



The impact of blockchain adoption on corporate investment efficiency

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ARTICLE INFO

JEL Classifications:

D8
G3

Keywords:

Blockchain technology
Investment efficiency
Corporate overinvestment

ABSTRACT

This study investigates the impact of blockchain technology adoption on corporate investment efficiency. Utilizing a difference-in-differences methodology on an international sample of Forbes Global 2000 companies between 2012 and 2021, we find that firms implementing blockchain exhibit significantly higher investment efficiency post-adoption compared to non-adopters. This effect is more pronounced among *ex ante* informationally opaque firms. Our results suggest that blockchain adoption reduces overinvesting activities by restricting avenues for managerial discretion through enhanced transparency. Our findings contribute to the growing literature on blockchain's real economic impacts and inform blockchain adoption decisions by demonstrating investment efficiency benefits.

1. Introduction

In recent years, the rapid proliferation of blockchain technology has attracted widespread attention due to its potential to revolutionize traditional business practices and operations (Jain and Jain, 2019). Although prior research explores blockchain's role in value creation and its implications for corporate governance (Cong and He, 2019; Yermack, 2017), less is known about its tangible effects on corporate investment policy, specifically in relation to investment efficiency. The extant literature focuses on the misallocation of capital, particularly overinvestment, as it represents a divergence from optimal investment strategies and can destroy shareholder value (Biddle et al., 2009; Richardson, 2006). Agency conflicts relating to investment policy intensify under conditions of information asymmetry, where company insiders have an informational advantage over outsiders, leading to increased moral hazard (Jensen and Meckling, 1976). Consequently, external stakeholders demand accurate and timely information to scrutinize potential suboptimal managerial investment decisions. Accordingly, blockchain technology emerges as a promising avenue to improve investment efficiency and curtail overinvestment by enhancing transparency and accountability, thereby serving as a self-regulatory mechanism that disciplines corporate investment decisions.

We posit that blockchain technology can act as a deterrent against suboptimal investment choices by restricting managerial opportunistic

behavior, reducing information asymmetry, and improving monitoring. In particular, the inherent transparency and immutability of blockchain's distributed ledger system strengthen corporate oversight and discourage misconduct (Yermack, 2017). Moreover, this technology facilitates better decision-making through real-time access to accurate information, enabling firms to align their investment activities more closely with their strategic objectives. In this context, this paper examines whether the adoption of blockchain technology improves investment efficiency by mitigating corporate overinvestment.

Using a difference-in-differences methodology, we test whether blockchain adopting firms demonstrate lower levels of overinvestment post-adoption, compared to a matched sample of non-adopting firms. We employ an international sample of Forbes Global 2000 companies during 2012–2021. We find that, relative to their non-adopting counterparts, firms implementing blockchain display a significant decline in overinvestment subsequent to adoption. This effect is more prominent among *ex ante* informationally opaque firms. This paper adds to the literature on blockchain's real economic impacts by demonstrating investment efficiency benefits, thereby offering valuable insights into both blockchain adoption decisions and the technology's role in improving governance mechanisms.

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<https://doi.org/10.1016/j.econlet.2024.111603>

Received 8 November 2023; Received in revised form 4 February 2024; Accepted 11 February 2024

Available online 13 February 2024

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2. Data and methodology

2.1. Methodology

We employ a difference-in-differences methodology using a global sample of firms that have adopted blockchain technology (treatment) and those that have not (control) to test our hypothesis that blockchain adoption improves investment efficiency by limiting overinvestment. To mitigate endogeneity concerns arising from selection on observable characteristics (Shipman et al., 2017), we match each treated firm to three control firms that operate in the same country and industry, based on the Fama and French (1997) 48 industry classification. Our propensity score matching (PSM) approach models the likelihood of a firm engaging in blockchain technology as a function of size, market-to-book ratio, leverage, profitability, and operating cash flow (Klöckner et al., 2022).

We build our empirical model based on the following specification shown in Eq. (1), which expresses total investment expenditure as a function of a firm’s propensity for overinvestment, alongside a set of control variables pertinent to corporate investment policy. We measure total investment expenditure as the sum of capital expenditure, research and development expenses, and acquisition expenditure, less cash receipts from sale of property, plant, and equipment (Richardson, 2006). We follow Biddle et al. (2009) and employ a decile-ranked variable based on cash holdings and financial leverage to proxy for the tendency to overinvest. Firms with higher cash reserves and lower financial obligations are more inclined to overinvest, so we multiply leverage by -1 before ranking to ensure both variables increase with the propensity for overinvestment. We scale the decile-ranked variable to range between 0 and 1.

$$INVEST_{it} = \beta_0 + \beta_1 OVERINV_{it} + \sum \beta_i Controls_{it} + \sum \beta_j Industry_FE_j + \varepsilon \tag{1}$$

Where *INVEST* represents total investment scaled by total assets, and *OVERINV* is our decile-ranked variable capturing the propensity to overinvest.¹ The model also incorporates a vector of control variables capturing firms’ underlying financial and economic characteristics. These include firm size (*SIZE*), market-to-book ratio (*MTB*), return on assets (*ROA*), cash flow from operations (*OCF*), sales growth (*GROWTH*), and a proxy for financial distress risk (*ZSCORE*). All variables are defined in the Appendix.

To test our hypothesis, we build upon the model in Eq. (1) to facilitate a difference-in-differences analysis that examines changes in overinvestment around the adoption of blockchain technology within the treatment firms, relative to the control sample. Eq. (2) extends the model in Eq. (1) as follows:

$$INVEST_{it} = \beta_0 + \beta_1 OVERINV_{it} + \beta_2 BC_i + \beta_3 POST_t + \beta_4 OVERINV_{it} \times BC_i + \beta_5 OVERINV_{it} \times POST_t + \beta_6 BC_i \times POST_t + \beta_7 OVERINV_{it} \times BC_i \times POST_t + \sum \beta_i Controls_{it} + \sum \beta_j Industry_FE_j \tag{2}$$

Where *BC* is an indicator variable for treatment firms, and *POST* is an indicator variable for years following the blockchain adoption year. Our variable of interest is the triple interaction term *OVERINV* × *BC* × *POST*, which captures the differential change in overinvestment among the treatment group relative to the control group following blockchain adoption, given the presumed change in their information environment.

2.2. Data

We manually collect data on blockchain adoption for an international sample of 115 firms featured in the Forbes Global 2000 rankings

¹ In line with our expectations, we find a positive and significant coefficient for *OVERINV*, indicating that firms with greater cash availability and lower financial obligations are more likely to engage in overinvestment (untabulated).

Table 1
Summary statistics.

Summary statistics for the full sample (N = 2250)					
Variable	Mean	StdDev	Q1	Median	Q3
<i>INVEST</i>	0.0249	0.0786	-0.0051	0.0026	0.0393
<i>RND</i>	0.0094	0.0263	0.0000	0.0014	0.0213
<i>OVERINV</i>	0.5294	0.2215	0.3500	0.5500	0.7000
<i>BIDASK</i>	-3.8856	0.5741	-4.2063	-3.8272	-3.4973
<i>SIZE</i>	7.9900	2.8018	5.7939	7.9599	10.3659
<i>MTB</i>	1.9452	3.1686	0.9483	1.1526	1.9258
<i>ROA</i>	0.0288	0.1398	0.0070	0.0301	0.0740
<i>OCF</i>	0.0804	0.0963	0.0156	0.0772	0.1305
<i>GROWTH</i>	0.0537	0.2655	-0.0127	0.0120	0.0824
<i>ZSCORE</i>	1.4137	1.5572	0.8550	1.5255	2.1614

All continuous variables are winsorized at 1 % and 99 %.

for the year 2018. Our sampled firms have integrated blockchain technology into their transaction ledger systems between 2015 and 2018. Our dataset mandates that each firm have a minimum of three years of data both preceding and following the year of blockchain implementation. Consequently, our final sample spans the period 2012–2021, and comprises 115 firms that have adopted blockchain technology and a matched set of 302 non-adopting firms, yielding 620 and 1630 firm-year observations, respectively. We obtain financial data and daily security information from Compustat North America and Compustat Global databases. Table 1 presents the summary statistics for all variables used in our study.

3. Results

Our findings provide evidence that blockchain adoption is associated with improved investment efficiency, as reported in Table 2. The coefficient on *OVERINV* × *POST* is statistically indistinguishable from zero for the control firms (Model 2.1), while it is negative and significant for the treated firms (Model 2.2), suggesting that overinvestment diminishes after adoption. The difference-in-differences results reported in Model 2.3 demonstrate that overinvestment significantly decreases for blockchain adopting firms relative to non-adopters post-implementation. The negative and significant coefficient on *OVERINV* × *BC* × *POST* (-0.0378) implies that blockchain adopters engage less in overinvestment compared to control firms after adoption. Overall, these findings support our prediction that blockchain adoption enhances investment efficiency by restricting avenues for managerial overinvestment.

In Table 3, we perform a cross-sectional analysis to identify the channel through which the blockchain effect occurs. The findings reveal that the overinvestment-mitigating impact of blockchain adoption is stronger for *ex ante* informationally opaque firms. Specifically, we split treated firms into high and low information asymmetry subsamples based on pre-adoption bid-ask spreads. The significant and negative triple interaction term *OVERINV* × *POST* × *HighBIDASK* in Model 3.3 indicates that firms suffering from greater information asymmetry exhibit a larger reduction in overinvestment after adopting blockchain. This finding corroborates Biddle et al. (2009) who show that firms with more transparent financial information environments tend to deviate less from optimal investment levels.

Collectively, our findings offer robust evidence that blockchain implementation enhances investment efficiency by curtailing overinvestment through the channel of reduced information asymmetry.² We further examine the impact of blockchain adoption on Research and Development (R&D) investments, which tend to exhibit greater information asymmetry due to their uncertain outcomes. Given blockchain’s

² Our results are robust to a placebo test using a lagged blockchain adoption indicator variable and Heckman’s two-step approach, mitigating concerns over potential reverse causality and self-selection bias.

Table 2
Overinvestment around blockchain adoption.

	Total investment			Research and development investment		
	Control	Treatment	DiD	Control	Treatment	DiD
	Model 2.1	Model 2.2	Model 2.3	Model 2.4	Model 2.5	Model 2.6
	<i>INVEST</i>	<i>INVEST</i>	<i>INVEST</i>	<i>RND</i>	<i>RND</i>	<i>RND</i>
<i>OVERINV</i>	0.0533*** (3.52)	0.0576*** (2.99)	0.0338** (2.38)	0.0112*** (3.66)	0.0188*** (3.26)	0.0071** (2.25)
<i>BC</i>			0.0172 (1.45)			0.002 (0.51)
<i>POST</i>	0.006 (0.56)	0.0194 (1.55)	0.0271* (1.83)	0.0018 (0.68)	0.0008 (0.22)	0.0054* (1.68)
<i>OVERINV</i> × <i>BC</i>			0.0045 (1.19)			0.0008 (0.10)
<i>OVERINV</i> × <i>POST</i>	-0.0206 (-1.13)	-0.0503*** (-3.63)	-0.0133 (-0.73)	-0.0002 (-0.04)	-0.0273*** (-2.87)	-0.0024 (-0.47)
<i>BC</i> × <i>POST</i>			0.0162 (0.99)			0.0016 (0.30)
<i>OVERINV</i> × <i>BC</i> × <i>POST</i>			-0.0378*** (-2.76)			-0.0284*** (-2.99)
Controls and industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1630	620	2250	1630	620	2250
R-squared	0.1429	0.1588	0.1281	0.2193	0.2666	0.2009

The t-statistics in parentheses are calculated based on clustered standard errors at the firm level. The asterisks indicate a 1 % (***), 5 % (**), and 10 % (*) levels of significance.

Table 3
Cross-sectional test by information asymmetry for the treatment group.

	Total investment			Research and development investment		
	Model 3.1	Model 3.2	Model 3.3	Model 3.4	Model 3.5	Model 3.6
	Low <i>BIDASK</i>	High <i>BIDASK</i>	DiD	Low <i>BIDASK</i>	High <i>BIDASK</i>	DiD
	<i>INVEST</i>	<i>INVEST</i>	<i>INVEST</i>	<i>RND</i>	<i>RND</i>	<i>RND</i>
<i>OVERINV</i>	0.0297 (1.29)	0.0499** (1.98)	0.0492** (2.16)	0.0120* (1.70)	0.0235*** (2.67)	0.0196** (2.27)
<i>POST</i>	0.0236 (1.38)	0.0038 (0.25)	0.0305 (1.63)	0.0064 (1.49)	0.0058 (1.25)	0.005 (0.95)
<i>POST</i> × <i>OVERINV</i>	-0.0439* (-1.74)	-0.0678*** (-3.14)	-0.0663* (-1.67)	-0.0175* (-1.88)	-0.0355*** (-3.82)	0.0128 (1.09)
<i>HighBIDASK</i>			-0.002 (-0.12)			-0.0018 (-0.34)
<i>OVERINV</i> × <i>HighBIDASK</i>			0.0186* (1.91)			0.0116* (1.76)
<i>POST</i> × <i>HighBIDASK</i>			-0.028 (-1.12)			-0.0098 (-1.37)
<i>OVERINV</i> × <i>POST</i> × <i>HighBIDASK</i>			-0.0293** (-2.26)			-0.0239*** (-3.27)
Controls and industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	310	310	620	310	310	620
R-squared	0.3249	0.2884	0.2969	0.4149	0.3823	0.3886

The t-statistics in parentheses are calculated based on clustered standard errors at the firm level. The asterisks indicate a 1 % (***), 5 % (**), and 10 % (*) levels of significance.

potential to enhance the information environment, we anticipate a more pronounced effect on R&D investments. In Table 2 (Models 2.4–2.6) and Table 3 (Models 3.4–3.6), we use R&D expenditure (*RND*) as the dependent variable for our difference-in-differences analysis. The results reveal a significant reduction in overinvestment in R&D following blockchain adoption, illustrating the technology’s heightened impact in areas with increased information asymmetry.

4. Conclusion

This study provides evidence that blockchain technology adoption enhances investment efficiency by reducing corporate overinvestment. Using an international sample of Forbes Global 2000 companies between 2012 and 2021, difference-in-differences analysis reveals that overinvestment declines after adoption, especially for informationally opaque firms *ex ante*. By reducing overinvestment, blockchain promotes more efficient capital allocation and shareholder value maximization.

Our findings suggest that blockchain technology can act as a quasi-regulatory force disciplining corporate investment decisions. Overall, this paper contributes to the growing literature on blockchain’s real economic impacts. The results are of interest to various stakeholders evaluating the costs and benefits of this emerging technology, including policymakers and companies considering investments in blockchain technologies.

Declarations of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix. Variable Definitions

Variable	Definition
<i>INVEST</i>	Sum of research and development expenditure, capital expenditure, and acquisition expenditure, less cash receipts from the sale of property, plant, and equipment, divided by total assets.
<i>RND</i>	Research and development expenditure divided by total assets.
<i>OVERINV</i>	Decile-ranked variable that is based on cash holdings and leverage. Leverage is multiplied by -1 prior to ranking to ensure that both variables are increasing in the likelihood of overinvestment. We scale the variable to range between 0 and 1.
<i>BIDASK</i>	Natural logarithm of the median of daily percentage bid-ask spread, calculated as the ask price minus the bid price, divided by the average of the bid and ask prices.
<i>BC</i>	Indicator variable that takes the value 1 for firms that adopt blockchain technology, and 0 otherwise.
<i>HighBIDASK</i>	Indicator variable that takes the value 1 if the firm's <i>BIDASK</i> is above the median value of the treatment sample prior to blockchain adoption, and 0 otherwise.
<i>POST</i>	Indicator variable that takes the value 1 for the years following a firm's blockchain adoption, and 0 otherwise.
<i>SIZE</i>	Natural logarithm of total assets.
<i>MTB</i>	Market value of equity to book value of equity.
<i>ROA</i>	Net income before extraordinary items to total assets.
<i>OCF</i>	Cash flow from operations to total assets.
<i>GROWTH</i>	Change in total sales from prior year to total assets.
<i>ZSCORE</i>	Proxy measure for financial distress, computed following Altman (1968).

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