An Empirical Examination of Users' Information Hiding in a Crowdfunding Context

Completed Research Paper

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Abstract

Online privacy remains an ongoing source of debate in society. Sensitive to this, many web platforms are offering users greater, more granular control over how and when their information is revealed. However, recent research suggests that information control mechanisms of this sort are not necessarily of economic benefit to the parties involved. We examine the use of these mechanisms and their economic consequences, leveraging data from one of the world's largest global crowdfunding platforms, where contributors can conceal their identity or contribution amounts from public display. We find that information hiding is more likely when contributors are under greater scrutiny or exhibiting "undesirable" behavior. We also identify an anchoring effect from prior contributions, which is eliminated when earlier contributors conceal their amounts. Subsequent analyses indicate that a nuanced approach to the design and provision of information control mechanisms, such as varying default settings based on contribution amounts, can help promote larger contributions.

Keywords: Crowdfunding, privacy, information hiding, anchoring, social comparison

Introduction

Individuals behave differently when they are subject to scrutiny. This fact is well documented across numerous contexts. Differences have been reported in everything from physiological responses during task performance (Bond and Titus 1983; Izuma et al. 2009), to consumption patterns (Goldfarb et al. 2012; Ratner and Kahn 2002), generosity (Haley and Fessler 2005) and community participation (Leshed 2008). These behavioral differences are growing increasingly salient as many transactions and processes, previously conducted solely offline, are now shifting online in greater proportion. With the transition to the digital realm, both the visibility and traceability of individuals and their actions increase in turn. It is therefore unsurprising that demands for online privacy are so prevalent, particularly when one considers the frequent attention that privacy breaches have recently received in the mainstream media. Sensitive to these issues, many online platforms have responded by providing users with a greater deal of control over their information (e.g., privacy controls).

However, while it is clear that users desire these features, recent work has noted that they are not always employed in an optimal manner (Acquisti and Grossklags 2005; Das and Kramer 2013) and, further, that their provision and use is not necessarily of economic benefit to all parties involved (Conitzer et al. 2012; Hann et al. 2008). In this work, we therefore seek to examine users' endogenous use of information hiding mechanisms and the economic consequences for others (observers). Specifically, we address the following research questions: ***What drives users to employ information hiding mechanisms? What are the economic consequences of doing so?***

We address these questions in the context of online crowdfunding, a digital manifestation of charitable contribution and entrepreneurial finance. Crowdfunded markets have recently emerged as a viable alternative for sourcing capital to support innovative, entrepreneurial ideas and ventures (Burtch et al. 2013c). As the economic potential of these markets has recently become more apparent, they have boomed. Crowdfunding platforms like IndieGoGo, Kickstarter and RocketHub are now facilitating extremely large volumes of transactions, in rather sizeable amounts. According to a recent industry report, crowdfunding helped new ventures to raise more than $2.7 billion in 2012, and is expected to facilitate more than $5 billion in 2013 (Massolution 2013). This explosive growth has resulted in significant attention, from both the media and U.S. legislators, as evidenced by President Obama's recent signing of the JOBS Act (2011).

On a crowdfunding platform, individuals propose projects and members of the crowd fund them in whatever increment they wish. When a contribution is made to a campaign, a record is created on the campaign's backer or funder page that contains details that, depending on the platform, variably include the identity of the contributor, the size of their contribution, and the timing of that contribution. Given the monetary, and thus relatively sensitive, nature of these contribution actions, a number of prominent crowdfunding platforms now go to great lengths to provide users with a degree of anonymity. In some cases, this is done by randomizing the ordering of contributors, as on Kickstarter, while in others this is achieved in a more granular fashion, namely by providing contributors with the option of concealing specific pieces of information in the contribution record (i.e., identity or amount). It is this latter, more nuanced approach that we consider here. Specifically, we aim to identify the drivers of information hiding in particular contribution instances, and the economic consequences of said information hiding – in this case the impact upon subsequent contributors.

This work addresses recent calls for i) attention to design and action in information privacy research (Belanger and Crossler 2011), ii) explorations of the antecedents and consequences of privacy concerns in online markets (Smith et al. 2011) and iii) examinations of the economics of information hiding and privacy online (Pavlou 2011). Further, our work addresses an ongoing need for empirically and theoretically informed research, to offer practitioners guidance around crowdfunding regulation, oversight and administration (Mollick 2013).

Our key findings are as follows. First, we find that individuals are more likely to conceal information i) when they are privacy sensitive, ii) when the campaign they are supporting has received greater public exposure and iii) when their behavior has the potential to be viewed as 'extreme' or undesirable by others. Second, we find evidence of an interesting tradeoff between an identified anchoring effect, where users employ prior others' contribution amounts as a benchmark for their own contribution, and prior others' information hiding behavior. While we do observe an anchoring effect, reflected by a positive sequential correlation in contribution amounts, that effect is attenuated (indeed, it is effectively eliminated) when the prior contributor chooses to conceal the amount of their contribution.

Examining the marginal effects of prior amount hiding, we find that its application is beneficial for the purveyor and fundraisers when prior others contribute in small amounts. In contrast, we find that its application is detrimental when prior others contribute in large amounts. This contrast is fairly intuitive, as it implies that the purveyor and campaigners only benefit from information hiding when it serves to conceal an anchor point from view when that anchor is small and likely to pull down subsequent contributions.

The remainder of this paper is structured as follows. We begin with a review of the literatures on crowdfunding, online privacy, and individual or consumer information hiding across various contexts. Integrating those literatures, we propose a series of empirically testable hypotheses, which motivate our econometric models. We then describe our data and study context, before estimating our models and reporting our results. We subsequently establish the robustness of those results, offering a description of the various ancillary analyses we ran to rule out different threats to validity. Finally, we offer a discussion of the implications of our findings and we propose a number of avenues for future research.

Literature Review

Crowdfunding

There is an emerging stream of research that has examined the concept of crowdfunded markets. Crowdfunding has been defined as a collective effort by individuals who network and pool their money together, usually via the Internet, to invest in or support the efforts of others (Ordanini et al. 2010). These markets typically come in one of four flavors: reward-based, loan-based, donation-based and equity-based (Burtch et al. 2013a). While there are examples of each around the world, the first three are by far the most common.

Loan- and reward-based crowdfunding markets have seen the most extensive consideration by academics to date, with a primary focus upon Prosper.com. Notable examples of such work include that by Lin et al. (2013) and Zhang and Liu (2012). These authors have attempted to identify the types of information that individuals consider in crowdfunded marketplaces when making contribution decisions. Lin and his colleagues conclude that the likelihood of credit being issued is greater when the borrower exhibits greater social capital (e.g., a larger social network), as lenders appear to take this as a sign of credibility or trustworthiness. Zhang and Liu find, counter to intuition, that lenders are more likely to herd when the borrower exhibits signals of low quality. They interpret this as a rational decision, likely made because the lender assumes that others have some private knowledge about the borrower that they are not privy to. In contrast, when a borrower exhibits high signals of quality, lenders are less likely to join a herd, likely because they perceive the herd as simply a reflection of the borrower's observable quality. Lastly, Lin and Viswanath (2013) have recently undertaken a study of distance-based frictions on Prosper, finding evidence of a home-bias.

Agarwal et al. (2011) have examined a similar notion in the context of reward-based crowdfunding, focusing on what they refer to as the "flat world hypothesis." They do so leveraging data drawn from what is generally acknowledged to be the earliest successful crowdfunding platform, Sellaband.com, a Dutch-based marketplace supporting musical artists. These authors similarly find evidence that crowdfunders are more likely to contribute when the artist resides in closer proximity. More recently, Mollick (2013) has considered the determinants of fundraising success for crowdfunding campaigns on Kickstarter.com, reporting a number of findings of particular usefulness for campaign organizers, including the importance of social networks, the role of campaign durations and the impact of the different fundraising target amounts.

With respect to donation- and equity-based crowdfunding, scant empirical research exists. In the equity space, Burtch (2011) provides one of the first empirical analyses of investment-style crowdfunding, exploring and confirming the notion that greater numbers of uninformed participants can drive an increase in herding amongst crowdfunders, to their detriment. Ahlers et al. (2012) study how firm efforts at disclosure (e.g., risk assessments) positively impact crowdfunder investment, while Kim and

Viswanathan (2013) examine the influence that expert investors have on the contribution decisions of other, non-expert crowdfunders.

Finally, in the donation-based space, Burtch et al. (2013c) present an analysis of social influence in contributions to a donation-based crowdfunded market for journalism projects, finding evidence of crowding out amongst contributors and demonstrating the importance of organizer marketing effort in driving demand for project output. Finally, Burtch et al. (2013b) explore the role of cultural differences between lenders and borrowers at Kiva.org, a pro-social lending platform on which crowdfunders support entrepreneurs in the developing world. These authors find that contributors exhibit a cultural bias, preferring similar others.

Online Privacy and Information Hiding

There is a lengthy IS literature dealing with online privacy concerns, their antecedents, as well as their implications for online consumer transactions and community participation. We offer a brief review of relevant work here, though we also direct the reader to three comprehensive literature reviews of the subject, which were recently published in MIS Quarterly (Belanger and Crossler 2011; Pavlou 2011; Smith et al. 2011).

A number of studies have sought to formulate scales to measure online privacy concerns (e.g., Smith et al. 1996). Malhotra et al. (2004), in particular, derive and empirically evaluate a scale of measurement for Internet Users Information Privacy Concerns (IUIPC), which has seen extensive application in the literature. This scale is rooted in three constructs: collection (of user data), control (on the part of users, over their data) and awareness (of policies, again, on the part of users). The authors find support for their measurement scale, suggesting that these three factors are highly predictive of privacy concerns online, as they each contribute to the formation of trust and the perception of risk on the part of users.

Nov and Wattal (2009) explore the antecedents and consequences of such information privacy concerns in online social networks. The authors find that individuals' privacy concerns, and in turn sharing intensity, are negatively associated with their trust in other members of the social network. More recently, Tsai et al. (2011) have conducted a field experiment on an online website, showing that customers are more likely to buy products from a website where privacy assurances are displayed in a more prominent, visible manner. Hui et al. (2007) report a similar finding based on their own field experiment. Rather than product purchases, however, these authors demonstrate that users are more willing to share their personal information in the presence of privacy assurances, whether written or in the form of a privacy seal.

Das and Kramer (2013) examine individuals self-censorship on Facebook, finding that, out of 3.9 million users, 71% self-censor at least once in a 17-day period. One of the biggest drivers of such behavior is reportedly the size of the users' social network, which drives an exposure effect, wherein users grow more concerned with a larger audience. Sleeper et al. (2013a) examine these same behaviors on Facebook, conducting interviews with users, who indicate that a primary reason for self-censorship is their inability to precisely target a desired audience. These findings are in keeping with earlier studies in the literature, which have repeatedly noted information hiding as a primary user response to perceived privacy risks (Milne et al. 2004; Son and Kim 2008).

Anonymity in Consumption and Charity

As noted earlier, individual behavior has been shown to vary widely when subject to scrutiny. Here, we focus on two contexts of direct relevance to our study context: consumption and charitable contribution. First, with respect to consumption, Ratner and Kahn (2002) demonstrate via a series of experiments that individuals exhibit greater variety seeking behavior in their consumption patterns when they are scrutinized by others. The authors argue that this is because subjects expect others to evaluate such behavior more positively (i.e., interesting or unique, as opposed to dull and boring). Further, a similar effect is reported by Ariely and Levav (2000), who examined subjects when asked to place food and drink orders sequentially, amongst a group of peers or independently. Those authors reported increases in the variety of orders when subjects were in the presence of scrutiny.

Related to this, Goldfarb et al. (2012) report upon two empirical studies that demonstrate how individuals' purchasing behavior is influenced by what they refer to as the potential for embarrassment. In their first study, these authors find that customers are more likely to purchase *difficult-to-pronounce* vodka brands when they are made available via a self-service counter (as opposed to a scenario in which customers must place a verbal order for the brand with a clerk). In their second study, these authors consider changes in the composition of pizza orders following a shift to an online ordering system. The authors find that customers are more likely to place complex, fattening pizza orders when using the online system.

Next, considering the literature dealing with charitable contribution, there are numerous studies that consider the impacts of anonymity. This literature, largely experimental in nature, has established fairly conclusively that individuals become increasingly generous in the face of scrutiny, though in a select few cases studies have actually documented a general regression toward the mean. Haley and Fessler (2005), conducting a laboratory experiment, have found that subjects respond with generosity in the presence of subtle cues of observation (i.e., images of pairs of eyes presented on a computer desktop background). Alpizar et al. (2008), conducting a field experiment around donations to a national park, found that subjects similarly respond with generosity in the direct presence of a contribution 'collector' (as opposed to an anonymous donation box). Soetevent (2005) finds that church donations increase when individuals' identities and contribution amounts are revealed via collection using an open basket, rather than a bag.

This last author attributes the result in the second condition jointly to i) a social comparison effect, and ii) the fact that subjects are afforded the opportunity for reputational gains. Importantly, however, Soetevent, in formulating his experiment, notes that individuals might generally be expected to regress toward the mean (i.e., upward deviation of below average contributors and downward deviation of above average contributors). This is because excess contribution, if observed by others, may similarly draw negative reactions from peers. It is worth noting here that IS scholars have also found evidence of similar behavior in regard to non-monetary contributions. Chen et al. (2010) have found that the rate at which users post movie reviews tends toward the average when users are provided with information about others' posting activity, while Zeng and Wei (2013) report that users post similar photos to Flickr shortly after they form a social tie[1].

Finally, one additional, important aspect of anonymity worth noting is the moderating role it plays in relation to social influence and social comparison. That is, the degree to which individuals respond to prior others actions, and the manner in which they respond, has been shown to depend in part on the amount and types of information revealed about or by said prior others. Soetevent's work touches on this fact, as noted above. However, other, empirical examples of this behavior are documented by Chen et al. (2010) and by Croson and Marks (1998).

Hypothesis Development

Bearing the above studies in mind, we begin by considering the expected drivers of information hiding behavior. We first anticipate that individuals will be more likely to conceal their information when they are privacy sensitive. This expectation perhaps extends most directly from the work of Son and Kim (2008), who highlight information hiding in their taxonomy of user responses to privacy concerns. We formalize this as hypothesis H1.

> ***H1 (Privacy Concern Effect): Crowdfunders will be more likely to conceal information associated with a contribution when they are privacy sensitive.***

The experimental economics literature has also noted that individuals respond to varying degrees of anonymity (Lamba and Mace 2010). Further, privacy risk is of course not a binary variable; rather, perceived risks vary in intensity. In particular, the perception of risk is likely to grow stronger with greater scrutiny (i.e., more detailed scrutiny or a larger audience). Our expectation in this regard extends from the

[1] These authors further find that users subsequently look to differentiate themselves from their social ties, after a time, suggesting some important differences in reputational outcomes from unique contribution, between monetary and non-monetary settings.

[2] The campaign organizer (rather than the marketplace purveyor) determines the campaign category. As such, there are no strict rules around the assignment of categories, thus these groupings are fuzzy and may overlap.

findings reported by Das and Kramer (2013), as well as those reported by Sleeper et al. (2013a), noted above, regarding Facebook self-censorship. This logic is also similar, though the inverse, of that set forth by Zhang and Zhu (2011), who consider increasing reputational gains from contributions to Wikipedia in the presence of a larger audience. Taken together, these studies lead us to our second hypothesis.

H2 (Exposure Effect): Privacy sensitive crowdfunders will grow more likely to conceal information as the audience for their actions increases in size.

Our review of the literature also suggests that scrutiny can drive changes in behavior, conditional on having taken action. That is, conditional on contribution, we expect that individuals will be more likely to conceal information when said contributions will be perceived as less desirable by others. This expectation represents the converse of relationships identified in the literature that has studied the effects of exogenous anonymity and identification. In particular, the studies by Ariely and Levav (2000) and Ratner and Kahn (2002) show that, under scrutiny, individuals wish to seem more "interesting." Similarly, the work by Goldfarb et al. (2012) suggests that individuals are more likely to purchase products when the risk of embarrassment is lower.

We consider two notable forms of behavior that others might view as embarrassing or undesirable in this setting: i) contribution in extreme amounts (Soetevent 2005), and ii) self-contribution (toward one's own campaign). First, we anticipate, based on the above discussion, that information hiding will be more likely when individuals' contributions represent a greater deviation from the norm, and second, we anticipate that information hiding will be more likely when an individual is contributing toward their own campaign. These expectations are formalized in hypotheses H3 and H4.

H3 (Extremity Effect): Crowdfunders will be more likely to conceal information associated with a contribution when the amount of their contribution is extreme.

H4 (Self-Contribution Effect): Crowdfunders will be more likely to conceal information associated with their contribution when they are contributing toward their own campaign.

Our review of the literature also offers a number of results that can inform our study in regard to the downstream impacts of information hiding behavior. First, the charity and IS literatures have noted that, when possible, social comparison drives similarity in contribution behavior (Chen et al. 2010; Soetevent 2005; Zeng and Wei 2013). Further, a lengthy stream of literature on the subject of anchoring effects (Tversky and Kahneman 1974) and censorship biases (Feiler et al. 2013) suggests that crowdfunders will draw on observable cues provided by others when deciding an appropriate contribution amount. Given all of the above, we anticipate that crowdfunders will be influenced by the observable contributions of prior others, and will tend to contribute in kind, a concept we formalize via hypothesis H5. Further, anchoring effects are only possible when prior others' contributions are observable. As such, we also anticipate that these anchoring effects will be moderated by prior others' decisions about whether to hide the amount of their contribution, leading us to hypothesis H6.

H5 (Anchor Effect): Crowdfunders will contribute in amounts similar to prior others.

H6 (Censorship Effect): The anchor effect (H5) will be weaker when prior others' contributions are concealed.

These various hypotheses are summarized below, in Figure 1, where we present a conceptual, diagrammatical representation of our models. Note that the dashed arrows reflect main effects that we do not draw formal hypotheses about, yet which contribute to hypothesized interactions and thus are included for the sake of maintaining hierarchical inheritance.

Study Context

Our study focuses on one of the leading global platforms for reward-based crowdfunding. This marketplace empowers anyone, in any location, to raise money for any venture. The marketplace is highly trafficked, facilitating millions of dollars in transactions each month for a wide variety of campaign types.

Since founding, the platform has attracted huge numbers of users, representing more than 190 countries around the world. Figure 2 presents screenshots from this marketplace.

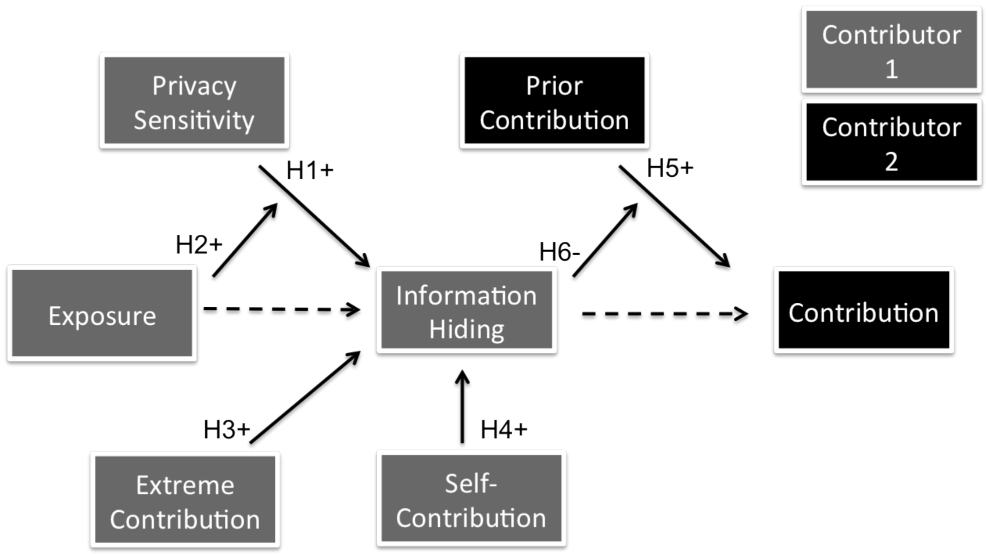

Figure 1. Conceptual Model

Campaign Flow

This marketplace allows submission of any and all ventures, regardless of subject matter (with the exception of prohibited / offensive content). Thus, rather than vetting campaign submissions, as is done in certain crowdfunding contexts (e.g., Kickstarter), this marketplace operates as a meritocracy, with no gate keepers, allowing any and all submissions to be posted. When campaign owners submit their project to the marketplace for posting, they must define a number of campaign characteristics.

These characteristics include the rewards the organizer plans to offer, what the organizer intends to do with the money, how much money they are attempting to raise and the planned funding duration. This platform earns revenues by charging fees to campaigns, based on the amount of money raised (between 4% and 9%, plus third party fees associated with payment processing and currency conversion). Individual contributors receive their claimed rewards following the completion of the fundraising process and project implementation.

Contribution Flow

Campaigns are presented to website visitors in order of popularity (measured algorithmically by the purveyor, based on organizer effort, contribution activity, media coverage, etc.), though there are a variety of filtering and sorting mechanisms available to support campaign search efforts. The home page also highlights new campaigns and campaigns that are ending soon. The visitor is presented with the ability to filter ongoing campaigns based on location (city) or proximity ("near me"), or by category (e.g., technology, small business, causes)[2]. After selecting a reward, a contributor is then presented with the option of hiding their name or the amount contributed. However, a contributor is not able to hide both pieces of information simultaneously. Importantly, a contributor's identity and amount will always be viewable to the campaign organizer; the hidden information is masked only from third parties (e.g., other contributors).

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[2] The campaign organizer (rather than the marketplace purveyor) determines the campaign category. As such, there are no strict rules around the assignment of categories, thus these groupings are fuzzy and may overlap.

Once an individual has decided to contribute to a particular campaign, they must then indicate how much they wish to contribute. A contributor will typically have the option of claiming a reward (perk), as compensation for their contribution, though rewards are not always offered. Usually, a campaign will offer different tiers (levels) of rewards, of different values. In order to claim a particular reward, a crowdfunder must contribute at least as much, or more, than the value of said reward. Further, at most one reward can be claimed as compensation for a particular contribution. Following reward selection, contributors are then asked to provide an e-mail address and (if a perk is being claimed) a shipping address.

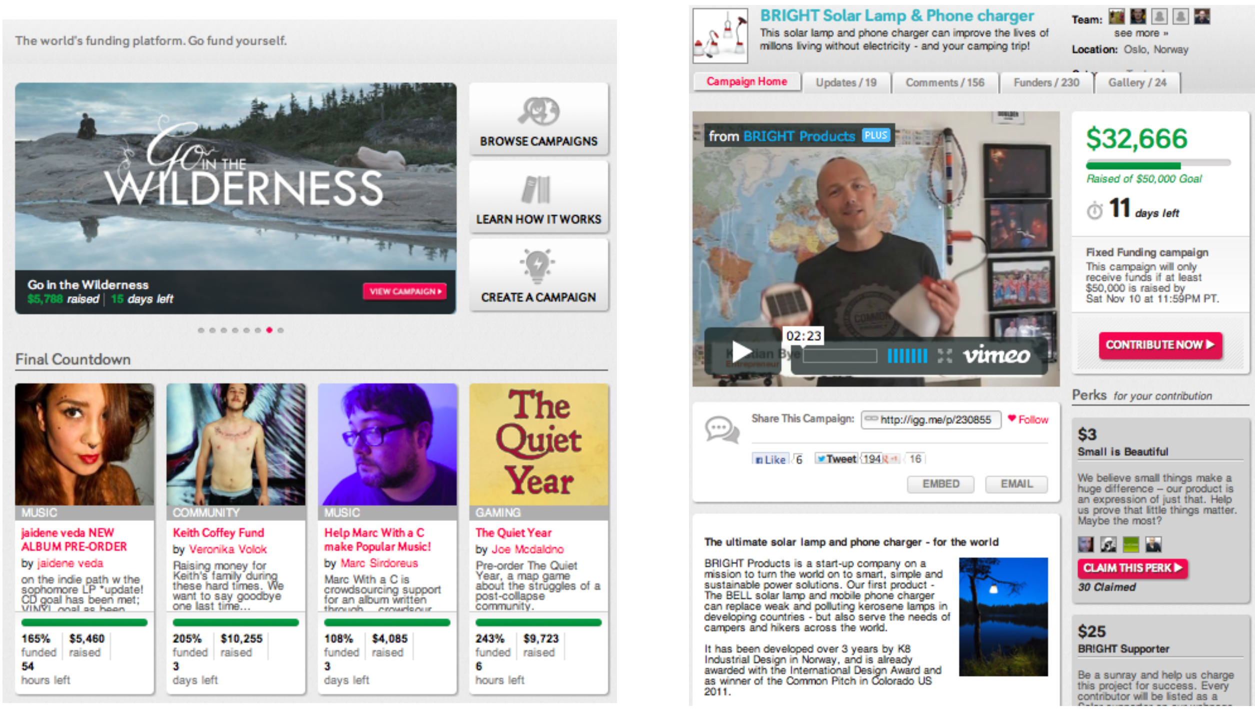

Figure 2. Market Landing Page (Left) and Campaign Details (Right)

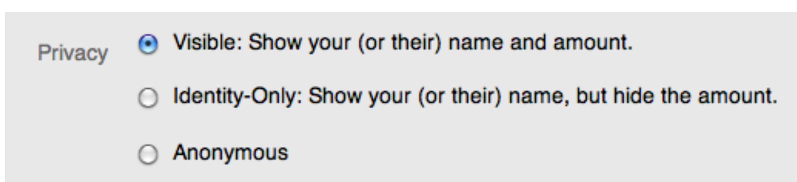

Figure 3. Information Hiding Option

At this point, the contributor is presented with a question about how they want their contribution record to appear on the campaign's Funders tab. The contributor is given the option to conceal their identity or the amount of the contribution[3]. Figure 3 provides a screenshot depicting this question. Lastly, the contributor is then given an option to leave a comment on their contribution record, and to share their contribution via social media (e.g., Twitter, Facebook), before being taken to the payment-processing page where they complete the transaction (e.g., PayPal).

[3] Information-hiding mechanisms of this sort are relatively common in online crowdfunding. Some other prominent platforms that employ these features include GoFundMe.com, GiveForward.com, and CrowdRise.com.

Methods

Model Formulations

Antecedents

In our first model, our outcome of interest is a three-value categorical variable capturing what we argue to be increasing degrees of information hiding: 0 – no hiding, 1 – amount hiding and 2 – identity hiding. These three possibilities are mutually exclusive – that is, it is not possible for contributors to hide both their identity and contribution amount simultaneously[4]. We view identity hiding as a more intense form of information hiding than amount hiding because this completely disassociates the contributor from their contribution.

The role of social norms in private contribution to a public good is well documented in the literature, as noted in our review above. However, unlike the prior literature, here, individuals are afforded the ability to control scrutiny, by opting to conceal their actions. Thus, as the literature supports the notion that individuals tend toward established norms when they perceive that they are being observed, here, we might expect, conversely, that individuals could also opt to conceal actions that constitute a deviation from an established norm. In more concrete terms, with more extreme contributions, one would expect greater information hiding behavior. We operationalize extremity here based on increasing size of the *Contribution* in question. We focus on large, rather than small, contributions because small contributions are very common in practice, and thus are less likely to be viewed as extreme. However, we subsequently explore alternative operationalizations for extreme contribution in our robustness checks, such as whether the amount of the contribution falls in the top or bottom 10% of the overall distribution.

Next, in order to address the impact of contributors' general attitude towards privacy, which, as noted in our literature review, has been shown to impact information revelation in a number of online settings, we include a dummy variable, *Facebook Connected*, which captures whether the contributor has connected their Facebook profile to their marketplace user account. This variable acts as a proxy for privacy sensitivity, as individuals who are willing to connect their Facebook profile in this manner are likely less concerned with privacy issues. Of course, given that this variable may correlate with other factors, we also consider robustness checks using an alternative measure of privacy concern, namely a binary indicator of whether the individual has chosen to (voluntarily) share their demographic info in their user profile. We obtain consistent results using either of these measures, indicating that our Facebook connectedness indicator is a valid proxy for privacy sensitivity.

Related to the issue of privacy concerns, we also control for the degree of exposure a campaign has received via the *Exposure* variable, which is operationalized as the number of prior contributors the campaign has received as of a point in time. Given that a privacy sensitive reaction to increasing campaign exposure is likely dependent on individuals' privacy sensitivity, we interact this exposure variable with the *Facebook Connected* dummy, in order to capture the anticipated moderating relationship. This aspect of our model reflects our expectation that contributors will perceive high profile campaigns as a greater risk from a privacy perspective.

Lastly, we operationalize self-contribution using a binary indicator, *Is Organizer*. We also incorporate a series of fixed effects at the campaign level, δ, to control for unobserved heterogeneity between campaigns, as well as time fixed effects, ϕ, to control for unobservable shocks across time periods (e.g., privacy breaches covered in the mainstream media).

Hypotheses H1 and H2 will be assessed via the coefficients associated with our *Facebook Connected* variable, and the interaction with our *Exposure* variable. H1 suggests a negative effect from Facebook connectivity—such users are expected to be less privacy sensitive, and thus less likely to conceal information. Further, H2 suggests that the interaction between *Facebook Connected* and *Exposure* will

[4] While it is possible for a contributor to indicate that they are contributing on behalf of someone else and to then provide an alias, effectively making their donation completely anonymous, we exclude such contributions from our sample, due to their inherent ambiguity.

also be significant and negative, as the effects of privacy sensitivity are anticipated to be stronger in the presence of a larger audience. Hypothesis H3 will be evaluated via our *Contribution* variable, which we anticipate to have a significant and positive coefficient given that contributions are bounded at zero (i.e., the most extreme contributions are the large ones), and hypothesis H4 will be evaluated via the *Is Organizer* variable, which we similarly expect to have a positive coefficient. Our model of the antecedents of information hiding is presented below in Equation 1, in simple linear form, for the sake of exposition. We describe the components of this model in more detail below[5].

$$\begin{aligned} InfoHide_{ijt} = \beta_0 + \beta_1 * Log(Contribution_{ijt}) + \beta_2 * FacebookConnected_i + \\ \beta_3 * Log(Exposure_{jt}) + \beta_4 * FacebookConnected_i * Log(Exposure_{jt}) + \\ \beta_5 * IsOrganizer_{ij} + \delta_j + \phi_t + \varepsilon_{ijt} \end{aligned} \quad (1)$$

Consequences

Next, we consider the consequences of information hiding in terms of its impact on later others' contribution amounts, as well as its impact on the focal contribution. The economic outcome of interest in our model is the dollar amount supplied (i.e., *Contribution*). We detail the various independent variables in this model, below.

Referring back to our literature review, we begin by addressing the issue of social comparison. As noted previously, a number of studies have reported evidence that individuals respond to observation of others contributions by increasing their generosity. Another framing for this relationship is that of an anchoring effect (Tversky and Kahneman 1974), where contributors, lacking an appropriate benchmark for what is fair, may refer to others' recent contributions.

To operationalize this potential anchoring effect (H5), we introduce a variable entitled *Last Contribution*, which captures the size of the most recent contribution to the campaign. Second, to capture potential variation in subsequent response due to information hiding on the part of the last contributor, we introduce a series of dummies (*Last Name Hide* and *Last Amount Hide*). Finally, we interact these dummies with the *Last Contribution* term, in order to assess hypothesis H6[6].

Beyond these key variables, we again introduce a series of controls. These include an estimate of the contributor's income, based upon their zip code – *Income*. This value is drawn from zip code level data about average taxable income for the year 2008, published by the IRS. It should be noted that one consequence of including this variable in our estimation is that we limit our analysis to only American contributors. Luckily, however, American contributors comprise the bulk of our data set (more than 70% of contributions). Further, however, we must acknowledge potential measurement error in this variable, given that crowdfunders represent a self-selected subset of the general population. It is possible that they deviate systematically from the average wealth in any given geographic region. For this reason, we consider alternative indicators of wealth in our robustness checks, namely the average prior contribution amount for the individual in question, finding comparable results.

We also consider that some component of contribution in this setting may be due to altruism and warm glow. These incentives as drivers of private contribution to public goods have seen extensive consideration

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[5] State-stickiness may also play a role if contributors exhibit persistent behavior across contributions out of habit or comfort. Fortunately, this is not particularly concerning in our sample for two reasons. First, 82% of contributions came from first-time (one-time) contributors. For the remaining 18% of contributions, where correlated behavior is possible, we offer additional, specific robustness checks after our main results.

[6] It is worth clarifying our focus on the most recent contribution only. A contributor could conceivably refer to multiple prior contributions, or employ a mental estimate of their average. We focus on the most recent for two reasons. First, that piece of information is the most prominently displayed reference point for a given contributor, being displayed first, at the top of the backer list. Second, we do so as a simple matter of convenience. Moderated anchoring is a challenge to operationalize if we incorporate multiple prior contributions into the model. If we employ the average it is not clear how we should operationalize the influence of information hiding associated with the various contributions comprising that average. If we incorporate multiple prior contributions separately, in tandem, positive serial correlation between them produces issues of collinearity.

in the economics literature (Andreoni 1989; Andreoni 1990). Recently, however, these factors have also seen consideration and examination in the crowdfunding literature. In particular, Burtch et al. (2013c) present evidence of altruism and crowding out in a crowdfunded marketplace for online journalism projects. Bolstering this finding, Aitamurto (2011) also reports that these crowdfunders perceive their contributions as supporting a social good. Thus, as per Burtch et al. (2013c), we operationalize altruism's effects by incorporating a measure of the degree to which the campaign "need" has already been met. Specifically, we focus on the campaign's outstanding budget as of the time of contribution: *Remaining Budget*. This value represents the gap between the dollars raised and the target fundraising amount.

Finally, we control for a contemporaneous effect of information hiding, bearing in mind that relative scrutiny can result in behavioral differences, as outlined in our literature review. Further, we once again incorporate fixed effects at the campaign level, as well as for time, to address unobservable heterogeneity between campaigns, and temporal trends such as seasonal effects (e.g., tax season may reduce disposable income). Finally, we include a relative time trend variable, *Days Posted* to capture effects such as diminishing contributions due to lost interest in a campaign, or increasing contributions due to nearing fundraiser deadlines. Equation 2 reflects our main consequences model, again indexed by contributor, campaign and time, or *i, j* and *t,* respectively.

$$\begin{aligned} Log(Contribution_{ijt}) = {} & \beta_0 + \beta_1 * Log(LastContribution_{ijt}) + \beta_2 * LastAmountHide_{ijt} + \\ & \beta_3 * LastNameHide_{ijt} + \beta_4 * Log(LastContribution_{ijt}) * LastAmountHide_{ijt} + \\ & \beta_5 * Log(LastContribution_{ijt}) * LastNameHide_{ijt} + \beta_6 * Log(Income_i) + \\ & \beta_7 * InfoHide_{ijt} + \beta_8 * Log(RemainingBudget_{jt}) + \beta_9 * Log(DaysPosted_{jt}) + \delta_j + \phi_t + \varepsilon_{ijt} \end{aligned} \tag{2}$$

Endogeneity and Estimation Approach

Our initial estimations employ a three-stage least squares (3sLS) estimator with time and campaign fixed effects (instituted via a within-transformation), as well as clustered robust standard errors. This choice of estimator is driven by the apparent endogeneity (simultaneity) in our models, because information hiding and contribution amounts are codetermined. Employing instruments for these endogenous regressors allows us to directly address this issue. We instrument for information hiding using our indicators of privacy sensitivity (i.e., Facebook connectivity, and demographic sharing), and we instrument for contribution amounts using our income estimate, the outstanding budget for the pitch in question and the average of past contribution behavior for the contributor in question. The logic behind the income instrument is that individuals with greater disposable income will be more likely to contribute in extreme (i.e., large) amounts.

We opt to estimate these models in tandem using three stage least squares (3SLS) because this estimator offers efficiency gains over isolated 2SLS estimations for each component of the system. However, most packaged 3SLS estimators assume a cross-sectional sample, and thus do not account for issues of serial correlation or panel data structures (e.g., nested / cross-correlated data structures). In contrast, there are a number of readily available packaged 2SLS estimators that are capable of handling these issues. Further, Wooldridge (2002, pg 199) notes that 3SLS estimation is only robust when all equations in the system are appropriately specified. If even one equation is misspecified, then all estimates are inconsistent. Bearing this in mind, we explore the stability of our results with the use of a 2SLS estimator, as part of our robustness checks.

We also acknowledge the unique characteristics and structure of some of our variables. In particular, our *Info Hide* variable is viewed as an ordered or nominal categorical variable. As such, alternative estimators may be called for, beyond those we employ in our main estimations, which assume a continuous outcome. Our robustness checks therefore include additional estimations employing Ordered and Multinomial Logit estimators. Finally, we consider a number of additional estimations, employing alternative operationalizations of our variables (some of which are noted above), as well as a number of data splits. These robustness checks help us to establish the robustness of our estimates under varying assumptions.

Data & Descriptive Statistics

We are fortunate to have access to all recorded data that is associated with this marketplace, over an 8-month period. Our dataset includes information associated with site-wide activity, pertaining to all campaigns, users and user behaviors, even when those behaviors are not publicly observable. We employ data associated with all campaigns on the platform, to ensure generalizability of our results. Table 1 provides a list of variable definitions, and Table 2 provides descriptive statistics for each.

In terms of information hiding behavior, we find that it is quite prevalent. In particular, individuals withhold their name and contribution amount in 19% and 27% of contribution instances, respectively. In terms of which individuals tend to hide their information at the time of contribution, we see a number of interesting correlations. We observe a negative correlation between information hiding and Facebook connectedness (rho = -0.07), as well as a positive correlation between information hiding and i) the number of prior contributors (rho = 0.15).

Table 1. Variable Definitions

Variable	**Definition**
Info Hide^{O}	A three value ordinal variable capturing the degree of information hiding exhibited by a contributor in a particular contribution instance.
Contribution^{O}	The dollar amount supplied by this contributor.
Facebook Connected	A binary indicator of whether the contributor has connected their Facebook profile to their marketplace user account.
Exposure	The count of prior contributors to the campaign in question, as of time *t*.
Last Name Hide	A binary indicator of whether the last contributor hid their identity (i.e., contributor i-1).
Last Amount Hide	A binary indicator of whether the last contributor hid the amount of their contribution (i.e., contributor i-1).
Is Organizer	A binary indicator of whether the contributor is a campaign organizer.
Last Contribution	The dollar amount supplied by the last contributor (i.e., contributor i-1).
Income	The average reported taxable income in the contributor's zip code, in 2008.
Days Posted	The number of days the campaign has been in the funding process.
Remaining Budget	The dollar amount outstanding toward the campaign's fundraising target, as of time *t*.

Notes: O – outcome variable.

Results

The results of our estimation are presented in Table 3. Looking at our Antecedents results in the upper panel, we see a number of expected significant coefficients. First, we see that individuals who are less privacy sensitive (i.e., have opted to connect their Facebook profile to their user account) are significantly less likely to hide information at the time of contribution, and that this effect is even more pronounced in campaigns that have received greater exposure (many prior contributors). These findings support hypotheses H1 and H2. We also see that individuals are significantly more likely to hide their information as they contribute in more extreme (larger) amounts, as well as when they are contributing to their own campaign. Together, these results support for hypotheses H3 and H4.

Table 2. Descriptive Statistics

Variable	Min	Max	Mean	Median	STDev.
Info Hide	0.00	2.00	0.66	0.00	0.78
Contribution	1.00	60,000.00	64.51	25.00	208.59
Facebook Connected	0.00	1.00	0.15	0.00	0.36
Exposure	0.00	32,323.00	1,875.06	31.00	5,597.76
Last Name Hide	0.00	1.00	0.19	0.00	0.39
Last Amount Hide	0.00	1.00	0.27	0.00	0.44
Is Organizer	0.00	1.00	0.01	0.00	0.12
Last Contribution	0.00	12,084.00	61.15	40.00	105.88
Income[X]	1,575.20	5,176,136.00	58,623.82	43,536.96	53,926.12
Days Posted	0.00	120.00	17.65	10.00	19.52
Remaining Budget	-698,903.00	5,000,000.00	-23,550.00	2,700.00	140,700.70

Notes: x – N = 179,746, all others – N = 352,575

Next, we consider our Consequences estimates in the lower panel, focusing first on our key variables, prior others' contribution and information hiding. We find a significant positive coefficient associated with the prior contribution (notably, this effect persists when we remove the interaction terms), which supports the presence of an anchoring effect, hypothesis H5. Looking at the interaction with amount hiding, however, we also find that this effect is attenuated (indeed, effectively eliminated) when the prior amount is concealed. This interaction effect provides support for our final hypothesis, H6. This result suggests that the positive effect from prior contribution is not due to homophily (Manski 1993), because we would expect the correlation in contributions to persist when prior amounts are concealed, if that were the case.

Finally, in terms of our control variables, we first find a positive effect from outstanding budget. This suggests that many contributors are driven by altruism or warm-glow, offering greater contributions when the campaign's need is greater[7]. Importantly, this finding is consistent with the results of Burtch et al. (2013c). We also find a positive effect from income. That is, individuals with greater disposable wealth contribute in greater amounts, on average. Finally, we find that individuals are more likely to contribute in extreme amounts when they have opted to conceal more information from public view. This is not unexpected, given our results in the Antecedent model demonstrating a positive association between contribution amounts and information hiding.

We subsequently explored the marginal effects of amount hiding, in order to determine its net effect at various points in the distribution of prior contribution amounts. Rather intuitively, we found that amount hiding is desirable from the platform purveyor's and fundraiser's perspective when the amount contributed is small, as this effectively conceals a benchmark that is likely to pull down subsequent contributions. Conversely, amount hiding is detrimental when the contribution amount is large, as such contributions have the potential to "pull up" subsequent contributions. Bearing this in mind, we surmise that the purveyor and campaign organizers would possibly benefit from using varied information hiding defaults, conditional on the size of the associated contribution. If small contribution amounts were

[7] If we operationalize peer effects using cumulative amount raised, rather than budget outstanding, and we then incorporate a control for possible payoff externalities as per Zhang and Liu (2012), we find very similar results. Cumulative contribution has a negative effect, suggesting crowding out, and our other coefficients remain generally stable.

concealed by default, and larger contributions were revealed by default, we anticipate that overall contribution volumes would increase in the market.

The economic significance of these effects is quite large as well. Based on a linear probability model we estimated, where we collapsed the amount and identity hiding outcomes into a single value, which we term simply *Hiding,* we observed that a 50% increase in contribution amount drives a 2% increase in the probability that some piece of information will be concealed. Conversely, a shift from revealed to concealed contribution is associated with a 150% increase in contribution amounts. These effects are especially notable when one considers the sheer volume of transactions taking place on the platform.

Table 3. Antecedents & Consequences Results (3SLS-FE)

Dependent Variable	Explanatory Variable	Coefficient
Info Hide	Log(Contribution)	**0.21*** (0.02)**
	Facebook Connected	**-0.11*** (0.02)**
	Log(Exposure)	**0.01** (0.00)**
	Facebook Connected X Log(Exposure)	**-0.02** (0.00)**
	Is Organizer	**0.36*** (0.02)**
Log(Contribution)	Log(Last Contribution)	**0.01*** (0.00)**
	Last Name Hide	-0.02 (0.02)
	Last Amount Hide	**0.05** (0.02)**
	Log(Last Contribution) X Last Name Hide	0.01 (0.02)
	Log(Last Contribution) X Last Amount Hide	**-0.01** (0.00)**
	Log(Remaining Budget)	**0.01*** (0.00)**
	Log(Days Posted)	0.00 (0.00)
	Log(Income)	**0.14*** (0.00)**
	Info Hide	**0.63*** (0.03)**

Notes: Fixed effects instituted via within transformation; we exclude estimates of time effects for the sake of brevity.
*** $p < 0.001$, ** $p < 0.01$.

Robustness Checks

Following our main estimations, we conducted a wide variety of robustness checks, beyond ruling out issues of multicollinearity and outliers (note: we exclude these estimations in light of space limitations). First, as noted in our modeling section, we evaluated the robustness of our estimates to the use of panel fixed effect 2SLS, finding virtually identical results.

Next, we considered the impact of possible differences in contributor motivations. In particular, we considered systematic differences between individuals who claim a reward in exchange for their contributions, and those who do not (e.g., different motivations for contributing). One concern might be that the amount contributed by a reward-claiming user could be driven in large part by the value of the reward they wish to claim. Further, such users may be particularly less concerned with other users on the platform, because they are not contributing to gain social benefits (e.g., reputation, social capital). To address this possibility, we re-estimated our Antecedents and Consequences models using only those observations where the contributor did not collect a reward for their contribution. The results of these estimations were effectively identical to those reported above.

As noted in a footnote in our modeling section, we also examined the role of state-stickiness in information hiding behavior (correlations across contribution actions for a given contributor). Given that 82% of contributions we observe were proffered by one-time contributors, we focus here on the remaining 18% of repeat contributors. Looking at this subsample, we incorporated an indicator of the contributor's information hiding decision in the prior contribution instance. We found a strong positive effect (i.e., *Beta* = 0.46, p < 0.001) from this indicator, suggesting that habit formation or comfort may play a role in the information hiding decision. However, most notably, our various other coefficients remained stable in the presence of this additional control[8].

We next considered our approach to operationalizing 'extreme contribution'. In particular, rather than focusing only on larger contributions, we re-estimated a model in which extreme contribution was operationalized based on the top and bottom 10% of the distribution, which equates to those contributions that were either equal to $1, or which were greater than $99. This estimation produced very similar results to those reported above. Our binary indicator for extreme contribution had a significant and positive effect on information hiding (*Beta = 0.06, p < 0.001)*. In terms of the economic significance, extreme contribution based on this definition was associated with a 4% increase in the probability that some piece of information would be hidden.

We also explored the sensitivity of our results to the choice of estimator—i.e., explicitly accounting for the categorical nature of our *Info Hide* variable. We re-estimated our Antecedents model using a Random Effects Ordinal Logit estimator, in tandem with a first stage prediction of our endogenous contribution amount variable to address simultaneity. This estimation produced results that closely paralleled those of our main estimation. Similarly, we considered a Multinomial Logit estimator with instruments and random coefficients for campaigns. This estimation allowed for the possibility of different drivers between identity and amount hiding. However, except for some small differences, the output paralleled much of our initial results as well. We saw that more extreme contribution was positively associated with both Amount and Identity hiding and that Facebook connectivity was negatively associated with both behaviors. This indicates that our initial choice of estimator is rather appropriate.

As a final measure, we considered some alternative operationalizations of some independent variables and instruments, replacing *Exposure* with a binary indicator of whether the campaign was featured by the purveyor on the home page, and replacing Facebook connectedness, which might correlate with other factors aside from privacy concern, with a binary indicator of whether individuals had previously chosen to reveal their year of birth in their platform profile (a voluntary, conscious choice). Finally, we tried replacing Income, which is a zip-code value that may introduce measurement error, with the average prior contribution amount for the user in question, though we only have this data for repeat contributors (18% of our panel). In each case, the alternative measures produced very similar results in terms of signs and significance, suggesting that our main measures are indeed valid.

Discussion & Future Research

Our finding that individuals are more likely to hide information when they behave in the extreme is as anticipated. However, additional details about the nature of this effect could prove useful. Which users are more likely to deviate in which direction, and to what degree? One likely driver of information hiding is the presence of a social tie between the contributor and campaign organizer. Consider that crowdfunders wishing to maintain social capital or reputation might be more concerned about scrutiny. A wide variety of interesting factors such as this would be worth exploring in the future.

In general, it is interesting to consider the possibility that the relationship between privacy sensitivity, exposure, extreme behavior and information hiding may vary with contributors' motivations and

[8] This estimation incorporates additional individual heterogeneity into our models, which we admit is somewhat lacking. Unfortunately, we cannot introduce contributor-level fixed effects because the majority of our sample is comprised of one-time contributors. Further, even if we could do so, this would preclude identification of certain key (static) variables in our models.

incentives for contributing. As noted in our robustness checks section, we considered the possibility that reward-claiming contributors might behave very differently than contributors who give money out of a desire for reputation, social capital or other such social incentives. Accordingly, we repeated our estimations excluding such users. However, when we focus explicitly on these users, we still see the same general results. As contribution amount grows more extreme, information hiding is more prevalent. Privacy sensitive users are more likely to conceal and the effect is increasing in Exposure. There is one interesting exception, however. We see that Exposure's main effect is significant and negative. This suggests that reward-claiming users are perhaps comforted by broader market approval for a campaign. This may be because such users worry more about market approval, as a quality signal, and less about the implications of exposure for scrutiny.

In terms of the impact that information controls have on contribution behavior, beyond the impact on subsequent contribution (via an anchoring effect), individuals' ability to withhold information about "undesirable" behavior has both positive and negative implications, conceptually. Although providing anonymity mechanisms is likely to increase participation, as users need not fear judgment (Goldfarb et al. 2012), it also may enable gaming, as campaign organizers can easily support their own projects unbeknownst to others, sending a false signal of campaign quality.

Our Consequences results highlight the impacts of information hiding for social comparison. Specifically, our results indicate that information revelation will be more desirable from the campaigners' and purveyors' perspectives, depending upon the size of prior contribution. Again, this finding suggests that a more nuanced approach to the provision and application of information hiding mechanisms is called for. This implication is interesting, as it provides a concrete example of how one might design a web platform to foster social comparison only when it is most desirable, a notion only recently raised in the literature (Roels and Su 2013).

The above being said, one particular concern with instituting policy changes based on these findings is that the identified effects are conditional on contribution (i.e., participation). That is, these analyses do not speak to the possibility that mere participation would decline were policy or design changes imposed in the marketplace. Notably, prior work examining the role of anonymity mechanisms in online communities has found that posting frequency declined by as much as 25% after the removal of such features (Kilner and Hoadley 2005; Leshed 2008). Thus, any changes to the user interface or platform design, in response to these results, would need to be taken with care and validated via experimentation.

As a final point of discussion, it is worth pointing out that we have focused primarily on the relationship between extreme contributions and information hiding. It would also be interesting to perhaps explore the antecedents and consequences of self-contribution by campaign organizers. This behavior is fairly prevalent on the platform – we observe 8,514 self-contributions out of the total 352,575 (roughly 2.5%). Since it is likely that this behavior can instigate negative reactions from the crowd, it is interesting to note that the contributor's identity is only concealed approximately 50% of the time. This seems to suggest that there are certain situations in which the campaign organizer is comfortable revealing this action. Accordingly, we plan to explore the conditions under which a campaign organizer is less (or more) likely to conceal their self-contributions. Further, we also plan to explore what impact observable self-contribution has on subsequent fundraising. At the moment, however, such analyses lie outside the scope of this work.

Conclusion

This work presents, what is to our knowledge, a first attempt to evaluate individuals' use of information hiding mechanisms at the transaction level, to conceal discrete behaviors, in a real-world setting. Whereas past work has explored individuals' behavior in response to exogenously imposed anonymity, here, we consider a user's endogenous decision to conceal information about themselves or their actions. Further, we have undertaken this evaluation in a particularly novel context – the burgeoning industry of online crowdfunding.

With the emergence of "crowdfunding" as a viable business model, marketplaces of this sort are now providing users with the opportunity to express themselves in new ways, and to examine others' behavior in new ways. Given crowdfunding's significant economic potential and recent growth as an industry, any increases in welfare or marketplace efficiency that can be achieved through modifications to the design of these platforms or their policies should be pursued wholeheartedly. Our work presents a solid first step in that direction. It is our hope that this work will provide insights to scholars and practitioners, informing design, as well as policy and regulation going forward.

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