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Blockchain adoption and analyst forecast accuracy

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A B S T R A C T

We examine the relationship between corporate blockchain adoption and analyst forecast accuracy. We manually collect the blockchain usage data of public firms from the Factiva news database. Using a staggered Difference-in-Differences method, we find that analyst forecast accuracy significantly improves after firms adopt blockchain technology. In addition, the change in analyst coverage could be the potential explanation for this result.

1. Introduction

Financial analysts' earnings forecasts frequently exhibit biases stemming from the analysts' limitations and the information environment surrounding firms. These inaccuracies in forecasting can lead to undercapitalization, underinvestment, and even misleading investors (Armstrong et al., 2011; Pellicani and Kalatzis, 2019). A robust body of literature has examined the influence of firm characteristics, analysts' expertise, and the regulatory landscape in reducing the forecast error issues (Clement, 1999; Mikhail et al., 2003; Leuz and Verrecchia, 2000). However, there remains a notable gap in our understanding of how emerging digital technologies might enhance the quality of these forecasts. Our study aims to bridge this gap by exploring the impact of blockchain technology, a burgeoning digital innovation, on the accuracy of forecasts made by analysts monitoring a particular firm.

Blockchain is a digital ledger technology that has revolutionized the way we understand monetary systems, most notably through cryptocurrencies like Bitcoin. Its decentralized structure is the cornerstone of its innovation, guaranteeing the integrity and immutability of data, alongside enhanced transparency in record-keeping practices (Cong and He, 2019; Chod et al., 2020; Murimi et al., 2023; Patel et al., 2022). Additionally, blockchain's benefits extend well beyond financial transactions. It is disrupting supply chain management with real-time tracking, improving identity verification processes, and automating agreements through smart contracts that execute themselves under set conditions (Autore et al., 2021; Chen et al., 2023).

Given its vast capabilities and the increasing complexities within business operations, blockchain technology stands out as an especially relevant subject for financial analysts. Analysts are tasked with scrutinizing data to forecast economic trends and firm performance (Miwa, 2022). Blockchain's inherent attributes, such as providing a single source of truth and reducing the scope for manual errors, could significantly refine the analyzing process. This raises an intriguing question: Will the adoption of blockchain

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lead to higher forecast accuracy among financial analysts? Answering this could unveil new dimensions in the synergy between advanced technology and financial expertise, marking a transformative shift in the digital age.

We analyze 19,941 firm-year observations from 2012 to 2021 and find significant improvement in the accuracy of analysts' forecasts following the adoption of blockchain technology by firms. Our primary findings reveal that the absolute error in analysts' forecasts decreases by approximately 24.22% of its average value post-adoption. In order to address potential endogeneity, we adopt two distinct methods. The first approach involves the use of "propensity score matching". This technique allows us to pair blockchain adopters and non-adopters possessing similar attributes, thus enabling a more balanced comparison. We find that the outcomes for these matched samples align closely with our primary results.

The second approach examines the "dynamic average treatment effect" using both the two-way fixed effects model and the CSDiD model proposed by Callaway and Sant'Anna (2021). The CSDiD model leverages an initial estimation of treatment effects specific to individual cohort-time settings, accommodating heterogeneity in treatment effects, and subsequently combines them to derive comprehensive measures of overall treatment effects. The two models both reveal a statistically significant decline in analyst forecast error three years after adoption, while there is no significant change in the pre-treatment trend. This supports the validity of our sample by confirming compliance with the "parallel-trends assumption", which postulates that barring the intervention, the treatment and control groups would have followed the same trajectory over time.

This study involves conducting a mediation analysis to investigate if analyst coverage may serve as a plausible conduit, elucidating why firms adopting blockchain technology witness enhanced analyst forecast accuracy. Our findings indicate that analyst coverage can potentially mediate 7.2% of the total impact triggered by blockchain adoption. This implies the considerable role of analyst coverage as a mediator variable, suggesting that the incorporation of blockchain technology could effectively capture analysts' attention.

Furthermore, we investigate how the varying objectives behind adopting blockchain might influence our results. To this end, we divide the firms within our treatment group into two distinct categories: "Finance" and "Management", based on their respective uses of blockchain technology. Upon conducting the primary regression analysis again, we observe a marked trend: analysts exhibit greater interest in the "Finance" category. Additionally, the enhancements in forecast accuracy by analysts are notably more substantial within this category. These observations indicate that analysts' preferences vary according to the specific operational uses of blockchain employed by the firms.

To enhance the robustness of our findings, we conduct a series of additional tests. These tests incorporate extra control variables and fixed effects to ensure thorough examination. Furthermore, we investigate the impact of blockchain adoption on analyst forecast dispersion. It is pertinent to consider both accuracy and dispersion since they jointly contribute to the overall quality of analyst forecasts. Our results indicate an improvement in analyst forecast dispersion, thereby reinforcing the strength of our conclusions.

Our paper contributes to the literature on signaling theory. Unlike previous studies that have focused on traditional forms of signals, such as financial disclosures (Song et al., 2024; L'Abate et al., 2024; Yu et al., 2017) or corporate governance mechanisms (Reuer et al., 2012; Reuer and Ragozzino, 2012; Vasudeva et al., 2018; Popli et al., 2021; Taj, 2016), our study delves deeper into the technological frontier. Our findings complement those of prior research by demonstrating that blockchain adoption can serve as a potent signal that amplifies analyst coverage, thereby enhancing forecast accuracy through collective intelligence. Therefore, our paper extends signaling theory into the domain of financial technology.

Our analysis also reveals insights into the complex dynamics governing analyst behavior post-blockchain adoption. This research diverges from conventional perspectives that typically associate technological adoption with firms' internal efficiency gains (Catalini and Gans, 2020; Chod et al., 2020; Nguyen and Nguyen, 2022; Alsharari, 2021) by spotlighting the externalities of such adoption in the form of improved performance of financial analysts. It underscores blockchain's transformative potential in refining firms' external information environment and broadens its impact scope.

Furthermore, similar to Autore et al. (2021), our blockchain adoption data is sourced from news texts, offering a more timely dataset than data extracted from corporate announcements (e.g., Cheng et al., 2019). Additionally, our DiD treatment is conducted at the firm level, enhancing our results' precision relative to studies employing state-level treatments based on blockchain legislation (e.g., Chen et al., 2023). Consequently, our methodological approach provides a robust framework for future investigations into the role of technology in financial markets, ensuring both timeliness and precision in the analysis.

In sum, this paper expands the empirical landscape of blockchain's implications in corporate finance and introduces a paradigm shift in understanding the ancillary effects of technological advancements on market forecasting mechanisms. Thus, it lays the groundwork for subsequent inquiries into the transformative potential of blockchain in the broader spectrum of financial reporting and analysis.

2. Hypothesis development

The theoretical basis for developing the relationship between blockchain adoption and analyst forecast accuracy lies in the signaling theory (Spence, 1973) and wisdom of crowds theory (Surowiecki, 2005). When a firm announces its adoption of blockchain technology, it may send several signals. First, blockchain is an emerging technology, and a firm's adoption demonstrates its ability to pursue innovation and integrate the latest technologies. Second, blockchain technology is known for its high degree of transparency and security, and a firm's adoption can convey to the market that it values data security and transparency of business processes. Third, blockchain can optimize supply chain management, reduce transaction costs, etc. Firms using blockchain may pursue operational efficiency.

Analysts typically look for potential investment targets, and their interest in a firm's strategic decisions is largely based on the impact those decisions may have on the firm's future performance and stock price (Litov et al., 2012). When a firm adopts blockchain, if analysts interpret it as one of the above signals, they may expect that the firm will improve market competitiveness and financial performance due to improved efficiency, security, or innovation. This expectation may prompt analysts to pay more attention to the firm, conduct more in-depth investigation and analysis, and even issue positive investment recommendations (Bourveau et al., 2022).

For example, if blockchain adoption can significantly reduce a firm's operating costs, this will directly impact the firm's net income, attracting the attention of investment analysts (Koester et al., 2016). On the other hand, if the application of blockchain technology enhances the value of the firm's products or services, this may also bring about expectations of revenue growth, which will also attract the attention of analysts. In summary, through signaling theory, a firm's adoption of blockchain technology can be viewed as a strategic signal that conveys information to the market about its future direction and potential value. Analysts are interested in such signals because they are tasked with identifying and evaluating potential investment opportunities (Brown et al., 2015), and these signals may signal positive changes in a firm's competitive position and financial condition.

Building upon the wisdom of crowds theory (Surowiecki, 2005), it stands to reason that as more analysts focus on firms integrating blockchain technology, the collective accuracy of their forecasts could increase. This phenomenon can be attributed to the diverse perspectives and unique information each analyst contributes. When these insights coalesce, the aggregated knowledge exceeds what any individual analyst possesses. Moreover, in competitive markets, analysts have incentives to provide accurate forecasts to maintain credibility and reputation (Benabou and Laroque, 1992). Thus, when there are more analysts, there is a greater drive to refine forecasts and conduct social learning (Kumar et al., 2022), leading to potentially higher accuracy. In light of this, we posit the following hypothesis:

Hypothesis 1a (H1a)**.** Blockchain adoption could increase analyst forecast accuracy.

However, blockchain has potential drawbacks as well. Given its complex and technical nature, blockchain poses a steep learning curve for analysts who may not have a background in emerging technologies. The intricate workings of blockchain, from understanding how blocks are created and chained to comprehending the nuances of smart contracts, require a specialized skill set (Wang et al., 2019; Yli-Huumo et al., 2016; Andoni et al., 2019). Without this expertise, financial analysts might find it difficult to gauge the true impact of blockchain integration on a firm's operations. This lack of insight can lead to an escalation in knowledge-based information asymmetry (He and Wang, 2009; Dawson et al., 2010), where there is a mismatch between what analysts understand and what is happening within the firm.

The issue becomes even more pronounced when firms opt for private or consortium blockchains. Unlike public blockchains, which allow anyone to view and validate the ledger, private and consortium blockchains restrict access to certain users (Franke et al., 2023). While these blockchains offer benefits such as enhanced privacy and control over transactions, they pose significant transparency challenges for analysts. With limited access to crucial data that could inform their evaluations and forecasts, analysts are at risk of producing less accurate reports. The lack of transparency associated with private and consortium blockchains means that critical financial information remains opaque, leaving analysts to speculate based on incomplete data.

Moreover, because the purpose of blockchain adoption varies greatly across different industries and firms, analysts must also grapple with inconsistent disclosure and reporting standards levels. In some cases, firms may tout their use of blockchain without providing substantive evidence of its impact on operational efficiency or profitability, leading to potential overvaluation by analysts unfamiliar with the specific applications and limitations of the technology. As such, while blockchain presents several advantages for analyst forecast accuracy, it may also inadvertently contribute to inaccuracies. Therefore, we propose the following hypothesis:

Hypothesis 1b (H1b)**.** Blockchain adoption could decrease analyst forecast accuracy.

3. Sample construction and research design

3.1. Data

Our research begins by identifying firms that invest in blockchain technology, utilizing news articles sourced from Factiva. We carry out our search using the following steps:

(i) We start by obtaining all firm names listed in NYSE/AMEX/NASDAQ from CRSP.
(ii) Next, we manually match each CRSP firm name with its corresponding Factiva firm name. This involves typing the CRSP name into Factiva's search box until it suggests a similar name. For instance, the CRSP name for Microsoft is "MICROSOFT CORP", while Factiva suggests "Microsoft Corporation". The high degree of similarity between these two names allows us to establish a link between CRSP and Factiva databases.
(iii) After establishing these links, we search each firm name alongside the term "blockchain" within the timeframe of 2009 to 2023.
(iv) We then read the news articles in chronological order until we find mention of the firms actively investing in blockchain technology within their operations. This approach enables us to identify the earliest blockchain investment news, and consequently, the first year each firm used blockchain technology.

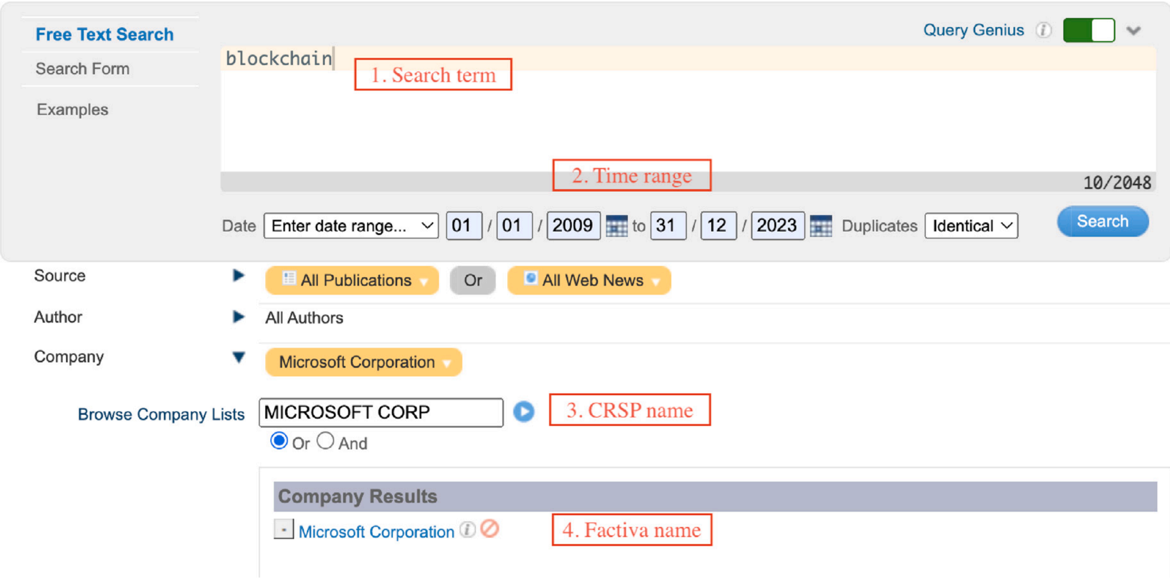

Fig. 1. Illustration of Factiva search steps.

Please refer to Fig. 1 for a visual representation of this process. In addition, Table A.2 shows the annual number of blockchain adoptions by firms, including the classification of the purpose of adoption each year. In order to maintain the accuracy of our results, we delegate tasks between three individuals: One person is dedicated to generating the initial search results. A second person is tasked with verifying the correctness of these results. In instances of disagreement, a third person makes the final judgment call. By implementing this multi-layered verification system, we strive to ensure the robustness of our research findings.

Our study utilizes a firm-year panel sample, drawing from several databases. We have sourced analyst forecast data from I/B/E/S, market data from CRSP, institutional ownership data from Thomson Reuters, and fundamental data from Compustat.

This sample combines all these datasets along with previous blockchain adoption data. Observations are filtered based on certain criteria. Only the EPS forecasts for common stocks listed on major US exchanges NYSE/AMEX/NASDAQ are retained. This step eliminates the potential influence of different country-specific regulations or rules. Furthermore, we only keep observations that have sufficient data to calculate forecast errors and the control variables, which we will detail below. Our objective is to maintain data consistency and accuracy throughout our research.

The first instance of blockchain adoption within our sample dates back to 2015. To test the parallel trend required by the Difference-in-Differences method, we also include observations from three years prior to 2015. Therefore, our final sample spans from 2012 to 2021, dictated by the data availability.

3.2. Main variables

3.2.1. Measure of analyst forecast accuracy

We use the absolute value of the forecast error as a reverse proxy for the forecast accuracy. Following Allee et al. (2023), we define the monthly forecast error as the difference between the mean forecast EPS and the actual EPS scaled by the previous close price of the stock in a given month. We then average the twelve-monthly absolute values of the forecast errors to produce the annual forecast errors for our sample.

When aggregating monthly frequency to annual frequency, we require twelve months of observations. Because the precision of the estimates increases proportionally with the number of months. To ensure consistency in this precision, it is crucial to estimate all firm-year forecast accuracy using an identical number of months, in this case, 12 months of observations. The formula we adopt for the annual absolute forecast error reflects this consideration.

$$AbsFE_{i,t} = \frac{1}{12}\sum_{m=1}^{12}\left|forecast\ EPS_{i,m} - actual\ EPS_{i,m}\right| / P_{i,m-1} \tag{1}$$

Where

- $AbsFE_{i,t}$ is the annual absolute forecast error for firm i during year t,
- $P_{i,m-1}$ is the stock close price for firm i in month $m-1$,
- $forecast\ EPS_{i,m}$ is the mean forecast EPS in month m,
- $actual\ EPS_{i,m}$ is the actual EPS corresponding to the forecast end of $forecast\ EPS_{i,m}$.

Table 1
Summary statistics.

	N	Mean	Median	SD	Skewness	P25	P75
$AbsFE_t$	19,941	1.903	0.618	4.405	6.509	0.249	1.650
$Treat \times Post_t$	19,941	0.007	0.000	0.082	12.076	0.000	0.000
$InstOwnership_{t-1}$	19,941	0.728	0.804	0.301	9.950	0.603	0.920
$Loss_{t-1}$	19,941	0.254	0.000	0.435	1.132	0.000	1.000
$EarnVolatility_{t-1}$	19,941	2.305	0.678	50.286	47.590	0.381	1.265
$DebtAssets_{t-1}$	19,941	0.218	0.185	0.190	0.783	0.049	0.343
$Assets_{t-1}$	19,941	17 470.435	1800.779	109 998.614	16.679	486.842	6566.890
Age_{t-1}	19,941	23.089	18.833	18.499	1.495	9.148	30.496
$Turn_{t-1}$	19,941	2.045	1.528	2.713	23.789	0.984	2.401
BM_{t-1}	19,941	0.597	0.483	0.536	4.992	0.260	0.792
$NumAnalysts_{t-1}$	19,941	11.583	8.833	8.943	1.382	5.000	16.000
$TimeForecast_{t-1}$	19,941	217.798	217.416	23.127	2.986	204.009	231.075
$IndAbsFE_{t-1}$	19,941	16.503	1.590	468.701	49.705	0.668	4.150
$IndConcentration_{t-1}$	19,941	0.367	0.267	0.301	0.956	0.151	0.521

3.2.2. Measure of blockchain adoption

In line with the staggered DiD methodology, we designate our variable $Treat$ to signify whether a firm has adopted blockchain technology in its operations. We focus on a six-year period: three years before and after a firm decides to implement this technology, excluding the year in which the adoption was announced. Hence, our main variable of interest, $Treat\times Post$, is set to one for treatment firms in the three years following their announcement to adopt blockchain technology and zero otherwise.

3.3. Summary statistics

Table 1 reports the summary statistics for our sample. We unlog the value of logged variables in Table 1 for ease of interpretation. All control variables are lagged by one year to avoid looking ahead bias. Table A.1 provides detailed definitions of these variables. The values for $AbsFE$, $InstOwnership$, and $IndAbsFE$ are given as percentages. The unit of $Assets$ is specified as million dollars. On average, the individual forecasts in our sample are approximately 217.793 days before the announcement date of the actual EPS. The mean number of unique analysts covering a firm during one year is 11.583.

3.4. Empirical model

We employ a Difference-in-Differences model to examine the impact of adopting blockchain technology on analyst forecast accuracy. This widely used approach allows us to estimate the change in accuracy before and after a firm adopts blockchain technology. Using the absolute value of the error as a reverse proxy for accuracy, we estimate the following specification for firm i and year t:

$$AbsFE_{i,t} = \beta_0 + \beta_1 Treat \times Post_{i,t} + \beta_2 Controls_{i,t-1} + \mu_i + \gamma_t + \varepsilon_{i,t} \tag{2}$$

where $Controls$ include $InstOwnership$, $Loss$, $EarnVolatility$, $DebtAssets$, $Assets$, Age, $Turn$, BM, $NumAnalysts$, $TimeForecasts$, $IndAbsFE$, and $IndConcentration$. μ_i and γ_t stand for firm and year fixed effects, respectively. Including the two fixed effects removes the $Treat_i$ and $Post_t$ terms present in the traditional DiD model (Baker et al., 2022). Please refer to Table A.1 for the detailed definitions of these variables. Standard errors are clustered at the firm level to reduce the serial correlation of the error terms within a given firm.

4. Results

4.1. Main results

We examine the impact of a firm's adoption of blockchain technology on the accuracy of analysts' forecasts covering that firm. Table 2 reports the results of the DiD analysis to test whether the analyst forecast accuracy is improved after the firms invested in blockchain technology in their operations. We gradually add firm-level, analyst-level, and industry-level control variables to the model. The coefficients of $Treat \times Post$ are all negative and statistically significant across all four columns of Table 2. This suggests that the adoption of blockchain technology can reduce analyst forecast errors and thus improve analyst forecast accuracy. Specifically, the coefficient of $Treat \times Post$ in column (4) is −0.461. This implies that after a firm adopts blockchain, $AbsFE$ is reduced by approximately 24.22% of its mean (1.903).

Table 2
Impact of the blockchain adoption on analyst forecast error.

	(1) $AbsFE_t$	(2) $AbsFE_t$	(3) $AbsFE_t$	(4) $AbsFE_t$
$Treat \times Post_t$	−0.572***	−0.431**	−0.432**	−0.461***
	(−4.26)	(−2.52)	(−2.53)	(−2.73)
$InstOwnership_{t-1}$		−1.187***	−1.171***	−1.166***
		(−4.52)	(−4.42)	(−4.43)
$Loss_{t-1}$		0.714***	0.697***	0.692***
		(5.37)	(5.23)	(5.20)
$EarnVolatility_{t-1}$		−0.001	−0.001	−0.001**
		(−1.61)	(−1.64)	(−2.32)
$DebtAssets_{t-1}$		4.612***	4.566***	4.560***
		(8.71)	(8.66)	(8.65)
$Assets_{t-1}$		−1.081***	−1.030***	−1.032***
		(−6.82)	(−6.46)	(−6.49)
Age_{t-1}		0.652**	0.626**	0.636**
		(2.12)	(2.04)	(2.07)
$Turn_{t-1}$		−0.200	−0.173	−0.175
		(−0.96)	(−0.83)	(−0.85)
BM_{t-1}		1.434***	1.410***	1.409***
		(12.63)	(12.38)	(12.38)
$NumAnalysts_{t-1}$			−0.139	−0.132
			(−0.75)	(−0.71)
$TimeForecast_{t-1}$			1.089***	1.090***
			(2.94)	(2.95)
$IndAbsFE_{t-1}$				0.000
				(0.26)
$IndConcentration_{t-1}$				0.669**
				(2.35)
Constant	1.907***	9.261***	3.370	3.093
	(2116.93)	(7.30)	(1.39)	(1.28)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	19,941	19,941	19,941	19,941
Adjusted R^2	0.377	0.411	0.411	0.412

Note: t-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3
DiD results using matched sample.

	(1) $AbsFE_t$	(2) $AbsFE_t$	(3) $AbsFE_t$	(4) $AbsFE_t$	(5) $AbsFE_t$
$Treat \times Post_t$	−0.480*	−0.640**	−0.477**	−0.471**	−0.488**
	(−1.72)	(−2.46)	(−2.07)	(−2.19)	(−2.38)
Firm controls	Yes	Yes	Yes	Yes	Yes
Analyst controls	Yes	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N	914	1,407	1,839	2,222	2,576
Adjusted R^2	0.379	0.315	0.278	0.306	0.349
Matching method	PSM 1:1	PSM 1:2	PSM 1:3	PSM 1:4	PSM 1:5

Note: t-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

4.2. Propensity score matching estimates

We take a propensity score matching method to reconstruct our sample and alleviate endogeneity. This matching procedure consists of two steps. First, we conduct logit regressions for each cross-section before the adoption event. These regressions use all the control variables in our sample and are carried out on the dummy variable $Treat$. The aim is to obtain the probability (PSCORE) of a firm choosing to adopt blockchain in the year before the adoption year of treatment firms. Second, we match the treated and untreated firms using the nearest-neighbor method by requiring the maximum PSCORE difference between them less than 0.01. We rerun the DiD model using the matched sample. Table 3 reports the results. All the coefficients of $Treat \times Post$ are significantly negative in Table 3, which is consistent with Table 2. This indicates that the adoption of blockchain improves analyst forecast accuracy is robust.

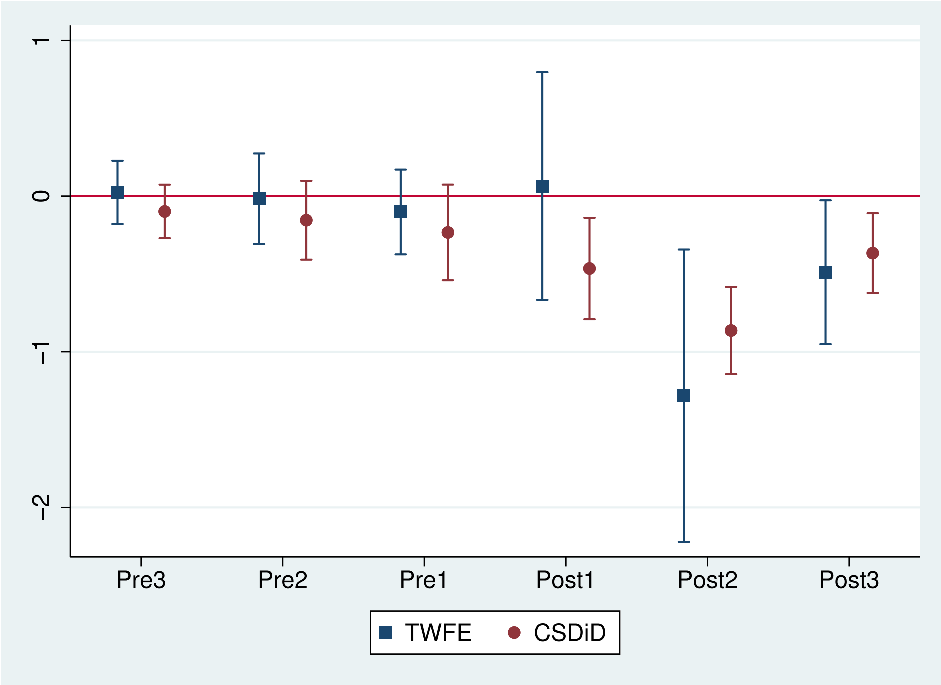

Fig. 2. Dynamic average treatment effect.

4.3. Time trends

The DiD method is built on the parallel-trends assumption. To ensure robustness, we examine the time trends using both the two-way fixed effects model (TWFE) and the CSDiD model proposed by Callaway and Sant'Anna (2021). Fig. 2 provides the time trends estimated by the two methods. The 90% confidence intervals are also plotted for each point. We find a marked drop in analyst forecast errors after the treated year, but there are no significant changes for the years before the treated year. This implies that our sample satisfies the parallel-trends assumption.

5. Potential explanation

This section explores the potential mechanisms underlying the observed improvement in analyst forecast accuracy following firms' adoption of blockchain technology. We consider three primary factors: institutional ownership ($InstOwnership_t$), earnings volatility ($EarnVolatility_t$), and analyst coverage ($NumAnalysts_t$). While the theoretical basis for the analyst coverage has been previously discussed, this analysis will concentrate on the theoretical foundations of the other two factors.

Regarding $InstOwnership_t$, Autore et al. (2021) provides evidence that stock returns tend to increase when firms implement blockchain technology. This rise in stock returns may attract institutional investors, leading them to increase their holdings in these firms. Firms with higher levels of institutional ownership are generally more likely to issue forecasts more frequently, with these forecasts being not only more accurate and precise but also less optimistic (Karamanou and Vafeas, 2005; Baik and Jiang, 2006; Ajinkya et al., 2005). This increased frequency and quality of forecasts can reduce the information asymmetry between firms and analysts and lower the information costs for analysts, thereby enhancing the accuracy of their forecasts.

In terms of $EarnVolatility_t$, blockchain technology facilitates more consistent and reliable transaction recording, which likely contributes to greater earnings stability (Mathiyazhagan et al., 2022; Paul et al., 2022). Reduced earnings volatility typically signifies lower uncertainty regarding future financial outcomes (Jayaraman, 2008; Cao and Narayanamoorthy, 2012; Lennox and Park, 2006). As a result, improved earnings predictability simplifies the forecasting process, making it less complex and more precise. Consequently, this enhanced predictability facilitates better forecast accuracy among analysts.

We utilize models similar to those used in our main results to investigate this. Our findings, presented in columns (1) to (3) of Table 4, reveal that among the factors studied, blockchain adoption seems to affect only the analyst coverage ($NumAnalysts_t$), with no discernable impact on the remaining two components under consideration. This suggests a potential pathway through which blockchain adoption might influence $AbsFE_t$, i.e., via $NumAnalysts_t$. For this reason, we additionally include $NumAnalysts_t$ in the regression on $AbsFE_t$ to explore the mediating effect of $NumAnalysts_t$ in column (4) of Table 4. The magnitude of $Treat \times Post_t$ is less than that in column (4) of Table 2. This suggests that $NumAnalysts_t$ partially mediates between $Treat \times Post_t$ and $AbsFE_t$.

Table 4
Potential explanation.

	(1) $InstOwnership_t$	(2) $EarnVolatility_t$	(3) $NumAnalysts_t$	(4) $AbsFE_t$
$Treat \times Post_t$	0.024	−0.070	0.028*	−0.427**
	(1.35)	(−0.31)	(1.71)	(−2.55)
$NumAnalysts_t$				−1.194***
				(−5.74)
Firm controls	Yes	Yes	Yes	Yes
Analyst controls	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	19,941	19,941	19,941	19,941
Adjusted R^2	0.855	0.979	0.954	0.413

Note: t-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

6. Cross-sectional analyses

So far, our study has provided substantial empirical evidence illustrating the impact of blockchain technology on analyst forecast accuracy. To build on these findings, we now turn our attention to examining potential variances across different sections of the dataset, which is a process known as cross-sectional analysis. Such scrutiny promises to shed light on the specific mechanisms driving the results observed. In pursuit of this deeper insight, we have classified the firms under study into two distinct categories based on their reported objectives for adopting blockchain technology. On the one hand, we have firms in the "Finance" group, which utilize blockchain primarily for financial operations. For instance, AKAMAI is a notable example within this category, as it has harnessed blockchain to execute up to a million transactions per second—showcasing a clear financial application. Conversely, the "Management" group comprises firms that integrate blockchain to enhance operational transparency and foster trust, thereby supporting management processes. KIMBERLY-CLARK exemplifies this group through its deployment of blockchain to increase the accountability of its advertising supply chain. By analyzing these groups separately, we aim to determine whether the benefits of blockchain adoption manifest differently depending on the firm's focus. This bifurcation allows for a nuanced understanding of blockchain's diverse utility in business contexts.

We present our findings in Table 5, focusing on the cross-sectional analysis. The coefficient for $Treat \times Post$ is significantly lower in column (1) compared to column (2), suggesting that blockchain technology's impact on improving the accuracy of analysts' forecasts is stronger when used to address financial problems. Meanwhile, this coefficient shows a significant increase from column (4) to column (3), highlighting analysts' growing attention to blockchain's financial applications.

The regression results indicate that the improvement in analyst forecast accuracy is significantly more pronounced for firms adopting blockchain for "Finance" purposes than those using it for "Management" purposes. This can also be attributed to the differential impact on analyst coverage, with blockchain adoption in "Finance" groups attracting more analyst attention and thereby improving forecast accuracy. Notably, while blockchain adoption for "Management" purposes does not significantly increase analyst coverage, a slight improvement in forecast accuracy is still observed. This suggests that factors other than analyst coverage also enhance forecast accuracy. Analyst coverage is an important but not exclusive channel through which blockchain adoption improves forecast accuracy, which aligns with the conclusions drawn in Table 4.

The observed heterogeneity in post-adoption analyst coverage between "Finance" and "Management" may be attributed to each group's disparate internal efficiency gains. Blockchain technology in financial operations can significantly improve transaction processing efficiency, cost reductions, and error minimization (Cocco et al., 2017; Ali et al., 2020). These tangible efficiency gains are critical metrics that financial analysts monitor closely, as they directly affect a firm's financial performance and profitability. Consequently, analysts are more likely to increase their coverage of firms demonstrating clear financial benefits from blockchain adoption. On the other hand, the efficiency improvements in management processes, while beneficial, may not translate directly or immediately into financial performance metrics, leading to a smaller rise in analyst coverage.

7. Additional analyses

7.1. Placebo test

To substantiate the robustness of our findings, we implement a placebo test designed to rule out the possibility that the observed effects are merely artifacts of arbitrary fluctuations. In this exercise, we replicate our principal regression analysis 1000 times, substituting the actual treatment firms and treatment years with randomly selected equivalents to construct a pseudo-treated group and the corresponding pseudo-control group comprised of the remaining entities. This procedure yields 1000 DiD estimates.

Upon careful analysis, we compute the average of these coefficients relating to the interaction of $Treat \times Post$ and evaluate the statistical significance using the t-statistics. The resulting mean coefficient is marginally positive at 0.0022, with a t-statistic of 0.272. Meanwhile, the two-sided p-value of the placebo test stands at 0.076. To visually assess the distribution of these placebo DiD

Table 5
The effect of blockchain adoption purpose.

	(1) $AbsFE_t$	(2) $AbsFE_t$	(3) $NumAnalysts_t$	(4) $NumAnalysts_t$
$Treat \times Post_t$	−0.667***	−0.373*	0.043**	0.022
	(−2.66)	(−1.80)	(2.11)	(1.01)
Firm controls	Yes	Yes	Yes	Yes
Analyst controls	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	19,646	19,819	19,646	19,819
Adjusted R^2	0.411	0.412	0.953	0.953
Purpose	Finance	Management	Finance	Management
Coff. Diff: (Finance-Management)	−0.294***(p-value = 0.00)		0.022***(p-value = 0.00)	

Note: *t*-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

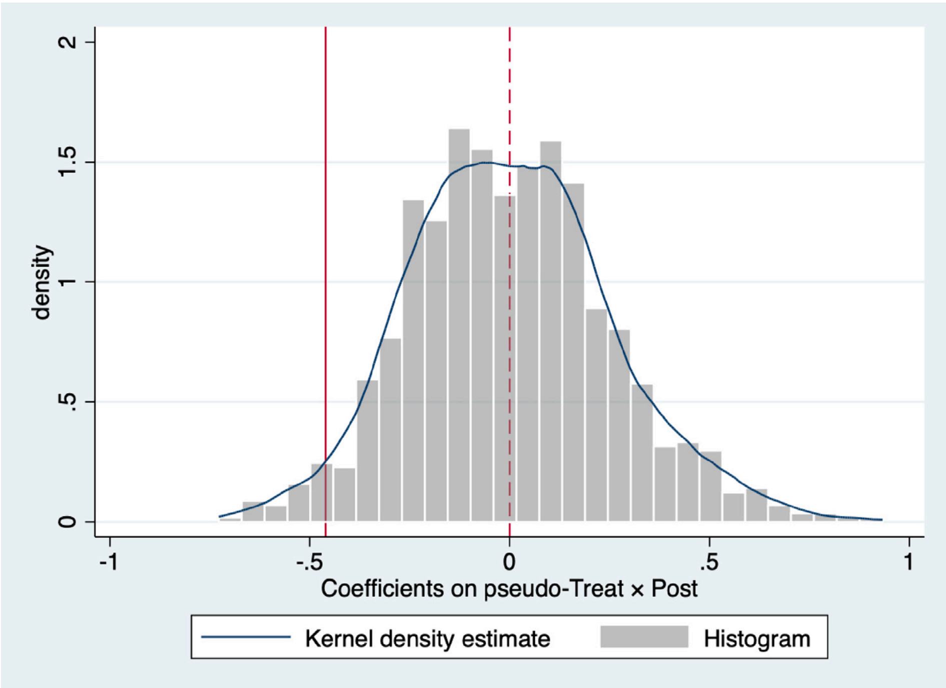

Fig. 3. Distribution of placebo effects.

estimates, we refer to Fig. 3 , where the average placebo effect is depicted by a vertical dashed line near the zero mark, distinctly separated from the primary DiD estimate displayed as a vertical solid line.

The divergence between the placebo outcomes and the original DiD estimates reinforces the integrity of our results, bolstering our conclusion that the enhancement in analyst forecast accuracy observed in our study is not attributable to random chance or spurious relationships but rather reflects a genuine economic phenomenon. Thus, the placebo tests lend credence to our assertion that our findings accurately capture the effects under investigation, free from underlying random biases.

7.2. Additional controls

To strengthen the robustness of our analyses regarding analyst forecast accuracy, we introduce additional control variables that hold potential influence. We commence with the firm's 8-K filing frequency, which serves as a proxy for the traditional disclosure channel. This addition aims to isolate the effects of traditional disclosure channels from those potentially introduced by blockchain technology, thereby focusing on the latter's unique impact on forecast accuracy.

Furthermore, we consider the R&D intensity of the firms. The opacity inherent in R&D activities is acknowledged as a factor exacerbating informational asymmetry (Brown and Martinsson, 2019). Controlling for this aspect enables us to mitigate one of the potential sources of informational asymmetry.

Table 6
Regression results with additional control variables.

	(1) $AbsFE_t$	(2) $AbsFE_t$	(3) $AbsFE_t$	(4) $AbsFE_t$	(5) $AbsFE_t$
$Treat \times Post_t$	−0.485***	−0.460***	−0.448***	−0.465***	−0.469***
	(−2.90)	(−2.73)	(−2.70)	(−2.58)	(−2.62)
$Num8\text{-}K_{t-1}$	−0.164				−0.097
	(−1.16)				(−0.68)
$R\&DIntensity_{t-1}$		0.001			−0.000
		(0.46)			(−0.80)
$Disp_{t-1}$			0.090***		−0.013
			(3.42)		(−0.22)
$DigitAttention_{t-1}$				−0.741***	−0.544*
				(−3.32)	(−1.94)
Firm controls	Yes	Yes	Yes	Yes	Yes
Analyst controls	Yes	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N	15,131	19,941	19,941	17,827	13,614
Adjusted R^2	0.407	0.412	0.413	0.408	0.389

Note: t-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Regression results with industry fixed effect.

	(1) $AbsFE_t$	(2) $AbsFE_t$	(3) $AbsFE_t$	(4) $AbsFE_t$
$Treat \times Post_t$	−0.525***	−0.452***	−0.456***	−0.497***
	(−3.85)	(−2.67)	(−2.68)	(−2.98)
Firm controls	No	Yes	Yes	Yes
Analyst controls	No	No	Yes	Yes
Industry controls	No	No	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	19,941	19,941	19,941	19,941
Adjusted R^2	0.368	0.403	0.403	0.403

Note: t-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Next, we incorporate analyst forecast dispersion $Disp_{t-1}$. We do not control for $Disp_{t-1}$ in our main model. Because there may be some overlap between $EarnVolatility_{t-1}$ and $Disp_{t-1}$ in representing forecast difficulty. We supplement our control for $Disp_{t-1}$ here to exclude its unique effects apart from the forecast difficulty.

Finally, we examine the impact of other digital technologies. Firms that adopt blockchain technology often simultaneously adopt other digital technologies, creating a complex interplay that could confound our analysis. To mitigate this concern, we introduce a novel variable, $DigitAttention_{t-1}$, which quantifies the extent of attention that financial analysts accord to digital technologies other than blockchain. According to Al-Ali et al. (2020) and Pataci et al. (2022), we categorize pertinent digital technologies as AI, cloud computing, IoT, virtual reality, augmented reality, robotics, analytics, mobile technology, social media, and 3D printing. These technologies are increasingly integral to modern business ecosystems, and thus, their collective influence must be disentangled from that of blockchain alone. To operationalize $DigitAttention_{t-1}$, we employ the Linguistic Inquiry and Word Count (LIWC) methodology, constructing a dictionary specific to these technologies based on the keyword terms identified in Al-Ali et al. (2020). Utilizing the textual corpus derived from analysts' questions during firms' earnings conference calls, we systematically analyze this text input to calculate the relative frequency of these keywords within each document. This analytical process enables us to generate a weighted measure of keyword prevalence, which serves as a robust proxy variable for quantifying analysts' attention toward these technologies using the LIWC-22 framework. Specifically, $DigitAttention_{t-1}$ is computed as the annual average of the keyword prevalence observed in each earnings conference call.

Table 6 shows the regression results after including the additional controls. Our conclusion is robust as the main variable $Treat \times Post_t$ remains significantly negative in all columns. Meanwhile, the $DigitAttention_{t-1}$ coefficient is significantly negative, indicating that the construction process for this variable is valid.

7.3. Industry fixed effect

We also investigate how varying industries influence blockchain adoption's effectiveness alongside our expanded set of control variables. We recognize that certain industries, such as high-tech and finance, are predisposed to embrace blockchain technology, potentially leading to endogenous biases. To mitigate this, we have included an industry-specific fixed effect in our primary model,

Table 8
Impact of the blockchain adoption on analyst forecast dispersion.

	(1) $Disp_t$	(2) $Disp_t$	(3) $Disp_t$	(4) $Disp_t$
$Treat \times Post_t$	−0.221***	−0.175***	−0.177***	−0.189***
	(−3.89)	(−2.73)	(−2.76)	(−2.91)
Firm controls	No	Yes	Yes	Yes
Analyst controls	No	No	Yes	Yes
Industry controls	No	No	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	19,941	19,941	19,941	19,941
Adjusted R^2	0.584	0.601	0.601	0.602

Note: t-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

aiming to isolate the influence of industry characteristics. Refer to Table 7 for detailed results. Our findings indicate a consistent trend; the inclusion of an industry-fixed effect does not alter the direction or statistical significance of the interaction term's coefficients. This consistency reinforces the robustness of our results, suggesting that the effects of blockchain adoption on our variables of interest hold true regardless of industry variations.

7.4. Impact on analyst forecast dispersion

To better understand how blockchain adoption affects the quality of analysts' forecasts, we explored changes in forecast dispersion following firms' integration of blockchain technology. Analyst forecast dispersion, much like accuracy, hinges on signaling theory (Spence, 1973). When firms announce the adoption of blockchain, they capture the attention of market analysts, prompting deeper research into these firms and their operations. This increased scrutiny tends to reduce information asymmetry between analysts and firms. Consequently, we anticipate a decrease in forecast dispersion as analysts gain a more uniform understanding of post-blockchain adoption.

Following Allee et al. (2023), we define analyst forecast dispersion as the average monthly standard deviation of EPS forecasts adjusted for the corresponding stock price. To examine the impact on analyst forecast dispersion, we employ models paralleling our core analyses. Table 8 displays the outcomes, revealing how analyst forecast dispersion adjusts following blockchain adoption.

In alignment with our prior main results, all the coefficients for the interaction term $Treat \times Post$ across the four columns of Table 8 are significantly negative. This suggests that the improvement in forecast accuracy previously observed extends to forecast dispersion; firms that implement blockchain technology see a refinement in both metrics. These findings bolster the theoretical framework underpinning our primary conclusions.

8. Conclusion

This research systematically examines the nexus between blockchain adoption within firms and the subsequent augmentation of earnings forecast accuracy by analysts. Anchored on signaling theory, this paper posits that blockchain technology acts as a signal to the market, resulting in heightened analyst engagement. A series of empirical studies focused on public announcements regarding blockchain adoption have substantiated that such technological embracement tangibly refines the accuracy of analysts' earnings forecasts. The robustness of these findings is methodically corroborated through an array of sample-matching procedures and control variables.

The implications of our study are twofold. Theoretically, it extends signaling theory into the financial technology domain, proposing that blockchain can serve as a credible signal of a firm's commitment to transparency and innovation, thereby altering the behavior of market intermediaries such as analysts. This adds a crucial layer to the existing literature by connecting technological adoption with informational outcomes in capital markets.

Practically, our findings suggest that firms may leverage blockchain technology not only for internal operational enhancements but also as a strategic tool to improve the firm's external information environment. By doing so, they could potentially lower the cost of capital through improved analyst coverage and forecast accuracy, which in turn may influence investment decisions and market perceptions. Furthermore, investors will likely increase their trust in analysts' reports due to improved forecast accuracy. At the same time, regulators might consider the role of blockchain as a facilitator of market efficiency through its positive influence on the information ecosystem.

Nonetheless, this work predominantly sheds light on analyst-related consequences of blockchain adoption. Future research could consider other quantifiable aspects of the information environment, such as the information density of disclosures, retail investors' attention and earnings management. Each of these components can play a substantive role in defining a firm's overall narrative and its relationship with the investing public.

Ethical approval

The conducted research is not related to either human or animals use.

Table A.1
Variable definitions.

Variables	Definitions
$AbsFE_t$	Average of the monthly absolute forecast error scaled by the stock price.
$Treat \times Post_t$	An indicator variable equal to one for firms adopting blockchain during the three years after the announcement year and zero otherwise.
Firm controls	
$InstOwnership_{t-1}$	Institutional ownership.
$Loss_{t-1}$	An indicator variable equal to one if a firm's net income is negative.
$EarnVolatility_{t-1}$	The standard deviation of actual EPS computed using a rolling window of ten years (minimum years of three).
$DebtAssets_{t-1}$	The ratio of total debt to total assets.
$Assets_{t-1}$	Natural logarithm of total assets.
Age_{t-1}	Natural logarithm of the number of years since firm IPO.
$Turn_{t-1}$	Natural logarithm of the average of the monthly turnover ratio, computed using shares traded divided by shares outstanding.
BM_{t-1}	Book-to-market ratio computed following Fama and French (1992).
Analyst controls	
$NumAnalysts_{t-1}$	Natural logarithm of the analyst coverage computed using the number of unique analysts.
$TimeForecast_{t-1}$	Natural logarithm of the average days from each forecast to the earnings announcement date.
Industry controls	
$IndAbsFE_{t-1}$	Average of the $AbsFE$ within an industry (4 digit SIC).
$IndConcentration_{t-1}$	Herfindahl–Hirschman Index computed using the revenue within an industry.
Other controls	
$Num8\text{-}K_{t-1}$	The disclosure frequency of 8-K files in a year.
$R\&DIntensity_{t-1}$	R&D intensity defined by Beyhaghi et al. (2023).
$Disp_{t-1}$	Analyst forecast dispersion computed following Allee et al. (2023).
$DigitAttention_{t-1}$	Analyst attention on digital technologies other than blockchain.

Table A.2
The distribution of blockchain adoption.

Year	(1) Adoption firms	(2) Finance	(3) Management
2015	4	3	1
2016	6	3	3
2017	23	8	15
2018	70	16	55
2019	43	7	35
2020	34	5	29
2021	47	23	26
total	227	65	164

Note: There are two firms whose purposes belong to both finance and management groups. That is why the sum of the total number of finance and management groups is not equal to the total adoption firms.

CRediT authorship contribution statement

Fenghua Wang: Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Qiang Ye:** Supervision, Resources, Project administration, Funding acquisition, Data curation. **Jiang Li:** Writing – original draft, Validation, Data curation. **Wen Shi:** Writing – review & editing, Validation, Data curation.

Declaration 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.

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Appendix

See Table A.1 and Table A.2.

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