The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/1029-807X.htm

The influence of network platform interaction on corporate total factor productivity: evidence from China stock exchange investor interactive platforms

Received 25 November 2021
Revised 14 February 2022
Accepted 6 March 2022

Yingbing Jiang, Chuanxin Xu and Xu Ban
School of Accountancy, China Internal Control Research Center, Dongbei University of Finance and Economics, Dalian, China

Abstract

Purpose – The aim of this paper is to study the impact of the questions and answers (Q&A) between investors and enterprises from the China stock exchange investor interactive platforms on the total factor productivity (TFP) of enterprises.

Design/methodology/approach – To show how the interaction influences the TFP of enterprises, the authors select Q&A records from the interactive platforms related to production, R&D and technology through the Latent Dirichlet Allocation (LDA) topic model and choose A-share listed companies from 2010 to 2019 in China as a sample. To treat the data and test the proposed hypothesis, the authors applied OLS regression and endogeneity testing methods, such as the entropy balance test, Heckman two-stage model and the two-stage least squares regression.

Findings – This paper finds that interaction between investors and enterprises is positively correlated with TFP, and that improvements in content length and the timeliness of response can promote TFP. Interactive behavior mainly improves the TFP of enterprises by alleviating financing constraints and encouraging enterprises to increase R&D investment. This positive effect is more pronounced in companies with higher agency costs, non-high-tech companies and companies not supported by industrial policy.

Originality/value – The novelty of the research stands in the application of Python's LDA topic model to screen out Q&A records that are directly related to TFP, such as production, R&D, technology, etc., and measures the degree of information interaction between investors and enterprises from multiple dimensions, such as interaction frequency, content length and the timeliness of response.

Keywords Interactive platforms, Financing constraint, R&D input, Total factor productivity (TFP)

Paper type Research paper

1. Introduction

The report of the 19th National Congress of the Communist Party of China pointed out that the Chinese economy has shifted from a stage of rapid growth to a stage of high-quality development. It is important for China to vigorously improve its total productivity factor (TFP) if it is to achieve higher quality, greater efficiency and more sustainable economic development.

JEL Classification — D24; D83; M41

The authors are grateful for the valuable comments and suggestions from the reviewer.

Funding: This work was supported by the MOE (Ministry of Education in China) Project of Humanities and Social Sciences [grant number 20YJA630026].

Conflict of Interest: This paper doesn't have any conflict of interest.

Author Statement: All the authors of this article have the same contribution.

China Accounting and Finance Review
Vol. 24 No. 4, 2022
pp. 445-463
Emerald Publishing Limited
e-ISSN: 2307-3055
p-ISSN: 1029-807X
DOI 10.1108/CAFR-03-2022-0015

Enterprises cannot improve TFP without the support of the capital market (Ashraf, Herzer, & Nunnenkamp, 2016). In April 2020, the State Council of China issued the *Opinions on Building a More Complete Factor Market Allocation System and Mechanism*, which emphasizes the need to promote the integrated development of technological elements and capital elements.

With the deepening of capital market reform and the rapid development of online big data, investors, especially individual investors, have gradually shifted the way they obtain information from one-way disclosure to interaction between investors and enterprises (hereafter referred to as *interaction*) [1] (Blankespoor, Hendricks, & Miller, 2017). As a result, major changes in the information access channels and information screening methods for investors have occurred. These changes include the interactive platforms of the Shanghai Stock Exchange, the Shenzhen Stock Exchange and Panorama.com (hereafter collectively referred to as the interactive platforms), which are considered third-party platforms through which investors can interact directly with listed companies; investors can directly pose questions to listed companies on the interactive platforms and companies can answer such questions. Interactive platforms play a significant role in capital markets in part due to the "wisdom of crowds" (Dyer & Kim, 2021). According to the statistics in this paper, by the end of 2019, the interactive platforms had more than 5 million Q&A records involving more than 3,800 listed companies [2]. The content of the Q&As covers multiple levels, such as research and development (R&D), production, technology and mergers and acquisitions (M&A) [3].

In Q&A interaction, the information demands of investors can be effectively presented, and the progress and transparency of online media provide a more accurate measure of the ability of investors to obtain information. Therefore, interactive platforms provide an excellent experimental context for studying the impact of interaction on corporate behavior characteristics. However, due to factors such as the difficulty of data acquisition and the complexity of Latent Dirichlet Allocation (LDA) topic model programming, no study has yet discussed the impact of interaction through the interactive platforms on corporate TFP. Previous literature has revealed that Python's LDA topic model can summarize the potential topics of the text based on relevant text statistics, making it suitable for accounting text research (Bao & Datta, 2014). Therefore, this paper adopts this approach and applies crawler technology to crawl the interaction data. We write and apply Python's LDA topic model to screen the Q&A records related to enterprise production, R&D, technology, etc., which are directly related to TFP. We discuss the frontier issue regarding the influence of interaction through the interactive platforms on the TFP of enterprises. The research results have important practical significance for reducing information asymmetry, improving the TFP of enterprise and promoting its high-quality development.

On the one hand, this information exchange effectively reduces information asymmetry, thus reducing the financing constraints of enterprises (Bushee & Miller, 2012). Companies make optimal resource allocation decisions, only through breaking financing constraints, which is a big bottleneck in the business development of enterprises (Zhang, 2019). The interactive platforms are open network platforms; that is, the Q&A records of investors and enterprises on the interactive platforms can be retained for a long time, and all investors can access the historical Q&A contents, which can reduce the financing constraints of enterprises as a whole (Reiter, 2021). The mitigation of financing constraints gives companies access to relatively sufficient funds to invest in technological improvement and innovation activities.

On the other hand, when investors ask many questions about production, R&D, technology, etc., which allow interactive platforms to harness the wisdom of crowds (Dyer & Kim, 2021), the "spotlight" effect will magnify their concerns (Bushee & Miller, 2012). To cater to investors' concerns, managers will increase the company's R&D investment, which will improve TFP. In addition, interactive platforms cover a large number of individual investors, and due to the openness of the platforms, individual investors interact with enterprises through a process that aggregates their voices and strengthens their supervisory role (Reiter, 2021). This process can motivate management to increase R&D investment, reduce short-sighted behaviors and ultimately help companies improve their TFP.

We use crawler technology to obtain all the data of the three interactive platforms and use the LDA topic model program to select Q&A records about production, R&D, technology and other contents which directly related to TFP from the topics. Finally, we summarize the Q&A data by company and year and merge it with corporate finance and governance data to form an initial sample and conduct a series of studies.

On this basis, we find that interaction on the interactive platforms is positively correlated with TFP, and that improvements in content length and the timeliness of response can promote TFP. We further find that interactive behavior mainly improves the TFP by alleviating financing constraints and encouraging enterprises to increase R&D investment. This effect is more significant in enterprises with higher agency costs, non-high-tech enterprises and enterprises not supported by industrial policy.

Considering possible endogeneity issues in the empirical process, we retest the model by using endogeneity testing methods, such as the entropy balance test, Heckman two-stage model and the two-stage least squares regression. We also test robustness by replacing the measurement methods of dependent variables and independent variables, adopting a fixed effect model, shortening the research interval and introducing missing variables. The results verify our conjectures.

This paper makes three contributions. Firstly, the paper expands the existing literature on individual investor concerns. Existing studies that explore the impact of investors on the TFP of enterprises generally take the perspective of institutional investors (Chiang & Lin, 2007). Based on this new information exchange mechanism, this paper explores in-depth the impact of investors on the sustainable development of enterprises and enriches the research results on individual investor concerns.

Secondly, this paper supplements the relevant research on this new information exchange mechanism. Most of the literature concerning investors focuses on traditional one-way information disclosure, and only a few studies explore the impact of interaction on the synchronization of stock prices and market response. By studying the influence of interaction through interactive platforms on TFP, this paper extends the research scope of information interaction from the level of market response to the level of high-quality enterprise development. The research conclusion is a useful supplement to the literature on Q&A interaction and its economic consequences.

Lastly, this paper deepens the existing investor interaction research. Prior literature based on interactive platform data mainly considers all Q&A records as the research sample, which may affect the pertinence and accuracy of the research. This paper compiles the program code of the LDA topic model using Python software; selects Q&A records about production, R&D, technology and other issues related to TFP; and measures the impact of information interaction on TFP from multiple dimensions, such as Q&A frequency, content length and the timeliness of response. This approach can achieve an in-depth study of the existing literature on investor interaction.

The rest of this paper proceeds as follows. In Section 2, we review the relevant literature and develop the hypothesis. Section 3 describes the research design and Section 4 presents the empirical results. In Section 5, we provide further research results. We briefly conclude our study in Section 6.

2. Literature review and hypothesis development

2.1 Literature review

TFP is an important factor in improving the level of national economic development; it is also an important indicator for measuring the quality of enterprise development. Early literature on the influencing factors of TFP considers the external factors at either the country level or the industry level. Based on provincial panel data in China, it is found that the loss of TFP in China mainly comes from the distortion of capital allocation between departments (Brandt, Tombe, & Zhu, 2013). The results of another paper showed that there is a "U-shaped" curve relationship between government administrative service expenditure, investment and development expenditure, security and governance expenditure and TFP (Wu, Li, Nie, & Chen, 2017). Based on industry-level data, Papaioannou (2018) found that EU services liberalization is positively correlated with TFP. In recent years, some literature has explored the impact of internal factors or business strategy on the TFP of enterprises. The existing literature has found that greenfield FDI has no statistically significant effect on TFP, while M&As have a positive effect on TFP (Ashraf *et al.*, 2016). Other literature found that increasing real estate prices negatively affect corporate TFP (Lu, Tan, & Zhang, 2019). Furthermore, some literature results show that haze pollution will reduce a firm's TFP (Li, Shi, & Zeng, 2020). Guan and Cheng (2020) found that product complexity was positively related to a higher productivity level. However, few studies have examined the influence of investors on enterprise TFP from the perspective of external investors, as they mainly discuss the influence of institutional investors (Chiang & Lin, 2007). There is no current literature that explores how interactive platforms affect the TFP of enterprises.

Regarding the impact of interaction through interactive platforms on corporate behavior, the existing literature mainly studies its impact on stock market liquidity, stock price synchronicity and stock price collapse risk (Ding, Lyu, & Huang, 2018; Jin & Li, 2017; Tan, Kan, & Cui, 2016). It has been examined in the paper that the role of interaction between managers and investors during cross-listing (Reiter, 2021). However, the current discussion on the interaction behavior is imperfect. The changes in information acquisition methods and their economic consequences against the background of the rapid development of the internet and big data have not received widespread attention from the academic community [4], and additional research on interaction behavior is needed. The content of the interaction covers R&D, production, technology, mergers and acquisitions. The Q&A process can greatly reduce the degree of information asymmetry and place individual investors in a supervisory role. Therefore, it is necessary to comprehensively explore how interaction through interactive platforms affects the TFP of enterprises.

2.2 Hypothesis development

TFP reflects the maximum output obtained from the input of enterprise capital, technology, labor, management and other factors and measures the quality of enterprise development. The key to improving TFP involves improving resource allocation efficiency and technological progress (Hsieh & Klenow, 2009). However, to achieve the optimal allocation of factors and technological improvement, enterprises require the support of the capital market (Ashraf *et al.*, 2016). Currently, China's securities market is retail-driven [5]. Compared with institutional investors, many individual investors lack the necessary financial knowledge and ability to process in-depth information (Kumar & Lee, 2006). With interactive platforms, individual investors can ask companies questions online directly, while companies can face investors by both asking and answering questions, and the content of these Q&As can be observed by other investors. This interaction mode not only reduces the degree of information asymmetry but also aggregates the voices of investors such that they will have a significant and collective impact on the TFP of enterprises.

The mechanism through which the interaction improves the TFP of enterprises mainly lies in the following two aspects.

Firstly, interaction improves TFP by providing financial support to effectively alleviate the financing constraints of enterprises. Through the operation of the interactive platforms and by communicating directly with listed companies, on the one hand, investors more easily obtain information about events such as M&A and future development strategies and resolve doubts about any ambiguous information (Tan *et al.*, 2016). This kind of information exchange effectively compensates for the lack of knowledge and ability among individual investors, reduces the information asymmetry and thereby reduces the financing constraints of enterprises (Ding *et al.*, 2018). On the other hand, the interactive platforms are open network platforms; that is, the Q&A records of investors and companies on the interactive platforms are preserved for a long time, and all investors can access to the historical Q&A content. Thus, open access to the Q&A content greatly reduces the cost of information collection for other investors, increases their understanding, and reduces the financing constraints of the company as a whole (Reiter, 2021). The alleviation of financing constraints enables enterprises to obtain relatively sufficient funds to invest in technological improvement and innovation activities, which helps to promote efficiency. Only by overcoming financing constraints, a big bottleneck for business development, can companies make optimal resource allocation decisions, which have a positive effect on TFP (Zhang, 2019).

Secondly, interaction can help encourage managers to increase investment in innovation, promote the integration of technology and capital factors and promote technological progress, thereby increasing TFP. The technological progress caused by R&D investment can increase productivity, support factor substitution, and help optimize the efficiency of resource allocation (Xu, Wang, & Zhu, 2019). Innovation is usually long-term, high-risk, and has a high degree of information asymmetry, which can easily cause resistance among managers (Abdoh & Liu, 2021); however, the opening of interactive platforms will reduce managers' short-sighted behaviors. The Q&A process is open and universal; that is, investors who follow listed companies can observe the questions of other investors and the companies' responses via interactive platforms. This kind of information sharing makes it easier for all investors to obtain information such as innovation, production and R&D, while the shared interaction also aggregates the concerns of investors, which allows interactive platforms to harness the wisdom of crowds (Dyer & Kim, 2021). If managers cannot give satisfactory answers to investors' inquiries about corporate production, R&D, technology, etc., other investors on the interactive platforms may follow up with more questions. This situation creates a "spotlight" effect that magnifies the problem and hence attracts the full attention of management. In response to this investor concern, managers will increase the company's R&D investment, which can help improve TFP. Moreover, the users of interactive platforms include a large number of individual investors, and in the interaction process, the openness of the interactive platforms aggregates their voices. A large number of individual investors can therefore put pressure on management by divesting their shares, namely "voting by foot", which strengthens their supervisory power (Reiter, 2021). Therefore, when Q&A content involves a large amount of information related to production, R&D, technology, etc., it can motivate managers to strive to act based on the long-term interests of shareholders, by increasing R&D investment, reducing short-sighted behavior and ultimately helping the enterprise improve TFP.

In summary, interaction can alleviate corporate financing constraints, improve resource allocation efficiency, spur companies to increase investment in innovation, promote the integration of technology and capital elements, and ultimately increase TFP. The preceding analysis leads to our hypothesis:

H1. Direct interaction between investors and companies through interactive platforms can help companies improve their TFP.

3. Research design

3.1 Sample selection and data sources

In China, the interactive platform of the Shenzhen Stock Exchange was first opened in 2010, and then the interactive platforms of the Shanghai Stock Exchange and Panorama.com were opened in 2013. There are several subcolumns, such as "Q&A", "Roadshow" and "Interview" in the three interactive platforms, among which the "Q&A" column, which is the most interactive, includes questions asked by investors and responses by listed companies. In addition, both the China Securities Regulatory Commission and the Stock Exchanges have relevant regulations that require enterprises to actively respond to questions from investors, which to some extent prevent the situation that enterprises respond to questions from investors selectively. Therefore, considering the availability of data and preventing the problem of sample self-selection, this paper chooses Chinese listed companies as samples.

Because the interactive platform of the Shenzhen Stock Exchange was first opened in 2010, this paper sets the research interval to 2010–2019. We use Python 3.8.5 software and the Requests, Re, Pymongo and Lxml module programs to obtain all the Q&A data of the three interactive platforms. Firstly, we eliminated uninformative and distracting words, such as "hello" and "excuse me". Secondly, we wrote the program code for the LDA topic model using Python and debugged the content text of the best topic based on the principle of error minimization. Thirdly, using the LDA topic model program, we identified and divided the topics of the Q&A records. Since production, R&D innovation and technological progress are directly related to TFP, this paper selected Q&A records related to production, R&D, technology and other contents from the topics, and produced a total of 1,068,975 pieces of data covering 3,798 listed companies. Finally, we summarized the Q&A data by company and year and merged it with corporate finance and governance data to form an initial sample.

We processed the initial sample according to the following requirements: (1) companies in the financial industry were excluded; (2) ST and *ST companies were excluded; and (3) companies with missing data were excluded. After processing the sample, we obtained a total of 16,665 sample observations from 3,207 listed companies. To control the interference of outliers, we winsorized continuous variables at 1 and 99 percentiles. To eliminate the interference of deviations, such as heteroscedasticity and sequence correlation, in the regression results, we introduced firm and annual double clustering robustness standard errors in the regression process. Data statistics and empirical tests were processed using Stata16 software, and corporate financial and governance data were derived from the Wind and CSMAR databases.

3.2 Variable definition

3.2.1 Dependent variable. 3.2.1.1 TFP. Following the practice of the existing literature (Levinsohn & Petrin, 2003), we use its method to measure the TFP of enterprises. In the robustness test, we follow another study (Ackerberg, Caves, & Frazer, 2015) and adopt its approach to redefine the TFP (hereinafter collectively referred to as the ACF method). The model for calculating *Tfp* is expressed as follows:

$$\ln Y = \alpha 0 + \alpha 1 \ln L + \alpha 2 \ln K + \alpha 3 \ln M + \varepsilon \qquad (1)$$

Where the output variable Y is expressed by operating income, labor input L is expressed by the number of employees in an enterprise, capital input K is expressed by net fixed assets and intermediate input M is expressed by cash paid to purchase goods and receive labor services. The calculated residual ε is an enterprise's TFP (*Tfp*).

3.2.2 Independent variable. 3.2.2.1 Interact. The interaction means that investors ask the enterprise questions on the interactive platforms and that the enterprise respond. This exchange comprises the interaction process. Therefore, we use the logarithm of the total number of responses from companies each year plus one to measure the degree of interaction. In the robustness test, we also use two other methods to further measure the degree of interaction. One measure is adding 1 to the sum of the number of annual questions from investors and the number of annual replies from enterprises and then taking the logarithm. The other is the ratio of the number of annual replies to the number of annual questions.

3.2.3 Control variables. To control the impact of other variables on TFP, this paper follows the relevant literature (Wu *et al.*, 2017; Xu *et al.*, 2019) and selects company size (*Size*), financial leverage (*Lev*), return on assets (*Roa*), operating cash flow (*Cfo*), price-to-book ratio (*PB*), reliance on external financing (*Exfin*), equity concentration (*Top1*), proportion of independent directors (*Indep*), size of the board of directors (*Board*), proportion of executive shares (*Exeshare*), executive pay (*Exepay*) and audit opinion (*Audit*) as the control variables of the model. In addition, to control industry differences and changes in TFP caused by time changes, we introduce and control industry and year fixed effects in the model. Refer to Table 1 for specific variable definitions.

Variable	Definitions
Tfp	Residuals calculated in model (1)
Interact	Taking the natural logarithm after the total number of responses from companies each year plus one
Size	Natural logarithm of total assets
Lev	Total liabilities/total assets
Roa	Net income/total assets
Cfo	Operating cash flow/total assets
PB	Price per share/net assets per share
Exfin	Long-term debt/net fixed assets
Top1	Percentage of shares held by the first largest shareholder
Indep	Number of independent directors/number of board of directors
Board	Natural logarithm of the number of board members
Exeshare	Percentage of shares held by the executives
Exepay	Natural logarithm of the total compensation of the top three executives
Audit	Indicator variable that is 1 if the audit opinion in that year is unqualified opinion, and 0 otherwise
Commun	Indicator variable that is 1 if the degree of interaction between investors and enterprises on the interactive platforms is higher than the median of the whole sample, and 0 otherwise
Word	Taking the natural logarithm after the total number of words in the company's replies to investors each year plus one
Time	Firstly, capture the date of each investor's question and the date of corporate response; secondly, calculate the difference between the two dates and add up the date difference at the firm-annual level; lastly, divide the total date difference by the number of corporate responses in the year to calculate the average time lag of the replies in that year
SA	SA index. See footnote 6 for detailed definitions
RD	R&D investment/total assets
Others	Mean of the degree of interaction between other companies in the industry and investors during the year
NewTFP	Modified TFP by performing an auto-correlation function
QA	Taking the natural logarithm after the sum of the annual number of questions and the number of replies plus one to redefine the interaction index
Inst	Indicator variable that is 1 if the percentage of shares held by the institutional investors is higher than the median of the whole sample, and 0 otherwise
Analyst	Indicator variable that is 1 if the number of analysts who track the enterprise is higher than the median of the whole sample, and 0 otherwise
AC	Indicator variable that is 1 if the agency cost is higher than the median of the whole sample, and 0 otherwise
High_tech	Indicator variable that is 1 if the enterprise in that year is recognized as a high-tech enterprise, and 0 otherwise
IP	Indicator variable that is 1 if the enterprise in that year is supported by industrial policy, and 0 otherwise

Table 1.
Variable definitions

3.3 Model setting

To test H1, we design model (2):

$$Tfp = \alpha 0 + \alpha 1 Interact + \lambda X + Year + Ind + \varepsilon \tag{2}$$

In this formula, *Tfp* represents a company's TFP, *Interact* represents the degree of interaction and *X* represents a series of control variables. According to H1, interaction can increase TFP, so we expect the coefficient of α_1 to be significantly positive.

4. Empirical test and result analysis

4.1 Descriptive statistics

We conduct a descriptive analysis of the relevant variables in model (2); the specific statistical results are shown in Table 2.

As seen in Table 2, the average value of *Tfp* is 7.177, the maximum value is 10.667, the minimum value is 3.345 and the standard deviation is 1.406, indicating distinct differences in the TFP of different enterprises. This finding facilitates an exploration of the factors influencing enterprise TFP. The average value of *Interact* is 2.338, with a minimum value of 0, a maximum value of 5.881 and a standard deviation of 1.782, indicating that the degree of interaction is quite varied and that a few companies even fail to respond to investors' inquiries about production and R&D. The numerical characteristics of other variables in the table are consistent with the findings in the existing literature.

To further observe the sample statistics for interaction and TFP, we divide the whole sample into two subsamples according to *Commun* (an indicator variable that is set to 1 if the degree of interaction is higher than the median of the whole sample, and 0 otherwise) and then use the mean test and Wilcoxon rank sum test to test the difference in the TFP level between the two groups. The test results are shown in Table 3.

As shown in Table 3, the mean and median of the subsamples reflect the significant differences in *Tfp* levels between companies with a higher *Interact* and lower *Interact*. We find that *Tfp* is lower with lower *Interact*, so the test results initially support H1.

Table 2.
Descriptive statistics

Variable	*N*	Mean	Std. dev	Min	p25	p50	p75	Max
Tfp	16,665	7.177	1.406	3.345	6.341	7.210	8.058	10.667
Interact	16,665	2.338	1.782	0.000	0.000	2.565	3.807	5.881
Size	16,665	22.176	1.284	19.520	21.247	22.006	22.899	26.048
Lev	16,665	0.424	0.204	0.049	0.262	0.417	0.578	0.934
Roa	16,665	0.049	0.049	−0.246	0.022	0.044	0.073	0.200
Cfo	16,665	0.048	0.069	−0.180	0.010	0.048	0.089	0.247
PB	16,665	3.603	2.916	0.517	1.794	2.754	4.406	20.803
Exfin	16,665	2.011	8.812	0.000	0.065	0.231	0.632	76.930
Top1	16,665	0.347	0.147	0.088	0.231	0.328	0.447	0.750
Indep	16,665	0.374	0.054	0.308	0.333	0.333	0.429	0.571
Board	16,665	2.137	0.198	1.609	1.946	2.197	2.197	2.708
Exeshare	16,665	0.077	0.143	0.000	0.000	0.002	0.077	0.616
Exepay	16,665	14.372	0.702	12.401	13.916	14.351	14.787	16.241
Audit	16,665	0.982	0.133	0.000	1.000	1.000	1.000	1.000

Note(s): This table contains descriptive statistics for our sample of 16,665 firm-year observations. To control the interference of outliers, we winsorized continuous variables at the 1 and 99 percentiles. See Table 1 for detailed definitions of all variables

4.2 Basic regression results

To test the impact of interaction on the TFP of enterprises, we perform ordinary least squares (OLS) regression on the research samples according to model (2). The specific results are shown in Table 4.

According to Table 4, when the regression includes only the industry and year control variables, we find that interaction has significant positive effect on the TFP of enterprises. When the regression adds all of the control variables, the coefficient of *Interact* is 0.030, and the *t*-value is 3.81, which is significantly positive at the 1% level; that is, the Q&A process can significantly improve TFP. From the perspective of the economic significance of the regression coefficient, each one increase in standard deviation (1.782) in the value of *Interact* will increase *Tfp* by approximately 5.35% (1.782*0.030), which is equivalent to 0.75% (0.0535/7.177) of the average *Tfp* of the entire sample. From a practical point of view, every additional response to investor questions on production and R&D on the interactive platforms will increase the company's *Tfp* by approximately 0.03 units (e^0.028–1). The sign of the coefficients of control variables in Table 4 are similar to those in the existing literature, which again indicates that the model setting is reasonable. The empirical results support H1.

		Tfp mean test		*Tfp* median test	
Subsamples	*N*	Mean	*T*-value	Median	*Z*-value
Commun = 1	10,615	7.206	3.60***	7.239	3.78***
Commun = 0	6,050	7.124		7.157	

Note(s): This table reports the results of the mean test and Wilcoxon rank sum test for our sample of 16,665 firm-year observations (10,615 firm-year observations for *Commun* = 1; 6,050 firm-year observations for *Commun* = 0). Standard errors after robust adjustment are clustered at the firm-year level. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels, respectively (two-tailed tests)

Table 3. Results of the mean test and Wilcoxon rank sum test

Variable	Coeff	*T*-value	Coeff	*T*-value
Interact	0.036***	4.12	0.030***	3.81
Size			0.303***	25.04
Lev			1.205***	16.34
Roa			7.306***	22.41
Cfo			−2.408***	−13.99
PB			0.036***	7.83
Exfin			0.026***	18.64
Top1			−0.058	−0.88
Indep			−0.535***	−2.61
Board			−0.407***	−6.77
Exeshare			0.451***	7.16
Exepay			0.080***	4.73
Audit			0.021	0.23
Constant	6.997***	76.34	−0.459	−1.49
Year and Ind	Yes		Yes	
N	16,665		16,665	
Adj·R^2	0.160		0.329	
F-test	54.82***		119.34***	

Note(s): This table reports results from OLS regressions of *Tfp* on *Interact* and control variables. See Table 1 for detailed descriptions of all variables. All specifications include year and industry fixed effects. Standard errors after robust adjustment are clustered at the firm-year level. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels, respectively (two-tailed tests)

Table 4. Regression results of the impact of interaction on TFP

4.3 Content length and timeliness of corporate response on TFP

Considering that the content length and timeliness of response may also affect TFP, we further discuss the impact of interaction on corporate TFP from the perspective of content length and the timeliness of response. As the interactive platform is an official information exchange platform established by the stock exchange, the interaction process is supervised by the stock exchange and has the legal effect of accountability, which ensures that the information acquisition behavior of investors on the interactive platform will not be disturbed by misinformation such as rumors. Since individual investors' ability to acquire and understand information differs greatly, the longer the reply content is, the more information asymmetry is reduced in the interaction process (Sandstrom, 2010). Therefore, following the practice of the existing literature (Bushee & Miller, 2012), we take the natural logarithm after the total number of words in the replies to investors each year plus one to measure the length of reply content (*Word*). Higher *Word* means longer response.

In addition, if the investor asks a question on the interactive platforms and the company responds in a timely manner, it may strengthen the interaction effect; conversely, if the company takes a long time to respond to the investor's inquiry on the interactive platforms, the answer may not be timely or the investors may have obtained relevant information from other information channels, which will reduce the effectiveness of interaction. Therefore, we measure the timeliness of corporate responses (*Time*) in the following ways: firstly, capture the date of each investor's question and the date of corporate response through Python; secondly, calculate the difference between the two dates and add up the date difference at the firm-annual level; finally, divide the total date difference by the number of corporate responses in the year to calculate the average time lag of the replies in that year. Higher *Time* means lower timeliness.

After introducing all the control variables in model (2), we successively examine the impact of content length (*Word*) and the timeliness (*Time*) of response on TFP. The regression results are shown in Table 5.

According to Table 5, the coefficient of *Word* is 0.021, and the t-value is 4.85, which is significantly positive at the 1% level. The coefficient of *Time* is −0.0004, and the t-value is −1.65, which is significantly negative at the 10% level. These results once again show that the Q&A process has information content. Improvements in the content length and the timeliness of replies can motivate enterprises to improve their TFP. The empirical results further support H1.

Table 5. Regression results of the impact of content length and the timeliness of corporate response

Variable	(1) Coeff	(1) T-value	(2) Coeff	(2) T-value
Word	0.021***	4.85		
Time			−0.0004*	−1.65
Constant	−0.478	−1.55	−0.293	−0.86
Controls	Yes		Yes	
Year and Ind	Yes		Yes	
N	16,665		14,713	
Adj·R^2	0.329		0.321	
F-test	119.53***		100.63***	

Note(s): This table reports results from OLS regressions of *Tfp* on *Word* or *Time* and control variables. See Table 1 for detailed descriptions of all variables. All specifications include year and industry fixed effects. Standard errors after robust adjustment are clustered at the firm-year level. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels, respectively (two-tailed tests)

4.4 Mechanism testing

As previously mentioned, interaction may improve TFP by alleviating corporate financing constraints and spurring the company to increase R&D investment. We will examine these effects now.

First, this paper considers financing constraints and R&D investment as intermediary variables. Because the calculation of investment-cash flow sensitivity involves many financial indicators of the enterprise, which can cause endogeneity; while the SA index includes two exogenous variables, namely, company size and age, which can avoid the interference of endogenous problems to some extent, we select the SA index to measure the financing constraints (*SA*) [6], where a larger *SA* means a higher degree of financing constraints faced by the company. The R&D input variable (*RD*) is measured as R&D investment divided by total assets, where a larger *RD* means a higher level of R&D investment.

Second, according to the logic and steps of testing for mediation (Baron & Kenny, 1986), we separately evaluate the mediating effect of financing constraints and R&D investment. The empirical results are shown in Table 6.

According to column (1) of Table 6, in the test of the intermediary effect of financing constraints, the coefficient of *Interact* is significantly negative at the 1% level, indicating that interaction significantly reduces corporate financing constraints. The result of adding *SA* to model (2) in column (2) shows that the *SA* coefficient is significantly negative, indicating that financing constraints have an inhibitory effect on companies' TFP. The *Interact* coefficient is significantly positive at the 1% level, and the absolute value of the *Interact* coefficient (0.029) is less than that (0.030) in Table 4. This finding shows that part of the effect of direct interaction on TFP is achieved through alleviating financing constraints.

In the test of the intermediary effect of R&D investment, the coefficient of *Interact* in column (3) of Table 6 is significantly positive at the 1% level, indicating that the interaction has significantly increased the R&D investment. The result of adding *RD* to model (2) in column (4) shows that the *RD* coefficient is significantly positive, indicating that R&D investment can promote the company's TFP. The *Interact* coefficient is significantly positive at the 1% level, and the absolute value of the coefficient (0.026) is less than that (0.030) in Table 4. These results show that part of the effect of interaction on TFP is achieved through increasing R&D investment.

Variable	(1) *SA*	(2) *Tfp*	(3) *RD*	(4) *Tfp*
SA		−0.423*** (−4.77)		
RD				3.162*** (5.06)
Interact	−0.003*** (−4.84)	0.029*** (3.62)	0.001*** (13.10)	0.026*** (3.26)
Constant	−22.236*** (−5.41)	−9.860*** (−4.89)	−0.032*** (−8.54)	−0.359 (−1.16)
Controls	Yes	Yes	Yes	Yes
Year and Ind	Yes	Yes	Yes	Yes
N	16,665	16,665	16,665	16,665
Adj·R^2	0.396	0.329	0.466	0.330
F-test	164.32***	118.37***	269.88***	118.02***

Note(s): This table reports the results from OLS regressions of the mechanism test, among which, we select the financing constraints variable *SA* and R&D investment *RD* as intermediary variables. See Table 1 for detailed descriptions of all variables. All specifications include year and industry fixed effects. Standard errors after robust adjustment are clustered at the firm-year level. The *t*-value is in parentheses. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels, respectively (two-tailed tests)

Table 6. Regression results of mechanism test

4.5 Endogeneity test

There may be endogeneity between the Q&A process and enterprise's TFP. We will now tackle the possible endogeneity issues in the regressions.

4.5.1 Model setting errors. To solve any possible errors in the model setting, this paper uses the entropy balancing method for further testing. Although the propensity score matching method can alleviate the problem of model setting bias to some extent, it is highly dependent on the setting and matching method of the one-stage logit model, and the matching process is prone to missing samples, which can be avoided by the entropy balance method (Shipman, Swanquist, & Whited, 2017). We divide the whole sample into two groups based on *Commun*, in which the high-interaction companies are the treated group, and the low-interaction companies are the control group. The control variables in model (2) are weighted to reduce the difference between the two groups in the first moment, second moment and third moment. Ultimately, we obtained 16,665 matching samples. Table 7 shows the matching results for the variables before and after entropy balancing.

According to Table 7, before entropy weighting, there are large differences in the covariables between the treated group and the control group, but after entropy weighting, the gap is significantly reduced, indicating that entropy balancing achieved the desired effect. The entropy-weighted regression results are shown in column (1) of Table 8, in which the *Interact* coefficient is significantly positive at the 1% level, demonstrating that H1 is still valid after solving the model setting errors.

4.5.2 Sample self-selection problem. To alleviate the self-selection bias that may exist in the model, this paper uses the Heckman two-stage regression method. First, in the first-stage regression, we define *Commun* (an indicator variable that is set to 1 when the degree of interaction is higher than the median of the whole sample, and 0 otherwise) as the dependent variable in the first stage. The Probit regression is performed after introducing all the control variables in model (2). Second, we add the *Inverse Mills Ratio* (*IMR*), calculated after the regression, as a control variable in model (2) to continue the regression. The results are shown in column (2) ~ (3) of Table 8. The *Interact* coefficient is 0.030, which is significant at the 1% level and consistent with the OLS regression results, showing that the positive impact of interaction on TFP is still significant. It is worth noting that the *IMR* coefficient in the two-stage regression is not significant, indicating that the model does not have the problem of self-selection.

4.5.3 Other endogeneity issues. To further solve other potential endogeneity issues of the model, this paper adopts the two-stage least squares method (2SLS) for testing. Following the practice of the relevant literature (Yang & Zhang, 2020), we select *Others* as the instrumental variable, which defines the mean of the degree of interaction between other companies in the industry and investors during the year. We perform 2SLS regression after introducing all the control variables in model (2). The results are shown in column (4) ~ (5) of Table 8, among which, the *Others* coefficient is significantly positive because the Q&As of other companies in the same industry on the interactive platforms produce peer effects, and spur the focal company to actively respond to investors' questions to reduce the gap with other companies in the same industry. The regression results of the first stage show that the selected instrumental variable meets the validity requirements. In the second stage, the *Interact* coefficient is still significant at the 1% level, and H1 is verified again.

4.6 Robustness test

To obtain more reliable and convincing research conclusions, this paper conducts robustness tests as follows: (1) we apply the ACF method to redefine the TFP (*NewTFP*) calculated by the method above. (2) In the previous section, we use the logarithm of the total number of responses each year plus one to measure the degree of interaction. Now, we use two other indicators to further measure the degree of interaction. First, we take the logarithm after the

Table 7. Matching results for the variables before and after entropy balancing

Variable	Treat Mean	Treat Variance	Treat Skewness	Control (before entropy weighting) Mean	Control (before entropy weighting) Variance	Control (before entropy weighting) Skewness	Control (after entropy weighting) Mean	Control (after entropy weighting) Variance	Control (after entropy weighting) Skewness
Size	22.140	1.610	0.731	22.240	1.707	0.729	22.140	1.610	0.731
Lev	0.422	0.043	0.181	0.428	0.039	0.214	0.422	0.043	0.181
Roa	0.051	0.002	−0.416	0.046	0.002	−0.792	0.051	0.002	−0.416
Cfo	0.047	0.005	−0.142	0.051	0.004	−0.026	0.047	0.005	−0.142
PB	3.561	7.925	2.664	3.677	9.505	2.646	3.561	7.925	2.664
Exfin	1.942	73.040	7.171	2.133	85.750	6.680	1.942	73.040	7.170
Top1	0.344	0.021	0.512	0.352	0.022	0.460	0.344	0.021	0.512
Indep	0.373	0.003	1.446	0.377	0.003	1.243	0.373	0.003	1.446
Board	2.145	0.039	−0.291	2.122	0.040	−0.288	2.145	0.039	−0.291
Exeshare	0.078	0.021	2.109	0.075	0.020	2.150	0.078	0.021	2.109
Exepay	14.34	0.518	0.162	14.43	0.441	0.232	14.34	0.518	0.162
Audit	0.982	0.018	−7.293	0.982	0.018	−7.178	0.982	0.018	−7.293

Note(s): This table reports matching results for the variables before and after entropy balancing. We divide the whole sample into two groups based on *Commun*, in which the high-interaction companies are the treated group and the low-interaction companies are the control group. The control variables in model (2) are weighted to reduce the differences between the two groups in the first moment (mean), second moment (variance) and third moment (skewness). Ultimately, we obtained 16,665 matching sample observations

Variable	Entropy balancing (1) *Tfp*	Heckman (2) *Commun*	(3) *Tfp*	2SLS (4) *Interact*	(5) *Tfp*
Others				0.667*** (25.02)	
IMR			0.006 (0.11)		
Interact	0.029*** (3.54)		0.030*** (3.79)		0.131*** (3.22)
Constant	−0.360	1.829***	−0.454	−2.089***	−0.242
	(−1.13)	(6.40)	(−1.46)	(−7.19)	(−0.78)
Controls	Yes	Yes	Yes	Yes	Yes
Year and Ind	Yes	Yes	Yes	Yes	Yes
N	15,805	16,665	16,665	16,659	16,659
Adj·R^2	0.327	0.136	0.329	0.597	0.324
F-test	112.24***	326.02***	117.54***	381.05***	117.78***

Note(s): This table reports the regression results of the endogeneity test (including the entropy balancing test, Heckman's two-stage instrumental variable method test and the 2SLS method test). See Table 1 for detailed descriptions of all variables. All specifications include year and industry fixed effects. Standard errors after robust adjustment are clustered at the firm-year level. The *t*-value is in parentheses. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels, respectively (two-tailed tests)

Table 8.
Regression results of endogeneity test

sum of the annual number of questions from investors and the number of replies from companies plus one to redefine the interaction index (*QA*) and hence redefine the degree of interaction. Second, taking into account the differing corporate responses to inquiries, we use the ratio of the number of annual replies to the number of annual questions (*RQ*) to further measure the degree of interaction. (3) To alleviate the interference of fixed factors that may not change over time, this paper applies the fixed effects model for further testing. (4) The Shanghai Stock Exchange launched an interactive platform in 2013. To ensure consistency of the sample research interval, we shortened the research interval to 2013–2019. (5) Considering that the attention of institutional investors and analysts may interfere with the empirical results for interaction and TFP (Ni, Spatareanu, Manole, Otsuki, & Yamada, 2017; To, Navone, & Wu, 2018), we also control variables such as shareholding ratio of institutional investors (*Inst*) and analyst attention (*Analyst*). The above robustness test results are shown in Table 9. All the robustness test results verify H1.

5. Additional research

5.1 The moderating effect of agency cost

Agency cost has become an important factor affecting the behavioral characteristics of enterprises, so how does the difference in agency cost affect the relationship between interaction and corporate TFP? Following the practice of the relevant literature (James, Rebel, & James, 2000), this paper measures agency cost by dividing administrative expenses by operating income and divides the sample into a high agency cost group ($AC = 1$) and a low agency cost group ($AC = 0$) based on the annual-industry median, then we regress model (2) to examine the moderating role of the agency cost in the relationship between the two. The specific results are shown in columns (1) ~ (2) of Table 10.

The results show that the *Interact* coefficient is significantly positive in the higher agency cost group but not significant in the lower agency cost group, which indicates that compared with enterprises with lower agency costs, the positive effect of interaction on TFP is more significant in enterprises with higher agency costs. This conclusion can be interpreted from two aspects. On the one hand, due to the agency problem, investors and creditors require companies to pay different degrees of "premium" for external financing to ensure serving

Variable	(1) *NewTFP*	(2) *Tfp*	(3) *Tfp*	(4) *Tfp*	(5) *Tfp*	(6) *Tfp*
QA		0.031***				
		(3.71)				
RQ			0.142**			
			(2.58)			
Inst						0.018 (0.94)
Analyst						0.078***
						(3.98)
Interact	0.023***			0.203***	0.026***	0.031***
	(2.96)			(8.62)	(3.08)	(3.86)
Constant	4.249***	−0.449	−0.521	−5.027***	−0.662*	−0.302
	(13.82)	(−1.46)	(−1.37)	(−7.69)	(−1.78)	(−0.96)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year and Ind	Yes	Yes	Yes	Yes	Yes	Yes
N	16,665	16,665	12,816	16,665	12,732	16,665
Adj·R^2	0.270	0.329	0.319	0.588	0.322	0.329
F-test	89.22***	119.33***	88.96***	422.65***	96.03***	116.73***

Note(s): This table reports the regression results of the robustness test (including redefining the dependent variable test in column (1), redefining the independent variable test in column (2) and (3), the fixed effect model test in column (4), shortening the research interval test in column (5) and introducing the missing variables test in column (6)). See Table 1 for detailed descriptions of all variables. All specifications include year and industry fixed effects. Standard errors after robust adjustment are clustered at the firm-year level. The *t*-value is in parentheses. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels, respectively (two-tailed tests)

Table 9. Regression results of robustness test

	Tfp					
Variable	(1) *AC* = 1	(2) *AC* = 0	(3) *High_tech* = 1	(4) *High_tech* = 0	(5) *IP* = 1	(6) *IP* = 0
Interact	0.040***	0.015	0.003	0.040***	0.008	0.050***
	(3.63)	(1.42)	(0.29)	(3.62)	(0.63)	(4.50)
Constant	−0.942**	1.426***	−0.166	−0.667*	−1.962***	0.127
	(−2.09)	(3.45)	(−0.32)	(−1.70)	(−3.54)	(0.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year and Ind	Yes	Yes	Yes	Yes	Yes	Yes
N	8,325	8,340	7,420	9,245	5,798	8,745
Adj·R^2	0.283	0.351	0.291	0.354	0.261	0.370
F-test	48.20***	69.52***	46.56***	80.95***	57.57***	88.53***

Note(s): This table reports the regression results of additional tests. See Table 1 for detailed descriptions of all variables. All specifications include year and industry fixed effects. Standard errors after robust adjustment are clustered at the firm-year level. The *t*-value is in parentheses. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels, respectively (two-tailed tests)

Table 10. Regression results of additional research

their own interests, which increases the external financing cost (Mark, 1992). Therefore, enterprises with high agency costs will face more serious financing constraints. Interaction can reduce the degree of financing constraints and improve TFP, so the positive effect of interaction on TFP is more obvious in companies with higher agency costs. On the other hand, enterprises with higher agency costs aggravate the short-sighted behavior of management and reduce the financial support for R&D investment (Su, 2013), while interaction can improve TFP by increasing R&D investment, which makes the effect of interaction on TFP more significant in enterprises with higher agency costs.

5.2 The moderating effect of high-tech qualification

We also classify the enterprise as a high-tech enterprise ($High\_tech = 1$) and a non-high-tech enterprise ($High\_tech = 0$) according to whether the enterprise has obtained the high_tech qualification recognized by the government in that year (*High_tech*) and regress model (2). The specific results are shown in columns (3) ~ (4) of Table 10.

The results show that the *Interact* coefficient is significantly positive in non-high-tech enterprises but not significant in high-tech enterprises, which indicates that compared with high-tech enterprises, interaction improves TFP more significantly in non-high-tech enterprises. This is perhaps due to high-tech enterprises being able to obtain more government support in terms of financial subsidies and tax preferences, and thus face lower financing constraints; besides that, the R&D investment level of high-tech enterprises is generally high, which weakens the positive impact of interaction on corporate TFP, resulting in this promotion effect being more significant in non-high-tech enterprises.

5.3 The moderating effect of industrial policy

Industrial policy is an important policy tool through which the state regulates the macroeconomy and promotes the development of industry. We divide the sample into two groups according to whether the enterprise is supported by industrial policy (*IP*): the group supported by industrial policy ($IP = 1$) and that not supported ($IP = 0$), and regress the model (2). The specific results are shown in columns (5) ~ (6) of Table 10.

The results show that the *Interact* coefficient is significantly positive in enterprises not supported by industrial policy but not significant in enterprises supported by industrial policy, which indicates that compared with enterprises supported by industrial policy, the effect of interaction on TFP is more significant in enterprises not supported by industrial policy. This is perhaps due to the tax benefits and government subsidies brought by industrial policy can help alleviate the financing constraints of enterprises, and that industrial policy support can attract extensive attention of external investors (Lazzarini, 2015), which weakens the effect of interaction.

6. Conclusion

This paper applies crawler technology to obtain all the Q&A data for investors and companies on selected interactive platforms, compiles the LDA topic model program through Python and selects Q&A records about production, R&D, technology and so forth. Choosing A-share listed companies from 2010 to 2019 in China as the samples, we empirically analyze the impact of interaction through the interactive platforms on corporate TFP. The results show that the higher the degree of interaction is, the higher the TFP, and that increases in content length and the timeliness of response contribute to improve the level of TFP. This conclusion is still valid after conducting endogeneity tests, such as Heckman's two-stage instrumental variable method, the 2SLS method, the entropy balancing method and various robustness tests. Further research in this paper finds that interaction mainly improves the TFP of enterprises by alleviating financing constraints and increasing R&D investment. This positive effect is more pronounced in enterprises with high agency costs, non-high-tech enterprises and enterprises not supported by industrial policy.

The research not only enriches the relevant literature on the influencing factors of TFP and broadens the research horizon for the consequences of investors' behaviors but also tests the role of interactive platforms for enterprises and investors. The unique role of such interactive platforms provides new research ideas and empirical evidence. According to the research conclusions, we propose the following recommendations from the perspectives of regulatory agencies and enterprises:

For the regulatory authorities, it is necessary to actively guide listed companies to respond to investors' inquiries on the interactive platforms. Q&As have information content and play a supervisory role, which can ease the financing constraints of enterprises and promote their high-quality development. Therefore, for questions raised by investors that do not violate the information disclosure standards, the regulatory authorities should require enterprises to respond in a timely manner. Enterprises that reply slowly or that do not respond to investors' inquiries should be notified or downgraded in their information disclosure ratings, which can guide them to better manage investor relations.

For enterprises, it is important to promptly respond to questions from investors that do not violate information disclosure standards on interactive platforms. The interactive platforms are valuable supplements to the statutory information disclosure of listed companies. The platforms not only effectively reduce the cost of information disclosure but also force enterprises to achieve high-quality development through the supervision and incentives of external investors.

Notes

1. For example, enterprises can interact directly with investors through roadshows, telephone interviews and other forms.
2. These data are crawled from three major platforms through crawler technology. Details are given in the "Sample selection and data sources" section.
3. The topics of the Q&A records are identified and divided using the LDA topic model program. Details are given in the "Sample selection and data sources" section.
4. The main reason for this restriction is that the data about investors' behavior is difficult to obtain.
5. According to the Statistical Yearbook of the Shanghai Stock Exchange (Volume 2019) issued by the Shanghai Stock Exchange, individual investors accounted for 99.7% of all investors in the trading accounts of the Shanghai Stock Exchange by the end of 2018.
6. The calculation formula of SA index is as follows: $SA = |-0.737 \times SIZE + 0.043 \times SIZE^2 - 0.04 \times AGE|$, where the $SIZE$ is corporate size, and the AGE is corporate age.

References

Abdoh, H., & Liu, Y. (2021). Does R&D intensity matter in the executive risk incentives and firm risk relationship? *Economic Modelling*, *96*(2), 13–24.

Ackerberg, D. A., Caves, K., & Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, *83*(6), 2411–2451.

Ashraf, A., Herzer, D., & Nunnenkamp, P. (2016). The effects of greenfield FDI and cross-border M&As on total factor productivity. *World Economy*, *39*(11), 1728–1755.

Bao, Y., & Datta, A. (2014). Simultaneously discovering and quantifying risk types from textual risk disclosures. *Management Science*, *60*(6), 1371–1391.

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173–1182.

Blankespoor, E., Hendricks, B. E., & Miller, G. S. (2017). Perceptions and price: Evidence from CEO presentations at IPO roadshows. *Journal of Accounting Research*, *55*(2), 275–327.

Brandt, L., Tombe, T., & Zhu, X. (2013). Factor market distortions across time, space and sectors in China. *Review of Economic Dynamics*, *16*(1), 39–58.

Bushee, B. J., & Miller, G. S. (2012). Investor relations, firm visibility, and investor following. *Accounting Review*, *87*(3), 867–897.

Chiang, M., & Lin, J. (2007). The relationship between corporate governance and firm productivity: Evidence from Taiwan's manufacturing firms. *Corporate Governance-An International Review*, *15*(5), 768–779.

Ding, H., Lyu, C., & Huang, H. (2018). Social media, investor sophistication and earning expectation: Evidence from SSE E-interaction. *Economic Research Journal*, *53*(1), 153–168.

Dyer, T., & Kim, E. (2021). Anonymous equity research. *Journal of Accounting Research*, *59*(2), 575–611.

Guan, S., & Cheng, L. (2020). Does product complexity matter for firms' TFP? *Technological Forecasting and Social Change*, *160*(11), 233–256.

Hsieh, C., & Klenow, P. J. (2009). Misallocation and manufacturing TFP in China and India. *Quarterly Journal of Economics*, *124*(4), 1403–1448.

James, S. A., Rebel, A. C., & James, W. L. (2000). Agency costs and ownership structure. *The Journal of Finance*, *55*(1), 2161–2164.

Jin, D., & Li, Y. (2017). Investor interaction and stock returns – empirical evidences of social media. *Finance Forum*, *22*(5), 72–80.

Kumar, A., & Lee, C. M. C. (2006). Retail investor sentiment and return comovements. *Journal of Finance*, *61*(5), 2451–2486.

Lazzarini, S. G. (2015). Strategizing by the government: Can industrial policy create firm-level competitive advantage? *Strategic Management Journal*, *36*(1), 97–112.

Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies*, *70*(2), 317–341.

Li, B., Shi, S., & Zeng, Y. (2020). The impact of haze pollution on firm-level TFP in China: Test of a mediation model of labor productivity. *Sustainability*, *12*(20), 1–21.

Lu, B., Tan, X., & Zhang, J. (2019). The crowding out effect of booming real estate markets on corporate TFP: Evidence from China. *Accounting and Finance*, *58*(5), 1319–1345.

Mark, G. (1992). Financial capacity and output fluctuations in an economy with multi-period financial relationships. *The Review of Economic Studies*, *59*(3), 455–472.

Ni, B., Spatareanu, M., Manole, V., Otsuki, T., & Yamada, H. (2017). The origin of FDI and domestic firms' productivity-evidence from Vietnam. *Journal of Asian Economics*, *52*(5), 56–76.

Papaioannou, S. K. (2018). EU services liberalization and TFP growth: Industry level evidence. *Economics Letters*, *172*(11), 16–18.

Reiter, N. (2021). Investor communication and the benefits of cross-listing. *Journal of Accounting and Economics*, *71*(1), 112–131.

Sandstrom, P. E. (2010). Information foraging theory: Adaptive interaction with information. *Journal of the American Society for Information Science and Technology*, *61*(10), 2161–2164.

Shipman, J. E., Swanquist, Q. T., & Whited, R. L. (2017). Propensity score matching in accounting research. *Accounting Review*, *92*(1), 213–244.

Su, Z. (2013). An empirical study of equity agency costs and R&D intensity: Evidence from listed companies on the ChiNext. *Advanced Materials Research*, *798*(18), 833–836.

Tan, S., Kan, S., & Cui, X. (2016). Can investors' online communication with listed firms improve the information efficiency of the stock market? *Journal of Financial Research*, *429*(3), 174–188.

To, T. Y., Navone, M., & Wu, E. (2018). Analyst coverage and the quality of corporate investment decisions. *Journal of Corporate Finance*, *51*(4), 164–181.

Wu, S., Li, B., Nie, Q., & Chen, C. (2017). Government expenditure, corruption and total factor productivity. *Journal of Cleaner Production*, *168*(12), 279–289.

Xu, Q., Wang, L., & Zhu, Y. (2019). The effect of OFDI intensity on TFP: The moderating role of R&D. *Transformations in Business and Economics*, *18*(3), 381–393.

Yang, F., & Zhang, Y. (2020). Could interactive information communication reduce stock price synchronicity? Evidence from the SSE e-interaction. *Journal of Zhongnan University of Economics and Law*, *243*(6), 108–119.

Zhang, D. (2019). Can export tax rebate alleviate financial constraint to increase firm productivity? Evidence from China. *International Review of Economics and Finance*, *64*(4), 529–540.

Corresponding author
Chuanxin Xu can be contacted at: xu_chuanxin@126.com