Walk this Way! Incentive Structures of Different Token Designs for Blockchain-Based Applications

Philipp Hülsemann
Johannes Gutenberg University Mainz, phhuelse@uni-mainz.de

Andranik Tumasjan
Johannes Gutenberg University Mainz, antumasj@uni-mainz.de

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Completed Research Paper

Philipp Hülsemann
Johannes Gutenberg University Mainz
55128 Mainz
Jakob-Welder-Weg 4
phhuelse@uni-mainz.de

Andranik Tumasjan
Johannes Gutenberg University Mainz
55128 Mainz
Jakob-Welder-Weg 4
antumasj@uni-mainz.de

Abstract

Cryptoeconomics is an emerging research area in the field of blockchain technology aiming at understanding token design mechanisms intended to incentivize certain behaviors. Whereas several blockchain ecosystems have been emerging in recent years, little is known about incentive design in blockchain protocols other than Bitcoin. To address this gap, we use agent-based modeling (ABM) to simulate the effects of different token designs on usage in the context of prediction markets. We find that network tokens (i.e., tokens providing services within a system) provide the largest incentive for individuals to join and become long-term active users. Moreover, we find that investment tokens (i.e., tokens used to passively invest in the issuing entity) provide the smallest incentive compared to network tokens and cryptocurrencies (i.e., means of payment in a blockchain ecosystem). We advance the literature by testing the boundary conditions of different token designs for blockchain-based ecosystems using a novel ABM approach.

Keywords: Agent-Based Modeling, Blockchain, Cryptoeconomics, Design Science, Simulation, Tokens

Introduction

Cryptoeconomics is a relatively new research area in the field of blockchain technology (Davidson, De Filippi, & Potts, 2016a; Swanson, 2015). Blockchain technology became famous in 2008 when a person or group using the pseudonym Satoshi Nakamoto introduced the technology in a whitepaper, which also introduced the decentralized cryptocurrency (i.e., means of payment in a blockchain ecosystem; Hileman & Rauchs, 2017) "Bitcoin" enabled by the technology (Nakamoto, 2008). Due to the newness of the research field, its typology and definition are inconsistent and involve heterogeneous use of the term "cryptoeconomics" (Østbye, 2017). Cryptoeconomics is the combination of cryptography and economic incentives (Buterin, 2015a, 2015b; Lin et al., 2017; Swanson, 2015). Cryptoeconomic incentives are designed to encourage all users to act honestly (Hileman & Rauchs, 2017). Consequently, cryptoeconomics studies the optimization of incentive-design to evoke honest behavior in a competitive environment. Cryptoeconomics is often part of blockchain-based ecosystems. Such ecosystems can be defined as "purposeful collaborating network[s] of dynamic interacting systems" (Sussan & Acs, 2017) and include all business areas along the creation of goods or services (Bauer, Zavolokina, Leisibach, & Schwabe, 2019).

One example of such incentives is that of tokens. These are economic incentives used in blockchains (Lipush, Dellermann, & Ebel, 2019; Shin, Kim, Hall, & Lang, 2019). They are native units of value and serve mainly as incentives to use or operate the blockchain (Shin et al., 2019). Since the total value of tokens

amounts up to of hundreds of billions of dollars (Haeringer & Halaburda, 2018), research in this field creates immense value to founders, developers, and users of blockchain technology by increasing their chances of economic success.

However, even though blockchain technology could lead to radical changes in various industries (De Rossi, Salviotti, & Abbatemarco, 2019; Dutra, Tumasjan, & Welpe, 2018; Friedlmaier, Tumasjan, & Welpe, 2018) and incentivization is a core aspect of blockchains disruptive power, current research focuses mainly on Bitcoin (Chen, Xu, Gao, Shah, Lu, & Shi, 2017; Risius & Spohrer, 2017). This focus results in a research gap with regard to the incentivization of users' behavior in other blockchain-protocols (Chen et al., 2017). To study incentivization in blockchain-based token systems, our study develops and tests an agent-based model (Treiblmaier, 2017). Our model enables researchers and developers of blockchain protocols to test the effects of token designs on user behavior and optimize token design with respect to usage (Tumasjan & Beutel, 2018) prior to their real-world implementation (Cai, Cai, Wang, Cheng, & Wang, 2019).

We make two major contributions to the literature. First, we contribute to the emerging blockchain research on cryptoeconomic token design (Conley, 2017; Lipusch et al., 2019; Meinel, Gayvoronskaya, & Schnjakin, 2018; Shin et al., 2019) by developing an agent-based model to test the effects of different token designs on usage. We use the popular example of blockchain-based prediction markets (Conley, 2017; Peretz, 2018) to test which token design provides the largest incentive for individuals to join and become long-term active users. Prediction markets are based on the concept of crowdsourcing. The traders who build the crowd try to predict the outcome of uncertain future events and earn rewards for accurate predictions. Therefore, they are buying shares of contracts for events they deem likely to happen in the future (Arrow et al., 2008; Atanasov et al., 2017; Berg, Nelson, & Rietz, 2008; Wolfers & Zitzewitz, 2006). The price of a share, which represents a particular outcome of an event, is derived from the number of shares bought predicting this exact same outcome relative to the total number of shares bought (Atanasov et al., 2017). An example of prediction markets that is well-known among economists is the Iowa Electronic Market run by the University of Iowa, which was established in 1988. The Iowa Electronic Market is the model for many other prediction markets established by other universities and runs prediction markets on political elections, how interest rates will develop, and other mainly economical events (Wolfers & Zitzewitz, 2004).

We investigate how key aspects of blockchain technology influence users' varying motivations (Wang, Luo, Hua, & Wang, 2019). Specifically, we enrich the literature by not only testing for varying design settings of those key aspects but also examining the effect of those design settings on users with different motivations (i.e., intrinsic and extrinsic motivation). Furthermore, we reply to calls to investigate decision-making in blockchain ecosystems by providing a framework for examining the incentives of actors (Ziolkowski, Parangi, Miscione, & Schwabe, 2019).

To translate the conceptual model into an environment that allows us to actually test different boundary conditions, we use the programming environment NetLogo for agent-based modeling (ABM; Wilensky, 1999). Providing evidence on the functionality of the newly built model, our research forms a basis for future research to further develop the model. Offering a structural framework to build on, the model provides major value by predicting short- and long-term usage prior to actual implementation of blockchain-based token ecosystems (Cai et al., 2019).

Our research responds to calls to investigate methods and techniques to examine key challenges in the emerging research field of blockchain technology (Welpe, Zavolokina, Krcmar, & Mehrwald, 2019). Specifically, we enrich the literature by testing a model that combines technological specifications and strategic organizational challenges. Hence, we contribute to both the IS and general management literature reflecting their increasing dependency on each other (Welpe et al., 2019).

Furthermore, we respond to calls to investigate complex systems with emergent phenomena using ABM (Treiblmaier, 2017). Specifically, we enrich the literature by exploring the potentials of ABM and by investigating how it can contribute to the testing and validation of theories. Hence, we also address calls to incorporate temporal dynamics by building a theory-based model and testing the fit of the model applying multivariate methods. In addition, we use ABM to "combine the strengths of dynamic modeling [...] with rigorous multivariate statistics" (Treiblmaier, 2017).

Second, we contribute to IS research in general using the design science approach (Arnott, 2006; Baskerville, Rossi, & Tunnanen, 2019; Holmström, Ketokivi, & Hameri, 2009; March & Storey, 2008; Pries-Heje, Baskerville, & Venable, 2008) to address a main controversy of the discipline - namely, "the low level

of professional relevance of many IS studies" (Arnott, 2006). Following March and Storey (2008), a design science research contribution requires (1) identifying and clearly describing a relevant organizational problem; (2) showing that the solution to this problem is unknown and that it is indeed a knowledge gap; (3) conceptualizing a novel construct, model, method or instantiation (called an "artifact") that addresses the problem; (4) evaluating of the artifact to assess its utility; (5) explaining the value added to research and practice; and finally (6) articulating implications for management and practice. Our study fulfils all these criteria by conceptualizing and simulating a novel model for the unsolved problem of how to design an ideal blockchain-based token system.

Theory

Design Science

We use a design science approach as our overall theoretical framework (Arnott, 2006; Baskerville et al., 2019; Holmström et al., 2009; March & Storey, 2008; Pries-Heje et al., 2008). The overall goal in design science approaches is to develop an artifact to solve a problem (Holmström et al., 2009). These artifacts include constructs, models, methods, and instantiations created to successfully solve a problem within an organization (March & Storey, 2008). The strength of design science is its "explicit focus on improving practice" (Holmström et al., 2009). Thus, it is fundamental to the IS discipline, since it increases the level of professional relevance of IS studies (Arnott, 2006).

Managers pursue the goal of long-term competitive advantage and therefore need to know why artifacts they have invested in are or are not increasing firm value and what artifacts will increase firm value. Both questions represent research questions in the IS discipline; the first is theory-based and causality related, while the second is design-based and related to problem solving. Design science aims to define the desired situation, the current situation, and the differences between the desired and the current states. Afterwards, it seeks to develop a solution (i.e., artifact) to remove differences between the desired and current states. Design science approaches contribute to theory and practice due to the novelty and utility of the artifacts constructed. Thereby, they aim at enabling the description and communication of solution components and constraints of the designed artifact. The problem and its solution space are then presented as a model (March & Storey, 2008).

To evaluate the novel solution (i.e., artifact) of a design science approach criteria have to be developed and compared to the artifact's performance. There are two forms of evaluation with regard to two evaluation episodes. The episodes are design evaluation and construct evaluation, while the forms are ex ante and ex post. "Ex ante" describes the evaluation of a design before construction of any artifacts, while "ex post" describes the evaluation of constructed artifacts (Pries-Heje et al., 2008). Since our study does not address a specific problem of a specific business but rather a general design problem related to incentivization in a blockchain-based ecosystem, we will perform ex ante evaluation.

There exist three subfields in design science. First, science of design focuses on creating completely new artifacts. Second, design theory focuses on developing improved systems from existing concepts. Third, design research focuses on how to perform actual design activities (Baskerville et al., 2019). Since we are examining the optimal design of existing blockchain-based token systems, our research falls under the second subfield of design science. The goal of design science and of this research is to learn through the building and application of artifacts (i.e., token design). We aim to initiate an iterative research process to produce knowledge of a problem (i.e., incentive structures for using blockchain-based prediction markets) and transferring the new knowledge to other domains (i.e., incentive structures for using other blockchain-based applications besides prediction markets; Baskerville et al., 2019).

Cryptoeconomics

In 2008, a person or group using the pseudonym Satoshi Nakamoto introduced the technology of blockchain in a whitepaper, simultaneously introducing the decentralized cryptocurrency "Bitcoin" enabled by the technology (Nakamoto, 2008). A blockchain is a continuously growing list of linked blocks. Blocks contain transaction data secured by cryptographic signatures (Bauer et al., 2019; De Rossi et al., 2019; Labazova, Dehling, & Sunyaev, 2019). To prevent retroactive changes, tampering and modification, a blockchain is distributed across several computers (Chandra, Ranjan, Sawale, Rajsekhar, Singh, & Wadki,

2018; Lee, 2018). Hence, a blockchain is a protocol that enables a trusted exchange between strangers (Bauer et al., 2019; Labazova et al., 2019), which otherwise would be restricted by "boundaries of possible mistrust" (Berg, 2017). To enable such exchanges, incentives are needed to encourage individuals or groups to behave in a certain way (Groves, 1973). The developers of a blockchain try to fundamentally integrate an incentive design serving to incentivize the users of the blockchain to act in accordance with the goals of the blockchain. However, due to the variety of possible combinations of individuals in a blockchain, it is difficult to develop an incentive design that is prepared for all possible emerging behaviors (Lee, 2018).

Cryptoeconomics is the optimization of incentive design to evoke social behavior in an economy detached from state authority and territorial borders. This definition follows from the two dominant research approaches regarding the essential meaning of cryptoeconomics in blockchain technology. On the one hand, there is a focus on building a new economy, independent of laws, country boarders, central governance and politics. According to this approach, cryptoeconomics represents a new economy, independent of both state authority and territorial economy (Berg, 2017; Rabah, 2017; Shin et al., 2019). In this sense, blockchains are the foundational ordering principles of the economy and socio-political order in cryptoeconomics (Davidson et al., 2016b). On the other hand, cryptoeconomics is understood as the combination of cryptography and economic incentives (Buterin, 2015a, 2015b; Hileman & Rauchs, 2017; Lin et al., 2017; Rabah, 2017; Swanson, 2015). Thereby, cryptography studies communication in a hostile environment (Rabah, 2017), while cryptoeconomic incentives are designed to encourage all users to act honestly (Hileman & Rauchs, 2017). Consequently, cryptoeconomics studies the optimization of incentive design to evoke honest behavior in a hostile environment. Notably, the two dominant approaches found in our literature review are not mutually exclusive.

Reviewing the literature on cryptoeconomics, the existing research focuses on exploring the block-building process in cryptocurrency systems on blockchain (e.g., Badertscher, Garay, Maurer, Tschudi, & Zikas, 2018; Jiao, Wang, Niyato, & Xiong, 2018; Lee, 2018; Pianese, Signorini, & Sarkar, 2018; Stone, 2018). This leads to a lack of research on the behavior of users in other systems built on blockchain (Chen et al., 2017). To successfully address this research gap, we will use the previously synthesized definition of cryptoeconomics as the optimization of incentive design to evoke social behavior in a decentralized token-based economy.

Blockchain Tokens

Tokens are economic incentives used in blockchain ecosystems (Lipush et al., 2019; Shin et al., 2019). They are native units of value and serve mainly as incentives to use or operate the blockchain (Shin et al., 2019). They allow users to use the blockchain's services and are used to incentivize users by rewarding social behavior (Hileman & Rauchs, 2017; Mougayar, 2017; Shin et al., 2019). Such token holders can also benefit financially, because tokens can be exchanged for currencies like cryptocurrencies. A token itself is not a financial asset but rather a digital good (Shin et al., 2019). Moreover, multiple designs of tokens exist (Conley, 2017; Lipusch et al., 2019; Müller et al., 2018). To classify different designs of tokens, we rely on the Token Classification Framework (TCF; Untitled Inc., 2018). The TCF defines tokens with respect to what they are designed to do: as means of payment in a blockchain ecosystem, they are called "cryptocurrencies"; when enabling access to networks or services, they are called "network tokens"; and when used for investing they are called "investment tokens". With respect to market capitalization, cryptocurrencies have the biggest economic impact of the different designs of tokens, with approximately 70% of total market capitalization ($173bn as of Q2 2019). Even though there exist more network tokens than cryptocurrencies, the former's total market capitalization is lower ($57bn as of Q2 2019). The economic impact of investment tokens is the smallest of the three token designs with approximately 1% of total market capitalization ($0.2bn as of Q2 2019; Spörer & Sandner, 2019). Classifying tokens provides an overview of the possibilities in incentive design and also aids in evaluating a token's worth (Müller et al., 2018), which is otherwise difficult to determine or measure (Conley, 2017; Hargrave, Sahdev, & Feldmeier, 2018). It is therefore useful to both developers and users of a blockchain protocol. We will use the blockchain-based prediction markets (Conley, 2017; Peretz, 2018) as an example of a token-based incentivization system.

The characteristics of blockchains (e.g., decentralization, "trustlessness", distribution) can help to motivate potential traders to actively participate in such prediction markets (Peretz, 2018). The overall value of a prediction market is determined by the accuracy of its forecasts (Atanasov et al., 2017). Prediction accuracy in turn depends on the size of the crowd. As a general rule, it can be said that the more traders participate

in a prediction market, the more precise is the forecast (Garcia Martinez & Walton, 2014; Hosio, Goncalves, Anagnostopoulos, & Kostakos, 2016; Hosseini, Moore, Almaliki, Shahri, Phalp, & Ali, 2015; Terwiesch & Xu, 2008). Wagner and Suh (2014) acknowledge the fact that a larger crowd compensates for individual errors. Peretz (2018) argues that prediction markets could unfold their full potential when applied to blockchain technology while not doing so under regulation. However, the utilization of this potential would depend on how effectively those blockchain tokens are designed. Hence, we formulate two research questions:

Research Question 1. Which token design provides the largest incentive for individuals to join blockchain-based prediction markets?

Research Question 2. Which token design provides the largest incentive for new users to become long-term active users of blockchain-based prediction markets?

To answer both Research Question 1 and Research Question 2, the token design has to be varied. According to the TCF, there are three different token designs (i.e., token purposes), which we utilize to represent different token designs: cryptocurrency, network token, and investment token. First, we follow Peretz (2018) and argue that blockchain technology enables prediction markets to reach higher potential compared to prediction markets in a regulated environment. The accuracy of a prediction market's forecast determines its overall value (Atanasov et al., 2017). Second, since, a forecast's precision increases if more traders participate (Garcia Martinez & Walton, 2014; Hosio et al., 2016; Hosseini et al., 2015; Terwiesch & Xu, 2008), we argue that, the number of users should increase independent of the token design, simply as a result of the prediction market being applied to blockchain technology.

Hypothesis 1a. The token design cryptocurrency increases the number of users.

Hypothesis 1b. The token design network token increases the number of users.

Hypothesis 1c. The token design investment token increases the number of users.

Individuals can be attracted to participate in prediction markets for various reasons. We use user motivation as a theoretical concept to comprehend usage behavior (Venkatesh, 1999). As motivation is a key driver of behavioral intentions to use (Davis, Bagozzi, & Washaw, 1992; Venkatesh, 1999), we agree with Cheng and Vassileva (2005) that reciprocation theory is a "basic norm of human society"; thus, for someone to be expected to do something, a reward must be offered. Applied to our research this means that in order to attract agents to participate in blockchain-based prediction markets, we need to reward them with worthwhile incentive designs (i.e., token designs). Servan-Schreiber, Wolfers, Penncock and Galebach (2004) found that money is one way to attract potential users. The findings of Wolfers and Zitzewitz (2004) are consistent with these findings, as they introduce two different types of motivation that can encourage active participation in prediction markets. They differentiate between, first, the motivation to earn money and, second, the motivation to process information better, and therefore to predict better, than others do. Following this description, agents who are motivated to predict better than others will hereinafter be referred to as "competition seekers" (CS), and agents who are motivated by earning money will hereinafter be referred to as "monetary profit seekers" (MPS).

The provided definitions of the TCF lead us to argue, first, that a prediction market token (PMT) designed as a cryptocurrency or investment token will not lead to active usage in the sense of predicting in prediction markets. Instead, a PMT cryptocurrency would be used as a currency or could be traded for other currencies like USD or Bitcoin as soon as the expected utility is lower than the current price and exchange rates favor trading. Thus, a user verifies whether the value of the token is expected to increase. If it is, she will buy or hold the token. If the present value is equal to or lower than the expected value and a user already holds the token, then she verifies weather trading is profitable. If it is, she will sell the token. If it is not, she will keep holding the token. A PMT investment token would be bought to hold and sell at a profit, trading it for currencies like USD or Bitcoin as soon as trading becomes profitable. Thus, we argue that a user verifies whether trading is profitable. If it is, she will sell the token. If it is not, and a user already holds the token, then she second, verifies if the value of the token is expected to increase. If it is, she will keep holding the token. If it is not, she will sell the token. Hence, the investment token design seems to lead to the least loyal behavior, because as soon as trading is profitable it will be sold, whereas the cryptocurrency will be held even if trading is profitable as long as the expected value is higher than the present value. Therefore, we propose:

Hypothesis 2. Cryptocurrencies provide a stronger incentive to users to remain long-term users than investment tokens do.

Second, since the PMT designs cryptocurrency or investment token will not lead to active usage, we argue that only PMT network tokens are designed to be actively used. Network tokens are primarily intended to be used and could therefore lead to active participation in prediction markets (Untitled Inc., 2018). Additionally, CS only enter a market with at least one competitor in the market. Thus, only the PMT design network token is able to motivate CS to participate in prediction markets. Therefore, network tokens, compared to cryptocurrencies and investment tokens, provide an additional use-case to MPS and thus represent the only PMT-design to motivate CS to actually enter the prediction market. We argue that this token design is of superior use for prediction markets compared to cryptocurrencies and investment tokens. Users of network tokens can also sell their token, but they will only have an intention to do so if they do not believe in their chances to predict correctly. If they do not believe in their chances, they will then only sell the token if the current value is higher than the expected value. Hence, the probability of selling (i.e., not holding) a network token appears to be less likely compared to cryptocurrency and investment tokens. Therefore, we propose:

Hypothesis 3. Network tokens provide a stronger incentive for users to remain long-term users than cryptocurrencies and investment tokens.

Methods

Conceptualization of the PMT Model

Our model uses PMT as an example to test for the effects of token design on usage. We provide an overview of the conceptualized model in Figure 1.
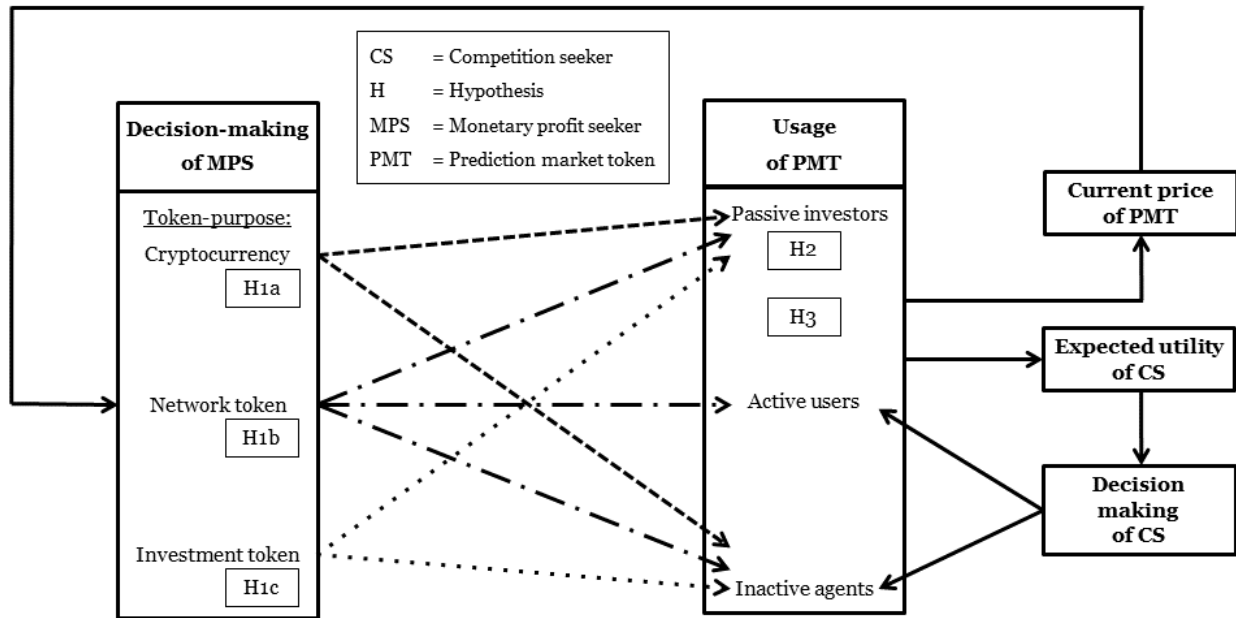
Figure 1. Research Model for Testing the Influence of PMT Design on Usage

The model examines a user perspective of MPS and CS on PMT to give valuable insights on the consequences of choosing a token design. First, the evaluation of PMT by MPS is based on the chosen token design of cryptocurrency, network token, or investment token, as described in the TCF (Untitled Inc., 2018). As explained previously, active usage is only possible for MPS in the case of the network token design. Generally, the value of tokens is difficult to determine or measure (Conley, 2017; Hargrave et al., 2018). The Behavioral model (Conley, 2017) states that individuals can deviate from evaluating tokens from a rationally justified point of view. It is therefore impossible to calculate the utility an individual attributes to a token

retrospectively (Conley, 2017). We implement the Behavioral model and the specific criteria of each token design according to the TCF (Untitled Inc., 2018) to simulate the decision process of MPS depending on PMT-design. Second, the evaluation of PMT by CS is not dependent upon the token's monetary value or growth. The number of competitors in a prediction market determines the value of PMT from a CS's perspective, since they need the token to access the competition. If the competition offers a sufficient utility to CS, they will become or remain users.

An inactive agent does not participate in the prediction market at all, meaning that she neither buys nor holds a PMT. We differentiate between two types of usage: active usage and passive investment. In both cases, an agent either buys or holds a PMT. Active usage involves participating in the prediction market by predicting the outcome of future events. Conversely, passive investment refers to buying PMT and later selling it for a profit. Naturally, active users also invest in their token; the difference is that they actively use the token to predict, while passive investors do not participate in any predicting. We encompass both the number of active users and the number of passive investors under the term "usage". The terms' effects differ, however, due to the influence of active users on the PMT valuation by CS, as discussed. Furthermore, the number of active users affects the current price, since the price is increases by prediction accuracy, and prediction accuracy increases by the number of predictors (Atanasov et al., 2017; Garcia Martinez & Walton, 2014; Hosio et al., 2016; Hosseini et al., 2015).

NetLogo Programming Environment

NetLogo (Wilensky, 1999) is a widely used multi-agent programming environment. It is suitable to model how complex phenomena evolve over time and to simulate changes in outcomes by varying conditions. It offers an environment of programmable agents, which can interact and perform multiple tasks simultaneously (Tisue & Wilensky, 2004). Tumasjan and Beutel (2018) explore under what circumstances blockchain-based business models may be adopted, also using the NetLogo programming environment. They find varying adoption patterns depending on different scenarios by changing variables. NetLogo meets all requirements to model variables like the token's design and investigating the changes in outcome over time. To simulate the effects of PMT designs we build the model "Prediction Market Tokens" (PMT model) as conceptualized previously (see Figure 1) in NetLogo (Wilensky, 1999).

Simulation Setup

Since the research questions demand a review over time, the research model displays loops. Separating all agents into two sets of agents (i.e., CS, and MPS) naturally leads to two loops, one for each agent set. Both loops show a similar structure. Agents estimate their utility from using PMT. Based on this expected utility, agents decide whether to be inactive or to use PMT and therefore classify themselves into one of the two possible states of usage: active usage or passive investment. Only MPS can decide to passively invest, because CS do not have an interest in seeking monetary profit due to trading. Hence, CS decide to either actively use PMT or be inactive. CS expect their utility only based on the number of active users, since their interest in participating in the prediction market depends on their competition. Therefore, because the PMT designs cryptocurrency and investment token will not yield to active usage, they will not yield to CS participating in the prediction market. Overall, the change in the number of active users determines the change in the price of PMT as discussed. The current price is positioned between the number of users and the expectation of utility by MPS and is therefore an additional factor in this loop. This is the case because the current price has an influence on the profitability of MPS trading tokens (i.e., MPS buying PMT and selling them at a profit). Since the utility of CS does not directly depend on the current price, the current price is not included in CS' loop (i.e., CS do not passively invest).

Every "tick" in the PMT model represents one time unit; in every time unit, a new prediction market takes place. In other words, it takes every agent exactly one time unit to run through her loop once. Agents mutate in every time unit within their agent set (i.e., MPS or CS) to decide on their usage of PMT. At the beginning of the loop, an agent has a usage status (i.e., active usage, passive investment, or inactivity). Inactive agents then decide to remain inactive or buy PMT to either actively use or passively invest. Agents already actively using or passively investing hold PMT from previous time units. They also decide to either remain in their current state of usage or switch to one of the other two states. Nevertheless, they do not need to buy PMT when deciding to actively use or passively invest in PMT, since they have bought PMT in the past (i.e., an earlier time unit). In addition, as long as agents hold PMT, they remember the price they initially bought it

for in the past when taking into consideration their individual profit as a result of trading their PMT now or in the future.

Since no empirical findings exist on the ratio between MPS and CS in prediction markets, it is unclear which ratio to test. Because the approach of maximizing monetary profits is dominant in the literature (e.g., Servan-Schreiber et al., 2004; Wolfers & Zitzewitz, 2004), but the influence of CS should be relevant (Wolfers & Zitzewitz, 2004), we suggest that forty percent of the population are CS and the remaining sixty percent are MPS. To gain a sufficient amount of data and test the robustness of the results, we run each simulation one hundred times. Since the PMT model is set to stop after one hundred ticks, this results in 30,000 data points (10,000 data points per each of the three token designs) with no missing data in any given data point. NetLogo's "BehaviorSpace" is used to collect the data. This built-in tool allows for running simulations with specified conditions and predefined characteristics of variables (Wilensky & Rand, 2015).

Analytical Strategy

The PMT model in NetLogo (Wilensky, 1999) simulates the effects of the different token designs included on usage with respect to becoming a user of PMT (Research Question 1) and remaining a long-term user of PMT (Research Question 2). First, to test our hypotheses referring to different token designs, we run an ordinary linear regression analysis (H1a, H1b, H1c). Second, to test our hypotheses referring to comparing the different token designs over time, we run a Two-Stage Least Squares (2SLS) analysis (H2, H3).

Results

We stated that the number of users should increase independent of the token design, since blockchain technology enables prediction markets to reach higher potential compared to prediction markets in a regulated environment (Peretz, 2018). We provide an overview of the mean numbers of users by token design in Figure 2.
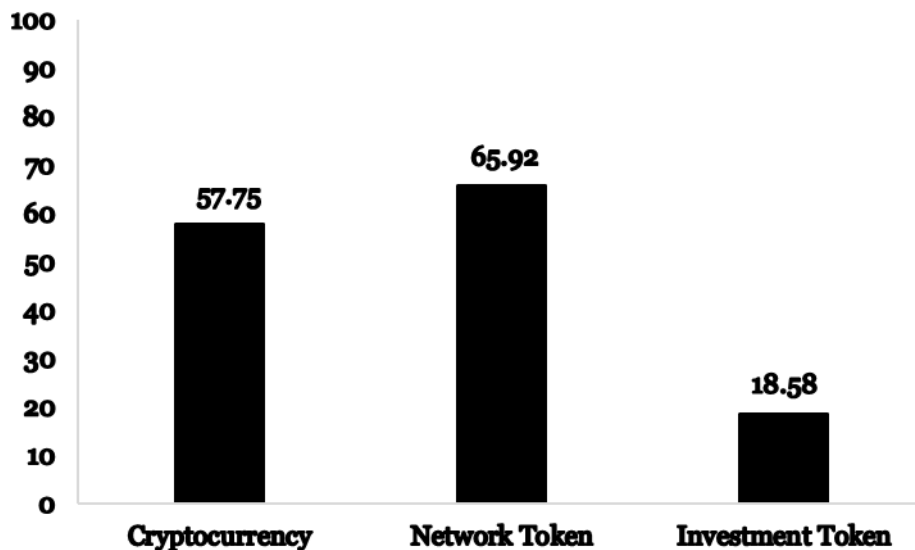
Figure 2. The Mean Number of Users by Token Design

In Hypothesis 1a, we stated that the token design cryptocurrency increases the number of users. To test Hypothesis 1a, we show that the mean number of users increases from zero to a positive number (57.75) of users. The mean number of users is chosen without a loss of generality and to simplify exposition. Supporting Hypothesis 1a, the effect of token design on usage is significant (B = 57.754, t = 1686.652, p = .000). In Hypothesis 1b, we stated that the token design network token increases the number of users. To test Hypothesis 1b, we show that the mean number of users increases from zero to a positive number (65.92) of users. The mean number of users is chosen without a loss of generality and to simplify exposition. Supporting Hypothesis 1b, the effect of token design on usage is significant (B = 8.162, t = 168.554, p = .000). In Hypothesis 1c, we stated that the token design investment token increases the number of users.

To test Hypothesis 1c, we show that the mean number of users increases from zero to a positive number (18.58) of users. The mean number of users is chosen without a loss of generality and to simplify exposition. Supporting Hypothesis 1c, the effect of token design on usage is significant (B = -39.172, t = -808.921, p = .000). An overview of all the coefficients of the different token designs is provided in Table 1.

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
Cryptocurrency (Constant)	57.754	.034		1686.652	.000**
Network token	8.162	.048	.184	168.554	.000**
Investment token	-39.172	.048	-.882	-808.921	.000**

To run the analysis, we dummy-coded the metrically scaled token designs. Therefore, we selected the token design cryptocurrency to be the reference category.

* p < .05; ** p < .01.

Table 1. Coefficients of the Different Token Designs

We proposed differences in the strength of the ability of the given token designs to incentivize users to remain long-term users (H2 and H3). To test these hypotheses, we performed 2SLS analyses. Table 2 displays the coefficients of the 2SLS analysis examining the change in the number of users over time. As shown in Table 2, we did not find any significant result from the 2SLS analysis. However, the 2SLS analysis shows a tendency to overvalue factors that decrease significance. Consequently, there is a tendency to find no statistical significance even though significance may actually exist (Greene, 2018; Stock, Wright, & Yogo, 2002). Hypothesis 2 stated that cryptocurrencies provide a stronger incentive to users to remain long-term users than investment tokens do. For the first stage of the 2SLS analysis, we set the randomized starting token price of PMT as the independent variable and the changing current price as the dependent variable. From this stage, we obtain the non-standardized predicted values of the instrument variable. The instrument variable has to fulfil the condition of exogeneity, i.e., a variable is needed that generates only exogenous change in the dependent variable (Greene, 2018; Stock et al., 2002). Since the given model contains loops (see Figure 1), we select the starting price of PMT (i.e., the price of PMT at the beginning of a simulation) to be the instrument variable. For the second stage of the analysis, we set the instrument variable from stage one (i.e., starting price of PMT) and the different token designs as the independent variables, and the change in the number of users as the dependent variable. In line with our expectations derived from existing research (Servan-Schreiber et al., 2004; Wolfers & Zitzewitz, 2004), we obtained less change in the number of users over time for the token design cryptocurrency (B = .005[1]) than for the token design investment token (B = -.011). Since we did not find statistical significance in the results from the 2SLS analysis, we cannot conclude that Hypothesis 2 is supported. Since our finding is in line with existing research and 2SLS analysis is prone to overvalue factors that decrease significance, our results tend to show findings in the direction of Hypothesis 2.

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[1] To run the analysis, we dummy-coded the metrically scaled token designs. Therefore, we selected the token design cryptocurrency to be the reference category. The unstandardized coefficient B for the token design cryptocurrency is the unstandardized coefficient B of the constant.

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
Cryptocurrency (Constant)	.005	.065		.080	.936
Starting price of PMT (Instrument variable)	1.921E-5	.001	.000	.015	.988
Network token	-.005	.063	-.001	-.084	.933
Investment token	-.011	.063	-.001	-.179	.858

To run the analysis, we dummy-coded the metrically scaled token designs. Therefore, we selected the token designs cryptocurrency to be the reference category.

* $p < .05$; ** $p < .01$.

Table 2. Coefficients of the 2SLS Analysis Examining the Changes in the Number of Users over Time

Hypothesis 3 stated that network tokens provide a stronger incentive for users to remain long-term users than do cryptocurrencies and investment tokens. To test Hypothesis 3, we used the results of the 2SLS analysis already performed and described previously for the test of Hypothesis 2 (see Table 2). Although not statistically significant, the results tend to show less change in the number of users over time for the token design network token (B = -.005) than for the token design investment token (B = -.011). However, the results tend to show more change in the number of users over time for the token design network token (B = -.005) than for the token design cryptocurrency (B = .005); this result does not support Hypothesis 3.

Discussion

This study set out to address two research questions: Which token design provides the largest incentive for individuals to join blockchain-based prediction markets (RQ1)? Which token design provides the largest incentive for new users to become long-term active users in blockchain-based prediction markets (RQ2)? In the context of these research questions, we proposed and tested five hypotheses (H1a, H1b, H1c, H2, H3).

From the data collected by running the PMT model, we find that all token designs – cryptocurrency, network token, and investment token – have a significant positive effect on the absolute number of users. Our findings are in line with the findings that prediction markets achieve their full potential in a blockchain ecosystem (Peretz, 2018). To answer Research Question 1 according to the simulation, we can conclude that the token designs of network token, cryptocurrency, and investment token provide the first, second, and third largest incentives to join prediction markets, respectively. We come to this conclusion by comparing the mean number of users derived for each token design.

We then proposed which token designs will be most successful to incentivize users to remain long-term users. Although we did not find statistically significant results, our results tend to show in the direction that the token design cryptocurrency may provide a stronger incentive for users to remain long-term users than the token design investment token does. Moreover, we hypothesized that the token design network token provides a stronger incentive for users to remain long-term users than the token design cryptocurrency and investment token. Our results, although not statistically significant, tend to show in the direction that the token design network token may provide a stronger incentive for users to remain long-term users than the token design investment token does, whereas the token design cryptocurrency may provide a stronger incentive for users to remain long-term users than the token design network token does.

Since we examined the fluctuation in the number of users over time, this finding may suggest the highest planning capability in the case of the token design cryptocurrency. Nevertheless, from an economical perspective and following the absolute (mean) numbers of users (see Figure 2) we argue that network tokens dominate over both cryptocurrencies and investment tokens. This argumentation can be encouraged further due to the specific case of prediction markets, whose monetary value depends on prediction precision (Atanasov et al., 2017), which in turn depends on active participation (Garcia Martinez & Walton,

2014; Hosio et al., 2016; Hosseini et al., 2015; Terwiesch & Xu, 2008). According to the definitions of the TCF, neither cryptocurrencies nor investment tokens can lead to active participation; only network tokens can do so (Untitled Inc., 2018).

We make two major contributions to the literature. First, our study contributes to research seeking to understand the effects of token design on usage (Lipusch et al., 2019; Shin et al., 2019; Conley, 2017; Meinel et al., 2018). As such, we add value to the relatively new research field of cryptoeconomics. Whereas previous research on cryptoeconomics has mainly focused either on clarifying the research field and understanding its significance (Meinel et al., 2018; Müller et al., 2018) or specifically on Bitcoin (Chen et al., 2017; Risius & Spohrer, 2017), the current study focuses on developing a computational model based on ABM to test the effects of token design on usage. Research on blockchain design (i.e., token design) and corresponding features is the basis for value and management propositions, which deal with identifying unique features and examining their respective impacts (Risius & Spohrer, 2017). We thereby address calls to investigate how key aspects of blockchain technology (i.e., tokens) influence users' varying motivations (Wang et al., 2019). Specifically, we advance the literature by not only testing for varying design settings of those key aspects but also examining the effect of those design settings (i.e., cryptocurrency, network token, investment token) on users with different motivations (i.e., intrinsic and extrinsic motivation; Casino, Dasaklis, & Patsakis, 2018). Furthermore, we investigate decision-making in blockchain systems by providing a framework for examining the incentives of actors in blockchain ecosystems (Ziolkowski et al., 2019).

To translate the conceptual model into an ABM simulation, which makes it possible to actually test different boundary conditions, our study develops and uses a model in the programming environment NetLogo (Wilensky, 1999). Simulation methods like ABM are currently still underrepresented in the field of information systems (Treiblmaier, 2017), despite the fact that they represent an important method to advance our knowledge in fields that need dynamic modelling approaches, such as token design (Risius & Spohrer, 2017). Providing evidence on the functionality of the newly built model, our study thus provides a basis for future research aiming at testing different token design mechanisms. Offering a structural framework to build on, the model provides major value by predicting short- and long-term usage prior to actual implementation of blockchain-based token ecosystems (Cai et al., 2019). We thus enrich the literature by examining the effects of dynamically changing variables, especially token design, on token usage (Jaoude & Saade, 2019).

Our research also responds to calls to investigate methods and techniques to examine key challenges in the field of blockchain technology (Welpe et al., 2019). Specifically, we enrich the literature by testing a model that combines technological specifications and strategic organizational challenges (i.e., how to design tokens to reach specific predefined goals). Hence, we contribute to the increasingly related IS and general management literature (Welpe et al., 2019).

Furthermore, we address calls to investigate complex systems with emergent phenomena using ABM (Treiblmaier, 2017). Specifically, we enrich the literature by exploring the potential of ABM and by investigating how it can contribute to the testing and validation of theories. Hence, we also address calls to incorporate temporal dynamics by building a theory-based model and testing the fit of the model by applying multivariate methods. In addition, we thereby "combine the strengths of dynamic modeling […] with rigorous multivariate statistics" (Treiblmaier, 2017).

Regarding our second major contribution, we contribute to IS research in general by using a design science approach (Arnott, 2006; Baskerville et al., 2019; Holmström et al., 2009; March & Storey, 2008; Pries-Heje et al., 2008), thereby, increasing the professional relevance of this study (Arnott, 2006). Following March and Storey (2008), we fulfil all six requirements (listed earlier) to make a design science research contribution. First, we identify the problem of incentivizing users to use prediction market applications in a blockchain ecosystem (Conley, 2017; Peretz, 2018). Second, we deduce the research gap for user behavior in blockchain protocols other than Bitcoin (Chen et al., 2017). Third, we conceptualize the PMT Model to address the issue of optimal design to incentivize usage of PMT. Fourth, we ex ante evaluate (Pries-Heje et al., 2008) the conceptualized model due to simulation in the programming environment of NetLogo (Wilensky, 1999). Fifth, we contribute to research seeking to understand the effects of token design on usage (Lipusch et al., 2019; Shin et al., 2019; Conley, 2017; Meinel et al., 2018). Thereby, we also articulate the value added to practice by showing the differences in usage occurring through varying token designs. Sixth,

we advise those responsible of present tokens to review their incentive design and those developing tokens to revise the design using agent-based models such as the PMT Model.

Our study also responds to calls to investigate factors affecting the practical implementation of blockchain technology (Hughes, Dwivedi, Misra, Rana, Raghavan, & Akella, 2019; Jaoude & Saade, 2019). Little guidance exists on how to actually design blockchain-based systems or what factors are needed to make a blockchain application work in practice (Jaoude & Saade, 2019). We enrich the literature with our simulation model, enabling developers and founders of future blockchain protocols to test optimal token designs in line with their envisioned goals for the blockchain technology system. We do so by using the real-world application of prediction markets to provide a tangible example for token design testing (Hughes et al., 2019).

Practical Implications

Our study has three key practical implications. First, our newly developed PMT model represents a first approach to test and predict optimal token design in prediction markets. It also provides a conceptualized structure to rebuild or advance the model. This research proved the functionality of this structure. The PMT model and its succeeding versions enable researchers as well as practitioners to collect a large amount of analyzable data and to prove assumptions regarding optimal token design without the need for time-consuming surveys.

Second, the PMT model, like every model, is an abstraction of reality. The PMT model constitutes the speculative environment of blockchain-based prediction markets and advances the knowledge about optimal token design in this environment to incentivize usage. The generated knowledge about optimal token and therefore incentive design can thus be transferred to blockchain-based applications other than prediction markets, such as blockchain-based energy markets, supply chains, lending and crowdfunding platforms (Tumasjan, 2018). Transferring knowledge from a specific problem domain to other domains is part of the design science approach we used in our research (Baskerville et al., 2019). Of course, our model is not immune to any future technological or business model changes (e.g., unforeseeable changes in blockchain industries). Nevertheless, our model provides a common ground for practitioners to start from. The programming environment of NetLogo (Wilensky, 1999) enables managers and specialists to adjust variables according to their specific goals and answer a variety of questions.

Third, we advise developers and founder of future blockchain protocols to use agent-based models such as the PMT model and its successors to predict the optimal token design according to their goals. This possibility provides value in increasing the chances of success of such protocols as shown in this paper. We advise those responsible of present tokens to review their token design using the PMT model to detect any possibilities of maximizing their success in whatever way they aim for. We thus respond to calls for filling the need on how practitioners can use blockchain technology (De Rossi et al., 2019).

Limitations and Future Research Avenues

This study also has limitations. First, the value of tokens is difficult to determine or measure (Conley, 2017; Hargrave et al., 2018). Nevertheless, the valuation of tokens is a key variable in predicting usage. Certainty about such measurement could provide a breakthrough for predicting the usage of and demand for tokens. It would be of great impact to acquire knowledge of any kind about the influence, strength of influence, and any moderating effects of token valuation. However, the PMT model includes the possibility to vary the underlying valuation theory for tokens. The model includes the used behavioral theory, as well as present value theory and efficient market theory as defined by Conley (2017). Using and comparing multiple valuation theories could be one way of addressing the research gap on token valuation. Moreover, we did not obtain statistical significance in our 2SLS analysis. Greater insights on the valuation of tokens could yield the missing statistical significance in our 2SLS analysis because the explanatory power of the instrument variable starting price of PMT may increase in future research. In our 2SLS analysis, the starting price is varied randomly to ensure exogeneity (Greene, 2018; Stock et al., 2002).

Second, the PMT model exploits PMT as an example of blockchain applications to test the model's practical applicability and functionality. Therefore, the model presented specializes in prediction markets in a blockchain environment. To exploit the full potential of the model, future research should contribute to further developing it, aiming for a universally adaptable model to test the effect of any token design on

initial and long-term usage as well as other dependent variables like token price. We hope the model will be used as a structural basis for future research and will be added to either by providing a variety of token designs aiming for a comprehensive collection of possible simulations, or by generalizing the model to be applicable to a variety of token designs.

Conclusion

The aim of this study was to develop a cryptoeconomic model and use ABM to simulate the effects of different token designs on user behavior in blockchain-based ecosystems. Our simulations corroborate the model's functionality and lay the groundwork for further research to model and test optimal token designs. Offering a structural framework to build on, our model provides value to scholars and developers alike by enabling the prediction of short- and long-term usage prior to actual roll-out of blockchain-based applications. We hope that future research will build on our study to further extend our knowledge on incentives in blockchain-based ecosystems.

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