Narrative R&D disclosures and firms' reliance on trade credit financing

Abstract: By adopting machine learning and textual analysis methods to construct narrative R&D disclosure measures, this paper probes into the relationship between the quantity of narrative R&D disclosures and trade credit ratio. Our findings reveal that more narrative R&D disclosures of Chinese listed firms can increase their reliance on private leading channels like trade credit. A battery of robustness tests supports the baseline result. Further analysis indicates that higher readability and lower similarity of R&D-related texts can mitigate the positive relationship between quantity of narrative R&D disclosures and trade credit finance ratio. More complicated information environments in public capital market due to higher information processing costs and managers' obfuscations of narrative R&D disclosure are the internal mechanisms. The heterogeneity analysis shows that the baseline result hold primarily when suppliers are more willing to provide trade credit, communication between suppliers and customers is more frequent and there is less capital market concentration. Taken together, our findings suggest extensive narrative R&D disclosures actually exacerbate firms' public information asymmetry, forcing them turn to private debt financing channels.

Keywords: textual analysis; R&D information disclosures, trade credit

1.Introduction

Firms generally have multiple creditors and a long-standing academic question of great interest is how information disclosures impact firms' debt financing choices. Numerous studies support the 'pecking-order theory,' which suggests that as information asymmetry increases, firms prefer less information-sensitive financing sources, such as internal cash, bank loans, or trade credit (Botosan and Plumlee, 2002; Denis and Mihov, 2003; Bharath et al., 2008; Dhaliwal et al., 2011; Chen et al., 2013). In China, where 'credit discrimination' is prevalent in formal financial sectors like banks, trade credit stands out as a major alternative private debt financing option for those public companies (Ge and Qiu, 2007). Compared to these formal financial institutions, suppliers often have better access to private information and can mitigate credit risks more effectively through ongoing transactions and communications with their customer firms. As a result, firms with lower information transparency are more likely to rely on trade credit financing. While previous research has examined the relationship between firms' information disclosures and their use of trade credit financing, their findings have been inconclusive (Niemi and Sundgren, 2012; Chen et al.,2017; Abdulla et al., 2017). Notably, much of these studies primarily have focused on financial disclosures, often overlooking the growing significance of widespread non-financial information disclosures.

Managers would voluntarily communicate R&D-related information (Hereafter narrative R&D disclosures) in the financial reports, earnings call or news press to reduce external financing costs (Lambert et al. ,2007), deter competitors (Pacheco-de-almeida and Zemsky, 2011; Glaser and Landsman,2021), manipulate firms' value or distract investors' attention from bad earnings performances (Merkley,2014). In spite of the increasing emphasize on narrative R&D disclosures, there are relatively few papers investigating the consequences of narrative R&D disclosures, especially from the perspective of trade credit financing. Different from most countries in the world where narrative R&D information is voluntarily disclosed, China's Security Regulation Commission (CSRC) began to mandate public firms to make narrative R&D disclosures in their financial reports since 2012[1]. In a capital market dominated by retail investors and marked by prevalent managerial misconduct, there are controversies over whether enhancing narrative R&D disclosures would effectively mitigate information asymmetry among public firms. Motivated by the ongoing debate, this paper aims to investigate whether increased narrative R&D disclosures would improve firms' information transparency. Additionally, we will analyze how such disclosures affect firms' debt financing practices, focusing particularly on trade credit financing.

For one thing, more narrative R&D disclosures will covey incremental R&D information and decrease information asymmetry in public capital market (Jones,2007; Li and Zou,2024). Higher information transparency can facilitate external financing and reduce the cost of outsourcing capital (Dhaliwal et al.,2011). With more narrative R&D disclosures, public firms may rely less on trade credit because they can obtain various outside financing resources at cheaper prices.

For another, narrative R&D disclosures are likely to be manipulated due to its complexity and professionalism especially in a market where regulation is weak (Huang and Liang, 2024). Hence, more narrative R&D disclosures can decrease public information transparency if the information conveyed is invalid or even misleading. Under this circumstance, firms will resort to more trade

[1] CSRC revised "*The No. 2 Guidelines on the Content and Format of Information Disclosure in Annual Reports by Companies Issuing Public Securities*" in 2012, requiring listed companies to make detailed explanations regarding the purpose, status and proposed objectives of current R&D projects during every reporting period. In addition, firms are supposed to make estimations of the current R&D projects' expected impact on future earnings performance. Firms should disclose information about the number, education and age structure of their staff engaged in R&D activities. If the ratio of total R&D expenditure to the company's latest audited net assets or operating income changes by 30% or more relative to the previous year, firms are required to provide reasonable explanations and justifications for this change.

credit financing because of limited financing sources in public capital market. As a result, the relationship between more narrative R&D disclosures and trade credit is mixed and requires further empirical investigations. To assess how narrative R&D disclosures affect firms' reliance on trade credit, we construct three measures of firms' narrative R&D disclosures by machine learning and textual analysis methods, consisting of the disclosure quantity, readability and similarity.

Our analysis provides significant insights. Firstly, firms with more narrative R&D disclosure quantity tend to have higher trade-credit financing ratio. A battery of robustness tests is consistent with our main finding including replacing the measures for narrative R&D disclosures and trade credit, constructing quasi-natural experiment, replacing regression sample with PSM and entropy balance method. Secondly, the positive relationship between narrative R&D disclosure quantity and the trade credit ratio is attenuated when R&D-related texts are more readable and in firms with better internal control environments, but accentuated when the similarity of R&D-related texts is higher. The above findings support the view that more narrative R&D disclosures increase firms' reliance on trade credit by aggregating firms' public information environment. Furthermore, we validate the channels by grouping tests from three aspects including suppliers willing to provide trade credit, the private communications on supply chain and the attention from capital market. Finally, the economic consequence analysis shows the innovation productivity will decrease in the future for firms with more narrative R&D disclosures. This finding is consistent with our notion that mandatory narrative R&D disclosures in China's capital market force firms rely more on trade credit financing by obfuscating public information environments. In the long run, mandatory narrative R&D disclosures can undermine firms' innovation output by distorting their financing behaviors.

Our study contributes to the literatures in several ways.

Firstly, our paper enriches the research regarding the economic consequences of narrative R&D disclosures. Given its great importance to firms' future performance, R&D-related information attracts attention from multiple capital market participants including but not limited to investors or regulators. Most existing research uses R&D expenditures or patent applications as proxies for R&D-related disclosures (Kim and Valentine, 2021; Saidi and Žaldokas,2021; Huang et al.,2021). Those proxies have difficulties in distinguishing the effects of R&D-related disclosures from firms' actual R&D behaviors. Our measures, to some degree, can avoid this problem and investigate the net effect of R&D-related disclosures by quantifying R&D-related disclosures from the perspective of managers descriptions or communications.

Secondly, we provide evidence on the role of non-financial information disclosures in firms' reliance on trade credit. Previous research investigated possible factors influencing firms' trade credit behaviors from the aspects like institutional environments, monetary policies, product market competition, financial report quality, managerial personalities and corporate governance characteristics (Lee and Stowe, 1993; Bharath et al.,2008; Ghoul and Zheng, 2016; Abdulla et al.,2017). Chen et al. (2017) predict a negative association between firms' financial disclosure quality and their access to trade credit. We argue and demonstrate that narrative R&D disclosures which is a kind of non-financial information, also play a part in shaping firms' trade credit financing ratio.

Finally, we document an unintended effect of mandatory R&D disclosure policy in China's capital market. China's regulation authority mandated narrative R&D disclosures for listed firms starting in 2012 with the intention to increase information transparency in public capital market and hence better safeguard individual investors' benefits. However, our empirical analysis uncovers a unique insight that firms may suffer from lower innovation output efficiency in the long run with more narrative R&D information disclosed. Over all, our conclusions remind the policy makers to rethink the potential unintended effects of an originally benign policy.

The reminder of this paper is structured as follows. Section 2 discusses policy background and related literature. Section 3 conducts the theory development. Section 4 describes our research design and data, while Section 5 discusses our empirical results, including those of robustness tests and additional analysis. Section 6 reaches to the conclusion.

2. Policy background and literature review

2.1. Mandatory narrative R&D disclosure policy

R&D investment plays a critical role in facilitating and promoting firms' future growth, especially those in technology-intensive industries. With the number of Chinese firms' patent applications increasing rapidly[2], R&D-related information is attracting great attention from the capital market. However, R&D activities would exacerbate firms' information asymmetry because of the complexities and uncertainties for such investments (Aboody and Lev, 2000). Distinct from regular capital expenditures, R&D projects are associated to higher operating risks and greater volatility in future earnings (Kothari et al, 2002; Zhang,2015; Dargenidou et al., 2021). To eliminate information asymmetry and respond to the market's demand for R&D-related information, China Securities Regulatory Commission (CSRC) introduced a mandatory requirement for public firms to make narrative R&D disclosures in their annual reports in 2012. Managers were required to make discussion about the progress, future plans and economic effects of their R&D projects, which provides more comprehensive and thorough information regarding

[2] The World Intellectual Property Indicators report released by the World Intellectual Property Organization (WIPO) on November 6, 2023, reveals that China accounted for approximately half of the world's overall patent applications in 2022, maintaining its first-place ranking globally for 12 consecutive years.

firms' R&D activities. Although narrative R&D disclosures constitute a large part of MD&A section in firms' annual reports, its economic consequences remain relatively unexplored due to the unstructured nature of textual data. However, the emerging of textual analysis and machine learning methods made it feasible for researchers to look deeply into narrative R&D disclosures.

2.2. Related studies on narrative R&D disclosures

Merkley (2014) extracted R&D-related information from the discussions in 10-K files with textual analysis. He found that firms would conduct narrative R&D disclosures to distract public attention from their bad performances. Kim and Valentine (2023) documented the quantity of narrative R&D disclosures in firms' 10-Ks contribute to more patent sales by alleviating the information frictions in patent market. Andreou et al (2023) use narrative R&D disclosure as a proxy for managerial rhetoric which is positively related to future idiosyncratic stock price crashes. Li and Zou (2024) demonstrate that mandating narrative R&D disclosures can help investors better interpret R&D expenditure. Mazzi et al. (2024) document that R&D disclosure conveys information about future earnings, which is incorporated in current returns. However, contradictory to the above findings, Huang and Liang (2024) find that narrative R&D disclosures under China's mandatory regime can facilitate insiders to trade opportunistically by increasing information asymmetry. Their conclusion is consistent with La Rosa and Liberatore (2014)'s research, which reveals that more mandatory R&D disclosures did not lead to lower capital costs. And also, in line with Chen et al. (2022), who found firms with greater R&D investments are more conservative with narrative R&D disclosures, in support of proprietary costs preventing firms from disclosing authentic R&D-related information. It can be summarized from the previous research that different normal information disclosures. Narrative R&D disclosures are more likely to suffer from managers' obfuscations and incur higher processing costs for investors due to its subjectivity and complexity nature.

2.3. The determinants of trade credit financing

It is a hot topic regarding the determinants of trade credit financing, especially in an emerging capital market where formal financing institutions are under developed and trade credit plays a necessary role in supporting firms' daily operations. Previous studies explain why trade credit financing is widespread from the aspects of demand and supply separately. Among others, the alternative financing theory, standing on the perspective of customer firms' financing demand, view trade credit as an alternative source of financing when formal financing sources are not available. Petersen and Rajan (1997) find that firms use more trade credit when the credit from formal financial institutions is unavailable, in support of the view that trade credit work as an alternative financing channel. Ge and Qiu(2007) utilize China's unique setting of which non-state-owned firms have limited access to bank financing, providing evidence that non-state owned companies in China use more trade credit than their state owned counterparts. Casey and O'Toole (2014) find that credit-rationed firms are more likely to use and apply for trade credit as a substitution. Carbó-Valverde et al (2016) find that credit constrained SMEs depend on trade credit instead of bank loans with increasing intensity during the financial crisis, while credit unconstrained firms are independent on bank loans rather than trade credit. Shi et al (2019) present evidence indicating that the substitution of trade credit for bank credit increases when firms' financial constraints are aggregated despite of firm size. Overall, the above literatures agree that firms would resort to trade credit as an alternative funding source when credit from formal financial institutions is not available.

3. Theory development

R&D-intensive firms are usually faced with greater information asymmetry because of the huge heterogeneities and high uncertainties associated with the R&D input (Aboody and Lev, 2001). In addition, R&D expenditure is required by accounting standards to be immediately expensed only in the case that it meets the rigorous requirements of capitalization[3]. A significant portion of firms' R&D investments is often not discernible in their financial reports, which exacerbates the information asymmetry in R&D-intensive companies. Narrative R&D disclosures offer managers a way to share detailed insights about firms' ongoing R&D projects with the public. Unlike quantitative accounting figures, qualitative narrative R&D disclosures provide a more adaptable channel for managers to communicate internal R&D-related information (Li and Zou,2024). However, narrative R&D disclosures can be easily manipulated or obscured due to their subjective nature and lack of verifiability (Andreou et al.,2021, Liang et al, 2024). It remains uncertain whether increasing the amount of narrative R&D disclosures will provide additional valuable information to the public. From the managers' perspective, they might be reluctant to share genuine R&D-related details through narratives, even if the CSRC requires public firms to do so.

Firstly, the high proprietary costs associated with R&D information can prevent managers from making credible disclosures (Saidi and Žaldokas, 2021; Glaeser, 2018). Under the pressure

[3] According to "*Chinese Accounting Standard for Business Enterprises No. 6 - Intangible Assets*", R&D expenditure can be recognized as intangible assets if the enterprise can demonstrate R&D expenditure meets the definitions of an intangible asset. To be specific, the conditions for an intangible asset to be recognized in financial reports include: 1) it is feasible for the intangible asset to be finished, used or sold; 2) firms have intentions to finish, use or sold the intangible asset; 3) The manner in which the intangible asset generates economic benefits can be demonstrated, including the existence of the market for the intangible asset or its products, or their usability if the intangible asset is intended for internal use; 4) Firms should have enough technology, financial resources and other resources to support the development of intangible assets, as well as the ability to sold the intangible asset; 5) Expenditure attribute to the development stage of an intangible asset can be measured reliably.

of mandatory disclosure policies, managers mindful of proprietary costs may obscure narrative R&D disclosures, thereby compromising information quality and further reducing corporate transparency. Information asymmetry in capital market is exacerbated as a result, potentially limiting listed firms' access to public capital. As predicted by pecking order theory, firms will increasingly turn to alternative financing channels like trade credit.

Secondly, the subjective and complex nature of narrative R&D disclosures gives managers considerable flexibilities in how they present information. Managers can obscure narrative disclosures by altering the tones, using metaphors, or strategically arranging words and sentences (Guay, 2016; Bushee et al., 2018). Given the inherent subjectivity and complexity of R&D-related texts, their potential misleading disclosures are more likely to be disguised (Devies et al., 2007). Thirdly, narrative R&D disclosures usually contain extensive jargon and technical terms, making the texts even more difficult to read and understand (Jones, 2007). This complexity demands that investors should possess a strong knowledge base and professional financial analysis skills. Increased narrative R&D disclosures can actually raise information processing costs for investors, particularly in China's capital market which is dominated by retail investors (Lim et al., 2018; Blankespoor et al., 2020).

Overall, our study demonstrate that managers possess the motivation, ability and conditions to obfuscate narrative R&D disclosures under China's mandatory disclosure policy. Consequently, rather than providing incremental and useful information as intended, increased narrative R&D disclosures may further worsen information asymmetry of listed firms. In this context, firms would resort to less information-sensitive financing sources. This paper explores the theory by focusing on trade credit financing, a significant form of private debts. Based on our analysis, we propose the following hypotheses:

H1a: Firms with more narrative R&D disclosures tend to have higher rate of trade credit financing.

H1b: Firms with more narrative R&D disclosures tend to have lower rate of trade credit financing.

4. Sample selection and model setup

4.1. Sample selection

This paper examines Chinese listed companies from 2007 to 2020. It develops and expands a list of R&D-related vocabulary using machine learning algorithms and analyzes company annual reports to create indicators for R&D-related information disclosure. The annual reports are from the Juchao information website[4], while financial data is obtained from the CSMAR database[5]. The sample processing includes: (1) excluding companies in the financial and real estate sectors; (2) removing ST companies; (3) discarding companies with missing variables or negative total assets; and (4) applying 1% winsorization to all continuous variables. After these steps, the final dataset consists of 17,376 company-year observations.

4.2. Definition of variables

4.2.1. Explanatory variable：narrative R&D disclosures（NarRD）

We adopted machine learning and textual analysis to construct measures of narrative R&D disclosure quantity, and the construction process can be divided into three steps.

[4] http://www.cninfo.com.cn/new/index
[5] https://data.csmar.com/

First, we use crawler technology to obtain the pdf version of the company's annual report from Juchao Information Network, download the pdf version of the Chinese government's work report from Wikipedia, and convert it to txt format using pdfplumber.

Secondly, the method of "seed words + Word2Vec similar word expansion" is applied to construct the list of R&D related words. we obtain the seed words by summarizing theoretical literature and government work reports, and manually selecting preliminary six most representative R&D related words (column (1) of Table 1). Then we use Word2Vec, a machine learning method to expand our list of R&D-related words. Word2Vec is a common word embedding method in the field of natural language processing to learn semantic knowledge of text in an unsupervised way. It was proposed by Mikolov, a developer at Google, in 2013.

Word2Vec includes two different training models, which are Bag of Words (CBOW) and Skip-gram, and the CBOW model is applied in this paper. After training of all listed companies' annual report texts as well as government work report texts using the Word2Vec model, the list of R&D vocabulary is expanded from the initial 6 seed words to more than 700 R&D related words. Then after manually reading and screening, including consulting with professional and technical staff, the 700 words were finally refined into 395 words (column 2 of Table 1). All of the R&D-related words in Merkley (2014) are derived by manual screening. In this paper, we adopt the approach of "seed words + Word2Vec machine learning model " to extend and obtain the list of R&D-related terms combining with the human jurisdictions. Compared with the research of Merkley (2014) who manually select the R&D words, our method is more rigorous and objective.

Table 1 Examples of R&D innovation vocabulary word sets

Seed vocabulary	Machine Learning Expanded Dictionary
（1）	（2）

Technological innovation, research, development, R&D, patents, inventions	Proprietary technology, research, cutting-edge, design, scientific research, utility model, cutting-edge technology, appraisal of results, proprietary, inventive, nanotechnology, selection, patented product, technical equipment, principle, innovation, practical, amplification, autonomy, copyright, inventor, modularity, research topic......

Third, using text analysis methods (including regular expressions, Jieba Chinese segmentation tool, and other python packages), combined with the list of R&D-related words obtained in step 2, the proportion of R&D-related words to the total number of words in each annual report is calculated as the indicator of narrative R&D disclosure volume]in this paper.

4.2.2. Explained variable： reliance on trade credit financing

Building on the methodologies of Chen et al. (2017) and Kong et al. (2020), this paper assesses the extent of a company's reliance on commercial credit financing by calculating the ratio of the book value of accounts payable to the total asset value at the end of the period.

4.3. Empirical model setting

The main focus of this paper is on the impact of narrative R&D disclosures on firms' reliance on trade credit financing. The primary regression model used in this analysis is as follows:

$$\mathrm{TradeCredit}_{\mathrm{it}} = \alpha + \beta \times NarRD_{\mathrm{i,t-1}} + \sum_{\mathrm{j}} \theta_{\mathrm{j}} \times \mathrm{Controls}_{\mathrm{j,i,t-1}} + \sum \mathrm{Firm} + \sum \mathrm{Year} + \varepsilon_{\mathrm{it}} \quad (1)$$

In model (1), $TradeCredit_{it}$ is the proportion of commercial credit financing of company i in period t. $NarRD_{i,t-1}$ is the narrative R&D disclosure of company i in period t-1. $\sum_j Controls_{j,i,t-1}$ is a series of control variables, and the specific calculation method is shown in Table2. In addition, $\sum Firm$ and $\sum Year$ are company and year fixed effects, α is the intercept term, and ε_it is the residual term. This paper mainly focuses on the regression coefficient β. If β is positive (negative), it means that the disclosure of R&D text information will increase (reduce) the company's reliance on commercial credit financing.

Table 2 Variable symbols and definitions

Type	Symbol	Definition
Explanatory variable	NarRD	Narrative R&D disclosures，equal to the ratio of R&D innovation vocabulary frequency to the total frequency of annual reports.
Explained variable	TradeCredit	Reliance on trade credit financing， equal to accounts payable divided by total assets.
Control variables	Size	Firm size, equal to the natural logarithm of total assets.
	Lev	Financial leverage, which is equal to total liabilities divided by total assets.
	Roa	Profitability, equal to net profit divided by total assets.
	Dual	The two positions are combined into one, which is a dummy variable. The value is 1 if the chairman and general manager are held by the same person, otherwise it is 0.
	IndDir	The proportion of independent directors is equal to the number of independent directors divided by the total number of directors.
	PPE	Fixed asset investment, equal to the book value of fixed assets divided by total assets.
	Bsize	The size of the board of directors is equal to the natural logarithm of the total number of directors plus 1.
	RDinv	investment, which is equal to the proportion of R&D investment to operating income.
	TobinQ	The company's market value is equal to (the market value of tradable shares at the end of the year + the market value of non-tradable shares + total long-term liabilities + total short-term liabilities) / total assets at the end of the year.
	Growth	Growth, equal to (the amount of main business income at the end of the year - the amount of main business income at the beginning of the year) / the amount of main business income at the beginning of the year.
	Cash	Cash holding level, equal to (cash and cash equivalents + trading financial assets) / total assets.
	Patent	The number of patents granted is equal to the natural logarithm of the number of patents applied for and granted by the enterprise in the year plus 1.
	BankFin	Bank financing ratio, equal to (short-term loans + long-term loans + non-current liabilities due within one year) / total assets.
	Soe	Enterprise nature, a dummy variable, takes the value of 1 when the enterprise is controlled by state-owned shareholders, otherwise takes the value of 0.

	InvPat	The number of invention patents authorized is equal to the number of invention patents applied for and authorized by the enterprise in the year plus 1 and the natural logarithm.
Intrinsic mechanism variables	NarRead	The readability of R&D text, equal to the frequency of occurrence of the less common words in the R&D information disclosure text. The list of less common words comes from the "Modern Chinese Less Common Word List (1998)".
	NarSemi	The similarity of R&D text, equal to the current year's narrative R&D disclosure text vector $vector_{i,t}$ and the previous year's narrative R&D disclosure text vector $vector_{i,t-1}$, and the cosine similarity between the two is obtained. The calculation formula is as follows: *Similarity*=$\cos(\theta) = \left(vector_{i,t} \times vector_{i,t-1}\right)/(\|\|vector_{i,t}\| \times \|vector_{i,t-1}\|\|)$。
	InterContr	Internal control level, equal to the internal control quality evaluation index developed by Dibo.
	ManHold	Management shareholding, equal to management shareholding ratio.
Other variables	InvenCost	Inventory replacement cost, which is equal to the book value of inventory divided by total assets.
	ManNet	The executive network centrality, equal to the degree to which a certain executive controls the contact paths of other executives in the executive network. $Betweenness_i = \frac{\sum_{j<k} g_{jk(n_i)}/g_{jk}}{(g-1)(g-2)/2}$, where g_{jk} is the path that can connect executives j and k, $\sum_{j<k} g_{jk(n_i)}$ is the number of paths that pass through i among the number of paths that can connect executives j and k, and (g-1)(g-2)/2 is used to eliminate the size differences of executive networks of listed companies in different years.
	SupChain	Supply chain concentration, equal to the ratio of purchases from the top five suppliers to the total annual purchases.
	Analyst	Analyst attention, equal to the number of analysts paying attention to the listed company in that year.
	Sell	Margin trading is a dummy variable. If short selling is allowed, the dummy variable is set to 1, otherwise it is 0.

4.4. Descriptive statistics

First, this section presents a descriptive statistical analysis of narrative R&D disclosure indicators by year and industry, with the results shown in Panel A and Panel B of Table 3. To provide a clearer understanding of the company's R&D information disclosure, NarRD is multiplied by 100 for the descriptive statistics. The analysis reveals that from 2007 to 2020, the average amount of narrative R&D disclosure (NarRD) has steadily increased. This trend indicates that as information disclosure standards have improved, the proportion of annual report texts dedicated to R&D and innovation activities has grown. Industry-specific results show that companies with higher narrative R&D disclosure are predominantly in the Computers and Electronics industries. In contrast, industries such as Commercial & Trading and Transportation generally exhibit lower levels of narrative R&D disclosure. These findings align with the nature and characteristics of the industries, as technology companies are typically more involved in R&D and innovation activities.

Secondly, Panel C of Table 3 provides descriptive statistics for all variables in the full sample. The average narrative R&D information disclosure quantity (NarRD) is 0.38%, with a median of 0.285%. This measure is influenced by the scope of R&D-related word vocabulary, consistent with findings from Liang et al. (2024). Variations in R&D vocabulary dictionaries and sample intervals could explain these differences. The average proportion of accounts receivable to total assets (TradeCredit) is approximately 9.7%, with a median of 8.1% and a standard deviation of 0.067. These figures align closely with similar indicators from previous studies (Brown and Tucker, 2011; Ertugrul, 2017). The proportion of bank financing to total assets (BankFin) averages 10.1%, slightly higher than commercial credit financing, with a median of 0 and a standard deviation of 0.145. This suggests that while China's listed companies heavily rely on commercial credit financing, their reliance on bank financing is also significant, with considerable internal variation. Additionally, the average corporate financial leverage (Lev) is about 42.7%, indicating a moderate level of financial risk among the sample companies. The average value of property rights (Soe) is 0.395, suggesting that state-owned enterprises constitute approximately 40% of the sample.

Table 3 Descriptive statistics

PanelA：Annual statistics of narrative R&D disclosures

Year	Mean	Median	Std	N
2007	0.260	0.170	0.260	693
2008	0.290	0.180	0.270	806
2009	0.290	0.200	0.270	803
2010	0.310	0.210	0.280	880
2011	0.330	0.220	0.280	1,184
2012	0.370	0.270	0.300	1,371
2013	0.380	0.270	0.300	1,438
2014	0.350	0.270	0.280	1,348
2015	0.390	0.310	0.290	1,395
2016	0.420	0.330	0.310	1,599
2017	0.420	0.330	0.300	1,792
2018	0.440	0.360	0.310	2,082
2019	0.440	0.350	0.310	1,985
Total	0.380	0.280	0.300	17,376

PanelB：Industry statistics of narrative R&D disclosures

Industries	Mean	Median	Std	N
Agriculture&Farm	0.380	0.260	0.330	608
Biomedicine	0.440	0.390	0.260	1,666
Building Decorations	0.300	0.240	0.220	564
Building Materials	0.290	0.200	0.260	486
Chemicals	0.340	0.270	0.240	1,884
Commercial&Trading	0.130	0.090	0.170	743
Computers	**0.710**	**0.650**	**0.340**	**818**
Electrical Equip	0.460	0.370	0.270	1,099
Electronics	**0.610**	**0.550**	**0.340**	**1,105**
Excavation	0.220	0.130	0.250	381
Foods&Beverages	0.220	0.180	0.150	564
General	0.300	0.160	0.300	225
Household Appliances	0.390	0.290	0.270	347
Leisure Services	0.130	0.100	0.110	231
LightManufacture	0.310	0.240	0.230	631
Machinery Equip	0.430	0.350	0.280	1,621
Media	0.370	0.280	0.270	630
Military Defense	0.570	0.460	0.360	301
MotorVehicles	0.290	0.220	0.220	870
Nonferrous Metal	0.330	0.250	0.270	809
Steel	0.270	0.200	0.190	227
Textiles&Apparel	0.250	0.200	0.170	576
Communications	**0.630**	**0.550**	**0.350**	**489**
Transportation	0.140	0.090	0.120	501
Total	0.380	0.280	0.300	17,376

PanelC：Descriptive statistics

Variables	N	Mean	Std	Min	Median	Max
NarRD	17,376	0.380	0.299	0.034	0.285	1.504
TradeCredit	17,376	0.097	0.067	0.002	0.081	0.350
Size	17,376	21.965	1.096	19.241	21.855	25.585
Lev	17,376	0.427	0.193	0.052	0.421	0.983
Roa	17,376	0.039	0.054	-0.311	0.037	0.206
Dual	17,376	39.061	15.368	0.000	38.140	89.990
IndDir	17,376	37.008	5.046	30.770	33.330	57.140

PPE	17,376	0.231	0.146	0.004	0.205	0.682
Bsize	17,376	2.267	0.140	1.946	2.303	2.708
RDinv	17,376	2.852	3.405	0.000	2.290	21.510
TobinQ	17,376	2.035	1.154	0.897	1.669	9.614
Growth	17,376	0.166	0.347	-0.607	0.113	3.261
Cash	17,376	0.185	0.122	0.012	0.153	0.698
Patent	17,376	1.272	1.357	0.000	1.099	5.505
BankFin	17,376	0.101	0.145	0.000	0.000	0.548
Soe	17,376	0.395	0.489	0.000	0.000	1.000
InvPat	17,376	0.983	1.191	0.000	0.693	5.094

5. Empirical analysis

5.1. Narrative R&D disclosures and firms' reliance on trade credit financing

Table 4 presents the basic regression results for this paper. Columns (1) and (2) show the influence coefficients before and after adding control variables, which are 1.241 and 1.289, respectively, and both coefficients are statistically significant at the 1% level. Specifically, Column (2) indicates that a 1% increase in the standard deviation of narrative R&D information disclosure (NarRD) is associated with a 3.97% increase in the company's trade credit financing ratio relative to its average value. These results confirm Hypothesis H1a, demonstrating that greater narrative R&D disclosures leads to increased reliance on trade credit financing.

Regarding control variables, the coefficient for cash flow level (Cash) is -0.018, significant at the 1% level. This suggests that higher cash flow reduces a company's dependence on trade credit financing. Additionally, the coefficient for bank financing (BankFin) is -0.029, also significant at the 1% level. This indicates that bank financing and trade credit financing are somewhat substitutable, aligning with real-world observations.

Table 4 Fundamental analysis

	(1) TradeCredit	(2) TradeCredit
NarRD	1.241***	1.289***
	(2.96)	(3.19)
Size		-0.002

		(-1.25)
Lev		0.072***
		(12.63)
Roa		-0.010
		(-1.07)
Dual		-0.000
		(-0.23)
IndDir		-0.000
		(-1.15)
PPE		-0.018***
		(-2.71)
Bsize		-0.009
		(-1.44)
RDinv		-0.000
		(-0.49)
TobinQ		0.000
		(0.12)
Growth		0.002***
		(2.60)
Cash		-0.018***
		(-3.91)
Patent		0.000
		(0.04)
BankFin		-0.029***
		(-6.16)
Soe		0.006*
		(1.73)
InvPat		0.000
		(0.14)
Intercept	0.086***	0.131***
	(36.58)	(3.54)
Year	Yes	Yes
Firm	Yes	Yes
N	17,376	17,376
Adj-R^2	0.01	0.06

Note: The T values in parentheses have been adjusted for heteroscedasticity and company-level clustering. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

5.2. Robustness test

To enhance robustness, the explanatory variable measurement is adjusted. Since the annual report encompasses a broad range of content, including both financial and extensive non-financial information, the focus is on R&D text information, which falls under non-financial data. The main hypothesis test utilizes the entire annual report text. For robustness testing, this analysis uses the text from the "Management Discussion and Analysis" (MD&A) section to calculate narrative R&D

disclosures (MD&A_NarRD). The results, shown in column (1) of Table 5, indicate that the coefficient for MD&A_NarRD remains significantly positive in relation to firms' reliance on trade credit financing (TradeCredit).

Furthermore, we replace the measures for trade credit by referring to Love et al. (2007), Ferrando and Mulier (2013), and Agostino and Trivieri (2019). Trade credit financing ratio then is calculated as follows: accounts payable divided by total liabilities (TC_R1), accounts payable divided by operating income (TC_R2), accounts payable divided by the cost of purchased raw materials (TC_R3), and accounts payable divided by the cost of sales (TC_R4). The results of these tests are presented in columns (2) through (5) of Table 5. The regression analyses consistently show that narrative R&D disclosure continues to increase the reliance on trade credit financing among listed companies.

Table 5 Robustness test

	(1)	(2)	(3)	(4)	(5)
	TradeCredit	TC_R1	TC_R2	TC_R3	TC_R4
MD&A_NarRD	0.217**				
	(2.29)				
NarRD		2.543**	1.682**	1.811	2.314**
		(2.44)	(2.04)	(1.54)	(1.96)
Size	-0.002	-0.015***	0.008**	0.015***	0.011**
	(-1.03)	(-4.52)	(2.21)	(3.06)	(2.27)
Lev	0.073***	-0.168***	0.058***	0.081***	0.062***
	(11.79)	(-12.98)	(4.87)	(4.39)	(3.40)
Roa	-0.010	0.015	-0.119***	-0.128***	-0.069**
	(-0.92)	(0.65)	(-5.13)	(-3.47)	(-2.09)
Dual	-0.000	0.000	-0.000	0.000	0.000
	(-0.47)	(0.41)	(-0.68)	(0.04)	(0.03)
IndDir	-0.000	-0.000	0.000	0.000	0.000
	(-1.55)	(-1.37)	(0.14)	(0.57)	(0.85)
PPE	-0.021***	0.005	-0.088***	-0.133***	-0.130***
	(-2.93)	(0.33)	(-5.21)	(-5.50)	(-5.21)
Bsize	-0.014**	-0.026**	-0.004	0.003	-0.005
	(-2.28)	(-2.00)	(-0.30)	(0.18)	(-0.23)
RDinv	0.000	-0.001	0.001**	0.003***	0.003***
	(0.06)	(-1.24)	(2.09)	(3.36)	(2.92)
TobinQ	-0.000	-0.001	-0.002	-0.002	-0.000

	(-0.01)	(-0.98)	(-1.45)	(-1.45)	(-0.16)
Growth	0.002*	0.002	-0.023***	-0.030***	-0.028***
	(1.94)	(0.79)	(-8.62)	(-8.19)	(-6.55)
Cash	-0.018***	0.044***	-0.042***	-0.069***	-0.054***
	(-3.50)	(3.65)	(-4.10)	(-4.59)	(-3.58)
Patent	-0.000	-0.001	-0.001	-0.003	-0.003
	(-0.20)	(-0.44)	(-0.79)	(-1.12)	(-1.22)
BankFin	-0.029***	-0.039***	0.002	-0.001	0.010
	(-5.88)	(-4.35)	(0.21)	(-0.06)	(0.75)
Soe	0.006*	0.005	0.002	0.001	0.005
	(1.72)	(0.62)	(0.26)	(0.07)	(0.37)
InvPat	0.000	-0.002	0.002	0.003	0.005**
	(0.36)	(-1.01)	(1.41)	(1.40)	(2.08)
Intercept	0.145***	0.689***	-0.007	-0.139	-0.046
	(3.72)	(8.58)	(-0.08)	(-1.29)	(-0.41)
Year	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes
N	14,452	17,256	17,238	17,061	17,210
Adj-R^2	0.06	0.09	0.09	0.10	0.07

5.3. Mitigation of endogeneity problems

5.3.1

To address potential systematic differences among companies with varying levels of narrative R&D disclosure, which may lead to biased regression results, this paper employs the propensity score matching (PSM) method. A dummy variable (Treat) is created based on the sample median of narrative R&D disclosure (NarRD). Companies with a Treat value higher than the median are assigned a value of 1, while those below the median are assigned a value of 0. The Treat variable is then used in a logit regression with control variables to estimate the propensity score. Matching is performed using the one-to-one nearest neighbor method with a caliper of 0.1, ensuring sampling without replacement to avoid sample loss.

The results of the balance test are presented in Table 6, showing that, post-matching, most covariates exhibit no significant differences between the treatment and control groups. Regression analyses using the PSM-matched samples are shown in Table 7. The results confirm that the coefficient for narrative R&D disclosure (NarRD) remains significantly positive in relation to trade credit financing (TradeCredit), reinforcing the validity of Hypothesis H1a.

Table 6 Balance test

Variables	Mean		%bias	T-test	
	Treated	Control		T	p>|t|
Size	21.868	21.898	-2.800	-1.300	0.195
Lev	0.405	0.411	-2.900	-1.380	0.168
Roa	0.041	0.040	1.700	0.770	0.443
Dual	38.329	38.438	-0.700	-0.330	0.745
IndDir	37.060	37.111	-1.000	-0.460	0.643
PPE	0.216	0.220	-3.200	-1.540	0.123
Bsize	2.260	2.264	-2.400	-1.110	0.266
RDinv	3.300	3.122	5.200	2.660	0.008
TobinQ	2.079	2.083	-0.400	-0.160	0.873
Growth	0.181	0.179	0.600	0.280	0.779
Cash	0.189	0.188	0.700	0.330	0.744
Patent	1.459	1.434	1.800	0.840	0.403
BankFin	0.091	0.091	0.100	0.050	0.959
Soe	0.309	0.332	-4.700	-2.220	0.027
InvPat	1.142	1.125	1.400	0.640	0.523
Pseudo R^2	Before PSM		0.060		
	After PSM		0.001		

Table 7 Fundamental analysis after PSM

	(1) TradeCredit	(2) TradeCredit
NarRD	0.001^{**}	0.001^{***}
	(2.45)	(2.78)
Size		-0.003^{*}
		(-1.92)
Lev		0.075^{***}
		(11.95)
Roa		-0.018^{*}
		(-1.67)
Dual		-0.000
		(-0.30)
IndDir		-0.000
		(-0.87)
PPE		-0.018^{***}
		(-2.60)
Bsize		-0.009
		(-1.32)
RDinv		0.000
		(0.11)
TobinQ		0.000
		(0.19)
Growth		0.003^{**}
		(2.45)
Cash		-0.016^{***}

		(-2.95)
Patent		-0.000
		(-0.10)
BankFin		-0.029***
		(-5.79)
SOE		0.007*
		(1.87)
InvPat		0.001
		(0.60)
Intercept	0.085***	0.154***
	(32.01)	(3.84)
Year	Yes	Yes
Firm	Yes	Yes
N	13,752	13,752
Adj-R^2	0.01	0.06

5.3.2. Difference-in-difference method（DID）

To address potential endogeneity issues, this paper employs a difference-in-difference (DID) model, utilizing the "Content and Format Guidelines for Information Disclosure by Companies Issuing Securities No. 2 - Content and Format of Annual Reports (Revised in 2012)" issued by the China Securities Regulatory Commission. These guidelines, which took effect on January 1, 2013, mandate that listed companies detail their R&D projects, including their objectives, progress, achieved results, and anticipated impact on future development. Additionally, companies are required to report their total R&D expenditure as a percentage of the most recent audited net assets and operating income. The revised guidelines also introduce stricter disclosing requirements for R&D plans and their future effect.

The implementation of these more rigorous disclosure requirements starting in 2013 creates a natural experiment, making it an ideal setting for a DID test. This paper sets up the following difference-in-difference model to evaluate the impact of the revised guidelines on narrative R&D disclosure:

$$\mathrm{TradeCredit}_{it} = \alpha + \beta_1 \mathrm{Treat}_i \times \mathrm{Post}_t + \beta_2 \mathrm{Post}_t + \sum_j \theta_j \times \mathrm{Controls}_{j,i,t-1} + \sum \mathrm{Firm} + \sum \mathrm{Year} + \varepsilon_{it} (2)$$

In model (2), this paper assesses the impact of the policy based on the intensity of R&D investment prior to the policy's introduction. Specifically, R&D investment intensity is measured by the proportion of a company's R&D investment to operating income over the three years before the policy was enacted. Companies are then classified into two groups based on this intensity, with the sample median serving as the cutoff. Companies with R&D investment intensity above the median are classified as the treatment group (Treat=1), while those below the median are classified as the control group (Treat=0). Additionally, a dummy variable (Post) is created to represent the policy's implementation period, with a value of 1 for 2013 and later years, and 0 otherwise. The primary focus is on the coefficient β_1 for the interaction term $\mathrm{Treat_i} * \mathrm{Post_t}$, with the expectation that β_1 will be positive.

First, a parallel trends test is conducted on the difference-in-difference model. Dummy variables are defined as follows: Pre_2 (1 for 2009 and 2010, 0 otherwise), Pre_1 (1 for 2011 and 2012, 0 otherwise), Current (1 for 2013, 0 otherwise), Post_1 (1 for 2014, 2015, and 2016, 0 otherwise), Post_2 (1 for 2017, 2018, and 2019, 0 otherwise), and Post_3 (1 for 2020, 0 otherwise). Interaction terms between these dummy variables and Treat are included in the regression model. The results, shown in Table 8, indicate that the coefficients for Pre_2×Treat and Pre_1×Treat are not significant, suggesting no substantial difference in commercial credit financing between the treatment and control groups before the policy implementation. In contrast, the coefficients for Current×Treat, Post_1×Treat, Post_2×Treat, and Post_3×Treat are significantly positive, indicating that the policy has had a sustained positive effect.

The results of model (2), presented in Table 9, show that the coefficient for Treat×Post on trade credit financing (TradeCredit) remains positive and statistically significant. Thus, after addressing endogeneity with the DID approach, the paper's conclusions are upheld.

Table 8 Parallel trend test

	(1)	(2)
	TradeCredit	TradeCredit
Pre_2×Treat	0.003	0.004
	(0.74)	(1.30)
Pre_1×Treat	0.000	0.004
	(0.02)	(1.07)
Current×Treat	0.004	0.008*
	(0.85)	(1.75)
Post_1×Treat	0.007	0.009*
	(1.62)	(1.88)
Post_2×Treat	0.010**	0.009*
	(2.07)	(1.82)
Post_3×Treat	0.014***	0.011**
	(2.61)	(2.20)
Size		-0.002
		(-1.34)
Lev		0.073***
		(10.98)
Roa		0.002
		(0.13)
Dual		-0.000
		(-0.13)
IndDir		-0.000
		(-1.07)
PPE		-0.012
		(-1.52)
Bsize		-0.011
		(-1.62)
RDinv		-0.000
		(-0.29)
TobinQ		0.000
		(0.16)
Growth		0.004***
		(3.04)
Cash		-0.013**
		(-2.11)
Patent		0.000
		(0.11)
BankFin		-0.030***
		(-5.93)
Soe		0.005
		(1.26)
InvPat		-0.000
		(-0.09)
Intercept	0.091***	0.147***
	(46.51)	(3.47)
Year	Yes	Yes
Firm	Yes	Yes
N	12,330	12,330
$Adj\text{-}R^2$	0.01	0.06

Table 9 Difference-in-difference test

	(1)	(2)

	TradeCredit	TradeCredit
Treat× Post	0.008***	0.005**
	(3.07)	(2.01)
Post	0.007**	0.012***
	(2.57)	(3.59)
Size		-0.002
		(-1.31)
Lev		0.073***
		(11.08)
Roa		0.002
		(0.16)
Dual		-0.000
		(-0.17)
IndDir		-0.000
		(-1.08)
PPE		-0.012
		(-1.51)
Bsize		-0.011
		(-1.64)
RDinv		-0.000
		(-0.27)
TobinQ		0.000
		(0.19)
Growth		0.004***
		(3.03)
Cash		-0.013**
		(-2.12)
Patent		0.000
		(0.13)
BanFin		-0.030***
		(-5.92)
Soe		0.005
		(1.29)
InvPat		-0.000
		(-0.08)
Intercept	0.091***	0.147***
	(50.16)	(3.46)
Year	Yes	Yes
Firm	Yes	Yes
N	12,330	12,330
Adj-R^2	0.01	0.06

5.3.3. Entropy balance method（EB）

This section employs the entropy balancing method to more accurately handle high-dimensional data, aiming to achieve optimal matching of covariates between the treatment and control groups, aside from differences in narrative R&D disclosure quantity. The method involves controlling for the first-order, second-order, and third-order moments of sample covariates from both groups, removing quadratic and cubic terms of the binary variable, and then performing a weighted regression. The descriptive statistics for covariates before and after balancing are shown in Panel A and Panel B of Table 10. (Note: The definition of Treat in the table remains consistent with its definition in the propensity score matching section.) After entropy balancing, the means, medians, and standard deviations of all covariates are largely comparable between the high and low narrative R&D disclosure groups.

Panel C of Table 10 presents the weighted test results. The coefficient for the relationship between Treat (representing high and low narrative R&D disclosure) and TradeCredit (trade credit financing) remains significant at the 1% level. This supports the primary conclusion of the paper.

Table 10 Entropy balance method

PanelA：before entropy balance

Treat	Variables	Size	Lev	Roa	Dual	IndDir	PPE	Bsize	RDinv	TobinQ	Growth	Cash	Patent	BankFin	Soe	InvPat
0	N	11202	11202	11202	11202	11202	11202	11202	11202	11202	11202	11202	11202	11202	11202	11202
	Mean	22.04	0.445	0.037	39.610	36.950	0.243	2.272	2.291	1.989	0.153	0.180	1.126	0.108	0.450	0.848
	Median	21.92	0.441	0.034	38.630	33.330	0.216	2.303	1.120	1.620	0.102	0.149	0.693	0	0	0
	Std	1.133	0.197	0.055	15.450	5.012	0.153	0.140	3.078	1.147	0.343	0.120	1.334	0.152	0.498	1.145
1	N	6174	6174	6174	6174	6174	6174	6174	6174	6174	6174	6174	6174	6174	6174	6174
	Mean	21.84	0.396	0.042	38.070	37.110	0.211	2.258	3.869	2.119	0.189	0.193	1.536	0.088	0.294	1.227
	Median	21.75	0.389	0.040	37.340	33.330	0.188	2.303	3.390	1.747	0.134	0.160	1.386	0	0	1.099
	Std	1.014	0.181	0.052	15.170	5.107	0.131	0.139	3.719	1.163	0.353	0.125	1.360	0.132	0.455	1.235

PanelB：after entropy balance

Treat	Variables	Size	Lev	Roa	Dual	IndDir	PPE	Bsize	RDinv	TobinQ	Gowth	Cash	Patent	BankFin	Soe	InvPat
1	N	11202	11202	11202	11202	11202	11202	11202	11202	11202	11202	11202	11202	11202	11202	11202
	Mean	21.840	0.396	0.042	38.080	37.110	0.211	2.258	3.868	2.118	0.189	0.193	1.535	0.088	0.294	1.226
	Median	21.750	0.390	0.040	36.790	33.330	0.191	2.303	3.380	1.776	0.131	0.161	1.386	0	0	1.099
	Std	1.014	0.181	0.052	15.150	5.107	0.131	0.139	3.720	1.163	0.353	0.125	1.361	0.132	0.455	1.236
0	N	6174	6174	6174	6174	6174	6174	6174	6174	6174	6174	6174	6174	6174	6174	6174
	Mean	21.840	0.396	0.0420	38.070	37.110	0.211	2.258	3.869	2.119	0.189	0.193	1.536	0.088	0.294	1.227
	Median	21.750	0.389	0.0400	37.340	33.330	0.188	2.303	3.390	1.747	0.134	0.160	1.386	0	0	1.099
	Std	1.014	0.181	0.0520	15.170	5.107	0.131	0.139	3.719	1.163	0.353	0.125	1.360	0.132	0.455	1.235

PanelC： Sample regression after entropy balance

	(1) TradeCredit
Treat	0.003^{***}
	(2.83)
First-order moment of control variable	Yes
Second-order moment of control variable	Yes
Third-order moment of control variable	Yes
Intercept	-0.061
	(-0.02)
Year	No
Firm	No
N	17,159
Adj-R^2	0.80

5.3.4. Instrumental Variables（IV）

To further address the existing endogeneity issue, this paper uses the average narrative R&D disclosures of other companies within the same industry as an instrumental variable (IV_NarRD). The rationale is that while the narrative R&D disclosures by other companies may influence management's decisions regarding their own R&D disclosures, they are unlikely to directly affect the company's trade credit financing behavior, thereby satisfying the exogeneity requirement. The analysis employs the two-stage least squares (2SLS) method for regression and robustly estimates the standard errors. The test results are presented in Table 11. Columns (1) and (2) show the first-stage regression results, where IV_NarRD and NarRD are significantly correlated, with both passing the 1% significance level test. The joint F-values for the first stage are 66.56 and 34.18, respectively, which exceed the threshold of 10, indicating that there is no issue with weak instrumental variables.

Columns (3) and (4) present the second-stage estimation results. These results demonstrate that after accounting for endogeneity using instrumental variables, narrative R&D disclosures continue to significantly increase the company's reliance on trade credit financing.

Table 11 Instrumental Variable Method

	(1) NarRD	(2) NarRD	(3) TradeCredit	(4) TradeCredit
IV_NarRD	0.286***	0.202***		
	(8.16)	(5.85)		
IV_NarRD			8.216**	11.662**
			(2.37)	(2.32)
Size		0.000***		-0.006***
		(9.54)		(-2.66)
Lev		-0.000*		0.075***
		(-1.87)		(17.31)
Roa		-0.000		-0.010
		(-0.05)		(-1.17)
Dual		-0.000***		0.000
		(-5.02)		(1.11)
IndDir		-0.000*		-0.000
		(-1.68)		(-1.04)
PPE		-0.001***		-0.009
		(-4.99)		(-1.34)

Bsize		0.000		-0.010**
		(0.47)		(-2.07)
RDinv		0.000***		-0.001**
		(9.58)		(-2.11)
TobinQ		0.000		-0.000
		(1.05)		(-0.33)
Growth		0.000***		0.001
		(3.09)		(1.10)
Cash		0.000		-0.018***
		(0.40)		(-4.83)
Patent		0.000***		-0.001
		(3.06)		(-0.89)
BankFin		0.000		-0.029***
		(0.32)		(-8.14)
SOE		-0.000		0.008***
		(-1.48)		(2.83)
InvPat		0.000		0.000
		(0.05)		(0.07)
Intercept	0.003***	-0.005***	0.129***	0.281***
	(20.27)	(-4.90)	(9.32)	(8.27)
Year	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
N	17,159	17,159	17,159	17,159
Adj-R^2	0.84	0.85	-0.25	-0.27

6. Analysis of internal mechanism

As previously discussed, this paper posits that ambiguous R&D disclosures and the complexity of R&D text information may act as internal mechanisms that exacerbate information asymmetry. This, in turn, can lead to an increased reliance on trade credit financing by the company.

6.1. Management's vague disclosure

The corporate governance environment influences management's willingness to disclose R&D information (Zhou, 2001). In a strong corporate governance environment, management has fewer opportunities to obscure R&D text information, leading to higher quality R&D disclosures. This paper examines the moderating effects of two corporate governance arrangements: internal control quality and management shareholding ratio.

Firstly, the internal control system, as a key component of corporate governance, directly impacts the accuracy of financial statements. High-quality internal control systems improve decision-making efficiency, ensure managerial accountability, reduce errors, and enhance the quality of information disclosures. Therefore, this paper posits that high-quality internal control negatively moderates the positive relationship between narrative R&D disclosures and trade credit financing, reducing the impact of ambiguous disclosures.

Secondly, management shareholding aligns management's interests with those of shareholders and mitigates internal agency problems (Andreou et al., 2021). A higher management shareholding ratio encourages clearer R&D disclosures. Thus, this paper argues that a higher management shareholding ratio negatively moderates the positive relationship between narrative R&D disclosures and trade credit financing, leading to less ambiguity in R&D disclosures.

Corporate governance intensity is measured using the internal control quality score (InterContr) and management ownership ratio (ManHold). These indicators are included in the regression model as interaction terms. The test results are shown in Table 12. The coefficients for the interaction term NarDis × InterContr are -0.599 and -0.547, both significant at the 1% level. The coefficients for the interaction term NarDis × ManHold are -0.901 and -1.065, significant at the 10% and 5% levels, respectively. These findings suggest that better internal control quality and higher management shareholding ratios diminish the positive impact of narrative R&D disclosures on trade credit financing, indicating that effective corporate governance reduces the incentive for vague R&D disclosures.

Table12 Management's vague disclosure

	(1) TradeCredit	(2) TradeCredit	(3) TradeCredit	(4) TradeCredit
NarDis×InterContr	-0.599^{***}	-0.547^{***}		
	(-2.97)	(-2.75)		
InterContr	0.003^{***}	0.004^{***}		
	(3.14)	(3.30)		

NarDis×ManHold			-0.901*	-1.065**
			(-1.87)	(-2.29)
ManHold			0.002	0.004
			(1.07)	(1.62)
NarDis	1.521***	1.546***	1.744***	1.887***
	(3.48)	(3.68)	(3.16)	(3.52)
Size		-0.002		-0.002
		(-1.24)		(-1.24)
Lev		0.072***		0.072***
		(12.62)		(12.66)
Roa		-0.011		-0.010
		(-1.16)		(-1.06)
Dual		-0.000		-0.000
		(-0.25)		(-0.21)
IndDir		-0.000		-0.000
		(-1.15)		(-1.20)
PPE		-0.018***		-0.018***
		(-2.71)		(-2.68)
Bsize		-0.009		-0.009
		(-1.42)		(-1.46)
RDinv		-0.000		-0.000
		(-0.51)		(-0.67)
TobinQ		0.000		0.000
		(0.02)		(0.10)
Growth		0.002**		0.002***
		(2.49)		(2.59)
Cash		-0.018***		-0.018***
		(-3.98)		(-3.91)
Patent		0.000		0.000
		(0.06)		(0.02)
BankFin		-0.029***		-0.029***
		(-6.16)		(-6.16)
Soe		0.006*		0.006*
		(1.71)		(1.70)
InvPat		0.000		0.000
		(0.15)		(0.18)
Intercept	0.084***	0.130***	0.085***	0.130***
	(33.54)	(3.48)	(29.23)	(3.50)
Year	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
N	17,375	17,375	17,376	17,376
Adj-R^2	0.01	0.06	0.01	0.06

6.2. Text analysis complexity

Management typically does not use a single language feature when disclosing information. R&D disclosures often include numerous technical terms and specialized vocabulary, making them highly complex and difficult for investors to understand due to their professional limitations.

This complexity can exacerbate information asymmetry (Rennekamp, 2012; Lang and Stice-Lawrence, 2015; Ertugrul et al., 2017). To measure the complexity of R&D text disclosures, this paper evaluates readability (NarRead) and similarity (NarSimi) of the texts (Brown and Tucker, 2011). More readable R&D text helps investors better comprehend and process the information, thereby reducing the information processing costs. Conversely, lower text similarity indicates more incremental and unique information.

Interaction terms between these indicators and R&D text disclosure are included in the regression model. The results, presented in Table 13, show that the coefficients for the interaction term NarRD × NarRead are -0.610 and -0.731 before and after adding control variables, respectively, both significant at the 10% and 5% levels. This indicates that greater readability negatively moderates the impact of R&D text disclosure, suggesting that more readable text reduces the adverse effects of complex disclosures. On the other hand, the coefficients for the interaction term NarRD × NarSimi are 0.589 and 0.428, significant at the 5% and 10% levels, respectively, showing that higher text similarity positively moderates the impact of R&D text disclosure.

Overall, these results imply that while increased narrative R&D disclosures might seem to provide more information, it does not necessarily offer effective incremental information. Instead, text complexity can heighten information asymmetry, reduce external financing options, and increase the company's reliance on trade credit financing.

Table13 Text analysis complexity

	(1) TradeCredit	(2) TradeCredit	(3) TradeCredit	(4) TradeCredit
NarRD	1.362***	1.430***	0.799*	0.963**
	(3.23)	(3.54)	(1.86)	(2.33)
NarRD×NarRead	-0.610*	-0.731**		
	(-1.69)	(-2.07)		
NarRead	0.002	0.003*		
	(1.38)	(1.73)		

NarRD×NarSimi			0.589**	0.428*
			(2.27)	(1.67)
NarSim			-0.000	0.000
			(-0.10)	(0.12)
Size		-0.002		-0.002
		(-1.23)		(-1.26)
Lev		0.072***		0.072***
		(12.64)		(12.59)
Roa		-0.010		-0.010
		(-1.06)		(-1.09)
Dual		-0.000		-0.000
		(-0.24)		(-0.17)
IndDir		-0.000		-0.000
		(-1.16)		(-1.14)
PPE		-0.018***		-0.018***
		(-2.72)		(-2.74)
Bsize		-0.009		-0.009
		(-1.42)		(-1.42)
RDinv		-0.000		-0.000
		(-0.46)		(-0.51)
TobinQ		0.000		0.000
		(0.12)		(0.13)
Growth		0.002***		0.003***
		(2.62)		(2.76)
Cash		-0.018***		-0.018***
		(-3.94)		(-3.84)
Patent		0.000		0.000
		(0.06)		(0.02)
BankFin		-0.029***		-0.029***
		(-6.17)		(-6.17)
Soe		0.006*		0.006*
		(1.75)		(1.69)
InvPat		0.000		0.000
		(0.15)		(0.18)
Intercept	0.086***	0.130***	0.086***	0.131***
	(36.19)	(3.51)	(33.92)	(3.53)
Year	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
N	17,376	17,376	17,376	17,376
Adj-R^2	0.01	0.06	0.01	0.06

7. Heterogeneity analysis and further research

7.1 Differences in trade credit provided by suppliers

This paper argues that narrative R&D disclosures decreases the transparency of information from listed companies. Suppliers, due to their business relationships with these companies, have a comparative advantage in processing complex public information. Consequently, companies with more extensive R&D text disclosures are likely to rely more on trade credit financing.

This section examines variations in suppliers' willingness to provide trade credit. Following Chen et al. (2017), this paper measures inventory replacement cost (InvenCost) as the ratio of inventory book value to total assets. Suppliers are generally more inclined to offer trade credit to companies with lower inventory replacement costs. The sample is divided into high and low inventory cost groups based on the mean of this measure.

The test results, presented in Table 14, reveal that in the low-cost group, the impact coefficients of narrative R&D disclosures (NarRD) on trade credit financing (TradeCredit) are 1.718 and 1.619, both significant at the 1% level. In contrast, in the high-cost group, NarRD does not have a significant effect on TradeCredit. This suggests that suppliers are more willing to extend trade credit to companies with lower inventory replacement costs, reinforcing the idea that R&D text disclosure impacts trade credit dependence differently based on inventory costs.

Table14 Differences in trade credit provided by suppliers

	Low-cost		High-cost	
	TradeCredit	TradeCredit	TradeCredit	TradeCredit
	（1）	（2）	（3）	（4）
NarRD	1.718***	1.619***	0.786	1.012
	(3.04)	(3.10)	(1.22)	(1.60)
Size		-0.002		-0.004*
		(-0.83)		(-1.66)
Lev		0.070***		0.066***
		(10.74)		(7.11)
Roa		-0.012		-0.001
		(-0.95)		(-0.09)
Dual		0.000		-0.000
		(0.79)		(-1.21)
IndDir		-0.000		0.000
		(-1.43)		(0.09)
PPE		-0.018**		-0.026***
		(-2.17)		(-2.96)
Bsize		-0.001		-0.007
		(-0.18)		(-0.74)
RDinv		0.000		-0.000
		(0.72)		(-1.23)
TobinQ		0.001**		-0.001*

		(2.25)		(-1.75)
Growth		0.004***		0.001
		(2.88)		(0.82)
Cash		-0.007		-0.031***
		(-1.20)		(-4.42)
Patent		0.001		-0.001
		(0.62)		(-0.63)
BankFin		-0.031***		-0.024***
		(-5.10)		(-3.85)
Soe		0.014***		0.003
		(3.38)		(0.58)
InvPat		-0.000		0.001
		(-0.47)		(0.48)
Intercept	0.075***	0.088*	0.094***	0.185***
	(22.99)	(1.84)	(27.65)	(3.36)
Year	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
N	9,061	9,061	8,315	8,315
Adj-R^2	0.02	0.07	0.01	0.05

7.2 Differences in private information communication

(1) Executive network center: unlike formal financing, which relies on structured processes, informal financing often hinges on reputation and personal relationships (Ayyagari, 2010). The social capital and networks of executives can significantly influence their ability to establish trust with suppliers, thereby securing more business credit (Liu et al., 2016; Kong et al., 2020). This paper posits that a stronger executive network enhances the richness of private information and facilitates the interpretation of R&D text disclosures, which in turn improves trade credit financing.

To measure the strength of executive networks, this paper uses standardized betweenness centrality (ManNet) and divides the sample into high and low network groups based on the mean value. The results are presented in columns (1) and (2) of Table 15. In the high-network group (High-degree), the coefficients for the impact of narrative R&D disclosures (NarRD) on trade credit financing (TradeCredit) are 1.652 and 1.493, both significant at the 1% level before and after controlling for other variables. Conversely, in the low-network group (Low-degree), the size and significance of NarRD's impact on TradeCredit are markedly reduced.

These results indicate that a higher executive network center enhances the ability to interpret R&D text disclosures, leading to a more significant positive impact on trade credit financing.

(2) Supply chain concentration: supply chain concentration impacts the exchange of information between customers and suppliers. Higher supplier concentration typically leads to more frequent interactions with downstream customers, providing suppliers with greater access to private information. This exchange fosters mutual trust and enables suppliers to better understand their customers and handle complex public information. Consequently, suppliers with greater concentration are more adept at interpreting R&D text information, thereby enhancing trade credit financing.

This paper measures supplier concentration using the ratio of the top five suppliers' purchases to total annual purchases and divides the sample into high and low supplier concentration groups based on the mean value. The results are presented in columns (3) and (4) of Table 15. In the high-supplier concentration group (High-supply), the coefficients for the impact of narrative R&D disclosures (NarRD) on trade credit financing (TradeCredit) are 1.422 and 1.46, both significant at the 1% level. Conversely, in the low-supplier concentration group (Low-supply), the impact of NarRD on TradeCredit is not statistically significant.

These findings suggest that in companies with more concentrated suppliers, the positive impact of narrative R&D disclosures on trade credit financing is more pronounced.

Table15 Differences in private information communication

	High-degree TradeCredit	Low-degree TradeCredit	High-supply TradeCredit	Low-supply TradeCredit
	（1）	（2）	（3）	（4）
NarRD	1.493^{***}	0.866^{*}	1.460^{***}	-0.148
	(2.69)	(1.90)	(2.96)	(-0.28)
Size	-0.003	-0.001	-0.001	-0.009^{***}
	(-1.26)	(-0.37)	(-0.62)	(-3.38)
Lev	0.086^{***}	0.052^{***}	0.061^{***}	0.078^{***}
	(10.12)	(7.30)	(8.25)	(7.93)
Roa	0.003	-0.018	-0.004	-0.036^{**}

	(0.22)	(-1.30)	(-0.36)	(-2.09)
Dual	-0.000	0.000	-0.000**	-0.000
	(-0.67)	(0.16)	(-2.04)	(-0.05)
IndDir	-0.000	-0.000**	0.000	-0.000
	(-0.46)	(-2.16)	(0.11)	(-0.39)
PPE	-0.027***	-0.014*	-0.002	-0.042***
	(-2.61)	(-1.72)	(-0.28)	(-4.16)
Bsize	-0.005	-0.016*	-0.003	-0.010
	(-0.61)	(-1.80)	(-0.41)	(-1.15)
RDinv	-0.000	0.000	-0.000	-0.000
	(-0.75)	(0.09)	(-0.51)	(-0.60)
TobinQ	-0.000	0.000	-0.000	0.000
	(-0.06)	(0.02)	(-0.07)	(0.24)
Growth	0.003*	0.003**	0.002	0.003
	(1.89)	(2.16)	(1.49)	(1.42)
Cash	-0.018**	-0.021***	-0.018***	-0.018***
	(-2.57)	(-3.55)	(-2.90)	(-2.68)
Patent	0.000	-0.001	-0.001	0.000
	(0.36)	(-0.52)	(-0.60)	(0.36)
BankFin	-0.029***	-0.020***	-0.015***	-0.036***
	(-4.66)	(-3.19)	(-2.72)	(-4.46)
Soe	0.003	0.008*	0.010*	-0.001
	(0.57)	(1.73)	(1.94)	(-0.18)
InvPat	0.000	-0.000	0.001	-0.000
	(0.36)	(-0.15)	(0.48)	(-0.00)
Intercept	0.137***	0.138***	0.093**	0.305***
	(2.69)	(2.81)	(2.05)	(5.24)
Year	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
N	8,742	8,321	9,588	6,763
Adj-R^2	0.07	0.04	0.05	0.06

7.3 Different capital market attention

(1) Analyst attention: management's tendency to provide vague disclosures can be influenced by market scrutiny. When capital market attention is high, the consequences for disclosing misleading information become more severe. Consequently, this paper argues that when market attention is lower, management may be more inclined to disclose vague R&D text information, leading to increased reliance on trade credit financing.

To measure capital market attention, this paper uses analyst attention and divides the sample into high and low attention groups based on the mean value. The results are presented in columns (1) and (2) of Table 16. In the low analyst attention group (Low-analyst), the coefficients for the effect of narrative R&D disclosures (NarRD) on trade credit financing (TradeCredit) are 1.217 and 1.206, both significant at the 10% and 5% levels respectively. In contrast, in the high analyst attention group (High-analyst), the coefficient for NarRD's impact on TradeCredit is not statistically significant.

These findings suggest that lower analyst attention correlates with a greater impact of narrative R&D disclosures on trade credit financing, indicating that reduced scrutiny may lead to increased reliance on trade credit.

（2) Short-Selling Targets: this paper also examines the effect of capital market attention by assessing whether a company is included in the list of short-selling targets. Companies that are targets for short selling receive heightened scrutiny from investors, making management's vague disclosures more likely to be detected and penalized by the market. Therefore, this paper hypothesizes that narrative R&D disclosures will have a more pronounced effect on increasing trade credit financing reliance in companies that are not included on the short-selling list.

The test results are presented in columns (3) and (4) of Table 16. For the non-short-selling target group (Non-sell), the coefficients for the effect of narrative R&D disclosure (NarRD) on trade credit financing (TradeCredit) are 1.217 and 1.244, both significant at the 1% level. In contrast, for the short-selling target group (Sell), NarRD does not significantly impact TradeCredit.

These results suggest that companies not subject to short-selling scrutiny experience a stronger relationship between narrative R&D disclosure and reliance on trade credit financing, indicating that higher market attention reduces the tendency for increased trade credit dependency.

Table 16 Different capital market attention

	Low-analyst	**High-analyst**	**Non-sell**	**Sell**
	TradeCredit	**TradeCredit**	**TradeCredit**	**TradeCredit**
	（1）	**（2）**	**（3）**	**（4）**
NarRD	1.206**	-0.411	1.244***	0.429

	(2.07)	(-0.76)	(2.79)	(0.61)
Size	-0.002	-0.004	-0.002	-0.009**
	(-0.86)	(-1.50)	(-1.06)	(-2.43)
Lev	0.067***	0.054***	0.061***	0.070***
	(6.96)	(6.73)	(10.18)	(5.61)
Roa	-0.028	-0.013	-0.018	0.001
	(-1.44)	(-0.68)	(-1.63)	(0.09)
Dual	0.000	0.000	-0.000*	-0.000
	(0.56)	(0.93)	(-1.79)	(-0.03)
IndDir	-0.000	-0.000	-0.000	-0.000
	(-0.76)	(-0.10)	(-0.83)	(-0.06)
PPE	-0.030***	-0.018*	-0.018**	-0.046***
	(-3.04)	(-1.86)	(-2.45)	(-3.70)
Bsize	-0.013	-0.012	-0.004	-0.002
	(-1.46)	(-1.37)	(-0.49)	(-0.15)
RDinv	-0.000	0.000	-0.000	-0.000
	(-0.15)	(0.15)	(-1.24)	(-0.45)
TobinQ	0.000	-0.000	-0.000	0.001*
	(0.28)	(-0.65)	(-0.31)	(1.75)
Growth	0.005***	0.004**	0.003**	0.002
	(3.16)	(2.44)	(2.16)	(1.31)
Cash	-0.029***	-0.013**	-0.017***	-0.021***
	(-3.57)	(-2.23)	(-3.31)	(-2.89)
Patent	0.002	-0.001	0.001	-0.002*
	(1.49)	(-0.88)	(0.96)	(-1.80)
BankFin	-0.025***	-0.023***	-0.024***	-0.017*
	(-3.36)	(-3.30)	(-4.68)	(-1.69)
Soe	0.010*	0.017***	0.009**	0.008
	(1.77)	(2.77)	(2.16)	(1.34)
InvPat	-0.002	0.001	0.000	0.001
	(-1.56)	(1.30)	(0.15)	(1.19)
Intercept	0.149***	0.174***	0.129***	0.291***
	(2.75)	(2.97)	(2.97)	(3.40)
Year	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
N	5,882	6,434	13,004	4,372
Adj-R^2	0.07	0.05	0.05	0.05

7.4 Economic consequences test of trade credit financing

This paper examines the economic implications of relying on trade credit financing. Unlike open market financing, which can be more suitable for long-term investments, trade credit financing is typically short-term and high-cost. This mismatch is particularly problematic in the context of R&D and innovation activities, which require substantial long-term investments. The short-term nature of trade credit financing can adversely affect a company's efficiency in investing in innovation, as it does not align well with the long-term and capital-intensive needs of R&D projects. This paper assesses the company's R&D innovation output efficiency by calculating the ratio of patent applications in the subsequent two periods to the current R&D investment (using the natural logarithm of this ratio). It further examines how changes in trade credit financing affect the company's R&D output efficiency. The results are presented in Table 17. Column (1) shows the overall R&D output efficiency (InvEft), measured by the total number of patent applications. Columns (2) to (4) break this down by patent type: invention patents (InvP), utility models (UmiP), and designs (DesiP). The findings indicate that an increase in trade credit financing is associated with a significant decrease in both overall innovation output efficiency and efficiency across the different patent types.

These results suggest that the current policy of mandatory narrative R&D disclosure might negatively impact long-term innovation output efficiency by altering the company's financing choices. Therefore, regulatory authorities should consider revising existing policies and introducing complementary intellectual property protection and financing policies to mitigate these effects.

Table 17 Economic consequences test of trade credit financing

	(1) InvEft	(2) InvP	(3) UmiP	(4) DesiP
TradeCredit	-1.501^{***}	-1.200^{**}	-1.544^{***}	-1.911^{***}
	(-2.94)	(-2.52)	(-3.29)	(-4.36)
NarRD	-31.941^{***}	-25.774^{***}	-40.036^{***}	-26.143^{***}
	(-3.12)	(-2.73)	(-4.61)	(-2.71)
Size	-0.525^{***}	-0.571^{***}	-0.585^{***}	-0.619^{***}
	(-9.75)	(-11.30)	(-11.48)	(-12.51)
Lev	0.316^{*}	0.377^{**}	0.301^{*}	0.336^{**}
	(1.81)	(2.31)	(1.88)	(2.10)
Roa	-1.302^{***}	-1.436^{***}	-1.644^{***}	-1.594^{***}
	(-3.64)	(-4.26)	(-4.80)	(-4.76)
Dual	-0.001	0.000	-0.002	-0.003
	(-0.40)	(0.03)	(-0.86)	(-1.34)
IndDir	-0.005	-0.006	-0.002	-0.003
	(-1.11)	(-1.34)	(-0.50)	(-0.64)
PPE	-0.228	-0.276	-0.294	-0.573^{***}

	(-1.06)	(-1.37)	(-1.46)	(-2.88)
Bsize	-0.254	-0.292*	-0.192	-0.302*
	(-1.41)	(-1.71)	(-1.13)	(-1.65)
RDinv	-0.067***	-0.069***	-0.066***	-0.077***
	(-8.05)	(-8.83)	(-9.04)	(-9.18)
TobinQ	-0.039**	-0.045***	-0.044***	-0.034**
	(-2.51)	(-3.12)	(-3.05)	(-2.28)
Growth	-0.059*	-0.088***	-0.065**	-0.108***
	(-1.77)	(-2.83)	(-2.10)	(-3.58)
Cash	0.247	0.223	0.292**	0.127
	(1.62)	(1.57)	(2.07)	(0.84)
Patent	0.032	0.021	0.029	0.004
	(1.28)	(0.89)	(1.18)	(0.17)
BankFin	0.088	0.012	0.072	-0.119
	(0.64)	(0.09)	(0.58)	(-0.89)
Soe	0.095	0.118	0.051	0.010
	(1.10)	(1.41)	(0.62)	(0.11)
InvPat	-0.015	-0.012	-0.031	-0.023
	(-0.57)	(-0.49)	(-1.21)	(-0.89)
Intercept	-3.701***	-2.825**	-2.729**	-1.150
	(-3.00)	(-2.43)	(-2.32)	(-1.00)
Year	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
N	13,826	13,826	13,826	13,826
Adj-R^2	0.13	0.17	0.21	0.23

8. Research conclusions and policy suggestions

This paper explores the impact of mandatory narrative R&D disclosure on corporate trade credit financing in China, leveraging machine learning and text analysis technologies to construct narrative R&D disclosure indicators. The empirical analysis reveals that narrative R&D disclosure increases a company's reliance on trade credit financing. Robustness checks using alternative variable measurement methods, difference-in-differences (DiD) analysis, propensity score matching (PSM), entropy balance, and instrumental variable (IV) regression consistently support this finding. Theoretical insights suggest that under China's mandatory narrative R&D disclosure system, rather than enhancing transparency, R&D text disclosure may exacerbate information asymmetry. This deterioration in the information environment diminishes public market financing opportunities, thereby amplifying dependence on trade credit. Further mechanism tests indicate that this increased information asymmetry arises from higher investor information processing costs and more ambiguous R&D disclosures by management. Group regression analyses show that the effect of narrative R&D disclosure on trade credit financing is more pronounced in firms where suppliers are more willing to extend trade credit, where private information exchange between suppliers and firms is frequent, and where public capital market attention is lower. Additionally, the paper examines the economic consequences of increased trade credit reliance and finds a significant decline in the efficiency of future innovation output as a result of higher trade credit dependence.

This study has the following two implications: Regulatory authorities should enhance the current regulations on R&D information disclosure by implementing more specific and clear requirements. These regulations should address the investors face in understanding complex R&D information, making it easier to process and interpret. Additionally, it is important to strengthen intellectual property protection to alleviate concerns about proprietary costs associated with disclosing R&D information. This will encourage more listed companies to provide transparent and accurate R&D disclosures. Management should also consider the long-term effects of R&D information disclosure on the company's innovation efficiency. It is crucial to balance the proprietary costs of disclosure with its impact on external financing. By doing so, companies can ensure that their R&D disclosures not only comply with regulatory requirements but also align with their long-term strategic interests.

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