Online Appendix

EC.1. Proofs

In this section, we provide proofs of theoretical results.

Proof of Lemma 1. (a) Suppose that $I \geq 0$, i.e.,

$$\Pi^I = \left(\frac{(q_i+q_u)-b(q_i+q_u)^2-p}{(q_i+q_u)-b(q_i+q_u)^2}\right)(2p-2c(q_i+q_u)^2)-C_iq_i-\frac{C_uq_u}{N+1} \geq \Pi^{NI} = \left(\frac{q_i-bq_i^2-p}{q_i-bq_i^2}\right)(2p-2cq_i^2)-C_iq_i.$$

This is possible if $\frac{(q_i+q_u)-b(q_i+q_u)^2-p}{(q_i+q_u)-b(q_i+q_u)^2} \geq \frac{q_i-bq_i^2-p}{q_i-bq_i^2}$, that is $(q_i+q_u)-b(q_i+q_u)^2-(q_i-bq_i^2) \geq 0$. So, customer 1 makes comments whenever she pledges, i.e., $v_1 \geq \frac{p}{(q_i+q_u)-b_1(q_i+q_u)^2}$. Thus, $\mathbb{P}(comment) = \frac{(q_i+q_u)-b(q_i+q_u)^2-p}{(q_i+q_u)-b(q_i+q_u)^2}$ and hence $E[\#of comments] = q_i^n \times \mathbb{P}(comment) = q_i^n\left(\frac{(q_i+q_u)-b(q_i+q_u)^2-p}{(q_i+q_u)-b(q_i+q_u)^2}\right)$. When $I \geq 0$, the creator improves the product whenever there are comments, and hence $\mathbb{P}(improve) = \mathbb{P}(comment)$. In this case, customer 2 also pledges with probability $\frac{(q_i+q_u)-b(q_i+q_u)^2-p}{(q_i+q_u)-b(q_i+q_u)^2}$, and hence $\mathbb{P}(success) = \left(\frac{(q_i+q_u)-b(q_i+q_u)^2-p}{(q_i+q_u)-b(q_i+q_u)^2}\right)^2$.

(b) If $I < 0$, then the creator does not improve the product during the campaign (i.e., $q_f = q_i$) even if customer 1 makes comments, and hence $\mathbb{P}(improve) = 0$. In this case, customer 1 is indifferent between making comments or not, and hence $\mathbb{P}(comment) = \frac{q_i-bq_i^2-p}{q_i-bq_i^2}$ and $E[\#of comments] = q_i^n\left(\frac{q_i-bq_i^2-p}{q_i-bq_i^2}\right)$ or $\mathbb{P}(comment) = E[\#of comments] = 0$. Also, customer 2 also pledges with probability $\frac{q_i-bq_i^2-p}{q_i-bq_i^2}$, and hence $\mathbb{P}(success) = \left(\frac{q_i-bq_i^2-p}{q_i-bq_i^2}\right)^2$. ■

Proof of Proposition 1. **(a)** From (1), we have

$$\begin{aligned}\frac{\partial I}{\partial q_i} = & -\frac{2p^2(2b)((q_i+q_u)-b(q_i+q_u)^2)(q_i-bq_i^2)}{(((q_i+q_u)-b(q_i+q_u)^2)(q_i-bq_i^2))^2} - \frac{2p^2[(1-2b(q_i+q_u))^2(q_i-bq_i^2)]}{(((q_i+q_u)-b(q_i+q_u)^2)(q_i-bq_i^2))^2}\\ & -\frac{2p^2((q_i+q_u)-b(q_i+q_u)^2)(1-2bq_i)(1-b(2q_i+q_u))}{(((q_i+q_u)-b(q_i+q_u)^2)(q_i-bq_i^2))^2} - 4c - 2c\frac{pb((1-bq_i)+(1-b(q_i+q_u))}{((1-b(q_i+q_u))(1-bq_i))^2}\\ & -nq_i^{n-1}\frac{C_u}{(1+q_i^n)^2}.\end{aligned}$$

Because $1-b(2q_i+q_u) \geq 0$; and by Assumption 1, $1-bq_i > 0$ and $1-b(q_i+q_u) > 0$, $\frac{\partial I}{\partial q_i} < 0$ as long as n is not too small when it is negative. So, we assume that

$$\begin{aligned}nq_i^{n-1}\frac{C_u}{(1+q_i^n)^2} > & -\frac{2p^2(2b)((q_i+q_u)-b(q_i+q_u)^2)(q_i-bq_i^2)}{(((q_i+q_u)-b(q_i+q_u)^2)(q_i-bq_i^2))^2} - \frac{2p^2[(1-2b(q_i+q_u))^2(q_i-bq_i^2)]}{(((q_i+q_u)-b(q_i+q_u)^2)(q_i-bq_i^2))^2}\\ & -\frac{2p^2((q_i+q_u)-b(q_i+q_u)^2)(1-2bq_i)(1-b(2q_i+q_u))}{(((q_i+q_u)-b(q_i+q_u)^2)(q_i-bq_i^2))^2} - 4c - 2c\frac{pb((1-bq_i)+(1-b(q_i+q_u))}{((1-b(q_i+q_u))(1-bq_i))^2}\end{aligned}$$

so that $\frac{\partial I}{\partial q_i} < 0$. Also, $\lim_{q_i \to 0^+} I = \infty$ and $\lim_{q_i \to \infty} I = -\infty$. Thus, there exists $\overline{q_i}$ (≥ 0) such that $I \geq 0$ and hence $q_f = q_i + q_u$ if and only if $q_i \leq \overline{q_i}$.

Suppose that $q_i \leq \overline{q_i}$. Then, the first derivative of $\mathbb{P}(comment)$ with respect to q_i is $\frac{\partial \mathbb{P}(comment)}{\partial q_i} = \frac{p(1-2b(q_i+q_u))}{((q_i+q_u)-b(q_i+q_u)^2)^2} > 0$ if and only if $b(q_i+q_u) < 0.5$. Now, suppose that $q_i < \overline{q_i}$. Then, $I < 0$, $q_f =$

q_i, and in one equlibrium, the first derivative of $\mathbb{P}(comment)$ with respect to q_i is $\frac{\partial \mathbb{P}(comment)}{\partial q_i} = \frac{p(1-2bq_i)}{(q_i-bq_i^2)^2} > 0$ if and only if $bq_i < 0.5$. In the other equilibrium, $\mathbb{P}(comment) = 0$.

(b) Suppose that $q_i \le \overline{q_i}$. Then,

$$\frac{\partial E[\#of comments]}{\partial q_i} = q_i^{n-1}\left(\frac{k((q_i+q_u)-b(q_i+q_u)^2-p)}{(q_i+q_u)-b(q_i+q_u)^2} + \frac{q_i p(1-2b(q_i+q_u))}{((q_i+q_u)-b(q_i+q_u)^2)^2}\right) > 0$$

if and only if

$$n > n' \equiv -\frac{q_i p(1-2b(q_i+q_u))}{((q_i+q_u)-b(q_i+q_u)^2)(((q_i+q_u)-b(q_i+q_u)^2-p))}.$$

Now suppose that $q_i > \overline{q_i}$. Then, in one equilibrium

$$\frac{\partial E[\#of comments]}{\partial q_i} = q_i^{n-1}\left(\frac{n(q_i-bq_i^2-p)}{q_i-bq_i^2} + \frac{q_i p(1-2bq_i)}{(q_i-bq_i^2)^2}\right) > 0$$

if and only if $n > n'' \equiv -\frac{q_i p(1-2bq_i)}{(q_i-bq_i^2)((q_i-bq_i^2-p))}$. ■

Proof of Proposition 2. Suppose that $q_i \le \overline{q_i}$. Then, the first derivative of $\mathbb{P}(improve)$ with respect to q_i is $\frac{\partial \mathbb{P}(improve)}{\partial q_i} = \frac{p(1-2b(q_i+q_u))}{((q_i+q_u)-b(q_i+q_u)^2)^2} > 0$ if and only if $b(q_i+q_u) < 0.5$. Now, suppose that $q_i < \overline{q_i}$. Then, $I < 0$, and hence $\mathbb{P}(comment) = 0$. ■

Proof of Proposition 3. When both $q_f = q_i$ and $q_f = q_i + q_u$, The first derivative of $\mathbb{P}(success)$ with respect to q_i is $\frac{\partial \mathbb{P}(success)}{\partial q_i} = 2\left(\frac{q_i - bq_f^2 - p}{q_f - bq_f^2}\right)\left(\frac{p(1-2bq_f)}{\left(q_f-bq_f^2\right)^2}\right)$. Suppose that $q_i \le \overline{q_i}$. Then, $I \ge 0$, $q_f = q_i + q_u$, $\frac{\partial \mathbb{P}(success)}{\partial q_i} \ge 0$ if and only if $b(q_i+q_u) \le 0.5$. Now, suppose that $q_i < \overline{q_i}$. Then, $I < 0$, $q_f = q_i$, and $\frac{\partial \mathbb{P}(success)}{\partial q_i} \ge 0$ if and only if $bq_i < 0.5$. ■

EC.2. Features with Random Value for Customers

In our main analysis, we assume that any additional feature deterministically increases the value that each customer assigns to the product. It is possible that a customer may value some features but not others. In this section, therefore, we consider a case where each customer likes a random fraction of the product features.

In a setting where the number of product features is q_i, we assume that a customer likes $\tilde{q}_i$ features, where $\tilde{q}_i$ follows a Uniform distribution with parameters 0 and q_i. The complexity of the product, though, depends on the actual number of product features q_i. Thus, when the product is not improved during the campaign, each customer i's effective valuation of the product is $v_i \cdot (\tilde{q}_i - bq_i^2)$; and when the product is improved during the campaign, each customer i's effective valuation of the product is $v_i \cdot (\tilde{q}_i + q_u - b(q_i+q_u)^2)$. Here, we assume that there is no uncertainty about q_u as it is suggested by the customer. Keeping the rest of the model as in §2, we numerically analyze these cases according to the setting that we use in §2. Taking the average of randomly generated 10,000 instances, we verify that our theoretical predictions hold.

This analysis enables us to capture the effect of multidimensionality of a design and to show that multidimensionality cannot explain why the probability of campaign success first increases but then decreases. Even if a creator may not be sure whether potential customers will like a certain feature, the creator will believe that an added feature is more likely to be liked than disliked. Thus, the ex-ante probability of campaign success will improve with the number of features as long as each feature is more likely to be liked than disliked.

EC.3. Cost of Commenting

In this section, we consider the case where customer 1 incurs cost of d (>0) when she makes a comment. Suppose that condition (1) holds so that customer 1 anticipates an improvement. Then, customer 1 decides whether to make comments or not by comparing U_1^C when she makes a comment and U_1^{NC} when she does not make a comment, where $U_1^C = \left(\frac{(q_i+q_u)-b(q_i+q_u)^2-p}{(q_i+q_u)-b(q_i+q_u)^2}\right)(v_1((q_i+q_u)-b(q_i+q_u)^2)-p)-d$ and $U_1^{NC} = \left(\frac{q_i-bq_i^2-p}{q_i-bq_i^2}\right)(v_1(q_i-bq_i^2)-p)$.

Thus, customer 1 makes a comment if and only if $U_1^C \geq U_1^{NC}$, i.e.,

$$v_1 \geq \frac{p^2}{(q_i-bq_i^2)((q_i+q_u)-b(q_i+q_u)^2)} + \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-(q_i-bq_i^2)}. \tag{EC.1}$$

Suppose that condition (EC.1) holds. Then, in the first stage, customer 1 decides whether to pledge or not by comparing U_1^P when she pledges and U_1^{NP} when she does not pledge, where $U_1^P = U_1^C$ and $U_1^{NP}=0$. Thus, customer 1 pledges if $U_1^P \geq U_1^{NP}$, i.e., $v_1 \geq \frac{p}{(q_i+q_u)-b(q_i+q_u)^2} + \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-p}$. Next, suppose that condition (EC.1) does not hold. Then, customer 1 decides whether to pledge or not by comparing $U_1^P = \left(\frac{q_i-bq_i^2-p}{q_i-bq_i^2}\right)(v_1(q_i-bq_i^2)-p)$ and $U_1^{NP}=0$. Thus, customer 1 pledges if and only if $v_1 \geq \frac{p}{q_i-bq_i^2}$. Finally, suppose that condition (1) is violated. Then, customer 1 pledges if and only if $v_1 \geq \frac{p}{q_i-bq_i^2}$. We characterize all possible outcomes of this model in the following lemma.

LEMMA EC.A1. ***(a)*** *Suppose that condition (1) holds.*
(i) *Suppose that* $1 \geq \frac{p}{(q_i+q_u)-b(q_i+q_u)^2} + \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-p} \geq \frac{p^2}{(q_i-bq_i^2)((q_i+q_u)-b(q_i+q_u)^2)} + \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-(q_i-bq_i^2)}$.

$$\mathbb{P}(comment) = \mathbb{P}(improve) = \left(1 - \frac{p}{(q_i+q_u)-b(q_i+q_u)^2} - \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-p}\right),$$
$$E[\#of comments] = q_i^n\left(1 - \frac{p}{(q_i+q_u)-b(q_i+q_u)^2} - \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-p}\right),$$
$$\mathbb{P}(success) = \left(1 - \frac{p}{(q_i+q_u)-b(q_i+q_u)^2} - \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-p}\right)\left(1 - \frac{p}{(q_i+q_u)-b(q_i+q_u)^2}\right).$$

(ii) *Suppose that* $\frac{p}{(q_i+q_u)-b(q_i+q_u)^2} + \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-p} < \frac{p^2}{(q_i-bq_i^2)((q_i+q_u)-b(q_i+q_u)^2)} + \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-(q_i-bq_i^2)} \leq 1$.

$$\mathbb{P}(comment) = \mathbb{P}(improve) = \left(1 - \frac{p^2}{(q_i-bq_i^2)((q_i+q_u)-b(q_i+q_u)^2)} - \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-(q_i-bq_i^2)}\right),$$
$$E[\#of comments] = q_i^k\left(1 - \frac{p^2}{(q_i-bq_i^2)((q_i+q_u)-b(q_i+q_u)^2)} - \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-(q_i-bq_i^2)}\right),$$
$$\mathbb{P}(success) = \left(1 - \frac{p^2}{(q_i-bq_i^2)((q_i+q_u)-b(q_i+q_u)^2)} - \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-(q_i-bq_i^2)}\right)\left(1 - \frac{p}{(q_i+q_u)-b(q_i+q_u)^2}\right)$$
$$+\left(\frac{p^2}{(q_i-bq_i^2)((q_i+q_u)-b(q_i+q_u)^2)} + \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-(q_i-bq_i^2)} - \frac{p}{q_i-bq_i^2}\right)\left(1 - \frac{p}{q_i-bq_i^2}\right).$$

(iii) *Suppose that* $\frac{p}{(q_i+q_u)-b(q_i+q_u)^2} + \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-p} \leq 1 < \frac{p^2}{(q_i-bq_i^2)((q_i+q_u)-b(q_i+q_u)^2)} + \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-(q_i-bq_i^2)}$. *Then,* $\mathbb{P}(comment) = \mathbb{P}(improve) = E[\#of comments] = 0$ *and* $\mathbb{P}(success) = \left(1 - \frac{p}{q_i-bq_i^2}\right)^2$.

(b) *Suppose that condition (1) does not hold. Then,* $\mathbb{P}(comment) = \mathbb{P}(improve) = E[\#of comments] = 0$ *and* $\mathbb{P}(success) = \left(1 - \frac{p}{q_i-bq_i^2}\right)^2$.

Overall, there are four possible cases. In Case (a), the creator is willing to improve the product further if customer 1 makes a comment. In Case (a-i), customer 1 makes a comment whenever she pledges. (Note that when $\frac{p}{(q_i+q_u)-b(q_i+q_u)^2} + \frac{d}{(q_i+q_u)-b(q_i+q_u)^2-p} > 1$, customer 1 never pledges.) In Case (a-ii), customer 1 *may not* make a comment although she pledges. In Case (a-iii), customer 1 *never* makes a comment although she may pledge. In Case (b), the creator is not willing to improve the product further.

We numerically analyze these cases according to the setting that we use in §2 and we select d from Uniform(0,0.1). Taking the average of randomly generated 10,000 instances, we show that our theoretical predictions continue to hold.

EC.4. Additional Benefit of q_u

In this section, we consider the case where q_u can have a different impact than q_i. Specifically, customers can benefit more from features added during the campaign than the product features added before the campaign, and hence the customer's utility can increase more with the addition number of features q_u than the initial number of features q_i. Therefore, when the product is improved during the campaign, each customer i's effective valuation of the product is $v_i \cdot (q_i + a \cdot q_u - b \cdot (q_i + q_u)^2)$, where $a \geq 1$. In this case, $(a-1)q_u$ represents the additional benefit of customer-supported product features to the customer's utility, if any (i.e., $a > 1$). This model captures the idea of improving the product during the campaign toward the most desirable paths.

We now explain the differences from our main model in §2. Instead of Assumption 1, we make the following assumption.

ASSUMPTION EC.1. *$q_i - bq_i^2 > p$ and $(q_i + aq_u) - b(q_i + q_u)^2 > p$ such that there exists v_2 such that customer 2's expected utility is positive.*

Following the same steps in backward induction explained in §2, we first revise condition (1) as follows:

$$I \equiv \frac{2p^2(a - b(2q_i + q_u))}{(q_i - bq_i^2)((q_i + aq_u) - b(q_i + q_u)^2)} - 2c\left(2q_i + q_u + \frac{p(q_u + (2-a)q_i)}{(1 - bq_i)((q_i + aq_u) - b(q_i + q_u)^2)}\right) - C_u \geq 0. \quad \text{(EC.2)}$$

Then, we obtain the following lemma.

Lemma EC.A2. *(a) Suppose that $I \geq 0$. Then $\mathbb{P}(comment) = \mathbb{P}(improve) = \frac{(q_i+aq_u)-b(q_i+q_u)^2-p}{(q_i+aq_u)-b(q_i+q_u)^2}$, $E[\#of comments] = q_i^n\left(\frac{(q_i+aq_u)-b(q_i+q_u)^2-p}{(q_i+aq_u)-b(q_i+q_u)^2}\right)$, and $\mathbb{P}(success) = \left(\frac{(q_i+aq_u)-b(q_i+q_u)^2-p}{(q_i+aq_u)-b(q_i+q_u)^2}\right)^2$.*
(b) Suppose that $I < 0$. Then, $\mathbb{P}(comment) = \frac{q_i-bq_i^2-p}{q_i-bq_i^2}$ and $E[\#of comments] = q_i^n\left(\frac{q_i-bq_i^2-p}{q_i-bq_i^2}\right)$ or $\mathbb{P}(comment) = E[\#of comments] = 0$. Also, $\mathbb{P}(improve) = 0$ and $\mathbb{P}(success) = \left(\frac{q_i-bq_i^2-p}{q_i-bq_i^2}\right)^2$.

We numerically analyze these cases according to the setting that we use in §2 and we select a from Uniform(1,2). Taking the average of randomly generated 10,000 instances, we show that our theoretical predictions hold. This analysis enables us to capture the effect of multidimensionality of a design and to show that multidimensionality of a design by itself cannot explain all our empirical observations.

EC.5. Endogenous Addition and Removal of Features during Campaign

In this section, we first theoretically analyze the case where the creator can add or remove an endogenously determined number of product features during the campaign. Then, we empirically test our theoretical prediction about removal of product features and show robustness of our results.

Theoretical Model and Analysis. In this section, we consider the case where customer 1 makes comments to entice the creator to add new feature(s) to the product or remove some of existing feature(s) from the product during the campaign. So, q_u represents the change in the number of features instead of the additional number of features. We only explain the differences from our main model in §2.

As q_u can be negative, the creator's expected profit with an improvement is $\Pi^I = \left(\frac{(q_i+q_u)-b(q_i+q_u)^2-p}{(q_i+q_u)-b(q_i+q_u)^2}\right)(2p-2c(q_i+q_u)^2) - C_iq_i - \frac{C_u}{N+1}|q_u|$. Thus, the creator improves the product during the campaign if and only if $\Pi^I \geq \Pi^{NI}$, i.e.,

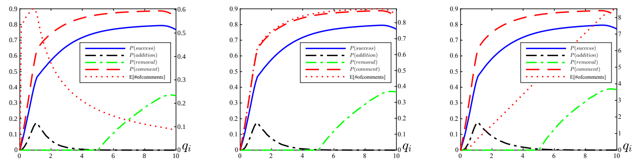
$$I \equiv \frac{2p^2(1-b(2q_i+q_u))q_u}{q_i(q_i+q_u)(1-b(q_i+q_u))(1-bq_i)} - 2cq_u\left(2q_i+q_u-\frac{p}{(1-b(q_i+q_u))(1-bq_i)}\right) - \frac{C_u}{N+1}|q_u| \geq 0. \quad \text{(EC.3)}$$

Suppose that $I \geq 0$. Then, customer 1 makes comments in Stage 2 if and only if $U_1^C \geq U_1^{NC}$, i.e.,

$$v_1((q_i+q_u)-b(q_i+q_u)^2-(q_i-bq_i^2)) \geq \frac{p^2\left((q_i+q_u)-b(q_i+q_u)^2-(q_i-bq_i^2)\right)}{(q_i-bq_i^2)(q_i+q_u)-b(q_i+q_u)^2}. \quad \text{(EC.4)}$$

We discuss two possible cases where q_u is endogenously determined. We first consider the case where customer 1 decides on q_u in stage 2 by maximizing her utility. So, the optimal change in the number of features is $q_u^* = arg\ \max_{q_u\in\mathbb{R}}\left(1-\frac{p}{(q_i+q_u)-b(q_i+q_u)^2}\right)(v_1((q_i+q_u)-b(q_i+q_u)^2)-p)$. Evaluating the first-order condition of this utility-maximization problem, we characterize q_u^* as $q_u^* = \frac{1}{2b} - q_i$.

We numerically analyze this case according to the setting that we use in §2 and where $q_u^* = \frac{1}{2b} - q_i$. Taking the average of randomly generated 10,000 instances, we show that our theoretical predictions about $\mathbb{P}(comment)$, $E[\#of comments]$, and $\mathbb{P}(success)$ continue to hold. As it can



(a) $n=-1$. (b) $n=0$. (c) $n=1$.

Figure EC.5.1 The impact of the initial development level q_i on $\mathbb{P}(comment)$, $E[\#of comments]$, $\mathbb{P}(improve)$, and $\mathbb{P}(success)$. The average of randomly generated 10,000 instances. The setting is the same as in Figure 3.

be seen from Figure EC.5.1, we also show that as q_i increases, the probability that the creator adds feature(s) during the campaign (i.e., $\mathbb{P}(addition)$) first increases but then decreases; and the probability that the creator removes feature(s) during the campaign (i.e., $\mathbb{P}(removal)$) first increases but then decreases. The intuition is as follows. When q_i is small, the customer prefers an increase in the number of features, and hence q_u is positive. In this case, $\mathbb{P}(addition)$ first increases because the probability that the customer pledges and makes comments increases, but then $\mathbb{P}(addition)$ decreases because it becomes too costly for the creator to make any additions. On the other hand, when q_i is large, the customer prefers a decrease in the number of features, and hence q_u is negative. Again in this case, $\mathbb{P}(removal)$ first increases but then decreases. Notice that when q_i is moderate, $\mathbb{P}(addition)$ and $\mathbb{P}(removal)$ are very small because in this case, q_i is very close to the number of features that maximizes the creator's profit. Thus, the additional cost of adding or removing a feature can not be compensated by the small increase in the chance of campaign success.

In addition to the case where customer 1 decides on q_u in stage 2, we also show similar results when the creator decides on q_u in stage 3, and hence the optimal change in the number of features is $q_u^* = arg\ \max_{q_u\in\mathbb{R}} \left(1 - \frac{p}{(q_i+q_u)-b(q_i+q_u)^2}\right)(2p - 2c(q_i+q_u)^2) - C_i q_i - \frac{C_u}{N+1}|q_u|$.

This analysis provides two key findings. First, our main result about the impact of q_i on $\mathbb{P}(improve)$ for any $q_u(>0)$ in §2.3 continues to hold when q_u is optimized either by the customer or by the creator and when q_u^* is positive. Second, when q_i is large, the likelihood of removal of features from the product first increases and then decreases.

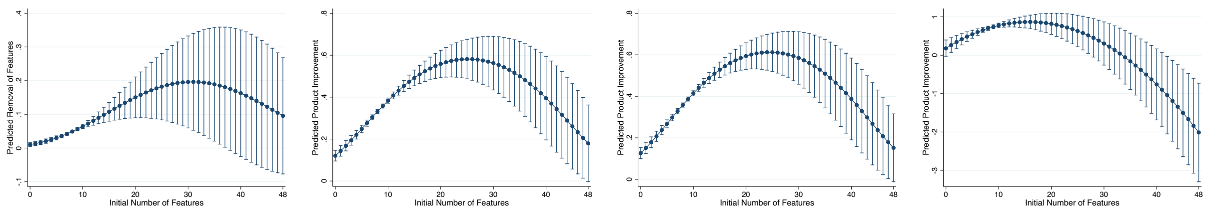
Next, we empirically test the impact of q_i on $\mathbb{P}(removal)$, and also show the robustness of our results considering the alternative definitions of product improvement.

Empirical Model and Analysis. To test the impact of the initial number of features on removal of features, we define removal of features R_k for each campaign k. Specifically, $R_k = 1$ if $q_{fk} < q_{ik}$; otherwise, $R_k = 0$. We observe that in 6% of campaigns, $q_{fk} < q_{ik}$. Replacing I_k in our IV Model 2 in §3.3 with R_k, we obtain the results in column (1) of Table EC.5.1. As Figure EC.5.2(a) illustrates, the likelihood of removal of features first increases and then decreases with the initial number of

Table EC.5.1 Results of IV model 2 with alternative definitions of product improvement.

	(1) Second Stage of IV Model 2 Removal of features	(2) Second Stage of IV Model 2 Removal of features	(3) Second Stage of IV Model 2 Product improvement (Alternative definition 1)	(4) Second Stage of IV Model 2 Product improvement (Alternative definition 2)	(5) Second Stage of IV Model 2 Product improvement (Alternative definition 3)
Initial number of features	.071***	.097***	.108***	.114***	.102***
	(.013)	(.014)	(.007)	(.007)	(.014)
Initial number of features^2	-.002***	-.002***	-.002***	-.002***	-.002***
	(0)	(0)	(0)	(0)	(0)
Residuals	.013	.007	-.023***	-.021***	-.06***
	(.013)	(.015)	(.007)	(.007)	(.012)
Residuals^2	0	0	0	0	0
Controls	Yes	Yes	Yes	Yes	Yes
Constant	-2.469***	-2.464***	-1.122***	-1.152***	.2*
	(.154)	(.136)	(.083)	(.081)	(.12)
Wald χ^2	1288.29	1270.06	2562.33	2709.80	319.41
R^2 or Pseudo R^2	.089	.134	.089	.105	.018
Observations	18,173	13,456	18,173	18,173	18,173

*Nonparametric bootstrap standard errors (100 replications) in parentheses. *** p<.01, ** p<.05, * p<.1*



(a) Removal of Features (b) Alternative Definition 1 (c) Alternative Definition 2 (d) Alternative Definition 3

Figure EC.5.2 Predicted likelihood of removal of features and product improvement.

features, supporting our theoretical prediction. We also run the same model after we remove 4,717 observations where $q_{fk} > q_{ik}$. As column (2) of Table EC.5.1 shows, our results continue to hold.

Robustness Analyses about Removals. As an additional robustness check, we also include both removal and addition of product features while defining product improvement I_k for each campaign k. Specifically, $I_k = 1$ if $q_{fk} > q_{ik}$ or $q_{fk} < q_{ik}$; otherwise, $I_k = 0$. We observe that in 26% of campaigns, $q_{fk} > q_{ik}$; and in 6% of campaigns, $q_{fk} < q_{ik}$. As shown in column (3) of Table EC.5.1, our results about H2 continue to hold when we consider the decrease in the number of product features as product improvement (see Figures EC.5.2(b)).

Additionally, we use another alternative definition of product improvement. Specifically, instead of comparing the final number of product features with the initial number of product features, we analyze any addition or removal of a feature during the campaign. By this way, we identify additional 394 campaigns where $q_{fk} = q_{ik}$ but there is a change in the existing features during the campaign, and we classify them as $I_k = 1$ in addition to campaigns where $q_{fk} > q_{ik}$ or $q_{fk} < q_{ik}$. As shown in column (4) of Table EC.5.1, our results about H2 continue to hold (see Figures EC.5.2(c)). Finally, as shown in column (5) of Table EC.5.1, our results about H2 continue to hold when we define a continuous measure of product improvement, i.e., $I_k = q_{fk} - q_{ik}$ (see Figures EC.5.2(d)).

EC.6. Impact of Existence of Comments on Product Improvement

In this section, we analyze the impact of the existence of comments EC_k on product improvement I_k. As in all IV models, we regress the initial number of features q_{ik} on the instrumental variable B_k and control variables in the first stage, and obtain the predicted residuals $\hat{u}_k$ to use in the second stage. Since our aim is to analyze the impact of the existence of comments EC_k on product improvement I_k, we have two steps in the second stage. First, as in our IV Model 1a, we analyze the exogenous impact of q_{ik} on the existence of comments EC_k. Second, as in our IV Model 2, we analyze the the exogenous impact of q_{ik} on product improvement I_k, but this time we add the existence of comments EC_k to this regression. Therefore, we obtain the following first-stage regression and two second-stage regressions, respectively:

$$q_{ik} = \alpha_0 + \alpha_1 B_k + \alpha_X X_k + u_k,$$

$$P(EC_k) = \Phi(\beta_0 + \beta_1 q_{ik} + \beta_2 (q_{ik})^2 + \beta_3 \hat{u}_k + \beta_4 (\hat{u}_k)^2 + \beta_X X_k + v_k), \text{ and}$$

$$P(I_k) = \Phi(\gamma_0 + \gamma_1 q_{ik} + \gamma_2 (q_{ik})^2 + \gamma_3 EC_k + \gamma_4 \hat{u}_k + \gamma_5 (\hat{u}_k)^2 + \gamma_X X_k + z_k).$$

As our two dependent variables in the second stage are binary, we use a biprobit model to jointly

Table EC.6.1 Impact of Customer Feedback on Product Improvement

	(1) First Stage of IV Models Initial number of features	(2) Second Stage of IV Model with Biprobit Existence of comment(s)	(3) Second Stage of IV Model with Biprobit Product improvement	(4) Second Stage of IV Model with Biprobit Existence of comment(s)	(5) Second Stage of IV Model with Biprobit Product improvement
Before relaxation of rules	3.051***				
	(.168)				
Customers' previous pledges	-.001***	0***	-.001***	-.001***	-.001***
	(0)	(0)	(0)	(0)	(0)
Customers' previous comments (log)				5.106***	
				(.438)	
Initial number of features		.134***	.052***	.141***	.056***
		(.012)	(.016)	(.013)	(.013)
Initial number of features^2		-.002***	-.002***	-.002***	-.002***
		(0)	(0)	(0)	(0)
Residuals		-.064***	-.002	-.071***	-.004
		(.011)	(.012)	(.012)	(.012)
Residuals^2		.001**	0	.001**	0
		(0)	(0)	(0)	(0)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	-2.025***	-.9***	-1.195***	-1.116***	-1.184***
	(.465)	(.093)	(.1)	(.095)	(.099)
Existence of comment(s)			.834***		.746***
			(.169)		(.062)
ρ			-.189***		-.145***
			(.104)		(.036)
Wald χ^2	7120.96	5589.41	5589.41	5896.59	5896.59
R^2 or Pseudo R^2	.415				
Observations	13,568	13,568	13,568	13,568	13,568

*Nonparametric bootstrap standard errors (100 replications) in parentheses. *** p<.01, ** p<.05, * p<.1*

estimate them (e.g., Liu et al. 2019, Freeman et al. 2021). Columns (1), (2), and (3) of Table EC.6.1 show the results of the first-stage regression and two steps in the second-stage (i.e., biprobit). As it can be seen from columns (2) and (3) of Table EC.6.1, the impact of the initial number of features on the likelihood of the existence of comments ($\beta_1 = 0.134$ and $\beta_2 = -0.002$, $p < 0.01$) and on the likelihood of product improvement ($\gamma_1 = 0.052$ and $\gamma_2 = -0.002$, $p < 0.01$) continue to hold. Also, as it can be seen from column (3) of Table EC.6.1, the coefficient of the existence of comments EC_k is positive and significant ($\gamma_3 = 0.834$, $p < 0.01$), which suggests that the likelihood of product improvement increases with the existence of comments. Although our biprobit model can be estimated without an instrumental variable for the existence of comments EC_k (e.g., Freeman et al. 2021), we use $log_{10}(Customers\text{'}\ previous\ comments + 1)$ as the instrumental variable for the existence of comments EC_k. As columns (4) and (5) of Table EC.6.1 show, the results are very similar to the results of the model without the instrumental variable.

Overall, these analyses show that our main results about the impact of the initial number of features on the existence of comments and product improvement continue to hold when we consider

Table EC.7.1 Mediating role of product improvement

	(1) First Stage of IV Model Number of improvements	(2) Second Stage of IV Model Campaign Success	(3) First Stage of IV Model Number of improvements	(4) Second Stage of IV Model Campaign Success	(5) First Stage of IV Model Number of improvements	(6) Second Stage of IV Model Campaign Success
Before relaxation of rules	.168***		.1*			
	(.04)		(.057)			
Customers' previous pledges					-.001***	-.007***
					(0)	(0)
Customers' previous comments (log)					1.274***	
					(.232)	
Number of improvements		1.494***		2.278		1.134***
		(.525)		(215.368)		(.201)
Number of improvements ^{2}		.006		.004		.014
		(.018)		(.022)		(.018)
Residuals		-1.398***		-2.167		-1.042***
		(.527)		(215.369)		(.202)
Residuals ^{2}		-.005		-.003		-.013
		(.018)		(.022)		(.018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	.253**	1.768***	.389**	1.269	.517***	2.289***
	(.124)	(.3)	(.168)	(130.138)	(.145)	(.214)
Wald χ^2	150.49	1576.92	127.60	472.63	191.63	1438.27
R^2 or Pseudo R^2	0.007	.206	0.009	.195	0.014	.254
Observations	18,173	18,173	13,568	13,568	13,568	13,568

*Nonparametric bootstrap standard errors (100 replications) in parentheses. *** p<.01, ** p<.05, * p<.1*

the impact of the existence of comments on product improvement; and the existence of comments has a positive effect on the likelihood of product improvement.

EC.7. Mediation Analysis

Impact of Product Improvements. In §3.6, we analyze the exogenous impact of product improvements. In this section, we analyze the mediating role of product improvements.

We first analyze the impact of the *initial number of features* (q_{ik}) on *campaign success* (S_k) through product improvements. In this analysis, product improvement is the mediator, and as we use the control function approach, we generate a continuous measure which is the *number of improvements* $NI_k = q_{fk} - q_{ik}$ for each campaign k. As our instrumental variable for q_{ik}—*before relaxation of rules* (B_k)—does not directly affect product improvements, we can use it to tease out the mediation. Specifically, by instrumenting the *number of improvements* NI_k with B_k, we estimate the impact the impact of q_{ik} on S_k mediated through NI_k. We obtain the following IV model (IV Model M1) with the first-stage and second-stage regressions, respectively:

$$NI_k = \alpha_0 + \alpha_1 B_k + \alpha_X X_k + u_k, \text{ and}$$
$$P(S_k) = \Phi(\beta_0 + \beta_1 \cdot NI_k + \beta_2 (NI_k)^2 + \beta_3 \hat{u}_k + \beta_4 (\hat{u}_k)^2 + \beta_X X_k + v_k).$$

We next analyze the impact of the number of comments on campaign success through product improvements. As the instrumental variable, *customers' previous comments* (PC_k), does not have a direct effect on product improvements (NI_k), we use it to tease out the mediation following the same approach as above. (Note that in this case, we control for the average number of previous campaigns that those customers pledge, i.e., *customers' previous pledges*.) So, we obtain the following IV model (IV Model M2) with the first-stage and second-stage regressions, respectively:

$$NI_k = \gamma_0 + \gamma_1 PC_k + \gamma_X X_k + u_k, \text{ and}$$
$$P(S_k) = \Phi(\theta_0 + \theta_1 \cdot NI_k + \theta_2 (NI_k)^2 + \theta_3 \hat{u}_k + \theta_4 (\hat{u}_k)^2 + \theta_X X_k + v_k).$$

Table EC.7.1 summarizes the results of the mediation analysis. Column (2) of Table EC.7.1 shows that the likelihood of campaign success increases with product improvements as a result of the

Table EC.7.2 Mediating role of customer feedback

	(1) First Stage of IV Model Number of comments	(2) Second Stage of IV Model Product improvement
Before relaxation of rules	2.016***	
	(.375)	
Number of comments		.096***
		(.017)
Number of comments^2		0***
		(0)
Residuals		-.069***
		(.017)
Residuals^2		0***
		(0)
Controls	Yes	Yes
Constant	-17.461***	.413
	(1.957)	(.301)
Wald χ^2	1109.71	573.93
R^2 or Pseudo R^2	.072	.064
Observations	18,173	18,173

*Nonparametric bootstrap standard errors (100 replications) in parentheses. *** p<.01, ** p<.05, * p<.1*

initial number of features ($\beta_1 = 1.494$, $p < 0.01$; and $\beta_2 = 0.006$, $p > 0.1$). Similarly, column (6) of Table EC.7.1 shows that the likelihood of campaign success increases with product improvements as a result of the number of comments ($\theta_1 = 1.134$, $p < 0.01$; and $\theta_2 = 0.014$, $p > 0.1$), consistent with Cornelius and Gokpinar (2020).

Recall that the data set about customers' previous comments is available for 13,568 campaigns launched before August 2015. When we run IV Model M1 using this smaller data set, as column (4) of Table EC.7.1 shows, the impact of product improvements is weaker.

Impact of Customer Feedback. In §3.6, we analyze the exogenous impact of customer feedback. In this section, we analyze the mediating role of customer feedback. Specifically, we first analyze the impact of the *initial number of features* (q_{ik}) on *product improvement* (I_k) through *number of comments* (NC_k). In this analysis, the *number of comments* (NC_k) is the mediator. As our instrumental variable for q_{ik}—*before relaxation of rules* (B_k)—does not directly affect the number of comments, we can use it to tease out the mediation. Specifically, by instrumenting the *number of comments* NC_k with B_k, we estimate the impact the impact of q_{ik} on I_k mediated through NC_k. We obtain the following IV model (IV Model M3) with the first-stage and second-stage regressions, respectively:

$$NC_k = \alpha_0 + \alpha_1 B_k + \alpha_X X_k + u_k, \text{ and}$$
$$P(I_k) = \Phi(\beta_0 + \beta_1 \cdot NC_k + \beta_2 (NC_k)^2 + \beta_3 \hat{u}_k + \beta_4 (\hat{u}_k)^2 + \beta_X X_k + v_k).$$

Table EC.7.2 summarizes the results of the mediation analysis. Column (2) of Table EC.7.2 shows that the likelihood of product improvement increases with the number of comments as a result of the initial number of features ($\beta_1 = 0.096$ and $\beta_2 = 0$, $p < 0.01$).

EC.8. Details of LDA Model

In this section, we discuss the details of the LDA method (Blei et al. 2003). The LDA method assumes that each document can be represented as a mixture of topics and each topic can be represented as a mixture of words. So, taking a corpus of documents as an input, the LDA method outputs the distribution of topics in each document and the distribution of words in each topic. The distribution of topics in each document is a vector of weights, where the weight of each topic

HAIZE is a new type of navigation system designed for urban cyclists. It works like a magic compass that, instead of pointing north, points to the destination you set in our app. HAIZE leaves you free to choose your own route through the city. It also makes your ride safer by letting you keep your phone in your pocket. HAIZE can easily be attached to any bike and is small and built-to-last so that you can always bring it with you. Our companion app will be available for both Android- and iOS-based smartphones. HAIZE is easy to use. Simply attach it to your bike, set the destination in our companion app, put your phone away and let HAIZE guide you. Its simple LED-based display will point you in the right direction and let you know the distance to your destination. You can select between two different modes of navigation. The compass mode points you in the direction of your final destination and lets you explore along the way. The navigation mode sets a specific route and gives you turn-by-turn directions. Check out the video of HAIZE in action: Check out this video of HAIZE and our app: HAIZE is stripped down to the essence, both the led-based display and the aluminium body combine simplicity with usability. The HAIZE led-display gives you all the information you need at a glance; direction and distance. HAIZE lets you focus on the road and explore the city. If you are interested in additional details about your trip, you can always check the app after your ride. Here you will find stats about your trips and saved routes. The rubber band integrated in the HAIZE body allows you to easily attach it on any bike and keep HAIZE comfortably in your pocket when leaving your bike on the street. The body of HAIZE has been created using machined anodized aluminium, making it both sturdy and stylish. The magnetometer tracks the direction to the destination The accelerometer and gyroscope are used to determine HAIZEs position The light sensor is used to regulate the LED brightness to accommodate different lighting conditions The battery with 300mAh delivers 2 weeks of normal usage and can be easily recharged using a micro usb connection HAIZE is connected to our app via a low power bluetooth 4.0 connection As you can see there is a lot of technology packed into HAIZE...

Existing Topic	0.058*"control" + 0.052*"smart" + 0.037*"sensor" + 0.030*"home" + 0.021*"mode" + 0.021*"button" + 0.019*"connect" + 0.017*"set" + 0.017*"remot" + 0.017*"monitor"

(a) Excerpt from the initial description where words corresponding to an existing feature are highlighted.

HAIZE is minimalist navigation device for urban cyclists. It is designed focusing on high quality materials, style and simplicity. HAIZE works like a magic compass that, instead of pointing north, points to the destination you set in our app. HAIZE leaves you free to choose your own route through the city. It also makes your ride safer by letting you keep your phone in your pocket. If you feel like sticking to the main roads HAIZE also offers turn-by-turn navigation. WHY YOU NEED ONE? 2 navigation modes: "turn-by-turn mode" and "compass mode" Self-regulating LED display for perfect day and night-time visibility Sturdy and high-quality materials Can be used on any bike Wristband to use HAIZE while running, hiking or geo-caching HAIZE is easy to use. Simply attach it to your bike, set the destination in our companion app, put your phone away and let HAIZE guide you. Its simple LED-based display will point you in the right direction and let you know the distance to your destination. You can select between two different modes of navigation. The compass mode points you in the direction of your final destination and lets you explore along the way. The navigation mode sets a specific route and gives you turn-by-turn directions. Check out the video of HAIZE in action: Check out this video of HAIZE and our app: HAIZE is stripped down to the essence, both the led-based display and the aluminium body combine simplicity with usability. HAIZE is made out of aeronautic-grade sandblasted aluminium and shockproof glass. A tested and durable combination that stands out from the first moment. To know a direction you don\'t need to get distracted processing numbers or symbols on a screen. The HAIZE led-display gives you all the information you need at a glance; direction and distance in a simple and intuitive way. HAIZE lets you focus on the road and explore the city. If you are interested in additional details about your trip, you can check them in the app. There you will find stats about your trips and saved routes. HAIZE automatically regulates the brightness of the LEDs to work perfectly under any light condition. It will help you navigate the city no matter what time of the day! The elastic band integrated in the HAIZE body allows you to easily attach it on any bike and keep HAIZE comfortably in your pocket when leaving your bike on the street. And it always stays in place! HAIZE was originally designed for urban cycling. But many of our backers wanted to use it in other situations. That is why we decided to give every backer a wristband to bring HAIZE along to any activity. Be it for hiking, running, or geo-caching. And of course finding your way back to last years perfect mushroom spot. HAIZE will be able to guide you to the best spots while wandering freely. And you can be confident about getting back to the basecamp no matter how many turns you make. The HAIZE wristband is made from high quality silicone and fits perfectly around the aluminum case, allowing you to take HAIZE everywhere. The magnetometer tracks the direction to the destination The accelerometer and gyroscope are used to determine HAIZEs position The light sensor is used to regulate the LED brightness to accommodate different lighting conditions The battery with 300mAh delivers 2 weeks of normal usage and can be easily recharged using a micro usb connection HAIZE is connected to our app via a low power bluetooth 4.0 connection As you can see there is a lot of technology packed into HAIZE...

Existing Topic	0.058*"control" + 0.052*"smart" + 0.037*"sensor" + 0.030*"home" + 0.021*"mode" + 0.021*"button" + 0.019*"connect" + 0.017*"set" + 0.017*"remot" + 0.017*"monitor"
Added Topic	0.059*"materi" + 0.038*"weight" + 0.032*"high" + 0.030*"durabl" + 0.027*"surfac" + 0.023*"made" + 0.022*"blade" + 0.021*"strong" + 0.020*"strength" + 0.020*"resist"

(b) Excerpt from the final description where words corresponding to an existing feature and an added feature are highlighted.

Figure EC.8.1 Initial and final descriptions of the product HAIZE with examples of an "existing" topic that is available in the initial description and an "added" topic that is added to the final description. Tables below excerpts illustrate the most relevant ten words with their weights in these topics.

represents how intensively the topic is used in the document. Similarly, the distribution of words in each topic represents the frequency of words. As product descriptions on campaign pages include explanation of product features, the LDA method is suitable for extracting topics related to these features from product descriptions (e.g., Tirunillai and Tellis 2014, Toubia et al. 2019).

To train the LDA model, we start with 43,536 initial and final descriptions of products in 21,768 campaigns. Following the standard practice (e.g., Tirunillai and Tellis 2014, Toubia et al. 2019), we first pre-process descriptions (e.g., remove stop words, remove descriptions that contain less than ten words and that are not written in English, and stem words). We then fit the LDA model on the corpus of the remaining 42,564 descriptions (from 21,380 campaigns, 196 of which only have a single description after pre-processing) using the standard hyperparameters of $\alpha = 1$ and $\beta = 0.01$ (e.g., Steyvers and Griffiths 2007, Toubia et al. 2019, Ghose et al. 2019), where α and β are parameters of the prior Dirichlet distributions of topics in documents and words in topics, respectively (Blei et al. 2003). Following the rule of $\alpha = 50/T$, where T is the number of topics, (e.g., Steyvers and Griffiths 2007, Tirunillai and Tellis 2014), we set the number of topics to 50. From the trained LDA model, we obtain weights of words in each of 50 topics and weights of topics in each of 42,564 descriptions; all weights are positive. See Table EC.8.1 for all topics with most frequent words and Figure EC.8.1 for an example product description and corresponding topics.

Table EC.8.1 Topics with most frequent words

Topics	Number of Campaigns	Words in Topics with Respective Weights
0	8,157	0.108*"video" + 0.041*"display" + 0.040*"see" + 0.039*"imag" + 0.036*"screen" + 0.033*"view" + 0.031*"photo" + 0.030*"pictur" + 0.029*"show" + 0.019*"digit"
1	15,651	0.098*"prototyp" + 0.070*"design" + 0.069*"product" + 0.057*"final" + 0.057*"test" + 0.043*"first" + 0.025*"readi" + 0.022*"work" + 0.022*"complet" + 0.019*"concept"
2	5,969	0.058*"car" + 0.052*"energi" + 0.040*"electr" + 0.039*"generat" + 0.031*"vehicl" + 0.028*"use" + 0.027*"save" + 0.020*"effici" + 0.020*"cost" + 0.019*"wind"
3	7,202	0.066*"board" + 0.038*"use" + 0.029*"modul" + 0.024*"sourc" + 0.024*"code" + 0.022*"open" + 0.021*"hardwar" + 0.020*"control" + 0.019*"program" + 0.017*"project"
4	8,925	0.037*"day" + 0.031*"page" + 0.027*"week" + 0.027*"month" + 0.025*"word" + 0.024*"goal" + 0.022*"note" + 0.022*"read" + 0.022*"paper" + 0.021*"share"
5	3,478	0.114*"card" + 0.067*"wallet" + 0.061*"pocket" + 0.038*"block" + 0.032*"slim" + 0.025*"carri" + 0.022*"credit" + 0.019*"slot" + 0.016*"hold" + 0.016*"back"
6	9,968	0.231*"one" + 0.117*"two" + 0.076*"small" + 0.054*"line" + 0.046*"three" + 0.033*"larg" + 0.027*"size" + 0.024*"four" + 0.018*"differ" + 0.018*"first"
7	4,949	0.139*"water" + 0.056*"air" + 0.027*"plant" + 0.024*"use" + 0.021*"grow" + 0.017*"pressur" + 0.016*"natur" + 0.015*"environ" + 0.015*"garden" + 0.014*"shower"
8	7,418	0.057*"patent" + 0.045*"comfort" + 0.038*"problem" + 0.030*"bodi" + 0.029*"posit" + 0.028*"head" + 0.027*"sleep" + 0.024*"help" + 0.023*"solut" + 0.022*"invent"
9	8,066	0.113*"part" + 0.105*"build" + 0.065*"kit" + 0.055*"assembl" + 0.031*"step" + 0.030*"need" + 0.028*"make" + 0.026*"built" + 0.024*"includ" + 0.021*"set"
10	9,775	0.068*"easi" + 0.046*"fit" + 0.041*"easili" + 0.034*"use" + 0.034*"quick" + 0.034*"remov" + 0.028*"attach" + 0.026*"simpl" + 0.021*"simpli" + 0.020*"clip"
11	12,480	0.060*"team" + 0.053*"develop" + 0.049*"technolog" + 0.038*"year" + 0.034*"engin" + 0.029*"world" + 0.024*"experi" + 0.024*"innov" + 0.021*"industri" + 0.016*"research"
12	18,106	0.050*"would" + 0.035*"like" + 0.031*"could" + 0.022*"time" + 0.021*"idea" + 0.020*"look" + 0.018*"work" + 0.017*"tri" + 0.016*"start" + 0.015*"think"
13	8,242	0.065*"unit" + 0.040*"current" + 0.036*"measur" + 0.034*"compon" + 0.031*"use" + 0.027*"test" + 0.022*"suppli" + 0.021*"requir" + 0.019*"standard" + 0.018*"wire"
14	4,482	0.061*"heat" + 0.052*"bottl" + 0.044*"glass" + 0.036*"pour" + 0.033*"coffe" + 0.031*"hot" + 0.030*"temperatur" + 0.029*"cup" + 0.025*"cold" + 0.024*"drink"
15	6,209	0.055*"steel" + 0.053*"machin" + 0.045*"pen" + 0.033*"finish" + 0.032*"metal" + 0.032*"stainless" + 0.030*"aluminum" + 0.025*"plate" + 0.023*"cap" + 0.022*"titanium"
16	5,178	0.096*"bag" + 0.056*"leather" + 0.043*"travel" + 0.037*"strap" + 0.028*"fabric" + 0.026*"carri" + 0.025*"pack" + 0.025*"belt" + 0.023*"pocket" + 0.017*"cloth"
17	6,097	0.087*"box" + 0.043*"shirt" + 0.041*"edit" + 0.034*"limit" + 0.029*"seri" + 0.029*"set" + 0.026*"figur" + 0.020*"name" + 0.019*"anim" + 0.019*"origin"
18	13,177	0.076*"reward" + 0.070*"ship" + 0.063*"campaign" + 0.049*"backer" + 0.049*"pledg" + 0.039*"goal" + 0.031*"receiv" + 0.031*"add" + 0.025*"stretch" + 0.023*"pleas"
19	10,970	0.073*"creat" + 0.039*"support" + 0.037*"communiti" + 0.030*"help" + 0.028*"creativ" + 0.023*"art" + 0.023*"dream" + 0.021*"world" + 0.020*"work" + 0.017*"share"
20	13,771	0.208*"product" + 0.056*"market" + 0.041*"compani" + 0.030*"cost" + 0.028*"custom" + 0.027*"price" + 0.025*"manufactur" + 0.025*"need" + 0.025*"order" + 0.023*"busi"
21	16,688	0.062*"want" + 0.057*"make" + 0.053*"get" + 0.032*"know" + 0.027*"peopl" + 0.023*"need" + 0.022*"help" + 0.020*"thing" + 0.019*"let" + 0.019*"way"
22	10,828	0.032*"provid" + 0.029*"peopl" + 0.027*"person" + 0.026*"inform" + 0.019*"servic" + 0.016*"individu" + 0.016*"user" + 0.014*"busi" + 0.014*"site" + 0.014*"locat"
23	3,626	0.076*"sound" + 0.062*"music" + 0.049*"record" + 0.036*"audio" + 0.033*"speaker" + 0.031*"play" + 0.021*"qualiti" + 0.019*"headphon" + 0.018*"listen" + 0.017*"hear"
24	6,136	0.063*"camera" + 0.062*"mount" + 0.048*"mold" + 0.043*"lock" + 0.028*"use" + 0.027*"arm" + 0.026*"angl" + 0.021*"holder" + 0.019*"inject" + 0.018*"design"
25	7,303	0.137*"color" + 0.064*"black" + 0.046*"red" + 0.045*"option" + 0.043*"choos" + 0.042*"avail" + 0.036*"choic" + 0.034*"white" + 0.034*"blue" + 0.028*"colour"
26	4,220	0.214*"light" + 0.082*"led" + 0.031*"use" + 0.031*"night" + 0.025*"len" + 0.022*"bright" + 0.021*"switch" + 0.017*"turn" + 0.016*"lens" + 0.016*"lamp"
27	7,599	0.058*"control" + 0.052*"smart" + 0.037*"sensor" + 0.030*"home" + 0.021*"mode" + 0.021*"button" + 0.019*"connect" + 0.017*"set" + 0.017*"remot" + 0.017*"monitor"
28	9,342	0.059*"materi" + 0.038*"weight" + 0.032*"high" + 0.030*"durabl" + 0.027*"surfac" + 0.023*"made" + 0.022*"blade" + 0.021*"strong" + 0.020*"strength" + 0.020*"resist"
29	6,324	0.056*"data" + 0.039*"access" + 0.032*"secur" + 0.030*"use" + 0.026*"web" + 0.025*"dog" + 0.025*"network" + 0.021*"user" + 0.021*"storag" + 0.020*"comput"
30	7,547	0.057*"made" + 0.057*"piec" + 0.048*"wood" + 0.041*"natur" + 0.038*"beauti" + 0.035*"make" + 0.028*"materi" + 0.027*"shape" + 0.023*"uniqu" + 0.022*"tree"
31	5,947	0.135*"case" + 0.108*"phone" + 0.079*"protect" + 0.052*"cover" + 0.021*"use" + 0.017*"anti" + 0.016*"also" + 0.014*"call" + 0.014*"safe" + 0.014*"back"
32	8,568	0.203*"project" + 0.061*"fund" + 0.034*"rais" + 0.029*"goal" + 0.023*"help" + 0.021*"hope" + 0.021*"money" + 0.021*"flight" + 0.020*"fli" + 0.018*"need"
33	11,045	0.220*"design" + 0.053*"qualiti" + 0.027*"style" + 0.025*"uniqu" + 0.023*"high" + 0.018*"look" + 0.018*"perfect" + 0.017*"function" + 0.016*"collect" + 0.016*"classic"
34	3,889	0.088*"bike" + 0.045*"frame" + 0.042*"ride" + 0.034*"road" + 0.032*"tube" + 0.026*"bicycl" + 0.025*"tire" + 0.025*"front" + 0.023*"seat" + 0.023*"cycl"
35	10,185	0.155*"new" + 0.054*"full" + 0.047*"featur" + 0.027*"plus" + 0.025*"rang" + 0.021*"includ" + 0.019*"great" + 0.019*"first" + 0.018*"offer" + 0.016*"best"
36	13,723	0.027*"use" + 0.022*"may" + 0.022*"mani" + 0.021*"howev" + 0.020*"differ" + 0.017*"result" + 0.016*"effect" + 0.015*"form" + 0.014*"requir" + 0.013*"possibl"
37	7,359	0.057*"famili" + 0.056*"friend" + 0.047*"love" + 0.039*"fun" + 0.037*"children" + 0.023*"child" + 0.022*"help" + 0.021*"toy" + 0.020*"stori" + 0.019*"play"
38	5,796	0.042*"wheel" + 0.026*"gear" + 0.023*"bar" + 0.023*"roll" + 0.020*"get" + 0.020*"ski" + 0.017*"run" + 0.017*"mountain" + 0.016*"feet" + 0.016*"race"
39	4,949	0.061*"clean" + 0.042*"food" + 0.034*"skin" + 0.034*"use" + 0.025*"organ" + 0.022*"contain" + 0.021*"safe" + 0.020*"make" + 0.019*"dri" + 0.019*"time"
40	6,710	0.159*"devic" + 0.064*"cabl" + 0.044*"mobil" + 0.037*"tablet" + 0.034*"use" + 0.028*"appl" + 0.025*"adapt" + 0.025*"work" + 0.021*"support" + 0.020*"station"
41	6,830	0.078*"top" + 0.068*"space" + 0.037*"side" + 0.034*"design" + 0.033*"place" + 0.032*"room" + 0.028*"home" + 0.027*"tabl" + 0.026*"ball" + 0.024*"sit"
42	4,246	0.133*"watch" + 0.033*"time" + 0.032*"movement" + 0.029*"fit" + 0.027*"train" + 0.025*"sport" + 0.025*"band" + 0.020*"strap" + 0.020*"exercis" + 0.018*"activ"
43	8,330	0.117*"system" + 0.038*"perform" + 0.028*"motor" + 0.028*"speed" + 0.025*"engin" + 0.020*"control" + 0.018*"high" + 0.016*"forc" + 0.016*"provid" + 0.015*"mechan"
44	5,661	0.156*"power" + 0.110*"charg" + 0.098*"batteri" + 0.025*"charger" + 0.021*"plug" + 0.020*"time" + 0.020*"panel" + 0.018*"hour" + 0.017*"cell" + 0.014*"portabl"
45	5,660	0.082*"key" + 0.074*"open" + 0.055*"ring" + 0.050*"magnet" + 0.047*"inch" + 0.039*"wall" + 0.033*"stick" + 0.032*"size" + 0.030*"door" + 0.023*"bit"
46	6,900	0.125*"tool" + 0.116*"hand" + 0.079*"use" + 0.051*"handl" + 0.046*"work" + 0.036*"die" + 0.031*"cut" + 0.028*"need" + 0.024*"make" + 0.023*"press"
47	5,031	0.120*"print" + 0.100*"model" + 0.044*"printer" + 0.032*"object" + 0.030*"use" + 0.027*"plastic" + 0.027*"design" + 0.026*"materi" + 0.021*"filament" + 0.019*"creat"
48	4,132	0.085*"stand" + 0.059*"carbon" + 0.045*"pro" + 0.037*"use" + 0.035*"fiber" + 0.028*"ultim" + 0.020*"instrument" + 0.019*"like" + 0.018*"work" + 0.017*"make"
49	7,204	0.053*"learn" + 0.049*"game" + 0.034*"school" + 0.030*"student" + 0.022*"educ" + 0.022*"program" + 0.022*"skill" + 0.020*"class" + 0.017*"experi" + 0.017*"scienc"

EC.9. Validation of Our Metric of Number of Product Features

We analyze the relationship between the development level of a product and the number of features in its description. For this analysis, we turn to another crowdfunding platform, Indiegogo. On Indiegogo, in addition to providing a textual description of a product, each creator also specifies the product's development stage (concept, prototype, production, or shipping). As a more advanced stage typically indicates a higher number of features (Indiegogo 2021), we fit the same LDA model as above to a corpus of 10,047 product descriptions on Indiegogo and analyze the relationship between the product's development stage and the number of features. Because *product stage* is a categorical variable (*concept*, *prototype*, *production*, or *shipping* stage), we use a multinomial logistic regression. We regress *product stage* on *features*, *category*, ln(*goal*), *delivery time*, and *funding type*. All variables are as defined in our main models, and *funding type* is either flexible or fixed, depending on whether the creator can keep the money raised or not when the goal is not reached.

As Table EC.9.1 summarizes, the number of features in concept-stage campaigns is significantly smaller ($p < 0.01$) than the number of features in prototype-stage campaigns, and the number of features in prototype-stage campaigns is significantly smaller ($p < 0.01$) than the number of features in production-stage campaigns. These results show that the number of features significantly predicts the product stage. (Although the number of features in production-stage campaigns is not significantly smaller than the number of features in shipping-stage campaigns, as shipping-stage campaigns are not launched on Kickstarter, this result is not important for our analysis.) As products that are more developed tend to have more features (e.g., Althuizen and Chen 2022), this analysis indicates that our LDA model generates a good proxy for the number of features that products have.

Table EC.9.1 Multinomial logistic regression result for Indiegogo.

mlogit (*N*=4153): Factor change in the odds of *Product stage*
Variable: Initial number of features (standard deviation=8.672)

	b	z	P>z	exp(b)	exp(b*SD)
Prototype vs. *Concept*	0.082	15.998	0.000	1.086	2.038
Production vs. *Concept*	0.108	16.254	0.000	1.114	2.553
Production vs. *Prototype*	0.026	4.572	0.000	1.026	1.252
Production vs. *Shipping*	0.006	0.716	0.474	1.006	1.057
Shipping vs. *Concept*	0.102	11.778	0.000	1.107	2.415
Shipping vs. *Prototype*	0.020	2.452	0.014	1.020	1.185

b = raw coefficient z = z-score for test of b=0
exp(b) = factor change in odds for unit increase in initial number of features
exp(b*SD) = change in odds for standard deviation increase in initial number of features

EC.10. Robustness Checks

In this section, we provide results of probit and IV models for robustness checks that we discuss in §3.4.

Table EC.10.1 Spline regressions for second-stage estimations in IV models.

	Second Stage of IV Model 1a Existence of comment(s)	Second Stage of IV Model 2 Product improvement	Second Stage of IV Model 3 Campaign success
Initial number of features (≤ 30)	0.092***	0.053***	0.073***
	(0.009)	(0.008)	(0.008)
Initial number of features (> 30)	-0.031	-0.115***	-0.056**
	(0.026)	(0.029)	(0.023)
Residuals	-0.074***	-0.036***	-0.046***
	(0.009)	(0.008)	(0.009)
Controls	Yes	Yes	Yes
Constant	-0.767***	-0.929***	2.292***
	(0.074)	(0.076)	(0.083)
Observations	18,173	18,173	18,173

*Nonparametric bootstrap standard errors (100 replications) in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table EC.10.2 Equal time periods before and after IV.

	First Stage of IV Models Initial number of features	Second Stage of IV Model 1a Existence of comment(s)	Second Stage of IV Model 1b Number of comments	Second Stage of IV Model 2 Product improvement	Second Stage of IV Model 3 Campaign success
Initial number of features		.121***	.004	.086***	.138***
		(.014)	(.247)	(.014)	(.016)
Initial number of features^2		-.002***	-.006	-.002***	-.003***
		(0)	(.005)	(0)	(0)
Before relaxation of rules	2.758***				
	(.169)				
Residuals		-.047***	.13	-.012	-.046***
		(.014)	(.245)	(.014)	(.015)
Residuals×Residuals		.001***	.011	0*	.001**
		(0)	(.015)	(0)	(0)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	-1.838***	-.884***	-16.171***	-1***	2.19***
	(.44)	(.1)	(2.915)	(.105)	(.11)
Wald χ^2	6797.80	2874.15	601.55	1045.94	2693.71
R^2 or Pseudo R^2	0.416	.148	0.071	.061	.189
Observations	11,764	11,764	11,764	11,764	11,764

*Nonparametric bootstrap standard errors (100 replications) in parentheses. *** p<.01, ** p<.05, * p<.1*

Table EC.10.3 Treating canceled campaigns as failed campaigns.

	First Stage of IV Models Initial number of features	Second Stage of IV Model 1a Existence of comment(s)	Second Stage of IV Model 1b Number of comments	Second Stage of IV Model 2 Product improvement	Second Stage of IV Model 3 Campaign success
Initial number of features		.121***	.134***	.756***	.103***
		(.014)	(.008)	(.142)	(.007)
Initial number of features^2		-.002***	-.002***	-.006**	-.002***
		(0)	(0)	(.003)	(0)
Before relaxation of rules	3.562***				
	(.134)				
Residuals		-.065***	-.538***	-.028***	-.037***
		(.007)	(.138)	(.007)	(.008)
Residuals×Residuals		.001**	.001	.001***	0*
		(0)	(.006)	(0)	(0)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	-2.738***	-.879***	-14.421***	-1.139***	2.167***
	(.366)	(.079)	(1.883)	(.075)	(.087)
Wald χ^2	11116.64	4251.10	1094.22	1479.75	4058.39
R^2 or Pseudo R^2	0.399	.145	0.057	.051	.178
Observations	21,184	21,184	21,184	21,184	21,184

*Nonparametric bootstrap standard errors (100 replications) in parentheses. *** p<.01, ** p<.05, * p<.1*

Table EC.10.4 When the number of topics is set to 40 in LDA Model.

	First Stage of IV Models Initial number of features	Second Stage of IV Model 1a Existence of comment(s)	Second Stage of IV Model 1b Number of comments	Second Stage of IV Model 2 Product improvement	Second Stage of IV Model 3 Campaign success
Initial number of features		.157***	.557***	.114***	.147***
		(.01)	(.184)	(.009)	(.01)
Initial number of features²		-.003***	.003	-.003***	-.003***
		(0)	(.006)	(0)	(0)
Before relaxation of rules	3.245***				
	(.109)				
Residuals		-.073***	-.524***	-.04***	-.043***
		(.01)	(.143)	(.009)	(.01)
Residuals×Residuals		.001**	.002	0	.001**
		(0)	(.01)	(0)	(0)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	-1.086***	-1.046***	-16.591***	-1.138***	2.078***
	(.334)	(.079)	(1.93)	(.075)	(.086)
Wald χ^2	9343.21	2750.55	2187.54	1067.58	3619.10
R^2 or Pseudo R^2	.411	.156	.073	.045	.207
Observations	18,173	18,173	18,173	18,173	18,173

*Nonparametric bootstrap standard errors (100 replications) in parentheses. *** p<.01, ** p<.05, * p<.1*

Table EC.10.5 When the number of topics is set to 60 in LDA Model.

	First Stage of IV Models Initial number of features	Second Stage of IV Model 1a Existence of comment(s)	Second Stage of IV Model 1b Number of comments	Second Stage of IV Model 2 Product improvement	Second Stage of IV Model 3 Campaign success
Initial number of features		.128***	.632***	.095***	.116***
		(.008)	(.119)	(.008)	(.008)
Initial number of features²		-.002***	-.004	-.002***	-.002***
		(0)	(.003)	(0)	(0)
Before relaxation of rules	3.74***				
	(.139)				
Residuals		-.067***	-.474***	-.028***	-.041***
		(.008)	(.125)	(.007)	(.009)
Residuals×Residuals		.001***	.003	0**	0***
		(0)	(.006)	(0)	(0)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	-3.2***	-.818***	-15.982***	-1.071***	2.266***
	(.385)	(.077)	(1.915)	(.083)	(.083)
Wald χ^2	7867.45	2498.67	1800.05	1682.61	3638.74
R^2 or Pseudo R^2	.391	.153	.073	.062	.203
Observations	18,173	18,173	18,173	18,173	18,173

*Nonparametric bootstrap standard errors (100 replications) in parentheses. *** p<.01, ** p<.05, * p<.1*

Table EC.10.6 When the threshold is set to 8 while counting the number of topics.

	First Stage of IV Models Initial number of features	Second Stage of IV Model 1a Existence of comment(s)	Second Stage of IV Model 1b Number of comments	Second Stage of IV Model 2 Product improvement	Second Stage of IV Model 3 Campaign success
Initial number of features		.125***	.505***	.106***	.116***
		(.008)	(.133)	(.007)	(.008)
Initial number of features²		-.002***	0	-.002***	-.002***
		(0)	(.003)	(0)	(0)
Before relaxation of rules	4.031***				
	(.145)				
Residuals		-.059***	-.429***	-.04***	-.035***
		(.008)	(.116)	(.006)	(.008)
Residuals×Residuals		0	0	0	0*
		(0)	(.01)	(0)	(0)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	-1.928***	-.989***	-16.514***	-1.181***	2.126***
	(.415)	(.078)	(1.944)	(.09)	(.085)
Wald χ^2	9497.34	2711.88	2150.86	1301.31	3583.78
R^2 or Pseudo R^2	.411	.155	.072	.053	.207
Observations	18,173	18,173	18,173	18,173	18,173

*Nonparametric bootstrap standard errors (100 replications) in parentheses. *** p<.01, ** p<.05, * p<.1*

Table EC.10.7 When the threshold is set to 12 while counting the number of topics.

	First Stage of IV Models	Second Stage of IV Model 1a	Second Stage of IV Model 1b	Second Stage of IV Model 2	Second Stage of IV Model 3
	Initial number of features	Existence of comment(s)	Number of comments	Product improvement	Campaign success
Initial number of features		.157***	.736***	.123***	.143***
		(.01)	(.149)	(.01)	(.01)
Initial number of features²		-.003***	-.004	-.003***	-.003***
		(0)	(.004)	(0)	(0)
Before relaxation of rules	3.043***				
	(.115)				
Residuals		-.082***	-.575***	-.046***	-.049***
		(.01)	(.151)	(.01)	(.01)
Residuals×Residuals		.001***	.005	.001*	.001***
		(0)	(.009)	(0)	(0)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	-2.364***	-.851***	-16.06***	-1.213***	2.241***
	(.325)	(.077)	(1.913)	(.083)	(.084)
Wald χ^2	8324.12	2464.41	1835.97	1487.08	3503.61
R^2 or Pseudo R^2	.389	.153	.072	.057	.204
Observations	18,173	18,173	18,173	18,173	18,173

*Nonparametric bootstrap standard errors (100 replications) in parentheses. *** p<.01, ** p<.05, * p<.1*

Table EC.10.8 Control for competition in the first week of each campaign.

	Second Stage of IV Model 1a	Second Stage of IV Model 1b	Second Stage of IV Model 2
	Existence of comment(s)	Number of comments	Product improvement
Initial number of features	.135***	.487***	.104***
	(.009)	(.134)	(.007)
Initial number of features²	-.002***	-.003	-.002***
	(0)	(.004)	(0)
Residuals	-.065***	-.357***	-.032***
	(.008)	(.122)	(.006)
Residuals×Residuals	.001**	.003	0
	(0)	(.007)	(0)
Competition	-.506*	-14.522***	-.499*
	(.262)	(4.437)	(.259)
Controls	Yes	Yes	Yes
Constant	-.862***	-14.876***	-1.107***
	(.076)	(1.671)	(.082)
Wald χ^2	2496.93	2009.62	1476.94
R^2 or Pseudo R^2	.154	.073	.057
Observations	18,173	18,173	18,173

*Nonparametric bootstrap standard errors (100 replications) in parentheses. *** p<.01, ** p<.05, * p<.1*

Table EC.10.9 Excluding Topics 4, 11, 12, 18, 19, 20, 21, 32.

	First Stage of IV Models	Second Stage of IV Model 1a	Second Stage of IV Model 1b	Second Stage of IV Model 2	Second Stage of IV Model 3
	Initial number of features	Existence of comment(s)	Number of comments	Product improvement	Campaign success
Initial number of features		.153***	.674***	.112***	.139***
		(.01)	(.152)	(.008)	(.01)
Initial number of features²		-.003***	-.003	-.003***	-.003***
		(0)	(.005)	(0)	(0)
Before relaxation of rules	3.242***				
	(.115)				
Residuals		-.075***	-.526***	-.033***	-.043***
		(.01)	(.141)	(.007)	(.01)
Residuals×Residuals		.001**	.003	0	.001**
		(0)	(.008)	(0)	(0)
Controls	Yes	Yes	Yes	Yes	Yes
Constant	-1.927***	-.928***	-16.397***	-1.108***	2.179***
	(.328)	(.077)	(1.921)	(.09)	(.084)
Wald χ^2	9413.41	2475.20	2097.97	1483.81	3577.26
R^2 or Pseudo R^2	.400	.154	0.073	.058	.205
Observations	18,173	18,173	18,173	18,173	18,173

*Nonparametric bootstrap standard errors (100 replications) in parentheses. *** p<.01, ** p<.05, * p<.1*