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Can local fintech development improve analysts' earnings forecast accuracy? Evidence from China

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A B S T R A C T

This paper examines the impact of local fintech development on the accuracy of analysts' earnings forecasts. We employ the method of web text mining to construct the local fintech development index for empirical test. Our findings indicate that local fintech development has a substantial positive impact on analysts' earnings forecast accuracy by promoting firm digital transformation and alleviating the information asymmetry between firms and outsiders. Additionally, this effect is particularly pronounced for analysts without equity pledge affiliation and those with weaker buy-side pressure. This study shows that local fintech development can enhance the information environment of the capital market.

1. Introduction

In recent years, the financial sector has witnessed the widespread adoption of emerging information technologies such as artificial intelligence, big data, and blockchain, leading to the rapid development of fintech. Fintech is a technology-supported financial innovation that introduces new business models, applications, processes, and products, thereby significantly influencing financial markets, institutions, and the delivery of financial services. Previous research has primarily concentrated on the effects of fintech on the behaviors of banks and micro-firms. From the perspective of banks, fintech has been shown to lower operating costs, enhance efficiency, increase risk tolerance, and improve performance (Ntwiga, 2020; Lee et al., 2021; Zhang et al., 2023). On the side of firms, fintech has been found to have a positive impact on firm financing, investment, and innovation (Cole et al., 2019; Huang, 2022; Ding et al., 2022; Tan et al., 2023). However, there is limited literature exploring the impact of fintech on the micro-level of the capital market (Wang et al., 2023).

This paper examines the impact of local fintech development on analysts' earnings forecast accuracy. Theoretically, analysts' earnings forecast accuracy is mainly affected by both information, which serves as the objective basis for analysts' decision-making, and conflicts of interest, which represent the subjective motivation for analysts' forecasts. In terms of information, existing literature suggests that both the public disclosure of listed firms (Byard and Shaw, 2003; Hope, 2003) and the private information obtained from analysts' research (Chen and Jiang, 2006) can significantly enhance analysts' forecast accuracy. In terms of conflicts of interest, previous studies confirm that analysts encounter conflicts of interest from listed firms, institutional investors, etc. (Easterwood and Nutt, 1999; Bradshaw, 2009) and that business pressures such as fund splits, brokerage, underwriting, and direct investment can lead analysts to make biased forecasts and issue more optimistic forecast ratings (Mola and Guidolin, 2009; Agrawal and Chen, 2012; Firth et al. 2013).

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We argue that fintech development can drive firm digital transformation, which in turn reduces information asymmetry between firms and outsiders, and ultimately improves analysts' earnings forecast accuracy. Specifically, fintech facilitates firm digital transformation in two ways. First, fintech breaks the limitations of traditional financial services on financial infrastructure and geographic dependence. It broadens firm financing channels and lowers the transaction costs of financial services for firms (Gomber et al., 2018), thereby providing stable financial support for firm digital transformation. Second, fintech offers effective resources for firm innovation activities, enhances the allocation efficiency of financial resources (Demertzis et al., 2018), helps firms accurately identify high-potential projects, and improves their innovation performance (Laeven et al., 2015). Consequently, it provides technical support for firm digital transformation. Digital transformation enhances the availability of internal information, assisting financial institutions in comprehensively and dynamically understanding the firm's internal operation, thus reducing information asymmetry between firms and outsiders. According to the information theory hypothesis, the availability and quality of information serve as the objective basis for analysts' decision-making. Therefore, the reduction of information asymmetry between firms and external financial institutions contributes to improving the accuracy of analysts' earnings forecasts.

We utilize Chinese data to empirically examine the effect of fintech development on the accuracy of analysts' earnings forecasts. The results show that local fintech development significantly reduces analysts' earnings forecast bias, divergence, and optimism by facilitating firm digital transformation and mitigating information asymmetry. In addition, fintech holds a more substantial impact on earnings forecasts of analysts without equity pledge affiliation and those encountering weaker buy-side pressure.

Our study makes two contributions. First, our study extends the literature on the impact of fintech on capital markets. Existing research on the economic ramifications of fintech primarily focuses on its effects on banks, micro firms, with limited research on its relationship with capital markets. Analysts play a crucial role in providing information to capital markets, particularly regarding firms' profitability and future growth opportunities (Bryan and Tiras, 2007). Thus, our study unveils the role of fintech in optimizing the capital market information environment.

Second, our research complements related research on analysts' earnings forecasts. Unlike previous research that tests information theory hypotheses from various perspectives, such as the launch of high-speed rail, media coverage, and political connections (Yang et al., 2019; Cao et al., 2022; Hou et al., 2022), our study adds to the literature by examining the impact of fintech. While Jame et al. (2022) investigate how increased competition stemming from an innovation in financial technology influences sell-side analyst research quality based on the conflict-of-interest hypothesis, our study differs by predominantly focusing on the information hypothesis and highlighting the role of local fintech development in enhancing analysts' earnings forecasting accuracy within the context of firm digital transformation and information asymmetry.

2. Research design

2.1. Sample construction and data sources

We use Chinese listed firms from 2007 to 2021 as the research sample. The data of listed firms are obtained from the China Stock Market and Accounting Research (CSMAR) database, while local fintech development data are collected based on the amount of news items searched for fintech-related keywords on Baidu News. We exclude financial firms, ST samples, and samples for which data cannot be obtained. The final sample includes 17,708 firm-year observations. All continuous variables are winsorized at the 1st and 99th percentiles.

2.2. Model settings and definitions of the variables

We use the following two-way fixed effects model to investigate the impact of local fintech development on the accuracy of analysts' earnings forecasts:

$$Y_{it} = \alpha_0 + \alpha_1 Fintech_{it} + \beta Controls_{it} + u_i + \varphi_t + \varepsilon_{it} \tag{1}$$

Where i represents firm, t represents year, Y_{it} represents analysts' earnings forecast accuracy, $Fintech_{it}$ represents local fintech development, $Controls_{it}$ represents a series of control variables, u_i indicates firms' individual fixed effects, φ_t indicates time fixed effects, and ε_{it} is the residual term. Regression results are adjusted using heteroskedasticity robustness standard errors.

Referring to the previous related literature (Huberts and Fuller, 1995; Barron et al., 2009; Yang et al., 2019), the accuracy of analysts' earnings forecasts is measured by three indicators: analysts' earnings forecast bias ($Error_{it}$), analysts' earnings forecast dispersion ($Dispersion_{it}$) and analysts' earnings forecast optimism ($Optimism_{it}$). The larger the value of these three indicators, the lower the accuracy of analyst earnings forecast.

Referring to existing relevant literature (Li et al., 2020), this study utilizes Python web crawler technology to obtain the amount of news items searched by fintech-related keywords on Baidu News, thereby constructing a local fintech development indicator. As the total search volume indicator is right-biased, it is processed through the min-max normalization method to yield the local fintech development indicator (*Fintech*).

The control variables include: firm size (*Size*), debt-to-assets ratio (*Lev*), profitability (*ROA*), firm age (*Age*), number of times the firm's earnings has been forecasted (*Numf*), stock price volatility (*Sigma*) and number of analysts followed (*Analyst*). The definition and calculation of control variables are shown in Appendix A. Table 1 reports the descriptive statistics of the main variables.

3. Empirical results

3.1. Baseline results

Table 2 reports the results of the benchmark regressions. The estimated coefficient of *Fintech* in column (1) is -0.018 and significant at the 1% level, suggesting that fintech reduces analysts' earnings forecast bias. The estimated coefficient of *Fintech* in column (2) is -0.033 and significant at the 5% level, which implies that fintech reduces analysts' earnings forecast divergence. The estimated coefficient of *Fintech* in column (3) is -0.017 and significant at the 1% level, which indicates that fintech reduces analysts' earnings forecast optimism. In conclusion, the results show that local fintech development enhances analysts' forecast accuracy.

3.2. Robustness tests

3.2.1. Alternative measures of fintech

We employ the principal component analysis method to synthesize the 48 fintech keyword variables into an indicator that measures local fintech development (*FintechP*). Subsequently, we substitute the original fintech variable *Fintech* with *FintechP* to re-estimate model (1), with the estimation results presented in Table 3 Panel A. The estimated coefficients of *FintechP* are significant at least at the statistical level of 5%, indicating that the baseline conclusion remains valid subsequent to the replacement the fintech indicator.

3.2.2. Excluding specific samples

Given that the level of fintech development in China's four major fintech center cities—Beijing, Shanghai, Shenzhen, and Hangzhou— is much higher that of prefecture-level cities, we exclude the samples of the center cities to mitigate any potential interference from extreme values associated with the center cities. The results of this estimation are presented in Table 3 Panel B, where the estimated coefficients of *FinTech* are all significant at the 1% level.

3.2.3. Consideration of possible omitted variables

To control for the effect of regional factors, we include city GDP per capita and city fixed effects as control variables. The regression results are shown in Table 3 Panel C. After controlling for the effect of regional differences, the coefficients of *Fintech* are still significantly negative, consistent with the baseline results.

Geographic proximity facilitates the collection of private information, so geographically proximate analysts make more accurate earnings forecasts than other analysts (Malloy, 2005). We manually collated the geographic locations of analysts' brokerages and calculated the average distance between all analysts and the forecasted firms for each year (*Distance*). We include the variable *Distance* to control for the effect of geographic factors on the results, and the regression results are shown in Table 3 Panel D. After controlling for geographical factors, the estimated coefficients of *Fintech* remain significantly negative.

3.3. Endogeneity issues

We further utilize quasi-natural experiments and difference-in-difference methods to address endogeneity issues stemming from omitted variables and variable measurement errors. On December 31, 2015, the State Council of China issued the first national-level strategic plan for financial inclusion, titled the Circular of the State Council on the Issuance of the Plan for Promoting the Development of Inclusive Finance (2016-2020). The policy marked the inaugural proposal to encourage financial institutions to integrate emerging information technologies, such as big data and cloud computing, into the financial service system. Given the regional variation in fintech utilization by financial institutions, those in regions with less advanced fintech development are subject to relatively greater policy shocks. Referring to Song et al. (2021), we construct the treatment group and the control group according to the median of the digitization process score of each city in the 2015 Peking University Digital Financial Inclusion Index and define the cities whose index is lower than the median as the treatment group, otherwise, they are the control group and defines *Treat* as the dummy variable of the

Table 1
Descriptive statistics.

Variable	N	Mean	Std dev	Min	Max
Error	17708	0.039	0.068	0.000	0.765
Dispersion	17708	0.272	0.267	0.002	2.080
Optimism	17708	0.037	0.069	-0.050	0.765
Fintech	17708	0.165	0.259	0.000	1.000
Size	17708	22.289	1.317	19.408	26.897
Lev	17708	0.426	0.207	0.026	0.908
ROA	17708	0.044	0.064	-0.505	0.256
Age	17708	2.007	0.887	0.000	3.367
TobinQ	17708	2.051	1.268	0.811	10.994
Sigma	17708	0.032	0.020	0.010	0.691
Numf	17708	3.230	1.161	1.099	5.930
Analysts	17708	3.612	1.230	0.693	6.455

This table presents descriptive statistics of main variables. The variables are defined in Appendix A.

Table 2
Baseline regression.

	(1) *Error*	(2) *Dispersion*	(3) *Optimism*
Fintech	-0.018***	-0.033**	-0.017***
	(-5.01)	(-2.30)	(-4.85)
Size	0.001	0.043***	-0.001
	(0.39)	(7.45)	(-0.46)
Lev	-0.015***	-0.158***	-0.017***
	(-2.83)	(-7.19)	(-3.32)
ROA	-0.819***	-0.457***	-0.872***
	(-37.88)	(-9.80)	(-41.48)
Age	0.000	0.076***	0.001
	(0.21)	(11.49)	(0.58)
TobinQ	-0.001**	0.005**	-0.001*
	(-1.97)	(2.07)	(-1.77)
Sigma	-0.008	-0.586***	-0.038**
	(-0.46)	(-4.47)	(-1.97)
Numf	0.007**	0.087***	0.008***
	(2.45)	(7.55)	(2.69)
Analysts	-0.003	-0.033***	-0.002
	(-1.14)	(-3.04)	(-0.83)
Constant	0.061*	-0.893***	0.086***
	(1.83)	(-7.27)	(2.60)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	17,708	17,708	17,708
R^2	0.629	0.474	0.651

This table reports the regression results for the effect of local fintech development on the accuracy of analysts' earnings forecasts. Detailed definitions of the variables are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics under robust standard errors are displayed in parentheses.

treatment group. *After* is defined as a time dummy variable. If the firm sample is in 2016 or later, the value of *After* equals to 1; otherwise, the value is 0. We use the following difference-in-difference model for estimation:

$$y_{it} = \beta_0 + \beta_1 Treat_i * After_t + \beta_2 Controls_{it} + u_i + \varphi_t + \varepsilon_{it} \tag{2}$$

The coefficient β_1 of $Treat_i{*}After_t$ in the above model measures the effect of the exogenous policy shock on analysts' forecast accuracy. Table 4 reports the difference-in-difference regression results. The interaction terms *Treat*After* in all columns are significantly negative, implying that the exogenous policy shock significantly improves analysts' earnings forecast accuracy.

We plot the dynamic effects of the policy (see Fig. 1, Fig.2, Fig. 3). These three figures show that prior to the introduction of the policy in 2016, there is no significant difference between the treatment group firms and the control group firms, thus satisfying the premise assumption of the parallel trend of the difference-in-difference model. Following the policy's enactment, the treatment group shows a significant decline in analysts' earnings forecast bias and optimism compared to the control group, albeit with a modest delay in the reduction of divergence.

4. Mechanism analysis

We use the interaction term model to test the mechanism of the impact of fintech on the accuracy of analysts' earnings forecasts. The specific model is set up as follows:

$$Med_{it} = \beta_0 + \beta_1 Fintech_{it} + \beta_2 Controls_{it} + u_i + \varphi_t + \varepsilon_{it} \tag{3}$$

$$Y_{it} = \gamma_0 + \gamma_1 Med_{it} + \gamma_2 Fintech_{it} + \gamma_3 Med_{it} \times Fintech_{it} + \gamma_4 Controls_{it} + u_i + \varphi_t + \varepsilon_{it} \tag{4}$$

Where Med_{it} is the mechanism variable. Model (3) is employed to test the effect of fintech on the mechanism variables and model (4) serves as the interaction term model to probe the underlying mechanism. In this study, we investigate the potential mechanisms through which local fintech development affects the accuracy of analysts' earnings forecasts from the perspectives of firm digital transformation and information asymmetry. Following the method of Wu et al. (2022), we measure the degree of firm digital transformation (*Digital*) by calculating the frequency of keywords related to digital transformation in the annual reports of listed firms. Table 5 Panel A presents the estimation results when *Digital* is used as a mechanism variable. The coefficient of *Fintech* in Column (1) is significant at the 1% level, indicating that fintech can promote firm digital transformation. Columns (2) to (4) present the regression results of model (4), respectively. Notably, the estimated coefficients of the interaction term (*Digital* × *Fintech*) are significantly positive, indicating that the facilitating effect of fintech on the accuracy of analysts' earnings forecasts is more pronounced when the degree of firms' digital transformation is low. This analysis suggests that fintech can improve the accuracy of analysts' earnings forecasts by facilitating firm digital transformation as a pathway.

Table 3
Robustness tests.

Panel A Alternative measures of fintech
The local fintech development indicator (*FintechP*) is constructed by the principal component analysis method.

	(1) *Error*	(2) *Dispersion*	(3) *Optimism*
FintechP	-0.001***	-0.003**	-0.001***
	(-4.16)	(-2.29)	(-3.82)
Controls	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	17,708	17,708	17,708
R^2	0.628	0.474	0.650

Panel B Excluding specific sample
This table reports the results of regressions with four fintech center cities deleted.

	(1) *Error*	(2) *Dispersion*	(3) *Optimism*
Fintech	-0.019**	-0.058*	-0.020**
	(-2.48)	(-1.90)	(-2.52)
Controls	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	11,969	11,969	11,969
R^2	0.638	0.472	0.662

Panel C Incorporating city-level control variable
This table reports the results of regressions incorporating city GDP per capita (*Pgdp*) and city fixed effects as control variables.

	(1) *Error*	(2) *Dispersion*	(3) *Optimism*
Fintech	-0.015***	-0.034**	-0.015***
	(-4.20)	(-2.30)	(-4.14)
Pgdp	-0.006**	0.014	-0.005*
	(-2.00)	(0.92)	(-1.92)
Controls	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
N	16,909	16,909	16,909
R^2	0.631	0.476	0.653

Panel D Incorporating geographic factor variable
This table reports the results of regressions incorporating geographic distance between analysts and listed firms (*Distance*).

	(1) *Error*	(2) *Dispersion*	(3) *Optimism*
Fintech	-0.012***	-0.035**	-0.010***
	(-3.44)	(-2.19)	(-3.13)
Distance	0.002*	0.011*	0.002*
	(1.70)	(1.92)	(1.71)
Controls	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
N	14,593	14,593	14,593
R^2	0.554	0.496	0.581

This table summarizes the results of various robustness checks. The control variables are included in all regressions. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics under robust standard errors are displayed in parentheses.

Referring to existing relevant literature (Amihud et al., 1997; Amihud, 2002; Pástor and Stambaugh, 2003), we calculate the stock liquidity ratio, the illiquidity ratio, and the reversal indicator, subsequently deriving the first two principal components through principal component analysis. From these components, we derive a weighted average as a proxy for information asymmetry (*ASY*). The estimation results, leveraging information asymmetry as a mediating variable, are presented in Table 5 Panel B. Column (1) presents the effect of fintech on information asymmetry, and the estimated coefficient of *Fintech* is significant at the 5% level, which indicates that the fintech development can reduce the level of information asymmetry between firms and the outsiders. Columns (2) to (4) display the regression results of model (4), respectively. Notably, the coefficient on the interaction term (*ASY* × *Fintech*) is significantly negative, indicating that the effect of fintech becomes more pronounced with the increase in information asymmetry. In sum, local fintech development can improve analysts' earnings forecast accuracy by reducing information asymmetry.

Table 4
The results of difference-in-difference model.

	(1) *Error*	(2) *Dispersion*	(3) *Optimism*
*Treat*After*	-0.019***	-0.043***	-0.018***
	(-4.89)	(-2.69)	(-4.70)
Controls	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	17,708	17,708	17,708
R^2	0.629	0.474	0.651

The table reports the results of difference-in-difference regressions analyzing the impact of exogenous policy shocks on analysts' forecast accuracy. On December 31, 2015, the State Council of China issued the first national-level strategic plan for financial inclusion, titled the Circular of the State Council on the Issuance of the Plan for Promoting the Development of Inclusive Finance (2016-2020). We employ this policy as an exogenous policy shock to local fintech development. The control variables are included in all regressions. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics under robust standard errors are displayed in parentheses.

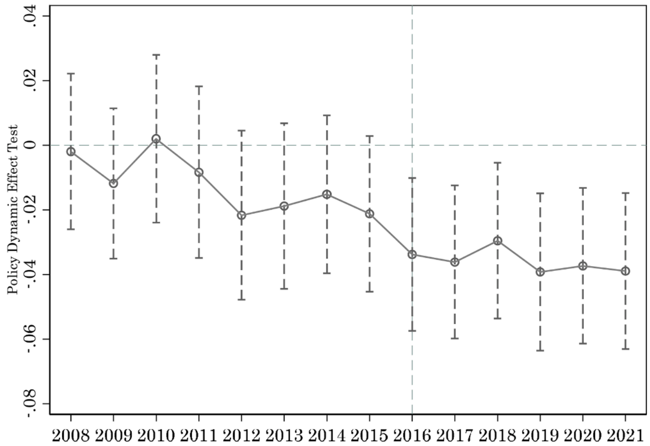

Fig. 1. Dynamic effects on *Bias*
This figure shows the dynamic effects of exogenous policy shocks on analysts' earnings forecast bias. The exogenous policy was implemented at the end of 2015.

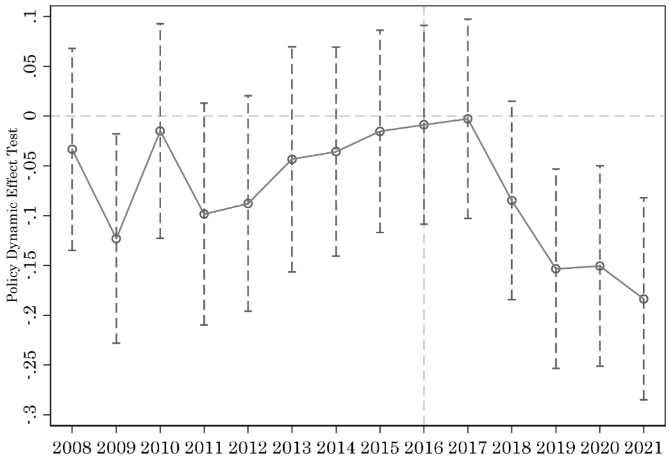

Fig. 2. Dynamic effects on *Dispersion*
This figure shows the dynamic effects of exogenous policy shocks on analysts' earnings forecast dispersion. The exogenous policy was implemented at the end of 2015.

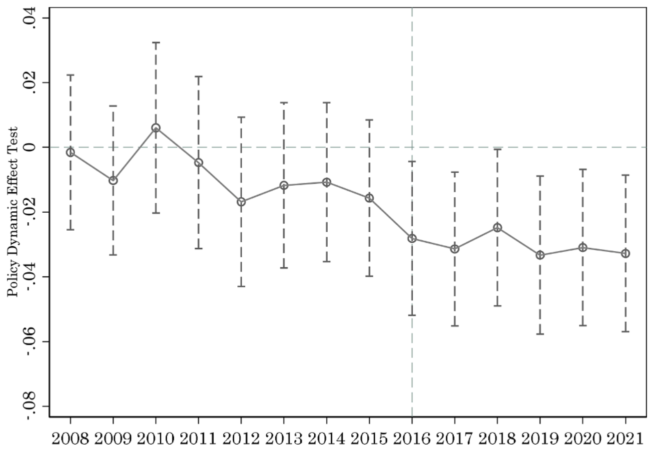

Fig. 3. Dynamic effects on *Optimism*
This figure shows the dynamic effects of exogenous policy shocks on analysts' earnings forecast optimism. The exogenous policy was implemented at the end of 2015.

Table 5
Mechanism analysis.

Panel A Firm digital transformation				
	(1) *Digital*	(2) *Error*	(3) *Dispersion*	(4) *Optimism*
Fintech	0.030***	-0.014***	-0.006	-0.013***
	(13.52)	(-3.52)	(-0.36)	(-3.39)
Digital		-0.048***	-0.064	-0.048***
		(-2.67)	(-0.72)	(-2.71)
Digital×*Fintech*		0.040**	0.042***	0.038**
		(2.45)	(3.00)	(2.39)
Controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	17,708	17,708	17,708	17,708
R^2	0.748	0.629	0.475	0.651
Panel B Information asymmetry				
	(1) *ASY*	(2) *Error*	(3) *Dispersion*	(4) *Optimism*
Fintech	-0.048**	-0.012***	-0.016	-0.012***
	(-2.18)	(-3.05)	(-1.10)	(-3.00)
ASY		0.003**	-0.014*	0.006***
		(2.26)	(-1.76)	(3.86)
ASY×*Fintech*		-0.014***	-0.044***	-0.013***
		(-5.26)	(-3.16)	(-4.89)
Controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	17,694	17,694	17,694	17,694
R^2	0.775	0.630	0.474	0.652

This table reports the results for the possible mechanisms of local fintech development on analysts' forecast accuracy. We use the interaction term model to test the mechanism from the perspectives of firm digital transformation and information asymmetry. We measure the degree of firm digital transformation (*Digital*) by calculating the frequency of keywords related to digital transformation in the annual reports of firms. We calculate the stock liquidity ratio, the illiquidity ratio, and the reversal indicator, subsequently deriving the first two principal components through principal component analysis. From these components, we derive a weighted average as a proxy for information asymmetry (*ASY*). The control variables are included in all regressions. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics under robust standard errors are displayed in parentheses.

5. Heterogeneity analysis

5.1. Affiliated analysts

Conflict of interest is an important determinant that affect the accuracy of analysts' earnings forecasts (Easterwood and Nutt, 1999; Mola and Guidolin, 2009; Firth et al., 2013). We anticipate that the impact of fintech on analysts' earnings forecast accuracy will display heterogeneity owing to analysts' conflicts of interest, particularly focusing on two types: affiliation of interest linked to equity pledges by major shareholders and buy-side pressure.

Using data on stock pledge of Chinese listed companies, we construct a binary variable of affiliated analysts (*Affiliation*), which takes a value of 1 if the analyst's brokerage is a pledger of the controlling shareholder of the listed firm during the equity pledge period and 0 otherwise. We divide the sample into two groups: unaffiliated and affiliated analysts. Table 6 Panel A reports the results of the subgroup regressions. The estimation results in columns (1), (3), and (5) show that the coefficients of *Fintech* for the sample of firms with unaffiliated analysts are significantly negative, suggesting that fintech is more likely to enhance the accuracy of analysts' earnings forecasts for firms in the unaffiliated analyst group. In contrast, the coefficient estimates of *Fintech* for the sample of the group of affiliated analysts who are more susceptible to conflicts of interest (columns (2), (4), (6)) are not statistically significant, indicating that conflicts of interest among affiliated analysts may nullify the potential effect of fintech in reducing analysts' earnings forecasting bias, disagreement, and optimism. The final row of Table 6 Panel A reports the results of the significance test of the coefficients between the two sample groups, with p-values less than 0.01, underscoring the significant impact of affiliated analysts on the heterogeneity of the underlying results.

5.2. Buy-side pressure

To ascertain the heterogeneous impact of buy-side pressure on baseline results, we construct a dummy variable for buy-side pressure (*Pressure*) using data on the percentage of fund ownership of listed firms, with *Pressure* taking the value of 1 if institutional ownership exceeds the mean, and 0 otherwise. In Table 6 Panel B, Columns (1), (3), and (5) report the regression results of the group with low buy-side pressure (*Pressure* equals 0), wherein the estimated coefficients of *Fintech* are all significantly negative at the level of 1%. Subsequently, Columns (2), (4), and (6) report the regression results for the high buy-side pressure group (*Pressure* equals 1), with the estimated coefficients of *Fintech* being either significantly negative at the 5% level or non-significant. The final row of Table 6 Panel B presents the results of the test for the significance of the difference in coefficients between the groups. Irrespective of the measure of analysts' earnings forecast accuracy, the absolute value of the estimated coefficient on *Fintech* in the low buy-side pressure group is significantly larger (with a p-value of less than 0.01), indicating that compared with the group with high buy-side pressure, fintech has a greater impact on analysts' earnings forecast bias, divergence, and optimism in the group with low buy-side pressure.

6. Conclusions

In this study, we explore the relationship between local fintech development and analysts' earnings forecast accuracy. Our findings indicate that local fintech development is positively associated with analysts' earnings forecast accuracy. This conclusion still holds after the robustness test and endogeneity test. Further, the mechanism test reveals that fintech enhances analysts' earnings forecast accuracy by promoting firm digital transformation and alleviating information asymmetry between firms and outsiders. Additional analysis shows that the impact of fintech on analysts' earnings forecast accuracy is moderated by analysts' conflicts of interest, with the facilitating effect of fintech being more significant for analysts without equity pledge affiliation and those with weaker buy-side pressure. Our study highlights the potential for local fintech development to enhance the accuracy of analysts' earnings forecasts, underscoring the role of fintech in improving the information environment of the capital market.

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Author agreement

All authors have seen and approved the final version of the manuscript being submitted. They warrant that the article is the authors' original work, hasn't received prior publication and isn't under consideration for publication elsewhere.

CRediT authorship contribution statement

Chaolin Zhang: Writing – review & editing, Supervision, Conceptualization. **Fangbo Yu:** Writing – original draft, Software, Methodology, Data curation.

Table 6
Heterogeneity tests.

Panel A Affiliated analysts

	(1) *Error*	(2)	(3) *Dispersion*	(4)	(5) *Optimism*	(6)
	Affiliation=0	*Affiliation*=1	*Affiliation*=0	*Affiliation*=1	*Affiliation*=0	*Affiliation*=1
Fintech	-0.017***	-0.027	-0.037**	0.054	-0.016***	-0.033
	(-4.70)	(-0.69)	(-2.55)	(0.43)	(-4.45)	(-0.84)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	17,164	387	17,164	387	17,164	387
R^2	0.626	0.758	0.473	0.765	0.649	0.764
p-value	0.000		0.000		0.000	

Panel B Buy-side pressure

	(1) Error	(2)	(3) Dispersion	(4)	(5) Optimism	(6)
	Pressure=0	*Pressure*=1	*Pressure*=0	*Pressure*=1	*Pressure*=0	*Pressure*=1
Fintech	-0.035***	-0.011**	-0.099***	-0.008	-0.036***	-0.010**
	(-5.57)	(-2.56)	(-4.06)	(-0.40)	(-6.06)	(-2.21)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	7,234	10,242	7,234	10,242	7,234	10,242
R^2	0.703	0.599	0.528	0.487	0.720	0.625
p-value	0.000		0.000		0.000	

Panel A of this table displays the subsample analyses based on analyst affiliation. Regressions are conducted separately for firms with unaffiliated analysts and those with affiliated analysts. Panel B reports the subsample analyses based on buy-side pressure. Regressions are conducted separately for firms with low buy-side pressure and those with high buy-side pressure. The control variables are included in all regressions. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The t-statistics under robust standard errors are displayed in parentheses. The p-value represents the significance of the difference between the estimated coefficients for fintech within two groups.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Appendix A

The definition of key variables.

Variable	Definitions
Error	Analysts' earnings forecast bias, as calculated with reference to Yang et al. (2019)
Dispersion	Analysts' earnings forecast divergence, as calculated with reference to Barron et al., (2009)
Optimism	Analysts' earnings forecast optimism, as calculated with reference to Huberts and Fuller (1995)
Fintech	Local fintech index calculated based on the amount of news items searched by fintech-related keywords on Baidu News
Size	The natural logarithm of total assets
Lev	The total liabilities / total assets
ROA	The net profit / total assets
Age	The natural logarithm of listed years
TobinQ	The stock market value / total assets
Sigma	The annual standard deviation of daily stock returns
Numf	The number of times a firm's earnings is forecast
Analysts	The natural logarithm of the number of analysts followed

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