Blockchain Adoption and Investment Sensitivity to Stock Price

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Abstract

This study examines the relation between blockchain adoption and investment efficiency. In particular, we investigate whether and how a firm's investment sensitivity to stock price changes after implementing blockchain technology. Using a difference-in-differences approach with a sample of U.S. listed firms that indicate blockchain adoption in 8-K filings during 2014 to 2019 versus non-adopters, we find that relative to non-adopters, blockchain adopters exhibit an increase in investment-Q sensitivity after the implementation of blockchain. This suggests a positive effect of blockchain adoption on firms' investment efficiency. We further find that this effect is concentrated in firms with poor information environments and those with a high level of engagement in blockchain technology. Our results provide some of the first empirical evidence on the real effects of blockchain adoption. Given that improved efficiency is one of the main goals that many companies seek to achieve from implementing blockchain, our results have implications for interested parties assessing the potential effects and benefits of adopting blockchain in business.

Keywords: *blockchain technology*; *blockchain adoption*; *investment efficiency*; *investment-Q sensitivity*

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1. Introduction

This study examines whether and how a firm's adoption of blockchain technology affects investment efficiency, proxied by investment sensitivity to stock price. Firms in various industries (e.g., IBM, Maersk Line, and Walmart) have started applying blockchain to their business and operations, while some are still hesitant to adopt this technology partly due to a lack of common standards and clear regulations. Blockchain adoption requires a commitment of resources, but the return on blockchain investment is uncertain, depending on a firm's market position and specific use cases (Carson et al. 2018). Therefore, it is important for managers to assess costs and benefits and the potential of blockchain for their businesses carefully when deciding whether to implement blockchain. Part of the appeal of adopting blockchain technology is to improve efficiency by streamlining the processes of transaction activities, operations, financing, auditing, reporting, etc.[1] However, the impact of blockchain adoption on efficiency has yet to be explored empirically in a new stream of literature on blockchain. Our study thus intends to shed light on this issue by investigating whether and how blockchain adoption affects firms' investment efficiency.

Blockchain is considered one of the most valuable FinTech innovations (Chen et al. 2019). A survey by the World Economic Forum in 2015 indicates that 10 percent of global GDP will be stored on blockchain by 2027.[2] Blockchain is a form of distributed ledger technology that records transactions using a secure system with continuously growing blocks, which verifies data immediately. It presents an alternative to traditional double-entry bookkeeping. Blockchain

[1] See, Gaur and Gaiha (2020), for an example of applications of blockchain in supply chain management.
[2] A full report of the survey is available at https://www.weforum.org/reports/deep-shift-technology-tipping-points-and-societal-impact

technology can afford more accurate record-keeping, and notably, more transparent, real-time accounting and financial reporting (Dai and Vasarhelyi 2017, FEI 2017, Yermack 2017).[3]

Blockchain adoption can lead firms to achieve greater investment efficiency, as reflected in higher investment-Q sensitivity, for the following reasons. First, real-time accounting afforded by blockchain leaves less opportunities for firms to manage earnings, which could improve the accuracy of financial statements that firms provide to the public (Yermack 2017). The stock price incorporates investors' firm-specific knowledge through their trades. If investors have more accurate public and private information, the informativeness of the price would be higher. Managers can thus learn more information from prices when making investment decisions, thereby improving their investment efficiency. Second, blockchain records and verifies all transactions immediately and permanently with a timestamp that prevents alterations, which enhances data integrity, accuracy, and reliability. It also allows users to view, aggregate, and analyze a firm's raw transaction data in any form at any time. With more efficient information aggregation as well as improved accuracy, transparency, and timeliness of data, managers would manage resources better and improve their decision making. Together, considering these features of blockchain technology, we expect firms' investment efficiency to increase as a result of blockchain adoption.

Using a difference-in-differences approach with a sample of U.S. listed firms that indicate adoption of blockchain technology in 8-K filings during 2014 to 2019 versus firms that do not adopt blockchain, we find that blockchain adopters have higher investment-Q sensitivity after implementing blockchain than non-adopters. This suggests that firms experience improvements in investment efficiency after adopting blockchain technology in their business and operations. Our results are robust to entropy-balanced and propensity-score matched samples. We further show

[3] Note that blockchain's impacts will depend on the type of blockchain used, i.e., whether it is public or private, permissionless or permissioned.

that this increased investment sensitivity to stock price appears only in the year of and the year after blockchain adoption but not in the year before adoption, indicating that the effect on investment efficiency continues in a later year. In addition, we find that higher investment-to-price sensitivity after blockchain adoption is concentrated in firms with weak information environments. This suggests that blockchain adoption is beneficial to firms with weak information environments, as managers would be able to learn additional information from stock prices when making investment decisions and hence improve their investment efficiency.

In our further analyses, we investigate in which situations blockchain adoption can facilitate the most managers' investment decisions and thereby enhance their investment efficiency. We document that only firms with greater engagement in blockchain technology (e.g., making a partnership or joint venture with established blockchain firms) or in a more advanced stage (i.e., beyond the R&D phase) exhibit higher investment efficiency after blockchain adoption. Lastly, to mitigate endogeneity concerns, we run a Heckman two-stage model and obtain similar findings. We also validate our results by performing a placebo test using a pseudo year of blockchain adoption. Our findings are robust to several sensitivity tests, including alternative variable measurements and controlling for additional variables.

Our study contributes to the literature in the following ways. We contribute to the emerging literature on blockchain (e.g., Biais et al. 2019, Cao et al. 2019, Cheng et al. 2019, Cong and He 2019, Chod et al. 2020) by providing some of the first empirical evidence on the real effects of blockchain adoption. Determining an appropriate level of spending on information technology (IT) could be challenging for managers given the uncertainty of return on IT spending and the high cost of IT investment (Ross and Weill 2002). Firms face decisions on whether to adopt blockchain and how to optimize the level of investment in blockchain technology if they choose to adopt. Our study is the first to provide systematic empirical evidence on whether and how the adoption of blockchain, an innovative information technology developed in recent years, affects managers' investment decisions and their efficiency. Our findings show that firms with greater engagement in blockchain technology exhibit higher investment sensitivity to stock price after implementing blockchain, suggesting that these firms' investment efficiency increases as a result of blockchain adoption. This evidence lends support to the argument that blockchain can enhance efficiency (e.g., Gaur and Gaiha 2020).

Furthermore, our study sheds light on whether and how blockchain adoption can add value to businesses by investigating the effect on investment efficiency. Autore et al. (2020) document a positive stock price reaction to the news related to firms' investments in blockchain technology, suggesting that investors perceive such news favorably partly because of the potential value creation from blockchain investments. Similarly, Cheng et al. (2019) and Cahill et al. (2020) find that investors' initial reactions are positive to speculative blockchain-related announcements and 8-K disclosures and that the positive stock price reaction is correlated with the performance of Bitcoin. We add to this line of research by providing further evidence on the real effect of blockchain adoption and showing in which situations firms benefit the most from implementing blockchain for their decision making. The impact of blockchain adoption on investment efficiency depends on firms' information environments and the level of engagement or stage of development in blockchain technology. Blockchain adoption appears to be most beneficial to firms with weak information environments or firms that engage greatly or are in an advanced stage of development in blockchain technology.

Our study also complements the existing research that examines the economics of blockchain adoption by documenting how the implementation of blockchain can facilitate managers' decision making through improving the accuracy, transparency, and timeliness of information. In recent theoretical work, Iyengar et al. (2021) demonstrate that even though blockchain adoption can increase total welfare, it fails to arise in equilibrium due to a misalignment between consumers that gain from the adoption and manufacturers that bear the cost of adoption. Our findings suggest that although blockchain adoption could be costly and might not be beneficial to all businesses, certain firms, in particular firms operating in poor information environments, should consider the potential of blockchain for their businesses with regard to improvements in information quality for managers' resource management and decision making. The positive effect of blockchain adoption on investment efficiency that we document in this study could be an incentive for some firms to adopt blockchain.

Lastly, our paper adds to existing research that examines the sensitivity of corporate decisions to stock prices (Chen et al. 2007, Foucault and Frésard 2012, Edmans et al. 2017, among others) by documenting how a firm's investment-to-price sensitivity changes as a result of blockchain adoption. According to the prior literature (see Bond et al. 2012 for a review of this literature), the stock price may provide managers with information that they do not have because it aggregates information from various market participants, which in turn can guide managers in making corporate (e.g., investment) decisions. Kim and Shi (2012) use voluntary IFRS adoption as a setting and find that stock prices are more likely to reflect firm-specific information following an increase in firm transparency. Consistently, our findings suggest that enhanced firm transparency through blockchain adoption could increase price informativeness, which in turn affects firms' investment sensitivity to stock price.

The paper proceeds as follows. Section 2 reviews the related literature and develops the hypothesis. Section 3 describes research design, including the data and sample as well as the main regression model. Section 4 presents empirical results and discusses additional analyses and robustness checks. Section 5 concludes the paper.

2. Related Literature and Hypothesis Development

Blockchain is an innovative cryptography and information technology, considered one of the most valuable FinTech innovations (Chen et al. 2019). According to a Gartner survey in 2019, blockchain technology is expected to create more than 176 billion dollars' worth of business value by 2025 and $3.1 trillion by 2030.[4] Since its introduction by Nakamoto (2008), blockchain has expanded its technical foundation to support various industries and fields because it offers reduced trading costs, increased speed, and improved assurance, trust, and efficiency (Fanning and Centers 2016, Dai and Vasarhelyi 2017, Gomber et al. 2018, Gaur and Gaiha 2020). For example, IBM has established the IBM Food Trust and entered into a partnership with Walmart to use blockchain for tracing fresh produce and other food products. IBM has also established a joint venture with Maersk Line to build a blockchain trade platform.

Blockchain presents an alternative of distributed ledgers to traditional financial ledgers, which could affect financial reporting by replacing double-entry bookkeeping (Yermack 2017). It allows entities to record transactions on a decentralized network, where all information is cryptographically secure and verified permanently, which prevents data from being altered ex post and hence protects data integrity. Industry interest in blockchain applications began to explode in late 2015 (e.g., Stratopoulos et al. 2021). Since then, blockchain has captured the attention of the business world, including big accounting firms. In fact, Big Four audit firms have started building capacity to provide blockchain-related services (e.g., Coleman 2018, Stevens 2020, Wolfson

[4] A summary of the survey by Gartner is available at https://media.consensys.net/gartner-blockchain-will-deliver-3-1-trillion-dollars-in-value-by-2030-d32b79c4c560

2020).[5] Blockchain technology offers the potential to improve interaction and collaboration between various parties as well as transparency of processes and data, which could ultimately revolutionize many business products and processes.

Advantages of blockchain technology include (1) strong security, (2) disintermediation, (3) record integrity, and (4) automation, which can help reduce the need for costly intermediaries, likelihood of fraud, and process inefficiency (Chod et al. 2020). Dai and Vasarhelyi (2017) discuss how blockchain can potentially afford a real-time, verifiable, and transparent accounting ecosystem. In an interview with *Financial Executives International Daily*, Jake Benson, CEO of Libra, a New York startup building front-end reporting software based on blockchain, said that "[Blockchain] is going to be more inherently trustworthy, it is going to be more accurate. Maybe you will get those [numbers] at a more frequent pace. …… You will have increased transparency, increased frequency of date of delivery. I think they will just generally be more real-time."[6] Similarly, according to Campbell Harvey, Professor of Finance at Duke University's Fuqua School of Business, the primary benefit of blockchain to financial statements can be summed up in one term—real time (FEI 2017).

In a global blockchain survey by Deloitte (2021), most respondents believe that they can gain a competitive advantage and develop new revenue streams through blockchain applications. Despite the benefits that blockchain potentially offers, some firms are still hesitant to adopt blockchain due to certain concerns. Specifically, in the survey, respondents point out several areas where regulations need to be modified to facilitate blockchain adoption, including data security

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[5] Cao et al. (2020) propose and design a blockchain-based platform called Future Auditing Blockchain to streamline and automate the reporting and auditing process. Appelbaum and Nehmer (2020) discuss how auditors can perform their audits on cloud-based blockchain accounting systems.

[6] Interview video and transcript are available at https://daily.financialexecutives.org/financial-reportings-logical-next-step-blockchain/

and privacy, industry-specific regulatory issues (e.g., FDA), geography-specific regulations (e.g., EU Data Protection Directive), internal controls and financial reporting, etc. Information distribution may trigger privacy and security concerns if anonymous users can access sensitive information (Cong and He 2019). After all, as Kumar et al. (2020) state, blockchain technology is not a silver bullet for all businesses; instead, it should be applied selectively on a case-by-case basis.

Simply adopting blockchain does not guarantee a sustained competitive advantage. Potential returns from blockchain adoption have remained the primary focus of attention in business and industry. Entities that consider implementing blockchain would be interested in knowing the economic consequences and real effects of blockchain adoption. A few recent studies (e.g., Cheng et al. 2019, Autore et al. 2020, Cahill et al. 2020) examine stock market reactions to firms' blockchain-related announcements and disclosures. In general, they document an initial positive stock price reaction to blockchain news, suggesting that investors appear to perceive firms' involvement in blockchain technology favorably.[7] However, blockchain adoption could be a lengthy and costly process. Guo et al. (2021) find that early blockchain adopters experience lower returns on assets and operating cash flow. It is unclear whether the implementation of blockchain adds sufficient value to businesses, considering the cost. Hence, it is worth examining the effects and consequences of blockchain adoption, which remain underexplored empirically in the growing literature on blockchain. It is of great interest for business and industry to assess the benefits and costs of blockchain adoption and understand its potential effects. Thus, our study attempts to shed light on one of the benefits and real effects (i.e., improved efficiency) by examining whether and

[7] Consistently, Yen and Wang (2021) document that blockchain-related disclosures in firms' annual reports are value relevant.

how blockchain adoption relates to firms' investment efficiency (as captured by investment-Q sensitivity).

Real-time accounting and reporting afforded by blockchain would likely reduce managers' incentives to distort investment policies to manipulate reported earnings (FEI 2017, Yermack 2017) because it can record and validate all transactions as they occur. Because of real-time accounting and reporting, firms' incentives to manage short-term (e.g., quarterly) earnings would become less, which would also reduce incentives to engage in accounting gimmicks and value-destroying investment activities. A survey by Graham et al. (2006) indicates that managers are willing to sacrifice long-term value (e.g., by making suboptimal investment decisions) to meet short-term earnings targets and that managers consider quarterly earnings for the same quarter last year and analyst consensus estimate to be the most important earnings benchmarks. Consistently, Kraft et al. (2018) document a negative relation between financial reporting frequency and the level of investment in U.S. firms, suggesting that increased financial reporting frequency could induce managerial myopia and short-termism.[8] With real-time accounting and reporting, firms would be more incentivized to manage their resources and expertise better to increase firm value than to manage earnings to meet investors' and analysts' expectations, reducing the likelihood of value-decreasing actions and investments.

Blockchain distributed ledger technology can enhance data integrity, accuracy, and reliability. All transactions are recorded and verified immediately on a decentralized network, and data stored in a block cannot be modified without consensus from the network. Gaur and Gaiha (2020) argue that blockchain can improve trust, speed, and efficiency "by creating a complete, transparent, tamperproof history of the information flows, inventory flows, and financial flows in

[8] In contrast, using a sample of U.K. firms, Nallareddy et al. (2017) find no impact of mandatory quarterly reporting on firms' investment decisions.

transactions." In other words, distributed ledgers based on blockchain can enhance accuracy, transparency, timeliness, and efficiency of transaction processes and related information. The technology also allows users to instantly view and aggregate verified transaction data at various levels for any kind of analysis according to their needs. With timely, accurate, and reliable information, managers are likely to manage resources better and improve their decision making.

Prior literature (e.g., Dow and Gorton 1997, Chen et al. 2007, Foucault and Frésard 2012, Edmans et al. 2017) suggests that investors can convey valuable information through stock prices, which may guide managers in making corporate decisions and improve their efficiency. Investors trade on a myriad of signals about a firm. The information that investors have is impounded and aggregated into the stock price. Managers can use this information from the stock market together with other information in their decision making. The informativeness of the price might increase when investors receive more accurate information that firms provide to the public, and as mentioned earlier, firms' information quality likely improves due to blockchain adoption. When price informativeness is higher, managers are likely to glean more decision-relevant information from prices, resulting in higher investment-to-price sensitivity (or investment efficiency).

Based on the above discussions, we expect that blockchain adoption can help firms achieve greater investment efficiency (as captured by higher investment-to-price sensitivity), which leads to the following hypothesis (stated in the alternative form).

Hypothesis. *Firms exhibit higher investment efficiency after they implement blockchain technology in their business and operations, all else being equal.*

The impact of blockchain adoption on investment efficiency likely varies with firms' information environments and level of engagement (or stage of development) in blockchain technology. Since blockchain can provide managers with more accurate, reliable, and timely information, the implementation of such technology would likely help improve firms' information environments and facilitate managers' decision making. It would be especially helpful for firms with poor information environments. We thus expect the impact of blockchain adoption on investment efficiency to exhibit mainly in firms with poor information environments (e.g., firms with internal control weaknesses or low analyst coverage). In addition, among firms that implement blockchain in their business and operations, the level of engagement or stage of development in blockchain technology may differ. Some may have a higher level of engagement (e.g., making a partnership or joint venture with established blockchain firms) or be in a more advanced stage of development (i.e., beyond the R&D phase) than others. Therefore, the impact of blockchain adoption on investment efficiency is likely to vary among blockchain adopters. We expect that only firms with a high level of engagement or in an advanced stage of development in blockchain technology would experience improved investment efficiency after adoption. We test these predictions in our additional analyses.

3. Research Design

3.1. Data Sources

Similar to a recent blockchain study by Cheng et al. (2019), we use keywords such as "blockchain," "bitcoin," or "cryptocurrency" in a full-text search of 8-K filings on the SEC Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system to gather our blockchain data. [9] These search terms provide an initial sample of 1,409 blockchain-related

[9] We also conduct a bag-of-words approach to validate our sample by re-checking blockchain keywords (*blockchain*), bitcoin keywords (*bitcoins*), and cryptocurrency keywords (*cryptocurrencies*; *digital currency/currencies*) in 8-K filings.

announcements/disclosures during January 1, 2013 to December 31, 2019.[10] After merging with firms' GVKEYs in Compustat, 416 observations are dropped because of a lack of coverage by Compustat.

Next, to identify a firm's commitment to blockchain adoption, three independent coders, one author, and two research assistants conduct an independent review of each disclosure.[11] We remove 608 duplicate or irrelevant announcements when 8-K reports contain (1) generic news without indicating firm-specific blockchain adoption; (2) overall interests or future plans towards blockchain-related applications or features; (3) a firm's name or URL with the term "blockchain" only; (4) the benefits of integrating with other technologies[12]; and (5) other collaborative events with non-publicly traded firms, including universities, government-related agencies, and foreign private firms. We also eliminate 167 announcements unrelated to current blockchain applications, mining, infrastructure, or products/services, as the commitment to blockchain adoption is unclear for these cases. Finally, we further delete 153 duplicate blockchain announcements and keep only the initial announcements. After this filtering process, we retain 65 announcements between May 2014 and December 2019, corresponding to 349 firm-year observations related to blockchain adoption.[13]

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[10] We select the period of 2013-2019 because the first blockchain adoption occurs in 2013 (as in Cheng et al. 2019). We verify the first blockchain announcement released through 8-Ks in 2013. We end our sample period in 2019 because this is the last year for which we had full-year data when we started this study.

[11] The interrater reliability among these coders is 93%, which is well above the recommended threshold of 70% (Cohen 1960). Follow-up discussions for any disagreements between coders are reconciled, which ensures greater fidelity of the coding scheme.

[12] For example, artificial intelligence (AI), which can simulate human judgment by classifying, recording, analyzing, and making decisions related to real-time data, and the internet of things (IoT), which can create devices that can take physical actions based upon information contained in blockchain.

[13] We define blockchain adopters as firms that at any point in time, during the sample period, implement blockchain technology.

To construct other regression variables used in our analyses, we obtain financial data from Compustat, analyst data from Thomson Reuters' I/B/E/S, internal control data from Audit Analytics, and institutional ownership data from Thomson Reuters' 13F Holdings.

3.2. Sample Selection

We begin our sample selection with all firms available on Compustat over the years 2014-2019, including the 349 observations of blockchain adopters. Panel A of Table 1 shows our sample selection procedure. First, we restrict the sample to firms listed on a U.S. stock exchange to ensure comparability across firms. Second, we delete firms with missing Standard Industrial Classification (SIC) codes or firms operating in the utility (SIC codes 4900-4999) and financial services (SIC codes 6000-6999) sectors (as in Chen et al. (2007)) because of the different nature of investments for these firms. Lastly, we remove firm-year observations with missing capital expenditure, total assets, or other data to construct main regression variables. We winsorize all continuous variables at the 1st and 99th percentiles. The final sample consists of 31,490 firm-year observations, with 202 observations (46 unique firms) pertaining to blockchain adopters and 31,288 (7,095 unique firms) pertaining to non-adopters.[14] We provide a few examples of blockchain adoption announcements in 8-K filings in Appendix 1.

Panels B and C of Table 1 present the sample distribution by year and industry, where industry is defined using the Fama and French (1997) 12 industry classification. Panel B shows that the distribution of blockchain adopters and non-adopters is stable over time, and Panel C indicates that half of the firms applying blockchain technology to their business and processes

[14] Cheng et al. (2019) use a sample of 82 unique blockchain firms (56 speculative and 26 existing firms) during January 2013 to June 2018, including firms in the financial services and utility sectors that we exclude from our sample. Excluding financial and utility firms would reduce Cheng et al.'s (2019) sample to 52 unique firms (34 speculative and 18 existing firms). Our definition of blockchain adoption, by construction, excludes speculative firms, which makes the number of observations in our sample differ from that in Cheng et al.'s (2019) sample.

operate in the "business equipment" industry. Non-adopters are clustered mainly in the industries classified as "other," "business equipment," and "healthcare, medical equipment, and drugs."

[Insert Table 1 Here]

3.3. Regression Model

We develop our empirical framework based on Chen et al. (2007) and Edmans et al. (2017), among others, to measure investment efficiency by investment sensitivity to stock price. To test our hypothesis, we estimate the impact of blockchain adoption on investment efficiency using the following regression model:

$$\begin{aligned} Invest_{it+1} = {} & b_0 + b_1\, Q_{it} + b_2\, Blockchain_{it} \times Q_{it} + b_3\, Blockchain_{it} + Firm\ Fixed\ Effects \\ & + Year\ Fixed\ Effects + e_{it+1} \qquad (1) \end{aligned}$$

where subscripts i and t indicate firm and year, respectively. The dependent variable $Invest_{it+1}$ is total investment at year t+1, measured as the sum of capital expenditure and R&D expense scaled by lagged total assets. The variable Q_{it} is an adjusted measure of stock price, calculated as the sum of the market value of equity and total assets less the book value of equity scaled by total assets. The variable $Blockchain_{it}$ is an indicator equal to one after a firm adopts blockchain technology, and zero otherwise. We include firm and year fixed effects to control for unobserved heterogeneity across firms and years and adjust standard errors for heteroskedasticity and firm-level clustering.

Equation (1) is equivalent to a standard difference-in-differences specification with firm and year fixed effects. Similar to Edmans et al. (2017), our approach compares investment-Q sensitivity before versus after blockchain adoption between treated (i.e., adopters) and control firms (i.e., non-adopters). The coefficient on the interaction term $Blockchain_{it} \times Q_{it}$ (i.e., b_2) therefore captures the change in investment-Q sensitivity for adopters as a result of blockchain adoption compared to non-adopters. We predict b_2 to be positive if the implementation of blockchain technology is associated with an improvement in firms' investment efficiency.

A major concern with our empirical approach is the endogeneity of blockchain adoption. In fact, a firm's decision to implement blockchain technology may reflect underlying firm characteristics, which could also impact a firm's investment propensity. Failure to adequately control for these characteristics would produce an omitted variable bias into our analysis, resulting in incorrect inferences of the relation between *Invest* and *Blockchain* × *Q* (Shipman et al. 2017).[15] We employ two different techniques designed to achieve covariate balance. First, we use entropy balancing to obtain a sample of non-adopters that exhibits covariate balance with the sample of blockchain adopters (Heinmueller 2012). Entropy balancing assigns weights to non-adopters so that differences in the mean, variance, and skewedness of the distribution of the selected variables are minimized across blockchain adopters and non-adopters.[16] Second, we match each blockchain adopter with the closest (the nearest neighbor) non-adopter using propensity score matching with common support and without replacement (Tucker 2010, Roberts and Whited 2013). The propensity score matched sample contains 404 observations, with 202 blockchain adopters and 202 non-blockchain adopters.[17] Further, in our additional analyses, we use a parallel trend analysis, a Heckman two-stage test, and a placebo test to validate our results.

4. Empirical Analyses

4.1. Descriptive Statistics

[15] If the omitted firm characteristics are time-invariant, the inclusion of firm fixed effects in Equation (1) would help mitigate the endogeneity concern related to a firm's choice to adopt blockchain.
[16] Because of its weighting mechanism, entropy balancing allows us to retain all 31,490 firm-year observations in the entropy-balanced sample.
[17] For both entropy balanced and propensity score matched samples, we predict the likelihood of blockchain adoption using the following model: $\Pr(\textit{Blockchain Adopter}_{it} = 1) = b_0 + b_1 Q_{it-1} + b_2 \textit{Size}_{it-1} + b_3 \textit{High Tech}_{it} + \textit{Industry Fixed Effects} + \textit{Year Fixed Effects}$, where all variables are defined in Appendix 2.

Panel A of Table 2 shows descriptive statistics on variables used in Equation (1). On average, blockchain adopters have higher investment levels in t+1 ($Invest_{it+1}$) than non-adopters (0.252 versus 0.170). The difference in means is positive and statistically significant at the 1% level (t-stat. = 3.025; p-value < 0.001). Blockchain adopters also have a higher Q_{it} relative to non-adopters (41.031 versus 9.466), with the difference in means being positive and significant at the 1% level (t-stat. = 10.048; p-value < 0.001). Panel B shows that the correlation between $Invest_{it+1}$ and Q_{it} is positive and significant, consistent with prior studies (e.g., Baker et al. 2003, Chen et al 2007), whereas the correlation between $Blockchain_{it}$ and Q_{it} is positive but statistically insignificant. $Blockchain_{it}$ is positively correlated with $Invest_{it+1}$ using the Pearson estimation, but the correlation coefficient becomes insignificantly different from zero when the Spearman estimation is employed.

[Insert Table 2 Here]

4.2. Main Results

Table 3 presents the results from estimating Equation (1). Column (1) shows the results from the unmatched sample of blockchain adopters and non-adopters using an ordinary least squares (OLS) regression. Consistent with prior research, we find that firms experiencing an increase in stock price in year t (Q_{it}) have greater investments in year t+1 ($Invest_{it+1}$). The coefficient estimate on Q_{it} is positive and statistically significant at the 1% level (coef. = 0.003; t-stat. = 9.371).

Consistent with our hypothesis, we find that the sensitivity of investment to price is more pronounced for firms implementing blockchain technology ($Blockchain_{it}$) relative to firms that do not apply this technology in the post-adoption period, as evidenced by the interaction term $Blockchain_{it} \times Q_{it}$. The coefficient estimate on $Blockchain_{it} \times Q_{it}$ is positive and significant at the

5% level (coef. = 0.029; t-stat. = 2.515). In terms of economic significance, this result suggests that the investment sensitivity to stock price is 2.9 percentage points higher for firms adopting blockchain technology relative to non-adopters.

Column (2) shows the results from Equation (1) using an entropy-balanced sample of blockchain adopters and non-adopters. We find results similar to those shown in Column (1). The coefficient estimate on Q_{it} is positive and significant at the 5% level (coef. = 0.003; t-stat. = 2.437). Moreover, consistent with our prediction of higher investment efficiency for firms implementing blockchain technology, we find a positive and statistically significant coefficient on $Blockchain_{it} \times Q_{it}$ (coef. = 0.029; t-stat. = 2.231).

Column (3) shows the regression results after matching each blockchain adopter with the closest (the nearest neighbor) non-adopter using propensity score matching with common support and without replacement.[18] In line with the analysis above, the coefficient estimate on Q_{it} is positive and statistically significant at the 5% level (coef. = 0.004; t-stat. = 2.057), and the coefficient on $Blockchain_{it} \times Q_{it}$ is positive and significant at the 1% level (coef. = 0.030; t-stat. = 2.800).

Overall, the results in Table 3 are consistent with our hypothesis that firms implementing blockchain technology exhibit higher sensitivity of investment to stock price, that is, higher investment efficiency, relative to firms that do not implement this technology.

[Insert Table 3 Here]

4.3. Additional Analyses and Robustness Checks

4.3.1. Parallel Trend Analysis

[18] Untabulated results show that the covariate balance assumption for the propensity-score matched sample is satisfied.

If blockchain adoption indeed helps facilitate managers' investment decisions, this effect should appear only after the implementation of blockchain and not before. To test this prediction, we conduct a parallel trend analysis in the two-year window (from year -1 to year +1) surrounding a firm's blockchain adoption, following Bertrand and Mullainaithan (2003). We estimate the following regression model:

$$\begin{aligned} Invest_{it+1} = {} & b_0 + b_1 Q_{it} + b_2 \, Before\ Adoption_{it} \times Q_{it} + b_3 \, Before\ Adoption_{it} \\ & + b_4 \, Adoption\ Year_{it} \times Q_{it} + b_5 \, Adoption\ Year_{it} \\ & + b_6 \, After\ Adoption_{it} \times Q_{it} + b_7 \, After\ Adoption_{it} \\ & + Firm\ Fixed\ Effects + Year\ Fixed\ Effects + e_{it+1} \end{aligned} \tag{2}$$

where $Before\ Adoption_{it}$, $Adoption\ Year_{it}$, and $After\ Adoption_{it}$ indicate the year before, the year of, and the year after the blockchain implementation, respectively. All other variables are as previously defined.

Table 4 presents the regression results of our parallel trend analysis. Column (1) shows the results using the unmatched sample of blockchain adopters and non-adopters, while Columns (2) and (3) present the results using the entropy balanced sample and the propensity score matched sample, respectively. Consistent with our prediction, we find that the effect of blockchain adoption on the investment-Q sensitivity is statistically insignificant in the year before the implementation of blockchain ($Before\ Adoption_{it}$) but is positive and significant in both the year of adoption ($Adoption\ Year_{it}$) and the following year ($After\ Adoption_{it}$).

Moreover, we find that the magnitude of the effect of blockchain adoption on investment-Q sensitivity increases after the implementation year. This is evidenced by the coefficient on $After\ Adoption_{it} \times Q_{it}$ ranging from 0.139 (t-stat. = 19.860) in Column (1) to 0.156 (t-stat. = 4.976) in

Column (3), compared to the coefficient on *Adoption* $Year_{it} \times Q_{it}$ ranging from 0.029 (t-stat. = 2.255) in Column (2) to 0.030 in Columns (1) and (3) (t-stat. = 2.686 and 2.676, respectively).

Overall, these results suggest that the impact of blockchain adoption on firms' investment efficiency materializes only after the implementation year and becomes more pronounced in the following year, which supports a causal interpretation of the relation between *Invest* and *Blockchain* × *Q*.

[Insert Table 4 Here]

4.3.2. Cross-Sectional Analysis

If it is true that the adoption of blockchain facilitates managers' decision making by improving firms' information environments, the effect of blockchain adoption on investment efficiency would be more evident in firms operating in weaker information environments. To test this prediction, we use several proxies for firms' information environments. We consider firms operating in weak information environments if they have high volatility of return on assets (*ROA* $Volatility_{it}$) or business dispersion (*Business* $Dispersion_{it}$), if they present weaknesses in their internal control systems (*Internal Control* $Weakness_{it}$), or if they have low institutional ownership (*Institutional* $Ownership_{it}$) or analyst following (*Analyst* $Following_{it}$).

Table 5 presents the regression results of our cross-sectional analysis based on firms' information environments. Consistent with our prediction, we find that the positive effect of blockchain adoption on investment efficiency exists only for firms with weak information environments. The coefficient estimates on $Blockchain_{it} \times Q_{it}$ are positive and statistically significant for firms with high ROA volatility (coef. = 0.027; t-stat. = 2.360), internal control weaknesses (coef. = 0.025; t-stat. = 2.056), high business dispersion (coef. = 0.029; t-stat. = 2.414), low institutional ownership (coef. = 0.012; t-stat. = 3.917), and low analyst following (coef. = 0.027; t-stat. = 2.339).[19]

Overall, these results suggest that the effect of blockchain adoption on investment efficiency is concentrated in firms with weaker information environments, consistent with our argument that the implementation of blockchain technology improves firms' information environments and facilitates managers' investment decisions, thereby helping them achieve greater investment efficiency.

[Insert Table 5 Here]

4.3.3. Level of Engagement in Blockchain Technology

It is likely that blockchain adopters engage in blockchain technology at different degrees or are in different stages of development. The effect of blockchain adoption on investment efficiency might vary accordingly. In this section, we identify three levels of engagement in blockchain technology. Level 1 includes firms with blockchain-related R&D projects. We characterize Level 1 as low engagement because firms at the R&D stage are unlikely to fully utilize the technology. Level 2 consists of firms that have made blockchain-related investments, including subsidiary investments. We characterize Level 2 as medium engagement in blockchain technology because it is unclear whether firms can completely benefit from blockchain at the investment stage. Finally, Level 3 comprises firms that derive their blockchain implementation from strategic alliances, partnerships, and joint ventures with established blockchain firms. We characterize Level 3 as high engagement because the benefits stemming from blockchain are likely larger when an adopter joins a network of established blockchain firms.

[19] We find similar results (untabulated) using entropy balanced and propensity score matched samples.

Table 6 presents regression results of the analysis based on level of engagement analysis. Consistent with our expectation, we find that the effect of blockchain adoption on investment-Q sensitivity is statistically insignificant for firms in the stage of developing blockchain R&D projects (Level 1) but is positive and significant when firms make blockchain-related investments (Level 2) and strategic alliances, partnerships, and joint ventures with established blockchain firms (Level 3). Specifically, the coefficient estimate on $\textit{Blockchain Level}_{it} \times Q_{it}$ is 0.009 (t-stat. = 1.674) for Level 2 in Column (2), and the coefficient is 0.031 (t-stat. = 2.343) for Level 3 in Column (3), suggesting that the magnitude of the effect of blockchain adoption on investment-Q sensitivity increases with the level of blockchain engagement or the stage of development.[20]

[Insert Table 6 Here]

4.3.4. Heckman Two-Stage and Placebo Tests

Table 7 presents the regression results of our validation tests. Panel A reports the results of the Heckman (1979) two-stage test. In the first-stage regression in Column (1), we find that $\textit{Blockchain}_{it}$ is positively and significantly associated with accounting losses (coef. = 0.309; t-stat. = 2.471), business combinations (coef. = 0.308; t-stat. = 2.573), advertising expenses (coef. = 2.137; t-stat. = 2.686), and analyst following (coef. = 0.004; t-stat. = 2.823), whereas it is negatively associated with firm size (coef. = -0.101; t-stat. = -4.577).[21] We include the inverse Mills ratio (*Inverse Mills Ratio*) obtained from the first-stage regression in the second-stage regression. In the second-stage regression in Column (2), we find that, despite a positive and significant coefficient estimate on the inverse Mills ratio, coefficients on Q_{it} and $\textit{Blockchain}_{it} \times Q_{it}$

[20] We repeat the analysis using entropy-balanced and propensity score matched samples and find results similar to those in Table 6.

[21] In the first-stage regression, we use the following model to predict blockchain adoption: $\Pr(\textit{Blockchain}_{it} = 1) = b_0 + b_1\textit{Size}_{it} + b_2\textit{Leverage}_{it} + b_3\textit{Capital Intensity}_{it} + b_4\textit{Loss}_{it} + b_5\textit{Payout}_{it} + b_6\textit{Foreign}_{it} + b_7\textit{M\&A}_{it} + b_8\textit{R\&D}_{it} + b_9\textit{Advertising}_{it} + b_{10}\textit{Analyst Following}_{it} + \textit{Year Fixed Effects} + e_{it}$.

present a similar statistical and economic significance to those reported in Table 3 using the unmatched sample of blockchain adopters and non-adopters.

Panel B shows the results of a placebo test, where we replace $Blockchain_{it}$ with *Pseudo* $Blockchain_{it}$, an indicator variable equal to one two years before a firm's actual blockchain adoption, and zero otherwise. The coefficient estimate on *Pseudo* $Blockchain_{it} \times Q_{it}$ is insignificantly different from zero, alleviating the concern that our results might be driven by endogeneity.

[Insert Table 7 Here]

4.3.5. Robustness Checks

Prior research has shown that firm size and cash flow are important determinants of firms' investments (Fazzari et al. 1988, Baker et al. 2003, Chen et al. 2007, Foucault and Frésard 2012). To mitigate concerns that our results are affected by firm size and cash flow, we additionally control for these variables in Equation (1). We measure firm size as the natural logarithm of total assets in year t ($Size_{it}$). We compute cash flow as the sum of income before extraordinary items, depreciation and amortization and R&D expense scaled by total assets in year t+1 ($Cash\ flow_{it+1}$).[22] Untabulated regression results show that both the statistical and the economic significance of our main results in Table 3 are unchanged after including control variables for firm size and cash flow. The coefficient on $Blockchain_{it} \times Q_{it}$ is positive and statistically significant at the 5% level (coef. = 0.027; t-stat. = 2.310). Moreover, the coefficients on Q_{it} and $Cash\ flow_{it+1}$ are positive and significant at the 1% level, and the coefficient on $Size_{it}$ is negative and significant at the 1% level, consistent with Foucault and Frésard (2012).

[22] We measure cash flow in year t+1 because prior research controls for the contemporaneous effect of cash flow on investment levels (e.g., Fazzari et al. 1988; Baker et al. 2003; Chen et al. 2007). We obtain similar results if we alternatively control for cash flow in year t.

Finally, we test whether our results are robust to two alternative definitions of total investment. We replace $Invest_{it+1}$ in Equation (1) with two commonly used measures of investments, that is, capital expenditure scaled by lagged total assets (Alt_Invest_{it+1}) and the percentage change in total assets (Ch_Asset_{it+1}) (Chen et al. 2007). Our results remain using these two alternative measures for total investment.

5. Conclusion

This paper investigates the relation between blockchain adoption and investment efficiency, particularly whether and how a firm's investment sensitivity to stock price changes after implementing blockchain technology. Many companies have started applying blockchain in their business and operations, seeking to improve efficiency and to develop new business models and revenue sources. Our study documents that relative to non-adopters, adopters exhibit higher investment-Q sensitivity after they implement blockchain, suggesting a positive effect of blockchain adoption on firms' investment efficiency. This effect is concentrated in firms with poor information environments and those with a high level of engagement or in an advanced stage of development in blockchain technology. Further, we find that the effect on investment efficiency continues another year after blockchain adoption. Our results are robust to a battery of tests that account for endogeneity concerns.

Our findings provide some of the first empirical evidence on the real effects of blockchain adoption. As companies are interested in blockchain applications that can create value and improve their efficiency, whether and how blockchain adoption affects firms' investment efficiency is hence relevant for businesses to know. By documenting whether and how a firm's blockchain adoption affects its investment efficiency, our study provides implications for interested parties such as business communities in assessing the potential benefits and effects of implementing blockchain.

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Appendix 1
Examples of Blockchain Adoption Announcements in 8-K Filings

International Business Machines Corporation
Exhibit 99.1 of the 8-K report filed on April 19, 2017:
https://www.sec.gov/Archives/edgar/data/51143/000110465917024360/a17-11403_2ex99d1.htm
In blockchain, we had over 40 new engagements in the quarter, and are working on over 400 more. And, as we've discussed in the past, the opportunities span multiple industries. This quarter we announced we're working with Maersk to use blockchain to transform the global shipping supply chain, partnered with Northern Trust to launch blockchain for the private equity market, and are collaborating with the FDA to explore how a blockchain can benefit public health.

Shineco, Inc.
Exhibit 99.1 of the 8-K report filed on July 9, 2018:
https://www.sec.gov/Archives/edgar/data/1300734/000121390018008923/f8k070918ex99-1_shinecoinc.htm
Shineco, Inc. Announces Investment in the Integrated Financial Services Platform and Formally Enters into the Blockchain Industry.

Mr. Yuying Zhang, the Chairman and CEO of Shineco, stated that, "The Company has focused on entering the blockchain field since the beginning of this year. This strategic investment in Hash Bank has launched a new journey for the Company's application of blockchain technology ... integrating resources in its apocynum growing and processing regions and increasing the intensity of R&D and innovation, gradually introducing blockchain technology into the apocynum industry chain. We expect that Shineco would benefit from reduced costs, improved efficiency, a more optimized collaborative environment, and the creation of a new industry ecosystem."

Mr. Zhaicai Su, the co-founder of Hash Bank commented, "Hash Bank is an integrated financial services platform offers depositary services to multiple and various cryptocurrency tokens, tokenized bonds, fund wealth management, investment banking services, and other financial services ... Through the POS (Proof of Stake) consensus mechanism, ... provide financial services for digital assets to promote the establishment and evolution of the global digital financial ecosystem, making the global financial system balanced and safe through blockchain technology. Meanwhile, building a platform for the top global investors, provides Shineco with the perfect services of investment and financing, entrepreneurship and innovation, assisting Shineco with entering the express lane of the blockchain revolution."

Walmart Inc.
Exhibit 99.1 of the 8-K report filed on August 15, 2019:
https://www.sec.gov/Archives/edgar/data/104169/000010416919000058/earningsrelease-7312019.htm
Launched blockchain traceability platform for Walmart China ... Announced new collaboration with other major companies as part of the FDA's program to evaluate the use of blockchain to protect pharmaceutical product integrity.

Appendix 2
Variable Definitions

Variable	Description (Source: Compustat, unless otherwise specified)
Investment variable	
$Invest_{it+1}$	Sum of capital expenditure (capx) and R&D expense (xrd) scaled by lagged total assets (at). Missing R&D expense is replaced with zero
Blockchain variables	
$Blockchain_{it}$	Indicator variable equal to one after a firm adopts blockchain technology, and zero otherwise. We identify a firm's adoption of blockchain using a keyword search in 8-K filings and attached exhibits for disclosures indicating blockchain implementation, such as Bitcoin/cryptocurrency mining/infrastructure/application or blockchain-related products/services.
$Before\ Adoption_{it}$	Indicator variable equal to one in the year before blockchain adoption, and zero otherwise
$Adoption\ Year_{it}$	Indicator variable equal to one in the year of blockchain adoption, and zero otherwise
$After\ Adoption_{it}$	Indicator variable equal to one in the year after blockchain adoption, and zero otherwise
$Blockchain\ Level_{it}$	Indicator variable equal to one if a firm's 8-K filings and attached exhibits indicate one of the following levels of engagement in blockchain technology in addition to those identified in the *Blockchain* variable, and zero otherwise Level 1: Blockchain-related R&D project Level 2: Blockchain-related investment, including subsidiary investment Level 3: Blockchain-related strategic alliance/partnership/joint venture
$Pseudo\ Blockchain_{it}$	Indicator variable equal to one two years before a firm's actual blockchain adoption, and zero otherwise
Tobin's Q variable	
Q_{it}	Sum of market value of equity (csho × prcc_f) and total assets (at) less the book value of equity (ceq) scaled by total assets (at)
Other variables	
$Size_{it}$	Natural logarithm of total assets (at)
$High\ Tech_{it}$	Indicator equal to one if a firm is in the computer, electronics, pharmaceutical, or telecommunication industry, and zero otherwise
$Leverage_{it}$	Total liabilities (lt) scaled by total assets (at)
$Capital\ Intensity_{it}$	Total assets (at) scaled by sales (sale)
$Loss_{it}$	Indicator variable equal to one if net income before extraordinary items (ib) is negative, and zero otherwise
$Payout_{it}$	Indicator variable equal to one if a firm pays dividends (dv), and zero otherwise
$Foreign_{it}$	Indicator variable equal to one if a firm reports foreign income taxes (txfo), and zero otherwise

Other variables (cont'd)	
M&A$_{it}$	Indicator variable equal to one if a firm reports special items related to merger and acquisition (aqp), and zero otherwise
R&D$_{it}$	Research and development expense (xrd) scaled by total assets (at). Missing R&D expense is replaced with zero
Advertising$_{it}$	Advertising expense (xad) scaled by total assets (at). Missing advertising expense is replaced with zero
Analyst Following$_{it}$	Number of analysts following the firm in a given year. Missing analyst following is replaced with zero (Source: I/B/E/S)
Cross-sectional variables	
ROA Volatility$_{it}$	ROA volatility measured from *t*-4 to *t*, where ROA is income before extraordinary items (ib) scaled by lagged total assets (at)
Internal Control Weakness$_{it}$	Indicator variable equal to one if internal control presents material weaknesses, and zero otherwise (Source: Audit Analytics)
Business Dispersion$_{it}$	Sum of the squares of a firm's sales (sales) in each business segment scaled by total sales less one, multiplied by minus one
Institutional Ownership$_{it}$	Sum of the shares held by 13F institutional investors scaled by total shares outstanding. Missing institutional ownership is replaced with zero (Source: Thomson Reuters)

Table 1
Sample Selection and Distribution

This table shows sample selection (Panel A) and distribution by year (Panel B) and industry (Panel C) for a sample of U.S. listed, non-financial and non-utility firms over the years 2014-2019. Industries are defined using the Fama and French (1997) 12 industry classification. Appendix 2 provides variable definitions.

Panel A. Sample Selection

	N	Blockchain adopter
All Compustat firm-years from 2014 to 2019	79,356	349
(non-U.S. listed firms)	(6,647)	(7)
(missing SIC code)	(25)	(0)
(utility firms)	(1,541)	(0)
(financial firms)	(26,451)	(76)
(missing capital expenditure or total assets)	(1,409)	(7)
(missing data to construct main variables)	(11,793)	(57)
Final sample	31,490	202

Panel B. Distribution by Year

Year	Blockchain adopter	Non-blockchain adopter
2014	31	5,553
2015	31	5,485
2016	33	5,275
2017	36	5,080
2018	37	4,989
2019	34	4,906
Total	202	31,288

Panel C. Distribution by Industry

Industry	Blockchain adopter	Non-blockchain adopter
Consumer non-durable goods	6	1,471
Consumer durable goods	0	785
Manufacturing	11	2,937
Oil, gas, and coal extraction and products	6	2,581
Chemicals and allied products	6	794
Business equipment	101	5,690
Telephone and television transmission	0	982
Wholesale, retail, and some services	28	2,596
Healthcare, medical equipment, and drugs	2	5,413
Other	42	8,039
Total	202	31,288

Table 2
Descriptive Statistics and Correlations

This table shows descriptive statistics (Panel A) and Pearson/Spearman correlations (Panel B) using a sample of U.S. listed, non-financial and non-utility firms over the years 2014-2019. Panel A shows descriptive statistics on main variables for blockchain adopters versus non-adopters. Panel B shows Pearson and Spearman correlations below and above the diagonal, respectively. Appendix 2 provides variable definitions. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A. Descriptive Statistics

	N	Mean	SD	P25	P50	P75	t-test (t-statistics)
Blockchain adopter							
$Invest_{it+1}$	202	0.252	0.668	0.002	0.048	0.183	
Q_{it}	202	41.031	103.342	1.391	2.808	11.621	
Non-blockchain adopter							
$Invest_{it+1}$	31,288	0.170	0.382	0.023	0.064	0.157	3.025***
Q_{it}	31,288	9.466	43.871	1.144	1.702	3.152	10.048***
Total							
$Invest_{it+1}$	31,490	0.171	0.385	0.023	0.064	0.158	
Q_{it}	31,490	9.669	44.574	1.145	1.706	3.168	

Panel B. Correlations (p-values in parentheses)

	$Invest_{it+1}$	Q_{it}	$Blockchain_{it}$
$Invest_{it+1}$	1	**0.241*** **	-0.007
		(0.000)	(0.213)
Q_{it}	**0.270*** **	1	0.007
	(0.000)		(0.241)
$Blockchain_{it}$	**0.014** **	0.007	1
	(0.011)	(0.227)	

Table 3
Blockchain Adoption and Investment Efficiency

This table shows regression results on the relation between blockchain adoption and investment efficiency using a sample of U.S. listed, non-financial and non-utility firms over the years 2014-2019. Appendix 2 provides variable definitions. t-statistics, adjusted for heteroskedasticity and firm-level clustering, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1) $Invest_{t+1}$	(2) $Invest_{t+1}$	(3) $Invest_{t+1}$
	Unmatched sample	Entropy-balanced sample	PSM sample
Q_{it}	0.003***	0.003**	0.004**
	(9.371)	(2.437)	(2.057)
$\boldsymbol{Blockchain_{it} \times Q_{it}}$	**0.029****	**0.029****	**0.030*****
	(2.515)	**(2.231)**	**(2.800)**
$Blockchain_{it}$	-0.061	-0.068	-0.063
	(-0.616)	(-0.748)	(-0.917)
Intercept	0.166***	0.128	0.124
	(36.250)	(1.529)	(0.965)
Firm FE	Included	Included	Included
Year FE	Included	Included	Included
Adj. R-squared	0.074	0.494	0.238
Observations	31,490	31,490	404

Table 4
Parallel Trend Analysis

This table shows regression results of the parallel trend analysis using a sample of U.S. listed, non-financial and non-utility firms over the years 2014-2019. Appendix 2 provides variable definitions. t-statistics, adjusted for heteroskedasticity and firm-level clustering, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1) $Invest_{it+1}$	(2) $Invest_{it+1}$	(3) $Invest_{it+1}$
	Unmatched sample	Entropy-balanced sample	PSM sample
Q_{it}	0.003***	0.002**	0.003*
	(9.329)	(2.362)	(1.785)
Before Adoption$_{it}$ × Q_{it}	**0.002**	**0.002**	**0.002**
	(1.413)	**(1.213)**	**(1.183)**
Before Adoption$_{it}$	-0.149*	-0.165	-0.179
	(-1.734)	(-1.517)	(-1.077)
Adoption Year$_{it}$ × Q_{it}	**0.030*****	**0.029****	**0.030*****
	(2.686)	**(2.255)**	**(2.676)**
Adoption Year$_{it}$	-0.217**	-0.271*	-0.354
	(-1.990)	(-1.683)	(-1.300)
After Adoption$_{it}$ × Q_{it}	**0.139*****	**0.144*****	**0.156*****
	(19.860)	**(7.945)**	**(4.976)**
After Adoption$_{it}$	-0.384***	-0.468***	-0.598
	(-6.886)	(-2.645)	(-1.507)
Intercept	0.166***	0.169**	0.159
	(36.552)	(2.438)	(1.318)
Firm FE	Included	Included	Included
Year FE	Included	Included	Included
Adj. R-squared	0.076	0.518	0.280
Observations	31,490	31,490	404

Table 5
Cross-Sectional Analysis

This table shows regression results of the cross-sectional analysis based on information environments using a sample of U.S. listed, non-financial and non-utility firms over the years 2014-2019. Appendix 2 provides variable definitions. t-statistics, adjusted for heteroskedasticity and firm-level clustering, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$Invest_{it+1}$	$Invest_{it+1}$	$Invest_{it+1}$	$Invest_{it+1}$	$Invest_{it+1}$	$Invest_{it+1}$	$Invest_{t+1}$	$Invest_{t+1}$	$Invest_{t+1}$	$Invest_{t+1}$
	ROA Volatility$_{it}$		*Internal Control Weakness*$_{it}$		*Business Dispersion*$_{it}$		*Institutional Ownership*$_{it}$		*Analyst Following*$_{it}$	
	High	Low	Yes	No	High	Low	High	Low	High	Low
Q_{it}	0.003***	0.001	0.002***	0.003***	0.003***	0.002***	0.005**	0.002***	0.005	0.002***
	(6.711)	(1.240)	(5.129)	(4.035)	(6.878)	(3.871)	(2.431)	(8.768)	(1.306)	(9.063)
$Blockchain_{it} \times Q_{it}$	**0.027****	**-0.006**	**0.025****	**-0.003**	**0.029****	**-0.010**	**-0.009**	**0.012*****	**-0.005**	**0.027****
	(2.360)	**(-0.941)**	**(2.056)**	**(-0.477)**	**(2.414)**	**(-0.380)**	**(-1.637)**	**(3.917)**	**(-1.103)**	**(2.339)**
$Blockchain_{it}$	-0.022	0.003	-0.006	0.023	-0.179	0.173	0.019	-0.075	0.001	-0.056
	(-0.275)	(0.235)	(-0.060)	(1.126)	(-1.321)	(1.101)	(0.663)	(-0.471)	(0.058)	(-0.373)
Intercept	0.207***	0.077***	0.147**	0.142***	0.149***	0.206***	0.128***	0.200***	0.138***	0.189***
	(22.145)	(41.600)	(2.344)	(21.467)	(21.624)	(26.427)	(18.878)	(22.779)	(12.682)	(20.563)
Firm FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Adj. R-squared	0.075	0.009	0.109	0.055	0.099	0.040	0.089	0.069	0.041	0.078
Observations	9,707	9,799	2,615	15,467	12,585	10,166	17,254	14,236	17,043	14,447

Table 6
Level of Engagement in Blockchain Technology

This table shows regression results of the analysis based on the level of engagement in blockchain technology using a sample of U.S. listed, non-financial and non-utility firms over the years 2014-2019. *Blockchain Level* is one if a firm's 8-K filings and attached exhibits indicate one of the following levels of engagement in blockchain technology in addition to those identified in the *Blockchain* variable, and zero otherwise. Level 1: Blockchain-related R&D project. Level 2: Blockchain-related investment, including subsidiary investment. Level 3: Blockchain-related strategic alliance/partnership/joint venture. Appendix 2 provides variable definitions. t-statistics, adjusted for heteroskedasticity and firm-level clustering, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1) $Invest_{it+1}$	(2) $Invest_{it+1}$	(3) $Invest_{it+1}$
	Level 1	Level 2	Level 3
Q_{it}	0.002***	0.002***	0.002***
	(9.267)	(9.238)	(9.276)
Blockchain Level $_{it}$ **×** Q_{it}	**0.001**	**0.009***	**0.031****
	(0.655)	**(1.674)**	**(2.343)**
Blockchain Level $_{it}$	0.126	0.099	-0.110
	(1.179)	(0.938)	(-1.120)
Intercept	0.166***	0.166***	0.166***
	(36.494)	(36.524)	(36.397)
Firm FE	Included	Included	Included
Year FE	Included	Included	Included
Adj. R-squared	0.069	0.072	0.073
Observations	31,490	31,490	31,490

Table 7
Validation Tests

This table shows regression results of the Heckman two-stage test (Panel A) and a placebo test (Panel B) using a sample of U.S. listed, non-financial and non-utility firms over the years 2014-2019. *Pseudo Blockchain* is an indicator variable equal to one two years before a firm's actual blockchain adoption, and zero otherwise. Appendix 2 provides variable definitions. t-statistics, adjusted for heteroskedasticity and firm-level clustering, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A. Heckman Two-Stage Test

	(1) Probit: $Blockchain_{it}$	(2) OLS: $Invest_{it+1}$
	First-stage	Second-stage
Q_{it}	0.000	0.003***
	(0.225)	(9.422)
$Blockchain_{it} \times Q_{it}$		**0.028****
		(2.506)
$Blockchain_{it}$		-0.060
		(-0.598)
$Size_{it}$	-0.101***	
	(-4.577)	
$Leverage_{it}$	-0.010	
	(-1.436)	
$Capital\ Intensity_{it}$	0.001	
	(1.458)	
$Loss_{it}$	0.309**	
	(2.471)	
$Payout_{it}$	0.038	
	(0.239)	
$Foreign_{it}$	0.116	
	(1.244)	
$M\&A_{it}$	0.308**	
	(2.573)	
$R\&D_{it}$	-0.261	
	(-1.441)	
$Advertising_{it}$	2.137***	
	(2.686)	
$Analyst\ Following_{it}$	0.004***	
	(2.823)	
$Inverse\ Mills\ Ratio_{it}$		0.059***
		(3.466)
Intercept	-3.443***	-0.060
	(-15.098)	(-0.902)
Firm FE	Excluded	Included
Year FE	Included	Included
Pseudo/Adj. R-squared	0.143	0.076
Observations	39,429	31,490

Panel B. Placebo Test

	(1)
	$Invest_{t+1}$
Q_{it}	0.002***
	(9.224)
***Pseudo Blockchain**$_{it}$ $\times$ Q_{it}*	**0.000**
	(0.154)
Pseudo Blockchain$_{it}$	-0.065
	(-0.570)
Intercept	0.166***
	(36.527)
Firm FE	Included
Year FE	Included
Adj. R-squared	0.069
Observations	31,490