Association for Information Systems

AIS Electronic Library (AISeL)

ICIS 2019 Proceedings | DLT, Blockchain and FinTech

Identify Multiple Types of Social Influences on Smart Contract Adoption in Blockchain User Network: An Empirical Examination of CryptoKitties in Ethereum

Xudong Cai
Xi'an Jiao Tong University, 565305019@qq.com

Xi Zhao
Xi'an Jiaotong University, zhaoxi1@mail.xjtu.edu.cn

Bin Zhang
University of Arizona, binzhang@arizona.edu

What Drives Adoption of Smart Contract?: Identifying Peer Influences in Blockchain User Network

Completed Research Paper

Xudong Cai
School of Management, Xi'an Jiaotong University
Xi'an, China
cxd1995@stu.xjtu.edu.cn

Bin Zhang
Eller College of Management, University of Arizona
Tucson, Arizona
binzhang@arizona.edu

Xi Zhao
School of Management, Xi'an Jiaotong University
Xi'an, China
zhaoxi1@mail.xjtu.edu.cn

Abstract

Smart contract brings more versatile functions in blockchain technology. However, its adoption rate is not as high as expected. Currently, there is no thorough study addressing such problem. To fill such gap, we propose to use peer influence to explain smart contract adoption in blockchain user network. We explore whether and how multiple types of peer influence including direct pee influence and indirect peer influence, simultaneously affect individual adoption decisions of smart contracts. Our hypotheses are examined in the context of CryptoKitties adoption in the Ethereum network using the public dataset of Ethereum including 350 million transactions from over 20 million distinct accounts. Our results suggest that the adoption of the software is positively affected by direct peer influence and indirect peer influence. Moreover, we find that users who have higher social status and greater diversity of experience in the blockchain network are less susceptible to peer influence. The results provide strong evidence of peer influence on smart contract adoption through various mechanisms.

Keywords: blockchain, smart contracts, technology adoption, peer influence

Introduction

Recently blockchain technology has received increasing attention as it is believed to provide a potential solution to the trust issue in business process (Tschorsch and Scheuermann 2016). However, the public perception of blockchain technology is always limited to cryptocurrency valuations and little is about an even more useful technology called smart contracts, which is built upon blockchains (Beck and Muller-Bloch 2017). Smart contracts are computer protocols that facilitate the execution of digital contracts in an algorithmically autonomous and conflict-free way. Inheriting the decentralized nature of blockchain technology, they could substitute intermediary services in multisided markets without relying on trusted authority (Glaser 2017). The implementations of smart contracts have expanded blockchain technology into various fields of applications including financial services, manufacturing, healthcare, and energy resources (Macrinici et al. 2018). For example, Initial coin offerings (ICOs), practical use case of smart contracts in fundraising, have raised about $20 billion in the past two years and proven themselves a viable funding tool.

Considering the potential benefits, it is surprising that the adoption of smart contracts is still in its infancy. According to a 2017 study conducted on Ethereum, the largest blockchain-based smart contract platform, 81% of smart contracts have never been used and 73% of externally owned accounts (EOAs) have never used smart contracts (Chen et al. 2018). Technology adoption is always a core area of the information systems (IS) research (Venkatesh 2007). While existing literature mainly focuses on the security, privacy and scalability issues of smart contracts, the adoption of smart contracts is still unexplored (Alharby and Moorsel 2017, Macrinici et al. 2018). Therefore, it is crucial for researchers and practitioners to understand the adoption of smart contracts and facilitate the diffusion of new applications and projects on blockchains.

Social influence has long been recognized as an important driver of technology adoption (Venkatesh and Brown 2001). Researchers have demonstrated the influence effects in many contexts, including online buying decision (Bell and Song 2007), mobile service application adoption (Aral et al. 2009), prescription choices (Nair et al. 2010), open source software license choice (Singh and Phelps 2013), and CRBT adoption (Zhang et al. 2018). However, social influence builds on the premise of uncertainty about the innovation (Wooten and Reed 1998) and sufficient homophily (Cialdini 2001, Burn 1991). In the context of blockchain network, individual identities are hidden by the anonymity of hashed address (Foley et al. 2019) and users are purely connected by transactional ties that convey no trust (Hawlitschek et al. 2018). The blockchain alters the informational environment (Cong and He 2019), and it may impede individuals to perceive and associate themselves with similar others that are critical processes to elicit social influence. Thus it is necessary to empirically investigate whether the theories still hold in the new environment.

Our study aims to provide deep insights into understanding smart contract adoption in blockchain network in several ways. First, to our knowledge, our study represents the first empirical work that studies the adoption of smart contracts. It also represents the first attempt to study social influence in blockchain user network—a novel information environment. Second, we identify and differentiate multiple types of social influences in blockchain user network. By theorizing and empirical estimating the effects of social influence, we provide evidence that network structure can trigger smart contract adoption. Third, empirical studies of large-scale social networks remain relatively novel. While traditional studies are limited to thousands of nodes, we construct the blockchain user network containing millions of nodes using the public dataset of Ethereum. Fourth, it contributes to practice by providing platform managers and smart contract developers with important insights into better diffusion of blockchain applications and projects.

To fill the gap, we propose that the adoption decision of smart contracts in blockchain user network is potentially subject to social influence using the context of CryptoKitties in Ethereum. CryptoKitties is one of the most popular game applications on the Ethereum platform. All financial transactions in the game such as purchasing, selling, breeding and siring are fulfilled by smart contract. Hence the adoption of CryptoKitties resembles a large-scale experiment of smart contract adoption in blockchain user network. For our investigation, we rely on the public dataset of Ethereum blockchain where all transactions are kept in consensus across the whole network and are characterized as transparent and tamper-proof. There have been over 400 million transactions among over 60 million distinct accounts since the release of Ethereum. Because of the large size of our data, our analyses are conducted on subpopulations to examine our hypotheses within reasonable computing time. The subpopulations are extracted from the dataset using the Louvain (Multilevel) algorithm (Blondel et al. 2008). Individuals in these subnetworks are densely connected with each other but sparsely connected with users out of the subnetwork (Newman 2003).

Our analysis yields several interesting results about social influences on smart contract adoption in blockchain user network. We find that an individual's adoption decision of smart contract in blockchain user network is simultaneously determined by multiple types of peer influences including the adoption decision of direct peers (adjacent neighbors) and indirect peers (non-adjacent neighbors). The existence of social influence suggests that network connections formed by transactions among blockchain users can very well trigger smart contract adoption. Our results suggest that the adoption of a smart contract is positively affected by direct peer influence and indirect peer influence. Moreover, we find that users who have higher social status in the blockchain network are less susceptible to peer influence.

Blockchain Context

A blockchain refers to a distributed ledger that could record transactions in a verifiable and permanent way (Iansiti and Lakhani 2017). The data is stored in a continuous flow of blocks chained together secured from tampering and revision (de Vilaca Burgos et al. 2017). It was first popularized through the cryptocurrency Bitcoin and has been subsequently adopted by other forms of digital platforms (Catalini and Gans 2016). While online platforms are characterized by increased transparency, financial transactions are sensitive in nature and participants still prefer privacy (Burtch et al. 2015). Bearing in mind the fundamental tension of transparency and privacy, the implementation of the blockchain technology typically offers a new option for managing the degree of transparency and privacy (Cong and He 2019). Focusing on public blockchains, we identify several intrinsic features of the technology that can affect the behavior of blockchain users, including transparency, pseudo-anonymity, and trustlessness.

First, blockchain provides users with increased transparency by offering a novel method for trading and tracking the ownership of anything of value (Yermack 2017, Francisco and Swanson 2018). While financial transactions kept in centralized ledgers (e.g. banks) can only be accessed and modified by highly trusted parties, the ownership records and transactions stored in blockchain are shared among all participants of the network (Malinova and Park 2016). The blockchain creates a decentralized public transaction ledger that could be used by any participant in the network to cheaply verify and settle transactions in cryptocurrencies (Catalini and Gans 2016). Any transaction data of the blockchain is visible and reliable, and any participant of blockchain has the permission to access the entire transaction information (Yang 2019). Briefly, all behaviors of blockchain users are observable to any participant in the network. Because the visibility of an influencers' behavior is one of the most important premises of peer influence (Marsden and Friedkin 1993, Mas and Moretti 2009), the increased transparency of blockchains also paves the way for peer influence to take place.

Second, blockchain provides users with pseudo-anonymity to implement privacy (Yin et al. 2019). While all transactions and ownership records in blockchain are publicly visible, it still preserves a certain amount of privacy through asymmetric cryptography (Zheng et al. 2017). Individual identities are masked by a public key that is an alpha-numeric pseudonymous address (Foley et al. 2019). Users could transact anonymously without disclosing their personal information. The apparent anonymity and ease to create pseudo-anonymous financial transactions in blockchain attract users who value their privacy (Yin et al. 2019). Users with anonymous communication channels become disinhibited, in that they are more likely to break settled patterns of behavior and challenge existing norms (Choi 2013, Suler 2004). Besides, anonymity would reduce the occurrence of homophily because most individual sociodemographic traits are not readily observable (Kang and Chung 2017). Given that homophily is a critical factor in the process of social influence, a low degree of homophily in blockchain may impede social influence to take place (Morvinski et al. 2017).

Third, blockchain creates the ability to carry out trustless transactions that shift the entire basis of trust in financial transactions (Blundell-wignall 2014, Hawlitschek et al. 2018). While the financial crisis led to a loss of trust in financial intermediaries, blockchain provides the ability to remove the need for a trusted third party (Blundell-wignall 2014). Transactions between participants in blockchain system will not require mutual trust relationships (Yang 2019). The need for trust in blockchain is not obliterated but rather shifts from financial intermediaries towards algorithms that govern users' interactions (Maurer et al. 2013, Beck et al. 2016). The blockchain uses peer-to-peer network protocols and purely mathematical methods (e.g. consensus mechanism with crypto-economic incentives) to verify authenticity of a transaction without the verification of any third parties. Given the positive relationship between trust and social influence (Tsai and Ghoshal 1998, Beyari and Abareshi 2019), transactional ties in blockchain convey no trust and it may impede social influence to take place.

Hypotheses development

Social influence refers to that an individual's opinions and behaviors are influenced by referent others (Leenders 1997, Arial et al. 2009, Hartmann 2010, Iyengar et al. 2011). In the context of technology adoption, an individual will typically turn to prior adopters as the influential frame of reference to determine their adoption choice because of the uncertainty about the adoption decision (DiMaggio and Powell 1983, Rogers 2003). A prominent framework that uncovers the causal effect behind social influence on technology adoption is the heterogeneous diffusion model (Strang and Tuma 1993). The model decomposes social influence into three factors including the social proximity between prior and potential adopters, the infectiousness of information from prior adopters, and the susceptibility of a potential adopter (Greve 2005). Following the heterogeneous diffusion model (Strang and Tuma 1993), we extend the framework and focuses more on peer influence on smart contract adoption in blockchain user network. Based on the theoretical lens of social influence and data available for our analysis, we propose hypotheses of peer influence and susceptibility to peer influence while controlling individual characteristics and homophily (individuals tend to connect to others with similar characteristics; Burkhardt 1994, Leenders 2002, Valente 2005).

Peer Influence

Peer influence refers that an individual adapt her attitude or behavior to those of her neighbors (Leenders 2002). There are two approaches to conceptualizing peer influence, including direct peer influence (formally defined as cohesion) and indirect peer influence (formally defined as structural equivalence; Leenders 2002, Zhang et al. 2018). It is measured by the social distance between individuals in social networks. Each approach provides the focal user with different frames of reference and has its own causal mechanism with peer influence.

Direct Peer Influence

Direct peer influence (cohesion) defines peer influence in terms of the number, length, and strength of the ties between individuals in a network (Marsden and Friedkin 1993). It is formally restricted to individuals who are directed connected in a network (Burt 1982). The literature notes that direct peer influence could be due to communication or observational learning (Chen et al. 2011). Connected neighbors have greater fidelity with each other and are probably to communicate more frequently. The communication process with prior adopters exerts social pressures on the potential adopter and leads to their adoption (Rogers and Kincaid 1981). Another possible mechanism is observing the adoption behavior of her direct peers that is a more informative and persuasive signal (Rogers 2003, Qiu and Whinston 2017).

In the context of CryptoKitties adoption, direct peers are users that the focal user transacts directly with. It is more likely that direct peers know of each other and observe each other's behavior as they have established trust relationship between each other after a successful transaction. Individual are more likely to be interested in the behavior of direct peers and get familiar with the product from them and eventually adopt CryptoKitties. Additionally, the utility of adoption is not just derived from the smart contract and the game per se, but also from the number of adopters among direct peers of the focal user. A greater proportion of CryptoKitties adopters among direct peers may provide users with additional utility including helpful tips, sufficient resources, and suitable recommendation. In sum, an individual is more likely to adopt CryptoKitties with a higer proportion of prior adopters among her direct peers.

H1 (Direct Peer Influence and CryptoKitties Adoption). The probability of adopting CryptoKitties for an individual is positively associated with the proportion of prior adopters among her direct peers in the blockchain network.

Indirect Peer Influence

Indirect peer influence (structural equivalence) defines peer influence in terms of the similarity of relations between individuals in a network (Marsden and Friedkin 1993). It is measured by the extent to which two individuals share common direct neighbors (Mizruchi 1993). Prior research finds indirect peer influence can be interpreted by the imitative behavior triggered by the competition over the same resources (Burt 1987). Although indirect peers are not directly connected, they share relations with the same third parties and compete with each other to maintain their existing ties because third parties view them as socially substitutable objects to interact (Guler et al. 2002). Competition among indirect peers increases their incentives to monitor and imitate the adoption behavior of equivalent ones (Guler et al. 2002).

In the context of CryptoKitties adoption, indirect peers have never interacted with each other but share the same common neighbors in the blockchain user network. In spite of not connected directly, they could know the existence of each other through the path between them in the blockchain network. To maintain the relationship with their common neighbors, an individual could be particularly sensitive to the behavior of her indirect peers that are similar in relation embedded in the blockchain user network and imitate the adoption decision of CryptoKitties because of the memetic process (DiMaggio and Powell 1983). The digital kitties sold on the platform are unique in appearance and could be seen as sparse resources. Thus, these indirectly connected customers who are willing to buy them are competitors. Such competition can be explained by the structural equivalence theory (Leenders 2002, Singh and Phelps 2013). Moreover, the competition over limited resources and first mover advantage increases the tendency to imitate the adoption decision of a smart contract of indirect peers. The more indirect peer influence an individual receives, the more she is likely to adopt a smart contract adopted by another one.

H2 (Indirect Peer Influence and CryptoKitties Adoption). The probability of adopting CryptoKitties for an individual is positively associated with cumulative similarities with prior adopters among her indirect peers in the blockchain network.

Susceptibility to Peer Influence

Susceptibility to peer influence refers to the extent how an individual is influenced by information available about the innovation adopted by others (Greve 2005). High susceptibility individuals are more sensitive and receptive to others' opinions or behaviors, and are consequently more likely to adopt the innovation. In many theoretical threshold-based contagion models, it is represented in which social influence occurs when the proportion of prior adopters among one's peers has exceeded her intrinsic adoption threshold (Granovetter 1978, Valente 1996, Watts and Dodds 2007). However, little research has examined how the characteristics of potential adopters moderate the effects of social influence on adoption behaviors (Wejnert 2002, Van den Bulte and Stremersch 2004). In addressing the limitation, we argue that potential adopters' susceptibility to peer influence is affected by social status and the diversity of experience.

Social Status

Social status refers to the position in a social structure based on esteem and respect (Turner 1988). It is formally measured by degree centrality in social networks. Prior research indicates that social status is relevant for individuals' adoption decision (Rogers 2003, Balkundi and Harrison 2006). Status could be seen as an esteemed source of information and influence relate to adoption behavior.

In the context of CryptoKitties adoption, social status represents the importance of a focal user in the Ethereum network. Since degree centrality in transactional networks could not capture social status (Hu and Van den Bulte 2014), we employ the balance (in ether) to capture the social status of individuals in blockchain user network. An individual with higher social status is more likely to deviate from the common normative expectancies of the group and thus are less susceptible to others' behaviors (Iyengar et al. 2015). Furthermore, an individual with higher social status always receives more attention regarding her behavior from others. They will be more cautious to make decisions and are less likely to conform to others' adoption behaviors. Thus, we propose the following hypothesis:

H3 (Social Status and Peer Influence). The effects of direct peer influence and indirect peer influence on the likelihood an individual will adopt CryptoKitties will decrease with her social status in the blockchain network.

Diversity of Experience

The diversity of one's experience will also influence individual susceptibility to social influence. As an individual gains experience, she will be more familiar with the situation and have less incentive to be influenced by external sources of information (Louis 1980). The diversity of experience is positively related with the knowledge about a particular setting which increases individuals' self-efficacy and reduces their incentives to alter their behavior (Bandura 1986). It also encourages individuals to consider the phenomenon from a variety of perspectives, which stimulates richer causal understandings and reduces the potential for decision biases (Argyris and Schön 1974). This richer understanding fosters skepticism in decision making and reduces the potential for decision biases (Janis 1972).

In the context of CryptoKitties adoption, users with a more diverse experience in smart contract will have richer knowledge about smart contracts. They are more likely to be familiar with the technology and have already purchased similar products using similar technology. Consequently, they are less likely to learn from others' behavior. In sum, a blockchain user with more diverse experience with smart contracts will be less susceptible to peer influence on her adoption decision. Thus, we propose the following hypothesis:

H4 (Diversity of Experience and Peer Influence). The effects of direct peer influence and indirect peer influence on the likelihood an individual will adopt CryptoKitties will decrease with the diversity of her prior experience in the blockchain network.

To ensure the effects of peer influence are not confounded by other plausible mechanisms, we control for individual characteristics and homophily. Prior studies have found that individual's behavior is also influenced by homophily which states that individuals with similar characteristics will tend to behavior similarly (Aral et al. 2009, Ma et al. 2015). Based on the theory and hypotheses outlined above, our research model is developed. Figure 1 presents our research model.

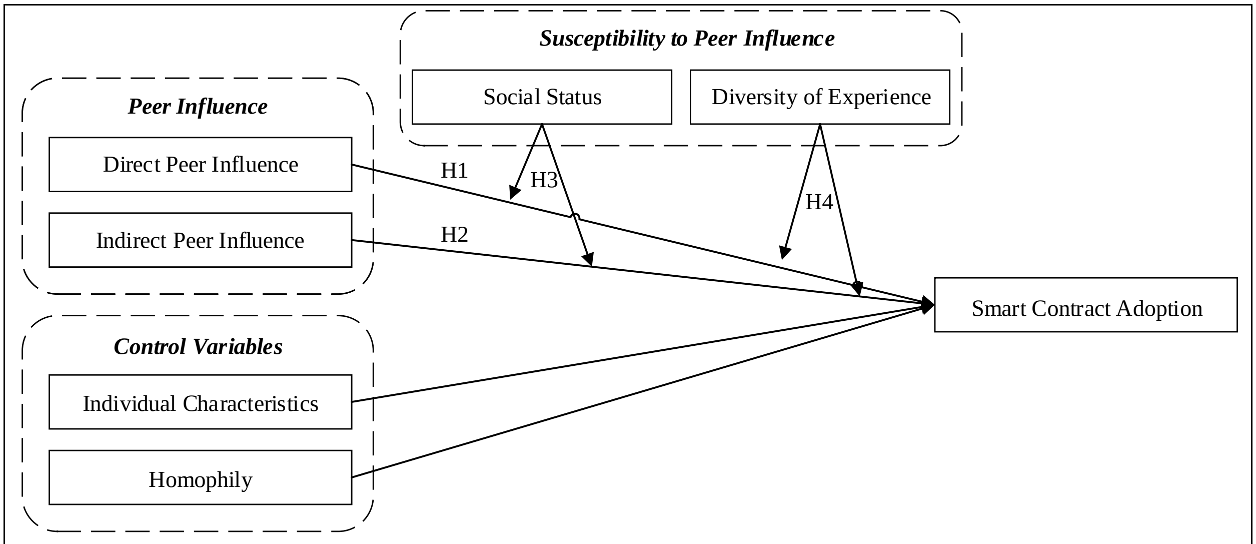


Figure 1. Research model

Data Description

Empirical Setting

Ethereum is the largest open-source software platform leveraged on blockchain and smart contract technologies. As Ethereum approaches mass adoption, there have been over 400 million transactions among over 60 million distinct accounts on Ethereum. Large scales of transaction and users in Ethereum network make it a fertile setting to study the effects of social influence in blockchain user network. Ethereum is not only the marketplace of cryptocurrencies, but also the smart contract platform that enable us to investigate the adoption decision of Ethereum users for smart contracts.

CryptoKitties is one of the most active and successful blockchain applications on Ethereum. It is one of the earliest applications of blockchain technology for recreational purposes, making the blockchain approachable for everyday consumer. It allows users to own, transfer, and breed collectable digital cats by specially-developed smart contracts. Each kitty has unique appearance and could be visualized on the game website (cryptokitties.co). The game was an instant success since its release on 28 November 2017. A massive increase in interest and transactions associated with the game even contributed to significant slowdown and congestion on the Ethereum platform for months. In the blockchain, each kitty is transferred in the form of non-fungible token (NFT), which allows for each entity to be indivisible and unique. The kitty' ownership is tracked and proven by smart contract associated with CryptoKitties. All financial transactions within the game including purchasing, selling, breeding and siring are enforced by smart contracts. It enables researchers to study the effects of peer influence on the adoption decision of Cryptokitties.

To test our hypotheses, we collected a unique dataset from Ethereum. The dataset comprises over 400 million transactions among over 60 million Ethereum accounts from 30 July 2015 (the release day) to December 31, 2018. Each transaction includes the Ethereum addresses (hashed and anonymous user accounts) of only one sender and one recipient, the type and value of cryptocurrency involved in the transaction, and time (Greenwich Mean Time). Before the measure of variables, we discarded failed transactions that are not seen as valid connections between users. And we discarded transactions associated with blockchain organizations or corporations, including exchanges, wallets or mining pools that are could not be seen as an individual. The data cleaning process was executed under the operator's big-data framework with Apache Spark and Yarn clusters. We could then measure the constructs and construct the blockchain user network.

Variables

To have reasonable observations for blockchain users, the temporal unit used in our study is set as a month. The response variable in our study is a binary variable indicating whether or not the Ethereum user have adopted the game CryptoKitties in a given month.

Based on the aforementioned discussion, multiple types of peer influences are measured by the network structure established by Ethereum users monthly. Direct peer influence (cohesion) reflects the influence received from adjacent neighbors. As tie strength has been found to be positive with the influence received from connected neighbors, we consider strength of direct ties as the primary dimension of direct peer influence. In our context, we use the frequency of transactions between connected users as the proxy for tie strength. As individuals vary in the frequency of transactions, the influence of each transaction for individuals with a large frequency of transactions is not the same size as that of individuals with few transactions. To avoid the inflation of direct peer influence from a large frequency of transactions, our measure of direct peer influence is the proportion of transactions with prior adopters in one's transactions. Indirect peer influence reflects the influence received from non-adjacent neighbors and is modeled by structural equivalence using the Euclidean distance as a measure for equivalence proximity between any neighbors. Following Zhang et al. (2018), we use the inverse of the Euclidean distances and a small constant–one to represent similarities in the relations between any indirect peers. Limited by the cognitive capacity to acquire and process information, users are simply unable to make inferences from the behavior of all others in the blockchain network. We restrict the sociometric distance between indirect peers less than 4. Our measure of indirect peer influence is the cumulative similarities with prior adopters among one's indirect peers.

Based on the aforementioned discussion, we consider two constructs of susceptibility to peer influence, including social status and the diversity of experience. We use balance to capture social status of an individual. It is measured by the amount of ether that a user owns in a given time period. To capture the diversity of experience for an individual, we use the number of smart contracts used by an individual before a given time period. In our context, because of the anonymity of blockchain system, some individual characteristics such as demographics (e.g. age and gender) and location could not be derived. Given the data available for our analysis, limited individual characteristics including degree centrality and transaction behavior are controlled in our research. Degree centrality is measured by the number of direct ties with others in the Ethereum network. Transaction behavior is measured from different perspectives including tenure, balance, in value, out value, in frequency, out frequency, in time, out time, contract creation, contract transaction and diversity. In value is measured by the amount of ether that an Ethereum user receives. Out value is measured by the amount of ether that an Ethereum user sends. In frequency is measured by the frequency of transactions that an Ethereum user receives. Out frequency is measured by the frequency of transactions that an Ethereum user sends. In time is measured by the average time between transactions that an Ethereum user receives. Out time is measured by the average time between transactions that an Ethereum user sends. Homophily is formally defined as the similarity of individual characteristics including individual demographics (e.g. age and gender), location and behavior. Following Aral et al. (2009), we use the multiplication of observed individual characteristics and network terms to measure homophily. The more similarity in degree centrality and transaction behavior between Ethereum users in the network, the higher level of homophily exists between them. Table 1 presents detailed definitions of variables and the summarized descriptive statistics of sample data used in our study.

Table 1. Variable Description and Summary Statistics

Variable	Description	Mean	SD	Min	Max

Adoption_{it}	Binary variable indicating whether user i adopts CryptoKitties in month t (yes=1, no=0)	0.07	0.25	0	1
$\text{DirectInfluence}_{it}$	Proportion of transactions with prior adopters for user i in month t	0.097	0.27	0	1
$\text{IndirectInfluence}_{it}$	Cumulative similarities with prior adopters among indirect peers of user i in month t	48.57	57.99	0	593
Degree_{it}	Number of neighbors directly connected to user i in month t	2.56	42.80	0	6456
Tunure_{it}	Number of months since the first transaction of user i before month t	5.87	4.33	0	40
Balance_{it}	Amount of ether user i owns in month t	10.13	442	0	62458
InValue_{it}	Amount of ether user i receives in month t	4.21	151.2	0	44450
OutValue_{it}	Amount of ether user i sends in month t	4.75	151.5	0	33138
InFrequency_{it}	Frequency of transactions user i receives in month t	9.18	115.9	0	31348
OutFrequency_{it}	Frequency of transactions user i sends in month t	15.53	193.1	0	25239
InTime_{it}	Average time between transactions user i receives before month t (in days)	6.07	13.99	0	400.8
OutTime_{it}	Average time between transactions user i sends before month t (in days)	5.50	15.36	0	398.7
$\text{ContractCreation}_{it}$	Number of smart contracts created by user i before month t	1.73	230.2	0	36723
$\text{ContractTransaction}_{it}$	Number of transactions with smart contracts of user i before month t	99.59	1021	0	179287
$\text{Diversity}_{\text{it}}$	Number of smart contracts used by user i before month t	5.31	30.12	0	4223

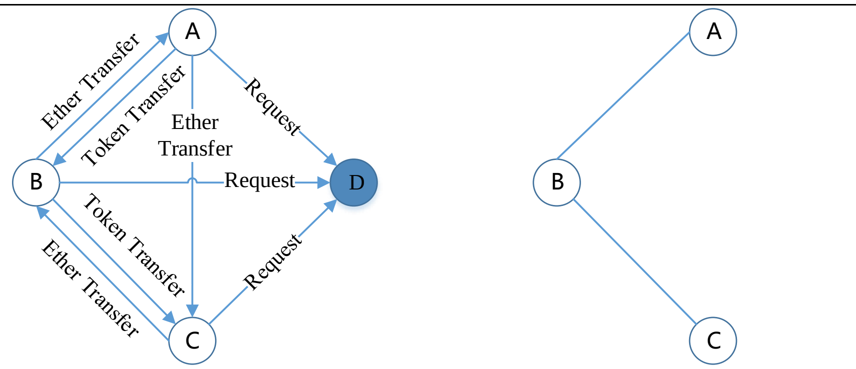
Methodology

Network Construction

Considering the longitudinal nature of our dataset, we construct the blockchain user network for each month. In the original Ethereum network, each node represents a distinct Ethereum account. Because accounts on Ethereum are classified into two categories including EOA and smart contracts, the original network is a two-mode network. In our study, each EOA is seen as an Ethereum user and the connection is defined by transactions on Ethereum blockchain. The connection between an Ethereum user and a smart contract represents the creation or usage of the smart contract. The connection between Ethereum users represents the transfer of various cryptocurrencies including ether and other tokens.

With the intention of capturing social influence that exists between connected people, we only retain nodes representing blockchain users and connections between them. Since the transaction is directed with the flow of cryptocurrencies, asymmetry may exist between senders and recipients. Asymmetric connection indicates an unequal and unstable relationship between peers, while the reverse is true for symmetric connection (Hanneman and Riddle 2005). Thus, we further restricted the blockchain user network by retaining reciprocal connections only. In our research, the reciprocity for dyads (A, B) is defined as the condition for which A sends a transaction to B and B sends a transaction to A in the same time period. Figure 2 presents the construction of the blockchain user network.

Accordingly, we define the structure of blockchain user network using an adjacency matrix $\mathbf{A}$. The value for the element of the adjacent matrix $\mathbf{A}$ is binary, in which element $A_{ij} = 1$ if user i and user j have reciprocal connections, and 0 otherwise. Since the network is undirected, the adjacent matrix is also symmetric. Since an Ethereum user could not have reciprocal connections with herself, the diagonals of the adjacency matrix $\mathbf{A}$ are set as zeros.



a) Two-mode Ethereum Network: Users (A,B,C) can send request to invoke contract (D) and users could transfer ether or other tokens among them.

b) Undirected Ethereum User Network: Nodes are only Ethereum users and the ties represent reciprocal transactional connection.

Figure 2. Illustration of Blockchain User Network Construction

Model

In the social network literature, the network autocorrelation models are commonly used for studying diffusion. They take network autocorrelation term into consideration and are used to study whether connected individuals tend to have the same behaviors.

To test our hypotheses, we need to compare the effects of different types of social influence while controlling for homophily. Hence, we use the multiple network-regime auto-probit (mNAP) model which supports a binary response variable and most importantly accommodates multiple network autocorrelation term simultaneously (Zhang et al. 2013). In the mNAP model, each user's adoption is modeled with all the factors including direct peer influence, indirect peer influence and homophily taken into consideration. The specification of the m-NAP model is described as

$$\mathbf{y}_t = \mathbf{1}(\mathbf{z}_t > 0),$$

$$\mathbf{z}_t = \mathbf{x}_t\boldsymbol{\beta} + \boldsymbol{\theta}_t + \boldsymbol{\eta} + \boldsymbol{\varepsilon}_t,$$

$$\boldsymbol{\theta}_t = \rho_1\mathbf{W}_{1t}\boldsymbol{\theta}_t + \rho_2\mathbf{W}_{2t}\boldsymbol{\theta}_t + \rho_3\mathbf{W}_{1t}\mathbf{H}_t + \rho_4\mathbf{W}_{2t}\mathbf{H}_t + \mathbf{u}_t,$$

$$\boldsymbol{\varepsilon}_t \sim N(0, I),$$

$$\boldsymbol{u}_t \sim N(0, \delta^2 I)$$

where $\mathbf{y}_t$ is the vector of observed binary choices whether users adopt CryptoKitties in time period t. $\mathbf{z}_t$ is the latent preference vector of users. If $\mathbf{z}_t$ is larger than the threshold 0, users would choose to adopt the application; if $\mathbf{z}_t$ is smaller than 0, users would choose not to adopt the application. The latent preference vector $\mathbf{z}_t$ could be represented as a function of vector $\mathbf{X}_t$, autocorrelation term $\boldsymbol{\theta}_t$, and fixed effects $\boldsymbol{\eta}$. Vector $\mathbf{X}_t$ is the degree centrality of all the users. Vector $\boldsymbol{\theta}_t$ is the autocorrelation term, which is described as the sum of product between network structure and unobserved preference $\mathbf{W}_{it}\boldsymbol{\theta}_t$. Scalar ρ_i is the correspondent coefficient for the autocorrelation term $\mathbf{W}_{it}\boldsymbol{\theta}_t$. Matrix $\mathbf{W}_{it}$ represents the network structure in each time period t. Matrix $\mathbf{W}_{1t}$ describes direct connections between one-hop neighbors, and elements are defined as transaction frequency of adjacent actors in time period t; Matrix $\mathbf{W}_{2t}$ describes indirect connection in time period t and elements are defined by inverse of Euclidean distance of adjacency actors. T To prevent indirect connections being blended with direct connections, we filter out elements between connected individuals by element-wise multiplication. The equivalence proximity between adjacent neighbors is set as zero. Thus the matrix $\mathbf{W}_{2t}$ is not correlated with $\mathbf{W}_{1t}$ mathematically. The matrix $\mathbf{W}_{2t}$ is defined as

$$d_{ij,t} = \sqrt{\sum_{k=1,k\neq i,j}^{n} (\mathrm{A}_{ik} - \mathrm{A}_{jk})^2}$$

$$\mathbf{W}'_{2\mathrm{t}} = \{s_{ij,t}\} = \left\{\frac{1}{d_{ij,t}+1}\right\}$$

$$\mathbf{W}_{2t} = (\mathbf{I} - \mathbf{A}) \circ \mathbf{W}'_{2\mathrm{t}}$$

where $d_{ij,t}$ is the Euclidean between two individuals, calculated by the sum of squared difference between adjacent vectors of node i and node j in time period t. $\mathbf{A}_{ik}$ is the element of adjacency matrix $\mathbf{A}$. If node i and node k are adjacent neighbors, $\mathbf{A}_{ik}$ equals to 1 and 0 otherwise.

Term $\mathbf{H}_t$ is the matrix of individual attributes in period t describing homophily including dimensions including degree centrality, tenure, balance, in frequency, out frequency, in value, out value, in time, out time, contract creation, contract usage, diversity. The terms $\mathbf{W}_{it}\mathbf{H}_t$ is used to control for the effects of homophily that come from direct peers and indirect peers. The detailed model notations are provided in Table 2.

Table 2. Notations of the model

Variables	Description
$\mathbf{y}_t$	Vector of response variable for all users indicating the adoption decision of CryptoKitties in time t
$\mathbf{x}_t$	Vector of degree centrality for all users in time t
$\mathbf{W}_{1t}$	Matrix describing direct connection in time t, elements are defined as the frequency of transactions of adjacent neighbors
$\mathbf{W}_{2t}$	Matrix describing indirect connection in time t, elements are defined as inverse of Euclidean distance of adjacent vectors
$\mathbf{H}_t$	Matrix describing homophily in time t, each column represents one measure of individual attributes including degree, account tenure, balance, in frequency, out frequency, in value, out value, in time, out time, contract creation, contract transaction, diversity

Identification Strategy

Extensive empirical studies have addressed the "reflection problem" which refers to the challenge in identification of the endogenous effect from the exogenous effects (Blume and Durlauf 2005, Soetevent 2006). According to the identification condition derived by Bramoullé et al. (2009) and Zhang et al. (2018), social influence can be identified if the network contains an individual's three-hop or higher neighbors. Figure 3 presents examples of extracted subnetworks. In these subnetworks, an edge from node i to node j represents that user i and user j have reciprocal transactions in that time period. As the network topology indicates, there are many paths between nodes with the distance higher than 3. Thus we could obtain asymptotically optimal estimates of social influence using the model.

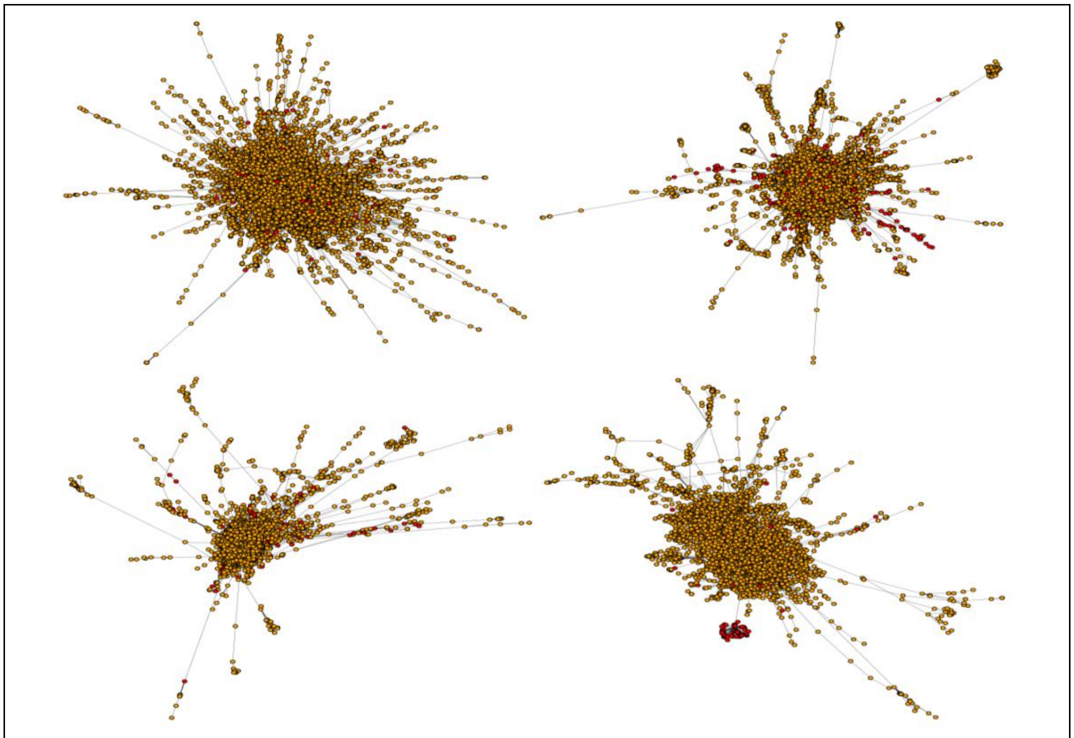


Figure 3. Example Subnetworks

Analytical results

Based on the aforementioned requirements, the symmetric Ethereum user network constructed in our study incorporates over 37 million transactions among about one million Ethereum users in the observed time period. Before examining the effects of multiple peer influences on smart contract adoption in the blockchain user network, we need to solve the problem of data size. The network is too large to analyze in reasonable time and also contains many clusters with different effect sizes. Hence, the model could only be analyzed using subnetworks of a smaller size and meta-analyses.

To extract independent subnetworks from the blockchain user network, we used the Louvain (Multilevel) algorithm that outperforms other algorithms including Infomap, Label propagation, Walktrap, and Spinglass algorithms in computing time and accuracy for large social networks (Zhao et al. 2016). Each individual is placed within the subgroup from which she has the most connections. As a result, we could avoid contaminated influence from external networks. Note that the Louvain algorithm does not require subnetwork size as a parameter, and thus the size of extracted subpopulations is not predetermined. In our study, we extract 122,569 distinct subnetworks from the Ethereum user network. Some subnetworks are not considered because of its star topology structure or the absence of CryptoKitties adopters. Interestingly, many estimation results in these subnetworks generally follow the same pattern.

Main Results

The results of our model estimation for two different subpopulations are presented in Table 3. We observed significant effects of direct peer adoption and indirect peer adoption across these subpopulations. It shows that individual receive strong social influence from prior adopters among her direct peers and indirect peers.

Table 3. Results of Analysis using mNAP model		
Variable	**Subpopulation (1)**	**Subpopulation (2)**
Peer Influence		
Direct peer influence	0.045***(0.0066)	0.065**(0.032)

Indirect peer influence	0.00037***(0.00011)	0.00017 *(0.0001)
Susceptibility to Peer Influence		
Balance* Direct influence	-2.3×10^{-6}*(1.3×10^{-6})	-1.1×10^{-5}*(5.8×10^{-6})
Balance* Indirect influence	-2.0×10^{-7}***(6.9×10^{-8})	-2.1×10^{-6}**(8.7×10^{-7})
Diversity* Direct influence	-1.5×10^{-5}(4.8×10^{-4})	-1.5×10^{-2}**(7×10^{-3})
Diversity* Indirect influence	-2.8×10^{-6}***(6.9×10^{-7})	-1.1×10^{-6}(1.6×10^{-5})
Direct Homophily		
Degree	4.7×10^{-5}*(6.2×10^{-5})	-1.4×10^{-5}***(5.1×10^{-6})
Tenure	-8.2×10^{-4}*(4.2×10^{-4})	-1.9×10^{-3}(1.9×10^{-3})
Balance	-4.9×10^{-7}(3.0×10^{-7})	1.5×10^{-5}(1.0×10^{-5})
In_Frequency	3.4×10^{-6}(4.2×10^{-6})	2.1×10^{-5}*(1.1×10^{-5})
Out_Frequency	1.2×10^{-6}(2.8×10^{-6})	-6.0×10^{-6}*(3.4×10^{-6})
In_Value	3.7×10^{-7}(4.1×10^{-7})	-1.2×10^{-5}(1.3×10^{-5})
Out_Value	-9.6×10^{-7}(6.0×10^{-7})	-1.4×10^{-6}(6.3×10^{-6})
In_Time	2.9×10^{-4}(2.4×10^{-4})	8.1×10^{-4}(5.8×10^{-4})
Out_Time	-3.7×10^{-5}(2.4×10^{-4})	7.1×10^{-5}(1.9×10^{-4})
Contract creation	3.4×10^{-5}(5.8×10^{-5})	4.0×10^{-4}(3.9×10^{-4})
Contract transaction	-1.9×10^{-8}(4.2×10^{-7})	2.5×10^{-5}(4.9×10^{-5})
Diversity	-1.5×10^{-4}***(4.7×10^{-5})	-3.9×10^{-4}(5.0×10^{-4})
Indirect Homophily		
Degree	-5.6×10^{-6}(3.4×10^{-6})	7.1×10^{-6}**(3.1×10^{-6})
Tenure	1.1×10^{-6}(2.0×10^{-6})	2.7×10^{-6}(1.7×10^{-6})
Balance	-1.4×10^{-6}**(5.6×10^{-7})	1.6×10^{-6}(1.6×10^{-6})
In_Frequency	-9.2×10^{-7}***(3.2×10^{-7})	1.2×10^{-5}***(4.7×10^{-6})
Out_Frequency	5.3×10^{-7}***(2.0×10^{-7})	-1.0×10^{-5}***(3.7×10^{-6})
In_Value	1.1×10^{-6}***(2.5×10^{-7})	9.5×10^{-6}(6.0×10^{-6})
Out_Value	-3.5×10^{-8}(1.9×10^{-7})	-4.9×10^{-6}(3.6×10^{-6})
In_Time	-6.3×10^{-5}*(3.4×10^{-6})	-9.5×10^{-6}***(2.7×10^{-6})
Out_Time	2.7×10^{-6}(2.5×10^{-6})	-3.5×10^{-6}(3.2×10^{-6})
Contract creation	2.8×10^{-6}(1.1×10^{-5})	1.1×10^{-4}(9.3×10^{-5})
Contract transaction	5.7×10^{-8}**(2.2×10^{-8})	-5.1×10^{-6}(3.5×10^{-6})
Diversity	-4.1×10^{-8}***(1.6×10^{-6})	1.3×10^{-4}***(9.3×10^{-5})

*: $p<0.1$, **: $p<0.05$, ***: $p<0.01$

We found that both direct peer influence and indirect peer influence play a positive role in the adoption of smart contracts in blockchain user network, thus supporting H1 and H2. It indicates that an Ethereum user will receive strong influence from prior adopters among her direct peers and indirect peers in the same subnetwork.

We also found that the coefficient estimate for the interactions of peer influence (direct peer influence and indirect peer influence) and balance are significant and negative, thus supporting H3. It indicates that if an Ethereum user owns more wealth, she is less likely to be influenced by prior adopters among her peers.

Nevertheless, we observed that the coefficient estimate for the interactions of peer influence (direct peer influence and indirect peer influence) and diversity are not significant. One possible explanation is that the number of contracts used by users could not depict the diversity of experience as many contracts are highly homogenous in functionality.

And we do not observe a significant effect of homophily across all subnetworks. It implies that CryptoKitties adoption is not mainly driven by homophily. Since we treat CryptoKitties as a binary variable and do not consider its type, the estimation results are expected as Ma et al. (2015) found that homophily only affects the purchase choice for production type.

Goodness-of-Fit Test

Because our model is non-nested and maximum likelihood is used to estimate parameters, Akaike information criterion (AIC) and Bayesian information criterion (BIC) are used to measure the goodness of fit. Models with the lowest AIC and BIC value represent the best model. The definition of AIC, BIC is presented below.

$$\mathrm{AIC} = 2k - 2\ln(\hat{L})$$

$$\mathrm{BIC} = k \times \ln(\hat{L}) - 2\ln(\hat{L})$$

where k is the number of estimated parameters, L is the maximum value of the likelihood function for the model, N is the number of observations.

As shown in Figure 3, when the model includes both direct and indirect peer adoption terms simultaneously, the model is best with the lowest AIC. Thus, both network autocorrelation terms should be incorporated in our model. The goodness-of-fit test also proves evidence that individual's adoption of CryptoKitties is influenced by the adoption decision of direct peers and indirect peers.

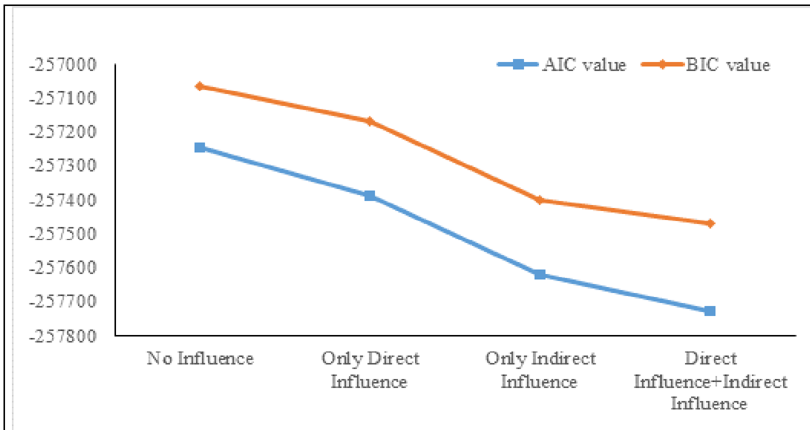


Figure 3. AIC of Four Completing Models

Discussion

While being a very useful technology built upon blockchain, smart contract is still not well adopted yet. Few studies have addressed the issue of how to facilitate the adoption. In this study, we analyzed the effects of multiple types of peer influence on the adoption of CryptoKitties in Ethereum using the mNAP model conducted on the subnetworks extracted from the Ethereum user network. Our study is the first work to investigate peer influence in blockchain user network. Our results show that the existence of peer influence in blockchain networks formed via reciprocal transactions among blockchain users. The adoption of CryptoKitties is positively affected by prior adopters among her direct peers and indirect peers. The results are obtained when homophily is controlled for, so the robustness of the estimation is assured. Based on these results, developers should use particular strategies to trigger more adoption. They need to focus on individuals with more direct connections in the Ethereum user network.

Implications

Our research has both theoretical and practical implications. First, it is the first to study the adoption of new technology – smart contract in blockchain network empirically. While being a very useful technology built upon blockchain, smart contract is still not well adopted yet and few have addressed the issue. Therefore it is critical to understand and facilitate the adoption of smart contract. Second, our research deepens the understanding of social influence and underlying mechanisms on the adoption of smart contracts. We are the first to analyze multiple types of social influences simultaneously including degree centrality, peer effects, and homophily in blockchain networks. And we provide evidence of the existence of social influences on the adoption decision of smart contract for blockchain users. Third, Empirical studies on blockchain systems and smart contracts are limited. Our study represents the initial attempt to apply systematic IS theory and method to develop and validate the diffusion model in the anonymous and transparent environment of blockchain systems. Fourth, our study provides useful guidelines for promoting the dissemination of smart contract technology and suggests a more effective way for smart contract developers and blockchain project marketers in their efforts to promote the adoption of new applications on blockchains. They could use these factors identified in our study and design corresponding marketing strategies to better facilitate the adoption. For example, they should target existing adopters with many direct neighbors who are probably to mimic the adoption decision and should also avoid existing adopters with many indirect neighbors, because they are probably not to follow the adoption decision.

Limitations and Suggestions for Future Research

As the initial empirical work on smart contract adoption in the blockchain network, our study has several limitations that provide opportunities for future research. While various heuristic algorithms (Meiklejohn et al. 2013, Lischke and Fabian 2016, Maesa et al 2016) have been proposed to cluster addresses into real users in the Bitcoin network, they could not be applied to the Ethereum network (Chen et al. 2019). Unlike the transactions of Bitcoin which could have multiple sender and receivers, each transaction of Ethereum is associated with only one sender and one receiver. To build the user network from the transaction list of Ethereum, we have to assume that each EOA of Ethereum blockchain represents a distinct user. The resulting network approximates the real user network to some extent.

Additionally, we consider all connections to be bidirectional or symmetric. While this is not a limitation in the present study, it could be useful to identify the directionality and separate out in-degree from out-degree. While indegree can be considered to be a measure of popularity, out-degree provides a better indication of activity level. Thus, by separating out the two effects, we will be able to investigate more complex social constructs in future studies.

References

Alharby, M., Moorsel, V. 2017. “Blockchain-based Smart Contracts: A Systematic Mapping Study,” in *Proceedings of 16th International Conference on Artificial Intelligence and Soft Computing*, Poland, pp. 125-140.

Aral, S., Muchnik, L., Sundararajan, A. 2009. “Distinguishing Influence Based Contagion from Homophily Driven Diffusion in Dynamic Networks,” in *Proceedings of the National Academy of Sciences*, USA, 106(51), pp. 21544–21549.

Argyris, C., Schön, D.A. 1974. “Theory in Practice: Increasing Professional Effectiveness,” 1st ed. (Jossey-Bass Publishers, San Francisco).

Balkundi, P., Harrison, D. 2006. “Ties, leaders, and time in teams: Strong inference about network structures effect on team viability and performance,” *Academy of Management Journal* (49:1), pp.49–68.

Bandura, A. 1986. “Social Foundations of Thought and Action” (Prentice Hall, Englewood Cliffs, NJ).

Beck, R., Czepluch, J.S., Lollike, N., Malone, S. 2016. “BLOCKCHAIN – THE GATEWAY TO TRUST- FREE CRYPTOGRAPHIC TRANSACTIONS,” in *Proceedings of the Twenty-Fourth European Conference on Information Systems*, pp. 1-16.

Beck, R., Muller-Bloch, C. 2017. “Blockchain as radical innovation: a framework for engaging with distributed ledgers,” in *Proceedings of the 50th Hawaii International Conference of System Sciences,* Waikoloa, pp. 5390-5399.

Bell, D.R., Song, S. 2007. "Neighborhood effects and trial on the Internet: Evidence from online grocery retailing," *Quantitative Marketing and Economics* (5:4), pp. 361–400.

Beyari, H., Abareshi, A. 2019. "The Interaction of Trust and Social Influence Factors in the Social Commerce Environment," in Recent Trends in Data Science and Soft Computing, Saeed F., Gazem N., Mohammed F., Busalim A. (eds) IRICT 2018. Advances in Intelligent Systems and Computing, vol 843. Springer, Cham.

Blondel, V.D., Guillaume, J.L., Lambiotte, R., Lefebvre, E. 2008. "Fast unfolding of communities in large networks," *Journal of Statistical Mechanics,* P10008.

Blume, L., Durlauf, S. 2005. "Identifying social interactions: A review," Mimeo, University of Wisconsin.

Blundell-wignall, A. 2014. "The Bitcoin Question: Currency versus Trust-less Transfer Technology," *OECD Working Papers* on *Finance, Insurance and Private Pensions* (37) OECD Publishing.

Burkhardt, M.E. 1994. "Social interaction effects following a technological change: A longitudinal investigation," *Academy of Management Journal* (37:4), pp. 869–898.

Burn, S.M. 1991. "Social psychology and the stimulation of recycling behaviors: The block leader approach," *Journal of Applied Social Psychology* (21:8), pp. 611–629.

Burt, R.S. 1982. "Toward a Structural Theory of Action" (Academic Press, New York).

Burt, R.S. 1987. "Social contagion and innovation: Cohesion versus structural equivalence," *American Journal of Sociology* (92:6), pp. 1287–1335.

Burtch, G., Ghose, A., Wattal, S. 2015. "The Hidden Cost of Accommodating Crowdfunder Privacy Preferences: A Randomized Field Experiment," *Management Science* (61:5), pp. 949-962.

Catalini, C., Gans, G.S. 2016. "Some Simple Economics of the Blockchain," Working Paper, Massachusetts Institute of Technology (MIT). https://ssrn.com/abstract=2874598.

Chen, T., Zhu, Y.X., Li, Z.H., Chen, J.C., Li, X.Q., Luo, X.P., Lin, X.D., Zhang, X.S. 2018. "Understanding Ethereum via Graph Analysis," in *Proceedings of the IEEE Conference on Computer Communications,* Honolulu, pp. 1484-1492.

Chen, Y., Wang, Q., Xie, J. 2011. "Online Social Interactions: A Natural Experiment on Word of Mouth Versus Observational Learning," *Journal of Marketing Research* (48:2), pp. 238-254.

Choi, B.H. 2013. "The Anonymous Internet," *Maryland Law Review* (72:2), pp. 501-570.

Cialdini, R.B. 2001. "Influence: Science and Practice" (Allyn & Bacon, Boston).

Cong, L.W., He, Z. 2019. "Blockchain Disruption and Smart Contracts," *The Review of Financial Studies* (32:5), pp. 1754–1797.

de Vilaca Burgos, A., de Oliveira Filho, J.D., Suares, M.V.C., and de Almeida, R.S. 2017. "Distributed ledger technical research in Central Bank of Brazil," *Working Paper.*

DiMaggio, P.J., Powell, W.W. 1983. "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields," *American Sociological Review* (48:2), pp. 147–160.

Francisco, K., Swanson, D. 2018. "The Supply Chain Has No Clothes: Technology Adoption of Blockchain for Supply Chain Transparency," *Logistics* (2:1): 1-13.

Foley, S., Karlsen, J.R., Putnins, T.J. 2019. "Sex, Drugs, and Bitcoin: How Much Illegal Activity Is Financed through Cryptocurrencies?" *The Review of Financial Studies* (32:5), pp. 1798–1853.

Glaser, F. 2017. "Pervasive decentralization of digital infrastructures: a framework for blockchain enabled system and use case analysis," in *Proceedings of the 50th Hawaii international conference on system sciences,* pp. 1543-1552.

Granovetter, M. 1978. "Threshold models of collective behavior," *American Journal of Sociology* (83:6), pp. 1420–1443.

Greve, H. 2005. "Interorganizational learning and heterogeneous social structure," *Organization Studies* (26:7), pp. 1025–1049.

Guler, I., Guillén, M.F., Macpherson, J.M. 2002. "Global competition, institutions, and the diffusion of organizational practices: The international spread of ISO 9000 quality certificates," Administrative Science Quarterly (47:2), pp. 207–232.

Hanneman, R., Riddle, M. 2005. "Introduction to social network methods," University of California Riverside, http://www.faculty.ucr.edu/~hanneman/nettext/.

Hawlitschek, F., Notheisen, B., Teubner, T. 2018. "The limits of trust-free systems: A literature review on blockchain technology and trust in the sharing economy," *Electronic Commerce Research and Applications* (29), pp. 50–63.

Hu Y., Van den Bulte C. 2014. "Nonmonotonic Status Effects in New Product Adoption," *Marketing Science* (33:4), pp. 509-533.

Iansiti, M., Lakhani, K.R. 2017. "The Truth About Blockchain," *Harvard Business Review (95:1)*, pp. 118-127
Iyengar, R., Van den Bulte, C., Valente, T.W. 2011. "Opinion leadership and social contagion in new product diffusion," *Marketing Science* (30:2), pp. 195–212.
Iyengar, R., Van den Bulte, C., Lee, J.Y. 2015. "Social Contagion in New Product Trial and Repeat," *Marketing Science* (34:3), pp. 408-429.
Kang, J., Chung, D.Y. 2017. "Homophily in an Anonymous Online Community: Sociodemographic Versus Personality Traits," *Cyberpsychology, Behavior, and Social Networking* (20), pp. 376–381.
Leenders, R. 2002. "Modeling social influence through network autocorrelation: Constructing the weight matrix," *Social Networks* (24:1), pp. 21–47.
Lischke, M. and Fabian, B. 2016. "Analyzing the bitcoin network: The first four years," *Future Internet* (8:7), pp. 1-40.
Louis, M. 1980. "Surprise and sense making: What newcomers experience in entering unfamiliar organizational settings," *Administrative Science Quarterly* (25:2), pp. 226–251.
Janis, I.L. 1972. "Victims of Groupthink: A Psychological Study of Foreign- Policy Decisions and Fiascoes," Oxford, England: Houghton Mifflin.
Macrinici, D., Cartofeanu, C., Gao, S. 2018. "Smart contract applications within blockchain technology: A systematic mapping study," *Telematics and Informatics* (35:8), pp: 2337-2354.
Maesa, D.D.F., Marino, A., Ricci, L. 2016. "Data-driven analysis of Bitcoin properties: Exploiting the users graph," *International Journal of Data Science and Anaytics* (6:1), pp. 1-18.
Ma, L., Krishnan, R., Montgomery, A.L. 2015. "Latent homophily or social influence? An empirical analysis of purchase within a social network," *Management Science* (61:2), pp:454–473.
Malinova, K., and Park, A. 2018. "Market Design for Trading with Blockchain Technology," Working Paper.
Marsden, P., Friedkin, N. 1993. "Network studies of social influence," *Sociological Methods & Research* (22:1), pp. 127–151.
Mas, A., Moretti, E. 2009. "Peers at work," *American Economic Review* (99:1), pp. 112–145.
Maurer, B., Nelms, T.C., Swartz, L. 2013. '"When perhaps the real problem is money itself!: the practical materiality of Bitcoin," *Social Semiotics* (23:2), pp. 261–277.
Meiklejohn, S., Pomarole, M., Jordan, G., Levchenko, K., McCoy, K., Voelker, G., Savage, S. 2013. "A fistful of bitcoins: characterizing payments among men with no names," in *Proceedings of the 2013 Internet Measurement Conference*, IMC 2013, Barcelona, Spain, pp. 127–140.
Mizruchi, M.S. 1993. "Cohesion, equivalence, and similarity of behavior: A theoretical and empirical assessment," *Social Networks* (15:3), pp. 275–307.
Morvinski, C., Amir, O., Muller, E. 2017. ""Ten Million Readers Can't Be Wrong!," or Can They? On the Role of Information About Adoption Stock in New Product Trial," *Marketing Science* (36:2), pp. 290–300.
Nair, H., Manchanda, P., Bhatia, T. 2010. "Asymmetric Peer Effects in Physician Prescription Behavior: The Role of Opinion Leaders," *Journal of Marketing Research* (47:5), pp. 883:895.
Newman, M.E.J. 2003. "The structure and function of complex networks," *SIAM Review* (45), pp. 167–256.
Qiu, L.F., Whinston, A.B. 2017. "Pricing Strategies under Behavioral Observational Learning in Social Networks," *Production and Operations Management Society* (26:7), pp. 1249–1267.
Rogers, E., Kincaid, D. 1981. "Communication Networks: Towards a New Paradigm for Research" (Free Press, New York).
Rogers, E. 2003. "Diffusion of Innovations," Free Press, New York.
Singh, P.V., Phelps, C. 2013. "Networks, Social Influence, and the Choice Among Competing Innovations: Insights from Open Source Software Licenses," *Information Systems Research* (24:3), pp. 539-560.
Soetevent, A. 2006. "Empirics of the identification of social interactions: An evaluation of the approaches and their results," *Journal of Economic Surveys* (20:2), pp. 193–228.
Strang, D., Tuma, N. 1993. "Spatial and temporal heterogeneity in diffusion," American Journal of Sociology (99:3), pp. 614–639.
Suler, J. 2004. "The online disinhibition effect," *Cyberpsychology & Behavior* (7:3), pp.321–326.
Tsai, W., Ghoshal, S. 1998. "Social capital and value creation: the role of intrafirm networks," *The Academy of Management Journal* (41:4), pp. 464–476.
Tschorsch, F., Scheuermann, B. 2016. "Bitcoin and beyond: a technical survey on decentralized digital currencies" in *Proceedings of the IEEE Communications Surveys & Tutorials* (18:3), pp. 2084–2123.
Turner, B.S. 1988. "Status," University of Minnesota Press, Minneapolis.
Valente, T.W. 1996. "Social network thresholds in the diffusion of innovations," *Social Networks* (18:1), pp. 69–89.

Valente, T.W. 2005. “Network Models and Methods for Studying the Diffusion of Innovations,” Carrington PJ, Scott J, Wasserman S (eds.) Models and Methods in Social Network Analysis (Cambridge University Press, Cambridge, UK), pp. 98–116

Van den Bulte, C., Stremersch, S. 2004. “Social contagion and income heterogeneity in new product diffusion: A meta-analytic test,” *Marketing Science* (23:4), pp. 530–544.

Watts, D.J., Dodds, P.S. 2007. “Influentials, networks, and public opinion formation,” *Journal of Consumer Research* (34:4), pp. 441–458.

Wejnert, B. 2002. “Integrating models of diffusion of innovations: A conceptual framework,” *Annual Review of Sociology* (28:1), pp. 297–326.

Wooten, D.B., Reed, A. 1998. “Informational influence and the ambi- guity of product experience: Order effects on the weighting of evidence,” *Journal of Consumer Psychology* (7:1), pp. 79–99.

Yang, L. 2019. “The blockchain: State-of-the-art and research challenges,” *Journal of Industrial Information Integration,* pp. 1-11.

Yermack, D. 2017. “Corporate governance and blockchains,” *Review of Finance* (21:1), pp. 7–31.

Yin, H.H.S., Langenheldt, K., Harlev, M., Mukkamala, R.R., Vatrapu, R. 2019. “Regulating Cryptocurrencies: A Supervised Machine Learning Approach to De-Anonymizing the Bitcoin Blockchain,” *Journal of Management Information Systems* (36:1), pp. 37–73.

Zhang, B., Thomas, A.C., Doreian, P., Krackhardt, D., Krishnan, R. 2013. “Contrasting multiple social network autocorrelations for binary outcomes: With applications to technology adoption,” *ACM Transactions on Management Information Systems* (3:4), pp. 1–21.

Zhang, B., Pavlou, P.A., Krishnan, R. 2018. “On Direct vs. Indirect Peer Influence in Large Social Networks,” *Information Systems Research* (29:2), pp. 292-314.

Zhao, Y., Algesheimer, R., Tessone, C.J. 2016. “A Comparative Analysis of Community Detection Algorithms on Artificial Networks,” *Scientific Reports*, pp. 1-16.

Zheng, X., Xie, S., Dai, H., Chen, X., Wang, H. 2017. “An Overview of Blockchain Technology: Architecture, Consensus, and Future Trends,” in Proceeding of 2017 IEEE International Congress on Big Data, pp. 557–564.