Fill-us-in: Information Asymmetry, Signals and The Role of Updates in Crowdfunding

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Abstract

In this empirical study, I examine the role of updates for projects listed on crowdfunding platform (CFP), Kickstarter.com. Using a novel dataset and fixed-effects (FE) regression, I corroborate existing research that updates do encourage future project support. Extant research uses this stylised fact to help support the hypothesis that funders are responding to signals of quality (Mollick, 2014). However, results from this study suggest that funders discriminate negatively on the objectivity of updates - a measure of update quality. Further analysis also reveals that updates mask a day-of-the-week effect that has been previously demonstrated (Vismara, 2018). This paper finds evidence that updates may mitigate reduced support experienced by projects on weekends. Limitations and implications to CFPs and fundraisers are also discussed.

Keywords: Crowdfunding, Information Asymmetry, Entrepreneurship, Updates

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1 Introduction

In 2012, Californian startup Oculus listed their virtual reality headset "The Rift" on the crowdfunding platform (CFP) Kickstarter with a funding target of $250,000. The project was spectacularly received, raising nearly $2.5 million from just shy of 10,000 funders (also called 'backers'). As a result of its successful campaign, the product was available for purchase in 2016. Oculus are just one example from thousands of fundraisers that have been able to locate funding through the facilitation of a CFP. However, descriptive statistics reveal a darker side of crowdfunding - only 38.15% of Kickstarter campaigns have reached their desired funding targets (www.kickstarter.com, 2020a). Furthermore, the attainment of sufficient funding does not guarantee the backers will reap any benefits soon thereafter or at all. The brief history of crowdfunding contains examples of campaigns that despite surpassing the requested level of funding, fail to ever officially launch their product(s) (Graham, 2016; Indiegogo, 2016). Early evidence for such failures led Agrawal et al. (2013) to predict similar phenomena transpiring for equity-based crowdfunding, later to be documented by Hornuf and Schmitt (2016).

Why are projects like The Rift able to fetch fantastic sums of funding when so many others fail? Despite the nascence of the field, determinants of crowdfunding - particularly reward-based - is becoming an increasingly well-studied area. As of 28th September 2020, there were over 70 cited publications with the keywords 'crowdfunding' and 'determinants' mentioned in their abstract or title; in 2012, there were none (app.dimensions.ai, 2020). Much of this research orients itself around funders and their response to signals, the theoretical importance of which is outlined by Belleflamme et al. (2015): incentives to produce and maintain high-quality projects are predicated on a fundraiser's ability to attain a fair valuation commensurate with their project's quality. Thus, when funders do not respond to signals appropriately incentives to produce and maintain high-quality projects are threatened. By understanding which project characteristics funders discriminate on, we can scientifically navigate a conversation on how to fine-tune guidelines such that CFPs incentivise high-quality activity. We are also able to advise fundraisers on which CFP features provide the most leverage in their entrepreneurial mission(s).

When a fundraiser creates a campaign on a crowdfunding site, she is typically asked to digitally imagine her campaign with videos, images, descriptions, et cetera (though precisely what information the entrepreneur is asked to enter depends on the CFP). Relevant scientific literature employs this user-inputted and other inferable data to quantify differences in projects and understand which characteristics influence success. Many signals of quality are therefore difficult to codify - consider 'the number of backers' versus 'production quality of the promotional video(s)'. Perhaps for these reasons, research on updates has only extended to their inclusion as a dummy variable in regressions (Mollick, 2014; Kuppuswamy and Bayus, 2015). Updates are the vehicle used by fundraisers to reveal information throughout the funding cycle - all other information is laid out at launch. They are not restricted to any type of information and can signal information about quality or about intention. While Kickstarter recommends founders utilise updates to provide insightful, honest statements regarding the progress of their project (www.kickstarter.com, 2020b), updates have the same costs of posting to high and low quality projects, are non-binding and can contain non-verifiable information - key ingredients for cheap talk (Farrell and Rabin, 1996). Research on updates finds that they are both statistically and economically significant to project success measures. Because he saw the use of updates as a positive signal of project quality, this suggested to Mollick (2014) that funders were responding appropriately in regards to updates. In this study, I employ a novel panel dataset that contains sentiment characteristics of project updates as posted by project founders on CFP, Kickstarter.com. By incorporating a measure of text objectivity for updates into FE regressions, I am able to differentiate low and high-quality updates to understand whether funders are responding to quality signals as previous research on updates has described.

My results indicate that when the outcome variable of my FE estimation is the additional backers a project receives on a given day, both updates and objectivity reveal statistical significance; updates manifest a positive coefficient and objectivity, a negative coefficient. The coefficient polarities evidence that more liberal use of objective language will diminish the expected future support: funders are discriminating against the quality of updates. Statistical significance of said variables does not manifest when the outcome variable measures the additional funding a project receives on a given day. In further investigations, I reinforce short-term seasonality findings that crowdfunding projects experience weakened support on the weekend (Vismara, 2018), as well as updates potentially being able to mitigate this effect on Sundays.

This paper continues as follows. Section 2 dives into the literature on determinants of crowdfunding success as partitioned into three subsections: (2.1) determinants that are relevant to funders response to signals; (2.2) determinants relevant to funders' response to passive characteristics and (2.3) determinants that arise from the finite time span of project funding cycles. Section 3 elaborates on the panel dataset employed in my analysis - how the data were collated and preprocessed, as well as a brief description of the summary statistics. Section 4 lays the framework for the empirical investigation and econometric modelling decisions. Section 5 elucidates the results of the analysis and further exploratory investigation; it also discusses implications to CFPs and fundraisers. Section 6 highlights limitations and key assumptions required for my analysis' validity. Lastly, section 7 concludes.

2 Literature Review

2.1 Funder Responses to Signals

Signals are economic activities performed by one party which conveys information (either explicitly or implicitly) to another concerned party (Spence, 1974). In crowdfunding, signals play a critical role in bridging the information asymmetry issues which have been noted by many researchers (Agrawal et al., 2013 and 2015; Belleflamme et al., 2015; Cumming et al. 2019). CFPs facilitate signalling and information exchange through a variety of features. Differential signal costs experienced by high and low-quality projects leads to a separating equilibrium (Akerlof, 1970); in crowdfunding, this is where high-quality projects can effectively distinguish themselves, signal their quality, and reap support commensurate with their quality (Visrama, 2018). In this subsection, I outline funders' response to CFP feature use and whether differential signal costs have the expected economic effect in predicting project outcomes.

2.1.1 Funding Policy

Many platforms enforce an all-or-nothing (AON) funding rule - investors are only charged if a project reaches its target. An exception to this is Indiegogo which also allows a keep-it-all (KIA) policy whereby funders will be charged regardless. As Cumming et al. (2019) posit, the choice to use AON acts as a costly signal indicating the fundraisers have 'skin in the game' and are committed to fulfilling their aims if successful. Therefore, we expect the funding policy of a campaign to be a determinant of success. Cordovaa et al. (2015) find that funding policy is not significant and funders do not respond to this signal in their cross-sectional regression analyses; however, Cordovaa et al. (2015) have little to no discussion as to the validity and causal impact of the AON/KIA treatment. Cordovaa et al.'s (2015) dataset pools together observations from many platforms, some of which do not have the option to keep-it-all (KIA). Therefore, a caveat of their findings is that fundraisers may choose a platform based on whether it has KIA functionality. This implies endogeneity in their models as the platform is excluded - funding policy in their regression may merely be reflecting platform choice. Leboeuf and Schwienbacher (2014) offer a more robust study on whether AON works as an effective signal. They employ instrumental variables and propensity score matching (PSM) to address correlation between AON and unobserved characteristics which have a causal impact on funding success. They evaluate several models with varying degrees of robustness. Their most straightforward second-stage regression on success reveals AON campaigns are 29.2% more likely to attain funding. While their other models do not demonstrate equally economically significant results, they consistently reveal statistical significance for the AON dummy. The researchers also investigate whether the positive effect of AON may be the result of platform choice whereby fundraisers decide which platform to use based on whether it offers a KIA policy. Utilising PSM to match Indiegogo with Kickstarter (which only allows AON) projects, they demonstrate the positive effect remains - choice of AON (opting for the costly signal) leads to a separate outcome for high and low-quality projects.

2.1.2 Video Pitch Inclusion and Quality

Major platforms give users the ability to post video pitches. Posting a video indicates a basic level of preparation and thereby acts as a signal which separates high and low-quality projects (Mollick, 2014). Mollick (2014) finds that a video pitch dummy variable is not only positively statistically significant to project success, but it was consistently one of the most economically significant explanatory variables in his models. Using an entirely different dataset, Cumming et al. (2017) corroborate this finding. Younkin and Kuppuswamy (2018) elevate this discussion on video's effects. They recruited volunteers to assess the quality of videos across several dimensions (persuasiveness, professionalism, speaker's enthusiasm, and overall quality). They run two regressions on whether it achieved funding, one with and one without a 'matched' dataset. The former revealed no significance of video quality while the latter did. This inconclusive result suggests that video quality may be influential, but there are likely other factors more influential. Although, the fact that the matched dataset method was more robust suggests it may not be influential at all. If video quality is inconsequential to project outcomes, this suggests funders are not responding rationally as they are unable to create a separating equilibrium from a signal which has differential costs to high and low-quality projects. Although, it is worth bearing in mind the limitations to their findings. Namely, the subjectivity of video quality and whether the volunteers they employed have preferences that align with the preferences of genuine crowdfunders. Given that the quality of the video is not significant, Mollick (2014) and Cumming et al.'s (2017) findings may not be spurious at least from excluding video quality.

2.1.3 Description

Founders are also often encouraged to write a description about their campaign. While textual information is difficult to codify, researchers have tried numerous feature engineering techniques to quantify what aspects of descriptions funders will discriminate on. The length of descriptions is a popular explanatory variable included in regressions on funding success (Cumming et al. 2017 and 2019; Crosetto and Regner, 2014). Cumming et al. (2017) find that even when including the readability of the text as a metric, projects with longer descriptions are more likely to meet their funding targets. This finding is somewhat at odds with Crosetto and Regner's (2014) findings. Specifically, Crosetto and Regner (2014) use data from 'StartNext' which has the unique 'starting phase' feature where projects must attain a set number of 'fans' before it can begin procuring funding. In their study, word count is significant to garnering initial support in the starting phase, but not during the funding phase. They do not elaborate on possible explanations for this. Nevertheless, length says nothing about the content or quality of a given description. Mollick (2014) creates a dummy 'spelling mistake' which is true for any project whose description contains at least one mistake. It was highly significant and negative across his OLS models but had relatively small practical significance.

These results are not particularly useful to fundraisers and could be misleading. For example, empirical research is implicitly encouraging longer descriptions without caveat. I postulate that without exploring the possible misspecification that funding success is not a linear function of text length, the aforementioned regressions are potentially spurious. This could be tested by including a non-linear flavour of the text length variable. Another interpretation of the evidence could be that the length of a description may offset spelling mistakes or readability of the text. However, the extent to which text length is a significant predictor of a project's success may vary with readability: a lengthy yet unreadable description is unlikely to help a project advertise itself. This would be tested by incorporating an interaction term.

2.1.4 Updates

Antonenko et al. (2014) observe in a purely descriptive study that successful projects make extensive use of update functionality. However, the causal impact thereof is not discussed in their paper. Mollick (2014) takes this a step further adding updates to his cross-sectional regressions. Specifically, he encodes updates as a dummy which is true if the founder posts an update within three days of the campaign's creation, finding both statistical and economical significance. Kuppuswamy and Bayus (2015) add to the discussion the role updates play throughout the lifespan of a campaign. They implement a dummy variable to their panel regressions and note that it is consistently, positively significant. They also run an auxiliary panel regression on updates with dummies for the first and last week, whether the project was successful, as well as pairwise interaction terms. The significance of 'lastweek*funded' and non-significance of 'lastweek' led the authors to conclude that successful fundraisers utilise updates to encourage backers to contribute toward the end of the funding cycle.

The analysis of update's impact on project success is still missing some nuance. The aforementioned studies that refer to updates only evaluate whether the inclusion of any update affects their dependent, omitting any descriptive content of the update itself. While posting an update does signal some additional effort is exerted than not having posted an update, there are more-or-less equal signal costs to posting an update between high and low-quality projects. Further, updates may contain information that is non-binding and non-verifiable: all the key ingredients for 'cheap talk' (Farrell and Rabin, 1996). On this basis, I would challenge the assumption that posting an update alone is a pertinent signal that meaningfully distinguishes high and low quality projects. Including some measure of update quality would allow this to be evaluated.

2.2 Funder Responses to Passive Characteristics

Passive characteristics - unlike signals - are typically immutable (at least for the duration of the funding cycle). In crowdfunding, these are foremostly physical attributes of the fundraisers. Jenq et al. (2015) conclude that when controlling for objective characteristics of the loans, donors respond to physical attributes of the fundraisers. This result was later tested by Luo and Ge (2018) who reveal more nuanced discrimination. In their study, there was no difference in the probability of funding, but that higher risk aversion when lending to African Americans was evidenced by smaller contributions per donor. Whether a similar pattern of behaviour extends to reward-based crowdfunding sites has also been studied. Younkin and Kuppuswamy (2018) employ data from Kickstarter to examine racial biases of funders on the platform. They incorporate a 'Black Founder' dummy variable to their regressions along with variables to control for project quality. Informed by Mollick's (2014) findings that network effects are significant in crowdfunding success, they also examine whether discrepancies between network effects of different ethnic groups could explain outcome disparities. They show that even when controlling for network effects, funders respond to skin colour as a signal of whether to fund and to what extent to fund.

2.3 Time-based Funding Dynamics

Belleflamme et al. (2015) theorise how funders respond to the behaviour of other funders on the same platform, and the implications thereof (within-group effects). Notably, they mention that selfishly motivated funders (those primarily concerned with collecting rewards) should exhibit positive within-group externalities whereby one funder's investment in a project increases the chance another funder's investment will yield them a payoff. This theoretical effect is especially pronounced in the early phase when the risk of failure is higher (Crosetto and Regner, 2014): the crowdfunding market where these funders dominate exhibits underfunding in the early phase of funding. Belleflamme et al. (2015) also suggest that these funders may utilise the level of funding secured as a signal for quality, exaggerating their proclivity to invest as a project secures more funding. Conversely, altruistically motivated funders exhibit very different behaviour. Their proclivity to invest is mediated by their perceived impact where perceived impact is a function of the proximity to the deadline, funding target and whether a project is in the early funding phase (Kuppuswamy and Bayus, 2017). Empirical results show that Kickstarter funders manifest both motivations (Gerber and Hui, 2013; Kuppuswamy and Bayus, 2017). In their study, Kuppuswamy and Bayus (2015) show funding across time transpires as a U-shape. They cite altruism, network effects, updates and initial excitement for strong early-stage support. Deadline effects where both altruistically and selfishly motivated funders exhibit increased proclivity to invest explains the uptick toward the end of a funding cycle.

Many publications also discuss network effects that play a salient role across the crowdfunding cycle (Mollick, 2014; Kuppuswamy and Bayus, 2015; Belleflamme et al., 2015; Agrawal et al. 2013 and 2015). Empirically measuring characteristics of a fundraiser's network is difficult; however, Mollick (2014) engineered a technique that inspired many other researchers (Kuppuswamy and Bayus, 2015; Younkin and Kuppuswamy, 2018). He extracted the number of Facebook friends the founder had as a proxy for her network size. All the above authors' analyses reveal that Facebook friends of the founder is positive and statistically significant. Kuppuswamy and Bayus (2015) run a separate regression for projects where the founder has higher than the median number of Facebook friends in the sample. They find the U-shaped pledge curve is emphasised in the "high-friend" panel regressions. This suggests to the researchers that networks are leveraged in the beginning and ending phase of the funding cycle.

3 Data and Summary Statistics

3.1 Data Overview

My analysis leverages a panel dataset that followed 23 projects throughout their funding cycles on crowdfunding website, Kickstarter.com. I collated a panel dataset by way of a python web scraping script that ran every day at 12:00 am (GMT +0) to collect both time-invariant and time-series (hence the need to run daily) data points as listed in table 1. The projects scraped were randomly selected from all projects that launched between the 24th November 2020 to 9th December 2020. Because project lifespans are not fixed (appendix E), my panel is unbalanced - there are 584 observations instead of 23 multiplied by a fixed project duration.

3.2 Data Cleaning and Preprocessing

Projects in the panel are not all located in the same geographical region and consequently not all denominated in the same currency (appendix A). To ensure monetary variables are comparable, these values have been converted to US Dollars taking the spot rate upon data scraping for the appropriate currency pairing.

Along with Mollick (2014), Kuppuswamy and Bayus (2017), and Cordovaa et al. (2015), I have chosen to remove projects with funding targets below $3000 as low goal projects rely more heavily on networks, rather than appealing to 'the crowd' (Mollick, 2014). This operation removed 4 projects from the panel leaving 19.

While it is possible for project founders to post more than one update per day, this was not evident in my sample. This allows for updates to be encoded as a dummy variable, taking a value of 1 if an update was posted on a given day and 0 otherwise.

3.3 Sentiment Encoding

Sentiment scores have been computed using the Python package 'TextBlob', which has been utilised in other Social Science publications (Mogaji and Erkan, 2019; Zhao et al., 2019). TextBlob uses tokenisation to calculate sentiment polarity and objectivity (textblob.readthedocs.io, 2018). Each word in the lexicon has a polarity, intensity and objectivity which all combine to compute an overall polarity score between -1 (very negative) and 1 (very positive) - 0 is neutral; the objectivity score is between 0 (very subjective) and 1 (very objective). The sentiment scores are thus a reflection of TextBlob developer's research and intuition of the relative sentiment of words. We therefore must approach these scores cautiously, and consider their algorithmic roots when interpreting them. I discuss the tenability of using these scores empirically in section 6.2.2 and 6.2.3.

3.4 List of Variables

The following table lists the raw variables contained in my dataset. Here, subscripts denote the dimension(s) along which the variable is varying: an i,t subscript indicates the variable is both project and time-varying; an i subscript denotes the variable is project-varying and not time-varying; only t indicates, the variable varies across time and not across projects.

Variable Name	**Description**
Update Text$_{i,t}$	The textual information contained in the update posted for project i at time t
Sentiment Polarity$_{i,t}$	A score from -1 to 1 which indicates the positivity (+1) or negativity (-1) of the update.
Sentiment Objectivity$_{i,t}$	I A score from 0 to 1 which indicates the objectivity of the language in the text
Country$_i$	The country from which the project's owner listed the project
Launched$_i$	The unix timestamp value indicating when the funding cycle for project i begins
Deadline$_i$	The unix timestamp value indicating when the funding cycle for project i ends
Funding Target$_i$	The monetary value project i's founder(s) is asking for. If this funding target is the surpassed, the project is deemed successful and backers funds are transferred to the entrepreneurs
Pledged$_{i,t}$	The cumulative monetary value of funding that project i has secured at time t
Backers$_{i,t}$	The cumulative number of individual funders project i has attracted at time t
Blurb$_i$	The description posted on project i's page
Category$_i$	The category which the project has been assigned to by its founder
State$_{i,t}$	Reflects whether project i has surpassed its deadline at time t and if so whether it has achieved its funding target

Table 1: Variable List

From these core variables, I also engineered the following for use in the empirical method:

Variable Name	Description
Backers Added$_{i,t}$	The difference in backers on day t and day t-1
Funding Added$_{i,t}$	Marginal monetary increase in funding for project i from time t-1 to time t. Denominated in USD
Funding Cycle Length$_{i,t}$	The number of days a project could receive funding for
Day of the Week$_t$	A set of dummy variables indicating the day of the week at time t, omitting Monday to avoid perfect collinearity
Day of the Funding Cycle$_t$	A set of dummy variables indicating how far into the funding cycle the project is at time t, omitting the first day to avoid perfect collinearity
Percentage Funded$_{i,t}$	The level of funding project i has secured at time t, divided by project i's funding target
Update$_{i,t}$	A dummy variable indicating that a campaign owner posted an update for their project i at time t
(Update · Sentiment)$_{i,t}$	Pairwise product of update and sentiment polarity score
(Update · Objectivity)$_{i,t}$	Pairwise product of update and sentiment objectivity score

Table 2: Engineered Variable List

Due to web scraping limitations, some key variables that other researchers have robustly demonstrated statistical significance for are absent from my panel. These namely include, a video pitch dummy and the number of Facebook friends of a founder. Insofar as these variables can be considered time-invariant measures, I will be able to circumnavigate problems arising from their exclusion with FE estimation.

3.5 Summary Statistics

Table 3: Summary statistics for project and time-varying measures
n = 584

Variable	Mean	Std	Min	Max
BackersAdded	6.64	14.11	0.00	149.00
FundingAdded	523.50	1303.80	0.00	13438.80
Update	0.086	0.256	0.00	1.00
Update Objectivity*	0.5997	0.207	0.16	1.00
(Update · Objectivity)*	0.041	0.157	0.00	1.00
Update Polarity*	0.192	0.147	-0.019	0.504
(Update · Polarity)*	0.041	0.063	-0.019	0.504

* summary stats do not include NA values when there was no update for an observation; n = 50

Table 4: Summary statistics for time invariant measures n = 19

Variable	Mean	Std	Min	Max
Funding Target	29832.00	49379.60	3000.00	214000.00
Funding Cycle Length	30.74	6.85	24.00	54.00
Overall Successful	0.632	0.496	0.00	1.00

4 Empirical Method

4.1 Aim

My empirical method aims to extend the current understanding of updates, their role in predicting success for crowdfunded projects and what this says about crowdfunders' response to signals. Use of updates has been shown to be predictive of future project support (Mollick 2014, Kuppuswamy and Bayus, 2015); my results will either challenge or corroborate these findings. Authors leverage this finding in their case to show that backers respond rationally to signals of quality - implicitly assuming updates are indicative of quality. Operationalising the update objectivity measure, my analysis will offer a deeper exploration which explicitly challenges this assumption. Updates provide the opportunity for fundraisers to bridge information asymmetry issues that crowdfunding suffers from. Kickstarter itself recommends founders utilise updates to provide insightful, honest statements regarding the progress of their project (www.kickstarter.com, 2020b). That being said, it is not necessarily the case that updates are used in this fashion - many updates are emotionally driven and do not discuss the progress of the project (appendix F). Under the assumption that objectivity proxies quality of updates, we can distinguish high and low quality updates and whether funders will respond appropriately as Mollick (2014) asserts. Intuitively, we expect funders to be more inclined to support a project that uses more objective language (assuming that the content of the language is not negative).

4.2 Outcome Variable

While much research chooses the ex-post attainment of funding as a measure for success (Mollick, 2014; Crosetto and Regner, 2014; Cordovaa et al., 2015), I have chosen to use the marginal increase in backers on a given day for a given project (BackersAdded). Studies that utilise the ex-post outcome are cross-sectional where the dynamics of intra-cycle funding is unobserved and/or irrelevant. When studying the effects of explanatory variables which readily change throughout the funding cycle (such as the posting of updates), a measure of success that reveals the short term impact of those intertemporal changes is more appropriate - something BackersAdded provides that ex-post success does not. For additional robustness, I will also evaluate my models using the marginal monetary contribution on a given day for a given project as the outcome variable; many additional backers may not be a signal of success if the monetary contributions of those backers is small.

4.3 Core Model

Where g(.) is a nonlinear function. Under the Poisson FE model, this is the exponential function.

$$BackersAdded_{i,t} = g(\beta_0 + \beta_1 Update_{i,t} + \beta_2 (Update \cdot Objectivity)_{i,t} + a_i + u_{i,t}) \quad (1)$$

Where g(.) is a nonlinear function. Under the Poisson FE model as implemented as xtpoisson in Stata, this is the exponential function.

Table of Variables	
BackersAdded	The difference in backers on day t and day t-1
Update	An event dummy variable which is true if the fundraiser(s) posted an update on that day
(Update · Objectivity)	Is the pairwise product of the whether the fundraiser posted an update, and the objectivity score of that respective update.
a_i	Are unobserved, time-invariant factors which influence the dependent variable
$u_{i,t}$	Is the idiosyncratic error term for each project in each time period

4.4 Estimation Method

If updates or update objectivity are correlated with unobserved factors that also influence the dependent variable, my regression estimates will be biased and inconsistent via endogeneity. While I am able to include controls for variables previously shown by researchers to be significant in predicting crowdfunding success that could also be associated with likelihood of updating, such as funding target (Kuppuswamy and Bayus, 2017) and category (Cumming et al., 2017), there are some factors I cannot include either due to data limitations (e.g. video pitch) or because they are difficult to measure (e.g. quality of the video pitch). FE estimation helps remedy this issue. Research with a similar panel model structure (Kuppuswamy and Bayus, 2015 and 2017), implements category level FE which eliminates any issues arising from heterogeneity between categories; however, because I have access to fewer control variables than Kuppuswamy and Bayus (2015 and 2017), I will employ project-level FE in case the excluded controls are resolving heterogeneity within the category groups and correlation with independent variables. This would arise if, for example, video pitch and updates are correlated, as well as there being a disparate likelihood for projects within the food category group to post a video pitch. Given these assumptions, a category FE model would still be endogenous from correlation with time-invariant factors.

My primary outcome variable (BackersAdded) assumes non-negative integer values and consequently warrants specifying my regressions as the Poisson FE model. This model has desirable robustness properties as demonstrated by Wooldridge (1999): estimates are consistent and asymptotically normal only under the structural conditional mean assumption. Furthermore, the distribution of BackersAdded indicates that there are many small values and a relatively small mean (table 3 and appendix D). While OLS can be robust for count data with a large mean (Long, 1997), it is unlikely to be robust in my case, strengthening the case for the Poisson model. Statistical inference of this model, however, is slightly trickier. The distribution of BackersAdded at both the overall level (table 3) and project-level (appendix D) ostensibly suggests a violation of the Poisson equidispersion assumption (overdispersion). To formally assess this, I run a one-sided test for overdispersion on model 5.2, as defined by Cameron and Trivaldi (1990). The test rejects the null hypothesis at the 0.00011% significance level, confirming suspicions that the model exhibits overdispersion. The statistical consequence of overdispersion is inflated and inconsistent standard errors; statistical tests are by extension invalid. Fortunately, by estimating the model using quasi-maximum likelihood estimation and the robust matrix, standard errors are valid only under the structural conditional mean assumption, are fully robust to serial correlation, and the distribution of BackersAdded conditional on the explanatory variables is unrestricted (Wooldridge, 1999). Moreover, the Poisson FE model has the same robustness properties for dependent variables that assume continuous, non-integer values (Wooldridge, 1999). Thus, I will not change my estimation method for the FundingAdded robustness checks.

4.5 Seasonality and Time Fixed Effects

Project level FE eliminates the possibility my regressions are spurious from correlation with time-invariant factors; however, it does not correct time-varying confounders such as seasonality. While evidence for long-term (monthly and/or yearly) seasonality in crowdfunding is thin (Vismara, 2018; Štofa and Zoričak 2016; Koch and Siering, 2019), Vismara (2018) highlights that crowdfunders exhibit short-term seasonal effects. In particular, there are day-of-the-week effects: funders are less likely to fund during the weekends. Projects commenced on weekends are thereby less likely to accumulate backers in the first few days of their project from this day-of-the-week effect. Vismara (2018) also investigates using a simultaneous equation model, that late stage support is a function of early support - a kind of momentum effect which is also evidenced by Kuppuswamy and Bayus (2017), and Cordovaa et al. (2015). Thus, projects listed on a weekend will have an overall reduction in backers from a combination of these effects. I aim to correct for this by including day of the week as a time-varying control to my model, as well as using the percentage funded variable to capture momentum effects. Furthermore, Kuppuswamy and Bayus (2015) show that the length of time elapsed into the funding cycle is also predictive of the pledges a project receives on a given day. Consequently, I implement the day into the funding cycle as a final time-varying, dummy control.

5 Results

Variable	BackersAdded 5.1	BackersAdded 5.2	FundingAdded 5.3
Update	1.738 ***	1.445 ***	0.484
	(0.352)	(0.365)	(0.606)
Update · Objectivity	-2.112 ***	-2.034 ***	-0.288
	(1.06)	(0.742)	(0.991)
PercFunded	-0.0488	-0.309 ***	0.392 ***
	(0.191)	(0.0538)	(0.0714)
Fixed-Effects			
Project Level	Yes	Yes	Yes
Day-of-the-week	No	Yes	Yes
Day-in-cycle	No	Yes	Yes
N	584	584	584
Log-Likelihood	-2602.486	-1661.567	-142537.88

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

5.1 Primary Regression Summary

By computing the above models, we can evaluate the ceteris paribus effect as described by the following (at the 1% significance level):

$$\frac{\partial BackersAdded_{i,t}}{\partial Update_{i,t}} = e^{(model)}(\beta_1 + \beta_2 Objectivity_{i,t}) \tag{2}$$

Both with and without the time fixed-effects, updates and their objectivity exhibit strong statistical significance for predicting future project support (5.1 and 5.2). The combined significance of these explantories suggests there is both a base level of support from updates (β_1), as well as there being an objectivity dependent component (β_2). The coefficient polarities evidence a counterintuitive phenomenon: objective language will diminish the expected future support for a project. Furthermore, the absolute value of the objectivity coefficient is larger than that of the update coefficient: a sufficiently objective update (0.714 for 5.2) will not only attenuate update's positive effect, but will also erode the effect such that posting an update will cause the project's expected future support to be less than the expected future support (expected future support is never negative due to the Poisson specification). Though, the precise marginal effect depends on the value of all other parameters in the model (equation 2).

Despite coefficient polarities remaining unchanged, updates and their objectivity appear to be uninfluential in the FundingAdded model - the standard errors become larger than the respective absolute coefficient values. While updates are able to help explain the number of additional funders a project will receive, they make no impression on the monetary value those funders will choose to invest. Moreover, the log-likelihood of 5.3 is nearly 10 times larger than the equivalent BackersAdded model - the FundingAdded model explains far less of the variance in the dependent variable. This is likely in part because the variance of FundingAdded is much greater than that of BackersAdded (table 4).

Together, these results imply that when an update is posted, the update and its objectivity can predict further support but that support which is predicted from the update, will not be monetarily large enough to consistently manifest as additional funding. This raises the idea that updates and objectivity influence funding from smaller investors who are not able to steer the overall funding level - a hypothesis which future research may wish to investigate.

5.2 Day-of-the-week effects

Coefficient deflation of the updatle dummy from 5.1 to 5.2 is also a curious finding. This result is likely because the day-of-the-week effect is both significant and correlated with updates (Appendix J).[1] Days on which updates are more likely to be posted are days that would receive higher funding regardless of whether the founder listed an update causing the encapsulation of the day-of-the-week effect within the 5.1 update coefficient. While 5.2 and 5.3 parse out respective effects for day-of-the-week and updates, the estimates in these regressions imply the response of funders to an update is consistent regardless of the weekday. I engineer new pairwise variables between update and the day-of-the-week dummies to assess whether this is the case.

The ceteris paribus effect (at the 5% significance level) is now described by the following:

$$\frac{\partial BackersAdded_{i,t}}{\partial Update_{i,t}} = e^{(model)}(\beta_1 + \beta_2 Objectivity_{i,t} + \beta_3 Sunday_t) \tag{3}$$

Statistical significance for the original update dummy is slightly weakened but still remains; however, the interpretation of the update variable has changed to represent any day that isn't Sunday due to the lack of statistical significance for those interaction terms. Statistical significance for negative coefficients of Sat and Sun are aligned with Vismara (2018) findings that crowdfunding ventures experience weaker support on weekends. However, the positive significant update*sunday suggests that this effect can be mitigated by posting an update (the absolute value of the sunday*update coefficient is approximately double that of the sunday coefficient absolute value). Although, this is not evidenced for saturday; while Saturday*Update's coefficient is similar to the equivalent Sunday variable, it exhibits too much variance for us to be confident that Saturday updates are able to mitigate the lower weekend support effect. A similar phenomenon manifested itself in the FundingAdded model - while updates alone are still insignificant - an update posted on the weekend appears to offset the reduced monetary support a project would have received on that day. This is an interesting finding considering weekends are days that receive the lowest exposure (Vismara, 2018). Ultimately, this additional regression analysis changes little about the interpretation of updates and objectivity on BackersAdded; it just adds an additional caveat that an update might have a bolstered effect on Sundays.

[1] running an auxiliary regression with days into the funding cycle and without day-of-the-week did not dramatically change the update coefficient

Variable	**BackersAdded 6.1**	**FundingAdded 6.2**
Update	1.109 **	-0.281
	(0.0466)	(0.735)
Update · Objectivity	-1.913 **	-0.092
	(0.951)	(0.953)
PercFunded	0.355 ***	0.407 ***
	(0.055)	(0.073)
Tue	0.138	-0.117
	(0.154)	(0.266)
Wed	0.123	0.086
	(0.140)	(0.229)
Thu	-0.103	-0.406
	(0.148)	(0.278)
Fri	-0.067	-0.511
	(0.241)	(0.392)
Sat	-0.278 ***	-0.304
	(0.102)	(0.206)
Sun	-0.385 ***	-0.615 **
	(0.081)	(0.282)
Update · Tue	0.034	0.474
	(0.384)	(0.603)
Update · Wed	0.102	0.465
	(0.226)	(0.603)
Update · Thu	0.518	0.850
	(0.320)	(0.388)
Update · Fri	-0.159	0.452
	(0.348)	(0.559)
Update · Sat	0.719	1.202 *
	(0.682)	(0.656)
Update · Sun	0.809 ***	1.188 ***
	(0.306)	(0.359)
Fixed-Effects		
Project Level	Yes	Yes
Day-in-cycle	Yes	Yes
N	584	584
Log-Likelihood	-1687.05	-141023.10

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

5.3 Implications

Ostensibly, these results suggest that crowdfunders are not responding to signals as rational economic intuition would expect: in all BackersAdded models, objectivity is both significant and negative. Further, while the coefficient was not negative in the FundingAdded models, it was not positively significant as we might predict. In either case, objectivity of a project's updates does not improve its level of future support across any dimension. Therefore, platforms seeking to maintain the long-term quality of project updates should understand there is limited incentive for entrepreneurs to post updates as Kickstarter recommends and may wish to monitor the quality of updates. Although it is worth noting - fundraisers are using objective language in their updates (Table 3), despite funders potentially penalising them for doing so.

I would be cautious to advise fundraisers seeking to maximise their campaign's future support to manipulate the language used in their updates to project more subjective sentiment. While my results suggest such a fundraiser may yield short term benefit in the form of additional funders, such a behaviour may produce long-term negative externalities. Insofar as a platform's reputation is a function of the perceived quality of projects, the behavior of posting subjective updates adopted on a platform wide level, will denigrate that platform's reputation. Actionable wisdom funders may want to source from this study, is additional evidence on which to base at their campaign launch date: not the weekend. Additionally, while it is not recommended to post overly objective updates, updates below a threshold objectivity (0.714 for regression 5.2) will still encourage future backer support.

6 Limitations

6.1 Sampling

6.1.1 COVID-19

The months in which my sampling occurred was affected by the COVID-19 pandemic. If a COVID-19 effect is correlated with my updates or objectivity, this would imply endogeneity in my models. To the best of my knowledge, whether the relationship between any of the variables included in my models has changed because of the COVID pandemic or otherwise, has not been closely examined. Battaglia et al. (2020) evidence in their study that followed 437 Italian, equity-based projects, that the strength of predictors for crowdfunding success has changed consequently from the pandemic; although, the predictors they study are relevant to equity-based crowdfunding and do not apply to my analysis. Ultimately, further research should be done to investigate whether a pandemic effect may have biased estimates for predictors of crowdfunding success. Further, Elmer et al. (2020) suggest a new breed of covid-specific crowdfunded projects has emerged in light of the pandemic, threatening the assumption of stationarity in group-level project characteristics across time. A keyword search in project descriptions for “covid”, “corona”, “pandemic” and “virus” yielded no results, alleviating concerns that my results would not extrapolate to crowdfunding samples that do not consist of covid-specific projects which Elmer et al. make reference to.

6.1.2 Platform Bias

Kickstarter.com has been a very popular platform for empirical studies on crowdfunding dynamics (Mollick, 2014; Courtney et al., 2016; Kuppuswamy and Bayus, 2017; Kromidha and Robson, 2016). It is one of the largest reward-based CFPs having received more than $4.6 billion (www.kickstarter.com, 2020a) and as with any platform, has its own idiosyncratic characteristics and features which influence the dynamics of the funding taking place there. (1) The platform uses an AON policy: funders are refunded if campaigns do not reach their funding targets. (2) It is reward-based whereby funders cannot receive financial compensation of any kind - funding motivations are primarily prosocial and/or driven by collecting rewards (Gerber and

Hui, 2013; Kuppuswamy and Bayus, 2017; Wasiuzzaman, 2021). (3) The platform targets itself toward the funding of creative endeavours, and its category system from which founders choose between 15 categories exemplifies this. While not directly assessing these specific dimensions, Rykkja et al. (2020) demonstrate that funders do discriminate across reward-based platform characteristics. This opens the possibility that the response to updates as described throughout this paper is associated with funders who are pro-socially inclined, prefer AON policy and/or desire to fund creative projects. If this is the case, my results may not extrapolate to other crowdfunding platforms with different characteristics.

6.1.3 Category Omission

As mentioned, Kickstarter.com allows project founders to assign their project a category from a list of fifteen, four of which have no representation in my sample: Art, Dance, Food and Theater (Appendix C). At this stage, it is impossible to evaluate whether the conditional likelihood of posting an update or sentiment given the category is different for the categories not included with my sample. If there were differences for those excluded categories, my results are only unbiased and consistent when applied specifically to the categories within my sample and could be biased and inconsistent otherwise.

6.2 Estimation

6.2.1 Simultaneity

While unable to sift through all updates, I identified an update which references their project's previous backer support (Appendix F). If this is a common occurrence, the model may suffer from simultaneity. Consider the structural equations:

$$Update_{i,t} = \omega_0 + \omega_1 BackersAdded_{i,t} + \omega_2 exa_{i,t} + a_i + u_{i,t} \tag{4}$$

$$BackersAdded_{i,t} = \pi_0 + \pi_1 Update_{i,t} + \pi_2 exb_{i,t} + \alpha_i + v_{i,t} \tag{5}$$

To estimate the structural parameters, the above model must satisfy the order and rank conditions which as a necessary condition require the inclusion of an exogenous variable in both equations that is excluded from the other equation. For (2), this is easily identified, examples could include duration or goal; however, locating an appropriate exogenous variable for (1) has been difficult with my given dataset. There are no time-varying variables that exogenously influence a founder's proclivity to post an update. Thankfully, auxiliary logistic fixed-effects regression on the model described in 6.2 (without the exogenous variable) only reveals significance of the lagged BackersAdded variable at the 50% level. Thus, there is insufficient evidence to suggest that BackersAdded has a consistent and significant effect on the likelihood for founders to post updates.

6.2.2 Sentiment Encoding

Perhaps the most pertinent criticism of my strategy is the interpretation of update objectivity. The pillar on which any further interpretations can be assumed is the validity of TextBlob's score. If objectivity does not accurately measure objectivity, the variable merely adds statistical noise to the models - nothing can be said about funders response to the quality of updates. If the encoding algorithm is accurate, there may still be limitations to its interpretation. To claim that crowdfunders are not responding rationally to updates, requires that objectivity be at least an approximate measure of quality. When this assumption is violated, the findings of this paper are limited and similar to existing research which shows updates encourage future support of projects as well as them being able to mitigate weekend effects. Content analysis of the most objective update (Appendix K) within the dataset suggests there are at least some updates not being used to explicitly disclose information regarding the behaviour of the funders. Whether the update as detailed in Appendix K implicitly signals behavioural information is subjective. Disclosure of information is not necessarily required for updates to be of quality but if objectivity did reflect disclosure of information, this would allow the interpretation of regression results to extend to comment on funders and their response to attempts to bridge moral hazard issues. I would be hesitant at this stage to make a claim - there is little to suggest objectivity maps to disclosure information. This assumption also is not required to make this paper's central claim that funders are not responding rationally to general signals of quality.

6.2.3 Sentiment Polarity

Not all updates listed on crowdfunding sites reveal positive information (Indiegogo, 2021a). If it was the case that a negative update could negatively influence future backer support and my dataset contained negative updates, not controlling for this could render my results spurious via OVB. Insofar as we can trust TextBlob's polarity scores, we can be equally assured that any potential update polarity effect would not skew my results: my dataset contained no updates with a negative polarity score (table 3 and appendix G - unilateral positive polarity assumption). Therefore, my results reflect the effect of posting either a neutral or positive update. Although, one avenue through which the rather strong assumption of trusting TextBlob's polarity score may be under threat in the presence of sarcasm. Sarcasm is notoriously difficult to detect for even the most sophisticated natural language processing algorithms in part because individuals state the opposite of what is implied (Rajadesingan et al., 2015). Thus, if an update contains sarcastic remarks, the sentiment algorithm may return a polarity score precisely opposite to polarity intended by the update's author. The implications of this are that the unilateral positive polarity assumption is violated - some updates may contain information funders would regard as negative.

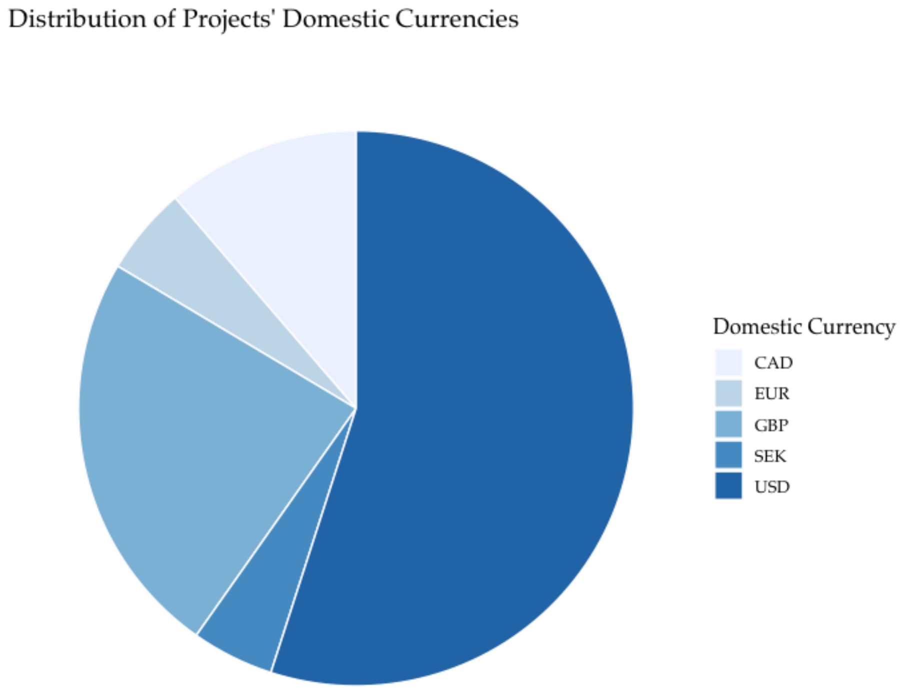
7 Conclusion

In this paper, I explore the role of updates in predicting crowdfunding success. Extant literature superficially demonstrates use of updates is indicative of project quality (Mollick, 2014; Kuppuswamy and Bayus, 2015). Regressions on project success which explore the effect of updates reveal positive coefficients and statistical significance which suggests that funders respond appropriately to quality signals. Leveraging sentiment analysis, my novel dataset contains a unique 'update objectivity' variable which I encode into Poisson FE regressions as a pairwise interaction term with the update dummy. In my results section, I evaluate the marginal effect on updates to the number of additional backers added, finding statistical significance for updates and their respective objectivity. Updates coefficient is consistently positive, evidencing that updates do encourage future support; however, objectivity's coefficient is consistently negative - objectivity appears to work against fundraisers, diminishing future support. Auxiliary regressions on the monetary value of support do not manifest the same statistical significance - additional backer support mediated by updates and objectivity is not monetarily large enough to consistently manifest as additional funding support. Together these results suggest that there are limited incentives for fundraisers to maintain quality of updates.

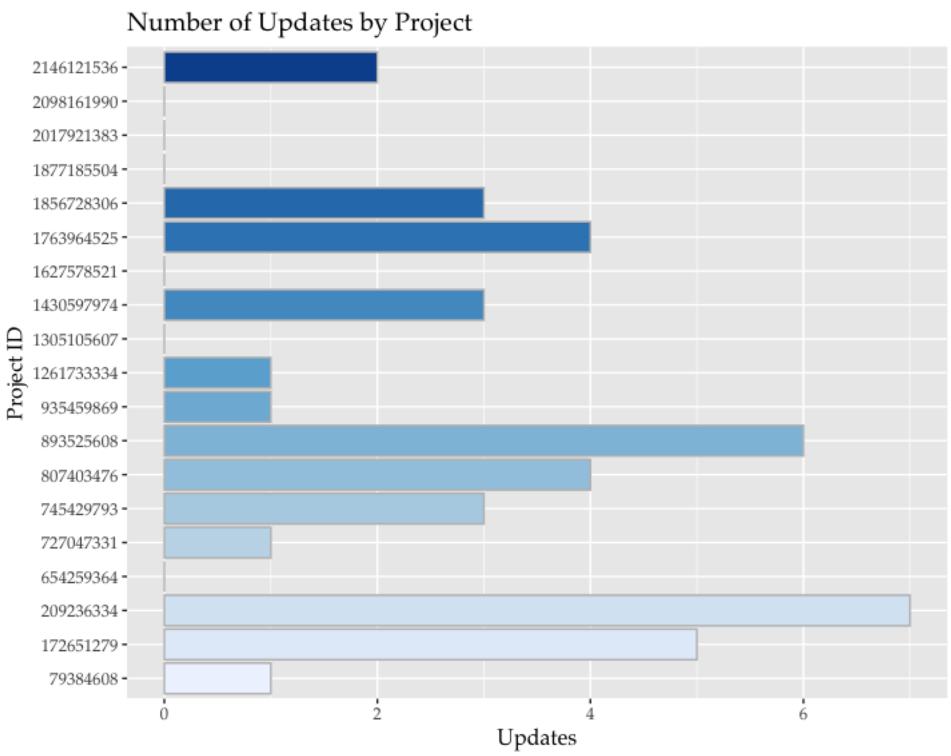
Estimates from my regression analyses can be considered unbiased and consistent insofar as the objectivity score reflects update quality; simultaneity is not an issue (previous support does not predict update likelihood); the Poisson FE structural mean assumption holds. The results may not extrapolate to projects outside the included Kickstarter categories, and to other projects if it is the case that the general characteristics of projects have changed significantly over time for reasons such as COVID-19. To understand whether these results are consistent for all reward-based crowdfunders, future research could identify whether these results extend to other crowdfunding platforms and/or to other time periods.

8 Appendix

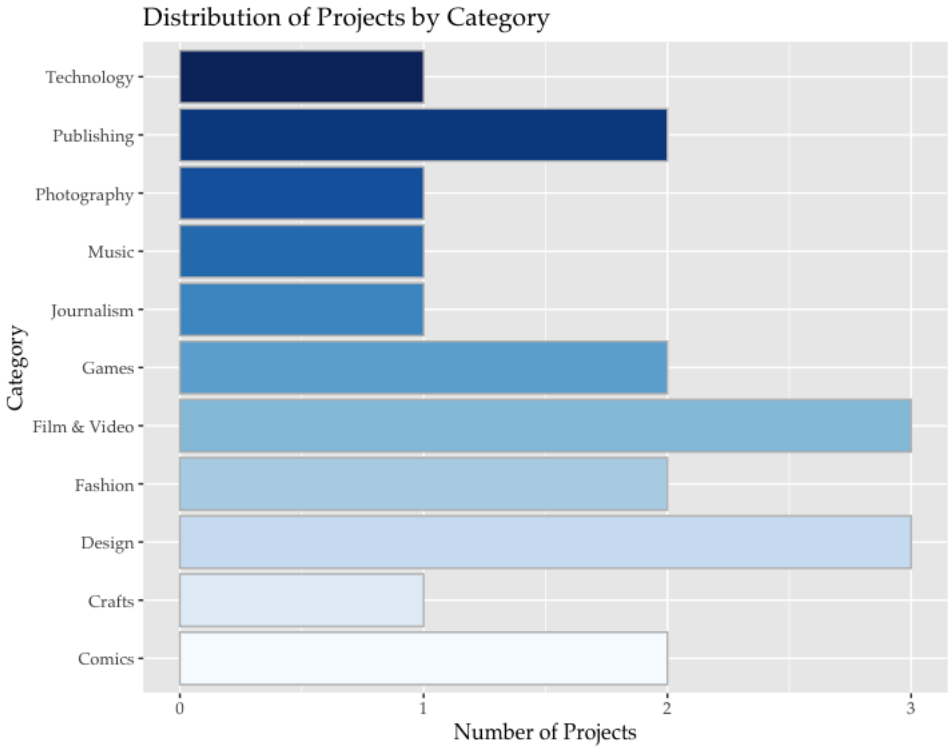
Appendix A



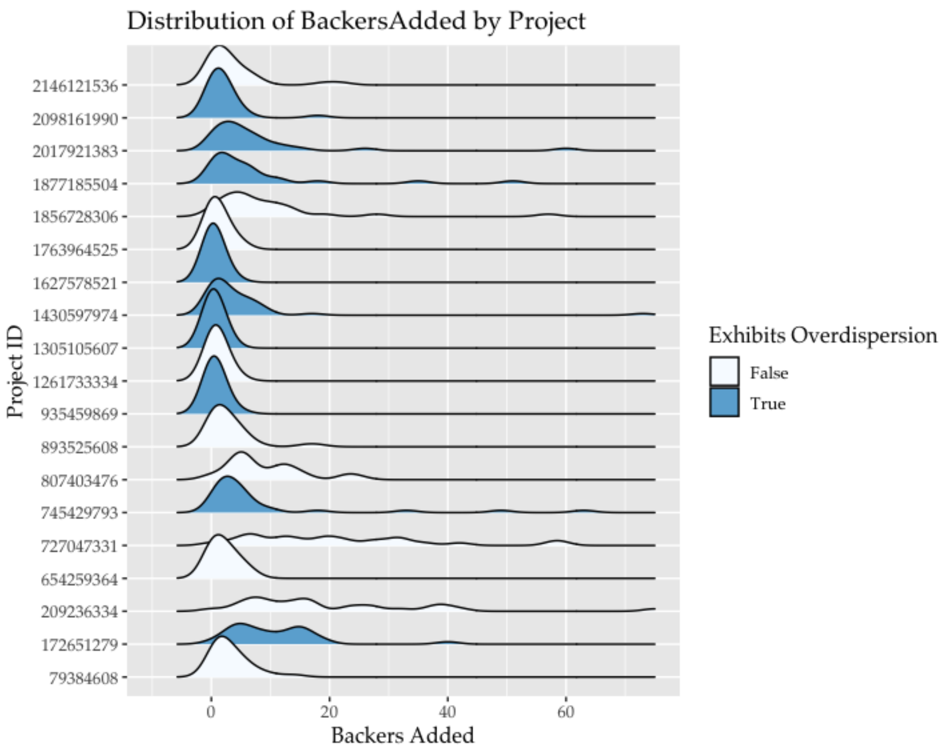
Appendix B



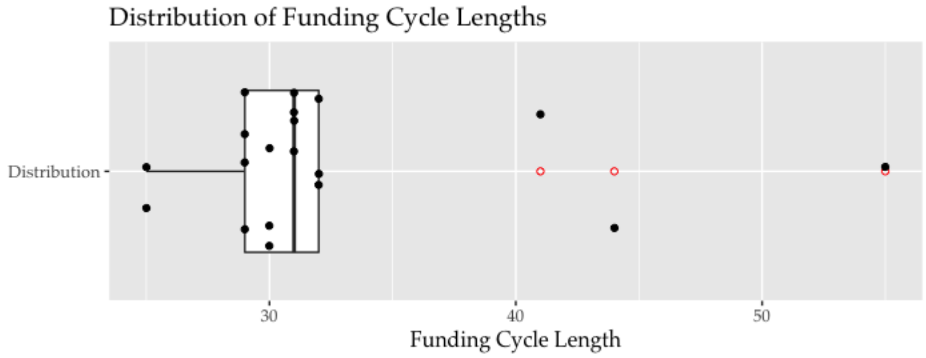
Appendix C



Appendix D



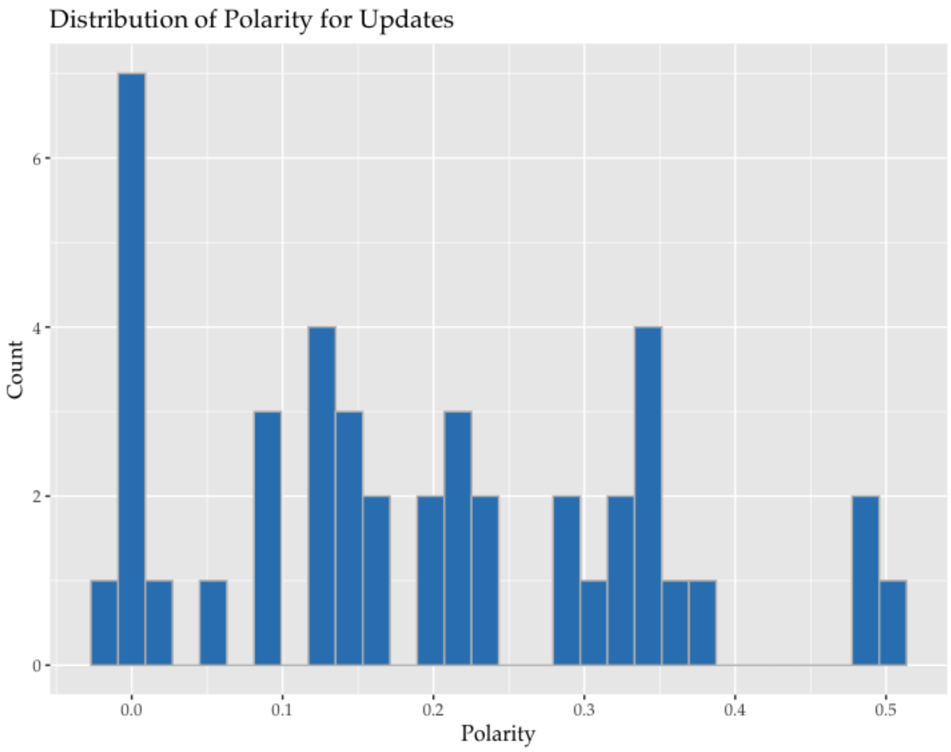
Appendix E



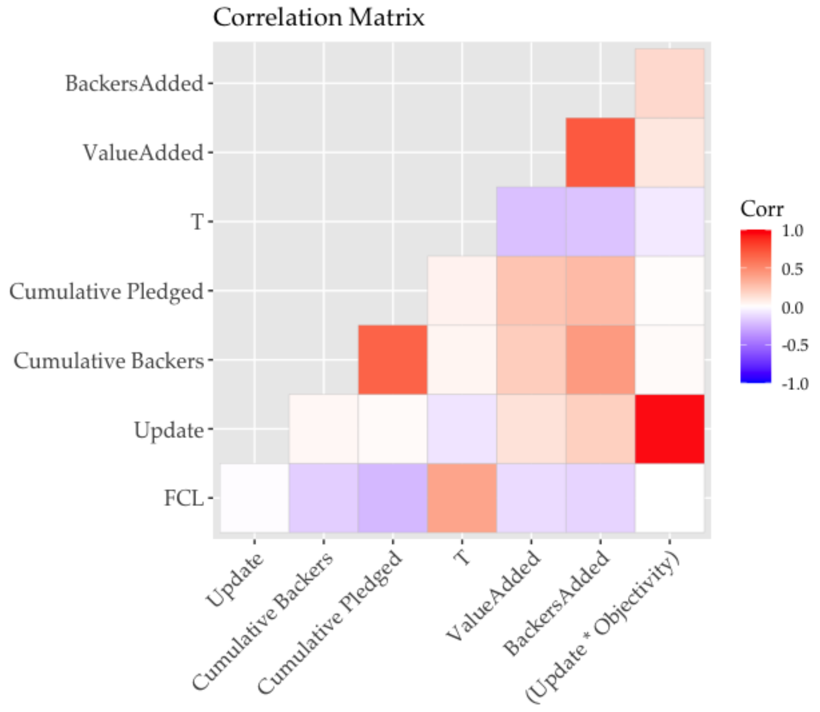
Appendix F

"£1372 raised in a week. Wow! Much appreciation to the 30 backers that have gotten us this far."

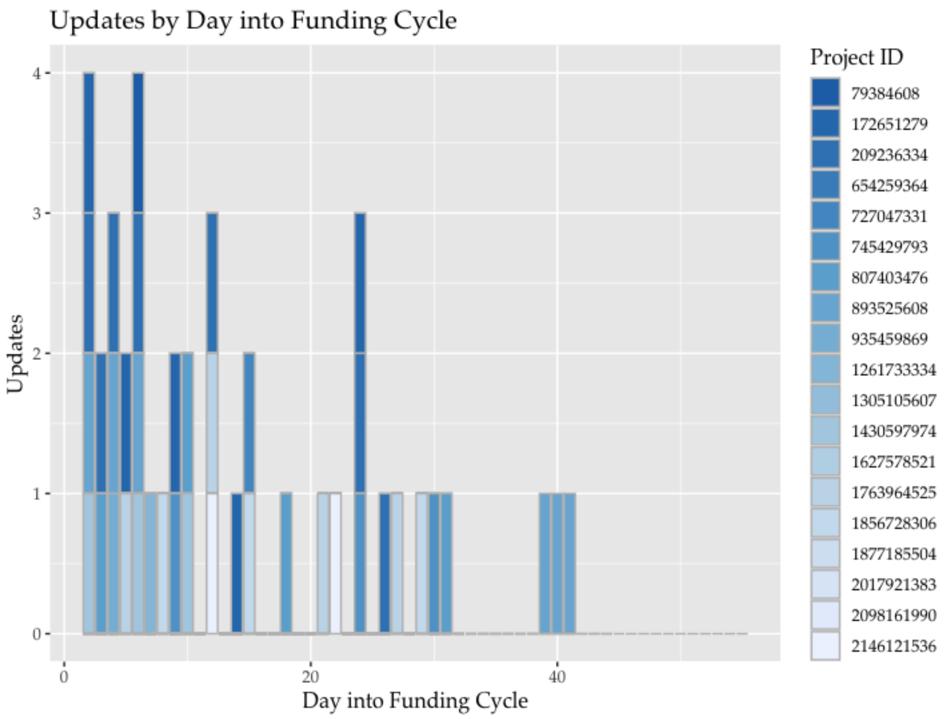
Appendix G



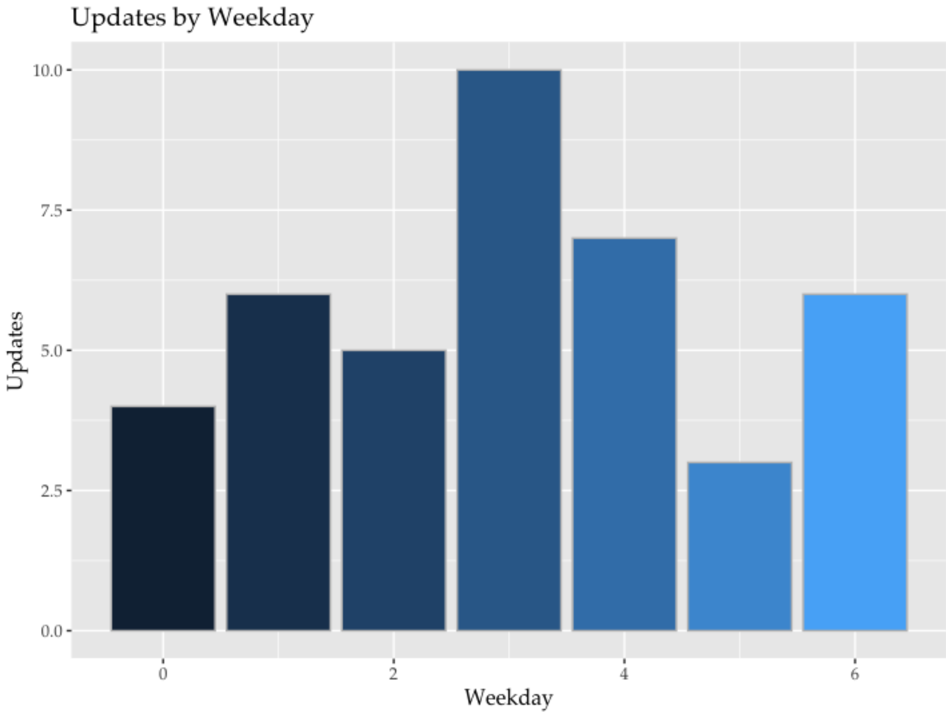
Appendix H



Appendix I



Appendix J



*0 is encoded as Monday; 6 is encoded as Sunday.

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