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How Does Fundraiser-claimed Product Innovation Influence Crowdfunding Outcomes

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Abstract

The crowdfunding platforms have always been dedicated to supporting and inspiring innovative, and creative campaigns. However, limited research has been done to examine the fundraiser-claimed product innovation in campaign descriptions and its relation to fundraising performance. In this paper, we aim to tackle this important yet understudied problem. More specifically, we adopt a deep learning-based approach to extract sentences that contain innovation claims from project descriptions. We then conduct an empirical analysis to study the relation between fundraiser-claimed product innovation and crowdfunding performance by using a large sample consisting of 11,521 projects collected from Kickstarter across 4 project categories. Findings show a statistically significant association between fundraiser-claimed product innovation and crowdfunding performance. Additionally, the number of focal project innovation claims has a curvilinear relationship (inverted 'U' shape) with crowdfunding performance. Our study contributes to both product innovation detection and crowdfunding literature by demonstrating the association between product innovation presentation and crowdfunding performance.

Keywords: reward-based crowdfunding, product innovation, text mining, deep learning

1. Introduction

Reward-based crowdfunding has become increasingly prevalent as it enables project creators to advertise innovative products (Butticè et al., 2017; Sayedi & Baghaie, 2017; Stanko & Henard, 2016)), obtain feedback on product development (Cornelius & Gokpinar, 2020; E. R. Mollick, 2015), test market demand (Althuizen & Chen, 2021), and seek financial support from the general public (Belavina et al., 2019; Butticè et al., 2017; Chakraborty & Swinney, 2020) in getting their creative works off the ground. However, running a successful crowdfunding campaign is always challenging and demanding. Extent literature showed that several antecedents (e.g., creators' characteristics, campaign design, platform competition) could influence the performance of crowdfunding campaigns (Bapna & Ganco, 2021; Kim et al., 2022; Roma et al., 2018; Younkin & Kuppuswamy, 2018). Innovativeness, as expected, is one of them. Reward-based crowdfunding has been particularly admired for its promise to bring innovative products to the market (E. Mollick & Robb, 2016). Individuals prefer to support campaigns that offer such novelty (Taeuscher et al., 2021) and value the experience involved in the innovative product development and realization process (Cornelius & Gokpinar, 2020). Thus, an exploration of how product innovations affect the crowd's backing decision on these crowdfunding platforms is needed.

Some existing works focused on examining how backers' perception of project innovativeness affects campaign performance (Chan & Parhankangas, 2017; J. J. Li et al., 2017). However, we are interested in studying the effort creators put into promoting innovativeness in the campaign (i.e., innovation presentation or claimed product innovation). Crowdfunding allows creators to crowdsource capital before the realization of their works. Potential backers mainly rely on campaign information provided by the creators to make the judgment. Therefore, creators may treat campaigns as promotion opportunities and carefully design "pitches" (aka project descriptions) to persuade potential backers by emphasizing how innovative their works are. Although a few studies also studied the impact of creator-claimed innovativeness in their campaigns, they defined innovation claims as innovation-related keywords, such as "innovative", "creative", or "unique" (Lins et al., 2016; Mukherjee et al., 2017; Seigner et al., 2022). In this work, innovation claims instead refer to sentences written by creators to describe the newness, improvement, or

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advantages of work with respect to certain features or functions.

To begin with, we adopt a deep learning-based natural language processing model to first identify creators' claimed innovativeness from campaign descriptions and then use empirical models to measure its association with campaign performance. Our empirical analysis suggests that the performance of campaigns has a curvilinear (inverted ‘U’) relationship with creators’ claimed innovativeness. Either too few or too many innovation claims degrade the performance. A balanced level of claimed innovativeness benefits campaigns the most. Our study enriches crowdfunding and innovation literature and provides practical guidelines to project creators for better design of their project “pitch”.

The remainder of this paper is organized as follows. In Sections 2 and 3, we present the related literature and develop our hypotheses. Next, we introduce the research context and data in Section 4, followed by empirical analysis, and robustness checks in Sections 5 and 6. Finally, we conclude the paper in Section 7 with a discussion of the limitations and implications.

2. Related Research

To fully unleash the benefits of crowdfunding, project creators need to get the crowd involved in their projects (Cholakova & Clarysse, 2015; E. Mollick, 2014; Valanciene & Jegeleviciute, 2013). A great amount of effort has been devoted to studying factors that influence a backer's investment behavior in a crowdfunding campaign from different perspectives. Some works investigated platform-related factors such as competition and platform types (Belavina et al., 2019; Coakley et al., 2021). From the creator’s perspective, prior studies examined the impact of location, gender, race, and social capital (Bapna & Ganco, 2021; Chan et al., 2018; Duan et al., 2020; Kao et al., 2022; Lin & Viswanathan, 2015; Younkin & Kuppuswamy, 2018; Zheng et al., 2014). Researchers also studied the motivation behind backers’ behavior (Cornelius & Gokpinar, 2020; Herd et al., 2021; G. Li & Wang, 2019; St John et al., 2021). Another stream of works focused on factors related to campaigns, such as reward options, funding goals, duration, and campaign descriptions (Du et al., 2020; Hu et al., 2015; Salahaldin et al., 2019; Wei et al., 2022; Wessel et al., 2019; Yang et al., 2020; Zhou et al., 2018).

Our research is closely related to the literature on project innovativeness and campaign design. Some related works examined how backers’ perception of project innovativeness affects campaign performance (Chan & Parhankangas, 2017; J. J. Li et al., 2017). For example, Chan and Parhankangas asked 390 participants to view video pitches, then rate the innovativeness of 334 campaigns (Chan & Parhankangas, 2017). Using a different angle from the creator's perspective, we focus on the creator-claimed innovativeness in project descriptions. A few studies also investigated claimed innovativeness (Seigner et al., 2022). However, in these studies, they defined innovation claims as innovation-related keywords or phrases, such as “innovative”, “creative”, “new product”, or “significant improvement”, and used pre-defined dictionaries to match those words or phrases (Lins et al., 2016; Mukherjee et al., 2017; Seigner et al., 2022). In our study, we refer to creator-claimed innovativeness as sentences that describe the newness, improvement, or advantages of a product with respect to certain features or functions.

A pre-defined word dictionary is not available and generalizable for such a complex task. It is hard to capture all the relevant keywords and their variants that are related to the newness, improvement, or advantages of different products. In addition, innovation claims may be captured by the entire sentences, instead of certain keywords. Therefore, we train a deep learning-based natural language processing model to understand the complex language patterns and then automatically identify creator-claimed innovativeness sentences in project descriptions. Other studies also benefit from prior research on information extraction which leveraged machine learning to extract desired information from massive text data. For example, Abrahams et al. used an integrated text analytic framework for product defects discovery from online user-generated content (Abrahams et al., 2015), and Zhang et al. proposed a deep learning-based approach to identify sentences that contain innovation ideas from online reviews (Zhang et al., 2021). However, studies that use machine learning methods to extract innovation-related information from crowdfunding campaign descriptions are rarely seen in the literature. This is likely due to the lack of annotated dataset. To tackle this issue, we train a machine learning model using a large manually annotated dataset and demonstrate the capability of this method to automatically detect innovation-related information in campaign descriptions.

3. Hypothesis Development

As mentioned earlier, reward-based crowdfunding is centered around innovation as it aims to help bring creative projects to the market. People generally view innovative crowdfunded products as of higher quality (Acar et al., 2021; Chan &

Parhankangas, 2017). Also, backers often value the experience involved in the innovation development and realization process (Cornelius & Gokpinar, 2020). Thus, emphasizing innovativeness in a campaign description encourages potential backers to support the project due to increased perceived value (Zeithaml, 1988). Thus, we have

H1 *Creator-claimed innovation presentation in campaign description is positively related to campaign performance.*

On the other hand, crowdfunding is high-noise and uncertain investment environment, which allows creators to crowdsource capital before the realization of their works. According to a study (E. R. Mollick, 2015), only 65% of backers were satisfied with the delivery time, and 9% of crowdfunding campaigns on Kickstarter even failed to deliver rewards. Too much emphasis on innovativeness in a crowdfunding campaign description draws potential backers' attention to the complexity and challenges of the project, thus may evoke perceived uncertainty (Aulia et al., 2016) about the creator's ability to fulfill the campaign promises. Therefore, promoting too much innovativeness may degrade the campaign's performance. Stated formally:

H2 *Too much innovativeness presentation in campaign description (measured by the number of innovation sentences) is negatively related to campaign performance.*

4. Research Context and Data

We collect data from Kickstarter, a leading reward-based crowdfunding platform launched in 2009. As of June 2022, Kickstarter raised over 6 billion dollars from 21 million backers to fund 221,880 creative projects[1]. On the platform, each project has a campaign page where creators (fundraisers) list information about, including but not limited to, creative work, fundraisers, rewards, updates, campaign duration, and funding goals. Individuals who visit the page decided whether they are willing to back the project based on the listed information.

4.1. Data

We collect a sample of 11,751 campaigns launched between June 2020 and November 2021 across 4 categories: Craft, Design, Technology, and Fashion. We choose these categories because they offer tangible and functional products. Thus, we can extract information related to product innovation. For each project, the data set covers information about creators (e.g., *# of created projects on Kickstarter*, *# of backed projects*), product (e.g., *story length*, *risk length*, *# of images*, *# of videos*), and campaign (e.g., *goal*, *duration*, *# of updates*). We use the total number of backers (*# of backers*) and total dollars pledged (*pledged money*) as two measures for the outcome of a project. We restrict our sample to English-language projects. Following prior studies (E. Mollick, 2014; Wei et al., 2022), we exclude projects with goals smaller than $100 or greater than $1,000,000.

4.2. Innovation claims

We utilize a deep learning model to automatically identify sentences related to product innovation claims. To train the model, we construct a dataset of annotated product description sentences. In detail, we randomly select 1000 project stories and ask 3 human labelers to annotate each sentence in these 1000 stories, where 1 indicates a sentence containing a product innovation claim and 0 otherwise. According to our definition, product innovation claims are sentences that describe the newness, improvement, or advantages of a product with respect to certain features or functions. We determine the final label of each sentence via a majority vote of the 3 labelers (kappa score of 0.81) (Fleiss et al., 2003). In total, there are 30,628 sentences extracted from 1,000 stories. 4,365 (14.25%) of them are labeled as product innovation claims. Table 1 presents 5 examples.

Table 1. Product innovation related sentences

1	This tool is fast and efficient, with low noise output.
2	It sucks the dust created from the finishing of all products directly into the table, drastically reducing the dust reaching the air.
3	What's important to know is our sunscreen does NOT contain parabens.
4	Our products are tougher, more sanitary, withstand much more use, and can potentially outlive the user.
5	It is one of the most enjoyed American hardwoods for its fine-yet-open grain, unique patterns, and bold dark color.

Due to its superior performance on a wide variety of text classification tasks, we use our annotated dataset to fine-tune a bidirectional transformer-based language model (BERT) (Devlin et al., 2019) pre-trained on Wikipedia and Books Corpus, to classify

[1]Source: https://www.kickstarter.com/help/stats

Table 2. Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
# of backers	265.2	1,005.22	0	36,728
pledged money (USD)	36,972.88	186,288.73	0	5,858,772
goal (USD)	19,013.72	50,355.55	100.49	988,900
duration	33.86	12.29	1	120
staff pick	0.08	0.28	0	1
# of faqs	1.92	4.78	0	77
# of updates	3.39	4.31	0	58
facebook connection	0.2	0.4	0	1
# of images	16.77	16.99	0	205
# of gifs	2.41	4.7	0	60
# of videos	0.87	1.88	0	30
story length	616.79	503.13	0	4,395
risks length	109.55	92.13	0	1,006
# of created projects	2.25	3.48	1	55
# of backed projects	6.05	25.61	0	804
# of collaborators	0.85	1.74	0	20
# of innoClaims	5.86	7.12	0	35

whether or not a product description sentence contains innovation claim. We use cross-validation to optimize hyper-parameters and early stopping to prevent overfitting. The best model achieved 0.87 accuracy with 0.84 F1-score (0.82 precision and 0.87 recall) on the test set.

To find out the number of innovation claims (*# of innoClaims*) for each project, we apply the trained model to sentences in each project story and count the total number of sentences containing innovation claims. We observe the minimum value for the *# of innoClaims* is 0 and the maximum value is 89. However, 95% of the projects have fewer than 35 innovation claims. We exclude projects with more than 35 claims to remove the outliers for further analysis. Table 2 shows the summary statistics for our data.

5. Empirical Models and Findings

To test our first hypothesis, we regress the log-transformed outcome of a project on *# of innoClaims*, while controlling other project features and creator characteristics. The equation below shows the model specification:

$$\begin{aligned} log(\#\ of\ backers_i) &= \alpha + \beta_1 \cdot \#\ of\ innoClaims_i \\ &+ \gamma' Project\ Controls_i \\ &+ \delta' Creator\ Controls_i + \varepsilon_i \end{aligned}$$

The specified model is estimated using OLS regression with robust standard error. Column (1) in Table 3 presents the estimated results. Hypothesis 1 is highly supported. The positive and significant coefficient of *# of innoClaims* ($\hat{\beta}_1 = 0.0306,\ p < 0.01$) demonstrates that fundraisers claimed product innovation is positively associated with crowdfunding outcomes.

In the second hypothesis, we want to test whether or not a project's outcome exhibits an inverted U-shaped relationship with *# of innoClaims*. On top of the previous model, we add a quadratic term of *# of innoClaims*. The model specification is shown as follows:

$$\begin{aligned} log(\#\ of\ backers_i) &= \alpha + \beta_1 \cdot \#\ of\ innoClaims_i \\ &+ \beta_2 \cdot \#\ of\ innoClaims_i{}^2 \\ &+ \gamma' Project\ Controls_i \\ &+ \delta' Creator\ Controls_i + \varepsilon_i \end{aligned}$$

Table 3. Regression results

DV: log(# of backers)	(1)	(2)
goal (USD)	-1.81e-06***	-1.84e-06***
	(2.37e-07)	(2.33e-07)
duration	-.0081***	-.0081***
	(.001)	(.001)
staff pick	.8203***	.8123***
	(.0472)	(.0471)
# of faqs	.0375***	.0382***
	(.0038)	(.0038)
# of updates	.1524***	.1528***
	(.0051)	(.0051)
facebook connection	-.0899***	-.0907***
	(.03)	(.0299)
# of images	.0129***	.0126***
	(.0011)	(.0011)
# of gifs	.0514***	.0501***
	(.0039)	(.0039)
# of videos	-.0109	-.0127*
	(.0077)	(.0077)
story length	-.0001**	-.0001***
	(3.34e-5)	(3.33e-5)
risks length	.0008***	.0008***
	(.0001)	(.0001)
category	-.1318***	-.1299***
	(.0124)	(.0123)
# of created projects	.0692***	.0706***
	(.0057)	(.0057)
# of backed projects	.0025***	.0026***
	(.0006)	(.0007)
# of collaborators	.2371***	.234***
	(.0108)	(.0107)
innoClaims	.0306***	.0763***
	(.0024)	(.0051)
innoClaims^2		-.0019***
		(.0002)
_cons	2.721***	2.6329***
	(.0571)	(.0573)
Observations	11521	11521
R-squared	.5969	.6008

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

We again use OLS regression with robust standard error for estimation. Column (2) of Table 3 reports the estimation result. The coefficient for the linear term *(# of innoClaims*) is positive and significant ($\hat{\beta}_1 = 0.0763$, $p < 0.01$), but the coefficient for the quadratic term *(# of innoClaims*^{2}) is negative and significant ($\hat{\beta}_2 = -0.0019$, $p < 0.01$). This result signals an inverted U-shaped relationship. To confirm that, we further conduct a u-test (Lind & Mehlum, 2010) based on the estimation shown in column (2). The u-test result is illustrated in Table 4. We also visualize the marginal effect of *# of innoClaims* on the log-transformed *# of backers*

$$\frac{d\,log(\widehat{\#\,of\,backers_i})}{d\,\#\,of\,innoClaims} = \hat{\beta}_1 + 2\cdot\hat{\beta}_2\cdot\#\,of\,innoClaims$$

in Figure 1. As *# of innoClaims* increases, the marginal effect on the log-transformed *# of backers* decreases. Marginal effect equals 0 around the extreme point = 19.86 (95% CIs = [17.59, 23.36]), and becomes negatives afterwards. Both u-test results and marginal effect visualization strongly support the inverted U-shaped relationship. So, we can confidently conclude that project stories that include too many innovation claims hurts funding outcomes.

Table 4. u-test *(# of backers* vs. *# of innoClaims*)

Specification: f(x)=x^2
Extreme point: 19.86375
Test:
H1: Inverse U shape
vs. H0: Monotone or U shape

	Lower bound	Upper bound
Interval	0	35
Slope	.0762966	-.2655523
t-value	14.85609	-8.755255
P > | t |	9.12e-50	1.16e-18

Overall test of presence of an Inverse U shape:
t-value = 8.76
P > t = 1.16e-18

95% Fieller interval for extreme point: [17.585; 23.364]

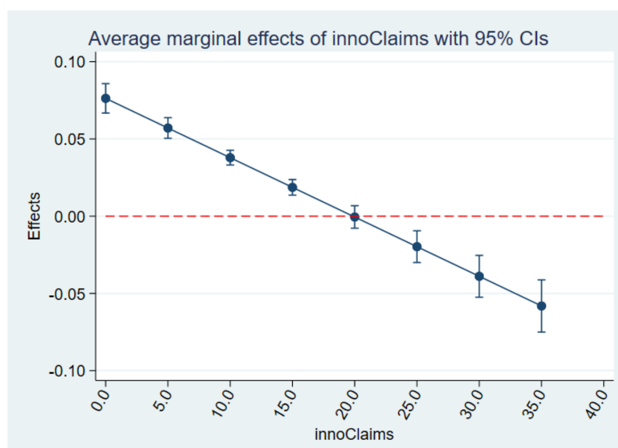

Figure 1. Average marginal effect on *# of backers*

Table 5. Robustness Check

DV: log(pledged money)	(1)	(2)
goal (USD)	-1.21e-06 **	-1.28e-06**
	(5.46e-07)	(5.37e-07)
duration	-.0166***	-.0165***
	(.0018)	(.0018)
staff pick	1.1451***	1.1249***
	(.0619)	(.0613)
# of faqs	.0406***	.0425***
	(.0052)	(.0051)
# of updates	.2135***	.2146***
	(.0072)	(.0072)
facebook connection	-.161***	-.1629***
	(.0513)	(.0509)
# of images	.0325***	.0317***
	(.0018)	(.0017)
# of gifs	.0612***	.0579***
	(.0052)	(.0051)
# of videos	.0602***	.0558***
	(.0124)	(.0121)
story length	-.0001***	-.0002***
	(.0001)	(.0001)
risks length	.0021***	.002***
	(.0002)	(.0002)
category	-.219***	-.2142***
	(.0224)	(.0221)
# of created projects	.0818***	.0854***
	(.0074)	(.0073)
# of backed projects	.0014**	.0016**
	(.0007)	(.0007)
# of collaborators	.2612***	.2532***
	(.0143)	(.014)
innoClaims	.0717***	.1869***
	(.0037)	(.0079)
innoClaims ^{2}		-.0048***
		(.0003)
_cons	5.9787***	5.7563***
	(.1002)	(.1002)
Observations	11521	11521
R-squared	.5344	.544

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

6. Robustness Check

Besides using the total number of backers of each project as the dependent variable, we also use total pledged money (*pledged money (USD)*) as an alternative outcome measure for robustness check. Column (1) and column (2) of Table 5 present the estimation results when using log-transformed *pledged money (USD)* as the dependent variable. The regression results are consistent when we utilize the alternative measure. We also conduct a u-test based on the estimation in column (2) and visualize the marginal effect of *# of innoClaims* on log-transformed *pledged money (USD)*. As *# of innoClaims* increases, the marginal effect on log-transformed *pledged money (USD)* decreases. Marginal effect equals 0 around the extreme point = 19.28 (95% CIs = [17.99, 20.90]), and becomes negatives afterwards. Both u-test results (Table 6) and marginal effect visualization (Figure 2) again strongly support that a project's outcome exhibits an inverted U-shaped relationship with *# of innoClaims*.

Table 6. u-test (pledged money vs. # of innoClaims)

Specification: f(x)=x^2
Extreme point: 19.28213
Test:
H1: Inverse U shape
vs. H0: Monotone or U shape

	Lower bound	Upper bound
Interval	0	35
Slope	.1869267	-.6758659
t-value	23.71521	-15.49329
P > | t |	1.0e-121	6.69e-54

Overall test of presence of an Inverse U shape:
t-value = 15.49
P > t = 6.69e-54
95% Fieller interval for extreme point: [17.987; 20.901]

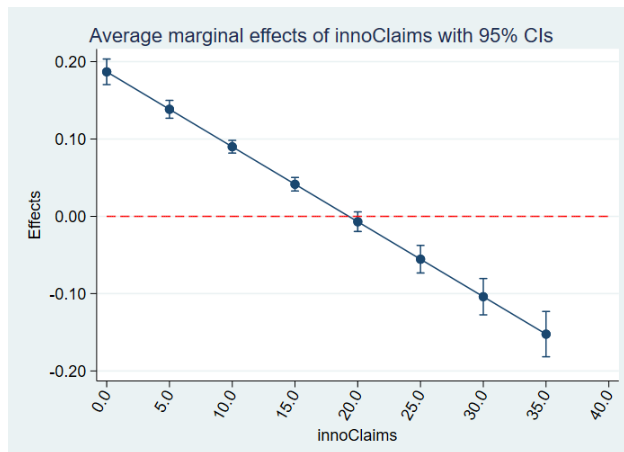

Figure 2. Average marginal effect on *pledged money*

7. Conclusion and Discussion

In this research, we aim to examine the effort fundraisers exert to promote innovativeness in crowdfunding campaigns. Specifically, we study how fundraiser-claimed product innovation is related to crowdfunding performance. The empirical analysis is conducted by leveraging a rich dataset from

Kickstarter. We first train a deep learning-based natural language processing model to identify innovation claims from campaign descriptions to operationalize product innovation construct and then use empirical models to examine its relation to campaign performance. We find a statistically significant and positive association between fundraiser-claimed innovation and campaign outcomes. Moreover, we find the number of product innovation claims has an inverted 'U' shape relationship with campaign performance.

Our study contributes to the literature on product innovation and crowdfunding by providing empirical evidence on the association between product innovation presentation and crowdfunding performance. We also offer a practical guideline to fundraisers for better design of their project "pitch". Either too few or too many claimed innovativeness degrades the performance. A balanced level of claimed innovativeness benefits campaigns the most. According to our empirical analysis, an appropriate number of innovation claims is around 19.

Our work also has limitations to be addressed in the future. We only consider the total number of innovation claims in each description. Future studies could examine whether multiple claims are presenting the same aspect of innovation, quantify how many different aspects of innovation are claimed by the fundraiser, and further analyze the effect of these aspects on campaign performance. Also, our analysis is based on data from 4 categories that often offer tangible and functional products. Future research may extend the analysis to a broader range of categories.

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