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Derivatives use and analysts' forecasts: new evidence on the mechanisms from China

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ABSTRACT

We examine whether and how corporate derivative use affects analysts' earnings forecast accuracy based on Chinese A-share listed firms during 2010 and 2020. We find that derivative users experience less accurate forecasts, compared to non-users. Such effects are more pronounced for SOEs and firms without risk exposure. Mechanism tests suggest that the negative effects of derivatives on analysts' forecasts are primarily due to ineffective hedging, high complexity and insufficient disclosure. Further analysis indicates that the implementation of *Hedging Accounting Standards*, the provision of management forecasts, and analysts' capabilities help to mitigate the adverse impact of derivative use on analysts' forecasts.

1. Introduction

The influence of corporate derivatives on capital market participants has been a topic of enduring debate. On one hand, derivatives can shield firms from macroeconomic risks, reducing uncertainty and stabilizing firm performance (Bartram, 2017; Guo et al., 2021; Zhang, 2009). In this view, derivatives are risk management tools that have positive impacts on capital market participants by enhancing transparency and predictability (Kim et al., 2021; Ranasinghe et al., 2023). On the other hand, critics argue that derivatives may negatively influence capital market participants due to their complexity and insufficient information disclosure, which increase the difficulty for external stakeholders to comprehend the associated risks and implications (Bratten et al., 2016; Campbell et al., 2015, 2019, 2023; Makar et al., 2013).

To address these conflicting perspectives, we examine whether and how derivative use influences the accuracy of analysts' earnings forecasts in China. Consistent with this literature, we find that derivative users experience less accurate analysts' forecasts, aligning with prior studies (Chang et al., 2016; Su et al., 2022). We find that the effects of derivatives on analysts' forecasts are more significant for SOEs and firms without risk exposure. Moreover, we investigate how derivative use influences analysts' forecast accuracy. Specifically, we explore the heterogeneity in corporate derivative use, focusing on hedging effectiveness, complexity, and disclosure quality. In addition, the Chinese institutional environment allows us to evaluate the moderating roles of improvements in accounting standards, information sources from management, and variations in analysts' competencies. Our study extends the existing literature (Campbell et al., 2023; Chang et al., 2016) by offering new insights into how derivative use affects analysts' forecast accuracy within the context of an emerging market.

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With a sample of Chinese A-shared listed firms from 2010 to 2020, we find that derivative use decreases the accuracy of analysts' forecasts. Our findings remain robust to the Heckman two-stage model, propensity score matching (PSM), alternative variable measurements, model specifications, and clustering of standard errors by firm and year. We then divide the sample based on ownership and risk exposure. The results demonstrate that the negative influence of derivatives on analysts' forecasts are more pronounced for SOEs and firms without risk exposure.

Next, we examine the mechanisms through which derivative use affects analysts' forecasts. First, prior studies suggest that uncertainty makes it difficult for analysts to make forecasts, leading to reduced forecast accuracy (Amiram et al., 2018; Manconi et al., 2017). While derivatives are essential tools for corporate risk management, their misuse, such as ineffective hedging, can amplify cash flow and earnings volatility. This heightened volatility creates additional challenges for analysts, thereby diminishing forecast accuracy. We term this the *hedging mechanism* and find evidence that ineffective hedging of derivative use negatively impacts the accuracy of analyst forecasts.

Second, we examine whether the complexity of derivatives undermines the accuracy of analysts' forecasts, a phenomenon we label the *complexity mechanism*. The complexity associated with derivatives has been widely discussed in previous literature (Campbell et al., 2015; Chang et al., 2016). Peterson (2012) points out that accounting complexity significantly hinders the interpretation and understanding of corporate financial statements, which serve as analysts' primary information sources. The reporting intricacies of derivatives can thus obscure financial information and impair analysts' ability to make precise predictions. To test our hypothesis, we employ three proxies for the complexity of derivatives and find a negative association between derivative complexity and forecast accuracy.

Lastly, we explore whether insufficient disclosure of derivatives negatively affects analysts' forecasts. As information intermediaries, analysts heavily rely on disclosed data to make predictions. The existing literature suggests that insufficient information obstructs analysts' ability to produce high-quality predictions, thereby reducing the accuracy of analysts' forecasts (Huang et al., 2022; Li et al., 2020). The disclosure of derivative transactions often suffers from deficiencies, making it challenging to develop a complete understanding of firm-specific derivative activities (Shao et al., 2019). Therefore, we propose that insufficient disclosure of derivative usage reduces analysts' forecast accuracy, a process we define as the *disclosure mechanism*. We manually collect data on derivative disclosure from annual reports and find a positive relationship between sufficient disclosure and the accuracy of analysts' forecasts.

In further analysis, we explore the conditions under which the negative influence of derivative use on analysts' forecast accuracy can be mitigated. The existing literature highlights that regulatory measures enhance derivative disclosure (Campbell et al., 2019, 2023). Leveraging the implementation of the *Revised Accounting Standards for Enterprises 24 Hedging Accounting* (CAS 24 *Hedging Accounting*) in 2019, we examine whether this regulation assists analysts in understanding corporate derivative use and improving forecast accuracy. Using a difference-in-differences (DiD) model, we find that the implication of CAS 24 *Hedging Accounting* alleviates the adverse effects of derivative use on forecast accuracy, suggesting that regulatory improvements enhance analysts' abilities to make accurate forecasts.

We then assess the role of management forecasts in moderating the relationship between derivative use and analysts' forecasts. Compared to analysts, management has privileged access to private information about a firm's risk exposures (Campbell et al., 2023) and can convey this information effectively through their earnings forecasts (Lang & Lundholm, 1996). Therefore, we examine the impact of derivative use on analysts' forecasts before and after the issuance of management forecasts. We find that the negative impact of derivative use on forecast accuracy is significant before the issuance of management forecasts but disappears after their issuance.

Finally, we explore whether analysts' capabilities can alleviate the challenges posed by derivative use. Specifically, we examine the moderating effects of industry expertise and forecasting experience. Our findings reveal that the negative influence of derivative use on analysts' forecasts persists only when analysts lack industry expertise or have limited experience. This is consistent with prior studies suggesting that more skilled analysts are better equipped to process complex information and produce higher-quality forecasts (Chang et al., 2016; Clement, 1999; Plumlee, 2003). These results underscore the importance of analysts' capabilities in addressing the complexities introduced by corporate derivative use.

Our findings make several contributions. First, we extend the research of derivative use on analysts' forecasts to an emerging market context. While previous studies have explored the consequences of corporate derivative use on capital market participants (Campbell et al., 2015, 2019; Huang et al., 2019; Ranasinghe et al., 2023), most focus on developed markets, particularly the U.S. Our study contributes to this literature by providing evidence from China, a representative emerging market with unique institutional characteristics, expanding upon prior findings from developed markets (Campbell et al., 2015; Chang et al., 2016; Manconi et al., 2017). Moreover, unlike Antônio et al. (2019), which find that derivatives enhance information transparency and reduce estimate bias for analysts in the Brazilian market, our research reveals that in China, derivative usage poses additional challenges for analysts. Moreover, China's distinctive regulatory framework and market development provide insights for future studies in other regions with varying institutional environments.

Second, we explore the mechanisms through which derivative use influence analysts' forecasts. While prior studies, such as Chang et al. (2016) and Campbell et al. (2015), have acknowledged the association between derivative use and analysts' forecast accuracy, they have not thoroughly explored the underlying mechanisms. Leveraging the significant heterogeneity in corporate derivative use among our sample firms, we confirm the negative association between derivative use and forecast accuracy and advance the literature by interpreting this relationship through three distinct mechanisms: hedging effectiveness, derivative complexity and information disclosure. This nuanced understanding complements and extends the frameworks proposed by Chang et al. (2016) and Campbell et al. (2015), offering a more comprehensive explanation of how derivative use affects analysts' behaviors.

Third, we discuss actionable pathways to mitigate the negative effects of derivative use on analysts' forecasts, emphasizing the role of government regulations, management forecasts, and analysts' characteristics. While the literature increasingly examines the impact of regulations and disclosure (e.g., Campbell et al., 2019; Zhang, 2009), we focus on the CAS 24 *Hedging*, implemented in China in 2019. Unlike prior studies that primarily focus on developed markets, our research provides complementary evidence on how derivative regulations in an emerging market setting can address deficiencies in disclosure and improve forecast accuracy, contributing to a broader understanding of the regulatory landscape.

Moreover, we quantify the disclosure quality of derivative use in annual reports, focusing on the inclusion of derivatives positions, fair values, and derivative-related losses and gains. Our findings underscore the importance of comprehensive disclosure in improving analysts' forecast accuracy. This insight is particularly relevant for regulators and practitioners seeking to enhance transparency and reduce information asymmetry. While Campbell et al. (2015) and Change et al. (2016) touch upon the complexities and challenges associated with derivative disclosure, our study not only validates these findings in a different market but also highlights the measurable impact of specific disclosure practices on analysts' performance, contributing actionable insights to the existing body of research.

By integrating these perspectives, our study not only bridges the gap in understanding the impact of derivatives in emerging markets but also provides a robust foundation for further inquiry into the mechanisms and regulatory interventions that can enhance market transparency and efficiency.

The remainder of this paper is organized as follows. Section 2 reviews existing literature and develops our hypotheses. Section 3 describes the sample and research design. Section 4 presents the empirical results and robustness tests. Section 5 discusses the mechanisms. Section 6 presents further analyses. Section 7 concludes the paper.

2. Institutional background, literature review and hypothesis development

2.1. Institutional background

The institutional framework governing derivatives in China significantly differs from that of the U.S. due to the disparities in regulatory oversight and market development. These differences make China a distinctive and valuable setting for examining the influence of derivatives on analysts' forecast accuracy.

To begin with, while U.S. firms operate under stringent and detailed regulations, Chinese firms have more flexibility in disclosing derivative information. In the U.S., frameworks, such as the *Financial Accounting Standards Board (FASB) Accounting Standards Codification (ASC) Topic 815,* mandate the comprehensive reporting of derivative-related information, including positions, fair values, hedging effectiveness, and gains or losses. These regulations aim to minimize information asymmetry, with articulated guidelines that are straightforward to implement. In contrast, the regulatory landscape in China is less stringent. Although the CAS 24 *Hedging Accounting* introduced in 2017 represents a significant regulatory improvement, its enforcement and implementation vary across firms. Common issues, such as incomplete, vague or non-compliance, remain prevalent, indicating that China's regulatory landscape of derivative disclosure is less stringent than that in the U.S.

Second, while the derivative market in the U.S. is highly developed and liquid, the Chinese market remains relatively nascent. In China, many firms have limited experience with derivatives and the subprime crisis has left a lingering impression of the catastrophic risks associated with these instruments. As a result, Chinese firms tend to approach derivatives cautiously. This conservative approach often results in less derivative use, ineffective hedging practices and inadequate disclosure, undermining the intended risk management benefits. For instance, the proportion of derivative users is 19.7 % in China, which is well below the global average of 60.5 % (Bartram, 2019). Chinese firms often fail to provide detailed information on derivative positions, fair values, and related gains or losses, complicating the task for external stakeholders like analysts to accurately assess the impact of derivative use on financial outcomes.

These differences highlight the complexities of studying the effects of derivative use in the Chinese context. The unique regulatory and market environment in China not only influences the nature and outcomes of derivative activities but also underscores the importance of examining these dynamics within emerging markets, where institutional frameworks are still evolving.

2.2. Literature review

Analysts, as key participants in financial markets, serve dual roles as information users and providers. Extent literature has examined the factors influencing analysts' earnings forecast accuracy, which can be broadly categorized into three domains. First, the complexity of financial statements increases the challenges associated with understanding, interpreting and forecasting financial outcomes (Peterson, 2012; Wang et al., 2024). Greater task difficulty is associated with diminished predictive ability (Filzen & Peterson, 2015; Bradshaw et al., 2007). Second, attributes such as firm size, performance volatility, disclosure quality, the provision of management forecasts, and strategic behaviors significantly affect the accuracy of analysts' forecasts (Lang & Lundholm, 1996). Third, analysts' capabilities, as well as the breadth of their firm coverage, also play a critical role in shaping forecast accuracy (Clement, 1999; Hilary & Shen, 2013).

Early research on derivatives primarily focused on their motivations, determinants and impacts on firm value and risk management effectiveness (Campbell et al., 2023). In recent years, scholars' attention has shifted toward the implications of derivatives for external stakeholders, particularly analysts, predominantly in the context of developed markets. However, findings remain inconclusive. Derivatives are found to increase the complexity of financial statements, thereby reducing forecast accuracy and increasing dispersion. For instance, Chang et al. (2016) and Campbell et al. (2015) report significant adverse effects for U.S. firms. Ranasinghe et al. (2023) further corroborate these findings from an auditing perspective. Conversely, some studies highlight the potential of derivatives to enhance forecast accuracy. Batta et al. (2016) observe a significant reduction in forecast errors and dispersion following CDS trading. Manconi et al. (2017) suggest that derivative use erodes institutional investors' information advantages, particularly in short selling, thereby benefiting external stakeholders. Campbell et al. (2023) find that derivative usage can increase the frequency of management earnings forecasts. Additionally, Antônio et al. (2019) argue that the estimate bias is more pronounced for non-users, challenging the findings of Chang et al. (2016) and suggesting that analysts are capable of understanding derivative information.

Despite the rich body of literature on developed countries, research focusing on emerging economies remains limited. To address this gap, we examine the influence of corporate derivative use on analysts' earnings forecast accuracy in the context of Chinese A-shared listed firms from 2010 to 2020. Furthermore, we explore mechanisms and strategies to mitigate the adverse effects of derivative use on forecast accuracy, thereby attributing to the literature on financial reporting and market transparency in emerging markets.

2.3. Hypothesis development

Risk management is a primary reason why firms use derivatives. Derivatives are designed to help companies hedge macroeconomic risks such as interest rates, exchange rates, and commodity prices, thereby reducing cash flow volatility and operational risks (Ranasinghe et al., 2023). For example, Guo et al. (2021) find that derivative use reduces total risks by 8.23 % based on evidence from China. By mitigating the impact of macroeconomic factors beyond management's control (Bartram, 2019; Zhang, 2009), derivatives can decrease profit volatility (Bartram, 2019). As an essential risk management tool, derivatives signal that management is aware of and actively addressing risk exposures. What's more, derivatives can provide analysts with valuable information, facilitating more accurate predictions (Sarens & D'Onza, 2017). Thus, effective hedging can inform analysts and enhance forecast accuracy.

However, the benefits of derivatives are contingent on their effective use. Ineffective hedging, high complexity and insufficient disclosure can complicate analysts' forecasts and potentially reduce their accuracy.

First, hedging may fail to achieve its intended purpose due to the inherent riskiness (Chang et al., 2016). Non-financial firms, lacking specialization in managing macroeconomic risks (Bartram, 2017), might misuse derivatives due to insufficient knowledge and experience, potentially increasing rather than mitigating risks. In addition, the leverage inherent in derivatives can amplify risks, worsening outcomes for firms. Public concerns often arise due to the ambiguous boundary between hedging and speculation. For instance, Lins et al. (2011) find that nearly half of derivative users engage in selective hedging based on market judgment, which is inherently speculative. Such practices can expose firms to greater uncertainty, making it tricky for analysts to make accurate forecasts. This phenomenon reflects the *ineffective hedging mechanism*.

Second, the complexity of derivatives adds another layer of difficulty for analysts. Financial instruments often involve intricate contracts and trading structures, making them challenging to regulate and understand (Campbell et al., 2019; Chang et al., 2016; Peterson, 2012). The complexity extends to accounting measurement and reporting, further impairing the transparency of financial statements (Filzen & Peterson, 2015). This opacity exacerbates information asymmetry between management and analysts, reducing forecast accuracy. Analysts may struggle to interpret the implications of derivative use due to the convoluted nature of these instruments, reflecting the *complexity mechanism*.

Third, the disclosure of key risk exposures and risk management activities is critical for analysts, as it saves time and resources while providing a foundation for accurate forecasting (Sarens & D'Onza, 2017). However, management may withhold essential information to maintain a competitive edge and protect business strategies (Sarens & D'Onza, 2017). In addition, in the absence of stringent regulatory requirements, many companies do not disclose comprehensive details about their derivatives positions, hedging ratios, or hedge effectiveness. The lack of transparency reduces analysts' ability to understand the purpose and effectiveness of derivative usage, as well as future price movements. Consequently, insufficient information disclosure creates additional challenges for analysts, encapsulating the *disclosure mechanism*.

In summary, while derivatives have the potential to enhance risk management and improve the accuracy of analysts' forecasts, ineffective use, high complexity, and poor information disclosure often undermine these benefits, complicating the task of analysts and reducing forecast reliability.

Based on this, we propose the following hypotheses:

H1a. Derivative users experience *more* accurate analysts' earnings forecasts than for non-users.

H1b. Derivative users experience *less* accurate analysts' earnings forecasts than for non-users.

3. Research design

3.1. Sample selection

The global crisis in 2008 raised wide public concerns in China regarding derivatives, it was not until 2009 that the usage returned back to normal. We begin with A-share listed firms in China from 2010 to 2020 and then exclude financial firms and ST firms. We also exclude observations without analyst following and observations with missing data, resulting in 3264 companies and 19,381 firm-year observations. Table 1 presents the sample selection process. Given the lack of compulsory requirements in China (Guo et al., 2021), we

Table 1
Sample selection.

	N
Firm-year A-share observations from 2010 to 2020	33523
Less: observations of financial industry	860
Less: observations of ST companies	3662
Less: observations not covered by analysts	7119
Less: observations with missing data	2501
Final sample of observations	19,381
Total number of firms	3264

hand-collect derivatives usage information for each firm from their annual reports (extracted from the *cniof* website[1]), following Campbell (2015) and Chang et al. (2016). We provide data collection details in Appendix A. We collect stock variables from WIND, and the rest from CSMAR.

Consistent with Chang et al. (2016), Kim et al. (2021) and Guo et al. (2021), we identify firms as derivative users and non-users by searching annual reports for keywords[2] relating to derivatives. A firm which reports no derivatives is classified as a *Non-User*. A *User* firm can be a *Non-User* in an earlier period if it did not use derivatives.

3.2. Research design

We estimate the influences of derivatives by the following regression model:

$$Accuracy_{it} = \alpha_0 + \alpha_1 DT_{it} + Controls_{it} + \sum Industry + \sum Year + \varepsilon_{it} \tag{1}$$

where *i* and *t* index firm and year, respectively. The dependent variable is *Accuracy*. Following Lang and Lundholm (1996) and Chang et al. (2016), *Accuracy* is calculated as follows:

$$Accuracy_{it} = -\frac{|CEF_{it} - EPS_{it}|}{P_{it-1}} \times 100 \tag{2}$$

where *CEF* is the average of analysts' most recent annual EPS forecasts. *EPS* is actual earnings per share and *P* refers to the lagged closing price. The larger the *Accuracy*, the more accurate the earnings forecast.

The independent variable, *DT*, is a dummy variable. It equals 1 if a firm is a *User* in a certain year and 0 otherwise. Following Campbell et al. (2019), Chang et al. (2016), and Manconi et al. (2017), we control for the following variables: *Afnum*, *Horizon*, *Size*, *Leverage*, *Z*, *EPS*, and *Surprise*. Variables are defined in Table 2. We also control for industry and year effects.

4. Empirical results

4.1. Descriptive statistics

Table 3 presents descriptive statistics. On average, 19.7 % of the sample are *User* observations, 29.5 % of which fail to hedge their risks effectively, 2.2 % of which disclose key information, 5.8 % of which use more than one type of derivatives or hedge more than one kind of risks. The average number of analysts following is 17 and the average period is 218.5 days. Panel B demonstrates that analysts' forecast accuracy of *Users* is significantly lower than that of *Non-User* observations.

4.2. Empirical results

To test H1, we use Eq. (1). As presented by column (1) of Table 4, the coefficient of *DT* is significantly negative, indicating that analysts' forecast accuracy is lower for *Users* compared to *Non-Users*, consistent with Chang et al. (2016). Compared to non-users, analysts experience a decrease of 7.71 % in forecast accuracy for derivative users. That is, in China, the use of derivatives makes it difficult for analysts to make accurate predictions, resulting in a divergence in analysts' forecasts. Such a conclusion is similar to that in the US. As for control variables, *AFnum*, *Size*, and *EPS* are positively associated with *Accuracy* while *Horizon*, *Leverage*, *Z*, and *Overseas* are negatively associated with *Accuracy*, which are generally consistent with previous studies.

[1] http://www.cninfo.com.cn/new/index.

[2] We first conduct text searches of annual reports using keywords about derivatives, hedges, options, future/forwards, swaps, and others. We then manually check to confirm that the above-mentioned derivatives are utilized by the firm based on various sources, including derivatives usage announcements, derivative loss announcements, comment letters related to derivatives usage, key audit matters related to derivatives usage in audit reports, and news about corporate derivatives usage.

Table 2
Variable definitions.

Dependent variable	
Accuracy	Analyst earnings forecast accuracy, see detailed calculation in Eq, (2).
Independent variables	
DT	Dummy variable, if a firm uses any derivatives, the value is 1 and 0 otherwise.
DTPL	The proportion of the sum of derivative-related fair value changes (gains and losses) and investment income to operating profit.
Ineffective Hedger	Dummy variable, if a firm uses only one type of derivative and its risk is not effectively hedged, it equals 1. When a firm employs multiple types of derivatives and only one type of risk is hedged effectively, it also equals 1. Otherwise 0.
DTtype	Number of types of derivatives used.
DTrisk	Number of types of risks hedged by derivatives.
DTC	Dummy variable, if a firm employs no less than two kinds of derivatives or hedges for no less than two kinds of risks and 0 otherwise.
Disclosure	Dummy variable, if a firm reports any information regarding *DTtype*, *DTrisk*, and *DTC*, it is 1 and 0 otherwise.
POST	Dummy variable, it equals 1 if the time is after the implementation of the Hedge Accounting standard (2019 and 2020) and 0 otherwise.
Control variables	
AFnum	The logarithm of the number of people tracked by analysts.
Horizon	Average analyst forecast period, the time between the release of analysts' earnings forecasts and the actual disclosure dates of the annual reports.
Size	Logarithm of total assets.
Leverage	Gearing ratio, total liabilities divided by total assets.
Z	The likelihood of a firm in financial distress.
EPS	Basic earnings per share.
Surprise	The difference between the current year's earnings per share and the previous year's earnings per share.
Intang	The proportion of intangible assets to total assets.
Oversea	The proportion of overseas business revenue to operating revenue.
Insti	Proportion of shares held by institutional investors.
FVA	The proportion of assets measured at fair value to total assets.
FVD	The proportion of liabilities measured at fair value to total assets.
Other variables	
Dispersion	Analyst earnings forecast dispersion, see detailed calculation in Eq. (3).
DTindustry	The percentage of derivative-users in the company's industry.
Frisk	Exposure to exchange rate risk, absolute value of the regression coefficient of the company's monthly stock return on the monthly change in the effective exchange rate of the Renminbi over the past three years (including the current year) (Zhang et al., 2009; Chang et al., 2016).
Irisk	Interest rate risk exposure, absolute value of the regression coefficient of the company's monthly stock return on the monthly change in SHIBOR over the past three years (including the current year) (Zhang et al., 2009; Chang et al., 2016).
Crisk	Commodity price exposure, absolute value of the regression coefficient of the company's monthly stock return on the monthly PPI change over the past three years (including the current year) (Zhang et al., 2009; Chang et al., 2016).
MI	Management compensation performance sensitivity, changes in directors' and supervisors' income from changes in company value as a proportion of total directors' and supervisors' income, number of shares held by directors and supervisors * closing price of shares/(Number of shares held by directors and supervisors * closing price of shares + total annual remuneration of directors and supervisors) (Chang et al., 2016).
CETR	Cash effective tax rate, The ratio of the sum of tax burden for the current year and the following year $t+1$ to the sum of operating profit. It equals to 1 if the ratio is more than 1 and it equals 0 if the ratio is less than 0 (Chang et al., 2016).

4.3. Robustness checks

4.3.1. Heckman two-stage model

Given that the decision to track a firm is an endogenous choice made by the analysts, we adopt the Heckman two-stage model to mitigate the issue of sample self-selection problem (Campbell et al., 2023; Guo et al., 2021). In the first stage, the explanatory variable is whether a firm is followed by analysts, while controlling for variables specified in Eq. (1), supplemented by the percentage of *Users* within the industry in the current year (*IVindustry*) as an exogenous instrument.[3] We derive the Inverse Mills Ratio (*IMR*), which is subsequently included in the second stage. Columns (2) and (3) of Table 4 present the results. *IMR* has a significant positive coefficient, confirming the presence of self-selection bias. After incorporating *IMR* into Eq. (1), the coefficient of *DT* remains significantly negative. That is, after accounting for the sample self-selection bias, *Users* still experience significantly less accurate analysts' forecasts. Our findings are robust.

4.3.2. Propensity score matching

To address differences in firm characteristics between *Users* and *Non-Users*, i.e., sample heterogeneity, we employ the propensity score matching (PSM) method, following Bartram (2017), Chang et al. (2016), and Guo et al. (2021). This approach matches the sample of *Users* with a comparable sample of *Non-Users* based on factors influencing derivative usage (Chang, 2016; Bartram, 2019; Guo et al., 2021). These factors include *Size*, *Leverage*, *MI*, *CETR*, *Frisk*, *Irisk*, *Crisk*, and industry-year fixed effects. We estimate the

[3] The sample of the first stage are all firms, including firms tracked and not covered by the analysts, but *Afnum* and *Horizon* only appear in samples tracked by analysts; hence, those two variables are excluded from the first stage regression.

Table 3
Descriptive statistics.

Panel A: Descriptive statistics

Variable	Obs.	Mean	STD	Min	Median	Max
Accuracy	19381	−0.921	1.483	−7.308	−0.435	−0.002
DT	19381	0.197	0.398	0	0	1
Ineffective Hedger	3610	0.295	0.456	0	0	1
Disclosure	19381	0.022	0.146	0	0	1
DTC	19381	0.058	0.233	0	0	1
AFnum	19381	17.440	14.120	1	14	62
Horizon	19381	218.500	81.020	25	213.800	427
Size	19381	22.424	1.342	18.952	22.225	28.636
Leverage	19381	0.425	0.200	0.049	0.422	0.876
Z	19381	5.020	5.705	0.148	3.181	35.910
EPS	19381	0.454	0.532	−1.315	0.350	2.682
Surprise	19381	−0.037	0.393	−1.740	0.000	1.400
Intang	19381	0.047	0.051	0	0.034	0.315
Oversea	19381	0.130	0.207	0	0.019	0.890
Insti	19381	0.460	0.249	0.003	0.491	0.910
FVA	19381	0.020	0.056	0.000	0.000	0.366
FVD	19381	0.000	0.001	0.000	0.000	0.011

Panel B: Univariate tests on Accuracy

Variable	*DT* = 0 (1)		*DT* = 1 (2)		Diff [(1)–(2)]		Diff [(1)–(2)]	
	Mean	Median	Mean	Median	Mean	T-value	Median	Z-value
Accuracy	−0.914	−0.431	−0.948	−0.435	−0.034	−1.725*	−0.004	−0.519

propensity score using a logit regression and nearest-neighbor one-to-one with put-back matching.

Fig. 1 shows the density function plots before and after matching. Prior to matching, the density score of the control group, *Non-Users*, is significantly higher than that of the treatment group, *Users*. After matching, the differences decrease, indicating that PSM effectively mitigates disparities between the two groups. Table 5 shows analysts' forecast accuracy for both *Users* and *Non-Users* before and after matching. Post-matching results demonstrate that analysts fail to make accurate predictions for *Users*, suggesting that our conclusions are not driven by firm characteristics. We further re-estimate the influence of derivatives using Eq. (1) on the matched sample. Column (4) of Table 4 presents the results. The coefficient of *DT* remains significantly negative, reinforcing the robustness of our findings.

4.3.3. *Alternative measurement and method*

First, we use an alternative explanatory variable. Analysts' forecast accuracy is traditionally proxied by the difference between the mean of analysts' EPS forecasts and the actual EPS, capturing the extent to which the forecast mean deviates from the realized value. As an alternative measurement, we calculate the forecast dispersion by the variance of analysts' EPS forecasts for the same company. This metric reflects the degree of disagreement or divergence in opinions among analysts. Accuracy and dispersion are usually negatively related (Chang et al., 2016). Following Chang et al. (2016) and Lang and Lundholm (1996),[4] we estimate *Dispersion* using the following ratio:

$$Dispersion_{it} = \frac{SD_{it}}{P_{it-1}} \times 100 \tag{3}$$

where *SD* is the standard deviation of analysts' annual EPS forecasts. A higher *Dispersion* indicates greater disagreement among analysts and, consequently, less accurate forecasts. To assess the effect of derivative use on analysts' forecast dispersion, we employ the following regression:

$$Dispersion_{it} = \alpha_0 + \alpha_1 DT_{it} + Controls_{it} + \sum Industry + \sum Year + \varepsilon_{it} \tag{4}$$

Column (1) of Table 6 presents the results. The coefficient of *DT* is significantly positive at the 5 % level, indicating that analysts' forecast dispersion is higher for *Users* than *Non-Users*, aligning with our findings.

Second, we employ an alternative dependent variable. Dummy variables are widely employed due to the lack of information. Due to data availability, we use a dummy variable to measure derivative usage in the baseline regression. We then manually collect detailed information on derivatives from annual reports. We utilize *DTPL*, which is calculated as the ratio of the sum of derivatives related fair value changes (gains and losses) and investment income to operating profit, to measure the intensity of derivative use.

Column (2) of Table 6 presents the results. *DTPL* is negatively associated with *Accuracy* and is significant at the 10 % level. This

[4] In calculating the dispersion of analysts' earnings forecasts, we remove samples with less than 3 analyst followers, thus the number of firms is 3145 and the sample size is 18,559 when analyzing the dispersion.

Table 4
Derivative use and analyst forecast accuracy.

Variable	(1)	(2)	(3)	(4)
	Baseline	Heckman		PSM
	Accuracy	*AF*	*Accuracy*	*Accuracy*
DT	−0.071**		−0.059***	−0.082**
	(-2.013)		(-2.612)	(-2.025)
AFnum	0.041**		0.018	0.040
	(2.557)		(1.594)	(1.421)
Horizon	−0.602***		−0.603***	−0.590***
	(-26.629)		(-36.935)	(-12.710)
Size	0.079***	0.536***	−0.110***	0.088***
	(4.811)	(44.208)	(-6.838)	(3.727)
Leverage	−0.207**	−0.402***	−0.020	−0.084
	(-2.109)	(-5.740)	(-0.280)	(-0.491)
Z	0.019***	0.025***	0.010***	0.024***
	(8.681)	(10.937)	(4.744)	(5.896)
EPS	0.308***	0.850***	0.044	0.262***
	(9.101)	(32.837)	(1.625)	(4.588)
Surprise	0.810***	−0.435***	0.924***	0.717***
	(24.843)	(-15.819)	(34.823)	(10.487)
Intang	1.228***	0.460**	0.998***	1.197***
	(4.759)	(2.213)	(5.278)	(2.692)
Oversea	−0.070	0.143***	−0.167***	−0.043
	(-1.058)	(3.043)	(-3.576)	(-0.502)
Insti	−0.113*	−0.101**	−0.094**	−0.309***
	(-1.914)	(-2.315)	(-2.250)	(-2.950)
FVA	0.425**	−1.297***	0.983***	0.085
	(2.241)	(-8.157)	(5.739)	(0.212)
FVD	16.835**	−3.061	15.542**	15.545
	(2.093)	(-0.380)	(2.146)	(1.286)
DTindustry		0.873*		
		(1.917)		
IMR(lambda)			−1.234***	
			(-16.772)	
Industry	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	19381	25891	19381	5078
_cons	1.164***	−12.618***	6.301***	1.133**
	(3.140)	(-44.084)	(14.664)	(2.200)
Adjusted/Pseudo R^2	0.305	0.214		0.270
F	64.63			78.49

Note: Robust standard errors (RSE) are clustered by firm. *, **, and *** denote statistical significance levels of 0.10, 0.05, and 0.01, respectively (two-tailed).

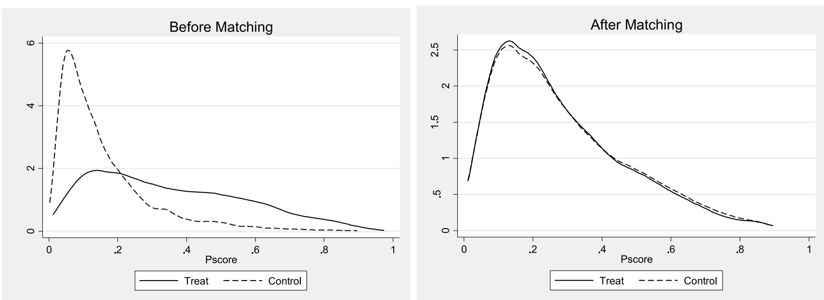

Fig. 1. Density functional plots before and after matching.

Table 5
Analysts' forecast accuracy before and after matching.

Variable Sample	Treatment group	Control group	difference	SE	T-statistic
Before matching	−0.945	−0.914	−0.031	0.024	−1.31
After matching	−0.948	−0.871	−0.077	0.038	−2.04

Table 6
Alternative measurements and methods.

Variable	(1)	(2)	(3)	(4)
	Alternative dependent variable	Alternative independent variable	Alternative clustered standard error	Alternative fixed effects
	Dispersion	*Accuracy*	*Accuracy*	*Accuracy*
DT	0.0674**		−0.0709*	−0.056*
	(2.38)		(-1.79)	(-1.891)
DTPL		−0.8965*		
		(-1.66)		
AFnum	−0.0166	0.0370**	0.0406*	−0.026
	(-1.30)	(2.33)	(1.88)	(-1.631)
Horizon	0.3433***	−0.6025***	−0.6025***	−0.627***
	(21.02)	(-26.64)	(-5.99)	(-27.214)
Size	−0.0184	0.0835***	0.0793**	0.111***
	(-1.36)	(4.92)	(2.41)	(7.065)
Leverage	−0.0676	−0.2297**	−0.2072	−0.095
	(-0.89)	(-2.34)	(-0.77)	(-1.042)
Z	−0.0145***	0.0189***	0.0187***	0.018***
	(-8.89)	(8.74)	(3.47)	(8.487)
EPS	−0.0626**	0.3045***	0.3082***	0.449***
	(-2.49)	(8.96)	(2.83)	(12.644)
Surprise	−0.1299***	0.8110***	0.8104***	0.665***
	(-6.56)	(24.87)	(8.50)	(22.859)
Intang	−0.8064***	1.2241***	1.2278***	0.968***
	(-3.86)	(4.76)	(4.18)	(4.085)
Oversea	0.0689	−0.0950	−0.0698	−0.178***
	(1.33)	(-1.49)	(-0.93)	(-2.930)
Insti	0.1134**	−0.1201**	−0.1129	−0.072
	(2.55)	(-2.04)	(-1.10)	(-1.230)
FVA	−0.4695***	0.4017**	0.4255**	0.103
	(-3.34)	(2.11)	(2.11)	(0.563)
FVD	−15.4876**	16.2891**	16.8353**	6.032
	(-2.53)	(2.04)	(2.21)	(1.007)
Constant	−0.5881*	1.1076***	1.1636**	0.068
	(-1.73)	(2.91)	(2.03)	(0.198)
Industry/Firm	YES	YES	YES	YES
Year	YES	YES	YES	YES
Observations	18,559	19,381	19,381	19,381
Adjusted R^2	0.206	0.307	0.307	0.290
F	62.47	64.60	94.04	98.47

Note: Robust standard errors (RSE) are clustered by firm. *, **, and *** denote statistical significance levels of 0.10, 0.05, and 0.01, respectively (two-tailed).

indicates that *Users* who use derivatives frequently experience less accurate analysts' forecasts, supporting the robustness of our findings.

Third, we adopt an alternative regression method. To account for potential firm-specific fixed effects and serial correlation issues, we cluster robust standard errors by both firm and year. Moreover, we incorporate firm-level fixed effects instead of industry-level fixed effects. Column (3) and (4) of Table 6 reports the results. The coefficient of *DT* is still significantly negative, confirming the robustness of our conclusions.

5. Heterogeneity tests

5.1. Ownership

Given the strict restrictions on derivative usage imposed on SOEs in China (Guo et al., 2021), we expect significant differences between SOEs and non-SOEs in derivative usage. Additionally, in China, SOEs are obligated to certain rules and are designed to achieve both economic and non-economic goals. As a result, SOEs often face more stringent regulations on financial instruments, including derivatives, to mitigate systemic risks and prevent excessive speculation.

Appendix B demonstrates that SOEs have significantly lower levels of derivative usage, which aligns with the fact that SOEs are closely supervised by the State-Owned Assets Supervision and Administration Commission (SASAC). Given that SOEs have more complicated governance structures, weaker market-driven incentives and closer political connections than non-SOEs, SOEs may have less incentive to engage in voluntary disclosure, resulting in a higher degree of information asymmetry.

We further examine the effect of derivatives on analysts' forecasts in SOEs and non-SOEs. Column (1) of Table 7 indicates that SOEs experience less accurate forecasts when using derivatives. This suggests that the lower transparency and higher information asymmetry associated with SOEs make it more challenging for analysts to interpret derivative usage and assess its implications for corporate

Table 7
Heterogeneity tests.

Variables	(1)	(2)	(3)
	Accuracy	Accuracy	Accuracy
DT	0.017	−0.139***	−0.185***
	(0.448)	(-2.965)	(-3.458)
*DT*SOE*	−0.194***		
	(-2.684)		
SOE	0.234***		
	(6.924)		
*DT*FR*		0.317**	
		(2.529)	
FR		0.016	
		(0.467)	
*DT*CR*			0.171***
			(2.585)
CR			−0.403***
			(-2.944)
AFnum	0.058***	0.037**	0.040**
	(3.642)	(2.312)	(2.503)
Horizon	−0.615***	−0.604***	−0.604***
	(-27.084)	(-26.693)	(-26.687)
Size	0.070***	0.091***	0.089***
	(4.098)	(5.345)	(5.222)
Leverage	−0.268***	−0.230**	−0.231**
	(-2.745)	(-2.347)	(-2.350)
Z	0.019***	0.019***	0.019***
	(8.694)	(8.817)	(8.736)
EPS	0.308***	0.305***	0.306***
	(9.168)	(9.049)	(9.038)
Surprise	0.802***	0.812***	0.811***
	(24.673)	(24.916)	(24.868)
Intang	1.219***	1.210***	1.215***
	(4.772)	(4.703)	(4.781)
Oversea	−0.053	−0.199**	−0.065
	(-0.802)	(-2.377)	(-0.993)
Insti	−0.239***	−0.125**	−0.122**
	(-3.981)	(-2.124)	(-2.080)
FVA	0.440**	0.408**	0.400**
	(2.293)	(2.151)	(2.105)
FVD	18.272**	16.525**	15.426*
	(2.282)	(2.034)	(1.942)
Constant	1.418***	0.951**	1.051***
	(3.742)	(2.515)	(2.800)
Industry	YES	YES	YES
Year	YES	YES	YES
Observations	19,381	19,381	19,381
Adjusted R-squared	0.310	0.306	0.306
F	63.24	62.04	63.45

Note: Robust standard errors (RSE) are clustered by firm. *, **, and *** denote statistical significance levels of 0.10, 0.05, and 0.01, respectively (two-tailed).

financial performance.

5.2. Risk exposure

Derivatives are primarily designed to hedge risk exposures related to exchange rates, commodity prices, and interest rates. Considering the relatively slow progress of interest rate marketization in China, interest rate risk remains relatively steady. Consequently, Chinese companies are more significantly influenced by exchange rate risks and commodity price risks (Guo et al., 2021). Appendix B indicates that firms with overseas business and companies in industries with high commodity price risk exposure tend to use derivatives.

To further examine the heterogeneity of derivative usage, we introduce two dummy variables. Following Makar and Huffman

(2001), we measure exchange rate exposure with *FR*, which equals 1 when a firm has overseas revenue and 0 otherwise. Similarly, following Purnanandam (2008), we measure commodity price risk exposure with *CR*, which equals 1 when a firm is in certain industries[5] and 0 otherwise. We incorporate interaction terms into Eq. (1) to analyze how the effect of derivative usage on analyst earnings forecasts varies across firms with different levels of overseas revenue and commodity price risk exposure. Column (2) and (3) of Table 7 presents the results, indicating that risk exposure significantly influences the impact of derivatives on analysts' forecasts. Specifically, compared to other firms, the negative effect of derivative usage on analyst forecast quality is weaker for firms with overseas business and those operating in industries with significant commodity price risk exposure. This finding suggests that for these firms, derivative usage is more likely motivated by risk hedging rather than speculative activities. That is, among firms with risk exposure, the negative influence of derivative usage on analysts' forecasts is weaker, supporting the conclusion that derivatives are more likely to be used for risk hedging in the presence of risk exposure. We further address these issues in Section 5.1, where we discuss risk hedging effect of derivatives.

6. Mechanism tests

6.1. *Ineffective hedging mechanism*

Low corporate risk and uncertainty improve analysts' forecast accuracy and reduce forecast dispersion (Manconi et al., 2017). In terms of derivative usage, if hedging is effective, changes in the fair value of derivatives offset the impact of changes in the price of the underlying asset on cash flows and profits. This significantly reduces exposures to risks such as interest rate, foreign exchange rate, and commodity price fluctuation, thereby decreasing the volatility of cash flows and earnings (Bartram, 2019; Zhang, 2009). Therefore, analysts' forecast accuracy improves. Conversely, when hedging is ineffective, earnings and cash flow volatility increases, making it challenging for analysts to make accurate forecasts.

To investigate the effect of hedging effectiveness, we define what constitutes an effective hedger. Following Zhang (2009) and Chang et al. (2016), we classify *Users* as either *Effective Hedgers* or *Ineffective Hedgers* based on the following steps: (1) we categorize *Users* into interest rate, exchange rate and commodity price *Users* according to the types of derivatives they employ and calculate their actual exposure to interest rate, exchange rate and commodity price fluctuation after derivative use; (2) we estimate the expected exposure to interest rate, exchange rate and commodity price fluctuation after the initiation of the respective derivatives; (3) we compare the actual exposure to the expected exposure for each type. (4) we define a type of risk as hedged *effectively* if its actual exposure is lower than expected. (5) we introduce a dummy variable, *Ineffective Hedger*, to measure hedging effectiveness at a firm-specific level. When a firm uses only one type of derivative and its risk is not effectively hedged, *Ineffective Hedger* equals 1. When a firm employs multiple types of derivatives and only one type of risk is hedged effectively, *Ineffective Hedger* equals 1. Otherwise 0. We substitute *Ineffective Hedger* with *DT* in Eq. (1). Columns (1) and (2) of Table 8 present the results. The coefficients of *Ineffective Hedger* are negative and significant at the 1 % and 5 % levels for both the full sample and the sub-sample of *Users*, respectively. The results indicate that analysts' forecasts for *Ineffective Hedger* are significantly less accurate than those for *Effective Hedgers*. In other words, hedge effectiveness significantly influences analysts' forecast accuracy.

6.2. *Complexity mechanism*

Derivatives are renowned for their extremely high complexity (Campbell et al., 2015; Chang et al., 2016; Peterson, 2012), which makes it challenging to understand, interpret, and predict financial statements (Peterson, 2012), thereby increasing firm opacity (Manconi et al., 2017). Thus, we further estimate how the complexity of derivative use affects analysts' earnings forecasts.

The variety of derivatives and the types of risk make it challenging for external stakeholders to access detailed information, such as the types and amounts of risk exposures, managerial motivations to use derivatives, accounting treatments, and their corresponding effects on risk exposures, cash flows, and earnings. Such information asymmetry between management and analysts leads to less accurate forecasts.

We measure the complexity of derivatives by three metrics: the number of derivative types (*DType*), the number of hedged risks (*DTrisk*), and whether no less than two kinds of derivatives or two kinds of risks are involved ($DTC = 1$). Columns (1)–(3) of Table 9 report the results. The coefficients of *DType*, *DTrisk*, and *DTC* are all significant and negative, indicating that the greater complexity negatively impacts the accuracy of analysts' earnings forecasts. That is, as the variety of derivatives or risks increase, analysts' abilities to accurately forecast earnings diminish due to heightened information asymmetry.

6.3. *Disclosure mechanism*

The availability and reliability of information critically determine the accuracy of analysts' earnings forecasts. Well-informed analysts are better equipped to make accurate predictions. However, managers may hesitate to disclose key information due to

[5] Following the 2012 China Securities Regulatory Commission (CSRC) Industry Classification Guidelines, we find that industries with substantial commodity price risk exposure include Agriculture, Forestry, Animal Husbandry, and Fishery (A), Mining (B), Textile, apparel, Leather, and Fur Products (C1), Paper, Printing, and Cultural & Educational products (C3), Petroleum, Chemical, Plastics, and Rubber Products (C4), and Transportation, Storage, and Postal Services (F).

Table 8
Test of ineffective hedging mechanisms.

Variable	(1)	(2)
	Accuracy	*Accuracy*
Ineffective Hedger	−0.184***	−0.173**
	(3.508)	(2.104)
AFnum	0.041**	0.036
	(2.576)	(0.840)
Horizon	−0.602***	−0.562***
	(-26.595)	(-7.979)
Size	0.064***	−0.013
	(3.943)	(-0.307)
Leverage	−0.234**	−0.047
	(-2.394)	(-0.190)
Z	0.018***	0.019**
	(8.584)	(2.209)
EPS	0.312***	0.482***
	(9.212)	(5.015)
Surprise	0.807***	0.500***
	(24.766)	(6.190)
Intang	1.224***	1.014
	(4.782)	(1.431)
Oversea	−0.132**	0.097
	(-2.056)	(0.675)
Insti	−0.110*	−0.423**
	(-1.869)	(-2.081)
FVA	0.407**	0.518
	(2.146)	(1.133)
FVD	8.787	21.433**
	(1.091)	(2.013)
Constant	1.112*	3.022***
	(1.882)	(2.798)
Industry	YES	YES
Year	YES	YES
Observations	19,381	2903
Adjusted R^2	0.307	0.285
F	64.65	10.88

Note: Robust standard errors (RSE) are clustered by firm. *, **, and *** denote statistical significance levels of 0.10, 0.05, and 0.01, respectively (two-tailed).

self-beneficial motivation or peer pressure. In China, the fragmented, poorly standardized, and inconsistent disclosure of derivative information reduces the comparability of financial statements and increases the cost of information processing.

According to China Accounting Standards (CAS) and the *Guidelines on the Content and Format of Annual Reports* issued by China Securities Regulatory Commission (CSRC), *Users* are required to disclose necessary information, such as types, positions, fair values, and profits or losses of derivatives, in seven sections of the annual report, including the *Statement of Derivative Investments*, *Balance Sheet*, *Gains and Losses from Changes in Fair Value*, *Income from Investments*, *Risks Associated with Financial Instruments*, and *Disclosure of Fair Values*.

However, we notice notable inconsistencies in the content and format of derivative disclosure during our hand-collection process. For example, some firms disclose their use of derivatives but fail to provide related information on the impact on profit or loss or other comprehensive income. Conversely, others omit disclosure of derivative usage and amounts in the *Balance Sheet* or its notes, despite reporting impacts on profit or loss in the *Gains and Losses from Changes in Fair Value* section.

Analysts can gain insight into derivatives through information on positions, such as contract types and risk exposures. In addition, the fair values of derivatives and related gains or losses help analysts evaluate the extent to which derivatives impact corporate performance. Therefore, when a firm discloses key information, such as positions, fair values and changes in gains or losses, analysts are better informed and can produce more accurate earnings forecasts.

To examine the impact of key information disclosure on the accuracy of analysts' earnings forecasts, we introduce a dummy variable, *Disclosure*. *Disclosure* equals 1 if a *User* discloses its positions, fair values, related changes in gains or losses, and investment income, and 0 otherwise. Substituting *Disclosure* with *DT* in Eq. (1), we present the results in columns (4) and (5) of Table 9. For the full sample, the coefficient of *Disclosure* is positive but insignificant., As for *Users*, the coefficient of *Disclosure* is positive and significant. This suggests that analysts' forecast accuracy improves when derivatives key information is disclosed, indicating that the absence of key information is a critical reason why analysts struggle to make accurate predictions for *Users*.

7. Further analysis

Considering that the use of derivatives reduces analysts' earnings forecast accuracy, we explore potential solutions from three

Table 9
Tests of complexity and disclosure mechanism.

Variable	(1)	(2)	(3)	(4)	(5)
	Complexity			Key information disclosure	
	Accuracy	Accuracy	Accuracy	Accuracy	Accuracy
DTtype	−0.0488**				
	(-1.99)				
DTrisk		−0.0363*			
		(-1.86)			
DTC			−0.0860**		
			(-2.13)		
Disclosure				0.0603	0.1208*
				(1.00)	(1.88)
AFnum	0.0403**	0.0411***	0.0406***	0.2259***	0.0025***
	(2.53)	(3.59)	(3.55)	(18.78)	(7.86)
Horizon	−0.6027***	−0.6024***	−0.6028***	−0.1448***	−0.0012**
	(-26.63)	(-29.23)	(-29.24)	(-7.20)	(-2.03)
Size	0.0805***	0.0772***	0.0777***	−0.0013	−0.0099
	(4.86)	(7.75)	(7.83)	(-0.13)	(-0.45)
Leverage	−0.2085**	−0.2106***	−0.2145***	0.0379	0.2252
	(-2.13)	(-3.10)	(-3.17)	(0.55)	(1.21)
Z	0.0188***	0.0187***	0.0188***	0.0145***	0.0168***
	(8.73)	(11.10)	(11.12)	(8.40)	(2.93)
EPS	0.3080***	0.3076***	0.3079***	0.2402***	0.2555***
	(9.10)	(12.26)	(12.27)	(9.23)	(4.84)
Surprise	0.8100***	0.8104***	0.8096***	0.8810***	0.7096***
	(24.84)	(24.20)	(24.18)	(26.34)	(9.65)
Intang	1.2290***	1.2247***	1.2240***	0.8004***	0.8176
	(4.77)	(7.41)	(7.41)	(4.52)	(1.60)
Oversea	−0.0729	−0.0855**	−0.0942**	−0.1357***	−0.0612
	(-1.11)	(-1.97)	(-2.24)	(-3.10)	(-0.71)
Insti	−0.1119*	−0.1122***	−0.1117***	−0.0302	−0.0952
	(-1.90)	(-2.87)	(-2.86)	(-0.75)	(-0.96)
FVA	0.4227**	0.4204***	0.4162***	0.6641***	−0.0364
	(2.23)	(2.65)	(2.63)	(4.19)	(-0.09)
FVD	17.8772**	15.8274***	16.4093***	5.7770	19.9395**
	(2.13)	(2.73)	(2.75)	(0.97)	(2.42)
Industry	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES
Constant	1.1582***	1.2068***	1.1965***	−0.2523	−0.5673
	(3.09)	(4.89)	(4.83)	(-1.21)	(-1.06)
Observations	19,381	19,381	19,381	19,381	3814
Adjusted R2	0.305	0.305	0.305	0.294	0.276
F	64.60	93.99	94.09	89.39	18.54

Note: Robust standard errors (RSE) are clustered by firm. *, **, and *** denote statistical significance levels of 0.10, 0.05, and 0.01, respectively (two-tailed).

perspectives: accounting standards, management forecasts and analysts' capabilities.

7.1. Accounting standards

Scholars conclude that accounting standards significantly influence both derivative users and information users, such as auditors and analysts (Choi et al., 2015; Gumb et al., 2018). In line with the objective of "reflecting the impact of risk management activities and improving risk management capabilities", China's Ministry of Finance issued the *Hedge Accounting Standard*s (CAS 24 *Hedging Accounting*) in March 2017, which came into effect on January 1, 2019, for A-share listed companies. The CAS 24 *Hedging Accounting* prioritizes the integration of accounting treatment with corporate risk management activities, broadening the scope of eligible hedging instruments and hedged items and replacing the quantitative assessments. These changes aim to capture corporate risk management activities and their outcomes in accounting statements,

We examine the impact of CAS 24 *Hedge Accounting* on the relationship between derivative usage and the accuracy of analysts' earnings forecasts by the following DiD model:

$$Accuracy_{it} = \alpha_0 + \alpha_1 DT_{it} + \alpha_2 POST_{it} + \alpha_3 DT_{it}{*}POST_{it} + Controls_{it} + \sum Industry + \sum Year + \varepsilon_{it} \tag{5}$$

The treatment group is *Users* and the control group is *Non-Users*. After the initiation of CAS 24 *Hedge Accounting* (2019 and beyond), *POST* equals 1 and 0 otherwise.

Table 10 presents the results. The coefficient of *DT* is significantly negative at the 1 % level, indicating that prior to the

Table 10
The impact of Hedging Accounting Standard and management performance forecast.

Variable	(1)	(2)	(3)
	Implementation of Hedge Accounting Standard	Pre-announcement	Post-announcement
	Accuracy	AccuracyMEF	AccuracyMEF
DT	−0.0968***	−0.0750***	−0.0090
	(-3.70)	(-2.66)	(-0.85)
*DT*POST*	0.0912*		
	(1.77)		
POST	−0.3097***		
	(-7.89)		
AFnum	0.0370***	0.0780***	0.0389***
	(3.22)	(5.57)	(7.19)
horizon	−0.6034***	−0.8671***	−0.0538***
	(-29.24)	(-29.21)	(-9.84)
Size	0.0891***	0.0725***	0.0044
	(8.68)	(6.07)	(0.75)
Leverage	−0.2288***	−0.2300***	−0.1913***
	(-3.36)	(-2.83)	(-6.35)
Z	0.0190***	0.0205***	0.0009
	(11.21)	(10.38)	(1.47)
EPS	0.3072***	0.3176***	0.0402***
	(12.25)	(10.57)	(3.64)
Surprise	0.8094***	0.9594***	0.0197
	(24.20)	(23.27)	(1.64)
Intang	1.2269***	1.4524***	0.2142**
	(7.43)	(7.86)	(2.33)
Oversea	−0.0708	−0.0654	−0.0136
	(-1.63)	(-1.26)	(-0.70)
Insti	−0.1212***	−0.1617***	−0.0616***
	(-3.10)	(-3.53)	(-3.92)
FVA	0.4154***	0.4853***	−0.0893
	(2.62)	(2.62)	(-1.01)
FVD	16.8063***	17.6540**	4.1223*
	(2.93)	(2.56)	(1.69)
Industry	YES	YES	YES
Year	YES	YES	YES
Constant	0.9920***	2.4287***	0.1598
	(3.99)	(5.59)	(1.19)
Observations	19,381	19,161	8021
Adjusted R^2	0.306	0.296	0.080
F	92.13	86.32	9.567

Note: Robust standard errors (RSE) are clustered by firm. *, **, and *** denote statistical significance levels of 0.10, 0.05, and 0.01, respectively (two-tailed).

implementation of CAS 24 *Hedge Accounting*, analysts were less accurate in forecasting the earnings of *Users*. The negative coefficient of *POST* indicates a significant decline in analysts' earnings forecast accuracy since 2019. However, the coefficient of *DT*POST* is significantly positive, indicating that compared to *Non-Users*, analysts have become more accurate in forecasting the earnings of *Users* after the implication of CAS 24 *Hedge Accounting*. We find that the sum of the coefficients of *DT* and *DT*POST* is not significantly different from zero. This indicates that after the implementation of CAS 24 *Hedge Accounting*, the negative effect of derivative usage on the accuracy of analysts' earnings forecasts is no longer significant. The results indicate that that CAS 24 *Hedge Accounting* helps mitigate the effect of derivatives on the accuracy of analysts' earnings forecasts.

7.2. Management forecasts

Hutton et al. (2012) find that analysts and management each possess distinct informational advantages. Management holds a superior informational advantage when it comes to firm-specific information and management behavior, which are often difficult for outsiders to predict. Analysts, on the other hand, possess an informational advantage when a firm's performance is more correlated with macroeconomic fluctuations. Derivative usage creates a unique environment for informational exchange between analysts and management, as it reflects the impact of macro price changes on the firm, while management holds an informational edge on firm-specific risk exposures (Campbell et al., 2023). If managerial performance forecasts include information related to derivative usage, such forecasts can help alleviate information asymmetry (Lang & Lundholm, 1996), reduce information processing costs for analysts, and mitigate the adverse impact of derivative use on analysts' earnings forecasts (Campbell et al., 2015). Thus, we examine the effect of management forecasts on the association between derivative use and analysts' forecast accuracy.

We divide the sample into two groups: pre- and post-management forecasts. We calculate analysts' forecast accuracy, the number of analysts tracked, and the forecast period, respectively, to interpret the role of management forecasts. Columns (2) and (3) of Table 10 present the results. We find that derivative use significantly decreases the accuracy of analysts' earnings forecasts in pre-management forecast period. In post-management forecast period, such an association is insignificant. The results indicate that management possesses an information advantage regarding derivative usage and that management forecasts could alleviate the information asymmetry between management and external analysts.

7.3. Analysts' capabilities

Clement (1999) finds that forecast accuracy is closely associated with analysts' capabilities, including factors such as expertise and experience. In this section, we examine whether analysts' capabilities can mitigate the information asymmetry caused by derivative use. Following Clement (1999), we measure individual analyst's performance using the proportional mean absolute forecast error (*PMAFE)*, as specified in the following model:

$$PMAFE_{ijt} = -\frac{AFE_{ijt} - \overline{AFE_{jt}}}{\overline{AFE_{jt}}} \tag{6}$$

where AFE_{ijt} is the absolute value of forecast bias of analyst i for firm j in year t, and $\overline{AFE_{jt}}$ represents the mean absolute forecast error for firm j in year t. The larger the $PMAFE_{ijt}$, the more accurate the forecast.

There is a total of 356,370 analyst-year observations between 2010 and 2020. We replace *Accuracy* with *PMAFE* in Eq. (1). Column (1) of Table 11 presents the results. The coefficient of *DT* is negative and significant, which is consistent with H1b.

7.3.1. Analysts' expertise

Industry information is crucial for analysts when making forecasts. Firms in certain sectors, such as mining, manufacturing, agriculture, forestry, livestock, and fishing, tend to use more derivatives than firms in other sectors. Companies within the same industry typically face similar exposures, as well as similar technology and growth opportunities. Analysts with industry expertise are better equipped to understand firm-specific risk exposures, hedging purposes, hedging effectiveness, future trends, and potential impacts, resulting in accurate forecasts.

Following Jacob et al. (1999), we measure industry expertise as the proportion of companies covered by the analyst in a given industry relative to the total number of companies they cover. We then divide the sample into two groups based on analysts' expertise: observations covered by analysts with expertise (*Spec* = 1) and observations covered by analysts without industry expertise (*Spec* = 0). Columns (2) and (3) of Table 11 present the results. The coefficient of *DT* is negative and significant for observations covered by analysts without expertise, while that of *DT* is insignificant for observations covered by analysts with expertise, suggesting that industry expertise can mitigate the negative effects of derivative use on the accuracy of analysts' earnings forecast.

7.3.2. Analysts' experience

According to the stem-learning theory, the quality of analysts' forecasts improves with experience. As analysts gain deeper insights and accumulate knowledge, they become more adept at forecasting, and their analytical skills become increasingly refined. Experienced analysts can also leverage information from other companies within the same industry, thereby enhancing forecast accuracy (Hilary & Shen, 2013).

Following Luo and Nagarajan (2015), we measure analysts' forecasting experience by the number of quarters between an analyst's first issued forecast and the timing of the current forecast. Then we divide the sample into two groups: observations covered by less-experienced analysts and observations covered by well-experienced analysts, based on the median of forecasting experience. Columns (4) and (5) of Table 11 show the results. The negative relationship between derivative use and analysts' forecast accuracy is significant only for observations covered by less-experienced analysts. For observations covered by well-experienced analysts, this negative relationship is insignificant, indicating that analysts' experience can effectively mitigate the negative effects of derivative use on forecast quality.

8. Conclusions

As the globalization process accelerates, companies face unprecedented fluctuations in interest rate, exchange rate, and commodity price fluctuation, driving the widespread use of derivatives. However, the inherent riskiness and complexity of derivatives make it challenging for outsiders to fully understand the activities of derivative users. Investors and regulators often express difficulties in comprehending the impact of derivative use on firms. Given their dual role as information providers and users, analysts play a vital role in bridging this gap through their forecasts, which serve as a key channel for conveying information (Bradshaw, Drtimur, & O'Brien, 2017). Thus it is of great importance to examine analysts' capabilities in understanding and assessing the impact of firm derivative usage.

We find that derivative users experience less accurate analysts' forecasts, compared to non-users. Our results remain robust after addressing potential endogeneity concerns. We find that the effects of derivatives on analysts' forecasts are more pronounced for SOEs and firms without risk exposure. We identify ineffective hedging, derivative complexity, and inadequate disclosure of key information as primary factors contributing to this discrepancy. Further analyses find that the implementation of CAS 24 *Hedge Accounting*, management forecasts and analysts' industry expertise and experience can help mitigate the negative effects of derivative use on forecast accuracy.

Table 11
The impact of analyst competence.

Variable	(1)	(2)	(3)	(4)	(5)
	Full sample	*Spec* = 0	*Spec* = 1	Lack of experience	Well-experienced
	PMAFE	*PMAFE*	*PMAFE*	*PMAFE*	*PMAFE*
DT	−0.0126**	−0.0154***	0.0005	−0.0232***	−0.0112
	(-2.41)	(-2.64)	(0.05)	(-2.79)	(-1.46)
Horizon	−0.4404***	−0.4507***	−0.4360***	−0.2992***	−0.4440***
	(-144.19)	(-95.37)	(-136.35)	(-98.33)	(-108.39)
Number	0.0341***	0.0512***	0.0191***	−0.0009	−0.0195***
	(16.30)	(12.83)	(7.74)	(-0.33)	(-5.27)
Size	0.0034	0.0007	0.0042	0.0297***	0.0062*
	(1.42)	(0.18)	(1.61)	(8.79)	(1.93)
Leverage	−0.0705***	−0.0429	−0.0812***	−0.1610***	−0.0715***
	(-5.00)	(-1.64)	(-5.13)	(-7.22)	(-3.40)
Z	−0.0023***	−0.0025***	−0.0021***	0.0013**	−0.0019***
	(-5.39)	(-3.22)	(-4.43)	(2.22)	(-2.80)
EPS	−0.0963***	−0.0875***	−0.0990***	−0.0791***	−0.1199***
	(-20.19)	(-12.01)	(-19.10)	(-11.71)	(-17.44)
Surprise	−0.0074*	−0.0297***	−0.0000	0.0141*	0.0266***
	(-1.79)	(-3.86)	(-0.01)	(1.92)	(4.11)
Intang	−0.0030	−0.1273*	0.0431	0.0483	−0.0379
	(-0.08)	(-1.88)	(1.06)	(0.79)	(-0.68)
Oversea	−0.0394***	−0.0282	−0.0414***	−0.0101	−0.0560***
	(-4.05)	(-1.46)	(-3.84)	(-0.68)	(-3.55)
Insti	−0.0629***	−0.0466***	−0.0700***	−0.0873***	−0.0660***
	(-7.16)	(-2.80)	(-7.22)	(-6.49)	(-4.96)
FVA	0.0156	0.0229	0.0089	−0.0542	0.0213
	(0.39)	(0.38)	(0.19)	(-0.91)	(0.37)
FVD	1.1994	−0.4163	1.9260	2.0714	−0.5508
	(0.97)	(-0.20)	(1.25)	(0.99)	(-0.25)
Industry	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES
Constant	2.3588***	2.2446***	2.2936	1.0132***	2.3778***
	(26.72)	(26.53)	(25.67)	(9.92)	(28.48)
Observations	356,370	85,895	270,475	103,232	107,570
Adjusted R^2	0.285	0.295	0.281	0.214	0.261
F	572.62	254.68	374.67	276.55	301.89

Note: Robust standard errors (RSE) are clustered by firm. *, **, and *** denote statistical significance levels of 0.10, 0.05, and 0.01, respectively (two-tailed).

CRediT authorship contribution statement

Guiling Zhang: Validation, Writing – original draft, Writing – review & editing. **Xu Lou:** Software, Writing – original draft, Writing – review & editing. **Danliang Yan:** Conceptualization, Supervision. **Hui Xu:** Methodology, Formal analysis, Visualization, All persons who have made substantial contributions to the work reported in the manuscript are listed above.

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Appendix A. Data Collection

We hand collect corporate derivative use data *primarily* from annual reports. We first download firms' annual reports from the cninf website. We then conduct a keyword search on annual reports. The keywords *in Chinese* are: *yansheng* (derivative), *taoqi* or *duichong* (hedge), *yuanqi* (forwards), *qihuo* (futures), *diaoqi* or *huhuan* (swaps), *lilv* (interest rate), *huilv* (exchange rate or currency rate) and *shangpin* (commodity).

Next, we ask human subjects to validate whether a firm is a derivative user or a non-user. Specifically, if a firm uses any above-mentioned keywords and reports any non-zero figure relating to derivatives, such as the nominal values and fair values of derivatives, derivative-related fair value changes (gains and losses), and derivative-related investment changes, in its annual reports, it is defined as a *User*. If a firm uses any keywords and yet fails to report any specific figures in its annual reports, such a firm is classified as a *Non-User*.

Last, if a firm is defined as a *User*, we collect key information, including the types of derivatives, the types of hedging risks and information quality.

Appendix B. T-test results of derivatives usage in different ownership and risk exposure

Panel A						
	SOE = 0 (1)		*SOE* = 1 (2)		Diff [(1)–(2)]	
Variable	Observations	Mean	Observations	Variable	Observations	Mean
DT	19,146	0.179	9855	*DT*	0.016906	3.600***

Panel B						
	FX = 0 (1)		*FX* = 1 (2)		Diff [(1)–(2)]	
Variable	Observations	Mean	Observations	Variable	Observations	Mean
DT	11,588	0.080	17,285	*DT*	−0.157	−35.269***

Panel C						
	CX = 0 (1)		*CX* = 1 (2)		Diff [(1)–(2)]	
Variable	Observations	Mean	Observations	Variable	Observations	Mean
DT	12,997	0.118	16,004	*DT*	−0.101	−22.887***

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