55	29.0%	26,223	80.2%
−13	2.3%	364	0.99	16.0%	1.24	10.7%	33,851	9.4%	0.9%	326	0.74	22.9%	0.95	17.1%	26,321	84.7%
−12	4.9%	364	1.83	3.4%	2.29	1.1%	35,018	25.2%	1.6%	326	1.09	13.9%	1.65	5.0%	25,577	52.8%
−11	5.7%	364	2.00	2.3%	2.50	0.6%	35,834	43.9%	2.6%	326	1.54	6.3%	2.02	2.2%	24,326	17.2%
−10	5.9%	364	1.85	3.2%	2.32	1.1%	33,164	4.7%	2.3%	326	1.23	11.0%	1.44	7.5%	25,023	33.9%
−9	4.8%	364	1.48	6.9%	1.86	3.2%	32,080	1.3%	2.3%	326	1.10	13.7%	0.91	18.3%	24,794	27.6%
−8	8.8%	364	2.45	0.7%	3.07	0.1%	34,146	12.3%	4.9%	326	2.19	1.5%	2.27	1.2%	23,062	3.5%
−7	9.8%	364	2.54	0.6%	3.17	0.1%	34,011	10.9%	4.9%	326	1.96	2.5%	2.19	1.4%	23,222	4.4%
−6	8.0%	364	2.16	1.6%	2.70	0.4%	33,416	6.1%	5.4%	326	1.96	2.5%	2.37	0.9%	22,903	2.8%
−5	8.5%	364	2.15	1.6%	2.69	0.4%	32,848	3.3%	6.6%	326	2.25	1.3%	2.51	0.6%	22,384	1.2%
−4	9.5%	364	2.39	0.9%	2.99	0.1%	33,494	6.6%	7.9%	326	2.41	0.8%	2.71	0.4%	22,135	0.8%
−3	9.2%	364	2.31	1.1%	2.88	0.2%	32,996	3.9%	8.6%	326	2.44	0.8%	2.59	0.5%	21,784	0.4%
−2	9.1%	364	2.27	1.2%	2.83	0.2%	33,592	7.3%	9.0%	326	2.45	0.7%	2.72	0.3%	21,817	0.5%
−1	13.1%	364	3.00	0.1%	3.75	0.0%	34,959	24.1%	10.3%	326	2.74	0.3%	3.13	0.1%	21,417	0.2%
0	16.2%	364	3.67	0.0%	4.59	0.0%	37,241	89.2%	12.7%	326	3.13	0.1%	3.34	0.0%	20,557	0.0%
1	12.4%	364	2.82	0.3%	3.52	0.0%	33,851	9.4%	10.7%	326	2.48	0.7%	2.47	0.7%	21,604	0.3%
2	14.0%	364	3.12	0.1%	3.90	0.0%	35,204	28.9%	11.9%	326	2.62	0.5%	2.74	0.3%	21,081	0.1%
3	10.6%	364	2.36	0.9%	2.95	0.2%	32,749	3.0%	10.9%	326	2.30	1.1%	2.40	0.8%	21,582	0.3%
4	10.9%	364	2.34	1.0%	2.93	0.2%	32,146	1.4%	11.0%	326	2.22	1.4%	2.33	1.0%	22,155	0.8%
5	11.5%	364	2.41	0.8%	3.02	0.1%	32,170	1.5%	12.0%	326	2.37	0.9%	2.30	1.1%	22,069	0.7%
6	9.9%	364	2.08	1.9%	2.60	0.5%	31,458	0.6%	12.6%	326	2.36	0.9%	2.42	0.8%	22,195	0.9%
7	11.3%	364	2.29	1.1%	2.86	0.2%	31,859	1.0%	13.4%	326	2.43	0.8%	2.50	0.6%	21,919	0.5%
8	11.7%	364	2.38	0.9%	2.97	0.2%	32,052	1.3%	14.3%	326	2.47	0.7%	2.40	0.9%	21,962	0.6%
9	10.6%	364	2.14	1.7%	2.67	0.4%	31,146	0.4%	14.5%	326	2.43	0.8%	2.35	1.0%	22,224	0.9%
10	12.5%	364	2.43	0.8%	3.03	0.1%	31,772	0.9%	15.4%	326	2.51	0.6%	2.44	0.8%	21,972	0.6%
11	15.3%	364	2.85	0.2%	3.57	0.0%	32,009	1.2%	16.5%	326	2.63	0.4%	2.64	0.4%	21,605	0.3%
12	15.5%	364	2.92	0.2%	3.65	0.0%	33,154	4.6%	18.1%	326	2.78	0.3%	2.89	0.2%	21,629	0.3%
13	11.8%	364	2.22	1.3%	2.78	0.3%	31,136	0.4%	16.0%	326	2.39	0.9%	2.38	0.9%	22,493	1.5%
14	14.3%	364	2.59	0.5%	3.24	0.1%	31,510	0.6%	16.3%	326	2.35	1.0%	2.29	1.1%	22,642	1.9%

Table 5 presents the average index adjusted cumulative token return around the date of the first cross-listing. USD Cumulative Token Return is defined as $\frac{Token\ price\ in\ USD_{t+14}}{Avg.Token\ price\ in\ USD\,[-28,-14]} - 1$. Crypto-specific three-factor model corresponds to the cumulative sum of abnormal returns measured as the observed return minus the expected return obtained using the crypto-specific three-factor model and risk premia from Liu, Liang and Cui (2020 T = 0 corresponds to the first day a token is traded in a second exchange. T- test corresponds to the t statistics, BMP corresponds to the Boehmer, Musumeci and Poulsen (BMP) standardized cross-sectional test which is robust to event induced variance and Wilcoxon corresponds to the Wilcoxon Z statistic. Token returns are winsorized on the right side of the distribution at 98%. No adjustments are made to the left side of the distribution. Heteroskedasticity-consistent standard errors, are shown in brackets.

4.4. Token characteristics, cross-listing characteristics, and index-adjusted cumulative returns

In this section, we report the results of a series of multivariate regressions to explore the relationship between the intrinsic characteristics of tokens, marketplaces, and the observed evolution of the index-adjusted price cumulative returns.[10] We first propose a baseline result using only token characteristics to later explore the effects of incorporating alternative categories of cross-listing characteristics (interactions between the initial and cross-listing marketplace) separately. Lastly, we comment on how the results relate to nascent token-valuation models based on network effects and pre-existing equity cross-listing theories. All regressions in this section follow a similar structure:

$$Dep_i = \alpha + \beta\ Controls_i + \gamma\ Cross - listing\ characteristics_i + \varepsilon_i$$

where *i* is a specific [token, initial marketplace, cross-listing marketplace, time]-tuple. This implies that the same [initial marketplace, cross-listing marketplace] combination can have varying cross-listing characteristics over time, and varying cross-listings characteristics at the same time if evaluated for a different token.

The dependent variable is defined as:

- Index-adjusted cumulative return:

$$\left[\left(\frac{Token\ price\ in\ USD_{t+14}}{Avg.Token\ price\ in\ USD\ [-28,-14]}-1\right)\Big/\left(\frac{Index\ value\ in\ USD_{t+14}}{Index\ value\ in\ USD_{t-14}}-1\right)\right]-1$$

4.5. Evidence consistent with network externalities

Table 6 shows the results of a regression, using only token characteristics as control variables. We include category dummies, assigned according to each token's proposed function, using the taxonomy created by the Blockchain Research Institute (crypto-currencies, platform-tokens, utility-tokens, security-tokens, asset-tokens, crypto-collectibles and crypto-fiat-currencies). Of these categories, crypto-currencies, platform-tokens, and utility-tokens are, by construction, digital tokens created to enable interactions within a network. Crypto-currencies (i.e., BTC, LTC, or Zcash) are tokens designed to enable peer-to-peer financial transactions between users who freely choose to accept them; platform tokens are the exclusive means of payment in specific virtual computer networks that allow for the creation and execution of applications/programs (i.e., Ether, Waves, or EOS), and utility tokens are the means of payment for a specific service (i.e., Sia for decentralized storage, Augur for prediction markets, or Basic Attention Token for online advertising). These three categories are subject to network externalities, meaning that the inherent value that a user can obtain from interactions and participation in a given network increases as the number and diversity of the participants in the network increase. Specifically, increases in network size and diversity imply that, in the case of crypto-currencies, more peers can receive and send payments; in the case of platform tokens, the applications created on the platform become available to a larger set of users; and lastly, in the case of utility tokens, more users can interact in the network.

In columns (1) and (2) of Table 5, we report the results of a regression on *Index-adjusted cumulative return*; Column (1) includes the same token characteristics used in the cross-listing probability regressions. Column (2) includes token category dummies. From the results reported in columns (1) and (2) we observe that tokens with fewer pricing denominations, lower past returns, lower trading volume, and higher market presence show a higher index-adjusted cumulative return. Having performed an ICO does not affect cross-listing returns. Most importantly, and consistent with digital token-valuation models that rely on network externalities, platform tokens and utility tokens receive a significant additional return premium.

4.6. Regression specifications including marketplace characteristics

As the equities' cross-listing literature suggests, it is very difficult to isolate channels related to reducing market segmentation, management bonding, or improvements in information production, as markets might also be segmented due to differences in management bonding and the information-production environment. For instance, some investors might be legally precluded from participating in unregulated markets, so while the addition of regulation in a market will directly affect management disclosures and information production, it will also indirectly reduce market segmentation, as some previously banned investors can now enter. Another example would be the entrance of sophisticated investors to a new market (market integration). While this directly reduces market segmentation, it might also indirectly affect the monitoring and information production of firms. More specifically, the proxies commonly used to measure the levels of market segmentation, management bonding, and information production are highly correlated.

The benefit of using the token ecosystem is that, given the lack of specific marketplace regulations, each marketplace has the ability to choose a broad variety of observable operational decisions that have varying levels of correlation with each theory. As distinct from

[10] We performed analogous estimations using abnormal trading volume as independent variable with similar and consistent results. The results are available from the authors upon request.

Table 6
Token characteristics and index-adjusted cumulative returns.

	(1)		(2)	
ICO	0.17		−0.15	
	(0.26)		(0.25)	
# of current pricing denominations	−0.11	***	−0.10	***
	(0.03)		(0.03)	
Past returns	−0.13	*	−0.15	**
	90.06)		(0.07)	
Past trading volume	−0.05		−0.08	**
	(0.03)		(0.04)	
Past market presence	0.42	*	0.44	**
	(0.20)		(0.19)	
Platform			0.65	**
			(0.29)	
Utility			0.67	**
			(0.27)	
Currency			0.19	
			(0.15)	
Security			−0.08	
			(0.24)	
Constant	0.34		0.42	
	(0.26)		(0.24)	
Adjusted R-square	0.04		0.08	
No. obs	364		364	

For all columns, the dependent variable is the index-adjusted cumulative return, defined as $\frac{1 + \textit{Raw Cumulative Token Return}}{1 + \textit{Cumulative Index Return}} - 1$. Raw Cumulative Token Return is defined as $\frac{\textit{Token price in USD}_{t+14}}{\textit{Avg.Token price in USD}\,[-28, -14]} - 1$ All explanatory variables are measured at t_{-14}, considering the first cross-listing date as t_0. The first cross-listing date is the first day a token is traded in the cross-listing exchange. *ICO* is a dummy variable that equals 1 if the tokens had an initial coin offering. *# of current pricing denominations* is the number of distinct tokens and fiat currencies used as price denominators in the initial marketplace. *Past returns* is the log of (1+ the 14-day cumulative index-adjusted return on a token). *Past volume* is the log of (1 + the 14-day average traded volume) measured in dollars. *Past market presence* is the 14-day average of a dummy variable equal to 1 if the token was traded during that day. *Platform, Utility, Currency*, and *Security* are dummy variables that equal 1 if the token is classified into that category, using the Blockchain Research Institute taxonomy. Omitted category is *Asset.* Standard errors are clustered at marketplace level and shown in parenthesis beneath the estimates. Asterisks denote significance level: one asterisk denotes significance at the 10% level, two asterisks denote significance at the 5% level, and three asterisks denote significance at the 1% level. Heteroskedasticity-consistent standard errors, are shown in brackets.

equity market, where marketplace rules are almost identical and thus difficult to isolate rules' impact, the token ecosystem may not bear that limitation. For instance, in terms of market segmentation, it is clear that users without access to a specific token denomination (ETH versus BTC, for instance) are segmented from those that do. This does not imply that one group has unique monitoring requirements or that a marketplace using predominantly BTC would provide a different signal quality from that of a marketplace using ETH. Therefore, we assign cross-listing characteristics according to the theory to which they are most closely related, without claiming full independence from alternative theories. Moreover, as some of the characteristics are correlated, we cannot test all characteristics jointly as it would result on a noisy estimate due to multicollinearity. We therefore test each set of characteristics independently and observe that characteristics related to market segmentation and quality signaling provide consistent results, but we are unable to isolate each characteristic's individual effect, nor rule out the existence of an omitted variable bias.

Regarding cross-listing characteristics that relate to the market-segmentation hypothesis, we include the relative trading volume of initial and cross-listing marketplaces, their pricing denominations, and additional service. In terms of cross-listing characteristics linked to information production, we consider the jurisdiction of the cross-listing marketplace, additional potentially regulated practices, and the token-selection process.

4.7. Evidence consistent with market segmentation

In columns (1) through (4) of Table 7, we present the results of regressions that add alternative measures of cross-listing trading volumes to the baseline control variables: differences in volumes from the initial marketplace and cross-listing marketplace, in terms of both total volume and volume per token, as well as dummy variables indicating cross-listing on a marketplace with higher total or per-token volume. These regressions enable us to evaluate the influence of cross-listing marketplace volumes on the returns of tokens. The results indicate that no measure of differences in trading volume is related to the index-adjusted cumulative return, rejecting access purely to a larger user/investor market as a source of value creation in the token ecosystem.

Columns (5) through (7) show the results of regressions that add measures of market diversity based on the pricing denominations used by each marketplace. Marketplaces are free to choose tokens and fiat currency to be used as price denominators on their platforms, and users/investors are required to pay in the chosen denomination for their transactions. Cross-listing to a marketplace that uses alternative pricing denominators could potentially expand the user/investor pool that can trade the token (if those investors

Table 7
Index-adjusted cumulative return and marketplaces' characteristics related to market segmentation.

	Dependent variable: Index Adj Cumulative Return								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Difference in marketplace volume	0.01								
	(0.02)								
Difference in token volume		0.01							
		(0.02)							
Cross-list to marketplace with higher volume			0.18						
			(0.14)						
Cross-list to marketplace with higher token volume				0.16					
				(0.13)					
Difference in pricing denominations					0.33 ***				
					(0.10)				
Cross-list to marketplace with more pricing denominations						0.69 ***			
						(0.11)			
Add BTC							0.34 ***		
							(0.07)		
Add ETH							0.08		
							(0.24)		
Add LTC							0.33		
							(0.27)		
Add DOGE							1.17 ***		
							(0.39)		
Add USDT							−0.06		
							(0.10)		
Add WAVES							−0.71 *		
							(0.37)		
Add USD							0.16		
							(0.18)		
Additional sophisticated services								0.00	
								(0.12)	
Add Maker-Taker fee structure									−0.12
									(0.15)
Add Rebates									0.02
									(0.19)
Add Margin trading									0.33 ***
									(0.16)
Add OTC trading									−0.42
									(0.33)
Constant	0.27	0.29	0.15	0.19	0.01	0.12	0.25	0.33	0.21
	(0.30)	(0.33)	(0.28)	(0.28)	(0.29)	(0.265)	(0.22)	(0.24)	(0.24)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-square	0.05	0.05	0.05	0.05	0.10	0.10	0.14	0.06	0.10
No. obs	364	364	364	364	364	364	364	215	215

For all columns, the dependent variable is the index-adjusted cumulative return, defined as $\frac{1 + \textit{Raw Cumulative Token Return}}{1 + \textit{Cumulative Index Return}} - 1$. Raw Cumulative Token Return is defined as $\frac{\textit{Token price in USD}_{t+14}}{\textit{Avg.Token price in USD}\,[-28, -14]} - 1$ All explanatory variables are measured at t_{-14} considering the first cross-listing date as t_0. The first cross-listing date is the first day a token is traded in the cross-listing exchange. Control variables include all token characteristics as defined in Table [10] (*ICO, # of current pricing denominations, Past returns*, *Past volume*, *Past market presence, Platform, Utility, Currency,* and *Security)*. *Difference in marketplace volume* is the log difference in the [−28, −14] average trading volume between the cross-listing marketplace and the initial marketplace. *Difference in token volume* is the log difference in the [−28,-14] average trading volume per token between the cross-listing marketplace and the initial marketplace. *Difference in pricing denominations* is the difference in the number of pricing denominations used in the cross-listing marketplace vs. the initial marketplace. *Cross-list to a marketplace with higher volume, Cross-list to a marketplace with higher token volume, Cross-list to a marketplace with more pricing denominations,* are dummy variables that equal 1 accordingly to their description. *Add [denomination]* is a dummy that equals I if cross-listing the token will add the respective denomination to the token's available trading pairs. *Additional sophisticated services* is the number of additional services that would be available after cross-listing. Maker–taker fee structure corresponds to the differentiated fee structure for liquidity makers and liquidity takers. In all observed cases, makers face a lower fee than takers. Rebates correspond to trading fee discounts based on trading volume. Margin trading corresponds to leveraged trading. OTC trading reflects services that allow trading without posting or matching orders through the order book. Add [service] is a dummy that equals 1 if cross-listing the token would provide access to that service. Standard errors are clustered at the marketplace level and are shown in parentheses beneath the estimates. Asterisks denote significance level: one asterisk denotes significance at the 10% level, two asterisks denote significance at the 5% level and three asterisks denote significance t the 1% level. Heteroskedasticity-consistent standard errors, are shown in brackets.

cannot access the pricing denominator of the initial exchange) or reduce the cost of trading (if those investors can access the denominator at the initial marketplace by paying a transaction fee).

We find that cross-listing to a marketplace with more pricing denominations is associated with higher index-adjusted cumulative returns, as shown in columns (5) and (6). In column (7), we report the results of exploring how each of the seven most frequently used denominations are associated with index-adjusted cumulative returns and find that cross-listing to a marketplace that adds BTC or DOGE to the available pricing denominations generates higher returns.

In columns (8) and (9), we report the results of exploring whether cross-listing to marketplaces that add service offerings for sophisticated investors and traders affects the pricing and trading dynamics of tokens. Marketplaces that provide these services are more likely to cater to sophisticated investors than those that do not, so cross-listing to a marketplace that adds these services would provide access to this segment of investors. In column (9) we show that cross-listings that add margin trading are associated with higher returns.

The results of higher returns associated with reducing market segmentation and accessing complementary markets also support token-valuation models that rely on network diversity and growth as sources of value creation.

4.8. Evidence consistent with improved information production and token quality-signaling

Regarding cross-listing characteristics associated with information production and quality-signaling, we first study the impact of marketplace jurisdiction, as shown in column (1) of Table 8. Cross-listing to marketplaces under the jurisdiction of countries with laws, regulations, or sandboxes that apply to the crypto-ecosystem (Canada, China, Japan, Malta, New Zealand, South Korea, the United

Table 8
Index-adjusted cumulative return and marketplaces' characteristics related to information production and quality signaling.

	(1)	(2)	(3)	(4)	(5)	(6)
Crypto-regulation jurisdiction	0.27 ***					
	(0.09)					
Cross-listing adds US customers		0.00				
		(0.10)				
Cross-listing adds mandatory KYC		−0.07				
		(0.24)				
Cross-listing adds KYC available		0.29 **				
		(0.12)				
Cross-listing adds fiat currency		0.29 *				
		(0.17)				
Cross-listing marketplace does not accept listing requests			−0.10			
			(0.28)			
Cross-listing marketplace requires listing review				0.43 **		
				(0.18)		
Cross-listing marketplace requires listing fee					0.44 **	
					(0.20)	
Cross-listing marketplace requires user votes						0.08
						(0.16)
Constant	0.33	0.24	0.33	−0.16	−0.12	−0.23
	(0.24)	(0.23)	(0.24)	(0.26)	(0.27)	(0.26)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Restricted sample	No	No	No	Yes	Yes	Yes
Adjusted R-square	0.06	0.09	0.06	0.09	0.08	0.06
No. obs	364	215	288	270	270	270

For all columns, the dependent variable is the index-adjusted cumulative return, defined as $\frac{1 + Raw\ Cumulative\ Token\ Return}{1 + Cumulative\ Index\ Return} - 1$.Raw Cumulative Token Return is defined as $\frac{Token\ price\ in\ USD_{t+14}}{Avg.Token\ price\ in\ USD\,[-28, -14]} - 1$. Control variables include all token characteristics as defined in Table [10] (*ICO*, *# of current pricing denominations, Past returns, Past volume, Past market presence, Platform, Utility, Currency,* and *Security)*. Crypto-regulation jurisdiction is a dummy that equals 1 if the country of jurisdiction of the cross-listing marketplace has enacted a regulation/sandbox addressing the crypto-ecosystem (in favor or against). *Cross-listing adds US customers, Cross-listing adds mandatory KYC, Cross-listing adds KYC available* and *Cross-listing adds fiat currency* are dummy variables that equal 1 if cross-listing the token gives it an attribute it previously did not have. For example, *Cross-listing adds US customers* equals 1 if cross-listing the token makes it available to US customers (and therefore was not previously available). *Cross-listing marketplace does not accept listing requests* equal 1 if the cross-listing marketplace chooses the tokens it lists without the influence of third parties (issuers, investors or users). *Cross-listing requires listing review, requires listing fee,* and *requires user votes* are non-mutually exclusive dummies defined according to their names. In columns (4), (5) and (6), the sample is restricted to tokens that cross-list to marketplaces that accept listing requests. Standard errors are clustered at the marketplace level and are shown in parentheses beneath the estimates. Asterisks denote significance level: one asterisk denotes significance at the 10% level, two asterisks denote significance at the 5% level, and three asterisks denote significance at the 1% level. Heteroskedasticity-consistent standard errors, are shown in brackets.

Kingdom, and the United States), regardless of whether they are favorable or not, results in higher index-adjusted cumulative returns.

Apart from the applicable jurisdiction, marketplaces can also be regulated according to the services they provide or the types of customers they choose to accept. For instance, marketplaces that accept US residents could be subject to jurisdiction of US institutions and hence are likely to be more selective in the set of tokens they list, as to comply with US regulations. Marketplaces that accept fiat currencies must maintain banking relationships and are usually subject to money-transmitter regulations. In column (2), we report the results of exploring the effects of adding potentially regulated practices and find that there is a higher index-adjusted cumulative return when cross-listing adds voluntary KYC practices or leads to the addition of trading in fiat currencies, but no effect if it adds US customers or enforces mandatory KYC practices.

It is important to mention that most of the potential regulations, whether they arise from the marketplaces' services or jurisdictions, will affect marketplaces and their customers, not token issuers. This is significantly different from what occurs in most equity markets, where listings require adherence to specific regulations, provision of timely financial and business disclosures, payment of transparent listing fees, and so on. In the current state of regulations, for the set of marketplaces and jurisdictions in the sample, the closest direct effect on token issuers relates to the ensuing risk of a token's being considered a security and therefore making any marketplace that lists it potentially liable for operating without compliance with the proper security market regulations. This in turn would influence the token-selection process performed by the marketplace.

We analyze the effects of these decisions and report the results in columns (3) through (6). In column (3) we report results of testing whether marketplaces that do not accept external listing requests (and hence perform independent evaluations to decide which tokens to list, making them less likely to be influenced unduly of issuers and users/investors) receive an additional return. We do not find evidence of such outcome. To obtain the results reported in the additional columns we restrict the sample to marketplaces that do accept outside listing requests. We find that cross-listing to marketplaces that require a listing review (any type of evaluation performed by the marketplace prior to the listing of a token) or charge a listing fee is associated with higher returns, whereas user voting (appealing to the "wisdom of the crowd") is not ((as shown in columns (4), (5) and (6)). Given the decentralized nature of blockchain and token projects, listing requests, listing reviews and payment of listing fees could be performed by parties other than the founders or leaders of such projects (for instance, large token holders, investors, or miners). This fact should not invalidate the result's interpretation, as the identity of the process initiator is not observable, hence the market participants' reactions should not be influenced by this characteristic.

Summarizing the above-reported results, there are positive returns on improved information production and token quality-signaling to be earned by cross-listing to marketplaces under stricter official or self-imposed regulations.

5. Conclusion

We provide the first empirical analysis of returns, trading activity and network behavior around cross-listings in the token ecosystem and find significant returns as well as increases in trading volume, market presence and user network growth for cross-listed tokens.

Tokens earn a raw cumulative return of 49% from two weeks prior to two weeks following a cross-listing day, with two-thirds of the returns accruing in the pre-cross-listing period. These higher returns remain highly positive and significant after adjusting for potential market-wide token appreciation and crypto-specific risk factors. Adjusting for returns on Bitcoin and the MVIS Index, the cumulative abnormal returns are 27.9% and 15.5% respectively. Lastly, the cumulative abnormal return is 16.3% adjusting for the expected return estimated using a three-factor pricing model based on crypto-specific risk premiums of the market, size and momentum of tokens.

In terms of trading volume, the initial marketplace displays an increase of 200% relative to the pre-cross-listing trading volume, and of 180% after controlling for changes in overall trading volume for all other tokens traded in the same marketplace. The joint trading volume (the sum of the volumes in both initial and cross-listing marketplaces) is almost 50 times higher than the pre-cross-listing baseline. This large increase in trading volume indicates the existence of market segmentation across marketplaces, as some users/investors seem to be able to trade a cross-listed token only after it is listed on a cross-listing marketplace.

We use heterogeneity in token and marketplace characteristics to identify specific mechanisms for value creation. With heterogeneity in the practices and policies of token marketplaces, we identify the specific characteristics that are relevant to value creation within each channel. We find that digital tokens that enable platforms and peer-to-peer networks earn higher returns and generate higher abnormal trading. This is consistent with current digital-token valuation theories that rely on network effects. To the best of our knowledge, this is the first paper to provide evidence of such a mechanism, which does not exist in traditional securities.

Cross-listings also earn higher returns when they involve marketplaces that target multiple user/investor segments. Higher returns are associated with cross-listings to marketplaces that cater to alternative sets of users/investors, but not to higher-volume marketplaces that cater to the same set of users/investors. This is consistent with the market segmentation hypothesis of equity cross-listings.

Cross-listings also earn higher returns when cross-listing leads to a stricter regulatory environment. This is consistent with value creation through improving information production by markets and quality signaling by issuers. These findings contrast directly to the popular opinion that a "Wild West" of unregulated trading causes prices and trading volumes of digital tokens to grow rapidly. Our findings show that stricter policies, whether voluntary or mandatory, lead to higher returns.

Lastly, for tokens issued on the Ethereum blockchain, we find that there is a large and significant increase of on-chain transactions (up to 300% higher than the baseline) and on-chain token volume (up to 600% higher than the baseline) around the date of cross-listing. We also find an increase in the number of addresses holding the cross-listed tokens, in accordance with the network effect theories.

As a caveat, the introduction of multiple channels of trading cross-listed digital tokens may create additional risks to market function and investor protection. Our reported findings of attractive returns and more volume and activities, post cross-listings, have policy implications in terms of scrutiny and more transparent regulations to reduce financial misconduct in the digital marketplace. Despite growing trends in regulations in different countries, it is plausible to anticipate that the new phase of trading on different platforms (cross-listings of digital tokens) would add another layer of complexity and disclosure requirements that demands a closer attention of the regulators at both domestic and global levels.

Appendix A

Table A1
Variable definitions.

Variable	Description
Token Characteristics	
Currency	Dummy variable equal to 1 if the token is classified as a currency token
Utility	Dummy variable equal to 1 if the token is classified as a utility token
Protocol	Dummy variable equal to 1 if the token is classified as a protocol token
Asset	Dummy variable equal to 1 if the token is classified as an asset token
Security	Dummy variable equal to 1 if the token is classified as a security token
Blockchain	Dummy variable equal to 1 if the token is hosted on its own blockchain
ERC 20	Dummy variable equal to 1 if the token is hosted on Ethereum and complies with the ERC 20 standard
Characteristics pre cross-listing ($t = -14$)	
Days since initial listing	Number of days from initial listing
Daily return since listing (USD)	Total buy and hold return divided by the number of days since listing, measured in USD
Daily return since listing (BTC)	Total buy and hold return divided by the number of days since listing, measured in Bitcoin
Cumulative return [−28,-14]	Cumulative return from t-28 to t-14, measured in USD
Bitcoin adjusted cumulative return [−28,-14]	Cumulative return from t-28 to t-14, adjusted for the return of bitcoin
Average volume (USD) [−28,-14]	Average daily traded volume from t-28 to t-14, measured in USD
Market presence [−28,-14]	Average from t-28 to t-14 of a dummy variable equal to 1 if the token was traded on a specific day
Characteristics post cross-listing (t = +14)	
Cumulative return from price at t-14	Cumulative return from price at t-14, measured in USD
Bitcoin adjusted CAR from price at t-14	Cumulative abnormal return from price at t-14, adjusted for the return in bitcoin
Index adjusted CAR from price at t-14	Cumulative abnormal return from price at t-14, adjusted for the return of the MVIS Index
Crypto-specific 3 factor model adjusted CAR	Cumulative abnormal return from price at t-14, adjusted for the expected token return based on a crypto-specific 3 factor model
Volume at initial marketplace (USD)	Traded volume at initial marketplace, measured in USD
Volume at cross-listing marketplace (USD)	Traded volume at cross-listing marketplace, measured in USD
Total volume (USD)	Sum of the traded volume at the initial and cross-listing marketplaces, measured in USD
Abnormal volume at initial marketplace	Ratio of Volume at initial marketplace (USD), divided by the average volume (USD) [−28,-14], minus 1
Abnormal volume at cross-listing marketplace	Ratio of Volume at cross-listing marketplace (USD), divided by the average volume (USD) [−28,-14], minus 1
Abnormal total volume	Ratio of Total volume (USD), divided by the average volume (USD) [−28,-14], minus 1
Market presence at initial marketplace	Dummy variable equal to 1 if the token is traded on the initial marketplace at t + 14
Market presence at cross-listing marketplace	Dummy variable equal to 1 if the token is traded on the cross-listing marketplace at t + 14
Market presence at any marketplace	Dummy variable equal to 1 if the token is traded on any marketplace at t + 14
Marketplaces' listing process	
Accepts listing proposals	Dummy variable equal to 1 if the marketplace accepts listings proposals
Charges listing fee	Dummy variable equal to 1 if the marketplace charges a listing fee
Requires listing review	Dummy variable equal to 1 if the marketplace applies a listing review process before listing a token
User vote on listings	Dummy variable equal to 1 if the marketplace approves listings based on a user voting system
Marketplaces' regulations	
Accepts US users	Dummy variable equal to 1 if the marketplace accepts US customers
KYC process required	Dummy variable equal to 1 if the marketplace requires a mandatory know your customer process
KYC process available	Dummy variable equal to 1 if the marketplace offers a voluntary know your customer process
Marketplaces' procedures and policies	
Maker-taker fees	Dummy variable equal to 1 if the marketplace offers a differentiated fee structure for liquidity makers and liquidity takers.
Rebates on trading volume	Dummy variable equal to 1 if the marketplace offers trading fee discounts based on trading volume
Margin trading	Dummy variable equal to 1 if the marketplace offers leveraged trading
OTC trading	Dummy variable equal to 1 if the marketplace offers services that allow trading without posting or matching orders through the order book
Institutional trading	Dummy variable equal to 1 if the marketplace offers a differentiated access or services targeting institutional investors
Derivatives trading	Dummy variable equal to 1 if the marketplace offers derivatives trading

(*continued on next page*)

Table A1 (*continued*)

Variable	Description
Marketplaces' jurisdiction	
Country	Dummy variable equal to 1 if the marketplace declares the respective country of jurisdiction in their "Terms of Service"

Table A2
Token characteristics and the probability of delisting.

	Dependent variable: De-listing dummy							
	Time-varying Cox Hazard Model		Static Cox Hazard Model		Time-varying Competing Risk Model		Static Competing Risk Model	
	(1)		(2)		(3)		(4)	
ICO	**0.61**	***	**0.54**	***	**0.45**	***	**0.37**	***
	(0.10)		*(0.08)*		*(0.07)*		*(0.06)*	
# of current trading pairs	**1.05**	**	**0.79**	***	**1.12**	***	**0.84**	***
	(0.02)		*(0.01)*		*(0.02)*		*(0.01)*	
Past returns	**0.90**	***	**0.93**	**	**0.90**	***	**0.92**	***
	(0.03)		*(0.03)*		*(0.03)*		*(0.03)*	
Past volume	**0.95**	***	**0.91**	***	**0.92**	***	**0.91**	***
	(0.02)		*(0.01)*		*(0.02)*		*(0.01)*	
Past market presence	**0.43**	***	**0.67**	***	**0.50**	***	**0.70**	***
	(0.06)		*(0.07)*		*(0.06)*		*(0.07)*	
# Tokens	*2741*		*2741*		*2741*		*2741*	
# De-listed	*1146*		*1146*		*1146*		*1146*	
# Censored	*1595*		*1595*		*950*		*950*	
# Cross-listed					*645*		*645*	
# Observations	*549,562*		*2741*		*549,562*		*2741*	

In all models, the dependent variable is a dummy that equals 1 at the time of delisting. *ICO* is a dummy variable that equals 1 if the tokens had an initial coin offering. *# of current trading pairs* is the number of distinct tokens and fiat currencies used as price denominators in the initial marketplace. *Past returns* is the log of (1.01+ the 14-day cumulative return on a token) measured in bitcoin. *Past volume* is the log of (1.01 the 14-day average traded volume) measured in dollars. *Past market presence* is the 14-day average of a dummy variable that equals 1 if the token was traded during that day. All explanatory variables are measured with a 14-day lag from delisting. The results reported in columns (1) and (2) correspond to Cox proportional hazard regressions, where tokens that are not cross-listed (delisted or listed in only one marketplace) are considered censored and the estimated coefficients are equal to the hazard ratio compared with the mean baseline. The results reported in columns (3) and (4) correspond to Cumulative Incidence Competing Risk (CIRC) regressions, where the competing risk is delisting, and observations from tokens listed in only one marketplace are considered censored. The estimated coefficients correspond to the sub-hazard ratios compared with the mean baseline. The results reported in columns (1) and (3) are time-series models that allow for time-varying variables, while models (2) and (4) are static models that use the last available observation for estimation. For models (1) and (3), standard errors are clustered at the token level. Asterisks denote significance levels: one asterisk denotes significance at the 10% level, two asterisks denote significance at the 5% level, and three asterisks denote significance at the 1% level.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcorpfin.2020.101853.

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