Cryptocurrency Cross-listing Incentives and Abnormal Returns

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Abstract

This paper is the first to test the applicability of stock market cross-listing theories to the cryptocurrency market. The tested theories include the market segmentation theory, the liquidity theory, the information disclosure theory, and the investor protection theory. It is the first to consider the impact of the exchange's individual trading volume, licensing, and reputation on cryptocurrency cross-listing returns. The dataset contains 390 cross-listing events on 11 major centralized cryptocurrency exchanges from January 2020 to December 2021. The abnormal cross-listing returns are measured in an event study setup based on the constant mean return model and the market model. This paper finds significant positive abnormal returns leading up to the cross-listing event that become negative from day one after the listing. The abnormal returns on the listing day are 2.35% for the constant mean return model and 2.02% for the market model. There are significant differences in cross-listing returns across individual exchanges that cannot be explained by differences in token-specific liquidity, and exchange-specific trading volume, reputation, and licensing. Cryptocurrency cross-listings significantly increase the token's social media volume up to on average 34.50% in the first three days following the cross-listing event. Overall, this paper finds evidence for the information disclosure theory but fails to find compelling evidence for the market segmentation, liquidity, and investor protection theory.

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1. Introduction

Cryptocurrencies are digital tokens that utilize blockchain technology to record transactions. They represent a new asset class that has drawn increasing attention among investors, researchers, and regulators. Cryptocurrencies are issued in an Initial Coin Offering either as coins that run on their own blockchain or as tokens on an existing blockchain. The latter has significantly reduced the technological entry barriers for projects to raise venture capital by issuing their own tokens. Once issued, tokens can be cross-listed on the secondary market. The trading infrastructure for digital tokens is provided by cryptocurrency exchanges that differ from traditional stock exchanges with regards to technological and regulatory features.

While stock market listings are extensively covered in the academic literature, the same does not apply to cryptocurrency listings. The existing literature on cryptocurrency listings focuses primarily on Initial Coin Offerings while less than a handful papers explicitly focuses on cryptocurrency cross-listings on the secondary market. This paper aims to fill this research gap by linking the theories developed in the stock market cross-listing literature to cross-listings within the new asset class of cryptocurrencies. For this purpose, this paper systematically tests the applicability of four popular stock market cross-listing theories, including the market segmentation theory, the liquidity theory, the information disclosure theory, and the investor protection theory. Section 2 introduces cryptocurrencies and blockchain technology and provides a detailed review on the stock market cross-listing literature and empirically testable implications for the four stock market cross-listing theories. Furthermore, the existing literature on cryptocurrency cross-listings is reviewed.

Section 3 introduces four hypotheses related to the stock market cross-listing theories. Due to its digital and distributed nature, the cryptocurrency market is expected to be highly integrated. One exception is the US-market where cryptocurrency exchanges must obtain licensing to legally serve US-customers. This results in an investment barrier that US-customers face since they are only able to invest in tokens listed on US-licensed exchanges. The market segmentation theory is tested based on the exchanges' US-licensing status and the assumption that a cross-listing on US-licensed exchanges removes the investment barrier and results in positive cross-listing returns. The liquidity theory suggests that a cross-listing of illiquid tokens is associated with improvements in liquidity measures that are reflected in abnormal returns. This paper tests the impact of the token-specific trading volume and market capitalization as well as the exchange-specific trading volume on cross-listing returns. The information disclosure theory suggests that cross-listings help to improve the token's information environment and remove information asymmetry among investors. This paper compares the token's social media volume before and after the cross-listing event as an indicator for improvements in the token project's information environment. Due to the lack of regulation, cryptocurrency cross-listings are associated with a lower level of investor protection compared to the stock market. This paper uses exchange-specific trust scores collected from popular cryptocurrency data provider websites as a measure for investor protection on a given exchange and tests if cross-listings on exchanges with a higher level of investor protection are associated with higher cross-listing returns.

Section 4 introduces the research design and provides descriptive statistics on the dataset. The dataset used in this paper contains 390 cross-listing events involving 216 individual tokens on 11 major centralized cryptocurrency exchanges from January 2020 to December 2021. The research is conducted in three steps. In the first step, the abnormal returns for the token associated with each cross-listing event are calculated based on the event study methodology introduced by MacKinlay (1997). For this purpose, the constant mean return model and the market model are applied. Both models measure the abnormal returns during several event windows. The multi-day event windows [-5, 5], [-3, 3], and [-1, 1] are used to track cumulative abnormal returns. To capture daily abnormal returns, single-day event windows ranging from 3 days before to 3 days after the cross-listing event are considered. The estimation window ranges from 28 to 7 days before the cross-listing event. The cross-listing dates vary across the individual cross-listing events. The mean return model takes the daily average return of the respective token during the estimation window as the benchmark for normal returns. The benchmark returns are used to identify abnormal returns during the event windows. The market model takes Bitcoin (BTC) as the market benchmark and estimates the linear relationship between the daily Bitcoin returns and the daily returns of the respective token during the estimation window. The resulting coefficients are applied to the returns during the event windows to calculate abnormal returns.

The empirical results are presented in section 5. The paper finds highly significant abnormal cross-listing returns at the 5% and 1% level as measured by both, the constant mean return model and the market model. Starting from 5 days before the event to 5 days after the event, the abnormal returns cumulate up to 13% on day 1 after the listing. From day 2 onwards the average daily and cumulative abnormal returns become negative. The day of the cross-listing event is associated with an average abnormal return of 2.35% as measured by the constant mean return model and 2.02% as measured by the market model. The highest single-day average abnormal returns are observed on day 1 after the cross-listing with 4.36% as measured by the constant mean return model and 4.50% as measured by the market model. In the second step of the research, a multivariate regression setup is introduced to test the implications derived from the market segmentation, liquidity, and investor protection theory. The paper fails to establish a statistically significant relationship between token- and exchange-specific liquidity measures and cross-listing returns and therefore fails to provide evidence for the liquidity theory. The same applies to the exchange's reputation measured by the exchanges' trust scores that are not found to be a significantly related to cross-listing returns. The US-licensing status is found to have a significant positive impact on cross-listing returns. In line with the market segmentation theory, a US-licensed exchange is all else equal associated with around 11.4% higher cumulative abnormal returns during the [-3, 3] event window after controlling for quarter-fixed effects. However, within the group of US-licensed exchanges, the abnormal returns are mainly driven by cross-listings on Coinbase. After removing cross-listing events on Coinbase from the dataset, the abnormal returns reduce to around 0.38%. In the third step, the social media volume of each individual token is compared before and after the listing. In line with the information disclosure theory, the social volume significantly increases after the cross-listing. Compared to the estimation window, the average daily increases in social media volume are around 35%, 26%, and 10% for the [0, 3], [0, 7], and [3, 14] event window, respectively.

Section 6 concludes the findings. Within the existing cryptocurrency cross-listing literature, this paper is the first to consider the impact of the exchange-specific trading volume, publicly available exchange trust scores, and the exchanges' US-licensing status on cross-listing returns. Furthermore, this paper is the first to link social metrics to cryptocurrency cross-listings to study the impact of cross-listing events beyond token returns.

2. Theoretical background

2.1 Blockchain technology and cryptocurrencies

Blockchain technology utilizes cryptography to create a permanent, chronological, and tamper-proof record of digital transactions (Treiblmaier, 2018). The transactions are authorized by digital signatures and aggregated into blocks that are time-stamped and linked to the data stored in previous blocks using cryptographic hash functions. Cryptographic hash functions are one-way functions that take an arbitrary-sized input to produce an alphanumeric output string of fixed length. Since any change in the input results in an unpredictable change in the output, changes in the data stored in earlier blocks of the chain are easily detectable (Andoni et al., 2019).

Blockchain technology can be applied in peer-to-peer networks to create a distributed database that is stored across multiple entities. Within a blockchain network, participants utilize a consensus mechanism to agree on the data stored on the blockchain. Popular consensus mechanisms include proof-of-work that ties the participants' voting power to their computing power and proof-of-stake that ties the participants' voting power to the amount of digital currency they deposited (Andoni et al., 2019). Depending on the distribution of voting power among the network participants, varying degrees of decentralization can be achieved within the network. In the context of cryptocurrencies, consensus mechanisms are not only used to verify the transaction data stored on the blockchain. In most cases they also control the issuance of newly minted units of digital currency in a process called mining. In this process network participants are rewarded with units of newly minted currency if their proposed block of transactions gets accepted as the next block in the chain by the remaining network participants. The rate of issuance and the total supply of the digital currency are specified in the blockchain protocol. Therefore, blockchain technology applied in a network governed by a consensus mechanism removes the need for a central authority to verify transactions or conduct monetary policies (Wang et al., 2019).

Haber and Stornetta (1991) were the first to introduce the concept of a chain of blocks secured through cryptographic functions. Referring to this initial concept, Bitcoin founder Satoshi Nakamoto combined blockchain technology with the internet to serve as the infrastructure for a blockchain-based digital payment system for peer-to-peer transactions (Nakamoto, 2008). Since Bitcoin's introduction in 2009, many alternative cryptocurrencies were developed. In June 2022 there are almost 10,000 cryptocurrencies with a total market capitalization of more than one trillion US-Dollar (Coinmarketcap, 2022a). Some of these Altcoins were created as forks from the original Bitcoin open-source code while others developed new approaches to utilize blockchain technology. Ethereum founder Vitalik Buterin detached blockchain technology from the single purpose of storing financial transaction data and put it in the context of a state transition system where transactions are used to update the data stored on the blockchain (Buterin, 2014). Compared to Bitcoin, the two major innovations of the Ethereum blockchain are smart contracts and decentralized applications. Decentralized applications are programs written in code that will operate autonomously once deployed in the blockchain. The business logic behind decentralized applications is implemented through smart contracts that are triggered through transactions with other blockchain addresses and run automatically once the predefined conditions are met (Treiblmaier, 2018).

The introduction of Ethereum and other blockchain-based platforms with smart contract functionality revolutionized and accelerated the issuance of digital tokens in a process called Initial Coin Offering (Momtaz, 2020). In recent years, ICOs became a novel means for ventures to raise capital in the form of fiat currencies or major cryptocurrencies such as Bitcoin and Ethereum in exchange for digital tokens. The main benefits over traditional forms of raising venture capital are the elimination of intermediary costs, lower administrative barriers due to a lack of consistent regulation, and immediate access to a large pool of investors and liquidity (Amsden & Schweizer, 2018). A contributive factor to the popularity of ICOs was the introduction of Token Standards such as the ERC20 Standard, which was developed to standardize token issuance and ensure interoperability between the issued tokens and applications built on the Ethereum blockchain. Fisch (2019) confirms the significance of Token Standards in ICOs and observes higher valuations for ventures when issuing tokens that utilize the ERC20 Token Standard. In recent years, Ethereum established itself as the most popular blockchain platform for token issuance with more than 930 tokens issued using the ERC20 Token Standard until June 2022 (Etherscan, 2022). The term cryptocurrency refers to both, coins that run on their own blockchain and tokens that are issued through smart contracts on an existing blockchain. In practice, both sub-concepts are often used interchangeably which also applies for this paper (Amsden & Schweizer, 2018). The lack of regulation and the technological flexibility allows token issuers to customize their tokens with regards to economic, technological, and legal properties, which makes blockchain tokens a heterogenous asset class (Schmitt & Faber, 2020).

2.2 Cryptocurrency exchanges

Cryptocurrency exchanges are marketplaces that allow users to trade their tokens for other fiat- or cryptocurrencies. In contrast to stock exchanges, cryptocurrency exchanges have no fixed trading hours and can in theory even list tokens without a project's permission if their token is compatible with the exchange's protocol (Ante & Meyer, 2021). Blockchain technology enables the creation of both, centralized and decentralized marketplaces that differ with regards to technological features and regulation.

Like traditional security exchanges, centralized exchanges act as intermediary between buyer and seller and charge transaction fees for their service. Centralized exchanges require users to transfer their tokens to blockchain addresses that are controlled by the exchange, thereby taking custody of the users' tokens (Benedetti & Nikbakht, 2021). The trading happens outside the blockchain, and users may withdraw their tokens back to their personal blockchain addresses after trading. Given this practice, the users of centralized exchanges face a counterparty risk since they hand over the control of their tokens to the exchange. Major centralized exchanges accept fiat currency deposits and are target to regulatory oversight. In the United States, cryptocurrency exchanges fall under the scope of the Banking Secrecy Act (BSA) as financial institutions and money transmitters. This implies that cryptocurrency exchanges must register with the Financial Crimes Enforcements Network (FinCEN), implement AML and KYC programs, and obtain money transmitter licenses in the states they operate in (Hyatt, 2021). The largest centralized exchange in 2021 was Binance with a total trading volume of 7.7 trillion US-dollars (Curry, 2022).

In contrast to centralized exchanges, decentralized exchanges allow users to retain custody of their tokens. The most popular mechanism to implement the trading infrastructure on decentralized exchanges is through Automated Market Maker (AMM) smart contracts that run on the blockchain. Decentralized exchanges rely on liquidity providers that add trading pairs of tokens to liquidity pool smart contracts. Other users can use the liquidity pool to directly exchange the two tokens and pay trading fees to the liquidity providers in return (Mohan, 2022). In contrast to centralized exchanges, decentralized exchanges do not act as intermediaries between buyers in sellers. Furthermore, they do not accept fiat deposits and utilize stable coins to mimic fiat currency trades, instead. Fiat stable coins are tokens that represent units of a fiat currency such as the US-Dollar and utilize different mechanism to maintain a 1:1 peg to the underlying currency. To convert tokens into fiat currency, investors must redeem their stable coins with the stable coin issuer or via centralized exchanges which usually involves a withdrawal fee (Hampl & Gyönyörová, 2021). Since decentralized exchanges do not act as intermediaries and do not take customer deposits, they are not target to the same regulatory oversight as centralized exchanges. The largest decentralized exchange in 2021 was Uniswap, a decentralized application first deployed on the Ethereum blockchain with a total trading volume of 681.1 billion US-dollars (Sun, 2022).

2.2 Cross-listings

2.2.1 Stock market cross-listings

The traditional cross-listing literature is focuses mostly on firms' incentives to cross-list their shares on foreign exchanges and the potential benefits associated with the cross-listing. The most popular cross-listing theories revolve around market segmentation, liquidity, information disclosure, and investor protection (Roosenboom & van Dijk, 2009). In the following section, literature on all four theories and testable implications are reviewed.

The *market segmentation theory* was first introduced by Errunza and Losq (1985) and suggests that investment barriers restrict international capital flows, which increases the cost of equity capital for firms in less integrated markets. In their model, Errunza and Losq (1985) consider two groups of investors, unrestricted and restricted investors. Government restrictions only allow restricted investors to invest in a subset of eligible securities, resulting in a positive risk premium on ineligible securities. A cross-listing makes the shares available to restricted investors, which reduces the risk premium, increases the share's equilibrium price, and decreases the firm's cost of equity capital. Examples for direct investment barriers that create market segmentation are taxes on foreign investments or restrictions on foreign ownership (Miller, 1999). The empirical literature is mainly centered around non-US firms that cross-list their shares on the US-market. Several studies find positive abnormal returns in the period leading up to the event and on the event date that the authors attribute to the market segmentation theory (Doukas & Switzer, 2000; Foerster & Karolyi, 1999). Dharan and Ikenberry (1995) find positive returns prior to and negative returns after the listing. In a sample of Canadian firms that cross-list their shares on the US market, Mittoo (2003) finds decreasing cross-listing returns in the post-1990 period compared to the pre-1990 period and suggests a greater market integration between both markets over time. You et al. (2013) analyses firms with multiple cross-listing events and observes diminishing abnormal returns as the number of cross-listings for a given firm increases.

The *liquidity theory* suggests that firms cross-list their shares on more liquid foreign markets to increase the shares' liquidity. Amihud and Mendelson (1986) provide the theoretical framework for positive cross-listing returns as they show that expected return is an increasing concave function of the bid-ask spread. Hence, increasing the liquidity through cross-listings leads to decreasing spreads and positive cross-listing returns. Some empirical studies find improvements in several liquidity metrics around the cross-listing date, including decreasing bid-ask spreads, and increasing trading volume (e.g., Elyasiani et al., 2000; Foerster & Karolyi, 1998), while more recent studies fail to observe significant improvements in liquidity metrics after the cross-listing (e.g., Berkman & Nguyen, 2010; Silva & Chávez, 2008).

The *information disclosure theory* suggests that firms cross-list their shares to improve their information environment and reduce the information asymmetry among investors. Easley and O'hara (2004) link the firm's information environment to its cost of equity capital since uninformed investors demand higher returns if informed investors possess private information. The premium associated with a poor information environment corresponds to the risk that informed investors react faster to new information. This suggests that improvements in the firm's information environment can reduce the risk premium and hence the cost of equity capital. The signaling theory developed by Spence (1978) states that information asymmetries between two parties can be reduced by sending costly signals. Applied to cross-listings, mandatory disclosure requirements in foreign markets in addition to the disclosure requirements in the home market are costly but can lead to improvements in the firm's information environment (Fuerst, 1998). Several studies find improvements in metrics of information environment, including improving media coverage, price informativeness, and analyst forecast accuracy (e.g., Baker et al., 2002; Fernandes & Ferreira, 2008; M. H. Lang et al., 2003). Cross-listing on exchanges with high disclosure standards are associated with positive returns, which in turn are positively related to the firms' growth opportunities (e.g., Amira & Muzere, 2011; Foucault & Gehrig, 2008). This is based on the idea that firms with more growth opportunities are associated with a higher degree of information asymmetry (Fosu et al., 2016). Lang et al. (2012) link the firm's information environment to liquidity metrics and find that firms with higher firm-level transparency have lower bid-ask spreads and fewer zero-return days.

The *investor protection theory* is based on the legal bonding theory introduced by Coffee Jr (1998, 2002) and suggests that firms cross-list their shares in jurisdictions with better investor protection to strengthen minority shareholder rights. Doidge et al. (2004) observes a cross-listing premium for firms who cross-list on the US market that is negatively related to the level of investor protection in the firm's home country. Abdallah et al. (2011) observes higher increases in trading volume for firms from countries with lower investor protection after the cross-listing.

2.2.2 Cryptocurrency cross-listings

The majority of literature on cryptocurrency listings centers around Initial Coin Offerings with cross-listings on secondary markets being less covered. Meyer and Ante (2020) link Initial Coin Offerings to cross-listings and study the relationship between ICO characteristics and cross-listing returns. According to their findings, the following four factors impact future cross-listing returns. These include the token allocation during the ICO, the ICO-regulation in the country the project is based in, the blockchain infrastructure used, and post-ICO returns. In contrast to the stock market literature (e.g., Miller, 1999), the cryptocurrency cross-listing literature fails to identify significant positive announcement returns after the initial cross-listing announcement (e.g., Ante & Meyer, 2021). The following studies all observe positive abnormal returns leading up to the cross-listing event. Ante (2019) and Ante and Meyer (2021) find negative returns after the listing event while the returns in Benedetti and Nikbakht (2021) remain positive post-listing. Ante (2019) identifies different returns across individual exchanges. Ante and Meyer (2021) observe higher returns for tokens with lower prior market capitalization and trading volume. Benedetti and Nikbakht (2021) observe increases in the tokens' trading volume and several blockchain metrics including on-chain transactions and on-chain token volume. Although existing cryptocurrency cross-listing literature addresses some of the metrics discussed in section 2.2.1, there is no systematic test for the applicability of the four traditional cross-listing theories on cryptocurrency cross-listings.

3. Hypothesis development

In order to fill this research gap, this paper tests the applicability of traditional stock market cross-listing theories on cryptocurrency cross-listings. For this purpose, the four most popular cross-listing theories presented in Roosenboom and van Dijk (2009) are considered. This includes the market segmentation theory, the liquidity theory, the information disclosure theory, and the investor protection theory.

The *liquidity theory* is tested by observing several liquidity metrics around the cross-listing date. The theoretical predictions of the liquidity theory are improvements in token-liquidity metrics, which will result in higher abnormal returns for less liquid tokens. The same applies for cross-listings on more liquid exchanges. The existing cryptocurrency cross-listing literature only considers token-specific liquidity metrics, including the market capitalization, trading volume, and the ratio between both metrics to estimate the effect of liquidity on cross-listing returns (Ante & Meyer, 2021; Benedetti & Nikbakht, 2021). This paper also takes into consideration the three token-specific metrics. In addition, the impact of exchange-specific liquidity on cross-listing returns is tested. To test the applicability of the liquidity theory, the following two hypotheses are developed.

Hypothesis 1a: The lower the token's trading volume relative to the market capitalization, the higher the cross-listing returns.
Hypothesis 1b: The higher the total trading volume on the exchange the token is listed on, the higher the cross-listing returns.

The *market segmentation theory* predicts positive returns on cross-listings that help to overcome market segmentation. A lack of regulation in combination with the digital and distributed nature of blockchain technology suggests a lower market segmentation in the cryptocurrency market compared to the stock market. The existing cryptocurrency cross-listing literature considers the effect of the exchange's country of jurisdiction on cross-listing returns (e.g., Ante, 2019; Benedetti & Nikbakht, 2021). However, major exchanges usually serve customers from multiple countries other than their country of jurisdiction. The United States is an exception since it requires exchanges to register with the FinCEN and obtain money transmitter licenses to legally serve US-customers (Hyatt, 2021). A cross-listing on US-licensed exchanges can therefore eliminate the market segmentation between US- and international markets by making the cross-listed tokens available to US-investors. Therefore, the US-licensing of an exchange is viewed as a more suitable measure to test for potential market segmentation. To test the applicability of the market segmentation theory, the following hypothesis is developed.

Hypothesis 2: Cross-listings on exchanges licensed to serve US-customers result in higher cross-listing returns.

The *information disclosure theory* predicts improvements in the token project's information environment after the cross-listing. In contrast to the stock market, cryptocurrency cross-listings usually come with no additional regulatory disclosure requirements to investors. However, cross-listings are expected to draw investor and analyst attention which improves the token project's information environment through third party coverage. This paper uses the token's social media volume as an indicator for the level of investor attention. Liu and Tsyvinski (2021) link the information environment to returns as they find that cryptocurrency returns are driven by investor attention and momentum. Significant increases in the token's social media volume around the cross-listing date for a given token project could indicate information disclosure motives. Unlike the existing cryptocurrency cross-listing literature, this paper is the first to examine social metrics around cross-listing events. To test the applicability of the information disclosure theory, the following hypothesis is developed.

Hypothesis 3: A cross-listing increases the token's social media volume.

The *investor protection theory* predicts a premium for cross-listings in countries with a higher level of investor protection. Since there is significant uncertainty on the regulatory treatment of cryptocurrency cross-listings in most countries, this paper uses another indicator for the level of investor protection on a given exchange. Established cryptocurrency data providers use exchange-specific metrics to construct a trust score for the individual exchanges. Some of the underlying metrics used to construct the trust scores are expected to correlate with the level of investor protection. This includes the amount and legitimacy of the trading volume reported, the regulation, and the level of security and data protection on a given exchange. As opposed to the existing cryptocurrency cross-listing literature, this paper is the first to consider the impact of the exchange's reputation on cross-listing returns. To test the applicability of the investor protection theory, the following hypothesis is developed.

Hypothesis 4: The higher the exchange's reputation measured by third-party trust scores, the higher the cross-listing returns.

4. Research design and data description

4.1 Event study methodology

Event studies are used to quantify the impact of a certain event on asset prices. This paper applies the event study methodology presented by MacKinlay (1997) to cryptocurrency cross-listing events between January 2020 and December 2021. The event study methodology consists of four steps.

1. Event definition

In the first step, the event of interest is defined. In the context of cryptocurrency cross-listings, the two events that come into question are the cross-listing announcement date and the actual cross-listing date. The sample used in this paper only contains cross-listings that were announced on the listing day as it is a common practice on major cryptocurrency exchanges. Since daily price data will be used for the estimation, there is no need to differentiate between the announcement and listing date. Hence, the event is defined as the day of the cross-listing. The cross-listing date differs across the individual cross-listing events and is referred to as t = 0.

The lack of regulation makes the cryptocurrency market prone to market manipulation and informed trading by insiders at exchanges or in the project team of the listed token (Feng et al., 2018). To get a robust estimation of abnormal returns in the presence of potential insider trading, this paper considers multiple event windows, including [-5, 5], [-3, 3], and [-1, 1]. Furthermore, pre- and post-listing abnormal returns are captured in the event windows [-5, -1] and [1, 5], respectively. The usual estimation window commonly used in the existing cryptocurrency cross-listing literature (e.g., Ante, 2019; Benedetti & Nikbakht, 2021) is adopted in this paper. It ranges from 28 to 7 days before the cross-listing event. Data points of overlapping estimation and event windows for cross-listings of the same token on different exchanges are removed from the dataset. Compared to the stock market, cryptocurrency cross-listings involving the same token occur more frequently, which is why a further expansion of the estimation window increases the risk of capturing the effects from multiple cross-listing events. Even though this paper considers major exchanges by trading volume, overlapping of cross-listing events with one of the 288 (as of 22/07/22) other centralized exchanges for any given token is possible (Coinmarketcap, 2022b). Furthermore, previous cross-listings may also include listings on other decentralized exchanges. This implies that the number of previous cross-listings for each individual token on any exchanges that are not part of the dataset varies.

2. Asset selection

In the second step, the selection criteria for tokens, exchanges and cross-listing events are determined. Compared to centralized exchanges, decentralized exchanges only play a minor role in cryptocurrency markets. In 2021, the total trading volume on the biggest centralized exchange Binance was ten times higher than the total trading volume on the biggest decentralized exchange Uniswap (Curry, 2022; Sun, 2022). Furthermore, the data on US-licensing and exchange reputation is only available for centralized exchanges. Decentralized exchanges are not target to the same regulation as centralized exchanges since decentralized applications operate autonomously once deployed on the blockchain and are not controlled by any legal entity. The traditional stock market cross-listing theories are developed for listings on centralized marketplaces with limited applicability to the innovation of decentralized marketplaces. Therefore, this paper only considers centralized exchanges to test the applicability of stock market cross-listing theories. The dataset consists of major centralized exchanges by average daily trading volume from January 2020 to December 2021. The individual exchanges are selected to create a heterogeneous dataset with regard to US-licensing and exchange reputation that is suitable for hypotheses testing. Cross-listing events for stable coins, token derivatives, tokens with incomplete price data, tokens with overlapping estimation- and event windows with other exchanges in the dataset, and tokens with public cross-listing announcements before the listing date are removed from the sample.

3. Establish normal and abnormal returns

To measure abnormal returns around the cross-listing date, a benchmark for normal returns needs to be introduced. This paper applies the constant mean return model and the market model to measure abnormal returns. MacKinlay (1997) defines the return measured by the *constant mean return model* as

$$R_{i,t} = \mu_i - \varepsilon_{i,t} \tag{1}$$
$$with\ E(\varepsilon_{i,t}) = 0, \qquad var(\varepsilon_{i,t}) = {\sigma_{\varepsilon_i}}^2$$

$R_{i,t}$ is the daily return for the token cross-listing event *i* that is calculated based on the mean return of the underlying token as observed during the estimation window μ_i with the error term $\varepsilon_{i,t}$.

For the market model, the Bitcoin (BTC) price is used as the market benchmark. Since its invention, Bitcoin has been the largest cryptocurrency by market capitalization. Furthermore, several studies identify the Bitcoin price as a significant factor to explain the return variation on other cryptocurrencies. Gonzalez et al. (2020) find that changes in Bitcoin returns explain around 50% of the return variation for the ten largest cryptocurrencies. Ciaian and Rajcaniova (2018) find that Bitcoin returns have significant explanatory power on short-term returns of other cryptocurrencies but reject this finding for long-term returns. Given that the estimation period used in this paper starts only four weeks prior to the cross-listing, Bitcoin returns are considered a suitable benchmark for the market return. According to MacKinlay (1997), the return measured by the *market model* is defined as

$$R_{i,t} = \propto_i + \beta_i R_{BTC,t} + \varepsilon_{i,t} \tag{2}$$

$$with\ E(\varepsilon_{i,t}) = 0, \qquad var(\varepsilon_{i,t}) = \sigma_{\epsilon_i}{}^2$$

$R_{i,t}$ is the daily return for cross-listing event *i*. The model parameters $\propto_i$ and β_i are calculated using ordinary least squares to map the linear return-relationship between the underlying token returns and the market benchmark Bitcoin (BTC) during the estimation window.

4. Measure and analyze abnormal returns

The constant mean return model and the market model result in the following daily abnormal returns for cross-listing event *i*, respectively.

$$AR_{i,t} = R_{i,t} - \mu_i \tag{3}$$

$$AR_{i,t} = R_{i,t} - \hat{\alpha}_i - \hat{\beta}_i R_{BTC,t} \tag{4}$$

Based on the abnormal returns, the average abnormal returns (ARRs) across N token cross-listing events are estimated. The cumulative abnormal returns (CARs) measure the cumulative return for the cross-listing event *i* during a specified event window that ranges from t_1 to t_2. The cumulative average abnormal returns (CAARs) capture the average cumulative return across the total sample of N token cross-listing events during an event window ranging from t_1 to t_2.

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \tag{5}$$

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \tag{6}$$

$$CAAR(t_1, t_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_i(t_1, t_2) \tag{7}$$

The event study methodology is based on the null-hypothesis that the cross-listing event has no impact, and the observed cumulative average abnormal returns during the event window [t_1, t_2] are different from zero only by chance (H_0: $E(CAAR(t_1, t_2)) = 0$). To test the significance of the measured cumulative average abnormal returns, the appropriate t-statistic is applied. $S_{CAAR(t_1, t_2)}$ is the standard deviation and $t_{CAAR(t_1, t_2)}$ the test statistic under the null hypothesis $E(CAAR(t_1, t_2)) = 0$.

$$t_{CAAR(t_1, t_2)} = \sqrt{N}\,\frac{CAAR(t_1, t_2)}{S_{CAAR(t_1, t_2)}} \tag{8}$$

$$S^2_{CAAR(t_{1,}t_2)} = \frac{1}{N-1}\sum_{i=1}^{N}(CAR_i(t_{1,}t_2) - CAAR(t_{1,}t_2))^2 \tag{9}$$

4.2 Regression methodology

In the following section, the regression methodology used to test hypothesis 1, 2, and 4 is introduced. Based on the multivariate linear regression, the impact of token- and exchange-specific metrics on cross-listing returns is analyzed to identify potential drivers of abnormal returns. In the following all variables and models are introduced.

4.2.1 Dependent variable: CAAR[-3, 3]

The results of the event study in section 5.1 indicate that the statistically most significant CAARs at the 1% level are observed in the event windows [-1, 1] and [-3, 3]. In terms of daily AARs, the returns on the days t = 1 and t = 2 are found to be statistically most significant. To capture all the statistically most significant abnormal returns, CAR_i[-3, 3] is selected as the dependent variable for each individual token cross-listing event *i*. The regression setup is applied to the abnormal returns measured by both, the constant mean return model and the market model. Since the event study results in section 5.1 are similar with regards to magnitude and statistical significance for both models, the results of the regression setup are expected to be similar for both models, as well.

4.2.2 Independent variables: Token-specific metrics

Hypothesis 1a states that a lower token-specific trading volume relative to the market capitalization during the estimation window leads to higher cross-listing returns during the event window. To test this hypothesis the variables *TTV*, *TMC*, and *TTV/TMC* are introduced. *TTV* is the token-specific average daily trading volume (in USD) during the estimation window [-28, -7] that is associated with a certain cross-listing event. *TMC* is the token-specific average daily market capitalization (in USD) during the estimation window [-28, -7] that is associated with a certain cross-listing event. *TTV/TMC* is the ratio between both metrics. It controls for the general tendency that tokens with a higher market capitalization are associated with a higher absolute trading volume and helps to identify illiquid tokens among tokens with a similar market capitalization. Since each individual token may be involved in more than one cross-listing event in the dataset, all token-specific measures are specific to an individual cross-listing event rather than to an individual token. A logarithmic transformation is applied to all token-specific metrics due to highly skewed distribution and the wide range of outliers in the dataset.

4.3.3 Independent variables: Exchange-specific metrics

Hypothesis 1b states that cross-listings on exchanges with a higher trading volume during the estimation window are associated with higher cross-listing returns during the event window. This is based on the assumption that the positive effect on token liquidity is more pronounced for cross-listings on exchanges with a higher trading volume which are therefore associated with higher abnormal returns. To test this hypothesis, the variable *ETV* is introduced. *ETV* is the exchange-specific average daily trading volume (in BTC) during the estimation window [-28, -7] on the exchange associated with a certain cross-listing event. Again, logarithmic transformation is applied. Hypothesis 2 states that cross-listings on exchanges licensed to serve US-customers are associated with higher cross-listing returns. The dummy variable *ExLicense* indicates if the exchange associated with a certain cross-listing event is registered with the FinCEN and obtained money transmitter licenses to legally serve US-customers. Hypothesis 4 states that cross-listings on exchanges with a higher average trust-score are associated with higher cross-listing returns. *ExReputation* is the average trust score the exchange received on the three popular cryptocurrency data provider websites coinmarketcap.com, cryptocompare.com, and nomics.com.

4.3.4 Final Regression setup

The final regression setup contains six models. Model 1 and 2 test hypothesis 1a and include all token-specific liquidity metrics. When combining the token-specific trading volume and market capitalization with the ratio between both measures, the Variance Inflation Factor (VIF) suggests significant collinearity between the measures. Therefore, the token-specific measures are tested in two separate models. Model 1 uses *ln(TTV)* and *ln(TMC)* as independent variables and Model 2 uses the ratio between both measures *ln(TTV/TMC)* as the independent variable. To control for unobserved effects related to the specific exchange the token is listed on and the time-varying market environment, exchange- and quarter-dummies are added to both regressions. Model 3 tests hypothesis 1b and includes the exchange-specific trading volume *ln(ETV)* and the quarter-dummies. Model 4 tests hypothesis 2 and includes *ExLicense* and the quarter-dummies. Model 5 tests hypothesis 4 and includes *ExReputation* and the quarter-dummies. Model 6 combines *ln*(*ETV), ExLicense*, *ExReputation*, and the quarter-dummies to assess the overall explanatory power of all three exchange-related variables on cross-listing returns in the dataset. All regression coefficients are calculated using an OLS-regression with the [-3, 3] event window measured by the constant mean return and the market model as the dependent variable, respectively. Since the Breusch-Pagan/Cook-Weisberg test rejects the null hypothesis of homoskedasticity for some of the models, heteroskedasticity-robust standard errors are used for the estimation.

4.3 Test for improvements in the information environment

Hypothesis 3 states that the cross-listing event increases the social media volume of the token. It is tested by comparing the token's social media volume before and after the cross-listing event. As applied in the event study, the estimation window [-28, -7] is used to calculate the average daily social media volume before each cross-listing event. Compared to the token returns used in the event study, the danger of capturing volume unrelated to the cross-listing event is even more relevant with regards to social media volume since it also captures token-specific information that is not reflected in price movements. In the event study, the event period was extended up to 5 days before the event date to capture potential insider trading activity leading up to the event. An expansion of the event window to pre-listing days is not necessary for the social media volume. Instead, three individual event windows starting from the cross-listing event date are considered. The event windows [0, 3] and [0, 7] are used to capture increases in social media volume immediately after the cross-listing. To test if potential increases in social media volume are only related to the listing announcements posted on social media platforms and assess if the increases are persistent, the event window [3, 14] is considered that starts 3 days after the initial listing announcement and covers the two weeks following the cross-listing event. A further expansion of the event window increases the likelihood that social media volume related to other token-specific events is captured. To test the statistical significance of the increases in social media volume during the three event windows relative to the estimation window, a paired sample t-test is applied. Since the t-test is based on the normality assumption and the observed social media volume significantly departs normality, a logarithmic transformation is applied to the social media volume data (e.g., *Social volume[-28, -7]* – skewness: 8, kurtosis: 71.5).

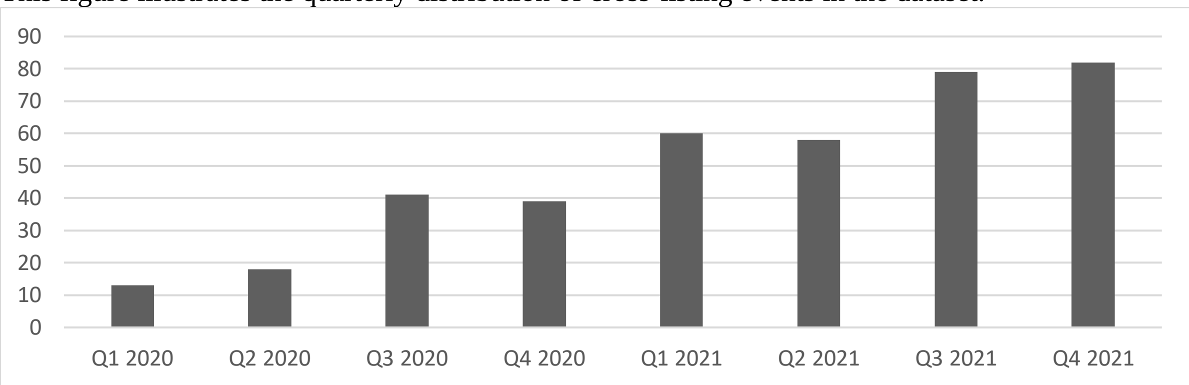
4.4 Data collection and descriptive statistics

The dataset used in this paper contains cryptocurrency cross-listing events at 11 major centralized exchanges by average daily trading volume from January 2020 to December 2021. The data on the exchange-specific daily average trading volume is obtained from the coingecko.com public API and reported in BTC. Table 1 reports that the largest exchange by daily average trading volume during the observation period is Binance with 424,931.4 BTC. The smallest exchange is Gemini with 4,214.3 BTC. The dates for the individual cross-listing events on all selected exchanges during the observation period are provided by cryptocurrencyalerting.com. After removing any cross-listing events for stable coins, token derivatives, and tokens with incomplete price data or overlapping estimation- and event windows, 390 cross-listing events are left in the dataset. Kucoin is the exchange with the most (115) and Gemini the exchange with the least cross-listing events (14) during the two-year observation period. Figure 1 reports that the total number of cross-listings on the 11 exchanges increased during the observation period. The quarter with the fewest cross-listings events is Q1 2020 with 13 cross-listings. The most cross-listings took place in Q4 2021 with 82 cross-listings.

Table 1: Exchange listings and trading volume
This table provides an overview on the distribution of the 390 cross-listing events across the 11 exchanges in the dataset. Descriptive statistics on the exchange-specific trading volume (in BTC) from January 2020 to December 2021 are provided.

		Average daily trading volume 2020-2021 (in BTC)				
Exchange	**Listings**	**Mean**	**Median**	**SD**	**Min**	**Max**
Binance	28	424,931.4	385,075.6	269,396.9	5,3639.9	2,780,971.0
Binance US	15	9,735.7	6,234.2	10,704.7	233.9	91,325.0
Bitfinex	21	23,694.1	18,936.9	20,779.0	3,452.8	268,595.8
Coinbase	38	69,441.1	58,648.0	48,884.7	8,458.7	476,409.8
FTX	23	22,233.7	12,143.1	23,411.3	191.3	161,517.9
Gemini	14	4,214.3	3,431.2	3,311.3	534.5	34,952.5
HitBTC	63	77,385.9	71,782.3	33,067.1	21,518.0	395,192.8
Huobi	22	155,717.0	134,494.9	95,150.3	43438.1	944,180.1
Kraken	26	30,030.1	25,002.0	19,802.7	4,932.6	216,023.4
Kucoin	115	22,920.0	15,294.8	19,843.7	2,992.5	120,939.0

Figure 1: Number of cross-listing events Q1/2020 – Q4/2021
This figure illustrates the quarterly distribution of cross-listing events in the dataset.



The exchanges are selected to construct a heterogenous dataset with regards to US-licensing and reputation that is suitable for testing the hypotheses developed in section 3. Table 2 reports the US-licensing status for each exchange that is taken from the respective exchange's website. The data on the exchanges' trust scores is taken from the websites of the three third-party cryptocurrency data providers coinmarketcap.com, cryptocompare.com, and nomics.com and transformed to a scale from 0 to 10. Some of the factors considered in the trust scores are the exchange's web traffic, the amount and legitimacy of the trading volume reported, regulation, security, and data provision. The exchange with the highest average trust score in the dataset is Binance (9.21), and lowest is HitBTC (5.39).

Table 2: Exchange reputation metrics

This table provides an overview on the exchanges' trust scores for each of the 11 exchanges in the dataset. The trust scores are provided by the exchange rating websites coinmarketcap.com, cryptocompare.com, and nomics.com. The exchange trust score on cryptocompare.com was transformed from a 0-100 to the same 0-10 scale that is used on coinmarketcap.com and nomics.com, respectively. All trust scores were captured on 25/07/22.

		Exchange trust scores			
Exchange	**US-licensed**	**Coinmarketcap**	**Cryptocompare**	**Nomics**	**Mean**
Binance	No	9.90	7.72	10.00	9.21
Binance US	Yes	7.40	6.19	6.66	6.75
Bitfinex	No	7.00	7.03	7.10	7.04
Coinbase	Yes	8.10	8.91	8.59	8.53
FTX	No	8.20	7.40	8.21	7.94
Gemini	Yes	6.80	8.28	6.46	7.18
HitBTC	No	3.90	5.00	7.27	5.39
Huobi	No	7.00	5.42	8.09	6.84
Kraken	Yes	7.80	7.56	7.47	7.61
Kucoin	No	7.50	6.12	7.65	7.09
Upbit	No	5.70	6.70	6.89	6.43

The token-specific data on daily returns, market capitalization, and trading volume is obtained from the coingecko.com public API. The same applies to the daily Bitcoin returns that serve as benchmark for the market model in the event study setup. Figure 2 reports the cumulative returns for the market benchmark Bitcoin during the observation period. The observation period falls into a general uptrend in the cryptocurrency market with the market benchmark Bitcoin yielding a return of 279% from January 1st, 2020, to its current all-time high on November 9th, 2021. Table 3 reports the descriptive statistics for the token-specific metrics *TTV*, *TMC*, and *TTV/TMC* that are measured during the estimation window [-28, -7] for each individual cross-listing event. 36 of the 390 cross-listing events are removed from the dataset due to incomplete data on *TTV*, *TMC*, and *TTV/TMC*. Both, the distribution of the token trading volume and market capitalization are highly right-skewed with a large standard deviation driven by outliers to the upside (TTV – skewness: 9.66, kurtosis: 119.99; TMC – skewness: 12.75, kurtosis: 187.49). On average, the daily trading volume of a given token amounts 27% of its market capitalization during the observation period. The dataset contains 216 individual tokens with each token being cross-listed on average 1.81 times on one of the eleven exchanges during the observation period. Around 50% of the tokens were cross-listed only once on one of the exchanges. Additional cross-listings on exchanges that are not part of the dataset during this period are possible. Detailed descriptive statistics on all variables are provided in Appendix A.

Figure 2: Bitcoin cumulative return Q1/2020 – Q4/2021

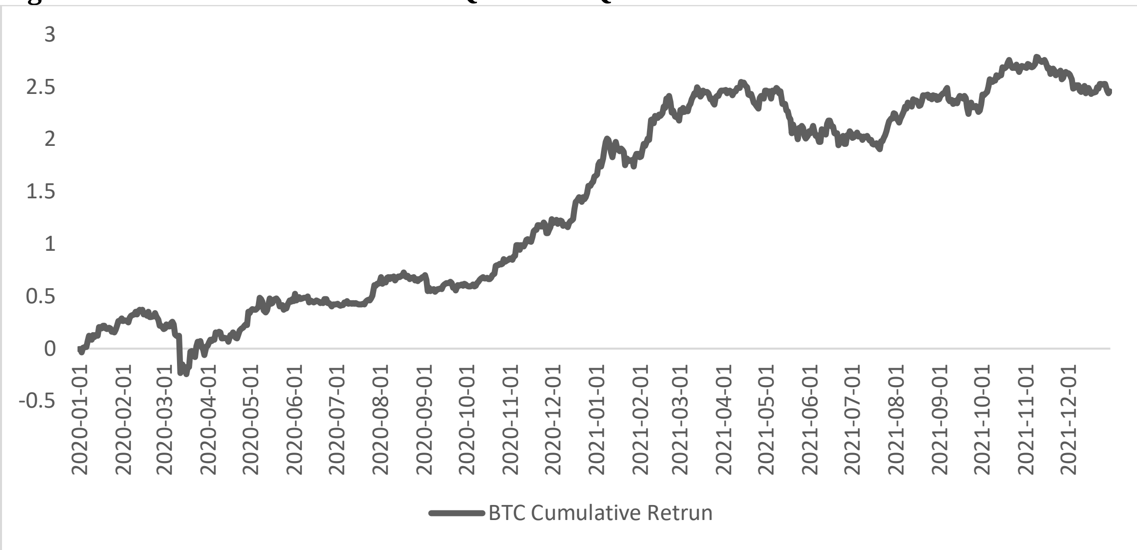


Table 3: Token cross-listing characteristics

This table provides the descriptive statistics for the token-specific variables. *TTV* is the token's average trading volume (in USD) during the estimation window of a certain cross-listing event. *TMC* is the token's average market capitalization (in USD) during the estimation window of a certain cross-listing event. *TTV/TMC* is the ratio between both metrics. *Cross-listings per token* indicates how often an individual token is cross-listed on one of the eleven exchanges in the dataset during the observation period. Any cross-listings on exchanges not included in the dataset are not considered.

	TTV	**TMC**	**TTV/TMC**	**Cross-listings per token**
N	354	354	354	390
Mean	147,815,842.49	1,181,846,646.83	0.27	1.81
Median	27,653,449.70	218,625,313.95	0.14	2
SD	529,958,973.70	6,369,207,013.00	0.48	1.02
Min	4,645.45	176,465.69	0.00	1
Max	7,596,107,026.00	102,006,000,000.00	4.89	6

5. Empirical results and analysis

The presentation of the empirical results is structured as follows. Section 5.1 discusses the observed abnormal returns during the event windows. Section 5.2 discusses the results of the multivariate linear regression setup and the applicability of the market-segmentation, liquidity, and investor protection theory. Section 3 analyzes the changes in social media volume of a given token after the cross-listing and discusses the applicability of the information disclosure theory.

5.1 Event study results

Both, the constant mean return model and the market model result in similar abnormal returns with regards to the magnitude and the statistical significance. Table 4 reports positive, statistically highly significant CAARs for all multi-day event windows that range from around 7.48% for the [-5, 5] window to 10.19% for the [-1, 1] event window. The AARs on the event day are 2.35% and 2.02% for the constant mean return model and the market model, respectively. Even though the announcement and event day for the token cross-listing events in the dataset is t = 0, there are already significant positive CAARs in the days leading up to the event. Figure 3 shows that the series of positive CAARs already starts 3 days before the cross-listing event.

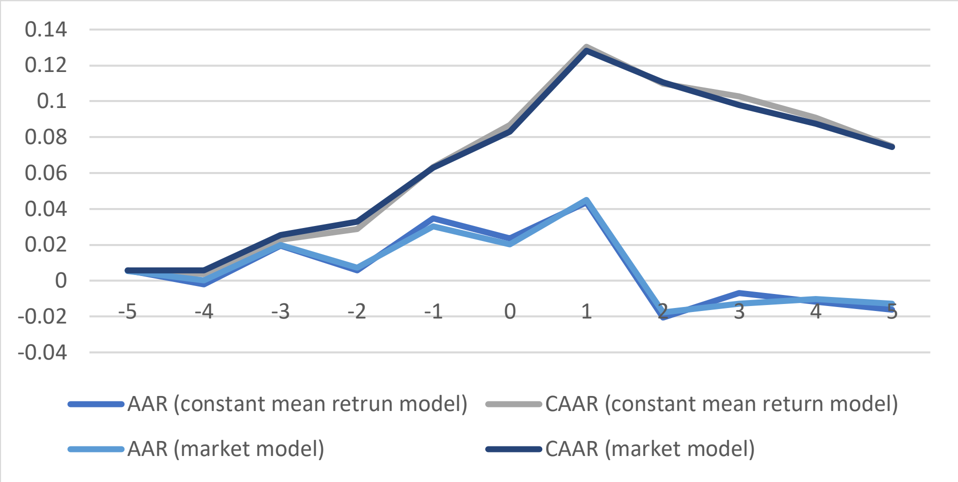
Table 4: Cross-listing event study results

This table contains the event study results for five multi-day and seven single-day event windows. The CAARs are reported for the constant mean return model and market model. Furthermore, the t-statistic and the share of positive CAARs for each event window are provided.

	(1) Constant mean return model			**(2) Market model**		
Window	**CAAR**	**t-statistic**	**% pos.**	**CAAR**	**t-statistic**	**% pos.**
-5 to +5	0.0748	2.3189**	0.5205	0.0742	2.2194**	0.5231
-3 to +3	0.0992	3.5391***	0.5333	0.0919	3.2079***	0.5436
-1 to +1	0.1019	4.5343***	0.6077	0.0953	4.1547***	0.6077
-5 to -1	0.0633	2.7827**	0.5231	0.0625	2.6309**	0.5282
+1 to +5	-0.0120	-0.5984	0.4513	-0.0086	-0.4410	0.4487
-3	0.0193	1.4789	0.4564	0.0197	1.5218	0.4385
-2	0.0056	2.4213**	0.4615	0.0073	0.9591	0.4641
-1	0.0347	2.6273**	0.5205	0.0301	2.2606**	0.4974
0	0.0235	2.8133**	0.5359	0.0202	2.2687**	0.4949
+1	0.0436	3.0788***	0.4897	0.0450	3.2591***	0.4872
+2	-0.0206	-3.5554***	0.4000	-0.0177	-3.2079***	0.3821
+3	-0.0069	-1.0562	0.4308	-0.0127	-1.9021*	0.3872

*, **, *** indicates the significance at the 10%, 5%, and 1% level for a two-tailed T-Test

Figure 3: Cross-listing event study results during the [-5, 5] event window
This figure illustrates the AARs and CAARs during the event window [-5, 5] as measured by the constant mean return model and the market model



For both models, the AARs measured the day before the cross-listing event (t = -1) even exceed the AARs on the event day (t = 0). At the same time the share of tokens with positive abnormal returns at t = -1 is comparable to the share observed at the event day. This suggests informed trading activity by insiders that receive the information on the upcoming cross-listing before the official announcement and listing date. In July 2022, the SEC filed charges against a Coinbase employee for leaking information on upcoming listings on the exchange (Versprille et al., 2022). The large share of positive abnormal returns leading up to the cross-listing event suggests that Coinbase is not the only exchange in the dataset associated with potential insider trading activity. Starting from t = 2, the AARs become negative and remain negative until the end of the event window (t = 5). Overall, CAARs during the [1, 5] window are slightly negative but not statistically significant.

A comparison to the magnitude of abnormal returns observed in the stock market cross-listing literature is difficult. In contrast to the cryptocurrency market, stock market listings are usually announced before the listing date and the cross-listings for an individual stock occur less frequently. Overall, the magnitude of abnormal returns observed in the stock market cross-listing literature is significantly smaller. Miller (1999) observes CAARs of 5.1% during the [-3, 3] window, including AARs of 1.35% on the listing day. Doukas & Switzer (2000) observe CAARs of 2.45% during the [-3, 3] window, including AARs of 1.04% on the listing day. The observed CAARs in this paper of around 9.5% during the [-3, 3] window and AARs of around 2.2% on the listing day for both types of models are significantly larger and more in line with the existing cryptocurrency cross-listing literature. Ante (2019) and Meyer and Ante (2020) both observe abnormal returns of around 10% during the [-3, 3] window. However, the returns of 5.7% and 6.5% on the listing day are larger than the listing day returns of around 2.2% observed in this paper.

5.2 regression results

Table 5 reports the results for the six multivariate regression models. The dependent variable is CAAR[-3, 3] as measured by the market model. As observed in the event study, the results for both, the market model and the constant mean return model are similar with regards to the magnitude and statistical significance. The results based on the dependent variable CAAR[-3, 3] as measured by the constant mean return model can be found in Table B1, Appendix B.

Overall, the results obtained for all six models are hardly statistically significant. As predicted in hypothesis 1a, all token-specific liquidity measures in models 1 and 2 appear to have a negative impact on cross-listing returns. This implies that more illiquid tokens as measured by their trading volume relative to their market capitalization during the estimation window are associated with higher abnormal cross-listing returns during the event window that can be attributed to a reduction in the illiquidity premium. However, since all results are associated with large standard errors and lack statistical significance, hypothesis 1a is not supported by the data. The same applies for the trading volume of the exchange the token is listed. Model 3 tests hypothesis 1b stating that cross-listings on an exchange with a higher average trading volume during the estimation window result in higher cross-listing returns. This paper is the first to considers the impact of exchange-specific liquidity on cross-listing returns. Even though the coefficient suggests a positive relationship between exchange's total trading volume during the estimation window and cross-listing returns, the results are not statistically significant and associated with a large standard error. Therefore, hypothesis 1b is not supported by the data. Overall, this paper does not find statistically significant evidence to support the liquidity theory.

The only statistically significant variable in the dataset is the exchange's licensing status that is tested in model 4. Hypothesis 2 states that cross-listings on exchanges licensed to serve US-customers result in higher cross-listing returns since they remove the market segmentation by making the token available to US-investors. The results are significant at the 5%-level and suggest that all else equal, the listing on an US-licensed exchange increases the cumulative abnormal returns on average by 11.39% during the [-3, 3] event window. Therefore, hypothesis 2 is supported by the data. However, since listings on exchanges that are not part of the dataset for each given token are possible, some of the tokens may already be available to US-customers through prior listings on other US-licensed exchanges.

Model 5 tests hypothesis 4 stating that a cross-listing on exchanges with higher trust scores on exchange rating websites result in higher cross-listing returns. Testing the impact of the exchange's trust score on cross-listing returns is a joint test with regards to the investor protection theory since it assumes that the trust score measured on third party exchange rating websites is a suitable measure for the level of investor protection on a given exchange. Even though the rating websites also consider the exchange's licensing as part of their evaluation, the coefficient is not statistically significant. Therefore, hypothesis 4 is not supported by the data. The relative importance of the exchange's US-licensing compared to the other exchange-specific factors in predicting cross-listing returns is confirmed by model 6 that includes all exchange-specific measures. Again, the US-licensing status the only metric that is statistically significance.

Table 5: OLS regressions on cumulative average abnormal returns (Market model)

This table contains the results for the OLS-regression for model 1-6. The dependent variable is CAAR[-3, 3] that was calculated based on the market model. The regression dataset contains 354 of the 390 cross-listing events with complete data on all six independent variables. *TTV* is the token's trading volume (in USD), *TMC* the token's market capitalization (in USD), TTV/TMC is the ratio between both metrics, and *ETV* the trading volume of the exchange the token is listed on (in BTC). All variables are calculated as the average values during the estimation window [-28, -7] of the respective cross-listing event. *ExLicense* is a dummy variable that indicates if the exchange is licensed to serve US-customers. *ExReputation* is the average trust score the exchange received on the three rating websites coinmarketcap.com, coingecko.com, and nomics.com, transformed to a 0-10 scale. Exchange- and Quarter-dummies are included to control for exchange- and quarter-fixed effects, respectively.

Variable	**Dependent variable: CAAR[-3, 3] (Market model)**					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(TTV)	-0.0124 (0.0194)					
ln(TMC)	-0.0406 (0.0238)					
ln(TTV/TMC)		-0.2918 (0.3503)				
ln(ETV)			0.0291 (0.0219)			0.0397 (0.0273)
ExLicense				0.1139** (0.0545)		0.1316** (0.0630)
ExReputation					0.0296 (0.0299)	0.0045 (0.0345)
Exchange-dummies	Yes	Yes	No	No	No	No
Quarter-dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	354	354	354	354	354	354
R^2	0.0884	0.0661	0.0135	0.0183	0.0134	0.0247

*, **, *** indicates the significance at the 10%, 5%, and 1% level. The heteroscedasticity-robust standard errors are indicated in parenthesis.

Figure 4 illustrates the CAARs for all US-licensed exchanges in the dataset during the [-5, 5] event window. This includes Coinbase, Kraken, Gemini, and Binance US. Furthermore, the group-specific CAARs for the US-licensed exchanges (ExLicense=1) and non-licensed exchanges (ExLicense=0) are included. The CAARs for the US-licensed exchanges are mainly driven by cross-listings on Coinbase.

Coinbase is the only exchange with CAARs above the group average captured by Exlicense = 1. Therefore, the abnormal cross-listings returns on Coinbase may largely be related to the case of insider trading at Coinbase that was discussed in section 5.1 and falls into the observation period (Versprille et al., 2022). To control for the insider trading activity on Coinbase and get a more robust estimation for the impact of the exchange's US-licensing status on cross-listing returns, cross-listing events on Coinbase are removed from the sample and models 4 and 6 are recalculated.

Figure 4: Cross-listing event study results during the [-5, 5] event window by US-licensing status
This figure illustrates CAARs during the event window [-5, 5] as measured by the market model for the US-licensed exchanges Coinbase, Kraken, Gemini, and Binance US. Furthermore, it contains the average CAARs for the US-licensed exchanges (ExLicense=1) and non-licensed exchanges (ExLicense=0)

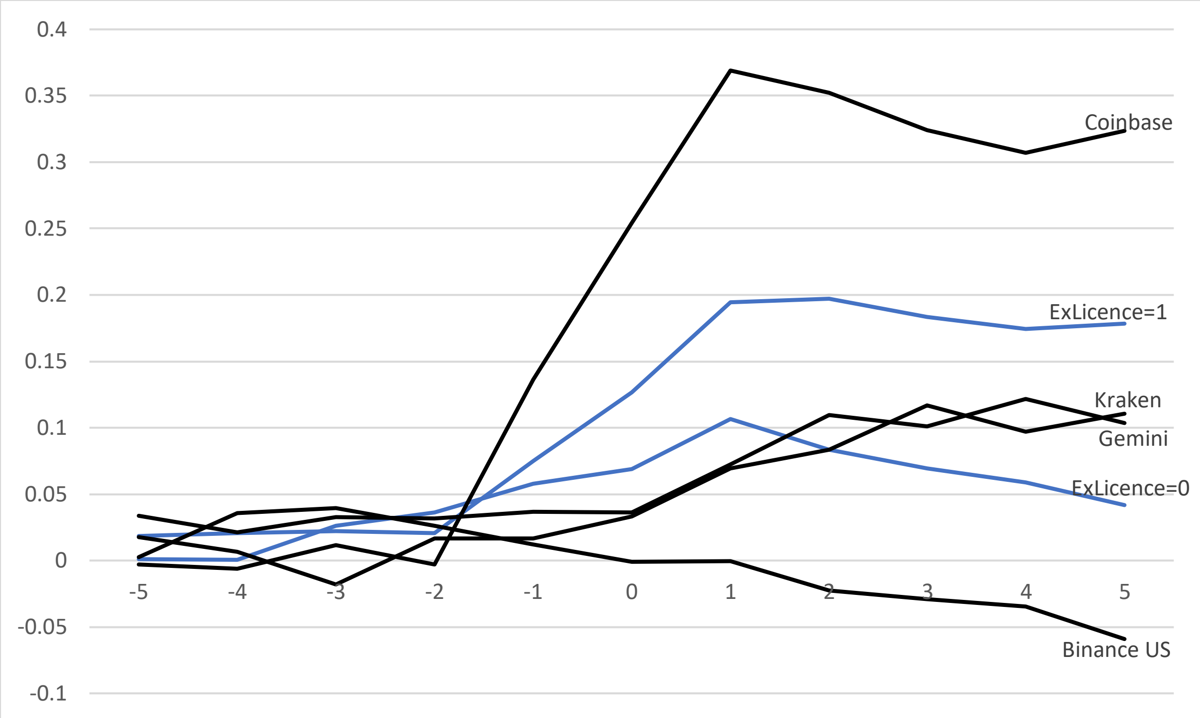


Table 6 contains the results for model 4 and 6 after removing all cross-listing events on Coinbase from the dataset. In model 4, the US-licensing status remains statistically significant at the 10%-level but the effect of US-licensed exchanges on cross-listing returns during the [-3, 3] event window decreases to 0.38% compared to the 11.39% observed before. In model 6, the US-licensing status is not found to be statistically significant, anymore. This suggests that the abnormal returns associated with US-licensed exchanges are mainly driven by the Coinbase exchange. Since Coinbase is known to be associated with insider trading activity and the coefficient obtained for all the remaining US-licensed exchanges is significantly smaller, this paper fails to find compelling evidence to support hypothesis 2.

Table 6: OLS regressions on cumulative average abnormal returns (Market model) without Coinbase

This table contains the results for the OLS-regression for models 4 and 6 without the Coinbase cross-listing events. The dependent variable is CAAR[-3, 3] that was calculated based on the market model across all 390 cross-listing events. After removing Coinbase from the dataset, 319 cross-listing events are left.

Variable	**Dependent variable: CAAR[-3, 3] (Market model)**	
	(4.2)	(6.2)
ln(ETV)		0.0267 (0.0289)
ExLicense	0.0038* (0.0502)	0.0389 (0.0661)
ExReputation		-0.0091 (0.0350)
Exchange-dummies	No	No
Quarter-dummies	Yes	Yes
N	319	319
R^2	0.0098	0.0124

*, **, *** indicates the significance at the 10%, 5%, and 1% level. The heteroscedasticity-robust standard errors are indicated in parenthesis.

5.3 Social media volume results

The social media volume data is obtained from sentiment.net and captures the number of daily mentions of a given token on the social media platforms telegram, reddit, twitter, and bitcointalk. All four platforms are commonly used for the communication between team and community members of token-projects. After removing cross-listing events with incomplete social media volume data from the dataset, 370 of the 390 cross-listing events are left in the dataset. Hypothesis 3 states that cross-listings improve the token's information environment through increased media or investor attention and predicts an increasing social media volume after a cross-listing event. Table 6 contains the average number of daily mentions of the tokens for different time windows. The distribution of social media volume is highly right-skewed suggesting that most of the public debate on the platforms is centered around a few popular token-projects. Compared to the estimation window [-28, -7], the daily social media volume on average increased for all three event windows. The highest increases are observed during the [0, 3] window with 34.5% and the [0, 7] window with 25.92%. Both windows include the announcement and event date t = 0 which implies that a substantial share of the increase in social media may result from coverage on the listing announcement. However, the event window [3, 14] confirms a significant increase of around 10% beyond the initial cross-listing date t = 0 which suggests that the increase in social media volume persists beyond the listing date. A paired t-test is used to assess the statistically significance of the increases in social media volume for all three event windows. The test pairwise compares the logarithmic average daily social media volume during the estimation window with the volume measured in each of the three event windows. The increases in all three event windows are found to be significant at the 1% level. The test statistics and the box plots for each time window are provided in Appendix C.

Table 7: Cross-sample daily average social media volume
This table contains the average daily social media volume for the tokens associated with the individual cross-listing events during the estimation window [-28, -7] and the three event windows [0, 3], [0, 7], and [3, 14].

	Time window			
	[-28, -7]	**[0, 3]**	**[0, 7]**	**[3, 14]**
Average daily social media volume	182.5156	245.4790	229.8237	200.8587
Percentage-increase relative to the estimation period		34.50%	25.92%	10.05%
N	370	370	370	370

Overall, the significant increase in social media volume suggests that one rational for cryptocurrency cross-listings are improvements in the information environment of given token project. The success of blockchain-based business models is usually highly dependent on network effects (e.g., Luther, 2016). In decentralized blockchain networks, users are not only the costumers of the blockchain application but also validate transactions by casting votes according to a consensus mechanism. The larger the network of individual validators and therefore the distribution of voting power, the higher the degree of decentralization in a token project. Therefore, an increasing user base not only creates value through additional customers but also through increased security within a decentralized blockchain network. The increasing social media volume after the cross-listing can help to draw attention towards a given token project and improve the information environment through third party coverage. In addition to the abnormal returns observed in the event study, a cross-listing can therefore also create value by increasing the token project’s user base and security. The results suggest that the information disclosure theory is one possible motivation for projects to cross-list their tokens on additional exchanges.

6. Conclusion

6.1 Conclusion

This paper provides first empirical evidence on the applicability of traditional stock market cross-listing theories to cryptocurrency cross-listings. The tested theories include the market segmentation theory, the liquidity theory, the information disclosure theory, and the investor protection theory. The dataset used in this paper contains 390 cross-listing events involving 216 individual tokens on 11 centralized cryptocurrency exchanges from January 2020 to December 2021. Compared to the existing literature, several new metrics are considered, including the total trading volume on the exchange the token is cross-listed on, the exchanges' US-licensing, the exchanges' trust score on cryptocurrency data provider websites, and the tokens' individual social media volume.

The abnormal returns associated with each cross-listing event are calculated based on the event study methodology introduced by MacKinlay (1997). For this purpose, the constant mean return model and the market model based on the market benchmark Bitcoin are applied. The estimation period ranges from 28 to 7 days before the cross-listing event. The observed cumulative returns are highly statistically significant at the 1% and 5%-level. Starting from day 3 before the cross-listing, the daily average abnormal returns are positive until they peak on day 1 after the cross-listing and turn negative by day 2 after the cross-listing. The average abnormal returns on the event day are around 2.2%. The general trend of positive abnormal returns before and negative abnormal returns after the cross-listing event is in line with some of the existing stock market (e.g., Dharan & Ikenberry, 1995) and cryptocurrency cross-listing literature (Ante, 2019; Ante & Meyer, 2021). Since the dataset used in this paper only contains cross-listings that were announced on the listing day, the significant positive returns leading up to the event are an indication for potential insider trading on the cryptocurrency exchanges in the dataset.

The liquidity theory is tested based on two hypotheses. First, tokens with a lower trading volume relative to their market capitalization are expected to experience higher cross-listing returns. Second, cross-listings on exchanges with higher total trading volume are expected be associated with higher cross-listing returns. Both hypotheses are not confirmed by the data due to the statistically insignificant results. The market segmentation theory is tested based on the hypothesis that cross-listing on exchanges licensed to serve US-customers are associated with higher cross-listing returns. Even though this paper finds that US-licensed exchanges are associated with higher abnormal returns than non-licensed exchanges, the results are mainly driven by cross-listings on Coinbase. This is in line with the insider trading activity at Coinbase that falls into the observation period. After removing cross-listings on Coinbase from the dataset, the average effect of US-licensed exchanges on cross-listing returns reduces from 11.39% to only 0.38%. Therefore, this paper does not find compelling evidence to support the market segmentation theory. The investor protection theory is tested based on the assumption that trust scores provided on cryptocurrency data provider websites are an indicator for the level of investor protection on a given exchange. The associated hypothesis suggests that cross-listings on exchanges with a higher trust score are associated with higher cross-listing returns. The hypothesis is not confirmed by the data due to statistically insignificant results. The information disclosure theory is tested based on the hypothesis that cross-listings increase a token's daily social media volume which in turn reflects improvements in the token's information environment. The results suggest significant increases in the social media volume of around 35% in the first three days after the cross-listing relative to the estimation period. The increase in social media volume persists for the following two weeks even if the first three days following the cross-listing event are excluded.

Overall, cryptocurrency cross-listings are associated with significant abnormal returns. This paper fails to find statistically significant evidence for the market segmentation theory, the liquidity theory, and the investor protection theory. However, cryptocurrency cross-listings significantly increase the token's social media volume beyond the announcement and cross-listing date which suggest that token projects may consider to cross-list their token to improve the token's information environment.

6.2 Limitations and further research

The applicability of stock market cross-listing theories to the cryptocurrency market is limited due to significant differences between both markets and asset classes. Some examples include the asset properties, the trading infrastructure, and the regulation. While stocks represent a fractional ownership in a publicly traded company, the utility of digital tokens is more diverse. Stocks are listed and traded on regulated, centralized exchanges with fixed trading hours, while cryptocurrency exchanges may be decentralized, less regulated with no fixed trading hours. Stock market listings are usually announced in advance and cross-listings for an individual stock occur less frequently. Compared to stock markets, the lack of mandatory regulatory disclosure requirements in cryptocurrency markets leads to higher information asymmetries regarding the activities, the financial performance, and the ownership structure of a given token project.

Another limitation comes from the selection of the dataset used in this paper. First, the observation period only spans from January 2020 to December 2021. As measured by the cumulative return on the market benchmark Bitcoin, it falls into a prolonged uptrend in the cryptocurrency market. Furthermore, this paper only includes cross-listing events on major centralized exchanges by daily average trading volume and does not consider cross-listings on other centralized or decentralized exchanges. Therefore, overlapping estimation- and event windows with cross-listings on exchanges not included in the dataset are possible and the number of previous cross-listing events for each individual token varies. For this reason, cross-listing events for tokens that are cross-listed more frequently are more likely to be excluded from the dataset which may create a bias in the dataset composition.

Since the research on cross-listing dynamics in cryptocurrency markets is still in the early stages, there are many opportunities to expand the research. Compared to the dataset used in this paper, the observation period and sample size can be increased to consider a larger time window or number of centralized and decentralized exchange. Since cryptocurrencies are a heterogenous asset class, further research might investigate the impact of token characteristics on cross-listing returns. This may also include on-chain metrics as indicators for changes in user activity around cross-listing events. Since the success of token projects is highly dependent on user adoption, the impact of cross-listing events on user activity might be a key area to focus on for the development of cryptocurrency-specific cross-listing theories that better describe cross-listing dynamics. Since the results of this paper suggests that key exchange-specific metrics, including the exchange's trading volume, licensing, and reputation have no statistically significant impact on cross-listing returns, the drivers of abnormal returns are likely be found among token-specific, rather than exchange-specific metrics. Compared to stocks, cryptocurrencies are a relatively new asset class. As cryptocurrency regulation around the world progresses, and new wide-spread use cases for cryptocurrencies emerge, the cross-listing incentives for token projects and cross-listing dynamics may change accordingly.

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Appendix A: Variable description

Table A1: Correlation matrix

This table contains the correlation matrix for all variables used in the multivariate regression.

	ln(TTV)	ln(TMC)	ln(TTV/TMC)	ln(ETV)	ExLicense	ExReputation
ln(TTV)	1.0000					
ln(TMC)	0.7259	1.0000				
ln(TTV/TMC)	0.6672	-0.0180	1.0000			
ln(ETV)	-0.1194	-0.0725	-0.0970	1.0000		
ExLicense	0.1468	0.1270	0.0842	-0.2079	1.0000	
ExReputation	-0.0948	-0.0054	-0.1203	0.1505	0.3469	1.0000

Figure A1: Bitcoin market benchmark return Q1/2020 – Q4/2021

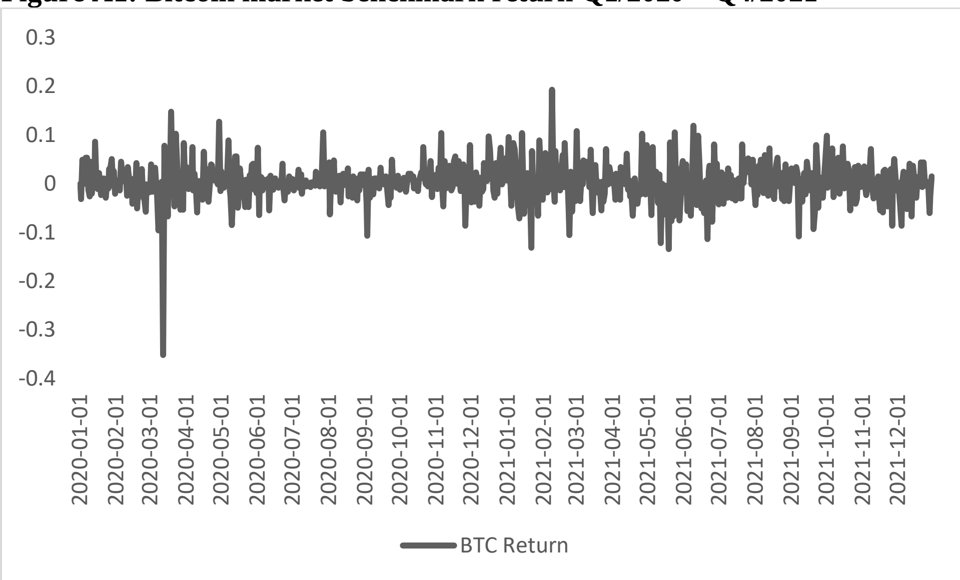

Table A2: Variable Definition

Variable	Description	Data source
TTV	Token-specific average daily trading volume (in USD) during the estimation window [-28,-7] associated with cross-listing event *i* as defined by $TTV_i = log(\frac{1}{22}\sum_{t-28}^{t-7} token\ trading\ volume_{t,i})$.	coingecko.com
TMC	Token-specific average daily market capitalization (in USD) during the estimation window [-28,-7] associated with cross-listing event *i* as defined by $TMC_i = log(\frac{1}{22}\sum_{t-28}^{t-7} token\ market\ capitalization_{t,i})$.	coingecko.com
TTV/TMC	Ratio between average daily trading volume and average daily market capitalization (in USD)	coingecko.com
ETV	Exchange-specific average daily trading volume (in USD) during the estimation window [-28,-7] associated with cross-listing event *i* as defined by $ETV_i = log(\frac{1}{22}\sum_{t-28}^{t-7} exchange\ trading\ volume_{t,i})$.	coingecko.com
ExReputation	Exchange-specific average trust score of the exchange associated with cross-listing event *i* retrieved from the three cryptocurrency data provider websites cryptocompare.com, coinmarketcap.com, and nomics.com. All three scores are reported on a 0 (min) to 10 (max) scale. The trust score received on coinmarketcap.com is transformed from a 0-100 scale to a 0-10 scale.	cryptocompare.com coinmarketcap.com nomics.com
ExLicense (dummy)	Exchange-specific US-licensing status of the exchange associated with cross-listing event *i* indicating if the exchange is licensed to legally serve US-customers.	individual exchange websites
Quarter (dummy)	Dummy variable to control for the quarter the cross-listing event *i* took place.	cryptocurrencyalerting.com
Exchange (dummy)	Dummy variable to control for the exchange the cross-listing event *i* took place on.	cryptocurrencyalerting.com
Social volume[-28, -7]	Token-specific average daily mentions on telegram, reddit, twitter, and bitcointalk during the estimation window [-28,-7] associated with cross-listing event *i*..	santiment.net
Social volume[0, 3]	Token-specific average daily mentions on telegram, reddit, twitter, and bitcointalk during the event window [0,3] associated with cross-listing event *i*..	santiment.net
Social volume[0, 7]	Token-specific average daily mentions on telegram, reddit, twitter, and bitcointalk during the event window [0,7] associated with cross-listing event *i*..	santiment.net
Social volume[3, 14]	Token-specific average daily mentions on telegram, reddit, twitter, and bitcointalk during the event window [3,14] associated with cross-listing event *i*..	santiment.net

Table A3: Descriptive statistics

Variable	N	Mean	Median	SD	Min	Max
Token-specific metrics						
TTV	354	147,815,842.49	27,653,449.70	529,958,973.70	4645.4490	7,596,107,026.0000
TMC	354	1,181,846,646,83	218,625,313.95	6,369,297,913.00	176,465.6893	102,006,000,000.0000
TTV/TMC	354	0.2717	0.1420	0.4796	0.00	4.8861
ln(TMC)	354	19.1240	19.2029	1.7689	12.0809	25.3483
ln(TTV)	354	16.9805	17.1353	2.1577	8.4436	22.7509
ln(TTV/TMC)	354	0.8876	0.8983	0.0771	0.5249	1.1016
Exchange-specific metrics						
ETV	354	77,995.6243	49,119.0991	115,675.1843	1,793.9774	1,280,131.6180
ln(ETV)	354	10.6845	10.802	1.0821	7.4922	14.0625
ExReputation	354	7.1383	7.0900	1.0313	5.3900	9.2100
ExLicense (dummy)	354	0.2401	0	0.4278	0	1
Social Volume metrics						
Social volume[-28, -7]	370	184.5016	29.6818	810.1060	0.0455	9278.3180
Social volume[0, 3]	370	248.1368	43.75	1019.3530	0.5000	13157.5000
Social volume[0, 7]	370	232.3143	43.5000	931.6230	0.2500	10847.7500
Social volume[3, 14]	370	203.0479	37.6667	783.2994	0.0833	7238.7500
ln(social volume[-28, -7])	370	3.3800	3.3905	1.7389	-3.0910	9.1354
ln(social volume[0, 3])	370	3.8055	3.7785	1.6190	-0.6931	9.4847
ln(social volume[0, 7])	370	3.7459	3.7728	1.6299	-1.3863	9.2917
ln(social volume[3, 14])	370	3.6055	3.6288	1.6569	-2.4849	8.8872

Appendix B: Multivariate regression

Table B1: OLS regressions on cumulative average abnormal returns (Constant mean return model)

This table contains the results for the OLS-regression for model 1-6. The dependent variable is CAAR[-3, 3] that was calculated based on the constant mean return model. The regression dataset contains 354 of the 390 cross-listing events with complete data on all six independent variables. *TTV* is the token's trading volume (in USD), *TMC* the token's market capitalization (in USD), TTV/TMC is the ratio between both metrics, and *ETV* the trading volume of the exchange the token is listed on (in BTC). All variables are calculated as the average values during the estimation window [-28, -7] of the respective cross-listing event. *ExLicense* is a dummy variable that indicates if the exchange is licensed to serve US-customers. *ExReputation* is the average trust score the exchange received on the rating websites coinmarketcap.com, coingecko.com, and nomics.com, transformed to a 0-10 scale. Exchange- and Quarter-dummies are included to control for exchange- and quarter-fixed effects, respectively.

Variable	**Dependent variable: CAAR[-3, 3] (Constant mean return model)**					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(TTV)	-0.0127 (0.0167)					
ln(TMC)	-0.0364 (0.0241)					
ln(TTV/TMC)		-0.3149 (0.3020)				
ln(ETV)			0.0272 (0.0208)			0.0358 (0.0260)
ExLicense				0.1119** (0.0545)		0.1212** (0.0610)
ExReputation					0.0351 (0.0299)	0.0121 (0.0340)
Exchange-dummies	Yes	Yes	No	No	No	No
Quarter-dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	354	354	354	354	354	354
R^2	0.0903	0.0703	0.0151	0.0203	0.0168	0.269

*, **, *** indicates the significance at the 10%, 5%, and 1% level. The heteroscedasticity-robust standard errors are indicated in parenthesis.

Appendix C: Social media volume

Table C1: Paired t-test logarithmic average daily social media volume

This table contains the results for the three paired t-tests of the logarithmic average daily social media volume during the different time windows. The first test compares the average daily social media volume during the estimation window and the [0, 3]-window. The second test compares the average daily social media volume during the estimation window and the [0, 7]-window. The third test compares the average daily social media volume during the estimation window and the [3, 14]-window.

Paired t-test						
*H_{0A}: There is no statistically significant difference in the social volume observed during the **estimation window [-28, -7]** and the **event window [0, 3]***						
Variable	**N**	**Mean**	**Std err**	**SD**	**[95% conf. interval]**	
ln(social volume [-28, -7])	370	3.3425	0.0927	1.7826	3.1603	3.5247
ln(social volume [0, 3])	370	3.7715	0.0861	1.6570	3.6021	3.9409
Difference	370	-0.4290	0.0525	1.0092	-0.5322	-0.3258
Test result	t = -8.1763	Degrees of freedom = 369			Pr(|T| > |t|) = 0.0000	
*H_{0B}: There is no statistically significant difference in the social volume observed during the **estimation window [-28, -7]** and the **event window [0, 7]***						
ln(social volume [-28, -7])	370	3.3425	0.0927	1.7826	3.1603	3.5247
ln(social volume [0, 7])	370	3.7067	0.0874	1.6814	3.5348	3.8786
Difference	370	-0.3642	0.0489	0.9412	-0.4605	-0.2680
Test result	t = -7.4435	Degrees of freedom = 369			Pr(|T| > |t|) = 0.0000	
*H_{0C}: There is no statistically significant difference in the social volume observed during the **estimation window [-28, -7]** and the **event window [3, 14]***						
ln(social volume [-28, -7])	370	3.3800	0.0908	1.7389	3.2015	3.5585
ln(social volume [3, 14])	370	3.6055	0.0865	1.6569	3.4354	3.7756
Difference	370	-0.2255	0.04813	0.9221	-0.3202	-0.1309
Test result	t = -4.6859	Degrees of freedom = 369			Pr(|T| > |t|) = 0.0000	

Figure C1: Box Plots average daily social media volume

This figure contains the box plots for the logarithmic average daily social media volume during the estimation window and the event windows *ln(social volume[-28, -7])*, *ln(social volume[0, 3]*), *ln(social volume[0, 7])*, and *ln(social volume[3, 14])*