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Corporate social responsibility and trade credit: the role of textual features

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Abstract

Purpose – Corporate social responsibility (CSR) is significant in the financial market. Despite plenty of existing research on CSR, few studies have quantified the fine-grained aspects of CSR and examined how diverse CSR aspects are associated with firms' trade credit. Based on the released CSR reports, this paper strives to measure the CSR fulfillment of firms and examine the relationships between CSR and trade credit in terms of textual features presented in these reports.

Design/methodology/approach – This research proposes a natural language processing-based framework to extract the overall readability and the sentiment of fine-grained aspects from CSR reports, which can signal the performance of firms' CSR in diverse aspects. Furthermore, this paper explores how the textual features are associated with trade credit through partial dependence plots (PDPs), and PDPs can generate both linear and nonlinear relationships.

Findings – The study's results reveal that the overall readability of the reports is positively associated with trade credit, while the performance of the fine-grained CSR aspects mentioned in the CSR reports matters differently. The performance of the environment has a positive impact on trade credit; the performance of creditors, suppliers and information disclosure, shows a U-shaped influence on trade credit; while the performance of the government and customers is negatively associated with trade credit.

Originality/value – This study expands the scope of research on CSR and trade credit by investigating fine-grained aspects covered in CSR reports. It also offers some managerial implications in the allocation of CSR resources and the presentation of CSR reports.

Keywords Corporate social responsibility, Sentiment analysis, Readability, Trade credit, Machine learning

Paper type Research paper

Introduction

Trade credit occurs when a supplier allows the buyer to delay payment during transactions (Ng, Smith, & Smith, 1999). Compared to traditional bank debt, firms are easy to access trade credit, and they can use trade credit to extend their debt. Hence, trade credit serves as one

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critical source of short-term funding at a low cost (Abdulla, Dang, & Khurshed, 2017). For example, in the US manufacturing industry, trade credit constituted 13% of the total liability (Cao, Ye, Zhang, & Li, 2018), and it was three times as large as bank loans (Barrot, 2016). A large body of literature has studied trade credit, e.g. the effect of trade credit, and the factors affecting trade credit, due to its economic significance.

As one short-term financing way, trade credit is a financial instrument provided by suppliers to their buyers. For suppliers, the most important issue is whether the buyer can repay on schedule. Thus, suppliers need to pay attention to the business operation as well as the reputation and responsibility of the buyer. It is intuitive that when the firm has a good reputation and a high sense of responsibility, it would strive to fulfill its commitments, which signals the low probability of delayed payment or refusal to pay. Corporate social responsibility (CSR), as the public welfare undertaking of a firm, can demonstrate the firm's responsibility. Thus, this paper proposes that CSR is valued by the suppliers, and it is closely associated with trade credit-relevant issues.

CSR refers to "*the responsibility of businessman to follow those strategies, to make those decisions and to pursue those lines of action which establish values for society*" (Ali, Danish, & Asrar-ul-Haq, 2020). The term CSR was first proposed in 1924, and it has received increasing attention and recognition. In order to enhance their image and then attract potential investors, customers and employees who value social responsibilities, firms spend a lot of resources on participating in corporate social responsibilities. Engagement in CSR helps firms to better obtain diverse financing sources (Breuer, Müller, Rosenbach, & Salzmann, 2018; Cheung, Tan, & Wang, 2018; Hong & Kacperczyk, 2009), increases the probability of recovery from bankruptcy (Gupta & Krishnamurti, 2018) and decreases the cost to access equity capital and debt (Bae, Chang, & Yi, 2018; Breuer *et al.*, 2018). Hence, CSR is an important factor in affecting the suppliers' decision-making, and thus the trade credit.

According to signaling theory, the disclosure of CSR can signal a firm's performance (Axjonow, Ernstberger, & Pott, 2018). Participating in CSR activities signals the high ethical standards of a firm to its suppliers (Zerbini, 2017). Specifically, the investment in CSR activities, e.g. charities, is a positive signal that the firm is socially responsible and committed to sustainable development (Lourenço, Callen, Branco, & Curto, 2014), thus resulting in a good image among suppliers (Dayanandan, Donker, & Nofsinger, 2018; Zerbini, 2017). When suppliers provide the trade credit to a firm, the supplier suffers from the corresponding risks. In order to reduce the risks, suppliers prefer firms with high creditworthiness (Ng *et al.*, 1999), and socially responsible firms are more likely to follow the social ethics and therefore less likely to delay payment or default. From the perspective of information asymmetry, because trade credit is based on business transactions, suppliers hold more information about one firm compared to other types of debt, which alleviates information asymmetry. In addition to the signals from business transactions, CSR activities can also reduce information asymmetry, and increase information transparency. Higher information transparency is beneficial for firms to obtain trade credit from suppliers. Cheng, Ioannou, and Serafeim (2014) indicate that firms with high CSR levels have better financing opportunities than others because the practice of social responsibility can improve the transparency of the information that the companies provide to their stakeholders, thereby reducing agency costs and information degree of asymmetry.

In other words, it is believed that by participating in CSR activities and the corresponding disclosure (i.e. CSR report), the associations between the firms and the stakeholders are strengthened, and the information transparency is increased, resulting in high trade credit from suppliers. Therefore, this paper strives to examine the relationships between CSR and trade credit.

Despite a large body of extant research on the economic impact of social responsibility, they mainly focus on the overall performance of CSR with diverse indicators, e.g. Kinder Lydenberg and Domini (KLD) index, and Rankings (RKS) ESG rating [1], but overlook the textual information in CSR reports, which can signal the details of CSR. Rich information is contained in unstructured data. For instance, a large number of researchers have studied the economic value of textual data embedded in financial disclosure, such as the annual reports, and analyst reports. Hence, this paper strives to examine how CSR reports that are publicly disclosed by firms are associated with trade credit. More specifically, this study focuses on two important textual features embedded in CSR reports, i.e. the overall readability, and the fine-grained aspect-based sentiment. Existing researchers have discussed the impact of textual information, including the two kinds of textual features, on the financial field. However, they fail to tap into the impact of the textual features on trade credit. In our context, based on the CSR reports, the readability signals the overall commitment of social responsibilities, and the aspect-based sentiment discloses the commitment of the fine-grained social responsibilities. We strive to examine how these measures are related with firm's trade credit from the perspective of machine learning.

Our study has two-fold contributions. First, this paper measures the social responsibility of a firm from a new perspective. Prior research measures social responsibility via some financial indicators, and this study can help analyze the responsibility from a fine-grained perspective, i.e. aspect-based sentiment, which can extend the literature on CSR. Second, this paper examines the relationships between the extracted textual features and trade credit through machine learning, which enriches the application of machine learning in the financial area. As discussed earlier, though textual information has been widely used in diverse areas, few studies examine how CSR reports are associated with trade credit. Our study utilizes machine learning techniques to extract two important textual features from CSR reports, and further investigate how these features are related to trade credit. Our study also provides some managerial implications. From our research, the stakeholders can analyze corporate social responsibility in a more detailed structure. Besides, this study also examines the relevant importance of each feature to trade credit, which can be conducive to the allocation of firms' resources. Furthermore, stakeholders can utilize the CSR-relevant features for analyzing trade credit.

This paper proceeds as follows. Section 2 reviews the related literature. Section 3 formally introduces our research methodology. Section 4 and Section 5 describe the data sources and data analysis. Finally, we discuss our main results and conclude the paper in Section 6.

Literature review

In this section, we review two relevant streams of literature: corporate social responsibility, and trade credit. We also highlight our contributions by comparing our work with past studies.

Corporate social responsibility

Corporate social responsibility (CSR) refers to "*the responsibility of businessman to follow those strategies, to make those decisions and to pursue those lines of action which establish values for society*" (Ali *et al.*, 2020). Some studies suggest that firms are supposed to take social responsibility to enhance social welfare and economic responsibility. A large body of literature has studied the topic of CSR. Despite the importance of CSR, no agreed measurement of CSR exists. There are some direct measures of social responsibility, e.g. Kinder Lydenberg and Domini (KLD) index (Fernandez, Burnett, & Gomez, 2019; Xu, Pham, & Dao, 2020), Sustainalytics (Lu & Herremans, 2019), the MERCO database (Benitez, Ruiz, Castillo, & Llorens, 2020), survey methods (Abu Zayyad *et al.*, 2021; Ferrell, Harrison, Ferrell, & Hair, 2019) and proxy variables in terms of other measures (such as employee satisfaction, customer satisfaction). Some researchers also evaluate the social responsibility through the rating by the existing databases. For example, Rankings (RKS) and Hexun.com provide corporate social responsibility ratings.

Some research studies how the top management affects the CSR of a firm. For instance, Lu and Herremans (2019) examine how gender diversity on the board is linked with CSR, and the results present a positive relationship. Besides, a number of existing studies have investigated how CSR is associated with other financial indicators. For example, Goss and Roberts (2011) examine the link between CSR and bank debt, and find that lenders value CSR as one determinant of spreads. Cheung (2016) investigates the relationship between CSR and corporate cash holdings, and the results reveal that firms with higher CSR scores have lower cash holdings.

Besides the direct measures, some studies evaluate the fulfillment of CSR through CSR disclosure, i.e. CSR reports. CSR reports discloses the details about the commitment and fulfillment of CSR activities. However, existing studies only focus on the numeric variables in CSR reports and some specific content in CSR reports, and little attention is paid to the detailed content of CSR disclosure.

Indeed, a large body of research has investigated the financial-relevant textual information, and examined the impact of extracted textual features on financial performance. In terms of readability, prior research has examined the impact of annual report readability on firm performance and earning persistence. For example, Li (2008) has examined the impact of annual report readability on earning persistence and firm performance, and Lehavy, Li, and Merkley (2011) have investigated how annual report readability affects the forecasts of analysts. Ertugrul, Lei, Qiu, and Wan (2017) explore the impact of annual report readability on financing costs. The sentiment is another common measure for analyzing textual information about a firm. It is generally divided into two categories: positive and negative, and can be also divided into more categories: happy, sad, excited, angry, etc. Among the related work, media is a widely used source of textual information about firms. For example, in news media such as the *Wall Street Journal*, the frequency of negative words is negatively related to stock returns (Tetlock, 2007), and is followed by a decrease of subsequent quarterly firm performance (Tetlock, Saar-Tsechansky, & Macskassy, 2008). Some studies also analyze the sentiment in annual reports. Li (2010) constructs one sentiment measure about executives from the MD&A (Management Discussion and Analysis) section of financial reports in the US market, and the results reveal the positive sentiment is positively associated with the future earnings of a firm.

Despite the importance of financial-relevant text, few studies tap into the details embedded in CSR reports. Thus, this paper strives to mine fine-grained aspects covered in CSR reports, which can represent diverse aspects of CSR activities, and extract the sentiment information about each aspect, which signals the fulfillment of these aspects, and the readability of CSR reports, which shows the general performance of CSR.

Trade credit

Trade credit refers to the delayed payment of the buyers' to suppliers (Xu, Wu, & Dao, 2020), which is a critical source of short-term financing. Many studies have investigated the underlying motivations to offer or use trade credit. For example, credit-constrained firms are more likely to use trade credit as a substitute source of funding (Atanasova, 2007), and on the contrary, larger firms rely less on trade credit since they have better access to other financing sources (García-Teruel & Martínez-Solano, 2010).

In addition to the motivations about trade credit, there are existing studies on the measure of trade credit. Despite the abundant research on trade credit, there is no agreed measure of trade credit. For example, Xu *et al.* (2020) and Shou, Shao, Wang, and Lai (2020) measure trade credit by the ratio of account payable to the book value of the cost of goods sold. There are other measures, e.g. the ratio of account payable to the book value of total liabilities (Xu *et al.*, 2020), the ratio of account payable to total assets (Zhang, Ma, Su, & Zhang, 2014), the variation in account payable divided by total assets (Zhang *et al.*, 2014), the ratio of account payable to total sales (Liu & Hou, 2019), and the ratio of accounts receivable to sales (Cheung & Pok, 2019).

In the meantime, some studies have explored the associations between CSR and trade credit. Zhang *et al.* (2014) examine the CSR activities about charitable donations can lead to more trade credit from suppliers, and the effect is significant in non-state firms. This finding is similar to that in the study of Yang, Yao, He, and Ou (2019), which found that more charitable donations help obtain more trade credit, but the relationship is only significant for those firms with positive free cash flows and no political connections. Besides the charitable donations, Xu *et al.* (2020) found that the higher overall CSR scores are associated with higher trade credit, and they further examined four CSR individual components, i.e. environment, employee relations, community and diversity, and found the positive relationships between these components and trade credit. However, Shou *et al.* (2020) claim that CSR performance has a U-shaped relationship with trade credit.

Based on the review of related work, the existing literature mainly focuses on the overall CSR commitment. Even though some studies have analyzed CSR activities through CSR reports, they fail to extract fine-grained aspects covered in these reports. We extend the understanding of CSR through natural language processing in CSR reports, and examine how the sentiment of these extracted aspects is related to trade credit. Specifically, we leverage machine learning techniques to investigate the relationships between trade credit and the aspect-based sentiment, which can extend the literature of CSR and trade credit.

Research methodology

CSR and trade credit

As noted earlier, the disclosure of CSR reports can signal CSR activities (Ting, 2021). Compared to the traditional financial indicators, unstructured data of CSR reports contains richer information about a firm's CSR. This study aims to extract textual features from CSR reports to analyze CSR activities of firms. In particular, this paper extracts the overall readability of the reports and the fine-grained aspect-based sentiment represented in the reports. Further, we examine the associations between the features and the trade credit (see Figure 1).

Readability refers to the ease of reading. Some studies have claimed that stakeholders' reactions to narrative descriptions in financial reports depend on the reports' readability (Lehavy *et al.*, 2011; Li, 2008). When firms tend to obfuscate negative information in financial reports, information overload arises, and then the readability of the reports is reduced since this kind of obfuscation can weaken stakeholders' reactions to negative information. In other words, when one firm discloses the social responsibility truthfully, the corresponding CSR report is supposed to have high readability. On the contrary, when the firm tries to manipulate the disclosure, it leads to lower report readability. Thus, a report with higher readability represents a lower level of perceived manipulation and can truly present higher CSR engagement and fulfillment. Accordingly, when a firm can accurately demonstrate their CSR activities, it has good CSR performance, and then suppliers may be more willing to provide trade credit. Therefore, we propose that CSR report readability is positively associated with trade credit.

Besides the overall readability, the details of CSR reports are also important to convey information to stakeholders. This paper investigates the sentiment of diverse CSR aspects covered in CSR reports. Prior researchers have recognized the importance of text sentiment in publicly released corporate reports. For example, some studies have shown that the positive sentiment of top management in earnings calls transcripts can signal positive information, and then positively reflect future performance (Price, Doran, Peterson, & Bliss, 2012).

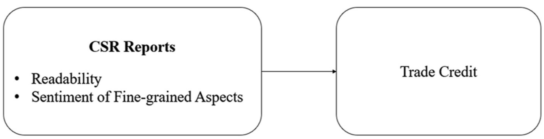


Figure 1.
Conceptual model

In our context, the sentiment of a CSR report is a good indicator of a firm's attitudes and confidence in the engagement and commitment to CSR activities. When the firm invests a lot of resources and energy in its social responsibility activities, it is supposed to be confident in CSR, and its narrative is more positive in the disclosure of its CSR report since it strives to describe what it has done in CSR to the stakeholders, e.g. suppliers, which signals the social responsibility, reputation and image of the firm. On the contrary, if the firm pays little attention to social responsibility activities, it would describe its CSR activities in a brand way with more neutral or even negative words in the narrative. Because socially responsible firms are perceived as more ethical and less likely to experience strategic payment delays or defaults, we argue that suppliers are more likely to extend business credit to firms with more positive sentiment in their social responsibility reports since these firms are more likely to be socially responsible. Therefore, we propose that the sentiment of CSR reports is positively associated with trade credit. Furthermore, in this paper, we extract the fine-grained aspect-based sentiment rather than the overall sentiment of the CSR report and examine the associations between each aspect-based sentiment and trade credit. This paper proposes that different aspects mentioned in the CSR report have different effects on suppliers, and then trade credit. For example, if a supplier is more concerned about the debt repayment or the profitability, the supplier may focus more on the fulfillment of the responsibilities about creditors and shareholders rather than other aspects, e.g. employees. If it cares about the reputation, image, or moral capital, it may focus more on the fulfillment of the responsibilities about employees, public welfare or the environment. Diverse aspects of social responsibility disclose diverse sides about a firm, and suppliers may pay attention to one or more specific aspects. Thus, it is significant to explore the aspects mentioned in CSR reports, and the corresponding sentiment information.

Measure construction

Our variables of interest are the overall readability and the aspect-based sentiment extracted from CSR reports. Further, we investigate the relationships between the textual features and trade credit.

In order to extract the textual features, we first preprocess and parse the text with Jieba package [2] that is a useful package for Chinese processing. The details for extracting features are described below.

Readability of the CSR report

Based on the literature review, we employ Gunning Fog Index as the proxy to measure the readability of each CSR report. Gunning Fog Index is a common measure to evaluate the reading difficulty. The procedure to calculate the Gunning Fog Index is described as follows:

(1) Calculate the average sentence length, which refers to the number of words divided by the number of sentences.

(2) Determine the percentage of complex words, which is the count of complex words divided by the number of words.

(3) Add the average sentence length and the percentage of complex words, and multiply the result by 0.4.

Notice that complex words in Chinese refer to words consisting of three or more characteristics. Meantime, the opposite number of the calculated value is our readability measure.

Fine-grained aspect-based sentiments

CSR reports are publicly available, and ex post facto disclosure. Thus, we believe that the reports can truly reveal CSR activities. If a firm is not highly involved in CSR activities, the report would disclose its involvement blandly, with a relatively neutral sentiment. Our study aims to examine the associations between the sentiment of CSR reports and trade credit. Moreover, as discussed above, the sentiment of fine-grained aspects has diverse impact on trade credit. We need to extract the sentiment of each fine-grained aspect from CSR reports. Each CSR report is divided into paragraphs, and each paragraph is labeled with an aspect.

In order to extract the sentiment features, we employ the lexicon-based sentiment analysis. This kind of method heavily relies on the sentiment lexicon. Therefore, constructing a domain-specific lexicon is important for the follow-up sentiment analysis. This paper expands the general sentiment lexicons for the CSR domain, and then extracts the sentiment information based on the constructed domain-specific lexicon.

(1) Domain-specific sentiment lexicon construction

General sentiment lexicons usually contain the commonly used sentiment words. They are robust across diverse domains but overlook the domain-specific sentiment words. Thus, this paper expands the general sentiment lexicons and incorporates the domain-specific sentiment words in CSR area for follow-up sentiment analysis.

Our construction starts with a combined lexicon integrating three components, (1) National Taiwan University Sentiment Dictionary, (2) one financial sentiment dictionary developed by Loughran and McDonald (2011) and (3) manually labeled sentiment words. The initial combined lexicon contains 4,755 positive words and 10,735 negative words. Afterward, we employ word2vec model to get the word embeddings for expanding. Word2vec is one widely used natural language processing (NLP) model, which utilizes a neural network to learn numeric vectors which can represent the semantics of words based on the words' context. In essence, the semantics of a word can be learned through the neighboring words. Through word2vec trained on the given corpus, we can get the word embedding of each word, and then calculate the similarity between every two words for lexicon construction. In this paper, we employ two corpora. One corpus contains all the CSR reports in our dataset, and another corpus is the content of Baidu Baike. Hence, we can get two word2vec models, denoted as CSR_word2vec and Baike_word2vec. Following the SO-SD algorithm proposed by Xue, Fu, and Shaobin (2014), we expand the initial sentiment lexicon. Suppose the dimension of the word embedding as n, and the word embedding of word i learned from word2vec is $[x_{i,1}, x_{i,2}, \ldots, x_{i,k}, \ldots, x_{i,n}]$. Then the similarity distance (SD) between two words is calculated below.

$$SD(word1, word2) = \frac{\sum_{k=1}^{n} x_{1k}\, x_{2k}}{\sqrt{\sum_{k=1}^{n} x_{1k}^2}\sqrt{\sum_{k=1}^{n} x_{2k}^2}} \tag{1}$$

We select the top-N sentiment words in the initial lexicon with the closest associations with the specific word i, and the set of top-N positive words is denoted as Pwords and the set of top-N negative words is denoted as Nwords. Then we can calculate the value which can determine the orientation of the candidate word. α_1 and α_2 are two boundary values.

$$\begin{aligned} SO - SD(word) = {} & \sum\nolimits_{pword \in Pwords} SD(word, pword) \\ & - \sum\nolimits_{nword \in Nwords} SD(word, nword) \end{aligned} \tag{2}$$

$$SO - SD(word) = \begin{cases} > \alpha_1, & \text{the word is positive} \\ \in (\alpha_2, \alpha_1), & \text{the word is neutral} \\ < \alpha_2, & \text{the word is negative} \end{cases} \tag{3}$$

According to the value of the equation, we can determine the sentiment of the candidate word. After that, we can get an expanded sentiment lexicon. Finally, we manually inspect all the generated sentiment words.

In our paper, N is set as 50, α_1 is 0.5 and α_2 is -0.8. The expanded sentiment lexicon contains 24,532 positive words and 20,900 negative words.

(2) Aspect-based sentiment extraction

As noted earlier, we need to measure the sentiment with the specific aspects rather than the sentiment of the whole CSR report. Before we train the aspect identification model, we need a labeled dataset. Each paragraph in CSR reports is regarded as one unit for labeling, and it can only cover one aspect. Thus, three experts labeled the paragraphs in CSR reports and determined the aspects of CSR reports. Based on the labeled dataset, we train a keyword-based method for labeling more CSR paragraphs.

For each CSR aspect, each word's TF-IDF can be obtained. Through this process, we can identify the most important words of one aspect. In the meantime, during the manual labeling, some keywords for each aspect have been also identified. The words involved in manual identifications, are accordingly adjusted with a higher TF-IDF weight. Based on the adjusted TF-IDF, we can identify the aspects of other paragraphs by summing the TF-IDF weights of the words after tokenization. The aspect with the highest sum is deemed to be the label of one paragraph.

For each paragraph, we analyze the corresponding sentiment in terms of our constructed sentiment lexicon. The details to calculate the positive valance and the negative valence are depicted below.

(1) Set the positive valence as 0, and the negative valence as 0.

(2) Scan each sentence of this paragraph. For each sentence, scan each word:

- If the word is not in the lexicon, continue to scan words.
- If the word is in the lexicon:
  - If the word belongs to the positive category, and if the previous word is not a negation, add 1 to the positive valence. Otherwise, if the previous word is a negation, add 1 to the negative valence.
  - If the word belongs to the negative category, and if the previous word is not a negation, add 1 to the negative valence. Otherwise, if the previous word is a negation, add 1 to the positive valence.

The scan procedure is repeated till all the words have been processed. Based on the procedure, we can get the positive valence and the negative valence for each paragraph, i.e. each CSR aspect. For each report, we separately sum all the positive valence and all the negative valence in terms of each aspect.

Thus, the sentiment of the aspect t in one CSR report d is calculated below.

$$Sentiment_{t,d} = \frac{Positive\ Valence - Negative\ Valence}{Positive\ Valence + Negative\ Valence} \tag{4}$$

Trade credit

The dependent variable is the trade credit, which refers to the delayed payment between firms and suppliers. In this paper, trade credit is measured by the ratio of accounts payable [3] to the total assets.

Model construction

This paper leverages machine learning to investigate the relationships between the textual features embedded in CSR reports and the trade credit. Specifically, we employ the tree-based model to rank the textual features for filtering the most important features, and meantime apply partial dependence plots (PDPs) to analyze how each feature is linked with trade credit.

In order to obtain the importance of our features as well as the relationships between the features and trade credit, we employ the ensemble trees for better ranking and modeling. Due to the time effect, cross validation is not feasible for model training and testing. We use a five-year rolling window, which indicates that the data of the first four years is as the training set and the data of the current years is as the testing set, and the window rolls till the final year. In order to validate the performance of our models, we utilize R^2 and mean squared error (MSE) as evaluation measures.

Besides the accurate performance, the ensemble trees can also output the importance of input features. In other words, the tree model has good interpretability. In this step, we use relative importance and partial dependency graph to explore the effect of each feature. Relative importance refers to the degree of importance of each feature relative to other features. During the model construction, we can get the relative importance, and rank each feature in our feature set. Besides the relative importance, we also strive to investigate how each feature is associated with the trade credit, i.e. how much each feature contributes to the trade credit. This study employs the partial dependency functions to interpret the generated model, and obtain marginal effect of each feature on the prediction.

Empirical analysis and results

Data description

Our dataset is based on the Chinese market. China's Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) issued relevant documents on corporate disclosure of CSR reports in 2008, and firms are mandatory to disclose CSR reports mandatorily in the following year. The mandatory disclosure policy can alleviate the problem of selection basis to a certain extent. The annual CSR reports are collected from http://www.cninfo.com.cn/, and the period is between 2007 and 2019. In the meantime, the financial data of listed corporations are obtained from the CSMAR database. The dataset contains 7,764 CSR reports. After filtering, e.g. removing the separate CSR reports in the same year for one corporation, the final dataset contains 5,760 reports of 1,135 firms.

Table 1 presents the variables and the measurement. In this paper, we extract the overall readability and fine-grained aspect-based sentiment through natural language processing from CSR reports. In the meantime, we incorporate some common control variables, e.g. firm age. The dependent variable is the trade credit. Notice that there are 13 aspects as mentioned

Variable	Description
Trade credit	The ratio of the sum of the ratio of the sum of account payable, note payable and account receivable to total assets
Readability	Opposite number of Gunning Fog Index
Sentiment	13 fine-grained aspects and the corresponding sentiment (*t* refers to one aspect) $Sentiment_t = \frac{Positive\ Valence - Negative\ Valence}{Positive\ Valence + Negative\ Valence}$
Leverage	The ratio of the total liabilities to the total assets
Assets	Total assets (natural logarithm)
Age	The number of years since a firm's establishment
State	If the enterprise is state-owned then 1, otherwise 0
ROA	Return on assets, the ratio of the net profit to the total asset
R&D	The ration of the net intangible assets to the total assets
CR	The ratio of the current assets to the current liabilities
Year	Year of observations
Ind	Industry dummies, two-Digit CSRC (China Securities Regulatory Commission) codes[a]

Source(s): [a]http://www.csrc.gov.cn/csrc/c101864/c1024632/content.shtml

Table 1. Variables

in previous section, and then there are corresponding aspect-based sentiment. The 13 aspects cover different topics mentioned in CSR reports, shown below.

(1) Shareholders

(2) Creditors

(3) Employees

(4) Suppliers

(5) Customers

(6) Party building

(7) Products

(8) Environment

(9) Community

(10) Intellectual property

(11) Disclosure

(12) Government

(13) Basic information

As noted earlier, we use a five-year rolling window, and according to our data, the window rolls nine times. R^2 and MSE are used for evaluating the performance of different models.

Descriptive statistics

In order to avoid the extreme values, we winsorize the data at the 1% level. Table 2 reports the descriptive statistics of key variables.

The dependent variable, i.e. trade credit, ranges from 0 to 0.561 with a mean value of 0.182, indicating most corporations only receive a small amount of trade credit. The readability is measured via the opposite number of Gunning Fog Index. Notice that Gunning Fog Index refers to the difficulty to read the text. Hence, we use the opposite number of Gunning Fog Index as the readability measure. A larger value represents higher readability. The difference between the maximum value and the minimum value is 12.7 and the standard deviation is 3.1, indicating that CSR reports vary in readability. This table also reports the statistics of the sentiment of 13 aspects. The firms are supposed to depict what they have done in terms of social responsibilities, and the sentiment can signal the extent of these social responsibility activities. If they do not undertake these activities well, the sentiment is relatively low even though firms strive to embellish what they do. On the contrary, if they have done a lot of work on social responsibilities, the sentiment valence is relatively high. For example, the variable *Community* represents the sentiment valence of the text related to "community" issues discussed in CSR reports. Among these aspect-based sentiments, the mean values of Employees, Customers, Shareholders and Basic information are relatively higher, indicating that the fulfillment of social responsibility activities about these aspects has received more attention among firms, while the mean values of Party Building, Government and other related aspects are relatively low, revealing the less attention among these aspects.

Results

This section utilizes an ensemble tree approach to analyze the predictive power of textual features extracted from CSR reports on corporate trade credit. Specifically, we employ the

Variable	Observations	Mean	Std. dev	Min	Max
Trade credit	5760	0.182	0.128	0.009	0.561
Readability	5760	−14.087	3.145	−19.884	−7.149
Community	5760	0.682	0.315	0.000	1.000
Environment	5760	0.632	0.182	0.000	0.955
Employees	5760	0.818	0.059	0.632	0.932
Customers	5760	0.700	0.309	0.000	1.000
Suppliers	5760	0.613	0.354	0.000	1.000
Products	5760	0.697	0.282	0.000	1.000
Government	5760	0.240	0.376	0.000	1.000
Party building	5760	0.298	0.398	0.000	1.000
Shareholders	5760	0.782	0.155	0.000	1.000
Creditors	5760	0.341	0.334	0.000	1.000
Disclosure	5760	0.534	0.221	0.000	0.899
Intellectual property	5760	0.196	0.368	0.000	1.000
Basic information	5760	0.816	0.056	0.651	0.936
State	5760	0.620	0.485	0.000	1.000
Age	5760	24.585	4.963	10.000	43.000
Assets	5760	23.019	1.440	20.168	26.852
CR	5760	1.878	1.783	0.238	12.494
R&D	5760	0.047	0.057	0.000	0.387
Leverage	5760	0.498	0.198	0.069	0.892
ROA	5760	0.043	0.052	−0.153	0.206
Year	5760	2013	3.02	2007	2019

Table 2.
Descriptive statistics

ensemble regression trees due to the continuous credit values. Furthermore, we propose that the decisions of suppliers also depend on the industry area of one corporation. Hence, the industry effect is included in our models. Finally, our feature set consists of 14 textual features, 45 industry classification dummies, and seven financial indicators (i.e. Leverage, Assets, Age, State, ROA, R&D and CR). As noted earlier, due to the time effect, we employ the window-rolling approach with a five-year window. For our dataset, the period is between 2007 and 2019. First, the data from 2007 to 2010 is training dataset, and the data in 2011 is the corresponding testing dataset. Then, the window rolls, and the data from 2008 to 2011 is the second training dataset, and that in 2012 is the second testing dataset. The five-year window rolls a totally nine times.

Models. In order to select an ensemble tree model with the best performance, we employ the grid search method GridSearchCV in a machine learning package Sklearn to select the optimal parameters, e.g. the number of base learners, and the depth of each tree, for diverse ensemble models.

(1) Random Forest (RF)

(2) Extreme Random Forest (ERF)

(3) Adaptive Boosted Regression (ABR)

(4) Gradient Boosted Regression Tree (GBRT)

Table 3 reports the optimal parameters.

We evaluate the performance of diverse models with the measures: R^2 and MSE. Table 4 reports the performance of the ordinary least squares (OLS) regression, and the aforementioned four ensemble models. It can be seen ERF outperforms others with R^2 of 0.727 and MSE of 0.0046. Hence, the results of the ERF models are used for the further analysis.

Table 3.
Parameter selection

Model	Parameters	Optimal parameters
RF	• No. of Trees • The number of features to consider when looking for the best split • The minimum number of samples required to be at a leaf node • Maximum depth of the tree	{200,"auto",1,30}
ERF	• No. of Trees • The number of features to consider when looking for the best split • The minimum number of samples required to be at a leaf node • Maximum depth of the tree	{180,"auto",1,30}
ABR	• No. of Trees • Learning Rate	{80,0.1}
GBRT	• No. of Trees • Learning Rate	{200,0.2}

Table 4.
Model performance

	Training dataset		Testing dataset	
Model	R^2	MSE	R^2	MSE
OLS	0.529	0.0888	0.174	0.0131
RF	0.626	0.0064	0.605	0.0067
ERF	*0.768*	*0.0040*	*0.727*	*0.0046*
ABR	0.590	0.0071	0.576	0.0071
GBRT	0.665	0.0058	0.643	0.0060

Relative importance. Based on the prediction results, this paper has examined the predictive power of our proposed features. We further strive to investigate the importance of these features for predicting, and meantime elaborate on the relationships between the textual features and the trade credit. Thus, according to the feature importance generated by ERF, this paper investigates the relative importance of each feature. In an ensemble tree model, the relative importance of one feature refers to the contribution of this feature. Considering the rolling windows, the relative importance of each feature is the average over sliding windows. Besides, we need to set a cut-off value for identifying the most important features among the total 66 features. If the relative importance of one feature is larger than the cut-off value, this feature is deemed to be one important feature. Based on the generated relative importance, we rank the features, and then we figure out the accumulated importance by incorporating the features one by one, and figure out the corresponding R^2 with these added features. Figure 2 shows the accumulated importance and the corresponding R^2.

The X axis shows the accumulated relative importance, and the range is from 60% to 90%. The Y axis represents the measure of R^2 in the testing data. It can be seen that when the accumulated relative importance increases from 60% to 75%, R^2 presents a rapid increase. After 75%, R^2 increases with a flat slope, indicating that incorporating features after this accumulated importance level for training does not significantly improve the performance of the model. R^2 even decreases after 80%. The possible reason is that the features with relatively low importance bring some noise to the prediction. Hence, based the results in Figure 3, we choose 80% of the accumulated importance as the threshold. The features, the accumulated importance of which achieves 80%, are defined as the important ones among the feature set. In other words, these identified features contribute to the prediction of our dependent variable, i.e. trade credit.

Table 5 reports the important features (i.e. the accumulated relative importance of these features is more than 80%). The results show that 22 features occupy the top 80% of

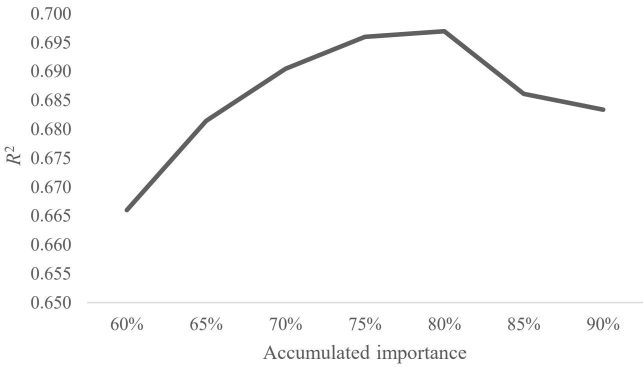
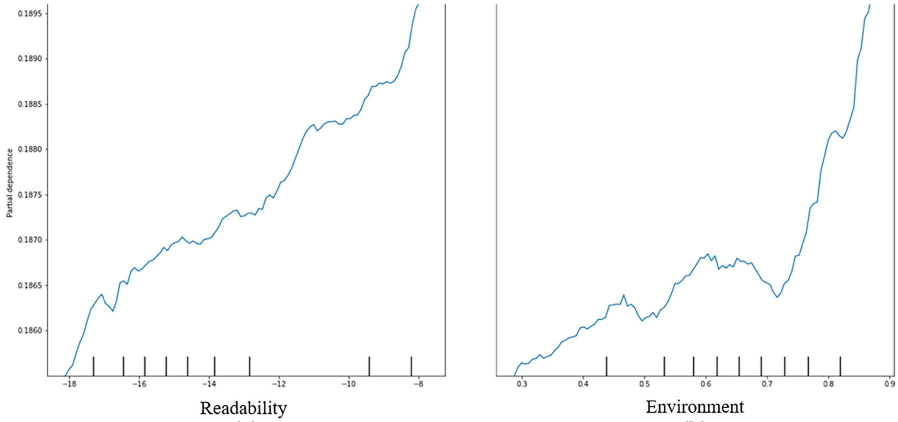


Figure 2.
Accumulated importance



(a) **(b)**

Figure 3.
Positive relationships (a) readability (b) environment

importance out of the total 66 features. Besides, the top 12 features are mainly control variables, which is reasonable since these features have been studied in previous literature and proved relative to trade credit. Among the 22 features, there are seven textual features, i.e. Readability, Creditors, Disclosure, Suppliers, Government, Customers and Environment.

Relationship. After identifying the important features, we further examine how these features affect corporate trade credit through partial dependency plots (PDPs).

As noted earlier, PDP visually presents the average marginal effect of the target feature S on the predicted value of trade credit given a specific value to the target. Through the figures of PDP, we can investigate the relationships between the features and the trade credit, i.e. how the trade credit changes as one feature changes. Based on ERF models, the PDP method generates figures about the relationship patterns of the identified important textual features. Table 6 concludes the relationships.

First, the readability, and the environment-based sentiment are positively associated with the trade credit. Figure 3(a) and (b) present the impact of the two features on trade credit. The readability of CSR reports can be used as an indicator of information manipulation. Higher readability represents lower information manipulation and reveals that this firm is highly involved in CSR activities. Hence, suppliers are more willing to provide trade credit.

Table 5.
Important features

No.	Feature	Relative importance (%)
1	Leverage	19.72
2	Ind = E	7.98
3	CR	4.39
4	Age	3.92
5	Assets	3.85
6	Ind = D	3.77
7	R&D	3.27
8	Ind = C36	3.20
9	Ind = C38	3.16
10	Ind = G	2.97
11	Ind = C35	2.29
12	Ind = F	2.23
13	*Readability*	2.23
14	Ind = C34	2.10
15	ROA	2.00
16	*Creditors*	1.94
17	*Disclosure*	1.86
18	State	1.80
20	*Suppliers*	1.77
19	*Government*	1.64
21	*Customers*	1.59
22	*Environment*	1.59

Table 6.
Relationships of important textual features

Important feature	Relationship
Readability	Positive
Environment	Positive
Suppliers	U-shaped
Disclosure	U-shaped
Creditors	U-shaped
Customers	Negative
Government	Negative

For the environmental aspect in CSR reports, if the sentiment valence of this aspect is high, i.e. the description of this aspect is positive, the firm would receive more trade credit. With the promotion of sustainable development, the industry focuses on the environment. When a firm describes its environment-related activities in a more positive tone, it means that this firm pays attention to the environment and invests a lot in this aspect, which builds a good image to suppliers. Then suppliers are willing to provide more trade credit. This is in line with the conclusion of Xu *et al.* (2020), whose study reveals the fulfillment of social responsibility in the environment positively affects the trade credit.

Second, Figure 4(a)–4(c) present the links between the supplier-based sentiment, the disclosure-based sentiment, the creditor-based sentiment and trade credit. The three relationships are nonlinear U-shaped patterns, which means that the trade credit decreases first and after one threshold it increases as the sentiment becomes more and more positive. There are diverse findings in existing studies about the relationship between CSR and trade credit. For example, Shou *et al.* (2020) revealed a U-shaped relationship between the overall social responsibility performance and trade credit. Our study disentangles social responsibility and divides the activities into 13 aspects. We further explain the U-shaped

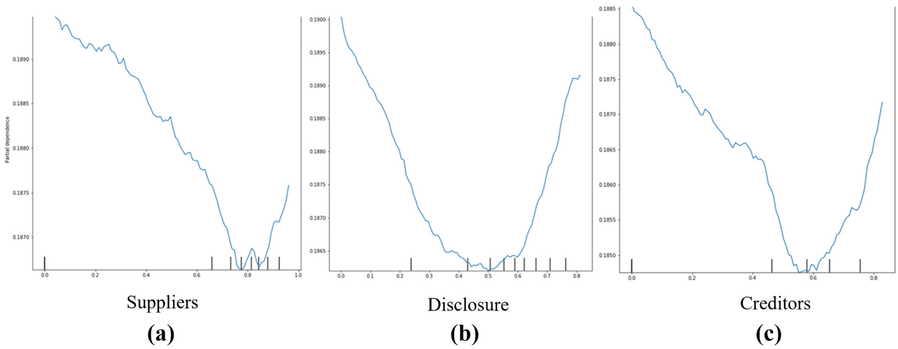


Figure 4.
U-shaped relationships (a) suppliers (b) disclosure (c) creditors

relationships of the three aspects with trade credit. First, due to the limited resources, firms with high social responsibility fulfillment invest much in these activities but gain less return from these expenditures, which may affect their competition and revenue in the market. Second, with the popularity of CSR, some firms may just "pretend" to fulfill the CSR activities. Thus, if the CSR report presents a low level of fulfillment, suppliers may presume that the firm just makes a show. Hence, suppliers may reduce the trade credit accordingly. However, when the extent of fulfillment to the three aspects exceeds some threshold, it is less likely that the firm just makes a show. Instead, the participation and undertaking of social responsibility activities signal high credibility and responsibility of the firm to suppliers. The suppliers would provide more credit to the corporation. In summary, there exists a turning point. If the fulfillment is below the turning point, it would be identified as perfunctory social responsibility in this aspect, and suppliers would punish the "show" by reducing the provided trade credit; while if the fulfillment is high, beyond the turning point, it is a signal of good fulfillment, and then the corporation can obtain more trade credit accordingly.

Specifically, as in Figure 4(a), suppliers are providers of trade credit, and thus supplier-relevant responsibility activities are important inevitably. When the fulfillment is relatively low, i.e. the sentiment of this aspect described in CSR reports is low, trade credit decreases. But when the sentiment exceeds 0.8, trade credit increases since suppliers have noticed the efforts of firms to complete the supplier-relevant social responsibility. In Figure 4(b), trade credit decreases as the disclosure-based sentiment increases because below the threshold 0.5, the disclosure is deemed to be low-quality disclosure, which is not enough to satisfy stakeholders. Hence, when the disclosure is beyond the threshold, the information asymmetry is reduced, which can positively affect the trade credit. The aspect about creditors reveals the solvency of one firm and its attitudes and solutions to the debt. Suppliers, as risk takers, naturally pay attention to this aspect. Similarly, if the sentiment of this aspect is low, it is a signal of a sloppy "show" to suppliers, but when the sentiment surpasses a threshold of 0.6, the fulfillment of this aspect positively affects the trade credit provided by suppliers.

Third, the customer-based sentiment, the government-based sentiment and the employee-based sentiment are negatively associated with the trade credit. The possible explanation is the limited resources and the perfunctory show of some firms. Furthermore, we manually review the CSR reports of some firms and during the process, we mainly focus on the customer and government aspects described in these reports. The results reveal that the corporations simply state the amount of taxes and describe the basic after-sales services to customers, and there is lack of details about the two aspects. Therefore, we presume that if firms can describe with more details about the two aspects, curves would also turn upwards after turning points (see Figure 5).

Robustness checks

In this section, we present robustness checks to validate the robustness of our analysis. We first change the size of the sliding window and evaluate how different sizes affect the results. Besides, we use an alternative measure of trade credit.

Sliding-window size. In the previous analysis, we set the window size as five years. In this robustness check, we change the window size to six years. Accordingly, the data from 2007 to 2011 is used as one training dataset, and the data of the following year, i.e. 2012, is used as the corresponding testing dataset. The window rolls eight times. The extreme random forest is still employed for prediction. Finally, the average of R^2 on the testing datasets is 0.730. Table 7 reports the 22 top features of 80% accumulated relative importance.

There are seven textual features extracted from CSR reports among 22 features. Accordingly, the relationships between these features and trade credit are presented in Figure 6. The results are consistent with the main results.

Alternative measure of trade credit. In our main analysis, we measure our dependent variable through short-term financing of a firm in the current year. In order to validate the robustness of the dependent variable, we use the lagged variable of trade credit as the dependent variable. The results are shown in Table 8, which are consistent with those in Table 5.

Conclusion

Prior studies have addressed the importance of trade credit. While the extant studies have mainly focused on the use of trade credit, and the impact of CSR on trade credit, we investigate the textual characteristics of CSR reports from the perspective of the content, which enriches the measures of CSR.

Discussion

Previous literature usually measures CSR performance with the existing indicators. Our study proposes a natural language processing method to analyze the CSR reports for measuring the fulfillment of different CSR activities. Further, we explore how these textual

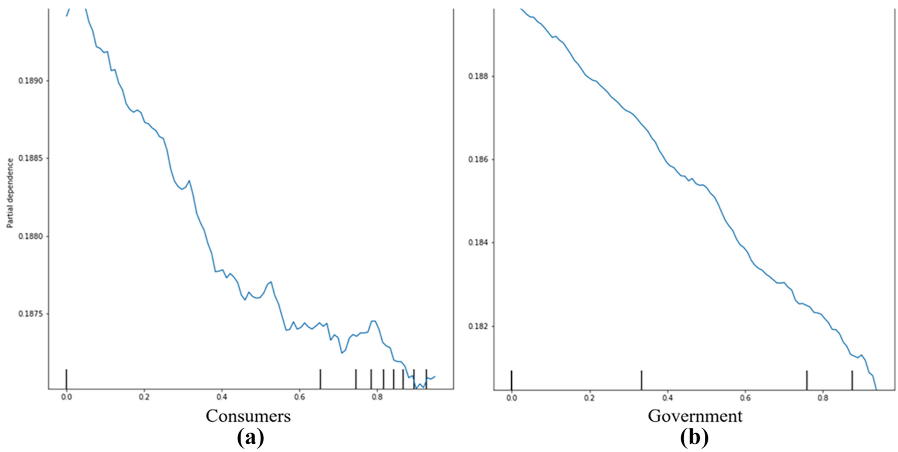


Figure 5.
Negative relationships (a) customers (b) government

No.	Feature	Relative importance (%)
1	Leverage	19.7
2	Ind = E	8.2
3	CR	4.5
4	Assets	4.3
5	Age	3.8
6	Ind = D	3.8
7	R&D	3.3
8	Ind = C36	3.2
9	Ind = C38	3.0
10	Ind = G	2.9
11	*Readability*	2.3
12	Ind = F	2.3
13	Ind = C35	2.3
14	Ind = C34	2.2
15	ROA	2.0
16	*Creditors*	1.9
17	*Disclosure*	1.8
18	State	1.8
19	*Suppliers*	1.8
20	*Government*	1.6
21	*Environment*	1.6
22	*Customers*	1.5

Table 7.
Important features (window size = 6)

characteristics are associated with trade credit with the machine learning techniques, which can explore the nonlinear relationships.

In particular, we mine 13 fine-grained aspects covered in CSR activities (i.e. CSR reports), and extract the sentiment of these 13 aspects which signals the fulfillment of different activities. Moreover, we examine the links between the overall readability of CSR reports and the sentiment and trade credit. Our results reveal that the overall readability is positively associated with trade credit. When the CSR reports are easy to read and understand, it means firms are confident about its CSR activities, and are highly involved in CSR, and therefore firms can obtain more trade credit from suppliers. Meantime, we identify six important aspects, and the relationships between different CSR aspects and trade credit are diverse. There are three kinds of relationships, i.e. positive relationships, U-shaped relationships and negative relationships. The sentiment of the aspect – environment, is positively associated with trade credit; the sentiment of three aspects, i.e. creditors, suppliers and information disclosure, has a U-shaped influence on trade credit, which means the relationships are negative and then positive after some threshold; the sentiment of the government and customers has the negative relationship with trade credit.

Implications

This research contributes to both IS research and finance research in several ways. First, most of the existing studies only measure the general social responsibility via some existing financial metrics, and we measure the social responsibility of firms from a new perspective. More specifically, our study analyzes the responsibility from a fine-grained perspective, which can extend the literature on CSR. Second, despite the importance of CSR reports, little attention has been paid to the associations between the reports and trade credit. This paper investigates the associations between the textual features extracted from CSR reports and trade credit.

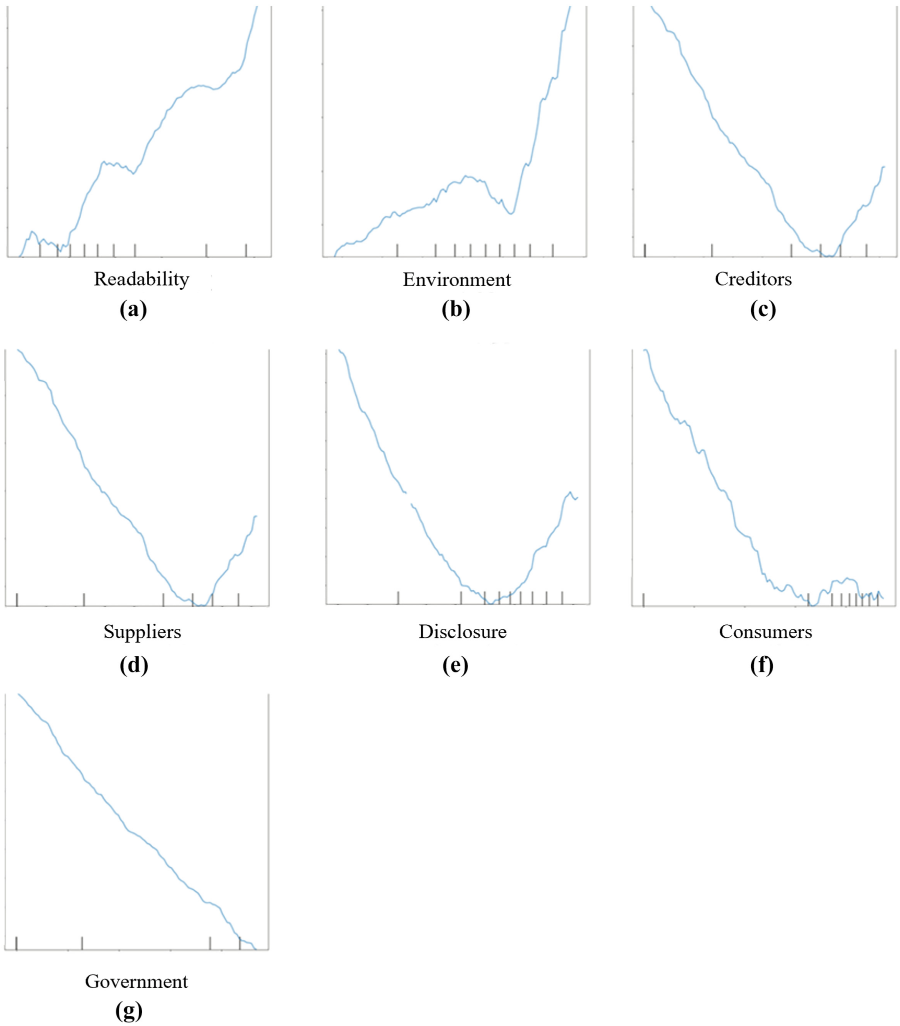


Figure 6.
Relationships

This paper also offers some managerial implications in the allocation of CSR resources and the presentation of CSR reports. CSR reports present the details of CSR activities about firms, but different aspects of CSR activities have diverse relationships with trade credit, a source of short-term financing. Firms need to pay attention to the aspects which are the most significant for obtaining trade credit from suppliers.

Limitations and future work
There are several limitations of our current study, which prompt for further research in the future.

First, we only examine two important textual features. In fact, CSR reports contain rich textual information not limited to the two. We intend to investigate other textual features in CSR reports, e.g. emotions, subjective/objective description in the future.

No.	Feature	Relative importance (%)	Accumulated importance (%)
1	Leverage	18.5	18.5
2	Ind = E	8.1	26.6
3	Age	4.3	30.9
4	Assets	4.2	35.1
5	CR	3.9	39.0
6	R&D	3.5	42.5
7	Ind = D	3.5	46.0
8	Ind = C36	3.2	49.2
9	Ind = G	2.9	52.1
10	Ind = C38	2.9	55.0
11	Ind = F	2.3	57.3
12	ROA	2.3	59.5
13	*Readability*	2.2	61.8
14	*Creditors*	2.1	63.9
15	*Suppliers*	2.1	65.9
16	Ind = C35	2.1	68.0
17	*Disclosure*	2.0	70.0
18	Ind = C34	1.9	72.0
19	*Customers*	1.9	73.8
20	*Government*	1.8	75.6
21	*Environment*	1.8	77.4
22	State	1.8	79.2

Table 8.
Important features (lagged trade credit)

Second, our research strives to examine how CSR reports are associated with trade credit. There are many potential financial indicators which may be affected by CSR reports, e.g. credit ratings, or stock performance. Future work should tap into other sources of financial indicators related to CSR reports.

Notes

1. http://www.rksratings.cn/
2. https://pypi.org/project/jieba/
3. The sum of account payable, note payable and account receivable.

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