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Market Reaction to Exchange Listings of Cryptocurrencies

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Abstract

Cryptocurrency markets operate at a global scale and are lightly regulated compared to traditional securities markets. Cryptocurrencies like Bitcoin trade across multiple secondary markets that differ significantly in term of liquidity, governance and trust. This study explores 327 exchange listings of 180 cryptocurrencies on 22 different cryptocurrency exchanges and examines the resulting price effects using event study methodology. The results show a significant average abnormal return of 5.7% on the day of the listing event and 9.2% in the window of three days before until three days after the listing. The effects clearly differ for individual cryptocurrency exchanges, with listings on only a few exchanges yielding significant positive short-term abnormal returns of up to 25.5% on the day of the listing. Other exchanges show no significant effects at all or even significant negative returns, which suggests informed trading or market manipulation. Additional tests show that higher market capitalization in combination with lower trading volume leads to higher abnormal returns at exchange listings of blockchain-based assets.

Keywords: Cross-listings; Cryptocurrency Exchanges; Blockchain; Informed Trading; Event Study

1. Introduction

Cryptocurrencies are digital media of exchange that do not require central authorities, as the underlying distributed ledger technology and its decentralized approach provide a foundation of trust. The cryptocurrency market has been growing since the launch of Bitcoin in 2009 (Nakamoto 2008), as thousands of digital currencies have been issued though the underlying blockchain technology and can be traded on hundreds of cryptocurrency exchanges. The phenomenon of token sales has brought further growth to the ecosystem, as projects are able to finance themselves via the sale of blockchain-based tokens that carry some form of value.

Once issued, tokens can be traded on secondary markets if the cryptocurrency exchanges decide to list them. Exchanges are usually privately-owned central entities that exist in parallel across different countries, though some of them are decentralized, i.e. they only exist as computer code on the blockchain. Projects have an incentive to list their tokens on as many secondary markets as possible, as each market promises new users/traders and higher liquidity, while exchanges look to list the projects that will generate the highest trading volume. The processes of listing cryptocurrency on exchanges remain non-transparent. Additionally, due to the decentralized architecture of the blockchain, the exchanges may introduce new trading pairs without the consent of a project. Usually information about a listing event is communicated by the exchange at the day or the day before the event. Before that, only informed entities, like the exchange itself, the project team or involved consultants possess knowledge about the upcoming event.

Since most cryptocurrency exchanges operate in very lightly regulated markets and in direct competition with other exchanges, many of them exaggerate their trading volume in order to signal liquidity and to attract users and projects (Alameda Research 2019; Yates 2019). If an exchange manipulates the market by overstating its volume, it may also misbehave in the context of listings, e.g. by leaking information about upcoming listings. The market capitalization of cryptocurrencies represents one of the major characteristics that imply overall market relevance. Statistic sites, like *coinmarketcap*.com or *coingecko.com*, use market capitalization as a metric to rank cryptocurrencies. Therefore, having a higher market capitalization brings a higher level of attention. Market capitalization can rather easily be inflated by only publicly distributing a relatively small share of the cryptocurrency. Additionally, implied market capitalization only

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possesses relevance if markets are liquid, which is often not the case for cryptocurrencies.

Cryptocurrency exchanges and financial intermediaries constitute the interface between virtual currency and fiat currency, which makes them a crucial access point for the ecosystem. As exchanges are located around the globe and operate across jurisdictions, the lack of regulation and oversight entails the absence of anti-money-laundering (AML) and know-your-customer (KYC) procedures. Exchanges are common targets for hackers and have been associated with market manipulation and money laundering schemes (Ante 2018).

To my knowledge, so far only a single academic work has specifically addressed the effects of secondary market listings on cryptocurrency exchanges. Benedetti (2019) analyzes 3,625 tokens on 108 marketplaces and identifies significant effects for returns, trading volume and other characteristics around the first cross-listing event. Raw cumulative returns amount to 49% for a 2-week window around the listing event. Listing events are classified as the reported start of trading of the data provider cryptocompare.com. This comes with the limitation that the data source does not report all existing exchanges.

Primary listings and returns on cryptocurrencies, especially those of initial coin offerings (ICOs) where new cryptocurrencies are issued through blockchain-based crowd-financing, have also been studied. Momtaz (2019) analyzes the performance of digital currencies after their initial exchange listings and identifies an average abnormal return of 14.8% for the first day. Metrics like liquidity and market capitalization also affect returns. Benedetti and Kostovetsky (2019) identify significant underpricing across a sample of initial listings of tokens, with abnormal buy-and-hold returns of 48% in the first 30 trading days. Drobetz et al. (2019) analyze first-day returns of ICOs and find them to be affected by market sentiment, competition and liquidity.

Potential market manipulation in the cryptocurrency ecosystem has been researched for informed trading of Bitcoin (e.g. Chen et al. 2019; Feng et al. 2018; Gandal et al. 2018), pump-and-dump schemes (e.g. Hamrick et al. 2018; Kamps and Kleinberg 2018; Xu and Livshits 2018), the issuance of fiat-backed assets, so-called stable coins, to influence the Bitcoin price (Griffin and Shams 2018; Wei 2018) and 51%-attacks (Shanaev et al. 2018). By contrast, to the best of my knowledge, the literature has yet to address informed trading for listings of cryptocurrencies on secondary markets.

This paper has three aims. First, to initiate academic research on the cross-listing effects on secondary markets in the cryptocurrency ecosystem. Second, to analyze a unique data set for a deeper understanding of how listings on secondary markets influence the price of cryptocurrencies and what abnormal effects can be observed. Listings are analyzed to assess if characteristics or assumptions are similar to existing findings from similar financial markets, like stocks. Third, to look for any signs of informed trading in this young and lightly regulated market.

The findings can provide a basis for the authorities' assessment as to whether the market needs regulation and, if so, to what degree. Additionally, managers of cryptocurrency projects and other market participants can gain an understanding how of price sensitive exchange listings can be in the short term and if there is any indication of information leakage. Lastly, cryptocurrency exchanges can use the information to assess their relevance across other exchanges based on short-term price effects of new asset listings and what kind of assets lead to higher relative price increases. They can also identify signs of informed trading or information leakage in anticipation of listings on their platform and their competitors'.

2. Related literature

2.1 Exchange (cross-)listings

The cross-listing of stocks has been extensively analyzed in the academic literature and represents the main theoretical foundation for assessing the phenomenon of (cross-)listings of cryptocurrencies. Cross-listing can increase stock prices (Foerster and Karolyi 1999; Miller 1999) or fail to have any significant effects (Lau et al. 1994; Varela and Lee 1993).[1] Stock prices tend to rise before exchange listings and perform rather poorly thereafter. Dharan and Ikenberry (1995) report a negative post-listing drift that supports their opportunism hypotheses, according to which managers who have a choice of listing their company's stock on an exchange will time the listing before a price decline.

Four drivers of the motivation to cross-list can be identified from the literature. They concern 1) market segmentation, 2) market liquidity, 3) information disclosure and 4) investor protection.

2.1.1 Market segmentation

Cross-border investment allows investors to diversify their portfolio but also creates barriers, like taxation rules or restrictions regarding the possession of foreign equity (Karolyi 1998). Errunza and Losq (1985) argue that cross-listing stocks can reduce barriers to international investment, thus reducing the cost of capital. According to the investor recognition hypothesis (Merton 1986), managers have an incentive to expand the number of investors in a firm, as the investors' expected return falls. One way to do so is the cross-listing of stocks. Baker et al. (2002) show that international firms that cross-list their shares can significantly increase their visibility and reduce their cost of equity capital. For cryptocurrencies, the requirements to list at an additional exchange are much

[1] For an overview of the academic literature on cross-listing effects on stock prices, see Karolyi (2006).

lower, as there are no uniform guidelines or regulations. The exchanges differ greatly, which creates market barriers for specific types of users. Most cryptocurrency exchanges use so-called stable coins, digital tokens that represent fiat currency, to resemble trading pairs for domestic currencies like the US-dollar. Platform users cannot directly withdraw fiat currency from these exchanges; they can only withdraw digital tokens that represent fiat currency. To receive real fiat currency, they must either transfer their tokens to an exchange that offers a direct fiat gateway or exchange the tokens with the issuer of the stable coin. This process also applies to buying cryptocurrencies. Traders cannot directly purchase cryptocurrency at an exchange that only offers stable coin support. Of the 22 exchanges analyzed in this paper, only eight offer fiat deposits and withdrawals. Other characteristics that enable market segmentation are the degree of anonymity for users, options for margin trading, (IP-)blocking of specific countries such as the US, or capital controls (e.g. China or South Korea) (Choi et al. 2018). The market segmentation hypothesis postulates that the effect of a cross-listing depends on the extent to which a specific target market is integrated with the global (cryptocurrency) market.

An idiosyncrasy of cryptocurrencies is that they can represent any form or value, like currency, a voucher or a security. In the case of so-called utility tokens that only serve a specific use, like a software license or a voucher, a new market means a new group of users or clients for a project. Therefore, cryptocurrency projects may have an incentive to cross-list on as many markets as possible. Similarly, the literature has identified access to customers and suppliers and product visibility as motives for cross-listings in specific jurisdictions (Bancel and Mittoo 2001; Mittoo 1992; Pagano et al. 2002).

2.1.2 Market liquidity

Listing cryptocurrencies on new markets can raise the liquidity of the asset and reduce the cost of capital. In stock markets, cross-listings lead to higher trading volume and lower spreads (Foerster and Karolyi 1999). The same likely applies to additional exchange listings of cryptocurrencies, as the activity of market makers and arbitrageurs can boost liquidity once several markets exist. Compared to stock or forex markets, cryptocurrency markets are rather inefficient (Carporale et al. 2018) and therefore all the more attractive for arbitrageurs. Chowdhry and Nanda (1991) state that multi-market trading promotes competition for order flow. The liquidity of an asset will improve in the market that attracts most of the liquidity traders. Informed traders follow, as they look to conceal their trading behavior by using the most liquid markets.

Cross-listing decisions have been associated with a reduction in trading costs for existing foreign investors (Sarkissian and Schill 2004). Analyzing an intraday dataset comprising 39 markets, Dang et al. (2015) find that cross-listings reduce liquidity commonality between the stocks and domestic markets and raise liquidity commonality for the host market. Elyasiani et al. (2000) show that various measures such as the bid-ask spread, volume and price precision improved for stocks that moved from the NASDAQ to the NYSE. Though cryptocurrencies do not move but are rather cross-listed multiple times, they should still experience similar effects when entering additional markets.

2.1.3 Information Disclosure

Traders base their decisions on the available information, which comprises 1) publicly accessible information and 2) private information that only specific groups can access and that implies information asymmetry (Miller and Rock 1985). Signaling theory (Spence 1973) holds that information asymmetries can be reduced through signals that should be costly to imitate or sent by trusted third parties (Fischer and Reuber 2007; Sanders and Boivie 2004). In Cantale's (1996) model, firms choose specific markets on which to list their shares as they try to communicate their private information of quality to investors. Greater disclosure signals quality to outside investors, as it facilitates their oversight and monitoring of the firm. Listing on a highly regulated market is a costly signal of quality. The extent of regulation differs widely across cryptocurrency exchanges. For instance, to ensure legal compliance, US-based exchanges like Bittrex or Poloniex often delist individual cryptocurrencies or revoke trading access specifically for U.S. customers (e.g. Bittrex 2019; Poloniex 2018). Decentralized exchanges even offer direct trading of cryptocurrencies via protocol on the blockchain, without the need for any centralized entity (Warren and Bandeali 2017). Only few exchanges have existing banking partners, while most of the market uses fiat-backed tokens to enable fiat-like trading pairs. By listing a cryptocurrency in a rather highly regulated market, e.g. in the U.S., projects can signal their willingness to comply with legal frameworks. Yet U.S. regulators have granted special disclosure exceptions for cross-listed foreign stocks (Licht 2001). Similar processes may therefore also happen for cryptocurrencies in the future. Premiums for cross-listings also occur in markets with weaker regulation, and the valuation premium may not be linked to metrics like information disclosure or investor protection (Sarkissian and Schill 2004).

2.1.4 Investor protection

Best practices in shareholder protection consist of transparency measures regarding trading practices and a high quality of accounting disclosures (Doidge et al. 2009). Bonding theory (Coffee 1999, 2002) suggests that firms from countries with weaker investor protection can increase their valuation by cross-listing their shares in the U.S., thus bonding themselves to the country's securities regulation. That way, the firms signal their willingness to respect the rights of their shareholders. The decision to cross-list can be modeled as a trade-off between growth opportunities and the management's loss of control. Doidge et al. (2004) find a valuation premium for companies that cross-list in the U.S. Research has also shown that cross-listings by firms whose home jurisdiction has weak investor protection promote subsequent equity issues (Lins et al. 2005; Reese and Weisbach 2002). Scrutiny by expert analysts is also tighter for cross-listed firms (Lang et al. 2003). This likely also applies to cryptocurrencies, as more exchanges means more analyst interest. While most of the empirical evidence concerns shares being cross-listed in the U.S. and the results from complying with U.S. securities regulation (e.g. Fernandes et al. 2010), the overall assumptions is that cross-listing in a tighter regulatory environment can yield a bonding premium (Troger 2007).

2.2 Informed trading

Price formation in financial markets is driven by the activities of informed traders (Baruch et al. 2017). Microstructure models (Glosten and Milgrom 1985; Kyle 1985) have shown how such traders obtain private signals regarding the value of an asset and place their orders before this information becomes public. Other traders notice the unusual market activity created by the informed traders and pick up the signal, which may trigger information cascades (Anderson and Holt 1997). Informed traders provide liquidity to exchanges and even more so in anonymous environments (Bloomfield et al. 2005; Hachmeister and Schiereck 2010). These findings are highly relevant for cryptocurrency markets, as some exchanges allow for (almost) full anonymity, while others admit only verified users.

Data availability on informed trading activity is very limited for traditional stocks, with information from the SEC being one of the very few sources (e.g. Meulbroek 1992; Seyhun 1986). For cryptocurrency markets, public accusations of informed trading have been made (e.g. Hancock 2018) but there is no hard evidence and there have been no high-profile convictions. The lack of regulation breeds informed trading.

The theory of detecting informed trading has been extensively researched for stock markets, but its methods are only of limited use for cryptocurrency markets. Stock markets are quote-driven and have market makers providing liquidity, while cryptocurrency exchanges are order-driven: Users directly place bids or asks and trade with other users of the exchange. According to Brockman and Chung (2000), the interaction between informed and uninformed traders in order-driven securities is important for corporate liquidity. Feng et al. (2018) state that information asymmetry models that measure the cost of market makers of engaging with informed traders (Huang and Stoll 1997) and the probability of information-based trading (PIN) method (Easley et al. 1996) are of limited use for cryptocurrency markets. As there is no data on informed trades, logistic models and vector machine methods are not applicable (Summers and Sweeney 1998).

Evidence on insider trading in stock markets shows that informed traders use private information on stock listings to schedule their trades (Lamba and Khan 1999). Korczak et al. (2010) argue that the decision to use private information results from a trade-off between the anticipated return and the risks of punishment and reputation loss. When applied to cryptocurrency markets, the trade-off is likely to produce a different result. As these markets lack regulation and therefore enforcement and punishment, the risk from exploiting foreknowledge is minimal, so insider trading is much more likely to be worthwhile than in traditional, tightly regulated markets.

To date, the study by Feng et al. (2018) is the only one to address informed trading of cryptocurrencies. It introduces a novel approach for detecting and assessing insider trading by analyzing imbalances in the buy and sell sides of exchanges. Focusing on Bitcoin, the findings suggest that informed traders enter into positions two days before positive events and only one day before negative events. In the present study, analyzing a market phenomenon where 1) private information can be exploited in a short time interval and 2) informed trading has been identified for similar processes in similar markets, I expect to at least identify signs of informed trading prior to exchange listings.

3. Data and methodology

3.1 Sample description

I collected data on listing events of cryptocurrencies for 22 cryptocurrency exchanges, where the listed assets must have a trading history of at least 31 days before and 7 days after the event. This means that the observations only refer to additional exchange listings (cross-listings) for assets that were already trading for at least a month. Listings of a specific cryptocurrency on a specific exchange and the respective dates were 1) directly reported through reported change of the APIs of the exchanges using the cryptocurrency market data Telegram bot @cryptoeventbot that directly connects to the APIs of various exchanges and sends notifications regarding new listings and 2) obtained from block.cc, a website that reports new trading pairs on cryptocurrency exchanges. If two event windows overlapped for a given asset, none of the events concerned were included in the sample, in line with McWilliams and Siegel (1997). To identify the events was challenging, as exchange listings are sometimes pre-announced or exchanges let their users vote on the implementation of a new trading pair. Therefore, some events are fully anticipated, while others are not. I found that in terms of their announcement habits, each of the 22 exchanges fell into one of three categories: announcement in $t = -1$, announcement in $t = 0$ and others.

For each event, the market statistics of the asset itself and the reference market Bitcoin were collected from coinmarketcap.com for the period 31 days before to 7 days after the event. I collected open, high, low and close prices, as well as trading volume and market capitalization. All data refer to market averages rather than to specific exchanges.

3.2 Event study methodology

Event studies evaluate returns on a sample of assets that experience a specific type of event. The procedure comprises five steps: 1) identification of an event, 2) modelling the price reactions, 3) calculation of abnormal returns, 4) calculation of summarized returns and analysis of the abnormal returns and 5) analysis of the results (Bowman 1983).

As cryptocurrency markets react to news very quickly, I define the event window as three days before and three days after the event (-3, +3). As argued above, an exchange listing is a significant positive event, especially for cryptocurrencies with low volume or few listings on relevant exchanges. Usually, exchanges announce new listings at the event day or a day prior. The period (-3, -2) represents a phase where no news about the exchange listing has hit the market. This allows to assess signs for informed trading. Using the 7-day event window, I can analyze the time frame prior to an event that Feng et al. (2018) identify as a point where informed Bitcoin traders enter into positions before major positive news. As an estimation window, I choose the 21 days (-30, -10) leading up to the event. As cryptocurrency markets are highly volatile, a longer estimation window is at greater risk of capturing other market forces, too. Additionally, there are hundreds of crypto exchanges that can independently choose to list an asset without interaction or permission by the project's management, so a long estimation period would likely involve multiple other listing events or other confounding effects. For robustness checks, I also test the event window of (-7, +7), which may provide additional insights on the overall market dynamics of exchange listings.

Abnormal returns equal actual less expected returns. To calculate the latter, I use the Constant Mean Return Model (Masulis 1980) and the Market Model (Brown and Warner 1085). While the Constant Mean Return Model predicts returns based only on an asset's mean return during the estimation period, the Market Model additionally relies on the return of the overall market as a linear predictor of expected returns. I use the Bitcoin price as a proxy for the overall cryptocurrency market. Bitcoin is the oldest and arguably the most relevant cryptocurrency with the highest market capitalization, and it is used as a trading pair on all of the exchanges covered by the dataset. The price of Bitcoin significantly correlates with various other cryptocurrencies (Burnie 2018; Hu et al. 2018). Gkillas et al. (2018) identify a pattern of high bivariate dependencies across the ten largest cryptocurrencies, which suggests that the use of Bitcoin is sufficient for the market model.[2] By initially using both return models, I can assess the relevance of the reference market. In later stages I only use the Market Model, as it represents the more conservative choice.

Expected returns are thus calculated over the estimation period (-30, -10) for each currency as $R_{i,t} = \mathrm{a}_i + \mathrm{b}_i \mathrm{R}_{BTC,t} + \mathrm{e}_{i,t}$, where R_{it} is the return of cryptocurrency i on day t and $R_{BTC,t}$ is the return of the market portfolio (i.e. Bitcoin). Abnormal returns (AR) are then calculated for (–1 to +1) as $AR_{i,t} = R_{i,t} - \alpha_i - \beta_i R_{BTC,t}$. Based on the AR, I calculate cumulative abnormal returns (CAR) by adding consecutive AR for the relevant time periods (t_1, t_2) of the event window: $CAR_i(t_1, t_2) = AR_{i,t_1} + \cdots + AR_{i,t_{n+1}}$. Averaging these metrics across all events, I obtain the average abnormal return (AAR) and the cumulative average abnormal return (CAAR).

A higher relative return of an asset may not necessarily represent a higher level of liquidity, as the market capitalization of the respective cryptocurrencies differ significantly. To account for such possibility, I introduce an adoption of the Constant Mean Return Model to calculate cumulative abnormal average market capitalization returns (CAAMCR) over the estimation period (-30, -10). This way, absolute changes in market capitalization for cryptocurrencies can be analyzed and compared. For test statistics, I 1) use a parametric t-test (t-statistic) and 2) the non-parametric Wilcoxon sign-rank test (z-statistic) (Wilcoxon 1992) to account for skewed distribution to calculate significance levels. P-values of the t-statistic will be depicted as p_t and for the z statistic p_z.

4. Descriptive statistics

Of the 327 identified listing events, 24% can be allocated to the year 2017. The majority of events happened in 2018 (65%) and the least number (11%) were identified for the year 2019. The last identified listing is the Korean project Fantom, whose token was added on the exchange Binance in June 2019 and the earliest is the cryptocurrency DASH that was listed in late April 2017 on the digital currency exchange Kraken. Dash is also the currency with the most individual observations (8).

[2] Another option for a market proxy could be a portfolio or an index of several highly relevant cryptocurrencies. Yet the inclusion of any currencies besides Bitcoin is necessarily an arbitrary decision. Another argument against a basket of currencies is the changing relevance of cryptocurrencies. If, for example, I was to select cryptocurrencies based on their market capitalization, that ranking could change very quickly.

Figure 1

Average (cumulative) returns

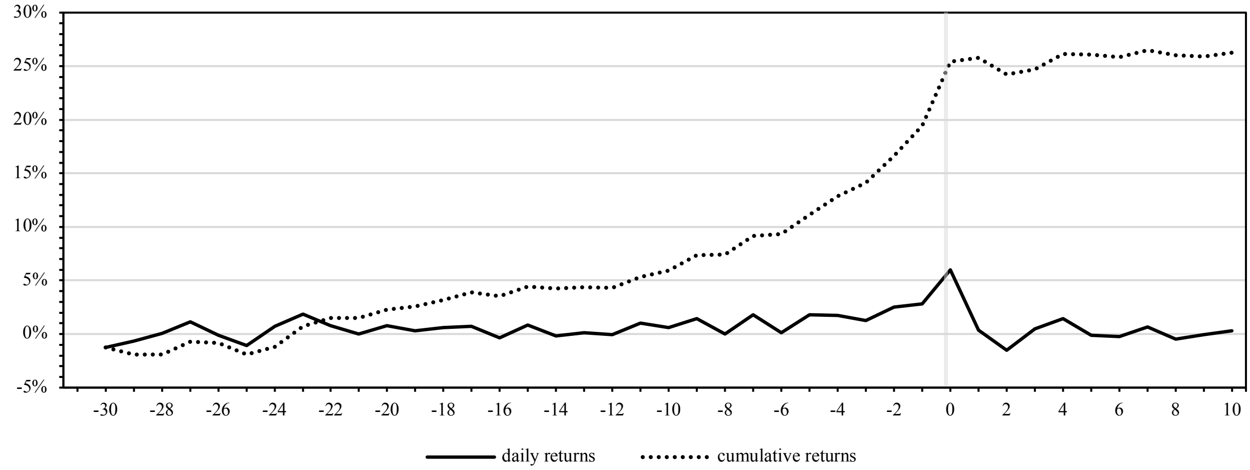

Figure 2

Average (cumulative) changes in trading volume

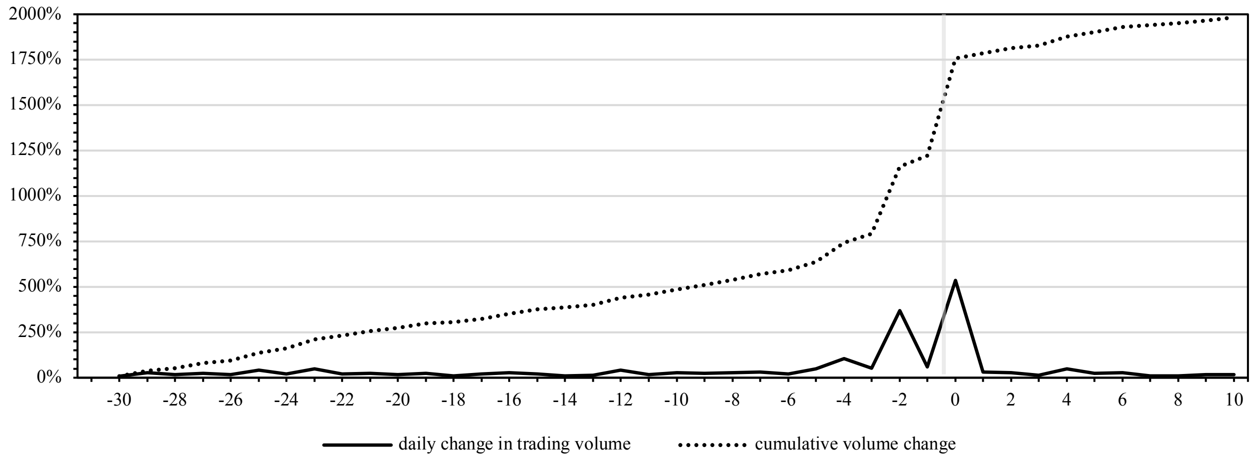

Figure 1 shows the average daily and cumulative returns over a window of 30 days before and 10 days after (-30, +10) the listing of a cryptocurrency on an exchange. Logically, the exchange where a cryptocurrency is listed is only added in the calculation of returns starting at t = 0. Only 7 of the 30 days before a listing show negative average daily returns. From t = -30 to t = -1, returns accumulate to 19.43%, before jumping to 25.42% due to a 5.99% price increase on the day of the listing. After the event, returns drift sideways, accumulating to 26.23% by t = 10. Of the 10 days after the event, half have negative returns. The descriptive results indicate that relevant price effects are realized before or on the listing day, whereas subsequent days are not associated with relevant effects.

Figure 2 presents average daily and cumulative changes in trading volume for the 237 cryptocurrencies. The exchange where an asset is listed is added in t = 0. Therefore, an increase in trading volume from that point can be expected. On the day of the event, the trading volume increases by 536%. From t = -30, the trading volume increases on every single day at an average rate of 40.68%, which accumulates to 1,221% by t = -1. Prior to the actual listing, the greatest increases in volume occur on days t = -4 (105%) and t = -2 (369%). The increase in trading volume could be a sign that informed traders build their positions on other exchanges in anticipation of the listing event. After the listing, the trading volume continues to increase at an average rate of 27.7% per day. These huge increases may be explained by the fact that before the listings, the currencies were only traded on small and/or illiquid exchanges[3]. I calculated the statistics for each exchange and found that the increases in trading volume clearly differ across the individual exchanges. This suggests that exchange differ based on the amount of liquidity they are able to provide. Yet, as pointed out by Yates (2019) and Alameda Research (2019), exchanges in the crypto ecosystem heavily overreport their volume to signal quality and to attract listing fees from cryptocurrency projects. Yates (2019) found that only 10 of 81

[3] Sadly, it is not possible to say which exchanges the assets traded on before the event.

exchanges reported the correct volumes, and of $6 billion in reported volume, only $273 million (4.5%) was legitimate.

5. Empirical results

The empirical results comprise, first, statistics on the entire market (5.1), then individual markets (5.2), and finally further analyses regarding market and exchange characteristics, such as market capitalization, trading volume or jurisdictions, and robustness checks (5.3).

5.1 Overall market results

Table 1 shows CAARs for all listing events across the seven-day event window (-3, +3) and the respective share of assets with positive ARs both for the Constant Mean Return Model and the Market Model. The event windows start with 7-, 5- and 3-day periods in the first three rows and single day observations for all 7 days. The next rows show results for periods leading up to the event, which are of special interest for the discovery of informed trading. The last rows show return statistics starting from the day of the event or the day after the event.

The overall trends are the same if instead of the Market Model we use the Constant Mean Return Model to calculate expected returns. The use of a reference market leads to a small decrease in the size of returns. Therefore, it represents a more conservative model and will be used for further analysis.

Table 1

CAARs around the event of an exchange listing of cryptocurrencies. This table shows results for different intervals around the event window of (-3, +3) for 327 events. Model 1 uses the Constant Mean Return Model to calculate abnormal returns, while Model 2 uses the market model with Bitcoin as a reference market.

	(1) Constant Mean Return Model				(2) Market Model			
Event window	CAAR	t-statistic	z-statistic	% positive	CAAR	t-statistic	z-statistic	% positive
-3 to +3	0.099	4.17***	4.32***	0.58	0.092	4.11***	4.49***	0.59
-2 to +2	0.087	4.06***	4.26***	0.60	0.081	3.87***	4.35***	0.61
-1 to +1	0.083	4.14***	4.53***	0.59	0.074	3.55***	4.15***	0.59
-3	0.010	1.45	-0.35	0.49	0.013	2.01*	0.06	0.49
-2	0.022	3.14***	3.01***	0.57	0.019	2.79***	2.38**	0.53
-1	0.025	3.06***	2.35**	0.54	0.018	2.27**	1.62	0.52
0	0.057	3.02***	3.71***	0.58	0.057	2.99***	3.32***	0.58
+1	0.001	0.11	-1.10	0.45	-0.002	-0.30	-2.33**	0.43
+2	-0.018	-3.96***	-4.61***	0.38	-0.011	-2.64***	-3.75***	0.42
+3	0.002	0.37	-0.26	0.49	-0.003	-0.65	-1.50	0.35
-3 to -2	0.032	3.14***	2.18**	0.55	0.032	3.26***	2.11**	0.54
-3 to -1	0.057	4.46***	3.72***	0.57	0.050	4.06***	3.41***	0.57
-3 to 0	0.114	5.19***	5.80***	0.61	0.107	5.04***	5.82***	0.63
-2 to -1	0.047	4.55***	3.85***	0.56	0.037	3.66***	3.10***	0.55
-2 to 0	0.104	5.01***	6.05***	0.64	0.094	4.67***	5.65***	0.48
-1 to 0	0.082	4.12***	4.96***	0.58	0.075	3.70***	4.38***	0.59
0 to +1	0.058	3.04***	3.34***	0.58	0.055	2.81***	2.85***	0.55
0 to +2	0.040	2.03**	1.30	0.53	0.044	2.17**	1.48**	0.41
0 to +3	0.045	2.26**	1.92*	0.42	0.042	2.06**	1.63	0.54
+1 to +2	-0.017	-2.36**	-3.13***	0.42	-0.012	-1.92*	-3.04***	0.33
+1 to +3	-0.015	-1.60	-2.12**	0.43	-0.015	-1.82*	-2.33***	0.32

*, **, *** indicates significance at the 10%, 5% and 1% level respectively

Averaged across all events, I identify a CAAR of 9.9% for model 1 and 9.2% for model 2 for the whole event window, which is significant at the 1%-level. 58% of the cryptocurrencies exhibit positive abnormal returns for the period (-3, +3) in model 1 and 59% in model 2. The AAR on the day of the event are 5.7% in model 1 and model 2 (significant at the 1%-level for both tests).

In an extended event window of (-7, +7),[4] CAARs are steadily positive with daily returns between 0.2% and 1.9% for the seven days leading up to the event. In

[4] For the sake of brevity, results for (-7, +7) are not presented in a table.

the week after the listings, with the exception of t+4, CAARs are negative but smaller. The CAAR assumes it maximum of 14.7% on the event day and declines to 12.8% for the full (-7, +7) window. The largest share of the CAAR is built up before the actual event but afterwards returns are actually negative. Of the 327 listings, 60.2% had a positive CAAR over the full 15-day period. CAARs are always positive (between 0.2% and 2.4%) in the week leading up to the event. On t = 0, the CAARs are 5.7%, for a CAAR of 16% for (-7, 0).

For t = -3, model 1 does not show a significant CAAR, while model 2 shows a positive effect of 1.3% that is significant at the 10%-level. The three-day period leading up to an event (-3, -1) has a positive CAAR of 5.7% (model 1) and 5% (model 2), both of which are significant at the 1%-level. In t = -2, both models show highly significant positive abnormal returns of 1.9% and 2.2%, respectively. The effects are even stronger on the day before the listing event, 5.7% ($p_{t/z} < .01$) for model 1 and 7.5% ($p_{t/z} < .01$) for model 2. The period (-3, -2) that may be the best fit for the identification of informed trading activity as potential announcement effect of t = -1 are excluded leads to highly significant returns of 3.2%.

In Model 2, all three days after the event show negative CAAR, of which only the -1.1% in t = -2 are significant. Summarized, results for the 3-day period after the listing amount to -0.9% (-1.5% in model 1). Returns are growing by the day until the event and decrease afterwards.

5.2 Individual market results

Table 2

CAARs based on the Market Model for specific cryptocurrency exchange samples and different intervals around the event window (-3, +3). '% pos' means the share of assets with positive AAR.

		-3 to +3		-3 to -2		-1		0		+1		+1 to +3	
Market	N	% pos	CAAR	% pos	CAAR	% pos	CAAR	% pos	CAAR	% pos	CAAR	% pos	CAAR
Binance	45	0.64	0.175^{ax}	0.58	0.074	0.42	0.016	0.76	0.147^{ax}	0.42	0.003	0.24	-0.063^{bx}
FCoin	27	0.63	0.032	0.63	0.031^{cz}	0.33	-0.012	0.48	0.009	0.41	0.003	0.52	0.014
HitBTC	26	0.35	-0.025	0.38	-0.022	0.38	0.006	0.58	0.001	0.38	-0.007	0.31	-0.010
Bitfinex	25	0.60	0.196	0.48	-0.020	0.64	0.048^{cz}	0.72	0.255^{y}	0.52	-0.016	0.48	-0.087^{z}
Huobi	24	0.58	0.033	0.58	0.019	0.75	0.055^{ax}	0.50	0.020	0.17	-0.034^{ax}	0.13	-0.061^{ax}
Bittrex	21	0.67	0.264^{by}	0.57	0.089^{z}	0.48	-0.053	0.67	0.235^{bz}	0.43	0.008	0.38	-0.006
Bithumb	18	0.72	0.110^{by}	0.67	0.069^{cz}	0.72	0.051^{by}	0.61	0.051^{ay}	0.22	-0.017^{y}	0.28	-0.061^{by}
Gate.io	16	0.50	0.102	0.31	-0.036	0.50	0.130	0.31	-0.045^{cy}	0.56	0.014	0.56	0.053
Coinbene	16	0.50	0.006	0.38	0.006	0.50	-0.005	0.50	-0.002	0.75	0.021^{z}	0.50	0.007
YoBit	15	0.47	0.046	0.60	0.023	0.47	-0.002	0.40	-0.009	0.47	0.001	0.67	0.033
Upbit	15	0.40	-0.008	0.27	-0.030^{cz}	0.47	0.015	0.67	0.031	0.20	-0.029^{by}	0.20	-0.024^{z}
KuCoin	13	0.54	-0.031	0.54	0.037	0.46	-0.002	0.54	-0.005	0.46	-0.028^{c}	0.31	-0.060^{cz}
OKEx	11	0.82	0.146^{by}	0.55	0.008	0.64	0.028	0.55	0.017	0.45	0.047	0.45	0.093
Bitforex	11	0.82	0.158^{by}	0.73	0.117	0.45	-0.002	0.36	-0.021	0.55	0.005	0.82	0.065^{cz}
Bibox	11	0.82	0.061	0.64	0.087	0.64	0.028	0.27	-0.036^{cz}	0.36	-0.007	0.36	-0.017
Coinbase	7	0.57	-0.006	0.43	-0.010	0.57	0.024	0.57	0.004	0.43	-0.011	0.57	-0.024
Liquid	6	0.33	0.035	0.50	0.047	0.50	-0.009	0.50	-0.025	0.50	0.018	0.33	0.022
LATOKEN	6	0.67	0.169	0.83	0.047	0.50	0.028	0.17	-0.016	0.50	0.061	0.83	0.110^{z}
Poloniex	3	1.00	0.387	1.00	0.258	1.00	0.052^{b}	0.33	0.080	0.33	-0.029	0.33	-0.004
Hotbit	6	0.50	-0.073	0.33	-0.025	0.50	-0.000	0.33	-0.048	0.83	0.035	0.67	-0.000
Kraken	3	1.00	0.214	1.00	0.104	0.67	0.009	0.33	0.051	0.67	0.008	1.00	0.049^{b}
STEX	2	0.50	-0.020	1.00	0.043^{b}	0.00	-0.038	0.50	-0.009	0.00	-0.023^{c}	0.00	-0.017

a, b, c indicates significance at the 1%, 5% and 10% level respectively for the t-statistic
x, y, z indicates significance at the 1%, 5% and 10% level respectively for the z-statistic

As discussed above, the cryptocurrency exchange market is highly segmented, which suggests that listing returns differ in terms of exchanges. In order to identify such effects, the sample is divided into 22 subsamples, each containing all available listings of an individual exchange. Table 2 shows results for individual markets. Six specific event windows are shown that are the full event window (-3, +3), post-listing returns that exclude potential announcement effects in t = 1 (-3, -2), post-listing returns in t = -1, returns at the day of the listing event (t = 0), the day after (t = 1) and returns for the 3-day period after the event (+1, +3).

For the full event window, significant positive CAARs are obtained for 'only' five trading venues:

Binance (17.5%, $p_{t/z} < .01$), Bittrex (26.4%, $p_{t/z} < .05$), Bithumb (11%, $p_{t/z} < .05$), OKEx (14.6%, $p_{t/z} < .05$) and Bitforex (15,8%, $p_{t/z} < .05$). Of the 22 exchanges, six have negative CAARs, while 16 are positive for (-3, +3). The two US-based exchanges Poloniex and Kraken have exclusively positive (though insignificant) event returns (their samples each comprise three listings each). Of the exchanges with 10 or more listings, OKEx, Bitforex and Bibox have the highest share of positive listing returns (82% each). The amount of associated returns differs significantly. Bittrex has the highest value of 26.4%, while Hotbit has negative returns of -7.3%.

The window (-3, -2) is chosen specifically because in that period, no news about the listing has reached the market. The day t = -1 is not included, as some exchanges announce new listings one day in advance. I will analyze announcement effects at a later stage of this paper to account for this issue. In total, 15 exchanges (68%) have positive ARs for at least half of their assets. If we only consider exchanges with 10 or more listings, the same applies to 10 out of 15 (66%) market places. Of the five exchanges that have a majority of negative reactions to listings, Upbit (73%) and Gate.io (69%) are the starkest examples. For this period, five exchanges show significant results, of which Upbit is the only one with a negative effect (-3%, $p_{t/z} < 0.1$). The US-based exchange Bittrex has the highest positive abnormal effect with 8.9% ($p_z < .1$), while the Korean exchange Bithumb has a CAAR of 6.9% ($p_{t/z} < .05$). STEX (4.3%, $p_t < .05$) and FCoin (3.1%, $p_{t/z} < .1$) have lower CAARs. The existence of significant CAAR in the window shows that information about listing events likely leak.

The third column (t = -1) shows results for the day before the trading pair is added. 59% of the exchanges have a majority of positive ARs, with Poloniex (100%), Huobi (75%) and Bithumb (72%) taking the lead. Among the predominantly negative exchanges, STEX (0%), FCoin (33%) and Binance (42%) are the top three. I identify four significant CAAR, all of which are positive. Of these, Huobi has the highest CAAR (5.5%, $p_{t/z} < .01$), followed by Poloniex with 5.2% ($p_t < .05$). The other two observations that are significant are the Korean exchange Bithumb (5.1%) and Bitfinex (4.8%).

The model (t = 0) investigates effects for the day of the actual listing. Six exchanges show significant results, four of which are positive. Binance has a positive CAAR of 14.7% ($p_{t/z} < .01$); 76% of the 45 events produced positive returns. Hong Kong-based Bitfinex has the highest significant positive coefficient (0.255), which is however only significant at the 5%-level for the z-statistic. Bittrex has an CAAR of 23.5% (67% positive reactions) that is significant at the 5%-level for the t-statistic and at 10%-level for the z-statistic. Bithumb is the exchange with the lowest positive significant CAAR (5.1%, 61% positive). Huobi and Poloniex had a significant effect in t = -1 but not so in t = 0. The two exchanges with negative CAARs are Gate.io (-4.5%, 31% positive) and Bibox (-3.6%, 27% positive). Both effects are significant at least at the 10%-level for both tests.

On the day after the listing (t = 1), only Coinbene (2.1%, 75% positive) has a significant ($p_z > .1$) positive CAAR, while five other exchange show significant negative returns. Huobi has highly significant negative returns (-3.4%, $p_{t/z} < .01$), with only 17% of its 24 events resulting in positive returns. Only 20% of the 15 events on the Korean exchange Upbit are positive, with an CAAR of -2.9% ($p < .05$). The CAAR of the other three exchanges KuCoin (-2.8%), STEX (-2.3%) and Bithumb (-1.7%) all are only significant with respect to one of the tests. 8 (36%) of the exchanges had positive ARs in at least half of their currencies.

The last column shows post-event performance from the day after the listing until three days after (+1, +3). Three exchanges have positive, six have negative and significant coefficients. Huobi (13% positive) has a CAAR of -6.1% that is significant at the 1%-level for both test statistics, while the CAAR for Binance (-6.3%, 24% positive) is significant at the 5%-level (1%-level for the z-statistic). Bithumb (28% positive) has negative CAAR of -6.1% that is significant at the 5%-level; the CAAR of KuCoin (-6%) is significant at the 10%-level. The other two exchanges Bitfinex (-8.7%) and Upbit (-2.4%) are significant at the 10%-level for the z-statistic. Bitforex (6.5%, $p_{t/z} < .05$) has a positive and significant CAAR, while LATOKEN (11%) and Kraken (4.9%) are both significant for only one test statistic.

5.3 Further analysis and robustness checks

5.3.1 Announcement effects

It remains unclear if or to what extend CAARs of e.g. 5.7% or 5.0% for the period (-3, -1) across the full sample indicate informed trading, as listing announcements usually happen in t = 0 or t = -1. Therefore, two different samples are built, one with exchanges that announce listings in t = -1 and the other one with exchanges that announce events in t = 0. Table 3 shows the results for two different samples of events for the event window (-3, +3). Model 1 covers the 79 events that happened on exchanges that announce new listings one day prior to the actual trading start. The second model comprises 243 events that occurred on exchanges that have no pre-announcement of new listings.

Table 3

CAARs based on the Market Model for different intervals around the event window of (-3, +3). Model 1 (79 events) covers exchanges that announce new asset listings one day in advance, while model 2 (242 events) covers those that do not pre-announce new listings.

	(1) Announcement in t = -1				(2) Announcement in t = 0			
Event time	CAAR	t-statistic	z-statistic	% positive	CAAR	t-statistic	z-statistic	% positive
-3 to +3	0.065	2.28**	2.09**	0.70	0.072	2.83***	2.88***	0.56
-2 to +2	0.028	2.28**	3.16***	0.58	0.071	2.69***	2.63***	0.57
-1 to +1	0.029	2.14***	1.97**	0.54	0.057	2.21**	2.17**	0.42
-3	0.009	1.20	1.48	0.49	0.013	1.84*	0.33	0.49
-2	0.028	1.55	0.76	0.61	0.006	1.18	1.17	0.51
-1	0.011	1.19	1.03	0.53	0.016	1.66*	1.18	0.51
0	0.024	2.33**	1.93*	0.64	0.047	1.93*	1.21	0.52
+1	-0.006	-1.21	-0.70	0.38	0.005	1.00	-0.29	0.36
+2	-0.003	-0.65	-0.38	0.27	-0.005	-1.01	-1.72*	0.47
+3	-0.013	0.34	0.56	0.27	-0.003	-0.75	-1.13	0.36
-3 to -2	0.037	1.76*	2.69***	0.62	0.019	2.12**	1.25	0.51
-3 to -1	0.049	2.15**	2.36**	0.65	0.023	2.29**	1.28	0.40
-3 to 0	0.072	2.46**	1.71*	0.74	0.071	2.84***	3.41***	0.46
-2 to -1	0.039	2.19**	2.00**	0.64	0.011	1.48	0.72	0.38
-2 to 0	0.064	2.62**	2.09**	0.54	0.058	2.46**	3.04***	0.47
-1 to 0	0.035	2.37**	2.73***	0.71	0.062	2.06**	1.49	0.40
0 to +1	0.018	2.11**	1.94*	0.69	0.052	2.07*	1.90*	0.41
0 to +2	0.015	1.59	1.47	0.51	0.048	1.89*	0.97	0.37
0 to +3	0.016	1.69*	1.56	0.44	0.039	1.51	0.65	0.52
+1 to +2	-0.009	-1.32	-0.40	0.31	0.001	0.22	-0.60	0.35
+1 to +3	-0.007	1.11	-0.39	0.30	0.002	0.28	-0.63	0.34

*, **, *** indicates significance at the 10%, 5% and 1% level, respectively. Cryptocurrency exchanges differ in their timing of announcing token listings. 14 of the 22 exchanges announce new listings on the same day, while seven do so on the day before launching new trading pairs. Coinbase announces listings much earlier and thus belongs to neither group.

The CAAR for the full event window (-3, +3) is 6.5% in model 1 and 7.2% in model 2 – both significant at the 1%-level. Model 1 lacks significant effects for the day of the announcement (-1, -1), while model 2 shows a small positive significant effect of 1.6% on that day. For model 2, the announcement day is t = 0, and it is associated with ARs of 4.7% ($p_t < .05$). On that day, model 1 has highly significant positive returns of 2.4%. The time interval (-3, -2) has a positive CAAR of 3.7% for model 1 that is significant at the 10%-level. The corresponding effect is weaker for model 2 (1.9%, $p_t < .05$). The interval (-3, -1), during which no information is announced for the events covered by model 2, is associated with a highly significant CAAR of 2.3% ($p_{t/z} > .01$). In model 1, the CAAR is also highly significant (4.9%, $p_{t/z} < .05$). For the days after the listing (and announcement), model 2 only shows insignificant results, with the exception of t = 2, where the AR amount to -0.5% and the z-statistic is significant at the 10%-level.

5.3.2 Effects of country characteristics

Table 4

OLS regressions of CAARs over the period (-3, +3) on the countries in which the exchanges are based. Heteroskedasticity-robust standard errors in parentheses. For descriptive statistics and variable explanations, see Table 8 in the appendix.

	(1)	(2)	(3)	(4)
United States	0.140 * (0.081)	0.137* (0.079)		
South Korea	-0.019 (0.044)		-0.039 (0.041)	
Tax haven	0.050 (0.070)			0.036 (0.068)
Observations	327	327	327	327
R^2	0.012	0.010	0.0009	0.0006

* indicates significance at the 10% level. Constant term included but not reported.

For a first understanding as to whether country characteristics affect the listings of cryptocurrencies, Table 4 show results from regressing the CAARs over the period (-3, +3) on the jurisdictions in which the exchanges are based. I distinguish four groups: (1) The

United States have a highly regulated financial system and a very active regulator, while (2) the opposite applies to tax havens (here, the Seychelles and the Cayman Islands). (3) South Korea has strict governance and capital restrictions. (4) All other countries make up the omitted category.

In model 1, I test for effects of all three groups simultaneously, finding a significant result for the United States (0.14, $p < .1$). Models 2 to 4 individually test the three country dummies, producing a significant result only for the United States in Model 2 (0.137, $p < .1$). That model also has the highest R^2 (1%), while models 3 and 4 have very little explanatory power.

5.3.3 Effects of trading volume and market capitalization

Cryptocurrency projects clearly differ in terms of their liquidity, which may be measured by their trading volume and market capitalization. As there is no linear relationship between a cryptocurrencies' market capitalization and its trading volume, the ratio between the two metrics provides an indicator of potential under- or overvaluation and liquidity risk. If only a fraction of the existing market capitalization is actually being traded, the implied valuation of a cryptocurrency may be too high, as investors could not liquidate their positions at the current valuation. If the traded percentage of cryptocurrency value is higher, the implied level of liquidity is also higher, and the current valuation could even be too low.

Table 5 shows results from seven regression models predicting CAARs for the period (-3, +3). Model 1 captures the effects of both asset trading volume and market capitalization. Only the former shows a (negative) significant effect. Model 2 tests for any effects of the volume and market capitalization of the reference market Bitcoin. Bitcoin trading volume (-0.758, $p < .01$) has a highly significant negative effect on CAARs, while Bitcoin market capitalization lacks significance. Models 3 to 7 capture individual characteristics. The results for asset trading volume in model 3 remain similar (-0.038, $p < .01$), while asset market capitalization has a strongly significant coefficient (-0.025, $p < .01$) in model 4. The ratio between the two metrics has a significant effect, suggesting higher listing returns for comparatively illiquid assets. The trading volume of the reference market Bitcoin has a highly significant negative effect on listing returns. In phases of high Bitcoin trading volume, exchange listing lead to lower returns, as traders may focus on Bitcoin.

Table 5

Regressions on cumulative abnormal returns for market characteristics. This table shows results from seven OLS regression models predicting CAAR for the period (-3, +3) across 327 listing events of cryptocurrencies on exchanges. Standard errors that are robust to heteroskedasticity are reported in parentheses. Descriptive statistics and variable explanations are presented in Table 8 in the appendix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Trading volume	-0.044** (0.019)		-0.038*** (0.012)				
Asset market cap	0.008 (0.138)			-0.025*** (0.009)			
Market cap / trading volume					0.056** (0.023)		
Bitcoin trading volume		-0.758*** (0.234)				-0.790*** (0.245)	
Bitcoin market cap		-0.064 (0.048)					-0.085 (0.054)
Observations	324	327	327	324	324	327	327
R^2	0.042	0.047	0.042	0.019	0.027	0.042	0.009

, * indicates significance at the 5% and 1% level respectively. Constant term included but not reported.

Table 6 shows the results of ordering all events according to three different metrics – average trading volume, average market capitalization, and the average ratio of market capitalization and trading volume over the estimation window – and then dividing them into quartiles. Event windows are the same as in Table 2. CAARs over different periods are presented for each quartile of each metric.

For asset trading volume across the whole event window (-3, +3), the first (0.199, $p_{t/z} < .01$) and second quartile (0.143, $p_{t/z} < .01$) are associated with highly significant positive effects while the two other quartiles show none. I identify a decreasing trend in the CAAR, from 19.9% in Q1 to 0.1% in Q4. For the pre-event window (-3, -2), Q2 (3.9%) and Q2 (4.5%) have positive effects that are only significant for the t-statistic. On the day before the actual listing, returns are significantly positive for Q1 (4.6%) and Q2 (2.8%). In t = 0, the CAARs show a clear decreasing trend from 14.6% (significant at the 10%-level for the t-statistic) in Q1 to 2.8% ($p_{t/z} < .01$) in Q2 to 2.9% ($p_{t/z} < .05$) in Q3. In Q4, the CAAR is -0.3% but remains insignificant, with only 42% of the events being positive. Q3 in t = 1 has a highly significant CAAR of -2.3%. For (+1, +3), all quartiles have negative CAARs, Q1 (-4.3%) and Q2 (-2.8%) being significant at the 5%-level and Q1 (-1.5%) showing significance at the 10%-level for the z-statistic.

For the full event window (-3, +3), market capitalization and trading volume have similar effects.

For both metrics, the CAARs decline monotonously over the quartiles, with significant effects only in Q1 and Q2. The share of positive events likewise declines from Q1 to Q4. For (-3, -2), market capitalization has significant effects in Q1 (4.6%) and Q4 (5.3) but not so in the intermediate quartiles. I only identify one significant effect for the day leading up to the event (Q1, 5.4%). On the day of the listing, the first three quartiles are all significant and positive, though with different effect sizes. Q2 has an CAAR of 11.2% that is significant at the 10%-level, followed by Q1 (7.6%, $p_t < .05$, $p_z < .1$) and Q3 (3.5%, $p_{t/z} < .05$). For (+1, +3), all CAARs are negative, but only Q3 shows a significant effect (-3.8%).

Testing the quartiles with respect to the ratio of reported market capitalization to trading volume yields a trend in size and significance for the full 7-day event window: The effects consistently increase from Q1 (1.2%, 54% positive) to Q2 (6.4%, $p_t < .05$, 58% positive), to Q3 (7.2%, $p_{t/z} < .05$, 60% positive) and finally to Q4 (21.5%, $p_{t/z} < .01$, 64% positive). For (-3, -2), I identify a trend from Q1 (1.6%) to Q4 (4.9%, $p_t < .1$). The fourth quartile of the day leading up to the listing has a positive CAAR of 2.3% that is significant at the 10%-level. 56% of the cryptocurrencies appreciate in value in Q4, in contrast to 46% in Q1. On the day of the listing, the results also drift from a negative and insignificant CAAR in Q1 (-0.2%, 46% positive) to significant and increasing results for the three other quartiles. In Q2, the CAAR amounts to 2.7%, growing to 5.8% in Q3 and 14.9% in Q4. All quartiles for both periods after the launch exhibit negative (C)AARs, with the exception of 0.4% for Q1 in t = 1. Yet the results are only significant for one test statistic, if at all.

Table 6

CAARs calculated on the basis of the market model for different intervals around the event window of (-3, +3) by quartiles according to three liquidity-related metrics (see Table 8 in the appendix for details). '*% pos*' means the share of assets with positive AAR.

			-3, +3		-3, -2		-1, -1		0, 0		+1, +1		+1, +3	
Metric	Quartiles	N	% pos	CAAR	% pos	CAAR	% pos	CAAR	% pos	CAAR	% pos	CAAR	% pos	CAAR
Asset trading volume (n = 327)	Q_1	82	0.61	0.199^{ax}	0.54	0.020	0.51	0.046_{c}	0.57	0.148^{by}	0.45	0.013	0.37	-0.015^{z}
	Q_2	82	0.71	0.143^{ax}	0.54	0.039^{b}	0.59	0.028_{ay}	0.59	0.051^{ax}	0.46	0.002	0.48	0.025
	Q_3	82	0.52	0.023	0.50	0.045^{c}	0.41	-0.008	0.61	0.029^{by}	0.37	-0.023^{ax}	0.38	-0.043^{by}
	Q_4	81	0.53	0.001	0.58	0.024	0.56	0.008	0.42	-0.003	0.42	0.002	0.40	-0.028^{by}
Asset market capitalization (n = 324)	Q_1	81	0.67	0.170^{ax}	0.57	0.046^{bz}	0.54	0.054_{bz}	0.56	0.076^{bz}	0.46	0.007	0.42	-0.006
	Q_2	81	0.60	0.130^{bx}	0.49	0.015	0.44	0.012	0.62	0.112^{cx}	0.40	-0.005_{y}	0.43	-0.010
	Q_3	81	0.56	0.027	0.49	0.018	0.54	0.013	0.56	0.035^{ay}	0.43	-0.011	0.35	-0.038^{bx}
	Q_4	81	0.54	0.036	0.60	0.053^{by}	0.53	-0.006	0.47	0.007	0.42	-0.001	0.41	-0.018
Market cap / trading volume (n = 324)	Q_1	81	0.54	0.012	0.52	0.016	0.46	0.027	0.46	-0.002	0.42	-0.004	0.44	-0.029^{c}
	Q_2	81	0.58	0.064^{bz}	0.53	0.024	0.52	0.027_{b}	0.58	0.027^{bz}	0.38	-0.009_{y}	0.37	-0.014
	Q_3	81	0.60	0.072^{by}	0.57	0.042_{b}	0.53	-0.004	0.56	0.058^{ay}	0.44	-0.002	0.40	-0.024^{z}
	Q_4	81	0.64	0.215^{ax}	0.54	0.049_{c}	0.56	0.023_{cz}	0.60	0.149^{bx}	0.44	0.004	0.40	-0.006

a, b, c indicates significance at the 1%, 5% and 10% level respectively for the t-statistic
x, y, z indicates significance at the 1%, 5% and 10% level respectively for the z-statistic

Overall, the results indicate that asset market characteristics and trading volume influence the effects of cryptocurrency listings. Therefore, the results regarding the CAARs of specific exchanges may lack informative value, as the exchanges could deliberately choose to list assets with low market capitalization or low trading volume (or a high ratio of these two metrics) to signal high listing returns to the market. By listing cryptocurrencies with lower volume and lower market capitalization, positive listing returns may be easier to reach, while the actual increase in liquidity may be lower compared to different exchanges that decide to list assets with higher existing liquidity. Therefore, absolute effects must also be analyzed.

Table 7 reports the cumulative abnormal absolute market capitalization changes (CAAMCs) for the whole market and for each individual cryptocurrency exchange sample. It shows the absolute increase or decrease in market capitalization adjusted by the average change in capitalization over the estimation period. The CAAMC allows to assess the absolute amount of change in market capitalization around the event window. The metric provides an additional insight and robustness test if relative returns are 'relevant' in terms of size. As the distribution of asset market capitalization is highly skewed, only the z-statistic is used to calculate significance levels.

For the whole sample of 322 events across 22 exchanges, I identify a highly significant increase in market capitalization ($81.2m), with 62% of the currencies experiencing an increase in capitalization over the 7-day window. In the period leading up to the event (-3, -2), 59% of the events lead to positive capitalization changes and the CAAMC amounts to $40.2m ($p_z < .01$). For the day before the event (when some listings were already announced), 57% of the cryptocurrencies have increases in capitalization and the CAAMC amounts to $25m ($p < .05$). The growth in market capitalization on the actual day of the listing is somewhat lower (22.3%) but significant at the 1%-level. After the listing event, less than half of the returns are positive (47% in t = 1 and 48% for t = 1 to t = 3). Increases in market capitalization remain insignificant but are negative for the (+1, +3) window ($ -6.3m).

Table 6

Cumulative abnormal average market capitalization changes in million USD for different intervals around the event window (-3, +3), calculated using the Constant Mean Return Model with a prediction window of (-30, -10). '*% pos*' means the relative share of cryptocurrencies whose market capitalization grew over the respective period.

		-3, +3		-3, -2		-1, -1		0, 0		+1, +1		+1, +3	
Market	N	% pos	CAAMC	% pos	CAAMC	% pos	CAAMC	% pos	CAAMC	% pos	CAAMC	% pos	CAAMC
All Obs.	322	0.62	81.20***	0.59	40.20***	0.57	25.00**	0.61	22.30***	0.47	18.40	0.48	-6.34
Binance	44	0.68	307.00	0.55	85.10	0.50	97.00	0.70	166.00***	0.48	43.10	0.43	-41.90
FCoin	27	0.44	-148.00*	0.56	-85.80	0.37	-25.50*	0.63	8.39	0.30	-28.00*	0.48	-45.30
Bitfinex	24	0.54	8.46*	0.54	173.00	0.54	-33.00	0.75	-48.00**	0.58	16.10	0.54	-83.20
Bittrex	21	0.86	63.4***	0.76	49.10***	0.67	14.10	0.62	-16.40	0.57	-20.10	0.52	16.60
HitBTC	26	0.50	-167.00	0.42	-111.00	0.50	-41.80	0.81	-11.30***	0.58	5.30	0.46	-3.20
Bithumb	18	0.89	14.70***	0.83	13.50**	0.78	4.52*	0.83	18.40**	0.28	24.50	0.39	-21.80
Coinbene	16	0.63	304.00	0.44	143.00	0.38	43.80	0.75	68.30*	0.69	118.00*	0.63	48.10
YoBit	15	0.67	4.23	0.80	6.02**	0.53	-786.80	0.53	-1.34	0.53	0.45	0.67	0.33
Upbit	15	0.20	-14.60**	0.40	-5.72	0.40	-1.48	0.53	0.71	0.07	-5.24***	0.20	-8.11**
KuCoin	13	0.62	67.00	0.69	74.20	0.62	67.80	0.54	-20.30	0.38	-36.30	0.38	-54.80
OKEx	11	0.73	-3.26	0.55	-31.30	0.91	38.40***	0.45	-19.00	0.64	30.50	0.64	8.67
Bitforex	10	0.80	363.00	0.90	176.00***	0.50	-19.90	0.50	26.80	0.70	61.90	0.80	180.00**
Bibox	10	0.60	713.00	0.60	368.00	0.70	148.00	0.40	3.66	0.30	143.00	0.50	195.00
Huobi	24	0.75	-7.00**	0.25	26.30*	0.79	68.00***	0.58	-9.76	0.50	-24.90	0.38	-91.50
Gate.io	15	0.60	142.00	0.47	-25.70	0.60	49.40	0.33	22.30	0.53	70.80	0.47	96.10
Coinbase	7	0.57	-41.90	0.29	-33.60	0.86	6.28	0.57	-2.28	0.00	-21.80**	0.29	-12.30
Liquid	6	0.33	-38.00	1.00	-19.60	0.33	-9.41	0.50	7.30	0.50	1.68**	0.33	-16.20
LATOKEN	6	0.83	9.14	0.50	2.56**	0.50	3.61	0.50	-0.26	0.83	-16.80	0.83	3.24*
Poloniex	3	0.00	-113.00	0.67	-28.10	0.67	17.10	0.33	-29.40	0.00	1.82	0.00	-72.40
Hotbit	6	0.33	4.50	0.17	2.14	0.50	0.57	0.33	0.28	0.67	12.10	0.50	1.50
Kraken	3	1.00	197.00	1.00	71.60	0.67	63.80	0.33	22.20	0.33	12.10	0.67	39.50
STEX	2	0.50	-3,01	1.00	5.96	0.00	-3.39	0.50	-2.29	0.00	-5.31	0.00	-3.29

***, **, * indicates significance at the 1%, 5% and 10% level, respectively, for the z-statistic.

The results for the individual exchanges show substantial differences in terms of the absolute changes in market capitalization and the significance levels across all observed periods. For (-3, +3), Binance has the highest CAAMC ($307m, 68% positive), while FCoin has the lowest (-$148m, $p_z < .1$, 44% positive). Bittrex ($63.4m) and Bithumb ($14.7m) have positive CAAMCs that are significant at the 1%-level. Bitfinex is the only other exchange with positive and significant results for this time period ($8.4m, $p_z < .1$). Besides FCoin, Upbit (-$14.6m, $p_z < .05$) and Huobi (-$7m, $p_z < .05$, 75% positive) have negative and significant CAAMCs in (-3, +3). Overall, 77% (17) of the exchanges list a majority of currencies whose market capitalization increased during the full event window.

In the window of three to two days prior to the event, all five significant CAAMCs are positive. The market capitalization changes of currencies listed on Bitforex ($176m, 90% positive) and Bittrex ($49.1m, 76% positive) are significant at the 1%-level, while the increases for Bithumb ($13.5m), YoBit ($6m) and LATOKEN ($2.6m) are significant at the 5%-level. Huobi has a positive CAAMC of $26.3m ($p_z < .1$). In t = -1, Huobi ($68m, $p < .01$), OKEx ($38.3m, $p_z < .01$) and Bithumb ($4.5m, $p < .1$) exhibit the only three positive CAAMCs. A listing on FCoin results in an average decrease in asset market capitalization of $25.5m ($p_z < .1$).

On the day of the listing, Binance stands out with a highly significant CAAMC of $166m (70% positive). Coinbene ($68.3m, $p_z < .1$) and Bithumb ($18.3m, $p_z < .05$) also show positive and significant increases in market capitalization. Bitfinex ($ -48m, $p < .05$) and HitBTC ($ -11.3m, $p_z < .01$) feature the only negative and significant average changes in market capitalization. On the day after the listing, the three projects FCoin ($ -28m), Coinbase ($ -21.8m) and Upbit ($ -5.2m) have significantly negative CAAMCs, while significant results for Coinbene ($118m) and Liquid ($1.7m) are positive.

For the (+1, +3) period, 59% (13) of the exchanges have a negative change in market capitalization, of which only Upbit ($ -8.1m, $p_z < .05$) is significant. Bitforex has a CAAMC of $180m that is significant at the 5%-level. The only other significant result is LATOKEN ($3.2m, $p_z < .1$).

6. Discussion

6.1 Market reactions to exchange listings

The results show that cross-listings of cryptocurrencies yield significant abnormal returns across the event window. This finding is in line with the stock market literature (e.g. Foerster and Karolyi 1999; Miller 1999), but the effects are much greater. For instance, Roosenboom and Dijk (2009) identify average (announcement) returns of 1.3% for cross-listed stocks. The CAAR in t = 0 of 5.7% or 9.2% for the full event window (-3, +3) far exceed these numbers. The CAAR of 9.2% was calculated using the Market Model, which, accounting for concurrent price increases in Bitcoin, is arguably the more conservative model and the best fit. On the day of the listing, the CAAR of 5.7% is highly significant, which confirms that listings of cryptocurrencies are positive new that surprise at least some market participants. The sheer size of returns indicates that cryptocurrency markets may be less efficient and less mature than stock markets.

The significant positive listing effect across all exchanges suggests that the cross-listing of cryptocurrency reduces barriers to investment similar to stock markets, as new users from additional jurisdictions or communities can now access the asset (Errunza and Losq 1985) and the project's visibility increases (Baker et al. 2002). This suggests that, in line with the investor recognition hypothesis (Merton 1986), cryptocurrency projects try to expand their investor base to reduce the returns expected by existing investors. By introducing new users to purchase options of a newly listed cryptocurrency, existing investors can realize gains.

For the three days after the listing, the returns are significant and negative (-1.5%). This finding is in line with the negative post-listing drift reported by Dharan and Ikenberry (1995) for stock markets. This indicates more traders use the increased liquidity of events to liquidate all or part of their holdings than new traders are attracted. For this reason, a cryptocurrency exchange listing only represents a positive event until the actual listing occurs. From the day after, it can be classified as a negative event. Of course, this statement only applies within the investigated timeframe.

In contrast to the literature on stock listing announcements (e.g. Miller 1999; Roosenboom and Dijk 2009), I fail to identify a relevant announcement effect for the 77 events that occurred on exchanges which usually announce new listings on t = -1. The empirical finance literature has shown that stocks tend to earn positive abnormal returns following listing announcements and experience significant negative returns after the actual listing event (e.g. Kadlec and McConnell 1994; Sanger and Mcconnell 1986). Though I do find such negative returns, the present data yield no evidence of announcement effects. A possible explanation is that exchanges that pre-announce listings leak information, as there are significant positive returns of 6% on the day before the announcement.

Using three dummy variables for the jurisdictions in which the exchanges are located, I analyzed whether specific market characteristics, such as stricter (U.S.) or weaker (Tax havens) governance or capital controls (South Korea) affect asset returns around the listing events. The U.S. market has a significant positive effect on returns, in line with evidence on stock listings (Anant and Dennis 1996; Doidge et al. 2004). This may suggest that cryptocurrency projects try to signal their private information of quality to existing and new investors by cross-listing in a country with stricter(er) regulatory oversight (Cantale 1996).

The descriptive statistics (see Figure 2) show that the overall trading volume generally increases heavily with new listings of cryptocurrency. In line with the literature on stock markets (Foerster and Karolyi 1999), exchange listings of cryptocurrency lead to higher trading volumes (and likely lower spreads), as market makers and arbitrageurs find additional scope for their activities. Due to the greater liquidity, trading costs decrease for investors from specific jurisdictions, suggesting a similar effect as for stocks (Sarkissian and Schill 2004). Trading volumes already increase heavily before information about the event hits the market, suggesting informed trading. While I cautioned above that the reported trading volume is likely to be manipulated and therefore only of limited value in itself, I find that reported trading volume and reported market capitalization have a negative effect on abnormal returns around new listing events. This makes sense as cross-listings of more liquid assets should generally dampen the price increase caused by the introduction into new markets. When analyzing quartiles of the metrics for the event and its run-up (see Table 6), the results indicate strong positive effects for the lower quartiles, while the results of the higher quartiles are much weaker and lack significance. After the listing event, this effect shifts, as higher quartiles are associated with significantly negative returns, while lower quartiles lack significance. When dividing market capitalization by trading volume, I find significant and strongly positive abnormal returns of up to 21.5% (Q4) over the full event window. This shows that the combination of existing market capitalization and trading volume can be an indicator of anticipated returns from exchange listings.

6.2 Exchange-specific effects

The listing effects clearly differ across individual exchanges, as the significant positive overall market returns for cross-listings of cryptocurrencies over the full event window rest on only five of the twenty-two exchanges: Binance (17.5%), Bittrex (26.4%), Bithumb (11%), OKEx (14.6%) and Bitforex (15.8%). Each of these have a CAAR in excess of 10%, while six exchanges feature negative but insignificant CAARs. In terms of absolute returns as measured by the abnormal changes in market capitalization, the overall abnormal change amounts to $81.2 million. Yet only six of the exchanges show significant changes for the full event window, some being positive (e.g. Bittrex $63.4m) and others being negative (e.g. FCoin $ -148m). These findings suggest that generalized results for the whole market should be interpreted with caution.

In the run-up to the listings, I identify significant positive abnormal returns for several exchanges. These finding will be discussed in the next section. On the listing day itself, I find six significant CAARs, four positive ones on Binance (14.7%), Bitfinex (25.5%), Bittrex (23.5%) and Bithumb (5.1%), and two negative ones on Gate.io (-4.5%) and Bibox (-3.6%). In terms of changes in market capitalization, three exchanges (Binance $166m, Bithumb $18.4m and Coinbene $68.3m) exhibit significantly positive effects, while Bitfinex ($ -48m) and HitBTC ($ -11.3m) are negative. This shows that listing events and their effects differ across individual cryptocurrency markets, and the significant overall market capitalization increase of $22.3m on the day of the listing must be interpreted with care. The overall market results are driven by major individual effects, such as the big listing premium of Binance.

For the day after the listing, all significant returns are negative, Coinbene (2.1%) being the only exception. The other five effects range between -3.4% (Huobi) and -1.7% (Bithumb). Over the full three-day period after the listing, six out of nine significant returns are negative. This trend changes for average changes in market capitalization, as two out of three significant results are positive. As with the event and pre-event windows, the effects of new listings differ significantly across individual exchanges.

The results highlight the effect of individual exchange features on absolute and relative returns from listings, one such feature being the jurisdiction in which an exchange is based. The findings suggest market segmentation and barriers to investment, which cross-listings serve to overcome, in line with analogous findings on stock markets (Karolyi 1998). That way, the projects can reduce their cost of capital, as suggested by Errunza and Losq (1985). Listing effects are likely driven by a number of additional factors, some of which are suggested by Benedetti (2019), who finds significant effects for exchange characteristics such as listing fees and reviews, specific country access, the availability of KYC procedures, fiat currency gateways, rebates, margin trading and OTC desks.

6.3 Informed trading

The positive CAARs of e.g. 5.7% or 5.0% for the period (-3, -1) across the full sample indicate that at least some of the market participants already knew about the upcoming listing. To test whether this information was publicly known or whether the results are indicative of informed trading, I divided the sample into events that were announced on the day before the listing and those that were only announced on the actual listing day. Without any informed trading, the market should only react in t = -1 for pre-announced events and in t = 0 for same-day announcements. For pre-announced events, I identify highly significant abnormal returns of 6% on the day before the announcement (i.e. two days before the listing). For the same-day announcements, I identify a hardly significant CAAR of 1.6% for t = -1.[5] Exchanges that pre-announce events seem to be more susceptible to informed trading. For the period (-3, -2), changes in abnormal market capitalization amount to $40.2m on average for 322 events. Feng et al. (2018) suggest that for positive events, informed traders of Bitcoin enter into positions two days before the events. My findings also suggest that informed trading is happening.

Baruch et al. (2017) show that informed traders influence price development in anticipation of events. Obtaining private signals, they enter into positions before the information becomes public (Glosten and Milgrom 1985; Kyle 1985). My findings suggest that such effects also exist in cryptocurrency markets, as I identify high abnormal returns at times when the information is not yet public knowledge.

To date, especially those cryptocurrency exchanges that are located offshore and do not offer fiat deposits and withdrawals lack regulatory oversight – which is why the indications of informed trading come as no surprise: The exchanges themselves can easily exploit their insider knowledge. Every exchange has its own rules regarding the admission of new trading pairs. As cryptocurrencies mostly represent decentralized computer protocol on public blockchain infrastructure, the exchanges can 1) list assets without the consent of the project or legal entity that controls the asset and 2) freely decide on their listing fees. It is common practice for crypto exchanges to demand payment denominated both in the asset itself and in fiat or other cryptocurrencies. This entails agency costs, as the exchanges look to sell the asset to its users. In an unregulated market, the exchanges can also purchase an asset elsewhere before listing it themselves, that way quietly accumulating positions before announcing or listing the asset and thus sharing their private information. The same applies to project teams who have concluded a listing agreement with a new exchange. Without effective rules on insider trading and market manipulation, market participants will misbehave, to the detriment of consumer protection.

At the level of the individual exchanges, I find that FCoin (3.1%), Bittrex (8.9%), Bithumb (6.9%) and STEX (4.3%) have significant positive CAARs for the

[5] When extending the event window to (-7, +7), the CAARs grow consistently from t = -7 until t = 0. They amount to 1.6% in t = -7, 2.3% in t = -6, 1.3% in t = -5 and 0.5% in t = -4. With CAARs of 2.2% in t = -2 and 5.7% and t = -1, this finding may be in line with Anderson and Holt (1997), who show how the market identifies the activities of informed traders, which leads to information cascades, as other traders pick up the signal and also enter into positions.

period (-3, -2), which may indicate that these four exchanges are the most likely to leak information about upcoming exchange listings or to otherwise act maliciously. Yet, these results may also be driven by other factors beyond the exchange themselves.[6] When assessing changes in market capitalization, Bittrex ($49.1m), Bithumb ($13.5m), YoBit ($6m), Bitforex ($176m) and LATOKEN ($2.6m) have positive abnormal returns over the (-3, -2) period. In total, seven of twenty-two exchanges show potential signs of informed trading, which raises concern for investor protection.

6.4 Limitations

As one of the first to investigate the phenomenon of cross-listings of cryptocurrencies, this study suffers from several limitations. In all likelihood, the abnormal returns from cross-listings decline with the number of pre-existing markets. As I cannot say on how many exchanges the tokens already traded before the new listing, the results may be blurred by this effect.

The source I rely on compiles data from various exchanges but ignores others. Additional cross-listings may have occurred during the time windows covered in the data set, which would give rise to problematic overlapping observations (McWilliams and Siegel 1997). Yet the data provider covers all major exchanges, so the risk is limited. My reliance on a single data source (coinmarketcap.com) may also affect the results per se. Alexander and Dakos (2019) show that the market betas of Bitcoin and Ethereum differ across data providers and results on coin returns are sensitive to the data source.

The suitability of the event study methodology in the fast-moving cryptocurrency markets is open to debate. The estimation window of 21 days chosen here is much smaller than what is the custom in the stock market literature. Although I justify this choice, it of course remains arbitrary. Additionally, traditional price models like the CAPM are not ideally suited for the cryptocurrency market (as there is no risk-free asset). There may be more fitting models than the ones I use.

[6] For instance, while integrating new tokens that run on the Ethereum blockchain, the exchange Bitfinex tested a transaction of 50 tokens on its publicly known blockchain address. Some traders detected the pattern and were able to anticipate the listings. For example, the transfer of 50 SPANK tokens (https://etherscan.io/tx/0xafdbb77cb377666ee1c756d913a59b8000f5f43620126255958e5175ca54aeef) occurred on 7 Jan 2018, while the token was listed two days later. Another example is voting mechanisms on listings on exchanges like OKEx or DeversiFi (then called Ethfinex). Owners of specific tokens can vote on future token listings. If they have enough votes, they know for sure that a token will be listed, while other market participants lack that knowledge.

6.5 Implications for Practice

My findings have practical implications for 1) authorities, 2) users and traders of cryptocurrency, 3) cryptocurrency projects and 4) cryptocurrency exchanges. Regulatory authorities have a statutory obligation to protect investors (within their jurisdiction) and to ensure fair competition across markets. The present findings show that listing processes of blockchain-based assets can entail positive abnormal returns before the listing and negative returns during or after the listing. This allows regulators to identify incorrect behavior in the ecosystem and to take legal action against it. Cryptocurrency exchanges are in many ways comparable to stock exchanges. Therefore, similar regulation against fraud and insider trading should be applied to that market. Auer and Claessens (2018) show that cryptocurrency returns respond to changes in national regulation, suggesting that regulators like the SEC can indeed make a difference.

The results of this paper will have different implications for the different roles that market participants may assume, such as financially motivated traders or entities looking to acquire cryptocurrency for specific purposes (e.g. as a software license or as a means of payment). For traders, the results show that financial gains may be reaped from exchange listings, though they differ across markets. Therefore, the strategies must be adapted to the individual target markets. Additionally, lower market capitalization and trading volume, and a higher ratio between these two factors indicate abnormal returns. Existing asset owners may interpret upcoming exchange listings as a cue to liquidate their positions to avoid the negative drift after the listing ("buy the rumor, sell the news"). For users of cryptocurrency, the findings suggest that exchange listings raise liquidity but also volatility. For users looking for larger positions, exchange listings can provide a suitable signal of liquidity. For traders, exchange listings can signal volatile asset prices, which may delay their decision to purchase the currency, as markets have a negative drift after the listing.

Cryptocurrency projects have an incentive to cross-list on multiple markets, for example to reduce market segmentation, to improve liquidity and to attract new users/investors. The weak regulation governing most exchanges means that the trade-off between potential legal sanctions and exploiting private information clearly leans in favor of the latter. To date, it remains unclear if and how misbehavior will be prosecuted.

For cryptocurrency exchanges, the results imply that listings of cryptocurrencies with lower market capitalization, lower trading volume or a high ratio between these two measures lead to higher average short-term returns from listings. Such returns constitute valuable signals of quality to market participants. Like cryptocurrency projects, exchanges have strong incentives to exploit private information, given the lax regulatory oversight and governance.

6.6 Future research

While this study provides initial evidence that listing effects differ across exchanges, it cannot fully explain these differences as it only assesses country-specific effects. Future research should try to identify the determinants of these differences.

As argued above, reported trading volumes tend to be manipulated, e.g. by means of so-called transaction mining, which may bias the effects. Yates (2019) shows that it is possible to distinguish honest from dishonest exchanges. Future research should adjust the reported figures to assess the effects of such practices. If such biases are properly considered, the true "size" and implied liquidity of exchanges can be determined. This study can provide a basis for such research, as I identify relative and absolute effects on prices and market capitalization. Market data providers like coinmarketcap.com, coingecko.com and block.cc have started to report adjusted trading volumes. Yet not all of them publish the methodology by which they distinguish fake from real volume, as it seems likely that manipulative exchanges adapt their strategies in order to circumvent such attempts at adjustment. On 5 July 2019, HitBTC reported a volume of $1.4 billion across 802 currency pairs, of which $230m accrued to Bitcoin alone, while Bittrex reported a trading volume of $90.2m across 359 pairs, with Bitcoin contributing $19.5m. HitBTC thus offers greater liquidity and should therefore, according to my results, exhibit stronger effects of cryptocurrency listings. Yet this is not the case – likely due to false reporting of trading volume. Signaling theory postulates that signals must be costly to be effective (Spence 1973) but research shows that market participants in the cryptocurrency ecosystem use cheap (to fake) quality signals (Ante and Fiedler 2019). Future research should look at the phenomenon of cheap signaling of cryptocurrency exchanges. Alameda Research (2019) provides a suitable basis for such endeavors.

Excess cash holdings of cross-listed firms are valued more highly than those of firms listed on only one exchange (Salva and Frésard 2010). Cryptocurrency projects are often funded through token sales, where cryptocurrency is collected in return for project-specific tokens that provide a utility like a software license or represent securities (Ante et al. 2018; Fisch 2019). Investors can often monitor the amount of cryptocurrency collected, as the blockchain technology enables a transparent view of these assets. Future research could analyze the connection between holdings of excess cryptocurrency and project valuation, also based on the implied market capitalization of cryptocurrencies. Another relevant metric are team tokens and the behavior of project teams. Projects often retain some cryptocurrency for themselves to benefit from future appreciation. By monitoring the blockchain and addresses with these specific tokens, it should be possible to see whether team tokens are transferred before the announcement of new exchange listings.

Data availability is a big obstacle for detecting informed trading. I was able to examine only cumulative market data but not the individual price and volume data of specific exchanges. As my findings suggest a significant likelihood of informed trading taking place in anticipation of the listings, the markets where insiders operate are of special interest. Identifying the specific exchange where insiders accumulate their positions can help to identify misconduct in the ecosystem. Future studies should therefore aim to use both individual exchange data and overall market data.

Based on this study, future research may want to look at the differences between exchanges that are tagged as suspicious and those that are not. Additionally, individual events should be analyzed to see whether information about listings leaks systematically or whether only specific events produce suspicious trading behavior. Analyzing individual exchanges rather than merely cumulative market data can yield additional findings, concerning for example the target markets of informed traders.

7. Conclusion

This paper is one of the first to provide initial evidence on the phenomenon of cryptocurrency cross-listings, especially on asset returns, their determinants and signs of informed trading. The analysis covers 327 exchange listings of 180 different cryptocurrencies across 22 exchanges. Overall, cross-listings yield high abnormal returns on the event day and over the window from three days before to three days after the listing. The effects differ significantly across individual exchanges, suggesting pronounced market segmentation. Some exchanges have positive abnormal returns leading up to the events, which suggests informed trading. The expected punishment for exploiting private, asymmetric information is negligible, which entails a severe temptation for cryptocurrency projects and exchanges, and corresponding concerns about consumer protection. Stricter governance has a positive effect on returns, suggesting that improved investor protection and information disclosure as relevant factors of cross-listing decisions.

The results contribute to the debate on the legitimacy of cryptocurrencies and their trading venues and have various implications for practice and theory. The findings can help the authorities identify important aspects of the cryptocurrency ecosystem and potential entry points for regulation. Cryptocurrency exchanges, projects and traders are able to identify what types of assets may lead to positive listing effects and which exchanges possibly leak private information. The study identifies various similarities between cross-listings of cryptocurrencies to cross-listings of stocks. As the market for cryptocurrency is still in its infancy but growing at a rapid pace, the quality of data will likely improve in the future what allows more in-depth analyses.

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9. Appendix

Table 8

Variable descriptions, descriptive statistics and data sources.

Variable	Description	N	Mean	SD	p50	Min	Max	Source
United States	Dummy variable: 1 if an exchange is incorporated in the United States (Bittrex, Poloniex, Kraken and Coinbase), 0 otherwise.	327	0.10	-	0	0	1	exchange websites
South Korea	Dummy variable: 1 if an exchange is incorporated in the Republic of South Korea (Bithumb and Upbit), 0 otherwise.	327	0.10	-	0	0	1	exchange websites
Tax Haven	Dummy variable: 1 if an exchange is incorporated in a tax haven (Seychelles / Cayman Island: Gate.io and Bitforex), 0 otherwise.	327	0.08	-	0	0	1	exchange websites
Trading volume	Logarithm of an asset's average trading volume in USD over the estimation period, calculated as $log(\frac{\sum_{t-30}^{t-10} ATV}{21})$, ATV being asset trading volume.	327	14.49	2.19	14.50	7.46	19.63	coinmarketcap.com
Asset market cap	Logarithm of an asset's average market capitalization in USD over the estimation period, calculated as $log(\frac{\sum_{t-30}^{t-10} AMC}{21})$, AMC being asset market capitalization..	324	17.73	2.21	17.75	0.73	22.77	coinmarketcap.com
Market cap / trading volume	An asset's average market capitalization over the estimation period divided by its average trading volume (non-logged).	327	0.69	0.10	0.69	0.36	0.93	coinmarketcap.com
Bitcoin trading volume	Logarithm of an asset's average trading volume in USD over the estimation period, calculated as $log(\frac{\sum_{t-30}^{t-10} BTV}{21})$, BTV being Bitcoin trading volume..	327	24.18	0.44	24.24	22.53	25.08	coinmarketcap.com
Bitcoin market cap	Logarithm of the average market capitalization of Bitcoin in USD over the estimation period, calculated as $log(\frac{\sum_{t-30}^{t-10} BMC}{21})$, BMC being Bitcoin market capitalization.	324	3.30	1.20	3.31	0.27	7.82	coinmarketcap.com