The Dynamic Effects of Updates in Crowdfunding: A Provision Point Model

Carlos Siri, Longxiu Tian, and Barry L. Bayus

When is the most effective time to post updates during a crowdfunding campaign? Answering this question requires a framework that accounts for the dynamic effects of updates, as well as a provision point mechanism. Crowdfunding platforms like Kickstarter involve an all-or-nothing structure such that no money exchanges hands if the target goal is not met. Addressing this question raises three interrelated challenges. First, entrepreneurs post updates strategically in response to evolving campaign conditions. Second, the provision point itself is an endogenous decision. Third, the effects of updates are not static but evolve nonlinearly across time. We tackle these challenges by developing a Bayesian provision point model that builds on the insight that entrepreneurs benchmark their decisions against similar past campaigns. This benchmarking provides exogenous variation that allows us to instrument for the non-random timing of updates and correct for endogenous goal-setting. We incorporate Gaussian Process priors to capture smooth, stage-specific dynamics in update effects. We find that updates have a modest and positive effects before the goal is reached, but their effectiveness becomes time-dependent once the goal is surpassed. Our framework also reveals that campaigns setting higher-than-benchmarked goals face weaker pre-goal and stronger post-goal support. Our research emphasizes the need for entrepreneurs to consider the sequence of updates as these have consequential effects on funding outcomes, and the need to consider the provision point when studying dynamics in crowdfunding.

Key words: Crowdfunding, Platforms, Changepoint, Dynamic Heterogeneity, Gaussian Process, Bayesian Non-Parametrics

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1. Introduction

Crowdfunding platforms have fundamentally changed how early-stage entrepreneurs raise capital and engage with potential consumers (Agrawal et al. 2014, Belleflamme et al. 2015). Since 2009, for example, the largest and most well-known crowdfunding platform, Kickstarter (the empirical setting for our study), has received over $8.7B in pledges to support over 660,000 campaigns (Kickstarter 2024). By hosting online funding campaigns for innovative ideas, entrepreneurs not only secure financial resources but also gather market feedback, gauge consumer demand, and build early brand awareness (Xu and Ni 2022). Among the different forms of crowdfunding, reward-based platforms (e.g., Kickstarter, Indiegogo) are particularly relevant to marketing research because they allow entrepreneurs to pre-sell their products, moving them from concept to market introduction (Hu et al. 2015, Xiang et al. 2019). Popular products that started on Kickstarter include the Oculus Rift virtual reality headset, Peloton exercise bike, Pebble smartwatch, and Allbirds shoes. According to the Pew Research Center (Smith 2016), in 2016, 22% of U.S. adults had contributed to at

least one crowdfunding campaign and 41% had heard of crowdfunding but had never contributed to a campaign. Crowdfunding has become a powerful marketing tool for entrepreneurs seeking initial funding and a community of engaged early-stage supporters who can contribute to product development and advocacy (Brown et al. 2017, Hervé and Schwienbacher 2018).

Despite its popularity, creating a crowdfunding campaign that successfully meets its financial goals remains challenging (Acar et al. 2021, Wei et al. 2021). For example, on Kickstarter, only about 40% of campaigns across all categories succeed, with technology-related campaigns achieving a 23% success rate (Kickstarter 2024). Success in crowdfunding is defined by whether a campaign meets its funding goal, which is specified upfront by the entepreneur at the time of a campaign's launch. Utilizing an all-or-nothing (AON) payout structure, pledges are held in escrow by the platform during the campaign duration. Should the funding goal not be met, then the escrowed pledges are returned to backers, and the campaign ends unsuccessfully. However, for campaigns that reach this minimum threshold, they may continue to generate additional 'post-goal' funding with the remaining duration of time. According to Kickstarter, this AON payout structure serves as "a measure to protect creators, and to minimize risk for everyone. This also assures backers that they're only funding creative ideas that are set to succeed."[1] From the literature, utilizing AON to facilitate crowdfunding campaigns reflects the fact that early-stage ideas are inherently risky for potential backers due to information asymmetry, i.e., entrepreneurs have more information than potential backers about the actual development stage of their product as well as their ability to deliver the promised product (Cumming et al. 2020, Zhang et al. 2023).

To reduce this asymmetry and maximize crowdfunding campaign success, the role of entrepreneurial communication is essential. A campaign's entrepreneurs – also referred to as 'creators' on Kickstarter – communicate with their potential backers via two primary channels provided by the platform. First, there are persuasive pitches and campaign descriptions that are revealed at launch (Jiang et al. 2024, Mollick 2014, Moradi et al. 2023, Zhang et al. 2023). Second, entrepreneurs can post campaign updates throughout the campaign duration (Bhargava et al. 2024, Block et al. 2018, Kuppuswamy and Bayus 2017). As the pitch and campaign description are static 'one-shot' forms of communication for a campaign, industry experts unequivocally advocate that updates over the course of the campaign should play a prominent role in effective crowdfunding communication strategies (Dushnitsky and Marom 2013, Steinberg 2012).

[1] https://help.kickstarter.com/hc/en-us/articles/115005047893-Why-is-funding-all-or-nothing

While considerable effort has been devoted to understanding how the initial pitch and description affect crowdfunding outcomes, the effects of updates have received relatively little empirical attention (see the comprehensive review by Deng et al. 2022). Extant empirical research on the effects of updates in crowdfunding limits their attention to update frequency, generally finding that the number of updates is positively related to campaign success (Deng et al. 2022). Few studies, however, consider the dynamics of updates. Crowdfunding literature that addresses the role of updates is sparse, and broadly suggests that entrepreneurs would benefit from insights on when to post updates to ensure campaign success. Yet, this research stream calls for action on several pertinent questions. For example, should updates be posted uniformly throughout the campaign (Dushnitsky and Marom 2013, Steinberg 2012)? Should updates be posted early or late in the campaign (Bhargava et al. 2024, Herd et al. 2022)? Should updates be posted before the campaign reaches its funding goal or once the campaign surpasses it (Pinkow 2022)? Our research seeks to address these questions.

To do so, our core premise is that while dynamics are well studied in many marketing domains and contexts — pricing, ad targeting, auctions, salesforce management, CRM, to name a few — the gap in crowdfunding communications is not for lack of interest or importance. Rather, researchers have been stymied by a set of identification challenges whose co-occurrence is unique to the crowdfunding context. First, campaign updates are not posted at random (Kuppuswamy and Bayus 2017, Xiang et al. 2019), as entrepreneurs strategically time and craft updates in response to evolving campaign conditions. Second, the funding goal is endogenous as it is a choice that entrepreneurs must make at the onset, yet with nontrivial ramifications on campaign outcomes (Chakraborty and Swinney 2021, Cumming et al. 2020, Kim et al. 2020). Third, the effects of updates are unlikely to be time-invariant, but rather evolving over the course of the campaign (Bhargava et al. 2024).

To address these challenges, we combine structured data (campaign metadata, daily pledges) with unstructured data (campaign descriptions, update feeds) to construct a fine-grained panel of campaign progression, pledging behavior, and entrepreneurial communication of Kickstarter campaigns from 2018 to 2020 (totaling 151,687 observations at the campaign-day level). Leveraging these data, our proposed empirical framework is comprised of three specification components, mirroring the challenges. First, to account for both pre- and post-goal stages of a campaign, as well as within-stage update dynamics, the basis of our model likelihood is a changepoint specification with Gaussian Process (GP) priors (Dew et al. 2020). The changepoint allows for discontinuous shifts in update effects pre- vs. post-goal while the GP captures their dynamic evolution within

each stage. Because a campaign funding goal is an observable, we term our framework a *provision point model* to avoid ambiguity for the reader familiar with existing changepoint models[2]. Second, this naming distinction also serves to highlight that the AON payout threshold is set strategically, and we account for this provision point endogeneity via an instrumental variable (IV) correction. Third, to deconfound the nonrandom timing of updates while ensuring granular and managerially-relevant inference, we utilize a panel IV approach based upon the shift-share 'Bartik instrument' (Bartik 1991, Goldsmith-Pinkham et al. 2020). Our unstructured data play a crucial role in the construction of both sets of instruments. Applying Wei et al.'s (2021) semantic-similarity network to campaign descriptions of past Kickstarter campaigns, we exploit entrepreneurs' tendency to benchmark against past campaigns as a source of exogenous variations for both goal setting and update timing.

Our proposed model reveals meaningful patterns in how update effectiveness evolves over the course of the campaign, such as mid-campaign 'dips' and subsequent 'rebounds'. By accounting for distinct stages, we demonstrate that update effectiveness is not static over the course of the campaign, but rather shifts once the funding goal is reached. In the pre-goal stage, updates exert a modestly positive and stable effect on daily pledges as the campaign progresses. Once a campaign crosses its goal, however, update effectiveness becomes significantly more varied in its time dynamics. Immediately after the goal is achieved there is a spike in pledge responsiveness, followed by a rapid dip. In the middle of the post-goal stage, updates are generally not effective. Finally, there is a renewed lift in update effectiveness in the final days of a campaign. In turn, our managerial recommendations for optimal update timing shall notably dissent from those of misspecified counterparts that fail to account for (any of) the three identification challenges.

Taken together, our research responds to the call for more research on the dynamics of crowdfunding communications in both the marketing (Moradi et al. 2023, Nyilasy et al. 2024) and the entrepreneurship (Bafera and Kleinert 2023, Colombo 2021) literature. Previous studies have treated the crowdfunding campaign as a homogeneous process, thus neglecting important structural shifts that may occur over the campaign duration. In contrast, we show that crowdfunding campaigns evolve distinctly between pre- and post-goal stages, and that entrepreneurs are likely exploiting this pattern via how they choose to set their funding goals. Our findings, therefore, suggest that the

[2] In a review article (Li et al. 2019b), it was noted that the most prevalent usage of changepoint models is to infer an unobserved point of discontinuity, modeled as a latent variable. The authors suggest less common scenarios, such as ours, as future extensions to the framework.

effectiveness of updates is more nuanced than what the existing literature proposes. While industry pundits recommend posting updates throughout the campaign (Dushnitsky and Marom 2013, Steinberg 2012), we find that this makes sense only in the pre-goal stage. While some research recommends that updates be posted in the early stages of a campaign (Bhargava et al. 2024, Herd et al. 2022), we find that early updates are most effective in the post-goal stage. Finally, while other research suggests that updates are not effective in the post-goal stage (Pinkow 2022), we find that updates can be very effective in the early and later stages of the post-goal stage – understandably, a model that omits within-stage dynamics likely 'cancels out' these early and late stage surges with the mid-stage slump in its parameter estimation.

Our framework also helps reconcile two seemingly conflicting views about the role of goals in crowdfunding campaigns. On the one hand, higher goals reduce the likelihood of success by making the funding threshold harder to reach (Mollick 2014). In the pre-goal stage, setting this target too high depresses daily pledges, as backers perceive their contributions as less pivotal and are less motivated to pledge (Kuppuswamy and Bayus 2017). On the other hand, once the target is reached, higher goals serve as a credible quality signal that reassures backers about the campaign's viability and attracts additional pledges (Chakraborty and Swinney 2021).

Our work makes other substantive and methodological contributions. We advance the study of pre-launch communications within the new product development literature by highlighting how dynamic communications can shape a new product's successful introduction. Firms can choose to engage with customers during the pre-launch period with strategies such as traditional pre-announcements (Kim and Hanssens 2017, Sorescu et al. 2007), as well as early customer engagement approaches, including co-creation (Schreier et al. 2012) and crowdfunding (Herd et al. 2022). Empirically, traditional pre-announcements helps us understand immediate consumer interest (Kim and Hanssens 2017), stock market reactions (Sorescu et al. 2007), and post-launch sales (Schreiner et al. 2025). However, traditional settings typically limit our ability to capture the direct, dynamic impact of communications because these effects occur before firms begin realizing any economic benefits. Crowdfunding provides a compelling empirical environment to explore the impact of pre-launch communications as it involves continuous and publicly visible campaign updates throughout campaign stages that could elicit near-immediate shifts in funding behavior.

Methodologically, previous studies employing a changepoint specification (Li et al. 2019b) assume its exogeneity. In contrast, our approach recognizes that entrepreneurs' choice of funding goals can influence both backers' perceptions and subsequent pledging behavior. Our framework's

approach to both goal and update endogeneity enable it to be readily extended to other provision point contexts such as group-buying platforms where meeting a collectively defined target can trigger changes in consumer outcomes and strategic communication (Jing and Xie 2011).

The remainder of this paper is organized as follows. The next section reviews the crowdfunding context and the AON provision point mechanism. We then develop our modeling framework and describe the data, before presenting results on the dynamic effects of updates. Additional analyses examine robustness, goal setting, and update content. We conclude with a discussion of contributions, managerial implications, and the broader relevance of our framework to other provision point settings.

2. Background

In this section, we discuss how the all-or-nothing (AON) structure in crowdfunding platforms creates distinct pre- and post-goal stages, each characterized by unique dynamics. Our objective is to highlight how modeling these stages has important implications for studying the dynamic effect of updates over the duration of a crowdfunding campaign. In tandem, we contextualize this research and our empirical framework within the current literature on crowdfunding, including those that have in part examined the role of update communications.

2.1. The Crowdfunding Campaign

At the heart of crowdfunding platforms like Kickstarter is the AON payout structure. Entrepreneurs must declare a funding goal at the time of launch, such that if a campaign's cumulative pledges fall short of this goal by the deadline, backers are refunded their pledges from the escrow, and the campaign ends unsuccessfully (Cumming et al. 2020).

The AON mechanism delineates crowdfunding campaigns into two distinct stages: the pre-goal stage, during which entrepreneurs strive to meet their initial funding target; and the post-goal stage, in which successful campaigns continue to attract additional pledges beyond their initial goal with any remaining duration of time prior to the deadline. Recognizing these distinct stages is important for modeling campaign dynamics (i.e., beyond just the consideration of the role of updates). Each stage is characterized by unique funding behaviors (Dai and Zhang 2019, Pinkow 2022, Weber et al. 2023), entrepreneur incentives (Cumming et al. 2020), and risks (Mollick 2014). During the pre-goal stage, entrepreneurs face the risk of receiving no funds if their target goal is not met (Cumming et al. 2020). Additionally, funding behavior for successful campaigns experiences a pronounced spike in pledging activity immediately before a campaign achieves its funding goal (Dai and Zhang

2019, Kim et al. 2020, Kuppuswamy and Bayus 2017, Li et al. 2019a). Consequently, during the pre-goal stage, risks and funding behaviors affect entrepreneur incentives. For example, researchers recommend that entrepreneurs engage in extensive campaign preparation such as detailed campaign descriptions to reduce the high risk of failing to meet the funding goal (Cumming et al. 2020). Once the funding goal is reached, the immediate risk of not achieving sufficient funds is eliminated. Yet, new opportunities and challenges emerge. On the one hand, entrepreneurs may be motivated by the possibility of collecting additional pledges that far exceed the goal itself (Weber et al. 2023). On the other hand, excessive overfunding can raise risks of increased campaign complexity, leading to delays in product delivery (Mollick 2014). Overfunding may also influence backer behavior by inflating expectations, potentially triggering scope creep that complicates further development (Mollick 2014, Weber et al. 2023).

These stage-specific dynamics motivate the importance of our aim to frame the pre- and post-goal stages as distinct but interrelated components that make up crowdfunding campaigns — both temporally, by considering the time remaining in the campaign, and financially, by assessing the campaign's progress relative to its funding target. As only a quarter of Kickstarter technology campaigns meet their funding goals, this delineation econometrically compartmentalizes unsuccessful vs. successful campaigns in terms of their contribution to the pre- vs. post-goal subcomponents of the model likelihood and parameter estimation.[3]

The entrepreneurs' upfront decision on the funding goal shapes how the pre- and post-goal stages unfold. Goal setting is an important entrepreneurial decision in the AON reward-based crowdfunding context. Although it may appear to be a simple declaration of the capital required for product development, the chosen funding goal conveys important information about campaign quality and thus influences backers' perceptions. From the entrepreneur's perspective, goals are strategically selected (Chakraborty and Swinney 2021, Cumming et al. 2020, Kim et al. 2020, Lin and Pursiainen 2021). Additionally, threshold-based funding conditions can incentivize moral hazard behaviors among backers, altering their willingness to pledge as campaigns near or surpass their goals (Orhun et al. 2022). Goal choice can shift backer aggregate participation through forward-looking expectations, making goals endogenous to pledging dynamics (Kim et al. 2020). Such goal-setting strategies blur distinctions between pre- and post-goal funding stages, highlighting

[3] Alternatively, successful vs. unsuccessful campaigns can be modeled via a selection model (Heckman 1979). However, such a framework would answer counterfactuals such as "How would an unsuccessful campaign behave had it been successful *instead*?" Our inferential goal, as detailed in the next section, is focused on the role of updates *given* a campaign's progression within a stage.

the need for an empirical approach that accounts for goal endogeneity. Our study addresses this via a novel set of IVs: first, by exploiting entrepreneurs' tendency to benchmark on similar past campaigns (Wei et al. 2021); and second, by jointly modeling the goal-setting decision and daily pledging behavior as simultaneous equations (Hausman 1975).[4]

From the entrepreneur's perspective, a high goal could affect crowdfunding outcomes in different ways. On one hand, it is a hurdle: higher goals raise the AON threshold and thus lower the ex-ante chance of being successful (Kim et al. 2020, Mollick 2014). On the other hand, it is a signal: ambitious goals can credibly signal quality, inducing some entrepreneurs to set higher targets at the cost of increased risk for 'nothing' in the AON outcome (Chakraborty and Swinney 2021, Cumming et al. 2020).

Goal-setting also has backer-side implications. Threshold-based goal conditions can distort demand-side behavior, and in our setting these distortions operate along two related, but distinct, channels. First, a long tradition of research on goal pursuit and goal–gradient behavior shows that effort often accelerates as individuals approach a salient threshold and attenuates once the threshold has been crossed (Kivetz et al. 2006, Dai and Zhang 2019). For instance, in the context of airline frequent-flyer programs, Orhun et al. (2022) show that travelers exhibit goal-seeking behavior, such that they are willing to pay higher fares and choose less convenient flight options near status tier thresholds. In the crowdfunding context, goal-gradient effects can manifest in two ways pre-goal: either as an accelerant of backer pledges for projects nearing success, or as a decelerator as backers perceive the campaign as a 'lost cause' (Kuppuswamy and Bayus 2017, Dai and Zhang 2019). Once the goal is attained, however, subsequent pledges no longer serve to 'make or break' the campaign. The crucial insight from the goal-gradient literature is that while such acceleration (deceleration) is correlated with time, this is by happenstance. The underlying driver, rather, is the notion of distance to goal. To this end, alongside a rich set of control variables in our model with respect to campaign duration (i.e., time), we additionally include a novel *Funding Progression* metric (R_{it}) with respect to the goal.

Second, the funding goal serves as a public barometer of a campaign's success and quality, and in turn shapes backers' pledging behavior through signaling (Chakraborty and Swinney 2021, Cumming et al. 2020). Yet, much like airline loyalty programs, there is a limit on the extent to which

[4] As to be detailed in the next section, we operationalize Hausman's 'full information maximum likelihood' (FIML) IV as a system of equations with correlated errors to parsimoniously integrate with our Bayesian estimation (Lopes and Polson 2014). Beyond its efficiency over 2SLS IV approaches, FIML IV explicitly estimates the correlation parameter, which we leverage in a counterfactual analysis to quantify the marginal impact of strategic goal setting on daily pledges.

backers will respond to goal over- and under-shooting. In the application of their semantic-similarity network model, Wei et al. (2021) quantify the level of goal over- and under-shooting among crowdfunding campaigns and show that a common strategy is to anchor goals to similar campaigns from the past. We leverage (Wei et al. 2021)'s operationalization of anchoring to past campaigns – that is, the part of the goal setting variation that is orthogonal to backer-side simultaneity – as the IV correction of goal endogeneity.

2.2. Updates

Updates serve as a direct channel for entrepreneurs to communicate evolving campaign information and sustain backer engagement (Jung et al. 2022). Updates reduce information asymmetries with potential supporters (Bhargava et al. 2024). Furthermore, because reward-based crowdfunding often features innovative products still in development (Chemla and Tinn 2020, Xiang et al. 2019), updates can mitigate the uncertainty potential backers face when considering unproven ventures (Xiao et al. 2021).

The crowdfunding literature identifies update frequency and timing as important dimensions influencing campaign outcomes (Dushnitsky and Marom 2013, Steigenberger and Wilhelm 2018). Many cross-sectional studies have investigated the relationship between update frequency and crowdfunding campaign outcomes, generally finding positive effects (Deng et al. 2022). However, these studies often face limitations due to their cross-sectional design which struggles to disentangle the dynamic nature of updates. This is important as entrepreneurs might post updates in reaction to heightened or diminishing campaign momentum, rendering them endogenous to at-the-moment progress on funding. For example, studies examining the funding progression of crowdfunding campaigns have shown that frequent updates enhance campaign outcomes by maintaining visibility and signaling continuous campaign progress (Deng et al. 2022). Yet, Jung et al. (2022) highlight that the benefits of frequent updates are not linear. Moreover, cross-sectional studies often use campaign success (i.e., a binary measure of whether the target goal is achieved) as the primary outcome measure, which can be confounded by updates posted after the goal has been reached.

The timing of updates therefore plays an important role because updates during the early or final stages of a campaign can significantly influence fundraising outcomes (Bhargava et al. 2024, Herd et al. 2022, Kuppuswamy and Bayus 2017). Although prior research suggests that the pre- and post-goal determinants of success are different (Pinkow 2022), none have modeled funding dynamics between both stages. As a result, it remains unclear whether the observed benefits are

driven by updates from campaigns that are truly early, or if the effects arise from other dynamics altogether.

Taken together, researchers note that isolating the effect of updates on pledging behavior is challenging (Du et al. 2022). Entrepreneurs frequently post updates in response to backer-side interest, making it difficult to disentangle the influence of updates from broader performance signals (Kuppuswamy and Bayus 2017). Addressing these challenges requires a modeling framework capable of capturing the dynamic effects of updates that differentiates between the crowdfunding campaign stages, while accounting for the fact that the very threshold between stages itself can be a strategic choice.

3. Methodology

3.1. A Provision Point Model

A defining characteristic of the AON crowdfunding environment is that funding dynamics can shift once a campaign reaches its target goal. To capture this shift, we propose a *provision point model* that extends the changepoint specification (Fader et al. 2004, Schweidel and Fader 2009, Wang et al. 2019) to allow for an observed-yet-endogenous point-of-change (i.e., henceforth referred to as the *provision point*). Specifically, our framework seeks to infer and capture shifts in funding behaviors before and after campaign i's goal G_i is achieved, in terms of how daily pledges P_{it} are affected by campaign updates U_{it}, where $i = 1, \ldots, N$ and $t = 1, \ldots, T$. In this section, we first present the baseline likelihood of the provision point model, then detail the three core identification challenges to its estimation, and introduce additional specification extensions to overcome these challenges to attain our proposed empirical framework.

3.2. Provision Point Likelihood (Baseline Model)

In the context of crowdfunding, we operationalize the provision point in terms of the binary indicator $I_{it} := \mathbf{1}\left\{\sum_{j=1}^{t} P_{ij} \geq G_i\right\}$, which tracks whether cumulative daily pledges (i.e., total U.S. dollars) from day 1 up to day t for campaign i have met or exceeded the funding goal G_i. I_{it} takes on the value of 0 pre-goal, and the value 1 post-goal. Akin to changepoint models, I_{it} enables the use of different coefficients pre- and post-goal, on the same covariates. Differing from changepoint models is that I_{it} is an observed value, as opposed to a latent variable to be parameterized and estimated

(Li et al. 2019b). Building on the provision point, we utilize a linear likelihood with Normal[5] errors for a campaign's observed daily pledges (P_{it}):

$$\begin{aligned} P_{it} = (1 - I_{it}) \ & \left[\beta_0 + \beta_1 U_{it-1} + \beta_2 R_{it-1} + \delta_t^{\beta} + \psi_i^{\beta}\right] \\ + I_{it} \ & \left[\alpha_0 + \alpha_1 U_{it-1} + \alpha_2 R_{it-1} + \delta_t^{\alpha} + \psi_i^{\alpha}\right] \\ + \epsilon_{it}, & \end{aligned} \tag{1}$$

where U_{it-1} is the lagged binary indicator equal to 1 if campaign i posts an update on day $t-1$. β_1 and α_1 measure the effect of an update during the pre- and post-goal stages, respectively (i.e., 'beta' and 'alpha' are mnemonics for 'before' and 'after' the goal).

To capture and rationalize the distinction between a campaign's duration in days vs. progression in accumulated pledges at the same point in time, we include the lagged *Funding Progression* covariate R_{it-1}, which represents a campaign's cumulative pledges up to the prior day $(t-1)$. We operationalize this covariate as, $R_{it} := \frac{\sum_{j=1}^{t} P_{ij}}{G_i} - 1$, where the numerator is the cumulative pledges until day t and the denominator is the campaign's funding goal. In the pre-goal stage, R_{it} can take on values between -1 and 0, denoting the funding *deficit* towards meeting the AON threshold as a proportion of a campaign's target goal. In the post-goal stage, R_{it} is the ratio of the incremental funding *surplus* relative to the declared goal, and as such, can take on values of zero and above.

The term δ_t captures all day-specific effects for the pre- and post-goal stages, superscripted by β and α, respectively. Similarly, campaign-specific effects at the pre- and post-goal stages $(\psi_i^{\beta}, \psi_i^{\alpha})$ absorb all time-invariant heterogeneity across campaigns (e.g., founder quality). As no unsuccessful campaigns estimates a post-goal ψ_i^{α} by virtue that there are no post-goal data for them, the existence of the set of estimatable ψ_i^{α} serves to control for unobserved heterogeneity unique to successful campaigns. Finally, ϵ_{it} is the Normally-distributed idiosyncratic error term, rendering Eq. 1 a likelihood function.

3.3. Empirical Challenges

To formally motivate the identification challenges of naively estimating the baseline model (Eq. 1), we develop a series of directed acyclic graphs (DAG) in Figures 1, 2, and 3 to pair with the following discussion. Figure 1 depicts the assumption of the (naive) baseline model that updates (U) and funding progression (R) cause daily pledges (P). Our premise is that this causal diagram

[5] While 'Gaussian' and 'Normal' distributions are synonymous, we reserve the term 'Gaussian' exclusive in reference the Gaussian Processes to ensure clarity and ease of comprehension for the readers.

is insufficient and misspecified in the study of update dynamics on crowdfunding outcomes due to several sources of interrelated confounding: (1) updates are not posted at random, (2) the funding goal provision point is endogenously chosen, and (3) update effects evolve nonlinearly over the campaign.

[insert Figures 1, 2, and 3 about here]

Then, expanding on the baseline model's DAG, Figure 2 illustrates the sources of endogenous and exogenous variations, mirroring the three challenges laid out, as well as intuiting our identification strategy. First, entrepreneurs post updates in response to evolving campaign conditions (L) such as a sense of backer excitement and momentum. While L is known to entrepreneurs but unobserved in the data, it is colored in gray (along with all other unobservables). Failing to control for this source of unobserved confounding leads to simultaneity between updates (U) and pledges (P). In other words, update propensity is, in part, a function of how much pledging a campaign has garnered thus far, which then impacts how effective an update is on further pledging. Yet, update propensity is also a function of entrepreneurs' benchmarking to how similar past campaigns schedule and post their updates, which is orthogonal to any contemporaneous considerations. We will leverage this source of exogenous variation (B^*) for causal identification of update effectiveness. Intuitively, we are cleaving the drivers of update occurrence into two: those that are tied to current campaign status and those that are tied to 'norms' of what's expected at any given point of time over the course of a campaign, and our goal is to isolate the latter while discarding the former. Second, the funding goal (i.e., provision point G) is endogenously set, which may bias any stage-specific and progression-dependent coefficients in the model. Specifically, an entrepreneur can over- or under-shoot ($\bar{O}$) the goal (G) for strategic reasons, as discussed in the previous section. Mirroring our approach to 'cleaving' apart the drivers of updates, the degree to which the entrepreneurs decide to over- or under-shoot is via benchmarking against the precedence of past campaigns ($\bar{G}^*$), a noncontemporaneous source of variation (Wei et al. 2021). Lastly, it would be naive to assume that crowdfunding backers are entirely unaware of such benchmarking behavior (i.e., they, too, have a sense of 'fair market value' of a campaign). As such, we also include a causal path $\bar{O} \rightarrow P$ – i.e., from goal over- or under-shooting to pledges – denoting another source of unobserved confounding in Figure 2.

The DAG in Figure 3 represents the desiderata for a deconfounded data generating process to address our three challenges and causally identify the dynamics of update effectiveness on daily pledges. To operationalize our target sources of exogenous variations – i.e., benchmarking to the

past similar campaigns' precedence on both updates (B^*) and goal setting ($\bar{G}^*$) – we shall introduce the observables B and $\bar{G}$, respectively. B takes the form of a 'Bartik' panel IV (Bartik 1991) capturing campaign-time-level benchmarking to similar past campaigns to tackle the challenge of nonrandom update timing. In parallel, $\bar{G}$ takes the form of start-of-campaign benchmarking to similar past campaigns' goal-setting to address endogenous over- or under-shooting. We shall operationalize both IVs via the similarity-network approach of Wei et al. (2021). B and $\bar{G}$ are instruments for updates (U) and goal (P), rendering exogenous estimates that can serve as plug-in estimators into the outcome (i.e., pledges) equation, denoted via the canonical IV notations of $\hat{U}$ and $\hat{G}$, respectively. In doing so, the unobserved confounders L and $\bar{O}$ no longer exhibit 'backdoor' causal pathways to P and R. Lastly, while not explicitly expressable via causal DAGs, we shall allow for update effects to vary smoothly over the campaign progression using Gaussian Process (GP) priors (Dew et al. 2020).

3.4. Challenge 1: Endogenous Updates — Network-Based Bartik Instrument

Entrepreneurs post updates in reaction to evolving campaign conditions and private information. Thus, U co-moves with the unobserved determinants of pledges in period t (e.g., latent quality, social buzz). This creates an endogenous pathway in ($U \rightarrow P$). As entrepreneurs respond to spikes in backer interest or pledge dynamics, then $Cov(U, \epsilon) \neq 0$ (Kuppuswamy and Bayus 2017).

However, there also exists a natural, exogenous rhythm to campaign updates. Similar to how entrepreneurs benchmark goals based on similar campaigns in the past (Wei et al. 2021), entrepreneurs also post updates based on the cadence of their technology category, such as the weekly habits, milestone events, and platform rhythms (Xiao et al. 2021). This external cadence has no direct path to pledges except through the entrepreneur's decision to post an update.

This gives us update variation that is plausibly orthogonal to the campaign's idiosyncratic performance to which entrepreneurs may act upon contemporaneously while a campaign is live. IV strategies exploiting benchmarking to peers as a source of exogenous variation, to address potential reverse causality and simultaneity bias, have been pivotal in extant marketing research. Lim et al. (2020) utilize a weighted peers' customer satisfaction IV to study the effect of customer satisfaction on cost of selling, where peers are defined based on ACSI sector and firm characteristics. Cheong et al. (2021) studies firm disclosure decision on advertising using the average disclosure behavior of peer firms in partially-overlapping strategic groups. Papies et al. (2022) classify peer-based instruments as a form of 'constructed' IV.

To construct the peer-network based IV for our context, we leverage the 'shift–share' or 'Bartik' panel IV specification. The seminal application of shift–share instruments comes from labor economics: researchers proxy exogenous local labor-demand shocks by interacting a location's industry employment shares (the "shares") with national industry growth (the "shifts") (Bartik 1991, Goldsmith-Pinkham et al. 2020). National shocks lie outside any one city's control. Because the shares are predetermined, the induced exposure moves local outcomes for reasons orthogonal to local idiosyncrasies. In our context, the analogy is direct: the "shares" are a campaign's category weights, and the "shifts" are the posting rhythms in those campaigns among those categories. This delivers an exogenous cadence that (1) causes updating but has no direct path to pledges beyond the decision to post, and (2) produces fine-grained panel variation that a cross-sectional IV would integrate over.[6]

To isolate variation in update timing that comes from broad category–time trends rather than those contingent on the contemporaneous performance of the campaign, we construct a shift–share instrument (Bartik 1991) that leverages each campaign's inferred category mix. Kickstarter requires entrepreneurs to select one single technology category per campaign. Yet, in reality, many campaigns can fit multiple categories (e.g., hardware–software hybrids, art–technology crossovers). For example, the original Pebble smartwatch was officially classified under Wearables, yet it embodies features of both Hardware (its casing and electronics) and Software (its companion apps and watch-face ecosystem). Our approach, then, recognizes that a campaign is similar to those from multiple categories. In turn, entrepreneurs would benchmark their campaign's update cadence to those across categories (Soublière et al. 2024).

In particular, we build on the insights of Wei et al. (2021), who show that the performance of past comparable campaigns provides valuable information about how new campaigns should be orchestrated. They operationalize this idea by exploiting the idea that similarity among crowdfunding campaigns can be quantified as a semantic network. To implement our instrument for nonrandom updates, we adopt one of their key building blocks: the pairwise distance matrix using Word's Mover Distance (WMD). We then use WMD to construct soft category-share weights via k–nearest neighbors, and combine these calculated shares with empirically observed update-share patterns to form Bartik panel instruments at the (i,t) level. In the remainder of Section 3.4 we outline the construction of this network-based Bartik instrument. Further empirical details about network metrics and the Bartik instrument can be found in Appendices A and B, respectively.

[6] For example, a conceivable cross-sectional IV for updates might be the entrepreneurial experience on past crowdfunding campaigns, or even their home city (i.e., entrepreneurs in a tech hub). However, these cross-sectional instruments would lack time-series variation vis-a-vis the panel variation enabled by Bartik IVs.

3.4.1. Pairwise Semantic Distances A critical building block in our identification strategy is the campaign–to–campaign pairwise semantic distances. We estimate this network once from campaign descriptions and operationalize it in two places: (1) to represent each campaign as a soft blend of technology categories—so the Bartik "shares" reflect what the campaign is rather than its single platform label—and (2) to quantify the benchmarking to similar past campaigns (Wei et al. 2021) when we address goal setting (i.e., provision point) endogeneity in the upcoming Section 3.5.

To quantify the semantic distance between every pair of campaign descriptions i and j we use WMD. Let W_i denote the tokenized campaign text of campaign i. We define the symmetric distance matrix $d_{ij} = \mathrm{WMD}(W_i, W_j)$. Detailed discussion and exploratory data analyses for the unstructured data to construct the network-based *Inferred Category Shares* and *Benchmarked Goal* instruments can be found in Appendix A.

3.4.2. Technology Category Shares We infer each campaign's technology category shares using distance-weighted k–nearest neighbors (kNN) on the precomputed WMD matrix. To remove self-neighbors, we set $d_{ii} = +\infty$.[7] For each campaign i, let $\mathcal{K}_i$ be the indices of its k nearest neighbors under D. Let $c_j \in \{1, \ldots, C\}$ denote the platform technology category of campaign j, where C is the total number of categories. The soft share for category $r \in \{1, \ldots, C\}$ is

$$\widehat{z}_{ir} = \frac{\sum_{j \in \mathcal{K}_i} d_{ij}^{-1} \mathbf{1}[c_j = r]}{\sum_{j \in \mathcal{K}_i} d_{ij}^{-1}}, \qquad \sum_{r=1}^{C} \widehat{z}_{ir} = 1.$$

We implement this with a kNN classifier (precomputed metric, inverse-distance weights) and assess via 5-fold stratified cross-validation (accuracy, macro-F1).

3.4.3. Category–time update shifts. For a given category c, we define the number of updates in time t as N_{ct}. We define the category–time share of updates as

$$g_{ct} = \frac{N_{ct}}{\sum_{t=1} N_{ct}},$$

and we calculate this for the pre- and post-goal stages.

3.4.4. Shift–Share Instrument Construction Finally, we merge $\hat{z}$ with the observed update-share patterns g_{ct}, where g_{ct} is the proportion of updates for category c at time t. We then form a fine-grained (i.e., continuous domain, panel varying) Bartik instrument:

[7] Implemented as $D_{ii} = \max_{j \neq i} D_{ij} + 1$.

$$B_{it} = \sum_{k=1}^{C} \widehat{z}_{ic} g_{ct}. \tag{2}$$

Intuitively, the category shares ($\hat{z}$) serve the role of weighing each campaign's expected update rate by the prototypical update cadence of each technology category (e.g, apps are frequently in early development, 3D Printing campaigns often update to showcase prototypes). The variability in these weights (1) represents common within-category historic shocks at time t, and (2) does not originate from the entrepreneur's contemporaneous decision to post updates at time t. Therefore, they capture the exogenous variation in update propensity for campaign (i), and advantageously, are unique at time t.[8]

Taken together, B_{it} captures the exposure of campaign i to historic category-time cadence of update occurrence, weighted by campaign i's similarity to past campaigns across categories. B_{it} then instruments the actual update indicator U_{it} to estimate a plug-in estimator $\hat{U}_{it}$ for the daily pledges outcome equation by estimating the following 'first stage' equation (in a 2SLS setup):

$$U_{it} = \pi_1 B_{it} + \pi_2 X_{it} + \nu_{it}, \tag{3}$$

The coefficient π_1 on the network-based Bartik instrument B_{it} (Eq. 2) isolates exogenous variation in posting propensity. X_{it} are the carryover controls[9] used in Eq.1, and π_2 are the respective coefficients. Finally, ν_{it} represents the idiosyncratic error term.

3.5. Challenge 2: Endogenous Provision Point — Bayesian IV with Goal Setting

Crowdfunding campaigns exhibit systematic differences in funding behavior between the pre- and post-goal stages. These differences manifest as shifts in campaign factors, as well as backer behavior as discussed in the previous section. In our provision point model, these latent goal–gradient dynamics are summarized by the *Funding Progression* index (R_{it}), which scales cumulative pledges by the entrepreneur's chosen goal G_i so that progression is measured relative to the provision point rather than calendar time. This construction provides a parsimonious, campaign-specific measure of both pre- and post-goal progression, but because R_{it} normalizes by G_i, it inherits the goal setting (i.e., provision point) endogeneity. To enable an IV correction here, we specify R_{it} to be linear in observables:

[8] Of course, its possible that the Bartik IV for two campaigns i and i' possess the same value at time t. However, the number of historic campaigns in our dataset renders this unlikely.

[9] $X_{it} = (1 - I_{it})\big(1,\ R_{it-1},\ \delta_t^{\beta},\ \psi_i^{\beta}\big) + I_{it}\big(1,\ R_{it-1},\ \delta_t^{\alpha},\ \psi_i^{\alpha}\big)$.

$$R_{it} = (1 - I_{it}) \quad \left[\theta_{\tau}^{\beta}\bar{G}_i + \delta_t^{\beta} + \psi_i^{\beta}\right] \\ +I_{it} \quad \left[\theta_{\tau}^{\alpha}\bar{G}_i + \delta_t^{\alpha} + \psi_i^{\alpha\prime}\right] + \omega_{it}, \tag{4}$$

Recall from Section 3.2 that R_{it} is constructed so as to undertake a sign change at the observed (but endogenous) goal. Here, R_{it} controls for the goal-gradient behavior, especially around the endogenously chosen provision-point. To account for this construction, note that Eq. 4 allows for different coefficients pre- and post-goal via indicator function I_{it}, without loss of generality.[10] Intercepts and fixed effects are specified in Eq. 4's δ and ψ terms, which are equivalent in interpretation to those from Eq. 1. Finally, ω_{it} is the idiosyncratic error.

We next leverage the insight of Wei et al. (2021) that entrepreneurs benchmark their goals against comparable past campaigns. Extending their semantic similarity methodology, we construct a time-invariant[11], campaign-level *Benchmarked Goal* measure, $\bar{G}_i$, which captures the noncontemporaneous component of goal-setting behavior. Intuitively, this represents the entrepreneurs' calibration of the campaign's goal against similar past projects, across categories (see DAG in Fig. 3). To construct $\bar{G}_i$, we build a semantic similarity network over past campaigns (see Appendix A). Specifically, let d_{ij} denote the WMD between any two campaigns i and j, and let t_i denote the launch date of campaign i. In line with Wei et al. (2021), $\lambda \in [0, 1]$ is an estimable temporal decay parameter capturing the degree to which entrepreneurs benchmark against more recent similar campaigns. Taken together, we define the time–decayed semantic weight between i and j (where $i \neq j$) as

$$w_{ij} = \lambda^{|t_i - t_j|} \times L(\gamma_0 - \gamma_1 d_{ij}), \tag{5}$$

where $L(x) = \frac{1}{1+e^{-x}}$ is the logistic function.[12] Given w_{ij}, the expected goal for campaign i is $\bar{G}_i = \frac{\sum_{j:T_j<t_i} w_{ij} G_j}{\sum_{j:T_j<t_i} w_{ij}}$, where G_j is the observed goal of campaign j. $\bar{G}_i$ serves as a plausibly exogenous, data–driven exclusion restriction arising from a campaign's goal benchmarking to norms of semantically similar and temporally proximate predecessors. Instrumenting R_{it} with $\bar{G}_i$ thus purges Funding Progression of endogenous goal choice while preserving its role as the primary control for goal-gradient dynamics in the pledges equation.

[10] Eq. 4 is a notational simplification for what otherwise would be separate 'first stage' IV equations for R_{it}, pre- and post-goal. R_{it} can be readily constructed in a way that doesn't exhibit a sign change (albeit less interpretable). In such case, Eq. 4 would simply do away with I_{it}. In either case, IV identification can proceed under standard linearity assumptions.

[11] The goal is set once at the onset of a campaign.

[12] Further discussion, including summary statistics, can be found in Appendix A.3.

While Challenge 1's (Section 3.4) Bartik IV is implemented as 2SLS plug-in estimator, here for Challenge 2, we proceed with a Bayesian IV specification (Lopes and Polson 2014) involving a system of equations with a correlated error structure (Hausman 1975). Before detailing the advantages of this specification choice for Challenge 2, note that for robustness, in Appendix C we also implement our full model using an equivalent 2SLS plug-in estimator, in lieu of the Bayesian IV. Neither our inferential nor substantive conclusions change.

The choice, then, to utilize a Bayesian IV for goal endogeneity is for its streamlined operationalization of another valuable insight from Wei et al. (2021): in calculating campaign i's benchmarked or 'fair market' value ($\bar{G}_i$), we can in turn readily isolate and empirically investigate a campaign's goal over- or under-shoot, $\bar{O}_i = G_i - \bar{G}_i$. In particular, we will examine the marginal impact of goal overshooting on update dynamics in a posterior predictive analysis (Section 6.1).

This analysis is made possible via the existence of the correlation parameter ρ in the Bayesian IV specification where the error terms of *Funding Progression* and *Daily Pledges* are jointly modeled under a bivariate Normal prior with a fully identified, positive definite covariance matrix:

$$\begin{pmatrix} \omega_{it} \\ \epsilon_{it} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_G^2 & \rho\,\sigma_R\,\sigma_P \\ \rho\,\sigma_R\,\sigma_P & \sigma_P^2 \end{pmatrix} \right). \tag{6}$$

Here, the error and variance terms for the *Daily Pledges* (Eq. 1) are ϵ_{it} and σ_P^2, respectively. Similarly, the error and variance terms for the *Funding Progression* (Eq. 4) are ω_{it} and σ_R^2, respectively. The correlation between the unobserved determinants of *Funding Progression* and *Daily Pledges* is ρ, and therefore can be interpreted as how a unit standard deviation in one outcome (e.g., *Daily Pledges*) is expected to covary the other outcome (e.g., *Funding Progression*), after controlling for observables. While such analysis is conceptually possible under a 2SLS IV implementation as a separate post hoc step, the Bayesian IV parsimonious provides this in tandem with all other parameters during the joint posterior inference via Markov chain Monte Carlo (MCMC).

3.6. Challenge 3: Nonlinear Update Effects — Gaussian Processes

Prior research has shown that when updates are posted, these can significantly influence campaign outcomes (Bhargava et al. 2024, Herd et al. 2022, Pinkow 2022). Addressing the endogenous confounders of Challenges 1 and 2 (see causal DAG in Fig. 3) enables us to introduce the mechanism to infer update dynamic in our provision point framework: hierarchical GP priors on the update coefficients (Dew et al. 2020).

GP priors are a flexible, nonparametric method that models the distribution over smooth and continuous random *functions* (as opposed to random variates). In our context, this is to assume update effectiveness evolves continuously over the campaign progression, which allows those among nearby periods to inform one other through a kernel-covariance structure. This enables our framework to (1) capture nonlinear dynamics that a homogeneous linear specification would miss even with time fixed effects, while (2) reducing noise and increase efficiency versus a conventional time-varying coefficient model (i.e., model with independent Normal priors on update coefficients across periods) by borrowing information across time and campaigns (see Appendix D for comparison). Moreover, a GP can infer any smooth, twice differentiable function that could hypothetically govern the evolution of update effectiveness through time. Our GP formulation enhances identification and interpretability by providing a contextual representation of how update effectiveness intercorrelates and jointly evolves over the campaign's progression.

To specify the hierarchical GP prior, we define an index set $\tau \in [0, 1]$ as the standardized campaign duration. For example, for some campaign i with a 50-day duration, then on day 1 it is $\tau_{i,t=1} = 1/50 = 0.02$, and on day 50 it is $\tau_{i,t=50} = 50/50 = 1.0$. We thus replace the homogeneous update coefficients β_2 and α_2 in the baseline model (Eq. 1) with functions $\phi^{\beta}(\tau_{it})$ and $\phi^{\alpha}(\tau_{it})$, respectively, so that the dynamic update effects are modeled as:

$$\begin{aligned} \phi^{\beta}(\tau_{it}) &\sim \mathcal{GP}\Big(m_{\beta}(\tau_{it}),\, K^{\beta}(\tau_{it}, \tau'_{it})\Big), \\ \phi^{\alpha}(\tau_{it}) &\sim \mathcal{GP}\Big(m_{\alpha}(\tau_{it}),\, K^{\alpha}(\tau_{it}, \tau'_{it})\Big), \end{aligned} \tag{7}$$

where the mean functions m_{β} and m_{α} are:

$$m_{\beta}(\tau) = \mu_0^{(\beta)} + \mu_1^{(\beta)}\,\tau, \quad m_{\alpha}(\tau) = \mu_0^{(\alpha)} + \mu_1^{(\alpha)}\,\tau. \tag{8}$$

For the covariance function, we choose a Matern-3/2 kernel.[13] In the one-dimensional case (as τ is a scalar), this is

$$K(\tau, \tau') = \eta^2 \left(1 + \frac{\sqrt{3}\,|\tau - \tau'|}{\kappa}\right) \exp\left(-\frac{\sqrt{3}\,|\tau - \tau'|}{\kappa}\right) \tag{9}$$

Here, η^2 is the estimable amplitude parameter of the GP prior. This parameter scales the magnitude of deviations around the mean function, controlling the extent of variability in the update effects. The parameter κ is the length scale, which determines how rapidly the covariance between

[13] In addition to the Matern 3/2 kernel, which was chosen for its balance between smoothness and computational efficiency, the Matern 5/2 and squared exponential kernels were tested. The choice of kernel did not affect our findings and are not further discussed. Results are available by request.

function values decays as the distance between two periods $|\tau - \tau'|$ increases. A smaller κ implies that the update effects become uncorrelated between periodss, whereas a larger κ leads to a smoother function with long-range correlations. In other words, the GP would converge onto a conventional dynamic coefficient model (i.e., independent Normal priors on each time-varying coefficient) if the data do not justify a more complex function governing the evolution of update dynamics.

Taken together, extending Eq. 1 to incorporate GP priors for dynamic update coefficients, we have:

$$\begin{aligned} P_{it} = (1 - I_{it}) \quad & \left[\phi^{\beta}(\tau_{it})\widehat{U}_{it-1}\right] \\ + I_{it} \quad & \left[\phi^{\alpha}(\tau_{it})\widehat{U}_{it-1}\right] + \pi X_{it} + \epsilon_{it}. \end{aligned} \tag{10}$$

3.7. Joint Posterior and Estimation

The full empirical framework combines the three components introduced above: (i) a panel IV correction for nonrandom update timing (Challenge 1), (ii) the goal–setting equation on *Funding Progression* with correlated errors (Challenge 2), and (iii) the provision point likelihood with time-varying update effects (Challenge 3). For (i), we first estimate the update equation (Eq. 3) and obtain fitted values $\widehat{U}_{it-1}$ from the network-based Bartik instrument. For (ii), the Bayesian IV includes a network-based *Benchmarked Goal*, $\bar{G}_i$ as the exclusion restriction. For (iii), we operationalize via the hierarchical GP prior.

Let $\mathcal{D}$ denote all data (observed and constructed IVs) entering the model estimation,

$$\mathcal{D} = \{P_{it}, R_{it}, \widehat{U}_{it-1}, \bar{G}_i\}, \forall i = 1, ..., N, t = 1, ..., T$$

and let

$$\Theta = \{\Theta_P, \Theta_R, \phi^{\beta}, \phi^{\alpha}, \Sigma\}$$

denote the set of parameters of the outcome (i.e., daily pledges) equation, the Bayesian IV (i.e., funding progression) equation, the GP priors, and the error covariance matrix in Eq. 6. Taken together, the joint posterior over Θ is

$$\begin{aligned} p(\Theta \mid \mathcal{D}) \propto & \prod_{i,t} p\Big(P_{it} \,\Big|\, \widehat{U}_{it-1},\, R_{it-1},\, \Theta_P,\, \phi^{\beta},\, \phi^{\alpha},\, \Sigma\Big) \\ & \times \prod_{i,t} p\big(R_{it} \,\big|\, \bar{G}_i,\, \Theta_R,\, \Sigma\big) \\ & \times\; p(\phi^{\beta})\, p(\phi^{\alpha})\, p(\Theta_P)\, p(\Theta_R)\, p(\Sigma). \end{aligned} \tag{11}$$

The first likelihood function corresponds to the provision point *Daily Pledges* equation with GP priors over update effects (Eq. 10), which flexibly captures nonlinear dynamics in update effectiveness over campaign progression (Challenge 3), and inclusive of the network-based Bartik instruments $\widehat{U}_{it-1}$ (Challenge 1). The second likelihood function corresponds to the *Funding Progression* equation (Eq. 4), jointly estimated with correlated errors to the *Daily Pledges* (i.e., outcome) equation to address provision point endogeneity (Challenge 2). The third set of probability density functions in Eq. 11 indicate the priors.

We place weakly informative Normal priors on all linear coefficients, half-Normal priors on variance components, and an LKJ prior on the correlation structure implied by Σ. Moreover, GP hyperparameters receive weakly informative priors on log-length scales. Posterior inference is conducted via Hamiltonian Monte Carlo (HMC), with 10,000 warmup iterations, 10,000 sampling draws, and 4 chains. We assess posterior convergence via the Gelman-Rubin diagnostic.

4. Data

Our study focuses on all crowdfunding campaigns in the technology category launched on Kickstarter in the U.S. between 2018 and 2020. Technology campaigns typically involve tangible products (e.g., electronics, hardware, or software, etc), which offer an environment where the crowdfunded products have viable outside options for consumers — a characteristic that might not apply to other categories like film or music. We source campaign-level metadata from webrobots[14], an online service that has been aggregating such data since 2016. We supplement this information with data extracted directly from the campaign campaign web pages. Additionally, we obtain daily pledges (our outcome variable of interest) from Kicktraq[15], which tracks and publishes daily funding data from Kickstarter campaigns. Our final sample consists of 4,000 campaigns with a total of 151,687 funding days distributed among them.

Our focal outcome variable is *Daily Pledges* in U.S. dollars. The sample mean for daily pledges is $944.22, and the standard deviation is $6,751.32. To mitigate scale effects in the model, we standardize daily pledges.[16]

Table 1 reports summary statistics for the full sample of and, where relevant, separately for the pre- and post-goal stages. Across the entire campaign, campaigns post on average 2.03 updates. Before reaching the goal, the average is 1.07 updates. Among campaigns that reach their goal

[14] Webrobots, https://webrobots.io/kickstarter-datasets/

[15] Kicktraq, https://www.kicktraq.com/

[16] Formally, for each daily pledge x, the standardized value is $z = \frac{x-\mu}{\sigma}$, where μ is the sample mean and σ is the standard deviation.

and therefore enter the post-goal stage, the mean rises to 3.54 updates. Successful campaigns (those that meet their target goal) post, on average, 4.86 updates over the campaign, about half of which occur pre-goal (mean = 2.37). Unsuccessful campaigns post fewer than one update in total on average. Stated funding goals also differ markedly by outcome: successful campaigns have a target goal of $17.5K, while unsuccessful campaigns set higher goals on average ($62.1K). These summary statistics show differences in entrepreneurial updating behavior and goal setting. Campaigns that ultimately succeed post updates more frequently and set more conservative goals, whereas unsuccessful campaigns update less and typically set more ambitious goals.

[insert Table 1 about here]

5. Results

This section reports the estimated effects of campaign updates on daily pledges under our provision point framework. We begin with the Main Model (Eq. 11), which nests the provision point structure in Eq. 1 and incorporates corrections for the three identification challenges. First, it tackles the non-random nature of updates using a Bartik instrument B_{it} (Eq. 2) and obtains a fitted update series $\widehat{U}_{it-1}$ via Eq. 3; instrument construction, strength tests, and first-stage results appear in Appendix B. Second, to address the endogenous provision point, we specify *Funding Progression* in Eq. (4), anchor it with the expected goal $\bar{G}_i$ computed from time-decayed similarity weights (Eq. 5), and allow correlated unobservables across goal setting and pledging as in Eq. (6); further discussion of the value of correcting for endogenous goals appears in Section 6.1. Third, to capture nonlinear update effects, we replace constant coefficients with smooth functions $\phi^{\beta}(\tau)$ and $\phi^{\alpha}(\tau)$ governed by GP priors (Section 3.6) and embed them in the changepoint pledges equation (Eq. 10) through the provision point indicator I_{it}; additional motivation for including GP smoothing is provided in Appendix D.

To demonstrate the value of the provision point itself, we first discuss our Main Model, and subsequently introduce three comparison models. Comparison Model 1 imposes homogeneous, time-invariant update effects over the entire funding progression (Eq. 12). Building on this, Comparison Model 2 introduces the provision point but keeps the homogeneous coefficients of updates for each stage. Finally, Comparison Model 3 removes the provision point and places a single GP over the full campaign progression (Eq. 13).

5.1. Main Model

Our Main Model (Eq. 11) posterior estimates of the dynamic effect of updates during the pre- and post-goal are shown in Figure 4. Two patterns emerge. First, in the pre-goal stage, updates

exert a modest positive effect on daily pledges with little drift over the campaign. Second, during the post-goal stage, update effectiveness becomes time-varying. The effect of updates spike right after achieving the goal, which is followed by a rapid decline. In the middle of the post-goal stage, updates are generally not effective. Finally, there is a rebound in update effectiveness in the final days of the campaign.

[insert Figure 4 about here]

Our results reconcile and refine prior evidence on update effects. Prior work finds that updates are positively associated with pledges but offers limited guidance on when to post (Deng et al. 2022). By tracing effects over the campaign progression and around the provision point, we show that timing is essential: pre-goal updates yield steady, modest effects throughout, while post-goal effects are more varied in its dynamics. Here, the "post early" advice by the literature remains valid, but our results add nuance: updates continue to matter across the entire pre-goal stage, just after achieving, and again in the final quarter of the post-goal stage.

5.2. Comparison Models

The objective of the comparison models in this section is to establish the importance of the provision point for identifying update effects. Below we introduce and discuss Comparison Models 1, 2, and 3 of increasing complexity, respectively. The objective of these comparison models is to isolate the incremental value of introducing the provision point.

[insert Table 2 about here]

We begin by considering Comparison Models 1 and 2 in tandem, to showcase that even under a homogeneous linear coefficient specification, the introduction of the provision point uncovers differences in update effectiveness on daily pledges, pre- and post-goal attainment. Comparison Model 1 is a linear homogeneous coefficient specification, minus the provision point. It assumes a time-invariant coefficient on update effectiveness across the entire campaign duration. As with all three comparison models, included is the Bartik IV plug-in estimators for updates ($\hat{U}_{it-1}$). Compared to our Main Model, Comparison Model 1 represents the most restrictive functional form:

$$P_{it} = \beta_1 \hat{U}_{it-1} + \beta_2 R_{it-1} + \psi_i + \delta_t + \epsilon_{it}, \tag{12}$$

As shown in Table 2, Comparison Model 1 reports a significant effect of updates on *Daily Pledges* ($\beta_1 = 1.279[1.108, 1.460]$). Over and above Comparison Model 1, Comparison Model 2 introduces a provision point such that the updates coefficients can differs pre- and post-goal.

This model allows us to determine if the implementation of the provision point specification is justified. The results show a significant difference in the effect of updates in the pre-goal stage ($\beta_1 = 0.830[0.676, 0.979]$) and the post-goal stage ($\alpha_1 = 3.417[3.057, 3.791]$), and show that the results are different even with a homogeneous specification for update effects.

Next, as our Main Model estimates the effect of updates dynamically throughout the campaign, then to illuminate on the value of the provision point for measuring the dynamic effect of updates, we introduce Comparison Model 3. This comparison model removes the provision point structure but maintains the Gaussian process prior of the Main Model. Comparison Model 3 is motivated by the possibility that given the flexibility afforded by the GP specification, an explicit provision point mechanism is no longer warranted. Formally, letting P_{it} be the daily pledges for campaign i on day t. Differing with the Main Model only in the ablation of the provision point, Comparison Model 3 is specified as:

$$P_{it} = \phi(\tau_{it})\widehat{U}_{it-1} + \beta_2 R_{it-1} + \delta_t + \psi_i + \epsilon_{it}. \tag{13}$$

$$R_{it} = \theta_\tau \bar{G}_i + \delta_t + \psi_i + \omega_{it}, \tag{14}$$

By omitting the provision point, this model can flexibly capture evolving update effects over time, but does not explicitly distinguish a pre- or post-goal stage. The posterior estimates of the dynamic effect of updates for Comparison Model 3 are shown in Figure 5. Interestingly, the results show a mostly negative effect of updates. This result is consistent with prior studies that have used daily outcomes as a variable of interest (Herd et al. 2022, Xiao et al. 2021). Omitting the provision point collapses stage-specific dynamics into a single, continuous evolution of update dynamics, leading to qualitatively different results. In other words, what the provision point buys even in a flexible specification such as a GP is a discontinuous shift in the dynamic evolution of updates, which we find to exist in the crowdfunding setting.

[insert Figure 5 about here]

Furthermore, in order to better understand the importance of how the provision point's allowance for discontinuous shifts in update effectiveness, we also implemented Comparison Model 3 with a split sample, i.e., for campaigns that never achieved the goal (unsuccessful campaigns), and for campaigns that achieved the goal at some point during the campaign (successful campaigns). The

results in Figure 6 show that, for unsuccessful campaigns, updates follow a U-shaped pattern and are effective at the beginning and towards the end of the campaign. Note that the end of campaign of a unsuccessful project necessarily does not involve a post-goal stage.

With this in mind, Comparison Model 3 estimated for the sample of only successful campaigns *did not converge* (i.e., not identified empirically). For the subsample of successful campaigns, identification fails because Comparison Model 3 requires continuity in the trajectory of update effectiveness when crossing over from pre-goal to post-goal. While Comparison Model 3 was estimable for the full data, every campaign in this subsample crosses the provision point. Without an explicit provision-point indicator to separate these 'regimes' of update dynamics, the model fails to discover a single continuous function that can fit this subsample's update dynamics (even after IV corrections), which we take as strong evidence on the robustness on the discontinuity in update effectiveness pre- vs. post-goal, and thereby, the central role of the provision point in understanding crowdfunding update dynamics.

[insert Figure 6 about here]

6. Additional Insights

6.1. The Dynamics of Setting Goals

A notable finding in our model is a statistically significant correlation parameter ρ between the *Funding Progression* Eq. (4) and the *Daily Pledges* Eq. (10) ($\rho = -0.073, [-0.083, -0.063]$) (Table 2). This supports treating R_{it} as being endogenous. If *Funding Progression* were treated as exogenous, its construction relative to an endogenously chosen goal would mechanically inherit goal endogeneity, biasing the estimated effect in the pledges equation.

As noted in Section 3.5, we chose to use a Bayesian IV specification for goal endogeneity as the correlation term ρ enables us to perform a secondary counterfactual analysis. To this end, our goal here is make use of the Bayesian IV's correlated error covariance structure to understand the effect of posting a goal different than what was benchmarked based on prior similar campaigns in the past.

In Eq. (4), the semantic-network derived *Benchmarked Goal* enters as the exclusion restriction for *Funding Progression*, whose error is jointly distributed with that of *Daily Pledges* as bivariate Normal (Eq. (6)). Let $\lambda \equiv \rho \frac{\sigma_P}{\sigma_R}$, which captures how one unit deviation in *Funding Progression* correlates with *Daily Pledges*. Intuitively, holding the cumulative amount of pledges of project i at some time t constant, then the only way *Funding Progression* can vary is by altering the goal, as *Funding Progression* is a relativistic notion with respect to the goal. Of course, in undertaking

this analysis, we must assume make the simplifying assumption that a marginal change in goal is ceteris paribus (e.g., does not create a cascading effect on pledging, as well as updates, from the start to finish of a campaign).

Extending the parallel notion in Wei et al. (2021), we define *Goal Overshoot*, $\Delta_i \equiv \ln G_i - \ln \bar{G}_i = \ln\left(\frac{G_i}{\bar{G}_i}\right)$, which is the 'gap' in log-scale between the stated endogenous goal and the expected goal. Changes in $\ln G_i$ operate mechanically through R_{it} and via λ. For a given time t either pre- and post-goal, marginal change in the pledges equation with respect to $\ln G_i$ yields the partial derivative: $\frac{\partial P_{it}}{\partial \ln G_i} = \left(1 + R_{it-1}\right)\left[\gamma + \lambda\right]$, where $\gamma \in \{\beta_2, \alpha_2\}$ is the stage-specific coefficient on R_{it-1}. Similarly, partial derivative of the pledges equation with respect to $\ln \bar{G}_i$ yields: $\frac{\partial P_{it}}{\partial \ln \bar{G}_i} = -\lambda\, \theta_\tau\, \bar{G}_i$. Thus, the marginal effect of goal overshoot (i.e., effect of a one-unit change in Δ_i) is

$$\frac{\partial P_{it}}{\partial \Delta_i} = -\left(1 + R_{it-1}\right)\left[\gamma + \lambda\right] + \lambda\, \theta_\tau\, \bar{G}_i. \tag{15}$$

We report the 10% marginal effect, with a multiplicative scaling factor of $\delta_{10} \equiv \ln(1.10) \approx 0.0953$ for visual ease, such that $\mathrm{ME}_{it}(10\%) \equiv \delta_{10}\, \frac{\partial P_{it}}{\partial \Delta_i}$.

[insert Figure 7 about here]

Figure 7 plots the mean of the posterior predictive distribution on 10% marginal effect of *Goal Overshoot* on *Daily Pledges*, over the campaign duration both pre- and post-stage (in normalized time τ). The pre-goal curve (dashed red) is small and negative throughout (about -$1 to -$3 per progression interval). This shows that setting the goal at 10% above the benchmarked goal modestly depresses before-goal contributions. In contrast, the post-goal curve (solid-red) is positive and increases over time, from $8.2 at the beginning of the post-goal stage to $28.9 at the end of the post-goal stage. These patterns suggest that *Goal Overshoot* hinders funding before-goal but boosts contribution after goal achievement.

Our pre–post decomposition helps reconcile and extend prior evidence on goal setting. Wei et al. (2021) show that *Goal Overshoot* has an inverted–U association with both success and funds raised, while the absolute log goal has a monotone negative association. Taken together, increasing the goal tends to harm outcomes once overshoot becomes sufficiently positive. Consistent with this pattern, our pre-goal 10% marginal effects are small and negative throughout (about $1–$3 less per interval), indicating that positive overshoot depresses early contributions when the threshold is still binding. Our provision-point framework further reveals stage-specific dynamics that aggregate models cannot capture: *post-goal* 10% marginal effects are positive and rise over time (roughly $8 to $29 per interval). Thus, while our pre-goal results align with the downward portion of the

inverted–U documented by Wei et al. (2021), our post-goal estimates show a distinct regime in which overshoot is beneficial, a nuance revealed when we explicitly model the provision point.

These findings reconcile two seemingly conflicting findings about high goals, as literature shows that they can have negative effect on the probability of success (Kim et al. 2020, Mollick 2014), but could also serve as a quality signal (Chakraborty and Swinney 2021). Our analysis, novelly, shows *both* are true. However, there is a nuance: it depends on the stage at which a campaign is at.

During the pre-goal stage, higher goals raise the threshold that must be cleared (Mollick 2014). Consequently, it is more difficult to achieve the target goal. Second, and what we show in this study, that high goals depress demand: when the goal appears out of reach, backers pledge less because each dollar feels less pivotal and prosocial "help-them-reach-it" motives weaken (Dai and Zhang 2019, Kim et al. 2020, Kuppuswamy and Bayus 2017). After the goal is achieved, however, the goal functions as information: a higher stated goal serves as a credible quality signal that can attract post-goal pledges (Chakraborty and Swinney 2021). Our stage-specific estimates thus show small, negative pre-goal marginal effects but positive, growing post-goal effects; these are not contradictions but stage shifts around the provision point.

6.2. KL Divergence Diagnostic

Having established that the consequences of goal setting differ pre- versus post-goal, we next ask whether the estimated update effects are themselves distorted by the endogenous evolution of funding. If shocks that move *Funding Progression* also move *Daily Pledges*, then treating the two equations as independent can bias the measured impact of updates. To answer this, we compare our Main Model specification that allows the errors of *Funding Progression* Eq. (4) and *Daily Pledges* Eq. (10) to be correlated against a naïve model that constrains this cross–equation correlation to zero. Because our update effects are modeled using GP priors, our update effect curves are marginal multivariate Normal distributions in the posterior (Dew et al. 2020). Accordingly, we need a metric that compares the entire posterior over the curve. We compute a symmetrized Kullback–Leibler divergence between the joint posteriors and obtain p-values via a label–permutation test. Pre-goal, we find a modest but statistically significant difference ($J = 1.764$, $p < 0.001$). Post-goal, the difference is large and significant ($J = 6.474$, $p < 0.001$), suggesting that correcting for correlated errors matters most after the provision point.

6.3. The Dynamics of Update Content

To further unravel why updates drive the pre- vs. post-goal dynamics discussed in Section 5, we classify each update into nine interpretable types: production (manufacturing/assembly progress),

product development (design changes, feature work, feasibility), delivery (shipping plans, timelines, status), engagement (community-building calls to action, feedback requests, social sharing), new rewards (added tiers, perks, limited offers), emotional appeals (gratitude, personal notes, affective language) urgency (deadlines and time-sensitive prompts), and other (content not captured above). Update types are not mutually exclusive as a single update can have multiple types. Details about the classification procedure can be found in Appendix E, and example excerpts for each of the update types can be found in Appendix F.

To undertake this analysis, we replace in the provision point GP specification from Eq. (10) the single update indicator with a nine-element vector describing the types present in the most recent update. Each type receives its own GP priors to capture the dynamic evolution of the specific update type. The semantic network derived Bartik instrument for update timing is also in turn modified such that the instrumented type vector then enters the pledges equation. The results from this analysis are shown in Figure 8.

[insert Figure 8 about here]

We find that the type-specific update dynamics are not uniform across stages of the crowdfunding campaign. In the pre-goal stage, effects are dynamically flat and only urgency delivers a meaningful, economically sizable lift during the later pre-goal periods. After the goal is reached, the effect of update types is heterogeneous across types and within each type's own progression. In the early post-goal period, new rewards have a significant and large impact. We speculate that entrepreneurs who introduce new rewards beyond those in the original plan induce a brief surge in pledges, as these refresh the value proposition and could reignite backer interest.

During the post-goal mid-campaign period, updates are generally ineffective. Here, a campaign has already reached its goal and is successfully funded, there may be no immediate need to communicate with potential backers (e.g., backers may respond negatively to communications unless there is some information that is really new). These effects could also be due to "scope creep" risks which can occur when new product features are introduced into a campaign, increasing the uncertainty of product quality and delivery delay (Pinkow 2023, Weber et al. 2023). Later in the post-goal stage, we find that stretch goal updates have a significant and large impact. These effects might emerge because backers' awareness of an approaching deadline is triggered by time-sensitive opportunities like those in stretch goal updates.

7. Discussion & Conclusion

Crowdfunding has changed the way early-stage entrepreneurs secure capital and connect with potential consumers. Throughout the prototypical month-long campaign, entrepreneurs observe real-time funding responses to their actions. This contrasts with traditional new product development settings where product pre-announcements occur before any economic benefits are realized. Within this dynamic and uncertain environment, entrepreneurs need to fine-tune their communication strategies to effectively convey their campaign's promise.

This study offers phenomenological and strategic insights into how entrepreneurs can more effectively deploy update strategies in crowdfunding contexts. Guided by our research question, our study addresses three empirical identification challenges: (1) updates are not posted at random, (2) the provision point (campaign goal) is endogenous, and (3) update effects evolve nonlinearly over the campaign. To this end, we propose a novel provision point framework utilizing a semantic-network IV strategy to attain causal identification, along with a flexible Gaussian process prior specification to richly model the consequently exogenous update dynamics.

Our findings reconcile and refine previous research on the impact of updates. Prior studies generally find a positive relationship between update frequency and pledges (Deng et al. 2022). However, these studies provide little insight into when to post. To address this problem, we employ a provision point model and show that updates play very different roles across the two stages of a crowdfunding campaign. In the pre-goal stage, updates have a modest positive effect on daily pledges, but their impact is relatively stable across the pre-goal stage. Once the goal is reached, however, update effectiveness becomes more varied in its time dynamics. Immediately after achieving the goal, there is a spike in update effectiveness, which is followed by a rapid dip. After the dip, updates are generally ineffective throughout the middle of the post-goal stage. Finally, there is a renewed lift in update effectiveness in the final days of the campaign.

Our findings, therefore, show that the effectiveness of updates is more nuanced than what the existing literature proposes. While industry pundits recommend posting updates throughout the campaign (Dushnitsky and Marom 2013, Steinberg 2012), we find that this strategy only makes sense in the pre-goal stage. While some research recommends that updates be posted in the early stages of a campaign (Bhargava et al. 2024, Herd et al. 2022), we find that early updates are most effective in the post-goal stage. Even though research suggests that updates are not effective in the post-goal stage (Pinkow 2022), we find that updates can be very effective in the early and later

stages of the post-goal stage – understandably, a model that omits within-stage dynamics likely 'cancels out' these early and late stage surges with the mid-stage slump in its parameter estimation.

To further investigate these patterns, we undertook a decomposition across different update types and examine how type-specific effects vary across campaign stages. In the pre-goal stage, update effects are generally flat, with urgency updates standing out as the only type to deliver a meaningful lift in later periods by highlighting the risk of time running out. After the goal is reached, heterogeneity across update types becomes more pronounced. Early in the post-goal stage, pledge responses are strongest following updates that give information on new rewards. By contrast, the late-stage lift is largely driven by stretch-goal updates.

Our proposed provision point framework also clarifies the dual role of funding goals. Higher goals can depress early contributions by making success appear less attainable, consistent with evidence that ambitious goals lower the probability of success (Kim et al. 2020, Mollick 2014). Yet once the goal is achieved, higher goals serve as a credible quality signal that attracts additional pledges in the post-goal stage (Chakraborty and Swinney 2021). Taken together, our findings show that both update strategies and goal-setting choices must be understood as dynamic and stage-dependent, rather than static determinants of crowdfunding performance.

Our methodological framework – a flexible, nonparametric Bayesian provision point model that accounts for the endogenous transition between the pre- and post-goal stages — is relevant broadly to provision point settings where the funding threshold is strategically chosen. Previous studies have typically predicted an exogenous changepoint (Li et al. 2019b), assuming that the changepoint is external to endogenous latent factors. By contrast, our approach recognizes that entrepreneurs select their target goals in ways that can influence both backers' perceptions and subsequent pledging behavior. Our methodology not only enables addressing the endogenous nature of the goal itself but also accommodates the dynamic update effects that unfold in the pre- and post-goal stages. As such, it can be readily extended to other provision-point contexts.

Many business initiatives require setting a goal that must be met for the campaign to proceed. Our approach captures the split-regime mechanism effectively and extends naturally to other provision-point settings that involve setting a goal that must be met in order for the campaign to succeed (Cheema and Bagchi 2011, Jin et al. 2023). For example, companies like Deal Share (The Brand Hopper 2023) utilize group-buying strategies, where users buy and share deals with friends, and discounts increase as more people participate (Jing and Xie 2011). Another example can be found in the gaming industry community goals, where the collective efforts of players contribute to

unlocking in-game rewards. For instance, in the Fortnite Battle Royale Community Goal event, players were encouraged to survive millions of game cycles together, receiving in-game rewards once the threshold was met (The Fortnite Team 2024). By accounting for the dynamic and heterogeneous effects of communications before and after a strategically chosen threshold, our approach provides a framework that can be readily extended to modeling communication strategies – and other dynamic endogenous marketing actions – in provision point settings of interest to marketers.

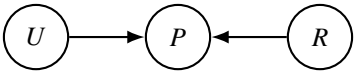


Figure 1 **Baseline provision-point.**

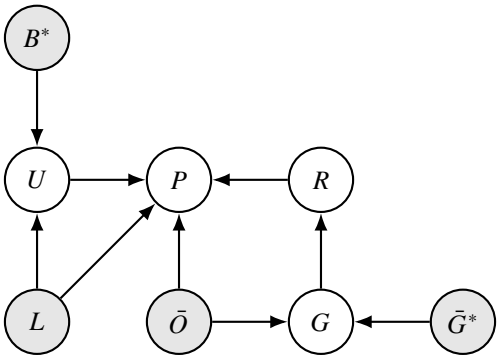


Figure 2 **Endogenous provision-point**

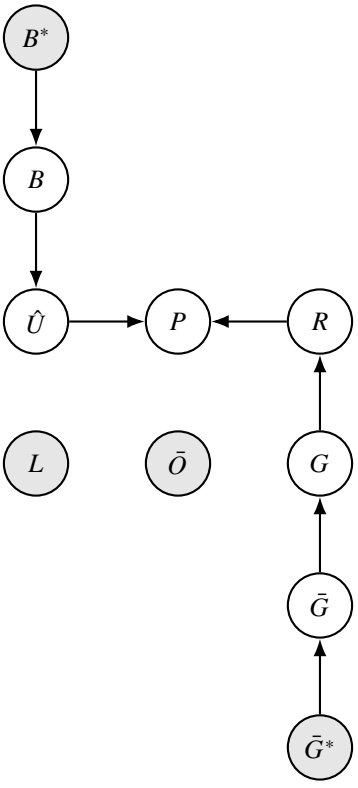


Figure 3 **Proposed Model**

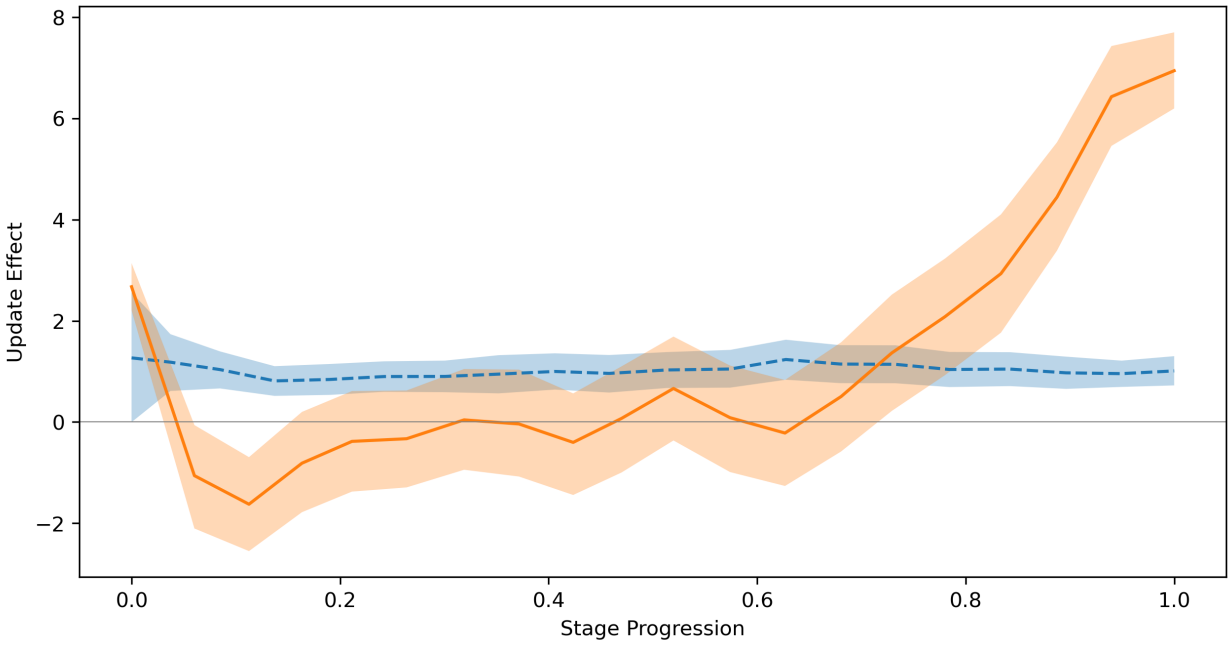


Figure 4 Effect of Updates during the pre- and post-goal stages by stage progression for Model 1

Notes: **Figure 4 illustrates the estimated effects of Updates on daily pledges, separated into pre- and post-goal stages, plotted against per stage progression. The dashed blue lines represent the effect of updates during the pre-goal stage, while the solid orange lines represent the post-goal stage. To allow both stages to appear on a single 0–1 scale, we map the time dimension onto a 0–1 scale by rescaling pre-goal values (0=launch, 1=goal attainment) and post-goal values (0=goal attainment, 1=campaign end).**

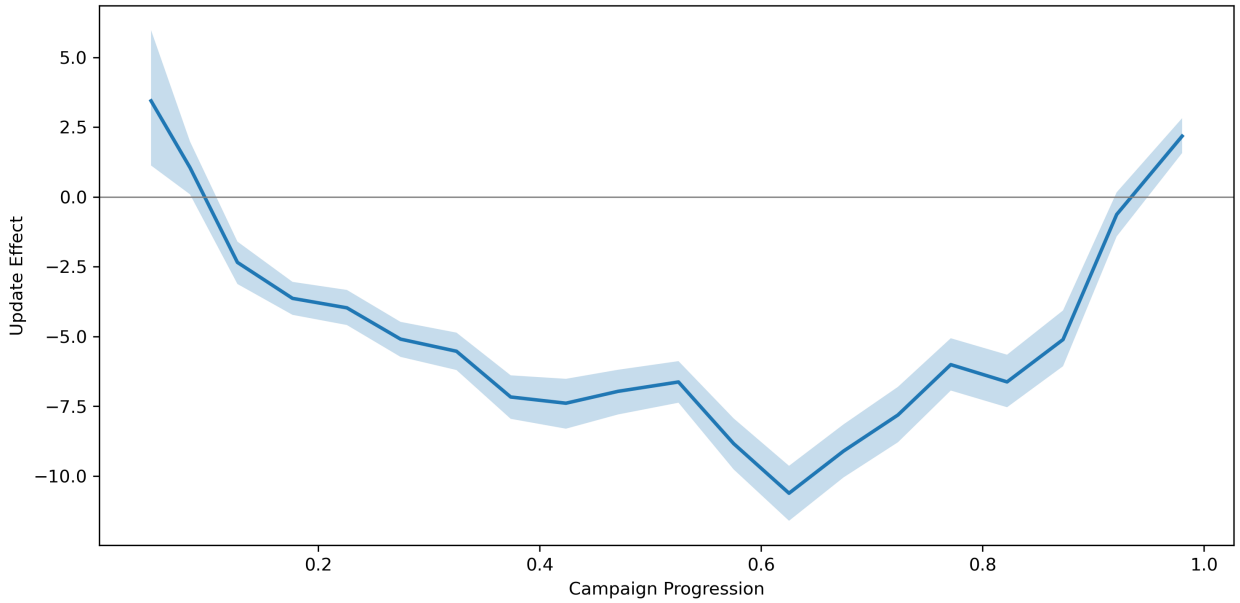


Figure 5 Effect of Updates throughout the entire campaign progression

Notes: **Figure 5 illustrates the estimated effects of Updates on daily pledges, plotted against the campaign's progression. We map the time dimension onto a 0–1 scale by rescaling the time values (0=launch, 1=campaign end).**

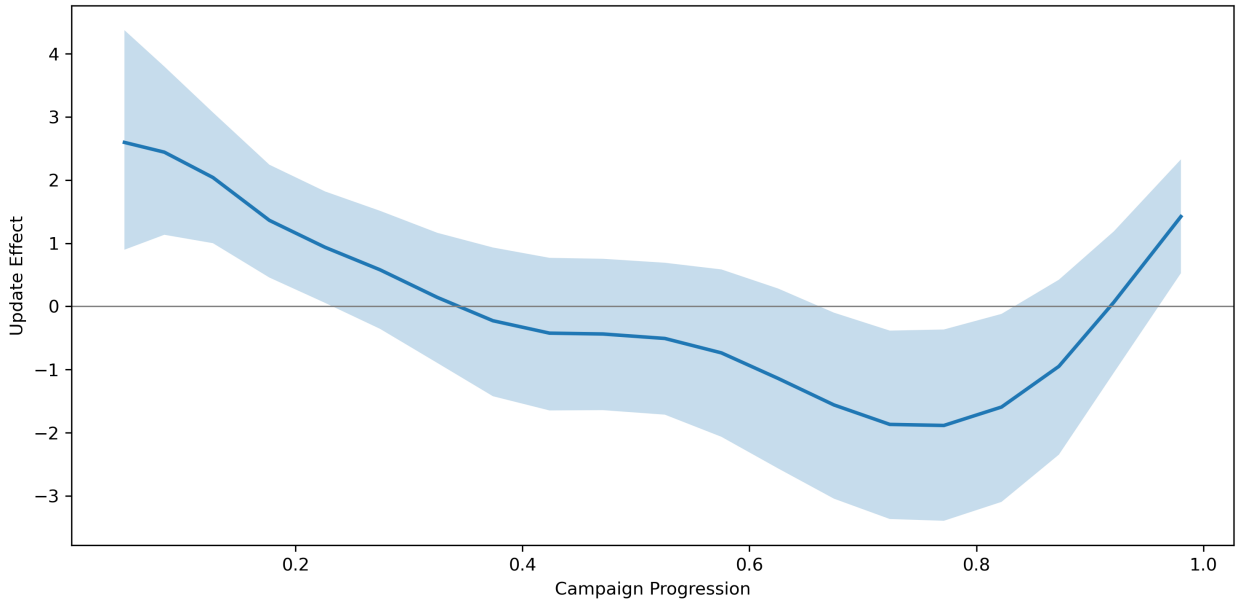


Figure 6 Effect of Updates throughout the entire campaign progression for unsuccessful campaigns

Notes: **Figure 6 illustrates the estimated effects of Updates on daily pledges, plotted against the campaign's progression. We mapped the time dimension onto a 0–1 scale by rescaling the time values (0=launch, 1=campaign end).**

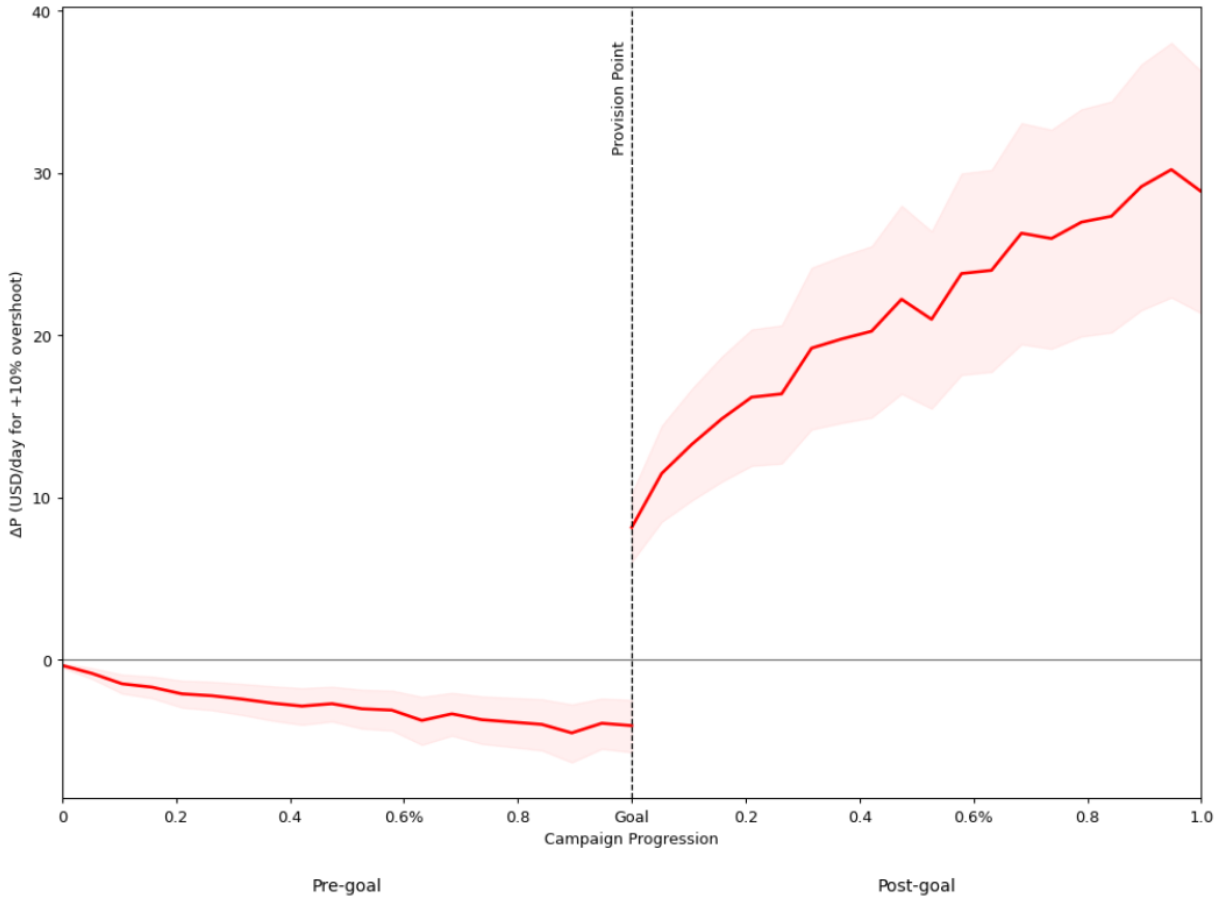


Figure 7 10% marginal effect of goal overshoot on expected daily pledges by stage.

Notes: **This graph shows the effect of overshooting during the before and after goal stages. Shaded bands are 95% credible intervals; the horizontal grey line marks zero. The y-axis reports change in pledges in USD/day for a +10% overshoot.**

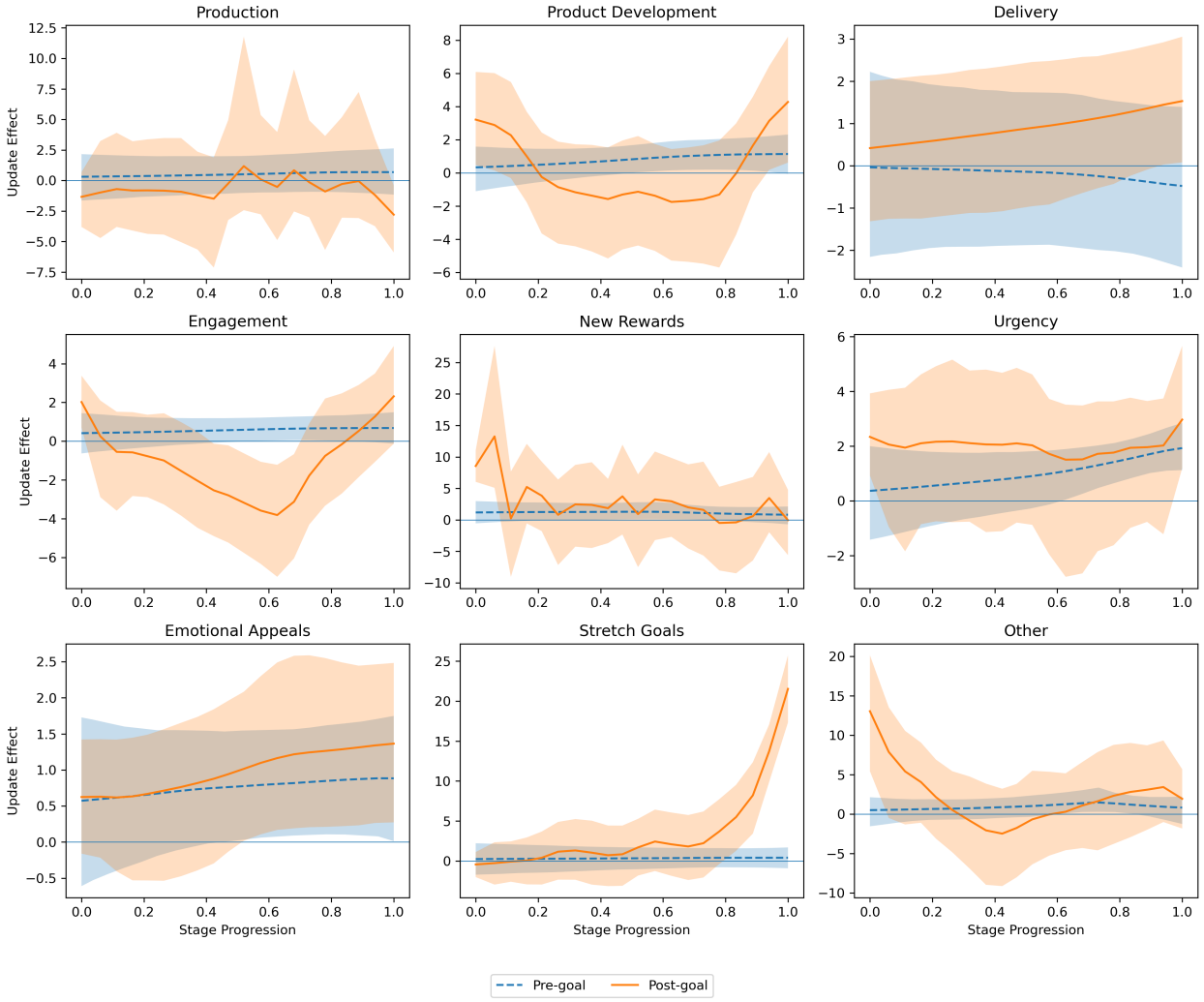


Figure 8 Effect of update types during the pre- and post-goal stages by stage progression for Model 1

Notes: **Figure 8 illustrates the estimated effects of different update types on daily pledges, separated into pre- and post-goal stages, plotted against per stage progression. The dashed blue lines represent the effect of updates during the pre-goal stage, while the solid orange lines represent the post-goal stage. To allow both stages to appear on a single 0–1 scale, we map the time dimension onto a 0–1 scale by rescaling pre-goal values (0=launch, 1=goal attainment) and post-goal values (0=goal attainment, 1=campaign end).**

Table 1 Summary Statistics

Variable	Entire Campaign	Pre-Goal	Post-Goal
N	4000	4000	1258
Updates	2.03 (3.45) [0, 55]	1.07 (2.32) [0, 44]	3.54 (3.64) [0, 23]
Goal (K$)	48.1 (174.4) [1, 100 M[a]]	–	–
Projects that Achieved the Goal			
Updates	4.86 (4.24) [0, 55]	2.37 (3.11) [0, 44]	3.54 (3.64) [0, 23]
Goal (K$)	17.5 (25.1) [1, 500]	–	–
Projects that didn't Achieve the Goal			
Updates	0.74 (1.94) [0, 25]	0.74 (1.94) [0, 25]	–
Goal (K$)	62.1 (208.4) [20, 100 M]	–	–

Notes: Results are reported in the format: mean (sd) [min, max].

[a]*The maximum goal for a project in our sample is $100,000,000.*

Table 2 Models Summary

	Main Model		Comparison Model 1		Comparison Model 2		Comparison Model 3	
Variable	**Est.**	**[2.5%, 97.5%]**	**Est.**	**[2.5%, 97.5%]**	**Est.**	**[2.5%, 97.5%]**	**Est.**	**[2.5%, 97.5%]**
Pre-Goal (Comparison Model 2 & Main Model) — Entire Sample (Comparison Model 1 & 3)								
Funding Progression (lag 1)	0.066	[0.046, 0.085]	-0.003	[-0.003, -0.002]	0.078	[0.061, 0.097]	0.015	[0.015, 0.015]
Homogeneous Updates (lag 1)		—	1.279	[1.108, 1.460]	0.830	[0.676, 0.979]		—
Post-Goal (Comparison Model 2 & Main Model)								
Funding Progression (lag 1)	0.010	[0.008, 0.011]		—	-0.001	[-0.002, 0.000]		—
Homogeneous Updates (lag 1)		—		—	3.417	[3.057, 3.791]		—
ρ	-0.072	[-0.083, -0.062]		—		—	-0.134	[-0.134, -0.134]

Notes: 95% posterior credible intervals shown as [lower, upper]. All models include per-stage project and day random effects.

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