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ABSTRACT: Extending recent work on market mechanisms in new fintech offerings, we explore the implications of a key mechanism in online crowdfunding-the use of a provision point. Under a provision point mechanism (otherwise known as all-or-nothing or fixed fundraising scheme), the fundraiser, typically an entrepreneur, only receives funds pledged toward his or her campaign if a preregistered fundraising target is met, rather than keeping everything that is raised. Provision points may weaken contributors' reliance on prior capital accumulation for judging a project's

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potential for success, by eliminating their concerns about a partial fundraising outcome and by signaling the project or entrepreneur's quality. Yet, provision points may also induce attention to prior capital accumulation, because the materialization of one person's contribution depends explicitly on sufficient contributions from others (a network effect). We assess this tension empirically, leveraging proprietary data from a leading crowdfunding platform that allows entrepreneurs to opt into a provision point. We consider the effects of prior capital accumulation on visitors' conversion and contribution decisions, and the moderating influence of a provision point. We find that provision points weaken the association between prior capital accumulation and visitor contribution, implying a reduction in potential herd behavior.

KEY WORDS AND PHRASES: crowdfunding, fintech, fundraising, market mechanisms, mechanism design, provision point mechanism, social proof.

The number of new *financial technology* (*fintech*) products and services entering the market has grown exponentially in recent years. This is reflected by the large volume of global investment in such technologies; in the fourth quarter of 2015 alone, global investment in fintech companies exceeded US$25 billion [18]. Yet, despite their promise, the success of these offerings is far from guaranteed; success depends on careful design of accompanying mechanisms with consideration for certain market principles [14]. Online crowdfunding platforms, which compose a substantial component of this recent fintech revolution, are a case in point.

Crowdfunding platforms provide a novel avenue by which entrepreneurs can solicit financial support for new ventures, taking their ideas directly to the crowd, rather than pursuing traditional gatekeepers such as venture capitalists, angels or banks. Indeed, the acquisition of start-up financing has traditionally been one of the most difficult hurdles that entrepreneurs face, because private investment is largely “hit or miss,” and accessible to only a few. Online crowdfunding platforms take the fundraising process online with the objective of democratizing access to capital, providing entrepreneurs with exposure to a much wider range of *potential contributors* (also referred to as backers or funders), over a broader geographic area. Notably, the online crowdfunding space is highly competitive; nearly 200 platforms were operating in the United States as of 2012 [13], and that number has likely only grown in subsequent years.

The design of fintech systems is critical to their success, growth, and sustainability. Many financial services today, including crowdfunding platforms, are underpinned by technology that enables a multisided market [22]. As such, crowdfunding platform operators must address several core market design problems to facilitate transactions [17]. A variety of prior work in the information systems (IS) literature has examined the design of various market mechanisms and features associated with fintech offerings, and online crowdfunding specifically, with an eye toward market efficiency, growth, and sustainability [7, 10, 40]. We build on such work here, focusing on the use of fundraising thresholds in crowdfunding, wherein a fundraiser must obtain a minimum level of aggregate contribution before collecting any proceeds. These thresholds, typically known as *fixed, all-or-nothing fundraising schemes* among crowdfunding practitioners, or as *provision point mechanisms* (PPMs) in the public economics literature [28, 32, 33],[1] guarantee that funded projects only proceed if they have reasonably adequate funds to meet their objectives, thereby reducing uncertainty for potential contributors. The alternative to the PPM is a "thresholdless" provision mechanism (known as a *voluntary contribution mechanism* in the public economics literature), where the entrepreneur retains all funds contributed by the crowd regardless of the aggregate amount raised [5].

Some online crowdfunding platforms provide the option for entrepreneurs to choose whether they adopt a PPM in the fundraising process (e.g., FundRazr, IndieGoGo), while others mandate the use of either a PPM (e.g., Kickstarter) or a thresholdless mechanism (e.g., FundAnything, Rockethub). It is important to note that even when a particular provision mechanism is mandated by a platform, entrepreneurs still have a choice; they can choose between platforms that use PPM and those that employ the thresholdless mechanism. The decision of whether to employ a PPM is important because it has the potential to impact contribution dynamics, amplifying or attenuating potential contributors' attention and response to prior capital accumulation.

Prior work in online crowdfunding has shown that potential contributors often engage in observational learning in an effort to reduce uncertainty, by drawing inferences from campaigns' prior capital accumulation when making a contribution decision [8, 38, 41]. Capital accumulation provides potential contributors with signals about the quality of the campaign or entrepreneur, and helps to alleviate uncertainty about whether the campaign will obtain sufficient funds to reasonably pursue its objectives. While it may make sense for individual contributors to rely on capital accumulation to infer campaign quality, rather than forming an independent evaluation, this sort of observational learning can have a detrimental effect on the efficiency of the crowdfunding market as a whole. This is because observational learning has been shown to lead to informational cascades, which override market participants' private information, increase the volatility of market outcomes, and sometimes even result in *irrational herd behavior* [6, 26]. Most notably, for crowdfunding markets, campaign contributors have a variety of motivations and offer funds for a multitude of reasons; contributors engaging in herd behavior ignore these differences, causing suboptimal contribution decisions and inefficient allocation of funds [34]. In light of the above, it behooves both crowdfunding platforms and entrepreneurs to carefully consider the design of crowdfunding mechanisms in achieving their goals.

A PPM may amplify or attenuate potential contributors' attention and response to prior capital accumulation. On one hand, a PPM may attenuate the response to capital accumulation because PPMs preclude the possibility of a partial fundraising outcome, thereby reducing a potential contributor's uncertainty about campaign output. Moreover, an entrepreneur's decision to use a PPM may signal positive information to potential contributors about the entrepreneur's confidence in their project, substituting for observational learning. On the other hand, a PPM may amplify sensitivity to prior capital accumulation by creating an explicit positive externality among contributors, because, under a PPM, any contributor's ability to derive value explicitly depends on sufficient aggregate contributions from his or her peers. We formalize this tension as follows, aiming to address the following research questions: (1) Does the use of a provision-point mechanism amplify or attenuate the effects of prior capital accumulation on visitor conversion and contribution decisions in online crowdfunding? (2) How do these effects vary over the fundraising lifecycle?

We leverage a large sample of more than a 250,000 campaign URL visits, from web traffic, and associated contributions at a leading online crowdfunding website. The unique, granular, and detailed nature of our data set also allows us to disentangle the relationship between PPM use and visitor conversion from the relationship with the amount of money visitors supply, conditional on conversion. Our analysis demonstrates positive associations between a visitor's conversion and contribution amount, and a campaign's prior capital accumulation, while also showing that these relationships are significantly weaker in the presence of a PPM. This result suggests that when a PPM is in place, campaign contributors rely less on observational learning, leading to earlier and presumably more independent contribution decisions. Digging deeper, we find that the above relationships also vary over the course of the campaign life cycle. Although the PPM's presence is associated with a weaker influence of prior capital accumulation early on, the relationship inverts as the campaign approaches its deadline, as the campaign's fundraising balance becomes a stronger predictor of project provision.

Related Work

Fintech has begun to receive a great deal of attention in the literature, as evidenced by this Special Issue of the journal and others previously [22, 27]. Of particular relevance are the various studies that have explored questions of mechanism design in relation to new fintech offerings. For example, the work by Chiu and Wong [14] considers feature and policy design around digital currencies, exploring how particular combinations of elements, for example, limited transferability and limited participation, can help to reduce frictions and enhance social welfare. Guo et al. [19] propose the design of mechanisms for a novel retail payment and settlement system.

A substantial body of IS research dealing with mechanism design has focused on crowdfunding markets, which enable individuals and organizations to solicit money from the crowd to pursue projects of various forms, ranging from social causes to artistic pursuits and entrepreneurial ventures. There are four types of crowdfunding, which generally vary in terms of the compensation provided to campaign contributors. These include donation-based crowdfunding (e.g., GoFundMe), in which no compensation is provided; reward-based crowdfunding (e.g., Kickstarter), in which tangible rewards are provided, such as product preorders; loan-based crowdfunding (otherwise known as *peer-to-peer lending*, e.g., LendingClub); and *equity-based crowdfunding* (e.g., FundersClub), in which individuals purchase small equity stakes in a business [1].

Research on the design of crowdfunding markets has addressed various market mechanisms. For example, Cai et al. [12] examine a funding scheme design for reward-based crowdfunding that combines the reward- and donation-based contribution models, studying the impact on contribution activity and fundraising outcomes. Wei and Lin [40] examine the peer-to-peer lending market, Prosper, exploiting the platform's shift from second-price auctions to posted prices, to understand how the choice of pricing mechanism (auction versus posted price) influences transaction terms and longer-term outcomes, such as interest rates and the probability of loan default. They find that posted prices simultaneously lead to both higher interest rates and higher default rates. Other work has examined information control mechanisms; Burtch et al. [10] report on an experiment around the provision of privacy and information controls on IndieGoGo, demonstrating the detrimental effect of these features on fundraising activity.

Other work by Agrawal et al. [3] explores investment aggregation mechanisms and decision-making rights. Those authors contrast individual investment with syndicated investments (where many investors delegate investment authority to a single lead investor) in equity crowdfunding, demonstrating that syndication can better align the incentives of various stakeholders, including lead investors, follow-on investors, and issuers. Hu et al. [21] examine reward tiers (menu pricing) in reward-based crowdfunding, articulating the different conditions under which uniform pricing for high- and low-value customers (versus tiered, discriminatory pricing) will result in optimal fundraising outcomes for the entrepreneur.

Finally, Strausz [37] explores theory for crowdfunding, as a whole, as an alternative mechanism for capital allocation, in contrast to alternative entrepreneurial finance schemes. He articulates a variety of beneficial features of crowdfunding for market efficiency. For example, he explores how crowdfunding's inherent reduction of demand uncertainty (consumers reveal themselves through pledging to the campaign) helps to promote welfare, and how offering deferred payments, in the form of conditional pledging, can help to manage an entrepreneur's moral hazard and potential for fraud.

We build on this prior work by examining the implications of PPM use. As noted in the introduction, various studies in the crowdfunding literature have reported on the effect of prior capital accumulation, noting its positive relationship with subsequent campaign contributions. This result is consistent with the notion of observational learning [6]: the idea that contributors infer campaign quality from others' willingness to contribute, and that, in the absence of prior capital accumulation, they may delay or withhold their contribution, until they have a better sense of how the campaign will fare [21]. This is logical, because crowdfunding is characterized by a significant degree of information asymmetry [1, 4], with respect to a number of factors, including the competence of the entrepreneur, the quality of the idea, and the potential for fraud [1, 35].

The lack of research on the effects of PPMs in crowdfunding is surprising, given their frequent discussion among practitioners and platform operators, and among the mainstream media. As articulated above, contributors may delay or withhold contributions from campaigns, for a variety of reasons, and the presence of a PPM has the potential to amplify or attenuate such behavior. Prior work in the public goods literature suggests that PPMs will make contributors more willing to offer their true valuation [32, 33], contributing independently, producing Pareto optimal outcomes. However, despite bearing many similarities to traditional public goods [9, 20, 39], crowdfunding also differs in many respects, most notably in that many campaigns offer private returns. Thus, the effect on contributor behavior in this setting is far from clear.

Study Context

Our study was conducted at a leading online crowdfunding platform based in the United States. The platform attracts more than 4 million visitors in a typical month, facilitating millions of dollars in contributions. Since 2008, the platform has attracted over 1 million users from nearly every country in the world. The platform allows fundraising for many different purposes. When campaign owners first submit their project, they are required to specify how the money will be used, the rewards that contributors can claim, the target amount to be raised, the number of days the fundraiser will run for, and the fundraising mechanism: PPM or thresholdless.

Our data are measured at the visit (impression) level. This level of granularity enables us to examine the effect of PPM use, not only on individual contribution amounts but also on the probability of conversion that is not publicly observable. Notably, the majority of prior work on crowdfunding dynamics has suffered from data limitations and, as a result, issues of selection, because visitors who opt not to contribute at all are by definition unobservable [11]. Our analysis of these visit-level observations incorporates campaign-specific fixed effects,[2] as well as time effects, which jointly enable us to control for unobserved heterogeneity in campaign characteristics and temporal trends, such as accounting for factors that may drive self-selection for PPM use.

When contributors visit a crowdfunding campaign, they can typically observe the status of fundraising progress in real time. Visitors can observe progress toward the fundraising target, and also progress toward the fundraising deadline. The presence of a PPM has the potential to shift how a visitor responds to this fundraising progress information. On the one hand, a PPM may result in greater sensitivity to prior capital accumulation, because its presence strengthens the positive externality among contributors, making it explicit, such that it is impossible for the project to move forward in any form unless sufficient contributions are made by the collective. For example, if a campaign could conceivably produce reasonable value when 90 percent of the preregistered fundraising target were achieved, introducing a PPM that mandates 100 percent of the target be acquired will increase the importance of peers' contribution behavior in an individual's contribution decision: if the aggregate total falls short by even a small amount, provision will not take place.

At the same time, a PPM may attenuate the influence of prior capital accumulation because its presence is something that an entrepreneur elects to implement; entrepreneurs who are particularly confident about their ability to reach a fundraising target, or entrepreneurs who have a strong network of supporters, are more likely to opt into PPM use [15]. This choice is also potentially costly, in that failure to achieve the fundraising target under a PPM will result in no capital acquisition by the entrepreneur. This setup suggests that the use of a PPM may in fact provide a costly signal of entrepreneur or venture quality [36]. This signal of positive information may also be expected to substitute for social proof, as indicated by prior capital accumulation.

In addition, the presence of the PPM eliminates any concerns about partial provision. In a thresholdless campaign, contributors face the risk of a partially funded campaign, one that may fail to obtain sufficient funds to address any fixed costs of production, or operate suboptimally due to inadequate funds. In either, contributors may wish to back out and use their funds elsewhere. Such risks may cause potential contributors to make funding decisions contingent on the campaign already having received enough funds from others. Under a PPM, a contributor no longer needs to be concerned the campaign will fail to obtain sufficient funds, eliminating risk and uncertainty associated with a partially funded campaign.[3] This suggests that potential contributors will be less sensitive to prior capital accumulation.

The effects of a PPM may also be expected to vary dynamically over the campaign fundraising life cycle. For example, if the PPM is ultimately a better demand revealing mechanism [32, 33], causing potential contributors to shift focus away from observational learning toward their own independent judgments, this can have the counterintuitive effect of magnifying observational learning. Cognizant of the independent evaluations of prior contributors, a subsequent arrival may perceive any prior capital accumulation as a more valid or robust indication of project quality. Thus, while we expect contributors to make more independent judgments under a PPM for the same amount of external information, at some point, we might also expect observational learning effects deriving from prior capital accumulation to override the contributor's own judgment, once the signal grows particularly strong. This would lead to the expectation that contributors will be less sensitive to capital accumulation under PPM in the early stages of fundraising, yet more sensitive to it at later stages of fundraising.

Related to this, as the fundraising deadline draws nearer, the explicit externality imposed by PPM can be more evident. At this stage, the prior capital accumulation can enable more accurate prediction of whether the threshold will ultimately be met. As the campaign draws to a close, and the strength of prediction improves, capital accumulation will make visitors likely to conclude that either (1) there is no point in supplying money (if the threshold is far out of reach), or (2) that supplying money is worthwhile (if the threshold is within reach). In both cases, potential contributors would be more sensitive to capital accumulation in a PPM campaign than in a thresholdless campaign.

In summary, there are countervailing arguments as to how PPMs might affect contributors' response to prior capital accumulation; they may either magnify or attenuate attention to it, and these effects may shift over the course of fundraising. Accordingly, we look to the data to make empirical observations about these relationships, both in terms of visitor conversion and visitor contribution amounts.

Methods

Data

Our analysis considers proprietary, visit-level data collected over a three-month period at the end of 2012 and beginning of 2013. Over the period of observation, we observe each new session that is initiated at the campaign URL. Each observation includes a time stamp, campaign ID, various campaign characteristics, as well as the outcome of the visit (especially whether the visitor contributed, and how much they contributed). If the visitor opts to contribute, we observe their user ID and, in turn, some of their characteristics, such as their tenure on the platform.

An important facet of our sample is that we observe contribution details even when the contributor has opted to conceal information from public view on the website. This is important because a large proportion of contributions on this platform are made anonymously (or the amount of the contribution is concealed), and thus the identity of the contributor or amount of the contribution are often not publicly observable. However, our proprietary sample enables us to observe the identity of each user and the amount of money they supplied, regardless of whether they have made an anonymous contribution. This sample includes 281,300 campaign visits and more than 102,000 contributions to more than 4,000 campaigns. Table 1 provides a list of variable definitions in our visit-level sample, and Table 2 the descriptive statistics.[4]

A number of systematic differences are immediately apparent between the static characteristics of campaigns that employ a PPM and those that do not. We do not incorporate these variables into our analysis, because they are all subsumed by our campaign fixed effects; however, it is nonetheless interesting to consider these differences because they highlight the extent of self-selection for PPM use, as we noted earlier. First, consistent with the observations of Cumming et al. [15], PPM campaigns typically seek much larger amounts of money. In our sample, PPM campaigns seek more than $400,000 on average, whereas thresholdless campaigns seek an average of $72,000. Second, PPM campaigns offer 6.57 reward tiers on average, while thresholdless campaigns offer just 5.24. Approximately 0.25 percent of PPM campaigns are featured on the platform home page (generally something

Table 1. Variable Definitions

Variable	Description
$Conversion_{ij}$	Whether visitor i contributed to campaign j.
$Contribution_{ij}$	Amount contributed by visitor i to campaign j.
$Percent_{ij}$	Campaign fundraising progress toward goal, as of i's visit to campaign j. This variable indicates the prior cumulative contributions, normalized with respect to campaign goal.
PPM_j	A binary indicator of whether campaign j employed a provision point mechanism.
$Days\ Left_{ij}$	The number of days remaining until campaign j's fundraising deadline, as of the arrival of visitor i.

Table 2. Descriptive Statistics

Variable	Mean	St. Dev.	Min	Max	N
$Conversion_{ij}$	0.366	0.482	0.000	1.00	281,300
$Contribution_{ij}$	75.773	272.041	1.000	35,000.00	102,874
$Percent_{ij}$	37.256	32.907	0.000	119.99	281,300
PPM_j	0.102	0.302	0.000	1.00	281,300
$Days\ Left_{ij}$	25.534	24.586	0.000	120.00	281,300

Notes: Percentage to target could exceed 100 percent, because even after the target is met, the crowd may continue to contribute to the campaign until the deadline expires. We limit our analysis to cases where the percentage raised was no more than 120 percent, to eliminate outlier observations—in so doing, we exclude just 5 percent of the campaigns that comprised our original sample.

that is determined by popularity as indicated by web traffic to the page), whereas just 0.042 percent of thresholdless campaigns are featured. PPM campaigns are also systematically longer in duration, operating for an average of 61 days, whereas thresholdless campaigns operate for an average of just 44 days. Finally, we observe differences in the most common categories that PPM campaigns are associated with: Technology, Design, Gaming, Writing, and Music, versus those that thresholdless campaigns are most often associated with: Film, Community, Education, and Health.

Beyond the above, selection for the use of a provision point is enabled by many platforms, directly. IndieGoGo, for example, in advising entrepreneurs on how to structure a campaign and whether to use a provision point, refers to the campaign's objectives. The advice suggests that a PPM "can be useful when your project requires a strict minimum amount of funding to be successful, which is common for technology or design projects with substantial up-front manufacturing costs." In contrast, *flexible funding*, with no provision point, can work well when the costs of developing a technology are already secured by other sources and the intent of the crowdfunding campaign is to test the idea publicly, to assess the size of the market.[5]

Estimation Models for Contribution and Conversion

To account for these obvious systematic differences, we employ a fixed-effect estimation framework. Incorporating campaign fixed effects, we are able to control for all static features of a campaign and the entrepreneur who organizes it, including reward tiers, category, goal, duration, description, videos, and so forth. More generally, fixed effects account for the entrepreneur's experience or expertise, as well as the average effort he or she puts into the fundraising process. Because the decision to use a PPM does not vary during the course of fundraising, the presence of a campaign fixed effect prevents us from identifying the main effect of PPM use on fundraising outcomes (the subject of [15]). However, our focus here is how PPMs moderate the effect of prior capital accumulation on visitors' conversion and contribution decisions. We first estimate the specification below, and we then repeat the same estimation for the alternative dependent variable, conditional contribution amounts, by replacing *Conversion* with *Contribution* amount in dollars.

$$Conversion_{ij} = Percent_{ij}\beta + \left(Percent_{ij} * PPM_j\right)\lambda + Days\ Left_{ij}\phi + \alpha_j + \tau_t + \epsilon_{ij},$$

where i indexes visitors, j indexes campaigns, and t indexes time. The relationship between prior capital accumulation and conversion probability is captured by β; this coefficient is expected to be positive, in line with past work. Our fixed effects for campaigns are captured by α, which represents a vector of campaign dummies, and our fixed effects for time are captured by τ, which represents separate vectors of week and day of week dummies. The effect of time remaining until the fundraiser deadline is captured by Φ. Finally, λ, our parameter of interest, represents the moderating effect of a PPM on the relationship between prior capital accumulation and our outcome variable.

We implement our analysis of capital accumulation's relationship with the outcome in a nonparametric manner, noting past work that has observed that the effects can be very nonlinear over the fundraising distribution [23]. We estimate a vector of capital accumulation dummies that reflect increments of 5 percent toward the fundraising target, up to 120 percent, omitting the dummy for capital accumulation between 0 and 4.99 percent of the target. Thus, β and λ ultimately reflect vectors of coefficients, covering the entire distribution of the campaign fundraising progress.[6] Following our initial baseline analyses, we explore the robustness of our results to a matching procedure, namely coarsened exact matching, and we further consider the dynamics of these effects, repeating our estimations on subsamples of our data, depending on whether observations took place earlier or later in the fundraising process. This latter estimation effectively amounts to the consideration of a three-way interaction between prior capital accumulation, PPM presence, and time.

Results

Contribution and Conversion

We begin with our estimation of conversion effects, which we present in a stepwise fashion, initially reporting the main effects of prior capital accumulation, and then introducing the interactions with PPM use. These results are presented in Table 3.

Table 3. Regression Results (*DV* = $Conversion_{ij}$)

Independent Variable	LPM-FE (1)	LPM-FE (2)
5 $Percent_{ij}$	**0.02** (0.004)**	**0.02*** (0.005)**
10 $Percent_{ij}$	**0.02*** (0.005)**	**0.02*** (0.005)**
15 $Percent_{ij}$	**0.03*** (0.006)**	**0.03*** (0.006)**
20 $Percent_{ij}$	**0.03*** (0.006)**	**0.03*** (0.006)**
. . .	. . .	. . .
85 $Percent_{ij}$	**0.07*** (0.009)**	**0.07*** (0.009)**
90 $Percent_{ij}$	**0.07*** (0.009)**	**0.08*** (0.010)**
95 $Percent_{ij}$	**0.11*** (0.010)**	**0.12*** (0.010)**
100 $Percent_{ij}$	**0.02** (0.009)**	**0.03** (0.009)**
105 $Percent_{ij}$	**0.06*** (0.010)**	**0.06*** (0.010)**
110 $Percent_{ij}$	**0.03** (0.010)**	**0.03** (0.011)**
115 $Percent_{ij}$	**0.04** (0.012)**	**0.03* (0.012)**
5 $Percent_{ij}$ * PPM_{ij}	—	**–0.04** (0.013)**
10 $Percent_{ij}$ * PPM_{ij}	—	**–0.05** (0.017)**
15 $Percent_{ij}$ * PPM_{ij}	—	**–0.04* (0.018)**
20 $Percent_{ij}$ * PPM_{ij}	—	**–0.05* (0.019)**
. . .	. . .	. . .
85 $Percent_{ij}$ * PPM_{ij}	—	**–0.04+ (0.023)**
90 $Percent_{ij}$ * PPM_{ij}	—	**–0.06** (0.021)**
95 $Percent_{ij}$ * PPM_{ij}	—	**–0.08*** (0.023)**
100 $Percent_{ij}$ * PPM_{ij}	—	**–0.04+ (0.022)**
105 $Percent_{ij}$ * PPM_{ij}	—	–0.02 (0.030)
110 $Percent_{ij}$ * PPM_{ij}	—	**–0.07* (0.029)**
115 $Percent_{ij}$ * PPM_{ij}	—	0.05 (0.035)
$Days\ Left_{ij}$	**–0.002*** (0.0003)**	**–0.002*** (0.0003)**
Campaign and Time Effects	Yes	Yes
Observations	281,300	281,300
F-stat	**52.72 (40, 276809)**	**34.14*** (63, 276786)**
R^2	0.109	0.109

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p \leq 0.10$; robust standard errors in parentheses.

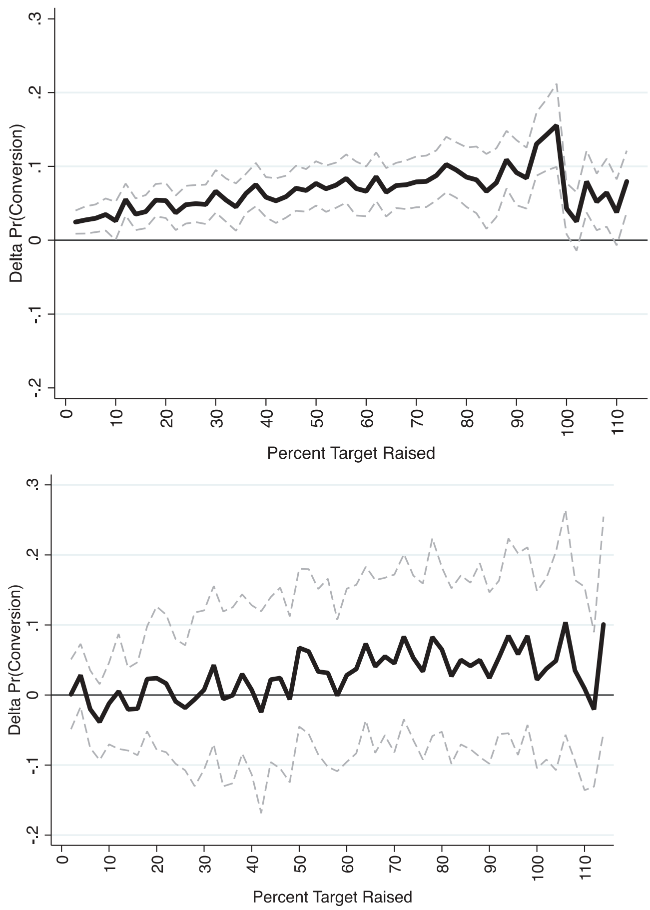

Figure 1. Marginal Effect on Pr(Conversion) from Capital Accumulation (Upper: without vs. Lower: with PPM)

First, we observe the same positive capital accumulation effects that have been reported in past work [2, 8, 41]. Second, upon introducing our interaction term, we see that these effects are significantly weaker when campaigns employ a PPM. In fact, the positive effects of prior capital accumulation are significantly attenuated (if not entirely eliminated) when a PPM is used at almost every point in the distribution. When we examine the estimated marginal effects of our capital accumulation dummies in Figure 1, under thresholdless (upper panel) and PPM (lower panel) campaigns, the differential effects of capital accumulation are readily apparent. Although the capital accumulation effects under PPM are generally insignificant, possibly in part because of the relatively smaller number of observations associated with PPM campaigns and thus reduced power[7], the point estimates are nonetheless consistently smaller than those obtained from our non-PPM sample, to a statistically significant degree (this is made apparent by the significant interaction terms in our regression).[8]

Table 4. Regression Results ($DV = Contribution_{ij}$)

Independent Variable	OLS-FE (1)	OLS-FE (2)
5 $Percent_{ij}$	**28.93*** (5.446)**	**31.11*** (5.838)**
10 $Percent_{ij}$	**33.23*** (6.873)**	**33.79*** (7.306)**
15 $Percent_{ij}$	**43.74*** (7.982)**	**42.58*** (8.374)**
20 $Percent_{ij}$	**44.05*** (8.797)**	**43.25*** (9.276)**
...	...	...
85 $Percent_{ij}$	**86.28*** (15.324)**	**83.36*** (15.995)**
90 $Percent_{ij}$	**88.02*** (15.038)**	**85.66*** (15.739)**
95 $Percent_{ij}$	**73.53*** (14.090)**	**76.17*** (14.921)**
100 $Percent_{ij}$	**110.79*** (23.608)**	**115.70*** (26.209)**
105 $Percent_{ij}$	**81.86*** (15.544)**	**80.83*** (16.486)**
110 $Percent_{ij}$	**74.96*** (17.615)**	**69.53*** (18.747)**
115 $Percent_{ij}$	**69.22** (21.861)**	**64.35** (24.187)**
5 $Percent_{ij}$ * PPM_{ij}	—	**–23.14*** (6.377)**
10 $Percent_{ij}$ * PPM_{ij}	—	–7.01 (8.272)
15 $Percent_{ij}$ * PPM_{ij}	—	9.52 (12.551)
20 $Percent_{ij}$ * PPM_{ij}	—	1.40 (11.713)
...	...	...
85 $Percent_{ij}$ * PPM_{ij}	—	37.03 (34.044)
90 $Percent_{ij}$ * PPM_{ij}	—	29.01 (28.353)
95 $Percent_{ij}$ * PPM_{ij}	—	3.70 (18.154)
100 $Percent_{ij}$ * PPM_{ij}	—	–16.81 (26.434)
105 $Percent_{ij}$ * PPM_{ij}	—	23.38 (22.215)
110 $Percent_{ij}$ * PPM_{ij}	—	**69.30* (31.600)**
115 $Percent_{ij}$ * PPM_{ij}	—	**57.32+ (32.323)**
$Days\ Left_{ij}$	0.32 (0.455)	0.34 (0.455)
Campaign and Time Effects	Yes	Yes
Observations	102,874	102,874
F-stat	**2.77 (40, 98743)**	**2.16 (63, 98720)**
R^2	0.076	0.077

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p \leq 0.10$; robust standard errors in parentheses.

Considering Table 4, we observe a similar, though less striking result when it comes to the effect of prior capital accumulation on the size of contributions that visitors offer, conditional on conversion.[9] The estimates are again presented in a hierarchical fashion, for a model of a similar form.

Incremental growth in prior capital accumulation has a significant positive effect on the size of individual contributions, yet these effects are roughly the same between both PPM and non-PPM campaigns, except at the very outset of fundraising. In particular, the 5 percent dummy, which reflects cases where the campaign had raised between 5 percent and 9.99 percent of fundraising, has a significant positive effect for thresholdless campaigns, yet the same increment in capital accumulation produces a much smaller effect in the presence of a PPM.

Cognizant of the apparent systematic differences in campaigns that do and do not employ PPMs, we next considered that, to some degree, these systematically different campaigns may also exhibit systematic, dynamic differences, which our fixed effects would be unable to capture. As such, we looked to evaluate the robustness of our results to a matching procedure, accounting for a wide variety of measures related to a specific visitor's web session, such as device, location, duration, and so on. We repeated our analysis of both the conversion and contribution regressions following the preprocessing of our data using *coarsened exact matching* (CEM).[10] CEM, which has seen increased application in the IS literature of late [29, 31] aims to improve the estimation of causal effects by preprocessing data to at least partially control for covariates that confound treatment: the presence of a PPM in our case. Although our campaign-level fixed effects account for any confounds that do not vary within a campaign or over time, the application of CEM helps to rule out other possible confounds, which may vary at the visit level.

The large size of our sample and the relatively high number of visit-level covariates at our disposal simplify the matching process, because we have a relatively easy time identifying exact matches for our treatment observations on many of the additional covariates we observe. In particular, we match on the following: an indicator of whether the visitor is using a *Mobile* (vs. desktop) device, an indicator of whether the visitor arrived at the campaign URL via a *Referral* link that was issued by another user, an indicator of whether the visitor resides in the *Same Country* as the target campaign, the project's dollar fundraising goal, the project's duration in days, the logged duration of the visitor's time spent on the campaign page (*Visit Duration*), a vector of indicators reflecting the *Visitor Language* (as determined by Internet browser language settings), a vector of indicators reflecting the visitor's *Internet Browser*, a vector of indicators reflecting the project's location (*Project Country*), and a vector of indicators reflecting the project *Category*, for example, Technology, Design, Health. We enforced exact matches on all indicator variables, including *Mobile, Referral, Same Country, Visitor Language, Internet Browser*, and *Project Country*, and *Category.*[11] The matching algorithm produces a series of weights as output, with unmatched observations receiving a weight of 0, treatment observations receiving a weight of 1, and matched control observations receiving a strictly positive weight, reflecting the strength of the match. The matching adjustments are implemented in our regressions through the inclusion of analytic weights.

We reestimated our main specification, applying these matching weights. The estimates for our matched *Conversion* regression are provided in Table 5, and those associated with *Contribution* are provided in Table 6.

Table 5. CEM Regression Results ($DV = Conversion_{ij}$)

Independent Variable	LPM-FE (1)	LPM-FE (2)
5 $Percent_{ij}$	0.01 (0.018)	0.01 (0.020)
10 $Percent_{ij}$	0.03 (0.019)	**0.04+ (0.022)**
15 $Percent_{ij}$	0.01 (0.022)	0.02 (0.024)
20 $Percent_{ij}$	0.03 (0.023)	0.04 (0.026)
...	...	...
85 $Percent_{ij}$	**0.13*** (0.033)**	**0.16*** (0.037)**
90 $Percent_{ij}$	**0.08* (0.033)**	**0.09* (0.037)**
95 $Percent_{ij}$	**0.11** (0.036)**	**0.13** (0.041)**
100 $Percent_{ij}$	−0.01 (0.032)	−0.07 (0.034)
105 $Percent_{ij}$	0.04 (0.040)	0.03 (0.045)
110 $Percent_{ij}$	0.05 (0.041)	0.07 (0.047)
115 $Percent_{ij}$	0.05 (0.053)	0.04 (0.060)
5 $Percent_{ij}$ * PPM_{ij}	—	−0.05 (0.029)
10 $Percent_{ij}$ * PPM_{ij}	—	**−0.10** (0.034)**
15 $Percent_{ij}$ * PPM_{ij}	—	**−0.08* (0.037)**
20 $Percent_{ij}$ * PPM_{ij}	—	−0.06 (0.039)
...	...	...
85 $Percent_{ij}$ * PPM_{ij}	—	**−0.14** (0.045)**
90 $Percent_{ij}$ * PPM_{ij}	—	**−0.07+ (0.045)**
95 $Percent_{ij}$ * PPM_{ij}	—	**−0.10* (0.050)**
100 $Percent_{ij}$ * PPM_{ij}	—	0.01 (0.044)
105 $Percent_{ij}$ * PPM_{ij}	—	−0.01 (0.055)
110 $Percent_{ij}$ * PPM_{ij}	—	**−0.11+ (0.057)**
115 $Percent_{ij}$ * PPM_{ij}	—	0.04 (0.070)
$Days\ Left_{ij}$	0.001 (0.003)	0.001 (0.003)
Campaign and Time Effects	Yes	Yes
Observations	105,735	105,735
F-stat	**4.61 (40, 103763)**	**3.99 (63, 103740)**
R^2	0.124	0.124

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p \leq 0.10$; robust standard errors in parentheses.

In both cases, our sample size is notably reduced by more than half due to the exclusion of unmatched observations, yet the remaining sample is nonetheless still quite large. In Table 5, we see coefficient estimates that resemble those of our main estimation, though statistical significance is reduced. Moreover, in Table 6, we see a set of estimates more consistent with our initial expectations than those reported in our main regression. However, although the *Conversion* estimates appear in line with our expectations, we must acknowledge that the model F-statistics are insignificant. The results in Table 6 should therefore be interpreted with caution.

Table 6. CEM Regression Results ($DV = Contribution_{ij}$)

Independent Variable	OLS-FE (1)	OLS-FE (2)
5 $Percent_{ij}$	**330.73+ (178.981)**	**360.73+ (193.421)**
10 $Percent_{ij}$	**443.88+ (247.535)**	**486.38+ (270.229)**
15 $Percent_{ij}$	**517.34+ (278.800)**	**554.45+ (299.562)**
20 $Percent_{ij}$	**614.55+ (317.984)**	**668.88+ (343.684)**
...	...	...
85 $Percent_{ij}$	**768.73+ (451.856)**	**806.78+ (471.380)**
90 $Percent_{ij}$	**784.29+ (460.061)**	**814.44+ (477.025)**
95 $Percent_{ij}$	**783.51+ (469.488)**	**816.74+ (485.697)**
100 $Percent_{ij}$	1,032.92 (729.256)	1,140.54 (836.016)
105 $Percent_{ij}$	**787.99+ (469.829)**	**809.57+ (475.296)**
110 $Percent_{ij}$	**770.05+ (461.628)**	**794.41+ (472.889)**
115 $Percent_{ij}$	**799.30+ (459.244)**	**829.01+ (470.814)**
5 $Percent_{ij}$ * PPM_{ij}	—	**–282.11+ (148.984)**
10 $Percent_{ij}$ * PPM_{ij}	—	**–399.58+ (226.104)**
15 $Percent_{ij}$ * PPM_{ij}	—	**–373.58+ (225.392)**
20 $Percent_{ij}$ * PPM_{ij}	—	**–501.04+ (260.886)**
...	...	...
85 $Percent_{ij}$ * PPM_{ij}	—	**–447.00+ (271.882)**
90 $Percent_{ij}$ * PPM_{ij}	—	–425.76 (272.403)
95 $Percent_{ij}$ * PPM_{ij}	—	**–434.85+ (266.494)**
100 $Percent_{ij}$ * PPM_{ij}	—	–734.78 (641.553)
105 $Percent_{ij}$ * PPM_{ij}	—	**–388.47+ (227.958)**
110 $Percent_{ij}$ * PPM_{ij}	—	–369.72 (230.674)
115 $Percent_{ij}$ * PPM_{ij}	—	**–400.06+ (237.082)**
$Days\ Left_{ij}$	3.876 (10.308)	4.27 (9.977)
Campaign and Time Effects	Yes	Yes
Observations	42,938	42,938
F-stat	0.60 (40, 41098)	0.59 (64, 41074)
R^2	0.114	0.116

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p \leq 0.10$; robust standard errors in parentheses.

Dynamics of the Moderating Effect of PPM

We next considered possible dynamics around the observed relationships reported above. To reiterate, as a campaign nears its fundraising deadline, under a PPM, it becomes increasingly likely that prior capital accumulation will begin to play a more important role in a visitor's contribution decision, because prior accumulation will become a stronger predictor of project provision. We therefore repeated the estimation of our conversion model, breaking down our data into three subsamples based on whether the observed campaign visit took place in the first, second, or third

Table 7. Regression Results by Duration (Dv = $Conversion_{jj}$)

Independent Variable	Early	Middle	Late
5 $Percent_{ij}$	**0.03** (0.008)**	**0.06** (0.019)**	**0.05** (0.017)**
10 $Percent_{ij}$	**0.03** (0.009)**	**0.06** (0.021)**	**0.10*** (0.021)**
15 $Percent_{ij}$	**0.04** (0.012)**	**0.06** (0.023)**	**0.10*** (0.022)**
20 $Percent_{ij}$	**0.04** (0.016)**	**0.06** (0.024)**	**0.10*** (0.023)**
. . .	. . .	. . .	. . .
85 $Percent_{ij}$	**0.05* (0.023)**	**0.17*** (0.036)**	**0.19*** (0.027)**
90 $Percent_{ij}$	−0.02 (0.035)	**0.18*** (0.037)**	**0.21*** (0.027)**
95 $Percent_{ij}$	**0.05+ (0.026)**	**0.23*** (0.040)**	**0.25*** (0.028)**
100 $Percent_{ij}$	0.02 (0.020)	**0.14*** (0.035)**	**0.15*** (0.027)**
105 $Percent_{ij}$	0.03 (0.036)	**0.17*** (0.038)**	**0.19*** (0.029)**
110 $Percent_{ij}$	−0.02 (0.029)	**0.20*** (0.038)**	**0.18*** (0.029)**
115 $Percent_{ij}$	0.01 (0.037)	**0.19*** (0.039)**	**0.15*** (0.031)**
5 $Percent_{ij}$ * PPM_{ij}	**−0.03* (0.016)**	**−0.09+ (0.041)**	**0.48** (0.144)**
10 $Percent_{ij}$ * PPM_{ij}	−0.04 (0.037)	−0.06 (0.088)	**0.46** (0.145)**
15 $Percent_{ij}$ * PPM_{ij}	−0.03 (0.054)	−0.07 (0.092)	**0.46** (0.144)**
20 $Percent_{ij}$ * PPM_{ij}	−0.01 (0.064)	−0.13 (0.095)	**0.39** (0.145)**
. . .	. . .	. . .	. . .
85 $Percent_{ij}$ * PPM_{ij}	*NS*	**−0.28* (0.117)**	**0.39** (0.147)**
90 $Percent_{ij}$ * PPM_{ij}	*NS*	**−0.23+ (0.121)**	**0.35* (0.146)**
95 $Percent_{ij}$ * PPM_{ij}	*NS*	**−0.32** (0.123)**	**0.33* (0.146)**
100 $Percent_{ij}$ * PPM_{ij}	*NS*	**−0.25* (0.118)**	**0.38** (0.147)**
105 $Percent_{ij}$ * PPM_{ij}	*NS*	**−0.23+ (0.122)**	**0.40** (0.149)**
110 $Percent_{ij}$ * PPM_{ij}	**0.25*** (0.039)**	**−0.32* (0.134)**	**0.34* (0.149)**
115 $Percent_{ij}$ * PPM_{ij}	*NS*	−0.17 (0.139)	**0.48** (0.151)**
Campaign and Time Effects	Yes	Yes	Yes
Observations	91,353	66,460	123,487
F-stat	**5.56 (55, 88873)**	**3.55 (62, 63207)**	**10.43 (62, 119683)**
R^2	0.119	0.144	0.118

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; + $p \leq 0.10$; Robust standard errors in parentheses; *NS* = no support, indicating a lack of observations with which to estimate the effect.

tercile of the campaign visit duration, measured as a percentage (i.e., Early < 33 percent, 33 percent ≤ Middle < 66 percent, Late ≥ 66 percent). The results for conversion are reported in Table 7.

We see that, although the presence of a PPM attenuates the relationship between prior capital accumulation and our outcomes of interest during the “Middle” portion of a fundraiser, when the campaign deadline approaches (i.e., in the “Late” portion), the PPM causes visitors to respond more positively to prior capital accumulation, essentially inverting the effect.

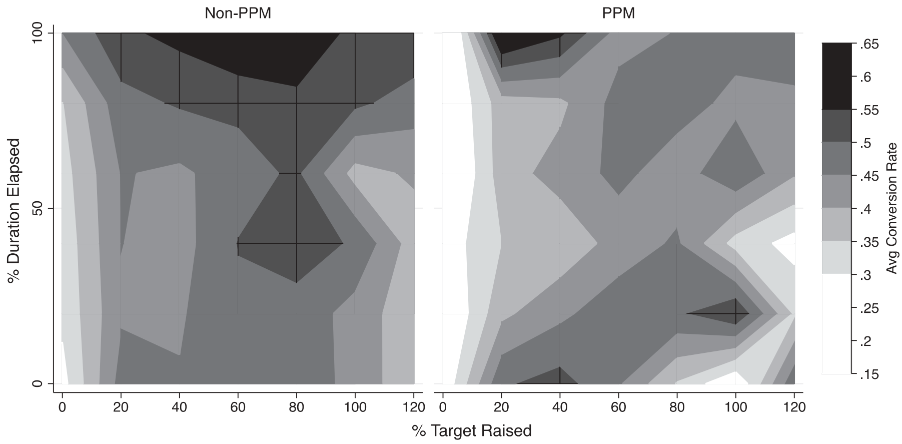

Figure 2. Pr(Conversion) Conditional on % Target Raised and % Duration Elapsed*Note: x*-axis extends to 120 percent of the fundraising target. As a result, conversion probabilities drop off on the right-hand portion of the plot, because campaigns have already attracted the requested amount of capital.

This result once again aligns with our expectations, because it suggests that at the outset of a campaign, the presence of a PPM initially reduces visitors' concerns about fundraising progress, yet as the deadline approaches, that progress becomes extremely important. Figure 2 provides a visual depiction of these dynamics in the form of two contour plots, comparing thresholdless campaigns with those that employ a PPM. In the case of thresholdless campaigns, there is a distinct upward trend in the probability of visitor conversion as we move from the bottom left toward the top right, as the campaign progresses in time and capital accumulation. In contrast, under a PPM, there is no such obvious trend.

Finally, considering the estimated effects on contribution, in Table 8, we see that the effects of capital accumulation are weakened under a PPM in the "Middle" portion of a campaign, yet once the deadline nears, this ceases to be the case. However, we do not observe an inversion here, strictly speaking, because the interaction terms are generally insignificant in the "Late" subsample regression. Nonetheless, the negative effect observed in the middle portion of campaigns essentially disappears.

General Discussion

Summary of Results

We have empirically examined how entrepreneurs' application of a PPM associates with crowdfunding campaign contributors' sensitivity to prior capital accumulation. We find that the presence of a PPM is associated with a weakening in the overall influence of prior capital accumulation on conversion and contribution decisions

Table 8. Regression Results by Duration (*Dv* = *Contribution$_{jj}$*)

Independent Variable	Early	Middle	Late
5 *Percent$_{ij}$*	**30.57*** (5.828)**	**61.51*** (15.393)**	18.72 (20.464)
10 *Percent$_{ij}$*	**29.78*** (5.683)**	**99.66*** (19.248)**	23.39 (32.724)
15 *Percent$_{ij}$*	**42.33*** (9.335)**	**117.26*** (23.197)**	31.88 (29.015)
20 *Percent$_{ij}$*	**22.10* (9.597)**	**138.09*** (25.042)**	38.04 (29.589)
...	...	...	...
85 *Percent$_{ij}$*	**56.19*** (12.887)**	**281.72** (102.516)**	**119.86** (35.523)**
90 *Percent$_{ij}$*	**55.77*** (14.000)**	**318.17** (109.467)**	**114.44** (34.601)**
95 *Percent$_{ij}$*	**48.56* (22.635)**	**265.97* (109.110)**	**115.35** (34.332)**
100 *Percent$_{ij}$*	**39.70** (14.129)**	**379.38+ (213.730)**	**151.82*** (36.188)**
105 *Percent$_{ij}$*	**42.09* (16.590)**	**256.50* (124.987)**	**131.39*** (35.899)**
110 *Percent$_{ij}$*	**26.58+ (14.841)**	**278.75* (114.338)**	**124.05** (40.282)**
115 *Percent$_{ij}$*	**53.73** (18.833)**	**278.06* (111.366)**	**110.95* (47.902)**
5 *Percent$_{ij}$* * *PPM$_{ij}$*	**–33.49*** (7.377)**	**–30.09+ (18.377)**	6.37 (25.319)
10 *Percent$_{ij}$* * *PPM$_{ij}$*	–16.31 (11.178)	**–51.81* (22.545)**	5.50 (54.137)
15 *Percent$_{ij}$* * *PPM$_{ij}$*	18.34 (42.562)	**–50.31* (25.382)**	5.91 (90.835)
20 *Percent$_{ij}$* * *PPM$_{ij}$*	**–51.55* (21.932)**	**–58.64+ (31.325)**	36.74 (86.093)
...	...	...	...
85 *Percent$_{ij}$* * *PPM$_{ij}$*	*NS*	–57.14 (91.692)	61.48 (96.235)
90 *Percent$_{ij}$* * *PPM$_{ij}$*	*NS*	–94.50 (95.900)	52.30 (94.402)
95 *Percent$_{ij}$* * *PPM$_{ij}$*	*NS*	–21.38 (97.800)	13.60 (90.085)
100 *Percent$_{ij}$* * *PPM$_{ij}$*	*NS*	–194.59 (195.690)	7.55 (90.233)
105 *Percent$_{ij}$* * *PPM$_{ij}$*	*NS*	–64.60 (102.985)	49.24 (91.192)
110 *Percent$_{ij}$* * *PPM$_{ij}$*	**–52.53* (23.003)**	–88.44 (96.289)	96.61 (97.994)
115 *Percent$_{ij}$* * *PPM$_{ij}$*	*NS*	–97.85 (93.810)	93.46 (99.372)
Campaign and Time Effects	Yes	Yes	Yes
Observations	28,948	22,472	51,454
F-stat	**2.82 (54, 26696)**	**1.74 (62, 19704)**	**2.24 (62, 48211)**
R^2	0.104	0.217	0.098

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; + $p \leq 0.10$; Robust standard errors in parentheses; *NS* = no support, indicating a lack of observations with which to estimate the effect.

among campaign visitors. At the same time, we find this association varies over time, with a PPM initially being associated with weakened sensitivity to capital accumulation in the early stages of fundraising, and the reverse relationship in the later stages of fundraising, as a campaign deadline nears.

These observations suggest that the application of a PPM can have important implications for fundraising activity in online reward-based crowdfunding. Should an entrepreneur opt to employ a PPM, they might expect an increase in early fundraising momentum, as campaign visitors appear to exhibit relatively little concern about prior capital accumulation when the PPM is in place. That is, our findings suggest that campaign visitors will be more likely to contribute early in the fundraising process when a PPM is present. At the same time, as the deadline draws near, capital accumulation becomes extremely important when a PPM is present. Notably, this is exactly the pattern that has been observed at Kickstarter, a platform that mandates PPMs for all campaigns; the platform's own FAQ states that "Projects either make their goal or find little support. There's little in between."

From a theoretical standpoint, this finding suggests that campaign visitors are more inclined to form an independent evaluation of the crowdfunding campaign under a PPM, rather than referring to the actions of others. The academic literature has recently explored the notion of crowd wisdom in the context of crowdfunding, reporting in the context of Kickstarter that the crowd typically chooses to support projects that would also be chosen by subject-matter experts [30]. Our observations here suggest that part of that result may be attributable to Kickstarter's mandate that all campaigns employ a PPM. Considering recent reports that independent decision making is an integral precursor to the emergence of collective intelligence via wise collective decision making [26], if PPMs do lead to greater independence of decision making, as our results suggest, collective judgments might also be expected to improve, and the average quality of funded campaigns expected to increase. Although we cannot test this implication directly with the data at hand, this logic, by extension, indicates that platforms that mandate the use of PPMs, for example, Kickstarter, indirectly encourage improvements to the project selection process, and thus a more sustainable marketplace in the long run.

Of course, there are also possible downsides to PPM use. A campaign that fails to "launch hard" [16] and achieve sufficient fundraising by its later stages may ultimately fail to reach its target, when it otherwise might have succeeded. If members of the crowd arrive, observe that a PPM is in place, and judge that the campaign is unlikely to hit its target in the remaining time, they may then exit without supplying funds. In the absence of a PPM, those same contributors might otherwise supply funds, perhaps believing that reaching 90 percent of the target is sufficient for the project to move forward, and the campaign might then overshoot the visitor's expectations and achieve its target. These diverging effects will be most relevant for campaigns that will land near their fundraising target, just shy or just in excess. As such, our findings suggest that entrepreneurs should be judicious in their use of a PPM if they are not confident about their ability to raise well in excess of the specified target, as the PPM has the potential to backfire.

The above having been said, shifting contributions earlier is likely to aid entrepreneurs in maintaining early momentum in the fundraising process, which a number of practitioner articles and academic studies have highlighted as critical to successful fundraising [16]. PPM use thus seems particularly well-suited for entrepreneurs who anticipate difficulties in building and sustaining momentum in the fundraiser, for example, because the entrepreneur does not have an extensive network or community of contributors that he or she can tap for early and ongoing support.

Finally, it is important to note that contrary results might manifest under other crowdfunding schemes, such as equity crowdfunding or peer-to-peer lending, where the size of contributions tends to be much larger. In such settings, it is possible that PPMs will in fact drive much greater sensitivity to prior capital accumulation. Moreover, contributors' preference profiles may differ dramatically across market types.

Contributions to the Literature

Beyond practical considerations, our findings build on a number of prior studies in the academic literature on crowdfunding and market mechanisms. First, we expand on past observations of the positive relationship that prior capital accumulation and social proof have with subsequent fundraising, showing that these may depend in part on the presence or absence of a PPM. We also extend the findings of Cumming et al. [15], who report that PPMs have a direct, positive relationship with fundraising outcomes.[12] We show here that the presence of a PPM is associated with larger volumes of contributions early on in the fundraising lifecycle. We also build on recent work that speaks to the importance of signaling mechanisms in crowdfunding [4, 24, 25]. Our observations are consistent with the idea that the presence of a PPM may signal an entrepreneur's quality, acting as a substitute for social proof that would be conveyed via prior capital accumulation.

This work is subject to a number of limitations. First, we acknowledge that, despite our application of a fixed-effect estimation framework, which jointly accounts for unobserved heterogeneity around campaigns and time, our results may nonetheless be endogenous with respect to dynamic unobservables, as well as unobserved heterogeneity associated with campaign visitors. In terms of the latter, it may be the case, for example, that prior capital accumulation, PPM use, and visitor conversion are spuriously correlated, with some unobserved characteristics of contributors simultaneously determining the timing of their arrival with respect to fundraising progress, and also their tendency to contribute. Our application of matching procedures helps alleviate concerns about estimation bias, but without experimental manipulation, readers should be cautious when applying causal interpretation to the results. Ultimately, the estimations we report are primarily associational in nature, reflecting correlation rather than causality.

Although we surmise that PPMs lead to independent decision making of campaign visitors and consequently higher average post-funding-project performance among funded projects, we are not able to directly test this theoretical mechanism, due to data limitations. Future work can seek out field evidence of our supposition that PPMs induce improved campaign selection by the crowd, by stimulating independent decision making [26]. This could be done by collecting data on downstream outcomes related to project performance or by collecting primary survey data that shed light on the contributors' decision-making process.

Going forward, we believe that it would be interesting to explore the platform-level decision to let entrepreneurs choose whether to employ a PPM, or to mandate its presence or absence. On the surface, it may appear attractive to allow entrepreneurs the flexibility to decide for themselves, because entrepreneurs are likely to prefer such freedom. However, the relationships we observe in our setting suggest that offering these features could be shortsighted, as it may lead to unintended consequences by indirectly enabling herd behavior.

This sort of trade-off between a myopically desirable choice and detrimental long-run implications, or unintended behavioral consequences, is a common theme reflected in other recent mechanism-design papers in the crowdfunding literature. For example, Burtch et al. [10] observed that providing contributors with the decision about whether to anonymize or publicize their contributions can have unintended consequences, leading to privacy and security concerns and a decline in fundraising activity. Similarly, Wei and Lin [40] found that employing posted prices rather than second price auctions in P2P lending may have the short-run benefit of elevating interest rates, and thus investor and platform returns, but in the long run may lead to higher rates of default. Therefore, it behooves platform operators (and perhaps industry regulators) to be judicious in considering the use of PPMs in crowdfunding markets.

Crowdfunding platforms are an important element of the recent fintech revolution. They have become a key channel that connects entrepreneurs and investors for start-up financing. Yet many questions remain about the ideal design for these markets. The degree to which these platforms make finance more efficient depends largely on this design. It is thus our hope that this work can set the stage for future work to design or evaluate the provision point mechanism in crowdfunding, or various other mechanisms and technologies that underpin these markets.

Notes

1. While crowdfunding campaigns do not necessarily produce public goods, they do share many characteristics with public goods [20, 39]. Specifically, crowdfunding projects often require a nontrivial up-front fixed cost before the first unit of outcome can be produced. Such a fixed cost is shared by contributors in a nonexclusive (every contributor benefits from it) and nonrival (its benefits does not decrease with the number of contributors) manner, akin to private provision of public goods.

2. The vast majority of campaign organizers in our sample executed just one campaign. Therefore, the campaign fixed effects are in essence also a campaign-organizer fixed effect. This implies that our fixed-effect framework accounts not only for time invariant features of a campaign that may influence selection for PPM use but also time invariant features of campaign organizers as well, such as awareness of the PPM feature or self-confidence.

3. In the presence of a PPM, a partial funding outcome can also impose costs on contributors. Although a campaign employing a PPM that ultimately fails to reach its target will refund all contributions, the contributors cannot use the money elsewhere until the fundraising process completes. This liquidity cost is arguably smaller than the cost associated with not getting one's money back should a partial fundraising outcome take place, under a thresholdless campaign.

4. The high conversion rate we observe here is not surprising, for two reasons. First, ample work notes that a substantial portion of contributions arrive from friends and family members of the entrepreneur [2]. Second, what we characterize here as a visit is in fact a set of prefiltered visitors, in some sense. This is because we observe individuals who in many instances have already elected to click on the brief campaign description on the initial campaign listings page.

5. We thank the anonymous reviewer for pointing us to this practical evidence of selection related to provision point use.

6. We have explored the robustness of our findings to the use of alternative increments, including a vector of dummies reflecting 2 percent increments, and another reflecting 10 percent increments. In both cases, we find consistent results, which are available from the authors upon request.

7. Given the size of our sample and the statistical significance of our estimates, it is worth noting two points that lead us to believe the findings are meaningful. First, although our overall sample is large, the support for specific dummies that we estimate in our models varies considerably, with the majority of the percentage-raised dummies having relatively few associated observations. This is particularly true in our subsequent regressions that consider the dynamics of the relationships in question, wherein we split the data into duration terciles. In many instances, we have just a few hundred observations supporting each percentage-raised dummy. Second, the practical (economic) significance of the estimates is rather large. Given that we estimate a linear probability model, the coefficients can be interpreted directly as shifts in the probability of conversion between stages of capital accumulation and zero fundraising. Thus, shifts on the order of 2–8 percent in the probability of conversion are observed here, which is particularly large when we consider the scale of the platform in question (i.e., Quantcast estimates that the platform we study now regularly receives upward of 4 million visitors each month).

8. We assessed whether the addition of the interaction terms produced significant improvements in model fit, based on information criteria. The AIC in the naive model (column 1) is 129,256.7, whereas the AIC of the interaction model is 129,209.8, a great deal lower. Similarly, the negative log-likelihood of the naive model is 64,587.33, whereas that of the interaction model is 64,540.92. A decline in the AIC of at least 2 is typically sufficient justification to prefer an alternative model. Here, we observe a decline of more than 30, supporting a preference for the interaction model.

9. We assessed robustness of the estimation to outliers in the dependent variable by excluding observations in the top and bottom decile of the distribution, that is, contributions of less than \$10 or greater than \$125, and then repeating the estimation. These results are reported in Table A1 of the Appendix.

10. We also performed a matching analysis employing *propensity score matching* (PSM) with a first-stage logistic regression determining the propensity to receive a PPM. The results of these conversion and contribution models are reported in the Appendix, in Table A2 and Table A3. We observe similar results.

11. The only covariates for which we do not enforce exact matches are the project dollar goal, the project duration in days, and the duration of the visit. The former two covariates are not of particular concern, because they are subsumed by the campaign fixed effect in our regression. We performed a t-test on log(*Visit Duration*), comparing the mean weighted value between PPM and non-PPM campaigns following the matching process, and determined that they are not statistically significant at conventional thresholds ($p = 0.071$).

12. For the sake of exploration, we also conducted a set of cross-sectional regressions, estimating the campaign-level, direct relationship between PPM use and fundraising outcomes, in terms of dollars raised. Controlling for campaign goal, duration, number of rewards and campaign category, we too observe a significant positive relationship between PPM use and success. However, we caution against reading deeply into this result, given that PPM use, duration, goal and reward-setup are all endogenously determined by an entrepreneur, and quite likely to be spuriously associated with fundraising outcomes. A more detailed analysis is reported by Cumming et al. [15], who similarly report a positive relationship between PPM use and overall fundraising outcomes.

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Appendix A

Table A1. Regression Results Excluding Contribution Outliers ($DV = Contribution_{ij}$)

Independent Variable	OLS-FE (1)	OLS-FE (2)
5 $Percent_{ij}$	**1.18* (0.562)**	**1.63** (0.585)**
10 $Percent_{ij}$	0.78 (0.627)	**1.28* (0.651)**
15 $Percent_{ij}$	**1.20** (0.662)**	**2.14** (0.685)**
20 $Percent_{ij}$	**1.84** (0.692)**	**2.16** (0.713)**
. . .	. . .	. . .
85 $Percent_{ij}$	0.49 (1.006)	0.52 (1.050)
90 $Percent_{ij}$	1.44 (1.014)	1.27 (1.076)
95 $Percent_{ij}$	0.26 (1.058)	0.84 (1.129)
100 $Percent_{ij}$	0.72 (1.040)	1.33 (1.101)
105 $Percent_{ij}$	**3.33** (1.236)**	**4.37** (1.301)**
110 $Percent_{ij}$	**3.40** (1.266)**	**3.35* (1.316)**
115 $Percent_{ij}$	2.19 (1.413)	**2.63+ (1.518)**
5 $Percent_{ij}$ * PPM_{ij}	—	**–6.21** (2.055)**
10 $Percent_{ij}$ * PPM_{ij}	—	**–7.08** (2.185)**
15 $Percent_{ij}$ * PPM_{ij}	—	–2.75 (2.212)
20 $Percent_{ij}$ * PPM_{ij}	—	**–4.06* (2.320)**
. . .	. . .	. . .
85 $Percent_{ij}$ * PPM_{ij}	—	–2.15 (2.753)
90 $Percent_{ij}$ * PPM_{ij}	—	–1.33 (2.553)
95 $Percent_{ij}$ * PPM_{ij}	—	**–5.33* (2.617)**
100 $Percent_{ij}$ * PPM_{ij}	—	**–5.95* (2.618)**
105 $Percent_{ij}$ * PPM_{ij}	—	**–9.53** (3.286)**
110 $Percent_{ij}$ * PPM_{ij}	—	–0.86 (3.769)
115 $Percent_{ij}$ * PPM_{ij}	—	–4.68 (3.581)
$Days\ Left_{ij}$	0.004 (0.050)	0.003 (0.050)
Campaign and Time Effects	Yes	Yes
Observations	78,420	78,420
F-stat	**3.65 (40, 74874)**	**3.00 (63, 74851)**
R^2	0.186	0.186

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p \leq 0.10$; robust standard errors in parentheses.

Table A2. PSM Regression Results ($DV = Conversion_{ij}$)

Independent Variable	LPM-FE (1)	LPM-FE (2)
5 $Percent_{ij}$	–0.01 (0.009)	0.0001 (0.013)
10 $Percent_{ij}$	**0.04** (0.012)**	**0.11*** (0.018)**
15 $Percent_{ij}$	0.02 (0.013)	**0.05** (0.017)**
20 $Percent_{ij}$	**0.06*** (0.014)**	**0.11*** (0.017)**
. . .	. . .	. . .
85 $Percent_{ij}$	**0.18*** (0.020)**	**0.34*** (0.027)**
90 $Percent_{ij}$	**0.14*** (0.020)**	**0.32*** (0.030)**
95 $Percent_{ij}$	**0.11*** (0.021)**	**0.14*** (0.033)**
100 $Percent_{ij}$	**0.08*** (0.019)**	**0.13*** (0.025)**
105 $Percent_{ij}$	**0.15*** (0.024)**	**0.22*** (0.032)**
110 $Percent_{ij}$	**0.04+ (0.024)**	**0.08* (0.031)**
115 $Percent_{ij}$	**0.14*** (0.029)**	**0.14** (0.042)**
5 $Percent_{ij}$ * PPM_{ij}	—	–0.03 (0.018)
10 $Percent_{ij}$ * PPM_{ij}	—	**–0.13*** (0.024)**
15 $Percent_{ij}$ * PPM_{ij}	—	**–0.06** (0.024)**
20 $Percent_{ij}$ * PPM_{ij}	—	**–0.13*** (0.026)**
. . .	. . .	. . .
85 $Percent_{ij}$ * PPM_{ij}	—	**–0.31*** (0.034)**
90 $Percent_{ij}$ * PPM_{ij}	—	**–0.29*** (0.036)**
95 $Percent_{ij}$ * PPM_{ij}	—	**–0.09* (0.039)**
100 $Percent_{ij}$ * PPM_{ij}	—	**–0.12*** (0.032)**
105 $Percent_{ij}$ * PPM_{ij}	—	**–0.16*** (0.043)**
110 $Percent_{ij}$ * PPM_{ij}	—	**–0.09* (0.041)**
115 $Percent_{ij}$ * PPM_{ij}	—	–0.03 (0.054)
$Days\ Left_{ij}$	**0.004** (0.001)**	**0.004** (0.001)**
Campaign and Time Effects	Yes	Yes
Observations	55,736	55,736
F-stat	**18.58 (40,53700)**	**19.00 (63,53677)**
R^2	0.150	0.155

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p \leq 0.10$; robust standard errors in parentheses.

Table A3. PSM Regression Results ($DV = Contribution_{ij}$)

Independent Variable	OLS-FE (1)	OLS-FE (2)
5 $Percent_{ij}$	45.58 (32.457)	64.43 (49.504)
10 $Percent_{ij}$	**84.71+ (46.332)**	**131.71+ (69.078)**
15 $Percent_{ij}$	**99.14+ (53.609)**	**121.92+ (72.537)**
20 $Percent_{ij}$	98.94 (69.884)	99.94 (76.840)
. . .	. . .	. . .
85 $Percent_{ij}$	**169.24+ (100.538)**	**264.72+ (137.130)**
90 $Percent_{ij}$	115.77 (98.130)	170.12 (120.744)
95 $Percent_{ij}$	103.11 (100.500)	191.74 (128.773)
100 $Percent_{ij}$	175.92 (138.489)	315.62 (229.397)
105 $Percent_{ij}$	144.12 (106.502)	171.60 (127.291)
110 $Percent_{ij}$	179.92 (107.742)	193.72 (126.640)
115 $Percent_{ij}$	167.01 (114.128)	178.79 (125.855)
5 $Percent_{ij}$ * PPM_{ij}	—	–41.04 (36.126)
10 $Percent_{ij}$ * PPM_{ij}	—	**–90.15+ (47.427)**
15 $Percent_{ij}$ * PPM_{ij}	—	–52.71 (46.152)
20 $Percent_{ij}$ * PPM_{ij}	—	–0.53 (22.837)
. . .	. . .	. . .
85 $Percent_{ij}$ * PPM_{ij}	—	**–159.70+ (88.408)**
90 $Percent_{ij}$ * PPM_{ij}	—	–101.34 (64.089)
95 $Percent_{ij}$ * PPM_{ij}	—	**–137.58+ (70.725)**
100 $Percent_{ij}$ * PPM_{ij}	—	–236.95 (168.461)
105 $Percent_{ij}$ * PPM_{ij}	—	–62.07 (58.269)
110 $Percent_{ij}$ * PPM_{ij}	—	–41.31 (56.167)
115 $Percent_{ij}$ * PPM_{ij}	–	–36.70 (48.258)
$Days\ Left_{ij}$	**6.42** (2.451)**	**6.52** (2.485)**
Campaign and Time Effects	Yes	Yes
Observations	18,273	18,273
F-stat	**1.69 (40,16814)**	**1.89 (63,16791)**
R^2	0.050	0.051

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p \leq 0.10$; robust standard errors in parentheses.