Research on the financing dynamics of product crowdfunding: based on the perspective of emotion

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Abstract: Product crowdfunding provides new financing channels for entrepreneurs. How to screen crowdfunding projects has become an important issue in this field, and the financing dynamics of projects is the starting point to study the filtering of crowdfunding projects. Based on the perspective of emotions, this paper uses text analysis technology to extract the emotions contained in the comments of crowdfunding projects, and analyzes the influence of emotions on the dynamics of project financing. The main conclusions are as follows: for financing dynamics, anticipation, trust and sadness can help to increase the number of subsequent investors, while joy and disgust have significant negative effects on the number of subsequent investors. The conclusion of this paper is useful to the protection of crowdfunding investors and the operation practice of crowdfunding platforms.

1. Introduction

Small and micro businesses and individual entrepreneurs are important force in China's economic development, but they have few tangible assets and the risk of seed-stage innovation projects is high, so it is difficult to obtain financing from traditional financial service institutions. The crowdfunding model based on the Internet and mass participation brings new financing channels for such groups. Crowdfunding refers to the financing method for entrepreneurs to raise funds for the public by releasing innovative projects on the Internet. According to the form of return to donors, crowdfunding can be divided into donation crowdfunding, product crowdfunding, lending crowdfunding (P2P lending) and equity crowdfunding. This paper studies product crowdfunding, the entrepreneur's reward to the sponsor is the project's product or service.

With the rapid development of the crowdfunding industry, it faces challenges and risks. Compared with mature products sold on e-commerce platforms, the products in the crowdfunding model are the first to be developed and put on the market. Some products even have only creative concepts, and there are still risks in the subsequent development and production. In the face of project failure and entrepreneur fraud risk, how to effectively filter the project is an important problem that the industry and academia need to solve. The screening of crowdfunding projects is generally divided into two steps: the first step is the platform's screening of the qualifications of project sponsors and project quality before the project is released, which includes manual auditing or automatic screening of machine
learning models. The second step is that during the project financing, the investment decision of the project investors can also realize the screening of the project, because only the project that achieves the financing goal can finally get the funding, so the analysis of the crowdfunding project financing dynamics is a key entry point for the project filtering.

At present, there are few results of financing dynamics in the process of project financing. Most scholars who study the performance of crowdfunding focus on the financing performance of crowdfunding, that is, the failure or success of financing and the proportion of financing completion. In project comments, it is not enough to focus on the number of comments in previous studies, and the information contained in the comments themselves is also a key factor affecting the investor's decision. An important reason is that there are complex emotional experience processes behind people's consumption and investment processes, and emotions will affect people's consumption and investment decisions. This paper focuses on the value of the emotional information contained in the project comments for project filtering, uses the text analysis technology of natural language recognition to analyze the crowdfunding project comments, extracts the various emotions contained in the comments, and analyzes the impact of different kinds of emotions on the project financing dynamics. This research extends the academic community's understanding of the behavior of crowdfunding participants, helps project sponsors to improve the success rate of financing from the perspective of emotion, and also helps investors and crowdfunding platforms to filter projects and establish early warning models.

2. Model

This paper takes the emotion variables as the main focus variables and a series of variables related to the basic information and quality information of the project as the control variables. Six quantified emotions were included in the model as main variables to explore the impact of emotional on financing dynamics. The model is as equation (1):

\[
\text{Model I: } y_{it} = \alpha + \beta_1 E_{it} + \beta_2 Z_{it} + e_t + v_{it}
\]

Where, subscript i represents the ith project, and subscript t represents the day t after the project financing starts. \(y_{it}\) represents the number of new investors on day t, which means the number of new investors in the project i on day t. \(E_{it}\) represents the variables of change over time, including the focus of this article 6 kinds of emotions in the accumulation value of days by the end of the first t days, by the end of the first t days cumulative number of investment, the t day in financing is the first week or the last week, the t day is which day of the week, and whether the project has been reach the target in t day. \(Z_{it}\) represents the variables in the ith project that do not change over time, including financing target amount, financing period, project title length, project description length, and project return type quantity. In addition, \(e_t\) represents residuals that do not change over time, and \(v_{it}\) represents residuals that change over time. At the same time, in order to increase the robustness of the model, improve the fitting effect of the model, and reduce the endogenous risk, variables related to basic project information and project quality information are included in the model as control variables of the model.

3. Data

In this paper, the data collected from the first domestic product crowdfunding platform: demohour (www.demohour.com), picked from July 1, 2011 to July 2, 2014, all the completed financing projects as data source. Data items are included in the basic project information, sponsors, investors, and the whole investors and sponsors’ text comments during project. After 2014, demohour transformed into a crowdfunding platform specializing in innovative hardware, and its business model changed. Therefore, the subsequent data of the platform is not suitable for this paper.

From 2011 to 2014, more than 900 projects were launched on the platform. After deleting the projects that did not complete the whole project process and the projects with incomplete collection data in this paper, the remaining 841 projects were effective. The data processing process of this paper is mainly aimed at project comments, collecting 71832 comments in 841 projects, including 23,705 comments from sponsors and 48,127 comments from investors. Based on Plutchik's theory of emotional evolution
and the NRC vocabulary, this paper uses a computer to slice each comment into six emotional dimensions (anticipation, joy, trust, surprise, sadness, disgust). Each comment constructs an emotional vector that measures the emotional value of the comment.

Calculate the sentiment vector for each comment. Felbermayr and Nanopoulos first try to use the NRC word library to build emotion vectors, they pick up the words in the text, matching the vocabulary and the NRC sentiment dictionary, matching to the words can be classified as 6 kinds of emotion, respectively, a comment of one kind of emotion word in the higher frequency, then the sentence can express the emotions of the greater the vector-valued. When a word appears many times in a sentence, this paper believes that the emotion it expresses will be attenuated, so the square root of the frequency of occurrence of the word is selected to be included in the final vector: [disgust, anticipation, joy, sadness, surprise, trust]. The emotional vector calculation formula for each comment is as equation (2):

\[ \text{sentence}_\text{Vector} = \sum_i \sqrt{\frac{\text{word}_\text{num}_i}{\text{word}_\text{Vector}_i}} \]  

\( i \), the number of emotional words in a comment (repeat as once); \( \text{word}_\text{num}_i \), the number of the ith emotional word; \( \text{word}_\text{Vector}_i \), the emotional vector of the ith emotional word in the lexicon; \( \text{sentence}_\text{Vector} \), the emotional vector of the comment.

Calculate the daily cumulative emotional vector for each item. The daily cumulative emotional vector of each item is mainly obtained by adding weights to the emotional vector of each comment published that day. Is weighted sum after first, mainly considering the because of the limitation of web page window size, investors cannot see all comments directly, and the first release comment will be displayed in the comments section the top or the first few pages, the more the greater the impact of new comments on subsequent investors, therefore this article comments on the new release with greater weight, the weight given to earlier published comments of the smaller.

Suppose a project has \( m \) days and \( N \) comments a day. You can calculate the daily emotional vector by following the following three steps: Calculate the emotional vector for each comment; Sort comments by date; Assign weight and sum to each day's comments in the order in which they are published. The earlier the comments are published, the smaller the weight. The calculation formula of the daily cumulative emotional vector of each item is as equation (3):

\[ \text{Day}_\text{Vector}_m = \sum_n \frac{1}{\sqrt{\frac{N_m}{n_m}}} \text{sentence}_\text{Vector}_{n_m} \]  

\( n_m \), the order in which comments are posted on day \( m \); \( N_m \), total number of comments posted on day \( m \); \( \text{sentence}_\text{Vector}_{n_m} \), the emotional vector of the mth day and nth comment.

Calculate the cumulative vector of all comment sentiment by the end of the day for each item. Panel data is used to study the influence of emotion on financing dynamics. From the perspective of investors, comments are dynamic and each comment has a different impact on investors due to its release time. Therefore, the cumulative impact of all comments on each item before the current date should be calculated. In this paper, the method of calculating the accumulation emotion vector of all comments by the end of the day for each item is basically consistent with the method of calculating the daily accumulation vector. The only difference is that all comments before that day are considered to have been posted at different times on the same day, and are given different weights according to the chronological order. After summing up, the cumulative vector of all comments before that day is obtained.

According to the calculation method of various emotional vectors described above, a total of 31401 valid samples were formed for financing dynamic research. In addition to the "0-1" variable, other explanatory variables are incorporated into the model after the logarithm is taken.

4. Conclusion
The explained variable of model I is the number of new investors in the next phase. When the explained variable is a discrete counting variable, poisson regression or negative binomial regression is generally selected to estimate the parameters. The variance of the number of new investors in the next phase of
the explained variable is 308.3997, while the expectation is 3.024671. The result of dividing is 101.96138. When the variance is greater than the expectation, the variable is too dispersed. Therefore, the negative binomial regression of panel data should be used for parameter estimation in this paper. The result of Hausman test is 825.73, and the p value is close to 0, indicating that the fixed effect model of negative binomial distribution should be used.

The results obtained by using Stata13 are shown in table 1, where model_1.1 represents the model results with only control variables, model_1.2 is the complete model, and model_1.3 is the robustness test model. The Wald test result of model_1.2 is 7362.31, and the p value approaches to 0, indicating that the overall model is relatively significant. Comparing the model with emotion variables and the model with only control variables, it is found that the Wald Chi^2 and Log likelihood values of the model increase after the addition of emotion variables, indicating that the overall fitting effect of the model is improved. However, as more variables were added, both AIC and BIC declined, but not by much, indicating that the "penalty" for adding these new variables was not serious.

| Variables                        | Model_1.1       | Model_1.2       | Model_1.3       |
|----------------------------------|-----------------|-----------------|-----------------|
| Ln_Anger_{it}                    | -0.0547**       | -0.0547         | -0.0547**       |
|                                 | (0.0206)        | (0.0206)        | (0.0206)        |
| Ln_Fear_{it}                     | 0.0688**        | 0.0688          | 0.0688**        |
|                                 | (0.0212)        | (0.0212)        | (0.0212)        |
| Ln_Joy_{it}                      | -0.0815***      | -0.0782***      | -0.0782***      |
|                                 | (0.0204)        | (0.0204)        | (0.0204)        |
| Ln_Anticipation_{it}             | 0.0536**        | 0.0533**        | 0.0533**        |
|                                 | (0.0193)        | (0.0193)        | (0.0193)        |
| Ln_Trust_{it}                    | 0.1396***       | 0.1393***       | 0.1393***       |
|                                 | (0.0211)        | (0.0211)        | (0.0211)        |
| Ln_Sadness_{it}                  | 0.0862***       | 0.0690***       | 0.0690***       |
|                                 | (0.0172)        | (0.0194)        | (0.0194)        |
| Ln_Surprise_{it}                 | -0.0180         | -0.0109         | -0.0109         |
|                                 | (0.0182)        | (0.0186)        | (0.0186)        |
| Ln_Disgust_{it}                  | -0.0523**       | -0.0495**       | -0.0495**       |
|                                 | (0.0174)        | (0.0186)        | (0.0186)        |
| Ln_PastBackersit_{it}            | -0.2212***      | -0.2373***      | -0.2372***      |
|                                 | (0.0074)        | (0.0075)        | (0.0075)        |
| Ln_DayofWeek_{it}                | -0.1216***      | -0.1216***      | -0.1216***      |
|                                 | (0.0103)        | (0.0103)        | (0.0103)        |
| FirstWeek_{it}                   | 0.7462***       | 0.7330***       | 0.7338***       |
|                                 | (0.0195)        | (0.0196)        | (0.0196)        |
| LastWeek_{it}                    | 0.2927***       | 0.2869***       | 0.2839***       |
|                                 | (0.0204)        | (0.0204)        | (0.0204)        |
| Postfunded_{it}                  | -0.0187         | -0.0592         | -0.0593         |
|                                 | (0.0242)        | (0.0245)        | (0.0245)        |
| Ln_Goal_{it}                     | -0.0241         | -0.0424**       | -0.0403**       |
|                                 | (0.0136)        | (0.0138)        | (0.0138)        |
| Ln_Duration_{it}                 | -0.0678         | -0.0418         | -0.0442         |
|                                 | (0.0403)        | (0.0405)        | (0.0407)        |
| Ln_TitleLength_{it}              | 0.1825***       | 0.1913***       | 0.1935***       |
|                                 | (0.0488)        | (0.0488)        | (0.0489)        |
| Ln_DescriptionLength_{it}        | -0.0321         | -0.0224         | -0.0228         |
|                                 | (0.0284)        | (0.0283)        | (0.0284)        |
| Ln_RewardOptions_{it}            | 0.2792***       | 0.2676***       | 0.2728***       |
|                                 | (0.0340)        | (0.0339)        | (0.0340)        |
5. Discussion

The data analysis results show that some hypothesizes are verified. First, the accumulation of anticipation will help increase the number of investors in the next phase. The accumulation of anticipation suggests that investors have high hopes of receiving products and services in the future and are more willing to invest in crowdfunding projects. Second, the accumulation of trust will help increase the number of investors in the next phase. In Harms research, it was found that trust was derived from the previous experience of the project sponsor and the attitude of project responsibility, which made investors more inclined to help the project sponsor complete the financing goal. Third, the accumulation of disgust is not conducive to the next phase of the increase in the number of investors. Disgust is different from the usual negative emotions, it is more intuitive than the other two negative emotions, like surprise and sadness.

Some hypothesizes are rejected by empirical results. First, the accumulation of joy is not conducive to the next phase of the increase in the number of investors. Joy is a typical positive emotion, but the project comment is a text message, its action path is different from the traditional video. The text of joy is generally short with little information content. Therefore, the outburst of joy is negatively correlated with the number of newly added investors. Secondly, the accumulation of sadness is conducive to the increase of the number of investors in the next phase. Crowdfunding platforms are highly interactive, and the sadness reflected in the comments is easy to detect. In addition, sadness can arouse sympathy, and investors' funding of projects has other motives, so sadness can encourage more investors to participate in funding. In addition, for project sponsors, in order to eliminate the adverse impact of such comments, they need to disclose more project information or upgrade the project, which reduces the information asymmetry. Third, the accumulation of surprise has no significant effect on the number of investors in the next period.

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