

A New Era of Entrepreneurial Finance? Three Essays on Decentralized Digital Platforms (DDPs)

Johannes Fuchs

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1. Prof. Dr. Dr. Paul P. Momtaz
2. Prof. Dr. Hossein Jahanshahloo

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ABSTRACT OF THE DISSERTATION

This dissertation delves into the intricate landscape of blockchain-based entrepreneurial finance, particularly focusing on decentralized digital platforms (DDPs). Through three comprehensive essays, this research examines the multifaceted implications of initial coin offerings (ICOs), public market listing, and regulatory environments on the development and performance of DDPs. The first essay investigates the challenges of asymmetric information in ICOs, emphasizing the potential of token governance mechanisms to mitigate investment risks associated with moral hazard, adverse selection, and fraud. Analyzing novel data on token retention and resale restrictions, the study reveals that retaining a higher percentage of tokens positively leads to increased ICO funding amounts, while resale restrictions tend to reduce post-funding financial performance. The effectiveness of these governance mechanisms is also found to be influenced by the quality of the venture's human capital. The second essay explores the strategic decision for DDPs to enter public markets post-ICO. Utilizing a difference-in-differences approach, the analysis demonstrates that public DDPs experience accelerated growth and enhanced decentralization compared to their private counterparts. The growth advantage of public DDPs is significantly driven by financial speculation, particularly under conditions of undervaluation, which accelerates network effects. Moreover, the study contrasts the effects of crypto fund endorsements against unendorsed public listings, highlighting the superior growth potential of endorsed public entries. The third essay addresses the international regulation of cryptocurrency markets, focusing on the risk-return dynamics influenced by diverse regulatory actions. Using a comprehensive dataset of regulations, the essay develops a digital asset regulatory strength index (DARSI) to evaluate the impact of regulatory enforcement quality on market risks and returns. Findings suggest that robust enforcement enhances the effectiveness of regulations, reducing market risks and shaping returns more significantly in environments with high compliance norms and cultural uncertainty avoidance.

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CHAPTER 1

Introduction

1.1 Entrepreneurial finance and decentralized digital platforms (DDPs)

Entrepreneurial finance is a unique segment of traditional corporate finance that integrates the domains of 'entrepreneurship' and 'finance' (Cumming & Johan, 2017; Wright & Robbie, 1998). This field primarily concerns private companies that have not yet been listed on stock exchanges, examining a range of capital providers and finance types such as venture capital, private equity, crowdfunding, and initial public offerings (Cosh et al., 2009; Cumming et al., 2019). Building on Denis's (2004) overview, research in entrepreneurial finance addresses several critical themes, including, inter alia: (i) sources of capital, (ii) financial contracting complexities due to information asymmetries and subsequent governance requirements, (iii) the challenges public policies face in balancing support for innovation with regulatory constraints, and (iv) the distinct risk and return profiles characteristic of early-stage ventures.

On October 31, 2008, when Satoshi Nakamoto introduced the Bitcoin whitepaper (Nakamoto, 2008), only the most optimistic could have predicted the profound impact that the underlying blockchain technology would have on the field of entrepreneurial finance. The inherent characteristics of blockchain technology — decentralization, immutability, transparency, and programmability — have enabled applications far beyond its initial use case as a form of decentralized currency over recent years (Singh et al., 2024). Driven by the incorporation of 'smart contracts,' which are programmable, self-executing agreements within a blockchain network (Zheng et al., 2020), blockchain technology has

started to fundamentally reshape how firms are governed and organized (Singh et al., 2024). Blockchain-based ventures that utilize smart contract technology often exhibit two common characteristics: (i) the business model is structured as a digital platform, and (ii) the venture issues a token.

Digital platforms, a specific type of multi-sided platform, leverage technology to facilitate connections across various stakeholders (Gawer, 2021) and to coordinate between innovative and competitive agents who offer complementary goods (Gawer, 2014). When these platforms are based on blockchain technology and employ smart contract technology, they can be defined as decentralized digital platforms (DDPs) (Cumming et al., 2025). A key difference between a DDP and its centralized counterpart is the issuance of a platform token — a cryptographically secured digital asset (Howell et al., 2020). This token typically serves as a utility token, embodying consumptive rights that grant the holder access to future services or products, and acts as the principal medium of exchange (Momtaz, 2020). For instance, the DDP *Aethir* operates as a decentralized platform enabling individuals to integrate their personal computers into the network via the internet. Participants can contribute unused graphics processing units (GPUs) from their devices to the platform, which then become accessible to other users in need of enhanced computational resources. All transactions on the platform are settled using *Aethir's* native platform token.

DDPs significantly impact all four identified areas of entrepreneurial finance. First, DDPs introduced a novel source of capital for early ventures — termed initial token issuance, or more commonly, initial coin offering (ICO). This alternative mechanism for fundraising is conceptualized as a blockchain-based crowdfunding campaign where ventures offer cryptographically protected digital asset units (i.e., tokens) to investors in exchange for either fiat money or cryptocurrencies (Fisch, 2019; Howell et al., 2020). The embedded smart contract technology automates the transaction process between the investor and entrepreneur at the time of issuance, enhancing efficiency relative to conventional fundraising methods (Amsden & Schweizer, 2018; Fisch et al., 2022). Distinct from

an initial public offering in the conventional financial markets, an ICO does not necessarily lead to a public listing of the token. Consequently, entrepreneurs are afforded the opportunity to access external financing from a more extensive array of investors than is typical with traditional early-stage financing approaches, owing to the lack of stringent investor prerequisites and the lower minimum investment threshold (Cumming et al., 2021; Schueckes and Gutmann, 2021), without the immediate necessity to participate in the secondary market.

Next, DDPs present several innovative opportunities to address prevailing information asymmetries in entrepreneurial finance and to mitigate moral hazard risks for investors. First, ventures can introduce token governance mechanisms during the ICO, such as token retention and token restrictions (e.g., Bourveau et al., 2022; Davydiuk et al., 2023; Lyandres et al., 2022). Second, allowing the DDP token to trade freely on a secondary market leads to information aggregation and provides investors with an observable fair token value (Momtaz, 2021). Third, DDPs have the option to embed governance rights directly into their platform tokens, paving the way for decentralized governance models like Decentralized Autonomous Organizations (DAOs) (e.g., Chen et al., 2021; Lumineau et al., 2021). DAOs are managed and owned collectively by their members through the deployment of smart contracts (Cristiano Bellavitis & Momtaz, 2023). This redistribution of governance rights allows platform users to safeguard against potentially harmful actions by non-users (Sockin & Xiong, 2023).

Furthermore, the far-reaching impact of blockchain technology on entrepreneurial ecosystems (Rawhouser et al., 2024) and the novel financial asset trading on a public market requires policy makers and regulators to develop new frameworks. The initially unregulated space of DDPs led to major fraud events (e.g. Barone and Masciandaro, 2019; Hornuf et al., 2023). The DDP token market faces increased risk of market manipulation practices, such as insider trading (Akyildirim et al., 2020), front running (Daian et al., 2019), wash trading (Cong et al., 2023), or ‘pump and dump’ strategies (Dhawan & Putniņš, 2022).

However, policymakers are confronted with a fundamental dilemma in entrepreneurial finance: balancing the need for regulatory oversight to ensure market integrity with the desire to foster an open environment that encourages innovation (Denis, 2004).

Lastly, investments in entrepreneurial finance were traditionally reserved for specific capital allocators, such as pension funds or sovereign wealth funds (Cumming et al., 2019). However, DDPs have radically transformed this landscape by offering primary market access and secondary market liquidity to a wider range of investors, significantly lowering the minimum investment thresholds (Momtaz, 2020). This shift not only diversifies the investor base but also results in a distinct risk-return profile for DDP tokens, setting them apart from traditional entrepreneurial finance investments and public equities (Liu & Tsyvinski, 2020).

1.2 Objective and outline

The purpose of this doctoral project is to shed light on how platform-level governance choices, listing strategies, and regulatory environments influence the operational and financial performance of DDPs. This cumulative dissertation consists of three essays, in which the first essay analyzes how the design of token governance mechanisms in ICOs affects fundraising success and post-offering performance, with a particular focus on the signaling role of token retention and restriction. The second essay studies the impact of token exchange listings on the growth and decentralization of DDPs, considering both direct and spillover effects from speculative to fundamental activity. The third essay explores how global cryptocurrency regulations influence market risk and return, and how the strength of formal and informal institutions shapes these effects. In the following Sections 1.2.1, 1.2.2, and 1.2.3, each essay is introduced in more detail, including the research objectives, dataset, methodological approach, and main contributions.

1.2.1 Token governance in initial coin offerings

The first essay investigates how decentralized platforms design token governance mechanisms and whether these can mitigate asymmetric information in primary token offerings. Prior ICO research has largely overlooked governance features, with few exceptions focused on how retained tokens, measured either as undistributed shares (Giudici and Adhami, 2019; Lyandres et al., 2022; Davydiuk et al., 2023) or insider allocations Bourveau et al. (2022), affect fundraising outcomes. As a result, key questions remain unanswered regarding the structure of token governance, its impact on post-offering financial performance, and the role of human capital in moderating this relationship. To address this research gap, we inductively analyze 759 token offerings and their published whitepapers. We identify two main types of token governance mechanisms: (i) retention and (ii) restriction. Token retention mechanisms include the disclosure of allocation reservations for different beneficiary categories (i.e., stakeholders, venture development, and reserve pool). Token restriction mechanisms limit the initial transferability or issuance of specific allocations.

Using a hand-collected sample of token governance variables from 759 token offerings, we first examine whether a higher share of retained tokens in the primary market is associated with stronger fundraising outcomes and better post-offering performance. This analysis tests the token retention outperformance hypothesis based on signaling theory. Leland and Pyle (1977) argue that high-quality entrepreneurs retain more equity because they believe in the venture, while lower-quality ones sell them to maximize short-term gains. This creates a separating equilibrium as described by Spence (1973) where retention reveals venture quality and fair value. Our findings confirm that token retention significantly improves fundraising success. Each additional 1% of retained tokens is associated with a 0.318% increase in funds raised. This effect is mainly driven by stakeholder allocations, while tokens reserved for venture development or ecosystem support play a lesser role. However, we do not find a significant effect of retention on post-offering performance, as

measured by the 12-month buy-and-hold abnormal return.

Next, we test whether limiting the reselling of tokens in the secondary market improves fundraising outcomes and post-offering performance. While traditional finance theory predicts a positive effect (Leland & Pyle, 1977), and some IPO literature supports this view (Brav & Gompers, 2003), our results do not support a positive effect in the context of token offerings. Instead, we find that token restrictions are associated with a 37.6% reduction in 12-month abnormal returns. Further analyses of the different restriction types reveal that the effect is mainly driven by initial restrictions such as lock-ups or cliffs, while vesting and reverse vesting show no significant impact. We also find no link between restrictions and fundraising success. These results suggest that limiting resale rights can undermine investor confidence in post-offering liquidity and performance.

Lastly, we explore whether the effectiveness of token governance mechanisms depends on the quality of human capital, using team size as a proxy. Theory points to two possible dynamics. Token signals may act as substitutes for human capital, becoming less relevant when team quality is high, or they may complement each other, with stronger teams enhancing the credibility of token-based signals. Our results reflect both effects. The positive impact of token retention on fundraising diminishes with larger teams, as each additional member reduces the marginal fundraising effect by 0.039 percentage points. In contrast, the negative effect of token restrictions on post-offering performance is softened by team size, with each added employee improving returns by 5.9 percentage points. These findings suggest that human capital can either offset or reinforce the influence of token governance, depending on the outcome considered.

1.2.2 Public markets for startups

The second essay of the dissertation explores the growth and decentralization dynamics of DDPs following token exchange listings. This analysis addresses the central challenge in platform economics on how to coordinate early adoption when network effects materialize

only with scale (Bakos and Halaburda, 2022; Rochet and Tirole, 2003; Weyl, 2010). DDPs can raise funds through an ICO without listing, deferring, or avoiding entry into public markets altogether (Cumming et al., 2025). This separation provides entrepreneurs with a form of real option value. The essay investigates whether secondary market entry, via token listings, facilitates DDP development.

Using a novel hand-collected dataset combining DDP-level data from the *Token Offerings Research Database* ¹, on-chain Ethereum activity, and exchange listing data, we apply a difference-in-differences framework to assess whether token listings drive DDP growth. Results show that listings lead to significant increases in core growth metrics, including transaction volume, user activity, and token turnover. Weekly blockchain activity increases by 143 to 283 transactions, token liquidity rises by 1.0 to 1.5 %, and user adoption grows by 103 to 191 users per week. These findings suggest that token listings act as a catalyst for platform growth by facilitating access, visibility, and user engagement. Building on this, we theorize that listings perceived as highly successful amplify the positive effects of going public. The empirical findings support this proposition, showing that listings associated with strong early returns and favorable sentiment reinforce the credibility of the venture through market affirmation (Drobetz et al., 2019). Moreover, they enhance the signaling power of founder and CEO characteristics, which play a critical role in shaping investor trust and expectations (e.g., Colombo et al., 2022; Momtaz, 2021; Xia et al., 2024). Successful listings also strengthen direct network effects by motivating adoption among previously hesitant users and attracting investors who either missed the primary sale or revise their prior assessments in light of the new market signal. Indirect network effects are evident as well. A rise in token value following a successful listing increases the worth of treasury-held capital stock, enabling ventures to allocate additional resources toward growth and development (Benedetti and Nikbakht, 2021; Howell et al., 2020).

A distinguishing feature of DDPs is that adopters and investors engage with the same

¹Available from www.paulmomtaz.com/data/tord

asset — the token. This shared asset structure creates a mechanism through which shifts in demand from one group can generate value for the other, producing bidirectional spillover effects (Athey et al., 2016; Bakos and Halaburda, 2022; Momtaz, 2024). Unlike traditional platforms, where user growth primarily translates into investor returns, DDPs allow financial market activity to influence core protocol engagement. The empirical results confirm this dynamic, showing that, on average, a single speculative transaction on a token exchange is followed by 1.7 additional non-speculative transactions on the underlying protocol. Similarly, a one percent increase in speculative token turnover leads to a 1.4 percent rise in fundamental token turnover, and each speculative investor is associated with 2.8 new users engaging with the protocol. These effects are especially strong when the token appears undervalued, suggesting that arbitrage-driven trading can redirect attention and activity toward underutilized platforms, supporting a more efficient growth trajectory.

Next, we examine how token listings affect the distribution of ownership within DDPs. Whereas primary markets often restrict access through mechanisms such as presales and minimum investment thresholds, secondary markets offer broader accessibility, particularly to smaller investors. However, this expansion is not uniform across the ownership spectrum. Our analysis shows that listings significantly increase the number of tokenholders in the lower end of the distribution, with an average rise of 2,590 addresses holding less than one percent of the total supply. In contrast, ownership concentration among large holders remains largely unchanged. The Nakamoto coefficient, which captures the minimum number of wallets needed to control a majority of tokens, increases only marginally — by the equivalent of one wallet — suggesting that control positions established in the primary market persist. These results indicate that while listings promote inclusivity and broaden participation, they do not substantially alter the underlying concentration of economic power. Lastly, we expand on prior findings by Drobetz et al. (2025) and Fisch and Momtaz (2020), which showed that crypto fund-backed ventures outperform others in secondary markets, by providing evidence that the most effective strategy combines public

listing with crypto fund backing. Our results indicate that the act of going public plays a more decisive role in enabling long-term growth than fund affiliation alone.

1.2.3 Market reactions to cryptocurrency regulation

The third essay examines how international cryptocurrency regulations influence the risk-return profile of listed tokens. The emergence of thousands of cryptocurrencies has triggered a range of regulatory responses (Hornuf et al., 2022, 2025), including specific AML/KYC laws, tax regulations, comprehensive frameworks, and outright bans. Yet, the effectiveness of these regulatory efforts remains largely untested, despite concerns that typical crypto investors, who often value high returns, privacy, and decentralization (Hackethal et al., 2021; Steinmetz et al., 2021), may react adversely to stricter rules. While prior work has analyzed short-term market responses to regulatory news (Auer & Claessens, 2018; Chokor & Alfieri, 2021), the long-term implications and the influence of institutional quality remain underexplored. This study addresses that gap by analyzing how regulatory approaches and the strength of formal and informal institutions shape market outcomes, and by testing a series of hypotheses on both immediate and persistent token-level performance effects.

Drawing on a manual review of over 2,000 official sources across 205 jurisdictions, we compile a novel dataset of 35 regulatory events between July 2018 and April 2023. Using daily price data from up to 1,213 tokens and applying standard event study methodology (Brown & Warner, 1980, 1985), we first examine how new regulations affect cryptocurrency market risk. Our results show that regulatory announcements reduce return volatility by an average of 0.496 percentage points, suggesting that policymakers are achieving their goal of stabilizing cryptocurrency markets. Second, we explore the immediate market reactions to regulatory announcements. Based on the efficient market hypothesis (Malkiel & Fama, 1970; Urquhart, 2016), regulatory announcements are expected to lead to immediate abnormal price reactions. Our results confirm the theory and show that in the context

of cryptocurrency markets, on average, the cumulative abnormal return (CAR) during the event window of a regulatory announcement is -1.414% . The negative coefficient implies that investors may place greater weight on potential costs of the new regulation, such as increased operational burdens (Christainsen & Haveman, 1981; Larcker et al., 2011) or reduced market access, than on potential benefits like enhanced investor protection (La Porta et al., 1997, 1998, 2002). Third, our study provides evidence that, on average, cryptocurrency investors profit on a risk-adjusted basis from new regulations. Comparing the Sharpe ratio during the 80-day post-event window with that of the pre-event window, it is observable that, on average, the ratio increases by 0.585.

Next, we provide evidence that regulations enacted in jurisdictions with stronger formal institutions, such as stronger property rights and more effective contract enforcement, lead to greater reductions in risk during the post-event window, in line with evidence from traditional equity markets (e.g., Bhattacharya and Daouk, 2009; Humphery-Jenner, 2013). This effect is particularly pronounced when the regulation is the first of its kind or issued by a financial regulatory authority. To distinguish between the effects of regulatory content strength and general uncertainty reduction, we develop a novel Digital Asset Regulatory Strength Index (DARSI), capturing the overall quality of the regulatory environment before and after each announcement. Higher DARSI scores are associated with stronger post-event risk reductions, confirming the amplifying role of institutional strength. Lastly, we assess the influence of informal institutions and find that stronger cultural norms around uncertainty avoidance, measured following Hofstede (2001), also enhance the effectiveness of regulation in reducing return volatility.

CHAPTER 2

Essay I: Token governance in initial coin offerings: Implications of token retention and resale restrictions for ICO success

Abstract

The high degree of asymmetric information in initial coin offerings (ICOs) increases the probability of moral hazard, adverse selection, and outright fraud. Token governance mechanisms may help mitigate such investment risks. Using novel data on *token retention* in the primary market and *resale restrictions* in the secondary market, we estimate the impact of these governance mechanisms on the fundraising success and post-funding performance of ICOs. First, we estimate the valuation elasticity of token retention, indicating that 10% fewer tokens sold increases the ICO funding amount by 3.2%. Second, restricting ICO investors' ability to resell tokens in the secondary market has a detrimental impact on the 12-month buy-and-hold abnormal return. We also discuss contingency effects of the specific implementations of these governance signals and show that the effects are moderated by the quality of the venture's human capital.

Authors: Johannes Fuchs and Paul P. Momtaz

First Author: Johannes Fuchs

2.1 Introduction

The structure and market characteristics of initial coin offerings (ICOs) are characterized by a high degree of information asymmetry between investors and entrepreneurs (Adhami et al., 2018; Chod & Lyandres, 2021; Fisch, 2019; Howell et al., 2020; Momtaz, 2021a, 2021b). Token offerings have long been unregulated in many jurisdictions (Bellavitis et al., 2021, 2022; Huang et al., 2020), with the absence of reporting requirements exposing investors to pronounced risks related to adverse selection, moral hazard, and outright fraud (Hornuf et al., 2022, 2023; Momtaz, 2021a). ICO ventures often lack proven track records and are very early-stage (Fisch, 2019; Howell et al., 2020; Momtaz, 2020). The high degree of disintermediation in the ICO market burdens individual investors with the due diligence, potentially leading to suboptimal information production outcomes in the aggregate (Giudici and Adhami, 2019; Momtaz, 2021a; Cumming et al., 2023). As a result, the contractual relationship between ICO ventures and investors is characterized by (i) complete power of the venture over the contract creation, (ii) no negotiation between both parties, and (iii) investors' practical inability to enforce legal rights in case the venture is in breach of disclosed investment terms. These characteristics underline the importance of the design of digital assets to de-risk ICOs.

However, the existing literature largely neglects the governance mechanisms of tokens sold in ICOs. Exceptions are studies focusing on the ICO fundraising effects of retained tokens, measured as the percentage of tokens either not distributed (Giudici and Adhami, 2019; Lyandres et al., 2022; Davydiuk et al., 2023) or allocated to insiders (Bourveau et al., 2022). By implication, the resulting research gap includes, *inter alia*, a lack of knowledge about the anatomy of token governance in ICOs, the effect of token governance on post-funding financial performance, and the moderating effects of human capital on the token governance and performance relationship.

To address this research gap, we explored ICO whitepapers in an inductive way, compiling all token governance mechanisms that ICO ventures might disclose. This exercise

resulted in two overarching token governance mechanisms: (i) *token retention mechanisms* and (ii) *token restriction mechanisms*. *Token retention mechanisms* encompass various purpose-bound token beneficiary categories (i.e., stakeholders, venture development, and reserve pool). The disclosed share of tokens reserved for different groups in the primary market allows the venture to communicate different types of goals. First, tokens retained for the founders, the venture team, and other internal and external stakeholders can be summarized as stakeholder allocations and are comparable to insider holdings in traditional financial markets. Allocations to this group aim to foster the long-term focus of the decision-makers and to reduce agency costs for the investors (Leland and Pyle, 1977; Vismara, 2016). Second, venture development retentions include all tokens retained with the main purpose of supporting future growth and operations of the venture, such as research, business development, or company allocations. This group communicates a commitment by the venture to longer-term growth. Third, tokens retained to support the ecosystem through future (incentive) distributions or other stability mechanisms can be summarized as reserve pool retentions. This group includes a variety of disclosed categories, such as reserves, mining pool, rewards pool, and other related categories, and might increase investor confidence in the underlying project. However, ventures also face significant drawbacks based on the retained tokens. Ventures are obligated to retain the token for the disclosed purpose, which leads to decreased flexibility and liquidity of the tokens.

Token restriction mechanisms prohibit the unrestricted transfer of a part of or all tokens in the secondary market. The restriction disclosures in the ICO whitepapers are based on four different types of restrictions: (i) cliff, (ii) lock-up, (iii) vesting, and (iv) reverse vesting. While a cliff prohibits the initial token issuance to the applicable group before the cliff date, a lock-up is preceded by a completed token issuance and prohibits any sales of the applicable tokens before the lock-up end date. Vesting and reverse vesting are both gradually released restrictions, realizing the token allocation and lifting the resale

restriction gradually over a defined period, respectively. The implementation of token restriction by the venture amplifies the previously described benefits and drawbacks of token retention. Interestingly, unlike traditional venture capital-backed startups that may also base incentive alignment mechanisms on board seats or voting rights (Cumming et al., 2019), ICO ventures are unique in that their incentive alignment efforts are almost comprehensively described by token allocation and token retention mechanisms.

With the institutional understanding of token governance in ICOs in hand, we derive two overarching hypotheses. The first hypothesis posits that a token allocation resulting in a higher degree of retained tokens in the primary market positively impacts the ICO venture's funding and the post-funding performance. We refer to the hypothesis as the **token retention outperformance hypothesis (TRetO)**. Leland and Pyle (1977) submit that, due to the implied costs of retaining equity, only good entrepreneurs are expected to retain tokens, leading to a “separating equilibrium” (Spence, 1973), and hence the number of tokens retained reveals the fair value and quality of the underlying venture. Prior research also shows that retained tokens are expected to increase the operational performance of the venture (Lyandres et al., 2022; Davydiuk et al., 2023). The liquid secondary market for ICO tokens provides an ideal setting to analyze the impact of token retention on the financial post-funding performance, measured as the 12-month buy-and-hold abnormal return. We expect that the token price reflects the market expectation about the future financial success of the underlying venture, which should be more positive for ventures retaining more tokens (Leland & Pyle, 1977), and that the forecasted superior operational performance translates to positive financial returns.

The second hypothesis posits that token restrictions that limit the reselling of tokens in the secondary market positively impact ICO ventures' funding and the post-funding performance. We refer to the hypothesis as the **token restriction outperformance hypothesis (TResO)**. We expect the restriction of retained tokens might also lead to a “separating equilibrium” (Spence, 1973). The restriction choice might be interpreted as a signal about

the quality of the underlying venture by potential investors (Leland & Pyle, 1977), mainly due to the voluntary exposure of entrepreneurs to the financial downside and the risk mitigation for investors that the entrepreneurs are selling their retained stakes immediately after token listing. Brav and Gompers (2003) provide empirical support for this theory in the IPO context, but prior research could not identify a clear relationship in other types of fundraising (Bourveau et al., 2022; Davydiuk et al., 2023). Lastly, our paper analyzes the moderating effect of human capital quality signals, such as the team size of the venture, on the effect of token governance signals. We find a supportive theory for both directions of a possible moderating effect. The moderating effect might be negative due to a possible substitution effect of the two signals, given that both signals have related underlying factors; the moderating effect could also be positive given that the retained or restricted tokens should have an increased value when the venture has higher human capital quality.

To assess our hypotheses, we derived a baseline sample of 759 token offerings with a start date before 2021 that included token governance details within their whitepaper. We hand-collected all related data points regarding token governance and restrictions and applied an econometric approach with a baseline regression to estimate the relationship between the token governance variables and fundraising success and post-funding performance under the consideration of a vector of different control variables. Additionally, we applied different two-stage models to control for observed and/or unobserved heterogeneity (e.g., Colombo and Grilli, 2010; Bertoni et al., 2011) and conducted robustness checks of the results with an expanded sample of 986 observations to correct for a potential sample selectivity bias.

The empirical results confirm our **TRetO** hypothesis. A 1% increase in the share of retained tokens leads, on average, to a 0.318% increase in the fundraising amount. We find additional evidence that the effect is mainly caused by the signal of tokens allocated to stakeholder groups rather than venture development or reserve pool allocations. Our regression models confirm that the increased firm valuation is based on the treatment

effect of token retention rather than being confounded by a selection bias. We do not find supporting evidence for a positive relationship between token retention and post-funding financial performance; hence, our results reject the **TResO**. However, we find empirical evidence for a significant negative relationship between token restriction and post-funding financial performance. The disclosure of a token restriction reduces the 12-month buy-and-hold abnormal return on average by 37.6%, with a p-value below 5%. Our findings suggest that the effect is mainly driven by the impact of the disclosure of an initial restriction rather than (reverse) vesting disclosures. The disclosure of an initial restriction leads, on average, to a 38.7% decrease in the 12-month buy-and-hold abnormal return. We believe that the negative is based on investors' concern about the restricted flexibility of the venture to unexpected liquidity needs and breaches of the restriction disclosures by the venture (Cohney et al., 2019).

Finally, we find evidence that the team size of the venture moderates the effects of token governance tools, described above. The 0.757% increase in fundraising amount based on a 1% increase in retained tokens is reduced, on average, by 0.039 percentage points per additional full-time employee (FTE) added to the venture team. Our results show a positive moderating effect of human capital on the relationship between token governance tools and the financial post-funding performance. We find evidence that the negative impact of the token restriction disclosure on post-funding performance decreases, on average, by 5.9 percentage points for each additional FTE added to the venture team.

Our study expands the literature on the design of digital assets and analyzes token governance in a novel and more granular way than existing empirical studies. To our knowledge, we are conducting the first research on token governance's impact on financial post-funding performance and provide the first evidence of how token governance signals are moderated by human capital quality. Thus, our research contributes to the advancement of the general understanding of the cryptocurrency market and helps to fill the research gap on factors that influence the abnormal returns of token offerings. Uncovering

several practical implications for entrepreneurs and investors, we show that the direction and strength of the token governance signals depend on the chosen incentive alignment tool and its defined characteristics. Ventures designing the structure of the token offering must also consider the present moderating effect of human capital quality signals on the effect of the included token governance mechanisms to maximize the probability of reaching the fundraising targets and achieving positive post-funding financial performance.

The remainder of the paper is structured as follows. Section 2.2 describes the institutional and theoretical background and derives testable hypotheses. Section 2.3 provides details on our empirical setting, including the data collection process, a description of the variables, and the econometric approach. Section 2.4 presents our empirical results of the main regressions and additional robustness tests. Finally, Section 2.5 discusses our theoretical contribution and practical implications, highlights limitations, and offers potential avenues for future research.

2.2 Background and hypotheses

2.2.1 Asymmetric information in initial coin offerings

Crowdfunding targets the disintermediation of the fundraising process to avoid payments to intermediaries. Individuals typically contribute small amounts of money via the Internet, which are then pooled to support a specific objective (Ahlers et al., 2015). The magnitude and type of objective and hence the structure of crowdfunding can take various forms (Schwienbacher and Larralde, 2010; Mollick, 2014). Based on blockchain technology, a further reduction of the degree of intermediation is possible (Y. Chen et al., 2021; Kher et al., 2021). Token offerings apply smart contract technology that allows the automated execution of pre-defined contracts, which leads to increased efficiency and ultimately decreased costs for the venture in comparison to other fundraising types (Fisch et al., 2022). However, the flip side of disintermediation is that crowdfunding markets are

often characterized by high levels of asymmetric information due to the absence of trusted intermediaries (Vismara, 2016), limited due diligence possibilities (Agrawal et al., 2015), inexperienced investor profiles (Ahlers et al., 2015; Boreiko & Risteski, 2021), and little opportunity for interaction between issuer and investor (Vismara, 2016). The asymmetric information issue in the context of token offerings can be amplified for various reasons, including: (i) the underlying projects in an ICO are often early-stage with inexperienced entrepreneurs (Howell et al., 2020); (ii) initial coin offerings (unlike, e.g., initial exchange offerings) typically do not involve independent platforms that could potentially certify project legitimacy and quality (Giudici and Adhami, 2019; Momtaz, 2021a; Schueckes and Gutmann, 2021) (iii) ICOs are unregulated in many jurisdictions (Bellavitis et al., 2022); and (iv) investors' payments in exchange for the tokens do not require any intermediating party (e.g., payment agent) (Giudici & Adhami, 2019)). Momtaz (2021a) has additionally highlighted the technology character (e.g., DLT) of the underlying ventures in ICOs as a reason for asymmetric information in the context of token-based crowdfunding. Investors may be required to have a certain level of technological knowledge to be able to perform an appropriate assessment of the venture (Cohney et al., 2019).

The market characteristics and resulting information asymmetry described above portend several consequences for token investors (Alshater et al., 2023; Chod et al., 2020). First, the information asymmetry prior to contract initiation might lead to adverse selection (K. Chen, 2019). Low-quality entrepreneurs will aim to promote their projects as high-quality, leading to an upward-biased valuation by potential investors (Vismara, 2018). Second, moral hazard might occur after investors provide funding to the entrepreneurs. Momtaz (2021a) argues that the lack of possibilities to verify signals *ex-ante* and to punish biased signals incentivizes the entrepreneurs to bias signals of the underlying venture quality. Third, the low level of regulation and the elimination of trusted intermediaries, especially in the context of payment, amplify the potential fraud risks in token offerings (Barone & Masciandaro, 2019). A possible solution for the suppliers of finance to en-

sure that their respective funds are not utilized for unfavorable undertakings or embezzled would be contracts between them and the entrepreneurs or managers of the companies (Shleifer & Vishny, 1997). However, the venture has complete power over the contract creation, and no negotiation takes place between the parties. Additionally, investors usually do not have the opportunity to assert any legal rights in case the entrepreneurs violate any of the disclosed investment terms.

Good token governance mechanisms are required to mitigate these risks and prevent market failure. Token governance addresses the options of how suppliers of finance ensure a return on their invested capital (Shleifer & Vishny, 1997). The underlying objective of all approaches is to align the interests of the agent with those of the principal and therefore limit potentially deviating activities (Jensen & Meckling, 1976). While these objectives are identical to those in the traditional financial markets, the unique characteristics of the token-based crowdfunding market and the expected sensitivity of investors to incentive alignment tools make it a particularly interesting environment for studying the impact of token governance on investor behavior. Prior investigations related to governance mechanisms in IPOs (Field and Hanka, 2001; Brav and Gompers, 2003) are conducted in an environment that strongly deviates from that of ICOs. Investors can usually rely on certain exchange rules that the companies must apply if they want to conduct an IPO. These rules provide not only regulatory clarity for the investor but usually also guarantee certain company characteristics, such as minimum size, revenue, or management quality. Additionally, the IPO process usually includes several third-parties (e.g., investment banks, payment agents, etc.) and marketing events (e.g., IPO roadshow), providing investors additional information and the option to interact with company representatives. These IPO market characteristics sharply reduce the information asymmetry during the investment and limit the transferability of the results to the ICO context, underpinning the importance of our study. In Section 2.2.2, we provide a detailed analysis of the governance mechanisms in the token-based crowdfunding market and further elaborate on the differences in the deal

characteristics among different types of fundraising.

2.2.2 Token governance in initial coin offerings

We focus on utility token offerings, for which most of the traditional governance tools (e.g., voting rights, board seats) are not available (Alshater et al., 2023; Block et al., 2021). The contractual power between ICO ventures and investors lies fully in the hands of the entrepreneurs, who define the terms of the investment contracts before the ICO launch. There is usually no direct negotiation between the ICO venture and its potential investors. The small minimum investment size, combined with the absence of specific investor requirements, such as a minimum income or wealth, and the convenience of online platforms, provides a large global base of potential investors, empowering the venture at the expense of a dispersed investor base (Cumming et al., 2021; Schueckes and Gutmann, 2021). There is also no regulatory requirement to disclose information, making the provision of information fully voluntary (Bourveau et al., 2022; Momtaz, 2021a). These ICO deal characteristics strongly deviate from the characteristics of an IPO. While we showed above that ICO investors have mostly no legal rights and the only information source is the voluntarily published whitepaper by the venture, IPO investors usually have strong legal rights attached to their investment and can rely on a standardized and compliant IPO prospectus. These differences provide further support for the importance of our study in investigating the impact of token governance mechanisms in the token-based crowdfunding market.

The low contractual power of investors and the unregulated environment could result in a full waiver of token governance mechanisms in initial coin offerings. This would require investors to trust solely in the good intentions of the entrepreneurs. In practice, however, the token issuer faces a trade-off between the costs of token governance commitments and the attractiveness of the offering to investors. If the venture implements incentive alignment tools, it must bear the inherent costs of the chosen type of tool but

would potentially increase the attractiveness to investors. On the other hand, if the venture fully removes token governance approaches, it would be less restricted in governing the company and would not be exposed to additional costs; however, this could make the investment less attractive and reduce fundraising. As explained below, our comprehensive manual analysis of all available ICO whitepapers revealed two types of token governance mechanisms: (i) token retention and (ii) token restriction.

2.2.2.1 Token retention

The token allocation split indicates the number of tokens reserved for different groups in the primary market, providing more extensive information than the sole disclosure of distributed shares in the equity crowdfunding context (Vismara, 2016). Aside from the tokens reserved for allocation to the public (e.g., pre-ICO and ICO sales), there are three main categories: (i) stakeholders, (ii) venture development, and (iii) reserve pool. The sum retained by these groups indicates the total amount retained by the venture in the signaling sense described by Leland and Pyle (1977).

In addition, each individual group has its own purpose with different benefits.

- The stakeholder allocation is comparable to the insider holdings in traditional financial markets and other fundraising types. Allocations to founders and other stakeholders, such as advisers or partners, aim to reduce agency costs and foster the long-term focus of the decision-makers.
- The venture communicates a commitment to longer-term growth through allocation to venture development purposes, such as research or business development.
- The reserve pool is usually a side pool to support the ecosystem of the issued token through (future) incentive distributions and provide stability to the issued token. Allocations falling into this category could increase the confidence of potential investors in the underlying project and the corresponding token.

Token retention within these three categories is one of the two key token governance mechanisms in ICOs. The venture also faces several drawbacks from token retention, such as (i) decreased flexibility if the allocated tokens can be solely used for their disclosed purpose and (ii) decreased liquidity of the token since the publicly distributed portion is reduced, ultimately reducing the number of free-floating tokens.

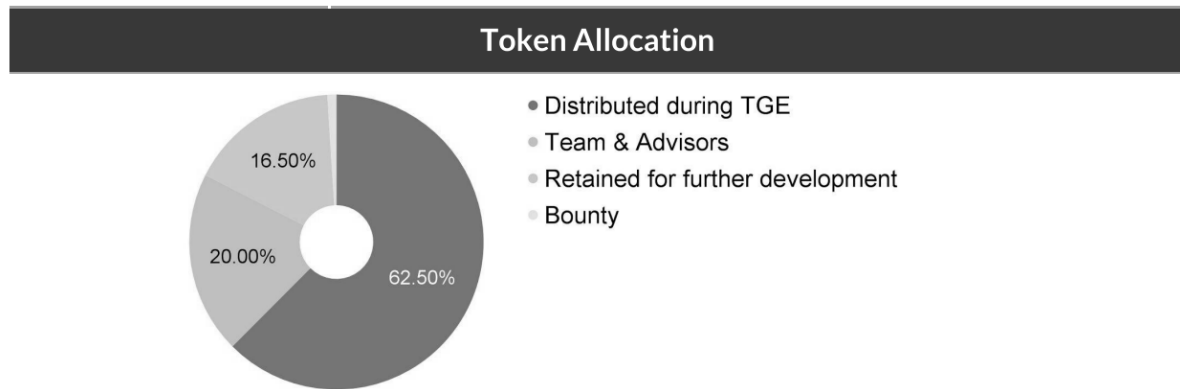
2.2.2.2 Token restriction

Token restriction refers to the decision of the venture to prohibit the unrestricted transfer of a part of or all issued tokens in the secondary market. Typically, the ICO whitepaper describes the restriction and the category of tokens it applies to. Even though the restrictions are typically only applicable to one specific group, several types of restrictions are often applied to different categories of tokens within one token offering. The most common allocation in an ICO that is restricted with one of the types shown below is the one to stakeholders (e.g., Bourveau et al., 2022; Davydiuk et al., 2023), in line with the insider share restrictions during an IPO or venture capital deal. There are four key terms used in the context of token restrictions: (i) cliff, (ii) lock-up, (iii) vesting, and (iv) reverse vesting.

- **Cliff:** A cliff prohibits any token issuance to the applicable group before an indicated date (known as the cliff date) and is often followed by a vesting period.
- **Lock-up:** A lock-up prohibits any sales of the issued tokens by the applicable group before an indicated date (the lock-up end date) and is often followed by a reverse vesting period.
- **Vesting:** The issuance of the allocated tokens to the applicable group is gradually realized over a defined time period (the vesting period).
- **Reverse vesting:** The issued tokens to the applicable group contain a resale restriction that is gradually lifted over a defined period (the reverse vesting period).

For cliffs and lock-ups, the initial restriction is typically fully lifted on a predetermined date in the future, while vesting and reverse vesting restrictions are released more gradually. Generally, the group of restrictions (cliff/lock-up vs. vesting/reverse vesting) is clearly identifiable based on the information in the whitepaper. Sometimes a combination of the different restriction types is used. On the one hand, the implementation of token restrictions as a token governance tool in ICOs targets the amplification of the previously described benefits of token retention. Ventures seek to align the interests of the entrepreneurs and investors to reduce agency costs. The restriction of the retained tokens could provide incentives to grow the company and keep a long-term focus, as well as show confidence in the project. On the other hand, the prohibition of receiving and selling the tokens on the market also amplifies the drawbacks of token retention. The venture further limits its flexibility to react to new information over the period of the restriction, such as a change in the market environment or other developments that would require a reallocation of financial resources. In addition, the token's liquidity will decrease during the restriction period, and the stakeholders holding restricted tokens will face high opportunity costs since they cannot liquidate their holdings (Cummings et al., 2020). Another important drawback is the need for investors to have proof that the ventures are adhering to the restriction. Unlike in regulated markets, the unregulated ICO market typically bears no consequences for breaches of any of these restrictions.

Figure 2.1 shows an example of the token governance mechanisms disclosed in the whitepaper of SwissBorg (2017). Investors can retrieve information about four different groups, together with the respective percentage of tokens allocated. Additionally, token restrictions are explained in text form below the chart. SwissBorg (2017) discloses that the tokens allocated to the group "Team and Advisors" are subject to a four-year distribution period (i.e., vesting period), which starts directly after the ICO.



***NB:** tokens allocated to the team and advisors are subject to a 4 years distribution period. Starting from the end of the TGE (10 January 2018), the team and advisors will receive 10% of their allocated tokens every 6 month until the distribution is fully completed. Therefore, if one of the current team member were ever to leave, no more tokens will be distributed to him. The remaining amount of tokens will be allocated to the newly appointed team member.*

Figure 2.1: Token Allocation and Restriction – SwissBorg (2017)

2.2.2.3 A comparison between governance in initial coin offerings and in other financing methods.

Table 2.1 provides a summary of the differences and similarities among the different types of fundraising. Token offerings share some common features with crowdfunding and traditional fundraising types, such as initial public offerings and venture capital, while also having many unique characteristics (e.g., Howell et al., 2020; Momtaz, 2020; Block et al., 2021). The table is based on Momtaz (2020) and has been further expanded with the identified information regarding the governance mechanisms of the different fundraising types. Table 2.2 summarizes the presented key terms in token governance and provides an overview of the corresponding definitions.

Table 2.1: Comparison of ICOs to crowdfunding, venture capital, and initial public offerings

	ICOs	Equity Crowdfunding	Venture Capital	IPOs
Project-/Company and Investor Characteristics				
Investment type	Utility tokens	Equity-like instruments	Equity shares	Equity shares
Funding stage	Early stage	Early stage	Balanced-stage	After later stage
Investors	All types	All types	Limited partners (LPs)	Public
Motivation	Financial and non-financial	Financial and non-financial	Financial	Financial
Deal characteristics				
Degree of regulation	Low	Low – Medium (dependent on jurisdiction)	Medium	High
Information basis	Whitepaper	Business plan and pitchdeck	Business plan and pitchdeck	IPO prospectus
Contractual relationships	• Venture has complete power over the contract creation • No negotiation between both parties • Investors have mostly no possibility to assert any legal rights in case the venture is in breach of disclosed investment terms	• Venture has complete power over the contract creation • No negotiation between both parties • Investors have limited possibilities to enforce any legal rights in case the venture is in breach of disclosed investment terms (dependent on jurisdiction)	• Strong contractual power of the VC-funds and the LPs, based on large ticket sizes • Negotiation and direct communication between Venture and VC-fund as well as VC-fund and LPs • Legally binding contracts with legal punishment in case one party is in breach of the terms	• Highly regulated and monitored market • Contractual terms are set by the firm within the allowed scope by the regulator • Investors have strong legal rights attached to their investment
Token governance mechanisms	1. Token retention a. Stakeholder tokens b. Venture development tokens c. Reserve tokens 2. Token restriction a. Cliff b. Lock-up c. Vesting d. Reverse vesting	1. Equity retention of the venture	I. VC-fund <> LP 1. Contractual covenants and restrictions 2. Performance-based compensation structures II. Venture <> VC-fund 1. Equity retention of founders 2. Restriction of retained equity (e.g., vesting schedules) 3. Variety of additional corporate governance tools, e.g., influence on board structure and VC-fund representation on the board	1. Variety of legally required corporate governance tools and reporting standards 2. Equity retention of the management team 4. Restriction of retained equity (e.g., vesting schedules)

Table 2.2: Token governance mechanisms: key terms

Mechanism	Definition
Token retention mechanisms	
Total token retention	• Total disclosed share of tokens reserved for different groups in the primary market
Stakeholder retention	• All tokens retained for the founders, the venture team, and other internal and external stakeholders • Comparable to insider holdings in traditional financial markets
Venture development retention	• All tokens retained with the main purpose of supporting future growth and operations of the venture, such as research, business development, or company allocations
Reserve pool retention	• All tokens retained to support the ecosystem through future (incentive) distributions or other stability mechanisms • This group includes a variety of disclosed categories, such as reserves, mining pool, rewards pool, and other related categories
Token restriction mechanisms	
Cliff	• Initial restriction • Prohibits any token issuance to the applicable group before an indicated date (i.e., cliff date)
Lock-up	• Initial restriction • Prohibits any sales of the issued tokens by the applicable group before an indicated date (i.e., lock-up end date)
Vesting	• Gradually released restriction • The issuance of the allocated tokens to the applicable group is realized over a defined time period (i.e., vesting period)
Reverse vesting	• Gradually released restriction • The issued tokens to the applicable group contain a resale restriction that is lifted over a defined period of time (i.e., reverse vesting period)

2.2.3 Hypotheses

The theoretical foundation of signaling in the context of informational asymmetries in financial markets is given by Leland and Pyle (1977). Due to the implied cost of equity retention or token retention in the case of ICOs, only “good” entrepreneurs are expected to retain tokens. This is based on the fact that good entrepreneurs believe in the quality and success prospects of the venture. Bad entrepreneurs, on the other hand, would decide to sell a larger share of tokens to outside investor because they are aware of the venture’s low quality. The immediate sale of all tokens would maximize the entrepreneurs’ return. This leads to a “separating equilibrium” (Spence, 1973), whereby the number of tokens retained reveals the quality and, ultimately, the fair value of the underlying venture.

Downes and Heinkel (1982) provide empirical evidence for Leland and Pyle’s (1977)

conjecture in the context of initial public offerings that a firm in which entrepreneurs retain high fractional ownership does indeed have a higher value, based on a large sample of unseasoned new issues. Additional studies provide further evidence for the positive relationship between equity retention as an incentive alignment mechanism and firm value due to the mitigation of principal-agent issues (e.g., Jensen and Meckling, 1976; Ritter, 1984). The theory of signaling also finds application in several fields of entrepreneurial finance, including venture capital (e.g., Busenitz et al., 2005; Conti et al., 2013) and crowdfunding (e.g., Anglin et al., 2018; Barbi and Mattioli, 2019). Prior research shows that the size of investment and equity shares held by the venture team has no significant effect on venture capital funding success (Busenitz et al., 2005; Conti et al., 2013). Conti et al. (2013) provide evidence that business angels, on the other hand, do consider entrepreneurs' "skin in the game" as an important value signal of the firm. The increased attraction of business angel investments due to the higher commitment of the founding team is in line with the research of Cassar and Friedman (2009), which shows that entrepreneurs with a greater investment in their ventures are expected to have higher confidence in their ability to perform the related tasks (i.e., entrepreneurial self-efficacy).

Ahlers et al. (2015) and Vismara (2016) provide empirical support that the share of equity retained in an equity crowdfunding campaign is interpreted by investors as a signal of the future success of the venture, in line with the theoretical foundation of Leland and Pyle (1977). Ahlers et al. (2015) argue that the level of uncertainty of investors, driven by the level of reliance on ambiguous information, is negatively related to fundraising success. The study provides evidence that an increased share of equity retention is a key factor in reducing this uncertainty, ultimately leading to an increased funding amount, an increased number of investors, and a faster completion time of the funding project. These findings are confirmed by Vismara (2016), showing that a larger amount of equity offered to outside investors during fundraising via equity crowdfunding decreases the number of participating investors and the total amount of capital raised.

2.2.3.1 Token Retention and the Success of Token Offerings

Our first hypothesis, the *token retention outperformance hypothesis (TRetO)*, relates to the impact of a higher degree of retained tokens in the primary market on ICO ventures' funding and post-funding performance. Investors in the token-based crowdfunding market are dependent on signals of the quality of the underlying venture to make their assessment before investing. Based on the high level of information asymmetry between insiders (e.g., entrepreneurs and the management team) and outside investors, incentive alignment mechanisms could be particularly valued by potential investors. The importance of these signals in the context of ICOs may be further supported by at least three of the market characteristics described above. First, a product is often unavailable due to the early stage of the underlying venture or project. Information about actual product or service tests is often limited, which makes the assessment of product-market fit highly speculative. The missing information requires investors to search for alternative signals to forecast the company's future success. Second, no financial data about the underlying venture is available. This is a common issue in entrepreneurial finance, given that the companies receiving investment are in their early stages. Nevertheless, the absence of a reporting standard further limits the availability of quantitative data for assessing ICOs, compelling investors to seek out qualitative signals in conducting their due diligence. Third, the market is mostly unregulated, increasing the probability of disclosure of wrong information and other fraudulent behavior by the firm. A high number of fraud cases in token-based offerings are observable (Andrieu & Sannajust, 2023), which led to a total write-off of the invested capital. Investors may thus be especially sensitive to incentive alignment signals, such as token retention, which would put the own money of the entrepreneurs at risk in case of dishonest actions.

Davydiuk et al. (2023) examine the impact of the share of tokens that cannot be sold directly to outside investors on, among others, the natural logarithm of the funding amount raised and the ratio of the funds raised during the ICO to the defined hard cap. The out-

come of the regressions shows a highly significant positive relationship between the token retention variable and the two different success metrics. The prior research of Giudici and Adhami (2019) and Lyandres et al. (2022) has shown a significant negative relationship between the share of distributed tokens during the ICO and the success probability and fundraising amount of the token offering. Despite the different approaches to defining and calculating token retention, we expect our study to confirm a positive relationship between the share of retained tokens and the funding amount based on the following rationales. First, we expect investors to interpret token retention as a quality signal based on the theory of Leland and Pyle (1977) and the high level of information asymmetry in token offerings. Second, we identify stakeholder allocation as one of the three main categories of token retention. Prior research in the context of alternative early-stage fundraising types, such as equity crowdfunding, provides empirical support for a positive relationship between the tokens that are allocated to insiders and the amount raised during the ICO (Conti et al., 2013).

In public equity markets, it has been observed that insider stock retention, in addition to its positive signal during the initial public offering, can have a positive impact on the firm's post-funding performance and valuation (e.g., Gompers et al., 2003; Bhagat and Bolton, 2008; McConnell et al., 2008). Alternative fundraising methods, such as equity crowdfunding, often lack liquid secondary markets, making a comparable analysis challenging (Hornuf & Schwienbacher, 2018; Lukkarinen & Schwienbacher, 2023). However, ICOs provide the required setting for an empirical study about the relationship between token retention and post-funding success. The existence of a liquid secondary market for tokens issued via initial coin offerings (Adhami et al., 2018) allows us to calculate a post-funding performance return of the tokens, such as the 12-month buy-and-hold abnormal return, and examine its variation based on the disclosure of different token retention amounts. We believe that the described effects of equity retention in the public markets persist in the ICO context.

The separating equilibrium (Spence, 1973) based on the signaling theory of Leland and Pyle (1977) would imply that the entrepreneurs who retain more tokens have superior skills to the ones who retain fewer. Therefore, these ventures should have increased success prospects based on stronger operational performance, which should ultimately translate to superior financial performance of the listed tokens. Despite conducting the first research on token governance's impact on financial post-funding performance, we can partially build our theory on the findings of prior studies related to operational post-funding performance in the ICO context. Davydiuk et al. (2023) analyze the relationship between the share of all issued tokens of the venture that cannot be sold to outside investors and the probability that an issuer has (i) an active website, (ii) a live product or platform, and (iii) an application available for download in the Apple App Store, at least six months after token listing. The empirical results show positive significant results in all three regressions and imply a positive relationship between the fraction of retained tokens and successful product development. Additionally, Lyandres et al. (2022) have found empirical evidence that an increased percentage of tokens distributed during the token offering has a significant negative impact on the social media activities of the venture, number of code revisions on GitHub, product/platform adoption measured based on the number of wallets containing the issued token and the post-ICO growth in the cumulative number of on-chain transfers of the respective token across wallets. These findings provide further support for a positive relationship between token retention and the post-funding success of the venture.

Hypothesis 1a: *The relationship between token retention and the funding amount in token offerings is positive.*

Hypothesis 1b: *The relationship between token retention and the post-funding performance (12-month BHAR) in token offerings is positive.*

2.2.3.2 Token Restriction and the Success of Token Offerings

Our next hypothesis, the **token restriction outperformance hypothesis (TresO)**, pertains to how the ICO ventures' funding and post-funding performance is impacted by reselling restrictions of tokens in the secondary market. Investors face the risk that entrepreneurs could sell their retained stakes immediately after token listing. This risk is more pronounced than in other types of fundraising for various reasons. First, due to the unregulated environment, the venture has no legal requirement to report any of its transactions or current holding split. This differs strongly from equity retention in public markets, where the regulator usually requires the reporting of transactions and holdings of insiders. Second, a liquid market for the retained tokens exists in many cases, which would allow an immediate sale. This would not be the case for other early-stage fundraising types. These risks are partially mitigated given the public nature of the blockchain, where all investors have access to the transaction history and can identify any insider transaction. However, this requires the know-how to be able to read primary blockchain data. A token restriction implies the voluntary commitment of the venture to hold a part of or the whole amount of retained tokens for a longer defined time period, alleviating the risk of entrepreneurs selling their retained tokens immediately after listing. The restriction of retained tokens is expected to lead to a "separating equilibrium" (Spence, 1973), whereby the decision to restrict the retained tokens reveals the quality of the underlying venture. This impact originates from the sharply increased implied costs for restricted tokens. Entrepreneurs are prohibited from freely transacting with the token, not only increasing the opportunity costs but also leading to a direct negative financial impact in case the venture has no success in the future. Therefore, the decision to voluntarily restrict the issued tokens might provide a quality signal about the underlying venture to potential investors (Leland & Pyle, 1977).

Even though empirical support for this theory exists in the IPO context (Brav & Gompers, 2003), the relationship in other types of fundraising is less clear. While Davydiuk

et al. (2023) show a significant positive effect of the inclusion of a vesting schedule for ICO tokens on the fundraising amount, Bourveau et al.'s (2022) empirical study only confirms a positive relationship between the token vesting disclosure and the probability that the token offering reaches the soft cap requirement. The latter study could not find a significant effect of the token vesting disclosure on the funding amount. The discrepancy between the findings in Bourveau et al. (2022) and Davydiuk et al. (2023) may stem from at least three factors. First, the underlying samples contain different token offerings. Second, Bourveau et al.'s (2022) study includes a larger set of control variables than that of Davydiuk et al. (2023). The results of Bourveau et al. (2022) show significant effects of additionally included variables on the fundraising amount. Third, Bourveau et al. (2022) included additional model specifications, such as the inclusion of country/region and industry indicators, which are not included in Davydiuk et al.'s (2023) model. For our study, this means the results of the relationship between token restriction and funding amount may be highly sensitive to the included control variables and other model specifications.

To our knowledge, our study is the first to also examine the impact of token restrictions on the post-funding token price performance. We show that, in the ICO context, the entrepreneurs have an information advantage compared to the investors. Entrepreneurs who decide to restrict their retained tokens are voluntarily exposing themselves to the adverse token performance during the restriction period and provide an important quality signal to investors (Leland & Pyle, 1977). Therefore, in line with our explanation for the **TRetO** hypothesis, we assume that entrepreneurs who implement a token restriction should strongly believe in the future success of the underlying venture and have superior skills to those who do not restrict the issued tokens. This assumption is expected to lead to a positive abnormal return among ventures that disclosed token restrictions in their whitepaper.

Hypothesis 2a: *The relationship between token restrictions and the funding amount in token offerings is positive.*

Hypothesis 2b: *The relationship between token restrictions and the post-funding performance (12-month BHAR) in token offerings is negative.*

Of course, it is possible that token restrictions impact the post-funding financial performance negatively for a number of reasons. First, the positive effect of token restrictions could already be priced in. If the initial funding valuation already includes the full positive price effect of the token restriction, there might be no further positive impact on post-funding performance. Second, if the venture decides to restrict the retained tokens, it also restricts its flexibility to react to unexpected liquidity needs or market environment changes, which might potentially negatively impact the operational performance. Third, investors face the risk that the restriction disclosures in the whitepaper are not incorporated into the source code (Cohney et al., 2019). Every post-funding experience that calls this accuracy into question might negatively impact the trust of the investor in the project and ultimately lead to increased selling of the token.

2.2.3.3 Moderator: Team Size

Finally, we examine the moderating effect of the venture's team size on the relationship between the token governance signals and the ICO ventures' funding and post-funding performance. Information about the founding and management team has been proven to be an important decision factor not only for venture capitalists (Gompers et al., 2020), angel investors (Bernstein et al., 2017), and equity-crowdfunding investors (Ahlers et al., 2015; Barbi & Mattioli, 2019; Piva & Rossi-Lamastra, 2018), but also for investors in token crowdfunding (e.g., Giudici and Adhami, 2019; Momtaz, 2020). The average ICO investor considers the size of the venture team as a quality signal of the project, which ultimately leads to a positive relationship between the team size and fundraising amount in token offerings (Roosenboom et al., 2020).

There are several reasons why the moderating effect may be negative. First, investors might consider human capital and token governance disclosures as signals from the same

category (e.g., signals that are not directly related to the product/service). These signals are interpreted as substitutes for each other, whereby the disclosure of additional information could lead to diminishing effects. Second, the specific human capital signal of venture team size increases with the number of full-time employees (FTEs) working on the project that is raising funds via token offering. Given that we identified insider token retention as one of the main categories of token retention, an increase in team size may also lead to an increase in retained tokens if the company wants to provide the same level of incentive alignment on a per-FTE basis as firms with smaller teams and therefore supposedly lower human capital quality. Having a common underlying driver may support the substitution thesis between the human capital and token governance signals. Prior studies on signaling in token-based crowdfunding show the first signs that could support our explanation above. For example, Giudici and Adhami (2019) empirically demonstrate that, after the introduction of additional team variables to their initial regression model, the significant effect of token retention on fundraising success disappears.

However, there are also several factors that may lead to a positive moderating effect of team size on the relationship between token governance incentive alignment tools and both funding amount and post-funding performance. First, the token retention and restriction should be more “valuable” the higher the human capital quality of the company is. Investors expect that the retained and restricted tokens may be (partially) used for future operations. The success prospects of these future operations should be enhanced if the personnel responsible for the operations are of higher quality. Second, token restriction and retention may also impact the importance given by investors to human quality signals. Even though a company may have strong founders and teams, the investor faces the risk that this team could leave the company at any time. The additional disclosure of token retention and token restriction may reassure investors that the team will stay with the company for longer due to their upside participation and potential financial losses in case of earlier departure. This would ultimately lead to a positive joint effect of team size and

token governance signals on funding amount and post-funding performance. Third, if we assume an investor considers all available disclosures and signals related to the venture in conducting due diligence, signals supporting each other might lead to an overall larger effect in combination than both would have had independently. This would mean investors do not see the human capital quality and token governance signals as substitutes with a diminishing effect in case they appear simultaneously but rather as supportive signals that enhance each other's importance for the assessment of venture quality.

***Hypothesis 3a:** The relationships in 1a-2b are negatively moderated by team size.*

***Hypothesis 3b:** The relationships in 1a-2b are positively moderated by team size.*

2.3 Data and methods

2.3.1 Data sources and sample construction

Our study sample is retrieved from our hand-collected Token Offerings Research Database (TORD).² With more than 6,400 token offerings, the TORD is the most comprehensive publicly available database for token offerings. The database contains ICOs, initial exchange offerings (IEOs), and security token offerings (STOs) with a start date before January 2021. For our empirical analyses, the sample only includes utility tokens issued during ICOs, given the differences in regulation and governance among the tokens of the three types of token-based crowdfunding. The exclusion of IEOs and STOs provides higher comparability of the observations and avoids potential biases within the dataset. The sample is further reduced due to several additional requirements, including: (i) the ICO published a whitepaper, (ii) the whitepaper included the allocation split of the issued tokens, and (iii) all control variables could be retrieved. The control variables are based on the information published in the whitepaper or other public sources, such as CoinMarketCap or GitHub.

²Available from www.paulmomtaz.com/data/tord.

The exclusion of ICOs without a published token allocation split in their public whitepaper opens the door to sample selection bias. To address this concern, we corrected for the potential sample selectivity in our robustness check in Section 2.4.4, using a broader sample of 986 observations. Based on all the described requirements above, the baseline sample consists of 759 observations.

2.3.2 Variable definitions

2.3.2.1 Dependent variables

This study analyzes two dependent variables, including one market performance indicator, the funding amount of the venture, and one after-market performance indicator, the post-funding financial performance.

Funding valuation. In line with previous studies on signaling in ICOs (e.g., Momtaz, 2021a; Bourveau et al., 2022; Mansouri and Momtaz, 2022; Colombo et al., 2023), the funding valuation variable is constructed as the logarithm of the total USD funding amount raised during the ICO. Following existing studies (e.g., Momtaz, 2021a), funding amounts reported in currencies other than USD are converted to USD based on the exchange rate quoted on CoinMarketCap at the start date of the ICO. The values represent the gross proceeds before any deduction of fees (e.g., advisory fees) or bounty programs.

Post-funding performance. Based on the advantages shown in previous studies (e.g., Fisch and Momtaz, 2020; Mansouri and Momtaz, 2022), the post-funding performance of the tokens is derived from the 12-month buy-and-hold abnormal returns (BHARs). The 12-month BHAR is calculated by subtracting the market benchmark's buy-and-hold return from the specific token's buy-and-hold return over a 12-month holding period after the token listing. This definition ultimately leads to the exclusion from post-funding performance analyses of all offerings that did not get listed on a secondary exchange. Given

the prominent disadvantages in value-weighted benchmarks, specifically the size differences of the listed tokens due to the high market value of Bitcoin and Ether, we used an equally-weighted market benchmark based on all tokens that are tracked on CoinMarket-Cap, following Momtaz (2021a) and Mansouri and Momtaz (2022).

2.3.2.2 Independent variables

Token retention variables. Token retention is usually not directly communicated but can be derived from the information in the whitepaper. Sections with headings such as “Token Allocation,” “Tokenomics,” or related terms often include an overview of the split of the issued token whereby neither the number of groups nor the definition of the groups is standardized. However, our manual in-depth analysis reveals that, despite the variety among the definitions used in a whitepaper, it is possible to categorize the groups based on the purposes of the allocations. All token offerings included in the sample published a split of their issued tokens within their whitepaper. However, the granularity and naming of the categories strongly vary among the ICOs. Our variables related to token retention are solely defined based on the values published in the venture whitepaper, which is published prior to the respective ICO (ex-ante retention). Token retention is calculated as the natural logarithm of $1 +$ the percentage of total tokens issued that did not get distributed to the public. The variable is log-transformed to account for potential skewness. For this study, we consider all tokens as retained tokens that did not get distributed in (i) the public sale and pre-sale, (ii) private sale and other kinds of offerings, such as direct exchange offerings, or (iii) promotional programs to support the offering (e.g., Airdrop, Bounty, or Promotions). We further divide the retained token into four subgroups: Stakeholder, Reserve, Venture Development, and Others. The stakeholder allocation includes all tokens distributed to the stakeholder groups of the venture, both internal and external. Depending on the token offering, this could include, for example, the founder of the venture, company employees, partners, advisors, or shareholders.

The reserve pool allocations include allocations that are retained by the company for future (reward) distribution to the network or stabilization of the project. Considered allocations are not only the ones explicitly allocated to “Reserve” but also those that are allocated to categories with a meaning that falls within our definition of reserve pool, such as mining pool, rewards pool, stabilization fund, or liquidity pool. Allocations to the development of the business, ecosystem, or strategic partnerships are captured under the “Venture Development” category together with the retained tokens for research, marketing, legal, or related purposes. All allocations to categories whose purpose does not fall into one of the three groups defined above are combined into “Others.” This could, for example, include allocations to social programs, project-type-specific purposes, or offering costs. This group only represents a small share of the distributed tokens and is not included as a separate category in our empirical analyses. All variables for the subgroups are calculated in line with the retained token variable, taking the natural logarithm of 1 + the percentage allocation to the subgroup in the token offering.

Token restriction variables. Ventures that decide to implement token restrictions in their ICO usually disclose this information in the same chapter of the whitepaper as the token retention. The token restriction variable is a dummy variable, which takes the value of 1 if the whitepaper of the token offerings contains information about a restriction on any of the distributed tokens. Additional dummy variables are included based on the defined restriction types in Section 2.2.2.2. The initial restriction variable is a dummy variable, which takes the value of 1 if either a cliff or a lock-up is disclosed within the whitepaper. The (reverse) vesting restriction variable is another dummy variable, indicating if any distributed tokens are attached with a vesting or reverse vesting restriction. The assessment of the exact restriction structure is notably demanding since individual token issuers sometimes interchange some of the terms (e.g., cliff and lock-up) in their restriction descriptions. The restriction variables do not consider the allocations to the reserve pool category. Allocations to the reserve pool are restricted by nature and often unlocked over many years

without a fixed (reverse) vesting schedule, strongly dependent on the development of the individual projects.

2.3.2.3 Control variables

Prior ICO studies (e.g., Howell et al., 2020; Momtaz, 2020; Mansouri and Momtaz, 2022) have identified a large number of factors that could impact the success of token offerings. Focusing on the variables that have already shown significant effects in previous studies and omitting the others, we define three categories of control variables for our research: (i) venture characteristics, (ii) offering characteristics, and (iii) market characteristics. Venture characteristics include human capital related variables, such as the total number of team members and the percentage of team members that have a technical background. We consider an employee to have a technical background when the team members' professional network profile (e.g., LinkedIn) shows a degree from a technical field, such as computer science, information technology, or comparable areas. Furthermore, we included dummy variables to control if the startup already has a minimum viable product available at the ICO date (MVP) and if it discloses the code on GitHub (open source). The whitepaper length variable is based on the natural logarithm of the total words included in the published whitepaper, often used as an indication for the total information available to the investor (e.g., Fisch, 2019; Mansouri and Momtaz, 2022). Related to offering characteristics, we identified important design features of the ICO and set the respective dummy variables to 1 if the features were included and 0 otherwise. Based on prior studies (e.g., Howell et al., 2020; Momtaz, 2020; Mansouri and Momtaz, 2022), we considered if the venture announced a minimum funding amount required to be successful (soft cap) or a maximum total amount accepted (hard cap), conducted a pre-sale event (pre-sale) or offered a bonus structure (bonus) or bounty program (bounty) to its investors. Separately, we controlled for a possible whitelist feature of the token offering and if the underlying technical standard is ERC20 (ERC20). Lastly, we also controlled for the market sentiment

during the ICO, including the bull market and bear market dummy variables. The bear market period is from February 2018 until January 2019, while the bull market considers the time prior to February 2018. The full set of included control variables and their definitions are listed in Table A.1.

2.3.3 Summary statistics

The summary statistics, including arithmetic mean, standard deviation, and the 25%, 50%, and 75% quantile, are presented in Table 2.3.

Dependent variables. Table 2.3 shows that, on average, the startup in our sample raised an amount of \$3.80 million (log. = 15.15; log. SD = 1.87) during the token offering and experienced a buy-and-hold abnormal return of -0.663 , with a standard deviation of 1.11.

Key variables. The mean of the token retention (log) variable is 3.48, which translates into a 31.5% average share of retained tokens by the startups. The split among the different categories shows that 12.2% (avg. log. = 2.58; log. SD = 0.93) were retained for purposes relating to stakeholder allocations, 2.55% (avg. log. = 1.60; log. SD = 1.52) for reserve pool allocations, and 4.0% (avg. log. = 1.27; log. SD = 1.40) and 0.2% (avg. log. = 0.20; log. SD = 0.66) for venture development and other allocations, respectively. In our baseline sample, all ventures published an allocation split in their whitepaper. Out of the 759 token offerings, in 749 offerings, a defined amount of tokens got retained, and in only 10 cases, 100% of the tokens were distributed during the ICO. The key restriction variable statistics show that, based on our sample, 49.4% of startups have a token allocation restriction disclosed within their whitepaper; 37.3% have an initial restriction of some or all distributed tokens, meaning that these startups incorporated either a lock-up or a cliff restriction; and slightly fewer ventures (30.4%) communicated a vesting period or a reverse-vesting period in their whitepaper relating to their token distribution. In 18.3%

of the offerings, we observed a combination of initial restrictions and (reverse) vesting restrictions.

Control variables. The summary statistics in Table 2.3 indicate that the average venture has a team size of 13.4 FTEs, of which approximately 24.8% have a technical background. On a scale from 1 to 5, with 5 indicating the highest venture quality, industry experts on ICObench rated the average venture 3.4. Among all sample ventures, 19.8% already had a minimum viable product (MVP) available at the ICO start, and 66.1% published their code on GitHub. The average whitepaper length for the startups under study was around 3,484 words (avg. log. = 8.156; log. SD = 0.591). A hard cap was announced for most of the token offerings in the sample (90%), and a soft cap (66.4%) for approximately two-thirds. Regarding the token offerings, 57.0% and 32.4% had an implemented pre-sale period and active whitelist, respectively. With respect to the possible promotion schemes in token offerings, 33.3% of the ventures offered a bounty program, and 0.7% offered a bonus structure. The technical ERC-20 standard was relied upon for 81.6% of the token offerings. Regarding the market sentiment during the ICO, 30.0% of the analyzed offerings took place during a bull market and 71.7% during a bear market.

Table 2.3: Descriptive statistics

	Mean	SD	Q1	Median	Q3
<i>Key variables:</i>					
Token retention, in % (0 to 100, log.)	3.480	0.700	3.180	3.584	3.932
Stakeholder allocation, in % (0 to 100, log.)	2.578	0.930	2.398	2.773	3.135
Venture development allocation, in % (0 to 100, log.)	1.268	1.397	0.000	0.693	2.565
Reserve pool allocation, in % (0 to 100, log.)	1.602	1.521	0.000	2.079	2.996
Other allocation, in % (0 to 100, log.)	0.202	0.663	0.000	0.000	0.000
Token restriction (dummy)	0.494	0.500	0.000	0.000	1.000
Restriction length, in months	11.820	17.210	0.000	0.000	24.000
Initial restriction (dummy)	0.373	0.484	0.000	0.000	1.000
(Reverse) vesting restriction (dummy)	0.304	0.460	0.000	0.000	1.000
<i>Dependent variables:</i>					
Funding amount (log)	15.150	1.874	14.210	15.420	16.450
BHAR, 12 months (equally weighted)	-0.663	1.109	-1.091	-0.416	-0.107
<i>Control variables (Venture characteristics):</i>					
Whitepaper length, in log-words	8.156	0.591	7.828	8.185	8.520
Expert rating (1 to 5)	3.428	0.578	3.000	3.500	3.900
Team size, in # FTE	13.430	8.204	8.000	12.000	18.000
Technical background, in % (0 to 100)	24.820	19.170	9.375	23.810	36.360
Minimum viable product (dummy)	0.198	0.398	0.000	0.000	0.000
Open source (dummy)	0.661	0.474	0.000	1.000	1.000
<i>Control variables (Offering characteristics):</i>					
Soft cap (dummy)	0.664	0.473	0.000	1.000	1.000
Hard cap (dummy)	0.908	0.290	1.000	1.000	1.000
Pre-sale (dummy)	0.570	0.495	0.000	1.000	1.000
Whitelist (dummy)	0.324	0.468	0.000	0.000	1.000
Bonus (dummy)	0.007	0.081	0.000	0.000	0.000
Bounty (dummy)	0.333	0.472	0.000	0.000	1.000
ERC-20 standard (dummy)	0.816	0.388	1.000	1.000	1.000
<i>Control variables (Market characteristics):</i>					
Bull market (dummy)	0.300	0.459	0.000	0.000	1.000
Bear market (dummy)	0.717	0.451	0.000	1.000	1.000

2.3.4 Correlations

Table 2.4 presents the pairwise correlation coefficients for all included variables. Given the high correlations among the different restriction variables, we run separate regression models to avoid multicollinearity.

Table 2.4: Correlation matrix.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.
<i>Key variables:</i>																								
1. Token retention (log)																								
2. Stakeholder allocation (log)	.37																							
3. Venture development allocation (log)	.35	.12																						
4. Reserve pool allocation (log)	.48	-.04	-.20																					
5. Other allocation (log)	.13	-.04	.00	.00																				
6. Token restriction (dummy)	.21	.24	.12	.02	.05																			
7. Initial restriction (dummy)	.14	.19	.07	-.01	.03	.78																		
8. (Reverse) vesting restriction (dummy)	.18	.17	.11	.03	.04	.67	.31																	
<i>Dependent variables:</i>																								
9. Funding amount (log)	.16	.06	.13	.06	-.01	.09	.08	.10																
10. BHAR, 12 months	.13	-.01	.12	-.03	.05	-.09	-.09	-.09	.07															
<i>Venture-related controls:</i>																								
11. Whitepaper length, in (log-words)	.15	.09	.11	.10	.02	.22	.13	.20	.29	.07														
12. Expert rating	.07	.05	.08	.04	-.07	.11	.09	.11	.14	-.11	.31													
13. Team size, in # FTE	.09	.08	.12	.02	-.04	.12	.07	.14	.18	.00	.34	.41												
14. Technical background, in %	.08	-.03	.07	.02	-.02	.05	.03	.07	.08	.04	.10	-.01	.07											
15. Minimum viable product (dummy)	.03	.04	.01	.03	-.05	-.01	.03	-.02	-.07	-.21	.07	.34	.20	-.08										
16. Open source (dummy)	.02	.00	.00	.03	-.06	.06	.04	.06	-.07	-.16	.13	.36	.16	.02	.21									
<i>Offering-related controls:</i>																								
17. Soft cap (dummy)	.01	.06	-.07	.09	-.01	-.02	.03	-.03	-.12	-.07	.02	.21	.12	-.10	.23	.22								
18. Hard cap (dummy)	.05	.00	.05	.05	-.03	.02	.01	.05	.00	.01	.13	.22	.14	-.03	.15	.13	.34							
19. Pre-sale (dummy)	-.03	.01	-.00	.03	-.04	.01	-.00	.05	-.06	-.07	.10	.20	.18	-.06	.11	.09	.15	.14						
2. Whitelist (dummy)	.11	.09	.03	.09	-.02	.05	.03	.06	.05	-.09	.20	.24	.21	.01	.20	.10	.17	.11	.08					
21. Bonus (dummy)	-.06	-.05	.06	-.05	-.03	.02	.04	.02	.01	.03	-.01	.04	.06	.00	-.04	-.01	.03	-.03	.05					
22. Bounty (dummy)	.02	.02	.00	.06	-.05	-.02	.02	-.02	-.11	-.22	.07	.24	.16	-.08	.41	.17	.20	.16	.15	.20	.01			
23. ERC-20 standard (dummy)	.04	.06	.03	-.02	-.03	.02	.02	.00	-.09	-.05	.03	.10	.09	-.04	.10	.07	.07	.11	.06	.05	.04	.11		
<i>Market-related controls:</i>																								
24. Bull market (dummy)	-.13	-.12	-.06	-.12	.01	.03	-.01	.02	.12	.18	-.06	-.25	-.18	.14	-.30	-.12	-.32	-.23	-.20	-.39	-.05	-.39	-.22	
25. Bear market (dummy)	.05	.05	.02	.08	-.02	.01	.04	-.02	-.01	-.20	.06	.16	.19	-.00	.12	.06	.22	.18	.15	.32	.02	.27	.21	-.63

2.3.5 Econometric approach

The substantial part of our empirical analyses aims to estimate the causal effects of token retention and token restriction on (i) the funding amount and (ii) the post-funding performance in token offerings. Therefore, in our defined baseline regression, we are interested in the effect of the amount of retained tokens (RT_i) and the token restriction dummy (TR_i) on the dependent variables $DV_i \in \{Valuation_i, Performance_i\}$, using an ordinary least squares model. The model further includes a vector of control variables (Ω_i):

$$DV_i = \beta_1 RT_i + \beta_2 TR_i + \Omega_i \gamma + \epsilon_i, DV_i \in \{Valuation_i, Performance_i\} \quad (1)$$

In the next steps, we address the natural concerns that the estimated regressors from the baseline regression (1) could suffer an endogeneity bias ($E[\Omega_i, \epsilon_i] = 0$). Following the techniques used in previous studies in the field of entrepreneurial finance, we applied three different two-stage models to control for observed and/or unobserved heterogeneity (e.g., Colombo and Grilli, 2010; Bertoni et al., 2011), specifically: (i) inverse Mills ratio (IMR model), (ii) generalized residuals (GR) as an estimator (GR model), and (iii) generalized residuals (GR) as instrumental variables (IV model). To address potential endogeneity problems, all of the chosen approaches above rely on a selection model estimation in the first stage. We are specifically interested in the selection of ventures into their token retention share. Section 2.2.3 shows that better startups should retain more tokens (Leland & Pyle, 1977). Therefore, to estimate the impact of token retention on fundraising success, we must control for this selectivity. Equation (2) models the probability that startup i has a token retention share above the median ($hiRT_i$), based on a vector of exogenous variables that could influence the selection mechanism, $\Omega_i^{(s)}$:

$$hiRT_i = \Omega_i^{(s)} \delta + \xi_i \quad (2)$$

In our first approach and based on the results of Equation (2), we compute the inverse

Mills ratio (IMR_i) for the selection of each startup i (e.g., Heckman and Navarro-Lozano, 2004; Mansouri and Momtaz, 2022). The cumulative density function of the standard normal distribution is indicated by $\Phi(\cdot)$, and the probability density function by $\phi(\cdot)$.

$$IMR_i = \frac{\phi(\frac{\Omega_i^{(s)}\delta}{\sigma_\xi})}{\Phi(\frac{\Omega_i^{(s)}\delta}{\sigma_\xi})} \quad (3)$$

We then add the computed IMR_i to our baseline regression in the second stage, where λ tests the null hypothesis that no selection effect exists:

$$DV_i^{IMR} = \beta_1 RT_i + \beta_2 TR_i + \lambda IMR_i + \Omega_i \gamma + \nu_i, DV_i^{IMR} \in \{Valuation_i^{IMR}, Performance_i^{IMR}\} \quad (4)$$

For our second and third empirical approaches, we compute generalized residuals (GRs) from the results from Equation (2). In line with Gouriéroux et al. (1987), we define the generalized residuals (GR_i) for startup i as:

$$GR_i = hiRT_i \times \frac{\phi(-\Omega_i^{(s)}\delta)}{(1 - \Phi)(-\Omega_i^{(s)}\delta)} + (1 - hiRT_i) \times \frac{-\phi(\Omega_i^{(s)}\delta)}{\Phi(-\Omega_i^{(s)}\delta)} \quad (5)$$

In the second stage of the GR model, we then add the computed GR_i to our baseline regression (Equation (1)), where ζ tests the null hypothesis that no selection effect exists:

$$DV_i^{GR} = \beta_1 RT_i + \beta_2 TR_i + \zeta GR_i + \Omega_i \gamma + \nu_i, DV_i^{GR} \in \{Valuation_i^{GR}, Performance_i^{GR}\} \quad (6)$$

To control for unobserved heterogeneity, we also use the computed GRs from Equation (5) as instrumental variables for startups' token retention share in the IV model. We restrict the standard deviation of the error term for startups with above-median token retention shares ($\sigma_{\epsilon, hiRT=1}$) to be equal to that of startups with below-median token retention shares

($\sigma_{\epsilon, hiRT=0}$), ensuring that GR_i can be added as an instrumental variable to our baseline regression (1) (Mansouri & Momtaz, 2022).

2.4 Empirical results

2.4.1 Token offering success

Table 2.5 shows the regression results for the effect of token retention and token restrictions on the startup funding valuation. The funding valuation is represented by the natural logarithm of the USD funding amount, which is the dependent variable for models (1), (2), (3), (4), and (5). The baseline (OLS) regression (1) estimates the effects of the natural logarithm of the percentage share of retained tokens and the token restriction dummy variable without considering the potential selection bias. We control for selection-related endogeneity in models (3), (4), and (5), which are based on inverse Mills ratios (IMRs), generalized residuals (GR), and generalized residuals as instrumental variables (IV (GR)), respectively. Model (2) is an additional control model, estimating the effects of all control variables without including the key variables regarding token retention and token restriction. All models include a variety of control variables related to the venture characteristics and specifics of the token offering, as well as country and quarter-year fixed effects. The reported standard errors are robust, and the R^2 exceeds 30% in all models, slightly higher than in most existing studies (e.g., Davydiuk et al., 2023). The key variables included in the analysis have variance inflation factors (VIFs) below 3, which is well below the widely accepted threshold of 5 (e.g., Leitterstorf and Rau, 2014; Mansouri and Momtaz, 2022). The additional control variables also have VIFs below 3, except for the two market characteristics controls. These results imply that multicollinearity is not a prominent issue in our study.

Table 2.5: The effects of token retention and restrictions on the funding amount

Model:	(1) Main	(2) Control	(3) IMR	(4) GR	(5) IV (GR)
Dependent variable: <i>Funding amount (log)</i>					
<i>Key variables:</i>					
Token retention (log)	0.318** (0.126)		0.314** (0.127)	0.308* (0.166)	0.308** (0.154)
Token restriction (dummy)	-0.141 (0.129)		-0.142 (0.129)	-0.142 (0.129)	-0.142 (0.119)
<i>Venture characteristics:</i>					
Whitepaper length, in (log-words)	0.689*** (0.155)	0.702*** (0.158)	0.611*** (0.169)	0.691*** (0.153)	0.689*** (0.143)
Expert rating	0.497*** (0.126)	0.511*** (0.127)	0.458*** (0.137)	0.497*** (0.126)	0.496*** (0.116)
Team size, in # FTE	0.029*** (0.010)	0.029*** (0.010)	0.028*** (0.010)	0.029*** (0.010)	0.029*** (0.009)
Technical background, in %	-0.006 (0.005)	-0.005 (0.005)	-0.007 (0.005)	-0.006 (0.005)	-0.006 (0.004)
Minimum viable product (dummy)	0.151 (0.219)	0.140 (0.218)	0.276 (0.251)	0.150 (0.220)	0.153 (0.202)
Open source (dummy)	-0.408*** (0.150)	-0.419*** (0.150)	-0.361** (0.166)	-0.408*** (0.150)	-0.407*** (0.139)
<i>Offering characteristics:</i>					
Soft cap (dummy)	-0.192 (0.159)	-0.203 (0.161)	-0.176 (0.160)	-0.192 (0.159)	-0.192 (0.147)
Hard cap (dummy)	0.137 (0.245)	0.123 (0.244)	0.122 (0.245)	0.136 (0.245)	0.136 (0.226)
Pre-sale (dummy)	-0.173 (0.140)	-0.198 (0.142)	-0.121 (0.144)	-0.174 (0.139)	-0.173 (0.130)
Whitelist (dummy)	0.025 (0.145)	0.039 (0.147)	-0.042 (0.168)	0.026 (0.145)	0.025 (0.133)
Bonus (dummy)	0.995 (0.649)	0.844 (0.671)	1.189* (0.680)	0.988 (0.648)	0.992* (0.598)
Bounty (dummy)	-0.172 (0.176)	-0.182 (0.177)	-0.198 (0.176)	-0.173 (0.178)	-0.174 (0.165)
ERC-20 standard (dummy)	-0.333** (0.168)	-0.321* (0.167)	-0.295* (0.174)	-0.332** (0.168)	-0.331** (0.155)
<i>Market characteristics:</i>					
Bull market (dummy)	-0.013 (0.207)	-0.043 (0.212)	0.097 (0.253)	-0.015 (0.209)	-0.012 (0.191)
Bear market (dummy)	0.384 (0.287)	0.281 (0.287)	0.463 (0.302)	0.383 (0.288)	0.385 (0.264)
IMR	X	X	✓	X	X
GR	X	X	X	✓	X
IV	X	X	X	X	✓
VIF [argmax(key)]	1.39	./.	1.39	2.40	./.
VIF [argmax(controls)]	4.94	4.88	5.58	4.95	./.
Quarter-year FEs	✓	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓	✓
Observations	759	759	759	759	759
R-squared	0.338	0.328	0.339	0.338	0.338

Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1

Overall, the regressions show different results for token retention and restriction effects. All models suggest that token retention has a significantly positive effect on the

fundraising amount in token offerings, with a marginal effect of the natural logarithm of the percentage of retained tokens ranging from 0.308 to 0.318 and a p-value always lower than 10%. Our baseline model (1) shows a coefficient for token retention (log) of 0.318, suggesting that a 1% increase in the share of retained tokens increases the average funding amount by 0.318%. These findings strongly support hypothesis 1a, that token retention has a positive signaling effect in initial coin offerings, and are in line with previous studies showing a negative effect of a larger share of distributed tokens (e.g., Giudici and Adhami, 2019; Lyandres et al., 2022). We thus provide further evidence that the signaling theory of Leland and Pyle (1977) holds in the context of initial coin offerings. Investors might interpret the amount of retained tokens as a quality signal that reveals the fair value of the underlying venture, given that good entrepreneurs should retain more tokens than bad entrepreneurs.

Additionally, the results of all models suggest that the inclusion of a token restriction is not statistically significant, implying that investors do not consider the whitepaper disclosure of token restriction mechanisms as an important signal of the quality of the underlying venture. These results indicate that investors might not give importance to the risk of entrepreneurs selling their retained tokens immediately after listing or do not believe in risk mitigation based on a token restriction disclosure. There are several possible reasons for this contradiction to our defined hypothesis 2a; for example, (i) investors may be concerned about the restricted flexibility of the venture to react to unexpected liquidity needs or market environment changes, or (ii) investors may doubt the accuracy of the disclosure. Cohn et al. (2019) find evidence supporting this second possibility, presenting that most ventures that disclose a token restriction do not embed those rights into the source code. Overall, these results are in line with the study by Bourveau et al. (2022), who also did not find a significant relationship between the disclosure of a vesting schedule and the fundraising amount. However, the findings are contrary to those of Davydiuk et al. (2023), which showed a positive significant relationship. This variation in findings might be due

to several factors. First, our study includes several additional significant control variables, such as whitepaper length and expert rating, which are not included in Davydiuk et al.’s (2023) model. Additionally, we include country fixed-effects and robust standard errors resulting in a higher R^2 (0.338 vs. 0.202). Second, we consider all types of token restrictions, while the prior study only mentions vesting schedules. It might be possible that our in-depth analysis of the whitepaper includes additional restrictions (e.g., lock-up or cliff) that are not included in the prior study.

Table 2.5 shows that the results in our baseline OLS model (1) closely correspond to the second-stage models (3), (4), and (5), providing evidence that the results in model (1) are not strongly biased by underlying selection-related endogeneity. This suggestion is further supported by the non-significant IMR and GR coefficients in models (3) and (4), respectively (not tabulated). We also note that the regression coefficients and correlating statistical significance of the control variables in models (1)–(5) are generally in line with those in previous studies (e.g., Fisch, 2019; Fisch et al., 2022; Mansouri and Momtaz, 2022). The length of the whitepaper, the score in the expert rating, and the number of FTEs related to the project show a significantly positive relationship to the fundraising amount. For example, we can observe in the baseline model that a 1-point increase in the expert rating leads to a 49.7% increase in the funding amount, significant at the 1% level. The choice of the ERC-20 standard and the venture’s decision to disclose its code on GitHub negatively impact the amount raised in the token offering, leading to a 33.3% and 40.8% decrease in the funding amount, respectively. Our sensitivity check in column (2) excludes the two key variables. The regression results show a high similarity to those of our baseline model (1) regarding the direction of the effects and their magnitude.

Table 2.6 presents the results of running the same regressions again, this time using the different token retention categories instead of the overall token retention share. It is observable that the main effect of token retention is driven by the share allocated to the stakeholder group. Model (1) shows a coefficient for stakeholder allocation of 0.162,

implying that a 1% increase in the share of retained tokens for stakeholders increases the average funding amount by 0.162%. This finding supports the theory that investors consider an increased number of tokens retained by insiders as a quality signal of the underlying venture and is in line with findings from alternative early-stage fundraising research (e.g., Conti et al., 2013). Allocations to stakeholders might also be interpreted as a further incentive alignment with the decision-makers of the venture, given that those groups are financially participating in the upside of the project. This alignment could moderate the risks investors face in the token offering market, such as moral hazard, adverse selection, and outright fraud. The venture development allocation shows a positive coefficient ranging from 0.081 to 0.101 among the 4 different models. However, when we control for selection-related endogeneity based on generalized residuals (GR) and generalized residuals as an instrumental variable (IV (GR)), the significance disappears.

Table 2.6: **The relations between token allocation options and the funding amount**

Model:	(1) Main	(2) IMR	(3) GR	(4) IV (GR)
Dependent variable: <i>Funding amount (log)</i>				
Stakeholder allocation (log)	0.162** (0.075)	0.159** (0.075)	0.145* (0.077)	0.144** (0.071)
Venture development allocation (log)	0.101** (0.051)	0.100* (0.051)	0.081 (0.055)	0.081 (0.051)
Reserve pool allocation (log)	0.075 (0.050)	0.073 (0.050)	0.053 (0.060)	0.052 (0.055)
Token restriction (dummy)	-0.152 (0.134)	-0.152 (0.134)	-0.158 (0.135)	-0.159 (0.124)
Controls	✓	✓	✓	✓
IMR	✗	✓	✗	✗
GR	✗	✗	✓	✗
IV	✗	✗	✗	✓
VIF [argmax(key)]	1.37	1.37	1.94	./.
Quarter-year FEs	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Observations	759	759	759	759
R-squared	0.337	0.337	0.337	0.337

Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1

2.4.2 Post-funding performance

Panel A of Table 2.7 presents estimates of the effect of token restriction and token retention on the post-funding performance of the tokens based on the 12-month buy-and-hold abnormal return. The 4 different models are defined as in the previous table, showing the OLS model in column (1) and the different two-stage models in columns (2), (3), and (4). We can observe that the share of retained tokens does not significantly impact the post-funding performance. Consequently, the findings do not support our hypothesis 1b, that investors considered token retention as a positive signal of firm quality even after the close of fundraising. Therefore, we also do not confirm the results shown in the context of the public equity market (e.g., Bhagat and Bolton, 2008; McConnell et al., 2008). A plausible explanation for the non-significant results is that the correlation between post-funding performance measured based on the price of the listed financial instrument and the operational performance of ventures using token-based crowdfunding might be less than for publicly listed companies in the traditional equity market. Our hypothesis was partially built on prior findings that token retention increases post-funding operational performance, which should translate to superior token performance. However, this might not be the case for several reasons. First, the investor has no audited report available to receive information about the operational performance of the venture. Second, it might be difficult for investors to assess the operational performance by themselves due to limited knowledge and resources. The previous studies created their own variables to measure operational success, such as the number of downloads (Davydiuk et al., 2023) or the number of wallets containing the issued token (Lyandres et al., 2022), which would be difficult to compute for an average investor. Third, token performance could be driven more by market speculation unrelated to the underlying operational performance than by the share performance in the traditional equity market. Additionally, the token retention variables are defined based on the published pre-ICO values in the whitepaper (ex-ante retention) and might differ from the actual retained amount of tokens (ex-post retention). The ven-

ture does not disclose updated information that could give the investors an indication of the ex-post retention amount. The validation of the exact ex-post retention amount on the blockchain might also be practically impossible since it would require knowledge about the relevant wallet addresses. This situation provides further reasoning as to why the ex-ante token retention amount might not be an important signal for post-funding performance, leading to the non-significant results in Table 2.7.

The relationship between token restrictions and post-funding performance is significantly negative, contradicting our initial hypothesis 2b. The marginal effect of the announcement of a token restriction in the whitepaper ranges from -0.376 to -0.385 , statistically significant with p-values below 5%. The fact that the coefficient from the main OLS model and those of the two-stage models closely correspond implies that the treatment effect of token restrictions on ICO ventures' funding is not impacted by any underlying selection effect. In economic terms, our findings indicate that the inclusion of token restrictions leads, on average, to a 37.6% decrease in the 12-month buy-and-hold abnormal return of the token. There are several possible reasons for this significant negative impact. First, the decision of the venture to restrict the retained tokens consequently restricts its flexibility to react to unexpected liquidity needs or changes in the market environment. It will not be possible to transfer or liquidate tokens, no matter which external factor arises. This consequence is accompanied by the related disadvantage of increased opportunity costs; the venture could not invest in any profitable project if an attractive opportunity arises. These disadvantages potentially negatively impact the operational performance of the venture and, ultimately, the token performance. Second, investors might have detected a breach of the disclosed restriction terms during the restriction period. These detections would decrease the overall trust of the investors in the project and lead to the divestment of their token holdings. Cohn et al. (2019) have found evidence that the majority of ventures that disclose a token restriction do not encode those rights into the smart contract, which, based on our explanation above, would lead to a negative impact on the

post-funding performance of the token after the investor becomes aware of the breach of the communicated restrictions.

In Panel B of Table 2.7, we examine separately the impact of the two different types of restrictions, (i) initial restrictions (lock-up and cliff) and (ii) restrictions that are gradually released over time (reverse vesting and vesting). The results clearly show that the impact of the disclosure of initial restrictions is more negative than that of the other types. While a reverse vesting or vesting schedule does not have a significant impact on post-funding performance, the initial restrictions (lock-up and cliff) do, on average, lead to a decrease of 38.7% in the 12-month buy-and-hold abnormal return of the token, statistically significant with p-values below 5%. A plausible explanation for this finding might be that the market impact around the end date of the token restriction might be more negative for initial restrictions since the prior restricted token holders are now able to transfer the full amount. By contrast, a restriction gradually released over time would be expected to have a less significant impact around the end date of the token restrictions (~ 12 months after listing), given that tokens are gradually unlocked over the horizon of the restriction length (e.g., monthly). This is supported by studies conducted in the context of IPO lockups (Field & Hanka, 2001), showing that increased trading volume and a negative abnormal return are observable after the expiration of the restriction. Additionally, a breach of an initial restriction is easier for investors to detect than a breach of a gradually released restriction since no transaction from the restricted token pool should be conducted. In the case of a vesting schedule or a reverse vesting restriction, transactions are expected because, starting from the first day after the ICO close, tokens could get unlocked. Therefore, it might be harder to detect if a breach of the restriction happens and the transactions are larger than allowed under the disclosed restriction terms.

Taken together, our results confirm the **token retention outperformance hypothesis (TRetO)** related to the initial fundraising but not to post-funding performance. In particular, ventures that retain a higher degree of tokens during the ICO outperform during the

funding period but do not have a significant difference in their post-funding performance. Overall, our results reject the **token restriction outperformance hypothesis (TresO)**. While showing no significant effect during the funding period, ventures that implement a token restriction underperform their peers in the 12-month post-funding period.

Table 2.7: **The effects of token retention and restrictions on the post-funding performance**

Model:	(1) Main	(2) IMR	(3) GR	(4) IV (GR)
Dependent variable: <i>BHAR, 12 months</i>				
Panel A: Restriction (dummy)				
Token retention (log)	0.171 (0.143)	0.163 (0.148)	0.022 (0.184)	0.015 (0.152)
Token restriction (dummy)	−0.376** (0.187)	−0.385** (0.186)	−0.379** (0.185)	−0.382*** (0.148)
Controls	✓	✓	✓	✓
IMR	✗	✓	✗	✗
GR	✗	✗	✓	✗
IV	✗	✗	✗	✓
Quarter-year FEs	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Observations	208	208	208	208
R-squared	0.455	0.457	0.460	0.461
Panel B: Restriction type				
Token retention (log)	0.154 (0.144)	0.148 (0.148)	0.007 (0.185)	0.000 (0.152)
(Reverse) vesting restriction (dummy)	−0.115 (0.187)	−0.129 (0.190)	−0.116 (0.187)	−0.121 (0.149)
Initial restriction (dummy)	−0.387** (0.177)	−0.382** (0.180)	−0.388** (0.176)	−0.387*** (0.140)
Controls	✓	✓	✓	✓
IMR	✗	✓	✗	✗
GR	✗	✗	✓	✗
IV	✗	✗	✗	✓
Quarter-year FEs	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Observations	208	208	208	208
R-squared	0.461	0.462	0.465	0.466

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

2.4.3 Team size as a moderator

Table 2.8 highlights the moderating effect of venture team size on token retention and token restriction in their relationship with the token offering funding amount (Panel A)

and post-funding performance (Panel B). Panel A shows that team size negatively moderates the impact of token retention on fundraising amount with a coefficient of -0.039 . In economic terms, this means that the 0.757% increase in fundraising amount based on a 1% increase in retained tokens is reduced by, on average, 0.039 percentage points per additional FTE added to the venture team. The moderating effect and the variables for token retention and team size are all statistically significant at the 1% level in the main model and in the second-stage models, implying that the moderating effect is not impacted by any underlying selection effect. The results do not show any significant moderating effect of team size on the relationship between token restriction and the funding amount. The results in Panel A support hypothesis 3a, that team size negatively moderates the impact of our defined token governance variables. The findings might be explained by the possibility that investors consider the signals as belonging to the same category and ultimately as substitutes for each other. The effect of token governance signals would therefore decrease when the human capital quality increases. Additionally, the size of token retention is mainly driven by the number of tokens retained for insiders, among which is the venture team, which means that the increase in the team size could consequently lead to an increase in the share of retained tokens. This common underlying driver may further support the substitution effect.

The moderating effect of venture team size in the context of post-funding performance (Panel B) shows no significance related to the effect of token retention, which is itself not a significant factor in the regressions. However, despite team size not showing any significance in explaining the post-funding performance variation of listed tokens, the variable has a statistically significant moderating effect on the relationship between token restriction and the 12-month buy-and-hold abnormal return. Post-funding performance would be decreased by an average of 107.9% in case the venture published a token restriction in the offering whitepaper and in the hypothetical case that the team size is 0. The larger the number of FTEs within the venture team, the lower the reduction in post-funding perfor-

mance caused by the token retention disclosure. For example, if the team consists of 10 FTEs, the average decrease of 12-month buy-and-hold abnormal return allocated to the token retention would be reduced to 48.9%. These findings provide evidence for our defined hypothesis 3b and might be explained by the fact that restricted tokens are seen as more valuable when the quality of the human capital of the venture is higher. The larger team size, representing increased human capital quality, in combination with restricted tokens, could therefore provide several positive signals to the investors. First, the future operations of the venture might have increased prospects of success because the persons responsible for the operations are of higher quality. Second, the personnel have an incentive to stay within the company due to its restricted token holdings.

Table 2.8: The moderating effect of the venture team size

Model:	(1) Main	(2) IMR	(3) GR	(4) IV (GR)
Panel A: <i>Funding amount (log) as the dependent variable</i>				
Token retention (log)	0.757*** (0.213)	0.751*** (0.213)	0.723*** (0.235)	0.722*** (0.217)
x team size, in # FTE	−0.039*** (0.011)	−0.038*** (0.011)	−0.039*** (0.011)	−0.039*** (0.010)
Token restriction (dummy)	−0.258 (0.272)	−0.259 (0.272)	−0.258 (0.273)	−0.258 (0.251)
x team size, in # FTE	0.009 (0.017)	0.010 (0.016)	0.009 (0.017)	0.009 (0.015)
Team size, in # FTE	0.161*** (0.039)	0.160*** (0.039)	0.164*** (0.039)	0.164*** (0.036)
Controls	✓	✓	✓	✓
IMR	✗	✓	✗	✗
GR	✗	✗	✓	✗
IV	✗	✗	✗	✓
Quarter-year FEs	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Observations	759	759	759	759
R-squared	0.349	0.349	0.349	0.349
Panel B: <i>BHAR, 12 months, as the dependent variable</i>				
Token retention (log)	0.392 (0.334)	0.381 (0.338)	0.213 (0.375)	0.206 (0.302)
x team size, in # FTE	−0.020 (0.019)	−0.020 (0.019)	−0.018 (0.020)	−0.018 (0.016)
Token restriction (dummy)	−1.079*** (0.362)	−1.081*** (0.365)	−1.092*** (0.361)	−1.095*** (0.287)
x team size, in # FTE	0.059** (0.027)	0.058** (0.027)	0.059** (0.026)	0.059*** (0.021)
Team size, in # FTE	0.043 (0.079)	0.043 (0.079)	0.035 (0.079)	0.034 (0.063)
Controls	✓	✓	✓	✓
IMR	✗	✓	✗	✗
GR	✗	✗	✓	✗
IV	✗	✗	✗	✓
Quarter-year FEs	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Observations	208	208	208	208
R-squared	0.476	0.478	0.480	0.481

Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1

2.4.4 Robustness Tests and Post-hoc Analyses

Not all ventures publish token allocation information in their public whitepaper; hence, this information being required for inclusion in our baseline sample for the quantitative analyses might lead to a potential selectivity issue. We thus run a two-stage least squares test to address this concern and correct any potential selectivity bias. First, we predict

the probability that the venture publishes the token allocation information based on an expanded sample of token offerings. Second, we compute the generalized residuals from our prediction results in the first step, following the approach we used for the main regressions and in line with Gouriéroux et al. (1987). Third, we add the computed generalized residuals as a control variable to the different regression models. Table 2.9 reports all results for the regression based on the above-defined adjustments. We find that our main results do not qualitatively change after the inclusion of the adjusted generalized residuals as a control variable. These findings suggest that our results are robust, and the selectivity does not bias the results of our regressions.

Table 2.9: **Robustness checks — controlling for token split-related selectivity**

Model:	Funding amount (log)			BHAR, 12 months		
	(1) T5	(2) T6	(3) T8a	(4) T7a	(5) T7b	(6) T8b
Token retention (log)	0.316** (0.127)		0.754*** (0.214)	0.169 (0.144)	0.154 (0.145)	0.377 (0.338)
x team size, in # FTE			−0.038*** (0.012)			−0.019 (0.020)
Token restriction (dummy)	−0.143 (0.129)	−0.152 (0.134)	−0.263 (0.273)	−0.376** (0.187)		−1.088*** (0.364)
x team size, in # FTE			0.010 (0.017)			0.059** (0.027)
Team size, in # FTE			0.157*** (0.041)			0.038 (0.081)
Stakeholder allocation (log)		0.160** (0.076)				
Venture development allocation (log)		0.099* (0.051)				
Initial restriction (dummy)					−0.387** (0.182)	
(Reverse) vesting restriction (dummy)					−0.115 (0.188)	
Controls	✓	✓	✓	✓	✓	✓
GRs	✓	✓	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓	✓	✓
Observations	759	759	759	208	208	208
R-squared	0.339	0.337	0.349	0.455	0.461	0.476

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We conducted additional tests about the sensitivity of our results to the inclusion of further control variables and fixed effects. This might have the advantage that more variation could be absorbed by the additional variables, with the cost of reduced sample size,

based on the limited availability of the variables. In Table 2.10 we additionally included control variables for the Shareholder Protection Index (SPI) and the Financial Development Index (FDI) to consider the institutional background. SPI is based on World Bank data and indicates the minority investor protection based on the ease of shareholder suits index, ranging from 0 to 10. FDI is published by the International Monetary Fund and ranges from 0 to 1, with 1 being the highest development score. We allocated each token offering the corresponding SPI and FDI score based on the published country of the project headquarters at the year of ICO start. While there are no significant effects of the FDI and SPI variables in the regressions related to the funding amount (log), we observe highly significant results related to the BHAR 12-month regressions. In column (4), (5), (6) we show that the Financial Development Index and Shareholder Protection Index have a positive significant effect on the post-funding performance at minimum the 5% level. A 0.1 point increase in the FDI increases the BHAR on average by 3.8%. A 1-point increase in the SPI increases the post-funding performance on average by 2.9%. However, we can conclude that the inclusion of FDI and SPI does not materially change the direction or significance of our identified main effects, suggesting that our results are robust.

Table 2.10: **Robustness checks — controlling for alternative control variables**

Model:	Funding amount (log)			BHAR, 12 months		
	(1) T5	(2) T6	(3) T8a	(4) T7a	(5) T7b	(6) T8b
Token retention (log)	0.305** (0.131)		0.692*** (0.216)	0.135 (0.132)	0.112 (0.133)	0.257 (0.308)
x team size, in # FTE			−0.034*** (0.012)			−0.013 (0.019)
Token restriction (dummy)	−0.080 (0.135)	−0.096 (0.142)	−0.295 (0.279)	−0.360* (0.201)		−1.053*** (0.363)
x team size, in # FTE			0.017 (0.017)			0.059** (0.026)
Team size, in # FTE			0.139*** (0.040)			0.017 (0.069)
Stakeholder allocation (log)		0.161** (0.081)				
Venture development allocation (log)		0.113** (0.054)				
Initial restriction (dummy)					−0.345* (0.175)	
(Reverse-) Vesting restriction (dummy)					−0.098 (0.199)	
Financial Development Index	4.766 (7.334)	4.723 (7.318)	5.609 (7.481)	37.614*** (14.035)	38.028*** (13.786)	34.844** (13.547)
Shareholder Protection Index	2.998 (1.951)	3.033 (2.008)	2.827 (1.944)	2.875** (1.218)	2.786* (1.202)	2.811** (1.170)
Controls	✓	✓	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓	✓	✓
Observations	686	686	686	185	185	185
R-squared	0.321	0.321	0.330	0.534	0.537	0.555

Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1

Seperately, we included a platform fixed effect to control for the fact that the underlying project can be a platform project. Our sample includes 453 offerings that are indicated as platform projects, representing 59.7% of all considered ICOs. The rationale behind this robustness check is that we expect tokens that represent a platform project to share some structural similarities with each other, comparable to companies that operate within the same industry. Table 2.11 summarizes the regression results of all models in the manuscript, including the platform fixed effect. We observe that our results are robust and the additional fixed effect does not materially change the direction or significance of our identified main effects. While we tested for a variety of other control variables, we did not report additional results for the sake of brevity.

Table 2.11: Robustness checks — controlling for platform fixed effect

Model:	Funding amount (log)			BHAR, 12 months		
	(1) T5	(2) T6	(3) T8a	(4) T7a	(5) T7b	(6) T8b
Token retention (log)	0.319** (0.126)		0.759*** (0.213)	0.153 (0.146)	0.139 (0.147)	0.338 (0.347)
x team size, in # FTE			−0.039*** (0.011)			−0.018 (0.020)
Token restriction (dummy)	−0.140 (0.129)	−0.150 (0.134)	−0.255 (0.272)	−0.374** (0.187)		−1.079*** (0.363)
x team size, in # FTE			0.009 (0.017)			0.059** (0.027)
Team size, in # FTE			0.162*** (0.039)			0.034 (0.081)
Stakeholder allocation (log)		0.162** (0.075)				
Venture development allocation (log)		0.101** (0.051)				
Initial restriction (dummy)					−0.376** (0.176)	
(Reverse-) Vesting restriction (dummy)					−0.129 (0.185)	
Controls	✓	✓	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓	✓	✓
Platform fixed effect	✓	✓	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓	✓	✓
Observations	759	759	759	208	208	208
R-squared	0.339	0.337	0.349	0.459	0.464	0.479

Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1

Further investigations regarding the relationship between token governance mechanisms and alternative dependent variables and human capital moderators were conducted during post-hoc analyses. We included the variable "crypto background" as alternative measure for human capital quality, which indicates the number of the total team members with prior crypto experience before ICO start. Crypto experience includes work experience directly related to previous initial coin offerings and other crypto business models. The underlying projects of the offerings considered in our sample have on average 4.6 team members with previous crypto experience. Table 2.12 shows that the number of team members with crypto experience has a significant negative moderating effect on the relationship between token retention and funding amount (log). In economic terms, this means for the main model (1) that the 0.569% increase in fundraising amount based on a 1% increase in retained tokens is reduced by, on average, 0.062 percentage points per

additional FTE with prior crypto experience added to the venture team. We believe this negative moderating effect might be based on the same reasons we derived for the positive moderating effect of the total number of team members on token retention. Investors might consider the human capital signals and the token governance signals as belonging to the same category and ultimately interpret them as substitutes for each other. The effect of token governance signals therefore decrease when the human capital quality increases. We do not observe any significant moderating effect of the crypto experience on the relationship between token governance mechanisms and post-funding performance. Further post-hoc analyses included the regressions of our variables on a set of different dependent variables, such as the fraction raised of the ICO soft-cap or hard-cap and the expert rating, could not show any significant results and are therefore not reported.

Table 2.12: The moderating effect of the venture team crypto experience

Model:	(1) Main	(2) IMR	(3) GR	(4) IV (GR)
Panel A: <i>Funding amount (log) as the dependent variable</i>				
Token retention (log)	0.569*** (0.185)	0.563*** (0.186)	0.540** (0.211)	0.539*** (0.195)
x crypto experience, in # FTE	−0.062*** (0.023)	−0.062*** (0.023)	−0.063*** (0.023)	−0.063*** (0.021)
Token restriction (dummy)	−0.240 (0.224)	−0.242 (0.224)	−0.242 (0.225)	−0.243 (0.207)
x crypto experience, in # FTE	0.024 (0.034)	0.024 (0.034)	0.024 (0.034)	0.024 (0.031)
Crypto experience, in # FTE	0.245*** (0.077)	0.242*** (0.078)	0.247*** (0.077)	0.247*** (0.071)
Controls	✓	✓	✓	✓
IMR	✗	✓	✗	✗
GR	✗	✗	✓	✗
IV	✗	✗	✗	✓
Quarter-year FEs	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Observations	759	759	759	759
R-squared	0.350	0.350	0.350	0.350
Panel B: <i>BHAR, 12 months, as the dependent variable</i>				
Token retention (log)	0.400 (0.262)	0.378 (0.268)	0.242 (0.284)	0.232 (0.229)
x crypto experience, in # FTE	−0.043 (0.041)	−0.040 (0.041)	−0.044 (0.040)	−0.044 (0.032)
Token restriction (dummy)	−0.386 (0.339)	−0.405 (0.336)	−0.420 (0.338)	−0.427 (0.267)
x crypto experience, in # FTE	0.004 (0.068)	0.006 (0.067)	0.011 (0.067)	0.012 (0.053)
Crypto experience, in # FTE	0.247* (0.146)	0.236 (0.146)	0.248* (0.144)	0.246** (0.114)
Controls	✓	✓	✓	✓
IMR	✗	✓	✗	✗
GR	✗	✗	✓	✗
IV	✗	✗	✗	✓
Quarter-year FEs	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Observations	208	208	208	208
R-squared	0.494	0.496	0.500	0.501

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

2.5 Discussion and Concluding Remarks

2.5.1 Summary of Main Results

This paper tests two overarching hypotheses related to the two main token governance mechanisms used in token-based crowdfunding and their impact on ICO ventures' funding

and post-funding performance. Our sample is based on initial coin offerings that issued utility tokens, which furnishes an optimal research environment due to (i) the lack of regulation that amplifies the importance of incentive alignment for investors, (ii) the absence of traditional contractual corporate governance tools for investors to rely on, and (iii) the listing of tokens on a liquid cryptocurrency exchange after ICO, which allows for the token holders to trade with other investors (Adhami et al., 2018) and for a transparent assessment of financial performance (Fisch & Momtaz, 2020).

The first hypothesis, the **token retention outperformance hypothesis (TRetO)**, posits that token allocation resulting in a higher degree of retained tokens in the primary market positively impacts ventures' fundraising amount during the ICO and post-funding performance. Our results confirm the **TRetO** relating to the initial fundraising but not to the post-funding performance. We find significant results that the amount raised by the venture is increased by 0.318% when 1% more tokens are retained. Additionally, we provide evidence that the effect is mainly driven by the signal generated by retention allocated to stakeholder groups rather than venture development or reserve pool allocations. We utilize various approaches to tackle potential endogeneity issues, including two-stage and instrumental variable methods. Our results affirm that the superior fundraising amount of the startup arises from the treatment effect of a higher share of retained tokens rather than being confounded by a selection bias.

The second hypothesis, the **token restriction outperformance hypothesis (TresO)**, posits that token restrictions that limit the reselling of tokens in the secondary market positively impact the venture's fundraising amount during the ICO and the post-funding performance. Our results do not confirm the **TresO**. Rather, we find that the disclosure of a token restriction has a significantly negative effect on the 12-month buy-and-hold abnormal return. The presence of the restriction reduces the return on average by 37.6%. Additionally, we divided the token restriction variable into its different types and found evidence that the effect is mainly driven by the impact of the disclosure of an initial re-

striction. While (reverse) vesting does not show any significant effect, the relationship between the inclusion of initial token restrictions (i.e., lock-up or cliff) and post-funding performance is negative. The disclosure of an initial restriction leads, on average, to a reduction of 38.7% in the 12-month buy-and-hold abnormal return. In addition, we do not find a significant relationship between the disclosure of token restrictions and the fundraising amount in initial coin offerings.

We also find evidence that the presence of human capital signals, such as the team size of the venture, moderates the effect of token governance. Our hypothesis 3a, that the relationships above are negatively moderated by team size, is partially confirmed with regard to the effect of token retention on the fundraising amount. We observe that the 0.757% increase in fundraising amount based on a 1% increase in retained tokens is reduced by, on average, 0.039 percentage points per additional FTE added to the venture team. Our hypothesis 3b, that the relationships are positively moderated by team size, is rejected with regard to fundraising amount. However, in the case of post-funding performance, we find supporting evidence. The negative impact of token restriction on post-funding performance is decreased by, on average, 5.9 percentage points for each additional full-time employee added to the venture team. Our robustness test based on a larger sample of token offerings suggests that our results are robust, and the selectivity related to the sole consideration of ICOs that published the token allocation split in the whitepaper does not bias the results of our regressions.

2.5.2 Theoretical Contributions and Practical Implications

Our study makes several important theoretical contributions to the early-stage crowdfunding literature. First, we provide new findings to the general literature on ICO success relating to both funding and post-funding performance. Prior research has already identified numerous important factors influencing ICO ventures' funding amount that are related to, for example, offering and venture characteristics (e.g., Belitski and Boreiko, 2022; Howell

et al., 2020; Momtaz, 2020), and founder CEO characteristics (Colombo et al., 2022; Xia et al., 2023). We expand this literature with new findings regarding the token governance features of the tokens. The literature on post-funding performance in early-stage fundraising mainly focuses on operational performance (Vanacker, Tom and Vismara, Silvio and Walthoff-Borm, Xavier, 2019; Lyandres et al., 2022; Davydiuk et al., 2023), while research about the characteristics that drive the post-ICO financial performance of the venture is still less conclusive (Benedetti & Nikbakht, 2021). Our research into token governance mechanisms identifies token restrictions as a salient token feature that negatively influences the financial return of the listed token. Our research thus helps to close the research gap regarding factors that influence the abnormal returns of token offerings and advances our general understanding of the cryptocurrency market. The additional findings related to funding amount and post-funding performance can also be supportive of the investors' due diligence prior to the submission of an investment.

Second, we present new knowledge about token governance and the design of digital assets. We analyze token governance in a novel and more granular way than existing empirical studies, using the implied purpose of the token retention and token restriction disclosures based on the information provided in the individual whitepapers. Prior work has measured the share of token retention as the percentage not distributed during the ICO (Giudici and Adhami, 2019; Lyandres et al., 2022; Davydiuk et al., 2023) or solely the portion allocated to insiders (Bourveau et al., 2022). Our process allows us to define subgroups, categorize the provided information, and potentially help investors assess the unstructured information in the various token offering documents, given the lack of standardization in the ICO market. The results of our study based on the more granular analysis of retained tokens confirm prior findings that token retention has a positive impact on ICO ventures' funding (Davydiuk et al., 2023; Lyandres et al., 2022; Giudici and Adhami, 2019). Our novel research setting also allows us to expand the existing literature (Cummings et al., 2020), allowing us to estimate the effects of the retentions allocated to

the different groups. We find empirical evidence that the positive effect of token retention is mainly driven by the tokens allocated to stakeholders while showing no constant significance of reserve pool or venture development allocations among our regression models. Additionally, prior research mainly focuses on the impact of token retention on the operational post-funding performance of the ventures that have raised funds via token offering (Lyandres et al., 2022; Davydiuk et al., 2023). We expand the literature in two directions. First, we analyze the impact on the post-funding financial performance of the listed tokens, showing that the increased operational performance does not translate to a significant increase in financial post-funding performance. Second, we provide evidence that token restrictions negatively impact the buy-and-hold abnormal return of the tokens. These findings have several practical implications for entrepreneurs and investors. Entrepreneurs should be aware that not all token governance tools are associated with positive financial returns or increased fundraising. The direction and strength of the signal depend not only on the chosen incentive alignment tool but also its defined characteristics in the offering document.

Third, we contribute to the literature on the role of human capital in new venture success. More specifically, we provide evidence of how token governance signals are moderated by human capital quality. Our results extend the findings of prior studies which unveiled the moderating effect of different variables on the effect of token governance mechanisms in ICOs, such as the scope of disclosures (Bourveau et al., 2022; Davydiuk et al., 2023), the number of active ICOs (Davydiuk et al., 2023), and investor rights embedded in the token (Giudici & Adhami, 2019). Our findings help to better understand the impact of governance signals in a market with a high level of information asymmetry and also have practical implications. Ventures that are conducting token offerings should keep in mind the potential substitution effect for token governance tools and other types of signals when designing the structure of the offering.

2.5.3 Limitations and Avenues for Future Research

Our study represents an important step towards understanding the token governance tools in ICOs and their impact on ventures' funding and token price performance. We thus propose potential directions for further research in this area.

Differences among the underlying offering types. Our study focuses on ICOs, in which utility tokens are issued during the token offering. While using this empirical setting for a study addressing the impact of token governance provides important insights, the transferability of the results to other offerings and token types might be limited. For example, ventures issuing security tokens (e.g., Lambert et al., 2022; Kreppmeier et al., 2023), which are usually considered securities and therefore must follow the security laws of the underlying jurisdiction, might be forced to implement other incentive alignment tools based on the applicable regulatory requirements. In addition, the required level of trust from investors in the accuracy of the disclosures of the entrepreneurs would decrease, given the possible legal enforcement in case of a breach of any clause by the venture. These variations in the offering characteristics provide potential research avenues regarding the effectiveness and investor perception of governance mechanisms for different token offering types. Avenues that will further develop as the research around policy and regulation of ICOs is expected to be increasingly urgent in the coming years (Brochado & Troilo, 2021).

Increase in investor sophistication. Our research is based on a hand-collected sample of token offerings before 2021, which allows us to examine the impact of token governance on the tokens' post-funding financial performance. However, the sophistication of investors, as measured by their understanding of the underlying technology, may have increased over the past years. An elevated knowledge among investors would lead to an enhanced ability to assess the underlying source code and hence the accuracy of ICO disclosures published by the venture. Given the blockchain's public nature, investors might

conduct their own expanded due diligence on the projects before investing to decrease the required level of trust, which could ultimately impact the signaling effect of the different disclosures. Further research might focus on the relationship between the level of investor knowledge and the signaling effect of the token governance tools.

Variety of available signals in token offerings. Our study finds empirical evidence that token governance and human capital signals might be perceived by the investor as substitutes or complementary signals. Future research could expand this study in two directions. First, we sought to capture human capital quality through the team size of the ventures and included a post-hoc analysis where we considered the crypto experience of the team members. It would be possible to include further human capital quality indicators, such as the educational and professional background of the funding team or the gender diversity of the management. Second, we solely analyzed the interaction of token governance signals with those of human capital quality. Examining the relationship with other signals, including social or intellectual capital, might yield equally compelling results.

2.5.4 Concluding Remarks

This paper has sought to shed light on the token governance mechanisms used in ICOs and their role in venture valuation and post-funding token performance. The main governance tools used in token offerings are token retention and token restriction. Our results suggest that token retention positively impacts the fundraising amount of the venture, mainly driven by allocation to stakeholders, but does not significantly impact the post-funding performance. Token restrictions include both initial restrictions and restrictions that are gradually released over time. We provide empirical evidence that initial restrictions negatively impact the 12-month buy-and-hold abnormal return. The signaling effects of the token governance disclosures are moderated by human capital signals, whereas the direction differs among the types of signals. This study contributes to understanding, develop-

ing, and implementing effective token governance to mitigate risks in early-stage venture financing.

2.6 References

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2.7 Appendix A

Table A.1: Variable Definitions

Variable	Definition
<i>Dependent variables</i>	
Funding amount (log)	Natural logarithm of the total amount raised during the token offering (in USD million).
BHAR, 12-mo	12-month Buy-and-Hold Abnormal Returns (BHARs). Calculated by subtracting the market benchmark's buy-and-hold return from a startup's buy-and-hold return over a 12-month holding period after the token listing. The equally-weighted market benchmark is based on all tokens that are tracked on Coinmarketcap.
<i>Key variables</i>	
Token retention (log)	Natural logarithm of $(1 + 100 \times (\text{number of tokens not allocated to public over total tokens issued}))$.
Stakeholder allocation (log)	Natural logarithm of $(1 + 100 \times (\text{number of tokens allocated to stakeholders over total tokens issued}))$.
Venture Development allocation (log)	Natural logarithm of $(1 + 100 \times (\text{number of tokens allocated to venture development over total tokens issued}))$.
Reserve pool allocation (log)	Natural logarithm of $(1 + 100 \times (\text{number of tokens allocated to reserve pools over total tokens issued}))$.
Other allocation (log)	Natural logarithm of $(1 + 100 \times (\text{number of tokens allocated to other categories over total tokens issued}))$.
Token restriction (dummy)	Dummy variable: 1 for token offerings with restricted tokens (excl. reserve pools), 0 otherwise.
Restriction length, in months	Maximum number of months a token allocation of the offering is restricted (excl. reserve pools).
Initial restriction (dummy)	Dummy variable: 1 for token offerings with lock-up or cliff restriction, 0 otherwise.
(Reverse) vesting restriction (dummy)	Dummy variable: 1 for token offerings with vesting or reverse vesting restriction, 0 otherwise.
<i>Control variables (venture characteristics)</i>	
Whitepaper length, in (log-words)	The natural logarithm of total words in any given whitepaper.
Expert rating	The overall project rating based on the consensus of industry experts on ICObench.
Team size, in # FTE	The total number of team members.
Technical background, in %	The percentage of team members with a technical background. The variable is hand-collected from team members' professional network profiles, such as LinkedIn.
Minimum viable product (dummy)	Dummy variable: 1 for startups that have a minimum viable product available, 0 otherwise.
Open source (dummy)	Dummy variable: 1 for startups that disclose their code on Github, which is often used as a proxy for a venture's technological sophistication, 0 otherwise.
<i>Control variables (offering characteristics)</i>	
Soft cap (dummy)	Dummy variable: 1 for startups that have announced a soft cap in its token offering, 0 otherwise. A soft cap is the minimum funding amount at which the offering is deemed successful, and funding campaigns that fail to reach the soft cap typically redeem investor money and end the project.
Hard cap (dummy)	Dummy variable: 1 for startups that have announced a hard cap in its token offering, 0 otherwise. A hard cap is the maximum funding amount that a startup accepts. If the hard cap is reached, the offering will end and excess funding will be returned to investors.

Pre-sale (dummy)	Dummy variable: 1 for token offerings that were preceded by a pre-sale event, 0 otherwise.
Whitelist (dummy)	Dummy variable: 1 for token offerings that have an active whitelist, 0 otherwise.
Bonus (dummy)	Dummy variable: 1 for startups offers a bonus structure, which typically involves discounted or free tokens if individual wallet addresses invest above and beyond a certain pre-determined investment amount, 0 otherwise.
Bounty (dummy)	Dummy variable: 1 for token offerings that offer a bounty program, which rewards individuals (mostly in the form of free tokens) for marketing activity that promotes the offering and the startup, 0 otherwise.
ERC-20 standard (dummy)	Dummy variable: 1 for token offerings that rely on the technical ERC-20 standard, 0 otherwise.
<i>Control variables (market characteristics)</i>	
Bull market (dummy)	Dummy variable: 1 for token offerings that took place during a bull market, i.e., prior to the so-called “crypto winter,” 0 otherwise.
Bear market (dummy)	Dummy variable: 1 for token offerings that took place during a bear market, i.e., during the “crypto winter,” 0 otherwise.

CHAPTER 3

Essay II: Venture tokenization and growth: The going-public decision of decentralized digital platforms

Abstract

After initial coin offerings (ICOs), decentralized digital platforms (DDPs) decide whether to go public or remain private. We explore the implications of the public-versus-private decision for the growth and decentralization of DDPs. Employing a difference-in-differences framework, we find that public DDPs scale faster post-listing relative to matched private DDPs. An important driver behind public DDPs' superior growth is a spillover effect of financial speculation on fundamental platform activity, especially when DDPs are undervalued, hastening network effects. The going-public decision also facilitates DDP decentralization, although this stems mostly from the left tail of the token ownership distribution, while blockholders largely remain in control. Exploring the trade-off between going public through token exchange listings and remaining private with the help of institutional investors, we find that crypto fund-endorsed token listings yield more platform growth than unendorsed listings, while crypto fund backings without listings create the least value. Overall, our study suggests that early-stage startups may economically benefit from tokenization and creating liquid markets for venture tokens.

Authors: Johannes Fuchs and Paul P. Momtaz

First Author: Johannes Fuchs

3.1 Introduction

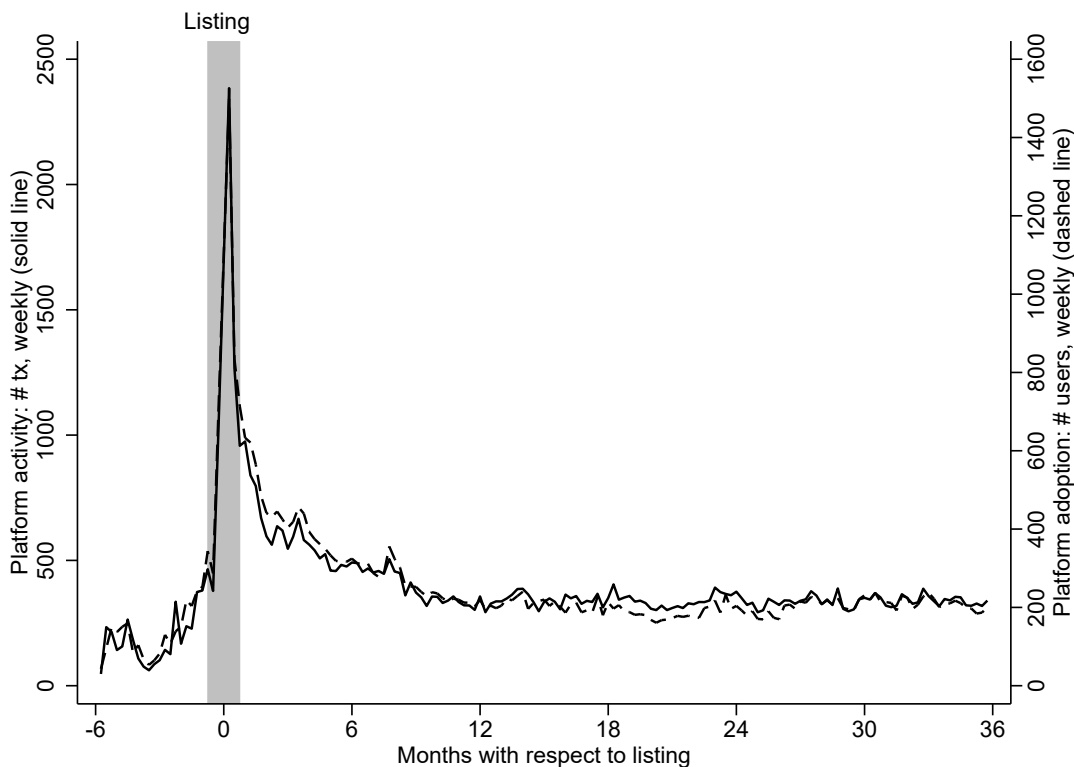
Recent studies in entrepreneurial finance focus on parallels between initial coin offerings (ICOs) and initial public offerings (IPOs), such as the valuation of the offering (e.g., Fisch, 2019), the short-term underpricing (e.g., Benedetti and Kostovetsky, 2021; Momtaz, 2021b), and the long-term underperformance (e.g., Fisch and Momtaz, 2020; Cumming et al., 2025; Drobetz et al., 2025). However, there is a critical difference between ICOs and IPOs that has been largely neglected in the literature thus far: in ICOs, the public sale of tokens (i.e., the primary market) is not necessarily followed by the public listing of the token (i.e., the secondary market). The gap between the primary and the secondary markets means that tokenized ventures, also known as decentralized digital platforms (DDPs) (Cumming et al., 2025), can decide whether to go public by entering the secondary market or remain private (or semi-public) by deferring secondary market entry. Therefore, unlike IPOs, the external financing decision is independent of the listing decision in ICOs, providing entrepreneurs with option value. The aim of our paper is to explore whether token exchange listings are related to the growth and decentralization of DDPs.

Our research question relates to the fundamental platform coordination problem of how to ensure platform adoption if early adopters have no incentive given that platform value comes from network effects that emerge only from a large user base (Rochet and Tirole, 2003; Weyl, 2010; Bakos and Halaburda, 2022a). The studies closest to ours are Cumming et al. (2025) and Drobetz et al. (2025). They show that crypto funds may help overcome coordination problems on DDPs by pre-buying tokens at a discount and attracting, through signaling and real activities, retail adopters. The implication, especially from Cumming et al. (2025), is that privately negotiated crypto fund deals may suffice to successfully scale DDPs. However, prior literature offers nothing to inform DDPs' trade-off in choosing between *remaining private* with the help of crypto fund investments and *going public* by means of token exchange listings. Thus, our study is a natural sequel to Cumming et al. (2025) by addressing the research gap concerning how the token listing

decision relates to DDP growth. Importantly, to link our study of the going-public decision with Cumming et al.’s (2025) study of the remaining-private decision, we also compare the DDP growth implications of pure going-public, pure remaining-private, and hybrid crypto-fund-endorsed going-public strategies. It is important to close this research gap to inform how blockchain technology may improve social welfare in the intersection of entrepreneurial finance and platform economics.

The post-ICO listing of tokens on cryptocurrency exchanges may help smooth coordination frictions on DDPs. Figure 3.1 presents stylized facts indicating that the listing is associated with spikes in DDP activity (number of on-chain transactions) and DDP adoption (number of on-chain users). While most of the “listing effect” is short-lived, roughly 15-20% of the activity and adoption are sustained in the long run, suggesting that exchange listings effectively overcome the platform coordination problem of early adoption.

Figure 3.1: **Exchange listing and DDP activity (# tx) and adoption (# users)**



Several reasons may help explain the pattern in Figure 3.1. First, listings may directly facilitate network externalities of DDPs because (i) token tradability attracts financial speculators who generate product-agnostic traction for DDPs (Athey et al., 2016; Bellavitis et al., 2022), (ii) token liquidity provides early-stage adopters with a realistic exit option to recover the investment at least partially in the event of a lack of DDP success (Drobetz et al., 2019; Momtaz, 2021b), (iii) token liquidity also helps early-stage DDP operators cash-out mining (in proof-of-work blockchains) or staking (in proof-of-stake blockchains) rewards (Benedetti and Nikbakht, 2021), (iv) liquid markets provide investors and adopters with the threat of exit as a corporate governance mechanism to discipline DDP founders and powerful stakeholders (Yermack, 2017; Lo Monaco et al., 2025), and (v) the token equilibrium price in public markets provides important information for individual investors and adopters and the decentralized network that may reduce collective action problems and facilitate early-stage DDP joining decisions (Cong and He, 2019; Benedetti and Nikbakht, 2021; Momtaz, 2021b). Second, listings may enhance platform credibility and increase trust in DDPs’ growth intentions because (i) token exchanges’ approvals of listing requests provide certification-type signals of DDP quality to the market (Fisch, 2019; Bellavitis et al., 2021; Momtaz, 2021b) and (ii) regulated exchanges have practices in place to reduce the threat of embezzlement of ICO proceeds and related financial fraud (Bellavitis et al., 2021; Hornuf et al., 2025), thereby mitigating an entry barrier for early-stage adopters. Third, listings may indirectly facilitate DDP growth because (i) token liquidity means that DDPs can sell treasury tokens as a means of external follow-on financing and (ii) DDPs can learn from public market behavior to infer demand for DDPs’ products and services along the development phase (Catalini and Gans, 2018; Howell et al., 2020; Benedetti and Nikbakht, 2021).

Following this logic is our overarching hypothesis, the “*Listing Hypothesis*,” that post-ICO token exchange listings facilitate DDP growth.³ An implication of the rationale behind

³Pros and cons for public markets are controversially discussed, in particular for small firms, inter alia because of short-termism problems (Stein, 1989) and overly intrusive external corporate governance by

our overarching hypothesis, and hence constituting our *second hypothesis*, is that listings that are perceived by the market as being very successful may amplify the listing’s positive effects on long-term DDP growth. Listings perceived as very successful reconfirm the credibility of and further increase trust in DDPs by means of market affirmation and positive sentiment in equilibrium (Drobetz et al., 2019) and an amplification of personal founder-CEO traits (Momtaz, 2021a; Colombo et al., 2022; Xia et al., 2024), direct network effects by convincing adopters who were hesitant in the primary markets and investors who missed the primary market or for whom the positive listing is news that makes them change their more skeptical prior, and indirect network effects, for instance, by increasing the value of capital stock held in treasury tokens that can be used to finance further DDP growth initiatives (Howell et al., 2020; Benedetti and Nikbakht, 2021).

The uniqueness of DDPs relative to all other platform models is that adopters and investors share the *same asset of interest*, namely, the token. Because of the feature of the shared asset, an increase in token demand by one stakeholder group may create network value that spills over to the other stakeholder group (Athey et al., 2016; Bakos and Halaburda, 2022a; Momtaz, 2024). Positive demand shocks may create network value for several reasons, including increased market liquidity and information dissemination. While it is well established that on traditional platforms (such as eBay, Meta, and Amazon), platform growth translates into investors’ equity value, the opposite spillover effect from investors to platform growth is a novelty on DDPs because of the shared assets (Bakos and Halaburda, 2022a; Cumming et al., 2025). Therefore, our third hypothesis, the “***Spillover Hypothesis***,” posits that financial activity on token exchanges spills over to fundamental activity on DDPs’ token protocols. The implications of the spillover mechanism are far-reaching as the mutual reinforcement of adopter and investor activities should lead to a more efficient DDP growth path. Deviations from DDPs’ growth equilibria should be “arbitraged away” by financial speculators (Momtaz, 2024). Consequently, we posit in our

activist investors (e.g., certification exploitation by crypto funds in Drobetz et al., 2025). Therefore, it is an empirical question whether listings benefit DDPs and, hence, our paper fills an important empirical gap.

fourth hypothesis that spillover effects on DDP growth are more pronounced when DDP tokens are temporarily undervalued. That is, if the token price is below the equilibrium price due to a shortage of underlying protocol activity, investors' demand will increase due to higher *expected* returns, which will increase the token price to its fair level and, hence, bring back the attention of DDP users.

Finally, our fifth hypothesis, the “*Asymmetric Decentralization Hypothesis*,” posits that listings democratize economic surplus capture on DDPs by promoting the dispersion of token ownership. Whereas the primary market distributes token ownership often to a privileged group in private pre-sales or wealthy bidders in ICOs due to minimum investment amounts, secondary market listings open (fractional) token ownership to every interested party. However, listings do not decentralize DDPs symmetrically in both tails of the token ownership distribution. Rather, the ownership structure in the secondary market is path-dependent on the primary market, where powerful ownership positions in the right tail of the ownership distribution were created. These control positions are rarely broken up in secondary markets for several reasons, often including insufficient market depth. Nevertheless, we expect substantial decentralization dynamics in the left tail of the token ownership distribution. This is in line with Fisch et al. (2022) and follows from the strict formal (e.g., minimum investment amounts) and informal (e.g., pre-sale participation privileges) investment conditions in the primary market. In a sense, secondary market listings may serve DDPs for market clearing by bringing aboard the mass of smaller-ticket individual investors that miss the primary market.

We test our empirical predictions in a novel hand-collected database that merges DDP-level data from the *TORD* with primary on-chain data from the *Ethereum* ledger and token exchange data, among several other data sources. The number of observations reaches up to 553,958 DDP-weeks depending on the model specification. Our identification strategy is a staggered difference-in-differences framework that compares DDPs that went public with matched DDPs that remained private along several DDP growth dimensions before

and after the listing decision. Of course, for the parallel trends assumption to hold (i.e., listed and unlisted DDPs have the same pre-listing growth trajectories), we need to ensure a precise matching of listed and unlisted DDPs. As most DDPs in our sample will list at some point, only the timing of the listing is an endogenous decision, which is a more tractable econometric task than if the listing decision *per se* were to be fully endogenous in our sample. We employ numerous matching approaches based on both observable and unobservable covariates, as well as an instrumental variable approach. Graphical checks support the parallel trends assumption and our results are consistent across all econometric approaches.

The empirical findings support the ***Listing Hypothesis***. Specifically, we find significantly positive effects of token exchange listings on various proxies for DDP growth, such as platform activity (# transactions), platform turnover (% traded tokens of total tokens), and platform adoption (# users, # new users, # recurring users, and # parting users). Economically, listings increase the weekly number of blockchain transactions by 143 to 283, the relative amount of tokens traded per week by 1.0 to 1.5%, and the weekly number of distinct protocol users by 103 to 191. We also find support for the second hypothesis that the positive effects from the listing hypothesis are amplified if the listing is perceived as successful. We proxy for successful listings with the abnormal token return in the first post-listing week and the market sentiment toward the listing. Strikingly, these first-week proxies have strong explanatory power for DDP growth over the following three years, in some cases even doubling the R-squared. The abnormal first-week token return has significantly positive marginal effects on DDP activity and adoption, but negative marginal effects on DDP turnover even after three years.

We also find strong support for the ***Spillover Hypothesis***. Financial speculation on token exchanges significantly positively impacts non-speculative fundamental DDP activity a week later. In economic terms, one speculative transaction on a token exchange leads to 1.7 additional non-speculative transactions on the underlying blockchain protocol,

1% speculative token turnover leads to 1.4% additional non-speculative token turnover, and one speculative investor leads to 2.8 additional non-speculative DDP adopters. The spillover mechanism from speculative to fundamental activity is more pronounced when the DDP is undervalued, supporting our fourth hypothesis and suggesting that financial arbitrageurs promote a more efficient DDP growth path.

Our results are also supportive of the *Asymmetric Decentralization Hypothesis*, which posits that listings disperse token ownership in the left but not in the right tail of the token ownership distribution. Listings are associated with an increase of 2,590 tokenholders that own less than 1%, 1.2 tokenholders that hold between 1 and 5%, 0.4 tokenholders that hold between 5 and 20%, and statistically zero blockholders with more than 20% token ownership. Similarly, we estimate a listing effect of 1.0 on the *Nakamoto* coefficient, suggesting that the minimum number of largest wallets to majority-control (i.e., 51%) a DDP increases through listings by (only) one additional wallet.

In post-hoc analysis, we explore the impact of the listing decision on DDP survival. The listing, positive market sentiment toward the listing, and financial speculation improve the probability of DDP survival. The results are consistent with the theoretical arguments and empirical results discussed above.

Finally, given that our results suggest that the going-public decision is positively related to DDP growth, it is important to qualify our results with the findings in Cumming et al. (2025) that remaining private with the help of institutional crypto fund investments facilitates DDP growth. To better understand the relative merits of DDP's private versus public decision, we estimate average treatment effects of a pure going-public strategy (i.e., exchange listing without crypto fund backing), a pure remaining-private strategy (i.e., crypto fund backing without listing), and a hybrid strategy (listing with crypto fund backing) in a triple differences model. The results suggest that DDP growth benefits most from the hybrid strategy followed by the pure going-public strategy, while the pure remaining-private strategy leads to DDP growth only in some cases. In other words, the going-public decision

facilitates DDP growth, which is amplified if listings are backed by crypto funds. The findings are important as they qualify the implications in studies that find crypto fund backed DDPs outperform non-crypto fund backed DDPs in the secondary market (Fisch and Momtaz, 2020; Cumming et al., 2025; Drobetz et al., 2025). While these results remain true, our study adds the important nuance that obtaining crypto fund backing is less important than going public for long-term DDP growth.

The remainder is organized as follows. Section 3.2 provides some background on DDPs and develops testable hypotheses, section 3.3 describes our data and the econometric approach, section 3.4 presents our results, and section 3.5 discusses theoretical contributions, practical implications, limitations, and avenues for future research, and concludes the paper.

3.2 Background and hypotheses

3.2.1 Decentralized digital platforms (DDPs), tokenization, and the feature of the shared asset

Digital platforms are multi-sided platforms that leverage technology to facilitate connections between multiple parties who might not otherwise be able to connect (Gawer, 2021). Perhaps more so than non-digital platforms, digital platforms suffer from coordination frictions related to early adoption. Digital platforms will create value for users proportionate to the number of users and, by implication, the first user has no incentive to join the platform, rendering early-stage platform adoption and the generation of positive network externalities challenging (Katz & Shapiro, 1985; Rochet & Tirole, 2003). The recent emergence of decentralized digital platforms is addressing the early-adoption problem with new technology (Bakos and Halaburda, 2019; Cumming et al., 2025).

Decentralized digital platforms (DDPs) are digital platforms that “tokenize” the platform. Tokenization refers to the securitization (in an *economic* and not necessarily in a *legal*

sense) of the DDPs' assets through blockchain technology. Tokens represent claims on the DDPs' future revenue streams from their products and services (J. Lee and Parlour, 2022; Cumming et al., 2025). For example, *FileCoin* is a tokenized file-storage platform, the DDP version of *Dropbox* so to speak. *FileCoin* provides a computer protocol that lets individuals connect their personal computers to the network through the internet. The aggregate file-storage volume is tokenized, and individuals who want to store files need to pay for the storage space with *FileCoin*'s native tokens. Individuals who provide storage space on their personal computers' hard drives to the network are compensated with the tokens paid by file storers. Tokens are often cryptographically secured smart contracts that are sold in ICOs (Fisch, 2019; Howell et al., 2020; Bellavitis et al., 2021; Lyandres et al., 2022). The sale of the *FileCoin* token was the most successful crowdfunding campaign ever, raising about \$4.3 billion. Sold tokens can then be exchanged over-the-counter or, if listed, on token exchange platforms, sometimes even before the DDP launches a product (Momtaz, 2021b; Drobetz et al., 2025).

Tokenization is the feature that critically sets DDPs apart from other digital platforms. On digital platforms, such as *eBay*, *Meta*, and *Amazon*, platform users and investors are interested in different assets, that is, products or services vis-à-vis equity, respectively. On DDPs, in stark contrast, platform users and investors share the same asset, i.e., the token. The feature of the shared asset of interest is important because it aligns, DDP users' and investors' objective functions, and thereby, tokenization helps reduce the coordination problem of early-stage platform adoption. In the *FileCoin* example, the first supplier of storage space would have no incentive to connect their personal computer to the network because the technical set-up costs exceed expected payments from (non-existing) storage demand without tokenization. Tokenization, however, attracts financial speculators who invest based on expected returns. Financial returns *in expectation* exceed platform user utility *in the presence*; hence, speculators buy tokens early on to secure low prices, which, in turn, provides early-adoption incentives for DDP users. Another example is *Akash*, a

decentralized marketplace for computing resources such as central and graphic processing units (CPUs, GPUs). *Akash* creates utility for individual and institutional users requiring additional computing power (demand side), which is largely determined by the number and capability of available GPUs and CPUs. However, the utility for the supply side, such as data centers or individuals with unused computing resources, depends on the size of *Akash*'s user demand. Because speculators have an early-investment incentive, they increase token demand, which hastens supply, kickstarting network effects. The example illustrates how the feature of the shared asset helps resolve the early-adoption coordination problem for platforms.

DDP adoption can be further accelerated in two ways. One is through the certification of institutional investors whose presence may help attract individual investors and DDP users. This is because institutional investors may credibly strengthen the ability of early-stage DDP adopters to monetize and exit DDPs. Cumming et al. (2025) argue that crypto funds can provide a transaction counterparty for DDP tokenholders, facilitating tokenholders' potential exit and thereby mitigating DDP coordination challenges. The other way, which has yet to be empirically explored, is the creation of public markets for tokenized platforms. Hence, the purpose of our paper is to show that, independent of crypto funds, token exchange listing may also overcome the early-stage DDP adoption problem because listing the DDP token on a public exchange facilitates the tradability of the asset and provides a liquid market, allowing DDP users to exit the DDP. In what follows, we lay out the rationale behind the "listing conjecture" regarding DDP adoption.

3.2.2 Hypotheses

3.2.2.1 Token listing and DDP growth

For the economic benefits of the feature of the shared asset to materialize, DDP tokens need to be listed on a token exchange, which creates a public and liquid market for the

token. Token exchange listings may facilitate DDP growth for several reasons related, *inter alia*, to token tradability, access to external financing, and the listing’s signaling effect.

First, listing the DDP token on a public exchange enables token tradability. Token tradability facilitates DDP growth because early adoption does not result in lock-in situations, as early adopters can exit anytime through public markets. Secondary-market exiting lowers DDP adoption costs *in expectation* and, in combination with the expected presence of financial speculators and investors, partially resolves the ‘chicken-egg’ problem (Bakos and Halaburda, 2022a; Cumming et al., 2025). In principle, the tokenization of DDP assets enables tradability over-the-counter even without listings; however, listings on exchanges create a central point where token supply and demand meet, reducing search costs and, therefore, facilitating DDP growth (Momtaz, 2024). Another important implication of the token exchange listing is the readily available and ubiquitously visible equilibrium token price. Market prices reduce entry barriers for risk-averse adopters because they abandon price uncertainty, leading to more efficient information production, as every trade reveals price-relevant information of the transaction counterparties (Grossman and Miller, 1988; Kyle, 1985). Information reduction reduces uncertainty about DDP valuations, facilitating informed adoption decisions (Ambrus and Argenziano, 2009; Weyl, 2010), as empirically shown for token markets in Momtaz (2021b).

Second, token exchange listings allow DDPs to raise additional funding to finance growth (Colombo et al., 2023). Liquid markets for listed tokens enable an efficient treasury liquidation to finance growth initiatives. Similarly, when token supply is uncapped, additional tokens can be minted with direct sale intentions. Liquid markets may also help raise additional growth capital from certain crypto funds (Dombrowski et al., 2023) or through proprietary trading strategies. Similarly, listed tokens can also be used as currency. For example, there is an emerging crypto M&A market, in which DDPs take over other DDPs and use their native tokens as acquisition currency.⁴ Also, treasury tokens can

⁴Crypto M&A deals and transaction details are available from <https://messari.io/screener/deal>, retrieved March 10, 2025.

be used to pay developers and community builders, and this type of incentivization for growth enablers is most effective when tokens have secondary markets.

Third, token exchange listings may overcome early-adoption problems because listings may function as a certification-type signal of DDP quality to potential platform adopters. Given the prevalent informational asymmetries in cryptocurrency markets (Hornuf et al., 2022; Meoli and Vismara, 2022), DDPs may convey credible information about their otherwise unobservable qualities to potential adopters (Spence, 1974; Connelly et al., 2011; Vismara, 2018; Bafera and Kleinert, 2023). Because the ex-post payoff for high-quality firms exceeds that for low-quality firms, high-quality DDPs are motivated to signal, whereas low-quality DDPs are not, creating a separating equilibrium and, thus, helping potential adopters discern high- from low-quality DDPs. For signals to be effective, they must be observable and costly to imitate, typically involving ex-ante implementation costs or ex-post penalty costs (Wang et al., 2019; Momtaz, 2021b; Bafera and Kleinert, 2023). Token exchange listings are widely disseminated through exchanges' websites, social media accounts, news outlets, and ICO aggregators, ensuring the signal's observability to potential adopters. There are also at least three types of signaling costs in the context of token exchange listings. First, with an average of 31% of retained tokens (Fuchs and Momtaz, 2024), token retention accounts for costs amounting to almost one-third of total DDP valuation in the event of DDP failure. Second, DDPs incur ex-ante implementation costs in terms of time and often monetary resources to facilitate an exchange listing, as exchanges charge a substantial listing fee (Howell et al., 2020; Momtaz, 2020). Lastly, there are costs related to reputational risks if the exchange listing fails, public scrutiny, regulatory compliance and disclosure costs, and investor relations in the secondary market. Therefore, listings plausibly deter low-quality DDPs from pursuing a public listing, making it an effective signal that enables potential adopters to distinguish between high- and low-quality firms, leading to more efficient capital allocation and increased platform growth rates in listed DDPs.

Hypothesis 1: *Token exchange listing has a positive impact on DDP growth. (Listing Hypothesis)*

As an implication of the above reasoning, if token exchange listings were very successful, the perceived success may amplify the exchange listing's signaling effect. For example, a positive post-listing return (i.e., token underpricing) indicates that the market consensus values the token higher than the DDP's set token launch price. When issuers possess informational advantages over investors, underpricing is perceived as a positive quality signal (Allen and Faulhaber, 1989; Ritter and Welch, 2002; Connelly et al., 2011) sometimes with longer-term token return predictive power (Drobetz et al., 2019). Because of the risk of deceptive signals (Johnstone & Grafen, 1993), signal receivers are sensitive to subsequent data that can confirm or disprove the initial signal (Momtaz, 2021b; Bafera and Kleinert, 2023). Validation of the token exchange listing signal may further reduce information asymmetry between the DDP and potential adopters, hastening network effects.

Hypothesis 2: *Initial token exchange listing success amplifies the listing's positive impact on DDP growth.*

3.2.2.2 Spillover effects from DDP investor to DDP user

Post-listing exchange-based (i.e., speculative) investor activity may positively influence non-exchange-based (i.e., non-speculative, fundamental) DDP user activity due to several spillover effects, including (i) liquidity spillover, (ii) information spillover, and (iii) demand spillover.

First, an increase in trading activity by financial investors also increases the liquidity available to DDP adopters. The decision to list an asset on a public exchange attracts speculative trading and increases the liquidity of the asset (Amihud & Mendelson, 1986). Improved token liquidity, facilitated by platform-agnostic cryptocurrency investors like quantitative crypto hedge funds, also increases the likelihood of DDP adopters finding trade

counterparts, thereby reducing coordination frictions by (i) giving early adopters a greater chance to realize potential gains from the DDP's success and (ii) reducing the risk of DDP operators, such as miners and stakers, being "locked in" with the DDP.

Second, the coordination problem of DDP adopters may be further mitigated due to information aggregation and price discovery in liquid financial markets. Traditional finance literature, such as Grossman and Stiglitz (1980), has shown that the information utilized by speculative traders contributes to a more accurate reflection of the asset's price based on available information. Put differently, trading predicated on asymmetric information aids the price discovery process (Kyle, 1985). For cryptocurrency markets, Momtaz (2021b) shows that post-listing equilibrium prices post hoc inform ICO investors about the fair token value, often leading to divestments. Consequently, trading reduces information asymmetry for DDP adopters and hastens network effects of DDPs.

Third, we anticipate a demand spillover from DDP token trading to non-speculative, fundamental DDP adoption and usage. Existing literature on demand spillovers on platforms primarily identifies positive spillover effects across complementary products and services offered on platforms (e.g., Garthwaite, 2014; Xu et al., 2014; M. H. Lee et al., 2023). The primary mechanism for most of these within-platform spillover effects is consumer awareness (e.g., Liang et al., 2019; Song et al., 2020), suggesting that awareness generated by one platform component naturally extends to and enhances the visibility of related components within the platform ecosystem and the platform itself. In the context of DDPs, speculative demand for the DDP token may spill over to non-speculative, fundamental demand for the platform's utility. DDP-agnostic token investors are naturally exposed to information about the underlying DDP, e.g., during the due diligence. DDP information is shared on exchange websites, external price aggregator websites, and other trading-related media. We anticipate that these factors will significantly increase awareness of the DDP, leading to a user demand spillover from exchange-related activities. Overall, these positive spillovers are expected to hasten network effects and increase DDP growth rates.

Hypothesis 3: Financial speculation increases fundamental DDP growth. (Spillover Hypothesis)

Financial speculation may be particularly critical for non-speculative, fundamental growth when the DDP token is trading below its fair value. First, the expected demand spillover effect from token investor demand to fundamental DDP activity may be stronger if the DDP is undervalued. As outlined in *Hypothesis 3*, the primary mechanism for demand spillovers is consumer awareness (e.g., Liang et al., 2019; Song et al., 2020). However, even after becoming aware of the underlying DDP, potential users still face initial financial costs to engage with the DDP, such as those they incur for the technical setup. Access to the products and services is granted through traded utility tokens, with the token market price directly determining the adoption cost. An undervaluation of the platform would decrease these costs, thus increasing the likelihood that potential users join. Second, the importance of increased speculative trading volume may become more critical when the DDP is undervalued. The ability to sell tokens at prices reflecting future revenues is crucial for initiating platform adoption and resolving the ‘chicken-egg’ problem (Bakos and Halaburda, 2022a). Financial uncertainty from token undervaluation might remove this fallback option for early investors, negatively impacting DDPs’ network effects. To rebuild potential users’ trust in their ability to exit the DDP, increasing token liquidity is essential, to which speculative trading significantly contributes (Amihud & Mendelson, 1986). Third, addressing DDP-related information asymmetry through speculative trading activity might be especially important when the platform is undervalued, as a deviation of the DDP from its fair market value may stem from asymmetric information. Reducing this asymmetry could close the gap between the token’s market price and its fair value. Financially motivated investors attracted by the misvaluation are likely to increase financial speculation and facilitate the aggregation of information (Grossman & Stiglitz, 1980; Kyle, 1985). Reducing informational asymmetries is expected to moderate DDP coordination frictions and hasten network effects.

***Hypothesis 4:** The positive impact of financial speculation on non-speculative, fundamental DDP growth is amplified for DDPs that are ex-ante undervalued.*

3.2.2.3 Token listing and DDP decentralization

Token exchange listings may promote the dispersion of token ownership and increase DDP decentralization for several reasons, including, inter alia, opening access to new investor groups and providing exit options for insiders and institutional investors. First, token listings on exchanges can broaden the investor base by lowering entry barriers to the DDP (Fisch et al., 2022). Primary market mechanisms often restrict token distribution to a select group through private pre-sales or require substantial minimum investments because regulatory KYC requirements would make it prohibitively expensive to issue small tickets to retail investors (Bellavitis et al., 2021), limiting access to affluent participants. In contrast, secondary market listings democratize access by enabling fractional ownership of tokens for all interested parties. Second, token exchange listings offer founders and other internal shareholders a liquid exit option for their token holdings (Drobetz et al., 2025). Prior IPO literature shows that public offerings reduce stock ownership among these groups (Brennan & Franks, 1997). A study by Larrain et al. (2024) analyzed 1,172 IPOs across 33 different European stock markets and found that, on average, insider shareholding decreased by 19%. We anticipate a similar outcome for DDPs after the token exchange listing, as network effects necessitate decentralization, leading to a more dispersed ownership structure. Lastly, token exchange listings may facilitate the exit of institutional investors. Institutional investors, such as crypto venture funds, often support DDPs before the project issues any tokens (e.g., Fisch and Momtaz, 2020; Momtaz, 2024; Cumming et al., 2025). To realize gains from potential increases in valuation, these investors may use token exchange listings as an exit strategy. This pattern mirrors practices in the traditional financial market, where venture capital funds commonly exit their investments post-IPO (Giot & Schwienbacher, 2007; Paeglis & Veeren, 2013). Consistent with this reasoning,

in the token context, Drobetz et al. (2025) relate post-listing token price depreciation to large-scale divestments of institutional holdings.

However, exchange listings may not uniformly decentralize ownership along all points of DDPs' token ownership distributions. The structure of token ownership in the secondary market often reflects the initial conditions set in the primary market, where dominant ownership stakes at the right tail of the distribution are established. These controlling stakes are rarely fully dissolved in secondary markets due to factors such as limited market depth, the ability of major tokenholders to accumulate additional tokens, and the reduction of coordination frictions. First, insufficient market depth on token exchanges stems from at least three reasons: (i) the number of token launches outpaces the influx of new capital into the market, (ii) for most DDPs, token liquidity is spread across several exchanges, and (iii) often only a small portion of DDPs' total token supply is freely floating in the market, as much of it is retained (Davydiuk et al., 2023; Fuchs and Momtaz, 2024). Second, the tradability of tokens may lead to increased centralization as it enables large shareholders to acquire more tokens. Bakos and Halaburda (2022b) find evidence of a positive correlation between the tradability of a platform token and the concentration of holdings. Furthermore, Fuchs and Momtaz (2024) show that DDPs typically retain a portion of their total issued tokens for release after the initial offering. Retained tokens are then sold on the open market once listed, providing an opportunity for liquid tokenholders to further increase their stakes and increase centralization. Lastly, an increased dispersion of tokenholders in a DDP might increase the risk that decision-making power becomes more widely dispersed. Coordinating decisions among an increased number of individuals can complicate processes and lead to inefficient decision-making (Chen et al., 2021; Cumming et al., 2025). To avoid negative consequences associated with such collective action problems, such as reduced DDP utility and dampened network effects, controlling tokenholders might prefer to maintain their holdings.

Hypothesis 5: Token exchange listings disperse token ownership only in the left tail of the ownership distribution. (Asymmetric Decentralization Hypothesis)

3.3 Data and methods

3.3.1 Data sources and sample construction

We construct a comprehensive DDP-week panel of 553,958 observations starting in April 2016 by merging four different data types: (i) primary market information from the *Token Offerings Research Database (TORD)*, (ii) cross-sectional DDP information from various sources, (iii) secondary market information from *CoinMarketCap*, and (iv) on-chain DDP transactions from the *Ethereum* ledger.

First, we obtain primary market data from the updated *TORD*⁵, which includes data on over 10,000 token offerings up to September 2024. Variables we extract from the *TORD* include *MVP*, *Pre-sale*, *Whitelist*, *KYC*, *Bonus*, *Bounty*, *Open source*, *Team size*, in # FTE, and *Expert rating*. Second, we collect and match investor data from all DDP fundraising rounds from *Messari* and *CryptoRank*, as well as the overview of crypto fund portfolio companies from *CryptoFundResearch* to identify DDPs with crypto fund backing and the dates of investment. Third, we manually map the *TORD* to secondary-market DDP token performance data via several characteristics, including the name, token code, website link, *Twitter* page link, and whitepaper link. Performance data come from *CoinMarketCap* and include closing prices, market capitalization, and trading volumes until October 2024.⁶ We use the secondary market data also to infer the DDP token listing dates based on the earliest available price date. Fourth, we obtain on-chain metrics for each DDP with an *ERC20* contract address from the *Ethereum* blockchain through *Google BigQuery*.⁷ The on-chain

⁵Available from www.paulmomtaz.com/data/tord. Retrieved October 1, 2024

⁶Depending on the variable, we trim the data at the 0.1 to 1.0% levels to mitigate potential measurement errors with which the data might be reported.

⁷Dataset: <https://console.cloud.google.com/marketplace/product/bigquery-public-data/blockchain-analytics-ethereum-mainnet-us> Retrieved December 1, 2024.

data include details of every transaction executed on the DDPs, including sender and receiver wallet addresses, transferred token amounts, timestamps, and the token balances of each wallet address at any given time. These immutable data points enable us to construct various DDP growth variables, as defined in Section 3.3.2. We lose some observations because some DDPs are not built on *Ethereum*, and others may lack information to identify the main *ERC20* contract address for matching purposes.

Overall, this leads to a final sample of 2,769 DDPs organized as a weekly panel going back to the token generation event (TGE) that might predate the primary market, resulting in a total of 553,958 observations spanning from April 2016 to September 2024.

3.3.2 Variable definitions

3.3.2.1 Dependent variables: DDP growth and decentralization

DDP growth variables. We gauge DDP growth with six distinct proxies obtained from on-chain *Ethereum* ledger data. *DDP activity* measures the total number of weekly transactions on the DDP. *DDP turnover* is the weekly number of tokens traded over the total token supply, in %. *DDP adoption* is measured as the weekly total number of unique wallet addresses interacting with the DDP. *New users* are identified as wallet addresses interacting for the first time with the token addresses in any given week. *Recurring users* encompass all users who have had at least one prior interaction with the protocol in any given week. *Last users* refer to wallet addresses that have no further interactions with the token address after any given week. For the DDP growth proxies, we distinguish growth related to speculative versus non-speculative behavior. Transactions are viewed as *speculative* if they involve wallet addresses associated with cryptocurrency exchanges. Information for whether wallet addresses belong to cryptocurrency exchanges come from *Etherscan*.

DDP decentralization. We proxy for DDP decentralization with (i) the total number of tokenholders (and by token ownership buckets as follows: less than 1%, 1-5%, 5-20%, and

more than 20% token ownership) in any given week and (ii) the “Nakamoto coefficient” (see Lo Monaco et al., 2025), which quantifies the minimum number of the largest wallets required to hold more than 50% of the circulating token supply.

3.3.2.2 Independent variables: Token exchange listing information

Token exchange listing. Our main independent variable, $\mathbb{1}[Listing]$, is an indicator variable that takes the value of one if a platform is listed on a public token exchange on all days of the week of the observation and zero otherwise. We derive the initial listing date from the first available price data point on *CoinMarketCap*.

Initial listing success. Similar to Drobetz et al. (2019), we proxy for the first-week listing success with the variable *Listing Success*, which equals one if the DDP token’s price return exceeds that of *Bitcoin* in the first week following the exchange listing, and zero otherwise.

Listing sentiment. *Listing Sentiment* is constructed as a crypto market sentiment score based on the 30 days preceding the token listing. It is calculated by subtracting the sum of days with negative *Bitcoin* returns from the sum of days with positive *Bitcoin* returns, yielding a higher score for more positive sentiment, with a maximum value of +30 and a minimum of −30.

Undervaluation. We proxy for ex-ante DDP undervaluation with an indicator variable equal to one if the DDP token return was lower than the *Bitcoin* return in four consecutive weeks and zero otherwise.

3.3.2.3 Control variables and fixed effects

We control a comprehensive list of variables related to (i) DDP-level controls, such as the availability of a minimum viable product, expert ratings, and team size, (ii) ICO-level characteristics, such as pre-sale arrangements and whitelists, as well as (iii) token-level controls, such as token volatility and liquidity.

Our large panel dataset allows to control for time-variant and -invariant confounders

with a rich fixed effects specification. In particular, to control for time-invariant confounders, we include DDP fixed effects; and we also include calendar week fixed effects for time-variant confounders and post-listing week fixed effects for DDP lifecycle-variant confounders.

All variables are defined in Table B.1 in the Appendix.

3.3.3 Summary statistics

Table 3.1 shows summary statistics for DDP growth-related (Panel A), all listing-related (Panel B), and control variables (Panel C). We report the number of observations, arithmetic mean, standard deviation, and the 25th, 50th, and 75th percentiles. Panel A shows that DDPs have, on average, 219.4 transactions per week ($SD = 1,321.0$), of which 39.2 are speculative ($SD = 239.7$) and 174.2 are non-speculative, fundamental activity ($SD = 1,120.0$). The average total DDP token turnover is 2.3% ($SD = 12.7\%$), of which 0.2% ($SD = 1.4\%$) is speculative and 2.0% ($SD = 11.6\%$) is non-speculative, fundamental turnover. Regarding DDP adoption, on average, 146.5 unique users ($SD = 801.0$) interact with a DDP each week. Of these, 130.6 ($SD = 745.5$) engage in non-speculative, fundamental protocol activities, and 20.4 ($SD = 103.9$) stem from speculative activities. The proxies for DDP dynamics show that there are, on average, 54.5 new users ($SD = 379.9$) and 87.0 recurring users ($SD = 421.4$) per week. Among these users, an average of 56.2 ($SD = 355.6$) are last-time users. For all three proxies of DDP dynamics, we observe similar distributions for speculative and non-speculative, fundamental dynamics. On average, there are 6.1 new ($SD = 39.1$), 14.0 recurring ($SD = 65.6$), and 6.6 last ($SD = 38.0$) speculative investors per week, while there are 51.8 new ($SD = 366.6$), 73.9 recurring ($SD = 376.3$), and 53.3 last ($SD = 348.3$) non-speculative DDP users per week.

As per DDP decentralization and token ownership, each DDP has, on average, 14,907 unique tokenholders ($SD = 28,613$), of which 14,891 tokenholders ($SD = 28,608$) own less than 1% of the token supply, 5.5 ($SD = 5.1$) hold between 1 and 5%, 2.0 ($SD = 1.9$)

between 5 and 20%, and 1.0 (SD = 0.7) more than 20%. On average, the largest 4.9 tokenholders per DDP (SD = 10.6) hold together more than 50% of the circulating DDP token supply, constituting a simple majority of governance rights.

Panel B shows that 43% of all DDPs are listed on a public cryptocurrency exchange. Of these listed DDPs, 31% outperformed the market in their first week of being publicly traded. The average listing sentiment score is 2.0 (SD = 5.0), and we observe that 16% of the tokens are undervalued post-listing.

Panel C indicates that, on average, 15% of DDPs received crypto fund backing, and 19% had a minimum viable product at the time of the ICO. Additionally, 30% conducted a pre-sale, 24% implemented a whitelist, 37% had a KYC process, 11% offered specific bonus structures, 24% provided a bounty program, and 53% made their code publicly available. The average DDP team consists of 10.3 full-time members (SD = 6.9), with an average expert rating of 14.6 (SD = 12.8). Regarding token characteristics, the average DDP token has a weekly USD trading volume of 1.05% (SD = 35.4%) of its total market cap, with 4% of all tokens being overvalued. The statistics for our control variables are comparable to those in related studies (e.g., Fisch, 2019; Xia et al., 2024; Cumming et al., 2025; Drobetz et al., 2025).

Table 3.1: Summary statistics

Panel A: Summary statistics for DDP growth and decentralization variables						
	Obs	Mean	SD	Q1	Median	Q3
DDP activity:						
Total: # tx, weekly	520,995	219.40	1,321.00	0.00	0.00	21.00
Fundamental: # tx, weekly	520,995	174.20	1,120.00	0.00	0.00	15.00
Speculative: # tx, weekly	520,995	39.22	239.70	0.00	0.00	1.00
DDP turnover:						
Total: $\frac{\text{tokens traded}}{\text{token supply}}$, in %, weekly	519,443	2.32	12.70	0.00	0.00	0.40
Fundamental: $\frac{\text{tokens traded}}{\text{token supply}}$, in %, weekly	519,443	2.02	11.59	0.00	0.00	0.28
Speculative: $\frac{\text{tokens traded}}{\text{token supply}}$, in %, weekly	519,449	0.23	1.43	0.00	0.00	0.00
DDP adoption:						
Total: # users, weekly	520,995	146.50	801.00	0.00	0.00	26.00

Fundamental: # users, weekly	520,995	130.60	745.50	0.00	0.00	21.00
Speculative: # users, weekly	520,995	20.42	103.90	0.00	0.00	2.00
DDP dynamics:						
Total: # new users, weekly	520,995	54.50	379.90	0.00	0.00	5.00
Fundamental: # new users, weekly	520,995	51.79	366.60	0.00	0.00	5.00
Speculative: # new users, weekly	520,995	6.12	39.12	0.00	0.00	0.00
DDP dynamics:						
Total: # recurring users, weekly	520,995	87.02	421.40	0.00	0.00	19.00
Fundamental: # recurring users, weekly	520,995	73.93	376.30	0.00	0.00	14.00
Speculative: # recurring users, weekly	520,995	14.04	65.56	0.00	0.00	2.00
DDP dynamics:						
Total: # last users, weekly	520,995	56.21	355.60	0.00	0.00	8.00
Fundamental: # last users, weekly	520,995	53.32	348.30	0.00	0.00	7.00
Speculative: # last users, weekly	520,995	6.63	37.97	0.00	0.00	1.00
DDP decentralization:						
# token holders	429,237	14,907	28,613	1,115	4,717	14,729
# token holders (<1% ownership)	429,409	14,891	28,608	1,103	4,706	14,723
# token holders (1-5% ownership)	433,471	5.54	5.10	2.00	4.00	8.00
# token holders (5-20% ownership)	435,053	1.98	1.86	0.00	2.00	3.00
# token holders (>20% ownership)	436,558	1.03	0.69	1.00	1.00	1.00
Nakamoto coefficient	432,980	4.899	10.63	1.00	2.00	4.00

Panel B: Summary statistics for listing-related variables

	Obs	Mean	SD	Q1	Median	Q3
1[Listing]	521,516	0.43	0.50	0.00	0.00	1.00
Listing success	255,381	0.31	0.46	0.00	0.00	1.00
Listing sentiment	255,381	2.03	5.03	-2.00	2.00	6.00
Undervaluation	233,052	0.16	0.37	0.00	0.00	0.00

Panel C: Summary statistics for control variables

	Obs	Mean	SD	Q1	Median	Q3
Platform controls:						
Crypto fund backing	521,516	0.15	0.36	0.00	0.00	0.00
Minimum viable product	451,860	0.19	0.39	0.00	0.00	0.00
Pre-sale	451,861	0.30	0.46	0.00	0.00	1.00
Whitelist	446,389	0.24	0.43	0.00	0.00	0.00
KYC	451,861	0.37	0.48	0.00	0.00	1.00
Bonus	451,861	0.11	0.31	0.00	0.00	0.00
Bounty	451,860	0.24	0.43	0.00	0.00	0.00
Open source	451,861	0.53	0.50	0.00	1.00	1.00
Team size, in # FTE	414,852	10.31	6.89	6.00	9.00	13.00

Expert rating	414,063	14.64	12.76	6.30	8.10	27.00
Token controls:						
Token volatility (z-standardized)	203,766	0.00	1.00	−0.02	−0.02	−0.02
Token liquidity (% of market cap)	233,052	1.05	35.38	0.00	0.01	0.37
Overvaluation	233,052	0.04	0.21	0.00	0.00	0.00

3.3.4 Correlations

Pairwise correlations are in Table 3.2. All correlations are below the commonly agreed threshold of 0.7, suggesting that multicollinearity is not an issue in our sample.

1. 2. 3. 4. 5. 6. 7. 8. 9. 10. 11. 12. 13. 14. 15. 16. 17. 18. 19. 20. 21. 22. 23. 24. 25. 26. 27. 28. 29. 30. 31. 32. 33. 34. 35. 36.

1. $\mathbb{I}[\text{Listing}]$

- .41
.28 .09
/. -.01.02

5. Total platform activity
.13 .01 .08 -.01

25. Crypto fund

- 16.15.19.06.06.08.16.15.19.12.12.14.19.18.21.13.12.16.16.22.03.03.02.00.00.03.03.02.02.02.02.03.03.02.02.02.05.02.02.02.01.01.02.02.02.02.02.02.02.03.02.02.02.00.01.00.00.01.00.00.00.00.01.00.00.00.00.01.00.00.00.01.00.00.00.01.00.00.00.01.00.02.03.00.01.01.00.02.02.01.02.02.01.03.03.00.02.02.01.03.03.02.01.01.00.03.03.02.03.02.04.04.03.03.02.07.04.04.04.02.02.02.04.04.04.03.03.04.05.05.04.04.04.06.02.01.03.00.02.03.03.02.02.02.04.04.03.02.02.02.07.01.01.00.01.00.01.02.02.00.01.01.00.02.00.01.01.00.07.08.08.06.03.03.02.09.09.06.06.05.11.11.06.07.07.06.23.16.13.19.14.13.12.18.15.21.18.16.24.17.14.19.16.14.24.03.00.03.03.01.01.01.03.03.03.02.04.03.02.03.02.02.03.00.03.03.03.01.01.01.03.03.03.02.04.03.02.03.02.02.03.00.

3.3.5 Econometric approach

The main part of our empirical analyses evaluates the effect of DDP token exchange listing on DDP growth. Our baseline model is a staggered difference-in-differences approach, estimating the effects of DDP token exchange listing on various DDP-level proxies for growth and decentralization. We control for DDP fixed effects, which capture all time-invariant characteristics of DDPs, post-listing week fixed effects, which account for the time-varying maturation process of DDPs, and calendar week fixed effects, which capture external time-variant factors affecting all DDPs. A potential concern regarding the identification of any effect of the token exchange listing on DDP growth is that DDPs endogenously select into the exchange listing. However, note that most of our sample DDPs will list eventually, thus it is not the listing decision that is endogenous *per se*, it is rather the listing timing decision that could suffer from selectivity. To address this concern, we adopt various methods that control for such potential selectivity from previous studies (Bertoni et al., 2011; Cumming et al., 2025; Drobetz et al., 2025). This involves estimating a selection model in the first stage, which calculates the likelihood of a DDP’s token being listed on an exchange, as shown in Table B.2 in the Appendix. This probability is derived from a vector of exogenous control variables influencing the selection mechanism. The selection probabilities are then utilized in two distinct second-stage models: (i) using generalized residuals as instrumental variables (IV) to control for potential selectivity in unobservables, based on Gourieroux et al. (1987) and Heckman and Navarro-Lozano (2004), and (ii) employing propensity score matching (PSM model) with inverse Mills ratios to control for potential selectivity in observables, following Colombo and Grilli (2010) and Bertoni et al. (2011). For a detailed description of the methods, we refer to Section 3.4 in Cumming et al. (2025).

3.4 Empirical results

3.4.1 Token listing and DDP growth

Regression results from our staggered difference-in-differences model of the impact of token exchange listing on various measures of DDP growth are in Table 3.3. The dependent variables are (i) *DDP activity*, proxied with the weekly number of on-chain transactions; (ii) *DDP turnover*, proxied with the percentage of tokens traded of total token supply per week; (iii) *DDP adoption*, measured as the weekly number of on-chain users; and *DDP dynamics*, measured by the weekly number of (iv) new on-chain users, (v) recurring on-chain users, and (vi) last on-chain users. All DDP growth proxies can be decomposed into on-chain activity from speculative and non-speculative, fundamental DDP activity. All models include DDP, calendar week, and post-listing week fixed effects to absorb any time-invariant DDP-level characteristics and time-variant market-wide covariates. We report three regressions for each dependent variable. The first is our baseline staggered difference-in-differences regression, the second is our instrumented staggered difference-in-differences regression where we instrument the listing decision with the generalized residuals from a first-stage selection-into-listing model (Gourieroux et al., 1987; Heckman and Navarro-Lozano, 2004; Cumming et al., 2025), and the third is a staggered difference-in-differences regression with matched samples from our PSM-on-observables first-stage procedure described in Section 3.3.5.

The results in Table 3.3 consistently indicate that token exchange listing has a positive effect on DDP growth across all proxies and model specifications. We estimate that token exchange listings increase (i) DDP activity by 149 to 283 additional transactions per week, (ii) DDP turnover by 1.0 to 1.5% more tokens traded relative to the total token supply, (iii) DDP adoption by 103 to 191 additional on-chain users per week, and (iv) to (vi) DDP dynamics by 35 to 61 additional new users, 64 to 134 additional recurring users, and 38 to 72 additional abandoning users per week, respectively. It is interesting to note

that the listing-related increase in weekly on-chain users stems from new users by roughly one-third and recurring users by two-thirds. The positive listing effect on the number of last users can be explained with speculators who join DDPs only with the myopic interest to pocket DDPs' "money left on the table" due to commonly-observed underpricing (e.g., Momtaz, 2020). All estimated average treatment effects in Table 3.3 are statistically significant at the 1% level. R-squared values vary across proxies, ranging from 2.1% (lowest) for the number of transactions in the IV model specification to 25.0% (highest) for the percentage of traded tokens in the IV model specification, which we conclude are satisfactory values for an imbalanced panel of up to 520,995 observations in Table 3.3. Further, note that the estimated treatment effects per proxy are relatively similar for the IV and PSM model specifications and lower than the baseline OLS model specification, indicating that, without our adjustment for selectivity-related endogeneity in the timing decision of DDP listings, one would overestimate the actual effect of the token exchange listing on DDP growth. The only exception is the percentage of traded tokens, for which the pattern is reversed, suggesting that the treatment effect would be underestimated, which makes sense given that this is the only metric that depends directly on the listing. Taken together, the evidence in Table 3.3 supports our *Listing Hypothesis* that token exchange listings positively impact DDP growth.

Table 3.3: Staggered difference-in-differences analysis of exchange listing and DDP growth

| Dependent variable: | DDP activity: # tx | | | DDP turnover: $\frac{\text{tokens traded}}{\text{token supply}}$, in % | | | DDP adoption: # users | | |
|-----------------------|---------------------------|--------------------|--------------------|---|-------------------|-------------------|----------------------------|--------------------|--------------------|
| Model: | Baseline | IV | PSM | Baseline | IV | PSM | Baseline | IV | PSM |
| 1 [Listing] | 283.3***
(32.1) | 143.9***
(27.7) | 149.2***
(27.9) | 1.0***
(0.3) | 1.2***
(0.3) | 1.5***
(0.3) | 191.6***
(20.8) | 103.7***
(15.5) | 123.6***
(30.2) |
| IV | X | ✓ | X | X | ✓ | X | X | ✓ | X |
| PSM | X | X | ✓ | X | X | ✓ | X | X | ✓ |
| DDP FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Calendar week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Post-Listing week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Obs. | 520,995 | 213,742 | 109,945 | 519,443 | 212,400 | 109,371 | 520,995 | 213,750 | 109,952 |
| R ² | 0.029 | 0.021 | 0.026 | 0.215 | 0.250 | 0.248 | 0.043 | 0.029 | 0.031 |
| Dependent variable: | DDP dynamics: # new users | | | DDP dynamics: # recurring users | | | DDP dynamics: # last users | | |
| Model: | Baseline | IV | PSM | Baseline | IV | PSM | Baseline | IV | PSM |
| 1 [Listing] | 61.4***
(8.8) | 35.3***
(8.3) | 42.2***
(11.1) | 134.0***
(11.7) | 64.1***
(10.5) | 71.1***
(12.0) | 72.8***
(7.7) | 38.9***
(7.7) | 42.5***
(10.5) |
| IV | X | ✓ | X | X | ✓ | X | X | ✓ | X |
| PSM | X | X | ✓ | X | X | ✓ | X | X | ✓ |
| DDP FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Calendar week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Post-Listing week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Obs. | 520,995 | 213,724 | 109,948 | 520,995 | 213,756 | 109,945 | 520,995 | 213,721 | 109,948 |
| R ² | 0.045 | 0.033 | 0.037 | 0.038 | 0.023 | 0.027 | 0.033 | 0.028 | 0.029 |

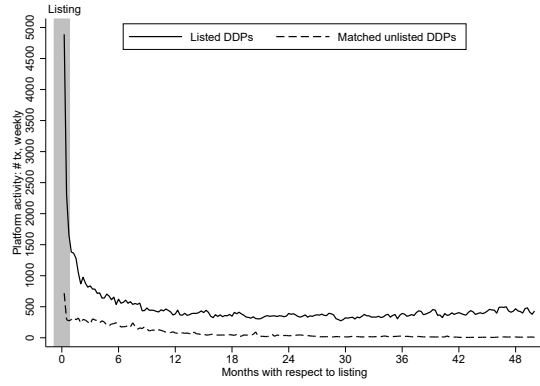
Note: These are regression results for the impact of exchange listing on DDP growth. The dependent variables are DDP activity, proxied with the number of transactions, DDP turnover, proxied with the percentage of tokens traded in total token supply, DDP adoption, measured as the number of users, new users, recurring users, last users. For each dependent variable, we estimate average treatment effects of exchange listing (i) in a basic staggered difference-in-differences model, (ii) in an augmented staggered difference-in-differences model that accounts for potential unobserved heterogeneity between the treatment and control group through an instrumental variable (IV) approach, and (iii) in another augmented staggered difference-in-differences model that accounts for potential observed heterogeneity between the treatment and control group through a propensity matching score (PSM) approach. The IV and PSM approaches show second-stage results, with the first-stage model shown in Table B.2 in the Appendix, and the econometric methodology is described in Section 3.3.5. Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

The results in Table 3.3 report *average* treatment effects of token exchange listing on DDP growth; however, we are also interested in exploring how DDP growth *evolves over time* post-listing. To that end, we plot all six DDP growth proxies for listed (solid line) and matched unlisted DDPs (dashed line) for the [0, 48] post-listing months in Figure 3.2. The overarching pattern is consistent across all six DDP growth proxies: There is a spike in activity immediately after the listing, which subsides dramatically in the six to twelve post-listing months, after which listed DDPs start growing again, although at a much slower yet sustainable rate. Also, comparing listed to matched unlisted DDPs, we observe that the initial patterns over the first six to twelve months are comparable, although activity on listed DDPs always exceeds that on matched unlisted DDPs, and, unlike for listed DDPs,

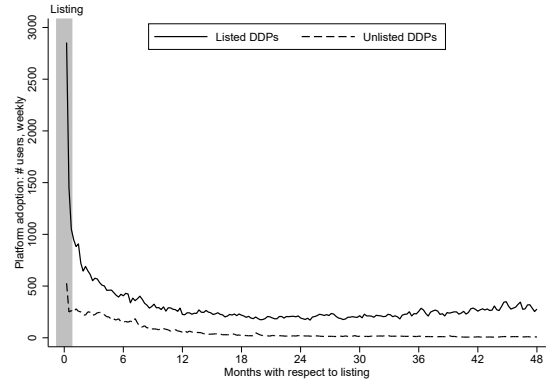
longer-term growth is actually negative after the first post-listing year. It should be noted that we zero the x-axis for listed DDPs at the listing date and for matched unlisted DDPs at the token generation event (TGE) date, which is comparable, as tokens of unlisted DDPs can also be exchanged over-the-counter post-TGE. Overall, the patterns in Figure 3.2 clearly indicate that the listing effect is not fully sustained over time, but listed DDPs nevertheless exhibit larger growth rates in the long run, suggesting that token exchange listings help platform entrepreneurs grow traction on their DDPs, further supporting the *Listing Hypothesis*.

Next, we test whether a *successful* first week of the token exchange listing and the *senti-*
ment around the token exchange listing moderate the positive long-term relation between token exchange listing and DDP growth. To that end, we interact our listing indicator with proxies for successful listings and listing sentiment for a moderated staggered difference-in-differences approach. Initial listing success is defined as a dummy variable equal to one if the DDP token outperforms *Bitcoin* in the first post-listing week, and zero otherwise. Listing sentiment is based on the 30 days preceding the token listing and is calculated as the difference between the sum of days with positive *Bitcoin* returns and the sum of days with negative *Bitcoin* returns. For each of the six dependent variables proxying for DDP growth, we estimate the baseline staggered difference-in-differences model (i.e., the first column for each DDP growth proxy in Table 3.3) for years 1, 2, and 3 following the token exchange listing to explore whether any potential effects of initial listing success and sentiment are sustained over time. For each dependent variable, the three columns in Table 3.4 therefore represent the baseline staggered difference-in-differences model estimated for different time horizons.

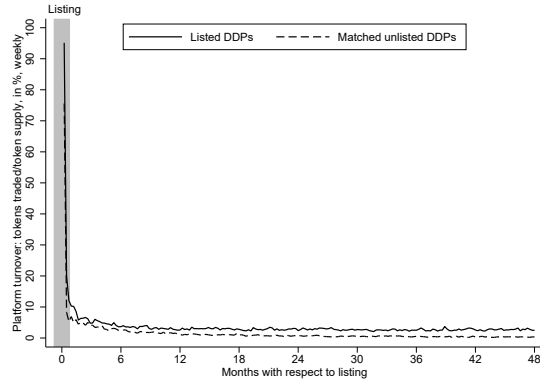
Figure 3.2: Long-term impact of exchange listing on DDP growth



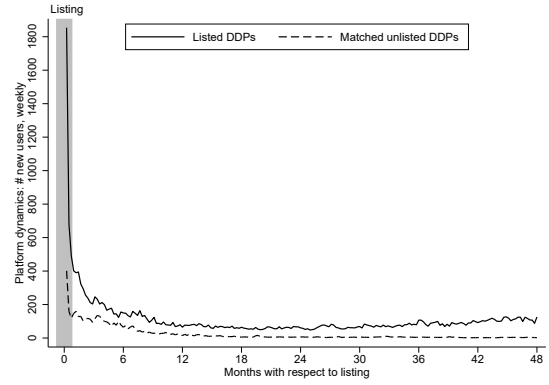
(a) DDP activity: # tx



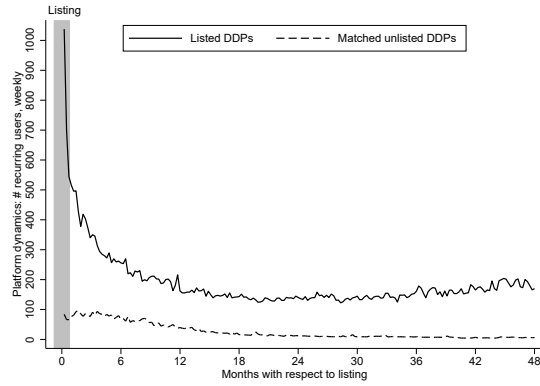
(b) DDP turnover: $\frac{\text{tokens traded}}{\text{token supply}}$, in %



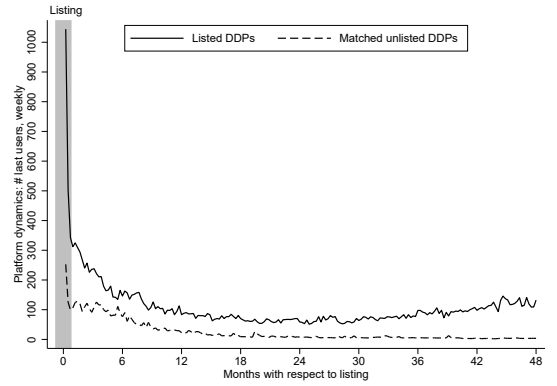
(c) DDP adoption: # users



(d) DDP dynamics: # new users



(e) DDP dynamics: # recurring users



(f) DDP dynamics: # last users

The results in Table 3.4 indicate that initial listing success can amplify the growth impact token exchange listings have on DDPs in the long term of up to three years after the listing, although the marginal effect decreases over time, at least for DDP activity, adoption, and dynamics. In economic terms, depending on the post-listing year, a successful initial listing leads, on average, to an additional 100.4 to 314.7 weekly transactions, 99.1 to 207.3 additional weekly platform users, and 78 to 147 additional weekly users. In contrast, for the listing sentiment, we observe shorter-lived effects, some of which may reverse over the course of the first three post-listing years. For example, platform activity (# transactions) and platform dynamics (# recurring users and # last users) are amplified by positive sentiment around the token exchange listing for, at most, the first two post-listing years, after which the effect evaporates. Similarly, for platform adoption (# users) and dynamics (# new users), a positive market sentiment around the listing also amplifies DDP growth in the first post-listing year, although the effect evaporates in the second post-listing year and is then eventually reversed in the third post-listing year, when a positive listing sentiment is associated with negative DDP growth rates relative to matched unlisted DDPs. Finally, in line with the pattern for DDP turnover above, we also find that the percentage of traded DDP tokens is negative when the market sentiment was positive at the time of the listing, and this effect is stable over all three post-listing years in our sample. It is noteworthy that the inclusion of the two initial listing success and sentiment moderators has a decisively positive effect on the model fit. The lowest R-squared for a baseline model in Table 3.3 was 2.9% (for platform activity proxy), which almost doubles in Table 3.4 to a range between 4.0 and 6.1%, which is reducing over time, highlighting the fading importance of the moderation effects of initial listing conditions over time.

Overall, the evidence in Table 3.4 partly supports our *Hypothesis 2* that initial token exchange listing success and positive market sentiment around the listing have an amplifying impact on the positive listing-growth relation for DDPs, although some of the effects evaporate and, in some cases, reverse in the long run.

Table 3.4: Exchange listing *success* and DDP growth: success begets success?

| Dependent variable: | DDP activity: # tx | | | DDP turnover: $\frac{\text{tokens traded}}{\text{token supply}}$, in % | | | DDP adoption: # users | | |
|-----------------------|--------------------|--------------------|--------------------|---|-----------------|------------------|-----------------------|--------------------|-------------------|
| Time period: | Year 1 | Year 2 | Year 3 | Year 1 | Year 2 | Year 3 | Year 1 | Year 2 | Year 3 |
| 1 [Listing] | 197.7***
(11.6) | 144.0***
(9.4) | 218.2***
(13.0) | 2.3***
(0.1) | 2.2***
(0.1) | 2.7***
(0.1) | 147.3***
(7.9) | 78.9***
(4.8) | 113.4***
(6.5) |
| × Listing success | 314.7***
(32.8) | 198.5***
(27.1) | 100.4***
(25.6) | −0.4
(0.3) | −0.3
(0.3) | −1.0***
(0.3) | 207.3***
(20.9) | 156.4***
(16.5) | 99.1***
(15.5) |
| × Listing sentiment | 12.6***
(2.8) | 10.9***
(2.8) | 0.0
(2.7) | −0.1**
(0.0) | −0.1**
(0.0) | −0.1***
(0.0) | 8.0***
(1.9) | 1.4
(1.7) | −3.2*
(1.7) |
| Listing success | 7.1
(15.5) | 19.1
(15.5) | 17.9
(15.5) | 0.2
(0.2) | 0.3
(0.2) | 0.3
(0.2) | 2.3
(10.4) | 4.7
(10.4) | 5.9
(10.5) |
| Listing sentiment | 5.8***
(1.8) | 6.9***
(1.8) | 6.9***
(1.8) | 0.0
(0.0) | 0.0
(0.0) | 0.0
(0.0) | 4.4***
(1.4) | 5.2***
(1.4) | 5.2***
(1.4) |
| DDP controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Calendar week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Post-listing week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Obs. | 272,397 | 271,486 | 269,520 | 270,841 | 269,927 | 267,943 | 272,389 | 271,491 | 269,513 |
| R ² | 0.061 | 0.040 | 0.040 | 0.263 | 0.253 | 0.254 | 0.074 | 0.046 | 0.046 |

| Dependent variable: | DDP dynamics: # new users | | | DDP dynamics: # recurring users | | | DDP dynamics: # last users | | |
|-----------------------|---------------------------|------------------|------------------|---------------------------------|------------------|------------------|----------------------------|------------------|------------------|
| Time period: | Year 1 | Year 2 | Year 3 | Year 1 | Year 2 | Year 3 | Year 1 | Year 2 | Year 3 |
| 1 [Listing] | 42.2***
(3.9) | 25.4***
(2.4) | 29.8***
(2.4) | 106.5***
(4.4) | 57.1***
(2.6) | 85.6***
(4.3) | 50.1***
(3.7) | 26.4***
(2.3) | 31.1***
(2.3) |
| × Listing success | 83.6***
(9.6) | 49.2***
(6.6) | 42.2***
(6.7) | 139.8***
(10.9) | 98.4***
(7.6) | 64.3***
(7.7) | 72.0***
(8.4) | 56.3***
(6.3) | 43.9***
(5.9) |
| × Listing sentiment | 3.7***
(1.0) | −1.3
(0.8) | −1.5*
(0.8) | 6.6***
(0.8) | 3.9***
(0.7) | 0.1
(0.7) | 4.3***
(0.8) | 0.0
(0.7) | −0.1
(0.7) |
| Listing success | −2.1
(4.5) | −0.9
(4.6) | −0.3
(4.6) | −5.0
(3.3) | −2.4
(3.2) | −2.3
(3.2) | −8.3**
(4.0) | −8.8**
(4.0) | −8.3**
(4.0) |
| Listing sentiment | 2.2***
(0.7) | 2.6***
(0.7) | 2.6***
(0.7) | 0.3
(0.4) | 0.8**
(0.4) | 0.8**
(0.4) | 1.1*
(0.6) | 1.4**
(0.6) | 1.4**
(0.6) |
| DDP controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Calendar week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Post-listing week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Obs. | 272,291 | 271,411 | 269,433 | 272,460 | 271,523 | 269,554 | 272,306 | 271,423 | 269,444 |
| R ² | 0.062 | 0.042 | 0.043 | 0.095 | 0.058 | 0.055 | 0.055 | 0.034 | 0.034 |

Note: These are regression results for the moderating effect of initial listing success and listing sentiment on the impact of exchange listing on DDP growth. Initial listing success is defined as a dummy variable that takes a value of one if the DDP token outperforms *Bitcoin* during its first week post-listing, and zero otherwise. Listing sentiment measures the cryptocurrency market sentiment at the time of listing. The dependent variables are DDP activity, proxied with the number of transactions, DDP turnover, proxied with the percentage of tokens traded in total token supply, DDP adoption, measured as the number of users, new users, recurring users, and last users. For each dependent variable, we estimate average treatment effects of (i) exchange listing, (ii) listing success, (iii) listing sentiment, and the interaction terms of (i) with (ii) and (i) with (iii) in a basic staggered difference-in-differences model. Regression results for each dependent variable are presented for years 1, 2, and 3 after the exchange listing. The estimated coefficients of the DDP control variables are suppressed for brevity and all models control for calendar week and post-listing week fixed-effects. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.4.2 Spillover effects from DDP investors to DPP adopters

The unique feature of the shared asset (i.e., the token) between investors and users may enable demand spillovers from speculative to non-speculative, fundamental activity on DDPs. Demand spillovers might be more likely to occur when tokens are undervalued

because informed investors will be able to pocket the token price appreciation *in expectation*. Intuitively, speculators may increase token turnover (e.g., because of high expected returns), kickstarting network effects, which reduce the early adoption-related coordination problem of users. The availability of identity information for token contract addresses that belong to cryptocurrency exchanges, allows to track and decompose DDP activity into speculative and non-speculative, fundamental activity on DDPs.

Table 3.5 explores whether speculative activity drives fundamental activity on listed DDPs a week later and whether any such effect is stronger for undervalued tokens. Panels A and B of Table 3.5 test the effect of speculation on *total* (i.e., speculative and non-speculative, fundamental) activity and the moderating effect of undervalued tokens, respectively. The dependent variables are our six proxies for DDP *total* growth, which measure aggregate growth from speculation and fundamental activity. Panels C and D of Table 3.5 test the effect of speculation on *fundamental* activity and the moderating effect of undervalued tokens, respectively. The dependent variables are our six proxies for DDP *non-speculative, fundamental* growth. We measure speculative activity in each of the six DDP growth proxies as the fraction of on-chain activity in total activity with token contract counterparties that can be traced back to crypto exchanges. We measure undervaluation as an indicator equal to 1 if the DDP token underperformed *Bitcoin* over four consecutive weeks, and zero otherwise. All models include all controls, as in Table 3.4, including DDP, calendar week, and post-listing week fixed effects. For brevity, we suppress control variables in Table 3.5.

The results in Table 3.5 lend strong support to the ***Spillover Hypothesis***. Speculative activity drives total and fundamental activity the week later. All coefficients are highly statistically significant at the 1% level, and the R-squared values explain a substantial amount of variation in our on-chain activity, ranging from 9.3% to 34.5% for non-speculative, fundamental, and from 15.8% to 44.3% for total activity on DDPs. The R-squared is noteworthy in comparison to Table 3.3, suggesting that most of the DDP growth is not actually

driven by the listing *per se*, but by the speculation *enabled* by listing DDP tokens.

Coefficient estimates in Panel C suggest that increasing speculative activity by one percentage point increases non-speculative, fundamental activity the week later by 1.4 (DDP turnover) to 2.9 (new DDP users) percentage points. These estimates suggest a multiplier effect of speculative activity (coefficients > 1), hinting at the presence of positive network effects originating from financial speculators. The interaction coefficients in Panel D further suggest that undervalued tokens benefit more from speculation, also supporting *Hypothesis 4*.

Table 3.5: **Spillover effects of speculation on DDP growth**

| Dependent variables: | DDP activity:
tx | DDP turnover:
$\frac{\text{tokens traded}}{\text{token supply}}$, in % | DDP adoption:
users | DDP dynamics:
new users | DDP dynamics:
recurring users | DDP dynamics:
last users |
|---|-----------------------|--|--------------------------|------------------------------|------------------------------------|-------------------------------|
| Panel A: Total growth (speculative and non-speculative, fundamental growth) in week t | | | | | | |
| Speculative activity (week $t-1$) | 2.6***
(0.1) | 2.2***
(0.1) | 3.4***
(0.1) | 3.2***
(0.1) | 3.4***
(0.1) | 3.3***
(0.1) |
| Undervaluation | 31.9***
(8.0) | 0.1
(0.1) | 19.2***
(4.5) | 8.7***
(2.0) | 11.8***
(2.8) | 8.8***
(2.1) |
| Token controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| DDP controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Calendar week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Post-listing week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Obs. | 132,077 | 131,888 | 132,092 | 132,095 | 132,079 | 132,090 |
| R ² | 0.371 | 0.158 | 0.389 | 0.285 | 0.442 | 0.271 |
| Panel B: Total growth (speculative and non-speculative, fundamental growth) in week t | | | | | | |
| Speculative activity (week $t-1$) | 2.5***
(0.1) | 2.2***
(0.1) | 3.3***
(0.1) | 3.1***
(0.1) | 3.3***
(0.1) | 3.2***
(0.1) |
| × Undervaluation | 0.9***
(0.2) | 0.3
(0.3) | 0.9***
(0.2) | 1.7***
(0.3) | 0.7***
(0.2) | 1.0***
(0.2) |
| Undervaluation | -19.6**
(8.9) | -0.0
(0.1) | -9.7*
(5.7) | -4.1*
(2.3) | -4.1
(3.2) | -1.0
(2.2) |
| Token controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| DDP controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Calendar week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Post-listing week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Obs. | 132,077 | 131,888 | 132,092 | 132,095 | 132,079 | 132,090 |
| R ² | 0.374 | 0.158 | 0.391 | 0.289 | 0.443 | 0.273 |
| Panel C: Non-speculative, fundamental growth in week t | | | | | | |
| Speculative activity (week $t-1$) | 1.7***
(0.0) | 1.4***
(0.1) | 2.8***
(0.1) | 2.9***
(0.1) | 2.6***
(0.1) | 2.9***
(0.1) |
| Undervaluation | 32.2***
(7.6) | 0.1
(0.1) | 19.6***
(4.5) | 8.9***
(2.0) | 12.6***
(2.8) | 8.8***
(2.1) |
| Token controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| DDP controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Calendar week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Post-listing week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Obs. | 132,066 | 131,875 | 132,091 | 132,094 | 132,074 | 132,090 |
| R ² | 0.262 | 0.093 | 0.312 | 0.251 | 0.339 | 0.233 |
| Panel D: Non-speculative, fundamental growth in week t | | | | | | |

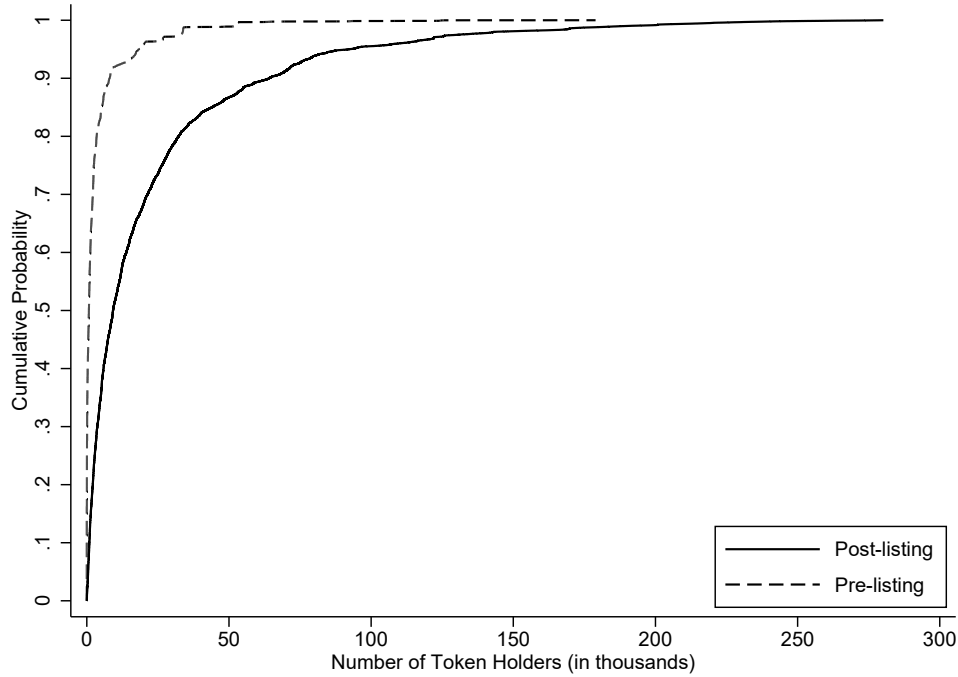
| | | | | | | |
|---------------------------------|------------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Speculative activity (week t-1) | 1.7***
(0.0) | 1.3***
(0.1) | 2.7***
(0.1) | 2.8***
(0.1) | 2.5***
(0.1) | 2.8***
(0.1) |
| × Undervaluation | 1.0***
(0.2) | 0.5
(0.3) | 1.0***
(0.2) | 1.8***
(0.4) | 0.8***
(0.2) | 1.1***
(0.2) |
| Undervaluation | -21.9**
(8.7) | -0.1
(0.1) | -10.7*
(5.8) | -4.6**
(2.3) | -5.2
(3.2) | -1.5
(2.2) |
| Token controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| DDP controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Calendar week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Post-listing week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Obs. | 132,066 | 131,875 | 132,091 | 132,094 | 132,074 | 132,090 |
| R ² | 0.271 | 0.098 | 0.319 | 0.260 | 0.345 | 0.240 |

Note: These are regression results for the impact of speculative activity and token undervaluation on DDP growth. The financial speculation (week t-1) variable in each regression corresponds to the type of DDP growth defined as the dependent variable in the model but is restricted to growth related to exchange-based activities. For example, in the second column of Panel A, we assess the impact of speculative transactions on the total number of transactions in the following week. Undervaluation is defined as a dummy variable, set to one if the DDP token underperformed *Bitcoin* over four consecutive weeks, and zero otherwise. The dependent variables are DDP activity, proxied with the number of transactions, DDP turnover, proxied with the percentage of tokens traded in total token supply, DDP adoption, measured as the number of users, new users, recurring users, last users. In Panels A and B, the dependent variables capture the total DDP growth (including both speculative and non-speculative, fundamental blockchain protocol growth). Panels C and D focus exclusively on non-speculative, fundamental growth. Panels B and D also feature an additional interaction term between the speculation variable and the undervaluation variable. The estimated coefficients of the DDP control variables are suppressed for brevity and all models control for calendar week and post-listing week fixed-effects. Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

3.4.3 Token listing and DDP decentralization

A central premise of DDPs is that decentralization facilitates network effects (Cumming et al., 2025). We explore in this section whether the DDP growth documented above is associated with an increasing degree of decentralization. For motivation, Figure 3.3 plots the cumulative ownership distributions of DDPs before (dashed line) and after (solid line) the listing, showing a strong pattern of post-listing dispersion of token ownership. Prior to the listing, the absolute number of tokenholders in approximately 90% of all DDPs is below 20,000 and never above 175,000, while the listing is associated with a notable shift, with more than 10% of all listed DDPs exceeding 50,000 tokenholders and some even surpassing 250,000 tokenholders.

Figure 3.3: Average token ownership distribution before and after exchange listings



Regression results from our staggered difference-in-difference models, as estimated in Tables 3.3, 3.4 (for the one-year horizon), and 3.5 Table, are in Panels A, B, and C of Table 3.6, respectively, with the only difference of regressing new dependent variables as proxies for DDP decentralization. The first model of Table 3.6 fits the number of tokenholders and the second fits the *Nakamoto* coefficient (i.e., the smallest number of the largest tokenholders in a DDP that would have enough token ownership to majority-control the DDP). The third to sixth models repeat the first regression of the number of tokenholders for the subsamples of tokenholders with less than 1% of token ownership, between 1 and 5%, between 5 and 20%, and more than 20%, respectively. The first model suggests that the listing leads to 2,515 additional tokenholders. The second model suggests, however, that the listing leads to an increase of 1.0 in the *Nakamoto* coefficient, meaning that the listing changes the smallest number of large tokenholders to majority-control a DDP only by requiring one additional large tokenholder. Taken together, these diverging results may

indicate that the listing leads to many more small tokenholders and not many large tokenholders. To corroborate the interpretation, we test the listing effect in different buckets of tokenholder ownership stakes in models three to six. Consistent with our interpretation, the number of small tokenholders with less than 1% of ownership increases because of the listing by 2,590, and this effect increases dramatically for larger ownership shares. Specifically, the number of tokenholders with 1% to 5% of ownership increases by 1.2, the number of tokenholders with 5% to 20% of ownership increases by 0.4, and the number of tokenholders with more than 20% is not impacted by the listing, supporting our *Asymmetric Decentralization Hypothesis*.

These results are consistent for our replications of Tables 3.4 (for the one-year horizon) in Panel B of Table 3.6 and 3.5 in Panel C of Table 3.6 and thus, for brevity, not further discussed.

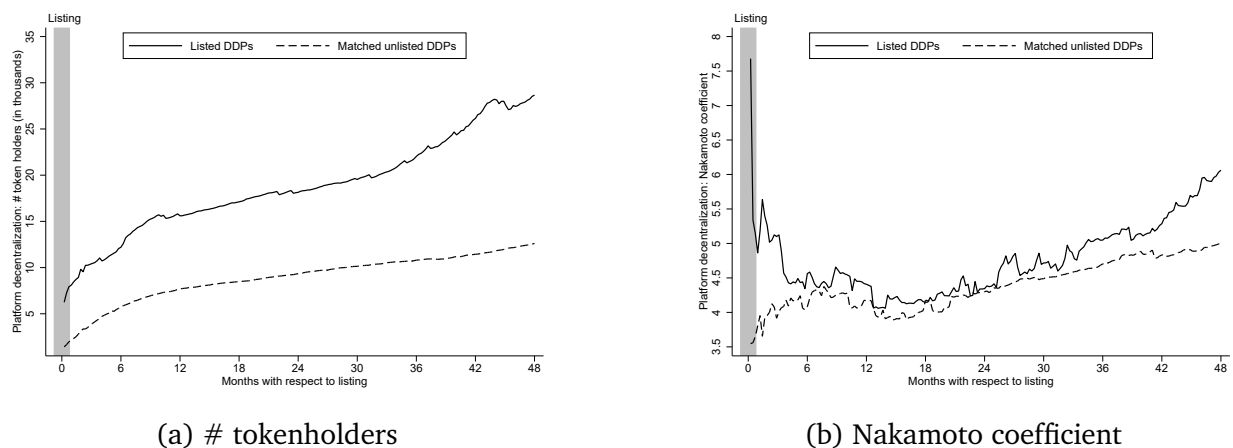
Table 3.6: Staggered difference-in-differences analysis of exchange listing and DDP decentralization

| Dependent variables: | DDP decentralization: | | # token holders by share: | | | |
|---|------------------------|----------------------|---------------------------|------------------|------------------|------------------|
| | # token holders | Nakamoto coefficient | <1% | 1–5% | 5–20% | >20% |
| Panel A: Analogous to Table 3.3 | | | | | | |
| 1 [Listing] | 2515.5***
(848.8) | 1.0***
(0.4) | 2,590.6***
(848.8) | 1.2***
(0.3) | 0.4***
(0.1) | –0.0
(0.0) |
| DDP FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Calendar week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Post-listing week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Obs. | 429,237 | 432,980 | 429,409 | 433,471 | 435,053 | 436,558 |
| R ² | 0.129 | 0.005 | 0.130 | 0.059 | 0.033 | 0.006 |
| Panel B: Analogous to Table 3.4 (for Year 1) | | | | | | |
| 1 [Listing] | 2,641.8***
(185.0) | –0.6***
(0.1) | 2,631.7***
(184.9) | 0.7***
(0.0) | 0.6***
(0.0) | –0.1***
(0.0) |
| × Listing success | 5,041.1***
(377.0) | 1.4***
(0.2) | 5,042.9***
(377.1) | 0.4***
(0.1) | –0.1**
(0.0) | 0.0*
(0.0) |
| × Listing sentiment | 347.9***
(31.0) | 0.1***
(0.0) | 350.7***
(31.0) | 0.0
(0.0) | –0.0***
(0.0) | 0.0***
(0.0) |
| Listing success | –1,224.5***
(141.2) | –0.4***
(0.1) | –1,228.5***
(141.4) | 0.3***
(0.1) | 0.1**
(0.0) | –0.0
(0.0) |
| Listing sentiment | 67.4***
(15.4) | –0.1***
(0.0) | 65.0***
(15.3) | –0.0**
(0.0) | 0.0***
(0.0) | –0.0***
(0.0) |
| DDP controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Calendar week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Post-listing week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Obs. | 243,394 | 244,111 | 243,480 | 244,102 | 245,510 | 245,878 |
| R ² | 0.087 | 0.042 | 0.087 | 0.069 | 0.033 | 0.040 |
| Panel C: Analogous to Table 3.5 | | | | | | |
| Speculative activity (week t–1) | 27.0***
(0.7) | 0.0***
(0.0) | 27.0***
(0.7) | 0.0***
(0.0) | 0.0***
(0.0) | –0.0***
(0.0) |
| × Undervaluation | 25.6***
(3.6) | 0.0***
(0.0) | 25.6***
(3.6) | 0.0***
(0.0) | –0.0
(0.0) | –0.0**
(0.0) |
| Undervaluation | –1,126.8***
(282.1) | –0.6***
(0.1) | –1,126.6***
(282.1) | –0.1***
(0.0) | –0.0
(0.0) | 0.0
(0.0) |
| Token controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| DDP controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Calendar week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Post-listing week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Obs. | 107,403 | 107,983 | 107,403 | 108,055 | 107,779 | 108,722 |
| R ² | 0.188 | 0.040 | 0.188 | 0.057 | 0.028 | 0.043 |

Note: This table presents regression analyses of our listing-related variables on DDP decentralization. Model specifications in Panel A correspond to those in Table 3.3, in Panel B to Table 3.4 (for Year 1), and in Panel C to Table 3.5. The dependent variables include: (i) the total number of token holders, (ii) the Nakamoto coefficient, which measures the minimum number of the largest wallet addresses required to control >50% of the circulating token supply in a given week, and the number of token holders with (iii) less than 1%, (iv) 1–5%, (v) 5–20%, and (vi) more than 20% of token ownership. DDP controls are suppressed for brevity. All models control for calendar week and post-listing week FEs. Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

Figure 3.4 plots the evolution of DDP decentralization over time, i.e., from the listing month to 48 months after the listing, for the number of tokenholders and the *Nakamoto* coefficient. Two observations are noteworthy. First, listed DDPs experience a disproportionately higher increase in the number of tokenholders compared to matched unlisted DDPs over the four-year post-listing period, suggesting that the listing effect has a persistent effect on DDP decentralization. Second, the *Nakamoto* coefficient spikes in the listing month, before subsiding to levels comparable to those of matched unlisted DDPs. This pattern is consistent with the interpretation that certain large tokenholders enter just after the listing, e.g., crypto hedge funds (Conlon et al., 2025; Cumming et al., 2025; Dombrowski et al., 2023), while others exploit the temporary liquidity increase to exit, which is why the *Nakamoto* coefficient subsides in the secondary market. Note that in the long term, after three years of listing, the *Nakamoto* coefficient of listed DDPs starts to rise above the level of that of matched unlisted DDPs.

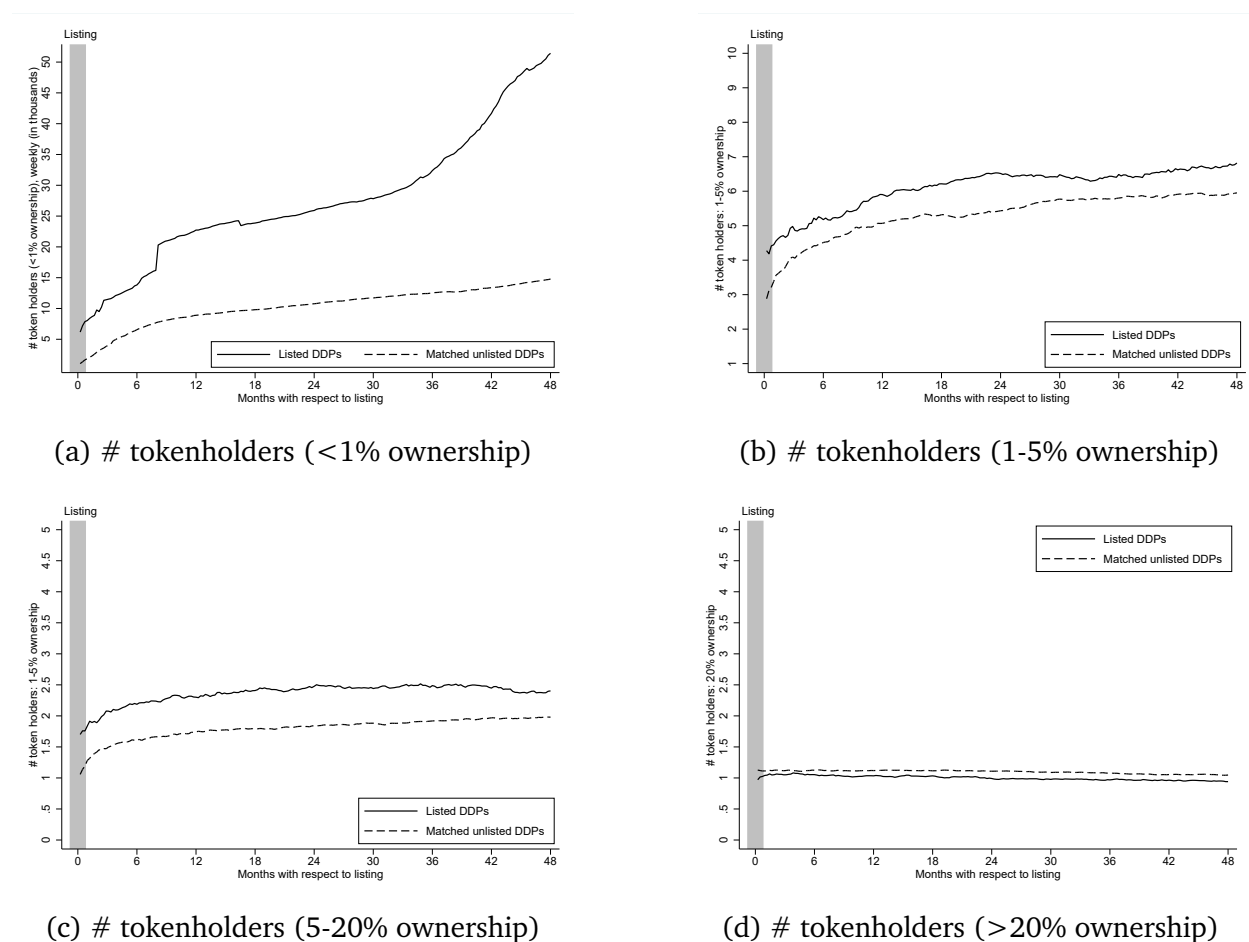
Figure 3.4: Long-term impact of token exchange listing on DDP decentralization



Finally, Figure 3.5 shows the evolution of the number of tokenholders by ownership share buckets (<1%, 1 to 5%, 5 to 20%, and >20%) for the four-year post-listing period. Three observations are noteworthy. First, it becomes clear that there is increasing decentralization on listed DDPs, primarily driven by small tokenholders (<1% token own-

ership). Second, there is no noticeable time trend for the medium buckets (1 to 5% and 5 to 20% token ownership), although listed DDPs have more tokenholders because of the initial listing effect. Third, for the largest bucket ($>20\%$ token ownership), there is no decentralization trend and matched unlisted DDPs are more decentralized than listed DDPs, plausibly because unlisted DDPs are backed by crypto funds, which leads to more larger tokenholders.

Figure 3.5: Long-term impact of token exchange listing on DDP token ownership



3.4.4 Post-hoc analyses

3.4.4.1 Token listing and DDP survival

Despite the benefits for DDP growth, token exchange listings may also bring substantial disadvantages, such as entrepreneurial myopia to cope with token price-related market pressures and an exposure to market misconduct by activist investors (Drobetz et al., 2025; Hornuf et al., 2025). Aggressive DDP growth may thus amplify existential threats to DDP survival. It is an empirical question whether the DDP growth effect of token exchange listings is also associated with higher DDP survival rates, which we explore in this section. Frailty analyses of DDPs' duration to failure are in Table 3.7. We employ frailty analyses, rather than, e.g., fixed-effects Cox proportional hazards models, because of their demonstrated robustness when working with entrepreneurial data. Momtaz (2021c) shows by simulation that, because of the endogeneity associated with duration dependency in entrepreneurial survival data, only frailty models deliver unbiased estimates, while Cox models yield biased coefficient estimates, where the bias may potentially even lead to coefficients on variables of interest even changing signs.

Models 1 and 2 in Table 3.7 re-run the main models from Tables 3.3, models 3 and 4 re-run those from 3.4, and models 5 and 6 re-run those from 3.5. All coefficients in Table 3.7 are hazard ratios (i.e., exponentiated coefficients), so that hazard ratios >1 (<1) suggest a longer (shorter) duration until failure. The uneven models contain results from Cox proportional hazard models for comparison, while the even models contain our frailty models. The frailty-based hazard ratios are smaller, suggesting that Cox proportional hazard models would overestimate the impact of token exchange listings on DDP survival. The hazard ratio in model 1 is 1.679, statistically significant at the 1% level. Economically, the output suggests that, on average, DDP exchange listings lead to a 57.3% longer survival time compared to matched unlisted DDPs. Models 3 and 4 suggest that DDP token exchange listing success does not significantly moderate the impact of token

listing on DDP survival, and a positive market sentiment at the time of the listing tends to reduce this effect. For instance, Model 4 suggests that an increase in market sentiment by one standard deviation (5.0) reduces the positive impact of DDP exchange listing by, on average, 27.2 percentage points. Furthermore, Table 3.7 shows statistically significant effects of financial speculation and DDP token undervaluation. According to the frailty estimates in model 6, DDPs that are ex-ante undervalued exhibit, on average, a 9.5% shorter survival time compared to those that are fairly valued.

Table 3.7: **A survival analysis of exchange listing and DDPs**

| <i>Dependent variable: Time until DDP failure</i> | | | | | | |
|---|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|--------------------------------|
| 1 [Listing] | 1.679 ^{***}
(0.038) | 1.573 ^{***}
(0.032) | 1.902 ^{***}
(0.060) | 1.614 ^{***}
(0.045) | | |
| × Listing success | | | 0.011
(79.084) | 0.001
(564.483) | | |
| × Listing sentiment | | | 0.941 ^{**}
(0.025) | 0.964 [*]
(0.021) | | |
| Listing success | | | 96.255
(79.084) | 835.475
(564.483) | | |
| Listing sentiment | | | 1.067 ^{***}
(0.024) | 1.037 [*]
(0.020) | | |
| Financial speculation (in week t−1) | | | | | 1.017 ^{***}
(0.003) | |
| × Undervaluation | | | | | 1.016
(0.022) | |
| Undervaluation | | | | | 1.586 ^{***}
(0.102) | 0.905 ^{**}
(0.041) |
| Model | log-logistics | log-logistics | log-normal | log-normal | log-logistics | log-logistics |
| Frailty | × | ✓ | × | ✓ | × | ✓ |
| Grouping variable | ./. | launch year | ./. | launch year | ./. | listing year |
| DDP controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Obs. | 379,790 | 379,790 | 379,790 | 379,790 | 132,758 | 132,758 |
| Log-likelihood | −1953.4 | −1755.93 | −2025.8 | −1824.8 | −1945.4 | −258.21 |

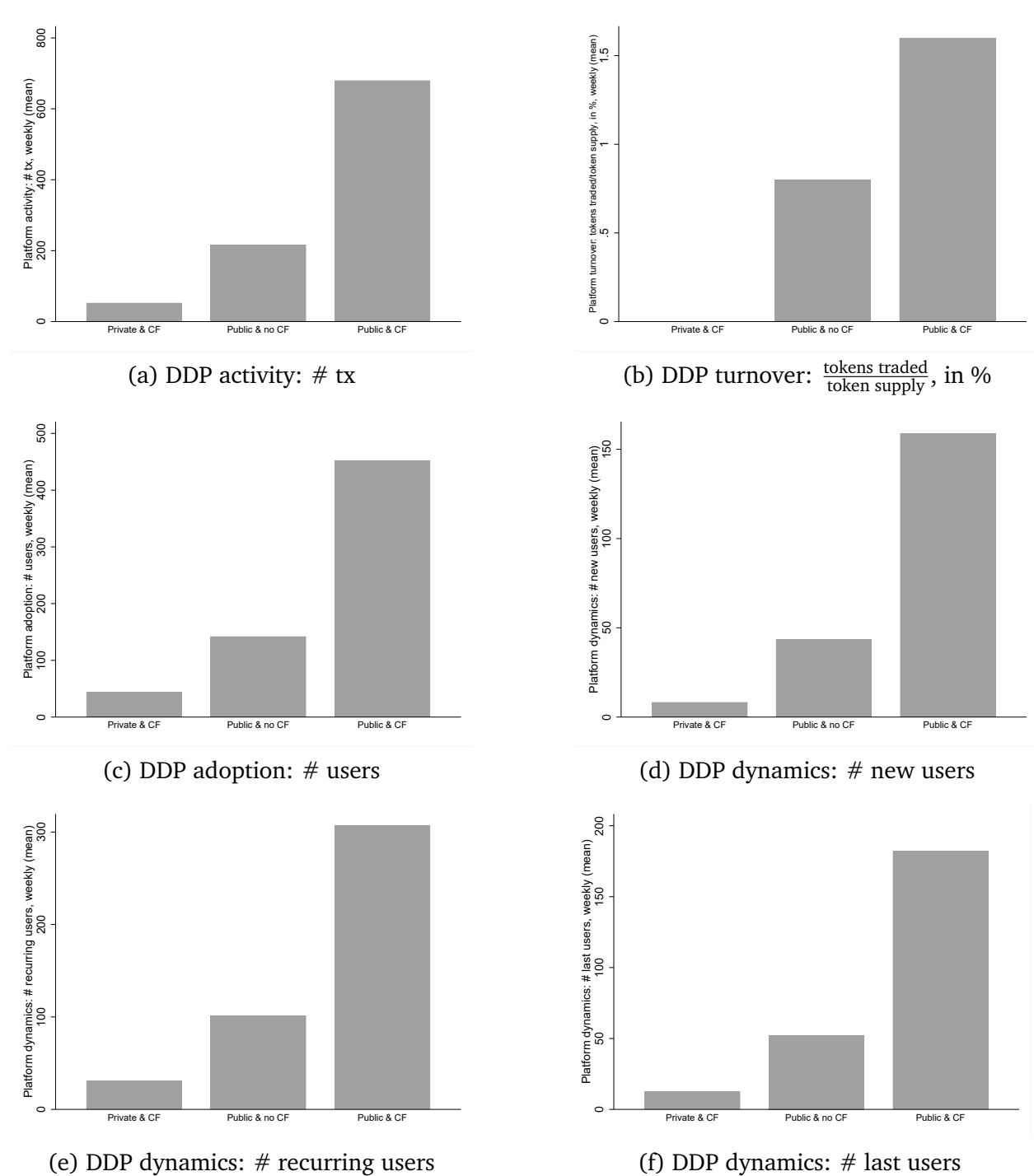
Note: This table presents the results from DDP survival analyses as functions of the token exchange listing and other key variables. Coefficients are expressed as exponentiated values (hazard ratios), such that a coefficient greater than one indicates a longer survival time, whereas one less than one suggests a shorter survival time. The models employ log-logistic or log-normal distributions, as detailed at the bottom of the table. Columns (II) and (IV) feature shared frailty models based on launch year, while column (VI) uses a shared frailty model based on listing year. All other columns report results from a Cox proportional hazards model for comparison. The estimated coefficients of the DDP controls are suppressed for brevity. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.4.4.2 Going public versus remaining private: the role of crypto funds

Cumming et al. (2025) show that crypto funds may help DDPs raise funding and grow, while our paper shows that the exchange listing of DDP tokens facilitates DDP growth. A natural next question is the relative contribution of exchange listings vis-à-vis crypto fund

backing for DDP growth. To that end, we re-run our models from Tables 3.3, 3.4, and 3.5, with the only modification of interacting exchange listings with an indicator for whether the DDP was backed by a crypto fund. For brevity, we also summarize our empirical findings in Figure 3.6. We plot the average treatment effects of remaining private with the help of crypto fund backings, going public without crypto fund backing, and going public with crypto fund backing. The overarching finding is that crypto-fund endorsed exchange listings have the strongest impact on DDP growth, followed by non-endorsed going-public decisions and remaining private. Therefore, as for the relative importance of the two strategies of going public versus remaining private, we qualify the evidence in Cumming et al. (2025) by showing that token exchange listings are more beneficial for DDPs than crypto fund investments *per se*.

Figure 3.6: A comparison of DDP growth between going-public and remaining-private decisions



For completeness, regression results from our modified staggered difference-in-difference models, as estimated in Tables 3.3, 3.4 (for the one-year horizon), and 3.5 are in Panels

A, B, and C of Table 3.8, respectively. The dependent variables are, as before, proxies for DDP activity (# transactions), turnover (traded tokens relative to token supply), adoption (# users), and dynamics (# new, recurring, and last users). In Panel A, the first model suggests that the exchange listing leads to 216 more transactions, while crypto fund backing is not associated with a significant increase in the number of transactions; nevertheless, crypto fund-endorsed exchange listings lead to 635 additional transactions per week, of which 418 transactions are associated with the interaction of listing and crypto fund backing. We observe the same pattern (i.e., a significant increase driven by exchange listings and amplified by crypto fund endorsement, but no significant effect of crypto fund backing *per se*) for all four DDP adoption and dynamics proxies. For DDP turnover, we also find a significant listing effect, as before, however, no amplification effect of crypto funds. In Panels B and C, the same pattern prevails: crypto fund backing amplifies the listing effect.

Table 3.8: The relation between exchange listing, crypto fund backing, and DDP growth

| Dependent variables: | DDP activity:
tx | DDP turnover:
$\frac{\text{tokens traded}}{\text{token supply}}$, in % | DDP adoption:
users | DDP dynamics:
new users | DDP dynamics:
recurring users | DDP dynamics:
last users |
|---|-----------------------|--|--------------------------|------------------------------|------------------------------------|-------------------------------|
| Panel A: Replication of Table 3.3 with CF backing | | | | | | |
| 1 [Listing] | 216.9***
(35.1) | 0.8***
(0.3) | 142.1***
(24.2) | 43.4***
(9.8) | 101.0***
(14.4) | 52.3***
(9.1) |
| × Crypto fund backed | 418.1***
(149.9) | 0.8
(0.6) | 310.4***
(101.6) | 115.5***
(37.1) | 205.8***
(64.6) | 130.0***
(39.2) |
| Crypto fund backed | 52.5
(117.4) | 0.0
(0.5) | 44.2
(80.1) | 8.3
(28.4) | 30.7
(51.5) | 12.7
(30.8) |
| DDP controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Calendar week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Post-listing week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Obs. | 520,995 | 519,443 | 520,995 | 520,995 | 520,995 | 520,995 |
| R ² | 0.030 | 0.215 | 0.045 | 0.046 | 0.042 | 0.034 |
| Panel B: Replication of Table 3.4 with CF backing (for Year 1) | | | | | | |
| 1 [Listing] | 163.6***
(11.6) | 2.3***
(0.1) | 127.2***
(7.8) | 33.2***
(3.7) | 93.8***
(4.4) | 38.9***
(3.5) |
| × Listing success | 249.6***
(28.5) | −0.4
(0.3) | 165.9***
(18.4) | 68.1***
(8.5) | 113.6***
(9.5) | 61.9***
(7.5) |
| × Listing sentiment | 7.2***
(2.7) | −0.1***
(0.0) | 4.6**
(1.8) | 2.4*
(0.9) | 4.7***
(0.8) | 3.2***
(0.8) |
| × Crypto fund backed | 473.4***
(37.7) | 0.1
(0.3) | 287.0***
(24.2) | 119.1***
(11.3) | 177.9***
(12.8) | 124.0***
(11.5) |
| Listing success | −18.3
(16.0) | 0.2
(0.2) | −13.7
(10.8) | −8.2*
(4.7) | −15.1***
(3.5) | −12.5***
(4.1) |
| × Crypto fund backed | 680.4***
(124.0) | 0.4
(0.6) | 429.6***
(73.9) | 166.0***
(33.3) | 273.0***
(41.2) | 115.6***
(29.4) |
| Listing sentiment | 2.4
(1.9) | 0.0
(0.0) | 2.3
(1.4) | 1.4*
(0.7) | −0.9**
(0.4) | 0.4
(0.6) |
| × Crypto fund backed | 42.9***
(6.5) | 0.1***
(0.0) | 26.6***
(4.3) | 10.0***
(2.0) | 14.9***
(2.1) | 9.1***
(1.8) |
| Crypto fund backed | 36.3***
(11.6) | 0.2*
(0.1) | 31.9***
(8.1) | 5.1
(3.3) | 14.5***
(3.8) | 12.4***
(3.6) |
| DDP controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Calendar week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Post-listing week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Obs. | 272,397 | 270,841 | 272,389 | 272,291 | 272,460 | 272,306 |
| R ² | 0.071 | 0.263 | 0.082 | 0.067 | 0.109 | 0.059 |
| Panel C: Replication of Table 3.5 with CF backing | | | | | | |
| Speculative activity (in week t−1) | 2.1***
(0.1) | 1.9***
(0.1) | 2.6***
(0.1) | 2.5***
(0.1) | 2.7***
(0.1) | 2.5***
(0.1) |
| × Crypto fund backed | 1.0***
(0.1) | 1.3***
(0.2) | 2.0***
(0.1) | 1.9***
(0.2) | 1.8***
(0.1) | 2.1***
(0.2) |
| Undervaluation | 0.4
(5.7) | 0.1
(0.1) | −3.5
(3.7) | 0.3
(1.7) | −3.1
(2.2) | 0.4
(1.8) |
| × Crypto fund backed | 161.1***
(38.0) | −0.2
(0.2) | 117.3***
(18.2) | 43.8***
(7.9) | 77.8***
(11.7) | 44.4***
(8.1) |
| Crypto fund backed | 257.3***
(15.5) | 2.0***
(0.1) | 85.5***
(8.1) | 36.0***
(3.1) | 52.2***
(4.4) | 41.5***
(3.1) |
| Token controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| DDP controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Calendar week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Post-listing week FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Obs. | 132,077 | 131,888 | 132,092 | 132,095 | 132,079 | 132,090 |
| R ² | 0.382 | 0.165 | 0.413 | 0.303 | 0.466 | 0.290 |

Note: These are regression results for the moderating effect of crypto fund (CF) backing on the impact of token exchange listing and other listing-related variables on DDP growth. Panel A replicates the analysis from Table 3.3, Panel B replicates the Year 1 analysis from Table 3.4, and Panel C replicates the analysis from Table 3.5, each incorporating CF backing as an additional variable. The

dependent variables are DDP activity, proxied with the number of transactions, DDP turnover, proxied with the percentage of tokens traded in total token supply, DDP adoption, measured as the number of users, new users, recurring users, and last users. DDP and token control variables are suppressed for brevity. All models control for calendar week and post-listing week FEs. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.5 Discussion and concluding remarks

3.5.1 Summary of main results

This paper tests five hypotheses. Our overarching hypothesis, the *Listing Hypothesis*, posits that DDPs with an exchange-listed token experience stronger growth than matched non-listed DDPs. Examining a large DDP-week panel of 553,958 observations in the period 2016–2024, we find that an exchange listing is associated with significant growth in platform metrics, including weekly transactions, token turnover, and user adoption rates. Specifically, when a DDP is listed on a public token exchange, weekly transactions increase by 283.3, platform turnover by 1.0 percentage points, and the number of users by 191.6. In post-hoc analysis, we find that exchange listings increase the probability of DDP survival. Similarly, our second hypothesis posits that successful token exchange listings may amplify the listing’s positive long-term effects on DDP growth, for which we also find supporting evidence. The first-week token price performance predicts DDP growth over the next three years.

Further, our *Spillover Hypothesis* posits that speculative activity spills over to non-speculative, fundamental activity on DDPs because of the feature of the shared asset; i.e., financial speculators and DDP adopters both own tokens. Consistent with this rationale, we find evidence that financial speculation increases subsequent non-speculative, fundamental DDP growth. Moreover, financial arbitrageurs might speculate especially on undervalued tokens, creating demand pressure until the equilibrium price is reached, thereby also impacting non-speculative, fundamental DDP activity, which we posit as our *fourth hypothesis*, for which we also find strong support.

Lastly, our *Asymmetric Decentralization Hypothesis* posits that listings promote the

dispersion of DDP token ownership. Our results reveal substantial decentralization dynamics in the left tail of the token ownership distribution, but not in the right tail. We also explore whether DDPs' growth benefits more from the going-public than the remaining-private decision. Cumming et al. (2025) show that crypto fund investments have a positive effect on DDP growth. Extending this line of research, we find, however, that crypto fund-endorsed going-public strategies benefit DDP growth most, followed by non-endorsed going-public strategies and crypto fund-endorsed remaining-private strategies.

3.5.2 Theoretical contributions and practical implications

Our study offers at least two theoretical contributions. First, our study contributes to the emerging literature on DDPs. Similar to non-decentralized digital platforms, DDPs face an early-adoption challenge, stemming from the coordination problem of incentivizing first adopters to join the platform when the platform will create value only if it is widely used (Rochet and Tirole, 2003; Weyl, 2010). Unlike non-decentralized digital platforms where investors and adopters are interested in different assets (equity versus products and services, the tokenization of DDPs creates a shared asset (i.e., the platform token), better aligning investors' and users' interests (Bakos and Halaburda, 2022a; Cumming et al., 2025). What remains to be shown is how exactly the feature of the shared asset helps DDPs overcome the early-adoption problem. Our study contributes to this question by exploring the role of the token exchange listing. Our empirical findings add to the literature in at least two regards. First, we show that, even though the listing-related spike in DDP adoption is rather short-lived, 15 to 20% of the peak adoption immediately after the listing is sustained in the long term, showing that token listings mitigate the early-adoption problem. Second, our spillover results suggest that the feature of the shared asset mitigates the early-adoption problem in large part because speculation appears identical to fundamental, non-speculative activity on the blockchain, thus attracting platform adopters by signaling prospects for network effects. Importantly, the spillover effect of speculation is

particularly salient when DDPs are undervalued, suggesting that DDP tokenization leads to a more efficient platform adoption path. These results are noteworthy as they empirically demonstrate the economic value of blockchain technology for platform economics.

Second, we contribute to the growing literature on blockchain-based entrepreneurial finance (Block et al., 2018, 2021; Belitski and Boreiko, 2022; Alshater et al., 2023). The literature has focused on various aspects of ICOs, such as offering valuations (e.g., Fisch, 2019; Momtaz, 2021b) short-term underpricing (e.g., Momtaz, 2020; Benedetti and Kostovetsky, 2021), long-term performance (e.g., Fisch and Momtaz, 2020; Benedetti and Nikbakht, 2021; Lyandres et al., 2022; Cumming et al., 2025; Drobetz et al., 2025), the impact of the regulatory environment (e.g., Huang et al., 2020; Bellavitis et al., 2021, 2022), and the signaling effects of founders' personal traits (e.g., Momtaz, 2021b; Colombo et al., 2022; Xia et al., 2024). A novelty of blockchain-based entrepreneurial finance is that the primary market (i.e., ICOs) is independent of the secondary market (i.e., the exchange listing). However, the listing decision's impact has not yet been studied for DDP growth, which is the gap we aim to fill. Our results indicate that listed DDPs grow faster than matched unlisted DDPs and, notably, the superior growth is driven by the attention received *because* of the listing (Figure 3.1). We also address the logical next question of how going-public decisions (i.e., the listing) compare to remaining-private decisions (i.e., crypto fund backing without listing) studied in Cumming et al. (2025). The marginal benefit for DDP growth is the highest for crypto fund-endorsed going-public strategies, followed by non-endorsed going-public and crypto fund-endorsed remaining-private strategies. Thus, the evidence from our study suggests that public markets for tokenized ventures may increase the welfare of market participants.

Finally, our study has practical implications for policymakers, entrepreneurs, and investors. First, for policymakers, our findings suggest that allowing early-stage DDPs access to public token markets — even with limited regulation — enhances DDP growth and survival. Given our finding that financial speculation can bolster fundamental protocol

growth, policymakers should develop novel regulatory frameworks that support regulated token listings, rather than applying existing securities laws that may restrict access to public markets for early-stage DDPs. Second, for entrepreneurs, going public correlates with positive network effects and should be a strategic target for the typical DDP. Founders should consider key factors that maximize the long-term impact of a listing on DDP growth, including securing prior crypto fund backing, timing the market to coincide with positive sentiment at launch, and implementing effective pricing and marketing strategies to ensure post-listing success. Lastly, for investors, investing in listed DDPs correlates with higher fair token values. Exchange listings enhance network effects, leading to more fundamental traction for the platform, and extend DDPs' expected lifetime. Institutional investors, such as crypto funds, should guide portfolio companies toward public listings to maximize their success prospects.

3.5.3 Limitations and avenues for future research

Our study represents only a first step toward understanding the impact of token exchange listing on DDP growth. In the following, we suggest several avenues for potentially fruitful further research.

Public market type. Our study focuses on tokenized DDPs, a novel platform type that emerged in the last 5-10 years. DDPs rely on asset tokenization, which raises concerns about the external validity of our findings, prompting several intriguing questions for further research. First, it would be interesting to analytically explore whether the tokenization of centralized digital platforms may function in a similar way and promote platform growth. Second, with regulations governing public token markets tightening and aligning more closely with those of traditional financial markets, it remains to be examined whether DDPs continue to benefit from token exchange listings to the same extent, as they did during our observation period.

Disaggregating financial speculation. Our results provide evidence that financial spec-

ulation increases future non-speculative, fundamental DDP growth. We suggest that this effect is driven by several spillover effects from token investors to platform users, including liquidity, information, and demand spillovers. To further uncover the underlying mechanisms of this effect, a more granular approach could be beneficial. First, analyzing the behavior of individual wallet addresses could yield insights into the behavioral patterns of financial token investors who transition to fundamental platform users. Second, distinguishing between different types of financial speculation seems to be interesting.

Finally, an increasing body of literature has been published around the optimal design of decentralized autonomous organizations (DAOs) (e.g., Tsoukalas and Falk, 2020; Chen et al., 2021; Cristiano Bellavitis and Momtaz, 2023; Lo Monaco et al., 2025). It would also be interesting to explore how different governance approaches affect listing probabilities and, ultimately, DAO growth. Moreover, we argue that token exchange listings provide DDPs with new opportunities to raise external finance through follow-on financing by divesting their treasury. Further analyses using on-chain data could explore the growth implications of this capital acquisition strategy and its impact on the operational performance of DDPs. Further, Drobetz et al. (2025) show that the timing of financing decisions in DDPs plays a crucial role for their future financial performance. A similar analysis related to the timing of token exchange listings and their impact on future DDP growth also appears as an interesting contribution to the platform literature.

3.5.4 Concluding remarks

This study has sought to shed light on the role of token exchange listings for the growth of decentralized digital platforms (DDPs), utilizing on-chain platform metrics. Our findings suggest that DDPs with a listed token attract more users, achieve higher platform activity, and experience increased token turnover. Token exchange listings disperse token ownership in the left but not in the right tail of the ownership distribution. Overall, our study contributes to the emerging literature on venture tokenization and public markets

for startups and outlines several promising avenues for future research.

3.6 References

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3.7 Appendix B

Table B.1: Variable definitions

| Variable | Definition | Data source |
|--|--|----------------------------------|
| <i>Listing-related variables</i> | | |
| 1 [Listing] | Dummy variable equal to 1 if the platform token was listed on a public exchange on the day of the observation, and 0 otherwise. | CoinMarketCap |
| Listing success | Dummy variable equal to 1 if the platform token has a higher price return than BTC in the week of listing, and 0 otherwise. | CoinMarketCap |
| Listing sentiment | Crypto market sentiment score calculated over the 30 days preceding the token listing. It measures market sentiment by subtracting the sum of days with negative BTC returns from the sum of days with positive BTC returns. | CoinMarketCap |
| Undervaluation | Dummy variable equal to 1 if the platform token return was below BTC return in four consecutive weeks, and 0 otherwise. | CoinMarketCap |
| <i>Platform growth variables</i> | | |
| Total DDP activity: # tx | Total number of weekly transactions conducted using the platform token. | Ethereum blockchain ⁸ |
| Fundamental DDP activity: # tx | Number of weekly transactions involving the platform token that exclude interactions with wallet addresses identified as exchanges. | Ethereum blockchain, Etherscan |
| Speculative DDP activity: # tx | Number of weekly transactions involving the platform token that include at least one wallet address identified as an exchange. | Ethereum blockchain, Etherscan |
| Total DDP turnover: $\frac{\text{tokens traded}}{\text{token supply}}$ | Weekly token transaction volume as a proportion of the total token supply. | Ethereum blockchain |
| Fundamental DDP turnover: $\frac{\text{tokens traded}}{\text{token supply}}$ | Weekly token transaction volume as a proportion of the total token supply, excluding transactions involving wallet addresses identified as exchanges. | Ethereum blockchain, Etherscan |
| Speculative DDP turnover: $\frac{\text{tokens traded}}{\text{token supply}}$ | Weekly token transaction volume as a proportion of the total token supply, including only transactions involving wallet addresses identified as exchanges. | Ethereum blockchain, Etherscan |
| Total DDP adoption: # users | Weekly count of unique wallet addresses involved in transactions with the platform token. | Ethereum blockchain |
| Fundamental DDP adoption: # users | Weekly count of unique wallet addresses involved in transactions with the platform token, excluding transactions involving exchange wallet addresses. | Ethereum blockchain, Etherscan |
| Speculative DDP adoption: # users | Weekly count of unique wallet addresses involved in transactions with the platform token, including only transactions where at least one participating address is identified as an exchange. | Ethereum blockchain, Etherscan |
| Total: # new users | Weekly count of unique wallet addresses that transacted with the token for the first time. | Ethereum blockchain |
| Fundamental: # new users | Weekly count of unique wallet addresses that transacted with the token for the first time, excluding transactions involving exchange wallet addresses. | Ethereum blockchain, Etherscan |
| Speculative: # new users | Weekly count of unique wallet addresses that transacted with the token for the first time, including only transactions where at least one participating address is identified as an exchange. | Ethereum blockchain, Etherscan |
| Total: # recurring users | Weekly count of unique wallet addresses involved in transactions with the platform token, excluding first-time transactions. | Ethereum blockchain |
| Fundamental: # recurring users | Weekly count of unique wallet addresses involved in transactions with the platform token, excluding both first-time transactions and those involving exchange wallet addresses. | Ethereum blockchain, Etherscan |

⁸All Ethereum blockchain data retrieved via *Google BigQuery* on 29 November 2024.

| | | |
|--|--|--------------------------------|
| Speculative: # recurring users | Weekly count of unique wallet addresses involved in transactions with the platform token that include at least one exchange wallet address, excluding first-time transactions. | Ethereum blockchain, Etherscan |
| Total: # last users | Weekly count of unique wallet addresses that conducted transactions with the platform token for the last time. | Ethereum blockchain |
| Fundamental: # last users | Weekly count of unique wallet addresses that conducted transactions with the platform token for the last time, excluding transactions involving wallet addresses identified as exchange. | Ethereum blockchain, Etherscan |
| Speculative: # last users | Weekly count of unique wallet addresses that conducted transactions with the platform token for the last time, including only transactions where at least one wallet address is identified as an exchange. | Ethereum blockchain, Etherscan |
| DDP decentralization: # tokenholders | Number of unique wallet addresses holding the platform token. | Ethereum blockchain |
| # tokenholders (<1% ownership) | Number of unique wallet addresses holding less than 1% of the token supply. | Ethereum blockchain |
| # tokenholders (1-5% ownership) | Number of unique wallet addresses holding between 1% and 5% of the token supply, including addresses with exactly 5%. | Ethereum blockchain |
| # tokenholders (5-20% ownership) | Number of unique wallet addresses holding between 5% and 20% of the token supply. | Ethereum blockchain |
| # tokenholders (>20% ownership) | Number of unique wallet addresses holding more than 20% of the token supply. | Ethereum blockchain |
| DDP decentralization: Nakamoto coefficient | The minimum number of largest wallet addresses needed to exceed 50% of circulating token supply in a given week. | Ethereum blockchain |

Control variables

| | | |
|------------------------|--|---|
| Crypto fund backed | Dummy variable equal to 1 if the platform secured crypto fund backing before or on the day of the observation, and 0 otherwise. | Messari, Crypto Fund Research, CryptoRank |
| Minimum viable product | Dummy variable equal to 1 if the platform has a minimum viable product available, and 0 otherwise. | ICOMarks, ICObench |
| Pre-sale | Dummy variable equal to 1 if the platform conducted a pre-sale before its public offering (e.g., ICO), and 0 otherwise. | ICOMarks, ICObench |
| Whitelist | Dummy variable equal to 1 if the platform implemented a whitelist during its initial offering, and 0 otherwise. | ICOMarks, ICObench |
| KYC | Dummy variable equal to 1 if the platform restricts certain investors via a know-your-customer (KYC) process, and 0 otherwise. | ICOMarks, ICObench |
| Bonus | Dummy variable equal to 1 if the platform offers a bonus structure, which typically involves discounted or free tokens if individual wallet addresses invest above and beyond a certain pre-determined investment amount, and 0 otherwise. | ICOMarks, ICObench |
| Bounty | Dummy variable equal to 1 if the platform offers a bounty program, which rewards individuals (mostly in the form of free tokens) for marketing or other activities, and 0 otherwise. | ICOMarks, ICObench |
| Open source | Dummy variable equal to 1 if the platform makes its source code available on GitHub, and 0 otherwise. | GitHub |
| Team size | The total number of full-time members of the platform. | LinkedIn, ICOMarks, ICObench |
| Expert rating | Average rating based on the consensus of industry experts, higher scoring indicates a higher overall platform quality. | ICOMarks, ICObench |
| Token volatility | weekly standard deviation of daily returns of the listed platform token, z-standardized. | CoinMarketCap |
| Token liquidity | weekly USD trading volume of the listed platform token, as % of the tokens' USD market cap. | CoinMarketCap |

| | | |
|---------------|--|---------------|
| Overvaluation | Dummy variable equal to 1 if the platform token outperformed BTC in four consecutive weeks, and 0 otherwise. | CoinMarketCap |
|---------------|--|---------------|

Table B.2: First-stage selection model of DDP token exchange listings

| Dependent variable: | Exchange listing |
|------------------------|------------------------------|
| Minimum Viable Product | 0.1 [*]
(0.1) |
| Pre-sale | −0.1
(0.1) |
| Whitelist | −0.1
(0.1) |
| KYC | 0.1
(0.1) |
| Bonus | 0.2 ^{**}
(0.1) |
| Bounty | −0.2 ^{***}
(0.1) |
| Open source | −0.1
(0.1) |
| Team size | 0.0
(0.0) |
| Expert rating | 0.2 ^{***}
(0.0) |
| ERC-20 | −0.1 ^{**}
(0.1) |
| Soft cap | −0.4 ^{***}
(0.1) |
| Hard cap | 0.1
(0.1) |
| BTC price | 0.0 ^{***}
(0.0) |
| Interest rate | −0.1 ^{***}
(0.0) |
| Crypto market cap | 0.0
(0.0) |
| Obs. | 4,497 |
| R ² | 0.093 |

Note: This table reports the regression results for the first-stage probit selection model used in the IV and PSM second-stage regressions detailed in Table 3.3. The dependent variable is a dummy variable that equals one if the DDP was listed on an exchange at any point during its lifetime, and zero otherwise. Robust standard errors are indicated in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

CHAPTER 4

Essay III: Market Reactions to Cryptocurrency Regulation: Risk, Return, and the Role of Enforcement Quality

Abstract

We explore the risk-return trade-off in international regulation of cryptocurrency markets using a unique sample of regulations implemented between July 2018 and April 2023. Various regulation types have reduced risk in cryptocurrency markets while having differential impacts on raw and risk-adjusted returns. Given the legal challenges for national jurisdictions in regulating international markets, we develop a digital asset regulatory strength index (DARSI) and study the impacts of national regulatory enforcement quality on the risk and return effects of cryptocurrency regulations. We find that strong enforcement quality, measured based on the strength of formal institutions, amplified the regulations' intended effects. The amplification effect is more pronounced for regulations announced by a financial regulator and for more liquid tokens. Consistent with the view that normative compliance-seeking facilitates the adoption of norms, we also find that cultural uncertainty avoidance amplifies a regulation's intended effects.

Authors: Douglas Cumming, Johannes Fuchs and Paul P. Momtaz

First Author: Johannes Fuchs

4.1 Introduction

The launch of many cryptocurrencies has created a challenge for policymakers (Hornuf et al., 2022), who have responded to their emergence through various regulatory approaches, including the development of integrative frameworks, the regulation of specific aspects such as taxation or anti-money-laundering laws, and even outright bans. Even though the scope and details of the regulations vary, the overall communicated goal of de-risking cryptocurrency markets is consistent across jurisdictions. Public statements from national regulators further emphasize this target. As the Monetary Authority of Singapore (MAS) has stated, ‘to reduce the risk to consumers from speculative trading in cryptocurrencies, MAS will require that [crypto] service providers ensure proper business conduct and adequate risk disclosure’.⁹ According to the UK government, ‘Our robust approach to regulation mitigates the most significant risks while harnessing the advantages of crypto technologies’.¹⁰ However, the effectiveness of cryptocurrency regulations is empirically understudied, a research gap that is all the more striking considering that the typical crypto investor — characterized by high-return seeking and preferences for privacy and permissionless access (Hackethal et al., 2021; Steinmetz et al., 2021) — might be repelled by such regulations. The present study addresses this research void, asking the research question: How do international cryptocurrency market regulations impact the risk-return profile of listed tokens and how are these effects shaped by the formal and informal institutions of their respective jurisdictions?

Auer and Claessens (2018) and Chokor and Alfieri (2021) provide initial evidence on short-term market reactions to regulatory announcements but leave the longer-term impacts largely unexplored. While insights into the effects and effectiveness of regulation can be drawn from traditional stock market studies (e.g., Armstrong et al., 2010; Ramiah et al., 2013), the applicability of these findings to cryptocurrency markets is limited due

⁹<https://thediplomat.com/2022/10/singapore-mulls-tighter-restrictions-on-crypto-trading/>

¹⁰<https://www.gov.uk/government/news/uk-sets-out-plans-to-regulate-crypto-and-protect-consumers>

to several key differences: (i) cryptocurrency markets have historically operated with little to no regulatory oversight prior to the introduction of new laws (Fuchs & Momtaz, 2024), (ii) regulatory announcements tend to affect the entire asset class rather than specific subsets, and (iii) the high degree of interconnectedness within the market is likely to result in spillover effects from regional regulations to the broader ecosystem (e.g., Borri and Shakhnov, 2020; Bellavitis et al., 2022).

Market participants have adopted various strategies to capitalize on the unique regulatory environment surrounding cryptocurrencies. For example, Mokhtarian and Lindgren (2018) show that crypto fund managers operating outside traditional fund regulatory regimes may be able to attract capital from a broader investor base and offer lower costs, benefiting from favorable tax treatment and custody rules. However, they also note that this environment introduces substantial uncertainty and contributes to the asset class's idiosyncratic risk profile. The heightened risk associated with regulatory ambiguity has led some cryptocurrency businesses to relocate to jurisdictions offering clearer legal frameworks. For instance, in 2021, FTX, one of the world's largest centralized cryptocurrency exchanges at the time, relocated its operations from Hong Kong to the Bahamas. The move came shortly after the Bahamian government enacted the Digital Assets and Registered Exchanges (DARE) Act,¹¹ which provided a formal regulatory framework allowing cryptocurrency exchanges to operate legally.

Given the advantages and disadvantages associated with varying levels of regulatory completeness, and the different ways in which market participants may respond, there is a clear need for further research to examine how cryptocurrency markets react to regulation and to assess whether traditional stock market theories apply in this setting. Our research aims to fill this gap by testing several hypotheses related to short- and longer-term market reactions, as well as key factors that influence these responses. First, we investigate changes in cryptocurrency market risk following new regulations. Using asset

¹¹<https://time.com/6266711/ftx-bahamas-crypto/>

return volatility, measured as standard deviation (Markowitz, 1952), as a risk indicator, we expect that increased regulatory clarity reduces uncertainties around future returns and will, therefore, lower the overall market risk for cryptocurrencies (H1). As regulatory announcements provide new information, they might not only modify immediate volatility but may also have lasting effects on the asset class by altering risk perceptions and investor confidence, thereby shaping market dynamics and potential capital inflows.

Second, we explore both the immediate and longer-term market reactions to regulatory announcements. If the efficient market hypothesis holds (Malkiel & Fama, 1970), we expect an immediate abnormal price reaction in the cryptocurrency market following the announcement of new regulation.. The direction of this reaction may be positive (H2b) due to anticipated benefits such as enhanced shareholder protection (La Porta et al., 1997, 1998, 2002), or negative (H2a) if regulations increase operational costs (Christensen & Haveman, 1981; Larcker et al., 2011) or reduce demand from certain investor groups. If the efficient market hypothesis does not hold or if investors do not respond rationally during the event window, longer-term return adjustments may occur following regulatory announcements. These changes could disrupt the previous risk-return relationship. A negative longer-term price response would lead to a lower post-event Sharpe ratio (H3a), while a positive response would result in a higher post-event Sharpe ratio (H3b).

Our fourth hypothesis focuses on the impact of the regulatory and political environment of the jurisdiction in which the regulation is announced. In line with prior studies based on the traditional stock market (e.g. Berglöf and Claessens, 2006; Bhattacharya and Daouk, 2009; Humphery-Jenner, 2013), we expect that a higher enforcement probability of the announced cryptocurrency regulations, due to stronger formal institutions, amplifies the risk reduction in the cryptocurrency market. Lastly, we assess the role of informal institutions in the effectiveness of regulation. Using cultural uncertainty avoidance as a proxy, as introduced by Hofstede (2001), we expect that the presence of stronger informal institutions in the jurisdiction announcing the regulation enhances the associated risk

reduction in the cryptocurrency market (H5).

To assess these hypotheses we compiled a dataset following a structured three-step approach: (i) extensive data collection, (ii) stringent confirmation of event-related criteria, and (iii) careful removal of overlapping announcements. Throughout the process, we manually reviewed over 2,000 websites, including official government and regulatory bodies, independent central banks, and various local news outlets and law firms across 205 jurisdictions from July 2018 to April 2023. This process yielded a refined sample of 35 distinct regulatory events, categorized into general regulatory frameworks (19), specific AML/CFT laws (5), tax regulations (9), and crypto bans (3). Following the categorization by Bongini et al. (2025), our token sample encompassed cryptocurrencies and utility tokens, excluding stablecoins, security tokens, and NFTs, due to their unique characteristics. The resulting token sample size ranges from 257 in 2018 to 1213 in 2022 and 1209 in 2023. We compiled daily price data from CoinMarketCap for all tokens included in our sample. To allow the assessment of initial market reactions, we adopt the event study methodology (Brown & Warner, 1980, 1985), which is widely applied in the financial literature. We use a 5-day event window centered on the announcement date and an 80-day estimation window preceding it. Post-event effects are measured using a second 80-day window beginning immediately after the event period. In addition to the event study, we estimate several ordinary least squares models with different specifications and include a vector of control variables to account for potential confounding factors.

Our post-event window risk analysis reveals that, on average, new regulations decrease the market standard deviation by 0.496 percentage points. These findings confirm our first hypothesis (H1) and provide evidence that regulators and governments are succeeding with their targeted risk reduction through new regulations. Our findings are significant at the 1% level and show an average risk reduction effect for all types of regulation. Our results also show that, on average, the cumulative abnormal return (CAR) during the event window of a regulatory announcement is -1.4137% . The results are significant at

the 1% level and confirm H2a. Surprisingly, we observe that the initial market reaction is negative for all types of investments except tax regulations. Further interesting findings emerge with regard to post-event return and Sharpe ratio changes. Our study provides evidence that, on average, cryptocurrency investors profit on a risk-adjusted basis from new regulations. Comparing the Sharpe ratio during the 80-day post-event window with that of the pre-event window, it is observable that, on average, the ratio increases by 0.585, significant at the 1% level. The mean return for cryptocurrency moves back closer to the pre-event level (Δ 0.018 percentage points), leading to a positive Sharpe ratio based on the overall risk reduction. This finding confirms H3b and indicates that the cryptocurrency market might not be fully efficient, given that the asset prices are still reacting in the post-event window (Malkiel & Fama, 1970).

Our study also shows that the level of risk reduction depends on the state of the regulatory and political environment of the jurisdiction where the law is announced. An increased governance enforcement index leads to amplified risk reduction, confirming H4 and demonstrating the dependency of the success of new regulation on the overall regulatory environment (Becker, 1968; Polinsky and Shavell, 2000; La Porta et al., 2006). In economic terms, an increase in the governance enforcement index of the jurisdiction by one percentile point leads, on average, to an increased risk reduction of -0.026 percentage points. This confirms the findings of Bhattacharya and Daouk (2009) and Humphery-Jenner (2013) that, if the jurisdiction does not provide an environment where investors believe in the enforcement of the new regulation, the new law is less successful and might even be counterproductive. We have also created a novel digital asset regulatory strength index (DARSI) to quantify cryptocurrency regulation status across the jurisdictions and evaluate the effect of regulatory strength on changes in the assets' risk-return characteristics. Using DARSI as an alternative metric for the strength of formal institutions, we confirm that a higher DARSI amplifies the risk reduction observed during the post-event period. We present evidence showing that if the regulation is the first of its kind, the

risk reduction effect is further amplified by -1.486 percentage points. We also show that informal institution quality is of importance for the ultimate success of cryptocurrency regulation. An increase of one unit in cultural uncertainty avoidance (Hofstede, 2001) leads, on average, to an additional return volatility reduction of -0.081 percentage points.

Our study makes several important theoretical contributions to the existing literature. First, we expand the findings regarding the impact of regulation on the post-event attributes of financial assets. While prior studies have mostly focused on the direct impact of regulation on valuation and shareholder wealth (e.g. Prager, 1989; Fields et al., 1990), we shed light on its impact on the post-event risk level. We present new evidence that regulation de-risks the market, measured based on the dispersion of the values around its mean. Our findings suggest that implementing regulations in a market that is mostly unregulated leads to disproportional risk reduction compared to return changes, decoupling the pre-event risk-return relationship. Based on these findings, we conclude that investors are profiting from new regulations on a risk-adjusted level. We also expand the cryptocurrency literature in several areas. Prior studies investigating the impact of regulation on the cryptocurrency market (e.g. Auer and Claessens, 2018; Chokor and Alfieri, 2021) were conducted based on a selected sample of the most prominent cryptocurrencies and events prior to 2019. Our study includes the most comprehensive token sample available and expands the time frame of regulatory announcements until April 2023. While our study generally confirms the initial negative price reactions to regulatory announcements, our setup additionally shows that the direction and size of the CAR depend on the type of regulation. Additionally, considering the post-event window returns, we provide evidence that the cryptocurrency market is not fully efficient. Our unique sample also allows us to determine the impact of regulations on different types of tokens. We show that larger and more traded tokens experience increased risk reduction compared to smaller and less traded tokens.

Our results show that post-event risk reduction varies across jurisdictions, indicating

that regulations announced by jurisdictions with stronger property rights and higher-quality contract enforcement lead to greater reductions in risk compared to those from jurisdictions with weaker governance. We observe similar results for informal institutional strength, as higher levels of cultural uncertainty avoidance are associated with amplified reductions in return volatility following regulation. Furthermore, our DARSI metric enables the strength of cryptocurrency regulation to be measured and compared across jurisdictions. These findings provide empirical evidence that the content and scope of policy changes play a significant role in driving post-event risk reduction. The findings are highly relevant for policymakers, regulators, investors, and other participants in the cryptocurrency market. The strong evidence of both immediate market reactions and longer-term post-event effects can support policymakers and regulators in anticipating the outcomes of their interventions. Moreover, our results demonstrate that different types and design features of new laws lead to varying market responses. As the first study to show that regulation can, on average, have a positive impact on investors' risk-adjusted returns, our findings may contribute to reducing initial overreactions to regulatory announcements and enhancing overall market efficiency.

The remainder of this paper is structured as follows. Section 4.2 provides an overview of the development of cryptocurrency regulation, explores the characteristics among the different types of regulation, and derives testable hypotheses. Section 4.3 shows the data collection process and descriptions of the included variables, followed by an overview of the summary statistics and chosen econometric approaches. Section 4.4 presents and analyzes the empirical results of our study. Section 4.5 discusses the theoretical contribution and practical implications of our results, highlights limitations, and offers potential avenues for future research.

4.2 Background and Hypotheses

4.2.1 Regulation of cryptocurrencies

Cryptocurrencies and the idea of issuing financial instruments within a decentralized ecosystem emerged from growing dissatisfaction with the perceived partiality of traditional financial markets (Nakamoto, 2008; Fisch, 2019), offering promises of a trustless system of transactional governance (Singh et al., 2024). Since the minting of the first Bitcoin in 2009, the cryptocurrency market has evolved rapidly into one of the largest asset classes, with a total market capitalization of approximately \$2.3 trillion.¹² All assets exist as tokens—a cryptographically protected digital unit on a blockchain (Fisch, 2019)—and can vary widely in design and underlying value drivers (Alexander & Dakos, 2024). In most jurisdictions, digital tokens were not initially covered by traditional financial market regulations and therefore remained (or still remain) unregulated. This regulatory gap has led to market inefficiencies such as moral hazard and adverse selection (e.g., Momtaz, 2021; Hornuf et al., 2022) as well as significant fraud events (e.g., Barone and Masciandaro, 2019; Allen et al., 2021; Hornuf et al., 2023). The digital asset market remains vulnerable to manipulation practices that are strictly prohibited in traditional financial markets, including insider trading (Akyildirim et al., 2020), front running (Daian et al., 2019), wash trading (Cong et al., 2023), and ‘pump and dump’ schemes (Dhawan & Putniņš, 2022).

Regulatory bodies across jurisdictions increasingly recognize not only the importance of the underlying blockchain technology (Rawhouser et al., 2024) but also the rapid expansion and growing risks associated with the cryptocurrency sector. In response, an expanding number of governments and financial market authorities have begun engaging more actively with the industry. Due to the unique characteristics of cryptocurrencies, market participants lack established regulatory frameworks based on comparable asset classes. As a result, regulators have issued new laws or guidelines clarifying how existing laws apply.

¹²As of 22 June 2024, according to CoinMarketCap.

Given the global fragmentation of financial authorities, this has led to a wide variety of regulatory approaches, often reflecting a trade-off between conservatism and innovation. Based on our analysis of all regulatory announcements from July 2018 to April 2023, four main categories emerge: (i) AML/CFT laws, (ii) crypto bans, (iii) regulatory frameworks, and (iv) tax regulations.

As summarized in Table 4.1, AML and CFT regulations typically require businesses and individual cryptocurrency participants to identify themselves in accordance with specific guidelines. This enhanced transparency enables regulators to trace the sources of wealth involved in transactions. Usually issued by financial regulators or government agencies, AML/CFT laws aim to de-risk the market and may lead to the exclusion of participants unable to meet compliance standards. Although the exact requirements and targeted activities vary, cryptocurrency exchanges and related businesses are generally obligated to implement stricter know-your-customer (KYC) procedures, reducing investor anonymity. In contrast, when governments, central banks, or financial regulators issue a crypto ban, market participants within the jurisdiction are prohibited from engaging in selected or all specified cryptocurrency activities.

Regulatory frameworks for cryptocurrencies can vary widely, ranging from comprehensive guidelines and laws that govern a broad spectrum of activities related to distributed ledger technologies, as seen in Switzerland's 2018 legal framework for blockchain, to the legalization of specific use cases, such as El Salvador's announcement in June 2021 declaring Bitcoin as legal tender. The exact details of regulatory frameworks are highly dependent on the general stance of the government or the financial regulator on cryptocurrencies. This stance can result in either the creation of a supportive environment that fosters innovation and future development, or in restrictive regulations that significantly limit cryptocurrency-related activities. In all cases, new frameworks provide market participants with increased regulatory clarity; however, the actual impact on these participants depends on the specific design and scope of the laws or guidelines. As a result, exchanges

and other cryptocurrency businesses may be required to comply with new standards and adjust their operations accordingly.

Announced regulation of tax authorities regarding the taxation of capital gains and income from cryptocurrencies, not only increases regulatory clarity for investors but also enables authorities to collect additional revenue. Typically, such regulations impose stricter bookkeeping requirements on investors, who are then obligated to report their trading gains and other cryptocurrency-related income and ultimately pay the applicable taxes. However, the transition to a regulated taxation regime can also open the door for investors to apply tax strategies, such as tax-loss harvesting. While individual investors are generally subject to the tax laws of their country of legal and tax residency, the situation is more complex for companies operating cryptocurrency-related businesses. For instance, centralized cryptocurrency exchanges must comply not only with the laws of their home jurisdiction but also with those of any jurisdiction in which they intend to operate. If a country introduces a new framework, for example, relating to AML measures or digital asset categorization, the exchange must either adjust its services accordingly for users in that country or cease operations there. In some cases, regulatory frameworks may also require exchanges to obtain a local license to legally operate within the jurisdiction.

Table 4.1: Comparison of regulation types

| | AML/CFT | Crypto Ban | Regulatory Framework | Tax |
|--|---|--|--|---|
| Entities ¹³ | <ul style="list-style-type: none"> Financial Regulator, Government | <ul style="list-style-type: none"> Government, Central Bank, Financial Regulator | <ul style="list-style-type: none"> Government, Financial Regulator | <ul style="list-style-type: none"> Tax Authorities |
| Content | <ul style="list-style-type: none"> AML and CFT requirements for businesses and/or investors that conduct activities related to cryptocurrencies (e.g., KYC/KYB) | <ul style="list-style-type: none"> Prohibition of some or all activities related to cryptocurrencies within the jurisdiction | <ul style="list-style-type: none"> Definition of legal framework of specific or all activities related to cryptocurrencies within the jurisdiction | <ul style="list-style-type: none"> Guidance and clarification on the taxation of capital gains and generated income from cryptocurrencies |
| Purpose | <ul style="list-style-type: none"> De-risking the cryptocurrency market through the identification of market participants Exclusion of bad actors | <ul style="list-style-type: none"> Prohibition of cryptocurrency-related activities | <ul style="list-style-type: none"> Definition of framework to provide regulatory clarity for current and future market participants Enablement of future developments in the cryptocurrencies sector | <ul style="list-style-type: none"> Enablement of collection of tax income for the authorities Provision of regulatory clarity regarding cryptocurrencies taxation |
| Possible impact on market participants | <ul style="list-style-type: none"> Exchanges and other cryptocurrency businesses must comply with defined requirements and potentially adjust operations (e.g., implementation of KYC process) Reduction of privacy for investors Potential exclusion of specific investor groups from certain cryptocurrency-related activities | <ul style="list-style-type: none"> Prohibition of residence to engage in defined cryptocurrencies related activities Prohibition of cryptocurrency businesses to operate within the jurisdiction | <ul style="list-style-type: none"> Exchanges and other cryptocurrency businesses must comply with defined requirements and potentially adjust operations Final impact strongly depends on the individual design of the framework | <ul style="list-style-type: none"> Requirement to pay taxes on financial gains and/or income generated from cryptocurrencies Possibility to apply tax strategies (e.g., tax loss harvesting) Increased book-keeping requirements |
| Subtypes | <ul style="list-style-type: none"> Variation in exact requirements and applicable activities | <ul style="list-style-type: none"> Ban of individual activities (ICOs, trading, etc.) or tokens vs. full ban (all activities and tokens) | <ul style="list-style-type: none"> Wide range of variation depending on targeted scope and general stance of the regulator to cryptocurrencies | <ul style="list-style-type: none"> Capital gains vs. income (staking, liquidity provision, etc.) |

Note: This table shows the key characteristics of the four different types of cryptocurrency regulations: (i) AML/CFT regulation, (ii) crypto ban, (iii) regulatory framework, and (iv) tax regulations. The different rows include details about the issuing entities, content, purpose, possible impact on market participants, and subtypes of the four regulation categories.

¹³Depending on the jurisdiction, the financial regulator and central bank can be either an independent entity or directly controlled by the government.

4.2.2 Hypotheses

4.2.2.1 Market risk reaction to regulatory announcements

While most traditional literature focuses on the direct impact of regulation on valuation and shareholder wealth (e.g., Prager, 1989; Fields et al., 1990), our event study setup allows us to investigate the effects of regulation on a broader set of key financial asset attributes. Regulatory announcements may influence not only investors' expectations about future returns but also their estimated risk premia, thereby affecting asset volatility (Yadav, 1992; Copeland and Stapleton, 1993). According to traditional portfolio theory, one of the most relevant indicators of an asset's risk is the dispersion of returns around the mean (Markowitz, 1952). Higher volatility (i.e., standard deviation) in asset price returns signals greater risk, leading investors to demand higher returns as compensation (e.g., Lintner, 1965a, 1965b; Sharpe, 1966). The announcement of a new cryptocurrency regulation may reduce market risk for two main reasons.

First, assuming asset prices reflect fundamental values, volatility can be interpreted as a proxy for information content (Yadav, 1992) and is closely tied to the flow of information in the market (Ross, 1989). Regulatory announcements represent new, relevant information and are therefore expected to immediately affect volatility in the short term. The longer-term impact on volatility may depend on how the regulation influences other fundamental characteristics of the investment.

Second, although investors are generally compensated for higher risk via elevated risk premia, increased volatility has broader negative implications for the overall market. Yadav (1992) highlights several of these, including the risk of inefficient capital allocation — particularly when volatility is unrelated to changes in fundamentals — as well as diminished investor confidence and higher transaction costs due to elevated liquidity premiums. These concerns may justify government and regulatory efforts to protect investors by reducing market risk through targeted regulation. In highly volatile markets such as cryptocurrency,

we expect that regulatory interventions will lower overall investor risk. Historical evidence from emerging markets supports this view: in those contexts, the introduction of investor protection laws was associated with decreased volatility and improved capital flows (Bhattacharya & Daouk, 2009). By enhancing contract enforceability and investor rights, such regulations lay the foundation for greater market confidence and sustained investment.

H1: Increased regulatory clarity decreases the risk in the cryptocurrency market, indicated by a reduced post-event standard deviation.

4.2.2.2 Immediate and longer-term asset return reaction to regulatory announcements

In an efficient market, asset prices reflect all available information (Malkiel & Fama, 1970), meaning that new, relevant information —such as regulatory announcements— should immediately affect prices. The initial market reaction of an asset is expected to reflect both the anticipated dollar impact on investor wealth and the perceived probability of enforcement (e.g., Schwert, 1981; Binder, 1985). However, due to behavioral biases, markets often react more strongly to recent information, as investors tend to overweight current news, leading to amplified price responses (Bondt & Thaler, 1985). As a result, the announcements of cryptocurrency regulation announcements are expected to cause immediate price adjustments in listed tokens, visible as abnormal returns on the event day.

Abnormal returns following regulatory announcements may be negative for several reasons. First, operating in unregulated environments tends to be less costly; the introduction and enforcement of regulation often increase compliance burdens, reducing profitability. Regulations that compel firms to reallocate resources toward non-productive uses, such as establishing internal audit functions or complying with stricter governance rules, have been shown to impair operational efficiency (Christainsen & Haveman, 1981; Larcker et al., 2011). Second, Investor identification requirements, particularly those introduced under AML/CFT laws, can further raise trading costs through heightened compliance and

reporting obligations. Moreover, such regulations may also restrict participation from certain investor groups, such as those in high-risk jurisdictions, potentially leading to increased selling pressure. Prior research based on a small sample of cryptocurrencies has provided first evidence of negative cumulative abnormal returns in response to regulatory news (Auer & Claessens, 2018; Chokor & Alfieri, 2021).

On the other hand, new laws can also create value and lead to positive stock price reactions. First, regulation can benefit shareholders of an asset class due to increased shareholder protection (e.g. La Porta et al., 1997, 1998, 2002), positively impacting shareholder value (Bruno & Claessens, 2010). Therefore, introducing regulatory frameworks in a market such as the cryptocurrency market, characterized by little or no shareholder protection, might lead to an increase in expected shareholder value. The higher level of protection and potential increase in enforcement rights of investors ultimately reduce uncertainty about future returns. Second, new regulations may improve governance practices within crypto ventures. Prior literature finds that regulatory interventions have historically prompted improvements in corporate governance structures (Becher & Frye, 2011; Kole & Lehn, 1999). When prior governance arrangements were weak or potentially extractive, such improvements can lead to meaningful gains in shareholder value (Larcker et al., 2011). A prior study by Auer and Claessens (2018) supports these theories by showing results that regulatory announcements translate to a positive CAR of cryptocurrencies.

***H2a:** Increased regulatory clarity decreases expected shareholder wealth, leading to a negative short-term price reaction.*

***H2b:** Increased regulatory clarity increases expected shareholder wealth, leading to a positive short-term price reaction.*

Assuming the efficient market theory holds (Malkiel & Fama, 1970), and that the price effect of the event is immediately reflected in the asset price during the event window, no delayed price reactions are expected. Therefore, the aforementioned effects would solely

lead to abnormal short-term price reactions, leaving longer-term post-event asset characteristics unchanged. The post-event risk-return ratio (i.e., Sharpe ratio) would remain constant, with the expectation that the forecasted risk reduction will ultimately lead to a proportional reduction in the asset's return (Sharpe, 1964; Lintner, 1965a, 1965b; Fama, 1971). However, if the efficient market theory does not hold, or if investors do not react rationally during the event window, further price responses in the post-event window may occur. While the direction of these price reactions may be either positive or negative, following the same reasoning as for the short-term reaction, cryptocurrencies in either scenario would decouple from their pre-event risk-return relationship after the regulatory announcement.

H3a: Increased regulatory clarity leads to a negative longer-term price reaction, reducing post-event Sharpe ratio.

H3b: Increased regulatory clarity leads to a positive longer-term price reaction, increasing post-event Sharpe ratio.

4.2.2.3 The impact of formal institution strength on regulation success

The strength of formal institutions may be positively associated with the success of cryptocurrency regulations for several reasons. First, the market impact of a newly announced regulation often depends not only on the design of the law itself but also on the effectiveness of its enforcement. Prior literature has explored the link between legal enforcement and economic outcomes in traditional securities markets (e.g., Becker, 1968; Polinsky and Shavell, 2000; La Porta et al., 2006). These studies suggest that enforcement success is largely determined by the quality of formal institutions and the broader legal framework within a jurisdiction (Bhattacharya & Daouk, 2009). Berglöf and Claessens (2006) further highlight that political and institutional barriers to enforcement, particularly in emerging markets, can hinder the creation of an effective business environment and sound corpo-

rate governance. Subsequent research supports this view, noting that the market can only fully benefit from regulation when strong legal enforcement mechanisms are in place (e.g., Daske et al., 2008; Chen and Qing, 2011).

Second, a weak regulatory environment and a low probability of enforcement may lead to worse outcomes than if no regulation had been introduced at all. Bhattacharya and Daouk (2009) argue that, in the absence of regulation, market participants operate within a “bad equilibrium.” When a law is both enacted and enforced, the system may shift to a “good equilibrium.” However, if a law is introduced but not enforced, those market participants who comply with the regulation may be worse off than under the initial no-law state. Humphery-Jenner (2013) supports this view in the context of disclosure laws, noting that unenforced regulation can exacerbate disparities: companies that do not comply may diverge even further from good practices, while compliant firms raise the standard of credibility, thus deepening the asymmetry.

Third, the laws introduced by various jurisdictions to regulate the cryptocurrency market often represent the first formal attempt to govern this previously unregulated asset class. In such a context, the strength of the regulatory environment becomes particularly crucial, as it directly affects the likelihood of successful enforcement.

***H4:** Stronger formal institutions in the jurisdiction that announce the cryptocurrency regulation amplify the risk reduction in the cryptocurrency market.*

4.2.2.4 The impact of informal institution strength on regulation success

Dau et al. (2022) define informal institutions as the unwritten rules and prevailing social norms within a society that influence market functioning. While extensive research exists on the role of formal institutions in the success of new regulation, the impact of informal norms that shape social behavior remains less explored (Dau et al., 2022). Prior studies in this context have examined a wide range of informal factors, including respect, loyalty, social trust, and corruption (e.g., Helmke and Levitsky, 2004; Sartor and Beamish, 2014;

Godinez and Liu, 2015). Hofstede (2001) developed a scoring method to assess the extent to which a society relies on established rules and interaction patterns. He argues that the higher this reliance, the more the society seeks to avoid uncertainty, reflecting discomfort with uncontrollable outcomes. We posit that in jurisdictions characterized by high levels of uncertainty avoidance, the announcement of new regulations is likely to have an amplified effect, as individuals are more inclined to adhere to formalized rules. In contrast, in societies more tolerant of uncertainty, the regulatory impact may be less pronounced.

H4: Stronger informal institutions in the jurisdiction that announces the cryptocurrency regulation amplify the risk reduction in the cryptocurrency market.

However, it is important to note that stronger informal institutions may also emerge in environments where formal institutional structures are weak or underdeveloped. In such settings, informal norms and societal coordination mechanisms might act as substitutes rather than complements of formal regulation. As a result, the presence of strong informal institutions might reduce the incremental impact of newly announced regulations, leading to a weaker rather than stronger market reaction.

4.3 Data and Methods

4.3.1 Empirical setting: Data sources and sample

4.3.1.1 Regulatory events

The generation of the regulatory event sample is based on three key steps: (i) data collection, (ii) confirmation of event requirements, and (iii) removal of overlapping announcements. First, we manually searched for cryptocurrency-related regulation announcements in 205 jurisdictions from July 2018 to April 2023. In this process, we considered official government and government-related regulator websites, the independent regulator and central bank websites and conducted a general Google web search, including the manual

screening of local law firms and news outlets within the different jurisdictions. In total, this step included the manual in-depth screening of more than 2,000 websites. Second, before we included the information from Step 1 in our regulatory event longlist, it had to satisfy three criteria: (i) the law text must be directly related to cryptocurrencies, (ii) the announcement must be related to an official law or regulation proposed to become effective within the jurisdiction of the announcement, removing pure ‘market rumors’ that were not announced or confirmed by official statements of the government, regulator, or other official bodies, and (iii) the date of the regulatory announcement must be identifiable.

Third, in scenarios where we had information on more than one regulatory announcement during a specific event window, we removed both observations from the sample. Given that the primary aim of our study is to assess the impact of distinct types of regulatory actions on market outcomes. Including events with overlapping regulations would introduce ambiguity into our analysis, as it would obscure which regulatory action is exerting the observed effects. Ultimately, we derived a baseline sample of 35 events, including regulatory announcements belonging to our categories of general Regulatory Frameworks (19) and specific regulations such as AML/CFT Laws (5), Tax (9), and Crypto Bans (3). All details about the data sources of the 35 included regulations, including announcement date, description, country, regulation type, source type, and web links to the announcements, are shown in Table C.7 in the Appendix.

4.3.1.2 Token sample

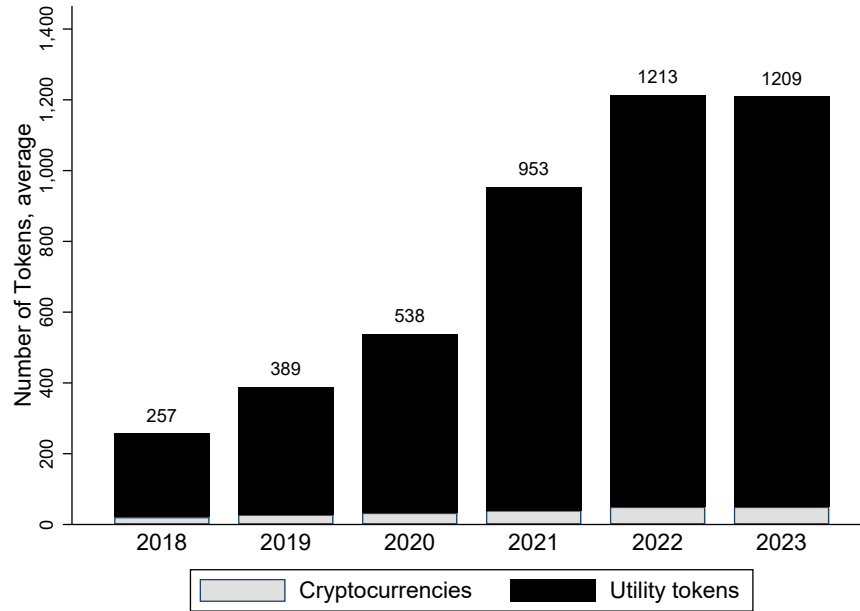
Following the categorization of Bongini et al. (2025), five different token types exist: (i) *cryptocurrencies*, which include virtual currencies like Bitcoin and Ether, defined by the ECB as unregulated digital currencies used within specific virtual communities; (ii) *stablecoins*, crypto-assets designed to maintain stable value by being pegged to assets such as fiat currencies or gold; (iii) *security tokens*, DLT-based assets that provide rights and obligations similar to traditional financial instruments like shares or debt; (iv) *utility tokens*, which

grant access to goods or services offered by the issuer; (v) Non-Fungible Tokens (*NFTs*), unique digital assets representing ownership of specific items like art or collectibles.

To construct an optimal sample for evaluating the impact of regulatory changes on crypto assets, our analysis encompassed all *cryptocurrencies* and *utility tokens* in existence at the time of each regulatory event. We specifically excluded *stablecoins* from our sample due to their direct pegging to tangible assets, rendering their returns ostensibly resistant to cryptocurrency-specific regulations. Similarly, *security tokens* were omitted as they are governed by existing regulations applicable to their underlying securities. *NFTs* were also excluded, given that their valuation is primarily derived from unique characteristics and their non-fungibility.

To assemble the most exhaustive sample of tokens possible, we extracted historical daily price data for all tokens listed on CoinMarketCap for our sample period from January 2018 until June 2023. This platform compiles price data for listed tokens from an extensive array of secondary exchanges. Due to the dynamic nature of the cryptocurrency markets, characterized by frequent listings of new tokens and delistings stemming from project failures or strategic decisions, the number of tokens analyzed varied for each event considered in the study. Figure 4.1 illustrates the average number of tokens subject to regulations in each year of our sample, revealing a significant increase in the number of tokens from 257 in 2018 to 1213 in 2022 and 1209 in 2023. Notably, the vast majority of tokens in the sample each year are utility tokens, consistently comprising over 90% of the total sample.

Figure 4.1: Token sample



4.3.2 Variable definitions

4.3.2.1 Dependent variables

We focus on four different dependent variables calculated based on daily price data. *CARs* indicates the cumulative abnormal return (CAR) over the 5-day event window (in %). Abnormal return is calculated based on the daily return of the event days minus the 80-day pre-event average return. The variables Δ *return volatility*, Δ *return*, Δ *sharp ratio* measure the differences in standard deviation of the return, price change, and sharpe ratio of the token between the 80-day post-event window and the 80-day pre-event window. Sharpe ratio is calculated as the average daily return multiplied by the window size (i.e., 80) divided by the standard deviation during the period.

4.3.2.2 Key variables

The key variable *Governance enforcement index* indicates the strength of the enforcement of contracts and other rights of the jurisdiction issuing the law, measured as the percentile rank based on World Bank data. We also include two alternative measures from the same source: (i) the *Government effectiveness index*, capturing perceptions of public and civil service quality, and of the independence and commitment of the government to its policies; and (ii) the *Regulatory quality index*, reflecting perceptions of the government's capacity to develop and enforce effective policies and regulations that support private sector growth. All three variables are measured in %tile.

The *Uncertainty avoidance* variable is derived from the cultural uncertainty avoidance score. This score is defined by Hofstede (2001) as the degree to which a society tries to control the uncontrollable and the extent to which a culture habituates its members to feel either uncomfortable or comfortable in situations that are novel, unknown, surprising, or different from usual. *First regulation* is a dummy variable that takes the value one if the regulation was the first of this type within the jurisdiction and zero otherwise. *Local token* is another dummy variable, taking the value one if the cryptocurrency is based in the same jurisdiction as the law got announced and zero otherwise.

4.3.2.3 Control variables and fixed effects

We control for a comprehensive list of variables related to regulation and market characteristics. *Financial regulator* is a dummy variable that takes the value one if the regulation is announced by a financial regulator or zero otherwise. The *Shareholder protection index* is provided by the World Bank and indicates the level of protection shareholders have within the jurisdiction against any misuse of corporate assets by directors, ranging from 0 to 1. The *Financial institution access index* is compiled by the IMF and indicates the number of ATMs and bank branches per 100,000 adults.

Additionally, we control for market sentiments and token characteristics, such as *Market cap*, *Trading volume*, *Illiquidity ratio*, and token type. The illiquidity ratio is based on Amihud (2002) and is calculated as the absolute value of the daily return divided by the daily total trading volume of the token (in thousands). To control for time-invariant confounders, we also include token fixed effects.

All variables are defined in Table C.1 in the Appendix.

4.3.3 Summary statistics

Table 4.2 presents summary statistics for our outcome variables (Panel A), key variables (Panel B), and vector of control variables (Panel C). Panel A will be analyzed in the context of the empirical results in Section 4.4.2. We report the number of observations, arithmetic mean, standard deviation, and the 25%, 50%, and 75% quantile.¹⁴ Panel B shows that the government enforcement index of the jurisdictions that announced new cryptocurrency regulation was on average 68.761 (SD = 25.276) with a median of 74.286. On average, the jurisdictions issuing new regulations are in the 71.870 (SD = 22.204) and 72.557 (72.154) percentile of the government effectiveness and regulatory quality indices, respectively. The average cultural uncertainty avoidance score of our sample is 56.659 (26.471). 48.8% of the regulations in our sample represent the first regulation of their type within their respective jurisdictions. In considering the jurisdictions of the underlying projects of the token sample, we observe that in 2.0% of the cases it matches the jurisdiction of the law's announcement (SD = 0.140).

Panel C indicates that, within our sample, 32.4% of the announced regulations were drafted by a financial regulator. The jurisdictions where the new law was introduced had, on average, a shareholder protection index of 6.994 (SD = 1.868) and a financial

¹⁴The token return data is trimmed at the 0.1%. This level of trimming ensures the mitigation of potential measurement errors affecting the reported values while preserving the typical strong deviations in daily cryptocurrency market returns. A sensitivity analysis is included in Table C.9 in the Appendix, which confirms the robustness of our findings at various trimming levels.

institution access index of 0.533 ($SD = 0.200$). In 24.9% of the cases, the regulation was announced during a bull market, and in 47.3% during a bear market. Out of the sample of 25,342 observations, 15.5% are based on tokens that have an underlying DeFi protocol, and 5.0% could be identified as a currency token. The market cap of the tokens at the announcement date shows a mean of \$5.438 million (avg. $\log.$ = 15.509; $\log.$ SD = 4.130) and median of \$9.093 million (median $\log.$ = 16.023). On the event day, we observe an average trading volume of \$0.627 million (avg. $\log.$ = 13.348; $\log.$ SD = 3.212) and an illiquidity measure of 0.002 ($SD = 0.135$).

Table 4.2: Summary statistics

| | Obs. | Mean | SD | Q1 | Median | Q3 |
|---|--------|-----------|--------|---------|--------|--------|
| Panel A: <i>Dependent variables</i> | | | | | | |
| <u>Cumulative abnormal returns (CARs), in %, [-2; +2 days]:</u> | | | | | | |
| All regulatory events | 25,353 | -1.414*** | 20.276 | -9.476 | -1.283 | 6.433 |
| AML/CFT events | 3,025 | 0.095 | 18.351 | -5.848 | -0.623 | 5.594 |
| Crypto Ban events | 2,103 | -2.838*** | 21.540 | -10.427 | -1.547 | 5.343 |
| Regulatory Framework events | 13,386 | -2.782*** | 21.634 | -11.895 | -2.649 | 5.587 |
| Tax events | 6,840 | 0.985*** | 18.261 | -7.024 | 0.681 | 8.255 |
| <u>Δ Return volatility, in % pts., [± 80 days]:</u> | | | | | | |
| All regulatory events | 25,353 | -0.496*** | 4.449 | -2.699 | -0.484 | 1.653 |
| AML/CFT events | 3,025 | -0.651*** | 4.696 | -3.015 | -0.418 | 1.941 |
| Crypto Ban events | 2,103 | -0.013 | 4.599 | -2.330 | -0.086 | 2.530 |
| Regulatory Framework events | 13,386 | -0.373*** | 4.537 | -2.579 | -0.391 | 1.783 |
| Tax events | 6,840 | -0.821*** | 4.080 | -2.823 | -0.781 | 1.088 |
| <u>Δ Return, in % pts., [± 80 days]:</u> | | | | | | |
| All regulatory events | 25,353 | 0.018** | 1.389 | -0.672 | 0.015 | 0.716 |
| AML/CFT events | 3,025 | 0.310*** | 1.247 | -0.238 | 0.338 | 0.937 |
| Crypto Ban events | 2,103 | -0.192*** | 1.308 | -0.887 | -0.131 | 0.520 |
| Regulatory Framework events | 13,386 | -0.050*** | 1.537 | -0.842 | -0.065 | 0.733 |
| Tax events | 6,840 | 0.086*** | 1.116 | -0.469 | 0.063 | 0.642 |
| <u>Δ Sharpe Ratio, [± 80 days]:</u> | | | | | | |
| All regulatory events | 25,353 | 0.585*** | 11.610 | -7.072 | 0.332 | 7.887 |
| AML/CFT events | 3,025 | 4.424*** | 9.903 | -1.687 | 4.390 | 10.336 |
| Crypto Ban events | 2,103 | -1.566*** | 10.150 | -8.194 | -1.064 | 4.820 |
| Regulatory Framework events | 13,386 | -0.078 | 12.394 | -8.480 | -0.574 | 7.807 |
| Tax events | 6,840 | 0.841*** | 10.709 | -6.097 | 0.643 | 7.622 |
| Panel B: <i>Key variables</i> | | | | | | |
| Governance enforcement index (%tile) | 25,352 | 68.761 | 25.276 | 52.381 | 74.286 | 88.679 |
| Government effectiveness index (%tile) | 25,352 | 71.870 | 22.204 | 58.019 | 75.714 | 90.952 |
| Regulatory quality index (%tile) | 25,352 | 72.557 | 22.154 | 52.830 | 81.132 | 92.857 |
| Uncertainty avoidance | 17,364 | 56.659 | 26.471 | 30.000 | 64.000 | 76.000 |
| First regulation | 25,352 | 0.488 | 0.500 | 0.000 | 0.000 | 1.000 |
| Local token | 25,352 | 0.020 | 0.140 | 0.000 | 0.000 | 0.000 |
| Panel C: <i>Control variables</i> | | | | | | |
| <u>Regulation and market characteristics:</u> | | | | | | |
| Financial regulator (dummy) | 25,352 | 0.324 | 0.468 | 0.000 | 0.000 | 1.000 |
| Shareholder protection index | 25,352 | 6.994 | 1.868 | 5.000 | 7.000 | 9.000 |
| Financial institution access index | 24,106 | 0.533 | 0.200 | 0.364 | 0.491 | 0.645 |
| Bull market (dummy) | 25,352 | 0.249 | 0.432 | 0.000 | 0.000 | 0.000 |
| Bear market (dummy) | 25,352 | 0.473 | 0.499 | 0.000 | 0.000 | 1.000 |
| <u>Token characteristics:</u> | | | | | | |
| Market cap (log) | 25,348 | 15.509 | 4.130 | 14.182 | 16.023 | 17.761 |
| Trading volume (daily, log) | 25,348 | 13.348 | 3.212 | 11.496 | 13.355 | 15.334 |
| DeFi token type (dummy) | 25,342 | 0.155 | 0.362 | 0.000 | 0.000 | 0.000 |
| Currency token type (dummy) | 25,348 | 0.050 | 0.218 | 0.000 | 0.000 | 0.000 |
| Illiquidity measure (Amihud, 2002) | 25,348 | 0.002 | 0.135 | 0.000 | 0.000 | 0.000 |

Note: This table presents the summary statistics of the dependent variables (Panel A), key variables (Panel B), and control variables (Panel C). For all variables, we report the number of observations, arithmetic mean, standard deviation, and the 25%, 50%, and 75%

quantiles. The number of asterisks behind the mean indicates the p-value of a t-test, testing if the average deviation is significantly different from zero; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3.4 Correlations

Table 4.3 shows the pairwise correlation coefficients across all variables of our regression models. The only pair among the control variables with a correlation above 0.3 is that of the bull market and bear market dummies (-0.545), reducing the risk of multicollinearity.

Table 4.3: Correlations:

| | 1. | 2. | 3. | 4. | 5. | 6. | 7. | 8. | 9. | 10. | 11. | 12. | 13. | 14. | 15. | 16. | 17. | 18. | 19. |
|---|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| <i>Dependent variables:</i> |
| 1. CARS |
| 2. Δ Return volatility | .153 | | | | | | | | | | | | | | | | | | |
| 3. Δ Return | .149 | .597 | | | | | | | | | | | | | | | | | |
| 4. Δ Sharpe ratio | .117 | .409 | .866 | | | | | | | | | | | | | | | | |
| <i>Key variables:</i> |
| 5. Governance enforcement index | .041 | -.085 | -.038 | -.045 | | | | | | | | | | | | | | | |
| 6. Government effectiveness index | .059 | -.085 | -.074 | -.097 | .913 | | | | | | | | | | | | | | |
| 7. Regulatory quality index | .036 | -.091 | -.047 | -.052 | .948 | .881 | | | | | | | | | | | | | |
| 8. Uncertainty avoidance index | -.050 | .076 | -.040 | -.018 | -.442 | -.572 | -.360 | | | | | | | | | | | | |
| 9. First regulation | -.028 | .093 | .096 | .122 | -.319 | -.379 | -.237 | .212 | | | | | | | | | | | |
| 10. Local token | .016 | -.024 | .005 | .007 | .136 | .154 | .133 | -.241 | -.058 | | | | | | | | | | |
| <i>Regulation and market characteristics:</i> | | | | | | | | | | | | | | | | | | | |
| 11. Financial regulator | .075 | -.006 | .036 | .044 | .447 | .486 | .469 | -.358 | -.095 | .138 | | | | | | | | | |
| 12. Shareholder protection index | .031 | -.058 | -.062 | -.114 | .231 | .353 | .374 | -.468 | -.051 | .087 | .242 | | | | | | | | |
| 13. Financial institution access index | .059 | .109 | .067 | .060 | .077 | .085 | .038 | .488 | .109 | -.091 | -.277 | -.027 | | | | | | | |
| 14. Bull market | -.090 | -.063 | -.014 | .024 | -.071 | .044 | -.141 | -.079 | -.039 | .014 | .155 | -.206 | -.038 | | | | | | |
| 15. Bear market | .019 | -.000 | .012 | -.003 | .130 | -.002 | .168 | .007 | -.037 | -.006 | -.039 | .237 | -.009 | -.545 | | | | | |
| <i>Token characteristics:</i> |
| 16. Market cap | .014 | -.030 | -.075 | -.067 | .002 | .008 | -.001 | .035 | .016 | -.006 | -.027 | -.026 | .006 | .059 | -.031 | | | | |
| 17. Trading volume | .047 | -.070 | -.126 | -.110 | -.013 | .009 | -.025 | .034 | .025 | -.000 | -.045 | -.028 | .004 | .124 | -.070 | .573 | | | |
| 18. DeFi token type | .001 | -.022 | -.014 | -.012 | -.015 | -.007 | -.011 | -.010 | -.033 | -.012 | -.001 | .026 | -.020 | .017 | .057 | .141 | .178 | | |
| 19. Currency token type | .015 | .006 | .006 | .013 | .010 | .005 | .009 | .009 | .017 | -.004 | -.001 | -.014 | .012 | -.010 | -.023 | .092 | .135 | -.044 | |
| 20. Illiquidity measure | -.001 | .001 | .021 | .008 | -.012 | -.012 | -.013 | .007 | .005 | -.002 | -.003 | -.003 | -.003 | .012 | -.005 | -.016 | -.070 | -.006 | -.003 |

4.3.5 Econometric approach

4.3.5.1 Event study

To assess the impact of regulatory announcements on the cryptocurrency market, we apply an event study framework (Brown & Warner, 1980, 1985)). We follow the event study framework of Brown and Warner (1980) and Brown and Warner (1985) to assess the impact of regulatory announcements on the cryptocurrency market. This methodology is widely used in the financial literature to assess price reactions of listed stocks to news announcements (e.g., Zhang, 2007; Armstrong et al., 2010) and has also been applied in prior cryptocurrency market studies (Chokor and Alfieri, 2021; Koenraadt and Leung, 2024). To identify cryptocurrency investors' reactions to a new regulation, we must define the key elements of the event study framework as laid out in MacKinlay (1997). Following Kothari and Warner (2007), we use daily returns to estimate the announcement effect, allowing the most precise calculation. The present study applies an event window size of 5 days centered on the event day for several reasons. Unlike the traditional financial market, the token market is open 24/7, leading to complications when defining the exact event date. To avoid this issue, an event window of no fewer than 3 days should be applied. Aiming to capture potential preceding effects due to information acquisition before the exact event date (MacKinlay, 1997), and to include sufficient post-announcement time to measure the initial reaction, we opted for a larger event window. However, an increased window size comes at the cost of overlapping risk among the events; hence we decided not to expand the window beyond 5 days. Prior event studies also applied extended event windows, pointing out the importance of the inclusion of the days directly preceding and following the actual news date (e.g. Zhang, 2007; Armstrong et al., 2010; Collevocchio et al., 2024).

The abnormal returns during the event window are measured based on the constant mean model. While event studies related to specific stocks or industries (e.g. Zhang, 2007;

Schäfer et al., 2015) are sometimes based on a model that regresses the security returns around the events against a benchmark return (i.e. ‘market model’), we identified the constant mean model as the most suitable for our study. This decision is based primarily on the following two factors: (i) cryptocurrency regulations usually target all assets and not only a subgroup, making it impossible to define a market index that might not be impacted by the regulation (Chokor & Alfieri, 2021); and (ii) as Brown and Warner (1980, 1985) have pointed out, despite the rather simple setup of the constant mean model compared to the other options, the results are often similar and do not consistently diverge from results obtained using more sophisticated models.

As the model name indicates, the mean return of an asset in the constant mean return model remains constant over time (MacKinlay, 1997). Based on Brown and Warner (1980, 1985), we define the estimation procedure for the abnormal returns under this assumption as follows. The abnormal return of token i at event day t is calculated as the actual return of token i on event day t minus the expected return of token i : $AR_{i,t} = R_{i,t} - \bar{R}_i$ where $\bar{R}_i$ is defined as the mean return of token i over a predefined estimation window. The estimation window is set as the period directly preceding the first day of the event window (MacKinlay, 1997). While the defined size of the estimation window varies within the literature, we’ve chosen an 80-day window in line with prior event studies related to cryptocurrencies (Koenraadt & Leung, 2024), as follows: $\bar{R}_i = 1/80 \sum_{t=-82}^{-3} R_{i,t}$. If another event window of our sample or other major market events (e.g. UST stablecoin collapse) falls into the estimation period of a respective event, we exclude this data point from the estimation period and widen the window accordingly to include 80 observations of daily returns, as applied in prior studies (e.g., Schäfer et al., 2015; Koenraadt and Leung, 2024). While this method leads to non-consecutive 80-day estimation window periods, it secures a higher accuracy of the expected return calculation. In the last step, we calculate the sum of the abnormal returns of the five individual days of each event window to retrieve the cumulative abnormal return: $CAR_i = \sum_{t=-2}^{+2} AR_{i,t}$. After estimating the

cumulative abnormal returns for each announcement of a new regulation in our sample, we test whether the average CAR of the tokens is statistically different from zero (Brown and Warner, 1985; Kothari and Warner, 2007). We conduct a t-test for each individual event based on the CARs of all tokens and perform an additional t-test to assess if the average CARs of the whole sample are statistically different from zero. The procedure is repeated for subsamples based on the regulation type, market sentiment at the event date, and other factors.

In the post-event window analyses, we calculate the change in return, return volatility (i.e. standard deviation), and the Sharpe ratio during the period after the event window and compare them with the respective values during the pre-event period. Following existing literature (e.g. Su et al., 2002), the length of the post-event window matches that of the pre-event window (i.e. 80 days) and excludes the event window to allow the best possible comparison.

4.3.5.2 Multivariate analysis

To estimate the causal effect of jurisdictions' enforcement probability on the realized risk reduction in the cryptocurrency market, we expand our empirical analyses with a multivariate approach. In our defined baseline model we apply an ordinary least squares regression to analyze the effect of the governance enforcement index (GEI_i) on the dependent variables DV_i . Furthermore, the model includes a vector of control variables related to specific characteristics of the regulation and jurisdiction (Ω_i^{RJC}) and a second vector of control variables related to the attributes of the tokens (Ω_i^{TC}):

$$DV_i = \beta_1 GEI_i + \Omega_i^{RJC} \gamma_1 + \Omega_i^{TC} \gamma_2 + \epsilon_i, DV_i \in \{\Delta ReturnVolatility_i, \Delta Return_i, \Delta SharpeRatio_i\} \quad (7)$$

4.4 Empirical Results

4.4.1 Market reactions to individual cryptocurrency regulations

Table 4.4 lists all regulatory events considered in our study. The columns show the announcement date, the name of the regulation, the corresponding jurisdiction, the regulation type, and the sample size of listed tokens at the time of the announcement. For each regulation, we report the CAR, calculated as the daily return on the event days minus the 80-day pre-event average return, as well as changes in return volatility (Δ Return volatility), raw return (Δ Return), and risk-adjusted return (Δ Sharpe ratio). The Sharpe ratio is computed as the average daily return multiplied by the window size (i.e., 80), divided by the standard deviation over the period. All values are reported with standard errors from a t-test in parentheses, testing whether the average deviation is significantly different from zero, along with the corresponding p-value significance levels.

Out of the 35 events, 29 exhibit statistically significant CARs within the event window, with 26 of these significant at the 1% level. These findings suggest that the announcement of cryptocurrency regulations generates abnormal price reactions, indicating that tradeable tokens respond immediately to new regulatory information. However, we also observe continued return adjustments beyond the event window: 30 events are associated with additional significant return reactions in the post-event period, 29 of which are significant at the 1% level. This indicates that the cryptocurrency market does not fully reflect new information instantaneously, suggesting a degree of market inefficiency. Moreover, the announcement of new regulation results in significant changes in return volatility in 26 of the 35 events, ultimately contributing to substantial and highly significant changes in the Sharpe ratio.

All measures vary in both magnitude and direction across the different events. The most positive short-term price reaction is observed for the announcement of the legalization of cryptocurrencies in the Ukrainian financial system on 16 March 2022, with a

CAR of 9.40%. In contrast, the strongest short-term price decline (−20.813%) and the largest risk reduction (−3.554 percentage points) are recorded following the official announcement by El Salvador to implement Bitcoin as legal tender (Decree No. 57 on 9 June 2021). While the observed risk reduction is consistent with H1, the negative price reaction appears counter-intuitive. We identify two potential explanations: (i) investors may have anticipated different regulatory details in the final law, and (ii) additional reports highlight negative user experiences with the application ‘Strike,’ which was intended to facilitate BTC transactions in El Salvador. These concerns, particularly around the platform’s centralization and the role of government involvement, may have contributed to the adverse market response.¹⁵ The strongest post-event return increase is associated with the announcement of the DARE Act in the Bahamas on 24 November 2020. With an average post-event return increase of 2.04 percentage points and a corresponding rise of 17.53 points in the Sharpe ratio, the results suggest that the market did not fully internalize the implications of the announcement within the event window. The initial CAR of −2.73% supports the theory of investor overreaction to the regulatory news (Bondt & Thaler, 1985), which was subsequently corrected in the post-event period.

Table 4.4: Overview of regulatory events

| Date | Description | Country | Type | Tokens | CAR | Δ Return volatility | Δ Return | Δ Sharpe ratio |
|-------------|--|-------------|----------------------|--------|----------------------|----------------------|---------------------|----------------------|
| 20 Jul 2018 | Virtual Financial Assets Act + Innovative Technology Arrangements and Services Act | Malta | Regulatory Framework | 230 | −7.585***
(0.840) | −0.129
(0.175) | −0.109**
(0.054) | −1.481***
(0.566) |
| 26 Jul 2018 | Circulaire L.I.R. n° 95_2 du 31.12.2010 | Luxembourg | Tax | 232 | 6.425***
(1.112) | 0.022
(0.180) | 0.069
(0.056) | 0.363
(0.585) |
| 14 Dec 2018 | Legal framework for distributed ledger technology and blockchain in Switzerland | Switzerland | Regulatory Framework | 308 | −0.857
(0.670) | −0.500***
(0.191) | 1.531***
(0.058) | 17.871***
(0.604) |
| 10 Jan 2019 | LEGE nr. 30 din 10 ianuarie 2019 | Romania | Tax | 317 | −7.433***
(0.686) | −0.838***
(0.196) | 1.330***
(0.060) | 14.891***
(0.552) |
| 21 Feb 2019 | Rulebook Module on crypto-assets (Module CRA) | Bahrain | Regulatory Framework | 326 | 5.518***
(0.781) | −0.102
(0.189) | 0.572***
(0.061) | 6.120***
(0.491) |

¹⁵<https://cointelegraph.com/news/traders-analysts-offer-mixed-reactions-to-el-salvador-s-btc-announcement>

| | | | | | | | | |
|-------------|--|-----------------------|----------------------|------|-----------------------|----------------------|----------------------|----------------------|
| 11 Apr 2019 | Loi PACTE - Regulatory Framework for Crypto-Activities and ICOs | France | Regulatory Framework | 340 | -13.010***
(1.007) | 0.341*
(0.203) | -0.573***
(0.059) | -7.548***
(0.482) |
| 31 Jul 2019 | PS19/22 Guidance on Cryptoassets | United Kingdom | Regulatory Framework | 382 | 1.188
(0.737) | -1.501***
(0.181) | -0.654***
(0.063) | -8.097***
(0.554) |
| 7 Oct 2019 | Taxation of virtual currencies | Finland | Tax | 405 | 6.199***
(1.163) | -0.468***
(0.176) | 0.400***
(0.052) | 4.429***
(0.494) |
| 29 Nov 2019 | Measures Against Money Laundering Act | Bulgaria | AML/CFT | 439 | 4.653***
(0.793) | 0.200
(0.209) | 0.743***
(0.063) | 9.528***
(0.532) |
| 26 Dec 2019 | QFC Regulatory Authority affirms that Virtual Asset Services may not be conducted in or from the QFC | Qatar | Crypto Ban | 450 | -0.440
(0.588) | 2.267***
(0.199) | 0.232***
(0.054) | 3.200***
(0.459) |
| 31 Dec 2019 | Money Laundering & Terrorist Financing Prevention Act | Estonia | AML/CFT | 451 | -3.600***
(0.640) | 2.246***
(0.200) | 0.215***
(0.056) | 3.145***
(0.461) |
| 23 Jan 2020 | Virtual Asset Bill 2020 | Saint Kitts and Nevis | Regulatory Framework | 457 | 0.024
(0.239) | 2.304***
(0.179) | -0.033
(0.051) | -0.250
(0.408) |
| 17 Apr 2020 | IRAS e-Tax Guide - Income Tax Treatment of Digital Tokens | Singapore | Tax | 479 | 5.538***
(0.903) | -1.805***
(0.213) | 0.819***
(0.054) | 8.820***
(0.401) |
| 8 Jun 2020 | Digital Assets Business Act | Antigua & Barbuda | Regulatory Framework | 494 | 4.452***
(0.968) | -1.014***
(0.193) | 0.442***
(0.059) | 3.618***
(0.380) |
| 31 Jul 2020 | Regulation on digital financial asset (DFA) | Russia | Regulatory Framework | 520 | -1.634*
(0.839) | 0.259
(0.197) | -0.778***
(0.054) | -8.621***
(0.443) |
| 15 Sep 2020 | Law No. 194 of 2020 prohibits cryptocurrency-related activities | Egypt | Crypto Ban | 548 | -9.474***
(0.819) | -1.074***
(0.194) | -0.424***
(0.058) | -3.492***
(0.438) |
| 25 Sep 2020 | Federal Act on the Adaptation of Federal Law to Developments in Distributed Ledger Technology | Switzerland | Regulatory Framework | 554 | -0.617
(0.750) | -1.060***
(0.202) | -0.178***
(0.058) | -0.888**
(0.433) |
| 9 Oct 2020 | IRAS e-Tax Guide - Income Tax Treatment of Digital Tokens (Adjustment) | Singapore | Tax | 556 | 5.405***
(0.698) | -0.654***
(0.199) | 0.272***
(0.054) | 4.348***
(0.403) |
| 24 Nov 2020 | Digital Assets and Registered Exchanges Act | Bahamas | Regulatory Framework | 603 | -2.732***
(0.908) | 2.049***
(0.197) | 2.040***
(0.061) | 17.534***
(0.438) |
| 21 Dec 2020 | Law on Digital Assets | Serbia | Regulatory Framework | 633 | -13.721***
(0.929) | 3.622***
(0.197) | 1.846***
(0.062) | 12.946***
(0.408) |
| 12 Mar 2021 | Spanish Royal Decree-Law 5/2021 | Spain | Regulatory Framework | 763 | 5.778***
(1.324) | 0.348*
(0.179) | -1.330***
(0.066) | -9.733***
(0.355) |
| 3 Jun 2021 | Electronic Securities Act (Gesetz zur Einführung von elektronischen Wertpapieren, eWpG) | Germany | Regulatory Framework | 869 | -11.982***
(0.924) | -3.510***
(0.153) | -0.764***
(0.050) | -3.272***
(0.295) |
| 9 Jun 2021 | Bitcoin as legal tender - Bitcoin Law (Decree No. 57) | El Salvador | Regulatory Framework | 870 | -20.813***
(0.759) | -3.554***
(0.152) | -0.864***
(0.049) | -3.956***
(0.292) |
| 30 Jun 2021 | Regulations Governing AML and CFT for Enterprises Handling Virtual Currency Platform or Transactions | Taiwan | AML/CFT | 920 | 2.251***
(0.718) | -3.290***
(0.145) | 0.064
(0.048) | 2.312***
(0.306) |
| 24 Sep 2021 | China's top regulators ban crypto trading and mining | China | Crypto Ban | 1106 | -0.402
(0.752) | -0.415***
(0.134) | -0.249***
(0.039) | -2.552***
(0.291) |
| 10 Dec 2021 | e Virtual Asset and Initial Token Offering Services Act 2021 | Mauritius | Regulatory Framework | 1194 | -7.250***
(0.497) | -1.940***
(0.115) | -0.900***
(0.039) | -8.773***
(0.318) |

| | | | | | | | | |
|-------------|--|---------------|----------------------|------|----------------------|----------------------|----------------------|----------------------|
| 2 Feb 2022 | Tax treatment of cryptocurrencies | Austria | Tax | 1206 | 8.391***
(0.466) | −1.816***
(0.112) | −0.044
(0.032) | −1.038***
(0.32) |
| 16 Mar 2022 | Legalisation of cryptocurrency within the country's financial system | Ukraine | Regulatory Framework | 1208 | 9.400***
(0.442) | 0.542***
(0.100) | 0.220***
(0.030) | 2.170***
(0.284) |
| 24 May 2022 | Royal Decree Exempting VAT on Digital Currency Transfers | Thailand | Tax | 1214 | −5.021***
(0.549) | 0.071
(0.111) | 0.035
(0.028) | 0.452*
(0.268) |
| 3 Aug 2022 | IRAS e-Tax Guide - GST: Digital Payment Tokens | Singapore | Tax | 1216 | 1.020**
(0.517) | −2.137***
(0.112) | −0.314***
(0.029) | −3.753***
(0.273) |
| 16 Sep 2022 | Comprehensive Framework for Responsible Development of Digital Assets | United States | Regulatory Framework | 1217 | −6.766***
(0.418) | 0.114
(0.112) | −0.332***
(0.026) | −4.311***
(0.258) |
| 12 Oct 2022 | Chile Tax Agency Clarifies Taxation of Financial Services, Digital Asset Transactions on Blockchain Platform | Chile | Tax | 1217 | −4.965***
(0.478) | 0.630***
(0.105) | −0.135***
(0.026) | −1.825***
(0.260) |
| 7 Dec 2022 | Passage of Anti-Money Laundering and Counter-Terrorist Financing (Amendment) Bill 2022 | Hong Kong | AML/CFT | 1216 | −1.697***
(0.504) | −0.035
(0.120) | 0.375***
(0.029) | 4.653***
(0.265) |
| 21 Dec 2022 | Legal Framework for Virtual Assets in Brazil (Cryptoassets Act) | Brazil | Regulatory Framework | 1218 | −0.800*
(0.434) | −0.016
(0.120) | 0.702***
(0.029) | 9.497***
(0.269) |
| 6 Feb 2023 | Kazakhstan introduces new regulation of Digital Assets | Kazakhstan | Regulatory Framework | 1210 | 5.069***
(0.627) | −0.439***
(0.122) | −0.136***
(0.030) | −2.278***
(0.261) |

Note: This table displays the key details and market impact of each regulation within our sample. It includes the announcement date, the name of the regulation, the corresponding jurisdiction, the regulation type, and the sample size of listed tokens. Additionally, it presents the corresponding values of the four outcome variables: (i) CAR, (ii) Δ return volatility, (iii) Δ return, and (iv) Δ Sharpe ratio. CAR indicates the cumulative abnormal return over the 5-day event window (in %). Abnormal return is calculated based on the daily return of the event days minus the 80-day pre-event average return. The variables Δ return volatility, Δ return, and Δ Sharpe ratio measure the differences in the standard deviation of the return, price change, and Sharpe ratio of the token between the 80-day post-event window and the 80-day pre-event window. The Sharpe ratio is calculated as the average daily return multiplied by the window size (i.e., 80) divided by the standard deviation during the period. We report the standard errors of a t-test in parentheses, testing if the average deviation is significantly different from zero; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4.2 Event-related cumulative abnormal returns

Panel A of Table 4.2 displays the average CAR as well as the average changes in return volatility (Δ Return volatility), raw return (Δ Return), and risk-adjusted return (Δ Sharpe ratio) following the announcement of a new regulation. Additionally, we report the number of observations, arithmetic mean, standard deviation, and the 25%, 50%, and 75% quantile. All results are shown for the whole sample, including all regulatory events, and four different subsamples for the individual event categories.

The overall average CAR of −1.414% (SD = 20.276) provides strong support for H2a, suggesting that investors, on average, anticipate a decline in wealth following the an-

nouncement of new regulations. This result is statistically significant at the 1% level. A breakdown by regulation type offers further insights into the drivers of this negative average effect. Regulatory framework announcements are associated with a particularly negative CAR of -2.782% ($SD = 21.634$), while crypto ban announcements similarly yield an average CAR of -2.838% ($SD = 21.540$). In contrast, tax law announcements are linked to a positive average CAR of 0.985% ($SD = 18.261$). We identify three potential explanations for the positive market reaction to tax regulations. First, tax laws typically not only impose taxes on capital gains or income but also allow investors to offset losses against other investment income. This enables the application of tax strategies, such as tax loss harvesting, that were previously unavailable, thereby increasing the after-tax value of investments. Second, greater regulatory clarity may be perceived as valuable by investors (e.g., Bruno and Claessens, 2010; La Porta et al., 2002; Larcker et al., 2011) because it reduces uncertainty and the risk of unexpected future costs, potentially lowering the applied discount rate. Third, investors may question the enforceability of the new tax regulations and, as a result, may not price in the anticipated tax burden (e.g., Bhattacharya and Daouk, 2009; Humphery-Jenner, 2013). The decentralized and pseudonymous nature of cryptocurrencies, including features such as self-custody and decentralized trading, makes effective tax enforcement challenging. According to the framework of Schwert (1981) and Binder (1985), such expectations may lead investors to interpret regulation announcements as having a positive net wealth effect.

4.4.3 Post-event changes in return volatility

Table 4.5 further expands on the presented changes in return volatility between the post-event and pre-event windows (Δ Return volatility) in Table 4.2 by displaying the pre-event and post-event values for different estimation windows (30-day, 50-day, 80-day), along with tests of whether the average deviation is significantly different from zero. We observe highly significant reductions in return volatility across all estimation windows, with an

average reduction of -0.496 percentage points ($SD = 4.449$) for the 80-day window. The 30-day and 50-day windows show average risk reductions of -0.775 and -0.607 percentage points, respectively. These results confirm H1, that regulatory clarity decreases the risk in the cryptocurrency market and leads to a reduced post-event standard deviation, ultimately indicating that the estimated risk premium of a listed cryptocurrency is directly linked to asset volatility.

In Section 4.2.2, we explain that governments and regulators may directly target risk reduction in the cryptocurrency market when announcing new regulations (e.g., Bhattacharya and Daouk, 2009) due to the inherent drawbacks of increased volatility for the broader market. Regulations are key to ensuring efficient capital allocation (Yadav, 1992) and protecting investors from exposure to incalculable risks resulting from bad actors and market fraud. Our results indicate that governments and regulators are, on average, succeeding in their aim of reducing market risk, as reflected by the reduced asset volatility in the post-event period. This finding is further supported by the observation that regulations explicitly aimed at reducing market risks, such as AML/CFT laws, lead to the largest reduction in post-event standard deviation (-0.651 percentage points). While we also observe statistically significant risk reductions following the introduction of new regulatory frameworks, the magnitude of the effect is smaller (-0.373 percentage points). The pronounced decrease in standard deviation after the announcement of new tax regulations (-0.821 percentage points) further supports the assumption that cryptocurrency investors value regulatory clarity in taxation. A clear tax approach reduces uncertainty about future returns and ultimately lowers asset volatility.

Table 4.5: Risk-return statistics for various estimation windows

| | Pre-event: | | | Post-event: | | | Difference: | | |
|-------------------------------------|------------|--------|--------|-------------|--------|--------|-------------|-----------|-----------|
| | 30-day | 50-day | 80-day | 30-day | 50-day | 80-day | 30-day | 50-day | 80-day |
| <u>All regulatory events:</u> | | | | | | | | | |
| Return volatility | 8.029 | 8.271 | 8.449 | 7.254 | 7.664 | 7.953 | -0.775*** | -0.607*** | -0.496*** |
| Return | 0.543 | 0.432 | 0.298 | 0.238 | 0.35 | 0.316 | -0.305*** | -0.082*** | 0.018** |
| Sharpe ratio | 1.066 | 1.178 | 0.807 | 0.112 | 1.065 | 1.392 | -0.953*** | -0.113* | 0.585*** |
| <u>AML/CFT events:</u> | | | | | | | | | |
| Return volatility | 7.986 | 8.048 | 8.615 | 6.527 | 7.215 | 7.964 | -1.458*** | -0.833*** | -0.651*** |
| Return | 0.431 | 0.477 | 0.148 | 0.554 | 0.819 | 0.458 | 0.123*** | 0.342*** | 0.310*** |
| Sharpe ratio | 0.311 | 1.749 | -0.831 | 2.024 | 5.355 | 3.593 | 1.712*** | 3.606*** | 4.424*** |
| <u>Crypto Ban events:</u> | | | | | | | | | |
| Return volatility | 7.824 | 8.391 | 8.814 | 7.273 | 8.179 | 8.801 | -0.550 | -0.212* | -0.013 |
| Return | 0.623 | 1.011 | 0.523 | 0.744 | 0.703 | 0.331 | 0.120** | -0.309*** | -0.192*** |
| Sharpe ratio | 1.554 | 5.351 | 3.156 | 2.454 | 3.104 | 1.590 | 0.899*** | -2.247*** | -1.566*** |
| <u>Regulatory Framework events:</u> | | | | | | | | | |
| Return volatility | 8.267 | 8.526 | 8.652 | 7.509 | 7.989 | 8.279 | -0.758*** | -0.537*** | -0.373*** |
| Return | 0.583 | 0.507 | 0.439 | 0.332 | 0.368 | 0.390 | -0.251*** | -0.139*** | -0.050*** |
| Sharpe ratio | 1.123 | 1.388 | 1.958 | 0.406 | 1.015 | 1.880 | -0.717*** | -0.373*** | -0.078 |
| <u>Tax events:</u> | | | | | | | | | |
| Return volatility | 7.653 | 7.838 | 7.872 | 7.074 | 7.071 | 7.051 | -0.579*** | -0.767*** | -0.821*** |
| Return | 0.490 | 0.087 | 0.018 | -0.242 | -0.001 | 0.104 | -0.732*** | -0.088*** | 0.086*** |
| Sharpe ratio | 1.138 | -0.766 | -1.441 | -2.028 | -1.363 | -0.560 | -3.166*** | -0.597*** | 0.841*** |

Note: This table presents the arithmetic mean of the return volatility, return, and Sharpe ratio for (i) all regulatory events in our sample, (ii) AML/CFT events, (iii) crypto ban events, (iv) regulatory framework events, and (v) tax events over different time horizons. The Sharpe ratio is calculated as the average daily return multiplied by the window size (i.e., 80) divided by the standard deviation during the period. The columns from left to right show the values during the 30-day, 50-day, and 80-day windows preceding the announcement, the 30-day, 50-day, and 80-day windows after the announcement, and the average of the differences between pre-event and post-event during the 30-day, 50-day, and 80-day windows. The significance of these differences is indicated by asterisks, with the p-values from a t-test testing if the average deviations are significantly different from zero: *** p < 0.01, ** p < 0.05, * p < 0.1.

4.4.4 Post-event changes in returns

Tables 4.2 and 4.5 present the results of the same analysis conducted for the change in daily return (Δ Return) and Sharpe ratio (Δ Sharpe ratio) as was done for the change in return volatility. The results show a Sharpe ratio increase of 0.585 (SD = 11.610) in the 80-day post-event window compared to the pre-event measure. This difference is statistically significant at the 1% level. While the Sharpe ratio difference is negative for the

30-day and 50-day windows, due to lower average returns immediately following the regulatory announcements, the mean return of cryptocurrencies moves closer to the pre-event level over the 80-day horizon (Δ 0.018 percentage points). Combined with the observed risk reduction, this leads to a positive Sharpe ratio change. The higher post-event Sharpe ratio confirms H3b and simultaneously leads to the rejection of H3a. We provide evidence that, on average, cryptocurrencies decouple from their pre-event risk-return relationship following the announcement of new regulations. Our findings suggest that the market is inefficient and exhibits delayed price reactions to regulatory announcements. These reactions may be partly driven by an initial negative overreaction to the announcement, later corrected by a recovery in asset returns. Overall, these results indicate that cryptocurrency investors benefit from new regulations when measured on a risk-adjusted basis.

To identify which type of events might have the most positive impact on Sharpe ratio development, Tables 4.2 and 4.5 show the differences between the post- and pre-event windows for each regulation type separately. We observe that the positive development of the Sharpe ratio is mainly driven by the announcements of AML/CFT and tax laws. After the announcement of AML/CFT regulations, the mean returns exceed pre-event levels during the 80-day window by, on average, 0.310 percentage points ($SD=1.247$), for which time we also observe a strong risk reduction of -0.651 percentage points ($SD=4.696$). This leads to an average increase of the Sharpe ratio of 4.424 ($SD=9.903$), statistically significant at the 1% level. While tax laws lead to an even higher reduction of the standard deviation (-0.821 percentage points), we observe a weaker increase in the average returns ($+0.086$ percentage points). Overall, this leads to an improvement of 0.841 ($SD=10.709$) in the average Sharpe ratio. After the announcement of a new regulatory framework, the risk-return relationship of the cryptocurrencies moves, on average, back to pre-event levels, leading to no statistically significant difference. Our relatively small sample of announcements of crypto bans led to a surprising result. On average, a crypto ban reduces the Sharpe ratio of a cryptocurrency by 1.566 ($SD=10.150$) based on the 80-day post-

event window. While the standard deviation reverts to its pre-event size, the average daily return is reduced by 0.192 percentage points ($SD=1.308$).

4.4.5 The impact of formal institution quality on regulation success

Tables 4.6, 4.7, 4.8, and 4.9 show the regression results of the impact of the governance enforcement index on the different market reactions to newly announced cryptocurrency regulations. All tables show the results of our baseline regression model together with two additional model specifications. First, we include interaction terms of the governance enforcement index with the financial regulator dummy variable, market cap size, and trading volume. This allows us to measure the potential moderating effects of the institution type announcing the new law and token-specific characteristics, such as size and liquidity. Second, we include interaction terms with the bull and bear market dummies to shed light on the impact of general market sentiment on the relationship between governance enforcement quality and market reactions. All three regression models are first shown for the whole sample, followed by the results for subsamples of the regulatory framework and tax law announcements. We do not show separate results for the crypto ban and AML/CFT announcements, given that the lower sample size does not allow for sufficient variation. All models include token fixed effects to control for differences among the tokens that do not vary over time and our reported standard errors are robust.

Table 4.6 shows that a higher governance enforcement index amplifies the negative initial return reaction. On average, the CAR decreases by an additional 0.026 percentage points for a 1-point increase in the governance enforcement index. While the size of the effect varies, we observe the same effect throughout all regressions at a significance level of 1%.

Table 4.6: Regression analysis of event-related CARs

| Dependent variable: <i>Cumulative abnormal returns (CARs), in %, [-2; +2 days]</i> | | | | | | | | | |
|--|----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|----------------------|----------------------|----------------------|
| | All events: | | | Regulatory Framework: | | | Tax: | | |
| <i>Key variables:</i> | | | | | | | | | |
| Governance enforcement index | -0.026***
(0.006) | -0.138***
(0.027) | -0.035***
(0.010) | -0.098***
(0.007) | -0.110***
(0.036) | -0.116***
(0.014) | 0.288***
(0.015) | 0.180***
(0.069) | 1.214
(1.073) |
| x financial regulator | | 0.317***
(0.021) | | | -0.061
(0.047) | | | -0.256***
(0.043) | |
| x market cap | | 0.001
(0.002) | | | 0.003
(0.002) | | | -0.000
(0.004) | |
| x trading volume | | 0.005**
(0.002) | | | -0.002
(0.003) | | | 0.015**
(0.006) | |
| x bull market | | | 0.202***
(0.015) | | | 0.267***
(0.019) | | | ./.
(./.) |
| x bear market | | | 3.163***
(0.849) | | | 8.388***
(1.466) | | | 87.591
(106.427) |
| <i>Regulation and market characteristics:</i> | | | | | | | | | |
| Financial regulator | 5.959***
(0.380) | -19.011***
(1.652) | 5.416***
(0.378) | 14.784***
(0.712) | 19.546***
(3.625) | 9.966***
(0.789) | -4.324***
(1.188) | 15.550***
(3.539) | -3.863***
(1.206) |
| Shareholder protection index | -0.127*
(0.066) | -0.406***
(0.070) | 0.139**
(0.068) | -1.088***
(0.102) | -1.149***
(0.108) | 0.521***
(0.156) | 0.295
(0.201) | 1.358***
(0.254) | 0.369*
(0.200) |
| Financial institution access index | 9.604***
(0.795) | 15.083***
(0.869) | 8.707***
(0.785) | 4.688***
(1.140) | 3.794***
(1.392) | 8.807***
(1.241) | 5.120
(3.527) | 2.794
(3.536) | 6.735*
(3.673) |
| Bull market | -7.800***
(0.427) | -6.740***
(0.428) | -20.105***
(1.061) | -16.045***
(0.588) | -16.542***
(0.721) | -27.560***
(1.379) | -0.814
(1.012) | -1.248
(1.008) | -0.319
(1.137) |
| Bear market | -1.892***
(0.321) | -1.129***
(0.321) | 3.163***
(0.849) | -1.824***
(0.437) | -2.047***
(0.472) | 8.388***
(1.466) | -4.405***
(0.924) | -5.533***
(0.927) | 87.591
(106.427) |
| <i>Token characteristics:</i> | | | | | | | | | |
| Market cap | -0.211***
(0.074) | -0.238*
(0.137) | -0.213***
(0.074) | -0.038
(0.099) | -0.200
(0.172) | -0.097
(0.098) | -0.333**
(0.130) | -0.351
(0.361) | -0.337***
(0.130) |
| Trading volume | 0.970***
(0.102) | 0.680***
(0.176) | 0.964***
(0.102) | 0.852***
(0.138) | 0.970***
(0.212) | 0.688***
(0.139) | 0.720***
(0.210) | -0.505
(0.496) | 0.716***
(0.211) |
| DeFi token type | 16.271
(13.096) | 16.378
(13.035) | 16.085
(12.926) | 33.828
(24.045) | 33.807
(24.076) | 33.884
(23.573) | -0.634
(8.303) | -0.672
(7.940) | -0.629
(8.300) |
| Currency token type | -9.236**
(4.499) | -9.939**
(4.474) | -8.959**
(4.352) | -8.126
(7.567) | -8.262
(7.624) | -3.425
(6.878) | -6.621
(7.128) | -6.244
(6.633) | -6.540
(7.143) |
| Illiquidity measure | 0.990
(1.053) | 0.793
(1.068) | 1.205
(0.970) | 1.832*
(1.032) | 1.879*
(1.037) | 2.072*
(1.102) | 1.953
(2.000) | 1.099
(2.043) | 1.937
(2.006) |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 24,097 | 24,097 | 24,097 | 13,054 | 13,054 | 13,054 | 6,836 | 6,836 | 6,836 |
| R ² | 0.099 | 0.108 | 0.115 | 0.193 | 0.193 | 0.221 | 0.263 | 0.269 | 0.263 |

Note: These are regression results for the impact of governance enforcement strength on the cumulative abnormal return (CAR) over the 5-day event window (in %). Abnormal return is calculated based on the daily return of the event days minus the 80-day pre-event average return. The *Governance enforcement index* represents the strength of enforcement of contracts and other rights within the jurisdiction issuing the law, measured as a percentile rank. Additionally, we report the coefficients for regulation and market characteristics, token characteristics, and several interaction terms of these variables with the *Governance enforcement index*. Token fixed-effects are included in all models to control for time-invariant confounders. The table presents regression results for three different samples: (i) all events, (ii) regulatory framework events, and (iii) tax events. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The regressions in Table 4.7 indicate that a higher government enforcement index amplifies the risk reduction in the post-event period. The main model shows that if the government enforcement index percentile of the jurisdiction that announces the regula-

tion increases by 1 point, on average, the negative delta between post-event and pre-event standard deviation increases by -0.024 percentage points. These findings strongly support H4, that a higher enforcement probability of the announced cryptocurrency regulation amplifies the risk reduction in the cryptocurrency market. The highly statistically significant results ($p\text{-value} < 0.01$) underline the dependency of the success of new regulation on the overall regulatory environment. The R^2 of the main model for the whole sample is 8.8%. Our regressions reveal further interesting facts about the drivers of the success of an announced regulation. A regulation issued by a financial regulator and an increase in the financial institution access by 1 unit impact the delta between post-event and pre-event standard deviation by $+1.322$ percentage points and $+3.300$ percentage points, respectively. However, if the shareholder protection index increases by one unit, the delta decreases by -0.140 percentage points. The negative impact of a higher shareholder protection index provides additional evidence for H4, given that it might be considered an alternative indicator of the strength of the regulatory environment within the jurisdiction.

Looking at the token characteristics, our study reveals that the impact of announced regulations differs among the tokens. While we do not see a significant difference for tokens of decentralized finance protocols, we observe an increased post-event return volatility change for currency tokens. Our results also show that more liquid and traded tokens experience a higher risk reduction. An increase of the daily trading volume by 1% leads to a greater negative risk delta of -0.266 percentage points, indicating an increased risk reduction during the 80 days after the event window. We observe the same statistically significant directional effect on larger tokens. A token with a 1% larger market cap at the event date experiences, on average, a -0.024 percentage-point greater risk reduction during the post-event window. We identify several plausible explanations for these highly significant effects. First, larger and more prominent tokens are often either directly targeted by the regulation or are the ones with the highest short-term enforcement probability. Given the high complexity of enforcing regulations in the cryptocurrency space due

to technical and structural variations among the different blockchains and tokens, regulators are expected to focus first on the tokens with the largest market cap. Second, a higher trading volume and market cap often indicate that the token is listed on a centralized exchange (CEX). Given the regulatory requirements and the centralized structure of a CEX, direct enforcement in this setting might be less complicated than for tokens that are purely traded on unregulated and fully decentralized exchanges.

Our first interaction model shows that regulations announced by a financial regulator negatively moderate the impact of the governance enforcement index on the average return volatility reduction. In economic terms, this means that the -0.011 percentage points risk reduction based on a 1 unit increase in the governance enforcement index is amplified by, on average, -0.050 percentage points. If the regulation is issued by a financial regulator. The findings are significant at the 1% level. A possible explanation could be that the governance enforcement strength of the jurisdiction might be of even higher importance if the regulations are announced by the regulator rather than directly by the government, given that the direct impact of a regulator announcement leads to smaller risk reduction in the post-event window. While we also observe statistically significant interaction terms between the governance enforcement index and the market cap and trading volume, the coefficients only indicate a marginal moderating impact. The -0.011 percentage points risk reduction based on a 1 percentile increase in the governance enforcement index increases by -0.001 percentage points on average if the daily trading volume of the token increases by 1%, and increases by the same amount if the market cap increases by 1%. Our second model variation reveals a highly significant moderating effect of market sentiment during regulatory announcements. If the market sentiment is bearish (bullish), the -0.013 percentage points change in return volatility is further decreased by -0.020 percentage points (-0.007 percentage points).

The additional regressions based on the two subsamples containing regulatory framework and tax regulation announcements confirm our findings. However, while the di-

rection and level of statistical significance of the coefficients are mostly the same, we observe differences in the coefficient sizes. The positive impact of a stronger regulatory environment on the change in return volatility reduction after cryptocurrency news announcements is amplified in the subsamples. It is observable that if only announcements related to new regulatory frameworks and tax laws are considered, the average risk reduction in the cryptocurrency market is further magnified by -0.031 percentage points and -0.063 percentage points, respectively, for every 1 percentile increase of the governance enforcement index.

Table 4.7: Regression analysis of post-event changes in return volatility

| Dependent variable: Δ Return volatility, in % pts., [$\pm$ 80 days] | | | | | | | | | |
|---|----------------------|----------------------|----------------------|-----------------------|----------------------|----------------------|----------------------|----------------------|------------------------|
| | All events: | | | Regulatory Framework: | | | Tax: | | |
| Key variables: | | | | | | | | | |
| Governance enforcement index | -0.024***
(0.001) | -0.011*
(0.006) | -0.013***
(0.002) | -0.031***
(0.002) | -0.027***
(0.008) | -0.007**
(0.003) | -0.063***
(0.004) | -0.038**
(0.015) | 1.298***
(0.217) |
| x financial regulator | | -0.050***
(0.005) | | | -0.028***
(0.010) | | | -0.046***
(0.010) | |
| x market cap | | 0.000
(0.000) | | | 0.001
(0.000) | | | 0.000
(0.001) | |
| x trading volume | | -0.001**
(0.000) | | | -0.001
(0.001) | | | -0.001
(0.001) | |
| x bull market | | | -0.007**
(0.003) | | | -0.013***
(0.004) | | | ./.
(./.) |
| x bear market | | | -0.020***
(0.003) | | | -0.058**
(0.005) | | | -1.363***
(0.218) |
| Regulation and market characteristics: | | | | | | | | | |
| Financial regulator | 1.322***
(0.077) | 5.244***
(0.373) | 1.275***
(0.078) | 0.637***
(0.146) | 2.829***
(0.776) | -0.488***
(0.171) | 1.874***
(0.250) | 5.469***
(0.833) | 2.551***
(0.257) |
| Shareholder protection index | -0.140***
(0.016) | -0.096***
(0.016) | -0.103***
(0.016) | 0.054**
(0.024) | 0.025
(0.026) | 0.401***
(0.037) | -0.241***
(0.049) | -0.057
(0.063) | -0.132***
(0.050) |
| Financial institution access index | 3.300***
(0.158) | 2.436***
(0.175) | 3.424***
(0.159) | 5.759***
(0.249) | 5.335***
(0.290) | 7.530***
(0.289) | 3.755***
(0.718) | 3.395***
(0.714) | 6.127***
(0.749) |
| Bull market | -0.362***
(0.095) | -0.529***
(0.097) | 0.132
(0.240) | 0.348**
(0.136) | 0.115
(0.164) | 2.093***
(0.311) | 0.491*
(0.260) | 0.430*
(0.261) | 1.218***
(0.299) |
| Bear market | 0.008
(0.072) | -0.112
(0.072) | 1.367***
(0.187) | 0.761**
(0.097) | 0.655***
(0.105) | 4.551***
(0.327) | -0.860***
(0.213) | -1.056***
(0.219) | 134.302***
(21.618) |
| Token characteristics: | | | | | | | | | |
| Market cap | -0.024*
(0.013) | -0.051*
(0.028) | -0.022
(0.013) | -0.011
(0.018) | -0.056
(0.036) | -0.011
(0.018) | -0.008
(0.028) | -0.019
(0.084) | -0.014
(0.028) |
| Trading volume | -0.266***
(0.021) | -0.204***
(0.040) | -0.269***
(0.021) | -0.245***
(0.030) | -0.185***
(0.049) | -0.268***
(0.030) | -0.150***
(0.042) | -0.090
(0.112) | -0.156***
(0.042) |
| DeFi token type | 1.883
(3.159) | 1.867
(3.119) | 1.880
(3.163) | 2.610
(4.569) | 2.595
(4.580) | 2.618
(4.459) | 4.172
(3.491) | 4.173
(3.463) | 4.178
(3.497) |
| Currency token type | 6.293***
(1.338) | 6.392***
(1.361) | 6.277***
(1.350) | 8.446***
(2.176) | 8.414***
(2.197) | 8.851***
(2.111) | 1.786
(1.104) | 2.036*
(1.163) | 1.905*
(1.077) |
| Illiquidity measure | -0.343**
(0.151) | -0.309**
(0.153) | -0.341**
(0.153) | -0.347
(0.247) | -0.319
(0.252) | -0.346
(0.250) | 0.142
(0.306) | 0.189
(0.315) | 0.117
(0.309) |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 24,097 | 24,097 | 24,097 | 13,054 | 13,054 | 13,054 | 6,836 | 6,836 | 6,836 |
| R ² squared | 0.088 | 0.092 | 0.090 | 0.143 | 0.144 | 0.152 | 0.169 | 0.172 | 0.175 |

Note: These are regression results for the impact of governance enforcement strength on Δ return volatility. Δ return volatility measures the difference in the standard deviation of the daily token price return between the 80-day post-event window and the 80-day pre-event window. The *Governance enforcement index* represents the strength of enforcement of contracts and other rights within the jurisdiction issuing the law, measured as a percentile rank. Additionally, we report the coefficients for regulation and market characteristics, token characteristics, and several interaction terms of these variables with the *Governance enforcement index*. Token fixed-effects are included in all models to control for time-invariant confounders. The table presents regression results for three different samples: (i) all events, (ii) regulatory framework events, and (iii) tax events. Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1

Tables 4.8 and 4.9 show a similar picture for the effects on average changes in daily returns and Sharpe ratios during the post-event window. We observe that an increase of the government enforcement index by 1 percentile leads, on average, to a -0.005 percentage-

point reduction in the raw post-event return and a -0.045 percentage-point reduction in the risk-adjusted post-event return (i.e. Sharpe ratio). The direction and significance of the effects are confirmed in the additional regression variations.

Table 4.8: Regression analysis of post-event changes in returns

| Dependent variable: Δ Return, in % pts., [± 80 days] | | | | | | | | | |
|--|----------------------|----------------------|----------------------|-----------------------|----------------------|----------------------|----------------------|----------------------|-----------------------|
| | All events: | | | Regulatory Framework: | | | Tax: | | |
| Key variables: | | | | | | | | | |
| Governance enforcement index | -0.005***
(0.000) | -0.001
(0.002) | 0.004***
(0.001) | -0.010***
(0.001) | 0.010***
(0.003) | -0.003***
(0.001) | -0.004***
(0.001) | -0.008**
(0.004) | -0.610***
(0.058) |
| x financial regulator | | -0.008***
(0.002) | | | -0.099***
(0.003) | | | 0.024**
(0.003) | |
| x market cap | | 0.000
(0.000) | | | 0.000*
(0.000) | | | 0.000
(0.000) | |
| x trading volume | | -0.000**
(0.000) | | | -0.001***
(0.000) | | | -0.000
(0.000) | |
| x bull market | | | -0.014***
(0.001) | | | -0.014***
(0.001) | | | ./.
(./.) |
| x bear market | | | -0.012**
(0.001) | | | -0.009***
(0.002) | | | 0.607***
(0.058) |
| Regulation and market characteristics: | | | | | | | | | |
| Financial regulator | 0.275***
(0.028) | 0.931***
(0.133) | 0.263***
(0.027) | 0.039
(0.054) | 7.726***
(0.252) | -0.059
(0.058) | -0.724***
(0.071) | -2.578***
(0.231) | -1.026***
(0.074) |
| Shareholder protection index | -0.045***
(0.005) | -0.037***
(0.005) | -0.028***
(0.005) | -0.078***
(0.007) | -0.182***
(0.007) | -0.053***
(0.012) | -0.153***
(0.014) | -0.249***
(0.018) | -0.201***
(0.014) |
| Financial institution access index | 0.629***
(0.058) | 0.488***
(0.061) | 0.763***
(0.057) | 1.123***
(0.083) | -0.345***
(0.095) | 1.421***
(0.092) | -1.440***
(0.212) | -1.247***
(0.206) | -2.497***
(0.223) |
| Bull market | 0.150***
(0.031) | 0.121***
(0.031) | 1.063***
(0.077) | 0.415***
(0.046) | -0.393***
(0.054) | 1.359***
(0.105) | -0.165**
(0.069) | -0.129*
(0.070) | -0.488***
(0.076) |
| Bear market | 0.223***
(0.021) | 0.202***
(0.021) | 1.036***
(0.054) | 0.425***
(0.030) | 0.059*
(0.031) | 1.006***
(0.110) | -0.861***
(0.054) | -0.757***
(0.055) | -61.054***
(5.740) |
| Token characteristics: | | | | | | | | | |
| Market cap | -0.040***
(0.005) | -0.046***
(0.010) | -0.038***
(0.005) | -0.036***
(0.007) | -0.050***
(0.012) | -0.033***
(0.007) | -0.034***
(0.008) | -0.041*
(0.024) | -0.031***
(0.008) |
| Trading volume | -0.148***
(0.007) | -0.126***
(0.013) | -0.150***
(0.007) | -0.180***
(0.011) | -0.107***
(0.016) | -0.179***
(0.011) | -0.071***
(0.011) | -0.037
(0.031) | -0.069***
(0.011) |
| DeFi token type | 0.156
(0.671) | 0.152
(0.668) | 0.162
(0.660) | 0.833
(1.163) | 0.810
(1.213) | 0.832
(1.144) | -0.313
(0.702) | -0.311
(0.737) | -0.316
(0.701) |
| Currency token type | 3.038***
(0.525) | 3.060***
(0.528) | 3.014***
(0.523) | 4.170***
(0.817) | 4.085***
(0.875) | 4.082***
(0.815) | 1.022*
(0.546) | 0.934
(0.602) | 0.969*
(0.536) |
| Illiquidity measure | 0.033
(0.099) | 0.045
(0.101) | 0.025
(0.096) | 0.021
(0.120) | 0.083
(0.129) | 0.011
(0.116) | 0.171*
(0.102) | 0.191*
(0.106) | 0.182*
(0.099) |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 24,097 | 24,097 | 24,097 | 13,054 | 13,054 | 13,054 | 6,836 | 6,836 | 6,836 |
| R ² | 0.103 | 0.105 | 0.114 | 0.169 | 0.246 | 0.177 | 0.225 | 0.236 | 0.241 |

Note: These are regression results for the impact of governance enforcement strength on Δ return. Δ return measures the difference in token price return between the 80-day post-event window and the 80-day pre-event window. The *Governance enforcement index* represents the strength of enforcement of contracts and other rights within the jurisdiction issuing the law, measured as a percentile rank. Additionally, we report the coefficients for regulation and market characteristics, token characteristics, and several interaction terms of these variables with the *Governance enforcement index*. Token fixed-effects are included in all models to control for time-invariant confounders. The table presents regression results for three different samples: (i) all events, (ii) regulatory framework events, and (iii) tax events. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.9: Regression analysis of post-event changes in Sharpe Ratios

| Dependent variable: Δ Sharpe Ratio, [± 80 days] | | | | | | | | | |
|---|----------------------|----------------------|----------------------|-----------------------|----------------------|----------------------|-----------------------|-----------------------|-------------------------|
| | All events: | | | Regulatory Framework: | | | Tax: | | |
| Key variables: | | | | | | | | | |
| Governance enforcement index | -0.045***
(0.003) | -0.023*
(0.013) | 0.045***
(0.006) | -0.085***
(0.004) | 0.083***
(0.018) | -0.046***
(0.008) | -0.057***
(0.009) | -0.163***
(0.033) | -6.631***
(0.500) |
| x financial regulator | | -0.023*
(0.014) | | | -0.899***
(0.023) | | | 0.289***
(0.027) | |
| x market cap | | 0.001
(0.001) | | | 0.003**
(0.001) | | | 0.002
(0.002) | |
| x trading volume | | -0.003**
(0.001) | | | -0.010***
(0.002) | | | -0.002
(0.003) | |
| x bull market | | | -0.121***
(0.008) | | | -0.114***
(0.010) | | | ./.
(./.) |
| x bear market | | | -0.137***
(0.007) | | | -0.025*
(0.015) | | | 6.588***
(0.501) |
| Regulation and market characteristics: | | | | | | | | | |
| Financial regulator | 2.624**
(0.215) | 4.423***
(1.132) | 2.435***
(0.211) | 0.219
(0.416) | 69.978***
(1.826) | 0.472
(0.468) | -8.103***
(0.720) | -30.596***
(2.197) | -11.372***
(0.761) |
| Shareholder protection index | -0.683***
(0.040) | -0.665***
(0.043) | -0.475***
(0.042) | -1.337***
(0.062) | -2.275***
(0.061) | -1.459***
(0.112) | -1.656***
(0.129) | -2.819***
(0.167) | -2.181***
(0.134) |
| Financial institution access index | 5.028**
(0.453) | 4.658***
(0.491) | 6.305***
(0.446) | 8.491***
(0.700) | -4.810***
(0.744) | 9.360***
(0.783) | -16.793***
(2.130) | -14.545***
(2.074) | -28.253***
(2.297) |
| Bull market | 2.237**
(0.230) | 2.151***
(0.227) | 10.181***
(0.553) | 4.828***
(0.339) | -2.505***
(0.373) | 11.383***
(0.818) | -0.354
(0.535) | 0.055
(0.542) | -3.866***
(0.553) |
| Bear market | 2.419**
(0.182) | 2.357***
(0.182) | 11.489***
(0.478) | 4.517***
(0.250) | 1.204***
(0.252) | 5.867***
(0.993) | -9.601***
(0.465) | -8.344***
(0.483) | -662.674***
(49.601) |
| Token characteristics: | | | | | | | | | |
| Market cap | -0.388***
(0.037) | -0.477***
(0.071) | -0.370***
(0.037) | -0.326***
(0.048) | -0.462***
(0.087) | -0.303***
(0.048) | -0.361***
(0.076) | -0.504**
(0.220) | -0.334***
(0.075) |
| Trading volume | -1.245***
(0.051) | -1.053***
(0.091) | -1.266***
(0.051) | -1.397***
(0.074) | -0.762***
(0.109) | -1.368***
(0.074) | -0.632***
(0.082) | -0.481**
(0.243) | -0.607***
(0.081) |
| DeFi token type | -1.604
(6.821) | -1.630
(6.791) | -1.568
(6.679) | 1.895
(8.730) | 1.698
(9.089) | 1.885
(8.576) | -6.032
(14.207) | -6.017
(14.471) | -6.063
(14.274) |
| Currency token type | 28.449***
(3.608) | 28.530***
(3.614) | 28.234***
(3.583) | 30.930***
(3.716) | 30.128***
(3.604) | 29.755***
(3.681) | 14.836**
(6.159) | 13.590**
(6.613) | 14.262**
(6.002) |
| Illiquidity measure | -0.931
(0.671) | -0.837
(0.688) | -0.990
(0.657) | -0.836
(0.680) | -0.282
(0.759) | -0.922
(0.624) | 0.050
(0.376) | 0.092
(0.434) | 0.170
(0.316) |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 24,097 | 24,097 | 24,097 | 13,054 | 13,054 | 13,054 | 6,836 | 6,836 | 6,836 |
| R ² | 0.113 | 0.114 | 0.129 | 0.215 | 0.312 | 0.223 | 0.264 | 0.280 | 0.284 |

Note: These are regression results for the impact of governance enforcement strength on Δ Sharpe ratio. Δ Sharpe ratio measures the differences in sharpe ratio of the token between the 80-day post-event window and the 80-day pre-event window. Sharpe ratio is calculated as the average daily return multiplied by the window size (i.e., 80) divided by the standard deviation during the period. The Governance enforcement index represents the strength of enforcement of contracts and other rights within the jurisdiction issuing the law, measured as a percentile rank. Additionally, we report the coefficients for regulation and market characteristics, token characteristics, and several interaction terms of these variables with the Governance enforcement index. Token fixed-effects are included in all models to control for time-invariant confounders. The table presents regression results for three different samples: (i) all events, (ii) regulatory framework events, and (iii) tax events. Robust standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1

4.4.5.1 DARSI development and measurement

Our empirical results provide evidence of a significant impact of regulatory announcements on cryptocurrencies' risk-return characteristics. However, it is important to assess whether the observed risk reduction is caused solely by a reduction in uncertainty resulting from the announcement itself, or if the actual content of the new regulation also plays a role. To shed light on the scope of each announced regulation and assess the cryptocurrency regulatory status across different jurisdictions, we developed the DARSI (Digital Asset Regulatory Strength Index) for each regulation category. This measure allows us to examine the relationship between the jurisdiction's regulatory strength and changes in asset characteristics, similar to regulation indices used in other law and finance research (e.g., Cumming et al., 2011). As detailed in Table 4.10, the index incorporates a set of dummy variables; each variable represents a key criterion of the law type, taking the value 1 if the cryptocurrency law within the jurisdiction addresses this criterion, and 0 otherwise. To construct the DARSI for the four regulation types, we executed a four-step process. First, we gathered content from over 100 cryptocurrency regulations, including those in our final sample and others removed during sample construction. Regulations not originally in English or German were translated using online tools. Second, we manually reviewed each law to determine which activities were regulated. Third, we categorized these activities into overarching groups, ensuring each activity was uniquely allocated. Fourth, we created dummy variables for each category and introduced the *Existence* index criterion, which indicates the presence of any regulation at all in the jurisdiction for this type of regulation. This meticulous process produced indices with 10 constituents for the AML/CFT, crypto ban, and tax indices, while the regulatory framework analysis yielded an index with 15 constituents.

Besides the *Existence* index criterion, each index incorporates the *Scope* and *Punishment* criteria, which assess whether all types of crypto assets are covered by the regulation and whether there are defined punishments for breaches, respectively. Additionally, the

AML/CFT index evaluates whether regulations include provisions for customer due diligence, suspicious transaction reporting, internal audits, information security management, record keeping, participation in international AML/CFT efforts, and compliance training programs. The crypto ban index assesses the extent of the ban, analyzing whether it prohibits a range of activities including exchange and transfer services, other crypto-related services (e.g., custody), primary offerings, mining, trading, and holding of cryptocurrencies, as well as the activities of national businesses and entities operating outside their own jurisdiction. The regulatory framework index determines whether the framework addresses key areas related to cryptocurrencies and businesses operating within the sector, such as categorization, issuance, exchange activities, custodianship, mining, use as a means of payment, technology specifications, corporate governance, market integrity, investor protection, innovation support, and supervisory authorities. The tax index evaluates the breadth of tax regulations, analyzing coverage of primary market activities, gratuitous receipt (e.g., airdrops), tax loss compensation, capital gains tax, income tax, taxation of cryptocurrency-related business activities (e.g., VAT), and requirements for record keeping and submission.

Next, to measure the level of DARSİ within a jurisdiction, we implemented a three-step process. Initially, we evaluated the pre-announcement DARSİ level using our collected data, which involved screening our database to determine if any DARSİ criteria had been met by previously announced cryptocurrency regulations or if non-cryptocurrency specific laws were applicable. Subsequently, we assessed which DARSİ criteria were satisfied by the newly announced regulation. Finally, we combined the results from the first two steps to measure the total post-announcement level of the DARSİ. There are two limitations of our approach to constructing and measuring the DARSİ that readers should be aware of. First, the definition of constituents involves subjective decisions and is based on data available up until April 2023. The introduction of new regulations or a different grouping logic to generate the categories might lead to variations in the constituents of the regulatory

strength index. Second, our application of the DARSi and subsequent empirical measurements focus only on the jurisdictions included in our sample. Future research could apply the DARSi across all jurisdictions to measure the status quo and conduct analyses based on a larger sample size. Despite these limitations, we believe that the DARSi and subsequent analyses offer significant value. This methodology represents the first known approach to quantify the strength of cryptocurrency regulation and make it comparable across jurisdictions. Moreover, it enables the study of the impact of regulatory strength on the risk and return characteristics of the overall cryptocurrency market and allows us to draw conclusions about the importance of the regulation's content.

Table 4.10: Regulatory strength index definitions

| Index Criteria | Definition |
|-----------------------------------|---|
| <i>AML/CFT index</i> | |
| Existence | Regulator/Government published guideline or regulation about AML/CFT related to cryptocurrency-related activities |
| Scope | AML/CFT framework includes all cryptocurrencies and not only a subsection or selected coins |
| CDD | AML/CFT framework addresses Customer Due Diligence requirements of enterprises handling cryptocurrency platform/transaction |
| Reporting | AML/CFT framework addresses suspicious transaction reporting for requirements enterprises handling cryptocurrency platform/transaction |
| Audit | AML/CFT framework addresses internal audits required for enterprises handling cryptocurrency platform/transaction |
| ISM | AML/CFT framework addresses information security management of enterprises handling cryptocurrency platform/transaction |
| Record | AML/CFT framework addresses record keeping requirements for enterprises handling cryptocurrency platform/transaction |
| International | AML/CFT framework addresses provisions for cooperation with international AML/CFT efforts of enterprises handling cryptocurrency platform/transaction |
| Program | AML/CFT framework includes required compliance (training) programs for enterprises handling cryptocurrency platform/transaction |
| Punishment | AML/CFT framework defines punishment in case of a breach of the AML/CFT laws |
| <i>Crypto ban index</i> | |
| Existence | Regulator/Government published opinion or regulation about cryptocurrency activities (incl. warnings) |
| Scope | Existing prohibitions include all types of cryptocurrencies and not only a subsection or selected coins |
| Exchange | Prohibition for businesses to offer exchange/transfer services |
| Custody | Prohibition for businesses to offer other non-exchange related crypto-related services (e.g., custody or admin) |
| ICO | Prohibition of facilitating cryptocurrency primary offerings (i.e., ICOs) |
| Mining | Prohibition of engaging in cryptocurrency mining |
| Trading | Prohibition for individuals to trade cryptocurrencies |
| Holding | Prohibition for individuals to hold cryptocurrencies |
| Cross-border | Prohibitions include activities of national businesses/citizens outside of their own jurisdictions |
| Punishment | Regulatory framework defined potential punishment in case of a breach of the cryptocurrency ban |
| <i>Regulatory framework index</i> | |
| Existence | Regulator/Government published opinion or regulatory framework about cryptocurrency-related activities |

| | |
|-------------|--|
| Scope | Regulatory framework includes all cryptocurrencies and not only a subsection or selected coins |
| Category | Regulatory framework addresses the categorization of cryptocurrencies |
| Issuance | Regulatory framework addresses the issuance of cryptocurrencies |
| Exchange | Regulatory framework addresses exchange activities/trading of cryptocurrencies (e.g., required licensing) |
| Custody | Regulatory framework addresses custody of cryptocurrencies (e.g., required licensing) |
| Mining | Regulatory framework addresses mining of cryptocurrencies |
| Payment | Regulatory framework addresses cryptocurrencies as a means of payments |
| Technology | Regulatory framework addresses technology specifications of cryptocurrencies and/or requirements (e.g., required certifications) |
| Governance | Regulatory framework addresses corporate governance of businesses related to cryptocurrencies (e.g., internal controls, risk management) |
| Integrity | Regulatory framework includes specific market integrity/market abuse laws related to cryptocurrency activities (e.g., addressing insider trading, market manipulation) |
| Protection | Regulatory framework addresses investor protection related to cryptocurrency activities (e.g., disclosure rules, fair practices) |
| Innovation | Regulatory framework includes targeted approaches to support innovation related to cryptocurrency activities (e.g., regulatory sandbox) |
| Supervisory | Regulatory framework defines supervisory authorities for cryptocurrency-related activities |
| Punishment | Regulatory framework defined potential punishment in case of a breach of the cryptocurrency-related regulations |

Tax index

| | |
|------------|---|
| Existence | Regulator/Government published opinion or regulation about taxation of cryptocurrencies and related activities (incl. guidelines) |
| Scope | Taxation framework/statement includes all cryptocurrencies and not only a subsection or selected coins |
| ICO | Tax framework addresses tax treatment of primary market activities (i.e., ICOs) |
| Airdrop | Tax framework addresses tax treatment of gratuitous receipt of cryptocurrencies (e.g., airdrops, forking) |
| Loss | Tax framework addresses tax loss compensation (tax loss harvesting) |
| Gain | Tax framework addresses capital gain tax applicable to cryptocurrency transactions |
| Income | Tax framework addresses income tax applicable to cryptocurrency activities (e.g., staking income, mining) |
| VAT | Tax framework addresses the taxation of cryptocurrency-related business activities (incl. VAT, corporate tax rates) |
| Record | Tax framework addresses record-keeping and submission requirements of cryptocurrency-related taxes |
| Punishment | Tax framework includes (directly or indirectly) punishment in case of a breach of the taxation laws |

Note: This table shows the definition of the different constituents of the four regulatory strength indices: (i) AML/CFT index, (ii) crypto ban index, (iii) regulatory framework index, (iv) tax index. Each index criteria represents a dummy variable that takes the value 1 if the point is included within the announced regulation and 0 if not.

4.4.5.2 Regulatory strength empirical results

In Table 4.11, we apply the DARSİ to each of the 35 regulatory announcements included in our sample. The last column displays the DARSİ value for the corresponding jurisdiction after the regulation is announced, with pre-announcement values provided in parentheses. At the bottom of each panel, we present the median values of the indices. It is notable that AML/CFT regulations often served as the first comprehensive, cryptocurrency-specific regulations within their jurisdictions, yielding a median DARSİ of 8.5. Similarly, crypto bans, which typically restrict nearly all cryptocurrency-related activities, show a median index

value of 9. Concerning tax regulations, while the median post-announcement DARSi is consistently high at 9, the pre-announcement values are also substantial. This suggests that several jurisdictions were already leveraging existing fiscal laws to govern cryptocurrency-related activities prior to formalizing specific crypto tax frameworks.

Our table illustrates that announced cryptocurrency regulatory frameworks significantly alter the pre-event DARSi values within jurisdictions. The data reveals a shift from a median pre-event value of 0 to a post-event value of 12, indicating that regulators typically introduce comprehensive frameworks rather than targeting specific subareas when they decide to actively regulate the sector. The most detailed regulation in our sample is found in Switzerland, which achieves a DARSi score of 15 out of 15. This jurisdiction not only regulates key cryptocurrency-related activities of companies and individuals, categorizes tokens, and outlines penalties for breaches but also addresses mining activities and government-enacted innovation programs to foster the development of cryptocurrencies. In contrast, the least comprehensive regulation is from El Salvador's announcement to adopt BTC as legal tender, which scores a DARSi of 3. Although it introduces a new law, it is not considered a full regulatory framework, focusing solely on the payment aspect of one cryptocurrency.

Table 4.11: Overview of regulatory strength index

| Country | Date | Event | Index value
Post (Pre) |
|--------------------------------|-------------|--|---------------------------|
| <i>AML/CFT</i> | | | |
| Bulgaria | 29 Nov 2019 | Measures Against Money Laundering Act | 6 (0) |
| Estonia | 31 Dec 2019 | Money Laundering and Terrorist Financing Prevention Act | 8 (0) |
| Taiwan | 30 Jun 2021 | Regulations Governing AML and CFT for Enterprises Handling Virtual Currency Platform or Transactions | 10 (9) |
| Hong Kong | 7 Dec 2022 | Passage of Anti-Money Laundering and Counter-Terrorist Financing (Amendment) Bill 2022 | 9 (0) |
| Median AML/CFT index | | | 8.5 (0) |
| <i>Crypto Ban</i> | | | |
| Qatar | 26 Dec 2019 | QFC Regulatory Authority affirms that Virtual Asset Services may not be conducted in or from the QFC | 6 (3) |
| Egypt | 15 Sep 2020 | Law No. 194 of 2020 prohibits cryptocurrency-related activities | 9 (2) |
| China | 24 Sep 2021 | China's top regulators ban crypto trading and mining | 9 (6) |
| Median Crypto Ban index | | | 9 (3) |

| <i>Regulatory framework</i> | | | |
|--|-------------|--|---------------|
| Malta | 20 Jul 2018 | Virtual Financial Assets Act + Innovative Technology Arrangements and Services Act | 11 (0) |
| Switzerland | 14 Dec 2018 | Legal framework for distributed ledger technology and blockchain in Switzerland | 14 (3) |
| Bahrain | 21 Feb 2019 | Rulebook Module on crypto-assets (Module CRA) | 13 (0) |
| France | 11 Apr 2019 | Loi PACTE - Regulatory Framework for Crypto-Activities and ICOs | 13 (0) |
| United Kingdom | 31 Jul 2019 | PS19/22 Guidance on Cryptoassets | 13 (0) |
| Saint Kitts and Nevis | 23 Jan 2020 | Virtual Asset Bill 2020 | 11 (0) |
| Antigua and Barbuda | 8 Jun 2020 | Digital Assets Business Act | 11 (0) |
| Russian Federation | 31 Jul 2020 | Regulation on digital financial asset (DFA) | 12 (0) |
| Switzerland | 25 Sep 2020 | Federal Act on the Adaptation of Federal Law to Developments in Distributed Ledger Technology | 15 (14) |
| Bahamas | 24 Nov 2020 | Digital Assets and Registered Exchanges Act | 13 (0) |
| Serbia | 21 Dec 2020 | Law on Digital Assets | 13 (0) |
| Spain | 12 Mar 2021 | Spanish Royal Decree-Law 5/2021 | 4 (0) |
| Germany | 3 Jun 2021 | Electronic Securities Act | 12 (4) |
| El Salvador | 9 Jun 2021 | Bitcoin as legal tender - Bitcoin Law (Decree No. 57) | 3 (0) |
| Mauritius | 10 Dec 2021 | e Virtual Asset and Initial Token Offering Services Act 2021 | 13 (0) |
| Ukraine | 16 Mar 2022 | Legalisation of cryptocurrency within the country's financial system | 12 (0) |
| United States | 16 Sep 2022 | Comprehensive Framework for Responsible Development of Digital Assets | 5 (2) |
| Brazil | 21 Dec 2022 | Legal Framework for Virtual Assets in Brazil (Cryptoassets Act) | 11 (0) |
| Kazakhstan | 6 Feb 2023 | Kazakhstan introduces news Regulation of Digital Assets | 14 (6) |
| Median Regulatory Framework index | | | 12 (0) |
| <i>Tax</i> | | | |
| Luxembourg | 26 Jul 2018 | Circulaire L.I.R. n° 95_2 du 31.12.2010 | 8 (0) |
| Romania | 10 Jan 2019 | LEGE nr. 30 din 10 ianuarie 2019 | 5 (0) |
| Finland | 7 Oct 2019 | Taxation of virtual currencies | 9 (9) |
| Singapore | 17 Apr 2020 | IRAS e-Tax Guide - Income Tax Treatment of Digital Tokens | 9 (0) |
| Singapore | 9 Oct 2020 | IRAS e-Tax Guide - Income Tax Treatment of Digital Tokens (Adj.) | 9 (9) |
| Austria | 2 Feb 2022 | Steuerliche Behandlung von Kryptowährungen | 9 (8) |
| Thailand | 24 May 2022 | Royal Decree Exempting VAT on Digital Currency Transfers | 7 (7) |
| Singapore | 3 Aug 2022 | IRAS e-Tax Guide - GST: Digital Payment Tokens | 9 (9) |
| Chile | 12 Oct 2022 | Chile Tax Agency Clarifies Taxation of Financial Services, Digital Asset Transactions on Blockchain Platform | 8 (7) |
| Median Tax index | | | 9 (7) |

Note: This table shows the regulatory strength index values for each regulation within our sample. The index value "Post" presents how many of the criteria of the regulatory strength index are fulfilled within the jurisdiction after the announced regulation becomes effective. A higher value indicates a more comprehensive legal framework applies to cryptocurrencies within the jurisdiction. The index value "Pre" indicates the same but as the status before the announced regulation becomes effective. Additionally, we report the median index values for each regulation type.

In Table 4.12, we categorize the four regulation types into subsamples based on their DARSİ values, comparing those regulations that result in DARSİ values below the median with those equal to or above the median. We conducted difference-in-means tests to assess the impact of regulatory strength on post-event changes in CAR, return volatility, return, and Sharpe ratio. The results indicate that higher DARSİ values are associated with greater risk reduction during the post-announcement period in three out of four subsamples, pro-

viding empirical evidence that the content and scope of policy changes have a meaningful impact on the resulting risk reduction. Specifically, the differences range from -1.806 percentage points for taxation laws to -2.674 and -2.899 percentage points for AML/CFT regulations and crypto bans, respectively. For regulatory frameworks, we initially observe no statistically significant differences between the low and high DARSI subsamples. However, a closer examination of individual events reveals that this result is largely influenced by the announcement from El Salvador regarding BTC as legal tender. Although this event is categorized as having the lowest regulatory strength and its classification as a regulatory framework is questionable, it significantly influences the key characteristics of the asset class. Excluding this outlier reveals a consistent effect across the other three subsamples, showing an average difference in return volatility reduction of -0.550 percentage points for stronger regulations. We do not find consistently significant differences for other outcome variables.

Table 4.12: **Impact of regulatory strength on outcome variables**

| | AML/CFT index | | Crypto Ban index | | Reg Framework index | | Reg Framework index (adj.) | | Tax index | |
|-------------------|---------------|------------------|------------------|-------------------|---------------------|-----------------|----------------------------|------------------|-----------|------------------|
| | <8.5 | >=8.5 | <9 | >=9 | <12 | >=12 | <12 | >=12 | <9 | >=9 |
| Observations | 890 | 2,135 | 450 | 1,652 | 5,246 | 8,139 | 4,377 | 8,139 | 2,978 | 3,862 |
| CAR | 0.471 | -0.062 | -0.440 | -3.258 | -4.235 | -1.851 | -0.912 | -1.851 | -4.296 | 5.057 |
| Difference | | -0.533 | | -2.818*** | | 2.383*** | | -0.939** | | 9.353*** |
| Return volatility | 1.237 | -1.438 | 2.267 | -0.632 | -0.416 | -0.344 | 0.207 | -0.344 | 0.199 | -1.607 |
| Difference | | -2.674*** | | -2.899*** | | 0.072 | | -0.550*** | | -1.806*** |
| Return | 0.476 | 0.241 | 0.232 | -0.308 | -0.217 | 0.058 | -0.088 | 0.058 | 0.106 | 0.070 |
| Difference | | -0.235*** | | -0.5391*** | | 0.275*** | | 0.146*** | | -0.036 |
| Sharpe ratio | 6.294 | 3.644 | 3.200 | -2.869 | -0.612 | 0.269 | 0.051 | 0.269 | 1.052 | 0.679 |
| Difference | | -2.649*** | | -6.070*** | | 0.881** | | 0.218 | | -0.373 |

Note: This table presents the average CAR, return volatility, return, and Sharpe ratio for 10 subsamples, divided according to five different sample split criteria. CAR indicates the cumulative abnormal return over the 5-day event window (expressed in %). Abnormal return is calculated as the daily return of the event days minus the 80-day pre-event average return. The sample splits are based on whether values are below or above/equal to the median regulatory strength index values for: (i) AML/CFT regulations, (ii) crypto ban regulations, (iii) regulatory framework regulations, (iv) an adjusted regulatory framework that excludes the Bitcoin as legal tender announcement by El Salvador in June 2021—since this does not represent a regulatory framework per se but rather a specific individual law with a disproportionately strong impact on our results, and (v) tax regulations. A higher index value suggests a more comprehensive legal framework for cryptocurrencies within the jurisdiction. For each split, the average difference between the below median and the above or equal median subsamples is reported. The significance of these differences is indicated by asterisks, with the p-values from a t-test testing if the average deviations are significantly different from zero: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4.5.3 Importance of initial regulation

Trading cryptocurrencies and operating related businesses in unregulated environments has been shown to detrimentally affect market efficiencies (Hornuf et al., 2022; Momtaz, 2021) and pose risks to investor capital (Barone and Masciandaro, 2019; Hornuf et al., 2023). Consequently, the initial regulation in jurisdictions may provoke a pronounced market reaction, signaling to investors that government and regulatory bodies are beginning to address the cryptocurrency market. Utilizing our unique regulatory strength indices, we can isolate the impact of instances where the announced regulation was the first of its type within the jurisdiction. As evidenced in Table 4.13, when no prior cryptocurrency regulation of the same type existed at the time of the announcement, the risk reduction effect is enhanced by -1.486 percentage points. Moreover, we observe a statistically significant positive moderating effect of the first regulation dummy variable (0.024 percentage points) on the risk reduction effect of the governance enforcement index. The introduction of initial regulations not only results in more favorable short-term (1.506 percentage points) and long-term return reactions (0.375 percentage points) but also significantly boosts the Sharpe ratio by 5.504 .

Table 4.13: The importance of the first regulation within the jurisdiction

| <i>Dependent variable:</i> | CAR | Δ Return
volatility | Δ Return | Δ Sharpe
Ratio |
|--------------------------------------|------------------------|-------------------------------|----------------------|--------------------------|
| Panel A: <i>All Events</i> | | | | |
| Governance enforcement index | −0.014
(0.009) | −0.036***
(0.002) | −0.002***
(0.001) | 0.001
(0.005) |
| x first regulation | −0.050***
(0.012) | 0.024***
(0.002) | −0.003***
(0.001) | −0.045***
(0.006) |
| First regulation | 1.506*
(0.866) | −1.486***
(0.181) | 0.375***
(0.054) | 5.504***
(0.447) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ |
| Observations | 24,097 | 24,097 | 24,097 | 24,097 |
| R-squared | 0.101 | 0.092 | 0.108 | 0.124 |
| Panel B: <i>Regulatory Framework</i> | | | | |
| Governance enforcement index | −0.204***
(0.009) | −0.050***
(0.002) | −0.015***
(0.001) | −0.124***
(0.005) |
| x first regulation | 0.094***
(0.021) | 0.041***
(0.005) | 0.008***
(0.001) | 0.052***
(0.011) |
| First regulation | −13.139***
(1.552) | −1.353***
(0.325) | −0.453***
(0.100) | −4.221***
(0.792) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ |
| Observations | 13,054 | 13,054 | 13,054 | 13,054 |
| R-squared | 0.205 | 0.161 | 0.172 | 0.216 |
| Panel C: <i>Tax</i> | | | | |
| Governance enforcement index | 0.285***
(0.015) | −0.069***
(0.004) | −0.001
(0.001) | −0.026***
(0.009) |
| x first regulation | 0.441***
(0.129) | −0.012
(0.027) | −0.002
(0.007) | −0.075
(0.065) |
| First regulation | −39.710***
(10.170) | −0.746
(2.176) | 0.949*
(0.569) | 15.095***
(5.323) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ |
| Observations | 6,836 | 6,836 | 6,836 | 6,836 |
| R ² | 0.268 | 0.179 | 0.256 | 0.307 |

Note: These are regression results for the moderating effect of the first regulation on the impact of governance enforcement strength on four dependent variables: (i) *CAR*, (ii) Δ *return volatility*, (iii) Δ *return*, and (iv) Δ *Sharpe ratio*. *CAR* indicates the cumulative abnormal return over the 5-day event window (in %). Abnormal return is calculated based on the daily return of the event days minus the 80-day pre-event average return. The variables Δ *return volatility*, Δ *return*, and Δ *Sharpe ratio* measure the differences in the standard deviation of the return, price change, and Sharpe ratio of the token between the 80-day post-event window and the 80-day pre-event window. The Sharpe ratio is calculated as the average daily return multiplied by the window size (i.e., 80) divided by the standard deviation during the period. *First regulation* is a dummy variable that takes the value one if the regulation was the first one of this type within the jurisdiction, 0 otherwise. The *Governance enforcement index* represents the strength of enforcement of contracts and other rights within the jurisdiction issuing the law, measured as a percentile rank. The table presents regression results for three different samples: all events (Panel A), regulatory framework events (Panel B), and tax events (Panel C). The estimated coefficients of the control variables are suppressed for brevity and token fixed-effects are included in all models to control for time-invariant confounders. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4.6 Robustness tests and post-hoc analyses

4.4.6.1 The impact of informal institution quality on regulation success

Table 4.14 shows the results of our post-hoc analysis to assess the impact of informal institution quality on the success of newly introduced cryptocurrency regulations. We ran the baseline regression for each possible outcome variable and added uncertainty avoidance as an additional key variable together with the interaction term of governance enforcement index and uncertainty avoidance. Uncertainty avoidance is based on the cultural uncertainty avoidance score, which Hofstede (2001) defines as the degree to which a society seeks to control the uncontrollable and the extent to which its members are conditioned to feel either uncomfortable or comfortable in situations that are novel, unknown, surprising, or outside the norm. The regression results show that the more a society relies on a specific set of rules and tries to avoid uncertainty, the greater the amplification of the regulation's intended effects. In economic terms, we observe that a 1 unit increase in the uncertainty avoidance score leads, on average, to an additional -0.081 percentage-point decrease in return volatility after the announcement of new cryptocurrency regulations. This finding is consistent with the view that normative compliance-seeking supports the adoption of norms and provides evidence for H5, that stronger informal institutions in the jurisdiction that announces the cryptocurrency regulation amplify the risk reduction in the cryptocurrency market. The interaction terms show a coefficient of 0.001 percentage points, indicating a statistically significant substitution effect between formal and informal institution strength.

Looking at the other outcome variables, we observe a similar amplification of the change in return. A 1 unit increase in the uncertainty avoidance score leads, on average, to an additional -0.009 percentage-point decrease in the change in return and a 0.011 increase in Sharpe ratio. No significant effect on the CAR is observable.

Table 4.14: The moderating role of uncertainty avoidance

| <i>Dependent variable:</i> | CAR | Δ Return
volatility | Δ Return | Δ Sharpe
Ratio |
|---|----------------------|-------------------------------|----------------------|--------------------------|
| Key variables: | | | | |
| Governance enforcement index | 0.006
(0.027) | -0.101***
(0.006) | -0.004**
(0.002) | 0.037**
(0.015) |
| x uncertainty avoidance | -0.000
(0.000) | 0.001***
(0.000) | 0.000
(0.000) | -0.001***
(0.000) |
| Uncertainty avoidance | -0.043
(0.031) | -0.081***
(0.007) | -0.009***
(0.002) | 0.011
(0.018) |
| Regulation and market characteristics: | | | | |
| Financial regulator | 5.350***
(0.578) | 1.196***
(0.106) | -0.202***
(0.033) | -1.903***
(0.243) |
| Shareholder protection index | -0.692***
(0.099) | 0.145***
(0.025) | -0.098***
(0.007) | -1.353***
(0.067) |
| Financial institution access index | 8.432***
(1.173) | 1.887***
(0.222) | -0.549***
(0.070) | -5.378***
(0.547) |
| Bull market | -2.474***
(0.653) | -0.874***
(0.142) | -0.578***
(0.043) | -3.472***
(0.328) |
| Bear market | -0.853**
(0.417) | -0.398***
(0.097) | 0.174***
(0.028) | 2.181***
(0.260) |
| Token characteristics: | | | | |
| Market cap | -0.322***
(0.089) | -0.019
(0.016) | -0.036***
(0.005) | -0.347***
(0.043) |
| Trading volume | 0.969***
(0.130) | -0.255***
(0.026) | -0.114***
(0.008) | -1.060***
(0.058) |
| DeFi token type | 4.944
(4.354) | 1.710
(3.797) | -0.108
(0.574) | -0.311
(9.353) |
| Currency token type | -6.688*
(4.021) | 4.426***
(0.875) | 2.121***
(0.400) | 25.163***
(4.526) |
| Illiquidity measure | 2.161
(1.794) | -0.217
(0.303) | 0.068
(0.108) | -0.927
(0.789) |
| Token FEs | ✓ | ✓ | ✓ | ✓ |
| Observations | 16,436 | 16,436 | 16,436 | 16,436 |
| R ² | 0.107 | 0.095 | 0.160 | 0.156 |

Note: These are regression results for the moderating effect of cultural uncertainty on the impact of governance enforcement strength on four dependent variables: (i) CAR, (ii) Δ return volatility, (iii) Δ return, and (iv) Δ Sharpe ratio. CAR indicates the cumulative abnormal return over the 5-day event window (in %). Abnormal return is calculated based on the daily return of the event days minus the 80-day pre-event average return. The variables Δ return volatility, Δ return, and Δ Sharpe ratio measure the differences in the standard deviation of the return, price change, and Sharpe ratio of the token between the 80-day post-event window and the 80-day pre-event window. The Sharpe ratio is calculated as the average daily return multiplied by the window size (i.e., 80) divided by the standard deviation during the period. The *Uncertainty avoidance* variable is derived from the cultural uncertainty avoidance score. This score is defined by Hofstede (2001) as the degree to which a society tries to control the uncontrollable and the extent to which a culture habituates its members to feel either uncomfortable or comfortable in situations that are novel, unknown, surprising, or different from usual. The *Governance enforcement index* represents the strength of enforcement of contracts and other rights within the jurisdiction issuing the law, measured as a percentile rank. Additionally, we report the coefficients for regulation and market characteristics, token characteristics, and token fixed-effects are included in all models to control for time-invariant confounders. Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

4.4.6.2 The impact of the token jurisdiction

Event studies in the traditional stock market usually allow the assessment of isolated local and jurisdictional spillover effects (e.g. Zhang, 2007; Schäfer et al., 2015), because com-

panies and exchanges have clear jurisdictions in which they operate and are regulated. While this is (up to a certain point) also possible in the primary cryptocurrency market (e.g. Bellavitis et al., 2022) or for individually selected tokens (e.g. Borri and Shakhnov, 2020), it is extremely challenging to assess these effects in the overall secondary cryptocurrency market due to several factors. First, many cryptocurrency projects are inherently decentralized, given that the protocol or application is purely code-based and has no physical location. Second, even though exchanges must adhere to local laws within the different jurisdictions, most of the centralized cryptocurrency exchanges operate multinationally and can onboard investors from a large variety of jurisdictions. In addition, a significant proportion of cryptocurrency transactions take place on decentralized exchanges that are not bound to a specific jurisdiction.

However, we still hand-collected all available jurisdictions for our token sample based on project-specific (e.g. whitepapers) and online sources (e.g. ICO aggregators or LinkedIn). We also considered public information about the project foundations that in some cases control the project operations. Based on this unique dataset, we created a new dummy variable, taking the value 1 if a token jurisdiction is the same as the one where the regulation was enacted and 0 otherwise. Including this variable in our main model, we show the findings for the different outcome variables in Table 4.15. No statistically significant effects on the CAR or change in return volatility are observable. However, we can see that the changes in longer-term return and Sharpe ratio are amplified. In economic terms, tokens within the jurisdiction where the law is implemented experience, on average, an increased return reduction of -0.753 percentage points and an increased Sharpe Ratio reduction of -9.325 . Even though our sample size of ‘local tokens’ is relatively small (2.0% of the whole sample), our findings might be an indication that the jurisdiction of the project matters even in decentralized markets.

Table 4.15: The importance of the token jurisdiction

| <i>Dependent variable:</i> | CAR | Δ Return
volatility | Δ Return | Δ Sharpe
Ratio |
|---|----------------------|-------------------------------|----------------------|--------------------------|
| Key variables: | | | | |
| Governance enforcement index | −0.028***
(0.006) | −0.024***
(0.001) | −0.005***
(0.000) | −0.046***
(0.003) |
| x local token | 0.078
(0.062) | −0.015
(0.012) | 0.010**
(0.004) | 0.117***
(0.037) |
| Local token | −4.735
(5.902) | 0.936
(1.105) | −0.753*
(0.392) | −9.324***
(3.502) |
| Regulation and market characteristics: | | | | |
| Financial regulator | 5.899***
(0.381) | 1.333***
(0.077) | 0.271***
(0.028) | 2.573***
(0.215) |
| Shareholder protection index | −0.142**
(0.066) | −0.138***
(0.016) | −0.046***
(0.005) | −0.696***
(0.040) |
| Financial institution access index | 9.772***
(0.797) | 3.270***
(0.158) | 0.640***
(0.058) | 5.153***
(0.454) |
| Bull market | −7.815***
(0.428) | −0.360***
(0.096) | 0.150***
(0.031) | 2.242***
(0.230) |
| Bear market | −1.878***
(0.321) | 0.005
(0.072) | 0.224***
(0.021) | 2.432***
(0.182) |
| Token characteristics: | | | | |
| Market cap | −0.210***
(0.074) | −0.024*
(0.013) | −0.040***
(0.005) | −0.386***
(0.036) |
| Trading volume | 0.971***
(0.102) | −0.266***
(0.021) | −0.148***
(0.007) | −1.245***
(0.051) |
| DeFi token type | 16.274
(13.084) | 1.882
(3.158) | 0.157
(0.671) | −1.598
(6.822) |
| Currency token type | −9.280**
(4.489) | 6.301***
(1.338) | 3.036***
(0.525) | 28.424***
(3.605) |
| Illiquidity measure | 0.990
(1.054) | −0.343**
(0.151) | 0.033
(0.099) | −0.934
(0.670) |
| Token FEs | ✓ | ✓ | ✓ | ✓ |
| Observations | 24,097 | 24,097 | 24,097 | 24,097 |
| R ² | 0.099 | 0.088 | 0.104 | 0.114 |

Note: These are regression results for the moderating effect of local tokens on the impact of governance enforcement strength on four dependent variables: (i) CAR, (ii) Δ return volatility, (iii) Δ return, and (iv) Δ Sharpe ratio. CAR indicates the cumulative abnormal return over the 5-day event window (in %). Abnormal return is calculated based on the daily return of the event days minus the 80-day pre-event average return. The variables Δ return volatility, Δ return, and Δ Sharpe ratio measure the differences in the standard deviation of the return, price change, and Sharpe ratio of the token between the 80-day post-event window and the 80-day pre-event window. The Sharpe ratio is calculated as the average daily return multiplied by the window size (i.e., 80) divided by the standard deviation during the period. *Local token* is a dummy variable that takes the value one if the cryptocurrency is based in the same jurisdiction as the law got announced and zero otherwise. The *Governance enforcement index* represents the strength of enforcement of contracts and other rights within the jurisdiction issuing the law, measured as a percentile rank. Additionally, we report the coefficients for regulation and market characteristics, token characteristics, and token fixed-effects are included in all models to control for time-invariant confounders. Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

4.4.6.3 Additional robustness tests

We conduct additional tests to assess the sensitivity of our results to changes in key assumptions. First, we examine the robustness of our main regressions to variations in the size of the estimation window. Table C.2 presents the results of our baseline regression

using alternative 30-day and 50-day estimation windows. The results show that changes in the estimation window do not materially affect the direction or significance of the main effects, suggesting that our findings are robust to this variation. Second, we address potential concerns related to changes in the token sample over time. As shown in Table 4.4, the size and composition of the token sample vary across events, which is an unavoidable feature of the dynamic crypto market, where new projects are frequently listed and others are delisted. To test whether this affects our findings, we define a subsample limited to tokens that were already listed at the time of the first event in July 2018 and repeat our main analyses. Tables C.3 and C.4 show that restricting the sample in this way does not materially change the direction or significance of the key results. These findings further support the robustness of our results.

Third, we test the robustness of our results to changes in the key variable. In our main analysis, we use the *Governance enforcement index* as the measure of the quality of formal institutions. To assess the robustness of our findings, we collect additional data for two alternative measures and substitute the key variable with the *Government effectiveness index* and the *Regulatory quality index*, as shown in Table C.5 and Table C.6, respectively. The *Government effectiveness index* captures perceptions of public and civil service quality and of the independence and commitment of the government to its policies. The *Regulatory quality index* reflects perceptions of the government's capacity to develop and enforce effective policies and regulations that support private sector growth. Our results show that the direction and significance of the identified main effects do not materially change, indicating that our findings are robust. The average additional reduction in return volatility, based on the 80-day estimation window, due to a one-unit increase in the *Government effectiveness index* and the *Regulatory quality index* is 0.025 percentage points and 0.029 percentage points, respectively. These values only marginally deviate from the effect of the *Governance enforcement index*, which is 0.024 percentage points. Fourth, we conduct a robustness test by re-estimating our main multivariate regression models with the inclusion

of year fixed effects to control for time-variant confounding factors. The results, reported in Table C.7, confirm that the inclusion of year fixed effects does not alter the significance or direction of our main findings. This provides reassurance that the effects we attribute to regulatory events are not confounded by general time trends. Figure C.1 confirms that there is no clear downward trend during our sample period in either returns or volatility that would systematically bias our results.

Lastly, to address potential endogeneity concerns related to the Governance Enforcement Index, we implement a Durbin-Wu-Hausman (DWH) test, following the methodology proposed by Davidson and MacKinnon (1993). This involves regressing the suspected endogenous variable on all exogenous regressors and adding the residual to the structural equation. We conduct this test for the main models reported in Tables 4.6, 4.7, 4.8, 4.9, 4.13, and 4.14. The resulting DWH residual is statistically insignificant in all cases, suggesting that endogeneity is not a concern. The corresponding regression outputs are reported in Table Table C.10 in the Appendix.

4.5 Discussion and Concluding Remarks

4.5.1 Summary of main results

This paper investigates the impact of international cryptocurrency market regulations on token risk and return attributes. We hand-collected a sample of 35 regulations that were announced between July 2018 and April 2023 and explored the risk-return trade-off based on a sample of up to 1,218 listed tokens. The cryptocurrency market furnishes an optimal research environment, given its unique characteristics, such as (i) a low level of initial regulation, (ii) regulations impacting the whole asset class, and (iii) expected regional spillover effects due to the interconnectedness of the market.

The first hypothesis posits that the announcement of cryptocurrency regulation leads to a reduction of post-event return volatility. Our analysis finds evidence that, on average,

regulators succeed and the announced regulations reduce the overall risk in cryptocurrency markets. In economic terms, the announcement of new regulation leads to a standard deviation decrease of -0.496 percentage points. We observe the highest reduction after the passing of AML/CFT laws and tax announcements, with an average reduction of -0.651 percentage points and 0.821 percentage points, respectively.

The second part of the study focuses on short- and long-term risk reactions in the cryptocurrency market, looking at raw and risk-adjusted measures. Based on our event study framework (Brown and Warner, 1980, 1985), we confirm abnormal returns around the event date and provide evidence that, on average, investors do react negatively to cryptocurrency regulation announcements (H2a). In economic terms, regulatory announcements lead to an average CAR of -1.414% . Additionally, we show that the reaction is most negative for crypto bans (-2.838%), followed by regulatory frameworks (-2.782%). However, after the announcement of tax regulation, we observe a positive reaction, with an average CAR of 0.985% . The longer-term return shows an average increase of 0.018 percentage points of the average daily return in the post-event window. Our results confirm H3b, showing an average post-event Sharpe ratio increase of 0.585 after the announcement of a new cryptocurrency regulation. Splitting our sample by regulation types, we provide evidence that this effect is mostly driven by AML/CFT regulations ($\Delta 4.424$) and tax regulations ($\Delta 0.841$).

The fourth hypothesis posits that stronger formal institutions in the jurisdiction that announce a cryptocurrency regulation amplify the risk reduction in the cryptocurrency market. Conducting a multivariate analysis based on 24,097 observations, we investigate the impact of different national regulatory enforcement quality indices on the risk and return effects of cryptocurrency regulations. Our findings strongly support this hypothesis, showing that, on average, an increase of the governance enforcement index level by one percentile leads to an additional risk reduction of -0.024 percentage points. The results are significant at the 1% level and robust to different variations of the baseline regressions.

Additionally, we have developed DARSI, a unique regulatory strength index, to make the cryptocurrency regulation status of a jurisdiction measurable and to assess its impact on changes in the risk-return relationship. Applying DARSI as an alternative measure of the strength of formal institutions, we confirm that increased regulatory strength amplifies risk reduction during the post-event window. Separately, we provide evidence that if the announced regulation is the first of its type, the risk reduction effect is amplified by -1.486 percentage points.

The fifth and final hypothesis arises from the understanding that normative compliance-seeking facilitates the adoption of norms, forecasting that stronger informal institutions in the jurisdiction that announces the cryptocurrency regulation amplify the risk reduction in the cryptocurrency market. Using the uncertainty score developed by Hofstede (2001) as a key variable, we provide evidence that the more a society relies on a specific set of rules, the more pronounced the amplification of the regulation's intended effects. In economic terms, our results show that a 1 unit increase in the uncertainty avoidance score leads, on average, to an additional decrease of -0.081 percentage points in post-event return volatility.

4.5.2 Theoretical contributions and practical implications

Our study makes several distinct contributions to the existing literature. First, prior studies in the traditional finance and law literature have mostly investigated the impact of regulation on shareholder wealth and the valuation of impacted companies (e.g. Fields et al., 1990; Prager, 1989). Our focus on the effects of regulation on the risk attribute and the overall risk-return relationship expands the literature on regulations' impacts on the post-event attributes of financial assets. Using the cryptocurrency market as a novel research setting for the study, we confirm the fundamental financial theory that return decreases when risk level decreases (e.g. Lintner, 1965a, 1965b; Sharpe, 1966). Additionally, we provide evidence that implementing regulations in a mostly unregulated market leads to

a disproportional risk reduction compared to the return decrease. The decoupling of the pre-event risk-return level suggests that investors might profit from new regulations on a risk-adjusted level.

Second, we offer a novel research setting to examine the role of governance effectiveness in shaping the outcomes of new regulations. In addition to drawing on existing governance enforcement measures, we introduce the Digital Asset Regulatory Strength Index (DARSI) which is a new metric designed to quantify the strength and scope of cryptocurrency-specific regulation. The DARSI allows us to assess the regulatory environment within a jurisdiction before and after the announcement of new laws and to demonstrate that market reactions are driven by the substance of the regulation itself and not only by a reduction in uncertainty. Our findings show that laws enacted in jurisdictions with stronger property rights and more effective contract enforcement lead to greater reductions in risk during the post-event window, in line with evidence from traditional equity markets (e.g., Bhattacharya and Daouk, 2009; Humphery-Jenner, 2013). This amplification effect is particularly pronounced when the regulation is the first of its kind or is introduced by a financial regulatory authority. We also find that the quality of informal institutions matters, as societies with higher levels of uncertainty avoidance tend to exhibit stronger market responses to regulatory announcements, further reinforcing the importance of institutional context.

Third, we expand the digital assets and cryptocurrency literature and provide new knowledge in several areas. Prior studies have investigated the impact of regulation on the cryptocurrency market based on a selected sample of the most prominent cryptocurrencies and events prior to 2019 (e.g. Auer and Claessens, 2018; Chokor and Alfieri, 2021). We not only apply the most comprehensive token sample but also expand the time frame of regulatory announcements until April 2023. We generally confirm the initial negative price reactions to regulatory announcements, but our findings also help close the research gap on the driver of this impact. Our setup shows that the direction and size of the CAR

depend on the type of regulation, with strong variation between the different categories. Our research also shows that the cryptocurrency market experiences longer-term price reactions, and investors might tend to overreact to regulatory announcements (Bondt & Thaler, 1985), indicating that the cryptocurrency market is not fully efficient (Malkiel & Fama, 1970). Our unique sample allows us to conduct additional analyses of the impacts of regulations on different types of tokens. We show that tokens with a higher market cap and trading volume experience greater risk reduction compared to tokens with a lower market cap and trading volume.

Our results carry direct implications for both policymakers and cryptocurrency investors by quantifying how regulatory announcements shape asset risk and return characteristics in economically meaningful ways. For policymakers and regulators, the average cumulative abnormal return (CAR) of -1.414% following regulation announcements signals that the market often interprets new laws as value-reducing and highlights the importance of anticipating investor response during the regulatory design process. Importantly, we show that stronger enforcement environments amplify regulatory effects: for every 1-percentile increase in enforcement quality, CARs fall by an additional 0.026 percentage points, and volatility drops by 0.024 points. This suggests that not only the content of the regulation but also the perceived enforceability significantly shapes market outcomes. Policymakers aiming to reduce risk in the crypto market should therefore focus not just on rule creation but also on clarity, scope, and institutional credibility to maximize the intended de-risking effect. Our results can serve as a benchmarking tool for lawmakers to estimate how the strength of their regulatory infrastructure might influence market stability.

For investors, the findings offer a framework for better risk management and strategic positioning. The significant reduction in volatility (-0.496 percentage points) and corresponding Sharpe ratio improvement ($+0.585$) suggest that well-designed regulations can increase the efficiency and appeal of crypto assets. This has portfolio allocation implications, as investors may benefit from monitoring the strength and credibility of global

regulatory developments to anticipate shifts in overall market risk and return dynamics. Moreover, knowing that not all regulation is equally impactful, investors can implement DARSI-based assessments to forecast which announcements are likely to lead to more favorable post-announcement conditions.

4.5.3 Limitations and avenues for future research

Our study represents an important step toward understanding the impact of new regulations in the cryptocurrency market. We propose several potential directions for future research in this field.

Long-term impact of cryptocurrency regulation. Our research design is focused on investigating the initial return impact of regulatory announcements during the 5-day event window and the risk and return reactions during the 80-day post-event window. To allow for a more comprehensive assessment of regulatory impact and, ultimately, the success of the new laws, future research could examine longer-term effects. While filtering out the increasing noise of unrelated market events becomes more difficult over extended periods, this remains an interesting avenue for future study.

Regulation impact on the primary cryptocurrency market. Our study focuses exclusively on the impact of regulation on the secondary token market. However, new laws may also affect activities in the primary cryptocurrency market. Future research could investigate post-announcement token offerings in the digital asset market to draw conclusions about investor preferences for certain types of offerings. Such studies might also consider regional dynamics, as the primary market still reflects jurisdictional characteristics depending on where a project is launched. While Bellavitis et al. (2021) and Bellavitis et al. (2022) have provided early insights in this direction, offering an overview of ICO regulation and the effects of the China and South Korea ICO bans, we believe further research in this area could be valuable. Although regulation for equity crowdfunding is already widely

available in many jurisdictions, it is generally not applicable to the cryptocurrency space (Cummings et al., 2020), which is why newly proposed regulations often include specific provisions tailored to token offerings.

Spillover effects between cryptocurrency and traditional financial markets. The interconnectedness between the cryptocurrency market and traditional financial markets, such as equities, is steadily increasing. While cryptocurrencies initially attracted niche investors, institutional adoption and the development of financial instruments such as Bitcoin ETFs and tokenized securities have strengthened this linkage. This growing overlap raises questions about how regulatory announcements in one market might affect the other. Future research could examine the impact of traditional financial market regulation on cryptocurrencies, or vice versa, exploring cross-market spillover effects triggered by new regulatory developments.

Omission of overlapping regulatory announcements. Our empirical design deliberately excludes events involving overlapping or concurrent regulatory announcements to ensure a clean identification of the impact of specific regulatory actions. This methodological choice allows for clearer attribution of observed market effects to individual events. However, we acknowledge that this approach may overlook real-world scenarios in which multiple regulations are announced or enacted concurrently. Such interactions could have meaningful implications for market outcomes and investor interpretation. Future research might explore this complexity through alternative methodologies designed to disentangle the effects of concurrent or overlapping regulatory announcements.

4.5.4 Concluding remarks

This paper sheds light on how new cryptocurrency regulation impacts the risk and return characteristics of the asset class. We provide empirical evidence that regulation announcements lead to an average risk reduction in the cryptocurrency market after the event period. This effect is further amplified if the regulation is announced in a jurisdiction that

has stronger formal and informal institutions. We show that, during the post-event window, average daily returns revert to pre-event levels, increasing the post-event Sharpe ratio compared to its pre-event level. This study contributes to understanding how various regulatory designs affect the attributes of the asset class and how formal and informal institution quality moderates these effects.

4.6 References

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4.7 Appendix C

Table C.1: Variable definitions

| Variable | Definition |
|--|--|
| <i>Dependent variables</i> | |
| Cumulative abnormal returns (CARs), in % | Cumulative abnormal return over the 5-day event window. Abnormal return is calculated based on the daily return of the event days minus the 80-day average return during the estimation window. |
| Δ Return, in % pts. | Difference of the average daily return during the post-event window and the pre-event window, measured in percentage points. The window length is 80-days if not specified otherwise. |
| Δ Return volatility, in % pts. | Difference of the standard deviation of the daily returns during the post-event window and the pre-event window, measured in percentage points. The window length is 80-days if not specified otherwise. |
| Δ Sharpe Ratio | Difference of the sharpe ratio during the post-event window and the pre-event window. The window length is 80-days if not specified otherwise. Sharpe ratio is calculated as the average daily return multiplied by the window size divided by the standard deviation during the period. |
| <i>Regulation types:</i> | |
| AML/CFT regulation (dummy) | Dummy variable: 1 for regulations that are focused on Anti-Money Laundering and Countering the Financing of Terrorism, 0 otherwise. |
| Crypto ban (dummy) | Dummy variable: 1 for regulations that focus on the ban of activities related to cryptocurrencies within the jurisdiction, 0 otherwise. |
| Regulatory framework (dummy) | Dummy variable: 1 for regulations that focus on a general regulatory framework related to digital assets/cryptocurrencies, 0 otherwise. |
| Tax regulation (dummy) | Dummy variable: 1 for regulations that are focused on taxation of cryptocurrencies, 0 otherwise. |
| <i>Key variables:</i> | |
| Governance enforcement index (%tile) | The index indicates the quality of contract enforcement and property rights of the jurisdiction issuing the law, measured as the percentile rank based on World Bank data. |
| Government effectiveness index (%tile) | The index captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies, measured as the percentile rank based on World Bank data. |
| Regulatory quality index (%tile) | The index captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development, measured as the percentile rank based on World Bank data. |
| Uncertainty avoidance | Uncertainty avoidance is defined by Hofstede (2001) as the degree to which a society tries to control the uncontrollable and the extent to which a culture programs its members to feel either uncomfortable or comfortable in situations which are novel, unknown, surprising, different from usual. Data are from Hofstede (2001). |
| First regulation | Dummy variable: 1 if the regulation was the first one of this type within the jurisdiction, 0 otherwise. |
| Local token | Dummy variable: 1 if the cryptocurrency project is based in the same jurisdiction as the law got announced, 0 otherwise. |

| <i>Regulation and market characteristics::</i> | |
|--|---|
| Financial regulator (dummy) | Dummy variable: 1 if the regulation is announced by a financial regulator, 0 otherwise. |
| Shareholder protection index | The shareholder protection index of the country where the regulation got announced. The score is provided by the World Bank, ranging from 0 to 1. |
| Financial institution access index | The index is compiled by the IMF and indicates the level of ATMs and bank branches per 100,000 adults, ranging from 0 to 1. |
| Bull market (dummy) | Dummy variable: 1 for token offerings that took place during a bull market, 0 otherwise. |
| Bear market (dummy) | Dummy variable: 1 for token offerings that took place during a bear market, 0 otherwise. |
| <i>Token characteristics:</i> | |
| Market cap (log) | The natural logarithm of the market capitalization of the token at the day the regulation got announced (in USD). |
| Trading volume (daily, log) | The natural logarithm of the trading volume of the token at the day the regulation got announced (in USD). |
| Illiquidity ratio | The absolute value of the daily return divided by the daily total trading volume of the token (in '000), based on (Amihud, 2002). |
| DeFi token type (dummy) | Dummy variable: 1 if the token is classified as a DeFi token, 0 otherwise. The classification is based on Messari. |
| Currency token type (dummy) | Dummy variable: 1 if the token is classified as a currency token, 0 otherwise. The classification is based on Messari. |

Table C.2: Regression robustness to different estimation windows

| | Δ Return volatility: | | | Δ Return: | | | Δ Sharpe: | | |
|--------------------------------------|-----------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| | 30-d | 50-d | 80-d | 30-d | 50-d | 80-d | 30-d | 50-d | 80-d |
| Panel A: <i>All Events</i> | | | | | | | | | |
| Governance enforcement index | -0.025***
(0.002) | -0.019***
(0.001) | -0.024***
(0.001) | -0.014***
(0.001) | -0.012***
(0.001) | -0.005***
(0.000) | -0.051***
(0.002) | -0.077***
(0.003) | -0.045***
(0.003) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 |
| R ² | 0.059 | 0.061 | 0.088 | 0.106 | 0.111 | 0.103 | 0.107 | 0.122 | 0.113 |
| Panel B: <i>Regulatory Framework</i> | | | | | | | | | |
| Governance enforcement index | -0.019***
(0.002) | -0.022***
(0.002) | -0.031***
(0.002) | -0.021***
(0.001) | -0.020***
(0.001) | -0.010***
(0.001) | -0.083***
(0.003) | -0.124***
(0.003) | -0.085***
(0.004) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 13,054 | 13,054 | 13,054 | 13,054 | 13,054 | 13,054 | 13,054 | 13,054 | 13,054 |
| R ² | 0.099 | 0.117 | 0.143 | 0.189 | 0.190 | 0.169 | 0.207 | 0.232 | 0.215 |
| Panel C: <i>Tax</i> | | | | | | | | | |
| Governance enforcement index | -0.109***
(0.005) | -0.092***
(0.004) | -0.063***
(0.004) | 0.001
(0.002) | 0.003***
(0.001) | -0.004***
(0.001) | 0.021***
(0.005) | 0.024***
(0.007) | -0.057***
(0.009) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 6,836 | 6,836 | 6,836 | 6,836 | 6,836 | 6,836 | 6,836 | 6,836 | 6,836 |
| R ² | 0.213 | 0.187 | 0.169 | 0.223 | 0.202 | 0.225 | 0.282 | 0.218 | 0.264 |

Note: These are regression results for the impact of governance enforcement strength on the four dependent variables(i): CAR, (ii) Δ return volatility, (iii) Δ return, and (iv) Δ Sharpe ratio. CAR indicates the cumulative abnormal return over the 5-day event window (in %). Abnormal return is calculated based on the daily return of the event days minus the 80-day pre-event average return. The variables Δ return volatility, Δ return, and Δ Sharpe ratio measure the differences in the standard deviation of the return, price change, and Sharpe ratio of the token between the post-event window and the pre-event window. We include three different window sizes: 30-days, 50-days, and 80-days. The Sharpe ratio is calculated as the average daily return multiplied by the window size divided by the standard deviation during the period. The *Governance enforcement index* represents the strength of enforcement of contracts and other rights within the jurisdiction issuing the law, measured as a percentile rank. The estimated coefficients of the control variables are suppressed for brevity and token fixed-effects are included in all models to control for time-invariant confounders. Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

Table C.3: Risk-return statistics based on initial sample (July 2018)

| | Pre-event: | | | Post-event: | | | Difference: | | |
|-------------------------------------|------------|--------|--------|-------------|--------|--------|-------------|-----------|-----------|
| | 30-day | 50-day | 80-day | 30-day | 50-day | 80-day | 30-day | 50-day | 80-day |
| <u>All regulatory events:</u> | | | | | | | | | |
| Return volatility | 7.465 | 7.698 | 7.970 | 7.043 | 7.485 | 7.823 | -0.422*** | -0.213*** | -0.147*** |
| Return | 0.483 | 0.384 | 0.274 | 0.290 | 0.400 | 0.389 | -0.193*** | 0.017 | 0.115*** |
| Sharpe ratio | 1.328 | 1.382 | 0.996 | 0.510 | 1.731 | 2.571 | -0.817*** | 0.348*** | 1.575*** |
| <u>AML/CFT events:</u> | | | | | | | | | |
| Return volatility | 7.598 | 7.562 | 7.967 | 6.343 | 7.026 | 7.912 | -1.255*** | -0.536*** | -0.055 |
| Return | 0.564 | 0.527 | 0.175 | 0.637 | 0.816 | 0.410 | 0.073 | 0.289*** | 0.235*** |
| Sharpe ratio | 1.177 | 2.266 | -0.677 | 2.697 | 5.629 | 3.509 | 1.520*** | 3.362*** | 4.186*** |
| <u>Crypto Ban events:</u> | | | | | | | | | |
| Return volatility | 6.618 | 7.077 | 7.707 | 6.462 | 7.26 | 8.171 | -0.156 | 0.183 | 0.464** |
| Return | 0.524 | 0.789 | 0.353 | 0.681 | 0.512 | 0.247 | 0.157** | -0.277*** | -0.106** |
| Sharpe ratio | 1.794 | 5.071 | 1.983 | 2.641 | 2.536 | 1.284 | 0.846*** | -2.535*** | -0.700* |
| <u>Regulatory Framework events:</u> | | | | | | | | | |
| Return volatility | 7.733 | 7.901 | 8.136 | 7.35 | 7.839 | 8.121 | -0.383*** | -0.062 | -0.015 |
| Return | 0.507 | 0.472 | 0.430 | 0.350 | 0.436 | 0.473 | -0.157*** | -0.036 | 0.043* |
| Sharpe ratio | 1.358 | 1.739 | 2.461 | 0.555 | 1.739 | 3.034 | -0.803*** | 0.000 | 0.573** |
| <u>Tax events:</u> | | | | | | | | | |
| Return volatility | 7.122 | 7.537 | 7.709 | 6.9 | 7.017 | 7.036 | -0.222** | -0.520*** | -0.673*** |
| Return | 0.382 | -0.003 | -0.038 | -0.124 | 0.101 | 0.251 | -0.506*** | 0.104*** | 0.289*** |
| Sharpe ratio | 1.176 | -1.009 | -1.690 | -1.278 | -0.302 | 1.606 | -2.454*** | 0.707*** | 3.29*** |

Note: This table only includes the tokens that were already listed during the first event in our sample (20 July 2018) and presents the arithmetic mean of the return volatility, return, and Sharpe ratio for (i) all regulatory events in our sample, (ii) AML/CFT events, (iii) crypto ban events, (iv) regulatory framework events, and (v) tax events over different time horizons. The Sharpe ratio is calculated as the average daily return multiplied by the window size (i.e., 80) divided by the standard deviation during the period. The columns from left to right show the values during the 30-day, 50-day, and 80-day windows preceding the announcement, the 30-day, 50-day, and 80-day windows after the announcement, and the average of the differences between pre-event and post-event during the 30-day, 50-day, and 80-day windows. The significance of these differences is indicated by asterisks, with the p-values from a t-test testing if the average deviations are significantly different from zero: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.4: Regression analysis of event-related CARs and post-event changes in return volatility, returns and Sharpe Ratios based on initial sample (July 2018)

| | CAR: | Δ Return volatility: | | | Δ Return: | | | Δ Sharpe: | | |
|---------------------------------|-----------------------|-----------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| | | 30-d | 50-d | 80-d | 30-d | 50-d | 80-d | 30-d | 50-d | 80-d |
| Panel A: Main regression | | | | | | | | | | |
| Governance enforcement index | −0.002
(0.009) | −0.012***
(0.003) | −0.013***
(0.003) | −0.019***
(0.002) | −0.012***
(0.001) | −0.010***
(0.001) | −0.002***
(0.001) | −0.046***
(0.004) | −0.065***
(0.005) | −0.009
(0.006) |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 |
| R ² | 0.096 | 0.041 | 0.046 | 0.066 | 0.095 | 0.098 | 0.089 | 0.095 | 0.108 | 0.092 |
| Panel B: Interactions | | | | | | | | | | |
| Governance enforcement index | −0.122**
(0.047) | −0.024
(0.021) | −0.016
(0.020) | −0.010
(0.017) | −0.014**
(0.007) | −0.010*
(0.006) | 0.002
(0.005) | −0.039**
(0.018) | −0.051**
(0.023) | 0.007
(0.031) |
| x financial regulator | 0.262***
(0.031) | 0.042***
(0.010) | −0.030***
(0.009) | −0.069***
(0.008) | −0.018***
(0.004) | −0.013***
(0.003) | −0.015***
(0.003) | −0.092***
(0.013) | −0.080***
(0.016) | −0.105***
(0.024) |
| x market cap | 0.008
(0.005) | 0.002
(0.002) | 0.002
(0.002) | 0.001
(0.002) | 0.001
(0.001) | 0.001
(0.001) | 0.001
(0.001) | 0.003
(0.002) | 0.002
(0.002) | 0.005
(0.003) |
| x trading volume | −0.004
(0.005) | −0.002
(0.002) | −0.002
(0.002) | −0.001
(0.001) | −0.001
(0.001) | −0.001
(0.001) | −0.001*
(0.000) | −0.003
(0.002) | −0.003
(0.002) | −0.006**
(0.003) |
| Financial regulator | −13.630***
(2.454) | −2.783***
(0.830) | 3.108***
(0.761) | 6.422***
(0.664) | 2.085***
(0.296) | 1.750***
(0.235) | 1.510***
(0.223) | 9.289***
(1.074) | 10.151***
(1.317) | 10.625***
(1.953) |
| Market cap | −1.036***
(0.385) | −0.297
(0.208) | −0.350*
(0.191) | −0.234
(0.150) | −0.227***
(0.070) | −0.181***
(0.058) | −0.140***
(0.045) | −0.581***
(0.157) | −0.754***
(0.195) | −1.186***
(0.257) |
| Trading volume | 1.314***
(0.363) | 0.039
(0.159) | 0.073
(0.140) | −0.073
(0.107) | 0.004
(0.056) | −0.014
(0.043) | −0.036
(0.032) | −0.170
(0.135) | −0.254
(0.166) | −0.397*
(0.206) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 |
| R ² | 0.105 | 0.044 | 0.047 | 0.075 | 0.098 | 0.101 | 0.095 | 0.102 | 0.112 | 0.096 |
| Panel C: Sentiment | | | | | | | | | | |
| Governance enforcement index | −0.027**
(0.013) | −0.006
(0.004) | −0.008**
(0.004) | −0.014***
(0.003) | −0.007***
(0.002) | −0.003**
(0.001) | 0.004***
(0.001) | −0.019***
(0.006) | −0.014**
(0.007) | 0.054***
(0.008) |
| x bull market | 0.217***
(0.021) | 0.011
(0.007) | −0.003
(0.007) | 0.001
(0.006) | −0.003
(0.003) | −0.012***
(0.002) | −0.012***
(0.002) | −0.044***
(0.010) | −0.086***
(0.012) | −0.105***
(0.013) |
| x bear market | −0.055***
(0.017) | −0.023***
(0.006) | −0.010*
(0.005) | −0.014***
(0.005) | −0.010***
(0.002) | −0.013***
(0.002) | −0.010***
(0.001) | −0.050***
(0.007) | −0.091***
(0.009) | −0.112***
(0.011) |
| Bull market | −21.095***
(1.535) | −0.136
(0.538) | −0.177
(0.490) | −0.312
(0.437) | −0.388
(0.241) | 0.671***
(0.182) | 0.997***
(0.135) | 1.409*
(0.773) | 5.737***
(0.890) | 9.787***
(0.962) |
| Bear market | 3.051**
(1.333) | 2.249***
(0.453) | 0.460
(0.417) | 0.631*
(0.356) | 0.318**
(0.148) | 1.020***
(0.121) | 0.915***
(0.091) | 2.558***
(0.532) | 7.105***
(0.711) | 10.554***
(0.834) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 | 7,534 |
| R-squared | 0.116 | 0.045 | 0.046 | 0.067 | 0.097 | 0.106 | 0.098 | 0.101 | 0.122 | 0.104 |

Note: This table only includes the tokens that were already listed during the first event in our sample (20 July 2018). These are regression results for the impact of governance enforcement strength on the four dependent variables(i): CAR, (ii) Δ return volatility, (iii) Δ return, and (iv) Δ Sharpe ratio. CAR indicates the cumulative abnormal return over the 5-day event window (in %). Abnormal return is calculated based on the daily return of the event days minus the 80-day pre-event average return. The variables Δ return volatility, Δ return, and Δ Sharpe ratio measure the differences in the standard deviation of the return, price change, and Sharpe ratio of the token between the post-event window and the pre-event window. We include three different window sizes: 30-days, 50-days, and 80-days. The Sharpe ratio is calculated as the average daily return multiplied by the window size divided by the standard deviation during the period. The *Governance enforcement index* represents the strength of enforcement of contracts and other rights within the jurisdiction issuing the law, measured as a percentile rank. In Panel B and C, we report several interaction terms of regulation and market characteristics variables as well as token characteristics with the *Governance enforcement index*. The estimated coefficients of the additional control variables are suppressed for brevity and token fixed-effects are included in all models to control for time-invariant confounders. Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

Table C.5: Regression robustness to alternative measures of formal institution quality - Government effectiveness

| | CAR: | Δ Return volatility: | | | Δ Return: | | | Δ Sharpe: | | |
|--|-----------------------|-----------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|-----------------------|-----------------------|
| | | 30-d | 50-d | 80-d | 30-d | 50-d | 80-d | 30-d | 50-d | 80-d |
| Panel A: <i>Main regression</i> | | | | | | | | | | |
| Government effectiveness index | −0.000
(0.007) | −0.026***
(0.002) | −0.017***
(0.002) | −0.025***
(0.002) | −0.016***
(0.001) | −0.016***
(0.001) | −0.008***
(0.000) | −0.058***
(0.003) | −0.106***
(0.003) | −0.076***
(0.004) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 |
| R ² | 0.098 | 0.057 | 0.058 | 0.084 | 0.105 | 0.116 | 0.107 | 0.106 | 0.134 | 0.121 |
| Panel B: <i>Interactions</i> | | | | | | | | | | |
| Government effectiveness index | −0.131***
(0.031) | −0.012
(0.009) | −0.006
(0.008) | −0.004
(0.007) | −0.015***
(0.003) | −0.016***
(0.003) | −0.005**
(0.002) | −0.055***
(0.010) | −0.102***
(0.012) | −0.056***
(0.015) |
| x financial regulator | 0.275***
(0.019) | −0.006
(0.006) | −0.043***
(0.005) | −0.048***
(0.004) | 0.026***
(0.002) | 0.024***
(0.002) | 0.015***
(0.001) | 0.138***
(0.008) | 0.179***
(0.009) | 0.208***
(0.012) |
| x market cap | 0.001
(0.002) | 0.001
(0.001) | 0.001**
(0.000) | 0.001
(0.000) | −0.000
(0.000) | −0.000
(0.000) | 0.000
(0.000) | −0.001
(0.001) | −0.001
(0.001) | 0.001
(0.001) |
| x trading volume | 0.006**
(0.003) | −0.002**
(0.001) | −0.001**
(0.001) | −0.002***
(0.001) | −0.000
(0.000) | −0.000
(0.000) | −0.000***
(0.000) | −0.001
(0.001) | −0.001
(0.001) | −0.005***
(0.001) |
| Financial regulator | −16.988***
(1.610) | 1.713***
(0.492) | 4.597***
(0.430) | 5.128***
(0.370) | −1.411***
(0.176) | −1.175***
(0.138) | −0.866***
(0.118) | −9.349***
(0.630) | −10.097***
(0.753) | −13.715***
(1.030) |
| Market cap | −0.245
(0.162) | −0.072*
(0.042) | −0.103***
(0.037) | −0.065**
(0.032) | −0.053***
(0.019) | −0.045***
(0.014) | −0.046***
(0.011) | −0.140**
(0.055) | −0.179***
(0.067) | −0.420***
(0.082) |
| Trading volume | 0.577***
(0.204) | −0.056
(0.057) | −0.109**
(0.052) | −0.149***
(0.045) | −0.073***
(0.023) | −0.104***
(0.019) | −0.110***
(0.014) | −0.312***
(0.068) | −0.580***
(0.084) | −0.862***
(0.102) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 |
| R ² | 0.105 | 0.057 | 0.061 | 0.089 | 0.110 | 0.122 | 0.112 | 0.118 | 0.147 | 0.132 |
| Panel C: <i>Sentiment</i> | | | | | | | | | | |
| Government effectiveness index | −0.021*
(0.012) | −0.006*
(0.004) | −0.007**
(0.003) | −0.017***
(0.003) | −0.017***
(0.001) | −0.011***
(0.001) | 0.001
(0.001) | −0.039***
(0.005) | −0.058***
(0.006) | 0.017**
(0.007) |
| x bull market | 0.328***
(0.019) | −0.004
(0.006) | −0.015***
(0.005) | −0.007*
(0.004) | 0.013***
(0.003) | −0.010***
(0.002) | −0.014***
(0.001) | 0.007
(0.008) | −0.070***
(0.009) | −0.124***
(0.010) |
| x bear market | −0.060***
(0.013) | −0.033***
(0.004) | −0.014***
(0.004) | −0.013***
(0.003) | −0.002
(0.002) | −0.007***
(0.001) | −0.010***
(0.001) | −0.035***
(0.006) | −0.063***
(0.007) | −0.126***
(0.008) |
| Bull market | −30.610***
(1.404) | 0.581
(0.423) | 0.734*
(0.388) | 0.269
(0.335) | −1.538***
(0.198) | 0.548***
(0.154) | 1.180***
(0.109) | −1.921***
(0.586) | 4.712***
(0.715) | 11.288***
(0.753) |
| Bear market | 2.172**
(1.002) | 2.914***
(0.292) | 0.790***
(0.263) | 0.719***
(0.226) | −0.272**
(0.109) | 0.467***
(0.090) | 0.908***
(0.066) | 1.346***
(0.394) | 4.035***
(0.502) | 10.879***
(0.564) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 |
| R ² | 0.120 | 0.060 | 0.059 | 0.085 | 0.108 | 0.118 | 0.114 | 0.109 | 0.138 | 0.131 |

Note: These are regression results for the impact of government effectiveness on the four dependent variables(i): CAR, (ii) Δ return volatility, (iii) Δ return, and (iv) Δ Sharpe ratio. CAR indicates the cumulative abnormal return over the 5-day event window (in %). Abnormal return is calculated based on the daily return of the event days minus the 80-day pre-event average return. The variables Δ return volatility, Δ return, and Δ Sharpe ratio measure the differences in the standard deviation of the return, price change, and Sharpe ratio of the token between the post-event window and the pre-event window. We include three different window sizes: 30-days, 50-days, and 80-days. The Sharpe ratio is calculated as the average daily return multiplied by the window size divided by the standard deviation during the period. The *Government effectiveness index* captures perceptions of public and civil service quality and of the independence and commitment of the government to its policies. In Panel B and C, we report several interaction terms of regulation and market characteristics variables as well as token characteristics with the *Government effectiveness index*. The estimated coefficients of the additional control variables are suppressed for brevity and token fixed-effects are included in all models to control for time-invariant confounders. Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

Table C.6: Regression robustness to alternative measures of formal institution quality - Regulatory quality

| | CAR: | Δ Return volatility: | | | Δ Return: | | | Δ Sharpe: | | |
|---------------------------------|-----------------------|-----------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| | | 30-d | 50-d | 80-d | 30-d | 50-d | 80-d | 30-d | 50-d | 80-d |
| Panel A: Main regression | | | | | | | | | | |
| Regulatory quality index | -0.048***
(0.007) | -0.030***
(0.002) | -0.025***
(0.002) | -0.029***
(0.002) | -0.022***
(0.001) | -0.016***
(0.001) | -0.006***
(0.001) | -0.075***
(0.003) | -0.094***
(0.003) | -0.049***
(0.004) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 |
| R ² | 0.100 | 0.059 | 0.062 | 0.087 | 0.118 | 0.115 | 0.104 | 0.119 | 0.123 | 0.112 |
| Panel B: Interactions | | | | | | | | | | |
| Regulatory quality index | -0.160***
(0.031) | -0.033***
(0.009) | -0.022***
(0.008) | -0.015***
(0.007) | -0.017***
(0.003) | -0.016***
(0.003) | -0.004*
(0.002) | -0.046***
(0.010) | -0.091***
(0.013) | -0.042***
(0.015) |
| x financial regulator | 0.263***
(0.021) | 0.030***
(0.006) | -0.015***
(0.006) | -0.048***
(0.005) | -0.003
(0.002) | 0.002
(0.002) | -0.008***
(0.002) | -0.012
(0.008) | 0.014
(0.010) | -0.034**
(0.015) |
| x market cap | 0.001
(0.002) | 0.001
(0.001) | 0.001**
(0.000) | 0.000
(0.000) | -0.000
(0.000) | 0.000
(0.000) | 0.000
(0.000) | -0.001
(0.001) | -0.000
(0.001) | 0.001
(0.001) |
| x trading volume | 0.004
(0.003) | -0.001
(0.001) | -0.001
(0.001) | -0.001
(0.001) | -0.000
(0.000) | -0.000
(0.000) | -0.000
(0.000) | -0.001
(0.001) | 0.000
(0.001) | -0.001
(0.001) |
| Financial regulator | -14.866***
(1.772) | -1.155**
(0.539) | 2.457***
(0.479) | 5.152***
(0.409) | 1.043***
(0.200) | 0.624***
(0.163) | 0.941***
(0.147) | 3.077***
(0.658) | 2.913***
(0.846) | 5.268***
(1.226) |
| Market cap | -0.298*
(0.155) | -0.069
(0.042) | -0.102***
(0.038) | -0.051
(0.032) | -0.062***
(0.019) | -0.055***
(0.015) | -0.046***
(0.011) | -0.146***
(0.053) | -0.228***
(0.066) | -0.457***
(0.081) |
| Trading volume | 0.759***
(0.203) | -0.118**
(0.059) | -0.132**
(0.054) | -0.218***
(0.046) | -0.079***
(0.025) | -0.122***
(0.020) | -0.139***
(0.015) | -0.337***
(0.068) | -0.741***
(0.087) | -1.174***
(0.105) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 |
| R ² | 0.106 | 0.060 | 0.062 | 0.091 | 0.118 | 0.115 | 0.105 | 0.119 | 0.123 | 0.113 |
| Panel C: Sentiment | | | | | | | | | | |
| Regulatory quality index | -0.021*
(0.011) | -0.023***
(0.003) | -0.018***
(0.003) | -0.016***
(0.003) | -0.010***
(0.001) | -0.003***
(0.001) | 0.005***
(0.001) | -0.011**
(0.004) | -0.007
(0.005) | 0.067***
(0.006) |
| x bull market | 0.092***
(0.017) | 0.009*
(0.005) | -0.012***
(0.004) | -0.017***
(0.004) | -0.021***
(0.002) | -0.020***
(0.002) | -0.017***
(0.001) | -0.105***
(0.006) | -0.113***
(0.007) | -0.133***
(0.009) |
| x bear market | -0.138***
(0.013) | -0.024***
(0.004) | -0.008**
(0.004) | -0.021***
(0.003) | -0.015***
(0.001) | -0.020***
(0.001) | -0.018***
(0.001) | -0.087***
(0.005) | -0.140***
(0.007) | -0.199***
(0.008) |
| Bull market | -13.504***
(1.212) | -0.492
(0.343) | 0.336
(0.311) | 0.697***
(0.265) | 0.593***
(0.150) | 1.150***
(0.112) | 1.300***
(0.082) | 5.143***
(0.441) | 6.925***
(0.525) | 11.468***
(0.610) |
| Bear market | 8.344***
(1.012) | 2.587***
(0.298) | 0.547**
(0.267) | 1.494***
(0.230) | 0.820***
(0.108) | 1.455***
(0.087) | 1.479***
(0.066) | 5.578***
(0.382) | 10.275***
(0.495) | 16.705***
(0.576) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 |
| R ² | 0.110 | 0.062 | 0.062 | 0.089 | 0.124 | 0.127 | 0.119 | 0.135 | 0.143 | 0.136 |

Note: These are regression results for the impact of regulatory quality on the four dependent variables(i): CAR, (ii) Δ return volatility, (iii) Δ return, and (iv) Δ Sharpe ratio. CAR indicates the cumulative abnormal return over the 5-day event window (in %). Abnormal return is calculated based on the daily return of the event days minus the 80-day pre-event average return. The variables Δ return volatility, Δ return, and Δ Sharpe ratio measure the differences in the standard deviation of the return, price change, and Sharpe ratio of the token between the post-event window and the pre-event window. We include three different window sizes: 30-days, 50-days, and 80-days. The Sharpe ratio is calculated as the average daily return multiplied by the window size divided by the standard deviation during the period. The *Regulatory quality index* reflects perceptions of the government's capacity to develop and enforce effective policies and regulations that support private sector growth. In Panel B and C, we report several interaction terms of regulation and market characteristics variables as well as token characteristics with the *Regulatory quality index*. The estimated coefficients of the additional control variables are suppressed for brevity and token fixed-effects are included in all models to control for time-invariant confounders. Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

Table C.7: Regulatory events - Additional details

| Date | Description | Country | Type | Add. Details | Source Type | Link ¹⁶ |
|-------------|--|----------------|----------------------|--|--|---|
| 20 Jul 2018 | Virtual Financial Assets Act + Innovative Technology Arrangements and Services Act | Malta | Regulatory Framework | ./. | Government Website | https://legislation.mt/eli/act/2018/30/eng/pdf |
| 26 Jul 2018 | Circulaire L.I.R. n° 95_2 du 31.12.2010 | Luxembourg | Tax | ./. | Government Website | https://impotsdirects.public.lu/dam-assets/fr/legislation/legi18/circulaireLIR14-5-99-3-99bis-3du26072018.pdf |
| 14 Dec 2018 | Legal framework for distributed ledger technology and blockchain in Switzerland | Switzerland | Regulatory Framework | ./. | Government document stored by perma.cc | https://perma.cc/S86K-URLX |
| 10 Jan 2019 | LEGE nr. 30 din 10 ianuarie 2019 | Romania | Tax | ./. | Government website stored by perma.cc | https://perma.cc/D5F2-3VLY |
| 21 Feb 2019 | Rulebook Module on crypto-assets (Module CRA) | Bahrain | Regulatory Framework | Date refers to first issuance of the module | Central Bank Website | https://cbben.thomsonreuters.com/rulebook/cra-crypto-asset |
| 11 Apr 2019 | Loi PACTE - Regulatory Framework for Crypto-Activities and ICOs | France | Regulatory Framework | Date refers to announcement date of official parliament approval of the regulation | Government Website | https://www.legifrance.gouv.fr/dossierlegislatif/JORFDOLE000037080861/ |
| 31 Jul 2019 | PS19/22 Guidance on Cryptoassets | United Kingdom | Regulatory Framework | ./. | Regulator Website | https://www.fca.org.uk/publication/policy/ps19-22.pdf |
| 7 Oct 2019 | Taxation of virtual currencies | Finland | Tax | ./. | Tax Authority Website | https://www.vero.fi/en/detailed-guidance/guidance/48411/taxation-of-virtual-currencies2/ |
| 29 Nov 2019 | Measures Against Money Laundering Act | Bulgaria | AML/CFT | Date refers to relevant amendment SG No. 94/29.11.2019 | Government Website | https://www.dato.bg/docs/Measures_Against_Money_Laundering_Act-%20%D0%97%D0%B0%D0%BA%D0%BE%D0%BD%20%D0%B7%D0%B0%20%D0%BC%D0%B5%D1%80%D0%BA%D0%B8%D1%82%D0%B5%20%D1%81%D1%80%D0%B5%D1%89%D1%83%20%D0%B8%D0%B7%D0%BF%D0%B8%D1%80%D0%B0%D0%BD%D0%B5%D1%82%D0%BE%20%D0%BD%D0%B0%20%D0%BF%D0%B0%D1%80%D0%B8.pdf |
| 26 Dec 2019 | QFC Regulatory Authority affirms that Virtual Asset Services may not be conducted in or from the QFC | Qatar | Crypto Ban | ./. | Regulator Website | https://www.qfcra.com/wp-content/uploads/2022/07/QFC-VASPS-ALERT-pdf-1.pdf |

¹⁶Latest access date: 16 March 2025.

| | | | | | | | |
|-------------|---|-----------------------|----------------------|--|-------------------------------|----------|---|
| 31 Dec 2019 | Money Laundering & Terrorist Financing Prevention Act | Estonia | AML/CFT | Date refers to relevant amendment RT I, 31.12.2019, 2 | Government site | Web-site | https://www.riigiteataja.ee/en/eli/ee/530062021006/consolide |
| 23 Jan 2020 | Virtual Asset Bill 2020 | Saint Kitts and Nevis | Regulatory Framework | ./. | Regulator Website | | https://www.nevisfsr.com/themencode-pdf-viewer-sc/?tnc_pvwf=ZmlsZT1odHRwcovL3d3dy5uZXZpc2ZzcmMuY29tL3dwLWNvbnRlbnQvdXBsb2Fkcy8yMDIwLzAyL1ZpcnR1YWwtQXNzZXQtQWN0LTlwMjAucGRmJnNldHRpbmdzPTExMTExMTExMTExMTExJmxhbmc9ZW4tVVM= |
| 17 Apr 2020 | IRAS e-Tax Guide - Income Tax Treatment of Digital Tokens | Singapore | Tax | ./. | Tax Authority | Web-site | https://www.iras.gov.sg/media/docs/default-source/e-tax/etaxguide_cit_income-tax-treatment-of-digital-tokens_091020.pdf?sfvrsn=91dbe1f7_0 |
| 8 Jun 2020 | Digital Assets Business Act | Antigua & Barbuda | Regulatory Framework | Date refers to announcement date of official parliament approval of the regulation ¹⁷ | Government document stored by | perma.cc | https://perma.cc/7UUH-N5UJ |
| 31 Jul 2020 | Regulation on digital financial asset (DFA) | Russia | Regulatory Framework | ./. | Government document stored by | perma.cc | https://perma.cc/5KZV-XDDN ¹⁸ |
| 15 Sep 2020 | Law No. 194 of 2020 prohibits cryptocurrency-related activities | Egypt | Crypto Ban | ./. | Government document stored by | perma.cc | https://perma.cc/47XC-W48R ¹⁹ |
| 25 Sep 2020 | Federal Act on the Adaptation of Federal Law to Developments in Distributed Ledger Technology | Switzerland | Regulatory Framework | ./. | Government | Web-site | https://www.fedlex.admin.ch/eli/oc/2021/33/de |
| 9 Oct 2020 | IRAS e-Tax Guide - Income Tax Treatment of Digital Tokens (Adjustment) | Singapore | Tax | ./. | Tax Authority | Web-site | https://www.iras.gov.sg/media/docs/default-source/e-tax/etaxguide_cit_income-tax-treatment-of-digital-tokens_091020.pdf?sfvrsn=91dbe1f7_0 |
| 24 Nov 2020 | Digital Assets and Registered Exchanges Act | Bahamas | Regulatory Framework | Date refers to announcement date of official parliament approval of the regulation | Government | Web-site | https://laws.bahamas.gov.bs/cms/images/LEGISLATION/PRINCIPAL/2020/2020-0028/2020-0028_1.pdf |
| 21 Dec 2020 | Law on Digital Assets | Serbia | Regulatory Framework | ./. | Central Bank | Web-site | https://www.nbs.rs/export/sites/NBS_site/documents-eng/propisi/zakoni/digitalna_imovina_e.pdf |

¹⁷<https://www.cfatf-gafic.org/home/what-s-happening/653-antigua-and-barbuda-pass-digital-assets-regulation-bill-in-lower-parliament>

¹⁸English translation: <https://cis-legislation.com/document.fwx?rgn=126432>

¹⁹English description: <https://www.tamimi.com/law-update-articles/restructuring-of-financially-distressed-banks-under-the-new-central-bank-and-monetary-sector-law-no-194-of-2020/>

| | | | | | | | |
|-------------|--|---------------|----------------------|--|--------------------|-----------------------------|---|
| 12 Mar 2021 | Spanish Royal Decree-Law 5/2021 | Spain | Regulatory Framework | ./. | Government site | Web-site | https://www.boe.es/eli/es/rdl/2021/03/12/5/con |
| 3 Jun 2021 | Electronic Securities Act (Gesetz zur Einführung von elektronischen Wertpapieren, eWpG) | Germany | Regulatory Framework | ./. | Government site | Web-site | https://www.gesetze-im-internet.de/ewpg/BJNR142310021.html |
| 9 Jun 2021 | Bitcoin as legal tender - Bitcoin Law (Decree No. 57) | El Salvador | Regulatory Framework | ./. | Government site | document stored by perma.cc | https://perma.cc/X5RJ-XKE7 |
| 30 Jun 2021 | Regulations Governing AML and CFT for Enterprises Handling Virtual Currency Platform or Transactions | Taiwan | AML/CFT | ./. | Government site | document stored by perma.cc | https://perma.cc/M8ET-S8QL |
| 24 Sep 2021 | China's top regulators ban crypto trading and mining | China | Crypto Ban | ./. | Central Bank site | Web-site | http://www.pbc.gov.cn/goutongjiaoliu/113456/113469/4348521/index.html |
| 10 Dec 2021 | e Virtual Asset and Initial Token Offering Services Act 2021 | Mauritius | Regulatory Framework | Date refers to announcement date of official parliament approval of the regulation | Government site | Web-site | https://police.govmu.org/police/?mdocs-posts=the-virtual-asset-and-initial-token-offering-services-act-2021 |
| 2 Feb 2022 | Tax treatment of cryptocurrencies | Austria | Tax | ./. | Government site | Web-site | https://www.parlament.gv.at/aktuelles/pk/jahr_2022/pk0111#XXVII_I_01293 |
| 16 Mar 2022 | Legalisation of cryptocurrency within the country's financial system | Ukraine | Regulatory Framework | ./. | News Outlet | | https://www.euronews.com/next/2022/03/17/ukraine-war-zelenskyy-signs-a-new-law-officially-legalising-bitcoin-and-other-cryptos |
| 24 May 2022 | Royal Decree Exempting VAT on Digital Currency Transfers | Thailand | Tax | ./. | News Outlet | | https://news.bloombergtax.com/daily-tax-report-international/thailand-gazettes-royal-decree-exempting-vat-on-digital-currency-transfers |
| 3 Aug 2022 | IRAS e-Tax Guide - GST: Digital Payment Tokens | Singapore | Tax | ./. | Tax Authority site | Web-site | https://www.iras.gov.sg/media/docs/default-source/e-tax/e-tax-guide_gst_digital-payment-tokens.pdf?sfvrsn=da8cafd_a_0 |
| 16 Sep 2022 | Comprehensive Framework for Responsible Development of Digital Assets | United States | Regulatory Framework | ./. | Government site | Web-site | https://bidenwhitehouse.archives.gov/briefing-room/press-briefings/2022/09/16/background-press-call-by-senior-administration-officials-on-the-first-ever-comprehensive-framework-for-responsible-development-of-digital-assets/ |
| 12 Oct 2022 | Chile Tax Agency Clarifies Taxation of Financial Services, Digital Asset Transactions on Blockchain Platform | Chile | Tax | ./. | News Outlet | | https://news.bloombergtax.com/daily-tax-report-international/chile-tax-agency-clarifies-taxation-of-financial-services-digital-asset-transactions-on-blockchain-platform |
| 7 Dec 2022 | Passage of Anti-Money Laundering and Counter-Terrorist Financing (Amendment) Bill 2022 | Hong Kong | AML/CFT | ./. | Central Bank site | Web-site | https://www.hkma.gov.hk/media/eng/doc/key-information/guidelines-and-circular/2022/20221207e1.pdf |

| | | | | | | |
|-------------|---|------------|----------------------|-----|--|---|
| 21 Dec 2022 | Legal Framework for Virtual Assets in Brazil (Cryptoassets Act) | Brazil | Regulatory Framework | ./. | Government document stored by perma.cc | https://perma.cc/DJ27-86BV |
| 6 Feb 2023 | Kazakhstan introduces new regulation of Digital Assets | Kazakhstan | Regulatory Framework | ./. | Lawyer Website | https://www.morganlewis.com/pubs/2023/02/kazakhstan-introduces-new-regulation-of-digital-assets |

Note: This table provides additional details of the regulatory events in the sample, including the announcement date, the name of the regulation, the corresponding jurisdiction, the regulation type, additional notes, and the type of source used. The 'Link' column contains online addresses that direct to the sources of the listed regulatory announcements.

Figure C.1: Cryptocurrency market risk-return development over time

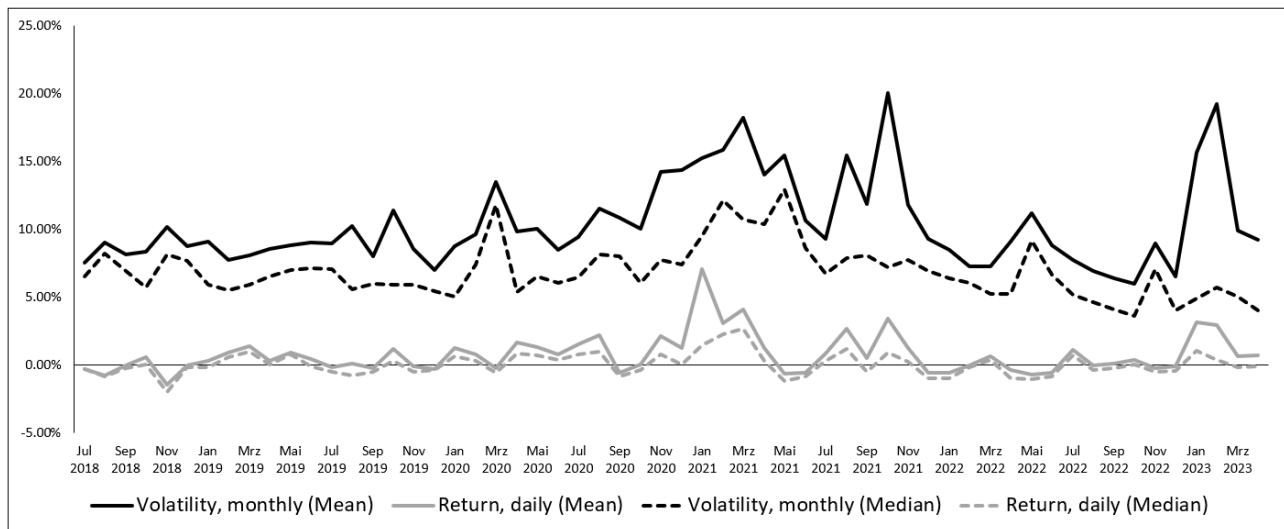


Table C.8: Regression robustness including year fixed effects

| | Δ Return volatility: | | | Δ Return: | | | Δ Sharpe: | | |
|--------------------------------------|-----------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| | 30-d | 50-d | 80-d | 30-d | 50-d | 80-d | 30-d | 50-d | 80-d |
| Panel A: <i>All Events</i> | | | | | | | | | |
| Governance enforcement index | -0.025***
(0.002) | -0.019***
(0.002) | -0.023***
(0.001) | -0.014***
(0.001) | -0.008***
(0.001) | -0.003***
(0.000) | -0.053***
(0.002) | -0.054***
(0.003) | -0.036***
(0.003) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 | 24,097 |
| R ² | 0.061 | 0.064 | 0.104 | 0.130 | 0.170 | 0.227 | 0.137 | 0.197 | 0.231 |
| Panel B: <i>Regulatory Framework</i> | | | | | | | | | |
| Governance enforcement index | -0.035***
(0.003) | -0.025***
(0.003) | -0.020***
(0.002) | -0.013***
(0.001) | -0.008***
(0.001) | 0.003***
(0.001) | -0.058***
(0.003) | -0.056***
(0.004) | 0.029***
(0.005) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 13,054 | 13,054 | 13,054 | 13,054 | 13,054 | 13,054 | 13,054 | 13,054 | 13,054 |
| R ² | 0.116 | 0.134 | 0.187 | 0.293 | 0.320 | 0.376 | 0.343 | 0.392 | 0.404 |
| Panel C: <i>Tax</i> | | | | | | | | | |
| Governance enforcement index | -0.110***
(0.005) | -0.095***
(0.004) | -0.066***
(0.004) | 0.000
(0.002) | 0.005***
(0.001) | -0.002**
(0.001) | 0.018***
(0.005) | 0.038***
(0.007) | -0.037***
(0.009) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Token FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 6,836 | 6,836 | 6,836 | 6,836 | 6,836 | 6,836 | 6,836 | 6,836 | 6,836 |
| R ² | 0.213 | 0.187 | 0.169 | 0.223 | 0.202 | 0.225 | 0.282 | 0.218 | 0.264 |

Note: These are regression results for the impact of governance enforcement strength on the four dependent variables(i): CAR, (ii) Δ return volatility, (iii) Δ return, and (iv) Δ Sharpe ratio. CAR indicates the cumulative abnormal return over the 5-day event window (in %). Abnormal return is calculated based on the daily return of the event days minus the 80-day pre-event average return. The variables Δ return volatility, Δ return, and Δ Sharpe ratio measure the differences in the standard deviation of the return, price change, and Sharpe ratio of the token between the post-event window and the pre-event window. We include three different window sizes: 30-days, 50-days, and 80-days. The Sharpe ratio is calculated as the average daily return multiplied by the window size divided by the standard deviation during the period. The *Governance enforcement index* represents the strength of enforcement of contracts and other rights within the jurisdiction issuing the law, measured as a percentile rank. The estimated coefficients of the control variables are suppressed for brevity. To control for time-invariant confounders, we include token fixed effects and to control for time-variant confounders we also include year fixed effects. Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

Table C.9: Risk-return statistics sensitivity to different trimming levels

| | Obs. | Mean | SD | Q1 | Median | Q3 | Min | Max |
|-----------------------------|--------|-----------|--------|--------|--------|-------|-----------|---------|
| Panel A: 0.01% level | | | | | | | | |
| CAR | 25,489 | -1.172*** | 30.374 | -9.471 | -1.242 | 6.560 | -1313.663 | 549.407 |
| Δ Return volatility | 25,489 | -0.498*** | 4.483 | -2.707 | -0.484 | 1.660 | -28.636 | 35.699 |
| Δ Return | 25,489 | 0.017* | 1.407 | -0.674 | 0.015 | 0.718 | -17.327 | 11.613 |
| Δ Sharpe Ratio | 25,489 | 0.580*** | 11.607 | -7.081 | 0.033 | 7.880 | -52.066 | 59.471 |
| Panel B: 0.1% level | | | | | | | | |
| CAR | 25,353 | -1.414*** | 20.276 | -9.476 | -1.283 | 6.433 | -360.007 | 180.151 |
| Δ Return volatility | 25,353 | -0.496*** | 4.449 | -2.699 | -0.484 | 1.653 | -28.636 | 35.699 |
| Δ Return | 25,353 | 0.018** | 1.389 | -0.672 | 0.015 | 0.716 | -13.367 | 10.926 |
| Δ Sharpe Ratio | 25,353 | 0.585*** | 11.610 | -7.072 | 0.332 | 7.887 | -52.066 | 59.471 |
| Panel C: 1.0% level | | | | | | | | |
| CAR | 23,842 | -2.017*** | 14.276 | -9.215 | -1.475 | 5.618 | -110.677 | 90.812 |
| Δ Return volatility | 23,842 | -0.500*** | 4.273 | -2.625 | -0.490 | 1.596 | -28.636 | 29.735 |
| Δ Return | 23,842 | 0.034*** | 1.314 | -0.637 | 0.021 | 0.707 | -8.319 | 8.583 |
| Δ Sharpe Ratio | 23,842 | 0.716*** | 11.585 | -6.930 | 0.414 | 7.994 | -52.066 | 56.560 |

Note: This table presents the summary statistics of the four outcome variables: (i) *CAR*, (ii) Δ *return volatility*, (iii) Δ *return*, and (iv) Δ *Sharpe ratio*. *CAR* indicates the cumulative abnormal return over the 5-day event window (in %). Abnormal return is calculated based on the daily return of the event days minus the 80-day pre-event average return. The variables Δ *return volatility*, Δ *return*, and Δ *Sharpe ratio* measure the differences in the standard deviation of the return, price change, and Sharpe ratio of the token between the 80-day post-event window and the 80-day pre-event window. We show the results for three different trimming levels of our sample, including 0.01% (Panel A), 0.1% (Panel B), and 1.0% (Panel C). For all variables, we report the number of observations, arithmetic mean, standard deviation, and the 25%, 50%, and 75% quantiles. The number of asterisks behind the mean indicates the p-value of a t-test, testing if the average deviation is significantly different from zero; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.10: **Durbin-Wu-Hausman (DWH) Test for Endogeneity**

| <i>Dependent variable:</i> | CAR | Δ Return
volatility | Δ Return | Δ Sharpe
Ratio |
|---|-------------------|-------------------------------|-------------------|--------------------------|
| Panel A: <i>Analogous to Table 4.6, 4.7, 4.8, and 4.9 (for Main Regression)</i> | | | | |
| DWH residuals | −2.504
(2.160) | 0.408
(0.448) | −0.119
(0.196) | −1.676
(1.272) |
| Panel B: <i>Analogous to Table 4.13</i> | | | | |
| DWH residuals | −2.568
(2.135) | 0.401
(0.456) | −0.108
(0.203) | −1.531
(1.352) |
| Panel C: <i>Analogous to Table 4.14</i> | | | | |
| DWH residuals | −3.384
(2.312) | −0.145
(0.326) | −0.233
(0.173) | −1.794
(1.710) |

Note: This table presents results from the Durbin-Wu-Hausman (DWH) test for endogeneity. We test for endogeneity for our main models in this study, including: (i) main regressions from Tables 4.6, 4.7, 4.8, and 4.9 (ii) 4.13, 4.14. According to the test procedure by Davidson and MacKinnon (1993), if the DWH residual is insignificant endogeneity is not a problem (see Section 4.4.6.3). Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

CHAPTER 5

Conclusion

This cumulative dissertation presents analyses of how the strategic decisions of entrepreneurs and policymakers impact the operational and financial performance of DDPs. The first essay reveals that token governance mechanisms, specifically retention and restriction, play crucial roles in influencing ICO outcomes by mitigating asymmetric information and affecting fundraising success. This contribution enriches the discourse on governance in early-stage fundraising. The second essay advances research by analyzing the effects of public token listings on the growth and decentralization of DDPs. It demonstrates that secondary market activities not only enhance visibility and user engagement but also crucially modulate the network effects essential for the scaling of DDPs. This essay provides comprehensive insights into how listings act as catalysts that drive both speculative and fundamental activities. The third essay broadens this exploration by assessing how varying global cryptocurrency regulations influence the risk and return profile of DDP tokens, offering a nuanced view of the regulatory impacts across different market contexts.

This dissertation uncovers significant implications for a range of stakeholders in the entrepreneurial finance ecosystem. It demonstrates that providing early-stage DDPs access to public token markets can substantially enhance their development. This suggests that policymakers might need to rethink traditional regulatory frameworks to better accommodate the unique needs of blockchain-based platforms, potentially fostering innovation and growth in this sector. Additionally, the findings offer strategic insights for entrepreneurs, emphasizing the benefits of public listings in driving network effects and long-term platform success. This should encourage founders to carefully plan their market entry strategies to optimize growth outcomes. Moreover, the analysis serves as a cautionary tale about the complexities of token governance, revealing that certain restrictions might in-

hibit rather than support post-listing performance. For regulators, the nuanced understanding of how policy design and enforcement affect the token market stability provides a valuable perspective, highlighting the importance of creating clear and enforceable rules that align with the dynamic nature of the new asset class. Overall, this research contributes to a broader understanding of the interplay between regulation, strategy, and technology in the emerging field of entrepreneurial finance.

This dissertation identifies numerous avenues for future research within blockchain-based entrepreneurial finance. Our analysis of DDPs introduces critical questions regarding the sustainability of their growth and the operational advantages they gain from public market listings, especially as regulatory frameworks become more stringent. Future studies could examine whether traditional centralized platforms might experience similar benefits from early-stage public listings, offering a broader understanding of how public accessibility influences venture success across different architectures. Moreover, our research highlights the significant role of financial speculation in the growth of DDPs. There is a compelling need for more granular investigations into the specific types of speculation and the behaviors of individual investors. Such studies could elucidate how speculative activities contribute to the fundamental growth of DDPs, potentially identifying the mechanisms through which liquidity, information, and demand spillovers occur.

CHAPTER 5

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