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Blockchain Value Creation Logics and Financial Returns

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BLOCKCHAIN VALUE CREATION LOGICS AND FINANCIAL RETURNS

A Dissertation

by

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ABSTRACT

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With its complexities and portfolio-nature, the advent of blockchain technology presents several use cases to stakeholders for business value appropriation and financial gains. This 3-essay dissertation focuses on three exemplars and research approaches to understanding the value creation logics of blockchain technology for financial gains. The first essay is a conceptual piece that explores five main affordances of blockchain technology and how these can be actualized and assimilated for business value. Based on the analysis of literature findings, an Affordance-Experimentation-Actualization-Assimilation (AEAA) model is proposed. The model suggests five affordance-to-assimilation value chains and eight value interdependencies that firms can leverage to optimize their value creation and capture during blockchain technology implementation.

The second essay empirically examines the financial returns of public firms' blockchain adoption investments at the level of the three main blockchain archetypes (private-permissioned, public-permissioned and permissionless. Drawing upon Fichman's model of the option value of innovative IT platform investments, the study examines business value creation through firm blockchain strategy (i.e., archetype instances, decentralization, and complementarity), learning (i.e., blockchain patents and event participation), and bandwagon effects using quarterly data of firm archetype investments from 2015 to 2020. The study's propensity score matching utilization and fixed-effects modeling provide objective quantification of how blockchain adoption leads to

increases in firm value (performance measured by Tobin's q) at the archetype level (permissionless, public permissioned, and private permissioned). Surprisingly, a more decentralized archetype and a second different archetype implementation are associated with a lower Tobin's q. In addition, IT-option proxy parameters such as blockchain patent originality, participation in blockchain events, and network externality positively impact firm performance, whereas the effect of blockchain patents is negative. As the foremost and more established use case of blockchain technology whose business value is accessed in either of the five affordances and exemplifies a permissionless archetype for financial gains, bitcoin cryptocurrency behavior is studied through the lens of opinion leaders on Twitter. The third essay this relationship understands the hourly price returns and volatility shocks that sentiments from opinion leaders generate and vice-versa. With a dynamic opinion leader identification strategy, lexicon, and rule-based sentiment analytics, I extract sentiments of the top ten per cent bitcoin opinion leaders' tweets. Controlling for various economic indices and contextual factors, the study estimates a vector autoregression model (VAR) and finds that bitcoin returns granger cause polarity, but the influence of sentiment subjectivity is with marginal and only stronger on Bitcoin price volatility. Several key implications for blockchain practitioners and financial stakeholders and suggestions for future research are discussed

DEDICATION

To my wife, son, and mum.

ACKNOWLEDGMENTS

"He hath made everything beautiful in his time: also, he hath set the world in their heart, so that no man can find out the work that God maketh from the beginning to the end" (Eccl. 3:11) – my utmost gratitude to my father in heaven whose inspiration continues to be a fountain of strength and life for me through the life in his Son! I am indebted to my wife and family who have been pillars on this journey.

My heartfelt gratitude to Dr. Bin Wang, my dissertation committee chair for all her mentoring, patience, advice and encouragement, and inspiring role that have shaped the scholar in me. She has been more than immense! My sincere thanks to my committee members: Dr. Diego Escobari, Dr. Jun Sun, and Dr. Siamak Javadi. Their tutelage and advice have been critical to this point. My appreciation to the faculty and staff of the information systems department. They have together been a bedrock for attaining this academic height. I am grateful to Dr. Gamel Wiredu whose inspiration continues to forge in me a high aptitude for greater scholarly endeavors.

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CHAPTER I

INTRODUCTION

Research Problem

The overall potential of the blockchain is not in question among industry watchers and players. Fintech and other business use cases such cryptocurrencies underlie the chunk of investments in blockchain technology. The potential of blockchain technology for financial and non-financial business cases (Crosby et al., 2016) is causing business managers to rethink their I.T. strategies. A Deloitte survey reports that 74% of large companies across seven countries – including the U.S.A., China, U.K., and Germany – see a compelling business case for blockchain technology (Floyd, 2018). Notwithstanding, Overstock – a US company that generates not less than $1 billion in revenue – spent over $200 million in blockchain implementation projects venturing in over 18 early-stage firms and is yet to have meaningful financial returns on its investments (Debter et al., 2020). Therefore, the outcome uncertainties surrounding the 'hyped' potential of blockchain technology has caused business managers to preach caution with the level of adoption investments that firms should commit to.

The uncertainties stem from the complexity of selecting suitable blockchain archetype solutions that offer competitive advantage to adopters, the technology compatibility with existing systems, and the nascency of empirical findings on the monetary value of blockchain technology to firms, the myriad of use-cases that still require maturation and documented best practices as found with ERP systems. Against the backdrops of realizing the technology's potential, exploiting relevant use-cases and understanding its financial value, the research focuses on the value creation and value capture logic of the blockchain technology from multiple perspectives. Each perspective provides avenues that will enable firms, IT managers and investors to identify and appropriate blockchain technology's loci of value to optimally justify blockchain's use-case adoption decisions and investments.

Research Questions and Research Design

Specifically, the research focuses on following research questions:

◊ What are the blockchain affordances that enable or constrain activities during organizational blockchain implementation, and how can these affordances be better explored to create and capture value for financial and non-financial business use-case goals?

◊ Does adoption of blockchain technology lead to positive firm business value?

◊ How do blockchain archetypes of different degrees of centralization (permissionless, public-permissioned, and private-permissioned) affect the business value of blockchain adoption?

◊ Which firm-specific blockchain strategy, learning and bandwagon factors affect the business value of blockchain adoption investment?

◊ How do social media opinion leaders' sentiments affect the price behaviors of Bitcoin cryptocurrency?

◊ How do Bitcoin cryptocurrency price behaviors affect social media opinion leaders' sentiments?

Drawing upon Fichman's model of value creation which is motivated by real options theory, IT investment and business value literature, IT affordance perspectives, and opinion mining and sentiment analysis within social network analysis lens, I explain the different ways stakeholders can create and capture (realize) value from blockchain technology, over time and empirically examine locus of value that stakeholders can leverage to optimally justify their investments in blockchain and its use-cases. I use a blend of the conceptual study via systematic literature review guided by theory and empirical econometric techniques, such as fixed effects model, propensity score matching approach and panel vector autoregressive models to answer the research questions.

The first study explores the value creation mechanisms available to firms as they implement blockchain technologies for strategic advantage. I use a comparative study of the underlying blockchain artifacts to elicit tradeoffs available to implementation stakeholders. Guided by IT affordance perspectives, I conduct a systematic literature review and I propose an affordance-experimentation model that leverages these tradeoffs, blockchain artifact characteristics, stakeholder perception to posit how firms can optimize value regarding their implementation activities. In the second study on blockchain investment positioning, I use Fichman's model to exploit the impact of strategic blockchain archetype adoption investments options among firms in the blockchain economy as critical loci of value[1] to enjoy positive returns on blockchain investments. I analyze the necessary conversion factors that firms can leverage in justifying and exercising adoption investments to empirically quantify the magnitude of financial returns on firms' blockchain investments (referred to in the study as firm value or firm growth options). In the third essay, I consider cryptocurrencies – an established use-case of blockchain – to understand how their price behavior are affected by sentiments of monomorphic and polymorphic opinion leaders on Twitter using sentiment analysis and econometric modeling. I

[1] Locus of value – a level of analysis chosen by a stakeholder to exercise their value conversion contingencies that transform potential value of a technology to realized value (Davern & Kauffman, 2000). Conversion contingencies act critical factors that can transform potential value of firms' IT investments into realized value and consequently higher return on investment at the chosen locus of value (Davern & Kauffman, 2000).

focus on Ethereum and Bitcoin cryptocurrencies as the two with highest market capitalization. This perspective of realizing value from blockchain technology is thus studied through lenses of social network analysis, specifically opinion mining and sentiment analysis on Twitter, which is argued as an important avenue to understand market returns.

The dataset for the second and third essays came from COMPUSTAT, Crunchbase database, USPTO, Factiva, Twitter, Coindesk, and Google Search Trends. The three essays provide strategic options that business managers and other stakeholders can exploit to realize and sustain value from their blockchain adoptions or investments.

Abstract of the Three Essays

With its complexities and portfolio-nature, the advent of blockchain technology presents several use cases to stakeholders for business value appropriation and financial gains. This 3-essay dissertation focuses on three exemplars and research approaches to understanding the value creation logics of blockchain technology for financial gains.

Essay#1: Value Creation Through Blockchain Technology Implementation: From Affordance to Assimilation

The first essay is a conceptual piece that explores five main affordances of blockchain technology and how these can be actualized and assimilated for business value. Based on the analysis of literature findings, an Affordance-Experimentation-Actualization-Assimilation (AEAA) model is proposed. The model suggests five affordance-to-assimilation value chains and eight value interdependencies that firms can leverage to optimize their value creation and capture during blockchain technology implementation. The affordances are direct transaction settlement, monetary and illiquid asset exchange, efficiently robo-automating transactions, structured and query-able big data appropriation, and enhanced financial reporting. The study offers discussions on the theoretical contribution and practical implications of the proposed theoretical framework.

Essay#2: Blockchain Technology Positioning Investment: Empirical Investigation of Firm Blockchain Growth Options

The second essay empirically examines the financial returns of public firms' blockchain adoption investments at the level of the three main blockchain archetypes (private-permissioned, public-permissioned and permissionless). Drawing upon Fichman's model of the option value of innovative IT platform investments, the study examines business value creation through firm blockchain strategy (i.e., archetype instances, decentralization, and complementarity), learning (i.e., blockchain patents and event participation), and bandwagon effects are examined using quarterly data of firm archetype investments from 2015 to 2020. The study, via propensity score matching technique, fixed-effects models and several robustness tests, shows that all three blockchain archetypes (permissionless, public permissioned, and private permissioned) lead to increases in firm performance measured by Tobin's q. However, surprisingly, an overall more decentralized archetype and a second different archetype implementation are associated with a lower Tobin's q. In addition, the study finds that blockchain patent originality, participation in blockchain events, and network externality positively impact firm performance, whereas the effect of blockchain patents is negative.

Essay#3: Cryptocurrency Market Discovery: Twitter and the Sentimental Power of Monomorphic Opinion Leaders on Bitcoin Price Behaviors

Bitcoin cryptocurrency is the foremost and more established use case of blockchain technology whose business value is accessed in either of the five affordances and exemplifies a permissionless archetype for financial gains. From value creation logics of affordances and archetypal categorizations, the third essay leverages the power of big data from Twitter to understand the hourly price returns and volatility in bitcoin via the lens of bitcoin opinion leader tweet sentiments (i.e., their polarity and subjectivity of hourly tweets). A dynamic opinion leader identification strategy was to identify and extract sentiments of the top ten per cent bitcoin monomorphic opinion leaders' tweets. Controlling for bitcoin trading volume, the volume of tweets, the volume of both opinion and non-opinion leader tweets, S&P, VIX, gold price indices, Google search trend index, the selection-order criteria lags of the variables, the study estimates a vector autoregression model to explain the bidirectional influences of bitcoin price behavior and bitcoin opinion leader sentiments. The study finds that BitcoinReturn granger cause Polarity, but the influence of sentiment subjectivity is marginal and only stronger on bitcoin price volatility. Several key implications for blockchain practitioners and financial stakeholders and suggestions for future research are discussed.

CHAPTER II

AN AFFORDANCE PERSPECTIVE OF VALUE CREATION IN BLOCKCHAIN TECHNOLOGY IMPLEMENTATION: FROM ACTUALIZATION TO ASSIMILATION

"A new technology is redefining the way we transact. If that sounds incredibly far-reaching, that [is] because it is. Blockchain has the potential to change the way we buy and sell, interact with government[s], and verify the authenticity of everything from property titles to organic vegetables. It combines the openness of the internet with the security of cryptography to give everyone a faster, safe way to key information and establish trust."

Goldman Sachs Group

Introduction

Business managers continue to rethink their IT strategies due to the value potential of blockchain technology (Crosby et al., 2016). A Deloitte survey reports that 74% of large companies across seven countries see a compelling business case for blockchain technology (Floyd, 2018). Rapid advancements in the blockchain solutions space (Liang et al., 2019; Liu et al., 2019; Xu et al., 2017; Yli-Huumo, Ko, Choi, Park, & Smolander, 2016), perceived disruptive uncertainties among the adoption community (Friedlmaier et al., 2018; Sraders, 2019; Stanley, 2018) and a growing myriad of value potentials afforded by the technology have led scholars to highlight the need for addressing how business value is created from blockchain implementation or investments (Chong et al., 2019; Du et al., 2019; Glaser, 2017). To better understand a new technology phenomenon with possibilities for actions, technology affordance perspectives have been advocated (Strong et al., 2014; Volkoff & Strong, 2017). A technology affordance perspective acknowledges the socio-materiality of information technology (IT) objects and human perception for effective IT usage (Fromm et al., 2020). Implementers' perceptions of the value potentials afforded by blockchain technology are instrumental for organizations to succeed in their production, recording, and actualization of business value (Pazaitis et al., 2017). In addition, such a perspective will provide insights on why people use the technology and what features enhance or constrain its dissemination among the community of interest (Risius & Spohrer's 2017).

Focusing on financial technology (fintech) use-case affordances during implementation, Du et al. (2019) propose the Affordance-Experimentation-Actualization (AEA) framework to guide effective organizational implementation of the blockchain technology. AEA posits effective implementation of blockchain as one that delivers requisite business value by first identifying important stakeholder perceptions of the technology's potentials that enable or constrain actions (i.e., affordances). AEA's three blockchain implementation affordances for value creation are the potential to settle payment directly, the potential of automating financial transactions, and the potential of securing loans from financial institutions. These focus only on narrow financial goals of blockchain implementation and undercut the possible innovation value due to non-financial blockchain-organization goals (Beck & Müller-Bloch, 2017; Seebacher & Schuritz, 2019). The potential of blockchain to facilitate stakeholder access to critical patient health records while ensuring requisite user privacy and direct transaction settlements (Rosenbaum, 2019) shows that organizational blockchain implementation affordance may go beyond organizational implementers' initial financial transaction goals. Our research explores an implementation framework that addresses both financial and non-financial blockchain technology affordances based on the following research questions:

(1) *What are the blockchain affordances that enable or constrain activities during organizational blockchain implementation, and*

(2) *How can these affordances be better explored to create and capture value for financial and non-financial business use-case goals?*

We leverage the AEA implementation framework and Fromm et al.'s (2020) affordance research guidelines to build a conceptual framework of blockchain implementation business value via a systematic literature review of 100 relevant value-laden blockchain research articles from the information systems (IS) and reference disciplines. Our systematic literature review reveals an assimilation phase beyond affordance actualization practices relevant to increase value for an emerging technology. In addition, we reveal two new blockchain implementation affordances (i.e., potential to appropriate structured and query-able big data and potential for real-time accounting systems 'informating' and diagnostic reporting), and eight value-based affordance interdependencies among five affordance-to-assimilation domains. Assimilation practices in our proposed affordance-experimentation-actualization-assimilation (AEAA) framework emphasize implementers' broader blockchain network view that increases legitimacy for the technology (Janssen et al., 2020; Toufaily et al., 2021). It marks a period of accelerated and transformative activities that increase the marginal utility of the technology to the organization, thereby creating more value.

The rest of the study is as follows. First, we provide an overview of the literature on blockchain technology. Next, we discuss the methodology and analyses of the systematic literature review. The literature review findings are then presented with implications for theory and practice, followed by the study's limitations, future directions, and conclusion.

Conceptual Background

Blockchain Technology

A blockchain is a system of decentralized peer-to-peer network of nodes (users and computers) for validating, timestamping, permanently storing transactions (stored in batches called blocks), and tamper-proofing stored transactions and agreements on a shared or distributed ledger accessible to all participating nodes (Glaser, 2017; Lacity, 2018a, 2018b). Several studies provide technical directions in understanding consensus protocols and blockchain artifacts for governing peer-to-peer network activities. Blockchain technology can considerably drive down transaction costs without the need for trusted intermediaries like banks (Chowdhury, 2020; Nofer et al., 2017; Ying et al., 2018). We provide a brief introduction to blockchain technology artifacts and characteristics in Appendix A. For a detailed overview of the blockchain technology literature and how blockchain works, see (Ali et al., 2020; Christidis & Devetsikiotis, 2016; Liu et al., 2019).

Blockchain maturation can be categorized into four stages: blockchain 1.0, 2.0, 3.0, and blockchain 4.0 (Angelis & Ribeiro da Silva, 2019; Swan, 2015). Blockchain 1.0 refers to cryptocurrency use cases, while blockchain 2.0 refers to other financial technology (fintech) use-cases. Blockchain 3.0 describes the application of blockchain beyond 1.0 and 2.0, including smart contracts for more complex programmable transactions and decentralized applications (Angelis & Ribeiro da Silva, 2019; Xu et al., 2017). Blockchain 4.0 describes blockchain-enabled decentralized artificial intelligence and autonomous decision-making as new value drivers for service and product offerings. Crosby et al. (2016) classify blockchain technology into financial and non-financial applications. Other classifications are artifact-based with the degree of decentralization regarding the blockchain technology the most popular categorizations – from Walsh et al.'s (2016) strategic archetypes to the more popular permissionless, public-permissioned (or consortium blockchain formed by the agreement among multiple firms) and private-permissioned archetypes (Ali et al., 2019; Beck, Müller-Bloch, & King, 2018; Pedersen et al., 2019; Rossi et al., 2019; Walsh et al., 2016). A blockchain typology for practice and research (M. Rossi et al., 2019) categorizes the blockchain system into application and protocol levels. Notably, these categorizations have unique combinations of blockchain artifacts and will elicit different value perceptions (affordances) and multi-implementation goals from actors.

Based on the general blockchain literature, we conducted a comparative survey of selected blockchain platforms (Appendix A). Examination of these platforms reveals the nuances in the material properties of blockchain artifacts. These inform necessary trade-offs that characterize the value affordances perceived by implementers and apply to how blockchain implementation goals are actioned (Du et al., 2019).

Our syntheses on blockchain research and practice frameworks (see Appendix A) reveal a paucity of research works on blockchain implementation from a value perspective which addresses the socio-material nuances of the technology artifacts and implementers' goals. To this, Du et al. leveraged affordance perspectives to posit the AEA framework for effective blockchain implementation within an organization. The present study follows in this regard. We see the affordance perspective as a key lens to understand value creation in an organization's blockchain implementation because it allows the conceptualization of stakeholders' goal-oriented actions from their value perceptions of this emerging technology – blockchain.

Affordance and IT Implementation Value

Affordances are possibilities for actions that humans perceive of an object in their environment as far as their capabilities can allow them (Gibson, 1977; 1979). Affordance is grounded in the assumption that when humans observe their environment, they directly perceive "*what it offers ....., what it provides or furnishes, either for good or ill*" (Gibson, 1979, p. 197). Gibson's environmental affordances have been applied in IS research to explore IT practices in social contexts – the socio-materiality of IT (Volkoff & Strong, 2017). Technology-related affordances are relational and domiciled in the physical characteristics or properties of the IT objects (Fayard & Weeks, 2014; Leonardi, Bailey, & Pierce, 2019). These technological possibilities for actions therefore constrain (i.e., negative affordances) or enable (i.e., positive affordances or "affordances" hereafter) specific goals of the perceiver (Zammuto et al., 2007)

Technological affordances can be categorized as functional or social affordances (Waizenegger et al., 2020). Functional affordances are perceived on the goal-orientation of the business use-cases, whereas social affordances are perceived on the needs of a focal user group (Knote et al., 2020) as far as technology (object of perception) is concerned. When actors' goals and capabilities align well with their perceptions of the material properties of the technology (perceived affordances), substantial functional affordances, known as shared affordances, are generated (Leonardi, 2013; Zeng et al., 2020). The enormity of value created when implementing IT from a functional affordance perspective are espoused in Ying et al.'s (2020) discovery process model of big data analytics (BDA) and Zeng et al.'s (2020) cascading affordance theory (CAT) which actualizes BDA potentials for implementing smart city technologies. CAT is consistent with the concept of affordance potency (Anderson & Robey, 2017), which addresses variations in affordance-actualizations to extract better IT implementation value. On the inherent value of shared affordances (i.e., potent functional affordances), Chatterjee et al. (2020) explored the existence of a covariance fit[2] and a matching fit[3] among affordances that influence IT-enabled organizational exploitative and exploratory innovation process during an organization IT implementation (Chatterjee et al., 2020).

Nonetheless, methodological incongruencies in identifying affordances in these empirical affordance studies have led to calls for more precise methodological guidelines (Seidel et al., 2013). Fromm et al. (2020) provide an eight-point recommendation in this regard, which guides our approach: 1) Aiming for a mid-range theory of IT-associated organizational change; 2) Applying critical realism paradigm; 3) Separation of affordances from IT features, use and usage outcomes; 4) Inculcating the relational nature of affordances; 5) Showing interrelations and interactions between multiple affordances; 6) Identification of contextual factors constraining or enabling affordance actualization; 7) Analysing paradoxical tension between technology affordances and constraints; and 8) Applying affordances identified in previous studies.

Affordance-Experimentation-Actualization Theory

With limited implementation knowledge for new IT, actors' perceptions often play a critical role in assessing the value of implementation (Palas & Bunduchi, 2020). Strong et al. (2014) critiqued the inadequacy of applying an adoption lens to capture the salient practices during new IT implementation and proposed the affordance-actualization (AA) theory. The theory highlights how implementers take goal-oriented actions in using the technology to realize an outcome and separates technology usage from its outcomes. Leveraging AA theory, Du and

[2] A covariance fit or a coalignment represents "an internal consistency within a set of theoretically relevant constructs" [14 p.3, 15]

[3] A matching "fit is defined as a match between a certain level of a variable to a certain level of another variable. For example, variables X and Y could match at various levels such as HI–HI, HI–LO, etc. Typically, a subset of the possible set of matches would be related to a positive theoretical outcome" [14 p.3].

colleagues propose an AEA framework where the implementation of blockchain technology is a process-actualization endeavour, and an effective implementation outcome requires experimenting with identified affordances to mitigate constraints. AEA considers affordance, experimentation, and actualization in phases, departing from prior affordance studies that often present the analyses of affordance and actualization as bundled concepts. Bundling affordance and actualization challenges the researcher's ability to identify and explain critical observable outcomes during affordance theory development.

AEA conceptualization identifies organizational contingencies that facilitate matching fits for actualizing blockchain-related financial use-case (fintech) affordances. However, AEA could be further extended to address how firms can capture more meaningful value in their blockchain implementation given multiple affordance-actualization goals to achieve co-alignment of IT and organizational strategic goals. When goals of the stakeholders change, a prior specified use-pattern or action and commensurate outcomes may change, resulting in partial actualization or non-actualization (Cécile et al., 2020). Thus, the level of value that could be created by organizational blockchain implementation stakeholders is affected as new goal-orientations are established.

Our study explores multiple (financial and non-financial) goal orientations available to blockchain implementation stakeholders for shared affordance actualizations through a systematic literature review and application of Fromm et al.'s guidelines.

Research Methodology

Document Identification Strategy

We performed a systematic literature review of business value-themed blockchain research works on the potential of blockchain technology. Following Leidner & Kayworth

(2006), we developed: (1) the criteria for the types of studies to be included in the review process (i.e., theme and database scope); (2) the search strategy (i.e., date and search terms); and (3) document analysis scheme and coding of studies. Our search strategy was also influenced by Pare et al.'s (2015) guidelines. We limited the initial sample of studies to the following search queries: (“blockchain” or “block chain”) and (“value” or “value creation”); (“distributed ledger” or “decentralized ledger”) and (“value” or “value creation”). We conducted database searches of ABI/Inform, Academic Search Complete (EBSCO Host), Business Source Complete, Association for Information Systems (AIS) Library, the Hawaii International Conference on System Sciences database, IEEE Xplore, Science Direct (Elsevier), and Springer Link databases.

Our first literature search was conducted in spring 2020 and then updated in February 2021 with any new article that matched the search criteria. The initial sample was 1,596 articles. Based on the reading of the titles and keywords of these manuscripts, 648 were identified as relevant. Next, based on readings of the abstracts, manuscripts that had mentioned value with no connotation to business value creation were dropped, resulting in 182 articles. We used forward/backward search (Webster & Watson, 2002) to identify 11 more studies that had been inadvertently omitted in the selection process by examining the citations of the 182 manuscripts resulting in 193 thoroughly-read articles. The final set of articles analysed was 100 after excluding manuscripts that primarily focused on hash value, nonce value, blockchain protocol improvements, and those only briefly mentioning business value in the introduction or nominally throughout the paper but are more technically focused (e.g., Fill & Härer, 2018; McAbee, Tummala, & McEachen, 2019; Samaniego & Deters, 2019). Also excluded were papers that designed or argued token creation without mentioning how the token is utilized for business value proposition (Glaser, 2017) – i.e. tokenism protocol level than application level. We kept articles that were had relevant real-world examples or case studies from which blockchain business value themes could be extracted, although technically focused. Many of the papers dropped in each round of assessments were from the IEEE Xplore and Springer Link searches. Figure 1 illustrates the literature selection process. Table D1 in Appendix A presents the distribution of final sample manuscripts across databases and publications. Table D2 presents the qualitative coding of the final 100 articles that later informed an affordance-experimentation-actualization-assimilation framework in Table 1.

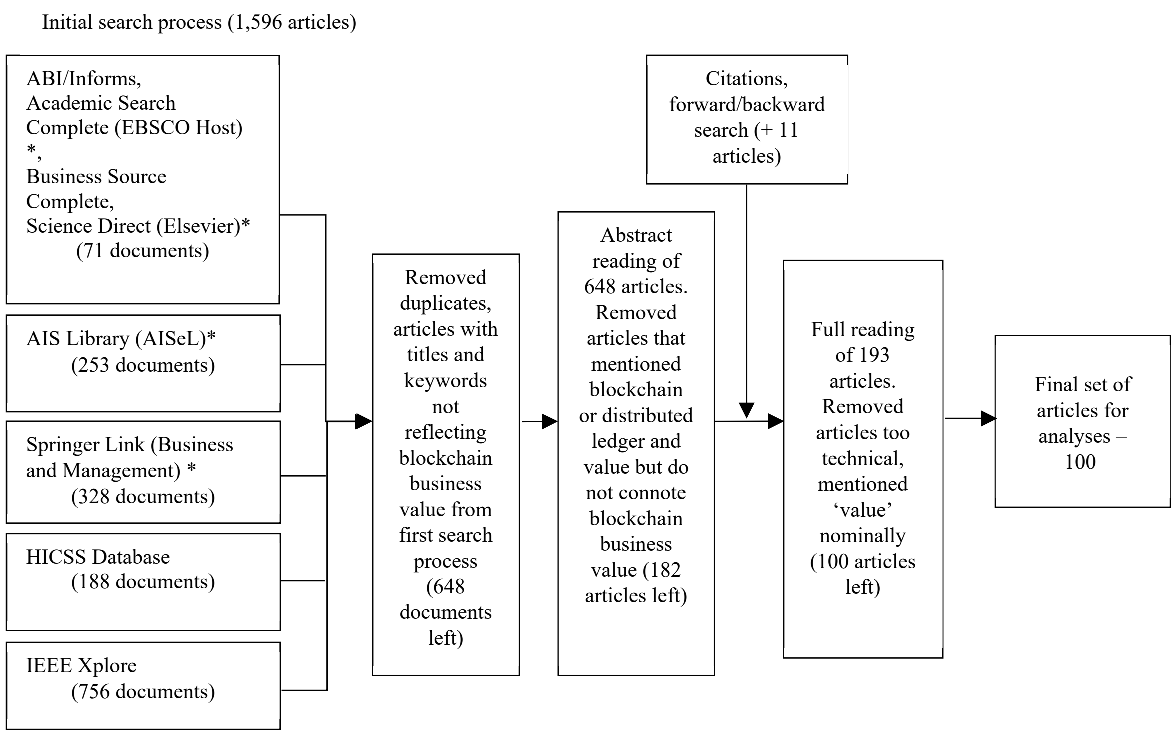

Figure 1: Summary of The Literature Selection Process

Document Analysis (Focal Literature Review) Approach

We analysed the 100 documents ('focal literature') to classify each study along the themes in AEA. Therefore, multiple themes could be assigned to each document. Robustness in the document analyses was realized through a theoretical definition (Du et al., 2019) of what constituted a conceptual construct of interest, *apriori,* and a triangulation of the researchers' analytical processes (Creswell, 2008; Jasperson et al., 2002; Olsen, 2004). Leveraging a framework made for fewer disparities between authors' coding of AEA constructs. Where there were differences, especially in establishing new affordances, the authors discussed thoroughly and reconciled their dispositions.

Each document was independently coded by authors (raters) in an open, axial, and selective coding manner to identify lower-level affordances that gave rise to higher-level themes as recommended by Fromm et al. We identified constraints to value potential realization and how these constraints could be mitigated. For conceptual adaptation identification, the related article discussed alternative terms associated with an identified affordance. The alternative terminology must also provide conceptual clarity to a black-boxed concept, yet this alternative specification should not take away from the focal implementation goal (Du et al., 2019). We found related constructs that could be adapted by implementation stakeholders for conceptual clarity and stakeholder goal alignment. The technology usage patterns and actualized outcomes that linked to identified experimentation processes were analysed together with identification of any organizational condition that facilitated them. These processes were performed twice to ensure coding accuracy. If a document discussed blockchain value conceptually different from any of the AEA themes, it was marked separately. We found two new high-order affordances after grouping related lower-level affordances. Also, their related experimentation processes, actualizations, and organizational facilitating conditions. We observed a new phase beyond actualization in the analyses process: the assimilation phase that would improve the success of blockchain implementation should stakeholders appropriate their goals with this phase in mind.

Our analysis also revealed value interdependences through which covariance fits between different affordance-actualizations can be explored.

Analysis of Findings

Blockchain Implementation Affordances

Our literature analysis reveals five blockchain implementation affordances: (1) the potential to settle monetary and illiquid transactions directly; (2) the potential to automate monetary and illiquid transactions efficiently; (3) the potential for securing and trading monetary and illiquid assets with non-traditional forms of collaterals; (4) the potential to appropriate structured and query-able big data in record time; and (5) the potential for enhanced real-time accounting systems informating and diagnostic reporting. Summaries of these higher-level affordances are presented in Table 1, with more detailed coding on each article presented in Table D2 in Appendix A.

Affordance 1 (A1): direct transaction settlement. This affordance consolidates AEA's affordance by defining the settlement in terms of settling monetary and illiquid transactions directly resulting from the elimination of third parties while ensuring integrity and trust in peer-to-peer (P2P) transactions.

Twenty-six (26) studies discuss this multi-goal higher-level affordance and identify the potential of blockchain where individuals, organizations, machines and algorithms would freely and directly transact and interact directly without intermediaries like lawyers, brokers and bankers (e.g., Iansiti & Lakhani, 2017; Zachariadis et al., 2019). Also, eliminating intermediaries in e-commerce and crowdlending transactions (Schweizer et al., 2017; Ying et al., 2018). The underlying lower-level affordances are the potential to record payment, the potential to prevent tampering via a consensus mechanism and a cryptographic mechanism, the potential to develop non-traditional forms of payment services (Chong et al., 2019; Du et al., 2019), the potential to create native cryptocurrencies and tokens for direct business services and transactions (Ying et al., 2018), and the potential to generate cooperative forms of crowdsourcing — known as "platform cooperativism" — where users qualify both as contributors and shareholders without an intermediary operator (Filippi, 2017). Kazan et al. (2015) show how the disintermediation portends different digital business models even within the bitcoin cryptocurrency network. Several studies provide more examples of different actor goals that identify with this affordance (e.g., Angelis & Ribeiro da Silva, 2019; Janssen et al., 2020; Miscione et al., 2019; Nofer et al., 2017; Pedersen et al., 2019; Priem, 2020). The underlying blockchain artifacts that enable these multi-goal oriented potentials are distributed ledger, consensus mechanism, smart contracts (Du et al., 2019; Zachariadis et al., 2019), cryptographic mechanism, interoperability standards[4] (Chong et al., 2019), immutable audit trail (Wallbach et al., 2020), and rewards systems and tokens (Babich & Hilary, 2019). The human actors involved in perceiving this affordance during implementation are subsidiaries and suppliers (Du et al., 2019), business operators (Chong et al., 2019), and possibly third parties offering blockchain platform-as-a-service (reintermediation).

This affordance leads to value-laden blockchain-related organizational (socio-material) change by removing the inefficiencies and information asymmetries associated with intermediaries (Miscione et al., 2019; Zachariadis et al., 2019) that increase transaction costs. Slock.it, Lazooz, Akasha are such examples in the sharing economy (Nowiński & Kozma, 2017). This affordance provides an avenue for further explaining or measuring the observable action outcomes associated with transaction costs and the impact of new trust forms – distributed trust

[4] For an in-depth study on blockchain interoperability see (Belchior et al., 2021)

or democratized trust (Du et al., 2019) – between P2P transacting parties. A practical case is a trustless cardossier platform Zavolokina et al. (2020).

Affordance 2 (A2): efficient robo-automated transaction. Fourteen (14) papers discuss themes related to this higher-level affordance of a more efficient automation of monetary and nonmonetary transactions.

This affordance extends and consolidates Du et al.'s (2019) affordance of automating payments enabled by blockchain artifacts such as encryption mechanism and smart contracts. The self-triggering automated business processes can be completed by interactive and imbricate algorithmic operators (Iansiti & Lakhani, 2017) – i.e., robo-automations in response to pre-specified conditions. Angelis and Ribeiro da Silva (2019) discuss automated decision making in the form of algorithmic management (AM) that assumes managerial functions and surrounding institutional devices via algorithms. Miscione et al. (2019) discuss affordance of automated governance processes and associated data privacy risks (constraint) as a governance issue among blockchain implementation stakeholders for a bazaar setting – the bazaar mode of governance (also known as hanseatic governance) is underpinned by open-source ideals and "relies upon licenses that protect the nearly zero marginal cost of reproduction and distribution of data" (p. 12).

Zavolokina et al. (2020) explain automating the execution of predefined rights and decisions as part of on-chain governance of digital platforms. Other studies suggest the underlying potentials of automating transaction management and contracts in response to pre-specified conditions (Babich & Hilary, 2019; Egelund-Müller et al., 2017; Kolb et al., 2019; Risius & Spohrer, 2017). Gomber et al. (2018) discuss the potential for automated portfolio allocation and investment recommendations tailored to the individual clients. Pedersen et al.

(2019) exemplifies the potential to drastically improve business operations. The artifacts and features that enable this affordance are distributed ledgers, cryptographic mechanism, smart contracts (Chong et al., 2019; Du et al., 2019), and domain-specific scripting language (Egelund-Müller et al., 2017) and scalability (Perboli et al., 2018). The actors that perceive the socio-materiality of these artifacts are procurement division, suppliers, and subsidiaires (Du et al., 2019; Kolb et al., 2019)*,* The array of multi-goal automation affordance presents dimensions of IT-associated organization change processes that require new theories and practices around IT governance, contract development and management, management of information resources, implications for firm resource-based view, error minimization, business process retooling and business value networks leading to increased process efficiencies. For instance, within a blockchain-enabled interbank transfer system, precise cash allocations that meet different stakeholder demands eliminate misguided and inefficient cash and inventory flows and make full use of holding cash for increased business value (Chong et al., 2019) – i.e. reduction in the bullwhip effect (Babich & Hilary, 2019; Chen, Drezner, Ryan, & Simchi-Levi, 2000). The value from these potential change processes can be empirically assessed from a critical realist perspective and associated constraints can lead to reconfigurations of the perceived IT artifacts.

Affordance 3 (A3): monetary and illiquid asset exchange. The affordance of securing and trading in monetary and illiquid assets with new non-traditional collaterals consolidates and extends AEA's (Du et al.'s 2019) potential for small suppliers to secure loans from financial institutions because of immutable audit trail and smart contracts configured into a blockchain-enabled financial system.

Six (6) papers discuss themes related to this affordance including "*potential to prove solvency via blockchain records"* (Du et al., 2019) and potential for revamping loyalty rewards and program participation behaviours and contractual assets (e.g., Wang et al., 2019). Less creditworthy borrowers can also have access to residential mortgages and digital assets (Jagtiani & John, 2018). Funding from different sources such as blockchain-enabled crowdfunding, marketplace lending and peer-to-peer lending platforms can be accessed by small organizations that might not meet mainstream funding requirements (Jagtiani & John, 2018). The artifacts that support this affordance are immutable audit trail and smart contracts (Du et al., 2019), interoperability standards to onboard firms with existing blockchain systems and tokenization (Wang et al., 2019). Illiquid assets can be traded with the aid of tokenization (Babich & Hilary, 2019). This is evident with the large volumes of non-fungible tokens (NFTs) being traded on marketplaces such as OpenSea[5] with digital creativity as the primary asset. Chong et al. (2019) discuss a use case where ChainSecurity LLC provides blockchain-enabled asset-backed security[6] (ABS) as a service for both asset lenders and borrowers by eliminating challenges (e.g., risk of bankruptcy, low liquidity in secondary markets and hard-to-price assets due to absence of underlying asset data) associated with the traditional system for issuing ABS, creating value from 'co-petition' processes. From a critical realist perspective, lenders can evaluate business value by comparing outcomes such as increase in asset crediting and honouring of contractual terms over different periods.

[5] OpenSea (opensea.io) – OpenSea is the world's first and largest NFT marketplace

[6] Asset-backed security (ABS) is a security collateralized by a pool of assets such as loans, leases, credit card debt, royalties, and other receivables (Chong et al., 2019)

Affordance 4 (A4): appropriation of structured and query-able big data. Twenty (20) papers discuss themes related to this higher-level affordance of perceiving the appropriation of structured and query-able big data.

Blockchain affords consumers, electronic data interchange (EDI) and Society for Worldwide Interbank Financial Telecommunications (SWIFT) operators, data curators, data analysts, and authorized personnel to validate and access structured big data in line with data protection regulations in record time (Jin et al., 2019; Xu et al., 2019; Yansen, 2020). Blockchain technology typifies aggregated data storage since data come from a variety of sources (Babich & Hilary, 2019). Everledger diamond blockchain exemplifies this potential as it stores tons of videos, certificates and geo-locations for diamond operations (Babich & Hilary, 2019).

The blockchain artifacts involved in this bundle of affordance (BA) are distributed ledger type (an instance of blockchain archetype), smart contracts, consensus mechanism, cryptographic mechanism (e.g., SHA-256 or SHA-128 hashing algorithms), reward system or tokenization, and data standards (Korpela et al., 2017; Wang et al., 2018). With cryptographic hashing algorithms, block data can be structurally stored, time-stamped, and accessed by the firm for daily or real-time business analysis (Chowdhury, 2020; Korpela et al., 2017). The hash function also affords utilization of structured data by several parties while preserving the users' privacy and together with a pair of public and private encryption keys, suppliers who may not know who is behind a transaction can verify the authentication of the customers (Ying et al., 2018). Smart contracts enable firm agreements on the aspects of the information requiring de-identification to satisfy data protection regulations (Wang et al., 2018).

For big data comprising a large amount of heterogenic, cross-domain data, blockchain affords extensive structuring of data points for real-time data sharing and analytics (Kolb et al., 2019). Thus, big data can easily be queried with structured query languages (SQL) in a cloud computing environment. Google's BigQuery cloud platform, for example, can be used to structurally query and analyse petabytes of data helping users to access real-time Ethereum transactions data. As data builds up, novel data models based on stakeholder consensus are needed to address all the characteristics of big data – volume, variety, velocity, value, and veracity (Kolb et al., 2019) – while maintaining structured novelty. The value potential within this affordance will increase as blockchain data application programming interfaces (APIs) are standardized across the blockchain ecosystem. However, firms looking to create value opportunities via blockchain data affordance may need to modify the implementation artifacts to mitigate the constraints of low efficiency or throughput in handling large numbers of data transactions. The value accessed from IT-associated change processes due to this affordance can be the considerable shortening of query response times thereby providing super-fast, insightful and cost-effective reach to big-data (Tanwar et al., 2020) while ensuring data privacy regulations.

Affordance 5 (A5): enhanced financial reporting. Ten (10) papers discuss themes on the affordance of real-time accounting systems informating7 diagnostic reporting. Blockchain affords certified professional accountants (CPAs), internal auditors and IT system analysts the potential for real-time informating, auditing and reporting of accounting and IT system information (Bible et al., 2017; Cao et al., 2019; Rooney et al., 2017; Tysiac, 2017).

[7] A term by Zuboff (1988) describing processes of translating descriptions and measurements of activities, events and objects into information.

Besides storing current information, blockchain can provide implementers validity checks in systems' information quality and tamper-proof log of historical transactions for auditing purposes (Babich & Hilary, 2019; Pedersen et al., 2019). Audit practice, thus, is set to see a paradigm shift with blockchain (Nathalie et al., 2019). Even though determining the veracity of a product or service transaction with only blockchain would be challenging, there will be increased transparency, reliability in monitoring, and shareholder confidence in the financial reports with CPAs and accountants exploring this affordance (Cao et al., 2019). The zkLedger is an example that supports this affordance (Narula et al., 2018). As a consensus protocol, it can be used by outside auditors and regulators to verify information accuracy while protecting privacy through zero-knowledge proofs of cryptography, even on permissionless blockchain platforms (Toufaily et al., 2021).

Blockchain offers the potential to support triple-entry accounting system through smart contracts (Cai, 2019), better facilitate record-keeping, internal auditing, and certification (Rooney et al., 2017), provide better security in document handling between different parties avoid financial penalties, and improve regulatory compliance (Pedersen et al., 2019).

The focal blockchain artifacts and characteristics needed for this bundle of affordance are smart contracts, immutable audit trail (immutability), distributed ledger type, and consensus protocol. These artifacts enable real-time access, verification and processing of large amounts of financial data at a pace that reduces the complexities of auditing extensive transactional data (Belchior & Correia, 2020). CPAs and accountants can add new roles such as auditors for smart contracts, service auditors of consortium blockchains, access-granting administrators, and arbitration functions (Bible et al., 2017; Tysiac, 2018).

Experimentation Phase

Conceptual adaptation. Table 1 references all conceptual adaptations identified in the analysed literature necessary for effective actualization. We discuss adaptations relating to affordance four and affordance five in this section. Three studies on data appropriation for value creation (Bauer et al., 2019; Pedersen et al., 2019; Zavolokina et al., 2020) highlight the conceptual adaptation required before actualizing the potential of querying structured big-data (A4).

In a car dossier system architecture use case, Zavolokina et al. (2020) find that blockchain supported the development of 'controlled access to trusted car data' and 'shared efficiency' and conceptually translated inefficiencies with data sharing and overhead minimization costs into experimental actions actualized during implementation. Similarly, Bauer et al. (2019) reported data-related value potentials of 'controlled customer intimacy' and 'shared operational efficiency.' These conceptual adaptations support blockchain data interoperability standards and data sharing rules while adhering to privacy laws. They also reduce overheads and eliminate errors optimizing the value from blockchain implementation. Regarding the affordance of enhancing financial reports (A5), blockchain technology makes triple-entry accounting implementation a reality (Cai, 2019). To have buy-in from stakeholders accustomed to double-entry bookkeeping, the concept of a blockchain system for better accounting practices needs to be adapted. For instance, the concept during implementation can be adapted as enhanced double-entry bookkeeping at the application level with the technical levels fashioned to deal with the intricacies of triple entry record-keeping (Cai, 2019). This adaptation allows stakeholders to experience the actualized outcomes before making sense of the complex underlying concept.

Constraint mitigation. The appropriation of structured and query-able big data has associated constraints such as the lack of a standardized data model for end-to-end supply chain data integration or application programming interfaces (Korpela et al., 2017). However, the careful selection of distributed ledger types, smart contracts, and interoperability chains could mitigate this constraint. Due to challenges with data accessibility and authorization issues, a blockchain implementation firm could develop an alliance chain for an appropriate access control strategy.

The enhanced financial reporting affordance (A5) could impose certain constraints that should be mitigated if the full potential is to be actualized. One constraint is introduced by extensive log pre-processing and automatic analysis and could be mitigated by compaction that simplifies information and minimization that eliminates redundant information (Belchior & Correia, 2020). The blockchain infrastructure would bear part of the governance, risk management, and control functionalities of the internal auditor. A continuous auditing system must be put in place to ensure user acceptance of the new blockchain-related roles (Rooney et al., 2017). Another constraint relates to data privacy. Privacy calculus can be ameliorated because of the immutability and cryptographic mechanism artifacts of the blockchain system. Hence, auditors can utilize private data while preserving consumer data privacy (Cao et al., 2019) or protecting sensitive financial information (Belchior & Correia, 2020). These experimental actions allow for the actualization of the related affordance by reducing implementation risks. Table 1 provides identification of the constraints to affordances one to five.

Actualization Phase: Usage Actions, Outcomes, and Organizational Context

Merging, de-identifying, sharing, or accessing data based on the smart contract's contractual terms and in line with data protection regulations are the usage actions enabled by the query-able and structured big data affordance (A4). This usage addresses the privacy and control paradox (Brandimarte et al., 2013) because smart contracts self-execute what actors have agreed upon regarding their data. The cryptographic mechanism ensures that an agreeable and beneficial level of de-identification is achieved, as evidenced in an implementation of a secure multiparty computation system on Enigma blockchain (Pentland, 2018). These user actions lead to increased business knowledge via business analytics, improved production processes, and new products and services.

A data value model is another actualized outcome that rewards all stakeholders. Unlike the user privacy controversy with Facebook and Cambridge Analytica (Ayaburi & Treku, 2020), all contributors can be assured of installed trust and privacy protection when divulging data in exchange for tokens or other rewards[8] (Yansen, 2020). Increased business knowledge and data value business model with shared benefits are critical actualized outcomes and can challenge platforms[9] that offer no benefits to users (Aitken, 2018), enabling platform organizations to increase consumer engagement. Blockchain also supports healthcare organizations that manage terabytes of patient data.

[8] "Steem.io" is a prime example (Filippi, 2017).

[9] Facebook generated nearly $27 billion in 2016 via targeted advertisement, platform users who generate contents benefited nothing (Aitken, 2018).

Table 1: Summary of Findings: The Affordance-Experimentation-Actualization-Assimilation Framework

	Elements giving rise to value-oriented affordances (Du et al., 2019)				Experimentation (Alternative actions) (Du et al., 2019) (Holotiuk et al., 2018; Murray, 2019)		Actualization (Du et al., 2019)		Organizati-onal Context facilitators (Du et al., 2019)*)*	Assimilation (Basole, 2018; Janssen et al., 2020; Murray, 2019)	Suggested Sources - Construct Operationa-lization
	Lower-Order concepts or affordances	Higher-Level Concepts (Bundles of Affordances)	Key I.T. or Blockchain Artifacts, Characteristics and Tradeoffs	Actors	Conceptual Adaptation (Du et al., 2019; Jagtiani & John, 2018)*)* (Frizzo-Barker et al., 2020)	Constraint Mitigation (Du et al., 2019) (Frizzo-Barker et al., 2020)	Usage actions (Du et al., 2019)	Actualized outcomes (Du et al., 2019)*)* (Lui & Ngai, 2019)		Transformative uses, acceleration, diffusion, or dissemination activities	
A 1	- *Potential to record payment via distributed ledgers* - *Potential to prevent tampering via a consensus mechanism* (Du et al., 2019) - develodping new payment service applications (Chong et al., 2019) - blockchain enables firms to create their local cryptocurrency or token for transactions (Ying et al., 2018)	Affordance 1: Potential to settle monetary and nonmonetary transactions directly (Du et al., 2019)	*Distributed ledger and consensus mechanism* (Du et al., 2019) *Cryptographic mechanism, interoperability standards* (Chong et al., 2019) *Smart contracts*(Zachariadis et al., 2019) Reward systems and tokens for non-monetary transactions or payments (Babich & Hilary, 2019) Immutable audit trail (Wallbach et al., 2020)	*Subsidiaries and suppliers* (Du et al., 2019) *Business operators* (Chong et al., 2019)	*Separation of blockchain from bitcoin by the implementation team leading to a commensurate development of a use case for payment settlement* (Du et al., 2019) (Chong et al., 2019; Pflaum et al., 2018) Separation of monopolistic from duopolistic market entry	*Due to difficulties in understanding the blockchain artifacts, the implementation team packaged the technology into a black box* (Du et al., 2019) In some cases, full-scale implementation will require updating the legal framework (Priem, 2020; Toufaily et al., 2021)	*Using a blockchain wallet system for payment settlement instead of using the banks*(Du et al., 2019) (Ma et al., 2018) Using electronic-draft management system for direct payment services (Chong et al., 2019)	*Instant money transfer and digitally recorded* (Du et al., 2019) (Gomber et al., 2018) Reduction in bank exceptions and reconciliations (Chong et al., 2019) The security, transparency, and speed of distributed ledgers make for cheaper, faster,	*A subculture that supports collaboration with start-ups* (Du et al., 2019)	Firms leverage outstanding value opportunities in new trust mechanisms that underlie direct transactions and enrichment in product options (Ying et al., 2018). Dramatic reduction in transaction costs by replacing trusted third parties and private trust services with an open mode transaction (Iansiti & Lakhani, 2017; M. Lacity et al., 2019; Lindman et al., 2019). An example is the case of Hainan Airlines (HNA)	Transaction cost value Collaborative organizational subculture (El Sawy, 1985; Huang et al., 2003) Decentrali-zation of blockchain archetype (Bian et al., 2018; Toufaily et al., 2021)

Table 1, cont.

Elements giving rise to value-oriented affordances (Du et al., 2019)				Experimentation (Alternative actions) (Du et al., 2019) (Holotiuk et al., 2018; Murray, 2019)		Actualization (Du et al., 2019)		Organizational Context facilitators (Du et al., 2019))	Assimilation (Basole, 2018; Janssen et al., 2020; Murray, 2019)	Suggested Sources - Construct Operationalization
Lower-Order concepts or affordances	Higher-Level Concepts (Bundles of Affordances)	Key I.T. or Blockchain Artifacts, Characteristics and Tradeoffs	Actors	Conceptual Adaptation (Du et al., 2019; Jagtiani & John, 2018)) (Frizzo-Barker et al., 2020)	Constraint Mitigation (Du et al., 2019) (Frizzo-Barker et al., 2020)	Usage actions (Du et al., 2019)	Actualized outcomes (Du et al., 2019)) (Lui & Ngai, 2019)		Transformative uses, acceleration, diffusion, or dissemination activities	
- Potential to run applications on a peer-to-peer network not controlled by centralized server or node - Facilitating the exchange of value in a secure and decentralized manner, without the need for an intermediary (Filippi, 2017) - Potential for cooperative form of crowd-sourcing — known as “platform cooperativism”— where				because both have different implementation outcome (X. Zhang, 2019)			safer, and reliable settlement in cross-border and mobile payments (Accenture, 2020; Ma et al., 2018) Reduction in information asymmetry (Miscione et al., 2019)		group, a Fortune 500 company (Ying et al., 2018) In some instances, the use of third parties such as banks as direct stakeholders will increase the liquidity of electronic-draft and wallet systems for payment services (Chong et al., 2019) Market transformation via new trust mechanism, the disruptive impact of a pervasive reduction in information asymmetry and increased networking	

Table 1, cont.

	Elements giving rise to value-oriented affordances (Du et al., 2019)				Experimentation (Alternative actions) (Du et al., 2019) (Holotiuk et al., 2018; Murray, 2019)		Actualization (Du et al., 2019)		Organizational Context facilitators (Du et al., 2019))	Assimilation (Basole, 2018; Janssen et al., 2020; Murray, 2019)	Suggested Sources - Construct Operationa-lization
	Lower-Order concepts or affordances	Higher-Level Concepts (Bundles of Affordances)	Key I.T. or Blockchain Artifacts, Characteristics and Tradeoffs	Actors	Conceptual Adaptation (Du et al., 2019; Jagtiani & John, 2018)) (Frizzo-Barker et al., 2020)	Constraint Mitigation (Du et al., 2019) (Frizzo-Barker et al., 2020)	Usage actions (Du et al., 2019)	Actualized outcomes (Du et al., 2019)) (Lui & Ngai, 2019)		Transformative uses, acceleration, diffusion, or dissemination activities	
	users qualify both as contributors and shareholders without an intermediary operator (Filippi, 2017)									value (X. Zhang, 2019)	
A 2	*- Potential to remove manual verification* *- Potential to remove manual reconciliation* *- Potential to build automatic triggers*	Affordance 2: Potential to automate monetary and nonmonetary transactions efficiently (Du et al., 2019)	*Distributed ledgers, Cryptographic mechanism, and smart contracts ((*Du et al., 2019) and Scripting language (domain-specific language) (Egelund-Müller et al., 2017),	*Procurement division, suppliers, and subsidiaries ((*Du et al., 2019), (Kolb et al., 2019)*)*	*Separation of blockchain transactions from cryptocurrency leading to a commensurate development of automated process*	*A complete distributed database was a constraint to processing transactions efficiently, so a separate database was created by the implementat*	*Actors used the blockchain for process transactions instead of using paper-based clearance systems they were traditionally accustomed*	*Reduction in delays and errors associated with process transactions* (Du et al., 2019) (Kolb et al., 2019) An example of a company	*Digitization as the corporate strategy* (Du et al., 2019)	There is an increased and sustainable process efficiency (Holotiuk et al., 2018). (Chong et al., 2019) Ex-post enforceability of contracts; thus, contractual	Process efficiency (Lee et al., 2015) Digital options (Sambamurthy et al., 2003) Decentralization of blockchain

Table 1, cont.

Elements giving rise to value-oriented affordances (Du et al., 2019)				Experimentation (Alternative actions) (Du et al., 2019) (Holotiuk et al., 2018; Murray, 2019)		Actualization (Du et al., 2019)		Organizational Context facilitators (Du et al., 2019)*)*	Assimilation (Basole, 2018; Janssen et al., 2020; Murray, 2019)	Suggested Sources - Construct Operationa-lization
Lower-Order concepts or affordances	Higher-Level Concepts (Bundles of Affordances)	Key I.T. or Blockchain Artifacts, Characteristics and Tradeoffs	Actors	Conceptual Adaptation (Du et al., 2019; Jagtiani & John, 2018)*)* (Frizzo-Barker et al., 2020)	Constraint Mitigation (Du et al., 2019) (Frizzo-Barker et al., 2020)	Usage actions (Du et al., 2019)	Actualized outcomes (Du et al., 2019)*)* (Lui & Ngai, 2019)		Transformative uses, acceleration, diffusion, or dissemination activities	
(Du et al., 2019) (Chong et al., 2019)	(Egelund-Müller et al., 2017)	Scalability (Perboli et al., 2018)		*transactions* (Du et al., 2019) Due to the unfamiliarity of the concept of blockchain to some supply chain stakeholder firms, “value is created by assisting these organizations [in isolating] best business practices for which blockchain can… make a difference and delivering the eventual solution.”	*ion team to store only the part of the transaction that needed to be stored on the blockchain and the rest on a traditional database* (Du et al., 2019). Interoperability chains such as Cosmos, which uses Tendermint protocol, could be leveraged to address this constraint (Toufaily et al., 2021)	*to* (Du et al., 2019) *(*An example is Honeywell Aerospace, which has created a digitized paper trail to prevent engines with incomplete paper from sitting unused (Debter et al., 2020)	is Broadridge Financial Services in New York City, which utilizes Hyperledger Fabric (Debter et al., 2020). Another example is with the streamlining of food traceability processes and the identification of possible contamination sources (Chong et al., 2019), such as with Walmart, Dole, and		parties cannot reverse their commitments (Blossey et al., 2019). E.g., As part of 70% refocus of traditional financing operations, Xbox Finance of Microsoft uses “blockchain solu tions to compute royalty statements for Xbox game publishers in hours, instead of months” (Microsoft, 2019) with the help of Microsoft Azure Blockchain-As-A-Service platform Other practical transformative	archetype (Bian et al., 2018; Toufaily et al., 2021)

Table 1, cont.

	Elements giving rise to value-oriented affordances (Du et al., 2019)				Experimentation (Alternative actions) (Du et al., 2019) (Holotiuk et al., 2018; Murray, 2019)		Actualization (Du et al., 2019)		Organizati-onal Context facilitators (Du et al., 2019))	Assimilation (Basole, 2018; Janssen et al., 2020; Murray, 2019)	Suggested Sources - Construct Operationa-lization
	Lower-Order concepts or affordances	Higher-Level Concepts (Bundles of Affordances)	Key I.T. or Blockchain Artifacts, Characteristics and Tradeoffs	Actors	Conceptual Adaptation (Du et al., 2019; Jagtiani & John, 2018)) (Frizzo-Barker et al., 2020)	Constraint Mitigation (Du et al., 2019) (Frizzo-Barker et al., 2020)	Usage actions (Du et al., 2019)	Actualized outcomes (Du et al., 2019)) (Lui & Ngai, 2019)		Transformative uses, acceleration, diffusion, or dissemination activities	
					([20, p.1321)			Driscoll blockchain projects. An automated soybean traceability system (Salah et al., 2019)		examples concern purchase orders, bill of ladings (Nærland et al., 2018), and letters of credit on the adopted blockchain, leading to fewer errors and disputes as with Accenture's blockchain adoption	
A 3	- *Potential to prove solvency via blockchain records* (Du et al., 2019) *Potential for loyalty rewards and reputation management as collaterals* rewards *(*Or contractual assets)	**Affordance 3:* Potential for securing monetary and non-monetary assets with new forms of collaterals (Du et al., 2019; Jagtiani	*Immutable audit trail and smart contracts* (Du et al., 2019). Interoperability system to onboard firms with existing blockchain systems and tokenism (L. Wang et al., 2019)	*Small suppliers* (Du et al., 2019)*,* consumers and clients	*Development of use case for small suppliers to prove solvency for easy access to secure loans* (Du et al., 2019) Development of non-financial use-cases for clients and	*Unknown risks were anticipated for the new financial services to small suppliers, so unknown risks were mitigated by experimenting in a small community.* (Du et al., 2019)	*Financial institutions are granted access to blockchain records, and loans are issued via Smart Contracts to applicants (small suppliers)* (Du et al., 2019)(Chong et al., 2019).	*Cost reduction (or avoidance) when securing loans and revenue increment by procurement* (Du et al., 2019)*,* (Ahluwalia et al., 2020)	*A culture that supports intrapreneurship* (Du et al., 2019)	Existence of sustained technical modularity and complementarity in the emergence of business ecosystems (Still et al., 2019). Complementary virtual assets, complementary customers, and machines	Solvency ratio (SolRa), Intrapreneurial organization culture (IOCul) or group-oriented organizational cultures – high flexibility and internally

Table 1, cont.

Elements giving rise to value-oriented affordances (Du et al., 2019)				Experimentation (Alternative actions) (Du et al., 2019) (Holotiuk et al., 2018; Murray, 2019)		Actualization (Du et al., 2019)		Organizational Context facilitators (Du et al., 2019))	Assimilation (Basole, 2018; Janssen et al., 2020; Murray, 2019)	Suggested Sources - Construct Operationalization
Lower-Order concepts or affordances	Higher-Level Concepts (Bundles of Affordances)	Key I.T. or Blockchain Artifacts, Characteristics and Tradeoffs	Actors	Conceptual Adaptation (Du et al., 2019; Jagtiani & John, 2018)) (Frizzo-Barker et al., 2020)	Constraint Mitigation (Du et al., 2019) (Frizzo-Barker et al., 2020)	Usage actions (Du et al., 2019)	Actualized outcomes (Du et al., 2019)) (Lui & Ngai, 2019)		Transformative uses, acceleration, diffusion, or dissemination activities	
(e.g., Wang et al., 2019)	& John, 2018)			consumers to prove reputation Development and evaluation of local use case for customer rewards program (Wang et al., 2019) Creating local use cases (i.e., both single-use and localized applications for contractual assets (Farahmand & Farahmand, 2019; Iansiti & Lakhani, 2017)	The high initial investment for small firms and maintenance costs could be reduced by intensifying early communications and increasing stakeholders' networks for cost-sharing. In the interim, the focus was on low-volume business processes that would not impact the majority of business processes [20 p. 1327],	Non-financial institutions have real-time access to records, verify qualified customers and issue redeemable tokens (L. Wang et al., 2019) Collateralization of supply chain assets via the issuance of corresponding financial claims using tokens (Blossey et al., 2019)	Increased monitoring and cost reduction in accessing financial services (Chong et al., 2019) Valid and reliable loyalty rewards system for customer participation and retention (*Exploring How Blockchain Impacts Loyalty Program Participation Behaviors. An Exploratory Case*		(Schlecht et al., 2020) Continuous co-creation of several use-cases around the focal use-cases. An example is Mindtree's creation of loyalty and onboarding. Social business use-cases, such as crowdlending (Schweizer et al., 2017). 'OurCrowd' provides a network that matches early-stage entrepreneurs and investors (Lehner & Simlinger, 2019).	focused (McDermott & Stock, 1999), SolRa X IOCul Decentralization of blockchain archetype (Bian et al., 2018; Toufaily et al., 2021)

Table 1, cont.

Elements giving rise to value-oriented affordances (Du et al., 2019)				Experimentation (Alternative actions) (Du et al., 2019) (Holotiuk et al., 2018; Murray, 2019)		Actualization (Du et al., 2019)		Organizational Context facilitators (Du et al., 2019))	Assimilation (Basole, 2018; Janssen et al., 2020; Murray, 2019)	Suggested Sources - Construct Operationa-lization
Lower-Order concepts or affordances	Higher-Level Concepts (Bundles of Affordances)	Key I.T. or Blockchain Artifacts, Characteristics and Tradeoffs	Actors	Conceptual Adaptation (Du et al., 2019; Jagtiani & John, 2018)) (Frizzo-Barker et al., 2020)	Constraint Mitigation (Du et al., 2019) (Frizzo-Barker et al., 2020)	Usage actions (Du et al., 2019)	Actualized outcomes (Du et al., 2019)) (Lui & Ngai, 2019)		Transformative uses, acceleration, diffusion, or dissemination activities	
					(Toufaily et al., 2021) Risks of non-participation in loyalty programs are mitigated by satisfying customers need for relatedness, competence, autonomy, and economic utility (*Exploring How Blockchain Impacts Loyalty Program Participation Behaviors. An Exploratory Case Study. Wang et al.*)		*Study. Wang et al.2019.Pdf*, n.d.)			

Table 1, cont.

	Elements giving rise to value-oriented affordances (Du et al., 2019)				Experimentation (Alternative actions) (Du et al., 2019) (Holotiuk et al., 2018; Murray, 2019)		Actualization (Du et al., 2019)		Organizational Context facilitators (Du et al., 2019))	Assimilation (Basole, 2018; Janssen et al., 2020; Murray, 2019)	Suggested Sources - Construct Operationalization
	Lower-Order concepts or affordances	Higher-Level Concepts (Bundles of Affordances)	Key I.T. or Blockchain Artifacts, Characteristics and Tradeoffs	Actors	Conceptual Adaptation (Du et al., 2019; Jagtiani & John, 2018)) (Frizzo-Barker et al., 2020)	Constraint Mitigation (Du et al., 2019) (Frizzo-Barker et al., 2020)	Usage actions (Du et al., 2019)	Actualized outcomes (Du et al., 2019)) (Lui & Ngai, 2019)		Transformative uses, acceleration, diffusion, or dissemination activities	
A 4	- Creating and sharing open-access, de-identified, and structured big data (Holotiuk & Moormann, 2018; Korpela et al., 2017; Wei et al., 2019) - Validating data for data integrity and accuracy (Kolb et al., 2019) - Timestamping of data [167] and ensuring data provenance (M. C. Lacity, 2018b)	*Affordance 4: Potential to appropriate valid, structured, and queryable big-data while preserving privacy (Jin et al., 2019; C. Xu et al., 2019)	A distributed ledger, Immutable audit trail, Consensus mechanism for validation, scalability for simultaneous access to data, cryptographic mechanism and smart contracts to conduct digital supply chain, data interoperability standards, and rewards systems (Jin et al., 2019; Ying et al., 2018)	Data analysts, data entry specialists and authorized validators, E.D.I. operators and SWIFT operators and data brokers (Yansen, 2020)	Development of 'controlled customer intimacy' and 'shared operational efficiency' for efficient data appropriation among the network of actors (Bauer et al., 2019; Zavolokina et al., 2020) -High-level business integration needs were translated into relatable system functionalities using analytical tools such as quality	- Due to challenges with data accessibility and authorization issues, the implementation firm developed an alliance chain for an appropriate access control strategy. - Lack of standardized data model for end-to-end supply-chain data integration mitigated by the distributed ledger and smart contract employed [167].	- Data merging, data de-identification, and data sharing/access (Korpela et al., 2017; X. Zhang & Chen, 2019) in light of the General Data Protection Regulations (GDPR) and other data privacy protection acts (Faber et al., 2019; Farshid et al., 2019) - Authorized nodes accessed and shared encrypted data within an improvemen	Increased business knowledge and data value for all platform stakeholders (Yansen, 2020). -Data integrity and increased confidence in data across all levels (H.-M. Chen & In, 2019; Faber et al., 2019) – e.g., integrity with medical records, asset registries, etcetera.	- Level of emphasis and exploration and exploitation activities for market arbitrage and firm agility (customer partnering and operational agility) (Sambamurthy et al., 2003)	Increasing data standards for integration or interoperability (Korpela et al., 2017), platform interoperability, and cross-platform smart-contracts interoperability are critical for value optimization and widespread adoption (Holotiuk et al., 2018) (Chong et al., 2019) Timestamping of data to improve association rule mining for strategic business decisions. As well, the diffusion of new potentialities for	Exploitable absorptive capacity or organizational learning – (Roberts et al., 2012; Todorova & Durisin, 2007; Zahra & George, 2002; Zou et al., 2018) (Years of R&D experience), Intensity of R&D investment, Number of patents, originality of patents (OriPat0 and generality of patents (H. Kim et al., 2020)

Table 1, cont.

Elements giving rise to value-oriented affordances (Du et al., 2019)				Experimentation (Alternative actions) (Du et al., 2019) (Holotiuk et al., 2018; Murray, 2019)		Actualization (Du et al., 2019)		Organizati-onal Context facilitators (Du et al., 2019))	Assimilation (Basole, 2018; Janssen et al., 2020; Murray, 2019)	Suggested Sources - Construct Operationa-lization
Lower-Order concepts or affordances	Higher-Level Concepts (Bundles of Affordances)	Key I.T. or Blockchain Artifacts, Characteristics and Tradeoffs	Actors	Conceptual Adaptation (Du et al., 2019; Jagtiani & John, 2018)) (Frizzo-Barker et al., 2020)	Constraint Mitigation (Du et al., 2019) (Frizzo-Barker et al., 2020)	Usage actions (Du et al., 2019)	Actualized outcomes (Du et al., 2019)) (Lui & Ngai, 2019)		Transformative uses, acceleration, diffusion, or dissemination activities	
(Chong et al., 2019)				function deployment to reduce concept abstraction [167]	Development of a data access system for resolving endogenous risks, especially in supply chains(Fu & Zhu, 2019) Privacy issues for nodes are mitigated by using an infinite number of public keys in a manageable and safe manner that makes pattern identification difficult, particularly in utilizing Internet of	t scheme that enabled federated machine learning [155, 202]	- Self-sovereign data guardianship and detecting biases in training data or biases in algorithms codified by designers (Rai et al., 2019) (Chong et al., 2019)		machine learning and deep learning in conjunction with other 4.0 technologies such as A.I. enables intelligent operations and transformational business outcomes (Burkhardt et al., 2019) - Data value optimization by leveraging the cybersecurity potential of blockchain usage has continuous implications for data privacy and security practices (Chong et al., 2019; Rieger et al., 2019; Smith & Dhillon,	Firm agility (Sambamurthy et al., 2003) Decentralization of blockchain archetype (Bian et al., 2018; Toufaily et al., 2021)

Table 1, cont.

Elements giving rise to value-oriented affordances (Du et al., 2019)				Experimentation (Alternative actions) (Du et al., 2019) (Holotiuk et al., 2018; Murray, 2019)		Actualization (Du et al., 2019)		Organizational Context facilitators (Du et al., 2019))	Assimilation (Basole, 2018; Janssen et al., 2020; Murray, 2019)	Suggested Sources - Construct Operationa-lization
Lower-Order concepts or affordances	Higher-Level Concepts (Bundles of Affordances)	Key I.T. or Blockchain Artifacts, Characteristics and Tradeoffs	Actors	Conceptual Adaptation (Du et al., 2019; Jagtiani & John, 2018)) (Frizzo-Barker et al., 2020)	Constraint Mitigation (Du et al., 2019) (Frizzo-Barker et al., 2020)	Usage actions (Du et al., 2019)	Actualized outcomes (Du et al., 2019)) (Lui & Ngai, 2019)		Transformative uses, acceleration, diffusion, or dissemination activities	
					Things (IoT) data (M. S. Ali et al., 2019). Also, zk-proof protocols can be used to mitigate privacy concerns, especially with permissionless ledgers (Toufaily et al., 2021)				2019). An example is being able to trade priced-assets in the secondary markets [20 p. 1324] -data as a value carrier in the digital supply chain via advanced analytics and pattern recognition and real-time analytics (Pflaum et al., 2017, 2018)	

Table 1, cont.

	Elements giving rise to value-oriented affordances (Du et al., 2019)				Experimentation (Alternative actions) (Du et al., 2019) (Holotiuk et al., 2018; Murray, 2019)		Actualization (Du et al., 2019)		Organizati-onal Context facilitators (Du et al., 2019))	Assimilation (Basole, 2018; Janssen et al., 2020; Murray, 2019)	Suggested Sources - Construct Operationa-lization
	Lower-Order concepts or affordances	Higher-Level Concepts (Bundles of Affordances)	Key I.T. or Blockchain Artifacts, Characteristics and Tradeoffs	Actors	Conceptual Adaptation (Du et al., 2019; Jagtiani & John, 2018)) (Frizzo-Barker et al., 2020)	Constraint Mitigation (Du et al., 2019) (Frizzo-Barker et al., 2020)	Usage actions (Du et al., 2019)	Actualized outcomes (Du et al., 2019)) (Lui & Ngai, 2019)		Transformative uses, acceleration, diffusion, or dissemination activities	
A 5	-Improving the effectiveness and efficiency of internal financial and system auditing (Rooney et al., 2017) - Potential to eliminate the need for hiring a neutral third party for data entry and instead have that third-party represented as a programmed technology (Lewtan et al., 2018) -Potential for single internal	*Affordance 5: Potential for new, enhanced financial and system information on auditing and reporting (Cai, 2019; Cao et al., 2019; Dai, 2017; Nathalie et al., 2019; Rooney et al., 2017; Taylor, 2017)	A distributed ledger, consensus mechanism, Immutable audit trail, and smart contracts needed scalability for multiple real-time access to continuous financial transactions (T. Cai et al., 2019)	C.P.A.s and internal auditors, public accountants, financial and system analysts (Bible et al., 2017; Cao et al., 2019; Rooney et al., 2017)	Delineation of triple-entry record-keeping from double-entry accounting (C. W. Cai, 2019)	Governance, risk management, and control functionalities of the internal auditors to be borne by the blockchain introduces user resistance and can be mitigated with a system of continuous auditing (Rooney et al., 2017) Issues with data privacy are addressed auditors can utilize private data while preserving	Collaborative audit process (Cao et al., 2019)	Real-time reconciliation and analyst's announcement for market buy-in. Reduction in clients' incentives to misreport and auditors' sampling costs (Cao et al., 2019)	The propensity for effective and transparent accounting practices.	The use of audit contracts to implement auditing business logic rules regarding every transaction (Belchior & Correia, 2020) Accountants and auditors relocate effort from transaction-based auditing to discretionary account auditing (Cao et al., 2019) Assimilation is achieved by increasing value from better forecasting activities around enhanced financial reporting and harnessing the embedded value	Quality of financial reporting (van Beest et al., 2009) Analyst coverage (Chang et al., 2006) Perception of the level of firm transparency and reputation Decentralization of blockchain archetype (Bian et al., 2018)

Table 1, cont.

Elements giving rise to value-oriented affordances (Du et al., 2019)				Experimentation (Alternative actions) (Du et al., 2019) (Holotiuk et al., 2018; Murray, 2019)		Actualization (Du et al., 2019)		Organizati-onal Context facilitators (Du et al., 2019))	Assimilation (Basole, 2018; Janssen et al., 2020; Murray, 2019)	Suggested Sources - Construct Operationa-lization
Lower-Order concepts or affordances	Higher-Level Concepts (Bundles of Affordances)	Key I.T. or Blockchain Artifacts, Characteristics and Tradeoffs	Actors	Conceptual Adaptation (Du et al., 2019; Jagtiani & John, 2018)) (Frizzo-Barker et al., 2020)	Constraint Mitigation (Du et al., 2019) (Frizzo-Barker et al., 2020)	Usage actions (Du et al., 2019)	Actualized outcomes (Du et al., 2019)) (Lui & Ngai, 2019)		Transformative uses, acceleration, diffusion, or dissemination activities	
bookkeeping and opposite entry on the shared public ledger - Potential to realize the ideals of new bookkeeping from double-entry to triple-entry accounting (C. W. Cai, 2019; Cohn, 2016; Dai, 2017; Tysiac, 2017, 2018) Potential for continuous auditing (Rooney et al., 2017; Tysiac, 2018) - potential to alleviate redundant auditor's work in real					data privacy (Cao et al., 2019) or protecting sensitive financial information (Belchior & Correia, 2020) - Compaction and minimization in automatic auditing (Belchior & Correia, 2020)				of the forecasting capability of triple-entry record keeping.	

Table 1, cont.

Elements giving rise to value-oriented affordances (Du et al., 2019)				Experimentation (Alternative actions) (Du et al., 2019) (Holotiuk et al., 2018; Murray, 2019)		Actualization (Du et al., 2019)		Organizati-onal Context facilitators (Du et al., 2019)*)*	Assimilation (Basole, 2018; Janssen et al., 2020; Murray, 2019)	Suggested Sources - Construct Operationa-lization
Lower-Order concepts or affordances	Higher-Level Concepts (Bundles of Affordan ces)	Key I.T. or Blockchain Artifacts, Characteristics and Tradeoffs	Actors	Conceptual Adaptation (Du et al., 2019; Jagtiani & John, 2018)*)* (Frizzo-Barker et al., 2020)	Constraint Mitigation (Du et al., 2019) (Frizzo-Barker et al., 2020)	Usage actions (Du et al., 2019)	Actualized outcomes (Du et al., 2019)*)* (Lui & Ngai, 2019)		Transformative uses, acceleration, diffusion, or dissemination activities	
time, potential to hinder fraud and collusion between organizations and auditors, and related stakeholders (Belchior & Correia, 2020) (Kokina et al., 2017)										

Italicized texts in the direct posits of Du et al.'s Affordance-Experimentation-Actualization constructs *A1 to A5 are the five (5) blockchain bundles of affordances.

Anthem – the second-largest health insurance provider in the US, has used the Hyperledger Fabric blockchain platform to provide controlled and real-time patient access to structured patient health records (Rosenbaum, 2019).

An organizational context that facilitates the actualization of real-time structured big-data potential is the level of firm agility in effectively balancing exploitation and exploration activities for market arbitrage (Sambamurthy et al., 2003). Agile firms will invest in data analytics infrastructure to improve their product and process decision-making. Therefore, firms can better inform and leverage customer, partnering, and operational agilities (Sambamurthy et al., 2003).

In actualizing the potential to enhance a firm's accounting practices and financial reporting, collaborative reporting and collaborative audit processes, which reduces the need, the time allocated, and the cost of external verification of accounting records present an important usage action (Cao et al., 2019). Further, real-time reconciliation and real-time analysts' assessments and the announcement of firm financial information which generate market buy-in and increase reputable stakeholder participation in the firm's activities are instances of actualized outcomes. Others include the elimination of accounting errors due to the inability to trace back ownership in long transaction chains, such as those that threatened JP Morgan's acquisition of Bear Stearns (Nofer et al., 2017). Incorporating blockchain into auditing and accounting practices reduces clients' incentives to misreport and auditors' sampling costs (Cao et al., 2019). Table 1 provides more textual references to the actualization phase for all domain affordances.

Assimilation Phase

Basole (2018) identified assimilation and productivity as the apex of a hyped technology's maturity and argued that "assimilation accelerates rapidly as a result of productive and useful value" with the technology experiencing a sharp uptick known as "hockey stick" (p. 4965). We next present findings that illustrate the importance of assimilating actualized blockchain affordances to extract sustainable business value during implementation.

Regarding assimilation with A1, direct payment settlement, a firm understands how the new trust mechanism of the blockchain impacts transaction cost and how it applies to its unique case (Iansiti & Lakhani, 2017; Lindman et al., 2019). The new and underlying blockchain trust mechanism (distributed trusting where users trust other users to the extent that those other users appropriate blockchain technology, albeit anonymously) enables direct transactions without third parties, which will continue to minimize transaction costs for the majority of the network of users (Miscione et al., 2018). Toufaily et al. (2021) speak to the transformation process associated with enterprises setting cost-efficient transactions through sacrificing blockchain trust and disintermediation design properties. Jagtiani and John (2018) discuss that sub-optimal high (rather than low cost) transaction prices may be associated with actualized processes in DLT-based settlements and warrant some degree of coordination with relevant authorities. Thus, the implementation goal needs to have a transformative agenda that aligns with mitigating such future value-inhibitive processes and should be considered as value-enabling processes at the direct transaction affordance actualization stage.

Regarding assimilation with A2, efficiently robo-automate transactions, implementers consider sustainable process efficiency improvements in time, quality, and cost (Lee et al., 2015). The gains in reducing delays and errors with automated transactions (Du et al., 2019) must be noticeable, communicated, and sustained through the implementation of blockchain investments. Innovative business models such as automated money and autonomous economic agents will create transformative impacts (Toufaily et al., 2021). "[For blockchain] to be accepted on a wider range, blockchain technology should prove that it can do better than the existing infrastructure in terms of speed, efficiency, and costs" (Holotiuk & Moormann, 2018). Thus, value gains from process efficiency are sustained when implementation best practices are established over time beyond short-term actualized blockchain practices.

For A3, monetary and illiquid asset transactions, assimilation refers to the case where a firm goes beyond the single-use case of leveraging the availability of blockchain records to prove solvency to use cases that create sustained complementarities among virtual assets, customers, and machines (Schlecht et al., 2020). An asset-backed security financing where the firm implements a mediator business model is an example of the transformative use of blockchain to increase adopters' network and value (Chong et al., 2019). This results in new digital business models while expanding the utilization of the implemented blockchain platform.

Regarding assimilation with A4 appropriation of structured and query-able big data, a firm's implementation activities establish and utilize blockchain's big-data value via real-time analytics and the appropriation of structured data models (Pflaum et al., 2018). Blockchain data standards and interoperability are critical for accelerating blockchain technology diffusion and maximizing its implementation value (Holotiuk & Moormann, 2018). A firm can leverage the cybersecurity potential of the blockchain with rapid real-time big data analysis to assimilate its reputation regarding robust security improvements and avoidance of data breach incidences (Toufaily et al., 2021). Hence, businesses can implement policies regarding blockchain data privacy concerns in usage routines – in terms of personal and sensitive data and information sharing (Toufaily et al., 2021). Also, navigating difficulties associated with data regulations compliance is an important transformative goal to sustain the actualized technology practices (Toufaily et al., 2021). Blockchain-enabled high-level big-data modelling assimilation will aid the creation and application of decentralized, trustworthy, and explainable artificial intelligence (XAI) for optimized value in autonomous decision-making (Angelis & Ribeiro da Silva, 2019; Nassar et al., 2020). At the minimum, various machine learning (ML) training models can be put on the blockchain, then shared among all ML stakeholders to give real-time access to information needed by all participants, without the need for a central cloud-based server (Cognilytica, 2018; Tanwar et al., 2020).

Assimilation with A5 enhanced financial reporting explores how effective financial reporting with blockchain could provide quality market signals for generating long-term firm value. One way of achieving this is via effective smart contract regimes. An audit contract (AC) can be leveraged to observe and report denied access control requests and suspicious accesses encoded dynamically by specific rules (Belchior & Correia, 2020). Business logic rules can be implemented to sustain enhanced accounting processes, translating into widespread adoption of the technology and long-term effective IT practices. Reducing clients' incentives to misreport (an actualized outcome) will allow firms to reallocate efforts from transaction-based auditing to discretionary account auditing. These assimilation activities will increase the blockchain implementation value attributable to the reduction in both time and cost of prior resource allocations (Cao et al., 2019).

Value-related affordance interdependences (VAI) among affordance-to-assimilation domains. Interconnections exist among evaluation factors underpinning blockchain implementation (Labazova, 2019).

Even at the affordance level, identifying dependencies among affordances is critical to the success of implementation (Strong et al., 2014; Volkoff & Strong, 2017). Interdependency is a central concept in the strategic management literature, existing at varying levels among firms' activities (Lenox et al., 2010). Viewing the five affordance-experimentation-actualization-assimilation links as implementation domains for value creation, we next discuss the affordance interdependencies among these domain activities.

First, we find value-related affordance interdependency between A1 direct payment settlement and A3 monetary and illiquid asset transactions. These domains reflect the “new value-laden forms of transaction settlement” and “increased asset accessibility and use of new systems of collateralization and solvency,” respectively (see Figure 2). Transaction costs arise due to bounded rationality, opportunism, environmental uncertainty, and asset specificity during resource exchanges, and blockchain technology can reduce transaction costs while ensuring the integrity of the exchanges via the use of verifiable smart contracts, non-dependency of third-party intermediaries, and the assignment of assets via tokenization (Ahluwalia et al., 2020).

Furthermore, actualizing A3 monetary and illiquid asset transactions increases stakeholder monitoring (Chong et al., 2019), decreases information asymmetry between finance-serving and finance-seeking firms (Ahluwalia et al., 2020), further reducing costs associated with financial service transactions (Chong et al., 2019; Du et al., 2019). This reduction is possible because blockchain provides a system that instils trust and removes the uncertainty about firms’ opportunistic behaviours. Therefore, there is an increased surety that each firm will honour its respective financial obligations, which can then be collateralized for increased value in the borrowing costs for all parties. The discussion points to the ability of firms to leverage the infrastructural core involving A1 to develop A3 and vice-versa. To surmise, we propose the existence of a value-based affordance interdependency between A1 and A3 affordance-to-assimilation mechanisms (A1-A3 VAI).

Chong et al. (2019) analysed five blockchain implementations to provide evidence for the existence of value interdependencies in mechanisms involving A1 direct payment settlement and A4 appropriation of structured and query-able big data, A2 efficiently automate transactions

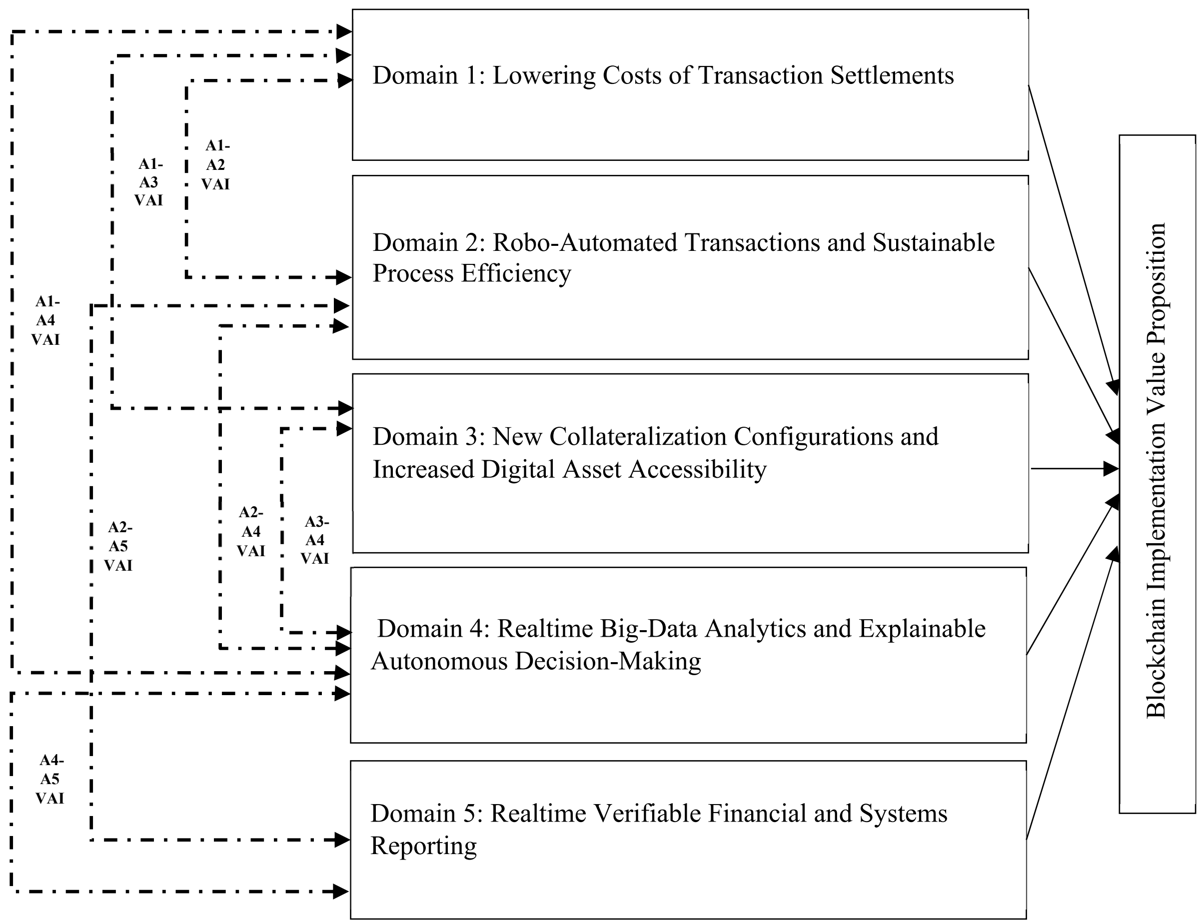

Figure 2**:** Value-Related Affordance Interdependencies Among Five Affordance-Experimentation-Actualization-Assimilation Domains[10]

and A4 appropriation of structured and query-able big data, and A3 monetary and illiquid asset transactions and A4 appropriation of structured and query-able big data (pp. 1336-7). For

[10] Domain (or affordance domain or affordance-to-assimilation domain) describes the entire elements of higher-level affordances and their respective experimentation processes, actualization, facilitating conditions and assimilation. Hence there are five domains. Interdependencies are between domains although largely anchored on the higher-level affordances by which the domains are named.

example, in the implementation of a blockchain-enabled interbank payment and settlement system, repeated usage of the system would lead to an accumulation of data on the interbank cash transfers, which could, in turn, generate value by improving the cash demand forecasting for commercial banks (p. 1336). This case exemplified the strategic goal of assimilating A1 direct payment settlement and showed how the implementation would lead to actualizing A4 appropriation of structured and query-able big data. Similarly, other stakeholders on the chain can implement A1 by leveraging the assimilation of A4 for a data model business proposition. This case analysis provided evidence for a value-based affordance interdependency between these two affordances (A1-A4 VAI).

The actualization made possible by the level of automaticity and coherent data processing (Pedersen et al., 2019) allows blockchain technology deployment to have realized "value from provenance tracking in supply chains at a faster rate than in banking and financial services" (p. 99). In a blockchain implementation case analysis on a rice supply chain business in China (Chong et al., 2019), the use of blockchain traceable features provided an avenue for transforming and innovating the traditional food industries via quality assurance of the production process and the manufactured products, the facilitation of logistical distributions, and the boosting of farmers' real income. With automatic triggers, a set of systematic standards for product traceability is created to upend pre-existing business practices, exemplifying the strategic goal of assimilating the actualized A2 efficiently automate transactions. Additionally, by combining blockchain with Internet of Things (IoT) sensors, the actualization and assimilation of A4 structured and query-able big-data become dependent on the platform created for A2 efficiently automate transactions. Burkhardt et al.'s (2019) design and analyses of autonomous assets also support this value interdependency. The case discussion above provides evidence for a value-based affordance interdependency between A2 and A4 (A2-A4 VAI).

A strategic goal of the implementation case above is to boost farmers' real income. With such a goal, the stakeholders could actualize direct payment settlement (A1) by leveraging the underlying infrastructure to automate transactions (A2) to create more value efficiently. Realizing this potential would, in turn, facilitate the assimilation of A2 because more process automation with high process efficiencies would ensue, creating added value in the long run. Lu et al.'s (2019) review of blockchain applications, opportunities, challenges, and risks support this value interdependency. Therefore, we propose a value-based affordance interdependency between A1 and A2 (A1-A2 VAI).

Chong et al.'s (2019) analyses of a case involving a financial subsidiary of a Fortune 500 Chinese e-commerce company (pp. 1322-1324) reveals an affordance interdependency in how the subsidiary exploited data resources to offer sophisticated financial solutions in asset management, consumer credit, payment, supply-chain financing and trading in secondary markets. The company leveraged blockchain to set up a data model enabling the network of firms on the blockchain to prove solvency and accrue benefit by receiving asset-backed securities (ABS) quickly. The implementation success was, in part, based on pricing ABS by a data-driven method that demands the standardization of securities and keeping track of large transactions securely. In addition, the actualization of blockchain big-data affordance (A4) was being leveraged to ensure firms secure cheap loans (i.e., actualizing A3 monetary and illiquid asset transactions). Further, as firms trade in the secondary market, the practices enable more business data whose value-potentials can be actualized. Thus, implementing firms can use customer data to improve business offerings while collateralizing this data to attract more customer engagement. Based on the discussion, the present study identifies a ***value-based*** affordance interdependency A3 and A4 (A3-A4 VAI) to improve multi-goal blockchain implementation outcomes.

Two examples support the affordance interdependency between domains involving A4 structured and query-able big data and A5 enhanced financial reporting. First, implementing Depository Trust & Clearing Corporation's (DTCC's) Trade Information Warehouse with the help of Axcore digital ledger – a blockchain platform – would store records for about 50,000 accounts to eliminate silos of databases provide a single real-time business analysis of structured trade data. These financial information records cover $10 trillion worth of credit derivatives, and DTCC can keep financial records of about 90 million transactions a day (del Castillo, 2019). Apart from the accounting services use case, which underlies the Axcore blockchain platform's implementation, the firm can also appropriate structured big data for real-time analyses. The second example is T-Mobile’s blockchain implementation of NEXT Identity blockchain to improve the company’s and customer data management so that only those defined by the company's auditors can access sensitive data (Debter et al., 2020). The interdependency exploitation is seen in the company’s implementation of wholesale roaming agreements with customers, further increasing the volume and velocity of transactional data using the same platform implemented for the NEXT project. In light of the discussion on how a single blockchain implementation is used to actualize A4 and A5, we propose a value-based interdependency between A4 and A5 (A4-A5 VAI).

In another real-world use-case analysis, Perboli et al. (2018) discuss certifiers and auditors’ roles in the automatic traceability of products within the supply chain system. Financial nodes could act as standard inspectors to enrich the solution modalities for automatic fresh food delivery blockchain systems. Finally, Chong et al.'s paper demonstrates how financial statements can be generated automatically via blockchain to reduce operational costs, further illustrating the existence of a value-based interdependency between A2 and A5 (A2-A5 VAI).

"The validation dimension of blockchain presents an opportunity to create digital claims on assets in the supply chains and engage in the trading of these assets" (Babich & Hilary, 2019, p. 9). Thus, although implementers may perceive the potential of blockchain for securing information quality, decentralized identity management features such as immutability and tokenization in facilitating this affordance provide an opportunity for trading illiquid assets (A3), signifying a value-based affordance interdependency between A3 and A5 (A3-A5 VI).

We provide an overarching framework for understanding the relationships between blockchain IT artifacts, characteristics, and functionalities and the proposed AEAA model for value creation in Appendix A.

Discussion

This study applied the affordance perspective to exploit blockchain implementation business value. Our systematic literature review analyses, guided by AEA theory, support and redefine three existing blockchain implementation affordances proposed in AEA (Du et al., 2019). In addition, we find two more affordances critical for a firm's effective blockchain implementation and propose a new AEAA theory by revealing how assimilation beyond actualization goals is critical for blockchain implementation.

Theoretical Contribution

The current research has three main theoretical contributions. First, we propose an assimilation phase to the existing affordance, experimentation, and actualization phases for firms to extract optimized business value post-implementation, especially for emerging technologies.

An assimilation phase goes beyond actualization because it is characterized by realizing the transformative capability of the blockchain (Murray, 2019). Noting this transformative phase, Post et al. (2018) argued that blockchain technology diffusion across industries is affected by strategic, tactical, and operational factors such as necessary collaboration between actors and blockchain artifacts, market position adoption, knowledge deficit, viable use cases, and technical shortcomings. The AEAA framework addresses these underlying factors in terms of how they influence each delineated affordance-to-assimilation mechanism. A lack of an assimilation phase hampers the success of the blockchain implementation and firm value proposition because sustained effectiveness of the implementation mostly depend on what stakeholders do post implementation. Together, the affordance-experimentation-actualization-assimilation consideration provides a broader yet parsimonious lens that fully explicates Iansiti & Lakhani's (2017) framework of four phases: adopting single-use applications low in novelty and complexity, adopting localized applications, adopting substitution applications, and adopting transformational applications (Farahmand & Farahmand, 2019).

Second, we identify two more bundles of affordances that contribute to effective blockchain implementation within the firm. The data-related affordance (A4) shows implications for big data analytics and firm value. This affordance-to-assimilation mechanism contributes to the data analytics literature as it offers an avenue through which the blockchain-related impact of big-data analytics can be studied inter-organizations regarding decentralized business model transformations (Du et al., 2020). The financial reporting-related affordance-to-assimilation mechanism (A5) is also critical to guide blockchain implementation as firms look to improve real-time financial and system audit decision-making as well as private investor and shareholder confidence. This affordance, therefore, has implications for the IS fintech literature and value realization. Further, we extend the three existing affordance-to-actualization mechanisms proposed by Du et al. from financial technology goals to non-financial implementation goals.

Third, this study contributes to the blockchain affordance literature by mapping the interdependencies within the five higher-level affordances. We argue that each AEAA mechanism is not an isolated event but relational (Strong et al., 2014; Volkoff & Strong, 2017). These interacting affordances perceived by implementers influence each other in creating value during blockchain implementation. This is evidenced in our findings which show how the potential to implement blockchain in one affordance-to-assimilation domain opens an opportunity for future implementations in another affordance-to-assimilation domain. The interdependency leads to the transformation premised on actors' shifting goal-orientations from actualizing given situations affordances to assimilating effective preferences that are strategic, long-term, and have broader considerations (Lange & Balliet, 2014). It is in the assimilation stage of blockchain implementation that more value-laden repeated patterns will suffice, be encountered, and entrenched, making implementation payoff more stable. The current worrisome level of uncertainty regarding blockchain implementation outcomes to organizations (Seebacher & Schuritz, 2019) warrants such assimilation sub-lens if implementation value is to be effective, adaptive, yet beneficially stable over the long term.

Practical Implications

The current research has four notable implications. First, managers can apply the AEAA framework to inform blockchain implementation when creating business models based on diversified goal-oriented value streams within the blockchain ecosystem beyond liquid asset transactions. For example, the assimilation component will help managers better understand how to maximize value post blockchain implementation (X. Zhang, 2019), and the five assimilations help them justify the blockchain investment better.

Second, managers can view value-based affordance interdependencies as opportunities to develop novel use-cases beyond original implementation goals. These offshoots will maximize the value associated with blockchain implementation while minimizing costs because of the economies of scale that utilize the underlying blockchain infrastructure. Lui and Ngai (2019) reported that strategic alliances for firms regarding blockchain might be less beneficial in the long run compared to the long-term value accrued by individual adoption. Long-term benefits may be in strategic alliances about the value interdependencies and not just strategizing around a core use case.

Third, the recommendation on how to operationalize the mechanisms proposed in this study provides a medium by which IT managers and firm analysts can assess the real monetary impact of their implementation activities amidst high uncertainties. Critical analyses of the recommended variables may be vital to increase the reliability of the value measurements when using AEAA to guide blockchain implementation. In addition, a face assessment of the value of a firm's proposed blockchain implementation can be performed during requirement analysis and use-case-to-be specifications using the AEAA framework.

Finally, our study has implications for industry players whose activities are affected by industry shifts. Profits are highest in industries with more extensive interdependencies, which positively skews these firms' performance distribution (Lenox et al., 2010). The mix of value interdependencies proposed in this study encourages firms' extensive use of interdependencies within and across industries because blockchain value interdependencies can be considered cross-industry firm activities, and these arguments hold for within-industry firm activities.

Within industries, the identification and appropriation of similar blockchain use cases between firms present cross-domain effects that can be exploited for firm performance via our proposed value interdependencies.

Conclusion, Limitations, and Future Research

Based on a systematic literature review and analysis from an affordance perspective, we proposed an AEAA blockchain implementation framework for organizations to explore their implementations' entire value proposition irrespective of the appropriated blockchain use case.

Our study has the following limitations and directions for future research. First, while the proposed framework will improve value creation during blockchain implementation, further contextual subjections across industries and exploring affordances of specific blockchain archetypes will improve its robustness, theoretical reach, and application. Thus, future studies may differentiate AEAA for permissionless blockchain affordances from public-permissioned or private-permissioned blockchains. Second, our study may also be limited by discipline-specific sample selection bias as disciplines other than IS field may construe blockchain value differently. Third, the current blockchain ecosystem is characterized by the rapid development of the blockchain design feature, which implies new advancements in platforms' capabilities and lowers adoption barriers that will further impact future implementation. Future research could consider AEAA-backed blockchain value co-creation considering newer dynamic capabilities of the blockchain. Lastly, our study suggested several constructs to be operationalized for quantitative investigations across the various affordance-to-assimilation value chains, but these have not been assessed for their nomological fits. Future studies may provide a quantitative evaluation of the framework for generalizability and nomological validity.

CHAPTER III

BLOCKCHAIN TECHNOLOGY POSITIONING INVESTMENT: AN EMPIRICAL INVESTIGATION OF FIRM GROWTH OPTIONS

"…asset prices in a portfolio may co-vary and exhibit different levels of correlation relative to shocks in marketplace, and in the same way, IT projects will covary in their potential payoffs with respect to strategic shocks that impact a company and its markets"- Rob Kauffman

(Tallon et al., 2002, p. 155)

Introduction

Organizations scout the potential business value with every emerging technology and blockchain technology is no different (Floyd, 2018). With blockchain, firms can improve their business value proposition because it affords a distinctive value-laden decentralized business modeling (Chong et al., 2019; Seebacher & Schuritz, 2019). However, the paucity of evidence on blockchain benefit dynamics hampers firm justification of blockchain investments. (Li et al., 2018; Lui & Ngai, 2019). A qualitative evaluation of 517 blockchain projects identifies a lack of clear problem definition and requisite project-backing as hindrances to justifying investments in blockchain solutions which may explain unexpected negative investment payoffs (Naqvi, 2020). In one instance, Overstock – a US company which generates about $1 billion in revenue – spent over $200 million in 18 early-stage blockchain implementation ventures but did not receive meaningful financial returns on its investments (Debter et al., 2020). While firms that indicate blockchain investments see positive abnormal returns within the first three months, the returns become negative after five months (Jain & Jain, 2019). To the contrary, empirical evidence suggests a higher return on investment in the long term for blockchain-adopting firms with a less collaborative strategy (e.g., Lui & Ngai 2019). Investments in blockchain technology also present complex and diverse implications and tradeoffs in risks, scalability, and security about the different blockchain ledger type. The unique complexities warrants scholars to improve theories of IT business value and business managers to apply new theories in IT effects, if positive returns are to be realized (Toufaily et al., 2021). Against this backdrop, our first research question examines broadly *whether blockchain investments lead to positive firm value (RQ1).*

Financial payoffs from IT investments are predominant when IT managerial capabilities and processes supplement the IT investments made (Mata et al., 1995; Turel & Bart, 2014). Thus, having ascertained the need to invest in blockchain technology, firms must navigate the necessities of effective adoption or implementation actions that extract value to realize the positive impact of their blockchain investments (Du et al., 2019; Pedersen et al., 2019). Moreover, expected benefits from IT investments tend to delay, especially for large project sizes, which negatively impacts the implementation timelines, the rapid integration of the IT into business processes, and stakeholders' acceptability of the technology (Brynjolfsson, 1993; David, 1990; Dehning et al., 2005). These exacerbate firms' challenges of identifying and justifying blockchain investments already riddled with uncertainties regarding the right investment option for potential adopters (Kannengießer et al., 2020). Nascent network technologies such as blockchain are also characterized by cross-sector stakeholder debates on expected maturation impacts adding to the levels of uncertainties perceived by potential adopters (Kannengießer et al., 2020; Toufaily et al., 2021). When faced with such challenges, IT business value theorists suggest application of real option perspectives to capture the upside of uncertainty minimization efforts, the irreversibility in investment initiatives and the conversion contingencies (managerial growth actions) that help to deal with the uncertainties in the investment cycle (Fichman, 2004). The embedded 'growth' options within IT infrastructure projects gives firms a 'right' but not an obligation to initiate contingent future projects or take intervening actions (Kambil et al., 1993; S. S. Khan et al., 2013; Taudes et al., 2000). Other financial valuations such as Net Present Value (NPV) rules are easy but do not handle impact of significant uncertainties associated with IT investments and assumes that capital investments are reversible and cannot be delayed (Dixit & Pindyck, 1995).

Yet, regarding firms' investments in blockchain technology, existing empirical research, e.g., (Bowman & Steelman, 2019; H. Kim et al., 2020; Lui & Ngai, 2019), is challenged by the omission of necessary conversion contingencies due to a non-application of IT (real) option perspectives and inappropriate locus of value (Davern & Kauffman, 2000) in analyzing technology's impact in the estimation model[11]. This research emphasizes the blockchain being an archetypal network technology[12] and identifies the archetypes of blockchain technology as the more strategic loci of value in understanding firm performance of blockchain investments (Rossi et al., 2019; Walsh et al., 2016; Weking et al., 2020). Leveraging the strategic management and IS literature on the determinants of IT option value, we address the following research questions

[11]The locus of value is the specific level of analysis chosen by a firm to exercise their value conversion contingencies that transform potential value of a technology to realized value (Davern & Kauffman, 2000). Conversion contingencies act as moderating and intervening factors that can transform potential value of firms' IT investments into realized value and consequently return on investment (Davern & Kauffman, 2000).

[12] Blockchain is identified as an archetypal network technology for the following reasons: Three different archetypes public-permissioned, private-permissioned and permissionless can be adopted. The internal system of decentralized network of peers/nodes is a basic component of all the archetypes for the purposes of technical functionality. This is different from software versioning and separate from the network effects resulting from increased utilization of a technology by adopters. This archetypal network technology is also different from social network technologies such as Facebook or Twitter.

to explicate any assertion of a positive firm performance with blockchain investment: *How do blockchain archetypes of different degrees of centralization (permissionless, public-permissioned, and private-permissioned) affect the business value of blockchain adoption? (RQ2). Which firm-specific blockchain strategy, learning and bandwagon factors affect the business value of blockchain adoption investment? (RQ3)*

We utilized a multi-quarter panel dataset of public US firms constructed by the researchers from multiple data sources. These firms have made blockchain adoption investments through the development, acquisition, or deployment of blockchain solutions, which offer the opportunity to quantitatively estimate the value of blockchain technology options exercised by the firm. These investments have been announced with supporting evidence of their validities and assessed by the researchers via Factiva (Lui & Ngai, 2019) and firm website publications. Based on propensity score matching technique and fixed-effects analysis, we find that, overall, investments in blockchain technology lead a positive Tobin's q. We also find that investments in all three blockchain archetypes lead to increases in the Tobin's q. Surprisingly, investments in a more decentralized archetype and the implementation of a second different archetype are associated with a negative Tobin's q. We also find that blockchain patent originality, participation in blockchain events, and network externality positively impact firm performance, whereas the effect of blockchain patents is negative.

In the following sections, we review the related literature and theoretical background to our study, develop hypotheses to assess the research questions, discuss our data and methods, present findings of the analysis and discuss the study's contribution to theory and practice. Finally, the conclusion section, which includes limitations and future directions of the study, is presented.

Literature Review: Blockchain Business Value

The literature on estimating firm value concerning enterprise IT investments can be categorized into the process-oriented and firm-value approach (Dehning et al., 2005). Most firm-value approaches apply event studies of IT investment announcements and econometric analysis techniques to explain new information that impacts firm value (Dehning et al., 2005; Ji et al., 2020; Wijayana & Achjari, 2020). Compared to existing enterprise technologies, blockchain is built on the concept of distributed ledger enabled an internal infrastructural network of anonymous peer-to-peer (P2P) nodes without which blockchain ceases to function as a decentralized and immutable ledger technology (Chong et al., 2019; M. A. Khan & Salah, 2018). In addition to the network externalities associated with IT adoption, blockchain technology may present new network information not addressed by prior firm value approaches to IT evaluation.

Empirical studies using text analytics, event studies and econometric modeling (Cahill et al., 2020; Jain & Jain, 2019; H. Kim et al., 2020; Lui & Ngai, 2019) of blockchain value is growing. For instance, Lui & Ngai's (2019) event study on blockchain adoption announcements from Factiva find the abnormal rate of return for collaborative and individual strategic blockchain investment dips from 5.4% in the sixth month to 2.3% in the ninth month, 1.9% in the twelfth month but a return of 3.4% was recorded for the third month. Given that returns dip over the period of study for certain strategies, assertion that “blockchain’ offers long-term benefits is less robust. Using latent Dirichlet allocation (LDA) topic modeling, Yen & Wang (Yen & Wang, 2021) also find firms’ disclosures of involvement in blockchain technology solutions and associated risk factors to favorably impact their market value. Whiles most of these studies focus on blockchain’s strategic adoption impact (i.e., individual or collaborative strategy), we contend that the salient roles played by the various blockchain network archetypes (private-permissioned, public-permissioned, and permissionless) will offer much theoretical granularity to explain financial returns because each archetype represents different value configurations.

Examining strategic blockchain impact via collaborative and individual categorizations may lead to highly sensitive and more biased estimations of their impact on firm performance because of the underlying assumption that private-permissioned archetypal adoption is synonymous to an individual strategy while both public-permissioned and permissionless archetypes are categorized as collaborative. However, the underlying decentralized configurations with respect to users' accessibility and transaction validation rules (Rossi et al., 2019) means that public-permissioned configuration share close affinity with private-permissioned ledgers than with permissionless ledgers. Thus, although their value delivery architecture may be similar for the same decentralized network (Chong et al., 2019), each archetype presents a degree of decentralization that affect managerial actions and project performance differently (Bian et al., 2018). Firms may adopt multiple archetypes as a matter of strategic necessity and not frivolity. Furthermore, perspectives on categorization and category meaning (Durand et al., 2017; Durand & Khaire, 2017; Lamont & Molnár, 2002) emphasizes the need for boundary creation to present a cognitive schema of shared meaning for understanding and evaluating a product. These perspectives [13,14] support the importance of identifying the most appropriate locus of value which is the appropriate strategic level for categorizing and analyzing blockchain impact to avoid severely biased empirical findings (Davern & Kauffman, 2000).

[13] Categorization refers to grouping of things that facilitate the understanding of what surrounds us by establishing boundaries among entities or products – in this case, blockchain as decentralized technology.
[14] Category meaning provides the cognitive schema that allows audience to easily understand and evaluate products based on shared meaning about the collective identities of the products – in this case, how accessibility and validation of transactions on a blockchain are determined following Rossi et al. (2019)

Moreover, clearly defined boundary conditions and uncertainty relationship influences technology option value (Mcgrath, 1997). Strategically, a firm can position its technology investments (i.e., amplify option value) via productive routines and/or appropriate timing of its exercises that shift defined boundaries to address prevailing uncertainties (Mcgrath, 1997). Specifying archetypal boundaries with blockchain investments therefore affords the measurement of ensuing boundary shifting activities by firms about the selection and appropriation of the archetypes in dealing with the uncertainties of blockchain adoption.

While traditional financial metrics (e.g., discount cash flow (DCF) firm-value approaches, NPV analysis, internal rate of return (IRR) and return on investment (ROI)) can be used in analyzing the impact of blockchain archetypes, their underlying assumption is that capital investment is reversible and cannot be delayed (A. K. Dixit & Pindyck, 1995; E. S. Schwartz et al., 1994). Applying this assumption of traditional economic models to blockchain investment valuation presupposes that the technology is matured, rather than emerging (D. Schwartz & Merhout, 2019)., and has more certain lower and upper payoff bounds for investors. On the other hand, the real options valuation of IT investments (Alessandri et al., 2012; Benaroch & Kauffman, 2000; Fichman, 2004; E. S. Schwartz & Zozaya-Gorostiza, 2003) asserts that firms could better harness business value of IT investments when the uncertainties surrounding the return on investments are high, and there is greater managerial flexibility to control the stages of the IT project implementation (Fichman, 2004). Such uncertainties during investments also create opportunities to exercise greater firm discretions and decision-making for value creation (Dixit & Pindyck, 1994; Schwartz & Trigeorgis, 2016). Regulatory uncertainty and trust dynamics remain the highest sources of uncertainties among adopters (Kannengießer et al., 2020; Stanley, 2018). For emerging technologies, uncertain costs could arise from bets on whether technical advancements will become standardized and the future costs associated with building on the standard which is unknown today (Benaroch & Kauffman, 1999). In such circumstances, traditional metrics (which only suggests immediate investment once there is an indication of expected positive net payoff present an asymmetrical value view (Lepak et al., 2007)) inhibits further innovation (Fichman, 2004) and undervalues IT infrastructure projects since the value of managerial interventions during the project course is ignored (Khan et al., 2013; Taudes et al., 2000).

This research exploits the impact of strategic blockchain archetype adoption investments among US public firms operationalizing technology and a host of option determinants that serve as conversion contingencies to broadly quantify the magnitude of financial returns of firm blockchain investments as measured by Tobin's q (firm growth option value or the business value). As such, the impact of narrower empirical perspectives such as innovation value (i.e., blockchain patenting impact) on firm performance, e.g., (Bowman & Steelman, 2019; H. Kim et al., 2020), are addressed. We leverage Fichman's two-stage technology options value creation model to develop our hypothesis for empirical testing. We use this model because it is developed on the assumptions of real options and encompasses the criticality of rationalizing the process-oriented IT approaches while estimating the import of firm-value approaches in firm value estimation.

Theoretical Background: Fichman's Two-Stage Options Value-Creation Model

Fichman's model (Fichman, 2004) leverages real options theoretical assumptions and proposes that firm can better position their IT investments by the option value created from four main antecedents (determinants): 1) the technology strategy perspective, 2) the organizational learning perspective, 3) bandwagon perspective and 4) technology adaption perspective. The proposed determinants can increase uncertainty and/or increase managerial flexibility (Fichman, 2004). If the determinant can increase the expected value of potential payoffs, it will lead to increase in the variance of payoffs or further increase in managerial flexibility, and hence the option value of the technology asset under investment (Fichman, 2004). Yang et al. (Yang et al., 2012) used this model to empirically evaluate the market response to virtual world initiatives (VWI) and found that the VWI are contingent on only four characteristics: strategic importance (technology strategy), exploitable absorptive capacity (organizational learning perspective), and interpretive flexibility and divisibility (technology adaptation). The findings suggest that certain determinants and underlying characteristics (parameters that measuring the perspective) may be salient for one IT and non-significant for another.

Scholars and practitioners point to a growing public interest in understanding the quantitative impact of blockchain technology on the firm (Risius & Spohrer, 2017). "The goal [of blockchain firms] is to achieve a form of organization with collective work and value generation in a decentralized economic environment" (Scholz & Stein, 2018). The type of marketplace implementation of value delivery architectural configuration informs the creation and sustainability of competitive advantage for Fintech firms (Kazan et al., 2018). With each blockchain archetype informing a different type of decentralized marketplace implementation and signifying a characteristic strategic goal of the firm, the business value created for each blockchain archetype investment will be different. (Bauer et al., 2019) argue that blockchain enables value creation via shared operational efficiency, distributed product innovation, increased access to customer data and controlled customer intimacy associated with managing tradeoffs between unpermitted control inherent in the blockchain network. The finding suggests dynamics in value creation with the different blockchain archetypes and the representation of the technology strategy perspective as with Fichman's model. The choice of investing in blockchain archetypes also presents a setting for exploiting internal and external conversion contingencies during the firm's blockchain strategic moves. Fichman stated that "a determinant will be considered to increase option value if it tends to increase the expected value of potential returns, increase the variance of potential returns, or increase managerial flexibility in the structuring/exercise of [the] options" (Fichman, 2004, p. 140). The internal conversion contingencies are explained in Fichman's model by the organizational learning activities towards lowering of knowledge barriers and innovating new products whereas the external conversion contingencies are the bandwagon perspectives afforded by the technology adoption beyond the direct influence of the focal organization.

Hypotheses Development

Overall Blockchain Investment and Firm Performance

Prior research has studied the relationship between IT effects and firm performance (Bharadwaj et al., 1999; Dehning et al., 2005). For example, Tafti et al. (Tafti et al., 2013) suggest that different dimensions of IT architecture flexibility affects the formation of strategic alliances which enhance firm value. Of note, IT investments that target collaborative alliances via intensive resource reconfigurations present greater value (Tafti et al., 2013). The value delivery architecture of a firm's digital business model revolves around technological resource exploitation and configuration (Al-Debei & Avison, 2010). Blockchain technology as a new digital resource with its sustaining distributed architecture, its promise of robo-automations and decentralized transformation of business processes afford firms new value configurations to improve their performances (Chong et al., 2019; Crosby et al., 2016).

Given that firms are announcing their blockchain investments (Cahill et al., 2020; Lui & Ngai, 2019), in addition to the noticeable rapid developments in the blockchain space, potential investors are likely to monitor the progress of firms blockchain-related strategic actions (configurations actions) and their exploitative or explorative moves in newswires, social media, firms' omnichannel, and financial statements following such disclosures. Yen & Wang (Yen & Wang, 2021) find firms' disclosures about their blockchain technology solutions in 10-K filings to positively influence firm performance whereas disclosures about bitcoin of transactions (a specific use-case of blockchain technology) are negative. The market has a growing and vested interest in blockchain technology even if investor motivations vary (Mattke et al., 2021). Modeled information from blockchain interactive platforms favorably predict firm market value (Zhang et al., 2020). These blockchain information channels affect firm value because they provoke sentiments among investors (Porshnev et al., 2013). Sentiments affect how investors respond to a firm's stocks and consequently the future growth options available to the firm (Bollen et al., 2011; Bryan, 2016).

Blockchain, thus, provides new decentralized resources for creating truly novel products and services (Chong et al., 2019). Blockchain ledger adoption also expands specific managerial options in decision-making and construe new IT capabilities to deal with increased level of investment uncertainties (Kannengießer et al., 2020; Nærland et al., 2018; Stanley, 2018). By the increment in managerial growth activities, investors are informed of the high value potential of the technology that undergirds positive sentiments towards adopting firm, provoking positive expected returns. Therefore, we posit the following:

Hypothesis 1 (blockchain investment firm value hypothesis, H1). Blockchain technology adoption is positively associated with firm value.

Blockchain Strategy Perspective and Firm Value

Fichman's (2004) options value-creation model identifies innovation activities as explanatory of firms strategic actions that can increase option value because they build or reinforce competitive advantages. Innovation activities can be radical leading to competency stretching (McDermott & O'Connor, 2002). In radical innovation, firms' unique scientific, manufacturing, and market knowledge (resources) are turned towards effectively new ventures (i.e. radical products toward the marketplace) that entail significant market and technological risks (McDermott & O'Connor, 2002). Radical innovation is mostly generally associated with high expected returns (higher firm value) because of increased managerial flexibilities (Yang et al., 2012).

Blockchain technology adoption is radical innovation because it presents sets of newly installed functionality that is the foundational architecture compared to incremental innovation in traditional technologies such as ERP (Beck & Müller-Bloch, 2017) and represents strategic actions by the firm (Chong et al., 2019). The blockchain infrastructure is the main underlying value delivery architecture for connecting network actors and configuring information and resource flow among these actors (Chong et al., 2019). The structural capabilities of the blockchain orchestrate technological resources towards other digital products and services (Chong et al., 2019; Kazan et al., 2015a) grounding blockchain ledger investments in the firm's resource-based view (RBV) of the firm. Notably, several firm performance discourses in relation to technology strategy perspectives have been inspired by the RBV of the firm (Bharadwaj, 2000; Mata et al., 1995; Turel & Bart, 2014).

The RBV theorizes the firm as a bundle of resources which contributes to sustained advantage if resource is valuable, if it is heterogeneously distributed among firms and, immobile (Barney, 1991; Fichman, 2004; Wernerfelt, 1984). Our prior arguments under hypothesis one posits the value of blockchain technology. Perhaps, Blockchain technology is a unique immobile resource considering that its distributed decentralized ledger rather has no single point of failure (i.e., the Byzantine Fault Tolerance problem). Immobility is underscored by the fact that blockchain technology resource cannot reside at a single node which heralds its observational difficulty arising from its causal ambiguity and social complexity (Fichman, 2004; Mata et al., 1995). The vast information network channels also make it most dynamic resource (as an IT architecture) for reconfigurations (Chong et al., 2019). Based on RBV, the blockchain-based strategic capability framework shows that firms can either build new capabilities with smart contract expertise and consortium-related managerial expertise or strengthen and leverage existing capabilities or share complementary capabilities through access to pooled data, risk sharing among partners and strengthening of collaborative relationships (Yuthas et al., 2021).

When a firm adopts blockchain technology, it may invest in one or more of the three archetypes of the technology – public-permissioned, private permissioned, and permissionless (M. Rossi et al., 2019). Process efficiencies maximizes strategic advantage in a given market (Lee et al., 2015) and we conjecture variations exist in process efficiencies among the different archetypes. As more investments is made in the same archetype, process efficiencies targeted at specific products and services will increase. So will growth options and the decision quality of managers. Therefore, we hypothesize the following.

Hypothesis 2a (blockchain archetype business value hypothesis, H2a). The number of each blockchain archetype (permissionless, permissioned, and private) adoption instances is positively associated with firm value.

Each archetype also represents a certain degree of decentralization that can influence the transformative business model of the firm (ShethVoss, 2018). The degree of decentralization is defined by the level of restriction and public access, and stakeholder validation dynamics of the platform (Kannengießer et al., 2020; Rossi et al., 2019). It has been shown to positively moderate the effect of leadership characteristics on the success of the projects (Bian et al., 2018).

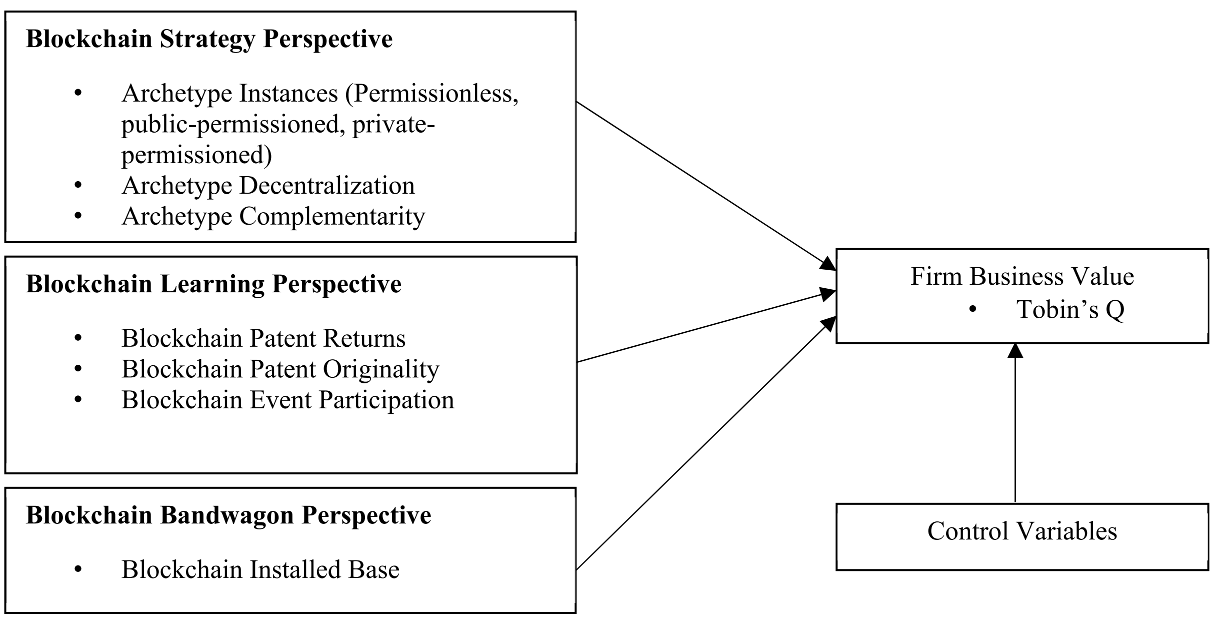

Figure 3: Research Model

Private-permissioned archetype is the most restrictive compared to public-permissioned while permissionless archetype is the most accessible ledger technology. Firms using permissioned distributed ledgers have higher throughput, better confidentially because of replications on only known nodes, and better maintainability because of less anonymity yet presents an expensive implementation of the three (Kannengießer et al., 2020; X. Xu et al., 2017). However, compared to permissionless, less decentralized archetypes are faced with relatively high cost of implementation because of low conversion technologies among adopters, high knowledge barriers, and high uncertainties stemming from lack of best practices. Thus, the risk of implementation is concentrated on few making the market less enthusiastic, culminating in a negative impact on firm performance. We therefore hypothesize that:

Hypothesis 2b (blockchain decentralized archetype business value hypothesis, H2b). The adoption of a more decentralized blockchain archetype (permissionless > permissioned > private) is associated with a higher firm value.

Further, the discussion so far suggests that the different combination of blockchain ledgers investment introduced into the firm business operations would produce different strategic moves leading to variations in their positive impacts on firm's growth options although the extent of capabilities and endowment will influence these strategic moves (Fichman, 2004; Turel & Bart, 2014). In essence, modeling a complementarity between different blockchain archetypes will provide understanding to the option created with multiple archetype adoption. Complementarity between different archetypes will underscore firms' managerial responses to uncertainty regarding blockchain technology. That is, firms are not sure which archetype will become the prevailing standard in the future, so they invest in multiple archetypes to maximize value outcome and minimize sunk costs or irreversible costs. Even if a firm is certain about the value of an archetype investment, what will work best for the specific firm and its future growth expansion may not be readily known. The complementarity between archetypes represents blockchain strategies available to managers for value creation. The study establishes the following hypothesis:

Hypothesis 2c (blockchain complementarity archetype business value hypothesis, H2c). Adopting a second different archetype is associated with a higher firm value.

Blockchain Learning Perspective and Firm Value

The evidence is overwhelming evidence that organizational learning improves firm performance (Do & Mai, 2021; Jiang & Li, 2008; Tippins & Sohi, 2003; W. Zhou et al., 2015). Rich organizational learning from firm's technological exploration and exploitation activities (Sambamurthy et al., 2003) enable better decision-making about IT because knowledge barriers to technology adoption are lowered and management of uncertainties about net IT investment payoffs are more effective (Fichman, 2004). Organizational learning will be hollow if organizations do not take a series of concrete steps and engage in widely distributed activities that construe either the generation, collection, interpretation or dissemination of information (W. Zhou et al., 2015). The unanimity among scholars that technological innovation strongly proxies for organizational learning is premised on the sense that firms engage in processes to exploit their current bundle of skills and routines while exploring new knowledge (Fichman, 2004; Yang et al., 2012; Zou et al., 2018).

Scholars have also underscored the close affinity of organizational learning to the concept of 'absorptive capacity' leading to organizational performance (Sun & Anderson, 2010; Todorova & Durisin, 2007). Absorptive capacity is a set of organizational routines and processes by which firms acquire, assimilate, transform and exploit knowledge to produce a dynamic organizational capability" (Zahra & George, 2002) or 'the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends" (Cohen & Levinthal, 1990, p. 128). Absorptive capacity is also defined as "a concrete example of organizational learning that concerns an organization's relationship with new external knowledge" (Sun & Anderson, 2010, p. 130). Increase in exploitable absorptive capacity eventually increases option value because of increased managerial flexibility in which firms follow-on IT investments are premised on the hope that future technological advancements will occur in the vicinity of the today's absorptive capacity acquisition (Fichman, 2004). As such, firms' technology patenting activities and participation in technology events contribute to present absorptive capacity acquisition because they expand the knowledge and skill base of the firm.

The granting of patents (patent returns) follows blockchain patent filing activities that are characterized by the exploitation of blockchain knowledge and awareness of related technology innovations. Patent applications and related activities are indications of the level of innovation readiness of the firm (Schoenhals et al., 2019) and strongly corroborate firms' willingness to improve their innovative capabilities that may positively influence future technological, strategic decisions (Fichman, 2004; Schoenhals et al., 2019). Firms use expert inventors and legal experts on the technology, utilizes established institutional knowledge, related literature and involvement of third-party investors, to improve the success of their returns (Schmidt, 2005; Vega-Jurado et al., 2008; Zahra & George, 2002). The patentability of IT software impacts the net payoffs regarding entry barriers of firms into the market, through the deterrence or promotion of new entrants, especially for firms without prior experience in the area of innovation (Cockburn & MacGarvie, 2011). By this, having patents serve as substitutes for complementary assets in the entry process (Cockburn & MacGarvie, 2011) and hence opportunities to increase growth options. Several artifacts underlying blockchain technology are also patentable (H. Kim et al., 2020) and thus provide more avenues for exploiting the upside potentials and downside risks of investing in blockchain technology.

Prior studies argue that a firm's patent returns grant intellectual property rights to the investor and provide legal protections to a firm's innovations (Andries & Faems, 2013; Cockburn & MacGarvie, 2011; H. Kim et al., 2020) and so patent returns are adequate proxies for firm technology innovation (Levitas & Chi, 2010). Acquiring blockchain patents therefore implies that firms have lowered their knowledge barriers for inventing new decentralized products and services. This absorptive capacity sends positive signals to investors of the a firm's innovation outlook (Zahra & George, 2002) in its engagement with blockchain technology. The market's positive acknowledgment of a firm's present and future blockchain-related product and service differentiation capacity will create additional resources for firms to undertake more growth actions. Consequently, amplifying growth option value of the firm. Therefore, we hypothesize:

Hypothesis 3a (blockchain patent returns business value hypothesis, H3a). Blockchain patent returns (number of blockchain patents granted) is positively associated with the firm value.

Firms have opportunities to increase the value of the option in their strategic decision-making because of uncertainties – a condition-precedent for the realization of option value embedded in patented IT assets (Levitas & Chi, 2010). Hence a more significant uncertainty bound increases the variation in managerial flexibility leading to increased option value on the upside. The examination of patent activities introduces a significant amount of value to uncertainty bound and impacts the firm realization of blockchain option value. In discussing patent returns, investors look to future benefits of new products creations therefore represents a forward-looking measure of patenting activities and associated organizational knowledge. Scholars argue that evaluating backward-looking measures of patenting activities provide rich information about the present quality of firm innovation activities (Gatteschi et al., 2018).

Bowman & Steelman (Bowman & Steelman, 2019) suggest that patent-related signals communicate potential value in emergent technologies to outside stakeholders (p. 5). Although forward-looking patent measures can positively affect firm value. The effect of blockchain patent returns may not apparent because the investment returns of blockchain adoption is not readily known (Gatteschi et al., 2018). We affirm a more constructive backward looking patent quality measure – the originality of blockchain patents. Kim et al. (H. Kim et al., 2020) asserts that originality of blockchain patents leads to positive firm value. Originality of patents shows the dearth and scope of patent knowledge utilized by a firm in its patent innovation activities (Koh & Reeb, 2015). Thus, the more original the blockchain patent is the more novel the invention. Such backward-looking patent-citation measure provide contemporaneous information that is more time-sensitive for investors to assess firm's economic prospects (Harrigan et al., 2018, p. 1). Increasing originality will signify a more quality innovation activity of the firm provoking positive reactions from investors and hence firm value. Our discussion leads to the following hypothesis.

Hypothesis 3b (blockchain patent originality business value hypothesis, H3b). Blockchain patent originality is positively associated with firm value.

The blockchain space is characterized by meetups, conferences, workshops, technology and science fairs and exhibitions that firms can participate in to improve their understanding of the technology and to inform later investment decisions (Adams et al., 2020) thereby reducing the adverse effects of sunk costs initiating investments leading to increased firm value. Thus, blockchain event participation will bolster entrepreneurial alertness[15] (Sambamurthy et al., 2003) thanks to the opportunity it offers firm to learn and utilize outside knowledge because these

[15] Entrepreneurial alertness is "the capability of a firm to explore marketplace, detect areas of marketplace ignorance, and determine opportunities for action"(Sambamurthy et al., 2003, p. 250)

events help bridge the knowledge gap between innovating and realization of value from investments. Participation in such activities enables firms to reduce knowledge barriers and capitalize on information asymmetry regarding blockchain uncertainties to launch new services or reengineer business processes that may provide net payoffs to the firm but may seem risky to other firms who may not be privy to the knowledge of the focal firm. By utilizing external knowledge, firms are able to increase their exploitable absorptive capacity for innovation.

Firms will also leverage the knowledge acquired to better manage their investment decisions. With attendance at these events, firm's will be helped with the knowledge of the artifacts of blockchain that will be more beneficial if adopted via blockchain-as-a-service schemes and will be better positioned to know when to take advantage of the new developments in the blockchain ecosystem. The firm, as a result, extends its capacity to acquire relevant and timely knowledge of blockchain potentialities. This will increase a firm' managerial flexibility in exercising its intermediate and final options surrounding their blockchain investment. Over time, such options will provide an increasing and effective investment regime that will positively affect firm value (Schmidt, 2005; Vega-Jurado et al., 2008). Therefore, we posit the following.

Hypothesis 3c (Blockchain event participation business value hypothesis, H3c). Blockchain event participation is positively associated with the firm value.

Blockchain Bandwagon Perspective

Blockchain network installed base and firm value. Generally, network perspectives describe how a technology adoption begets more adoption through instrumental effects such as economic drivers of new technology investments that give rise to a re-enforcing pattern of diffusion (Fichman, 2004). Due to extremities that may arise out of failure to reach a critical mass of adoption or avoiding a “stranded” technology, uncertainty faced by adopters are magnified, making option analysis critical for understanding network effects that new technologies may have on firm value (Fichman, 2004).

Hines et al. (Hines et al., 2017) note that as the value of stakeholders' reliability on technology platforms increases, network sizes increase abruptly. Several studies on the blockchain are also unanimous in this assertion of positive network externalities. Zhang (X. Zhang, 2019) reports that blockchain has strong network effects, which increase the value of blockchain as the number of participants increases. Lindman et al. (Lindman et al., 2017) assert that blockchain systems operate in many-sided markets, and “the value of [blockchain system] membership to one user is positively affected by another user joining and enlarging the network”. The World Economic Forum emphasizes that “blockchain’s value as a solution multiplies when more players participate and when stakeholders come together to cooperate on matters of industry-wide or system-level importance” (WEF, 2018, p. 6). That network effects exist in blockchain applications and have ramifications of firm value is evident. Fichman's (Fichman, 2004) proposes that increased susceptibility to network externalities will increase expected value and variance of potential returns culminating in an increased option value, it is not clear how much positive empirical value can be attributed to the increasing adoption of blockchain technology. Consequently, the study posits following hypothesis.

Hypotheses 4 (Blockchain network externality business value hypothesis, H4). The installed base of firms that adopted blockchain is positively associated with firm value.

Data and Methods

Data Collection and Sample

Our data spans the period from January 1, 2015, to December 31, 2020, including 1,488 observations on a quarterly basis from four data sources. Factiva (Lui & Ngai, 2019) was used to determine the type and count of blockchain archetypes a firm has invested in and the time of the adoption investment. Other sources include: COMPUSTAT (H. Kim et al., 2020) for firm-specific factors and the computation of our dependent variable (*Tobins q*); USPTO database (Bowman & Steelman, 2019) for firms' blockchain patenting activities; Crunchbase database (Crunchbase, 2020; Friedlmaier et al., 2018; Momo et al., 2019; Riasanow et al., 2018) facilitated the operationalization of blockchain event participation and network externalities of blockchain adoption. We chose January 1, 2015, as the start date of our data span because it encompasses the earliest and sustainable blockchain investments (to date) by public firms. This start date also allows at least two years before the first recorded blockchain patent granting date in 2017 on the USPTO database, which also captures the period preceding the filing of the respective blockchain patent. Finally, the date allows six years since Nakamoto (Nakamoto, 2008) bitcoin white paper which provides a balance between the nascency of blockchain technology and the awareness of the technology to investors, critical to study its longer-term impacts on firm value.

Variables and Measures

Firm performance (business value). To empirically estimate the firm performance of blockchain technology investment as a growth option, we use Tobin's q (q ratio) – a forward looking market-to-book ratio as our dependent variable (Bardhan et al., 2013).

"Tobin's q is a market-based measure of firm's tangible and intangible value, and it is forward looking, risk-adjusted, and less susceptible to change in accounting practices" (Chung et al. 2019, p.275). It has been used to empirically estimate the firm performance of technology investments (Bharadwaj et al. 1999) and, specifically, firm value of blockchain patent activity (Kim et al. 2020). We use the more theoretically correct definition provided in Bharadwaj et al. (1999), Chung et al. (2019) and (Kohli et al., 2012) which is calculated as follows**:**

$\mathbf{Tobin's}\ \boldsymbol{q} = (\mathbf{MVE} + \mathbf{PS} + \mathbf{DEBT})/\mathbf{TA}$ where:

MVE = (closing price of share at the end of the quarter X number of common shares outstanding); PS = liquidating value of the firm's outstanding preferred stock; DEBT = (current-liabilities-current assets) + book value of inventories + long term debt and TA = book value of total assets.

Blockchain strategy perspective. To capture a firm's blockchain strategy, we consider (1) the number of instances of blockchain ledger or archetype (2) the decentralization of the archetype and (3) the complementarity between archetypes. For the number of instances, we count, respectively, the number of public-permissioned ledgers (*NPublicPermissioned*) or private-permissioned ledgers (*NPrivatePermissioned*) or permissionless ledgers (*NPermissionless*) adopted in quarter t since the quarter in which investment announcement was made. The categorization of these archetypes of blockchain was based on the descriptions of the instance of the ledger technology in the announcement and the white paper on the instance of the archetype. We corroborated the information from Factiva newswires via the firms' websites and Twitter posts where available using a python script. A firm may have one or more different archetypes or may have more of the same archetype in a quarter. The corroboration approach ensured that if any firm ditched their adoption later on in the data period, the adoption record would be updated as such, although this was a rare case. For the degree of decentralization of the archetype, we assign rank values: permissionless = 3, public-permissioned=2, private-permissioned = 1 according to theoretical level of decentralization among users and validators (Rossi et al., 2019). For the weighted degree of decentralization scenario, we compute the weighted average of the three archetypes for each of time periods. Thus, the final degree of decentralization is given as follows:

$$WDDec = \frac{(NPermissionless\ x\ 3 + NPublicPermissioned\ x\ 2 + NPrivatePermissioned\ x\ 1)}{NPermissionless + NPublicPermissioned + NPrivatePermissioned}.$$

For the complementarity between archetypes, we use dummies for cooccurrence of two archetypes adoption: These are (1) Complementarity between NPermissionless and NPublic-permissioned (*CPermissionlessPublicPermissioned*) (2) between NPermissionless and NPrivate-permissioned (*CPermissionlessPrivatePermissioned*) and (3) between NPublic-permissioned and NPrivate-permissioned (*CPublicPermissionedPrivatePermissioned*).

Blockchain-related organizational learning. We use blockchain patents returns (*LnBPatR*), the originality of blockchain patents granted (*LnBPatO*) and blockchain event participation (*LnBEvent*). *LnBPatR* is the natural log of the number of patents granted a firm in quarter t. *LnBPatO* describes the extent of cited documents by focal patents in quarter t. *LnBEvent* is the natural log of the total number of blockchain events a firm attended in a time, t.

Blockchain installed base (network externality). We obtain the periodic cumulative totals of blockchain companies (start-ups and existing companies) from Crunchbase database (*LogNetworkExternality*). We updated the quarterly cumulative records when companies bought or have folded up.

Control variables. To mitigate potential omitted variable bias and endogeneity concerns, we include an extensive set of control factors may be related to firm performance (financial controls), blockchain-related independent variables (blockchain controls), the firm (firm-specific controls) and industry controls. For blockchain-related controls we control for non-blockchain patents (*LnOtherPatents*) that were granted the firm in quarter t so that innovation activities that are non-blockchain related will not be correlated with the error term. We control for average citation lag (*LnAvgCitationLag*) which measures the average of the time periods between citation of a blockchain patent and the date of its publication with respect to each quarter t. We also control for technology events or conferences (*LnOtherEvents*) a firm attended that are not blockchain-related based on data obtained from Crunchbase Database.

To control for growth options (Tobin's q) available to them, R&D Intensity (*R&DIntensity*) which is the total R&D expenditures divided by total sales in a given quarter (Chung et al., 2020) is included in the estimation. In addition we control for the impact of missing R&D expense (*MissingR&DDummy*) values which have been shown to behave differently from reported R&D observations (Koh & Reeb, 2015). Thus, rather than using reported industry R&D averages or replacing them with zeros, we estimate the more theoretically accurate dummy effect on firm's growth options (Koh & Reeb, 2015). A leverage which is its ratio of long-term debt to total sales affects the ability of to invest such that high leverage generate underinvestment problem (Fosu et al., 2016). Hence, we control for *Leverage* because of its likely influence on how firm exercise their growth options. We also control for *Profitability and DividendYieldDummy,* which describes whether a firm pays dividends or not. Generally, a firm with a dividend policy often experiences the market's reaction to its stocks and consequently its Tobins q. We also include ratio of cashflow to assets (*Cashflow_To_Assets*), *Cash Holding*, and *Tangibility.* Tangibility is a firms asset structure that affects the firm's corporate financial choices (Koralun-Bereźnicka, 2013) which can enable managers to create more growth options. The value of this option cannot be attributable to investment made in blockchain technology hence we control for it. We include Total Assets (*LnTotalAssets*) to control for firm size. We also include firm age in years.

At the industry level we control industry Tobin's q (*Industry_Q*) that may signal to investors that firm in the industry have more flexibility with their growth options. The financial and firm-specific controls are computed based on data obtained from COMPUSTAT. To reduce the impact of outliers, we winsorized *Tobin's q* at the 5th and 95th percentiles, following Campbell, Hilscher, & Szilagyi (2008) so that any observation below the 5th percentile is replaced with the 5th percentile, and the observation above the 95th percentile with the 95th percentile. Table 2 presents the descriptive statistics, operational definition, and specific data source of each variable used in our analysis. Finally, we controlled for firm-specific and quarter-specific common shocks.

Table 2: Descriptive Statistics, Operationalization and Variable Data Sources

Variables	**Definition/operationalization**	**N**	**Mean**	**SD**	**Min**	**Median**	**Max**	**Source**
Dependent variable								
Tobin's q	Tobin's q measure, as in Bharadwaj et al. (1999) and Chung et al. (2019), of a firm in quarter t to estimate the optimal value of the firm's technology option	1,429	1.77	1.70	-0.15	1.33	5.81	COMPUSTAT
Independent variables								
NPublicPermissioned	The number of adoption investments in public-permissioned blockchain archetypes by a firm in time *t*	1,488	0.20	0.50	0.00	0.00	3.00	Factiva
NPrivatePermissioned	The number of adoption investments in private-permissioned blockchain archetypes by a firm in time *t*	1,488	0.26	0.44	0.00	0.00	2.00	Factiva
NPermissionless	The number of adoption investments in permissionless blockchain archetypes by a firm in a quarter *t*	1,488	0.03	0.17	0.00	0.00	1.00	Factiva
lnBPatR	Natural Log of the number of blockchain patents granted (count) to a firm in quarter *t*	1,456	0.08	0.32	0.00	0.00	3.33	USPTO
lnBPatO	Natural log of the accumulated number of citations made by all the patents granted to a firm in quarter *t*. Adapted from Kim et al. (2020) and Koh and Reeb (2015)	1,488	0.31	1.05	0.00	0.00	6.29	USPTO
lnBEvent	Natural log of the number of all blockchain events, conferences, and workshops attended, organized, or participated in by a firm in quarter *t*	1,432	0.10	0.41	0.00	0.00	4.32	USPTO
lnNetworkExternality	Natural log of the cumulative number of active firms using blockchain in quarter *t*	1,488	7.01	0.86	5.15	7.53	7.74	Crunchbase Database
Control variables								
LnOtherPatents	Natural log of the number of all patents granted to a firm other than blockchain patents in quarter *t*	1,488	3.02	2.38	0.00	3.37	8.00	USPTO
LnAvgCitationLag	Natural log of the average age of citations referenced by the patents granted to a firm in quarter *t*. Adapted from Koh and Reeb (2015)	1,488	0.25	0.82	0.00	0.00	4.09	USPTO
LnOtherEvents	Natural log of the number of all other event, conferences, and workshops attended, organized, or participated in by a firm in quarter *t*	1,448	0.89	0.96	0.00	0.69	4.03	Crunchbase Database
BookToMarketValue	Ratio of market value equity to book value equity of the firm in quarter *t*	1,454	4.32	5.70	-7.42	2.79	18.67	COMPUSTAT

Table 2, cont.

Variables	Definition/operationalization	N	Mean	SD	Min	Median	Max	Source
Firm Age	Calendar year minus year a firm first appeared in COMPUSTAT	1,488	34.27	21.53	0.00	29.50	70	COMPUSTAT
FirmSize	Natural log of the total assets of a firm in a quarter *t*	1,454	11.13	2.03	3.96	11.44	15.04	COMPUSTAT
R&DIntensity	The ratio of R&D expense to revenue (sales) of a firm in quarter *t*	1,488	0.07	0.11	0.00	0.00	1.28	COMPUSTAT
MissingR&DDummy	Dummy of '1' for missing R&D expense values of a firm or 'o' for non-missing values in quarter *t*. Adapted from Koh and Reeb 2015	1,488	0.51	0.50	0.00	1.00	1.00	COMPUSTAT
Leverage	Long-term debt divided by the sum of long-term debt and market value of equity of a firm in quarter *t*	1,448	0.25	0.22	0.00	0.17	1.00	COMPUSTAT
Profitability	Net income divided by total assets of a firm in quarter *t*	1,454	0.01	0.03	-0.13	0.01	0.42	COMPUSTAT
DividendYieldDummy	Dummy of '1' if a firm paid dividends and 'o' if a firm did not pay dividends in quarter *t*	1,488	0.74	0.44	0.00	1.00	1.00	COMPUSTAT
CashflowToAssets	Operating income before depreciation minus dividend paid (cash flow) divided by firm total assets in time *t*	1,355	0.02	0.03	-0.69	0.02	0.12	COMPUSTAT
CashHolding	Cash and cash equivalents of a firm divided by total assets in quarter *t*	1,454	0.23	0.18	0.00	0.17	0.84	COMPUSTAT
Tangibility	Gross total of plant, property, and equipment of a firm divided by total assets in quarter *t*	1,435	0.11	0.12	0.00	0.08	0.59	COMPUSTAT

Note. SD, standard deviation.

Estimation Procedure

To examine whether firms' adoption of blockchain technology is associated with firm performance Hypothesis 1), we use propensity score matching. We discuss the estimation procedure for testing hypothesis 1 below.

Propensity score matching and fixed effects regression. I implemented a propensity score matching (PSM) to address concerns for potential self-selection bias owing to the relatively small sample of US public firms that have adopted blockchain for their business and used the matching scores to test hypothesis one in a fixed effects model. Tables 12 and 13 in Appendix B provide summary statistics and t-tests for the treated and control samples for full sample and two-digit industry-specific samples.

Propensity scores which are conditional probabilities of treatment assignments allow the investigator to match firms on more than one characteristic of the firms compared to traditional matching approaches. We implemented separate logit models for all treatment and control firms for each quarter of each year that a firm had ongoing adoption investment. We used a one-to-one nearest neighbor matching algorithm which uses local minimization of the difference between the treated and control's propensity to make adoption investment in blockchain technology. We forced potential control firms for each adopting firm to have the same two-digit SIC code as the adopting firm. Therefore, we did not have to identify characteristics that will induce industry clustering, which further reduces selection bias within the nearest neighbor algorithm run to choose a controlled firm. Aside using two-digit SIC code, we matched based on firm size, leverage, profitability, cash holding, tangibility, R&D intensity, R&D dummy for missing R&D values in COMPUSTAT, dividend yield dummy, which describes whether the firm pays dividends or not, cashflow-to-assets and market-to-book value of equity. These factors have been shown in the finance literature to contribute to the value of the firm. We obtained the matched Tobin's q and covariances for each treatment firm in each quarter as applicable. If the treated firm's adoption investment of blockchain occurred in quarter q, we match the firm to a control firm based on the following propensity score model:

$$\Pr(T_{(q)}) = \boldsymbol{f}(R\&DIntensity_{(q)}, R\&DIntensityDummy_{(q)}, FirmSize_{(q)}, Leverage_{(q)}, Profitability_{(q)}, CashHolding_{(q)}, Tangibility_{(q)}, CashflowToAssets_{(q)}, DividendYieldDummy_{(q)}, BookToMarketValue_{(q)})$$

Having generated the propensity scores, we run a doubly robust fixed-effects regression analysis using the sample weights of the covariances generated as part of the propensity score matching output which optimizes the balance of covariates between the treatment and control groups (Fan et al., 2021). We controlled for firm and time-fixed effects and applied Huber-White robust standard errors to separate estimations, as shown in Table 3. The fixed-effects regression estimation is based on the following model specification:

$$Tobin's\ q_{(i,j,t+k)} = Treatment\ (BlockchainAdoptionDummy)_{(i,j,t)} + R\&DIntensity_{(i,j,t)} + MissingR\&DDummy_{(i,j,t)} + LogTotalAssets_{(\mathrm{i,j,t})} + Leverage_{(i,j,t)} + Profitability_{(i,j,t)} + CashHolding_{(i,j,t)} + Tangibility_{(i,j,t)} + CashflowToAssets_{(i,j,t)} + DividendYieldDummy_{(i,j,t)} + MarketToBookValue_{(i,j,t)} + \theta_i + \varphi_j + \delta_t + \mu_{ijt}$$

where t first or initial quarter and *k* is either 1, 2, 3, 4 and 8. The firm's time-invariant heterogeneity (i.e., firm-fixed effects), the industry-fixed effects, the year fixed effects, and the error term are represented by θ_i, φ_j, δ_t, and μ_{ijt}, respectively. Specifying robust specification (i.e., *[fweight = _weight]*) in STATA ensures that the weights of the covariances generated from the PS matching are used in the estimation providing another layer of robustness (i.e., doubly robust estimation) in ascertaining the impact of firm blockchain adoption. This layer which improves the covariate balancing propensity score (CBPS) estimation better addresses estimator-sensitivity problem that is due to misspecification of the propensity score model (Shipman et al., 2016).

Blockchains options determinants, firm performance, and fixed-effects modeling. To account for firm-level unobserved heterogeneity in our data, we consider fixed and random effects. We chose a fixed-effects model based on the Hausman test that rejected the null hypothesis that the errors are not correlated with the explanatory variables (Prob $>\chi^2$ =0.000) with χ^2 =71.11. This statistical significance that differences in coefficients are systematic points to the need for a fixed effect linear panel data model. Our base fixed effects estimation model is specified as follows:

$$Tobin's\ q_{i,t+k} = \beta_0 + \beta_1 NPer_{i,t} + \beta_2 NPub_{i,t} + \beta_3 NPri_{i,t} + \beta_4 WDDec_{i,t} + \beta_5 CPubPri_{i,t} + \beta_6 CPubPer_{i,t} + \beta_7 CPriPer_{i,t} + \beta_8 \log(BPatR)_{i,t} + \beta_9 \log(BPatO)_{i,t} + \beta_{10} \log(BEvent)_{i,t} + \beta_{11} \log(BNetExt)_{i,t} + \sum \gamma_m Blockchain\ Controls_{i,t} + \sum \gamma_n Financial\ Controls_{i,t} + \sum \gamma_j Industry\ Controls_{j,t} + \theta_i + \delta_t + \mu_{it}$$

where *t* is quarter, *k* is either 1, 2, 3, 4 or 8. The γ_m, γ_n and γ_j notations are coefficients of t control variables examined in the study. The firm's time-invariant heterogeneity (i.e., firm-fixed effects), the quarter fixed effects (i.e., time dummies), and the error term are represented by θ_i, δ_t, and μ_{it}, respectively. Thus, to investigate the effects of different quarter lags on firm value, we estimate the base model using $Tobin's\ q_{i,t+1}$ to $Tobin's\ q_{i,t+4}$ and $Tobin's\ q_{i,t+8}$.

The alternative fixed effects estimation for other degree of decentralization variable and dummy complementarity variable is as follows:

$$Tobin's\ q_{i,t+k} = \beta_0 + \beta_1 NPer_{i,t} + \beta_2 NPub_{i,t} + \beta_3 NPri_{i,t} + \beta_4 DDec_{i,t} + \beta_5 CArch_{i,t} + \beta_6 \log(BPatR)_{i,t} + \beta_7 \log(BPatO)_{i,t} + \beta_8 \log(BEvent)_{i,t} + \beta_9 \log(BNetExt)_{i,t} + \beta_{10} BDivisibility_{i,t} + \sum \gamma_m Blockchain\ Controls_{i,t} + \sum \gamma_n Financial\ Controls_{i,t} + \sum \gamma_j Industry\ Controls_{j,t} + \theta_i + \delta_t + \mu_{it}$$

Results

First, we assess hypothesis one from the PSM estimation and fixed effects model with dummy blockchain adoption dummy variable. Secondly, following Greene (2003) we performed a modified Wald test for groupwise heteroskedasticity in the residuals of our fixed effect regression model involving variables for the strategic archetypes, blockchain learning and installed base of adoption. The results (Prob $>\chi^2 = 0.000$) confirmed the presence of heteroskedasticity so we estimate out models with Huber-White robust standard errors to correct this. Finally, we perform robustness checks to ascertain the sensitivity of our estimation results.

Main Analyses and Results – Fixed Effects Using Weighted Propensity Scores (H1)

Generally, our results reveal that treated firms (i.e., firms that have or likely to adopt blockchain) increase in Tobin's q by 0.24 *($\beta = 0.24$, $p < 0.01$)* confirming hypothesis 1 that adoption in blockchain technology increases firm value. This result is consistent for both short term (within 1 year) and long-term (2 years) adoption impact.

Main Analyses and Results – Fixed Effects Analyses of Impact of Blockchain Options

We estimate our fixed effects model hierarchically (see Table 4). First, we estimate with only control variables (Model 1 of Table 4), followed by the model with the blockchain strategy variables (Model 2). We then included blockchain-related organizational learning variables (Model 3 of Table 4). We test our hypotheses (Hypotheses 2, 3, and 4) after adding blockchain adoption network externality variable (Model 4 of Table 4) and accounting for firm and quarter fixed effects at robust standard errors.

For firm blockchain strategy variables, we find that the instances of blockchain adoption: public-permissioned, private-permissioned and permissionless archetype adoption have a significant positive association with firm performance at quarter *t+1* (β=0.49, p<0.01; β=0.17, p<0.05; β=1.10, p<0.01, respectively, in Model 4) supporting hypothesis 2a. Thus, on average, one standard deviation increases in adoption of public-permissioned, private-permissioned and permissionless archetypes is associated with 0.49, 0.17, and 1.10 increases in Tobin's q, respectively. Also, in the long run, public-permissioned archetypes maintain a steady rise in Tobin's q (see Model 6, Model 7 and Model 8) indicating that adoption of public-permissioned ledger is more strategic owing to a more sustained positive effects on the market and consequently, firm performance. The coefficient on the weighted degree of decentralization (β=-0.35, p<0.01) is significantly negative which is contrary to our hypotheses 2b. This contrary finding suggests that the more decentralized an instant of blockchain archetype the lesser the impact on firm performance. This underscores the point that the market, generally, is still skeptical about too much decentralized digital business model and continue to hedge their bets on blockchain business models that has more degree of centralization.

Regarding complementarity between archetypes strategy, we find in Model 4 that coefficients on the complementarity between public-permissioned and private-permissioned (β=-0.40, p<0.01) and that of public-permissioned and permissionless (β=-0.92, p<0.01) are significantly negative whereas complementarity between private-permissioned and permissionless (β=-0.30, p>0.10) is negative but not significant although it is negatively significant in Model 6, 7 and 8. These results contradict our hypothesis 2c in that, a firm's adoption of one or more archetype in addition to their existing archetype leads to decrease in firm performance, even in the long run. In general, an additional archetype adoption connotes increased decentralization strategy, and we note that complementarity between public-permissioned and permissionless has the greater negative impact because it represents the most decentralized combination of the three complementarities. On average, one standard deviation increase in the complementarity between (i.e., adoption of both) public-permissioned and permissionless archetypes is associated with 0.94 decrease in Tobin's q. Hence, this finding supports the market being unsure about a more decentralized business models as they may perceive it as risky to the more tried and tested centralized models. Also, investors may view the managerial moves of adopting additional archetypes negatively because it indicates to them that the firm is not confident of having positive returns on their prior adopted blockchain archetype.

Regarding blockchain-related organizational learning impact (hypothesis 3a, 3b and 3c), we find that blockchain patents granted is negatively related to firm performance (β=-0.21, p<0.01) which is opposite our hypothesis 3a. Hypotheses 3b which investigates impact of originality of patents (β=0.06, p<0.1) and hypotheses 3c which tests relationship between blockchain events participation and firm performance (β=0.08, p<0.1) are all supported in Model 5. Specifically, 1% increase in blockchain patents on average is associated with a 0.21% decrease in Tobin's q. However, a 1% increase in the originality of blockchain patents is associated with 0.06% increase in Tobin's q. This means that whereas patents granted is negative, firms stand to gain from their patenting activities if they increase the spread and quality of references used in their patent filings. The finding also suggests that organizations are more exploitative of blockchain knowledge resources as they prepare to acquire blockchain patents than when they have actually acquired the blockchain patents. Also 1% increase in participation in blockchain events is associated with 0.08% increase in Tobin's q.

Regarding blockchain adoption network effects, we find that firms are positively susceptible to increased utilization of blockchain technology by existing and start-up firms in the longer term. Thus, we do not find any significance of effect of blockchain network externality in quarter t+1 or Model 5 (β=0.04, p>0.10) although the coefficient is positive but Model 6 (β=0.10, p<0.05), Model 7 (β=0.15, p<0.01) and Model 8 (β=0.39, p<0.01) show increasing positive effects of network externality on firm performance. These findings therefore provide support for our hypotheses 4 albeit from quarter t+3 (Model 6). The result in Model 6 suggests that, on average, a 1% increase in blockchain adoption by existing and start-up firms in the United States blockchain ecosystem is associated with 0.10% in Tobin's *q*.

Regarding our blockchain control variables in Model (i.e., non-blockchain patents granted, average citation lag, and non-blockchain technology events a firm participated in), we do not strong evidence that these sources of organizational learning are associated with firm performance when managers exercise their blockchain options. In Model 4, we find support for the following financial control variables: missing R&D dummy (β=0.21, p<0.05), leverage (β= -0.72, p<0.01), profitability (β=1.42, p<0.1), cash holding (β= -0.63, p<0.05), firm size (log of total assets) (β= -0.22, p<0.01) and industry mean Tobin's q (β=0.38, p<0.01).

Table 3: Overall Impact of Blockchain Adoption on Tobin's q

Dependent variable	*Tobins* $q_{(t+1)}$		*Tobins* $q_{(t+2)}$	*Tobins* $q_{(t+3)}$	*Tobins* $q_{(t+4)}$	*Tobins* $q_{(t+8)}$
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Treatment:						
Blockchain Adoption Dummy		0.24***	0.19***	0.25***	0.29***	0.32***
		(0.05)	(0.06)	(0.07)	(0.07)	(0.09)
R&DIntensity	-4.42***	-4.37***	-4.63***	-8.46***	-7.66***	-9.16***
	(0.15)	(0.15)	(0.16)	(0.23)	(0.22)	(0.31)
Missing R&D_Dummy	-1.11***	-1.09***	-0.94***	-1.17***	-1.01***	-1.02***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)
LogTotalAssets	0.11***	0.12***	0.11***	0.18***	0.13***	0.18***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Leverage	-2.82***	-2.82***	-3.09***	-3.16***	-2.57***	-1.07***
	(0.12)	(0.12)	(0.13)	(0.15)	(0.17)	(0.23)
Profitability	-0.94***	-0.77**	-6.21***	-7.15***	-10.02***	-17.86***
	(0.34)	(0.35)	(0.36)	(0.35)	(0.36)	(0.52)
Cash Holding	0.08	0.18	0.07	1.68***	1.22***	1.95***
	(0.13)	(0.13)	(0.15)	(0.15)	(0.15)	(0.16)
Tangibility	-0.30	-0.33*	0.01	0.41*	0.52**	0.83***
	(0.18)	(0.18)	(0.21)	(0.24)	(0.22)	(0.30)
Cashflow-to-Assets	-2.68***	-2.61***	0.27	0.39**	1.60***	1.76***
	(0.16)	(0.15)	(0.17)	(0.18)	(0.17)	(0.20)
DividendYield_Dummy	-0.24***	-0.25***	-0.44***	-0.32***	-0.31***	-0.30***
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)
MarketToBookValueofEquity	0.19***	0.19***	0.20***	0.18***	0.20***	0.19***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Constant	2.12***	1.72***	1.95***	1.41***	1.64***	1.24***
	(0.17)	(0.20)	(0.21)	(0.22)	(0.21)	(0.25)
Observations	9,928	9,928	9,603	8,894	8,512	7,387
Adjusted R-squared	0.83	0.83	0.81	0.78	0.82	0.81
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Doubly robust propensity score estimation using the covariates.

Table 4: Impact of Blockchain Technology Options Determinants on Tobin's q

Dependent variable	*Tobins* $q_{(t+1)}$				*Tobins* $q_{(t+2)}$	*Tobins* $q_{(t+3)}$	*Tobins* $q_{(t+4)}$	*Tobins* $q_{(t+8)}$
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Independent variables								
Blockchain Strategy								
NPublic-Permissioned Archetype		0.56***	0.50***	0.49***	0.58***	0.73***	0.95***	0.91***
		(0.14)	(0.14)	(0.14)	(0.16)	(0.17)	(0.18)	(0.20)
NPrivate-Permissioned Archetype		0.20**	0.17**	0.17**	0.22**	0.30***	0.41***	0.52***
		(0.08)	(0.08)	(0.08)	(0.09)	(0.11)	(0.11)	(0.16)
NPermissionless Archetype		1.16***	1.10***	1.10***	1.00***	1.06***	1.19***	0.69
		(0.29)	(0.30)	(0.30)	(0.32)	(0.33)	(0.34)	(0.42)
Weighted Degree of Decentralization		-0.37***	-0.35***	-0.35***	-0.36***	-0.44***	-0.54***	-0.37***
		(0.08)	(0.08)	(0.08)	(0.09)	(0.10)	(0.11)	(0.14)
CPublicPermissioned-PrivatePermissioned		-0.45***	-0.40***	-0.40***	-0.49***	-0.61***	-0.76***	-0.92***
		(0.11)	(0.11)	(0.11)	(0.13)	(0.15)	(0.15)	(0.17)
CPublicPermissioned-Permissionless		-0.99***	-0.92***	-0.92***	-0.94***	-1.08***	-1.29***	
		(0.18)	(0.18)	(0.18)	(0.20)	(0.23)	(0.23)	
CPrivatePermissioned-Permissionless		-0.33	-0.30	-0.30	-0.35	-0.51*	-0.68**	-0.94*
		(0.28)	(0.27)	(0.27)	(0.28)	(0.30)	(0.30)	(0.55)
Blockchain-related Organizational Learning								
Blockchain Patents (log)			-0.21***	-0.21***	-0.25***	-0.21***	-0.29**	-0.13
			(0.06)	(0.06)	(0.07)	(0.07)	(0.12)	(0.25)
Originality of Blockchain Patent (log)			0.06*	0.06*	0.09**	-0.00	0.04	-0.07
			(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.10)
Blockchain Events Participation (log)			0.08*	0.08*	0.13**	0.20***	0.16***	0.11*
			(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
Blockchain Adoption Network Effects								
Network Externality (log)				0.02	0.04	0.10**	0.15***	0.39***

Table 4, cont.

				(0.04)	(0.04)	(0.04)	(0.04)	(0.07)
Control variables								
Other Patents(log)	-0.01	0.01	0.00	0.00	-0.01	-0.03*	-0.04*	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Average Patents Citation Lag (log)	-0.00	0.00	-0.02	-0.02	-0.04	0.04	0.00	0.07
	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.08)
Other Event Participation(log)	-0.01	0.02	0.02	0.02	-0.00	0.03	0.06*	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
R&D Intensity	-0.06	-0.14	-0.48	-0.48	-0.02	-0.05	-0.40	0.51
	(0.49)	(0.48)	(0.33)	(0.33)	(0.38)	(0.44)	(0.53)	(0.53)
Missing R&D Dummy	0.28***	0.25**	0.21**	0.21**	0.16	0.09	0.02	0.12
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)	(0.08)
Leverage	-0.69***	-0.66***	-0.74***	-0.72***	-0.74***	-0.62***	-0.55*	0.01
	(0.16)	(0.16)	(0.17)	(0.18)	(0.17)	(0.22)	(0.33)	(0.17)
Profitability	1.67**	1.46**	1.42*	1.42*	1.63**	1.28**	0.84	-0.24
	(0.80)	(0.74)	(0.74)	(0.74)	(0.72)	(0.56)	(0.58)	(0.46)
Dividend Yield Dummy	0.03	0.01	0.03	0.03	-0.00	-0.03	-0.13	-0.14
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.11)
Cashflow to Assets	-2.23	-2.51	-2.53	-2.53	-0.47	-0.29	-0.11	0.88*
	(1.70)	(1.62)	(1.63)	(1.63)	(1.11)	(0.75)	(0.47)	(0.51)
Cash Holding	-0.58**	-0.58**	-0.63**	-0.63**	-0.31	-0.01	0.30	-0.10
	(0.28)	(0.29)	(0.30)	(0.30)	(0.35)	(0.36)	(0.34)	(0.35)
Tangibility	1.26**	1.14*	1.08	1.09	0.32	0.27	0.16	0.18
	(0.64)	(0.63)	(0.66)	(0.67)	(0.68)	(0.67)	(0.66)	(0.78)
Firm Size (log of Total Assets)	-0.23***	-0.25***	-0.22***	-0.22***	-0.10	-0.02	-0.02	0.02
	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Industry Mean Tobin's q	0.39***	0.37***	0.38***	0.38***	0.31***	0.26***	0.27***	0.23**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)
Constant	3.75***	4.02***	3.74***	3.61***	2.28**	1.12	0.75	-1.31
	(0.90)	(0.85)	(0.89)	(1.09)	(1.10)	(1.00)	(0.98)	(1.00)

Table 4, cont.

Observations	1,254	1,254	1,197	1,197	1,141	1,086	1,031	810
Adjusted R-squared	0.93	0.93	0.94	0.94	0.93	0.94	0.94	0.95
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

CPublishedPermissioned-PrivatePermissioned - complementarity of public-permissioned and private-permissioned archetypes, CPublishedPermissionedPermissionless - complementarity of public-permissioned and permissionless archetypes, CPrivatePermissionedPermissionless - complementarity of private-permissioned and permissionless archetypes. Huber-White robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Discussion and Implications

Academics and practitioners both assert the potential benefits blockchain technology would generate for investing firms. Yet, there is a lack of comprehensive study that assesses and quantifies the value created by firm blockchain investment initiatives. Understanding and justifying blockchain investments remain a challenge because the benefits are soft or intangible and the value proposition has more futuristic component although firms recognize that blockchain business model will improve strategic actions. Drawing upon Fichman's real options perspective, our study shed light on the issue by examining the relationship between blockchain technology options determinants and firm performance after firm blockchain investments. Our findings suggest blockchain technology investments lead to significant positive returns for the firm which demonstrates that business value of blockchain technology is real. We also find that irrespective of the type of archetypes (public-permissioned, private-permissioned and permissionless archetype) firms enjoy positive returns on their investments. Although we assert an overall positive impact of blockchain investments, our comprehensive options analysis shows, that not all blockchain investments are created equal.

Firm performance varies considerably depending on several characteristics with the blockchain archetype and associated managerial decisions. Surprisingly, we found that investments in less-decentralized archetype (i.e., private-permissioned archetype) reduces susceptibility of negative payoffs compared to more decentralized archetypes. Investors' hopes of future benefits in firm decentralized technology aspirations may be mixed with worries that centralized business model may yet offer lesser risks for the firm. Hence more decentralization is seen as increasing business risks leading to negative market response and consequently decreasing firm performance. This finding contradicts studies that argue a more positive impact on project success with a more decentralized blockchain archetype (Bian et al., 2018). Also, contrary to our hypothesis, adopting a second different archetypes leads to negative firm performance, more so for complementarity involving permissionless blockchains (the most decentralized archetype of the three archetypes). Our robustness analysis on blockchain divisibility buttresses this point by revealing the importance of investing in a less decentralized archetypes before investing in higher decentralized archetype if a firm must make more than one archetype investment.

Thus, for firms to experience positive performance of returns on more than one archetype investments, they must follow their private-permissioned archetype adoption with public-permissioned or follows their public-permissioned with a permissionless adoption. All other investment sequences apart from these two cases lead to negative firm performance. The reasons for negative complementarity effects on firm value could be explained by the idea of radical innovation. Blockchain technology adoption represents a radicalness because of its requirements of intra- and inter-organizational cooperation in discovering, incubating and accelerating to fully leverage its potential (Beck & Muller-Bloch, 2017). Leveraging Fichman (2004) and Yang et al. (2012) assertions, potentially high returns from a well-resourced radicalness in initial blockchain archetype adoption may be offset by tangible and intangible expenses in deploying a second archetype as well as costs due to complementarity changes in firm policies and structures. The cost impact may stretch a firm resources, increase technological risks (McDermott & O'Connor, 2002) and reduce their managerial flexibilities in exercising valuable options resulting in negative responses by the investors and overall reduction in firm performance (Yang et al., 2012).

As hypothesized, our results also suggest that blockchain patent originality, participation in blockchain events, and network externality positively impact firm performance, but to the contrary, the effect of blockchain patents is negative. There are three potential explanations why blockchain patent returns (count) have negative effect on firm performance. First as articulated by Harrigan et al. (2018), patent counts are forward-looking citation analysis (future prior-art measures such as generality of patents) and are less-helpful because investors require time for such measures to amass. More so, considering that the Tobin's *q* ratio reflects whether investors expect higher or lower future value creation or their expectation of firm growth opportunities which demand better discretionary decisions by managers to maximize shareholder value. Forward-looking patent activities rather reduces patents' usefulness as measures of patent quality and consequently as non-financial indicators of a firm prospects (Harrigan et al., 2018). Hence blockchain patent count may not elicit the expected positive response from the market thereby negatively influencing firm performance. In the long term, this may not be the case as the market would have enough information to assess the relative impact of such 'past' patent activities.

Second, the developmental space for blockchain is vast and so there are opportunities to easily publish a patent. High patent turnover in this space may construe less patent quality. Investors may therefore be skeptical about the quality of blockchain patents and subsequently their ability to provide clues about the nature of the firm's organizational learning. This skepticism may play on how investors perceive firms' innovation activities response and consequently affect firm value negatively. Perhaps the market will be more confident in how a firm exploits certain patents in new product and service announcements than expending resources on acquiring the patents. However, backward-looking citation analysis such as originality of patents (Trajtenberg et al., 1997) provide useful information on a firm future prospects as measured by the Tobin's *q* and provide the market with quality information on the inventive trajectories in the innovation (Harrigan et al., 2018), hence its positive impact on firm performance in our study.

Finally, patents positive influence can be expected with certain conditions are associative and so is the converse. Chung et al. (2019) assert that "software patent portfolio having higher levels of explorative orientation is associated with a higher firm value (as measured by Tobin's q) in environments exhibiting low dynamism and high competitiveness…. [while patents] … with higher levels of exploitative orientation is associated with a higher firm value in environments with high dynamism and low competitiveness (p. 1073). These finding conjectures that negative effect of patent returns on firm performance may be predominant if the right conditions for explorative and exploitative organizational learning are not in place.

Our study is one of the first to provide such comprehensive estimation of the effects of blockchain investments options on firm value and proposes blockchain options lens as contribution to IT investment literature. Although recent studies have examined the importance of different blockchain platforms to firm, we extend previous studies by showing an array of strategic moves as options that firm can exploit in addition to their strategic blockchain adoption. Lui and Ngai (Lui & Ngai, 2019) reported that strategic alliances for firms regarding blockchain might be less beneficial in the long run compared to the long-term value accrued by individual adoption. Our finding shows that if strategic alliances are well categorized, such as delineating public-permissioned from permissionless archetypes as collaborative strategies, claims of long-term benefits can be made for public-permissioned archetypes because they have lower susceptibility for future negative payoffs of the two archetypes. Our study also answers calls in IT business value literature, e.g., (Bardhan et al., 2013), to investigate the type of IT investment being made by the firm to delineate its specific strategic impact on business value from other IT in the firm. Finally, study also supports (Koh & Reeb, 2015) assertion that missing R&D values are significant control parameters in IT innovation research and behaves differently when assumed to be zero or replaced with industry R&D values. This means IT innovation studies that assume '0' values for missing R&D or omit them from estimations may be biasing their empirical findings. Prior studies (e.g., (Yang et al., 2012) have used adjusted firm R&D intensity measures to proxy for exploitable capacity regarding specific IT investments. Methodologically, our use of blockchain event participation measure as proxy for a specific exploitable absorptive capacity (EAC) while controlling for R&D intensity is more descriptive and provides a less-noisy (higher quality) information about the impact of the specific technology investigated – i.e., blockchain technology.

The study has various implications for managers. First, the study provides practical guidance on how to invest in different blockchain archetypes to maximize business value. Because less decentralized archetypes provide less susceptibility to negative firm performance, we suggest that managers should focus on private or public-permissioned archetypes before adopting permissionless archetypes. Although permissionless archetype drives the market to over-value firm stocks, the benefits are adversely affected by market hesitation to running a more decentralized business model. Second the study highlights the importance of having more novel (original) blockchain patents than racing to have high absolute blockchain patent counts. Firms should focus more on backward-looking patenting activities to send the rich signals to investors about their blockchain-related innovation activities.

Conclusion, Limitations and Future Research

In this study, we have investigated the determinants of blockchain option value for firms to better position their blockchain investments. Blockchain adoption impact on firm value is yet establish robust findings for leverage in justifying blockchain investments. We therefore asked the initial research question if blockchain adoption leads to firm value. We assert that each adoption case by a firm represents a category of blockchain archetype which presents different strategic decisions to be made. Using Fichman's value creation model, we propose and empirically test our research model using data from multiple sources. Initially, we performed a within two-digit SIC (industry) code propensity score matching on the Tobin's q using firm-specific factors as matching variables between our data sample and sample of US public that are likely to adopt blockchain and run the total observations (treatment and matched samples) with a fixed effect model to test our initial research question. The PSM approach in this study helped to alleviate some concerns about self-selection bias with the relatively small sample size and assesses the overall impact of blockchain adoption on firm performance. With further analysis, we have findings that both support and contradict our hypotheses. We provided further explanations in the discussion section.

We highlight some limitations to our study. The data span is relatively short so long-term effects in our results table must be interpreted with caution. We did not include blockchain technology adaptation in the main hypotheses but our robustness test with the divisibility variable (i.e., sequential adoption of blockchain archetypes) provide an opportunity for future studies to investigate our mixed findings of negative and positive effects of blockchain technology adaptation. We acknowledge that the observed complementarities between archetypes represent equilibrium relationships that warrant future investigation on whether the duration between investments in first archetype and second archetype will affect our complementarity findings and what time is optimal. Also, future studies could investigate what leads to firms adopting more than one archetype and how firms can improve expected payoffs with this strategy. A more robust valuation of blockchain network effects of blockchain adoption could be applied in future studies. Kemper (2009) shows the complexities with software market network effects. We conjecture those similar, if not more, complexities may abound for decentralized ledger technologies. Finally, future studies may explore the effect of key regulatory policies on firm performance in our empirical model as it represents the biggest barrier to blockchain adoption.

CHAPTER IV

CRYPTOCURRENCY MARKET DISCOVERY: TWITTER AND THE SENTIMENTAL POWER OF BITCOIN OPINION LEADERS

Introduction

Within cryptocurrency price behavior discourses, scholars are divided on the influence parameters underlying social media sentiments, with suggestions that prior findings are less robust and susceptible to extreme price volatility and improper sentiment classifiers (Abraham et al., 2018; Burnie & Yilmaz, 2019). The jury is out on what asset class defines cryptocurrencies to understand their behavior better. Particularly for Bitcoin cryptocurrency which has enjoyed much research focus, Yermack (2015) identifies 'scarcity' and instability of the Bitcoin price behavior as the reasons for the lack of definitive asset classification. Kraaijeveld & De Smedt (2020) explain, unlike established currencies such as US Dollar (USD) and Euro (EUR), that the value of cryptocurrencies is not stable over time, and the assets are not government guaranteed. These factors play on the psychological states of investors when expressing their sentiments (Porshnev et al., 2013). Thus, investors have higher psychological biases that influence their sentiments (Daniel et al., 1998), and these sentiments can be gauged by related expressions on vast social media platforms such as Twitter (Porshnev et al., 2013) aside from conventional sources like company disclosures and analyst reports (X. Li et al., 2014; Schumaker et al., 2012).

Social media sites such as Twitter and Facebook, discussion fora like Reddit, and public interest sites such as Google and Wikipedia are notable sources (Burnie & Yilmaz, 2019) that have users or investors publishing their thoughts and opinions (Giachanou & Crestani, 2016). In addition, empirical studies (e.g., Bollen et al. 2011; Bryan 2016; Deng et al. 2018) have found evidence of social media sentiments predicting future market returns.

Deng et al. (2018) showed that negative sentiment significantly influences stock returns at the first and sixth hourly lags. Within the diverse cryptocurrency market, with millions of cryptocurrency exchanges between the same and different traders each day, Twitter sentiment has been shown to have predictive power for the returns of multiple (nine) cryptocurrencies (Kraaijeveld & De Smedt 2020). Of the 24, 035,075 total tweets collected in Kraaijeveld & De Smedt's study, Bitcoin and Ethereum make up nearly 70 percent of the number. This study attempts to make sense of the disparate Twitterverse of cryptocurrency price influences by providing a coherent understanding of the power of Bitcoin opinion leaders to predict next-day Bitcoin cryptocurrency prices via the lens of Twitter network sentiment analysis. Bitcoin is the largest cryptocurrency by market capitalization (Abraham et al., 2018; Kraaijeveld & De Smedt, 2020).

Opinion mining is "the computational study of people's opinions, appraisals, attitudes, and emotions toward entities, individuals, issues, events, topics, and their attributes" (B. Liu & Zhang, 2012). Sentiment Analysis (SA) and opinion mining (OM) are commonly used interchangeably, but the distinction between the two is critical for this study. Liu (2012) defines opinion as "a quintuple of e_i, a_{ij} , s_{ijkl}, h_k, t_l; where e_i is the name of an entity, a_{ij} is an aspect of e_i, s_{ijkl} is the sentiment on aspect *aij* of entity *ei* , h_k is the opinion holder, and t_l is the time when the opinion is expressed by h_k." In exploring bitcoin cryptocurrency behavior, the critical question will be; whose sentiments are being analyzed, and how do these niche sentiments affect cryptocurrency returns? Methodologically, this delineation is vital to apply lexicons that robustly define the peculiarity of the opinion leaders for textual analysis of curated sentiments. Leadership, in general, is a critical factor in technology innovation adoption (Hameed et al., 2012; Sharma & Rai, 2003), and opinion leaders will be no different in influencing the drive towards digital currency adoption and hence cryptocurrency price behaviors.

Mai et al. (2018) find that Bitcoin values are affected by the sentimental power of the silent majority (i.e., less active users). This group of users represents non-opinion leaders whose activities largely mimic the entire set of authors tweeting about bitcoin on social media. In our preliminary assessment of the 78 million bitcoin tweets collected by this research and spanning 2014 to 2021, we find in each year that these silent majority (i.e., non-opinion leaders) represent users with only 1 retweet per tweet within multiple 3-month windows and makeup about 90 percent of the total number of users within the focal 3-month window. Their impact in previous studies has been based on an aggregated and static measurement of the volume of tweets. Additionally, the predictive models used in these studies lacked explanatory power to explicate the underlying causal parameters. However, the activities of opinion leaders, who make up a relatively smaller percentage of total users with a high retweet count and whose sentiments might influence bitcoin price behavior or the activities of the rest of the entire Twitterverse of bitcoin community is not readily known. Thus, we assume that opinion leaders would be fulfilled seeing the impact of their influential tweets via retweets, and over time, their activities would lead them to build in-depth knowledge to inform a richer and higher quality tweet later. Essentially, these ‘noisy few’ (i.e. bitcoin opinion leaders) are like monomorphic opinion leaders who provide better signal because of the depth of understanding and specificity of their knowledge (Bamakan et al., 2019). Such quality signals will help to elicit further market response, and movement in bitcoin cryptocurrency prices (Xie et al., 2020). We explore the influence of periodic and dynamic opinion leader sentiments in Twitter Bitcoin network on bitcoin cryptocurrency price behavior and vice versa. We address the following research questions:

(1) How do social media opinion leaders' sentiments affect the pricing behaviors of Bitcoin cryptocurrency?

(2) *How do Bitcoin cryptocurrency pricing behavior affect social media opinion leaders' sentiments?*

We operationalized opinion leader sentiments in terms of the polarity and subjectivity of their tweets. Estimating a vector autoregression model as an explanatory model, we find that bitcoin price return granger causes polarity, and polarity has a significant influence on the volume of tweets of the silent majority (non-opinion leaders). Subjectivity has a bidirectional relationship with bitcoin volatility. The rest of the paper is as follows: theoretical background and a hypothesis development section is followed by methodology, results, discussion and implications. We conclude with limitations and future directions of the study.

Theoretical Background and Hypothesis Development

Cryptocurrencies and Bitcoin Pricing

"Cryptocurrencies are digital currencies based on cryptographic technology, which regulates the generation, verification and transaction between two or more parties" (Kazan et al., 2015b, p. 3). Cryptocurrencies are the first major use-case for blockchain and remain the most successful and by late 2017, had spiked to a value of nearly US$20,000 (Gomber et al., 2018) and even US$60, 000 in late 2021. Yet, this meteoric rise has been scampered on many occasions by unexpected quantum fall in prices to the current US$30,000-40000 price range, the first quarter of

2022. Bitcoin's price volatility is well cataloged (e.g., Polasik et al., 2015), and the complex trends have called into question the rationality behind most valuation implications of cryptocurrency studies (Eglitis & Seputyte, 2017; Gomber et al., 2018). Whiles some have referred to Bitcoin valuation as a Ponzi scheme and called for the outlaw of cryptocurrencies, many scholars have provided richer findings and shown how a better boundary rationality definition and critical data scale and availability coupled with the right analytical assumptions and techniques improve cryptocurrency price forecast.

Social Media Sentiment Analysis and Market Returns

Sentiment analysis or opinion mining is "the computational study of people's opinions, appraisals, attitudes, and emotions toward entities, individuals, issues, events, topics, and their attributes" (B. Liu & Zhang, 2012) in which polarity scores are used to assign weights to unstructured text. Using a large text discussion dataset from Yahoo Finance, Kim and Kim (2014) find no support that investor sentiments forecast future stock returns either at the aggregate or individual firm levels. However, Xie et al.'s (2020) study finds such support and shows that prior studies neglected the moderating role of the network cohesiveness (i.e., the degree centrality and the average density of the network) of discussion threads.

Mainly, sentence-or phrasal analyses present the most granular level of analysis for Twitter owing to the limited number of 280 characters per tweet. Twitter offers a combination of both news and investor sentiments, making it attractive for discovering price behavior in the markets (Kraaijeveld & De Smedt, 2020). Several methodological approaches have been used to measure sentiments on Twitter and other social media sites; supervised machine learning approaches (e.g., Porshnev et al. 2013), lexicon-based approaches (e.g. Li et al. 2014) and hybrid of machine and lexicon-based (e.g., Loughran and McDonald 2011) remain popular. Loughran &

Mcdonald's (2011) showed improvement in the prediction accuracy when sentiment analysis classifier leverages context-specific dictionaries in their hybrid approach.

Other approaches include graph-based analysis (Giachanou & Crestani, 2016) and economic modeling approaches such as regression analysis and models that afford Granger causality tests (Bollen et al., 2011; Mao et al., 2011). Kraaijeveld and De Smedt (2020) tests a bilateral Granger-causality to determine the predictive power of Twitter sentiment. They argue that the assumptions of data stationarity and linearity in existing Granger-causality methods are challenged by non-linear relations that may exist between stock returns and exogenous variables. Regardless of the domain of approach and the data platform accessed, several mixed findings have been reported. To the extent that Lachanski and Pav (2017), for incongruent statistical assumptions, have challenged Bollen et al. (2011) 's widely cited findings on the effectiveness of Twitter sentiments in predicting financial market returns. Derwent Capital Markets – a sentiment-based trading platform – leveraged the findings for their trading business model but was later unsuccessful and failed to survive the market. The platform was later auctioned for $186,000 with an initial expectation of $7.8 million (O'Connor et al., 2010). A similar example is the catastrophic failure of Japan's Mt. Gox Bitcoin Exchange platform in 2014 (Gomber et al., 2018). Similar challenges have led to many retractions and new forecasts about cryptocurrency returns, particularly with bitcoin prices.

Leadership Theory and Online Opinion Leadership

The idea of opinion leadership is rooted in the long-held thought that an "item in the newspaper has no influence unless it becomes the subject of conversation" (Katz, 2015). Opinion leaders mediate the flow of opinion and information from mass media to the public audience (Katz, 1957; Lazarsfeld et al., 1944). The two-step flow of communication theory states that “ideas often flow from radio and print to opinion leaders and from these to the less active sections of the population” (Katz, 1957). The lack of face-to-face communication, the primacy nature of text-based asynchronous exchanges interactions and the mediated nature of interactions makes online opinion leadership different from traditional settings (Johnson et al. 2015).

To determine the emergent online community or network leader, Johnson et al. (2015) offer points of departure and points of leverage in a synthesis of the four main leadership theories in traditional organization settings – functional leadership theory (Burke et al., 2006; Morgeson et al., 2010), leader-member exchange (LMX) theory (Graen & Uhl-Bien, 1995) shared leadership perspective (Pearce & Sims, 2000) and communication as constitutive of organizing (CCO) theory. Interrogating these perspectives as applicable to online network leadership is necessary because online networks are of fluid membership and not stable designations. Given the large groups of sub-networks, online leadership is thus broadly distributed and shared (Johnson et al., 2015). Concerning functional leadership theory, Johnson et al. (2015) apply the view of the functions performed by the leaders rather than its assumption of apriori designation as in traditional settings. From the view of LMX theory, online leadership is contingent and situated but constrained by the large group differences on online networks. This is consistent with opinion leadership literature that reveal that the roles of ‘influentials’ and ‘influences’ (other terms for opinion leaders) could change with time and in different domains (Bamakan et al., 2019). The perspective of shared leadership theory is akin to online organizing in that leadership is not restricted to designated leaders. Lastly, CCO theory emphasizes the interdependency of textual communications of a leader and constituted actions members in that the interactions serve as structuring and reinforcing processes towards the emergence of the network leader (Robichaud & Cooren, 2013). Thus, eventual leaders are members who to co-lead each other and are not independent from their text communications.

The discussion reveals that no single leadership view is sufficient to examine the role of Bitcoin opinion leaders in shaping crowd sentiments to predict financial returns. Johnson et al.'s (2015) synthesis of leadership theories enabled the determination of online leaders not only from the perspective of high network centralities but also from communication network positions defined by membership in a core or periphery and low boundary-spanning and from the characteristics of written text. Specifically, online leaders are also those with a high volume of positive concise posts with simple language familiar to other participants (Johnson et al. 2015). This study shares these views to identify Bitcoin opinion leaders and their salient role from a sentiment analysis perspective. Opinion leadership literature also (Bamakan et al., 2019) categorizes leaders as monomorphic opinion leaders given a predominant knowledge domain or polymorphic opinion leaders given their knowledge of more than one peripheral knowledge domain. In this study, the focus is on the salient role played by Bitcoin opinion leaders in predicting Bitcoin price behavior and vice versa.

Twitter Opinion Leader Sentiments and Bitcoin Price Behavior

Xie et al. (2020) advance that the cohesiveness of a discussion network affects the relationship between social media sentiment and bitcoin returns. Less cohesive networks are better at predicting future market returns due to the quality of information (signal) available rather than noise. Less cohesive or sporadic networks (with fragmented communities) are synonymous with local opinion leaders (Bamakan et al., 2019). Thus, loose networks better shape social media sentiments and provide relevant information for predicting cryptocurrency returns than dense networks with synonymity with global opinion leaders (Bamakan et al., 2019).

In our case, considering a more dynamic opinion leader sentiments on Twitter, especially on hour levels, reveals a further vast amount of highly fragmented communities and so the signal quality of our opinion leader sentiment.

The psychology literature has established the relationship between emotions and sentiments, and the appraisal of emotion theoretical perspective posits threatening and beneficial appraisal resulting in negative and positive emotions, respectively (Lazarus, 1991; Roseman & Smith, 2001). The finance literature posits that traders have strong emotional responses (Lo et al. 2005). Investors' psychological biases from these emotions (stimuli) influence their sentiments (Daniel et al., 1998) which can be captured by related expressions on vast social media platforms such as Twitter (Porshnev et al., 2013).

Emotions are thus not just feelings as they also create impulses to act (Frijda, 1986; J. J. Gross & Thompson, 2007), and one action that is commonly associated with triggered emotions is the posting of messages on social media (R. Aggarwal et al., 2012) studies in sentiment analysis and opinion mining have also suggested the emotional richness in social media messages (e.g., Chen and Zimbra 2010; Liu 2012). Deng et al. (2018) also assert that fluctuations of a stock market serve as emotional stimuli, while Twitter microblog sentiment is an affective psychological state expressed in communication. To evaluate these psychological biases with respect to their determination of the sentiments of interest, emotion-aware polarity lexicons (EAPLs) have been

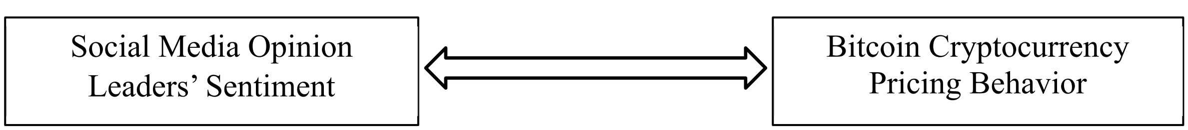

Figure 4: Research Model

championed (Bandhakavi et al. 2018). EAPLs lead to better sentiment classifications and prediction of sentiment intensity tasks, particularly in Twitter analysis when compared with supervised latent Dirichlet allocation (sLDA) and word-document-frequency (WDF) statistics (Bandhakavi et al. 2018).

At the least, two categories of human emotional response have been posited: *arousal* and *valence* (L. Deng & Poole, 2010). While the former is a nonspecific and nondirectional category, the latter refers to the directional component of emotional response, which ranges from positive to negative. This view is prevalent in most sentiment analysis studies and primarily assumes that valence responses can only be negative and positive, respectively, emanating from negative emotions and positive emotions. There are enormous benefits to considering sentiments as positive and negative, such as in EWOM perspectives, which show that negative reviews inform buyer decisions better than positive reviews (Doh & Hwang, 2009; Ismagilova et al., 2016). However, responses that reflect positive psychological biases even when the stimuli are negative and reflection of negative investor psychological biases when the stimuli are positive are such that they cannot be assumed only on the bases of positive and negative sentiment scores. Hence the use of a polarity measure and the intensity of this polarity (i.e., subjectivity measure). On average, microblogs may elicit positive and negative emotions in the same cross-section of people over time because of the volume, velocity, and veracity of tweets even in an hour. Juxtaposing this with a traditional news item on a subject that may have far lesser update frequency. Hence the psychological biases of the cross-section of Twitter micro-bloggers at any time may be a function of the composition of negative and positive emotions, and a polarity measure of sentiment helps to capture this composition.

The positive feedback trading theory also posits that the beliefs of noise investors (i.e., the larger cross-section of Twitter users) about future stock returns are heavily influenced by the returns in the previous period (de Long et al., 1990; Nofsinger & Sias, 1999). The latest stock market price behavior movements constantly update investors' forward-looking opinions (Deng et al., 2018). Thus, there are bidirectional impacts in light of our discussion above. In this study, we consider Bitcoin cryptocurrency price behavior as close to stock market price behavior. The discussion thus far leads to the following hypothesis.

Impacts of opinion leader sentiments on bitcoin pricing behavior.

H1. Bitcoin opinion leader sentiments will be positively associated with Bitcoin price return.

H2. Bitcoin opinion leader sentiments will be positively associated with Bitcoin price volatility.

Impacts of bitcoin pricing behavior on opinion leader sentiments.

H3. Bitcoin price return will be positively associated with Bitcoin opinion leader sentiments.

H4. Bitcoin price volatility will be positively associated with Bitcoin opinion leader sentiments.

Methodology

Data Sources and Variables

The study collected archival data on bitcoin from Twitter spanning from January 1, 2014, to December 31, 2021. A final sample of over 74 000 000 tweets was aggregated by the hour based on an opinion leader identification strategy to construct a time series model. A feeds-hour data on Bitcoin price indices over the same period was collected from CoinDesk. S&P500 was used to access data on the S&P index, whereas COMEX data was used to collect data on gold prices. Google Search Trends provided data for indices for keywords "Bitcoin" that may have impacted Bitcoin prices and tweets.

Key variables. Next-hour Bitcoin return, and Bitcoin volatility are used as key bitcoin cryptocurrency behavior variables. Hour t Bitcoin return is measured by $ReturnBitcoin_t$=($lnBitcoinPriceIndex_t - lnBitcoinPriceIndex_{t-1}$) $x100$, where *BitcoinPriceIndex*$_t$ is the closing bitcoin price average of 10 crypto 'stock' exchanges at hour t. Bitcoin volatility is measured as the square root of the squared predicted residuals from the periodic moving averages.

The key sentiment variables for opinion leaders are Polarity (valence) and Subjectivity in opinion leaders' tweets at the hourly level. Polarity is a measure of the combined influence of positive and negative sentiments. It is a 'normalized, weighted composite score computed by summing the valence scores of each word in the lexicon, adjusted according to the rules, and then normalized to be between '-1' (most extreme negative) and '+1' (most extreme positive). Subjectivity measures the level of objectivity of expressed sentiments which may be characterized by excessive speculation and sensationalism, and it is normalized between 0 and 1.

Control factors. The study uses the following control factors: Bitcoin trading volume, bitcoin tweet volume, bitcoin tweet volume of opinion leaders, tweet volume of non-opinion leaders, S&P 500 Index, COMEX gold price return, Google Trends index for keyword Bitcoin, periodic fixed effects. Bitcoin trading volume of institutional traders as with high-frequency traders (HFTs), in addition to individual strategies of bitcoin 'faithful', are likely to cause fluctuations in the bitcoin cryptocurrency market. To control for implied volatility which is reflective of the market expectation of share price's direction, the study used the Chicago Board Options Exchange Volatility Index (symbol: VIX).

Identification Strategy for Opinion Leaders

One is a part of Twitter network if they post or reply to a message in the focal conversation thread. Given that replies and other textual communications on Twitter are highly limiting in character length, focal networks may not be robust enough to identify the functional opinion leader. Where applicable, it becomes imperative to include the functional designation of the leader via the prior period's tweets. The inclusion of this identification criterion will be in addition to the evaluations via the differentiating behaviors between leaders and non-leaders. Even when leaders emerge in later Twitter networks, there are no granting of formal authority to designated administrators and moderators as with other online community platforms hence the need for assigning this criterion in a dynamic manner as far as Twitter is concerned to assume pre-assigned functionality of identified opinion leaders on Twitter.

To identify dynamic opinion leaders, I first aggregate users' last three months' posts on a rolling base on the entirety of our dataset per unique user – posts for the period below the initial three months are aggregated, regardless. This approach allows for running analysis on the aggregated and average parameters, following Johnson et al. (2015). I then leverage the retweet count of user tweets within every focal three months measures to determine ranking scores for each user within the focal window. A retweet is a simple measure of the role and importance of user tweets and, consequently, the user as far as the focal window is concerned. "A formal role is the most important predictor for online community leadership" (Johnson et al., 2015, p. 178). A formal role of authority in an online community is mostly ascribed to users who are most active and relevantly engaged (Johnson et al. 2015). Retweets help reveal the importance of a user tweet to the community and make for a "pseudo" formal role of authority ascription by the crowd hence the use of this parameter in our study. The top 10 percent of the user ranking by retweets (excluding users with a retweet count less than 2) is identified as the group of opinion leaders that might influence the next hour's bitcoin price return or price volatility.

Data Mining Opinion Leader Sentiment Scores

Applying the language model of Johnson et al. (2015), our Twitter textual analysis parameters are premised on the following four language dimensions: semantics, morphology, lexicography, and syntax. Semantics deals with the construction and application of posts through the meaning of texts rather than their structure. A VADER (Valence Aware Dictionary and sEntiment Reasoner)-based sentiment analysis algorithm was used to generate the sentiments because it correlates best with bitcoin prices, especially over shorter timespans. VADER assesses the sentiments of posts in terms of their polarity (i. e. positive, negative, and neutral) to determine the semantic influence of opinion leaders' posts and is a robust EAPL for sentiment analysis of Bitcoin tweets (Pano & Kashef, 2020). Average sentiments from users on their last three months' posts were analyzed with VADER.

Econometric Modeling

The general form of each equation in the VAR systems presented above is a vector autoregression model that was estimated using the panel data constructed.

VAR model specification. Vector autoregression model (VAR) is used to capture the interrelationships among multiple time series. In our case, multiple time series of hourly involving polarity subjectivity of opinion leaders' tweets and bitcoin returns and price volatility were analyzed as main variables of interest, among other control factors.

Consider the equations 1.1, 1.2, and 1.3 below for the three-variable structural VAR model; given only *ReturnBitcoin*, *Polarity,* and *Subjectivity* represented by B_t, P_t, and S_t, respectively, where ε_{Bt}, ε_{Pt} and ε_{St} are uncorrelated white-noise disturbances (shock terms) with standard deviations of are σ_B, σ_P σ_S respectively. Each variable has its univariate equation based on its lagged autoregression (AR) values and enters the VAR analyses at the same time as the other variables on the assumption of stationarity and one lag.

$$B_t = a_{10} + a_{13}S_t + a_{12}P_t + \gamma_{11}B_{t-1} + \gamma_{12}P_{t-1} + \gamma_{13}S_{t-1} + \varepsilon_{Bt} \quad (1.1)$$

$$P_t = a_{20} + a_{23}S_t + a_{21}B_t + \gamma_{21}B_{t-1} + \gamma_{22}P_{t-1} + \gamma_{23}S_{t-1} + \varepsilon_{Pt} \quad (1.2)$$

$$S_t = a_{30} + a_{32}P_t + a_{31}B_t + \gamma_{31}B_{t-1} + \gamma_{32}P_{t-1} + \gamma_{33}S_{t-1} + \varepsilon_{St} \quad (1.3)$$

This set of theoretical estimations represents the non-reduced first-order structural VAR which is the ideal model. However, it is not practically feasible to estimate this model because of under-identification. Thus, a simple identification strategy that imposes restrictions on the parameters a_{21} and a_{31} in Equations 1.2 and 1.3, respectively, will produce a more practical and intuitive VAR estimation – the standard VAR model – represented by equations 2.1, 2.2, and 2.3 assuming multiple lags.

$$B_t = a_{10} + \sum_{i=1}^{k} a_{i1}B_{t-i} + \sum_{j=1}^{k} a_{j2}P_{t-j} + \sum_{m=1}^{k} a_{m3}S_{t-m} + e_{Bt} \quad (2.1)$$

$$P_t = a_{10} + \sum_{i=1}^{k} a_{i1}B_{t-i} + \sum_{j=1}^{k} a_{j2}P_{t-j} + \sum_{m=1}^{k} a_{m3}S_{t-m} + e_{Pt} \quad (2.2)$$

$$S_t = a_{30} + \sum_{i=1}^{k} a_{i1}B_{t-i} + \sum_{j=1}^{k} a_{j2}P_{t-j} + \sum_{m=1}^{k} a_{m3}S_{t-m} + e_{St} \quad (2.3)$$

To test the bidirectional relationships between opinion leader tweet sentiment and bitcoin returns and between opinion leader tweet sentiment and bitcoin volatility, I specify a standard VAR estimation model (shown in Figure 4) where α_i is the intercept equation *i*. $\varphi_{i,j}^{t-k}$ estimates the effect of one endogenous variable*, j, on* another endogenous variable*, i.* at time *t.* $\gamma_{1,u,t}$ measures the effect of Hour Period on variable *i* at time *t.* ReturnBitcoin is the hourly return on Bitcoin cryptocurrency.

The selection-order criteria for all endogenous variables were determined by the number of lags with the lowest Bayesian information criterion (SBIC) (Luo et al., 2013), given the estimation model in Figure 5. Table 6 shows the optimal lag selection of four for the specified model.

$$\begin{bmatrix} ReturnBitcoin_t \\ VolatilityBitcoin_t \\ Polarity_t \\ Subjectivity_t \\ lnTradingVolume_t \\ lnOPLTweetVolume_t \\ lnNOPLTweetVolume_t \\ GoogleSearchIndex_t \\ ReturnS\&P500_t \\ ReturnVIX_t \\ ReturnCOMEXGold_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \\ \alpha_6 \\ \alpha_7 \\ \alpha_8 \\ \alpha_9 \\ \alpha_{10} \\ \alpha_{11} \end{bmatrix} + \sum_{k=1}^{K} \begin{bmatrix} \varphi_{1,1}^{t-k} \ldots . \varphi_{1,11}^{t-k} \\ \varphi_{2,1}^{t-k} \ldots . \varphi_{2,11}^{t-k} \\ \varphi_{3,1}^{t-k} \ldots . \varphi_{3,11}^{t-k} \\ \varphi_{4,1}^{t-k} \ldots . \varphi_{4,11}^{t-k} \\ \varphi_{5,1}^{t-k} \ldots . \varphi_{5,11}^{t-k} \\ \varphi_{6,1}^{t-k} \ldots . \varphi_{6,11}^{t-k} \\ \varphi_{7,1}^{t-k} \ldots . \varphi_{1,11}^{t-k} \\ \varphi_{8,1}^{t-k} \ldots . \varphi_{8,11}^{t-k} \\ \varphi_{9,1}^{t-k} \ldots . \varphi_{9,10}^{t-k} \\ \varphi_{10,1}^{t-k} \ldots . \varphi_{10,11}^{t-k} \\ \varphi_{11,1}^{t-k} \ldots . \varphi_{11,11}^{t-k} \end{bmatrix} \begin{bmatrix} ReturnBitcoin_{t-k} \\ VolatilityBitcoin_{t-k} \\ Polarity_{t-k} \\ Subjectivity_{t-k} \\ lnTradingVolume_{t-k} \\ lnOPLTweetVolume_{t-k} \\ lnNOPLTweetVolume_{t-k} \\ GoogleSearchIndex_{t-k} \\ ReturnS\&P500_{t-k} \\ ReturnVIX_{t-k} \\ ReturnCOMEXGold_{t-k} \end{bmatrix} + \begin{bmatrix} \gamma_{1,u,t} \\ \gamma_{2,u,t} \\ \gamma_{3,u,t} \\ \gamma_{4,u,t} \\ \gamma_{5,u,t} \\ \gamma_{6,u,t} \\ \gamma_{7,u,t} \\ \gamma_{8,u,t} \\ \gamma_{9,u,t} \\ \gamma_{10,u,t} \\ \gamma_{11,u,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ \varepsilon_{4,t} \\ \varepsilon_{5,t} \\ \varepsilon_{6,t} \\ \varepsilon_{7,t} \\ \varepsilon_{8,t} \\ \varepsilon_{9,t} \\ \varepsilon_{10,t} \\ \varepsilon_{11,t} \end{bmatrix}$$

Figure 5: Estimation Model (Model 1)

Results

Pre-estimation Diagnostics

The summary statistics are shown in Table 5, and the correlations among key variables are shown in Appendix C. The VAR models are estimated using Stata. Aside from the main estimation variables with all the control variables, a second model was estimated with only the key variables of interest: ReturnBitcoin, VolatilityBitcoin, Polarity, and Subjectivity.

Table 5: Summary Statistics

Variable Name	Obs	Mean	SD	Min	Median	Max
Panel A: Statistics on Key and Control Variables						
ReturnBitcoin	67761	0.007	1.132	-20.221	0.007	20.842
VolatilityBitcoin	67761	-1.280	1.420	-11.402	-1.156	3.014
Polarity	66970	0.150	0.042	-0.053	0.151	0.436
Subjectivity	66970	0.443	0.037	0.223	0.446	0.668
lnTradingVolume	67762	7.316	1.092	-3.730	7.385	11.741
lnOPLTweetVolume	67762	5.932	0.545	1.386	5.844	8.528
lnNOPLTweetVolume	66970	5.532	1.527	0.000	5.704	9.642
GoogleSearchIndex	67762	58.567	17.579	3.000	60.000	100.000
ReturnSnP500	44340	0.003	0.219	-4.715	0.003	5.607
ReturnVIX	44296	-0.005	1.109	-14.792	0.000	21.357
ReturnCOMEXGold	43157	-0.000	0.303	-6.968	0.000	6.762
Panel B: Statistics on Raw Bitcoin and Tweet Data						
BitcoinPriceIndex	67762	10152.338	15426.950	178.930	4745.700	68640.203

Table 5, cont.

TradingVolume	67762	2580.813	3547.663	0.024	1612.213	125596.000
TweetVolume	67762	975.755	998.755	9.000	623.000	19106.000
OPLTweetVolume	66970	445.540	315.996	3.000	344.000	5051.000
NOPLTweetVolume	66970	535.203	724.821	0.000	299.000	15394.000

Table 6: Selection-order Criteria for All Variables

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-302858.84				2.8e-06	18.427	18.428	18.429
1	-200455.11	204807.460	121	0.000	5.5e-09	12.204	12.215	12.237
2	-190101.86	20706.511	121	0.000	3.0e-09	11.581	11.602	11.646
3	-185992.56	8218.604	121	0.000	2.3e-09	11.339	11.369	11.434
4	-184347.44	3290.245	121	0.000	2.1e-09*	11.246	11.286*	11.372*

Notes: N = 32873; LL: Log-likelihood; LR: Likelihood Ratio; FPE: Final Prediction Error; AIC: Akaike Information Criterion; SBIC: Schwartz Bayesian Information Criterion; HQIC: Hannan and Quinn information criterion. Optimal order of four lags was accessed by all models reported in this study.

An augmented Dickey-Fuller unit root test was performed to assess the assumption of stationarity of the VAR model variables (Dickey & Fuller, 1979; Said & Dickey, 1984). Thus, in solving the system of multivariate linear equations in the specified VAR models, the convergence requires that the root of the polynomial must lie outside the unit circle for unbiased estimation coefficients.

Model Results

Table 7: Vector Autoregression Results (Model 1)

Equation	Parms	RMSE	R-sq	χ^2	P> χ^2
ReturnBitcoin	45	1.120	0.060	2113.045	0.000
Polarity	45	0.031	0.451	27018.190	0.000
Subjectivity	45	0.030	0.350	17668.570	0.000
VolatilityBitcoin	45	1.295	0.165	6502.235	0.000
lnTradingVolume	45	0.678	0.566	42914.940	0.000
lnOPLTweetVolume	45	0.166	0.903	304331.900	0.000
lnNOPLTweetVolumne	45	0.785	0.772	111217.500	0.000
GoogleSearchIndex	45	9.305	0.726	86945.710	0.000
ReturnSnP500	45	0.236	0.004	145.458	0.000
ReturnVIX	45	1.189	0.003	86.294	0.000

Table 7, cont.

Equation	Parms	RMSE	R-sq	χ^2	P> χ^2
ReturnCOMEXGold	45	0.309	0.123	4622.790	0.000

Notes: N = 32,873; RMSE: Root Mean Square of Error, Parms: Parameters

The optimal lag for Model 1 based on BIC was five (days). For the equation using ReturnBitcoin and ReturnVolatility as the dependent variables (i.e., the return equation), none of the lags of polarity sentiment are significant. However, subjectivity impact on ReturnVolatility is significant and persistent over the first and second hour, picking up in the fourth hour. Interestingly polarity negatively impacts the volume of tweets of non-opinion leaders, whereas subjectivity positively impacts non-opinion leader tweets. Polarity as the dependent variable is positively affected by the Bitcoin Return only in the first hour (Table 8). Figure 7 shows the IRF plots of the responses of polarity and subjectivity to bitcoin return and volatility. The curves show the accumulated orthogonalized responses of sentiments by the number of hours. The grey bands are the 95% confidence intervals. The plots (in Figure 6) show that volatility and subjectivity significantly respond to shocks of polarity and subjectivity.

Table 8: VAR Results on Lag Coefficients (Model 1)

VARIABLES	(1) ReturnBitcoin	(2) VolatilityBitcoin	(3) Polarity	(4) Subjectivity	(5) lnTradingVolume	(6) lnOPLTweetVolume	(7) lnNOPLTweetVolume	(8) GoogleSearchIndex	(9) ReturnSnP500	(10) ReturnVIX	(11) ReturnCOMEXGold
L.ReturnBitcoin	-0.247***	0.029***	0.001***	0.000	-0.011***	-0.000	-0.004	-0.130***	-0.001	-0.008	0.001
	(0.006)	(0.006)	(0.000)	(0.000)	(0.003)	(0.001)	(0.004)	(0.046)	(0.001)	(0.006)	(0.002)
L2.ReturnBitcoin	-0.093***	0.002	0.000*	-0.000	-0.002	-0.001	0.001	-0.058	0.002*	-0.012**	0.001
	(0.006)	(0.007)	(0.000)	(0.000)	(0.003)	(0.001)	(0.004)	(0.048)	(0.001)	(0.006)	(0.002)
L3.ReturnBitcoin	-0.024***	-0.014**	0.000	0.000	0.004	-0.002*	0.002	-0.004	0.000	0.004	-0.002
	(0.006)	(0.007)	(0.000)	(0.000)	(0.004)	(0.001)	(0.004)	(0.048)	(0.001)	(0.006)	(0.002)
L4.ReturnBitcoin	-0.005	-0.010	-0.000	0.000	0.003	-0.001*	0.008**	0.057	0.003***	-0.010	-0.001
	(0.006)	(0.007)	(0.000)	(0.000)	(0.003)	(0.001)	(0.004)	(0.047)	(0.001)	(0.006)	(0.002)
L.VolatilityBitcoin	-0.029***	0.147***	-0.000	0.000***	0.039***	0.004***	-0.009**	0.104**	0.001	-0.004	-0.002
	(0.005)	(0.006)	(0.000)	(0.000)	(0.003)	(0.001)	(0.004)	(0.043)	(0.001)	(0.005)	(0.001)
L2.VolatilityBitcoin	-0.011**	0.090***	0.000**	0.000**	-0.019***	-0.003***	0.001	-0.065	-0.001	0.002	-0.003**
	(0.005)	(0.006)	(0.000)	(0.000)	(0.003)	(0.001)	(0.004)	(0.043)	(0.001)	(0.006)	(0.001)
L3.VolatilityBitcoin	0.011**	0.078***	0.000*	0.000	-0.011***	-0.000	0.006*	-0.029	0.001	-0.006	0.002
	(0.005)	(0.006)	(0.000)	(0.000)	(0.003)	(0.001)	(0.004)	(0.043)	(0.001)	(0.006)	(0.001)
L4.VolatilityBitcoin	-0.001	0.075***	0.000	0.001***	-0.010***	0.001	0.005	-0.021	-0.002	0.001	0.001
	(0.005)	(0.006)	(0.000)	(0.000)	(0.003)	(0.001)	(0.004)	(0.043)	(0.001)	(0.005)	(0.001)
L.Polarity	0.265	0.153	0.356***	0.013**	-0.176	0.203***	-0.896***	-3.739**	0.015	0.266	-0.079
	(0.211)	(0.244)	(0.006)	(0.006)	(0.128)	(0.031)	(0.148)	(1.755)	(0.044)	(0.224)	(0.058)
L2.Polarity	-0.012	0.140	0.146***	0.013**	0.040	0.174***	-0.380**	0.902	0.038	-0.160	0.059
	(0.222)	(0.257)	(0.006)	(0.006)	(0.134)	(0.033)	(0.156)	(1.842)	(0.047)	(0.235)	(0.061)
L3.Polarity	0.363	-0.021	0.130***	0.021***	-0.311**	0.073**	-0.008	-0.578	0.013	-0.318	0.005
	(0.222)	(0.256)	(0.006)	(0.006)	(0.134)	(0.033)	(0.155)	(1.842)	(0.047)	(0.235)	(0.061)
L4.Polarity	0.067	-0.130	0.112***	0.009*	-0.120	-0.019	-0.171	-0.694	0.053	-0.414*	-0.027
	(0.210)	(0.242)	(0.006)	(0.006)	(0.127)	(0.031)	(0.147)	(1.741)	(0.044)	(0.222)	(0.058)
L.Subjectivity	0.209	0.612**	0.003	0.321***	0.237*	0.079**	-0.226	5.675***	-0.016	0.028	0.158***
	(0.220)	(0.255)	(0.006)	(0.006)	(0.133)	(0.033)	(0.154)	(1.829)	(0.046)	(0.234)	(0.061)
L2.Subjectivity	-0.127	0.667**	0.004	0.101***	-0.270*	-0.123***	0.608***	-1.435	-0.038	0.151	-0.066
	(0.229)	(0.265)	(0.006)	(0.006)	(0.139)	(0.034)	(0.161)	(1.906)	(0.048)	(0.243)	(0.063)
L3.Subjectivity	-0.327	0.304	0.015**	0.113***	-0.083	-0.086**	0.792***	1.556	0.024	0.049	-0.017
	(0.229)	(0.265)	(0.006)	(0.006)	(0.139)	(0.034)	(0.161)	(1.905)	(0.048)	(0.243)	(0.063)
L4.Subjectivity	0.098	0.638**	-0.003	0.081***	-0.136	-0.133***	-0.021	-0.975	-0.015	0.075	0.005
	(0.219)	(0.253)	(0.006)	(0.006)	(0.132)	(0.032)	(0.153)	(1.818)	(0.046)	(0.232)	(0.060)
L.LnTradingVolume	0.026***	0.133***	-0.001***	-0.001**	0.446***	0.004***	0.008	0.310***	-0.003	0.023**	0.004

Table 8, cont.

VARIABLES	(1) ReturnBitcoin	(2) VolatilityBitcoin	(3) Polarity	(4) Subjectivity	(5) lnTradingVolume	(6) lnOPLTweetVolume	(7) lnNOPLTweetVolume	(8) GoogleSearchIndex	(9) ReturnSnP500	(10) ReturnVIX	(11) ReturnCOMEXGold
	(0.010)	(0.011)	(0.000)	(0.000)	(0.006)	(0.001)	(0.007)	(0.082)	(0.002)	(0.010)	(0.003)
L2.LnTradingVolume	0.001	0.025**	-0.001**	-0.000	0.139***	-0.006***	0.000	0.024	-0.000	-0.006	0.001
	(0.011)	(0.012)	(0.000)	(0.000)	(0.006)	(0.002)	(0.007)	(0.089)	(0.002)	(0.011)	(0.003)
L3.LnTradingVolume	0.002	0.000	-0.001*	-0.000	0.112***	-0.000	-0.017**	-0.016	0.004	-0.013	-0.005
	(0.011)	(0.012)	(0.000)	(0.000)	(0.006)	(0.002)	(0.007)	(0.088)	(0.002)	(0.011)	(0.003)
L4.LnTradingVolume	0.000	0.082***	-0.000	-0.000*	0.136***	0.004**	-0.005	-0.023	0.001	-0.004	0.001
	(0.010)	(0.011)	(0.000)	(0.000)	(0.006)	(0.001)	(0.007)	(0.080)	(0.002)	(0.010)	(0.003)
L.LnOPLTweetVolume	0.038	0.216***	0.005***	0.006***	0.272***	0.735***	1.520***	3.783***	0.008	-0.162***	-0.004
	(0.042)	(0.049)	(0.001)	(0.001)	(0.025)	(0.006)	(0.029)	(0.349)	(0.009)	(0.045)	(0.012)
L2.LnOPLTweetVolume	-0.039	-0.058	0.000	0.001	-0.063*	0.220***	-0.452***	-0.583	-0.021*	0.213***	0.000
	(0.057)	(0.066)	(0.002)	(0.002)	(0.035)	(0.008)	(0.040)	(0.474)	(0.012)	(0.061)	(0.016)
L3.LnOPLTweetVolume	0.011	-0.051	0.004***	0.002	-0.059*	0.054***	-0.265***	-1.057**	0.009	-0.033	0.006
	(0.057)	(0.066)	(0.002)	(0.002)	(0.034)	(0.008)	(0.040)	(0.472)	(0.012)	(0.060)	(0.016)
L4.LnOPLTweetVolume	-0.042	-0.034	-0.003**	-0.004***	-0.102***	-0.063***	-0.576***	-1.209***	0.005	-0.009	-0.005
	(0.044)	(0.051)	(0.001)	(0.001)	(0.027)	(0.007)	(0.031)	(0.365)	(0.009)	(0.047)	(0.012)
L.LnNOPLTweetVolume	-0.001	0.019*	-0.001***	0.001***	0.013**	0.016***	0.271***	0.220***	-0.001	-0.018**	0.001
	(0.009)	(0.010)	(0.000)	(0.000)	(0.005)	(0.001)	(0.006)	(0.073)	(0.002)	(0.009)	(0.002)
L2.LnNOPLTweetVolume	-0.006	0.013	-0.000**	0.000	0.011**	0.010***	0.250***	0.084	-0.001	0.026***	0.004
	(0.009)	(0.010)	(0.000)	(0.000)	(0.005)	(0.001)	(0.006)	(0.074)	(0.002)	(0.009)	(0.002)
L3.LnNOPLTweetVolume	0.005	0.005	0.001**	0.001***	-0.002	-0.002*	0.270***	-0.019	0.002	0.002	-0.002
	(0.009)	(0.010)	(0.000)	(0.000)	(0.005)	(0.001)	(0.006)	(0.075)	(0.002)	(0.010)	(0.002)
L4.LnNOPLTweetVolume	0.012	0.001	-0.000	-0.000	-0.009*	-0.013***	0.130***	-0.274***	0.000	-0.006	-0.002
	(0.008)	(0.009)	(0.000)	(0.000)	(0.005)	(0.001)	(0.005)	(0.064)	(0.002)	(0.008)	(0.002)
L.GoogleSearchIndex	0.000	-0.000	-0.000***	-0.000***	-0.000	-0.000***	0.002***	0.443***	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.001)	(0.000)
L2.GoogleSearchIndex	0.000	-0.000	-0.000**	-0.000	-0.000	-0.001***	0.002***	0.229***	0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)	(0.001)	(0.000)
L3.GoogleSearchIndex	-0.000	0.001	0.000**	0.000	0.000	-0.000***	0.000	0.139***	0.000	-0.001	-0.000

Table 8, cont.

VARIABLES	(1) ReturnBitcoin	(2) VolatilityBitcoin	(3) Polarity	(4) Subjectivity	(5) lnTradingVolume	(6) lnOPLTweetVolume	(7) lnNOPLTweetVolume	(8) GoogleSearchIndex	(9) ReturnSnP500	(10) ReturnVIX	(11) ReturnCOMEXGold
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)	(0.001)	(0.000)
L4.GoogleSearchIndex	-0.000	0.001	0.000	-0.000	0.000	0.000***	-0.002***	0.088***	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.001)	(0.000)
L.ReturnSnP500	-0.065*	0.042	-0.001	-0.000	-0.015	-0.020***	0.016	0.148	-0.068***	0.067	0.004
	(0.038)	(0.045)	(0.001)	(0.001)	(0.023)	(0.006)	(0.027)	(0.320)	(0.008)	(0.041)	(0.011)
L2.ReturnSnP500	-0.025	-0.046	-0.001	0.000	0.003	0.005	0.004	0.165	-0.014	0.032	-0.052***
	(0.041)	(0.047)	(0.001)	(0.001)	(0.025)	(0.006)	(0.028)	(0.337)	(0.009)	(0.043)	(0.011)
L3.ReturnSnP500	0.084**	-0.064	-0.002	0.001	0.000	0.004	0.018	-0.016	0.003	0.041	-0.036***
	(0.041)	(0.048)	(0.001)	(0.001)	(0.025)	(0.006)	(0.029)	(0.343)	(0.009)	(0.044)	(0.011)
L4.ReturnSnP500	-0.013	-0.032	-0.000	-0.000	-0.021	-0.010	-0.004	0.122	0.020**	0.041	0.041***
	(0.042)	(0.049)	(0.001)	(0.001)	(0.025)	(0.006)	(0.029)	(0.348)	(0.009)	(0.045)	(0.012)
L.ReturnVIX	-0.014*	0.021**	-0.000	0.000	0.001	-0.003***	-0.002	0.015	-0.012***	0.031***	0.004**
	(0.008)	(0.009)	(0.000)	(0.000)	(0.005)	(0.001)	(0.005)	(0.064)	(0.002)	(0.008)	(0.002)
L2.ReturnVIX	0.005	0.003	-0.000	-0.000	0.001	0.000	-0.007	0.012	-0.001	-0.003	-0.007***
	(0.008)	(0.009)	(0.000)	(0.000)	(0.005)	(0.001)	(0.006)	(0.066)	(0.002)	(0.008)	(0.002)
L3.ReturnVIX	0.004	-0.009	-0.000	0.000	-0.001	-0.002	0.010*	-0.070	0.001	-0.002	-0.003
	(0.008)	(0.009)	(0.000)	(0.000)	(0.005)	(0.001)	(0.006)	(0.067)	(0.002)	(0.009)	(0.002)
L4.ReturnVIX	-0.006	-0.006	-0.000	-0.000	-0.002	-0.001	-0.000	-0.009	0.007***	-0.014	0.006**
	(0.008)	(0.010)	(0.000)	(0.000)	(0.005)	(0.001)	(0.006)	(0.069)	(0.002)	(0.009)	(0.002)
L.ReturnCOMEXGold	0.014	-0.015	-0.001	0.000	-0.005	-0.001	-0.006	0.081	0.007*	0.011	-0.370***
	(0.020)	(0.023)	(0.001)	(0.001)	(0.012)	(0.003)	(0.014)	(0.166)	(0.004)	(0.021)	(0.006)
L2.ReturnCOMEXGold	0.008	0.001	-0.000	0.000	0.006	0.002	-0.010	-0.017	0.006	-0.000	-0.138***
	(0.021)	(0.025)	(0.001)	(0.001)	(0.013)	(0.003)	(0.015)	(0.176)	(0.004)	(0.022)	(0.006)
L3.ReturnCOMEXGold	0.039*	-0.011	-0.000	0.001	-0.009	0.002	-0.021	0.539***	0.009**	0.001	-0.047***
	(0.021)	(0.025)	(0.001)	(0.001)	(0.013)	(0.003)	(0.015)	(0.176)	(0.004)	(0.023)	(0.006)
L4.ReturnCOMEXGold	0.047**	-0.013	-0.000	0.000	-0.000	-0.002	0.011	-0.052	0.007	-0.016	-0.005
	(0.020)	(0.023)	(0.001)	(0.001)	(0.012)	(0.003)	(0.014)	(0.166)	(0.004)	(0.021)	(0.005)
Constant	-0.153	-4.227***	0.012***	0.139***	1.108***	0.385***	-1.247***	-3.928***	-0.015	-0.114	-0.035
	(0.140)	(0.162)	(0.004)	(0.004)	(0.085)	(0.021)	(0.098)	(1.166)	(0.030)	(0.149)	(0.039)
Observations	32,873	32,873	32,873	32,873	32,873	32,873	32,873	32,873	32,873	32,873	32,873

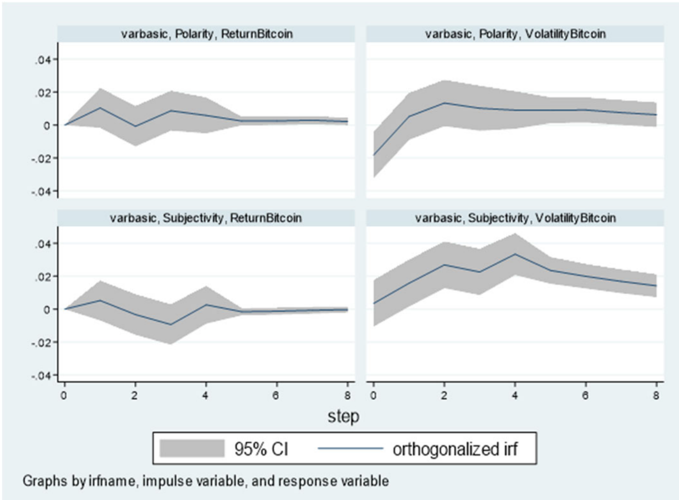

Figure 6: Bi-directional IRF Graphs with ReturnBitcoin and ReturnVolatility as Response Variables (Model 1)

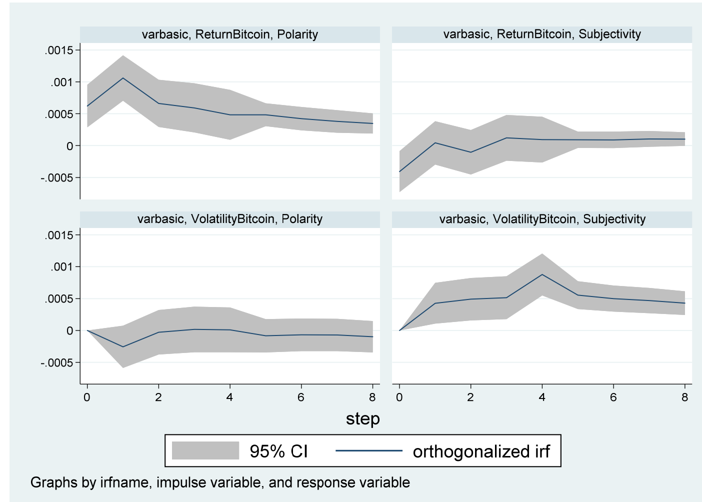

Figure 7: Bi-directional IRF Graphs with Polarity and Subjectivity as Response Variables (Model 1)

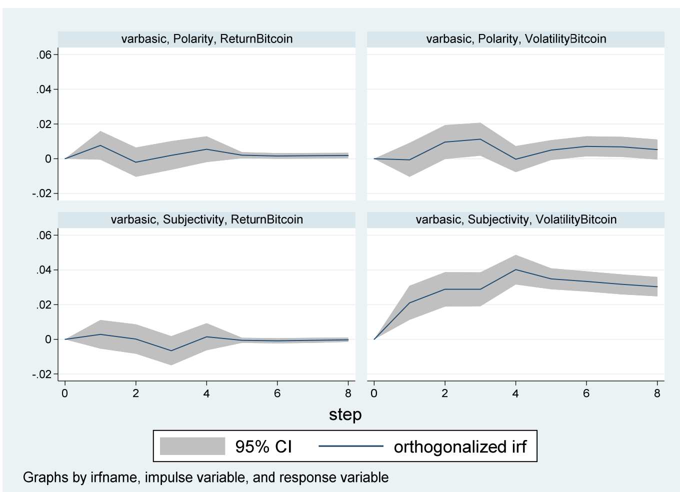

Figure 8: Bi-directional IRF Graphs with ReturnBitcoin and ReturnVolatility as Response Variables (Model 2)

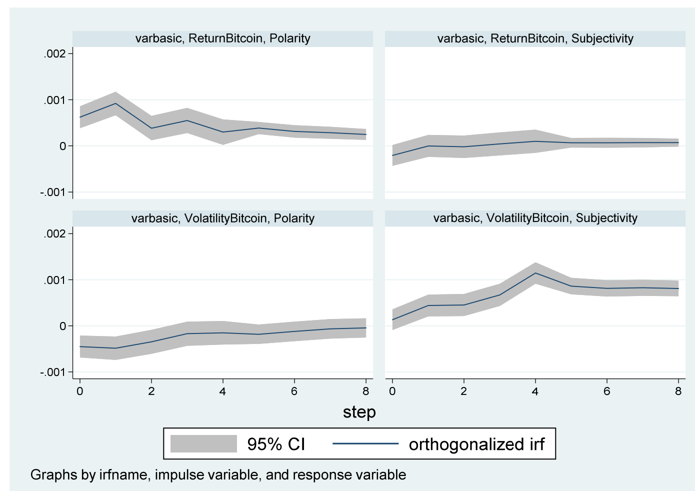

Figure 9: Bi-directional IRF Graphs with Polarity and Subjectivity as Response Variables (Model 2)

Robustness Checks

Table 9: Vector Autoregression Results (Model 2)

Equation	Parms	RMSE	R-sq	χ^2	P> χ^2
ReturnBitcoin	17	1.095	0.068	4905.105	0.000
Polarity	17	1.305	0.158	12539.810	0.000
Subjectivity	17	0.031	0.445	53556.790	0.000
VolatilityBitcoin	17	0.030	0.357	37092.880	0.000

Notes: N = 66929; RMSE: Root Mean Square of Error

Several robustness checks were run to ascertain the strength of our findings. First, we change the order of appearance of the sentiment variables (Subjectivity before Polarity) in the VAR model 1. The Cholesky ordering of VAR parameters impacts the VAR results. In the original model 1, Polarity preceded Subjectivity after specifying ReturnBitcoin and VolatilityBitcoin. This arrangement implies that on the assumption that investors on Twitter observe Bitcoin return in the first hour, the next hour is characterized by investor observations of the volatile nature of the Bitcoin price and its impact on ReturnBitcoin. The third hour observes the impact of Polarity on both ReturnBitcoin and VolatilityBitcoin. The fourth hour is characterized by the observation of the impact of Subjectivity on Polarity, VolatilityBitcoin, and ReturnBitcoin. Thus, changing the order, we show whether observing a less or more objective tweet (subjectivity) before observing the composition of negativity and positivity of the tweet (polarity) is of any importance and if this changes the findings in the original model. This rendering is also assessed when considering Polarity and Subjectivity as response variables and compared with the original findings. In all cases (ordering) for both case comparisons (bidirectional influences), the VAR results and IRF graphs were consistent with the original findings in Model 1 and show the ordering of our sentiment variables and our Bitcoin price behaviors have no significant impact on the initial findings.

Second, I specify a lag of 2 to restrict the optimal lag of 4. The 2-lag restriction was applied to the new ordering of sentiment variables (Subjectivity before Polarity) in the VAR model 1. In both 2-lag restriction scenarios, we find the results consistent with our original Model 1 findings.

Third, split samples of the first half and second half of the data are used to estimate Model 1. The findings are consistent with our initial results in Model 1.

Fourth, I specify another econometric model: VAR with exogenous variables (VARX). We use GoogleSearchIndex, ReturnCOMEXGold, and Year dummies as exogenous variables. Thus, we assume that the response variables may affect these exogenous variables in the VAR model, but these do not impact the response variables. We estimate three VARX models in this regard; first VARX has only GoogleSearchIndex as exogenous and the rest of the variables as endogenous; second VARX has both GoogleSearchIndex and ReturnCOMEXGold variables. The third VARX estimates the effects of all three sets of exogenous parameters. The IRF graphs for the second and third VARX estimations are shown in Figures 10, 11, 12, and 13. All IRF graphs are plotted with a 24-hour time span to show the stable behavior of bitcoin price after the optimal lag of 4 hours. The findings shown in Figures 10, 11, 12, and 13 and those not shown are consistent with findings in the original Model 1. Including year fixed effects as exogenous variables and having consistent findings show the robustness of our dynamic opinion leader identification strategy. We plot IRF graphs to analyze how each endogenous variable responds to one standard deviation of unexpected shock from another endogenous variable, holding other endogenous effects constant (Love & Zicchino, 2006)

Fifth, we estimate our Model 1 with bihourly and quad-hourly (2-hour and 4-hour data frequency, respectively). Whereas in the original estimation on hourly frequency, a moving average one – MA (1) – process was used when calculating VolatilityBitcoin, we used MA (2) in the case of bi-hourly estimation and MA (4) for quad-hourly estimation. VolatiltiyBitcoin_2 and VolatilityBitcoin_4 are the new variable designations. In all instances, a suffix _2 or _4 is applied to the new variables. For ReturnBitcoin_2, the calculation involves the natural log of the current closing price minus the natural log of the second lag closing price, all multiplied by 100. A fourth lag is used in the case of the quad-hourly estimation. Similar estimations are used for all the other return variables. Subjectivity_2 and Polarity_2are estimated based on the average of the 2-hour polarity and 2-hour subjectivity scores. Measures for the volume of tweets measures (opinion leader tweets and non-opinion leader tweets) are bi-hourly or quad-hourly aggregations. GoogleSearchIndex_2 is the average index over 2 hours.

Finally, it is noteworthy that our model 2 (reduced variable VAR model) serves as a robustness estimation for model 1. Although model 1 is the model of choice and specifies all the study's variables, the vast number of variables may be inimical to VAR's performance. Most studies in the Finance and Econometric literature specify VAR models of 3 to 5 variables for optimal VAR model performance. Nonetheless, our findings in Model 2 are consistent with the Model 1 findings, except that polarity's impact on ReturnBitcoin is positively significant. With this observation, the study could assert granger causality in the bidirectional influences of Polarity and ReturnBitcoin. We leave this assertion for future studies, although it could be emphasized in the present study since our optimal lag is 4 hours and aligns with the first four variable ordering of our VAR Model 1.

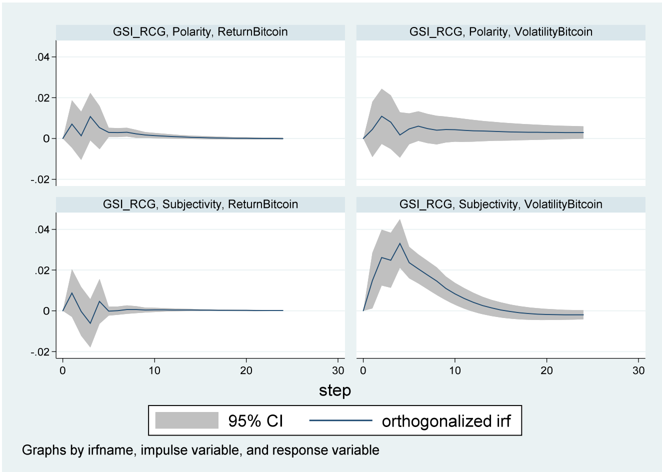

Figure 10: Bi-directional IRF Graphs with ReturnBitcoin and ReturnVolatility as Response Variables and GoogleSearchIndex and ReturnCOMEXGold as Exogenous Variables (Model 1)

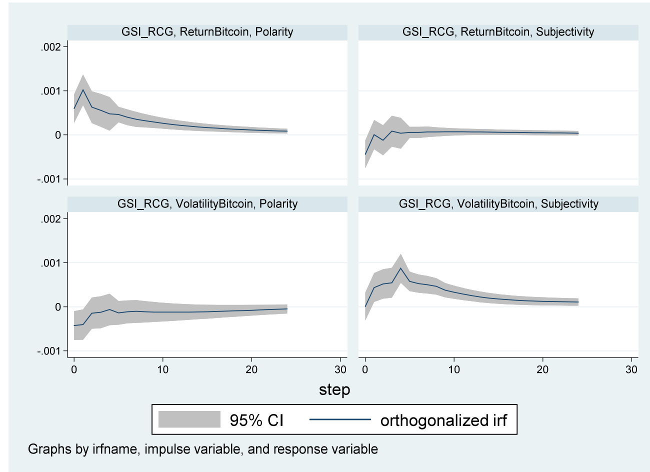

Figure 11: Bi-directional IRF Graphs with Polarity and Subjectivity as Response Variables and GoogleSearchIndex and ReturnCOMEXGold as Exogenous Variables (Model 1)

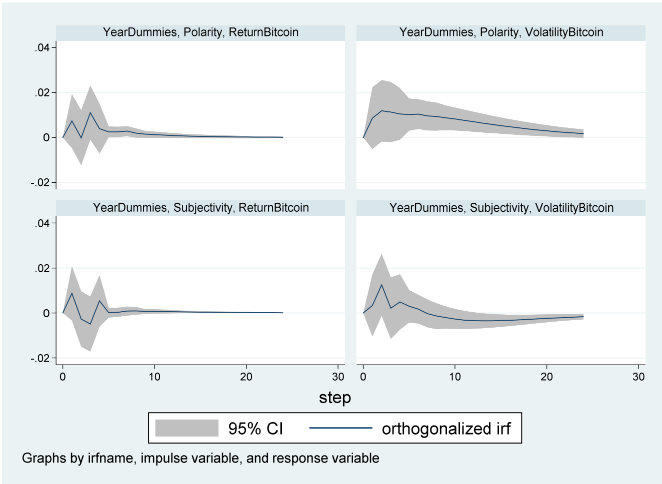

Figure 12: Bi-directional IRF Graphs with ReturnBitcoin and ReturnVolatility as Response Variables and YearDummies as Exogenous Variables (Model 1)

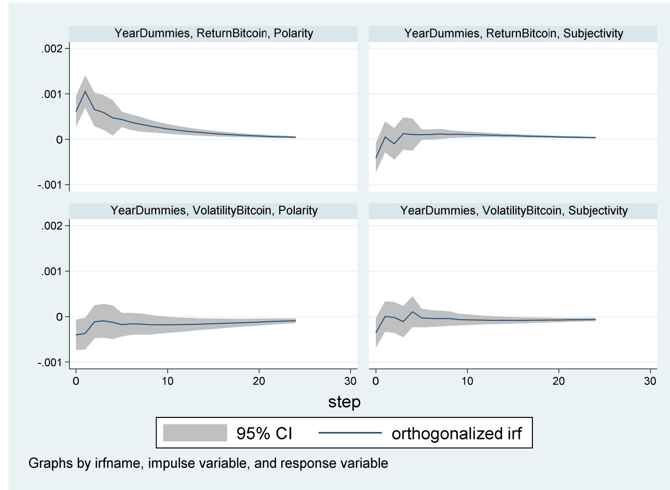

Figure 13: Bi-directional IRF Graphs with ReturnBitcoin and ReturnVolatility as Response Variables and YearDummies as Exogenous Variables (Model 1)

Discussion of Findings and Implications

The relationship between tweet sentiments and cryptocurrency pricing has drawn a lot of attention in the last few years. Current research efforts in the area have focused extensively on bitcoin price behavior and argued for exploring this relationship using predictive models as well as explanatory models. The predictive models demonstrated the usefulness of tweet sentiment for predicting future stock returns (e.g., Nann et al. 2013; Oh and Sheng 2011; Oliveira et al. 2013, 2017) with emphasis on negative and positive tweet sentiments. However, previous studies on the influence of polarity in such predictive models (e.g., Bollen et al. 2011) have indicated an insignificant impact. As predictive models lack explanatory power (Shmueli, 2010), they may not account for the insignificance of this measure. Even with studies on the influence of sentiments on returns in explanatory modeling, findings have been mixed (e.g., Bollen et al. 2011; Sprenger et al. 2014; Yu et al. 2013), suggesting the need to understand the nature of sentiments being studied.

In these regards, this study focused on dynamic opinion leader sentiments and to test the presence of a significant relationship between bitcoin opinion leader tweet sentiment and bitcoin price behaviors. Using explanatory models, the vector autoregression modeling, this is the first study to reveal and explain the significant influence of polarity and subjectivity of sentiment expressed in dynamic opinion leader tweets on bitcoins cryptocurrency. It contributes not only to the cryptocurrency literature by empirically showing how a composite measure of polarity (negative and positive) explains bitcoin price behavior at the hourly level, but it also contributes to the broad IS literature by demonstrating an important economic impact of a universally adopted IT artifact: a dynamic opinion leader microblog sentiment (DOPLMS). As data is streamed and opinion leaders change in their makeup, it is this dynamic artifact that provides a high-velocity platform for true big data analysis thereby helping us uncover a major phenomenon in the domain in real-time. It also affords the measurement and application of the effect of online opinion leaders' who cannot be identified apriori as with functional leaders are assigned with formal roles in most online platforms.

Thus, our study contributes to leadership theory and opinion leadership theory by revealing the impact of organically formed online/social media leaders who are dynamic in their make-up. Moreso opinions vary, and so do opinion leaders hence a system of identification that focuses on the dynamism rather than the impact of a static set of opinion leaders presents a welcome departure for business managers to appropriate the impact of real-time big data. As a methodological implication, the dynamic identification, rather than static, mimics a random assignment of subject treatment (i.e., the elicitation of emotional and psychological dimensions that inform sentimental microblogs of investors) over time and hence provides a more robust measure of the impact of opinion leader sentiment.

Essentially, the findings show that subjectivity is a vital measure to understand the risk of investors holding bitcoin (VolatilityBitcoin). The importance of polarity is pronounced not only when assessing key variables in the VAR model but critical in explaining the activities of non-opinion leaders. Using a series of rigorously designed analyses on a very large data set, the study did not find the influence of bitcoin opinion leader tweet sentiment on stock returns (neither for index nor for individual stocks) to be significant at the hour level. Our finding challenges the assertion (e.g., Bollen et al. 2011) that polarity is not significant in predicting the stock market returns. We have shown that the bidirectional influence of polarity and Bitcoin price return. Even with the silent majority (i.e., non-opinion leaders) which is a reflection of most static estimations of the effects of online sentiments, we see that polarity could be used to explain how sentiment impact the stock market via non-opinion leader tweet volume. This finding is consistent with the Granger causality test results of Bollen et al. (2011) and the time-sequencing regression results in (Sprenger et al., 2014). However, we did find the influence at the hour level polarity on Bitcoin volatility and for both subjectivity and Bitcoin volatility. This effect is both statistically and economically significant. At the bi-hourly and quad-hourly levels, this effect was partially reversed, providing evidence for the overreaction bias of noise traders. Our study is also the first to provide empirical evidence for the influence of dynamic bitcoin opinion leader tweet sentiment on cryptocurrency price behavior in relatively short time window: an hour.

Although not the focus of this study, the bidirectional relationship observed between bitcoin price volatility and bitcoin price return is worthy of comment. Bitcoin price volatility impact on Bitcoin return persists for three hours but the impact is negative in the first two hours and positive in the third hour. Regarding the impact of return on price volatility, the impact is significantly positive in the first hour and then negative in the third hour. Ang et al. (2006) explore the relationship between volatility and stock market return and our results of these significant associations are consistent with the extant literature on stock prices and volatility, giving further credence to our key findings.

Conclusions and Future Research

The study considered the bidirectional influences of Polarity and Subjectivity of opinion leader tweets sentiments on bitcoin returns and bitcoin volatility. Regarding our DOPLMS artifact contribution, we will use different opinion leader identification strategies in the future to identify who the leaders are although research has shown that different identification strategies tend to identify the same leaders, albeit such studies have been on systems of dyad relationships and traditional settings (Katz, 2015) other than a social network context like Twitter. In this regard, other parameters such as the network structure and their natural language (i.e., posts) analysis could be used to determine opinion leaders. In-degree centrality and eigenvector centrality allow for structural identification of top 10% opinion leaders and could be used instead of retweet count, and we provide robustness tests with such variations in the identification strategy. Future studies could explore the relative impact of negative and positive sentiments in comparison with polarity impact using our DOPLMS artifact. Within these comparison sets, the study could be based on emojis in microblogs as the conduits for estimating sentiment scores rather than the textual communications.

Since the polarity of opinion leader influence persists on non-opinion leader tweet volume, a non-linear estimation may be critical. A test of *bilateral Granger-causality* to determine the predictive power of Twitter sentiment shows that the assumptions of data stationarity and linearity in existing Granger-causality methods can be challenged by non-linear relations that may exist between stock returns and exogenous variables (Kraaijeveld & De Smedt 2020). This argument may hold well in our case, where we see a diminishing impact on polarity on Bitcoin return in Model 1 but a seemingly stronger and persistent impact on non-opinion leader tweet volume in the reduced VAR Model 2. A call for future studies to explicate the special role of polarity on cryptocurrency price behavior is therefore in order.

CHAPTER V

SUMMARY AND CONCLUSION

Blockchain, the technology underlying bitcoin, is a burgeoning financial technology (FinTech) and non-financial technology with several use-cases engendered: from health to digital identity, food traceability to asset pricing and to implications for explainable artificial intelligence, security, and data analytics. This dissertation examines the value creation logics of blockchain technology for stakeholders from multiple perspectives to explain the impact of the technology on financial returns. Drawing upon theories from IS, strategic management and finance, my research findings reveal different streams by which the technology can be appropriated to maximize value for each perspective taken. The use of multiple research methods: qualitative studies, econometrics, sensitivity analysis, and text mining to address the research questions help to provide balance between the nascency of the technology and its sustainable impact in the theory development process.

Major Findings

My dissertation has three major findings: First, I establish an affordance-experimentation-actualization-assimilation framework that firms can exploit to create and capture optimal value during blockchain implementation and suggests. From the framework, I proposed a model of five affordance-to-assimilation mechanisms (value-chains) and seven value interdependencies across the value chains to optimize blockchain value. Using a comparative survey of top-ranked blockchain platforms, I show the criticality of blockchain underlying artifacts and the tradeoffs they generate for consideration in appropriating the AEAA framework.

Second, I explored public US firms that have made adoption investments in blockchain technology (treated firms) from 2015 to 2020 in the second essay. I empirically tested a firm and quarter fixed effects model motivated by via Fichman's value model real options literature with Tobin's q as the object of measure. To address self-selection bias, I used a propensity score matching (PSM) approach, which provides matched Tobin's q values for each treated firm from the universe of COMPUSTAT US firms after matching on firm financial factors and restricting algorithm matching to a 2-Digit industry specification. This approached established a positive relationship between blockchain adoption and Tobin's q (firm value). Based on a fixed effect modeling, the study different dynamic market's responsiveness to firm single and multi-blockchain adoption decisions regarding public-permissioned, private-permissioned and permissionless archetypes of the blockchain. Other factors, blockchain patents, originality of blockchain patents, blockchain event participation and network effects, that ensure that financial returns on investments in emerging technologies are contextually understood were assessed in the fixed-effects model. I controlled for a several firm financial factors. Together, the empirical analysis provides an objective quantification of firm investments with a forward-looking measure (Tobin's q) of market response to expectation or estimation of future value from the investment.

Third, in my third essay, I study the financial returns in appropriating the most successful blockchain use case – bitcoin cryptocurrency. Using a robust domain-specific dictionary, VADER, text analytics and vector autoregression modeling, I investigated the prediction of the next hour Bitcoin cryptocurrency returns and volatility based on the role of Bitcoin opinion leader Twitter sentiments – polarity and subjectivity of sentiments. The bidirectional influences of these relationships were examined while controlling for trading volume, tweet volume, non-opinion leader tweet volume, S&P 500 returns, google search index on 'bitcoin' keyword, VIX returns and COMEX gold returns.

Contributions

The dissertation contributes to theory, research methodology and practice.

Contribution to Theory

This dissertation contributes to the IS affordance literature by showing how perceived potentialities of the technology can be assimilated with each implementation case for increased value. Firms leveraging this framework will be in the position to exploit the upside of the uncertainty surrounding blockchain technology as a strategic IT. As firms make adoption investment decisions, the need to justify their decisions requires theories based on objective estimation of the financial returns on investments. Considering the three main archetypes of blockchain technology and the emergent nature of the technology, there is the need to capture the value associated with the uncertainty bounds and the managerial flexibilities that are exercised by stakeholders. This study is one of the first to propose a blockchain options lens at such a granular level that incorporates both timing and growth options surrounding an archetypal network technology using panel data. By incorporating firm-specific financial factors and further investigating 2-digit industry-restricted Tobin's q from propensity score matching, this research establishes several levels of robustness for the blockchain options lens. The study also contributes to the literature on bitcoin cryptocurrency price behavior and opinion leader sentiment mining influences on stock returns in general.

Contribution to Methodology

In proposing a blockchain options lens at the archetypal network level of the technology, this study shows how the value from technology options can be specified and quantified regarding a specific IT – blockchain. Our specification addresses the peculiarity of blockchain technology yet is generalizable enough to explicate the salient value of firm's specific IT investment. The third paper implements a robust-domain specific dictionary built on financial literature and context-specific blockchain terminologies to improve our sentiment classification.

Contribution to Practice

For practitioners, the recommendation on how to operationalize the mechanisms proposed in this study provides a medium by which IT managers and firm analysts can assess the real monetary impact of their implementation activities amidst high uncertainties. Also, a face assessment of the value of a firm's proposed blockchain implementation can be performed during requirement analysis and use-case-to-be specifications using the AEAA framework. Also in Appendix A is an example of a summarized narration of a blockchain implementation project, which can be interrogated with a tool based on the framework. In the absence of such implementation narrations, future studies and business managers could explore action research approaches and iterative analysis during implementation to improve and increase the robustness and usefulness of the evaluation tool for practitioners' future use. IT managers have been presented with objective quantification to justify blockchain investments. The dynamic opinion leader microblog sentiment tool can be used on streaming Twitter data to make sense of cryptocurrency price behaviors.

Limitations and Future Research

Regarding our first study, while the model contributes to optimizing value during blockchain implementation, it will benefit from more contextual subjections across industries and blockchain archetype specializations. Thus, there may be the need to differentiate AEAA for either permissionless blockchain or public-permissioned or private-permissioned. Future studies may also provide a quantitative evaluation of the framework to ensure robustness in its application as well as the objective generalized use of the theory. The study may also be limited by discipline-specific sample selection bias as other disciplines other than IS discipline may construe blockchain value differently. Such value definition differences may be more prevalent with the design features of the technology. However, our findings make room for the redefinition of blockchain artifacts, what they engender and the resulting tradeoffs in the event massive blockchain artifact reconfigurations. Further, a critical analysis of the recommended operational variables may be vital to provide the needed reliability and nomologic validity of the value measurements when using AEAA to guide blockchain implementation.

On the second study, it would be ideal to apply the exact dollar amount of firm blockchain investments. However, controlling for firm financial variables that affect value implies that an adoption case proxies well for the impact of the dollar amount. This means that our estimation applies a more modest investment option for value estimation, which presupposes that firms can expect better returns for exercising investment options deemed positively favorable in our study. This approach helps to accommodate the fact that mere investment in IT does not lead to firm performance. Instead, expected returns are based on how managers exploit uncertainties and flexibilities available to them when appropriating the technology.

In the future, estimate a panel vector autoregression with exogenous variables (VARX) to address other potential biases, such as endogeneity, autocorrelations, and reverse causality, could be estimated to investigate the dynamic interactions between a firm's specific conversion contingencies and firm value and addressing further endogeneity issues. For instance, the interactive effect of the only blockchain archetypes among firms that adopted more than one archetype. In this study, only the count of their adoption investments was analyzed. In the future, alternative measures of investment could be estimated. Also, alternative, dependent variables on firm options could be specified to understand periodic dynamics of market response to the futuristic expectation of the present investment decisions.

The third study in chapter four provides several avenues for future research. Several identification methods could be utilized to identify opinion leaders. A mathematical model could be applied to understand the optimization of the identification process. The study could be extended to other cryptocurrencies, and understanding the interplay between a few cryptocurrencies from an opinion leader sentiment perspective would be a fascinating investigation.

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APPENDIX A

APPENDIX A

AN AFFORDANCE PERSPECTIVE OF VALUE CREATION IN BLOCKCHAIN TECHNOLOGY IMPLEMENTATION: FROM ACTUALIZATION TO ASSIMILATION

Blockchain Technology Artifacts and Characteristics

The technology feature and design considerations that make blockchain technology unique from other technologies and make blockchain platforms such as Ethereum different from Corda is the amalgamation and functionality of underlying I.T. artifacts and the need to exploit tradeoffs within underlying artifacts (M. Rossi et al., 2019). These artifacts affect actors' perception of the blockchain technology's potential (Du et al., 2019) and inform the choice of the blockchain platform to implement (Brandon, 2016; Kuo et al., 2019). Blockchain artifacts also tell the value opportunities for firms' blockchain activities (Angelis & Ribeiro da Silva, 2019). The artifacts, particularly the blockchain archetype,[16] inform an organization's degree of decentralization of an adopted blockchain network (Bian et al., 2018) that has implications for the digital transformation of business and revenue models (ShethVoss, 2018). Several blockchain platforms (as shown in Appendix A) fit either of these archetypes, depending on

[16] The main archetypes of blockchain technology are public-permissionless (or permissionless) - all agents can read, submit, and validate transactions), private-permissioned - only authorized agents can read, submit, and validate transactions) and public-permissioned where agents can read and submit transactions, but only authorized agents do validations (Beck et al., 2018; M. Rossi et al., 2019). Public-permissioned archetypes can also be referred to as consortium blockchains.

on their technical configurations. Table 9 presents brief descriptions of the I.T. artifacts and critical characteristics of a blockchain technology identified in the literature with adapted contributions from (Du et al., 2019; Weking et al., 2020).

Table 10: Description of The Underlying Artifacts and Characteristics of Blockchain

Blockchain Artifact[17]	**Description**
Blockchain archetype (distributed ledger type)	Blockchain's primary value proposition requires that the ledger provide a single historical record, which means validators must agree to contents before committing to the block (Jagtiani & John, 2018). Blockchain is a decentralized and distributed ledger (Zachariadis et al., 2019), with each node containing a complete record of all network transactions (Beck, Stenum, Lollike, & Malone, 2016).
Consensus mechanism or protocol	Consensus protocols specify how the rights to validate new transactions are assigned (M. Rossi et al., 2019). The characteristics of different consensus mechanisms impact the integrity and consistency of the blockchain (Beck et al., 2018). The most widely adopted consensus protocol is the proof-of-work (P.O.W.)[18]. A lack of consensus will lead to the creation of a new blockchain (referred to as a "fork") from the original chain (Beck et al., 2018). The consensus also determines the mining technique used to update the existing blockchain with new transaction blocks of information and ensures that information is only changed when all relevant parties agree (Ølnes et al., 2017).
Cryptographic mechanism	The cryptographic mechanism employs encryption algorithms that utilize cryptographic public keys and private keys for data encryption authentication of participants, respectively (Ølnes et al., 2017; Underwood, 2016). It may also employ hashing algorithm, which ensures a one-way data mapping to maintain data integrity. The tamper-proof property of the blockchain results from the cryptographic techniques that ensure changes in transaction data are observed by all nodes in the blockchain network (Z. Liu et al., 2019).
Smart contracts and their functionality	Smart contracts (Szabo, 1994) are autonomous computer-scripted enforcement mechanisms or negotiated agreements that execute without interference from third parties (Beck et al., 2018) or a computerized transactional protocol set up to digitally facilitate, verify, or enforce the negotiation, terms, or performance of a contract under

[17] Our understanding of blockchain artifacts is based on the harmonization of the following definitions: IT artifacts are "bundles of material and cultural properties packaged in some socially recognizable form such as hardware and/or software' (Orlikowski & Iacono, 2001, p. 121). The IT artifact is a conceptualization of "the application of IT within a context to enable or support some task(s) embedded within a structure(s) that itself is embedded within a context(s) (Benbassat & Zmud, 2003, p. 186). IT artifacts "are broadly defined as constructs (vocabulary and symbols), models (abstractions and representations), methods (algorithms and practices), and instantiations (implemented and prototype systems)"(Hevner et al., 2004).

[18] Proof-of-work (POW) which underlies bitcoin blockchain (Z. Liu et al., 2019) and as well as public-permissionless Ethereum platforms. requires solving of a computationally intensive and difficult puzzle before new blocks are added the existing blockchain (Yeow et al., 2018). Besides POW, Ethereum platforms also utilize proof-of-stake (POS) consensus protocol; where miners mine blocks based on miners' account balance of stakes (Yeow et al., 2018).

Table 10, cont.

	the supervision of all network actors digitally (Chong et al., 2019; Crosby et al., 2016; Underwood, 2016). The varying complexity of computations describes the functionality of smart contracts (Hileman & Rauchs, 2017)
Application programming	This artifact describes the supported scripting language, the availability of the source code, the primary scripting language that implements the source code as well as the copyrighted software license for the source code (Kuo et al., 2019)
Reward systems and tokens	The reward system (tokenization) of the blockchain is to ensure sound and secure use of the blockchain by all actors (Schoenhals et al., 2019). Tokenization is the process of converting the rights of an off-chain asset into a digital token on a blockchain for use as a medium of exchange and for rewarding the network of validators that validate blockchain transactions (Babich & Hilary, 2019; T. Cai et al., 2019). Tokens can either be utility tokens or asset tokens (Werner et al., 2020). They can also be categorized as fungible and non-fungible (Regner et al., 2019). The application of tokens is sometimes facilitated by the consensus mechanism to create appropriate incentives for validators (Jagtiani & John, 2018) and stakers.
Immutable audit trail	This functionality enables the technology to prevent modifications to validated and recorded information on the distributed ledger (Wallbach et al., 2020)
Interoperable interfaces and standards[19]	The interoperability or compatibility of different devices within networks will be a significant determinant for increased blockchain implementation (Albrecht et al., 2018) and widespread adoption. Such standards are initiated at the basic levels (e.g., common data definition standards), operational level, and open source and open standards levels (Seebacher & Schuritz, 2019) are expected. Interoperability blockchains development would allow interconnections between different consensus protocols and platforms (Toufaily et al., 2021).

Blockchain Characteristics	Description
Scalability	This characteristic of the blockchain indicates whether a platform is scalable and, if so, examines the performance tradeoffs amongst network throughput or the transaction processing rates, the degree of decentralization, the latency of data transmission system, security and privacy concerns (Toufaily et al., 2021; X. Xu et al., 2017; Yli-Huumo et al., 2016). In addition to these tradeoffs, the type of crypto or digital assets being transacted, data needs, and expected utilizations inform an actor's perception of scalability.
Governance and control of the blockchain archetype	This characteristic of blockchain sets the modalities for negotiations, approval, enforcement, accountability, and the determination of reward systems by which validators and agents at the network and protocol layers of the blockchain system will run and sustain the operations of the technology (Zachariadis et al., 2019). Thus, it informs the archetype's operational and management rules regarding the human, consensus protocols, and the computer system agencies (Beck et al., 2018).

Exploring blockchain technology affordances requires an understanding of the ways stakeholders perceive the role each artifact plays (Du et al., 2019). Aside from the affordances that these artifacts elicit, they help eliminate value-inhibiting human-technology agencies that

[19] For an in-depth study on blockchain interoperability see (Belchior et al., 2021)

jeopardize widespread adoption of the technology. For instance, adopting or leveraging a blockchain platform, such as Polkadot, with perceived well-defined governance and control structures, helps to better apportion implementation resources to manage and mitigate security risks that could be posed by clandestine actors (Zachariadis et al., 2019). Having such perception may also reduce regulatory concerns and limit perceived threats of the creation of new chains ('forking' phenomenon) – overall, reducing perceptions of high risks of adoption, which could be detrimental to business development strategies and sustainability (Zachariadis et al., 2019).

Different blockchain protocols have different value creation and value capture logics at the interplay of protocol levels and application levels of a blockchain system (Chong et al., 2019; M. Rossi et al., 2019). This interplay is conceptually represented by the underlying blockchain (I.T.) artifact dispositions and functionalities. Questions surrounding the feasibility and viability of implementing blockchain solutions are centered around these artifacts and what they afford or constrain (M. Rossi et al., 2019; Seibold & Samman, 2016). Often, the development documentation of the platforms or white papers provides the best use-case scenarios to inform firms' choices and deployments. Identification and suitability of use-cases and development decisions are therefore shaped by the platforms and the underlying artifacts that describe them (Blossey et al., 2019). Appendix A presents a comparative sample of top-ranked blockchain platforms, which underlies the conceptual import of the blockchain artifacts described in Table 1. The variableness in these platforms means that the perceptions they enable or constrain regarding implementation stakeholders must be cultivated in terms of the best tradeoffs suitable for the business case and not just an instance of an archetype.

Table 11: Comparison of Selected Blockchain Platforms Across Underlying Artifacts/ Characteristics

Selected Blockchain Platforms	Underlying IT or Blockchain Artifacts and Artifacts' Characteristics							
	Blockchain Archetype (distributed ledger type) (Beck et al., 2018; Chong et al., 2019; M. Rossi et al., 2019)	**Consensus Mechanism or Protocol** (Bach et al., 2018; Beck et al., 2018; Eigelshoven et al., 2020)	**Smart Contract and Functionality** (Rouhani & Deters, 2019)	**Application Programming or Scripting Language** (Egelund-Müller et al., 2017)	**Reward Systems and Tokens (Native Currency)** (Schoenhals et al., 2019)	**Support for DApps[20]** (M. Rossi et al., 2019; Underwood, 2016; Zachariadis et al., 2019)	**Scalability (Scalable, TPS[21])** (Bach et al., 2018; Beck et al., 2018)	**Blockchain Governance and Control Body** (Zachariadis et al., 2019)
*Bitcoin[22] (Nakamoto, 2008)	Public-permissionless (or Permissionless)	Proof-of-Work (POW[23]) (Huberman et al., 2019a, 2019b)	No, except with the support of side chains	Bitcoin script, C++ Ivy, RSK	Bitcoin (BTC) for mining rewards and transaction fees	No	7[24](Miraz & Donald, 2019)	None
Ethereum 1.0 (V. A. Buterin, 2014)	Permissionless and public-permissioned (V. Buterin, 2015)	POW algorithm called Ethash	Yes (uses ERC233 token standard)[25] on Ethereum	Python, Go, C++ and Solidity for smart contracts, SCILLA, Flint	Ether (ETH) to pay for 'Gas' cost and ERC2020 tokens	Yes	15 (Miraz & Donald, 2019)	Ethereum Developers via Ethereum Improvement Proposals (EIPs)

[20] Decentralized Apps (DApps)

[21] Transaction processing per second. VISA currently allows throughput of 24,000 TPS worldwide to over 65000 TPS at peak times on its network. Also, VISA allows 150 million transactions per day in the US alone (Miraz & Donald, 2019; VISA, 2017). Also, see (Miyamae et al., 2018) for detailed assessment of blockchain TPS vis-à-vis that of traditional financial transactions and latency.

[22] Bitcoin has the largest market share of cryptonetworks and several firms such as Blockfi, Square and Ebay have begun differentiating products and services that leverage bitcoin cryptocurrency.

[23] POW two primary components: miners and electricity cost.

[24] Two solutions – Segwit (or Segregated Witness) and Lightning Network are being explored to offer instant bitcoin transactions with higher scalability (Greenspan, 2015b; MacManus, 2018; Poon & Dryja, 2016) capable of a million to billions transactions per second

[25] ERC (Ethereum Request for Comment) 233 token standards is an umbrella of fungible tokens that can listen and react to Ether transfers between parties in smart transactions. Smart contracts are signed off by the exchange of transferable tokens. Unlike ERC233 non-fungible tokens are not exchangeable as currency units and are normally used to create scarce digital assets hence not used as smart contract utilities (Riady, 2019).

Table 11, cont.

			Virtual Machine (EVM)					(Zachariadis et al., 2019)
Ethereum 2.0 (Muzzy, 2020)	Private-permissioned, public-permissioned	POW, Proof-of-Stake[26] (POS)	Yes, on Ethereum WebAssembly (eWASM) – a new EVM	Solidity	Ether 2 (ETH2)	Yes	Sharding[27] on the Beacon chain can run in 64 parallel shards, each with the ability for a TPS as in Ethereum 1.0	Stakers[28] on Ethereum improvement proposals (EIPs)[29]
Hyperledger Fabric[30] (Cachin, 2016)	Private-permissioned	A set of pluggable consensus protocols[31] such as Practical Byzantine Fault Tolerance **(PBFT[32])**, Prototype of	Yes (known as chaincode)	Java, Go, and Node.js for smart contracts, python C++	None	No[33]	Theoretically, 3500 for Fabricz; can be scaled to 20,000 TPS[34]	Linux Foundation – low decentralized governance

[26] The algorithm underlying Ethereum's PoS is 'Casper' (Buchko, 2018)

[27] A total of 64 shared chains (separate or island chains all interconnected) on the beacon chain (main Ethereum 2.0 chain). Also, cross-shared transactions and Lightweight clients to be implemented by 2022 to further improve scalability while ensuring security.

[28] At least 32ETH is needed must be in a staker's account to validate transaction. Validators and stake replace miners and electricity needs associated with Ethereum 1.0.

[29] EIPs is an open-source model which stakers and a vast community of contributors to strategically debate platform improvements and control (Zachariadis et al., 2019)

[30] It is important to stress that IBM Blockchain is blockchain-as-a-service offering from IBM which uses Hyperledger fabric to render the service just as Microsoft Azure which also is a service platform that offers blockchain platform services based on Ethereum protocol.

[31] Pluggable consensus protocol means different protocol depending on the context of application is selected to optimize performance, security and throughput (Hyperledger, 2020)

[32]See (Castro & Liskov, 2002). Also, consensus approach is permissioned voting.

[33] DApps are geared towards B2C blockchain usage because of the need for more decentralization or permissionless ledgers for end-users to generate business value. Hyperledger, on the other hand, primarily focuses on B2B usage and focuses on providing more scalable, secure, and private platforms such as associated with permissioned ledgers. In comparison, Ethereum allows for creating private networks for B2B transactions known in blockchain as 'forks,' e.g., JP Morgan's Quorum. Through the Ethereum Enterprise Alliance (EEA), they also ensure B2B-oriented permissioned ledgers (Brock, 2018).

[34] See (Hyperledger, 2020)

Table 11, cont.

		SIEVE and NOOPS(Cachin, 2016), Crash Fault-Tolerant (CFT)						
Multichain - An opensource fork of Bitcoin (Greenspan, 2015b)	Public-permissioned & Private-permissioned	Mining Diversity[35] (Greenspan, 2015b)	No	C, C++, Python, JavaScript, and V8 for smart filters	Mining rewards - 50 native currency units per block	No	500 to 1000	Multichain Permissions Management
Hydrachain [36]	Public-permissioned or consortium chain setup	Byzantine Fault Tolerant[37]	Yes	Python	Gas units purchased with ETH for direct mining[38]	Yes	1000 (Tsai et al., 2016)	Registered and accountable set of validators
Ripple[39]	Public-permissioned	Ripple Consensus Protocol – (Federated Byzantine Fault Tolerance (Mazières, 2016) enables probabilistic voting approach	No	Mostly C++	XRP which acts as a bridge to trade other currencies (both crypto and non-crypto)	Not yet	1500 (Miraz & Donald, 2019)	Ripple Labs
Corda	Private-permissioned and public-permissioned	Corda – a flexible plug-in feature for consensus	Yes	Kotlin	None	Yes (CorDapps)	600	R3 Consortium

[35] The consensus approach is probabilistic voting.

[36] This is an extension of Ethereum blockchain platform.

[37] Byzantine voting on each new block is the consensus approach (Tsai et al., 2016)

[38] Indirect mining with the help of SHA256 hashing algorithm to exchange ETH rewards for another cryptocurrency like bitcoin and zeta coin.

[39] A cryptocurrency platform

Table 11, cont.

BigChainDB	Private-permissioned and public-permissioned	Tendermint's BFT[40]	No	JavaScript and Python	Fiat currencies through traditional channels	No	One million writes per second (not TPS)	Native Consensus
OpenChain (Digital Asset Management)	Private-permissioned and public-permissioned	Partitioned Consensus	Yes	JavaScript	Tokens pegged to bitcoin (BTC)	No	1000	CoinPrism
IOTA	Public-permissionless public-permissioned	Tangle	No	Quibic programming, Abra, A	US Dollar	No	~50 to 1500	IOTA Foundation and community input
Litecoin[41]	Permissionless	Lightning Network Protocol	Yes	C++, Java, Python, Perl	Litecoins: currently 12.5 litecoins per block[42]	No	56	Switzerland Falcon Private bank
Cardano[43]	Permissionless	PoS[44]	Yes	Plutus (Functional language)	ADA	Yes	1000 TPS per stake pool[45]	The community of token holders [46]
Quorum (Built on a restricted version of Ethereum – A	Private-permissioned	Raft-based and Instanbul BFT [47]	Yes	Python, Solidity	JPM Coin	Yes	~175 to 180(Eroğlu, 2018)	Ethereum and JP Morgan Chase

[40] Native consensus voting on every asset transacted is the consensus approach.
[41] A cryptocurrency platform
[42] 12.5 coins per block will decrease to 6.25 coins per block post halving on Aug 5, 2023. Halving is every 4 years (Litecoin, 2020), similar to bitcoin halving.
[43] A cryptocurrency platform
[44] Proof-of-Stake but uses an algorithm called 'Ouorobosros'
[45] With 1,000 stake pools, each processing at 1,000 TPS, Cardano could thus achieve a throughput of 1,000,000 transactions per second (Simmons, 2020)
[46] Individuals are incentivized to play a role and a voting system where votes are immutably recorded. Voting is done on Funding Proposal (FPs) and Cardano Improvement Proposals (CIPs) (Cardano, 2020)
[47] Raft consensus algorithm and consensus is reached by majority voting.

Table 11, cont.

fork of Ethereum)								
Hyperledger Sawtooth (Olson et al., 2018)[48]	Private-permissioned Public-permissioned	Pluggable Framework which includes Proof of Elapsed Time (PoET), RAFT, PoET simulator, and Dev_mode for test networks	Yes	Python, Javascript, C++, Golang, Java, and Rust[49],	None - Uses a serialization process for exchanges	DApps can be ported on Sawtooth with only EVM integration	70 to 80[50]	Linux Foundation – a highly decentralized governance
Hyperledger Iroha (Rampen, 2016)[51]	Private-permissioned	Chain-based Byzantine Fault Tolerant	Yes	C++, Python, Java, JavaScript	None[52]	Yes	Theoretically, 1000-2000	Linux Foundation - Consortium of companies
EOS[53]	Permissionless	Delegated Proof-of-Stake (DPoS)	Yes	C++	EOSDT and Native Utility Token (NUT)[54]	Yes	4000[55]	EOSIO Core Arbitration Forum (ECAF)[56]
Hedara Hashgraph	Private-permissioned	Asynchronous Byzantine Fault Tolerance	Yes	Python and Solidity for smart contracts	HBAR	Yes	10 TPS for smart contracts and DApps transaction[57]	Hedara Governing Council[58]

48 Sawtooth provides integration support for running Ethereum Virtual Machine smart contracts by replicating Ethereum JSON RPC API. It also has planned integration with other smart contract engines such as Chain's Ivy, and Digital Asset Holding's DAML.

49 Hyperledger Sawtooth Raft and Sawtooth Sabre are written in Rust. Hyperledger Indy is another platform in the Hyperledger family.

50 For 5 Validators on Sawtooth, TPS is 70-80 and above 10 Validators is also 70 TPS.

51 Iroha is a Hyperledger project by a couple of Japanese companies,

52 A native currency can be created on Iroha by an eligible participant as required for their own enterprise use.

53 A cryptocurrency platform

54 1 NUT = 8.65 EOSDT

55 See (de Candia, 2020)

56 Governance is by top 21 block producers (BPs) who are elected by EOS token holders from a broader set of block producer candidates (EOS, 2019)

57 Theoretically, 10,000 TPS for dumb account-to-account token transfers

58 Made up of 39 term-limited and highly diversified organizations.

Table 11, cont.

NEO[59]	Permissionless and private-permissioned	Delegated Byzantine Fault Tolerance (dBFT)	Yes	C, C++, Java, JavaScript, Python, VB.Net. Kotlin	NEO currency	Yes	33	NEO Group Governance Advisory
Stellar[60] (A Crypto Platform)	Public-permissioned and private-permissioned	Stellar Consensus Protocol	Yes	JavaScript, Java	XLM	Under development [61]	1000[62]	Stellar Development Foundation
Cosmos Network[63]	Private-permissioned for now	Tendermint BFT	Yes	Go, Any language	ATOM	Yes	14,000 and scalable	Cosmos governance [64]
Waves[65]	Public-permissioned	LPoS	Yes	RIDE	WAVES	Yes		Community-driven monetary policy
NEM[66]	Permissionless and private-permissioned	Proof of importance	Yes	Java	XEM		4000	NEM Foundation

[59] A Cryptocurrency platform

[60] A cryptocurrency platform.

[61] Stellar has released Horizon Go SDK, JavaScript, and Java packages to support the hosting of DApps

[62] Can scale up to 4,000 TPS with powerful hardware integration such as cloud servers.

[63] Tendermint, Cosmsos SDK and inter-blockchain communication (IBC) protocol which is like TCP/IP are the major components of COSMOS project – the internet of blockchains. The platform is connected to an Application Blockchain Interface protocol which allows other development languages. See (Cosmos, 2020). Also https://www.itu.int/en/ITU-T/Workshops-and-Seminars/201908/Documents/Shakil_Muhammad%20_Presentation.pdf. Cosmos is an example of huge blockchain interoperability platforms expected to influence widespread adoption of blockchain. Other examples include Polkadot projects with Web3 Foundation and Chainlink. Polkadot runs on 'substrate' instead of smart contracts.

[64] Every holder of ATOM can take part in network governance and receive staking rewards.

[65] A cryptocurrency platform. 'Waves' does not require expensive computing equipment for block generation: an instance with Dual-core processor, 4 GB RAM and 50 GB (SSD) storage is sufficient. This advantage may be eroded with other blockchain-as-a service platforms in the cloud, especially for large firms.

[66] New Economic Movement (NEW) cryptocurrency. Along with Ethereum, Hyperledger, Waves and Stellar, Nem forms part of the top and unique smart contract platforms available to implementation actors.

Syntheses of Blockchain Frameworks for Value Creation

The need to understand blockchain technology for business value exploitation has led scholars to propose research and practice frameworks from different perspectives. These studies predominantly focus on addressing technological challenges and have less-focused on value creation and capture (Chong et al., 2019; Risius & Spohrer, 2017).

Hardware design and software-related conceptions about bitcoin and other cryptocurrencies examined across either protocol, network or eco-system layer (Morisse, 2015) which dominated earlier systematic blockchain studies or frameworks (Risius & Spohrer, 2017) with 80% of prior studies focused on bitcoin and cryptocurrencies and 20% on smart contracts and licensing/regulatory issues (Yli-Huumo et al., 2016). Even within these studies that address technology challenges, scalability-related challenges such as throughput and latency which are critical value creation characteristics for blockchain implementation success are understudied (Yli-Huumo et al., 2016; Q. Zhou et al., 2020). This stream of research studies or frameworks only interrogates the blockchain impact on current e-business and security streams of I.S. literature but do not show how blockchain can be implemented or adopted to have positive impacts within an organization (Morisse, 2015). The conceptual gap between blockchain technology complexity and business use for stakeholders (Toufaily et al., 2021) which requires a socio-technical adaptation before effective business value can be extracted (Du et al., 2019) may explain the narrow focus of this stream. Other related works on blockchain evaluation frameworks include a ‘crypto 2.0 Lenses’ evaluation framework suitable for cryptocurrency implementation (Jaffrey, 2015), a taxonomic digital business model for bitcoin companies (Kazan, Tan, & Lim, 2015), a generic eightfold checklist for the assessment of the pre-feasibility of blockchain use-case (Greenspan, 2015a) and an evaluation framework produced by the

Ministry of Economy, Trade, and Industry [METI] in Japan for comparing conventional systems with blockchain systems (METI, 2017). METI's framework addresses weaknesses in the International Standard Organization's (ISO/IEC) evaluation model for introducing new technologies, which is biased towards centralized technologies. The framework focuses solely on system replacement options.

Others include a blockchain-enabled novel use-case and business model (Valtanen et al., 2019) which applies to only telecommunication and energy use-cases; Labazova's (2019) framework for evaluating blockchain implementation, Weking et al.'s (2020) taxonomy and archetypal patterns (business model taxonomy); Angelis and Ribeiro da Silva (2019) blockchain business value enablers and value drivers: identify transaction cost, added service-offerings, organizational boundaries, and autonomous decision-making; Fleischmann and Ivens' (2019) four subcategories of blockchain benefits afforded by the blockchain at the intersection of intersection of application and technicalities: personal, social benefits (emotional benefits), system- and process-related benefits, and economic benefits (functional benefits); Blossey et al. (2019) framework of use-case clusters; Labazova et al. (2019) developed a taxonomy of six blockchain applications combining the business application of the blockchain with technical perspectives; Toufaily et al., (2021) framework for blockchain adoption; Janssen et al., (2020) broader view analytical framework that integrates institutional, market and technical factors; and Werner et al. (2020)'s five archetypes of blockchain platform for value creation from a governance perspective, namely: funding, codebase, type of token, price stability, and services. Hitherto, decision rights, reward systems and the degree of centralization have been advanced as critical for the governance structure of blockchain platforms if sustainable value is to be created (Zachariadis et al., 2019).

Although these frameworks allude to the strategic potential of the technology and the need for long-term user goals that integrates several facets of the blockchain economy, they focus on the blockchain use-case suitability and mostly, access value-creation based on the blockchain's material features. The capabilities of blockchain artefacts are consistently being via new feature installations and reconfigurations of the blockchain ecosystem as the technology strives for growth. Therefore, evaluation or analytical frameworks solely premised on the blockchain's physical specificities may prove to be limiting with time considering necessitated shifting socio-technical configurations to address adoption uncertainties. In other respects, the studies treat value creation and value capture as very separate from blockchain's value proposition without clear linkage of these closely related concepts. Some studies also combine both artifacts and the blockchain's potential in the value proposition, such that how agencies between human and artifact agencies can turn value opportunities into viable adoptions are obscured.

The discussion above reveals the need for theorizing more frameworks that inform blockchain implementation through a lens that imbibes the technology's numerous potentials for actions and the multi-goal orientations these blockchain potentials elicit from implementers to create the needed business value.

Table 12: Final Sample Articles by Source

Journals, conference proceedings, and other manuscripts	**Search results**	**Final sample**	**Citation**
Journal of the Association of Information Systems (AISel)	10	1	(Chong et al., 2019)
Communication of the Association of Information Systems (AISel)	21	1	(Murray, 2019)
Journal of Strategic Information Systems (Elsevier)	1	1	(Du et al., 2019)

Table 12, cont.

Journals, conference proceedings, and other manuscripts	Search results	Final sample	Citation
Information and Management (Elsevier)	2	2	(Toufaily et al., 2021; Zachariadis et al., 2019)
Journal of Management Information Systems (Academic Search Complete)	1	1	(Gomber et al., 2018; Kazan et al., 2018)
Journal of Economics and Business (Elsevier)	1	1	(Jagtiani & John, 2018)
International Journal of Information Management (Elsevier)	14	5	(Frizzo-Barker et al., 2020; Hughes et al., 2019; Janssen et al., 2020; Kshetri, 2018; Ying et al., 2018)
MISQ Executive (AISel)	16	5	(Lacity, 2018b; Lacity, Sabherwal, & Sã, 2019; Pedersen et al., 2019; Rieger, Guggenmos, Lockl, Fridgen, & Urbach, 2019; Zavolokina, Ziolkowski, & Bauer, 2020)
Technological Forecasting & Social Change (Elsevier)	9	2	(Ahluwalia et al., 2020; Pazaitis et al., 2017)
Business Horizons (Elsevier)	7	1	(Angelis & Ribeiro da Silva, 2019)
Journal of Accountancy, Journal of Financial Economics, Business Information Review, Decision Support, Journal of Enterprise Information Management Systems, Sloan Management Review (EBSCOhost – Business Source Complete)	30	2	(Michelman, 2017; M. Xu et al., 2019)
Journal of Strategic Innovation & Sustainability	1	1	(Nathalie et al., 2019)
Business and Information Systems Engineering (AISel)	21	3	(Egelund-Müller et al., 2017; Nofer et al., 2017; Risius & Spohrer, 2017)
Organization Science, Manufacturing & Service Operations Management (Informs)	2	2	(Babich & Hilary, 2019; Bailey et al., 2019)
AIS Conference papers without HICSS proceedings (AISel)	185	16	(Belchior & Correia, 2020; Holotiuk & Moormann, 2018; Kazan et al., 2015a; Labazova, 2019; Lui & Ngai, 2019; Miscione et al., 2019; Nærland et al., 2018; Post et al., 2018; Riasanow et al., 2018; M. Rossi et al., 2019; Schlecht et al., 2020; Scholz & Stein, 2018; Schweizer et al., 2017; Seebacher &

Table 12, cont.

Journals, conference proceedings, and other manuscripts	**Search results**	**Final sample**	**Citation**
			Schuritz, 2019; Smith & Dhillon, 2019; Wei et al., 2019; X. Zhang, 2019)
HICSS Proceedings (HICSS Database)	188	26	(Basole, 2018; Bauer et al., 2019; Beck & Müller-Bloch, 2017; Blossey et al., 2019; Burkhardt et al., 2019; H.-M. Chen & In, 2019; Faber et al., 2019; Farahmand & Farahmand, 2019; Farshid et al., 2019; Fleischmann & Ivens, 2019; Friedlmaier et al., 2018; Glaser, 2017; Holotiuk et al., 2018; Kolb et al., 2019; Korpela et al., 2017; Labazova et al., 2019; M. Lacity & Khan, 2019; Lehner & Simlinger, 2019; Y. Li et al., 2018; Lindman et al., 2017; Miscione et al., 2018; Pflaum et al., 2017, 2018; Still et al., 2019; L. Wang et al., 2019; Welpe et al., 2019)
IEEE Journal articles (IEEE Xplore)	756	18	(Abou Jaoude & George Saade, 2019; M. S. Ali et al., 2019; T. Cai et al., 2019; Christidis & Devetsikiotis, 2016; Dinh et al., 2018; Fernandez-Carames & Fraga-Lamas, 2019; Fraga-Lamas & Fernandez-Carames, 2019; Fu & Zhu, 2019; Jin et al., 2019; Lu et al., 2019; Ma et al., 2018; Perboli et al., 2018; Salah et al., 2019; Valtanen et al., 2019; S. Wang et al., 2018; C. Xu et al., 2019; X. Xu et al., 2017; X. Zhang & Chen, 2019)
Journal articles in Springer Link - Business and Management Category, e.g., Financial Innovation	328	2	(Priem, 2020; Weking et al., 2020) A few identified articles were duplicates.
Business, Technology Innovation Management Review, Accounting & Finance, Harvard Business Review, Entrepreneurial Business and Economics Review, Journal of Strategic Innovation & Sustainability, MIT Sloan Management Review, Scholarly Book/Dissertation	F/B	11	(Cai, 2019; Cao, Cong, & Yang, 2019; Dai, 2017; Filippi, 2017; Iansiti & Lakhani, 2017; Lewtan, McManus, & Roohani, 2018; Nathalie et al., 2019; Nowiński & Kozma, 2017; Rooney, Aiken, & Rooney, 2017; Tapscott & Tapscott, 2016; Yansen, 2020)
Final Set		**100**	

F/B: forward/backward search - these articles were identified as relevant citations in our search articles, not through the database search.

Table 13: Qualitative Coding of Documents

Documents/ Final Sample[67]	Bundle of Affordances (BA)					Experimentation: Conceptual Adaptation					Experimentation: Constraint Mitigation					Actualization: User Actions					Actualization: Actualized Outcomes					Organizational Context					Assimilation: Transformative uses, acceleration and diffusion activities					General Descriptions on Phase Concept
	A 1	A 2	A 3	A 4	A 5	CA 1	CA 2	CA 3	CA 4	CA 5	CM 1	CM 2	CM 3	CM 4	CM 5	UA 1	UA 2	UA 3	UA 4	UA 5	AO 1	AO 2	AO 3	AO 4	AO 5	OC 1	OC 2	OC 3	OC 4	OC 5	AM 1	AM 2	AM 3	AM 4	AM 5	
Chong, Lim, Hua, Zheng, & Tan, 2019	X	X	X	X		X	X						X			X		X	X		X	X	X	X									X	X		
Murray, 2019																																				AM
Du, Pan, Leidner, & Ying, 2019	X	X	X			X	X	X			X	X	X			X	X	X			X	X	X			X	X	X								
Zachariadis, Hileman, & Scott, 2019	X																																			
Toufaily, Zalan, & Dhaou, 2021											X	X	X	X																	X	X		X		BA, CA
Gomber, Kauffman, Parker, & Weber, 2018																					X															CM
Jagtiani & John, 2018			X																													X				
Frizzo-Barker et al., 2020																																				BA, CM, CA
Hughes et al., 2019																																				BA, CM, AM
Janssen, Weerakkody, Ismagilova, Sivarajah, & Irani, 2020																																				AM
Kshetri, 2018																																				BA, EX,

[67] Using AEA to guide rating/coding ensured a very high rating agreement between raters. Studies that offered disparities between raters yet had strong supporting argument by rater was classified under general description of phase concepts.

Table 13, cont.

Documents/ Final Sample[67]	Bundle of Affordances (BA)					Experimentation: Conceptual Adaptation					Experimentation: Constraint Mitigation					Actualization: User Actions					Actualization: Actualized Outcomes					Organizational Context					Assimilation: Transformative uses, acceleration and diffusion activities					General Descriptions on Phase Concept
	A1	A2	A3	A4	A5	CA1	CA2	CA3	CA4	CA5	CM1	CM2	CM3	CM4	CM5	UA1	UA2	UA3	UA4	UA5	AO1	AO2	AO3	AO4	AO5	OC1	OC2	OC3	OC4	OC5	AM1	AM2	AM3	AM4	AM5	
																																				AC, AM
Ying, Jia, & Du, 2018	X			X																											X					
Filippi, 2017	X		X	X																																
Iansiti & Lakhani, 2017	X																														X					
Lacity et al., 2019																															X					
Pedersen et al., 2019	X			X	X							X		X			X		X			X														
Rieger, Guggenmos, Lockl, Fridgen, & Urbach, 2019																																		X		
Zavolokina, Ziolkowski, & Bauer, 2020									X																											
Rai, Constantinides, & Sarker, 2019				X																				X												
Nowiński & Kozma, 2017	X	X																																		AM
Ahluwalia, Mahto, & Guerrero, 2020																							X													
Pazaitis, De Filippi, & Kostakis, 2017																																				EX
Angelis & Ribeiro da Silva, 2019	X	X																																X		EX
Cai et al., 2019					X										X					X															X	
Priem, 2020	X										X										X												X			

Table 13, cont.

Documents/ Final Sample[67]	Bundle of Affordances (BA)					Experimentation										Actualization										Organizational Context					Assimilation					General Descriptions on Phase Concept
						Conceptual Adaptation					Constraint Mitigation					User Actions					Actualized Outcomes										Transformative uses, acceleration and diffusion activities					
	A1	A2	A3	A4	A5	CA1	CA2	CA3	CA4	CA5	CM1	CM2	CM3	CM4	CM5	UA1	UA2	UA3	UA4	UA5	AO1	AO2	AO3	AO4	AO5	OC1	OC2	OC3	OC4	OC5	AM1	AM2	AM3	AM4	AM5	
Rooney, Aiken, & Rooney, 2017					X										X																					
Xu et al., 2019																																				BA
Nathalie, Marion, Jean-Henry, & Arber, 2019					X																															
Egelund-Müller, Elsman, Henglein, & Ross, 2017		X																																		
Nofer, Gomber, Hinz, & Schiereck, 2017	X																				X															
Risius & Spohrer, 2017																																				BA
Michelman, 2017																																				BA, CM
Babich & Hilary, 2019	X	X	X	X	X						X	X	X	X		X	X	X	X	X	X	X	X	X												
Cai, 2019					X					X																									X	
Belchior & Correia, 2020					X										X																				X	
Holotiuk & Moormann, 2018				X																												X			X	
Kazan, Tan, & Lim, 2015																																				AM
Labazova, 2019																																				BA, AM
Lui & Ngai, 2019																																				AC
Miscione, Goerke, Klein, Schwabe, &	X																				X															

Table 13, cont.

Documents/ Final Sample[67]	Bundle of Affordances (BA)					Experimentation: Conceptual Adaptation					Experimentation: Constraint Mitigation					Actualization: User Actions					Actualization: Actualized Outcomes					Organizational Context					Assimilation: Transformative uses, acceleration and diffusion activities					General Descriptions on Phase Concept
	A 1	A 2	A 3	A 4	A 5	CA 1	CA 2	CA 3	CA 4	CA 5	CM 1	CM 2	CM 3	CM 4	CM 5	UA 1	UA 2	UA 3	UA 4	UA 5	AO 1	AO 2	AO 3	AO 4	AO 5	OC 1	OC 2	OC 3	OC 4	OC 5	AM 1	AM 2	AM 3	AM 4	AM 5	
Ziolkowski, 2019																																				
Nærland, Müller-Bloch, Beck, & Palmund, 2018																																X				
Post, Smit, & Zoet, 2018				X																																AM
Riasanow, Burckhardt, Setzke, & Bã, 2018																																				BA
Rossi, Mueller-Bloch, Thatcher, & Beck, 2019																																				BA, CM, AM
Schlecht, Schneider, & Buchwald, 2020																																	X			
Scholz & Stein, 2018																																				BA, AM
Schweizer, Urbach, Schlatt, & Fridgen, 2017																																	X			
Smith & Dhillon, 2019																																		X		
Chong et al., 2019				X															X																	
Murray, 2019	X					X																									X					
Du et al., 2019																																				AM
Zachariadis et al., 2019							X																													
Toufaily et al., 2021																																				BA, EX, AC, AM
Gomber et al., 2018	X	X	X									X				X	X	X				X	X		X							X				

Table 13, cont.

Documents/ Final Sample[67]	Bundle of Affordances (BA)					Experimentation										Actualization										Organizational Context					Assimilation					General Descriptions on Phase Concept
						Conceptual Adaptation					Constraint Mitigation					User Actions					Actualized Outcomes										Transformative uses, acceleration and diffusion activities					
	A1	A2	A3	A4	A5	CA1	CA2	CA3	CA4	CA5	CM1	CM2	CM3	CM4	CM5	UA1	UA2	UA3	UA4	UA5	AO1	AO2	AO3	AO4	AO5	OC1	OC2	OC3	OC4	OC5	AM1	AM2	AM3	AM4	AM5	
Frizzo-Barker et al., 2020																								X												
Hughes et al., 2019																			X					X												
Janssen et al., 2020	X																																X			
Kshetri, 2018																			X																	
Iansiti & Lakhani, 2017	X	X			X																															
Lacity et al., 2019																																X		X		EX
Lacity, 2018				X																		X														
Pedersen et al., 2019				X					X					X					X															X		
Rieger et al., 2019				X																																
Zavolokina et al., 2020	X	X		X																																
Nowiński & Kozma, 2017																																				AM
Ahluwalia et al., 2020																															X					
Pazaitis et al., 2017	X																														X					
Angelis & Ribeiro da Silva, 2019																																		X		
Cai et al., 2019						X																												X		
Rooney et al., 2017					X								X					X					X													
Xu et al., 2019																																				BA
Nathalie et al., 2019																																				BA
Egelund-Müller et al., 2017	X	X		X										X																						
Nofer et al., 2017	X																																			
Risius & Spohrer, 2017	X	X									X	X		X																						AM

Table 13, cont.

Documents/ Final Sample[67]	Bundle of Affordances (BA)					Experimentation: Conceptual Adaptation					Experimentation: Constraint Mitigation					Actualization: User Actions					Actualization: Actualized Outcomes					Organizational Context					Assimilation: Transformative uses, acceleration and diffusion activities					General Descriptions on Phase Concept
	A1	A2	A3	A4	A5	CA1	CA2	CA3	CA4	CA5	CM1	CM2	CM3	CM4	CM5	UA1	UA2	UA3	UA4	UA5	AO1	AO2	AO3	AO4	AO5	OC1	OC2	OC3	OC4	OC5	AM1	AM2	AM3	AM4	AM5	
Michelman, 2017				**X**																																
Babich & Hilary, 2019	**X**			**X**																																CM
Belchior & Correia, 2020				**X**										**X**																						
Holotiuk & Moormann, 2018				**X**																																
Kazan et al., 2015	**X**						**X**				**X**	**X**									**X**	**X**														
Labazova, 2019																**X**					**X**															EX
Lui & Ngai, 2019												**X**					**X**					**X**														
Miscione et al., 2019		**X**																				**X**														
Nærland et al., 2018																																				BA, AM
Post et al., 2018				**X**																																
Riasanow et al., 2018				**X**																																
Rossi et al., 2019																																				BA, EX
Schlecht et al., 2020																			**X**																	
Scholz & Stein, 2018																																				AM
Schweizer et al., 2017																																				
Seebacher & Schuritz, 2019					**X**																															CM
Smith & Dhillon, 2019	**X**																						**X**													
Tapscott & Tapscott, 2016	**X**																																			

Table 13, cont.

Documents/ Final Sample[67]	Bundle of Affordances (BA)					Experimentation										Actualization										Organizational Context					Assimilation					General Descriptions on Phase Concept
						Conceptual Adaptation					Constraint Mitigation					User Actions					Actualized Outcomes										Transformative uses, acceleration and diffusion activities					
	A 1	A 2	A 3	A 4	A 5	CA 1	CA 2	CA 3	CA 4	CA 5	CM 1	CM 2	CM 3	CM 4	CM 5	UA 1	UA 2	UA 3	UA 4	UA 5	AO 1	AO 2	AO 3	AO 4	AO 5	OC 1	OC 2	OC 3	OC 4	OC 5	AM 1	AM 2	AM 3	AM 4	AM 5	
Kolb, Becker, Fischer, & Winkelmann, 2019		**X**																																		
Farahmand & Farahmand, 2019																					**X**	**X**														AM
Bauer, Zavolokina, Leisibach, & Schwabe, 2019									**X**																											
Kazan, Tan, Lim, Sørensen, & Damsgaard, 2018																																				AM

Overarching Framework of Blockchain Implementation Affordances

Based on the analyses and as illustrated in Figure 3, we specify an overarching view of relationships between IT artifacts (Level 1), characteristics and functionalities (Level 2), and the proposed AEAA model (Level 3) for blockchain implementation value-creation given multi-goal orientation of implementers.

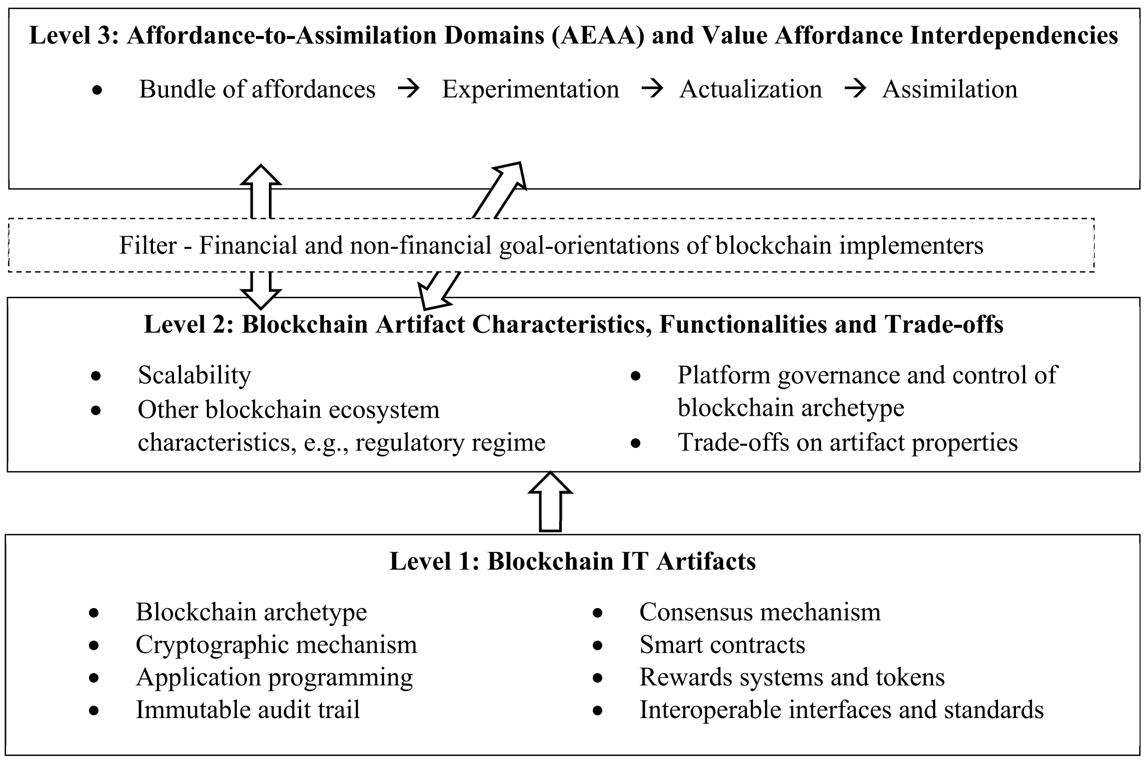

Figure 14: Overarching Framework for Exploiting Value-Based Blockchain Implementation Affordances

APPENDIX B

APPENDIX B

BLOCKCHAIN TECHNOLOGY POSITIONING INVESTMENT: AN EMPIRICAL INVESTIGATION OF FIRM BLOCKCHAIN GROWTH OPTIONS

Related Empirical Work on IT Options and Firm Value

This section presents key assumptions, the IT focus and findings of related studies that leverage IT options perspectives.

Table 14: Key Technology (Real) Options Perspectives in the IS & Reference Literature

Study	**Specific IT Investment**	**Empirical Data/ Data Sources/IT Case**	**Methodology and Measure**	**Theories/Key Literature**	**Key Independent Variables**	**Key Dependent Variable and Moderating Variable**	**Control factors**	**Relevant Findings/Models/Contributions**	**Limitations/Future Studies**
(H. Kim et al., 2020)	Blockchain technology	COMPUSTAT, USPTO	Econometric Modeling (Panel Regression),	Real Options	A patent of blockchain originality (PBO)	Firm value (Tobin's q)		Influence of sustainable value PBO value is exclusive to the firm in the software industry software industry	Whereas the majority of the blockchain innovations are in the private domain, the study focused on only public companies (excludes startups and private firms) Only the IT industry or firms were analyzed, whereas Friedlmaier et al. (2018) argue that the financial industry has the largest share of activities in the blockchain ecosystem. Non-IT firms and firms that acquire IT-firms and end up owning the patent rights were also excluded in the analysis.
					t-1 lagged effects of a patent of blockchain generality (PBG)			PBG influence is exclusive to firms in the hardware industry	

Table 14, cont.

Study	Specific IT Investment	Empirical Data/ Data Sources/IT Case	Methodology and Measure	Theories/Key Literature	Key Independent Variables	Key Dependent Variable and Moderating Variable	Control factors	Relevant Findings/Models/Contributions	Limitations/Future Studies
Benaroch & Kauffman, 1999	Point-of-sale (POS) debit services	Development of POS by the Yankee 24 shared electronic banking network of New England	Black-Scholes and Cox-Rubinstein (binomial model) option pricing models. Sensitivity analysis using Black-Scholes derivatives	Modeling issues with IT investment options	Value of call option (C), Value of option underlying risky asset (A), Rate of return expected on A, Volatility, Option's exercise price or initial investment (X), The risk-free interest rate, Option's time to maturity or expiration, deferral time in years	Timing option to find optimal timing	Annual risk-free interest rate	The logic of option pricing is highly persuasive to justify IT investments as the structure of many IT projects involves infrastructure development and wait-and-see deployment opportunities. Options valuation approach will be ideal for emerging technology investments in the face of adoption, diffusion and uncertain cost for both the analyst and the marketplace.	Potential effect of a non-traded underlying IT asset is not accounted for.
Benaroch & Kauffman, 2000	Point-of-sale (POS) debit services	Development of POS debit by the Yankee 24 for a shared electronic banking network of New England	Black- Scholes formula	Real options perspective, Pricing of real IT investment options – managerial flexibility value	Convenience yield to capture effect	Investment timing option			
Fichman, 2004	General IT Platforms	None	Conceptual modeling	Real Options and IT innovation	Twelve factors drawn from our complementa	Option value	None	Fichman's Real Options Value Creation Framework or	Model is based on conceptual conjectures which warrants underlying factors to be quantitively assessed

Table 14, cont.

Study	Specific IT Investment	Empirical Data/ Data Sources/IT Case	Methodology and Measure	Theories/Key Literature	Key Independent Variables	Key Dependent Variable and Moderating Variable	Control factors	Relevant Findings/Models/Contributions	Limitations/Future Studies
					ry perspectives on innovation (strategy perspective, organizational learning, adaptative and bandwagon perspectives				
Taudes, 1998	Software	None (Hypothetical investment in software platforms)	Comparative modeling of traditional financial metric (NPV) and option pricing model	Option pricing theory	IS functions present in a software system	Software growth option		Option pricing reveal the value of embedded growth options not captured by NPV analysis	Study does not differentiate between IS functions and value generating applications. Option valuation model is not tested on any real-world case.
Kauffman et al., 2015	General IT investments	Proposed model assessed on two real world business cases: data mart consolidation project by Western Global Airlines and mobile payments infrastructure investment project by	Option-based stochastic valuation modeling. Model incorporates mean reversion process, project value sensitivity analysis, simulation-based least-squares Monte-Carlo valuation	Decision-making under uncertainty, Real options theory, Options pricing, Timing of new technology adoption	Parameters include initial investment cost, Cost reversion speed, Benefit reversion speed, Maximum mean benefit, Investment horizon, Technology life cycle, and number of simulated paths (see	Exercising of timing/deferral option (measured with return on investment – ROI)	Benefit flow volatility, cost flow volatility, risk-free discount rate.	1) IT Investment decision model with mean-reverting benefits and costs 2) When the benefits are expected to flow over a longer time horizon, a firm has more flexibility with timing its investment decision to achieve a higher total payoff. 3) High volatility and high risks associated with future benefits from	The model does not address advantage of being a first-mover nor the entry of competing firms. Also the proposed model assumes that IT system will become available immediately investment decision is made as well as benefit flows but in reality, additional period of time is needed to develop the infrastructure and the lag in the accrual of business value is likely to have ramifications on ROI

Table 14, cont.

Study	Specific IT Investment	Empirical Data/ Data Sources/IT Case	Methodology and Measure	Theories/Key Literature	Key Independent Variables	Key Dependent Variable and Moderating Variable	Control factors	Relevant Findings/Models/Contributions	Limitations/Future Studies
		Square (Both US Companies)			paper for full list of parameters)			technology adoption leads to a higher return on investment 4)Applicability of Longstaff-Schwartz simulation-based option valuation – useful when market experiences shocks that affect firm-level and market-level perceptions with IT investments	
Khan et al., 2013	IT Infrastructure investments	A numerical experiment (example) on hetical IT project with more than two exercise periods for managers using a hypothetical IT project	Used two time periods binomial model for option valuation, and utility model for inter-temporal managerial preferences	Real options and managerial biases, IT growth options, Time-inconsistent preferences of business managers	Expected upward movement in future benefits, Expected downward movement in future benefits; Option expiration time; Uncertainty around future payoffs; Subjective probability of the event; One time follow-up investment (to exercise	Project value (Net strategic value) is the real options value	Risk-free discount rate, Time-inconsistent preferences	Present-biased managers are more likely to exercise options early when the net payoffs are low, the option payoffs have high volatility, and the risk-free discount rate is small. Demonstrated the option value is greater than discount cash flow (DCF) with uncertain future payoffs/benefits	Understanding of the exact effects of present managerial bias warrants further investigation with respect to application of other operational call-like options such as options to defer investment, scale and switch use. Time-inconsistent preferences may also impact put-like real options such as abandonment option geared towards loss minimization in the project instead of profit maximization in growth options. Analytical exploration of the impact of present bias in such compound options where sequential interdependency exists will give insights into the long-term

Table 14, cont.

Study	Specific IT Investment	Empirical Data/ Data Sources/IT Case	Methodology and Measure	Theories/Key Literature	Key Independent Variables	Key Dependent Variable and Moderating Variable	Control factors	Relevant Findings/Models/Contributions	Limitations/Future Studies
					the growth option benefits realized after exercising the real option, and				impacts of such decisions, in terms of timing and realized value
(Yang et al., 2012)	Virtual World (VW) technology	LexisNexis[68]	Event study, Empirical (cross-Sectional regression Analysis)	Real options, Fichman's (2004) Value Creation Framework	Radicalness, Interpretive flexibility Divisibility, Strategic importance of affected products or processes, and Contribution to exploitable absorptive capacity (EAC)	Market reaction (Cumulative abnormal return)	Firm size, Industry (finance, service, manufacturing), product type, Solution provider	Investors' reactions to virtual world businesses are contingent on interpretive flexibility, divisibility, strategic importance and EAC	Excluded susceptibility to network effects due to the paper's argument that network externalities will be comparable for the majority of cases in the study. Excluded prospects of network dominance class because the data sample includes only VW technology class. Other excluded factors were prospects of network dominance instance, sustainability of advantage, knowledge barrier, innovative capabilities, learning-related endowment (See paper for explanations) Sample included only large firms that voluntarily disclose virtual world initiatives however small and medium organizations embark on strategic adoption of VWs

[68] Also used by Goddard et al. (2015) in Investor attention and FX market volatility.

Table 14, cont.

Study	Specific IT Investment	Empirical Data/ Data Sources/IT Case	Methodology and Measure	Theories/Key Literature	Key Independent Variables	Key Dependent Variable and Moderating Variable	Control factors	Relevant Findings/Models/Contributions	Limitations/Future Studies
Benaroch et al., 2010	IT Service contracts	Simulation of sourcing model	real options analysis on contingent claims and decision making	IT Services outsourcing flexibility, Real options	Vendor perspectives: vendor profit, Client perspectives: demand volatility			IT services outsourcing decision model	The gains of the client, come only at the cost of a loss for the other party, the vendor who undercuts representation of the outsourcing decision-making problem in game-theoretic terms which would be possible had the paper embedded real option analysis concepts in a separately conceived model. The modeling approach does not consider other reasons, such as contracts that do not specify all the details for sourcing mode, for back-sourcing and subscription fee changes beyond shifts in IT services demand.
(Taudes et al., 2000)	ERP software platform investment	Proposed model was used for the comparative value assessment of switching from SAP R/2 to SAP R/3	Option valuation of decision on "implementation opportunies" as managerial flexibility on software implementation using Black-Scholes formula for valuing	Option Valuation in IT	The gain when supporting a particular task, the number of tasks supported by the type of software application today, the percentage increase in	Option values (in USD) of several implementation opportunities: EDI[69]-based purchasing, EDI-based invoicing, workflow for sales,	Discount rate as measure of uncertainty	In comparison to NPV analysis which punishes higher uncertainty of possible future implementation opportunities, option valuation of software platform decision-making provides higher potential benefits from these opportunities (i.e.,	Parameter values were based on sales development, hence proposed valuation require modification in the presence of financial market data,

[69] EDI – Electronic data interchange

Table 14, cont.

Study	Specific IT Investment	Empirical Data/ Data Sources/IT Case	Methodology and Measure	Theories/Key Literature	Key Independent Variables	Key Dependent Variable and Moderating Variable	Control factors	Relevant Findings/Models/Contributions	Limitations/Future Studies
			European call option model		the number of tasks at the end of one year, Range in which that percentage will lie, earliest date application can be implemented, Total cost of ownership	engineering document handling, WWW-based e-commerce system		value of "long-run potential" in the decision process)	

Additional Analyses and Robustness Checks

Different measures for degree of decentralization and archetypes complementarity. For the decentralization of the archetype, we only use the base ranking utilized in computing the weighted degree of decentralization. Thus, the degree of decentralization (*DDec*) ranks the ledgers as follows: permissionless = 3, public-permissioned=2, private-permissioned = 1. For the new complementarity measure, we use Complementarity of Archetypes dummy variable (*CArch*) where '1' for periods where firm has more than one archetype and '0' for period with zero or only one archetype adopted. We re-estimated model results in Table 3 using these new measures. The results of these re-estimations are shown in Table 10. Overall, the significant results are qualitatively consistent with our main results.

Blockchain archetype divisibility (adaptation) and business value. IT adaptation captures behaviors that change an IT that has been implemented (Barki et al., 2007) – the adjustments and changes following the installation of a new technology in a given setting (Tyre & Orlikowski, 1994).With the development of interoperability chains and solutions to the oracle problem, firms will be able to connect different blockchain archetypes as one internetwork of blockchain platform if warranted, hence the different sequences or order of archetype adoption can construe a set of technology divisibility available to firms currently. Each adoption is able can also function on its own. Adoption of a particular ledger type represent managerial decision-making to increase the variance of payoffs from overall blockchain investment. Such exercising flexibility create more growth options for the firm. We expect the sequential adoption of blockchain archetypes to have dynamic impacts on firm value.

To capture the effect of blockchain divisibility, we identify all unique ordered sequences of adoption. The archetype position is determined by the date of announcement with older announcement preceding later archetype investment if any. We have three permutations with replacement cases and the total is computed as $\sum_{r=1,2,3}^{n=3} \boldsymbol{P^R}\,(n, r) = \sum_{r=1,2,3}^{n=3} n^r$, where P^R is permutation with replacement function, n is the number of distinct archetypes, r is the number of elements being permuted. This can only be 1, 2 or 3 in our case. The total unique sequences of 1 or 2 or 3 elements is $27 = 3^1 + 3^2 + 3^3$. We did not expect our data set to have representations for all 27 sequences, but the identification allows for constructing divisibility dummies. The reference group has zero archetype adopted. This is usually the case before firms make their first archetype investment. Following the construction of these measurement, we re-estimated our fixed effects model 4 in Table 11 to include divisibility dummies to measure the impact of the specific sequence of adopting blockchain archetypes. The new estimation results presented in Model 4 Table 11 are qualitatively consistent with findings in model 4, Table 4. We find that the sequence by which firms adopt blockchain archetypes (i.e., blockchain archetype adaptation) has different ramifications on firm performance. Future studies may substantiate and explicate these measurements and findings to present a robust theorization blockchain adaptation effect.

Table 15: Fixed-Effects Model Estimation Results – Impact on Tobin's q (Alternative Coding for Strategy Variables)

Dependent variable		***Tobins q(t+1)***			***Tobins q(t+2)***	***Tobins q(t+3)***	***Tobins q(t+4)***	***Tobins q(t+8)***
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Independent variables								
Blockchain Strategy								
NPublic-Permissioned Archetype		0.17	0.12	0.12	0.20	0.28**	0.40**	0.92***
		(0.11)	(0.11)	(0.11)	(0.12)	(0.14)	(0.16)	(0.20)
NPrivate-Permissioned Archetype		0.03	-0.00	-0.00	0.04	0.09	0.15	0.53***
		(0.07)	(0.07)	(0.07)	(0.08)	(0.09)	(0.11)	(0.16)
NPermissionless Archetype		0.54**	0.52**	0.52**	0.44*	0.40	0.36	0.76*
		(0.24)	(0.25)	(0.25)	(0.25)	(0.27)	(0.31)	(0.43)
Degree of Decentralization		-0.15**	-0.14**	-0.14**	-0.15**	-0.20**	-0.24***	-0.38***
		(0.06)	(0.06)	(0.06)	(0.07)	(0.08)	(0.09)	(0.13)
Complementarity of Archetypes Dummy		-0.11	-0.08	-0.08	-0.15	-0.19	-0.21	-0.70***
		(0.09)	(0.10)	(0.10)	(0.10)	(0.12)	(0.14)	(0.17)
Blockchain-related Organizational Learning								
Blockchain Patents (log)			-0.23***	-0.23***	-0.27***	-0.24***	-0.30**	-0.13
			(0.07)	(0.07)	(0.08)	(0.08)	(0.12)	(0.25)
Originality of Blockchain Patent (log)			0.08**	0.08**	0.11**	0.03	0.05	-0.07
			(0.03)	(0.03)	(0.04)	(0.05)	(0.05)	(0.10)
Blockchain Events Participation (log)			0.08*	0.08*	0.13**	0.21***	0.16***	0.11*
			(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
Blockchain Adoption Network Effects								
Network Externality (log)				0.02	0.05	0.10**	0.15***	0.39***
				(0.04)	(0.04)	(0.04)	(0.04)	(0.07)
Control variables								
Other Patents	-0.01	-0.01	-0.01	-0.03	-0.03	-0.04**	-0.05**	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Average Patents Citation Lag (log)	-0.00	-0.00	-0.04	-0.07	-0.07	0.00	-0.01	0.07
	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.08)
Other Event Participation	-0.01	-0.00	-0.00	-0.03	-0.03	0.01	0.02	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
R&D Intensity	-0.06	-0.00	-0.37	0.10	0.10	0.14	-0.22	0.53
	(0.49)	(0.51)	(0.34)	(0.38)	(0.38)	(0.45)	(0.55)	(0.53)

Table 15, cont.

Dependent variable	***Tobins q*** $_{(t+1)}$				***Tobins q*** $_{(t+2)}$	***Tobins q*** $_{(t+3)}$	***Tobins q*** $_{(t+4)}$	***Tobins q*** $_{(t+8)}$
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Missing R&D Dummy	0.28***	0.30***	0.25**	0.20*	0.20*	0.14	0.07	0.13
	(0.10)	(0.11)	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)	(0.08)
Leverage	-0.69***	-0.70***	-0.75***	-0.76***	-0.76***	-0.67***	-0.62*	-0.01
	(0.16)	(0.16)	(0.19)	(0.19)	(0.19)	(0.23)	(0.34)	(0.17)
Profitability	1.67**	1.65**	1.57**	1.78**	1.78**	1.45**	1.03	-0.22
	(0.80)	(0.78)	(0.77)	(0.77)	(0.77)	(0.61)	(0.64)	(0.46)
Dividend Yield Dummy	0.03	0.04	0.05	0.05	-0.05	-0.07	-0.17**	-0.15
	(0.08)	(0.08)		(0.08)	(0.08)	(0.08)	(0.08)	(0.11)
Cashflow to Assets	-2.23	-2.34	(0.08)	-0.33	-0.33	-0.13	0.07	0.90*
	(1.70)	(1.70)	-2.38	(1.18)	(1.18)	(0.82)	(0.53)	(0.51)
Cash Holding	-0.58**	-0.54*	(1.71)	-0.30	-0.30	-0.00	0.29	-0.10
	(0.28)	(0.29)	-0.60**	(0.35)	(0.35)	(0.37)	(0.34)	(0.35)
Tangibility	1.26**	1.43**	(0.30)	0.58	0.58	0.56	0.47	0.19
	(0.64)	(0.63)	1.35**	(0.68)	(0.68)	(0.67)	(0.66)	(0.78)
Firm Size (log of Total Assets)	-0.23***	-0.23***	(0.67)	-0.07	-0.07	0.01	0.02	0.02
	(0.08)	(0.08)	-0.19**	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Industry Mean Tobin's q	0.39***	0.38***	0.39***	0.31***	0.31***	0.27***	0.28***	0.23**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)
Constant	3.75***	3.68***	3.25***	1.92*	1.92*	0.75	0.30	-1.41
	(0.90)	(0.88)	(1.12)	(1.13)	(1.13)	(1.03)	(1.00)	(0.97)
Observations	1,254	1,254	1,197	1,141	1,141	1,086	1,031	810
Adjusted R-squared	0.93	0.93	0.94	0.93	0.93	0.94	0.94	0.95
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Alternative coding for degree of decentralization variable. Alternative coding for complementarity between archetypes variables. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 16: Effect of Blockchain Archetypes Divisibility on Firm Performance

Dependent variable			***Tobins q***$_{(t+1)}$			***Tobins q***$_{(t+2)}$	***Tobins q***$_{(t+3)}$	***Tobins q***$_{(t+4)}$	***Tobins q***$_{(t+8)}$
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Independent variables									
Blockchain Strategy									
NPublic-Permissioned Archetype		0.56***	0.50***	0.49***	0.66***	0.69***	0.77***	0.86***	0.82***
		(0.14)	(0.14)	(0.14)	(0.14)	(0.15)	(0.14)	(0.15)	(0.17)
NPrivate-Permissioned Archetype		0.20**	0.17**	0.17**	0.25***	0.27***	0.32***	0.35***	0.44***
		(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.10)	(0.15)
NPermissionless Archetype		1.16***	1.10***	1.10***	1.00***	0.90***	0.91***	0.89***	0.46
		(0.29)	(0.30)	(0.30)	(0.26)	(0.28)	(0.28)	(0.29)	(0.39)
Weighted Degree of Decentralization		-0.37***	-0.35***	-0.35***	-0.44***	-0.42***	-0.46***	-0.49***	-0.30**
		(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.13)
CPublicPermissioned-PrivatePermissioned		-0.45***	-0.40***	-0.40***	-0.65***	-0.65***	-0.73***	-0.80***	-0.87***
		(0.11)	(0.11)	(0.11)	(0.12)	(0.13)	(0.13)	(0.13)	(0.16)
CPublicPermissioned-Permissionless		-0.99***	-0.92***	-0.92***	-1.05***	-1.01***	-1.09***	-1.14***	
		(0.18)	(0.18)	(0.18)	(0.18)	(0.19)	(0.19)	(0.19)	
CPrivatePermissioned-Permissionless		-0.33	-0.30	-0.30	1.15**	0.89*	1.10***	-0.09	-0.79
		(0.28)	(0.27)	(0.27)	(0.45)	(0.47)	(0.40)	(0.37)	(0.54)
Blockchain-related Organizational Learning									
Blockchain Patents (log)			-0.21***	-0.21***	-0.22***	-0.26***	-0.22***	-0.28**	-0.14
			(0.06)	(0.06)	(0.06)	(0.08)	(0.07)	(0.12)	(0.25)
Originality of Blockchain Patent (log)			0.06*	0.06*	0.06*	0.09**	-0.00	0.03	-0.07
			(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.10)
Blockchain Events Participation (log)			0.08*	0.08*	0.09*	0.14**	0.22***	0.16***	0.11*
			(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
Blockchain Adoption Network Effects									
Network Externality (log)				0.02	0.03	0.05	0.11**	0.16***	0.39***
				(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.07)
Blockchain Archetypes Divisibility (Adaptation)									
Divisibility Dummy A					0.14*	0.10	0.14	0.24**	0.03
					(0.08)	(0.09)	(0.09)	(0.11)	(0.10)
Divisibility Dummy C					0.20**	0.11	0.09	0.08	
					(0.08)	(0.08)	(0.08)	(0.09)	

Table 16, cont.

Dependent variable	Tobins $q_{(t+1)}$					Tobins $q_{(t+2)}$	Tobins $q_{(t+3)}$	Tobins $q_{(t+4)}$	Tobins $q_{(t+8)}$
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Divisibility Dummy E					-0.14	-0.12	0.10	-0.04	
					(0.09)	(0.08)	(0.07)	(0.10)	
Divisibility Dummy F					-2.47***	-1.99***	-2.17***	-0.88**	
					(0.50)	(0.51)	(0.44)	(0.36)	
Divisibility Dummy H					-0.67***	-0.68***	-0.76***	-0.62***	-0.54***
					(0.14)	(0.15)	(0.16)	(0.15)	(0.21)
Divisibility Dummy I					-0.51**	-0.54**	-1.00***		
					(0.20)	(0.26)	(0.15)		
Control variables									
Other Patents	-0.01	0.01	0.00	0.00	-0.03	-0.04*	-0.05***	-0.05**	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Average Patents Citation Lag (log)	-0.00	0.00	-0.02	-0.02	-0.02	-0.05	0.04	0.01	0.07
	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.08)
Other Event Participation	-0.01	0.02	0.02	0.02	0.04	0.01	0.05	0.06**	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
R&D Intensity	-0.06	-0.14	-0.48	-0.48	-0.56*	-0.08	-0.09	-0.44	0.53
	(0.49)	(0.48)	(0.33)	(0.33)	(0.32)	(0.38)	(0.43)	(0.52)	(0.53)
Missing R&D Dummy	0.28***	0.25**	0.21**	0.21**	0.19**	0.14	0.08	0.01	0.13
	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)	(0.10)	(0.10)	(0.09)	(0.08)
Leverage	-0.69***	-0.66***	-0.74***	-0.72***	-0.44**	-0.51***	-0.44*	-0.43	0.01
	(0.16)	(0.16)	(0.17)	(0.18)	(0.17)	(0.18)	(0.23)	(0.34)	(0.17)
Profitability	1.67**	1.46**	1.42*	1.42*	1.25*	1.52**	1.22**	0.79	-0.21
	(0.80)	(0.74)	(0.74)	(0.74)	(0.70)	(0.67)	(0.53)	(0.57)	(0.46)
Dividend Yield Dummy	0.03	0.01	0.03	0.03	-0.03	-0.05	-0.07	-0.17**	-0.15
	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)	(0.11)
Cashflow to Assets	-2.23	-2.51	-2.53	-2.53	-2.74*	-0.63	-0.46	-0.25	0.84
	(1.70)	(1.62)	(1.63)	(1.63)	(1.53)	(1.03)	(0.67)	(0.44)	(0.51)
Cash Holding	-0.58**	-0.58**	-0.63**	-0.63**	-0.56*	-0.26	0.06	0.36	-0.06
	(0.28)	(0.29)	(0.30)	(0.30)	(0.30)	(0.35)	(0.36)	(0.34)	(0.35)
Tangibility	1.26**	1.14*	1.08	1.09	1.32**	0.47	0.42	0.27	0.17
	(0.64)	(0.63)	(0.66)	(0.67)	(0.65)	(0.67)	(0.66)	(0.66)	(0.79)
Firm Size (log of Total Assets)	-0.23***	-0.25***	-0.22***	-0.22***	-0.36***	-0.20**	-0.11	-0.08	0.02
	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.08)

Table 16, cont.

Dependent variable	Tobins $q_{(t+1)}$					Tobins $q_{(t+2)}$	Tobins $q_{(t+3)}$	Tobins $q_{(t+4)}$	Tobins $q_{(t+8)}$
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Industry Mean Tobin's q	0.39***	0.37***	0.38***	0.38***	0.33***	0.27***	0.23***	0.26***	0.23**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)
Constant	3.75***	4.02***	3.74***	3.61***	5.14***	3.46***	2.12**	1.50	-1.31
	(0.90)	(0.85)	(0.89)	(1.09)	(1.06)	(1.13)	(1.00)	(1.01)	(1.00)
Observations	1,254	1,254	1,197	1,197	1,197	1,141	1,086	1,031	810
Adjusted R-squared	0.93	0.93	0.94	0.94	0.94	0.94	0.94	0.94	0.95
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Propensity score matching summary statistics

Table 17: Panel A: Full Sample Summary Statistics for Adopting and Potential Control Firms (Unmatched Sample)

	Treated Sample						Unmatched Control Sample						T-test	
Variables	Obs.	Mean	SD.	Min	Median	Max	Obs.	Mean	SD.	Min	Median	Max	t-value	Prob
Treatment Dummy	1,382	1.000	0.000	1.000	1.000	1.000	68,607	0.000	0.000	0.000	0.000	0.000	-	-
Tobin's q	1,045	2.247	1.598	-0.148	1.744	5.810	50,142	1.934	1.487	-0.113	1.410	5.403	-6.277	0.000
R&D intensity	1,486	0.064	0.092	0.000	0.000	0.825	68,607	0.196	0.500	0.000	0.000	2.285	43.496	0.000
R&D intensity dummy	1,486	0.511	0.500	0.000	1.000	1.000	68,607	0.534	0.499	0.000	1.000	1.000	1.797	0.073
Firm size	1,445	11.118	2.032	3.963	11.425	15.035	67,669	6.674	2.413	0.000	6.665	14.993	-81.929	0.000
Leverage	1,421	0.235	0.204	0.000	0.165	0.857	66,631	0.176	0.215	0.000	0.095	0.999	-10.890	0.000
Profitability	1,445	0.014	0.026	-0.383	0.011	0.199	67,570	-0.034	0.106	-0.641	0.002	0.199	-59.629	0.000
Cash holding	1,443	0.232	0.183	0.003	0.180	0.838	67,533	0.278	0.291	0.000	0.151	1.000	9.389	0.000
Tangibility	1,369	0.122	0.121	0.001	0.083	0.587	66,225	0.115	0.152	0.000	0.057	0.951	-2.102	0.000

Table 17, cont.

Variables	Treated Sample Obs.	Mean	SD.	Min	Median	Max	Unmatched Control Sample Obs.	Mean	SD.	Min	Median	Max	T-test t-value	Prob
Cashflow to assets	1,336	0.019	0.028	-0.591	0.016	0.123	62,552	-0.025	0.098	-0.591	0.004	0.123	-51.593	0.000
Dividend yield dummy	1,486	0.741	0.438	0.000	1.000	1.000	68,607	0.426	0.494	0.000	0.000	1.000	-27.329	0.000
Book-to-market value	1,425	4.227	3.715	-0.011	2.842	11.586	67,340	3.250	3.148	-0.011	2.019	11.586	-9.853	0.000

Notes. Observation (Obs.), Standard Deviation (SD.). Prob: probability (|T| > |t|) or p-value for t-test. The null hypothesis is that there is no characteristic difference between the means of treated sample and the unmatched control sample. The results show that there is a difference between these two samples on each matched variable justifying need for propensity score matching.

Table 18: Panel B: Summary Statistics for Adopting and Control Firms by Industry Group (Matched Sample)

	Treated Obs.	**Mean**	**SD**	**Min**	**Median**	**Max**	**Control Obs.**	**Mean**	**SD**	**Min**	**Median**	**Max**	**T-test t-value**	**Prob**
2 Digit SIC: 28, 30														
Tobin's q	47	3.088	1.704			5.403	15,873	2.205	1.594	0.312	1.742	5.403	1.244	3.560
R&D intensity	48	0.078	0.084			0.295	16,431	0.576	0.836	0.000	0.062	2.285	0.000	0.062
R&D intensity dummy	48	0.500	0.505			1.000	16,431	0.373	0.484	0.000	0.000	1.000	0.000	0.500
Firm size	47	11.036	0.988			12.095	16,172	5.326	2.132	0.339	4.998	12.199	9.930	10.458
Leverage	47	0.085	0.058			0.218	15,955	0.108	0.171	0.000	0.025	0.994	0.011	0.074
Profitability	47	0.028	0.022			0.071	16,161	-0.104	0.146	-0.641	0.079	0.199	-0.041	0.032
Cash holding	47	0.169	0.079			0.339	16,164	0.554	0.343	0.000	0.634	0.999	0.053	0.139
Tangibility	47	0.140	0.066			0.293	16,140	0.124	0.164	0.000	0.055	0.951	0.071	0.139
Cashflow to assets	44	0.014	0.024			0.064	15,474	-0.095	0.133	-0.591	0.075	0.123	-0.066	0.014
Dividend yield dummy	48	1.000	0.000			1.000	16,431	0.193	0.395	0.000	0.000	1.000	1.000	1.000
Book-to-market value	47	6.467	3.502			11.586	16,106	4.124	3.449	-0.011	3.159	11.586	2.788	6.729

Table 18, cont.

	Treated						Control						T-test	
	Obs.	**Mean**	**SD**	**Min**	**Median**	**Max**	**Obs.**	**Mean**	**SD**	**Min**	**Median**	**Max**	t-value	Prob
2 Digit SIC: 35, 36, 38, 48														
Tobin's q	325	1.605	0.902	-0.016	1.392	5.403	17,778	1.686	1.325	0.312	1.245	5.403		
R&D intensity	360	0.057	0.064	0.000	0.045	0.241	18,436	0.137	0.313	0.000	0.057	2.285		
R&D intensity dummy	360	0.328	0.470	0.000	0.000	1.000	18,436	0.293	0.455	0.000	0.000	1.000		
Firm size	356	11.180	1.226	8.672	11.395	13.221	18,192	6.478	2.388	0.204	6.498	12.520		
Leverage	343	0.226	0.139	0.043	0.175	0.611	17,994	0.173	0.209	0.000	0.099	0.996		
Profitability	356	0.018	0.019	-0.070	0.016	0.114	18,165	-0.025	0.102	-0.641	0.004	0.199		
Cash holding	356	0.156	0.136	0.003	0.115	0.697	18,169	0.241	0.224	0.000	0.166	0.994		
Tangibility	356	0.166	0.122	0.024	0.113	0.417	18,127	0.168	0.152	0.000	0.117	0.918		
Cashflow to assets	352	0.022	0.018	-0.029	0.021	0.123	17,301	-0.011	0.091	-0.591	0.015	0.123		
Dividend yield dummy	360	0.850	0.358	0.000	1.000	1.000	18,436	0.363	0.481	0.000	0.000	1.000		
Book-to-market value	343	3.643	3.293	-0.011	2.527	11.586	18,147	3.238	2.925	-0.011	2.326	11.586		

	Treated						Control					
	Obs.	**Mean**	**SD**	**Min**	**Median**	**Max**	**Obs.**	**Mean**	**SD**	**Min**	**Median**	**Max**
2 Digit SIC: 37												
Tobin's q	67	0.989	0.646	0.440	0.601	2.406	2,008	1.498	1.128	0.312	1.128	5.403
R&D intensity	96	0.041	0.064	0.000	0.000	0.199	2,167	0.071	0.280	0.000	0.011	2.285
R&D intensity dummy	96	0.563	0.499	0.000	1.000	1.000	2,167	0.431	0.495	0.000	0.000	1.000
Firm size	96	11.489	1.132	9.566	12.050	12.504	2,149	7.317	2.190	0.106	7.592	13.228
Leverage	96	0.405	0.245	0.047	0.385	0.857	2,121	0.234	0.207	0.000	0.187	0.962
Profitability	96	0.008	0.013	-0.055	0.010	0.038	2,149	-0.004	0.076	-0.641	0.011	0.199
Cash holding	96	0.116	0.039	0.041	0.116	0.212	2,149	0.133	0.137	0.000	0.097	0.981
Tangibility	96	0.216	0.081	0.074	0.199	0.375	2,148	0.223	0.132	0.000	0.198	0.822

Table 18, cont.

	Treated						Control						T-test	
	Obs.	**Mean**	**SD**	**Min**	**Median**	**Max**	**Obs.**	**Mean**	**SD**	**Min**	**Median**	**Max**	t-value	Prob
Cashflow to assets	96	0.012	0.013	-0.053	0.015	0.033	2,088	0.007	0.076	-0.591	0.023	0.123		
Dividend yield dummy	96	1.000	0.000	1.000	1.000	1.000	2,167	0.551	0.498	0.000	1.000	1.000		
Book-to-market value	96	2.892	3.680	-0.011	1.499	11.586	2,130	3.174	2.993	-0.011	2.314	11.586		
2 Digit SIC: 53, 59														
Tobin's q	47	3.401	1.672	1.385	3.720	5.403	1,781	1.596	1.211	0.312	1.184	5.403		
R&D intensity	47	0.059	0.059	0.000	0.092	0.136	1,849	0.002	0.015	0.000	0.000	0.251		
R&D intensity dummy	47	0.489	0.505	0.000	0.000	1.000	1,849	0.966	0.181	0.000	1.000	1.000		
Firm size	47	11.978	0.507	10.821	12.204	12.680	1,816	7.197	1.923	1.796	7.117	12.369		
Leverage	47	0.101	0.056	0.033	0.073	0.194	1,797	0.244	0.250	0.000	0.166	0.988		
Profitability	47	0.013	0.007	-0.004	0.015	0.027	1,807	-0.003	0.058	-0.641	0.007	0.199		
Cash holding	47	0.147	0.106	0.029	0.205	0.312	1,816	0.146	0.168	0.000	0.077	0.842		
Tangibility	47	0.477	0.080	0.334	0.475	0.587	1,816	0.248	0.171	0.000	0.212	0.708		
Cashflow to assets	47	0.033	0.013	0.011	0.032	0.053	1,627	0.010	0.049	-0.374	0.016	0.123		
Dividend yield dummy	47	0.489	0.505	0.000	0.000	1.000	1,849	0.472	0.499	0.000	0.000	1.000		
Book-to-market value	47	7.691	4.062	2.309	11.586	11.586	1,797	3.014	2.935	-0.011	2.032	11.586		

	Treated						Control					
	Obs.	**Mean**	**SD**	**Min**	**Median**	**Max**	**Obs.**	**Mean**	**SD**	**Min**	**Median**	**Max**
2 Digit SIC: 60, 61, 62, 63												
Tobin's q	154	1.973	2.019	-0.148	0.888	5.403	1,065	1.426	1.455	-0.113	0.871	5.403
R&D intensity	456	0.000	0.000	0.000	0.000	0.000	16,726	0.002	0.018	0.000	0.000	0.643
R&D intensity dummy	456	1.000	0.000	1.000	1.000	1.000	16,726	0.985	0.121	0.000	1.000	1.000
Firm size	436	12.465	1.782	7.663	12.807	15.035	16,498	8.351	2.073	0.000	8.061	14.993

Table 18, cont.

	Treated						Control						T-test	
	Obs.	**Mean**	**SD**	**Min**	**Median**	**Max**	**Obs.**	**Mean**	**SD**	**Min**	**Median**	**Max**	t-value	Prob
Leverage	436	0.356	0.214	0.000	0.353	0.814	16,179	0.267	0.235	0.000	0.202	0.999		
Profitability	436	0.009	0.016	-0.016	0.003	0.083	16,487	0.003	0.028	-0.641	0.003	0.199		
Cash holding	434	0.205	0.113	0.011	0.202	0.530	16,394	0.100	0.126	0.000	0.056	0.994		
Tangibility	360	0.019	0.016	0.001	0.013	0.063	15,201	0.022	0.041	0.000	0.014	0.676		
Cashflow to assets	340	0.012	0.017	-0.030	0.005	0.086	14,328	0.004	0.025	-0.591	0.004	0.123		
Dividend yield dummy	456	0.991	0.093	0.000	1.000	1.000	16,726	0.798	0.402	0.000	1.000	1.000		
Book-to-market value	435	2.498	2.969	0.340	1.397	11.586	16,379	1.615	1.586	-0.011	1.234	11.586		
2 Digit SIC: 73														
Tobin's q	405	2.843	1.571	-0.148	2.534	5.810	11,637	2.117	1.563	0.312	1.515	5.403		
R&D intensity	479	0.133	0.111	0.000	0.129	0.825	12,998	0.099	0.179	0.000	0.038	2.285		
R&D intensity dummy	479	0.175	0.381	0.000	0.000	1.000	12,998	0.456	0.498	0.000	0.000	1.000		
Firm size	463	9.646	2.092	3.963	9.593	13.334	12,842	6.314	1.958	0.009	6.281	13.629		
Leverage	452	0.120	0.146	0.000	0.073	0.819	12,585	0.128	0.194	0.000	0.040	0.994		
Profitability	463	0.015	0.039	-0.383	0.016	0.199	12,801	-0.015	0.082	-0.641	0.001	0.199		
Cash holding	463	0.355	0.228	0.018	0.343	0.838	12,841	0.255	0.232	0.000	0.187	1.000		
Tangibility	463	0.112	0.067	0.031	0.094	0.353	12,793	0.105	0.158	0.000	0.055	0.925		
Cashflow to assets	457	0.024	0.041	-0.591	0.021	0.123	11,734	-0.001	0.066	-0.591	0.010	0.123		
Dividend yield dummy	479	0.367	0.483	0.000	0.000	1.000	12,998	0.304	0.460	0.000	0.000	1.000		
Book-to-market value	457	6.006	3.528	-0.011	5.407	11.586	12,781	4.310	3.690	-0.011	2.975	11.586		

Notes. Standard deviation (SD).

APPENDIX C

APPENDIX C

BITCOIN CRYPTOCURRENCY BEHAVIOR AND OPINION LEADER SENTIMENTS ON TWITTER

Table 19: Pairwise Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) ReturnBitcoin	1.000											
(2) Polarity	0.014*	1.000										
(3) Subjectivity	-0.004	0.438*	1.000									
(4) VolatilityBitcoin	-0.006	0.000	0.065*	1.000								
(5) lnTradingVolume	-0.014*	-0.125*	-0.031*	0.483*	1.000							
(6) lnTweetVolume	0.000	0.173*	0.281*	0.149*	0.233*	1.000						
(7) lnOPLTweetVolume	0.004	0.228*	0.238*	0.164*	0.242*	0.886*	1.000					
(8) lnNOPLTweetVolume	0.001	0.043*	0.263*	0.113*	0.137*	0.740*	0.429*	1.000				
(9) GoogleSearchIndex	-0.004	-0.046*	0.019*	0.069*	0.128*	0.155*	0.110*	0.167*	1.000			
(10) ReturnSnP500	-0.013*	0.007	0.006	-0.006	-0.001	0.001	0.001	0.000	0.007	1.000		
(11) ReturnVIX	0.003	-0.012*	0.000	0.005	0.005	0.002	0.000	0.005	0.003	-0.715*	1.000	
(12) ReturnCOMEXGold	-0.004	-0.001	0.005	0.001	-0.002	0.001	-0.001	0.003	-0.003	-0.015*	0.040*	1.000

**** p<0.01, ** p<0.05, * p<0.1*

BIOGRAPHICAL SKETCH

Daniel Narh Treku earned his Ph.D. in Business Administration with a concentration in Information Systems (IS) from the University of Texas Rio Grande Valley after successfully defending his dissertation on blockchain value creation logics and financial returns and fulfilling all degree requirements in May 2022. His research focuses on blockchain value creation and financial returns, cryptocurrency price behavior and investor sentiments from social media, the economics of IS, big-data analytics, and machine learning. He has publications in the International Journal of Information Management, multiple Springer Lecture Notes (book chapters) on Computer Science and IS, and several conference proceedings.

Prior to his doctorate at the University of Texas Rio Grande Valley, he attended the Ghana Institute of Management and Public Administration, Ghana, where he was awarded an MPhil in Management Information Systems the June of 2015. He earned his undergraduate degree in Physics from Kwame Nkrumah University of Science and Technology, Ghana, the July of 2007. His academic employment history includes Graduate Associate Instructor at UTRGV (January 11, 2020, to May 10, 2022), Research Assistant at UTRGV (September 1, 2017, to December 10, 2021), and Lecturer position at Ghana Institute of Management and Public Administration (September 1, 2015, to August 31, 2017). He will be joining the Business School at Worcester Polytechnic Institute (WPI), Worcester, Massachusetts, in the Fall of 2022.

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