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# Does the crowd support innovation? Innovation claims and success on kickstarter

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# DOES THE CROWD SUPPORT INNOVATION?

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**Abstract:**

Online crowdfunding is a popular new tool for raising capital to commercialize product innovation. Product innovation must be both novel and useful (*1-4*). Therefore, we study the role of novelty and usefulness claims on Kickstarter. Startlingly, we find that a single claim of novelty increases project funding by about 200%, a single claim of usefulness increases project funding by about 1200%, and the co-occurrence of novelty and usefulness claims lowers funding by about 26%. Our findings are encouraging because they suggest the crowd strongly supports novelty and usefulness. However, our findings are disappointing because the premise of crowdfunding is to support projects that are innovative, i.e. that are both novel and useful, rather than projects that are only novel or only useful.

**Keywords:** Crowdfunding, Entrepreneurship, Innovation.

Crowdfunding is the process of sourcing “funding” for a new venture from a large community (the “crowd”). A World Bank study projects that the global crowdfunding market will reach $90 billion annually — roughly 1.8 times the size of the global venture capital industry today—with more than $70 billion coming from countries outside of North America and Western Europe (*5*). Due to its scope and efficiency, scholars have theorized that online crowdfunding may help “democratize” product innovation — it allows small entrepreneurs, who would otherwise lack resources, find funding and markets, erasing geographic, social, and economic boundaries of product innovation (*6-9*).

However, such optimism belies a more fundamental question: Does the crowd support product innovation? Evidence on how people perceive and respond to product innovation is mixed. On the one hand, research on consumer response to product innovation suggests that a higher level of innovation is preferred — consumers evaluate products that are both novel and useful most highly (*10-12*). They are also more likely to spread favorable Word-Of-Mouth for products that are both highly novel and useful (*13*). On the other hand, research on idea screening suggests that a lower level of innovation is preferred. People underestimate the originality of truly novel ideas (*14*), select feasible and desirable ideas at the cost of original ideas (*15*), and hold an implicit bias against novel and useful ideas (*16*). Importantly, project backers are both potential consumers and participants in collective idea screening at one and the same time. Therefore, it is difficult to predict how they may react to innovation.

In this research, we investigate the role of claimed innovativeness, i.e., claims of novelty and usefulness, in crowdfunding product innovation. The word “innovative” is semantically ambiguous. For example, several English dictionaries define “creative”, “innovative”, “novelty”, and “originality” to be synonyms. However, for product innovation, novelty and originality are not sufficient. To be innovative, the novel elements of a product must also be more useful – they must better accomplish the tasks the product was designed for. Thus, product innovations have two dimensions, novelty and usefulness (*1-4*). Furthermore, in order to seek funds, entrepreneurs describe their innovation on a project webpage. Potential backers base their decisions on the project webpage. Therefore, we focus on the extent of novelty and usefulness claims in the description on the project webpage to measure innovativeness, and relate these measures to funding outcomes.

Our analysis yields three main results. We find that the amount pledged on Kickstarter (1) increases with the number of novelty claims, (2) increases with the number of usefulness claims, but (3) decreases with the interaction of novelty and usefulness claims. Our findings are encouraging because they suggest that the crowd is appreciative of novelty and usefulness. Our findings are disappointing because they suggest that the crowd does not view novelty and usefulness (the two constituent elements of innovation) as synergistic.

Our findings are somewhat surprising given that, similar to a consumer purchase context, backers in the crowdfunding context choose the product they want. Moreover, given that Kickstarter's goal is to create a crowdfunding platform for innovation, it should attract backers (consumers) who are more open to and searching for innovation; individuals that Rogers (*17*), in his seminal work on the diffusion of innovation, would classify as "innovators." Such consumers should be more attracted to projects that are innovative (i.e. both novel and useful), rather than only novel or useful. Last, the success or failure of a project has minor financial ramifications for a backer as their loss is limited to the token non-monetary reward. This should make backers more open to supporting innovative projects. Yet, we find that the crowd is most supportive of projects that are either very novel or very useful, rather than very innovative (i.e. both very novel and very useful). In the conclusion section, we speculate as to why this is the case.

**Institutional context and data**

Kickstarter is organized around projects created by its users. Kickstarter requires projects to identify specific funding goal(s). This process is tailor-made for new product development — Kickstarter is perfectly suited, and frequently used by entrepreneurs, to raise funds with the goal of bringing a specific product innovation(s) to market. Users "back" projects by pledging a dollar amount to support the project (in return for a token, nonmonetary reward from the project creator). If the total amount pledged by backers (within a time period) exceeds the project target (i.e., the project goal), the project is funded and the project creator gets the pledged amount (net of fees). Otherwise, the project creator gets nothing and the pledged funds are returned to the pledgees (backers).

We collect a novel, comprehensive dataset describing all projects in nine product oriented categories on Kickstarter from its inception on April 28, 2009 to Feb 15, 2017. We limit our attention to categories on Kickstarter that meet two conditions: (1) the category relates to product innovation and not to the arts and (2) the category is consequential in representation (the category accounts for at least 1% of listed projects on Kickstarter). The first condition ensures that our sample matches our research question. The second condition ensures that we have sufficient data to pinpoint category-specific estimates, an important robustness check that we describe in the results section of this article. These two conditions are met by nine categories: Apparel, Apps, Fashion, Food, Hardware, Product Design, Tabletop Games, Technology, and Video Games.

Our primary data comes from Web Robots, who make their data publicly accessible at https://webrobots.io/kickstarter-datasets/. Additional data were downloaded directly from

Kickstarter, who publicly archive project webpages. Specifically, for each project, we collect the text and project video (the video that is launched if the play button at the center of the project image is clicked). In addition, we collect various variables describing the project (for example, the category of the project) and the funding outcome (the total amount pledged).

We focus on projects from the United States where Kickstarter originated and is based. From the outset, residents of the United States could both back and create projects on Kickstarter. While Kickstarter is open to backers from all over the world, project creation has only been gradually made available to individuals residing outside the United States. Given the longer history and larger participation from the United States, it may be easier for projects from the United States to find funding than projects from other countries.

The verbal account of projects comes from two sources: the project text and the audio of the project video. To analyze project videos, we extract the audio track from each project video, and transcribe the audio track to text. To ensure our measures are defined off a single language, we limit our attention to projects in English. As the data does not identify the language used in a project, we use the Cavnar and Trenkle method of n-gram language detection (*18*). The Cavnar and Trenkle method compares character n-grams from a focal text to a multi-lingual vocabulary of character n-grams (our application considers 74 languages, see (*19*) for further details). The method tabulates the distance between a focal text and each language in the library, and assigns the best match language to a focal text. We retain 50,310 projects categorized as being in English. We count the number of occurrences of the words “novel” and “useful” and its synonyms in the verbal account:

1. novel: “avant-garde”, “creative”, “distinctive”, “groundbreaking”, “imaginative”, “ingenious”, “inventive”, “new”, “novel”, “original”, “remarkable”, “revolutionary”, and “unique”;

2. useful: “appropriate”, “beneficial”, “constructive”, “convenient”, “easy to use”, “effective”, “efficacious”, “functional”, “handy”, “practical”, “productive”, “useful”, “utilitarian”, “utility”, and “valuable”.

Table 1 provides a category-specific summary of the dependent variable and focal independent variables (“novel” and “useful”). The incidence of novelty and usefulness claims varies across these nine categories. The incidence of novelty claims is most common in table-top games and video games, and is least common in apps. The incidence of usefulness claims is most common in hardware, product design, and technology, and is least common in food. Given these category-specific differences in incidence, we add a category fixed effect in our empirical model, and also undertake analyses at the category-level.

--- INSERT TABLE 1 HERE ---

**Empirical strategy**

Figure 1 depicts the total amount pledged as a function of the count of novelty and usefulness claims. We split the sample into two sub-samples: projects that make no usefulness claims and projects that make at least one usefulness claim. The upper panel plots a generalized additive model (GAM) of the amount pledged (in logarithmic scale) on the number of novelty claims, for the two sub-samples. We also split the sample into two other sub-samples: projects that make no novelty claims and projects that make at least one novelty claim. The lower panel plots a GAM of the amount pledged (in logarithmic scale) on the number of usefulness claims, for the two sub-samples.

--- INSERT FIGURE 1 HERE ---

We find that the incidence of both novelty claims and usefulness claims are strongly associated with higher funding. Note that the y-axis is in natural logarithms. Therefore, the range of (non-parametrically fitted) pledged amounts varies by approximately a factor of $e^5$, i.e. by approximately 15,000%, across the range of each variable (the number of novelty or usefulness claims). Furthermore, projects that make at least one novelty claim have systematically different funding outcomes than projects that make no novelty claim. The incidence of a single novelty claim affects both the intercept and the slope of the curve depicting the expected funding of projects as a function of the number of usefulness claims. Similarly, projects that make at least one usefulness claim have systematically different funding outcomes than projects that make no usefulness claim. The incidence of a single usefulness claim affects both the intercept and the slope of the curve depicting the expected funding of projects as a function of the number of novelty claims. In sum, the model-free evidence suggests both a main and an interaction effect of the number of novelty and usefulness claims on amount pledged.

To formalize this intuition, we regress the logarithm of the amount pledged on the count of synonyms of novel and useful:

$$(1)\quad \log(\text{pledged}_p) = \alpha_0 + \alpha_1 * \text{novel}_p + \alpha_2 * \text{useful}_p + \alpha_3 * \text{novel}_p * \text{useful}_p + \\ + \sum_{i=2}^{12} \gamma_{mi}\,\text{month}_{pi} + \sum_{j=2010}^{2017} \gamma_{yj}\,\text{year}_{pj} + \sum_{k=2}^{9} \gamma_{ck}\,\text{category}_{pk} + \varepsilon_p,$$

where $\alpha_1$ and $\alpha_2$ measure the impact of novelty and usefulness claims respectively, and $\alpha_3$ measures the impact of their interaction. $\text{pledged}_p$ is the total amount pledged for project $p$, $\text{novel}_p$ is the extent of novelty claims made by project $p$; $\text{useful}_p$ is the extent of usefulness claims made by project $p$; $\text{month}_{pi}$ is a calendar month-specific dummy, which is 1 for the calendar month in which project $p$ was listed and 0 for the remaining calendar months; $\text{year}_{pj}$ is a year-specific dummy, which is 1 for the year in which project $p$ was listed and 0 for the remaining years; $\text{category}_{pk}$ is a category-specific dummy, which is 1 for the category in which project $p$ was listed and 0 for the remaining categories. $\{\gamma_{mi}\}_{i=2}^{12}$, $\left\{\gamma_{yj}\right\}_{j=2010}^{2017}$, and $\{\gamma_{ck}\}_{k=2}^{9}$ are fixed effect coefficient vectors. $\varepsilon_p$ is the error term. To account for common funding shocks and heteroscedasticity (across projects), we cluster the standard errors by the month of observation (our data spans 93 months).

Our earlier observations stand (see Table 2). The incidence of novelty claims *increases* project funding. The incidence of usefulness claims *increases* project funding. The co-incidence of novelty and usefulness claims, i.e. their interaction, *decreases* project funding. To examine if our findings vary across categories, we estimate the regression separately for the each of nine categories in our data. Table 3 shows that despite the diminished power of the category-specific test, we replicate our findings in all nine categories.

--- INSERT TABLE 2 HERE ---

--- INSERT TABLE 3 HERE ---

We test the sensitivity of these findings to the choice of synonyms in constructing "novel" and "useful". We conduct a "bootstrap" exercise where in each iteration we randomly remove five synonyms of "novel" and five synonyms of "useful" from our list of synonyms. We re-compute our measures and re-estimate equation (1). Figure 2 plots the density of the coefficients of novel, novel * useful, and useful, across the 250 iterations. It shows that our results are relatively insensitive to the choice of synonyms: in all cases, the estimated coefficient is comparable in magnitude and statistical significance.

--- INSERT FIGURE 2 HERE ---

In addition, we consider the following sensitivity analyses:

1. drop small projects (project goal less than $1000);

2. drop large (project goal more than $100,000);
3. log transform the count of novelty and usefulness claims to account for any non-negativity and skew in these variables;
4. transform novel and useful from a (absolute) count measure to a percentage measure: we divide "novel" and "useful" by the total number of words in the verbal account and multiply by 100;
5. estimate a Probit model where the dependent measure is funding success—the dependent variable is 1 if total amount pledged > goal, and 0 otherwise.

The first two analyses test if our findings are sensitive to the omission of large or small projects. The third analysis tests if our findings are sensitive to any non-negativity and skew in the independent variables. The fourth analysis tests if our findings are not sensitive to the length of the verbal account. The fifth analysis tests if our findings are sensitive to classifying projects as being successful or unsuccessful in raising targeted funds. Table 4 shows that our findings remain unchanged across these models.

--- INSERT TABLE 4 HERE ---

**Endogeneity**

Novelty and usefulness claims may be endogenous in equation (1) (see (*20*)). For example, variables (such as project quality) may be unobserved by the researcher and may be correlated with both the measures of novelty and useful claims and the dependent variable.

To account for endogeneity, we turn to the method of instrumental variables. We rely on the following rationale for generating instruments. When writing project descriptions, project creators likely benchmark against currently active projects; Particularly, if prior projects use more synonyms of novelty/usefulness, then it is likely that current projects will use more synonyms of novelty/usefulness. Therefore, the extent of novelty and usefulness claims of prior projects is likely to predict the extent of novelty and usefulness claims in current projects.

Novelty and usefulness claims in prior projects are unlikely to materially influence (1) the unobserved quality of the innovation described in current projects, and (2) the funding success of current projects. Commercialization is a major undertaking for an entrepreneur; an entrepreneur only crowdfunds an innovation that she truly believes in. Fewer than 12% of creators launch more than 1 project and fewer than 4% of creators launch more than 2 projects in the 8-year span of our data. Thus, the unobserved quality of the innovation described in a current project is unlikely to vary with the extent of novelty and usefulness claims of prior projects. Furthermore, crowdfunding projects describing product innovations, vary considerably and attract a diverse group of backers. For example, less than a third of backers on Kickstarter back more than one project. Thus, backers are unlikely to substitute backing activity across different months. Thus, the funding success of current projects are unlikely to vary with the extent of novelty and usefulness claims of prior projects.

In sum, variables describing the (aggregate) incidence and extent of novelty and usefulness synonyms are likely to be both relevant and valid instruments in our econometric model. We use the first two moments, and their two-way interactions, of lagged monthly claims of novelty and usefulness in a category as instruments. The corrected conditional F-statistic (see *21* for details) of the instruments is above the accepted cutoff of 10, which suggests our instruments are relevant. We estimate equation (1) by two-stage least squares. The Hansen test of over identifying restrictions does not reject the null ($p > 0.05$), which suggests our instruments are valid.

We find that $\alpha_1$=1.100 ($p$ < 0.01), $\alpha_2$=2.554 ($p$ < 0.01), and $\alpha_3$=-0.359 ($p$ < 0.01); see Table 5. Note that the dependent measure is in natural logarithms. Therefore, the effect size is calculated by taking exponents of the coefficients[2]. Our estimates suggest that, on average, a novelty claim increases funding by about 200%, and a usefulness claim increases funding by about 1200%. The difference in effect size between novelty and usefulness may imply individuals value the usefulness of a proposed innovation more than its novelty (*22*). The interaction effect implies that the crowd does not view novelty and usefulness as synergistic. For example, project that make at least two usefulness claims have a higher expected funding outcome if they do not also claim to be novel, than if they also claim to be novel. For example, project that make at least six novelty claims have a higher expected funding outcome if they do not also claim to be useful, than if they also claim to be useful. Across our sample, on average, the interaction effect decreases funding by about 26%.

--- INSERT TABLE 5 HERE ---

**Conclusion**

As noted earlier, our findings are consistent with the literature on idea screening but not that on consumer evaluation of innovation (*9-11*), as modest innovations are more likely to get funded than more extreme innovations, i.e., innovations that are high on both novelty and usefulness. What is a possible reason for this inconsistency, given that backers in a crowdfunding context typically receive the product in exchange for their support, thus making their decision more like a product choice decision than a typical idea screening decision? We speculate that this

[2]Suppose the estimated coefficient is $\alpha$. Then (exp($\alpha$) -1) * 100 is the percentage change in the continuous dependent variable due to a one unit increase in the discrete independent variable.

may be due to the high degree of uncertainty associated with the choice in a crowdfunding context, compared to a consumer purchase context.

In the prototypical purchase context, consumer protection laws guarantee receipt of the purchased product. In the crowdfunding context, however, there is much greater uncertainty regarding (a) receiving the product and (b) features of the product, than in purchasing, for the following reasons. First, a project may not successfully reach its funding goal. In this case, backers are refunded but do not receive the product. Second, a successfully funded project may be delayed or may fail (the creator may be unable to follow-through). For example, a recent study (see (*23*)) found that more than three-quarters of successfully funded projects (on Kickstarter) are either delayed or failed. In this case, backers are neither guaranteed refunds – they may lose the entire amount pledged – nor guaranteed receipt of the product. Third, projects on Kickstarter are proposed blueprints, rather than descriptions, of the final product. As a project evolves, the creator may make significant changes to the product, without the assent of backers.

Based on preliminary evidence (*24*) that shows that when faced with uncertainty consumers are more likely to choose products that are more traditional, i.e. less innovative, options than when they perceive less product uncertainty, we speculate that the higher level of uncertainty in the crowdfunding context drives backers to choose modest innovations and shy away from more extreme innovations, i.e., innovations that are high on both novelty and usefulness. Future research could explore the validity of this hypothesized reason for our findings.

## REFERENCES


1. Anderson N, Potočnik K, & Zhou J (2014) Innovation and creativity in organizations: A state-of-the-science review, prospective commentary, and guiding framework. *Journal of Management* 40(5):1297-1333.
2. Amabile TM (1983) The social psychology of creativity: A componential conceptualization. *Journal of Personality and Social Psychology* 45(2):357-376.
3. Amabile TM (1996) *Creativity in Context* (Westview press, Colorado).
4. Grant AM & Berry JW (2011) The necessity of others is the mother of invention: Intrinsic and prosocial motivations, perspective taking, and creativity. *Academy of Management Journal* 54(1):73-96.
5. World Bank (2013) Crowdfunding's potential for the developing world. pp 42-43.
6. Kuppuswamy V & Bayus B (2016) A review of crowdfunding research and findings. forthcoming in P. Golder and D. Mitra (eds.), *Handbook of New Product Development Research*.
7. Lakhani KR, Garvin DA, & Lonstein E (2010) Topcoder (a): Developing software through crowdsourcing. *Harvard Business School General Management Unit Case No. 610-032*.
8. Mollick E & Robb A (2016) Democratizing innovation and capital access. *California Management Review* 58(2):72-87.
9. Sorenson O, Assenova V, Li G-C, Boada J, & Fleming L (2016) Expand innovation finance via crowdfunding. *Science* 354(6319):1526-1528.10. Dahl DW, Chattopadhyay A, & Gorn GJ (1999) The use of visual mental imagery in new product design. *Journal of Marketing Research* 36(1):18-28.

11. Moreau CP & Dahl DW (2005) Designing the solution: The impact of constraints on consumers' creativity. *Journal of Consumer Research* 32(1):13-22.

12. Yang H, Chattopadhyay A, Zhang K, & Dahl DW (2012) Unconscious creativity: When can Unconscious Thought Outperform Conscious Thought? *Journal of Consumer Psychology* 22(4):573-581.

13. Moldovan, S, Goldenberg J, & Chattopadhyay A (2011) The different roles of product originality and usefulness in generating Word-of-Mouth. *International Journal of Research in Marketing* 28:109-119.

14. Licuanan BF, Dailey LR, & Mumford MD (2007) Idea evaluation: Error in evaluating highly original ideas. *The Journal of Creative Behavior* 41(1):1-27.

15. Rietzschel EF, Nijstad BA, & Stroebe W (2010) The selection of creative ideas after individual idea generation: Choosing between creativity and impact. *British Journal of Psychology* 101(1):47-68.

16. Mueller JS, Melwani S, & Goncalo JA (2012) The bias against creativity: Why people desire but reject creative ideas. *Psychological Science* 23.1: 13-17.

17. Rogers EM (2003) *Diffusion of Innovations*. Free Press, New York: 551.

18. Cavnar WB & Trenkle JM (1994) N-gram-based text categorization. In Proceedings of SDAIR-94, 3rd Annual Symposium on Document Analysis and Information Retrieval, pp 161-176.

19. Feinerer I*, et al.* (2013) The textcat package for n-gram based text categorization in R. *Journal of Statistical Software* 52(6):1-17.

20. Varian HR (2016) Causal inference in economics and marketing. *Proceedings of the National Academy of Sciences*, pp 7310-7315.

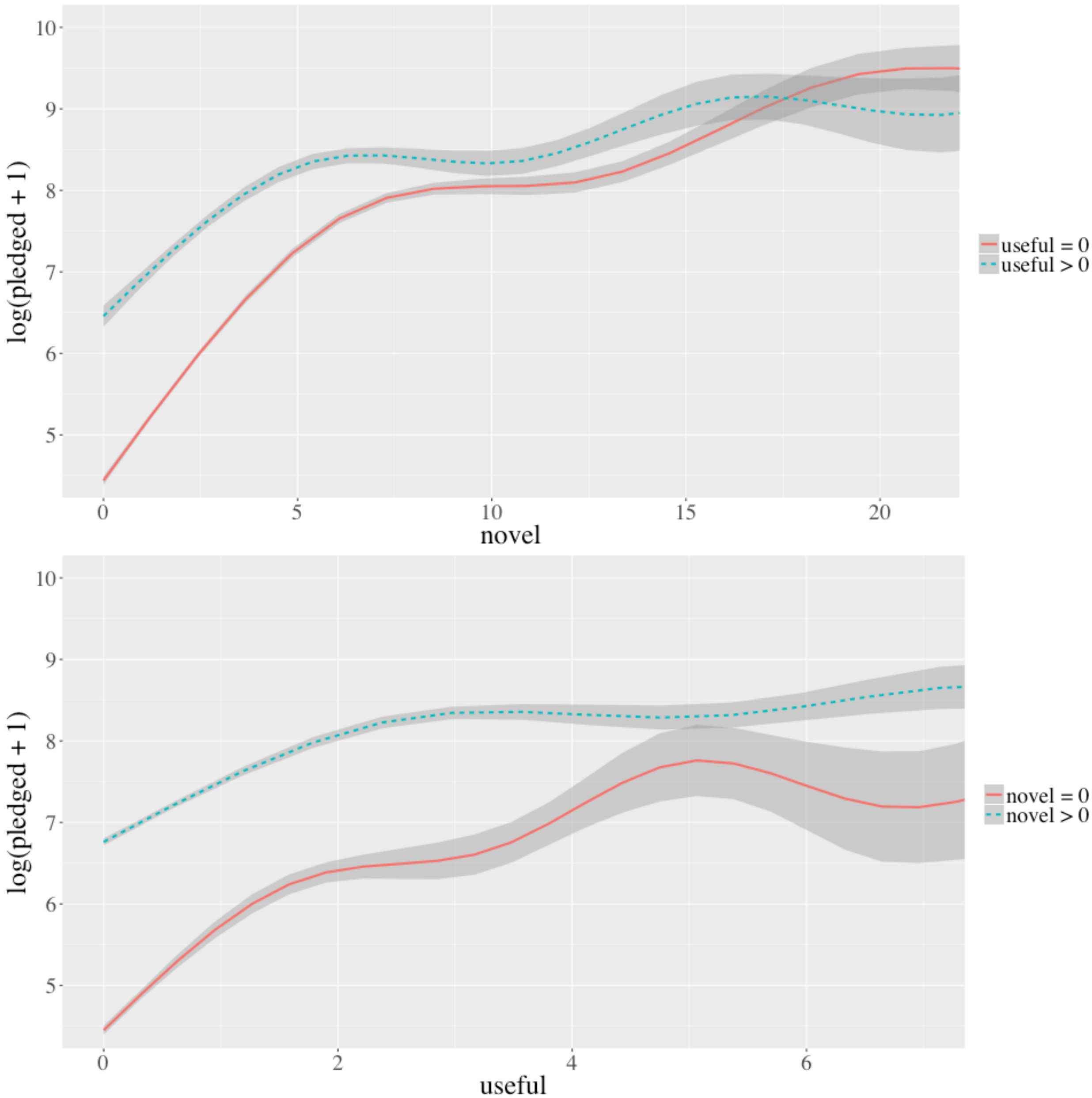
21. Sanderson E & Windmeijer F (2016) A weak instrument F-test in linear IV models with multiple endogenous variables. *Journal of Econometrics* 190.2: 212-221.

22. Kumar M & Noble CH (2016). Beyond form and function: Why do consumers value product design?. *Journal of Business Research*, *69*(2), 613-620.

23. Mollick E (2014) The dynamics of crowdfunding: An exploratory study. *Journal of Business Venturing* 29.1: 1-16.

24. Campbell MC & Goodstein RC (2001) The moderating effect of perceived risk on consumers' evaluations of product incongruity: Preference for the norm. *Journal of Consumer Research* 28.3: 439-449.

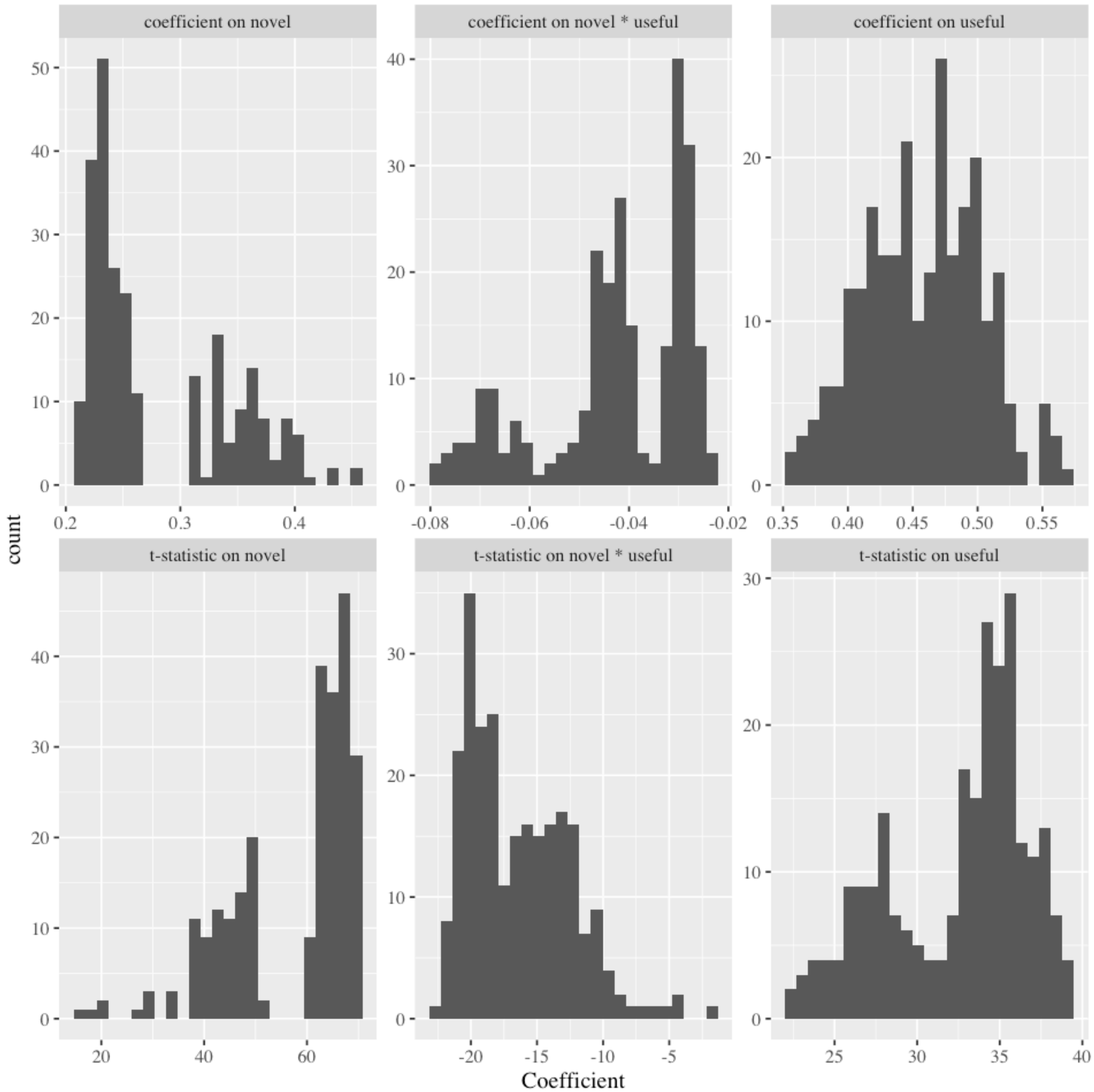
**Figure 1: Plot of pledged by novel and useful**




Notes:

1. novel = count of "novel" and its synonyms in verbal account, range limited to the 95th percentile.
2. useful = count of "useful" and its synonyms in verbal account, range limited to the 95th percentile.

**Figure 2: Density of Estimated Coefficient of novel * useful**




Notes:

1. Density of estimated coefficient from 250 bootstrap iterations, with each iteration randomly removing five random words from the list of novel and five random words from the list of useful synonyms.
2. novel = count of "novel" and its synonyms in verbal account.
3. useful = count of "useful" and its synonyms in verbal account.
4. Standard errors clustered by month of observation.

**Table 1: Descriptive Statistics**

| | N | Mean goal | Std Dev goal | Mean pledged | Std Dev pledged | Mean novel | Std Dev novel | Mean useful | Std Dev useful |
|---|---|---|---|---|---|---|---|---|---|
| Apparel | 4134 | 44521 | 1567140 | 3800 | 22966 | 2.276 | 3.026 | 0.343 | 1.000 |
| Apps | 3147 | 60295 | 264695 | 1396 | 6508 | 2.241 | 3.457 | 0.804 | 1.427 |
| Fashion | 5691 | 13060 | 52872 | 5568 | 27348 | 3.237 | 3.534 | 0.387 | 1.164 |
| Food | 7399 | 19976 | 130663 | 6178 | 31785 | 2.981 | 3.517 | 0.343 | 0.858 |
| Hardware | 2284 | 90647 | 658828 | 35250 | 130499 | 3.641 | 3.851 | 1.880 | 2.395 |
| Product Design | 11444 | 33495 | 475867 | 26109 | 270343 | 3.483 | 3.911 | 1.421 | 1.993 |
| Table-top Games | 7693 | 14483 | 44354 | 27252 | 153085 | 5.693 | 6.308 | 0.575 | 1.155 |
| Technology | 2534 | 149013 | 2517549 | 21152 | 109875 | 3.712 | 4.638 | 1.387 | 2.142 |
| Video Games | 5984 | 60711 | 244895 | 18550 | 143156 | 5.212 | 5.792 | 0.509 | 1.058 |

Notes:

1. N = number of projects.
2. goal = project goal.
3. Std Dev = standard deviation.
4. pledged = total amount pledged.
5. novel = count of “novel” and its synonyms in verbal account.
6. useful = count of “useful” and its synonyms in verbal account.

**Table 2: Ordinary Least Squares**

| | *Dependent variable:* log (pledged + 1) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| novel | .228*** | .227*** | .219*** |
| | (.014) | (.013) | (.012) |
| useful | .440*** | .437*** | .428*** |
| | (.034) | (.032) | (.033) |
| novel * useful | -.029*** | -.029*** | -.028*** |
| | (.006) | (.006) | (.005) |
| Fixed effects | | | |
| category | YES | YES | YES |
| calendar month | | YES | YES |
| year | | | YES |
| Observations | 50,310 | 50,310 | 50,310 |
| $R^2$ | .276 | .280 | .297 |
| Adjusted $R^2$ | .276 | .280 | .296 |

Notes:
1. All tests two-sided. *p<0.1; **p<0.05; ***p<0.01.
2. Standard errors clustered by month of observation.
3. pledged = total amount pledged.
4. novel = count of "novel" and its synonyms in verbal account.
5. useful = count of "useful" and its synonyms in verbal account.

**Table 3: Category-Specific Ordinary Least Squares**

| | *Dependent variable:* log (pledged + 1) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| novel | .403*** | .321*** | .263*** | .258*** | .304*** | .211*** | .123*** | .211*** | .269*** |
| | (.025) | (.029) | (.015) | (.026) | (.026) | (.014) | (.006) | (.031) | (.010) |
| useful | 1.139*** | .544*** | .649*** | .560*** | .417*** | .342*** | .266*** | .418*** | .653*** |
| | (.098) | (.071) | (.096) | (.101) | (.044) | (.022) | (.046) | (.047) | (.057) |
| novel * useful | -.092*** | -.057*** | -.055*** | -.054*** | -.042*** | -.028*** | -.011*** | -.026*** | -.046*** |
| | (.010) | (.010) | (.008) | (.011) | (.005) | (.004) | (.004) | (.005) | (.005) |
| Fixed effects | | | | | | | | | |
| category | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| calendar month | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| year | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 4,134 | 3,147 | 5,691 | 7,399 | 2,284 | 11,444 | 7,693 | 2,534 | 5,984 |
| $R^2$ | .191 | .135 | .128 | .296 | .190 | .114 | .133 | .207 | .268 |
| Adjusted $R^2$ | .187 | .129 | .125 | .294 | .182 | .113 | .130 | .201 | .265 |

Notes:
1. All tests two-sided. *p<0.1; **p<0.05; ***p<0.01.
2. Standard errors clustered by month of observation.
3. pledged = total amount pledged.
4. novel = count of "novel" and its synonyms in verbal account.
5. useful = count of "useful" and its synonyms in verbal account.
6. (1) – (9) = models estimated on the following categories respectively: Apparel, Apps, Fashion, Food, Hardware, Product Design, Table-top Games, Technology, and Video Games

**Table 4: Alternative Specifications**

| | Dependent variable: | | | | |
|---|---|---|---|---|---|
| | log (pledged + 1) | | | | success |
| | (1) | (2) | (3) | (4) | (5) |
| novel | .209*** | .214*** | | | .047*** |
| | (.011) | (.013) | | | (.004) |
| useful | .405*** | .481*** | | | .065*** |
| | (.031) | (.035) | | | (.013) |
| novel * useful | -.026*** | -.028*** | | | -.005** |
| | (.006) | (.007) | | | (.025) |
| % novel | | | 1.697*** | | |
| | | | (.338) | | |
| % useful | | | 5.037*** | | |
| | | | (.686) | | |
| % novel * % useful | | | -11.172** | | |
| | | | (4.455) | | |
| log (novel + 1) | | | | 1.378*** | |
| | | | | (.060) | |
| log (useful + 1) | | | | 1.442*** | |
| | | | | (.074) | |
| log (novel + 1) * log (useful + 1) | | | | -0.438*** | |
| | | | | (.041) | |
| Observations | 44,610 | 47,355 | 50,310 | 50,310 | 50,310 |
| $R^2$ | .286 | .289 | .206 | .326 | |
| Adjusted $R^2$ | .286 | .289 | .206 | .326 | |

Notes:
1. Regressions includes category-, calendar month-, and year-specific fixed effects.
2. All tests two-sided. *p<0.1; **p<0.05; ***p<0.01.
3. Standard errors clustered by month of observation.
4. pledged = total amount pledged.
5. novel = count of "novel" and its synonyms in the verbal account.
6. useful = count of "useful" and its synonyms in the verbal account.
7. (1): estimated on sample after removing projects with a goal of less than $1000.
8. (2): estimated on sample after removing projects with a goal of more than $100,000.
9. % novel = (novel / length of verbal account) * 100.
10. % useful = (useful / length of verbal account) * 100.
11. (5): probit model, with success = 1{pledged > project goal}.

**Table 5: Two-stage Least Squares**

| | *Dependent variable:* log (pledged + 1) |
|---|---|
| novel | 1.100*** |
| | (.132) |
| useful | 2.554*** |
| | (.781) |
| novel * useful | -.359*** |
| | (.125) |
| Fixed effects | |
| category | YES |
| calendar month | YES |
| year | YES |
| Observations | 50,310 |

Notes:
1. All tests two-sided. *p<0.1; **p<0.05; ***p<0.01.
2. Standard errors clustered by month of observation.
3. pledged = total amount pledged.
4. novel = count of “novel” and its synonyms in the verbal account.
5. useful = count of “useful” and its synonyms in the verbal account.