Environmental Research ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Credit risk evaluation based on social media

Yang Yang [a,b], Jing Gu [c,*], Zongfang Zhou [a]

[a] University of Electronic Science and Technology of China, Chengdu, 611731, China
[b] University of Delaware, Newark, DE 19716, USA
[c] Sichuan University, Chengdu 610065, China

ARTICLE INFO

Article history:
Received 30 August 2015
Received in revised form
10 December 2015
Accepted 20 December 2015

Keywords:
Credit risk
Social media
Textual analysis
Logit
Probit

ABSTRACT

Social media has been playing an increasingly important role in the sharing of individuals' opinions on many financial issues, including credit risk in investment decisions. This paper analyzes whether these opinions, which are transmitted through social media, can accurately predict enterprises' future credit risk. We consider financial statements oriented evaluation results based on logit and probit approaches as the benchmarks. We then conduct textual analysis to retrieve both posts and their corresponding commentaries published on two of the most popular social media platforms for financial investors in China. Professional advice from financial analysts is also investigated in this paper. We surprisingly find that the opinions extracted from both posts and commentaries surpass opinions of analysts in terms of credit risk prediction.

1. Introduction

Credit risk evaluation, one of the most important considerations of investors, has always been considered as the exclusive domain of specific experts. Various models have been proposed by previous studies to evaluate credit risk (e.g., Li and Zhou, 2011) and for crisis prevention (e.g., Zadeh, 2014), but few of them attempted data driving approaches for risk management based on the internet, especially the effect of social media on the credit risk evaluation process (e.g., Huang, 2013, 2015). In consumer markets, since the emergence of social media and the associated creation and consumption of user-generated content, the advice from experts seems to not be as significant as before. Chen and Xie (2008) reported this new trend in consumer markets during the past five years and Datamonitor (2010) empirically illustrated that the influence of peer-based advice is increasing while that of suggestions from professional experts is decreasing. However, in financial markets, due to the professional technical requirements, the advice from analysts, who eloquently appear in finance channels and irresponsibly forecast the credit risk of financial markets, still affects most investors' assessment of credit risk and investment decisions. Do the opinions pertaining to credit risk from analysts have equal or even greater value than peer-based opinions? And do peer opinions impart value-relevant news or only provide "random chatter", even misleading other participants in contrast? These are the questions we attempt to answer in this paper. A few available studies have mentioned the impact of social media on financial markets. Antweiler and Frank (2004) and Das and Chen (2007) examined the relationship between stock returns and conversation on Internet message boards. Both of them have concluded that the message board information does not make much sense to stock returns. On the other side, Cogent Research (2008) argued that nearly one in four investors in the US directly rely on investment advice imparted via social media outlets.

In this study, logit and probit approaches, which have been proven effective and are widely used in credit risk evaluation are first introduced as the benchmarks. We then conduct textual analysis of posts and their associated commentaries published in the two largest financial social media platforms in China, i.e. Hexun.com and Finance.sina.com.cn. The opinions of analysts from different online resources are also considered, such as their articles, speeches, and financial and economic news, etc. Finally, we investigate the extent to which information asymmetry affects the value of social media and that of analysts. Perhaps this study is most closely related to the research of Chen et al. (2014). They analyzed the articles, and the commentaries written in response to these articles, published in Seeking Alpha and DJ News Service, and pointed out that opinions revealed on social media outlets strongly predicts future stock returns and earning surprise. However, four main facets represent the differences between the study of Chen et al. (2014) and ours. First, our study distinguishes itself from Chen et al. (2014) through its focus on credit risk. Unlike stock returns, credit risk is a more specific consideration which

* Corresponding author.
E-mail address: gj0901@scu.edu.cn (J. Gu).

http://dx.doi.org/10.1016/j.envres.2015.12.024
0013-9351/© 2015 Published by Elsevier Inc.

may provide some detailed insight into understanding how social media affects the financial market. Second, since logit and probit approaches are chosen as the benchmarks, we compare the prediction accuracy of a social media oriented approach and traditional methods. Third, the investors who post or write commentaries in our sample lack incentives, while users can derive significant utility from posting in their samples. Therefore, intuitively, we can expect the posts and commentaries in our sample to be much more arbitrary and relatively less professional and systematic. On the other hand, these posts and commentaries may more realistically reflect the opinions of investors themselves, but not a further interpretation of the mainstream view of analysts. Finally, an information asymmetry effect is also embedded in our study. This is particularly important in Chinese phenomenon. Compared with developed countries, information asymmetry is an important feature in the financial markets of emerging countries such as China. Many investors believe that information superiority, or even internal information, is a determinant factor for whether they will follow the suggestions of analysts about the performance of financial market, in addition to the analysts' expertize.

To preview of our findings, we conclude that the attitudes illustrated both on posts and their associated commentaries by investors can predict the credit risk of enterprises to an extent, although there is lack of incentive for them to do so. The opinions of analysts seem not to make any sense when predicting credit risk, and even perform worse than those of individuals, when we follow suggestions from a specific analyst. Besides, information superiority of analysts, which is a widespread speculation of small investors, does not actually exist. According to our examination, the prediction accuracy of social media is decreased with (increases in) the information asymmetry level. However, even in the Chinese financial market, there is no evidence to show that the analysts can predict credit risk more accurately when there is serious information asymmetry.

This study is, in total, an initial attempt to consider credit risk in big data phenomenon. It contributes to several lines of research. First, our study is a response to the literature pertaining to the effect of social media on financial markets (e.g., Dougal et al., 2012, Gurun and Bulter, 2012, Solomn, 2012), and provides Chinese evidence that the "crowd" can not only provide value-relevant prediction of credit risk, but also seems more wise than professional analysts. In addition, we speak to literatures that discuss peer-based advice in different domains (e.g., Chevalier and Mayzlin, 2006, Chen and Xie, 2008). Arguably, credit risk is complicated and should be better analyzed by investment professionals. However, our evidence shows that the analysts seem to not make any sense in prediction of it or are even worse than large plausible crowds. This may illustrate that the analysts' job is fraught with built-in conflicts of interest and competing pressures (e.g., Daniel et al., 2002) on one hand. And on the other hand, it also indicates that data-driving technology may transform the traditional credit risk evaluation approach and change the position of professional analysts. In the future, I believe there will be no babble of so called professional analysts, but only you and me.

The remainder of our study is organized as follows. We explain the approaches, proxies, and samples applied in our study in Section 2. In Section 3, we first evaluate the credit risk using logit and probit approaches as the benchmarks, and then conduct textual analysis to investigate the impact of opinions both revealed in social media and by professional investment on credit risk prediction. Information asymmetry is introduced in our model, while an analysts' view is considered in detail at last. Section 4 is the conclusion and discussion of this study.

2. Methods and samples

There are various methods for evaluating the credit risk of firms, including classical statistical discrimination approaches (e.g., Altman et al., 1977, Scott, 1981), neural network algorithm (e.g., Shah and Murtaza, 2000), data mining technology (e.g., Sung et al., 1999) and rough sets theory (e.g., Mckee, 2000) etc. Nevertheless, logit and probit approaches are justified by many previous studies as the most appropriate approaches for credit risk evaluation (e.g., Su and Huang, 2010, Hassan and Hassan, 2013). In this paper, both logit and probit approaches are used to provide the benchmarks. These two approaches are essentially two classification methods, which are proposed by Martin (1977) and Zmijewski (1984) respectively, and are widely used in credit risk evaluations. To extract investors' opinions about credit risk, we build on prior literature (e.g., Morinaga et al., 2002) in part. Key sentences or expressions pertaining to credit risk are extracted with an information criterion, which was derived using some key words involved in different facets of credit risk. This criterion was developed, and is now continuously improved, by us. Table 1 partially shows the framework of this criterion.

Furthermore, drawing on Tetlock et al. (2008) and Loughran and McDonald (2011), we make frequent use of negative words used in posts, commentaries, and articles to capture the tone of the opinions, since positive words are often negated to convey negative expressions. In this study, $Neg_i$and $NegCom_{i,}$ are used as the key indicator variables, which represent the average fraction of negative words across all posts and commentaries or articles and commentaries in response to aforementioned posts, commentaries or articles. Following Chen et al. (2014), we organize our main analysis around the regressions specification.

$$Cr_i = \alpha + \beta_1 Neg_i + \beta_2 NegCom_i + X\delta + \epsilon_i \tag{1}$$

Cr_i is a dummy that represents the credit status of a specific enterprise i. And X includes the following variables: total amount of posts, commentaries or articles for a specific enterprise, $Tpub_i$; The size of the enterprise is measured as the total assets, Siz_i; Market value of the enterprise $MarV_i$; and average trading volume Vol_i.

We use the Chinese listed companies from 2009 to 2014 as our samples. The sample size is 11,034 after data cleaning and exclude the samples with less than 30 posts of information or with financial data anomalies, including 2361 ST samples and 8673 non-ST samples. We divide these samples into two parts. The first is the training sample, which consists of 1981 ST samples and 7278 non-ST samples. And the second part is the testing sample, which consists of 380 ST samples and 1395 non-ST samples. The variables we used in benchmarks are listed in Table 2. According to Yang et al. (2013), to avoid the inconsistencies of different enterprises, we standardized all indicators and made the value of all variables fall within internal [0, 1].

The regression (1) actually illustrates two models we proposed in this study. In model one, Neg_i and $NegCom_{i,}$ refer to the fraction of negative words in posts and associated commentaries published in Hexun.com and Finance.sina.com.cn respectively by crowd

Table 1
Framework of extracting criterion.

Content	Opinions
Financial status	Worries, predictions, explanations, etc.
Operation	News, technologies, strategic changes, etc.
Executive	Risk attitude, experience, etc.
Marketing	Prospect, competitors, upstream and downstream etc.
Major Issues	Mergers, restructuring, major investment, etc.