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Financial derivatives, analyst forecasts, and stock price synchronicity: Evidence from an emerging market

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ABSTRACT

Against the backdrop of the role of financial derivatives in the recent financial crisis, this paper aims to identify the effects of financial derivative usage on the amount of firm-specific information incorporated into stock prices, as measured by stock price synchronicity (SPS), using an emerging market from 2009 to 2019. We find strong evidence consistent with this information asymmetry view. Specifically, our results exhibit that financial derivative usage deters firm-specific information into stock prices, thus increasing SPS. Further analyses indicate that financial derivative usage indirectly affects SPS via analyst forecasts (i.e., analyst forecast accuracy, analyst forecast dispersion, analyst forecast optimism, and analyst following). In addition, our results imply that both the economic complexity and accounting complexity of financial derivatives affect SPS positively. The results are robust to a batch of robustness tests. The findings not only add to the literature on financial derivative usage and SPS but also have policymaking implications for the emerging market.

1. Introduction

A financial derivative is a contract between two or more parties whose value is derived from the value of an underlying instrument, which typically changes in value following changes in an underlying market variable, such as a rate (i.e., interest rate, foreign exchange rate) or a price (i.e., stock or commodity) (Campbell et al., 2019). Over the last few decades, growing market turmoil and evident of a global financial crisis has made risk-management a priority for firms (Cohen et al., 2017). As a result of this trend, financial derivative usage has increased exponentially. According to the Bank for International Settlements, the total notional amount of global financial derivatives rose from $9.4 trillion in 2000 to $60.7 trillion in 2020[1]. However, derivatives are financial weapons of mass destruction (Warren E. Buffet, 2003)[2]. Failures of financial derivative usage (i.e., Enron and Sinopec) have prompted regulators to examine the role of financial derivatives played in the capital market. The Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) require firms to disclosure financial derivative usage in detail (i.e., fair value changes and reasons for such changes, accounting treatments involved)[3].

While numerous studies have investigated the determinants of financial derivatives (Choi et al., 2013; Bartram, 2019) and their economic consequences (Choi et al., 2015; Blanco and Wehrheim, 2017; Deng, 2020), evidence of the impact of financial derivative

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[1] https://www.bis.org/
[2] Berkshire Hathaway Annual Report, 2003
[3] http://www.sse.com.cn/disclosure/credibility/supervision/inquiries/

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usage on the amount of firm-specific information in stock prices is limited. Specifically, Bai et al. (2017) find that there is additional firm-specific information conveyed or stimulated by the derivative market through either the price discovery function or the information production function of financial derivatives. Meanwhile, empirical evidence shows that high level use of financial derivatives are associated with an increase in the synchronicity of stock price movements with the market index, which indicates less revelation of firm-specific information to the market (Dewally and Shao, 2013; Wang and Yu, 2020). While these mixed valuation results are puzzling, they can be explained in part by manager's financial derivative usage to hedge exposure risks versus manager's selective use of financial derivatives for speculation and self-interests (Fauver and Naranjo, 2010).

Therefore, in this paper we continue the debate by examining the impact of financial derivative usage on the amount of firm-specific information in stock prices, thus affecting SPS in the emerging market. The literature suggests two conflicting predictions about whether financial derivative usage hinders or promotes the flow of firm-specific information; they are the information discovery view and the information asymmetry view, respectively. As discussed in previous studies (Batta et al., 2016; Bai et al., 2017; Kim et al., 2021), the information discovery view predicts that additional firm-specific information is conveyed or stimulated to market participants by firms' financial derivative usage through either the price discovery function or the information production function. Thus, financial derivative usage is expected to positively influence the amount of firm-specific information in stock prices and reduce SPS. On the other hand, the information asymmetry view proposes that financial derivative usage intensifies agency problems and exacerbates information opacity in financial reports (Dewally and Shao, 2013; Choi et al., 2015; Wang and Yu, 2020), thus deterring the flow of firm-specific information into stock prices. Hence the information asymmetry view suggests a positive relation between financial derivative usage and SPS. As financial experts and information intermediaries, analysts specialize in the production of firm-specific information. However, Campbell et al. (2015) highlights that the disclosure of financial derivatives is complex and incomplete, whereas analysts and investors cannot properly understand the earning implications of financial derivatives (Chang et al., 2016; FASB, 2010). Therefore, we further investigate the role of analyst forecasts played in the relation between financial derivative usage and SPS.

This paper aims to explore the economic consequences of financial derivative usage in one of the largest and most important emerging markets—the Chinese stock market. While multiple literature has examined the economic consequences of financial derivatives in the developed capital market, little attention has been paid to the emerging markets. The case of China is of academic interest for the following reasons. (i) The development of China's financial derivatives still in its infancy. Due to the conservative concept and backward technology, the variety of financial derivatives is small, and the use of financial derivatives is far from widespread in China (11% of listed firms with financial derivative usage)[4]. Therefore, firms with financial derivative usage cannot hedge exposure risks to a particular rate or price, and even cause greater uncertainty in their operating performances. In 2018, Sinopec's failed futures transactions led to its stock price plummeted by 6.75% and its market value evaporated by $68.1 billion. Moreover, many listed companies, including China Aviation Industry, COSCO, Shennan Electric, and China Southern Airlines, faced huge losses as a result of failed financial derivative transactions. (ii) The accounting standards of financial derivatives are complex. FASB and IASB, the two of the world's most influential standard-setters, have chosen to use fair value to measure financial derivatives; China's accounting standards are converging. Due to the complex design of financial derivatives, some financial derivatives need to use mathematical models to estimate their market value, that is, the mark-to-market model, the Black-Scholes. All those models are complicated to calculate with flexible selection of equation parameters. Thus, the measurement of financial derivatives which involves managers' assumptions and estimates, is easily manipulated by managers (Guo et al., 2017). (iii) The evaluation and supervision mechanisms are not sound. A large number of financial derivatives transactions have deviated from the original intention of risk aversion. The high leverage, the lower entry threshold, and transaction costs of financial derivatives has led to a lack of evaluation and regulatory mechanisms in terms of firms' financial derivative usage. Therefore, a series of derivatives speculation incidents such as CITIC Bank, have sparked debates among scholars on the role of financial derivative usage in the emerging market. (iv) Lack of professional financial talents (Cheng and Cheung, 2021). Financial derivatives are characterized by high leverage, high price volatility, and high risk. The slightest carelessness may lead to failed financial derivative transactions, and thus causing huge losses. In firms with financial derivative usage, managers do not pay sufficient attention to the economic consequences of financial derivative usage. Due to the lack of proper understanding of financial derivatives, relevant business processes are not established in time to manage and regulate derivatives business.

Taking a sample of non-financial listed firms from 2009 to 2019 in China, we examine the relation between financial derivative usage and SPS. First, our results suggest that financial derivative usage are positively correlated to SPS in China. This result implies that firm-specific information hoarding incentives arising from financial derivative usage incrementally contribute to SPS over and above other predictors identified by previous SPS research. Second, we find that financial derivative usage indirectly affects SPS via analyst forecasts (lower analyst forecast accuracy, higher analyst forecast dispersion, analyst forecast optimism, and more analyst following). This finding suggests that analyst forecasts paly a mediating role in the relation between financial derivative usage and SPS. Besides, analysts cannot properly understand firms' financial derivative activities, which is in line with the literature (Chang and Choi, 2017), thus reducing firm-specific information in stock prices and increasing SPS. Third, additional analyses reveal that both the accounting complexity and economic complexity of financial derivatives have a positive association with SPS. Overall, the evidence supports the information asymmetry view, that financial derivative usage intensifies agency problems and exacerbates information opacity in financial reports, thus hindering the flow of effective information and lowering the amount of firm-specific information in stock prices. This paper conducts several analyses to test the robustness of empirical results, including the two-stage instrumental variable test,

[4] The data collected in this paper on page 15.

propensity score matching (PSM), Bootstrap test, Sobel-Goodman test, and Structural Equation Model (SEM). The results hold up to a batch of robustness tests.

This paper contributes to different streams of literature. First, this paper extends the current literature on the economic consequences of financial derivatives from the perspective of SPS and sheds light on the role of financial derivatives in the emerging market. This paper complements the research on the economic consequences of fair value measurement. Firms are required to measure financial derivatives at their fair value, so this study is an important branch of the study of the economic consequences of fair value measurement. Second, this paper adds to the growing literature on the determinants of heterogeneity in the stock return co-movement by identifying financial derivative usage as an important factor that can help explain differences in SPS. By restricting our attention to a specific emerging market, our findings lend further support to the crucial role of financial derivative usage in affecting capital market outcomes. Third, this paper employs analyst forecasts as a mediating effect and explores the correlation between financial derivative usage, analyst forecasts, and SPS. Our findings contribute to understanding the role of analysts as information intermediaries and the effects of the complex financial derivative information on the usefulness of this information. Fourth, our empirical findings provide more insights into the Chinese emerging market, which is now among the top economies in the world and attracts world-wide investors. Such information is important for investors to diversify their portfolios and also for policymakers in other emerging economies when regulating their own equity markets.

Our findings have several important implications for both regulators and managers. Regulators should further improve China's financial market system, including financial derivatives exchange market, as well as the over-the-counter market. Meanwhile, regulators should strengthen scientific supervision of financial derivative transactions, preventing the emergence of vicious and excessive speculations, protecting the fairness, impartiality and openness of the market, so as to provide a convenient environment for investors to use financial derivatives. Managers should standardize the accounting treatments of financial derivatives and develop a specific and standardized accounting treatment process, so as to provide stakeholders with more detailed and accurate information. Moreover, the disclosure of financial derivatives should include the basis for the selection of pricing models and valuation parameters, which make analysts and investors correctly interpret the information content and improve the information quality and transparency.

The remainder of the paper proceeds as follows: Section 2 presents a literature review and hypothesis development; Section 3 is the research design; Section 4 discusses empirical results; Section 5 performs additional tests, and section 6 concludes the paper.

2. Related literature and hypothesis development

2.1. The use of financial derivatives

Financial derivatives, including futures, forwards, swaps, and options, have been some of the major financial innovations in the capital market in recent years. In the efficient and integrated capital markets studied by Modigliani et al. (1958), using financial derivatives to hedge exposure risks is irrelevant. That is, investors could manage these risks by diversifying their investments. In inefficient or segmented capital markets, firms make extensive use of financial derivatives as a result of market imperfections. Guay and Kothari (2003) classifies these imperfections into four types of situations: (i) financial distress costs, (ii) costly external financing, (iii) asymmetry in tax costs, and (iv) costs of managerial risk aversion. Consistent with these frictions, the research shows that financial derivatives can effectively and efficiently reduce firm risks. That is, financial derivative usage allows firms to smooth earnings and cash flow, and as a result reduce their capital costs (Campbell et al., 2019; Deng, 2020). However, other research finds evidence that firms use financial derivatives for speculation (Bartram, 2019) or earnings manipulation (Choi et al., 2015; Guo et al., 2017).

There is mixed evidence between financial derivative usage and firm value. Financial derivative usage can avoid under-investment (Lobo et al., 2020), reduce corporate taxes (Donohoe, 2015), and, thus, increase firm performance (Chen et al., 2017) and firm value (Geyer-Klingeberg et al., 2020). However, financial derivative usage has a negative impact on firm value in firms with greater agency and monitoring problems (Fauver and Naranjo, 2010; Narayanan and Uzmanoglu, 2018). Apart from these studies that examine the fundamental relation between financial derivative usage and firm value or risks, the extant literature relates financial derivative usage to firm-level characteristics, such as its effects on investors' risk assessments (Campbell, 2015), executive compensation (Manchiraju et al., 2015), analyst forecasts (Chang et al., 2016), and audit quality (Lambert et al., 2017).

One unique feature of this literature is that many studies are industry-specific, focusing only on, for example, oil and gas, mining (Adam et al., 2017), or financial firms (Lenee, 2017). While there are benefits to focusing on smaller samples, there are also inherent limitations, such as less powerful tests due to smaller sample sizes and limited generalizability. In addition, the above-mentioned studies use only indicator variables to identify whether or not a firm uses financial derivatives to proxy for a firm's financial derivative usage; these do not capture the extent of financial derivative usage at the firm-level. Due to the inherent complexity and unavailability of data about financial derivative usage in China (Guo et al., 2017), the relation between financial derivative usage and SPS is controversial and the channel through which financial derivative usage affects SPS is insufficiently investigated.

2.2. The determinants of SPS

An individual firm's stock price reflects market-level, industry-level, and firm-specific information. King (1966) proposes that stock prices covary with both market- and industry-level information by employing the capital asset pricing model (CAPM), but Roll (1988) shows that stock return co-movement depends on the relative amounts of firm-specific and market-level information incorporated into stock prices, with a significant portion of stock return variation being attributable to the impounding of firm-specific information into stock prices. The R^2 statistic from the market model has been widely used to analyze SPS (Morck et al., 2000; Gassen et al., 2020); a high R^2 indicates less firm-specific information in stock prices and a higher degree of SPS (Jin and Myers, 2006).

Built upon this foundation, a growing body of studies provides evidence that is consistent with this information-based interpretation of SPS. For example, Morck et al. (2000) finds that the R^2 statistic is lower in countries with developed financial systems and better corporate governance. This finding indicates that strong property rights promote informed arbitrage, which leads to the inclusion of more firm-specific information and less co-movement in stock prices across firms. These seminal studies have motivated several follow-up studies examining the association between SPS and corporate governance (Nguyen et al., 2020), analyst activities (Gao et al., 2020), earnings informativeness (Choi et al., 2019), corporate transparency (Jin and Jorion, 2006; Ntow-Gyamfi et al., 2015), voluntary disclosure (Gong et al., 2013), earnings management (Neifar and Ajili, 2019), the largest shareholder, foreign ownership (Tas and Tan, 2016; To et al., 2021), CEO media exposure (Li et al., 2019), institutional investors (Liu et al., 2018; Shen et al., 2021), audit quality (Cheong and Zurbruegg, 2016), the adoption of accounting standards (Patro and Gupta, 2016), social trust (Qiu et al., 2020), and trade-secret protection (Kim et al., 2021).

As a notable example, Jin and Myers (2006) document that opaque financial reporting increases R^2 by shifting firm-specific risk to managers, indicating a lower amount of firm-specific information in stock prices. That is, a possible condition for a lower amount of firm-specific information in stock prices is caused by opacity combined with managers' cash flow management. They justify these results by the fact that limited information produced by opacity combined with the poor protection of investors allow managers to capture more of firms' cash flow, by gripping more firm-specific information variance, which leads to a higher SPS.

2.3. Correlation between financial derivatives and SPS

The effect of financial derivative usage varies greatly, and we propose using the information discovery view and the information asymmetry view to explain the relation between financial derivative usage and SPS.

In terms of the information discovery view, financial derivative usage (1) mitigates agency problems and (2) improves information transparency, thus enhancing the flow of firm-specific information into stock prices and reducing SPS. Firstly, financial derivative usage mitigates agency problems between inside managers and outside investors (DeMarzo and Duffie, 1995). These facilitate outside investors learning about managerial ability and project quality. Similarly, Breeden and Viswanathan (2016) argue that hedging can enhance investors' learning process about managerial ability. By reducing the information asymmetry, financial derivative usage makes it more difficult and costlier for managers to pursue their self-interest (Jensen and Meckling, 1976). Secondly, prior research provides evidence that financial derivative usage improves transparency of firms' financial reports. Chen and King (2014) document that financial derivative usage reduces cost of debt by improving transparency. Manconi et al. (2017) find that financial derivative usage reduces uncertainty and erodes the informed investors' information advantage and profitability. Hence, financial derivative usage conveys more firm-specific information to market participants, thus reducing SPS (Hutton et al., 2009; Batta et al., 2016). Drawing on the above discussion, we posit the following hypothesis.

H1a: Financial derivative usage decreases stock price synchronicity (SPS).

According to the information asymmetry view, financial derivative usage (1) intensifies agency problems and (2) exacerbates information opacity, thereby hindering the firm-specific information incorporating into stock prices, as reflected in SPS.

On the one hand, the inherent complexity of financial derivatives gives rise to agency problems between managers and investors, which deters investors from incorporating effective information into stock transactions. Because of perceived informational advantages, managers have an incentive to cover up their self-serving behaviors, or to limit related information leakage, by withholding unfavorable information or selectively disclosing such information that helps them camouflage their self-serving behaviors (Bao et al., 2019). China's accounting standards have required firms to disclose financial derivatives in financial reports since 2007 but with considerable limitations (Guo et al., 2021). For example, firms are not required to disclosure the motivation of financial derivative usage, the notional principal of financial derivative positions, and the sign or magnitude of their derivative exposure in financial reports. Therefore, firms' voluntary disclosures of financial derivatives make it difficult for outsiders to classify their positions into either hedging or speculation (Cheng and Cheung, 2021). Managers may use financial derivatives to their advantage, such as stock-based compensation, personal benefits, or career concerns (Cheng and Cheung, 2021). Thus, managers could use financial derivatives to speculate, meet or beat benchmarks, and smooth earnings, leaving investors with no idea as to what risk exposure exists, how much of this exposure is hedged, and whether financial derivative usage reduces or enlarges the risk exposure (Campbell et al., 2015).

On the other hand, the complex financial derivatives make it difficult and costly for investors to interpret the earning implication of financial derivatives activities (Campbell et al., 2015), which, in turn, hinders the flow of firm-specific information. The exponential increase in financial derivatives has led to increased demand from investors for information about firms' financial derivative usage to enable a better assessment of firms' risk and value. Yet, there is no consensus on the best way to recognize and disclose firms' financial derivative usage. Until recently, it has been difficult, if not impossible, for users of financial reports to identify the earning implications of financial derivative activities in a given period; the publicly available disclosures on financial derivative activities are opaque (Manconi et al., 2017; Park and Park, 2020). In practice, many firms use multiple kinds of financial derivatives including futures, forwards, swaps, options and some structured financial derivatives, and these financial derivatives are different in terms of their risk profiles. A great majority of these firms report only the aggregate fair value of their multiple financial derivatives positions without showing their risk profiles, thus leading to opaque financial reports. When a firm's financial reports are opaque, investors cannot observe the firm-specific component of changes in value and, as a result, the firm's stock prices move only with common information. Moreover, investors may have to bear the higher costs of acquiring and processing firm-specific information to overcome the information opacity related to financial derivatives (i.e., disclosures of financial derivatives are incomplete, inconsistent across firms, and disaggregated across footnotes) (Blankespoor, 2019). The high cost associated with firm-specific information search, however, discourages informed trading, and thus, impedes the incorporation of firm-specific information into stock prices (Huang et al., 2020). Drawing on the above discussion, we posit the following hypothesis.

H1b: Financial derivative usage increases stock price synchronicity (SPS).

2.4. Correlation between financial derivatives and analyst forecasts

As financial experts and information intermediaries of the capital market, analysts specialize in interpreting and disseminating financial information and providing outputs, such as earnings and cash flow forecasts, recommendations, and long-term growth forecasts (Wang and Yu, 2020). Analyst forecast quality (analyst forecast accuracy, analyst forecast dispersion, analyst forecast optimism, and analyst following) is influenced by analysts' ability to obtain and process information, the informativeness of analysts' research outputs, and economic incentives (Ramnath et al., 2008). The complex transactions and financial information resulting from a firm's choice to use financial derivatives could affect each of these factors and, thus, the analyst forecast quality.

The complexity of financial derivatives could hinder analysts' ability to forecast earnings accurately. In fact, analysts have explicitly said that the nature of financial derivatives is difficult to understand and analyze, and that there is a lack of transparent information in the financial reports on financial derivative usage and the complexity of the accounting requirements (IASB, 2010). From an accuracy standpoint, the accounting treatments and disclosure of financial derivatives rarely provide the details necessary to evaluate what risk exposures exist, their magnitude, and how they vary over time, as financial derivatives are reported in vastly different ways among the users (Blankspoor, 2019). As a result, analysts cannot properly understand or judge the earning implications of firms' financial derivative usage (Campbell et al., 2015), resulting in less accurate analyst forecasts. From a dispersion standpoint, the difficulty and high costs involved in obtaining and analyzing financial derivative usage information leads analysts to rely on their own expertise to forecast earnings; thus, greater dispersion is expected. With regard to analyst earning optimism, analysts are less likely to be penalized for inaccuracy and can stimulate more trading activities from an optimistically biased output when market uncertainty is high (Chang and Choi, 2017). Since financial derivatives are highly complex, leveraged and risky (Guo et al., 2019), a firm's financial derivative usage implies that its managers face high uncertainty. Therefore, analysts issue more optimistically biased earnings forecasts under firm's financial derivative usage. In terms of analyst following, an increasing demand for analyst services for firms with less readable communication and a greater collective effort by analysts for firms with less readable disclosures (Lehavy et al., 2011). The demand for analyst services is more valuable in firms with financial derivative usage, implying greater analyst following. Drawing on the above discussion, we posit the following hypothesis.

H2: Financial derivative usage reduces analyst forecast quality (i.e., lower analyst forecast accuracy, higher forecast dispersion, more forecast optimism, and analyst following).

2.5. The mediating role of analyst forecasts

Analysts are agents who seek and interpret both public information (i.e., macro-economy, industry-wide, individual company) and private information to forecast earnings. This raises the important issue of whether the presence of analyst forecasts increases market-level or firm-specific information in stock prices, as measured by SPS. Accurate analyst forecasts enable market participants to predict future firm-specific events with precision (Dasgupta et al., 2010). Jiang et al. (2019) provides support for the information advantage argument of analysts' information production, that is, analysts' private information acquisition enhances the firm-specific information impounded into stock prices. What is more, analyst following helps the market incorporate more firm-specific information into stock prices, resulting in lower SPS (Bai et al., 2016). These findings indicate that analysts have already been playing an important role in improving stock price informativeness. However, severe information opacity in the emerging market, it is challenging for analysts to provide more firm-specific information to investors in the emerging market (Gao et al., 2020).

Due to ambiguity relation between financial derivative usage and SPS, it seems imperative to adopt a more complex approach to elucidate the likely transmission mechanism between them. As mentioned above, if financial derivative usage affects analyst forecast, the impact of financial derivative usage on SPS might be partly influenced through the relation between analyst forecasts and SPS. Hence the existence of this indirect influence would reveal the mediating role of analyst forecasts. On one hand, financial derivative usage could hedge the influence of external noise, thus reducing information asymmetry, increasing the amount of information in financial reports and improving information transparency (Kim et al., 2021). At this point, analysts are able to interpret the disclosed information more accurately. In this way, the operating performance of listed companies can be more clearly reflected to market participants through analyst forecasts (Wang and Yu, 2020), thus improving the firm-specific information in stock prices and reducing SPS. On the other hand, financial derivative usage and its disclosure are complex economic activities (Pierce, 2020). Although firms disclosure quantitative information on financial derivative usage in their financial reports, the complexity of financial derivatives affect the transparency and understandability of financial reports and reduce analysts' earnings forecasts quality (Badenhorst, 2018). The complexity of financial derivative usage causes analysts to misjudge the earning implications of firms' financial derivative activities, such as, their diverse motivations, economic substance, and accounting treatment (Campbell et al., 2015; Chang et al., 2016). Therefore, more information disclosure about financial derivatives leads to a higher information asymmetry between managers and analysts (Abudy and Shust, 2020). Conceptually, lower analyst forecast quality could produce less firm-specific information in the emerging market and thus increasing SPS. With all this taken together, financial derivative usage hinders analysts' production and transmission of effective information, thus leading to a lower amount of firm-specific information in stock prices. Drawing on the above discussion, we posit the following hypothesis.

H3: ***Financial derivative usage indirectly affects SPS via analyst forecast quality (analyst forecast accuracy, analyst forecast dispersion, analyst forecast optimism and analyst following).***

3. Research design

3.1. Data

Our sample consists of all the non-financial firms listed on Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) from 2009 to 2019. We extract all data from CSMAR database and 26,175 observations as the sample. Following Guo et al. (2021), We identified firms' financial derivative usage by searching for the following words in the financial reports: "hedge, " "hedging," "derivatives," "risk management," "financial derivative assets," "financial derivative liabilities," "options," "future," "swaps," "forwards," "deferred," "extension," and "NDF." We then checked each report manually to identify financial derivative usage. This search identified 2,679 firms with financial derivative usage. The samples are screened as follows: (i) exclude ST, PT firms; (ii) exclude financial firms; (iii) exclude samples without complete data. After that, there were 25,717 observations. All continuous variables have been winsorized at the 1% and 99% levels to reduce the impact of outliers. Panel A of Table 1 reports the distribution of our sample firms by year. The number of firms with financial derivative usage increases monotonically over the sample period (from 108 in 2009 to 424 in 2019). Panel B of Table 1 shows the industry distribution of financial derivative users. Among the 18 non-financial industries, only one have no financial derivative usage: the education industry. There is a great variation in our sample with 72.86% (1,952/2,679) of financial derivative usage being in the manufacturing industry, compared to the U.S. sample of Zhang (2009) where 23.5% of firms are in manufacturing except machinery and equipment, 20.4% are in industrial machinery and equipment, and15.9% in mining and

Table 1
Sample distribution.

Panel A: Sample distribution by year

Year	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
Derivatives Users	108	136	170	172	198	232	244	247	324	424	424	2679
Derivatives Non-Users	1284	1496	1761	2009	2020	1954	2045	2200	2509	2820	2940	23,038
Total	1392	1632	1931	2181	2218	2186	2289	2447	2833	3244	3364	25,717

Panel B: Sample distribution by industry

Industry name	Industry code	Derivatives Users	Derivatives Non-Users	Total	Pct (%) of users within an industry	Pct (%) of users in all industries
Agriculture, forestry, livestock farming, & fishery	A	37	356	393	0.0941	0.0138
Mining	B	127	565	692	0.1835	0.0474
Manufacturing	C	1952	14,243	16,195	0.1205	0.7286
Utilities	D	64	822	886	0.0722	0.0239
Construction	E	57	717	774	0.0736	0.0213
Wholesale and retails	F	163	1258	1421	0.1147	0.0608
Transportation,						
Transportation, warehousing and postal service	G	116	808	924	0.1255	0.0433
Lodging and cantering	H	2	91	93	0.0215	0.0007
Information and technology	I	68	1453	1521	0.0447	0.0254
Real estate	K	5	1297	1302	0.0038	0.0019
Leasing and business services	L	38	264	302	0.1258	0.0142
Scientific research and technical services	M	3	257	260	0.0115	0.0011
Water conservancy, environment and public facilities management	N	17	252	269	0.0632	0.0063
Resident, repair and other services	O	6	17	23	0.2609	0.0022
Education	P	0	17	17	0	0
Sanitation and social work	Q	4	47	51	0.0784	0.0015
Culture, sports and entertainment	R	15	296	311	0.0482	0.0056
Conglomerate	S	5	278	283	0.0177	0.0019

Panel C: Average market value of sample firms and financial derivative usage firms 2009–2019

	Sample firms (25717)	Financial derivative users (2679)	Ratio of market value of financial derivative users to sample firms	Ratio of market value of financial derivative non-users to sample firms
Average market value	37.53	8.64	23.02%	76.98%

Panel A presents year distribution by derivative users during 2009–2019. Panel B presents industry distribution by derivative users during 2009–2019. Panel C shows the average market value (from 2009 to 2019) of sample firms and derivative users in trillion RMB. The ratio of market value of derivative users to sample firms is calculated as the market value of derivative users divided by that of sample firms. The ratio of market value of derivative non-users to sample firms is calculated as the market value of derivative non-users divided by that of sample firms.

services. Panel C of Table 1 presents the average market value of sample firms and financial derivative users. Following Guo et al. (2021), we measure annual market value with the market value of tradable shares in the end of year obtained from the CSMAR database. From 2009 to 2019, the market value of firms that use derivatives (2,679 firms) on average accounts for 23.02% of sample firms, suggesting that financial derivative users play an important role in the Chinese capital market.

3.2. Measures

3.2.1. Stock price synchronicity–SPS

Stock price synchronicity measures the extent to which stock price movement is attributed to firm-specific information. More studies show that additional firm-specific information lowers SPS. Following Gul et al., (2010) and Kim et al. (2021), we regress weekly firm stock returns on the current and lagged market and industry value-weighted returns as follows:

$$\mathrm{Ret}_{i,t} = \hat{\mathrm{I}}\pm + \beta_1 \mathrm{Mktret}_t + \beta_2 \mathrm{Mktret}_{t\text{-}1} + \beta_3 \mathrm{Indret}_{k,t} + \beta_4 \mathrm{Indret}_{k,t\text{-}1} + \mathrm{e}_{i,t} \tag{1}$$

Where, for firm i, industry k and week t, *Ret* denotes the weekly return on A-shares traded on either the Shanghai or Shenzhen exchange markets; *Mktret* and *Indret* denote the value-weighted market return and industry return, respectively; and $\mathrm{e}_{i,t}$ represents the unspecified random factors. This A-share market return is based on the composite (value-weighted) index, which reflects A-share price movements in both the Shanghai and Shenzhen exchanges. The industry return is calculated by using all firms within the same industry, with firm i's weekly return omitted. In Eq. (1), we include lagged market and industry returns to alleviate concerns about potential non-synchronous trading biases that may arise from the use of weekly returns for estimating the market model (French et al., 1987). Following Morck et al. (2000), SPS can be defined as:

$$\mathrm{SPS}_i = \ln\left[\mathrm{R}^2/(1\text{-}\mathrm{R}^2)\right] \tag{2}$$

where R^2 the R-squared value from Eq. (1) for firm i. A high SPS_i indicates a lower amount of firm-specific information incorporated in stock prices.

3.2.2. Financial derivative usage–FDU

The ideal measure of a firm's financial derivative usage *(FDU)* is the ratio of the financial derivative position to the amount of risk exposure that the firm is trying to hedge (Tufano, 1996). Unfortunately, firms do not disclose enough information to calculate this ratio. Following prior studies (Fauver and Naranjo, 2010; Bai et al., 2017; Cheng and Cheung, 2021), we use two scientific methods to measure firms' financial derivative usage: FDU_1 is defined as an indicator variable to identify whether or not a firm uses financial derivatives; FDU_2 is defined as the logarithm of the fair value of financial derivatives at term-end to identify the extent of financial derivative usage.

In order to evaluate whether the economic consequences of financial derivative usage are due to accounting complexity, economic complexity, or both. We use the accounting complexity and economic complexity of financial derivatives to further investigate the relation between financial derivative usage and SPS. According to Chang et al. (2016) and Guo et al. (2020), accounting complexity of derivatives (*Acomp*) is measured by fair value hierarchy of derivatives, that is *Acomp* = 1, 2, 3 stand for using levels 1, 2 and 3 fair value hierarchy estimates respectively. As for the economic complexity of financial derivatives (*Ecomp*), if a firm uses one, two or more financial derivatives, we designate that *Ecomp* equals 1, 2, 3. The above grouping is based on the idea that uncertainty about the mapping of derivative transactions increases with the number of financial derivatives and the fair value accounting standards used (Peterson, 2012).

3.2.3. Analyst forecasts

Analyst forecast accuracy (*Analyst_bias*). This paper measures analyst forecast accuracy using forecast bias (*Analyst_bias*), with greater values indicating less accurate forecasts (Muslu et al., 2019). *Analyst_bias* is computed as the absolute value of the difference between analyst forecast of earning per share ($F_{i,n,t}$) and actual earnings per share ($A_{i,t}$), deflated by the prior term-end stock price ($P_{i,t-1}$). Where, for firm i, number of analyst forecasts n and year t., *F* denotes analyst forecast of earning per share, A denotes actual earnings per share and P denotes the prior term-end stock price. If an analyst issues more than one earning forecast in a calendar year (N), we calculate the average forecast bias. The following formula describes the bias of analyst forecast:

$$\mathrm{Analyst}\backslash\_\mathrm{bias}_{i,t} = \frac{1}{\mathrm{N}_{i,t}} \sum_{n=1}^{\mathrm{N}_{i,t}} \left|\mathrm{F}_{i,n,t}\text{-}\mathrm{A}_{i,t}\right| / \mathrm{P}_{i,t\text{-}1} \tag{3}$$

Analyst forecast dispersion (*Analyst_disp*). We follow Batta et al. (2016) in constructing a measure of analyst forecast dispersion (*Analyst_disp*), which is the standard deviation of the earliest individual analyst earnings forecasts following the financial reports, deflated by the beginning-of-year stock price. $\overline{\mathrm{F}_{i,n,t}}$ denotes the average analyst forecasts for firm i in year t. The specific formula is as follows:

$$\mathrm{Analyst}\backslash\_\mathrm{disp}_{i,t} = \left[\frac{1}{\mathrm{N}_{i,t\text{-}1}} \sum_{n=1}^{\mathrm{N}_{i,t}} \left(\mathrm{F}_{i,n,t}\text{-}\overline{\mathrm{F}_{i,n,t}}\right)^2\right]^{1/2} / \mathrm{P}_{i,t\text{-}1} \tag{4}$$

Analyst forecast optimism (*Analyst_opti*). The forecast optimism variable captures the difference between the average of analysts' forecasts on earnings per share ($F_{i,n,t}$) and the actual earnings per share ($A_{i,t}$) in financial reports. The average of analysts' forecasts is regarded as the "consensus," which is normally viewed as the reference or target that investor expect firms to meet. Following Prokop and Kammann (2018), we construct the variable of analyst forecast optimism (*Analyst_opti*) by Eq. (5):

$$\text{Analyst}\backslash\_\text{opti} = \frac{1}{N_{i,t}}\sum_{n=1}^{N_{i,t}}(F_{i,n,t}\text{-}A_{i,t})/P_{i,t-1} \tag{5}$$

Analyst following (*Analyst_foll*). The number of analysts following the firm captures the level of market scrutiny of firm performance and managerial behavior. Because analysts are rewarded partly for forecast precision, they have an incentive to collect private information and provide accurate forecasts of future firm earnings. As a result, greater analyst following would reflect the level of market following of the firm and managerial actions. Analyst following (*Analyst_foll*) is calculated as the natural logarithm of the number of analysts issuing an annual forecast for a firm in a fiscal year (Lee and So, 2017).

3.3. Model

According to the Breusch and Pagan Lagrangian multiplier test (B-P test) and hausman test, we use the fixed-effect models to test the effects of financial derivative usage (*FDU*) on SPS, as well as the effects of financial derivative usage (*FDU*) on analyst forecasts (*Analyst forecasts*). The details can be seen in Eq. (6) and (7).

$$SPS_{i,t} = \beta_0 + \beta_1 FDU_{i,t} + \beta_2 Controls_{i,t} + \hat{I}\mu \tag{6}$$

$$\text{Analyst forecasts}_{i,t} = \beta_0 + \beta_1 FDU_{i,t} + \beta_2 Controls_{i,t} + \hat{I}\mu \tag{7}$$

According to Guo et al. (2018), Two-stage mediation models are employed in Eq. (8) and (9) to investigate the mediating effect of

Table 2
Descriptive statistics.

Panel A: Summary statistics of firm characteristics

Variable	Number	Min	Mean	Median	Max	SD
SPS	25,717	−2.102	−0.720	−0.633	0.371	0.788
FDU_1	25,717	0.000	0.105	0.000	1.000	0.307
FDU_2	25,717	0.000	1.636	0.000	24.320	4.840
Acomp	25,717	0.000	0.168	0.000	3.000	0.541
Ecomp	25,717	0.000	0.132	0.000	4.000	0.423
Analyst_bias	25,717	0.003	0.026	0.017	0.078	0.024
Analyst_disp	25,717	0.003	0.016	0.012	0.042	0.013
Analyst_opti	25,717	−0.019	0.015	0.011	0.055	0.021
Analyst_foll	25,717	0.000	1.278	1.099	3.045	1.171
Turnover	25,717	0.002	0.563	0.396	4.880	0.526
Lev	25,717	0.146	0.436	0.433	0.735	0.195
Age	25,717	7.606	7.608	7.608	7.610	0.001
Mash	25,717	1.235	7.496	3.888	25.170	7.809
Largest	25,717	16.730	34.273	32.640	55.440	12.792
Board	25,717	0.333	0.369	0.333	0.429	0.041
Dual	25,717	0.000	0.254	0.000	1.000	0.435

Panel B: Summary statistics of firm characteristics by financial derivative users and non-users

Variable	Derivatives Users		Derivatives Non-Users		Difference test	
	Mean	Median	Mean	Median	MeanDiff (T value)	MedianDiff (Z value)
SPS	−0.671	−0.586	−0.726	−0.640	−3.270***	−3.802***
Analyst_bias	0.029	0.020	0.026	0.017	2.406***	5.587***
Analyst_disp	0.019	0.016	0.016	0.012	7.600***	12.250***
Analyst_opti	0.016	0.013	0.015	0.011	2.373***	3.179***
Analyst_foll	1.640	1.946	1.235	1.099	17.171***	16.927***
Turn	0.445	0.300	0.577	0.409	12.322***	16.803***
Lev	0.452	0.448	0.434	0.430	4.491***	4.466***
Age	7.608	7.608	7.608	7.608	0.273	0.295
Balance	7.018	3.669	7.552	3.921	3.290***	3.576***
Topsh	36.200	36.140	34.050	32.190	8.114***	8.356***
Board	0.370	0.364	0.369	0.333	1.606	2.076**
Ceodual	0.228	0.000	0.257	0.000	3.210***	3.210***

Panel A presents descriptive statistics of the variables used in this study. Panel B presents summary statistics of firm characteristics by financial derivatives users and non-users. The sample period is from 2009 to 2019. All continuous variables are winsorized at the 1% and 99% levels. All variables are defined in Appendix 1.

Table 3
Correlation matrix.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
SPS (1)		0.019**	0.020**	0.018**	0.020**	0.063***	0.055***	0.090***	−0.064***	−0.137***	0.074***	−0.065***	0.097***	0.028***	−0.035***	−0.082***
FDU_1 (2)	0.022***		0.987***	0.990***	0.998***	0.040***	0.097***	0.020**	0.094***	−0.124***	0.037***	0.001	−0.017**	0.044***	0.012	−0.025***
FDU_2 (3)	0.024***	0.974***		0.985***	0.988***	0.039***	0.097***	0.019**	0.100***	−0.129***	0.040***	0	−0.020**	0.045***	0.014	−0.028***
Acomp(4)	0.021***	0.904***	0.891***		0.990***	0.038***	0.094***	0.020**	0.093***	−0.125***	0.036***	0.001	−0.022***	0.043***	0.011	−0.024***
Ecomp(5)	0.027***	0.908***	0.910***	0.834***		0.040***	0.097***	0.020**	0.095***	−0.127***	0.037***	0.001	−0.017**	0.045***	0.014	−0.026***
Analyst_bias (6)	0.049***	0.035***	0.033***	0.026***	0.028***		0.661***	0.543***	−0.248***	−0.097***	−0.018**	−0.029***	−0.034***	−0.091***	0.0410***	0.010
Analyst_disp (7)	0.044***	0.087***	0.088***	0.075***	0.077***	0.670***		0.442***	0.026***	−0.170***	0.015*	−0.042***	−0.006	−0.039***	0.008	−0.033***
Analyst_opti (8)	0.091***	0.025***	0.023***	0.020**	0.020**	0.420***	0.440***		−0.089***	−0.118***	−0.049***	0.003	−0.034***	−0.031***	0.026***	0.021**
Analyst_foll (9)	−0.018***	0.106***	0.117***	0.110***	0.115***	−0.244***	−0.013	−0.053***		−0.120***	0.009	−0.018**	−0.016*	0.070***	−0.022***	−0.01
Turnover(10)	−0.059***	−0.077***	−0.086***	−0.073***	−0.085***	−0.105***	−0.140***	−0.122***	−0.132***		−0.114***	0.095***	−0.020**	−0.135***	0.007	0.119***
Lev(11)	0.060***	0.029***	0.034***	0.020***	0.030***	−0.012	0.016*	−0.046***	−0.024***	−0.091***		−0.041***	0.136***	0.067***	−0.047***	−0.135***
Age(12)	−0.040***	0.002	0	0.004	−0.001	−0.025***	−0.039***	0.009	−0.023***	0.098***	−0.040***		−0.040***	0.002	0.020**	0.059***
Mash (13)	0.082***	−0.021***	−0.022***	−0.026***	−0.018***	−0.034***	0.006	−0.044***	−0.055***	−0.026***	0.138***	−0.050***		0.640***	−0.003	−0.075***
Largest(14)	0.027***	0.051***	0.054***	0.052***	0.054***	−0.090***	−0.035***	−0.018**	0.090***	−0.061***	0.044***	0.001	0.549***		0.031***	−0.048***
Board(15)	−0.038***	0.01	0.01	0.008	0.012*	0.044***	0.015*	0.035***	−0.032***	0.021***	−0.052***	0.021***	−0.004	0.030***		0.119***
Dual(16)	−0.072***	−0.020***	−0.023***	−0.015**	−0.025***	0.008	−0.033***	0.024***	0.008	0.090***	−0.119***	0.055***	−0.100***	−0.049***	0.123***	

Table 3 reports correlation matrix between the main variables. Lower-triangular cells report Pearson's correlation coefficients, upper-triangular cells are Spearman's rank correlation. All variables are defined in Appendix 1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

analyst forecasts in the relation between financial derivative usage and SPS.

$$\text{Analyst forecasts}_{i,t} = \beta_0 + \beta_1 \text{FDU}_{i,t} + \beta_2 \text{Controls}_{i,t} + \hat{\text{I}}\mu \quad (8)$$

$$\text{SPS}_{i,t} = \beta_0 + \beta_1 \text{FDU}_{i,t} + \beta_2 \text{Analyst forecasts}_{i,t} + \beta_3 \text{Controls}_{i,t} + \hat{\text{I}}\mu \quad (9)$$

According to the prior literature (Wang, 2018; Wang and Yu, 2020; Shen et al., 2021), we control for a wide array of firm characteristics that prior literature has shown to be related to SPS in Eq. (6) and (9), as well as control variables that determines analyst forecasts in Eq. (7) and (8). They are defined as follows: annual trading volume turnover (*Turnover*), leverage (*Lev*), the listed years (*Age*), executive shareholding ratio (*Mash*), the proportion of largest shareholder (*Largest*), board size (*Board*), CEO / chairman duality (*Dual*). Moreover, industry fixed-effects, year fixed-effects, firm-level fixed effects and cluster standard error are included to control for any time trend and the unobserved heterogeneity at the sector level.

4. Empirical results

4.1. Descriptive statistical analysis

Panel A of Table 2 presents descriptive statistics. In terms of *SPS*, the mean value is −0.720 and the median is −0.633. Moreover, *SPS* has a standard deviation of 0.778, indicating that the flow of firm-specific information to the market varies widely across firms. As expected, the mean value of financial derivative usage (FDU_1) is 0.105, which indicates that there are only 10.5% of firms with financial derivative usage. The mean value of accounting complexity of financial derivatives (*Acomp*) is 0.168, suggesting that plenty of firms measure financial derivative usage on the fair value of levels 2 and 3, resulting in firms' accounting treatment of financial derivatives containing more subjective judgments. The average economic complexity of derivative usage (*Ecomp*) is 0.132. The mean value of analyst forecast optimism (*Analyst_opti*) is 0.015, which is consistent with empirical results indicating that analysts concerned with the accuracy of their forecasts are more likely to bias their forecasts upward than downward (Beyer, 2008).

We further divide our sample into financial derivative users and non-users and report the univariate analysis of main variables in Panel B of Table 2. The mean (median) of *SPS* in derivative users is −0.671 (-0.586), which is higher than the −0.726 (-0.640) for non-users with a significance level of 1%. The differences of *SPS* between derivative users and non-users are also significant and positive. The findings suggest that financial derivative usage reduces the stock price informativeness.

Table 4
Test of Hypothesis 1: financial derivative usage and SPS.

Variable	*SPS*	
	(1)	(2)
FDU_1	0.0390**	
	(2.2381)	
FDU_2		0.0024**
		(2.0715)
Turnover	−0.3075***	−0.3075***
	(−27.2567)	(−27.2448)
Lev	0.0193***	0.0192***
	(3.6783)	(3.6741)
Age	(0.0299)	(0.0247)
	(−0.0100)	(−0.0083)
Mash	0.0900***	0.0900***
	(3.7125)	(3.7090)
Largest	−0.0033***	−0.0033***
	(−6.4405)	(−6.4316)
Board	−0.2622**	−0.2623**
	(−2.0626)	(−2.0629)
Dual	(0.0177)	(0.0178)
	(−1.5056)	(−1.5089)
Constant	1.1204	1.0815
	(0.0494)	(0.0477)
Firm	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
Clustered standard error	Yes	Yes
Observations	25,717	25,717
Adj−R^2	0.358	0.358
F−statistics	390.8	390.7

Table 4 reports the regression results of the relation between financial derivative usage and *SPS*. The independent variables in column (1) and (2) are FDU_1 and FDU_2, respectively. T-values are reported in parentheses. All variables are defined in Appendix 1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

4.2. Correlation analysis

Table 3 presents the correlation coefficients between the main variables. The results show that *SPS* is positively associated with financial derivative usage *(FDU)* at 5% significance level, indicating that financial derivative usage reduces the amount of firm-specific information in stock prices. The correlation coefficients are below than 0.5, and variance inflation factors (VIFs) are below than 5, suggesting that there are no multicollinearity problems for the models in this paper.

4.3. Hypothesis tests

4.3.1. The effect of financial derivative usage on SPS: H1

Table 4 presents the results of hypothesis 1 testing. Column (1) shows that the FDU_1 coefficients are uniformly positive and significant at 5% level in Eq. (6), which strongly supports Hypothesis H1b. Our results remain qualitatively unchanged when different measures of financial derivatives are used. The coefficient of financial derivative usage (FDU_2) on *SPS* (0.0024) remains positive and significant at 1% level, indicating that financial derivative usage reduces the amount of firm-specific information in stock prices and increases SPS; thus, Hypothesis H1b has been approved. That is to say, financial derivative usage hinders the flow of effective information. The effective information about financial derivative usage that is reflected in stock transactions cannot be obtained and interpreted by investors, resulting in lower firm-specific information in stock prices, as measured by SPS.

With respect to control variables, the signs of coefficients are generally consistent with previous studies. For example, *Lev* is significantly positively related to *SPS*, indicating that the greater risk of financial difficulties or leverage increases the cost of collecting private information, thereby reducing the flow of firm-specific information (Hasan et al., 2014). Largest shareholder (*Largest*) has a negative relationship with *SPS* (Gul et al., 2010). Consistent with Qiu et al. (2020), we find that *Turnover* has significantly negative coefficients on *SPS*.

4.3.2. The effect of financial derivatives on analyst forecasts: H2

We examine the effect of financial derivative usage on analyst forecasts; the results are represented in Table 5. The coefficients of *FDU* are positive and significant at the 5% level in both columns (1) and (2). Thus, financial derivative usage decreases analyst forecast accuracy (*Analyst_bias*). For the analyst forecast dispersion (*Analyst_disp*), we find that the coefficient is positive and significant at the 1% level in both columns (3) and (4), suggesting that financial derivatives lead analysts to have divergent opinions on firms' future

Table 5
Test of Hypothesis 2: financial derivative usage and analyst forecasts.

Variable	*Analyst_bias*		*Analyst_disp*		*Analyst_opti*		*Analyst_foll*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FDU_1	0.0016**		0.0026***		0.0011*		0.3146***	
	(2.1783)		(6.1640)		(1.7760)		(7.1255)	
FDU_2		0.0001**		0.0002***		0.0001*		0.0220***
		(2.1426)		(6.1020)		(1.8136)		(7.7469)
Turnover	−0.0028***	−0.0028***	−0.0030***	−0.0030***	−0.0021***	−0.0021***	−0.4848***	−0.4810***
	(−6.9571)	(−6.9292)	(−11.8132)	(−11.7475)	(−5.9401)	(−5.9117)	(−21.9365)	(−21.7931)
Lev	0.001	0.001	0.0002	0.0002	−0.0023**	−0.0023**	−0.2255***	−0.2281***
	(0.8587)	(0.8523)	(0.3008)	(0.2825)	(−2.3006)	(−2.3068)	(−3.2110)	(−3.2540)
Age	−0.5306***	−0.5304***	−0.2285***	−0.2279***	0.1935	0.1937	2.0177	2.0592
	(−3.7565)	(−3.7545)	(−3.0084)	(−3.0013)	(1.5320)	(1.5332)	(0.3895)	(0.3983)
Mash	0.0002***	0.0002***	0.0001***	0.0001***	0	0	−0.0232***	−0.0231***
	(5.1978)	(5.2086)	(4.3051)	(4.3345)	(−1.5059)	(−1.4950)	(−11.1722)	(−11.1203)
Largest	−0.0002***	−0.0002***	−0.0001***	−0.0001***	0	0	0.0142***	0.0141***
	(−9.6431)	(−9.6468)	(−6.0738)	(−6.0894)	(−0.0834)	(−0.0900)	(10.1445)	(10.0852)
Board	0.0185***	0.0185***	0.0029	0.0029	0.0108**	0.0108**	−0.8441**	−0.8495**
	(3.2724)	(3.2700)	(0.8756)	(0.8636)	(2.2927)	(2.2899)	(−2.5170)	(−2.5371)
Dual	−0.0007	−0.0007	−0.0008***	−0.0008***	−0.0001	−0.0001	0.0765**	0.0773**
	(−1.3712)	(−1.3639)	(−2.7526)	(−2.7339)	(−0.3390)	(−0.3317)	−2.4923	−2.5267
Constant	4.0684***	4.0666***	1.7526***	1.7483***	−1.4739	−1.4751	−13.8163	−14.1561
	(3.7866)	(3.7846)	(3.0339)	(3.0267)	(−1.5336)	(−1.5348)	(−0.3507)	(−0.3600)
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,717	25,717	25,717	25,717	25,717	25,717	25,717	25,717
Adj−R^2	0.177	0.177	0.161	0.161	0.109	0.109	0.114	0.115
F−statistics	87.62	87.72	85.32	85.18	51.27	51.25	52.55	52.88

Table 5 reports the regression results of the relation between financial derivative usage and analyst forecasts. The independent variables in column (1) (3), (5), (7), and (2), (4), (6),(8) are FDU_1 and FDU_2, respectively. The dependent variables are *Analyst_bias, Analyst_disp, Analyst_opti, Analyst_foll* respectively. T-values are reported in parentheses. All variables are defined in Appendix 1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

expectations. As shown in columns (5) and (6), the estimated coefficients on *FDU* are highly significant, with the expected positive signs (0.0011 and 0.0001) at 1% level. In columns (7) and (8), the *FDU* coefficients are significantly positive (0.3146 and 0.0220) at 1% level. This result suggests that financial derivatives increase the number of analysts who follow the firms. Taking the above results into consideration, financial derivative usage significantly reduces analyst forecast quality, which supports H2. Specifically, financial derivative usage decreases analyst forecast accuracy, and increases analyst forecast dispersion, analyst forecast optimism, and analyst following. That is to say, analysts have difficulty incorporating information about financial derivatives into their earnings forecasts, resulting in an inefficient flow of firm-specific information.

4.3.3. The mediating role of analyst forecasts: H3

This paper employs Two-stage mediation models (Eq. (8) and (9)) to test the mediating effect of analyst forecasts in the relation between financial derivative usage and SPS. The results in Table 5 and 6 indicate that the relation between financial derivative usage and SPS is mediated by analyst forecasts (i.e., analyst forecast accuracy, analyst forecast dispersion, analyst forecast optimism, and analyst following). In columns (1), (3), (5), and (7) of Table 5, financial derivative usage (*FDU*) is shown to significantly reduce analyst forecast accuracy (*Analyst_bias*) and increase analyst forecast dispersion (*Analyst_disp*), analyst forecast optimism (*Analyst_opti*), and analyst following (*Analyst_foll*). In columns (1), (2), and (3) of Table 6, analyst forecast accuracy (*Analyst_bias*), analyst forecast dispersion (*Analyst_disp*), and analyst forecast optimism (*Analyst_opti*) are all significantly and positively associated with *SPS*, while analyst following (*Analyst_foll*) is significantly and negatively related to *SPS* at the 1% levels. At the meantime, financial derivative usage (FDU_2) is still positively correlated with *SPS* at the 1% levels, showing that analyst forecast accuracy (*Analyst_bias*), analyst forecast optimism (*Analyst_opti*), analyst forecast dispersion (*Analyst_disp*), and analyst following (*Analyst_foll*) mediate the effect of financial derivatives on SPS. The coefficients on *SPS* are significantly positive for both measures of financial derivative usage (*FDU*).

Table 6
Test of Hypothesis 3: the mediating effects of analyst forecasts.

Variable	*SPS*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FDU_1	0.0588***	0.0592***	0.0568***	0.0688***				
	(2.8577)	(2.8070)	(2.7747)	(3.8811)				
FDU_2					0.0039***	0.0040***	0.0038***	0.0044***
					(2.9242)	(2.8946)	(2.8189)	(3.8551)
Analyst_bias	1.3455***				1.3422***			
	(4.9047)				(4.8943)			
Analyst_disp		2.6513***				2.6391***		
		(5.0689)				(5.0448)		
Analyst_opti			3.0230***				3.0186***	
			(10.7707)				(10.7584)	
Analyst_foll				−0.0136***				−0.0138***
				(−2.8564)				(−2.8919)
Turnover	−0.3161***	−0.3159***	−0.3132***	−0.3459***	−0.3160***	−0.3156***	−0.3131***	−0.3457***
	(−23.4748)	(−20.9992)	(−23.3629)	(−31.5764)	(−23.4479)	(−20.9702)	(−23.3363)	(−31.5574)
Lev	0.0719**	0.0750**	0.0802**	0.0462*	0.0718**	0.0748**	0.0801**	0.0460*
	(2.2885)	(2.3188)	(2.5707)	(1.7392)	(2.2842)	(2.3125)	(2.5666)	(1.7317)
Age	−3.267	−4.018	−4.5125	−0.2045	−3.265	−4.015	−4.5104	−0.1987
	(−0.8545)	(−1.0135)	(−1.1943)	(−0.0704)	(−0.8540)	(−1.0127)	(−1.1937)	(−0.0684)
Mash	0.0091***	0.0099***	0.0094***	0.0075***	0.0091***	0.0099***	0.0095***	0.0075***
	(9.1888)	(9.5608)	(9.6621)	(9.0663)	(9.1876)	(9.5620)	(9.6609)	(9.0719)
Largest	−0.0038***	−0.0041***	−0.0041***	−0.0022***	−0.0038***	−0.0041***	−0.0041***	−0.0022***
	(−6.2812)	(−6.6035)	(−6.8117)	(−4.3900)	(−6.2855)	(−6.6113)	(−6.8157)	(−4.3965)
Board	−0.2272	−0.1982	−0.2379	−0.3520***	−0.2275	−0.1987	−0.2382	−0.3524***
	(−1.5361)	(−1.2976)	(−1.6137)	(−2.7903)	(−1.5380)	(−1.3015)	(−1.6155)	(−2.7937)
Dual	−0.0447***	−0.0397***	−0.0451***	−0.0370***	−0.0446***	−0.0396***	−0.0451***	−0.0369***
	(−3.2338)	(−2.7970)	(−3.2805)	(−3.2370)	(−3.2306)	(−2.7925)	(−3.2777)	(−3.2319)
Constant	25.8481	31.6365	35.3664	1.8629	25.8318	31.6121	35.3498	1.8177
	(0.8890)	(1.0493)	(1.2307)	(0.0843)	(0.8883)	(1.0483)	(1.2301)	(0.0823)
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,717	25,717	25,717	25,717	25,717	25,717	25,717	25,717
Adj−R^2	0.274	0.278	0.28	0.357	0.274	0.278	0.28	0.357
F−statistics	202.4	195.2	209.6	429.3	192.3	195.2	209.6	429.1

Table 6 reports two-stage mediation regression results of the relation between financial derivative usage and SPS. The mediating variables in column (1) (5), (2) (6), (3) (7), and (4) (8) are *Analyst_bias, Analyst_disp, Analyst_opti, Analyst_foll* respectively. All variables are defined in Appendix 1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

4.4. Robustness tests

To address the potential endogeneity of financial derivatives, we use the two-stage instrumental variable regressions and PSM to re-examine hypotheses. Moreover, this paper employs the Bootstrap test, Sobel-Goodman test, and Structural Equation Model (SEM) to test hypotheses in order to eliminate the influence of the empirical test method.

4.4.1. The two-stage instrumental variable regressions

Following Fauver and Naranjo (2010) and Lookman (2009), we employ the firm's quick ratio (*Quick ratio*) as an instrument variable for financial derivative usage. Quick ratio is an instrumental variable that satisfies both relevance and exclusion conditions. Following the two-stage least squares in Wooldridge (2010), in the first stage regression, we instrument financial derivatives usage (*FDU*) with our instrumental variable, *Quick ratio*, and compute the fitted value of financial derivatives usage (FDU_1) as Quick ratio. In the second stage regression, we replace financial derivatives usage (FDU_1) with the *Quick ratio* variable. Table 7 presents the results from the two-stage instrumental variable regressions. As shown, in the First stage regression, the coefficient on *Quick ratio* is negative and statistically significant at 1% level, indicating that firms with a higher Quick ratio are less likely to use financial derivatives. In the second stage regression, the coefficient on financial derivative usage remains positive and statistically significant. The evidence here suggests that the relation between financial derivative usage and SPS remains robust with the potential endogeneity issue controlled.

4.4.2. PSM approach

This paper employs the Propensity Score Matching (PSM) approach to control for the endogeneity derived from the financial derivative usage (Becker and Ichino, 2002). We classify the samples into two groups: (1) the incentive group, including firms with

Table 7
The two-stage instrumental variable test: financial derivative usage and *SPS*.

Variable	*First stage*	*Second stage*	*First stage*	*Second stage*
	FDU_1	*SPS*	FDU_2	*SPS*
FDU_1		0.9504***		
		(2.6514)		
FDU_2				0.0600***
				(2.6547)
Quick ratio	−0.0036***		−0.0578***	
	(−6.3909)		(−6.4406)	
Turnover	−0.0538***	−0.2772***	−0.9410***	−0.2718***
	(−11.4103)	(−12.1978)	(−12.7117)	(−11.0927)
Lev	0.0417***	0.0277	0.6954***	0.0256
	(3.8832)	(0.9372)	(4.1261)	(0.8522)
Age	0.1931	−0.1815	1.0687	−0.0622
	(0.1401)	(−0.0575)	(0.0494)	(−0.0197)
Mash	−0.0025***	0.0108***	−0.0422***	0.0110***
	(−7.9081)	(9.7287)	(−8.4884)	(9.4962)
Largest	0.0019***	−0.0048***	0.0319***	−0.0049***
	(10.0669)	(−5.9089)	(10.5771)	(−5.8334)
Board	0.1531***	−0.3156**	2.5177***	−0.3212**
	(3.0582)	(−2.4964)	(3.2011)	(−2.5259)
Dual	−0.0107**	−0.0302**	−0.1910**	−0.0289**
	(−2.2382)	(−2.5437)	(−2.5348)	(−2.4020)
Constant	−1.3607	1.5443	−5.9987	0.6112
	(−0.1298)	(0.0643)	(−0.0364)	(0.0255)
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Clustered standard error	Yes	Yes	Yes	Yes
Observations	25,717	25,717	25,717	25,717
Adj−R^2	0.052		0.058	

Table 7 presents the results from the two-stage instrumental variable regressions. *Quick ratio* is the instrument variable. All variables are defined in Appendix 1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 8
PSM: financial derivative usage and SPS.

Variable		ATT	T-value
Nearest neighbor matching	*SPS*	0.065	3.143***
Radius matching		0.055	2.954***
Kernel matching		0.054	3.002***

Table 8 reports results from the PSM tests for the relation between financial derivative usage and SPS. All variables are defined in Appendix 1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 9
PSM: the correlation between financial derivatives, analyst forecasts and SPS.

Panel A: The correlation between FDU_1, analyst forecasts and SPS

Variable	*SPS*	*Analyst_bias*	*SPS*	*Analyst_disp*	*SPS*	*Analyst_opti*	*SPS*	*Analyst_foll*	*SPS*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
FDU_1	0.0660***	0.0030***	0.0620**	0.0027***	0.0687**	0.0017**	0.0603**	0.2652***	0.0680***
	(2.8987)	(3.1722)	(2.2590)	(4.8440)	(2.4285)	(2.0613)	(2.2126)	(5.3905)	(2.9831)
Analyst_bias			1.4294**						
			(2.4265)						
Analyst_disp					2.8597**				
					(2.5204)				
Analyst_opti							3.4643***		
							(5.5496)		
Analyst_foll									0.0075
									(0.7467)
Turnover	−0.3287***	−0.0019**	−0.3227***	−0.0027***	−0.3402***	−0.0020***	−0.3186***	−0.5879***	−0.3520***
	(−14.2119)	(−2.1172)	(−11.2662)	(−4.9611)	(−10.8852)	(−2.6496)	(−11.1990)	(−14.1712)	(−14.9893)
Lev	0.0849	0.0054**	0.1278*	0.0022	0.1242*	0.0006	0.1326*	−0.1267	0.0798
	(1.5082)	(2.1397)	(1.8781)	(1.5562)	(1.7741)	(0.2938)	(1.9530)	(−1.0364)	(1.4190)
Age	−17.1088**	−0.4071	−21.9948**	−0.2789	−23.6238**	0.8560***	−25.3165***	12.7492	−16.6036**
	(−2.4426)	(−1.2048)	(−2.4783)	(−1.5714)	(−2.5781)	(3.1066)	(−2.8928)	(1.0368)	(−2.3751)
Mash	0.0068***	0.0002*	0.0084***	0.0001	0.0088***	0	0.0085***	−0.0209***	0.0060***
	(3.5999)	(1.8849)	(3.6405)	(1.0268)	(3.6476)	(0.1760)	(3.7255)	(−5.4967)	(3.1207)
Largest	−0.0044***	−0.0002***	−0.0055***	−0.0001***	−0.0055***	−0.0001	−0.0056***	0.0150***	−0.0038***
	(−4.0240)	(−4.7074)	(−4.1280)	(−2.8997)	(−4.0272)	(−1.2553)	(−4.2348)	(6.4027)	(−3.4498)
Board	0.0597	0.0228*	0.1337	0.0016	0.0405	−0.0023	0.1708	−0.4832	0.0406
	(0.2143)	(1.9078)	(0.4098)	(0.2408)	(0.1192)	(−0.2184)	(0.5239)	(−0.8279)	(0.1461)
Dual	−0.0631**	−0.0026**	−0.0541*	−0.0001	−0.0623**	−0.0012	−0.0537*	0.1250**	−0.0582**
	(−2.4713)	(−2.3776)	(−1.8073)	(−0.2000)	(−2.0265)	(−1.2036)	(−1.8016)	(2.2900)	(−2.3013)
Constant	130.2040**	3.1069	168.4725**	2.1318	180.9124***	−6.5147***	193.7632***	−94.1662	126.4724**
	(2.4437)	(1.2088)	(2.4957)	(1.5786)	(2.5955)	(−3.1079)	(2.9108)	(−1.0066)	(2.3782)
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,358	5,358	5,358	5,358	5,358	5,358	5,358	5,358	5,358
$Adj-R^2$	0.347	0.157	0.287	0.158	0.295	0.128	0.294	0.122	0.350
F−statistics	78.64	18.37	38.48	20.08	38.34	13.87	40.26	15.91	77.68

Panel B: The correlation between FDU_2, analyst forecasts and SPS

Variable	*SPS*	*Analyst_bias*	*SPS*	*Analyst_disp*	*SPS*	*Analyst_opti*	*SPS*	*Analyst_foll*	*SPS*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
FDU_2	0.0043***	0.0002***	0.0042**	0.0002***	0.0046**	0.0001**	0.0040**	0.0193***	0.0045***
	(2.9546)	(3.2040)	(2.3708)	(5.0137)	(2.5292)	(2.4069)	(2.2935)	(6.0879)	(3.0572)
Analyst_bias			1.4188**						
			(2.4087)						
Analyst_disp					2.8186**				
					(2.4836)				
Analyst_opti							3.4495***		

(*continued on next page*)

Table 9 (*continued*)

Panel A: The correlation between FDU_1, analyst forecasts and SPS

Variable	*SPS*	*Analyst_bias*	*SPS*	*Analyst_disp*	*SPS*	*Analyst_opti*	*SPS*	*Analyst_foll*	*SPS*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
							(5.5299)		
Analyst_foll									0.0082
									(0.8162)
Turnover	−0.3276***	−0.0019**	−0.3214***	−0.0027***	−0.3386***	−0.0020***	−0.3172***	−0.5767***	−0.3507***
	(−14.1778)	(−2.0283)	(−11.2032)	(−4.7955)	(−10.8192)	(−2.5952)	(−11.1362)	(−13.9662)	(−14.9532)
Lev	0.0846	0.0053**	0.1274*	0.0022	0.1239*	0.0006	0.1323*	−0.1282	0.0795
	(1.5038)	(2.1283)	(1.8727)	(1.5419)	(1.7687)	(0.2886)	(1.9471)	(−1.0524)	(1.4126)
Age	−17.0768**	−0.404	−21.9569**	−0.2752	−23.5819**	0.8575***	−25.2736***	12.9178	−16.5585**
	(−2.4378)	(−1.1952)	(−2.4748)	(−1.5512)	(−2.5748)	(3.1116)	(−2.8887)	(1.0535)	(−2.3683)
Mash	0.0068***	0.0002*	0.0084***	0.0001	0.0088***	0.0000	0.0085***	−0.0208***	0.0060***
	(3.6136)	(1.9050)	(3.6495)	(1.0502)	(3.6571)	(0.1880)	(3.7340)	(−5.4800)	(3.1317)
Largest	−0.0044***	−0.0002***	−0.0055***	−0.0001***	−0.0055***	−0.0001	−0.0056***	0.0149***	−0.0038***
	(−4.0483)	(−4.7235)	(−4.1412)	(−2.9279)	(−4.0405)	(−1.2653)	(−4.2471)	(6.3629)	(−3.4725)
Board	0.0601	0.0229*	0.0001	0.0016	0.0394	−0.0023	0.1708	−0.4843	0.0406
	(0.2156)	(1.9108)	(0.4109)	(0.2355)	(0.1161)	(−0.2170)	(0.5247)	(−0.8333)	(0.1464)
Dual	−0.0629**	−0.0026**	−0.0537*	−0.0001	−0.0618**	−0.0011	−0.0533*	0.1272**	−0.0578**
	(−2.4622)	(−2.3507)	(−1.7949)	(−0.1615)	(−2.0135)	(−1.1890)	(−1.7891)	(2.3472)	(−2.2870)
Constant	129.9598**	3.0828	168.1781**	2.1029	180.5865***	−6.5262***	193.4306***	−95.4546	126.1303**
	(2.4388)	(1.1991)	(2.4921)	(1.5582)	(2.5921)	(−3.1130)	(2.9066)	(−1.0232)	(2.3715)
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,358	5,358	5,358	5,358	5,358	5,358	5,358	5,358	5,358
Adj−R^2	0.347	0.157	0.288	0.159	0.295	0.128	0.294	0.126	0.35
F−statistics	78.53	21.31	38.46	20.07	38.32	13.86	40.23	16.23	77.54

Table 9 reports the regression results of the correlation between financial derivative usage, analyst forecasts, and SPS. Panel A presents the correlation results using FDU_1 as the independent variable, and Panel B using FDU_2 as the independent variables. All variables are defined in Appendix 1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 10
Bootstrap test: the mediating effect of analyst forecasts.

variable	Paths	Observed coefficient	S.E.	Z-value	95% confidence interval	
					Lower limit	Upper limit
FDU_1	*Analyst_bias*	0.0027	0.0009	2.78	0.0008	0.0046
	Analyst_disp	0.0044	0.0015	3.00	0.0015	0.0072
	Analyst_opti	0.0036	0.0018	2.01	0.0001	0.0071
	Analyst_foll	−0.0087	0.0013	−6.86	−0.0111	−0.0062
FDU_2	*Analyst_bias*	0.0002	0.0000	2.90	0.0001	0.0003
	Analyst_disp	0.0003	0.0001	3.22	0.0001	0.0004
	Analyst_opti	0.0002	0.0001	2.27	0.0001	0.0004
	Analyst_foll	−0.0006	0.0001	−7.65	−0.0008	−0.0004

Table 10 reports the Bootstrap test results of the mediating effects of analyst forecasts. All variables are defined in Appendix 1.

Table 11
Sobel test: the mediating effect of analyst forecasts.

Variable		Test	Coef	Std Err	Z	P > Z
FDU_1	*Analyst_bias*	Sobel	0.0027	0.0001	3.090	0.0020
		Goodman-1(Aroian)	0.0027	0.0001	3.050	0.0023
		Goodman-2	0.0027	0.0001	3.130	0.0017
	Analyst_disp	Sobel	0.0044	0.0013	3.290	0.0010
		Goodman-1(Aroian)	0.0044	0.0013	3.270	0.0010
		Goodman-2	0.0044	0.0013	3.320	0.0009
	Analyst_opti	Sobel	0.0036	0.0017	2.190	0.0290
		Goodman-1(Aroian)	0.0036	0.0017	2.180	0.0300
		Goodman-2	0.0036	0.0016	2.190	0.0281
	Analyst_foll	Sobel	−0.0097	0.0013	−6.925	0.0000
		Goodman-1(Aroian)	−0.0097	0.0013	−6.907	0.0000
		Goodman-2	−0.0097	0.0013	−6.943	0.0000
FDU_2	*Analyst_bias*	Sobel	0.00017	0.0001	3.109	0.0019
		Goodman-1(Aroian)	0.00017	0.0001	3.071	0.0021
		Goodman-2	0.00017	0.0001	3.149	0.0016
	Analyst_disp	Sobel	0.0003	0.0001	3.299	0.0009
		Goodman-1(Aroian)	0.0003	0.0001	3.279	0.0010
		Goodman-2	0.0003	0.0001	3.319	0.0009
	Analyst_opti	Sobel	0.0002	0.0001	2.314	0.0206
		Goodman-1(Aroian)	0.0002	0.0001	2.306	0.0211
		Goodman-2	0.0002	0.0001	2.322	0.0202
	Analyst_foll	Sobel	−0.0006	0.0001	−7.317	0.0000
		Goodman-1(Aroian)	−0.0006	0.0001	−7.300	0.0000
		Goodman-2	−0.0006	0.0001	−7.334	0.0000

Table 11 reports the Sobel-Goodman test results of the mediating effects of analyst forecasts. All variables are defined in Appendix 1.

financial derivative usage, and (2) the control group, including firms without financial derivative usage. A comparison of the two subgroups with respect to the effectiveness of financial derivative usage (ATT) is shown in Table 8. Using the nearest neighbor matching method, radius matching method, and kernel matching method, we find significant differences between the two subgroups. The results demonstrate that financial derivative usage can effectively hinder the flow of firm-specific information, thus increasing SPS.

After conducting Propensity Score Matching (PSM), this paper obtains a matched sample of 5,358, including 2,679 firms with financial derivative usage (the treated subsample) and 2,679 firms without financial derivative usage (the matched subsample). Two-stage mediation tests are employed to re-test the hypothesis based on the matched sample, and the results are reported in Table 9. Those results provide important support for the existence of evidence that financial derivatives significantly increase *SPS* and that financial derivative usage influences *SPS* by reducing analyst forecast accuracy and increasing analyst forecast dispersion, analyst forecast optimism, and analyst following, resulting in an inefficient flow of information and a higher SPS. These are consistent with the previously reported results.

4.4.3. Bootstrap test

Bootstrap test analysis is performed to re-examine the mediating effect of analyst forecasts. Table 10 presents the multi mediator model results with 1,000 bootstrapped samples. The Bootstrap test confirmed that *Analyst_bias* (Indirect effect = 0.0027, CI = [0.0008,0.0046]), *Analyst_disp* (Indirect effect = 0.0044, CI = [0.0015,0.0072]), *Analyst_opti* (Indirect effect = 0.0036, CI = [0.0001, 0.0071]), and *Analyst_foll* (Indirect effect = -0.0087, CI = [-0.0111, −0.0062]) play mediating roles in the relation between financial derivative usage (FDU_1) and SPS. The empirical results of this paper are robust to different measurements of financial derivative usage

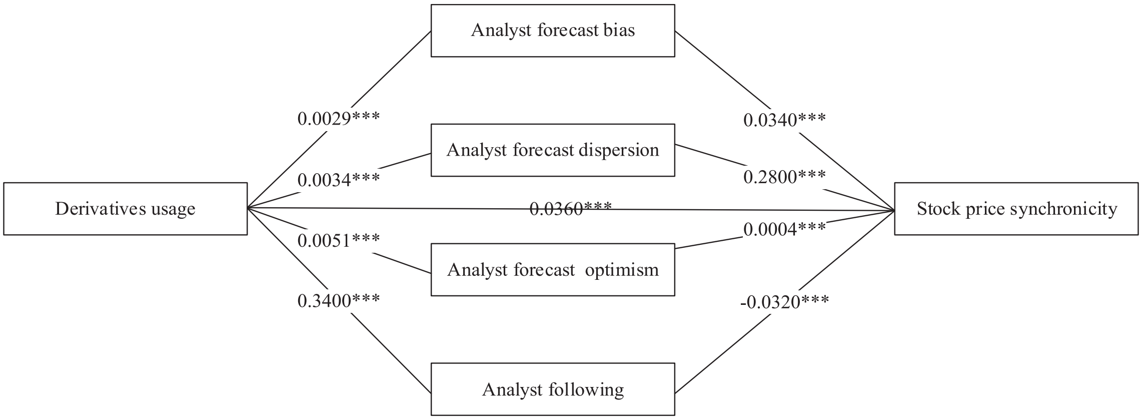

Fig. 1a. Test of financial derivative usage (*FDU_1*) and SPS.

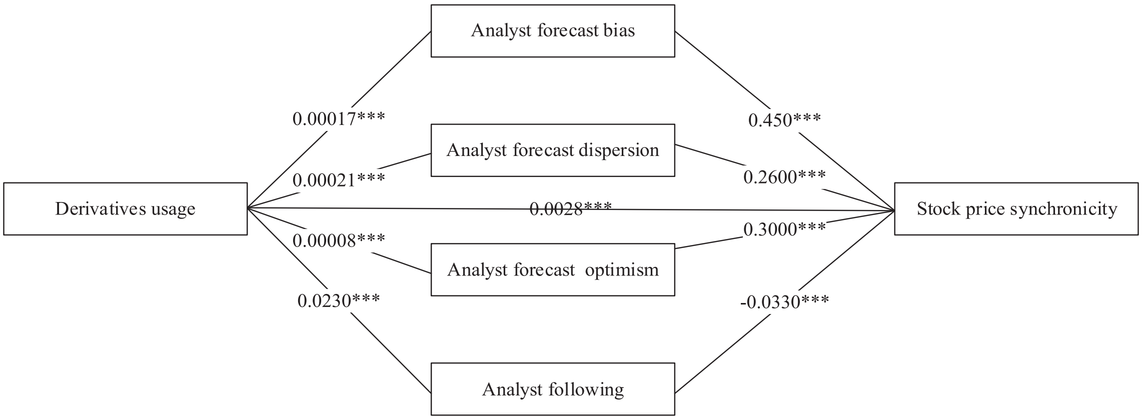

Fig. 1b. Test of financial derivative usage (*FDU_2*) and SPS. This Figure presents the channels that financial derivative usage affects SPS. Fig. 1a. presents the results using *FDU_1* as the independent variable, and Fig. 1a. using *FDU_2* as the independent variable. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

(*FDU_2*), and the main results are unlikely to be influenced by different empirical models.

4.4.4. Sobel-Goodman test

To test the mediating effect of analyst forecasts, this paper also conducts a Sobel-Goodman test (Table 11). The results indicate that *Analyst_bias* (b = 0.0027, z = 3.090, $p < 0.01$), *Analyst_disp* (b = 0.0044, z = 3.290, $p < 0.01$), *Analyst_opti* (b = 0.0036, z = -2.190, $p < 0.05$), and *Analyst_foll* (b = -0.0097, z = -6.925, $p < 0.01$) are significant and partially mediate the effect of financial derivatives on *SPS*. The results of the Sobel-Goodman tests are consistent with the different measurements of financial derivative usage (*FDU_2*). In short, the above results indicate that the correlation between financial derivatives, analyst forecasts, and *SPS* is robust to different methods.

4.4.5. Structural Equation model

In this paper, we use the Structural Equation Model to test the effect of derivative usage on *SPS* (Fig. 1a). The results of the path analysis are schematically presented in Figs. 1a and 1b. In detail, financial derivatives have a significant negative direct effect on analyst forecast quality, and analyst forecast quality has a negative direct effect on *SPS*. We can see that financial derivatives significantly reduce the analyst forecast quality (lower forecast accuracy, higher forecast dispersion and forecast optimism, more analyst following), and lower analyst forecast quality leads to higher *SPS*. The empirical results are consistent with different measures of financial derivative usage (*FDU*) in Figs. 1a and 1b. In summary, the findings of this paper are robust to different empirical methods.

5. Additional tests: The complexity of financial derivatives and SPS

In the presence of financial derivatives, it is not only the accounting complexity of financial derivatives that affects *SPS*, but also the economic complexity of financial derivatives. As for the accounting treatment, the existence of complexity at the level of complete

Table 12
Test of complexity of financial derivatives and SPS.

Panel A: the accounting complexity of financial derivatives and SPS

Variable	*SPS*	*Analyst_bias*	*SPS*	*Analyst_disp*	*SPS*	*Analyst_opti*	*SPS*	*Analyst_foll*	*SPS*
Acomp	0.0318***	0.0011***	0.0279**	0.0013***	0.0279**	0.0008**	0.0269**	0.1405***	0.0337***
	(3.1295)	(2.8072)	(2.4338)	(5.6631)	(2.3579)	(2.3095)	(2.3623)	(6.1020)	(3.3090)
Analyst_bias			1.3563***						
			(4.9433)						
Analyst_disp					2.6858***				
					(5.1378)				
Analyst_opti							3.0302***		
							(10.7927)		
Analyst_foll									−0.0133***
									(−2.8008)
Turnover	−0.3270***	−0.0029***	−0.3164***	−0.0030***	−0.3161***	−0.0021***	−0.3134***	−0.4849***	−0.3461***
	(−29.7574)	(−7.0092)	(−23.4962)	(−11.9097)	(−21.0199)	(−5.9812)	(−23.3867)	(−21.9676)	(−31.5894)
Lev	0.0556**	0.0011	0.0723**	0.0003	0.0755**	−0.0023**	0.0806***	−0.2210***	0.0469*
	(2.0914)	(0.8912)	(2.3016)	(0.3869)	(2.3355)	(−2.2715)	(2.5833)	(−3.1502)	(1.7645)
Age	−0.2986	−0.5322***	−3.2793	−0.2314***	−4.0339	0.1925	−4.5249	1.8418	−0.2261
	(−0.1026)	(−3.7650)	(−0.8579)	(−3.0413)	(−1.0176)	(1.5234)	(−1.1978)	(0.3558)	(−0.0779)
Mash	0.0084***	0.0002***	0.0090***	0.0001***	0.0099***	0.0000	0.0094***	−0.0231***	0.0075***
	(10.2890)	(5.1803)	(9.1777)	(4.3301)	(9.5526)	(−1.5157)	(9.6539)	(−11.0961)	(9.0712)
Largest	−0.0028***	−0.0002***	−0.0038***	−0.0001***	−0.0041***	0.0000	−0.0041***	0.0141***	−0.0022***
	(−5.4990)	(−9.5886)	(−6.2696)	(−6.0279)	(−6.5943)	(−0.0581)	(−6.8019)	(10.1318)	(−4.3903)
Board	−0.3179**	0.0186***	−0.2265	0.003	−0.1973	0.0109**	−0.2373	−0.8365**	−0.3508***
	(−2.5118)	(3.2851)	(−1.5308)	(0.9073)	(−1.2913)	(2.3044)	(−1.6088)	(−2.4952)	(−2.7807)
Dual	−0.0402***	−0.0007	−0.0449***	−0.0008***	−0.0399***	−0.0002	−0.0453***	0.0749**	−0.0372***
	(−3.4977)	(−1.4052)	(−3.2449)	(−2.8226)	(−2.8083)	(−0.3666)	(−3.2906)	(2.4416)	(−3.2588)
Constant	2.5226	4.0806***	25.945	1.7755***	31.7629	−1.4655	35.4647	−12.4413	2.033
	(0.1139)	(3.7955)	(0.8924)	(3.0679)	(1.0536)	(−1.5247)	(1.2344)	(−0.3160)	(0.0920)
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,717	25,717	25,717	25,717	25,717	25,717	25,717	25,717	25,717
$Adj{-}R^2$	0.354	0.177	0.274	0.16	0.278	0.109	0.28	0.114	0.357
F−statistics	436.1	87.59	202.4	84.77	195.1	51.23	209.5	52.61	429.1

Panel B: the economic complexity of financial derivatives and SPS

Variable	*SPS*	*Analyst_bias*	*SPS*	*Analyst_disp*	*SPS*	*Analyst_opti*	*SPS*	*Analyst_foll*	*SPS*
Ecomp	0.0537***	0.0015***	0.0471***	0.0017***	0.0475***	0.0011***	0.0456***	0.2044***	0.0565***
	(3.9700)	(2.8295)	(3.0865)	(5.6704)	(3.0323)	(2.6715)	(3.0112)	(6.5171)	(4.1766)
Analyst_bias			1.3473***						
			(4.9163)						
Analyst_disp					2.6547***				
					(5.0775)				
Analyst_opti							3.0225***		
							(10.7718)		
Analyst_foll									−0.0139***
									(−2.9178)

(*continued on next page*)

Table 12 (*continued*)

Panel A: the accounting complexity of financial derivatives and SPS

Variable	*SPS*	*Analyst_bias*	*SPS*	*Analyst_disp*	*SPS*	*Analyst_opti*	*SPS*	*Analyst_foll*	*SPS*
Turnover	−0.3260***	−0.0029***	−0.3155***	−0.0030***	−0.3152***	−0.0021***	−0.3126***	−0.4813***	−0.3452***
	(−29.6658)	(−7.0068)	(−23.4212)	(−11.8942)	(−20.9511)	(−5.9853)	(−23.3067)	(−21.7636)	(−31.5084)
Lev	0.0546**	0.0011	0.0715**	0.0002	0.0746**	−0.0023**	0.0798**	−0.2265***	0.0456*
	(2.0551)	(0.8791)	(2.2747)	(0.3322)	(2.3040)	(−2.2847)	(2.5560)	(−3.2300)	(1.7160)
Age	−0.2672	−0.5299***	−3.2528	−0.2267***	−4.0015	0.194	−4.4985	2.1713	−0.1806
	(−0.0917)	(−3.7505)	(−0.8505)	(−2.9832)	(−1.0088)	(1.5360)	(−1.1901)	(0.4200)	(−0.0622)
Mash	0.0084***	0.0002***	0.0091***	0.0001***	0.0099***	0	0.0095***	−0.0231***	0.0075***
	(10.3453)	(5.1558)	(9.2241)	(4.2493)	(9.5951)	(−1.5333)	(9.7001)	(−11.1501)	(9.1107)
Largest	−0.0028***	−0.0002***	−0.0038***	−0.0001***	−0.0041***	0	−0.0041***	0.0141***	−0.0022***
	(−5.5646)	(−9.5904)	(−6.3233)	(−6.0212)	(−6.6454)	(−0.0529)	(−6.8549)	(10.0944)	(−4.4455)
Board	−0.3209**	0.0185***	−0.229	0.0029	−0.2002	0.0108**	−0.2397	−0.8552**	−0.3550***
	(−2.5367)	(3.2737)	(−1.5485)	(0.8664)	(−1.3115)	(2.2926)	(−1.6262)	(−2.5535)	(−2.8156)
Dual	−0.0397***	−0.0007	−0.0445***	−0.0008***	−0.0395***	−0.0001	−0.0449***	0.0778**	−0.0366***
	(−3.4570)	(−1.3877)	(−3.2210)	(−2.7720)	(−2.7858)	(−0.3519)	(−3.2671)	(2.5428)	(−3.2046)
Constant	2.2621	4.0630***	25.7294	1.7386***	31.4972	−1.4777	35.2498	−15.096	1.6602
	(0.1021)	(3.7806)	(0.8845)	(3.0080)	(1.0441)	(−1.5376)	(1.2261)	(−0.3839)	(0.0751)
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,717	25,717	25,717	25,717	25,717	25,717	25,717	25,717	25,717
$Adj{-}R^2$	0.354	0.177	0.274	0.16	0.278	0.109	0.28	0.116	0.357
F−statistics	436.2	113.2	202.4	85.05	195.2	51.25	209.6	53.67	429.3

Table 12 reports the relations between the complexity of financial derivatives and SPS. Panel A reports the effects of the accounting complexity of financial derivatives on SPS, Panel B reports the effects of the economic complexity of financial derivatives on SPS.

regulation (Johansen and Plenborg, 2013), disclosures (Chang et al., 2016), determination of deterioration models (Novotny-Farkas, 2016), determination of fair value (Romo, 2015), and disclosures of risk management (Bratten et al., 2016) presents a high degree of complexity in dealing with financial derivatives (Chang et al., 2016). Specifically, most financial derivatives contracts had been off-balance-sheet items, lacking in transparency, and the accounting treatment of financial derivatives had been applied inconsistently among firms (Blankespoor, 2019). In addition to the issues related to measurement and recognition, the disclosure of financial derivatives and hedging activities is complex, inconsistent across firms, and presented in a disaggregated matter in the notes to the financial reports (Campbell et al., 2019). The accounting complexity of financial derivatives poses great challenges to financial report users in terms of obtaining a full picture of the financial derivative activities. It has also been documented that investors with expertise cannot properly obtain and interpret complex information about financial derivative usage (Chang et al., 2016).

As important risk management tools, financial derivatives allow investors to trade exposures, diversify risks, and reduce earnings volatility. Not surprisingly, firms' financial derivative usage has grown dramatically over the last decades, and financial derivatives have moved beyond the familiar instruments used for managing interest rate, currency, commodity, equity, and credit market risk, so that they are now instruments used for mitigating risks such as catastrophe, pollution, electricity, weather, and inflation (Purnanandam and Amiyatosh, 2016). While the innovation of financial derivatives satisfies the development in the derivatives market, the complexity of trading and operations makes it difficult for users to obtain and interpret them (Lobo, 2017), which further prevents effective information from being reflected in stock transactions.

Therefore, this paper introduces the accounting (economic) complexity of financial derivatives (*Acomp/Ecomp*) to further test the effect of the accounting (economic) complexity of financial derivatives on *SPS*, as well as the mediating effect of analyst forecasts in this relation. The accounting complexity of derivatives (*Acomp*) is measured by the fair value hierarchy of derivatives, that is *Acomp* = 1,2,3 stands for using levels 1, 2, and 3 fair value estimates, respectively. The empirical results are shown in Panel A of Table 12, suggesting that the accounting complexity of financial derivatives (*Acomp*) is significantly positive with *SPS*, and the accounting complexity of financial derivatives leads to poor analyst forecast quality. This paper also employs the two-stage mediation model to test the mediating effect of analyst forecasts. The results show that the relation between the accounting complexity of financial derivatives and *SPS* is mediated by analyst forecast (analyst forecast accuracy, analyst forecast dispersion, analyst forecast optisim, and analyst following). Additionally, this paper employs the economic complexity of financial derivatives (*Ecomp*), which equals 1,2,3 if the firm uses one, two, or more financial derivatives, to test the relation between the economic complexity of financial derivative usage and *SPS*. The empirical results are shown in Panel B of Table 12. The economic complexity of financial derivatives has a significant positive correlation with *SPS*, and the economic complexity of financial derivatives reduces analyst forecast quality. This paper also shows that the relation between the economic complexity of financial derivatives and *SPS* is mediated by analyst forecasts. Therefore, we can see that the accounting complexity and economic complexity of financial derivative usage mean that analysts cannot obtain and interpret effective information related to financial derivatives, leading to a lower amount of firm-specific information in stock prices.

6. Conclusions

A large stream of prior literature examines the determinants of financial derivative usage and their economic consequences on firm characteristics. In contrast, little empirical evidence pertains to the consequences of financial derivatives on stock prices in emerging market. Using a sample of Chinese non-financial listed firms from 2009 to 2019, this paper finds that financial derivative usage significantly increases SPS. Moreover, financial derivatives indirectly affect *SPS* via analyst forecasts. Those findings are robust to several sensitivity tests. An additional analysis reveals that both the accounting complexity and economic complexity of financial derivatives have a positive association with *SPS*. Overall, our evidence supports the negative role of financial derivative usage in reducing informativeness of stock prices.

Although the results of this paper are robust, several limitations are identified, as follows. First, due to the information disclosure constraints for Chinese listed firms, this paper cannot explore some unique firm characteristics, such as the purpose of financial derivative usage. As a result, sample firms in this paper are identified to use financial derivatives for hedging risks, which causes the research to lack certain pertinency. Second, this paper uses the fair value of financial derivatives as a proxy of firms' financial derivative usage; future research may consider other measures such as the ratio of the financial derivatives position to the amount of risk exposure that the firm is trying to hedge if such information becomes available.

Data available statement

The data that support the findings of this study are openly available and hand collected from multiple sources, including financial reports, the CSMAR database (https://cn.gtadata.com/) and the Wind database.

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CRediT authorship contribution statement

Kun Su: Conceptualization, Funding acquisition, Resources, Supervision, Formal analysis, Writing – review & editing. **Miaomiao Zhang:** Conceptualization, Data curation, Methodology, Investigation, Formal analysis, Writing – original draft. **Chengyun Liu:** Conceptualization.

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.

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