PRIVATE DISPLAYS OF AFFECTION: AN EMPIRICAL EXAMINATION OF ONLINE CROWDFUNDER INFORMATION HIDING BEHAVIOR

Abstract

The demand for online privacy remains an ongoing source of debate. Sensitive to this fact, many online platforms now offer users greater, more granular control over how and when their information is revealed. However, little research exists on peoples' willingness to use these information control mechanisms, or on their economic benefit to the various parties involved. In this study, we leverage transaction-level data from one of the world's largest online crowdfunding platforms, where campaign contributors are given the option of concealing their identity and contribution amounts from public display. First, we find evidence that individuals are more likely to conceal information when the campaign they are supporting has received a greater deal of public exposure and ii) when their contribution amount is "extreme." Second, we find evidence of an anchoring effect, where contributors refer to the amounts supplied by prior others as a point of reference when deciding upon their own contribution. Considering the marginal effects, we find that concealing the prior contribution amount can be beneficial or detrimental for the purveyor or campaign organizer, depending on the contribution size. If prior contributions are small, concealing the amount is likely to be preferred, in order to prevent a downward influence on subsequent contributions. In contrast, when prior contributions are large, it is to the purveyor and campaign organizer's benefit if the amount is revealed, as this can create an upward influence on subsequent contributions. This finding implies that a nuanced approach to the provision of information hiding mechanisms can help promote larger crowdfunder contribution. We discuss the implications for the design and provision of online information hiding mechanisms.

Keywords: crowdfunding, privacy, information hiding, entrepreneurial finance, anonymity.

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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. Sensitive to this fact, 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 notes that they are not always used when it would seem logical to do so (Acquisti and Grossklags 2005; Das and Kramer 2013; Jiang et al. 2013). Further, the provision and use of information controls is not necessarily of economic benefit to all parties involved (Conitzer et al. 2012). This is notable because individuals' decisions to conceal or reveal their information have important implications in many respects. For example, a wide body of work touches on observational learning, social influence and social norms in online contexts, each of which is dependent upon individuals being able to observe the activities or characteristics of others. Further, numerous business practices rely on consumers sharing their data, including targeted marketing, personalization and price discrimination (Goldfarb and Tucker 2011). In this work, we therefore seek to examine users' application of information hiding mechanisms, and the economic consequences for their peers. Specifically, we address the following research questions: ***What drives users to employ information hiding mechanisms? What are the economic consequences of this?***

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. 2013b). 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 (Massolution 2013), crowdfunding helped new ventures to raise more than $2.7 billion in 2012, and is expected to facilitate more than $5.1 billion in 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 public record is created on the campaign's backer or funder page, containing 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 actions, many crowdfunding platforms now go to great lengths to provide users with a degree of anonymity. In some cases, this is achieved by randomizing the ordering of contributors, as on Kickstarter, while in others it is achieved in a more granular fashion, by providing contributors with the option of concealing particular 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 for other users (e.g., the impact upon subsequent contributors). Notably, this work addresses recent calls in the literature for explorations of the antecedents and consequences of privacy concerns in online markets (Smith et al. 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 2012).

Our key findings are as follows. First, we find that individuals are more likely to conceal information i) when the campaign they are supporting has received greater public exposure and ii) when their contribution amount deviates from that of prior others. Second, we find evidence of an anchoring effect, where users employ prior others' contribution amounts as a benchmark for their own contribution.

As one would expect, we also see that this anchoring effect is eliminated when prior others conceal their contribution amount. This produces an interesting trade off.

Examining the marginal effect of amount hiding on subsequent contributions, we find that such mechanisms are beneficial for the purveyor and fundraisers when the associated contribution is small. In contrast, we find that information-hiding mechanisms are detrimental when the associated contribution is large. This contrast is fairly intuitive, as it implies that the purveyor and campaigners only benefit from information hiding when it serves to conceal a small anchor point from view; one that is likely to pull down subsequent contributions.

Our results are quite robust, as we account for various potential sources of endogeneity, including unobservable heterogeneity across campaigns, via fixed effect estimation, as well as simultaneity, via the use of three-stage least-squares (3SLS). We also consider alternative data splits and instruments. Notably, regardless of the choice of estimator, sample or instrument set, we obtain largely consistent results.

Literature Review

Crowdfunding

There is an emerging stream of research that has examined the concept of crowdfunding, 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). Loan- and reward-based crowdfunding markets have seen greatest consideration by academics. Lin et al. (2013) study a loan-based market, Prosper.com, finding that the likelihood of credit being issued is greater when the borrower exhibits greater social capital. In the same context, Zhang and Liu (2012) find evidence of herding and, counter to intuition, that lenders are more likely to herd when the borrower exhibits signals of low quality. Most recently, Lin and Viswanathan (2013) report evidence that lenders prefer geographically proximate borrowers, evidence of a home-bias. Agarwal et al. (2011) have studied reward-based crowdfunding at Sellaband.com, reporting on the role of physical distance between contributors and fundraisers. Mollick (2012) examines Kickstarter.com, quantifying the impact of various factors associated with fundraising success, such as the size of the fundraiser's social network, the duration of fundraising and the size of the fundraising target.

Two recent studies have considered equity-based crowdfunding. Ahlers et al. (2012) examine data from CrowdCube, reporting on the impacts of signaling mechanisms for firm quality (e.g., publication of risk assessments) on fundraising outcomes, while Kim and Viswanathan (2013) study the AppBackr marketplace, reporting on the important influence of opinion leadership and investment expertise.

Burtch et al. (2013a; 2013b) study two donation-based platforms. In their first study, the authors find evidence of social influence and crowding out between contributors in the crowdfunding process. In their latter study, these authors examine the role of cultural differences between contributors and fundraisers, finding that these differences impact contributors' selection of borrowers.

Online Privacy and Information Hiding

The online privacy literature is replete with studies of when privacy concerns manifest, and how subjects' respond to those concerns. For example, Nov and Wattal (2009) study user content production on Flickr and find that individuals' privacy concerns and sharing intensity are negatively associated with their trust in other members of the platform. Further, Hui et al. (2007) report a similar finding, demonstrating 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.

Studies in this area have looked at consumer purchasing behavior as well. For instance, Tsai et al. (2011) show that customers are more likely to buy products from a website where privacy assurances are displayed in a more prominent, visible manner. Taken together, the above findings are generally 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).

It is also worth considering how privacy concerns have been measured in the prior literature. The vast majority of studies have relied on survey measures. Measures have been proposed by a number of scholars, though perhaps the most notable in the IS literature are the scales formulated by Smith et al. (1996) and by Malhotra et al. (2004). The latter derive and empirically evaluate a scale of measurement they refer to as capturing Internet Users Information Privacy Concerns (IUIPC), which 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.

Although numerous studies, such as those above, report on the sources of individuals' privacy concerns, their demand for online privacy (Dinev and Hart 2006), and for privacy control mechanisms in particular (Acquisti and Grossklags 2004), scholar shave noted that this desire does not necessarily translate into actions as one would expect (Jiang et al. 2013). This is because a number of other factors can influence behavioral outcomes. Specifically, scholars have noted that subjects' response to privacy risks will depend on their ability to perceive those risks. This, in turn, is dependent upon the presence of informational cues (John et al. 2011), such as audience size. Acquisti and Gross (2006) find that privacy sensitive Facebook users frequently enroll and share personal information because they are unable to accurately assess the size of their audience. Empirical evidence for the importance of perceived audience size, in relation to information sharing and content production, has also been documented by Zhang and Zhu (2011) on Wikipedia, as well as by Das and Kramer (2013) and Sleeper et al. (2013) on Facebook.

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 charitable contribution, Haley and Fessler (2005) find 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) find that subjects respond with generosity in the direct presence of a contribution 'collector'. Finally, Croson and Marks (1998; 2005) report on an experiment involving donations, where the level of anonymity was subject to manipulation. These authors find that a reduction in anonymity produces a general increase in donations and, interestingly, a decrease in variance. Soetevent (2005) argues that this latter result—a regression toward the mean with the removal of anonymity—may occur because excess contributions, like small contributions, may set an "unfair" precedent, drawing negative reactions from peers.

Other studies have offered empirical support for this notion. For example, Wang (2010), in a study of online reviews across different platforms, finds that reviews on Yelp tend to be less extreme, attributing the result to the increased visibility of reviewers in that venue. Further, Huberman et al. (2005) find that subjects in an experiment demand a higher amount of money before they will agree to reveal personal information when they anticipate that the information will be perceived as less desirable by others.

As a final point, it is worth noting the moderating role that information hiding has been found to play 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 provided in the work of Chen et al. (2010).

Hypothesis Development

Bearing the above studies in mind, we begin by considering the expected drivers of contributor information hiding. On the surface, the literature clearly suggests that individuals will be more likely to conceal their information when they are privacy sensitive or perceive privacy risks. 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.

At the same time, however, the literature also offers a number of studies, namely those by Acquisti and Gross (2006), John et al. (2011) and Das and Kramer (2013), which indicate that this response depends on individuals' ability to appropriately perceive any risk, and the capability of privacy controls to address said risk. As such, it is not immediately apparent whether privacy sensitive users will be more likely to apply the available information hiding mechanisms.

The experimental economics literature has also noted that individuals respond to varying degrees of anonymity (Lamba and Mace 2010). Further, privacy concerns are not binary; 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), a notion supported by the findings of both Das and Kramer (2013) and Sleeper et al. (2013), around Facebook self-censorship. Based on the above discussion, we propose our first hypothesis, H1a.

Notably, however, the literature also suggests that the "membership size" of online communities has both costs and benefits (Butler 2001). In this particular case, a possible countervailing effect may result from the fact that increasing audiences for one's actions offer a greater potential for reputational gains. This logic is set forth by Zhang and Zhu (2011), for example, who consider increasing reputational gains from contributions to Wikipedia in the presence of a larger audience. Bearing this in mind, we also propose a countervailing hypothesis, H1b, that information hiding may in fact become less likely with exposure.

H1a: Contributors will be more likely to hide information when they support highly exposed/trafficked campaigns.

H1a: Contributors will be less likely to hide information when they support highly exposed/trafficked campaigns.

The literature further suggests that information-hiding responses are associated not only with the characteristics of an individual, but also with the specific actions they have undertaken. For instance, our review notes a number of studies that indicate that scrutiny can drive changes in behavior, conditional on a particular action being taken. In a crowdfunding context, this translates into behavior conditional on contribution.

It seems reasonable to expect that individuals will be more likely to conceal information about themselves or their activities when others will perceive their contributions as less desirable. This represents the converse of relationships identified by Ariely and Levav (2000) and Ratner and Kahn (2002), who show that, under scrutiny, individuals generally wish to seem more "interesting" to others. Similarly, the work by Goldfarb et al. (2012) suggests that individuals are more likely to purchase products when the risk of embarrassment is lower. Finally, the results reported by Huberman et al. (2005) indicate that individuals require greater economic compensation before they will agree to reveal personal information that might be viewed as undesirable by others.

In a crowdfunding context, "undesirable" behaviors can take on two readily apparent forms: contribution in extreme amounts (Croson and Marks 1998; Soetevent 2005), and contribution toward one's own campaign. Bearing this in mind, we anticipate that information hiding will be more likely to take place when individuals' contributions are more extreme (larger) and when individuals' contributing are made toward their own campaign. We formalize this expectation in hypothesis two, below.

H2: Contributors will be more likely to hide information when their contributions are "extreme" or undesirable.

Next, considering the downstream impacts of information hiding for the behavior of later contributors, namely in regard to the potential for social comparison to emerge, our review of the literature also offers a number of results that can inform our study. 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 may draw on observable cues provided by prior others when deciding an appropriate contribution amount.

Obviously the availability of said cues will depend on whether prior others have concealed the amount of their contribution. Given all of the above, we anticipate that crowdfunders will be positively influenced by the contributions of prior others, tending to contribute in kind. Further, however, because these anchoring effects are dependent upon the transparency of prior contributions, we also anticipate that any sequential correlation in contributions will be moderated (attenuated) by prior others choosing to hide the amount of their contribution. This leads us to hypotheses three and four. We summarize our four hypotheses in Table 1.

H3: Higher contributors by prior others will lead an individual to contribute more.

H4: The Social Comparison effect (H3) will be attenuated when prior others' hide information about their contribution.

Table 1. Summary of Hypotheses

Hypothesis	Description	Direction
	DV = Information Hiding	
H1a (Exposure Privacy):	Contributors will be more likely to hide information when they support highly exposed/trafficked campaigns.	+
H1b (Exposure Reputation):	Contributors will be less likely to hide information when they support highly exposed/trafficked campaigns.	-
H2 (Extreme Behavior):	Contributors will be more likely to hide information when their activities are "extreme" or undesirable.	+
	DV = Contribution	
H3 (Social Comparison):	Higher contributors by prior others will lead an individual to contribute more.	+
H4 (Transparency):	The Social Comparison effect (H3) will be attenuated when prior others' hide information about their contribution.	-

Study Context

Our study focuses on one of the world's largest global platforms for reward-based crowdfunding. This marketplace enables anyone, in any location, to raise money for a venture. The marketplace is highly trafficked, attracting upwards of 200,000 visitors per day, and facilitating millions of dollars in campaign contributions each month. Since being founded approximately five years ago, the platform has attracted more than 1 million registered users from more than 190 countries around the globe.

Campaign Flow

Figures 1a and 1b present screenshots from our study context, depicting a campaign description and contribution records, respectively. This marketplace allows submission of any and all ventures, regardless of subject matter (except for prohibited content). Thus, rather than vetting campaign submissions, as is done in certain crowdfunding contexts, 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, the planned funding duration and the "funding format."[1]

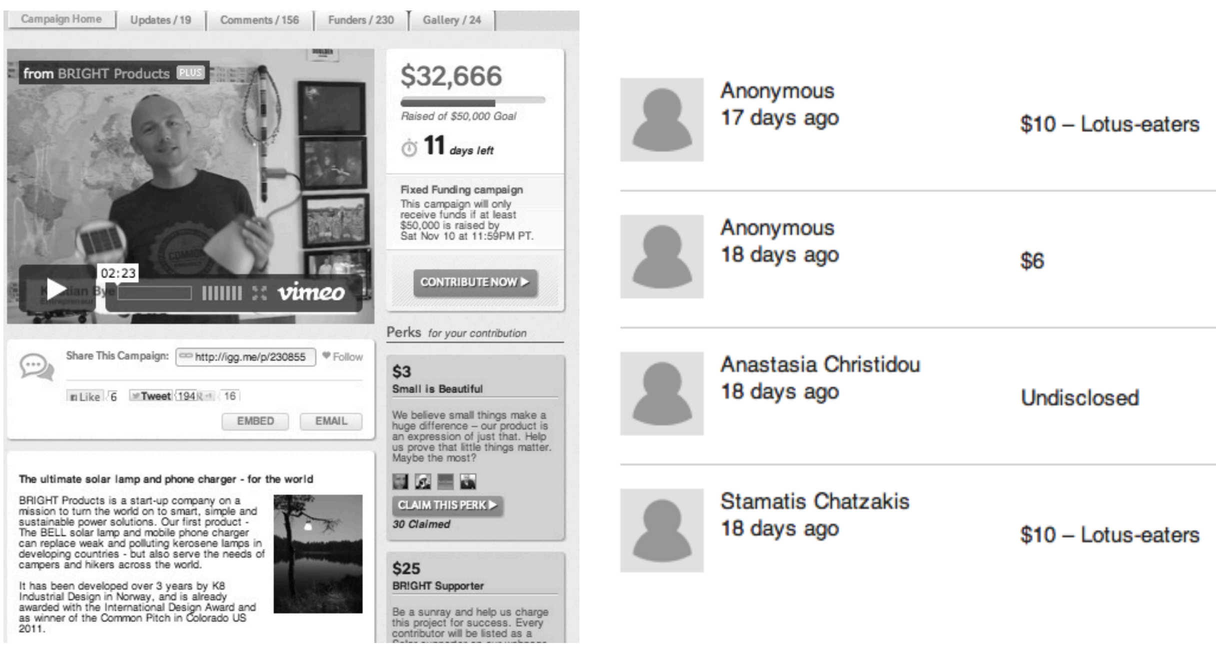

Figure 1a, b. Campaign Details (a-Left) and Contribution Records (b-Right)

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[1] In the *all-or-nothing* format, the fundraiser only receives the contributed funds if the campaign's funding target is met. The benefit of this approach is that, if the fundraiser should succeed, the platform fees that the organizer must pay are quite a bit smaller (~5% of all funds). In contrast, in the *incremental* format, the fundraiser receives funds even if the target is not met. However, they are then required to pay a much higher fee (~10%). Note: we offer a number of robustness checks considering these differences.

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 (e.g., location-based, recency-based). 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].

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.

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 (but not both)3. 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). Figure 2 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).

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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.

[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.

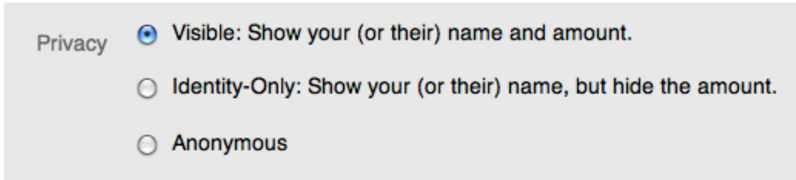

Figure 2. Information Hiding Option

Methods

Model Formulations[4]

In our first model, our outcome of interest is a three-value categorical variable capturing 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.[5] 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.

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

We measure *Exposure* as the as the number of prior contributors the campaign has received as of a point in time. A positive coefficient on *Exposure* would provide support for H1. 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 will opt to conceal actions that constitute a deviation from an established norm. In more

[4] Our models are constructed based on campaign-contributor pairs. Thus, we consider repeated observations of the same campaign, where each observation pertains to a single user's contribution event. A notable implication of this is that the concept of a lagged dependent variable is meaningless in this setting, because repeated contributions toward the same campaign, by the same user, are not the norm.

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

concrete terms, with more extreme contributions, one would expect greater information hiding behavior. We therefore include the size of the *Contribution* in question.

Our operationalizations of extreme (undesirable) behavior, referenced in hypothesis 2, include our measure of contribution size (i.e., *Contribution)*, which we anticipate to have a significant and positive coefficient, given that contributions are bounded at zero (i.e., the most extreme contributions are thus large ones), and our measure of self-contribution, captured via the binary *Is Organizer* variable, which we similarly expect to have a positive coefficient.

It is also worth noting here that extreme contributions are likely to be best captured by upward deviations in amount. This is because contribution is of course truncated at $0, which constrains the potential for downward deviation. To this point, the mean contribution is approximately $60 and the median is $25, yet the top decile of contributions exceeds $100. As such, relatively large contributions are less common on the platform, and are thus more likely to be viewed as extreme, both by contributors and by their audience. Additional detail on this is provided below in our section detailing the data and descriptive statistics.

Next, in order to control for 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.

This operationalization for privacy sensitivity is largely rooted in our reading of the prior literature. We are working with archival, observational data, and thus do not have access to users to obtain survey responses. We must therefore identify objective indicators of privacy concerns or privacy sensitivity in the data. Referring to the papers proposing survey scales, noted in our literature review, Smith et al.'s (1996) survey items include a subset of measures that they refer to as the "Collection Subscale." Malhotra et al. (2004) similarly incorporate respondents attitudes toward data collection as a key component of their measurement scale. Bearing these in mind, the most feasible approach to measuring privacy concerns in our case would therefore appear to be leverage indicators of subjects' prior information sharing (such as granting the platform access to their Facebook profile and friend data). We also explore alternate measures for privacy sensitivity (or sensitivity to scrutiny) such as whether the individual provides gender and year of birth when they create a profile on the website. We find that our results are qualitatively supported with the alternate specification.

Given that a privacy sensitive reaction to increasing campaign exposure is likely dependent on individuals' privacy sensitivity, we interact the *Exposure* variable with the *FB 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. Acknowledging that Facebook connectivity can represent other tendencies and behaviors, beyond privacy sensitivity, we also explore alternative indicators in our robustness checks, namely binary indicators of whether the user has revealed their year of birth or gender in their profile.

Finally, we incorporate a series of fixed effects at the campaign level, δ, to control for unobserved heterogeneity between campaigns. Further, the campaign fixed effects have the added benefit of eliminating observable static differences across campaigns from our estimation (e.g., funding format, campaign type), allowing us to maintain a more parsimonious model. As well, we include time fixed effects, ϕ, to control for unobservable shocks across time periods (e.g., privacy breaches covered in the mainstream media).

We assess the role of privacy sensitivity with increasing exposure (hypothesis one) via the coefficients associated with our *Exposure* variable, and its interaction with our *Facebook Connected* variable. Our integration of the literature suggests a negative effect from Facebook connectivity control is likely because such users should be less privacy sensitive (or less sensitive to public scrutiny), and thus less likely to conceal information. Further, the interaction between *Facebook Connected* and *Exposure* is expected to be significant and negative, as the effects of privacy sensitivity are anticipated to be stronger in the presence of a larger audience.

Next, we consider the consequences of information hiding in terms of its impact on later others' contribution amounts. The economic outcome of interest in our model is the dollar amount of subsequent, individual contribution, *Contribution*. Equation 2 reflects our main consequences model, again indexed by contributor, campaign and time, or *i, j* and *t,* respectively. Again, we detail the components of this model below.

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

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. Again, 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 an anchoring effect (hypothesis three), 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 (hypothesis four), we introduce a series of dummies (*Last Name Hide* and *Last Amount Hide*) capturing the degree of information hiding exhibited by the prior contributor. Finally, we interact these dummies with the *Last Contribution* term, to capture the anticipated moderating effect of information hiding on anchoring.

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 consequences analysis to only American contributors. Fortunately, however, American contributors comprise the bulk of our data set.

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 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. (2013b) 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. (2013b), 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 information hiding behavior in this model, 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 time trend variable, *Days Posted* to capture effects such as diminishing contributions due to lost interest, or increasing contributions due to nearing fundraiser deadlines.

Endogeneity and Estimation Approach

Our initial estimations employ three-stage least squares (3SLS), incorporating campaign fixed effects via a within transformation. This choice of estimator is driven by the apparent endogeneity (simultaneity) in our models. That is, the contributor determines how much to contribute given their information hiding decision, and vice versa. Employing instruments for these endogenous regressors on each side of the system allows us to directly address the simultaneity issue. We instrument for information hiding using an indicator of privacy sensitivity (i.e., Facebook connectivity). The logic behind this instrument is that privacy sensitive users should be less likely to reveal information to the platform purveyor, particularly when that information is fairly sensitive. Opting to log into the platform using one's Facebook account necessarily divulges a large amount of information to the platform purveyor, as doing so grants the purveyor access to one's Facebook profile information and a list of the user's Facebook friends. As the same logic applies for subjects' willingness to share their year of birth or gender in their platform user profile, we also explore these alternative instruments in our robustness checks.

We instrument for the contribution amounts using our estimate of the user's income, based on their identified zip code (either from their reported shipping address or based on a lookup performed using their IP address). The logic in this case is that individuals with greater income should have a greater amount of disposable wealth, and thus will be more likely to contribute in larger amounts. Further, we consider alternative, additional instruments in our robustness checks, including the outstanding budget and funding duration for the campaign as of the observation (i.e., the campaign funding status), because prior work has found that these factors can impact crowdfunder contribution amounts (Burtch et al. 2013b).

The use of 3SLS allows for efficiency gains over single-equation estimation methods because it takes into account the cross-equation error correlation. When the disturbance covariance matrix is not known, generalized least squares is generally inefficient compared to full information maximum likelihood or 3SLS estimation (Lahiri and Schmidt 1978). However, we also consider that there is a tradeoff between robustness and efficiency in this choice of estimator. This is because 3SLS estimation typically does not account for heteroskedastic residuals (and other violations of the i.i.d. assumption), nor does it account for panel data structures. Further, Wooldridge (2002, pg 199) points out that 2SLS estimation is generally more robust than 3SLS as, if even one equation in the system is misspecified (e.g., endogeneity and invalid or weak instrumentation), then all estimates will be inconsistent. Considering these potential issues, we also report a series of single-side 2SLS estimations for each side of the system.[6] Fortunately, our estimates are consistent across both cases, regardless of the chosen estimator.

We also acknowledge the unique characteristics of some of our variables. In particular, our *Info Hide* variable can be viewed as an ordered or nominal categorical variable. As such, our robustness checks 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 additional controls (e.g., funding format, funding status) and data splits. These robustness checks help us to establish the robustness of our estimates under varying assumptions.

[6] Wooldridge (2002) states: "When estimating a simultaneous equations system, it is important to remember the pros and cons of full system estimation … single-equation methods are more robust. If interest lies, say, in the first equation of a system, 2SLS is consistent and asymptotically normal provided the first equation is correctly specified and the instruments are exogenous. However, if one equation in a system is misspecified, the 3SLS or GMM estimates of all the parameters are generally inconsistent."

Data & Descriptive Statistics

We are fortunate to have access to all recorded data that is associated with this marketplace, over an 8-month period, between January and August of 2012. Our dataset includes proprietary information associated with site-wide activity, campaign-level activity, users and user behaviors. Table 2 provides a list of variable definitions, and Table 3 provides descriptive statistics for each. In terms of information hiding behavior, we find that it is quite prevalent. 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 same by prior others (rho = 0.12), and ii) the number of prior contributors (rho = 0.15). As noted in our model formulation section, contributions are skewed, with only the top decile exceeding $100. Figure 3 provides a Kernel Density plot of contribution amounts.

Table 2. Variable Definitions

Variable	Definition
Info Hide	A three value ordinal variable capturing the degree of information hiding exhibited by a contributor in a particular contribution instance.
Contribution	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*.

Table 3. Descriptive Statistics

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

Note: ^{X} is based on IRS data, thus N = 177,574; although N is greater than 300,000 for other variables, we focus on subsample X in our estimations (~50% of sample).

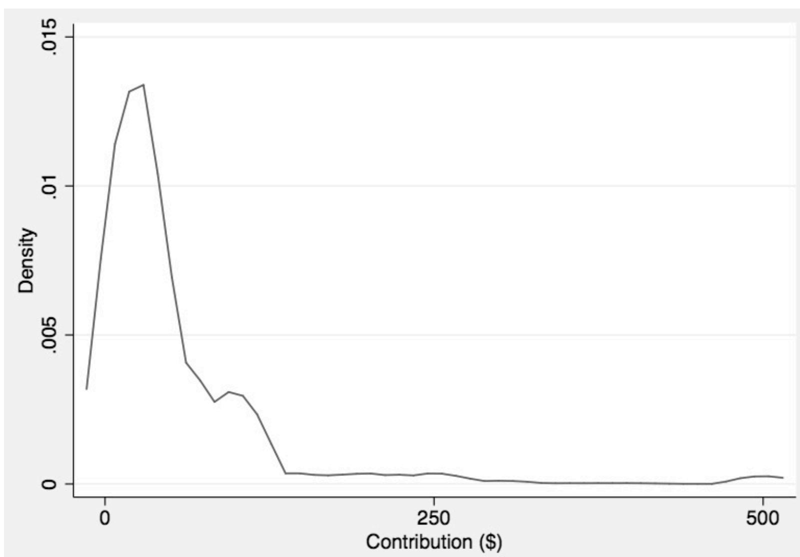

Figure 3. Kernel Density Plot of Contributions

Results

Antecedents

The results of our Antecedent and Consequences estimations are presented in Table 4. Here, we see a number of expected significant effects, supporting our first two hypotheses. First, we see that individuals who are less privacy sensitive (i.e., have opted to connect their Facebook profile to their marketplace 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), providing support for H1a (and evidence contrary to hypothesis H1b). Second, we 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 provide support to hypothesis H2.

Table 4.
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.
*** $p < 0.001$, ** $p < 0.01$.

Next, considering our consequences estimates in the lower panel of Table 4, we find a significant positive coefficient associated with the most recent prior other's contribution, which supports the hypothesized presence of an anchoring effect (H3). Looking at the interaction with amount hiding, we also find that this effect is attenuated when the prior amount is concealed, supporting hypothesis 4.

Importantly, this result suggests that the positive effect from prior contribution is not likely due to homophily (Manski 1993), because we would expect the correlation in contributions to persist even when the prior contribution amounts are concealed, in that scenario. These results, taken in tandem, provide support for hypotheses H3 and H4.

We also see that the effect of prior contributions is stronger when prior others' have concealed their identity. It is possible that this effect results from social comparison, wherein contributors may err on the side of caution, presuming that anonymous others are in fact acquaintances. In contrast, when prior others' identities are revealed, it is perhaps more likely that, more often than not, those prior others are not acquaintances, and thus do not represent an important point of reference.

Finally, we consider the coefficients on our control variables. First, we find a positive coefficient associated with outstanding budget. This suggests that many contributors in the marketplace are driven by altruism or warm-glow, offering greater contributions when the campaign's need is greater (i.e., crowding out). This finding is consistent with the results of Burtch et al. (2013b), while it runs contrary to the findings of Zhang and Liu (2012)[7]. We also find a significant positive effect from the contributor's estimated income, as one would expect. 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, a finding quite similar to that reported by Huberman et al (2005).

We also explored the marginal effects of amount hiding, in order to determine its net effect at various points in the distribution of prior contribution amounts. Doing so, we discover, rather intuitively, 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,

[7] This crowding out effect is not entirely surprising—while evidence of herd behavior has been found in P2P lending contexts, such as Prosper.com, where the primary incentive to contribute is monetary returns, the platform we consider here hosts a wide array of campaigns, large fraction of which represent charitable causes, where contributions are more likely to represent private contributions to public/social goods.

we surmise that the purveyor and campaign organizers would likely benefit from restricted use of information hiding mechanisms, imposed costs on usage, varied information hiding defaults conditional on the size of the associated contribution or, alternatively, efforts at highlighting large contributions, so they receive greater focus.

For example, if small contribution amounts were concealed by default, and larger contributions were revealed, we anticipate that overall contribution volumes would increase in the market. Similarly, if contributors were presented with an indication of the most sizeable prior donation, this might help stimulate larger contributions, by providing a larger point of reference for downstream contributors. A plot of the calculated marginal effects is presented in Figure 4, below. Notably, these marginal effects are articulated on a non-linear scale, given that log-log model specification. As such, the effects of information hiding at the top of the distribution for prior contributions (i.e., large dollar amounts) are much larger in real dollar terms than those at the bottom of the distribution.

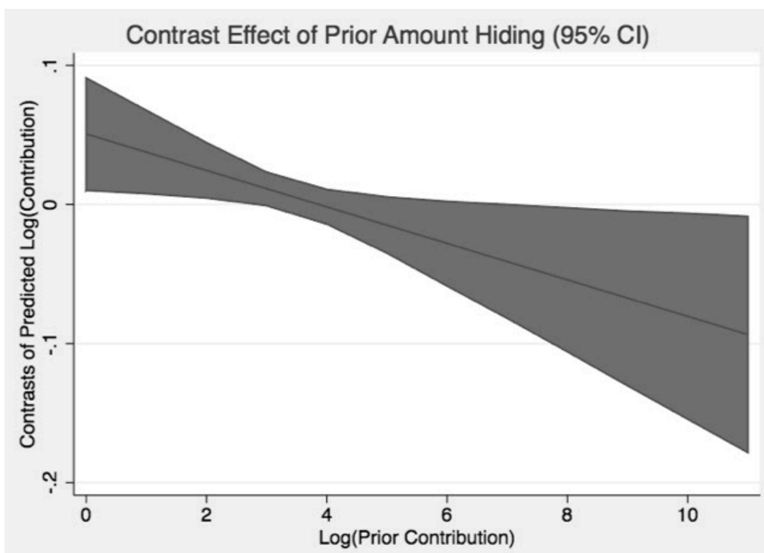

Figure 4. Marginal Effects of Prior Amount Hiding

Robustness Checks

Following our main estimations, we conducted a number of robustness checks. First, we explored potential issues of multicollinearity and outliers. To assess multicollinearity, we obtained variance inflation factors (VIFs) for all of the variables in our models. All values were found to be less than four, which is well below the commonly accepted threshold of ten (Kennedy 2003, pg 213). As such, multicollinearity does not appear to be of great concern. To assess robustness to outliers, we excluded observations associated with campaigns in the top 1% of the distribution in terms of funding goal and those associated with campaigns in the top 1% of the distribution in terms of amount raised. In both cases, this resulted in the exclusion of approximately 11,000 observations. Re-estimating our models on these subsamples produced no notable differences in our coefficients. Again, this resulted in no notable differences in our estimates.

Next, we explored the sensitivity of our results to the choice of estimator, considering single equation estimation (2SLS) rather than system-estimation (3SLS). We did so for a couple of reasons. First, although 3SLS is preferred for the reasons outlined above (i.e., efficiency), it is possible that 2SLS may offer increased robustness over system-based estimation. As outlined above, in our section on endogeneity and identification, 2SLS panel fixed effect estimators explicitly account for heteroskedastic residuals and panel data structures, unlike the 3SLS estimator. Further, 2SLS estimation also provides assessments of instrument strength[8] and exogeneity. Lastly, as Wooldridge (2002) points out, 3SLS is inconsistent if even one equation in the system is misspecified. Fortunately, looking at the estimation results in both tables (Table 5 and Table 6), we can see that all of our key results are robust to the choice of estimator. Further, the convergence between our 2SLS and 3SLS estimation results has the added benefit of suggesting that our instruments are indeed valid.

[8] Some generally accepted statistical measures of instrument strength include those based upon Stock-Yogo (2002) cutoff values, which we employ here.

Table 5.
Antecedents Robustness Checks (2SLS-FE)

DV = Info Hide	**(1)**	**(2)**
Log(Contribution)	**0.20*** (0.02)**	**0.20*** (0.02)**
Facebook Connected	**-0.17*** (0.01)**	**-0.04*** (0.01)**
Log(Exposure)	0.01 (0.00)	-0.00 (0.00)
Facebook Connected X Log(Exposure)	--	**-0.03*** (0.00)**
Is Organizer	**0.54*** (0.02)**	**0.51*** (0.02)**
Time Effects	Yes	Yes
Campaign Effects	Yes	Yes
Observations	177,574	177,574
R^2	0.16	0.16
F-stat	**64.10 (35,169236)**	**65.06 (36, 169325)**
Hansen J	**42.17 (2)**	**39.51 (2)**

Notes: Robust standard errors in brackets, degrees of freedom for test statistics; All Stock-Yogo cutoffs of instrument strength are met.
*** $p < 0.001$, ** $p < 0.05$, * $p < 0.01$.

Following the above, we next considered the possibility that differences in behavior might manifest between individuals who claim reward in exchange for their contributions, and those who do not. For example, one concern might be that the amount contributed by a user could be driven by the cost of a reward they wish to claim. Further, information hiding behavior might prove different for such individuals, who are often required, to share their shipping information with the campaign organizer in order to receive their reward. As such, it is possible that rewards produce a selection bias, drawing in users who are inherently more willing to share personal information. In order to address these types of issues, we re-estimated both of our models, using only those observations where the contributor did not collect a reward for their contribution (approximately one third of our sample). These results, which are fairly consistent with those reported above, are presented in Tables 7 and 8, below.

Table 6.
Consequences Robustness (2SLS-FE)

DV = Log(Contribution)	**(1)**	**(2)**
Log(Last Contribution)	**0.01** (0.00)**	**0.01* (0.00)**
Last Name Hide	0.01 (0.01)	-0.05 (0.02)
Last Amount Hide	0.01 (0.01)	**0.05* (0.02)**
Log(Last Contribution) X Last Name Hide	--	**0.02* (0.01)**
Log(Last Contribution) X Last Amount Hide	--	**-0.01* (0.00)**
Log(Remaining Budget)	**0.01*** (0.00)**	**0.01*** (0.00)**
Log(Days Posted)	**0.01** (0.00)**	**0.01* (0.00)**
Log(Income)	**0.14*** (0.00)**	**0.14*** (0.00)**
Info Hide	**0.57*** (0.04)**	**0.57*** (0.04)**
Time Effects	Yes	Yes
Campaign Effects	Yes	Yes
Observations	170,950	170,950
R^2	0.29	0.29
F-stat	**46.02 (38, 163319)**	**43.96 (40, 163317)**
Hansen J	**150.90 (2)**	**151.11 (2)**

Notes: Robust standard errors in brackets, degrees of freedom for test statistics; All Stock-Yogo cutoffs of instrument strength are met.
*** $p < 0.001$, ** $p < 0.05$, * $p < 0.01$.

Turning our attention to Table 7, our Antecedents re-estimation, we see that information hiding continues to be associated with more extreme contribution and (weakly) greater campaign exposure. When we introduce the exposure interaction with Facebook connectedness, the privacy sensitivity effect fades (*Facebook Connected*). However, we do again see a significant interaction, supporting an audience effect, in line with our past results. Finally, we again see that self-contributors are significantly more likely to conceal information, as before.

Table 7.
Antecedents Robustness (2SLS-FE, No Rewards)

DV = Info Hide	**(1)**	**(2)**
Log(Contribution)	**0.25*** (0.03)**	**0.25*** (0.03)**
Facebook Connected	**-0.25*** (0.01)**	-0.00 (0.02)
Log(Exposure)	**0.01^{X} (0.01)**	**0.01* (0.005)**
Facebook Connected X Log(Exposure)	--	**-0.04*** (0.00)**
Is Organizer	**0.47*** (0.04)**	**0.41*** (0.04)**
Time Dummies	Yes	Yes
Campaign Effects	Yes	Yes
Observations	57,338	57,338
R^2	0.17	0.17
F-stat	**22.04 (35, 53357)**	**23.32 (36, 53356)**
Hansen J	**9.37 (2)**	**8.79 (2)**

Notes: Robust standard errors in brackets, degrees of freedom for test statistics; All Stock-Yogo cutoffs of instrument strength are met.
*** $p < 0.001$, * $p < 0.05$, ^{X} $p = 0.29$.

Next, looking at Table 8, our re-estimation of the Consequences model, we again see a significant, positive association between prior contribution and present contribution (the anchor effect). Further, we see once again that the anchor effect is eliminated by prior others concealing the amount of their contribution. We again observe that information hiding is positively associated with more extreme contribution and self-contribution, and that it is negatively associated with privacy sensitivity. We do not, however, find the same level of support for our exposure hypothesis—we see that the interaction term is only weakly significant (p = 0.17). Interestingly, we also note that the effect of prior contribution is stronger in this subsample analysis, which is to be expected, given that these contributions are in fact donations (thus social information will have a stronger impact). Further, we note that the variance explained is also much higher (39% vs. 29%).

Table 8.
Consequences Robustness (2SLS-FE, No Rewards)

DV = Log(Contribution)	**(1)**	**(2)**
Log(Last Contribution)	**0.02*** (0.01)**	**0.03*** (0.01)**
Last Name Hide	-0.00 (0.01)	-0.01 (0.04)
Last Amount Hide	0.01 (0.01)	**0.11** (0.04)**
Log(Last Contribution) X Last Name Hide	--	0.00 (0.01)
Log(Last Contribution) X Last Amount Hide	--	**-0.03** (0.01)**
Log(Remaining Budget)	**0.05** (0.001)**	**0.005** (0.001)**
Log(Days Posted)	**0.04*** (0.01)**	**0.04*** (0.01)**
Log(Income)	**0.16*** (0.01)**	**0.16*** (0.01)**
Info Hide	**0.47*** (0.05)**	**0.47*** (0.05)**
Time Effects	Yes	Yes
Campaign Effects	Yes	Yes
Observations	55,780	55,780
R^2	0.39	0.39
F-stat	**18.77 (38, 52072)**	**18.02 (40, 52070)**
Hansen J	**25.82 (2)**	**25.69 (2)**

Notes: Robust standard errors in brackets for coefficients, degrees of freedom for test statistics; All Stock-Yogo cutoffs of instrument strength are met.
*** $p < 0.001$, ** $p < 0.01$.

Next, explicitly accounting for the categorical nature of our *Info Hide* variable. First, we employed a Fixed Effects Ordinal Logit estimator, known as the "Blow Up and Cluster" (BUC) estimator. This estimator was recently proposed by Baetschmann et al. (2011), and evaluated by Dickerson et al. (2012) against alternative approaches. Leveraging a random subsample of observations in order to alleviate computational burden[9], in tandem with a first stage prediction of our endogenous contribution amount variable, to address simultaneity, we obtained the results reported in Table 9. These estimates closely parallel those of our main estimation.

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[9] We randomly sampled 10,000 observations, of which 5,675 were dropped because of no within-project variance in the outcome. Because the estimator wraps a standard conditional logit estimator, within-project variance in the outcome variable is necessary to identify fixed effects.

Table 9.
Antecedents Robustness (OLOGIT-FE, Instruments)

DV = Info Hide	**(1)**	**(2)**
Log(Contribution)	**0.87** (0.33)**	**0.87** (0.33)**
Facebook Connected	**-0.93*** (0.11)**	**-0.65* (0.28)**
Log(Exposure)	0.01*** (0.05)	0.02 (0.05)
Facebook Connected X Log(Exposure)	--	**-0.04^{X} (0.03)**
Is Organizer	**1.38*** (0.42)**	**1.32** (0.41)**
Time Effects	Yes	Yes
Campaign Effects	Yes	Yes
Observations	4,325	4,325
-2LL	-2,018.13	-2,017.53
Wald Chi^2	**146.59 (34)**	**443.61 (35)**

Notes: Robust standard errors in brackets for coefficients, degrees of freedom for test statistics.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ^{x} $p = 0.17$

We then employed a Mixed Multinomial Logit estimator (Hole 2007), again with a first stage prediction of contribution to address endogeneity. Doing so, we obtained the estimates reported in Table 10[10]. The output again appears to parallel our initial results in many respects. We see that Facebook connectivity is negatively associated with both amount and identity hiding. Further, though we do see that exposure and self-contribution have opposite influences on each outcome—exposure decreases identity hiding and increases amount hiding, while self-contribution is positively tied to identity hiding and negatively to amount hiding—we surmise that this simply reflects shifts between amount hiding and identity hiding behavior, which indirectly supports our application of an Ordinal Logit estimator. That is, shifting between one outcome and the other would indicate that these two behaviors truly are just varying degrees of the same form of response.

[10] This estimation was implemented using Stata's mixlogit command.

Table 10.
Antecedents Robustness (MLOGIT, Random Intercept)

IV-MLOGIT	**DV** = Amount Hide	**DV** = Name Hide
Log(Contribution)	**0.13* (0.05)**	0.04 (0.07)
Facebook Connected	**-0.34*** (0.04)**	**-0.46*** (0.06)**
Log(Exposure)	**0.013* (0.006)**	**-0.05** (0.01)**
Facebook Connected X Log(Exposure)	0.02 (0.01)	**-0.16*** (0.02)**
Is Organizer	**-0.37*** (0.07)**	**1.98*** (0.06)**
Time Effects	No	No
Campaign Effects	Yes	Yes
Observations	177,574	
-2LL	-139,336.94	
Wald Chi^2	**13,970.68 (12)**	

Notes: Standard errors in brackets for coefficients, degrees of freedom for test statistics; Baseline: fully revealed contribution, model incorporates alternative specific random intercepts.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

We then considered some alternative operationalizations of the independent variables in our models. We re-estimated our Antecedents model replacing our measure of *Exposure* (number of contributors to date) with a binary indicator of whether the campaign was featured on the marketplace homepage. Further, we considered that Facebook connectedness might capture other factors, beyond privacy concern. For example, individuals' willingness to connect via their Facebook profile may simply represent laziness on the part of the user.

Bearing this in mind, we re-estimated or model employing binary indicators of whether individuals actively chose to reveal their year of birth in their account profile on the crowdfunding platform. Unlike Facebook connectedness, such behavior represents additional effort on the part of crowdfunders to share their information (note: even if this detail auto-populated by the crowdfunding platform, users must still consciously opt to share it within their Facebook profile). The results of re-estimations using these different variables are presented in Table 11.

Although the main effect of the *Featured* indicator falls out of our fixed effects estimation due to the within transformation, given that it does not vary over time, we still see, nonetheless, that the information hiding effect associated with privacy sensitive individuals is positively moderated (strengthened) by this condition. Further, we see that our alternative indicator of privacy sensitivity conveys the same result as our Facebook connectedness variable, as individuals who are willing to share their year of birth are less likely to conceal information associated with their campaign contribution.

Table 11.
Antecedents Robustness (2SLS-FE, Alternative Instruments)

DV = Info Hide	**(1)**	**(2)**
Log(Contribution)	**0.21*** (0.02)**	**0.22*** (0.02)**
Revealed YoB	**-0.09*** (0.01)**	**-0.02+ (0.01)**
Revealed YoB X Featured Campaign	--	**-0.22*** (0.02)**
Is Organizer	**0.54*** (0.02)**	**0.51*** (0.02)**
Time Dummies	Yes	Yes
Campaign Effects	Yes	Yes
Observations	177,574	177,574
R^2	0.15	0.15
F-stat	**26.17 (35, 169237)**	**27.99 (36, 169235)**
Hansen J	**47.29 (2)**	**41.88 (2)**

Notes: Robust standard errors in brackets for coefficients, degrees of freedom for test statistics; All Stock-Yogo cutoffs of instrument strength are met.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$.

Finally, we explored some alternative controls in our consequences model. First, we explored the use of a cumulative prior contribution variable, in place of remaining budget, in order to capture the effects of the campaign funding status. We do this primarily because the prior literature has typically operationalized a campaign's funding status by focusing on contributions to date, as opposed to contributions outstanding toward the target. However, although this operationalization has typically been preferred in past work, it is less desirable in our context because it will be confounded with the prior contribution, which we use to operationalize the anchoring effect. As such, we consider this operationalization only as a robustness check, and for the sake of comparison with results reported elsewhere. Doing so, we discover a significant, negative effect and we find no notable changes in our key coefficient estimates. Thus, the results generally parallel our earlier findings.

Second, we considered the role of the campaign's funding format. The platform purveyor enables fundraisers to select one of two funding schemes, which we refer to here as *incremental* and *all-or-nothing*, as outlined previously in our description of the study context. These funding schemes differ in terms of the requirements for payout and campaign fees, thus we wished to confirm that the effects we identified were not driven by a failure to control for these differences (~5% of the contributions in our sample were associated with *all-or-nothing* campaigns). To control for these differences, we expanded our model, incorporating a dummy variable to capture the *all-or-nothing* format, and we then interacted it with our control for remaining budget. Re-estimating our model consequences model with these adjustments, we found no notable differences in our key coefficient estimates.

Managerial Implications

The results of our study have significant implications for practice, policy and website design, both for crowdfunding and online venues more broadly. Understanding the motivations of a user base is key to designing the hosting platform. For instance, considering the results of our antecedent model, consider that individuals' tendency to withhold information when undertaking extreme behavior has both positive and negative consequences.

On the one hand, providing anonymity mechanisms to users is likely to increase rates of participation on a platform, as users need not fear embarrassment or judgment (Goldfarb et al. 2012); instead, they can simply conceal themselves and act as they wish. However, at the same time, disinhibition of this sort can lead to potentially negative behavior, as has been noted extensively in the literature. Perhaps most notable in the present context is that these information-hiding mechanisms create the potential for gaming, as campaign organizers can easily support their own project, unbeknownst to others, sending a false signal of campaign quality (notably, our analysis indicates that such behavior does indeed take place in this market).

This implies that platform purveyors would do well to consider the ancillary impacts of providing information hiding mechanisms to users, which are likely to be context specific, and plan to address them accordingly. Fortunately, recent work notes that even slight modifications to the design of human-computer interfaces can result in significant changes to user behavior, impacting, for example, participation and the quality of user contributions in collective settings (Jung et al. 2010). In the present context, one possible approach to addressing overcoming negative behavior could be to explicitly block self-contributors from concealing their information in a campaign record. Of course, other user actions, such as the contribution of content (e.g., inflammatory comments or product reviews), might be more difficult to address in an automated fashion such as this, and thus might require human oversight.

Additional details about the nature of this relationship could prove useful. For instance, a likely moderator of this relationship between extreme behavior and information hiding is the presence of a social tie between the contributor and the campaign organizer (or their audience). 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.

The relationship between extreme behavior and information hiding is in keeping with prior work on the online disinhibition effect (Suler 2004), however, we would stress that our study actually addresses the converse relationship. That is, whereas online disinhibition speaks to changes in user behavior subject to relative anonymity online, here, we have documented changes in individuals' information hiding behavior conditional on extreme behavior, driven by social comparison. Broadly speaking, future work might attempt to derive the implications of these information-hiding mechanisms for contributor, campaign and marketplace welfare, more broadly. Further, it may also be worth exploring different approaches to enabling information hiding, to achieve an optimal balance across incentives and impacts, including users' desire for privacy, social comparison and reputational gains.

Our finding that privacy sensitive individuals are more likely to withhold their information, particularly as a campaign receives increased exposure, also has important implications for fundraisers and platform purveyors. This is because it is quite likely that privacy sensitive individuals will be less inclined to contribute at all once the campaign exposure crosses some threshold. In turn, this implies that privacy sensitive individuals should be targeted early in the fundraising process, in order to avoid the loss of their contributions altogether.

Further, this suggests that privacy assurances are likely to grow increasingly important as crowdfunding campaigns become more successful or, in a sales context, as products begin to draw greater demand, because of increased attention. An implication of this is that, although campaign organizers or online retailers might be able to get by while neglecting the privacy concerns of contributors at the outset, particularly as early adopters opt in (perhaps desiring the product to the point that they are willing to ignore their privacy concerns), eventually, efforts must be made to accommodate privacy sensitive contributors or consumers if growth is to continue.

Our work offers some insight into potential objective indicators of individuals' willingness to be profiled or to share their information. In particular, as we have done here, such individuals might be identified based on their observable behaviors. In our case, we have considered users' willingness to grant the purveyor access to their Facebook user information via the Open Graph. As well, we have considered their willingness to share personal demographic information (either in their platform user account, or their Facebook profile). Similar indicators are generally available to many online platforms and retailers at this time, thus a similar approach could be leveraged elsewhere.

Once these privacy sensitive users are identified, campaigners or retailers could consider offering an alternative contribution or purchase channel, such as via a third party intermediary in whom privacy sensitive individuals might have more trust. Alternatively, transactions for these individuals could be conducted offsite, or offline entirely, via telephone.

Our consequences results also have important implications, as they highlight the impacts of information hiding on the potential for social comparison, and suggest approaches to stimulating social comparison only when it might be desirable from the purveyor's perspective. 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.

As suggested above, there are a number of strategies that the platform purveyor could undertake to facilitate information hiding primarily in desirable scenarios; the purveyor might institute varied default settings, contingent on the size of the contribution. Further, an additional incentive could be offered to the suppliers of large contributions, in order to encourage them to reveal information (Huberman et al. 2005) or, alternatively, contributors might be made to pay for the ability to observe others' information (Savikhin and Sheremeta 2010).

Our study is of course subject to a number of limitations. First, our findings here are all conditional on contribution (i.e., participation, conversion). As such, a particular concern with instituting any policy changes based on our results is that they do not account for possible shifts in participation rates (and the demographics of the altered user base) that might arise with modifications to the platform design. As a clarifying example, we direct the reader to prior work that has looked at online communities and discussion forums, where empirical evidence suggests that users' posting frequency may decline by as much as 25% with the removal of anonymity features (Kilner and Hoadley 2005; Leshed 2008).

At the same time, however, the relationship is not so obvious as it might at first seem. This is because it is also quite possible that rates of participation can increase with the removal of information hiding mechanisms, particularly if the user base is comprised of individuals who are not particularly privacy sensitive. This is because the provision of such mechanisms may spur otherwise comfortable users to become more privacy sensitive (Tucker 2011). As such, further work is called for, in order to understand how the provision of information control mechanisms of this sort can impact conversion, both in term of users' willingness to share information with the platform purveyor and in terms of consumption or contribution. Of course, any effort to assess the impacts on conversion should also be paired with a parallel assessment of shifts in the quality or nature of contribution and consumption, because it is quite possible that any shifts in conversion could also be offset by countervailing changes in contribution quality or volume. In short, the relationship between privacy sensitivity, human-computer interface and user behavior is quite complex. While our work sheds initial light on one component of the system, further work can help us to understand the remainder.

Prior work suggests that our objective measures of privacy concern (e.g., Facebook connectedness, year of birth, gender) will provide reasonable indications of individuals' true sensitivity, given that they reflect prior decisions to reveal particularly personal information within the same marketplace. Thus, to the degree that privacy sensitivity is inherent and/or static, our archival measures can be expected to act as suitable proxies. However, future work could undertake an explicit evaluation of their correlation with established survey measures of privacy sensitivity in the literature (Dinev and Hart 2006; Malhotra et al. 2004; Smith et al. 1996).

Finally, we would acknowledge that our results are necessarily focused upon American users, because of our need for a sound instrument to address simultaneity between contribution amounts and information hiding (i.e., income, based on IRS data). As such, it is possible that our findings may vary to some degree in other geographies. While all cultures value privacy, the manifestation of privacy concerns and associated responses have been found to vary somewhat across cultures (Milberg et al. 1995). That being said, it is also important to note that Americans comprise more than 50% of visitors to the platform on an average day, and Canadians (who are arguably rather similarly) constitute another 10%. As such, our analysis considers the bulk of extant users in this context. Further, these countries both consist of extraordinarily diverse populations, thus they may in fact provide the optimal context for analyses intended to produce generalizable results.

Our 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 associated with themselves and a specific action they have undertaken. Further, whereas a small volume of prior work has explored endogenous information revelation practices, those scenarios have typically been "all-or-nothing" in nature, in which users were capable only of blanket decisions with respect to hiding or revealing information (e.g., revealing a piece of information to all or none of the external population of observers, revealing all or none of their information to observers). Here, we have explored the determinants of individuals' information hiding (revealing) behavior based across discrete activities (i.e., contribution events). As well, there is likely to be significant differences in behavior between scenarios pertaining to information revelation versus information hiding (i.e., a different default state).

We have also presented one of the first empirical attempts to understand the dynamic influence of individuals' information hiding behavior. Further, we have done so in a 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. The results of our empirical analysis need to be understood in light of some limitations. First, as noted previously, our analyses are conditional on contribution, as we do not observe contributors' decisions about whether to contribute in the first place, or which campaign to support. As such, we would caution the reader about inferring too much from our results. Bearing this in mind, future research can build on our analysis by leveraging clickstream data to identify shifts in conversion rates with the provision, removal or modification of information hiding mechanisms.

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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