



# Follow the money: Techniques for pricing rewards in crowdfunding projects

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## ARTICLE INFO

### Keywords:

Crowdfunding  
Pricing  
Consumer behavior

## ABSTRACT

Crowdfunding, the practice of funding projects by appealing to the mass market, has grown in the past decade to become a significant path of raising money for various ventures. It works by offering people the ability to give a certain amount of money for some reward they will receive once the project is done. But while plenty of academic research investigates what makes projects successful, there is relatively little dealing with understanding how rewards should be priced and understood, and how they affects a project's success. In this paper, we wish to examine if common pricing techniques used in the “regular” consumer space apply to crowdfunding as well. We constructed the largest dataset of crowdfunding projects, by collecting approximately 180,000 projects from Kickstarter, the largest crowdfunding platform. Using this extensive dataset, we explored several known pricing techniques used for consumers — such as putting a 9 as the last digit, bundle pricing, and anchoring prices — wishing to understand if they work for crowdfunding projects as well. Our results indicate that generally, they do with very high significance (with a few notable exceptions and changes). This helps to show that crowdfunding pricing is more akin to product pricing than to investment-type pricing modes.

## 1. Introduction

The question of how to fund a project, a product, or a venture, when one does not have the necessary money for it, has been at the core of financial innovation for millennia. This is why loans (and interest) were created, the banking system set up, bonds and stock markets established, and, more recently, venture capital firms. Making use of the ability to reach people via the internet, we have seen the rise of *crowdfunding* (Hossain and Oparaocha, 2017). Crowdfunding is the practice of funding projects (or any type of venture) by raising money from an extremely large number of people (Rossi, 2014). This is done typically by designated websites, with Kickstarter<sup>1</sup> being the largest one (Hossain and Oparaocha, 2017; Mollick, 2018).

Crowdfunding has several types, such as donation-based, reward-based, lending-based, or equity-based (Zhao et al., 2019; Bi et al., 2017). We will focus on a reward-based model, in which rewards are offered to potential investors (hereinafter referred to as *backers*) as incentives to *pledge* to a project. Different rewards are offered in return to different amounts of monetary contribution, and the reward can be either physical (e.g., book, meal, signed CD, a pre-purchase of a product) or non-physical (e.g., message, e-book, meet-up). Backers pledge money to a project by paying the amount for desired rewards, usually within a limited timeframe. Once the project is pledged enough money to pass a pre-defined *funding goal*, the project entrepreneur

receives the money, and is supposed to deliver the rewards in due course (Zhao et al., 2019; Bi et al., 2017; Hossain and Oparaocha, 2017; Mollick, 2018). In this “all or nothing” funding method, the pledge is not final, and the backer will only give the money once the funding goal is reached. The crowdfunding platforms themselves take a certain percentage of successfully funded projects' money (Gerber et al., 2012).

Since backing with a certain amount is associated with a particular reward in the main crowdfunding platforms, those rewards play a crucial role in projects' success. Rewards offer a strategy to engage backers in projects, since they answer both selfish motivation — offering an immediate gain for backers — and benevolent motivations, as crowdfunding contributors feel as if they were part of the product and its creation and success (Gerber et al., 2012; Mollick, 2014). Backers may be motivated to invest in the project by a variety of reward strategies, including a limited number of special rewards, the opportunity to receive the product first or as a limited edition, or a bundle of products included in the same pledge (Gerber et al., 2012).

Pricing the rewards of a project is somewhat akin to the pricing of a restaurant menu, with the rewards as dishes. It is quite understandable that people have different tastes and preferences when ordering from this menu, but the price itself may influence their choice. This means that the choice may be influenced by psychological pricing strategies such as the presence of the dish next to cheaper or pricier dishes, or

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<sup>1</sup> <https://www.kickstarter.com>.

the existence of special dishes that are not available every day (Thaler and Sunstein, 2008). We will show that pricing strategy is a significant factor that affects backers' inclination to pledge to a project, regardless of their initial predilections and preferences.

We will focus on Kickstarter, as one of the most used and visited crowdfunding platforms in the world today (Mollick, 2018). Thanks to its popularity, using its data allows us to reach conclusions which are not unique to a specific country or to a particular, niche community (which may have some particular behavior unique to them). Kickstarter raised, up to 2020, over \$5.9 billion in pledges, in more than 200,000 successful projects.<sup>2</sup> The data we collected from its projects (as far as we could ascertain, the largest dataset of crowdsourced projects to be academically studied) offers a unique approach to examine the role of rewards in decision process of backers and in projects' success. Although many studies have been conducted to understand the effect of various aspects on projects success, only few have focused on rewards and even fewer have considered the effect of pricing strategies on projects' final results (Thürriidl and Kamleitner, 2016).

Rewards can be examined from various angles and methodologies, borrowing from economics, marketing, and psychology. In this work, we analyze the impact of rewards' pricing strategies on the success of Kickstarter projects, using factors such as the total number of rewards offered, the items they consist of, and most of all, their pricing. Unlike previous studies, we will focus on financial factors and will examine the pricing strategies used for pledges and explore their relation to projects' success and demand for particular rewards.

## 2. Related work

Crowdfunding has received a lot of research attention in the last decade (including several research overviews Moritz and Block, 2016; Shneur and Vik, 2017; Kaartemo, 2017; Bouncken et al., 2015), in various fields (Hoegen et al., 2018), much of it to do with finding what works for successful projects. Some focus on project updates (Xu et al., 2014; Hobbs et al., 2016) and entrepreneur enthusiasm (Cardon and Stevens, 2009; Chen et al., 2009; Hobbs et al., 2016), some on the dynamic making the early period particularly important (Colombo et al., 2015; Kuppusswamy, 2018), some on the social-network aspect (Lu et al., 2014; Wang, 2016; Kunz et al., 2017), and some on a variety of other topics, including the number of images, videos, project phrasing, etc. (Mitra and Gilbert, 2014; Kunz et al., 2017).

Looking a bit closer at rewards, Cumming et al. (2014) examined "all-or-nothing" reward-based crowdfunding models (like Kickstarter), and compared them to models in which entrepreneurs keep all the donations, regardless of reaching the funding goal. The former was shown to be more profitable.

Indeed, due to its popularity, much research focuses on reward-based crowdfunding, in which the rewards are a major reason for participation (Kuppusswamy, 2018). Hobbs et al. (2016) suggested that the offering of high-quality rewards increases a project's chance of success. Tietz et al. (2016) demonstrated a strategy in which they used "decoy-rewards" from the most popular categories rewards in Kickstarter (a book, a video game, a movie) in order to persuade backers to pledges that most effectively increase the project's profits. Kunz et al. (2017) claim a more straightforward link: an increase in the number of pricing levels for the rewards, as well as limiting the numbers of each reward, is associated with higher success rates.

Ryu and Kim (2016) explored the motivations that drive sponsors to participate in reward-based crowdfunding projects, and identified four types of crowdfunding sponsors: *angelic backers* (akin to charitable donors), *reward hunters* (looking for getting a high return), *avid fans* (passionate regarding the project they invest in), and *tasteful hermits* (who like particular projects but less passionate than the avid fans).

While one may perceive only the reward hunters to be those relevant to this study, we wish to stress that *all* types of agents, regardless of their motivation, need to choose a specific reward from those presented in the project. Thus, various pricing techniques can serve to direct them to particular ones, and their motivation may not be crucial at all (though, due to the nature of our dataset, we are unable to compare them to each other).

Kaartemo (2017) notes that while on donation platforms reward prices do not seem to affect campaign success, they are crucial for other platforms, with larger minimal rewards decreasing the chance of success, despite most projects being funded thanks to a small number of backers who give significant amounts (also, cheap material rewards, i.e., physical ones, not a "thank you" note, hurt donation-based platforms). Kaartemo (2017) also notes that a range and variety of pricing tiers and reward quality matter more than just reward numbers; and also that while projects are often successful with a low funding goal, for some platforms (such as equity-based ones), a higher target helps.

### 2.1. Pricing strategies

Researchers have been working for decades to find optimal *pricing strategies* for the seller, the consumer, or for social welfare (Ng, 2009; Nair, 2019; Nagle et al., 2016; Dudu and Agwu, 2014; Babaioff et al., 2014; Lev et al., 2015). Pricing strategies refer to methods used to price products or services. The research on this topic is extensive, and we cannot possibly do it justice in a few paragraphs.

We will note two papers which have inspired us to look at pricing behaviors in crowdfunding settings: Khoso et al. (2014) on the pharmaceutical sector, and more importantly, Nair (2019) in the hotel sector. We wish to compare crowdfunding pricing strategies with those that are investigated and appearing in areas far-removed from crowdfunding, and so to see if the behavior is similar or not. These particular papers allow us to compare the wildly different domains of the regular, commercial world, with crowdfunding. We use them, in a sense, as a real-world industry baseline to crowdfunding.

Looking concretely at crowdfunding, Hu et al. (2015) examined several crowdfunding strategies,<sup>3</sup> and claimed that changing pricing over time (intertemporal pricing) or offering pricing options (menu pricing) are more profitable than the uniform pricing strategies under certain conditions. The same pricing strategies were used by Du et al. (2020) to evaluate optimal pricing strategy, but no mechanism was found to be strictly dominant in terms of the entrepreneur's expected payoff. Guan et al. (2020b) and Zhang and Tian (2021) examined optimal pricing strategies and optimal funding targets in reward-based crowdfunding setting, based on these strategies as well, using both the all-or-nothing mechanism (as in Kickstarter, where project gets the money only if project is fully funded) or the keep-it-all mechanism (where the money is given to the project even if it is not fully funded). Peng et al. (2020) tied consumer valuations to optimal pricing decisions and connected them to the funding target's decision. Liu et al. (2022) compared menu pricing with and without information disclosure for low price, high price, and intertemporal price. When the target goal is relatively low, the menu price without information disclosure is optimal, while when the target is high and intertemporal pricing strategy is used, information disclosure benefits the creator.

On pricing strategies and whether to set prices higher or lower than average, Tian and Zhang (2022) consider two cases: with and without online reviews, to examine the effect of online reviews on strategic consumer behavior and the choice of pricing strategy. They found that under the influence of information asymmetry and online

<sup>3</sup> *Margin pricing*, in which price is set according to the highest value for investors; *Volume pricing*, where price is set according to lowest value for investors; *Intertemporal pricing*, where price changes over time; and *menu pricing*, when both high and low prices are offered.

<sup>2</sup> According to Kickstarter's public statistics.

reviews, entrepreneurs should adjust their decisions: when the funding goal is low, the penetration pricing strategy (defined below, basically means low initial price) is preferred; while when the funding goal is high the skimming pricing strategy (defined below, basically means high initial price) may be adopted under certain conditions. [Chen and Liu \(2023\)](#) studied how companies with limited capital can communicate the quality of their crowdfunding products to potential customers through advertising and pricing. Their findings revealed that companies offering high-quality products tend to demonstrate their quality by setting lower prices for their crowdfunding products at the beginning. This strategy imposes a cost on companies with lower-quality products, as it diminishes their initial profits and raises the likelihood of crowdfunding failure. Additionally, superior-quality products effectively signal their quality by reducing advertising expenses and maintaining an optimal price under conditions of clear information and minimal herding and independent coefficients. Conversely, when these conditions are not met, high-quality products convey their value through increased advertising spending. [Sewaid et al. \(2021\)](#) examined whether price commitment, discount, and reward classes play a role in conveying information about product quality. According to them, setting a low crowdfunding price when committing to a high retail price enhances campaign performance, although it can prove to be a hurdle when reaching the retail market. They also claimed that larger number of rewards significantly enhances the campaign's outcome, given the rewards' ability to implicitly convey information regarding the future retail price.

On specific pricing strategies in crowdfunding, [Chen et al. \(2019b\)](#) analyzed significant differences in early-bird and versioning pricing strategies (creating different versions of same item) in crowdfunding. [Yang et al. \(2020\)](#) examined the impact of reward limits where campaign creators restrict the number of backers per reward tier and the role of goal-directed mechanisms on crowdfunding success, and [Kuo et al. \(2020\)](#) examined whether showing the current average amount pledged in the fundraising process has an anchoring effect on the subsequent backers' pledge amount.

Our approach is quite similar to that of [Thürriidl and Kamleitner \(2016\)](#), who demonstrated the impact of rewards as strategic assets on campaign success. Using an analysis of 180 successful and unsuccessful Kickstarter projects, they classified rewards along eight dimensions such as Reward Type, Tangibility, Scarcity, Geographical Limitation, Monetary Value/Reward Tier, Recognition, Level of Collaboration and Core Features.

### 3. Data-set

#### 3.1. Context

Among all crowdfunding platforms, Kickstarter is the best known and the largest one. The site is mainly a platform for creators from North America and Europe, hosting projects that range from for-profit to artistic. Entrepreneurs open a page for their project where they pitch it to the crowd of potential backers, set a funding goal to achieve and create pledges with rewards to promote participation. The site claims no ownership over the projects, and takes a 5% fee from the funds if the project succeeds.

In order to extract key data points from Kickstarter crowdfunding platform, we wrote a custom crawler to download Kickstarter projects. A total of 183,943 projects have been extracted (after cleaning), live projects between 2008 and 2019, which are 34.1% of all Kickstarter projects ever launched.<sup>4</sup> Kickstarter offers a wide range of project types, grouped into 15 categories and 160 subcategories. The data set is relatively balanced and includes 46.1% unsuccessful projects and 53.9% successful projects. Over- or under-representation of parameters is unlikely because no variable thresholds have been set (if a project has been hidden it cannot be downloaded, but those are a minuscule amount of projects).

#### 3.2. Measurement

The attributes we collected are listed in [Tables 1 and 2](#), though we did not use all of them. The attributes we used in the statistical tests are described in [Table 3](#).

The structure of Kickstarter pages includes many features, which we divided into 3 types:

**Entrepreneur's properties** Such as: length (time from joining Kickstarter) and breadth of experience in Kickstarter (number of previous projects created/backed by creator).

**Pitch, Media & Marketing properties** Such as: number of images, videos or words in the project page.

**Financial aspects** Such as: number of rewards and the funding goal. Since multiple rewards are offered in a single project, we have a data set containing over a million rewards.

The data at our disposal is significantly larger than the data researched in previous studies, which allows us to conduct statistically significant research and to understand previously unexplored financial factors.

Generally, data was extracted after a campaign has been completed, i.e., we consider the attributes available at the end of the campaign. It is possible that some of these attributes were not available at the start of the project since throughout the campaign, creators can offer new rewards or update the details and images on their project pages. However, most projects do not fundamentally change their reward structure during the project, so our analysis of rewards should still stand.

We adopt the terms commonly used by Kickstarter in this paper:

**Backers** Individuals who support the project by funding at least the minimum amount from funding tiers are called backers.

**Goal** The funding goal is the amount of money that is announced as the final target for the project. Following the closing date announced for funding, the project is no longer open to potential backers. The amount of money raised by the end of the funding period determines whether the project was successful — if the amount raised is greater than the goal.

**Pledges and rewards** There are a number of funding tiers from which a potential backer can select when considering funding a particular project (see [Fig. 1](#)). Each funding tier offers a certain reward, and the pledged amount represents the money collected so far. Terminology wise, we use reward and pledge mostly interchangeably when discussing the funding tier itself, but reward refers to what is offered in return to money, while pledge is the money given by the backer.

### 4. Research questions and hypotheses

Rewards are a major reason why people participate in crowdfunding ([Kuppuswamy, 2018](#)). There are a variety of reward options available, ranging from simple "thank you" emails to exclusive experiences. We examine whether (and how) some pricing strategies affect crowdfunding project success (projects that exceed their fundraising goal) and pledges' demand (the amount of rewards purchased), aiming to help entrepreneurs make useful choices. We hypothesize that there are some pricing strategies that affect backers' inclination to pledge to a project, beyond their initial preference. Many of the strategies that will be presented in this section have been researched in the past in various forms in a wide range of areas, but little in the field of crowdfunding.

We will examine five key pricing strategies: psychological pricing, bundle pricing, market penetration and market skimming, anchoring pricing and scarcity pricing. For each of them we will also show some of the current research on their effectiveness, as well as what existing research exists on using these strategies in a crowdfunding context.

<sup>4</sup> According to Kickstarter Statistics, October 13, 2021.

**Table 1**  
Variables collected from each project.

Conceptual variable	Measurement	Variable label	Operationalization
Project success ratio	Ratio between the amount reached and the funding goal	Rate_of_success	$\frac{Reached}{Goal}$ (continuous)
Project success	Binary variable, which receives a value of 1 if the project succeeded or 0 if the project failed.	Succeeded	$\begin{cases} 1 & \text{If } \frac{Reached}{Goal} > 1 \\ 0 & \text{Else} \end{cases} \quad (1)$ (binary)
Project category	Project category: Film & video, Art, Games etc.	Category	Directly observed (nominal)
Project subcategory	Project subcategory: Action, Drama, Family	Subcategory	Directly observed (nominal)
Project duration	Funding period for the project in days	Length	Directly observed (continuous)
Project start year	The year the project was opened for funding	StartY	Directly observed (continuous)
Updates	The number of updates made by the campaign creator	Updates	Directly observed (continuous)
Comments	The sum of comments from backers and responses from the creator	Comments	Directly observed (continuous)
<b>Pitch, Media &amp; Marketing</b>			
Number of images	The number of images in the project	Images	Directly observed (continuous)
Number of videos	The number of videos in the project	Videos	Directly observed (continuous)
Number of gifs	The number of gifs in the project	Gif	Directly observed (continuous)
Abstract length	Number of characters in the project abstract	AbstractLength	Character counting (continuous)
Description length	Number of characters in the project description	DescriptionLength	Character counting (continuous)
Title length	Number of characters in the project title	TitleLength	Character counting (continuous)
Risks length	Number of characters in the project risks description	RisksLength	Character counting (continuous)
Main image	Binary variable, which receives a value of 1 if the project has a main image or 0 if the project has a main video.	MainImg	Directly observed (binary)
<b>Financial aspects</b>			
Goal	Funding goal amount	Goal	Directly observed (continuous)
Funding tiers	Number of funding tiers related to the project	Number_of_pledges	Pledges counting (continuous)
Funding tiers' median price	Pledge tiers' median price	MinMoney_median	For each project med(minMoney) (continuous)
Variance of funding tiers	Variance in funding tiers prices	Variance_minMoney_ddof0	For each project Variance(minMoney) (continuous)
Number of new backers	The number of new backers	NewBackers	Directly observed (continuous)
Number of returning backers	Number of returning backers	ReturningBackers	Directly observed (continuous)
Rate of limited pledges	Ratio between the number of limited rewards and number of all rewards in the project	Limited_percent	$\frac{limited(yes,max)}{number\_of\_pledges}$ (continuous)
Funding tiers sorted	Whether the pledges' values are displayed in descending order (1-displayed in descending order, 0-else).	Are_pledge_list_sorted	$\begin{cases} 1 & \text{if } sorted(minMoney) \\ 0 & \text{else} \end{cases} \quad (2)$ (binary)
Number of project collaborators	The number of additional creators listed on the campaign page	CollaboratorsAmount	Directly observed (continuous)
<b>Entrepreneur</b>			
Creator facebook	Whether the creator shared his Facebook page	Facebook	Directly observed (binary)
Creator Instagram	Whether the creator shared his Instagram page	Instagram	Directly observed (binary)
Creator Twitter	Whether the creator shared his Twitter page	Twitter	Directly observed (binary)
Creator Youtube	Whether the creator shared his YouTube page	Youtube	Directly observed (binary)
Previous projects created by creator	The number of previous projects the creator has created	Created	Directly observed (continuous) Fixed without the current project
Projects backed by creator	The total number of other projects backed by the creator	Backed	Directly observed (continuous)
Joining date	The creator's joining date to Kickstarter	creator_j_date	Directly observed (nominal)
Time since joining date	The time from creator's joining date to project start date	creator_len_experience	project_s_date - (continuous)

**4.1. QUESTION 1: Does psychological pricing strategy have a significant relationship with pledges demand?**

Psychological pricing is a pricing approach that considers the psychological or subconscious impact on consumers and takes an advantage of common heuristics. It refers to applying prices that appeal to consumers' emotions and relies on emotional reactions, subjective assessments, and feelings towards specific purchases (Blythe, 2005; Dudu and Agwu, 2014; Brassington and Pettit, 2005)

A common psychological effect is rooted in the first digit of a price (far left) being considered the most dominant with regards to purchase decisions. Changes in price may cause 'left-digit effects', meaning that two prices that differ only by one cent are found to be valued at significantly different levels (e.g., \$1.99 and \$2.00; or for whole dollar amounts \$19 and \$20 Carmin and Norkus, 1990; Manning and Sprott, 2009; Kreul, 1982). Prospect theory describes how consumers make decisions based on relative gains and losses, with an inherent bias in perception, since losses appear more meaningful than gains of similar magnitude (loss aversion). Small deviations from a reference point



**Table 2**  
Variables collected from each reward.

Conceptual variable	Measurement	Variable label	Operationalization
Pledge title	Linguistic features of the pledge title	Title	Directly observed (Text)
Pledge description	Linguistic features of the perk descriptions	Words	Directly observed (Text)
Pledge price	Reward value (note that backers can pledge more than the suggested value)	MinMoney	Directly observed (continuous)
Pledge purchases amount	The number of perk purchases	Sold	Directly observed (continuous)
Number of rewards included in the pledge	The number of rewards included in the pledge	Included amount	Directly observed (continuous)
rewards included in the pledge	The names of rewards included in the pledge	Included list	Directly observed (Text)
Whether the pledge was set to limited	Was there a limit on how many pledges can be purchased? values are: yes, max (reached the maximum limit), no	Limited	Directly observed (nominal)
Currency	The pledge payment currencies	Currency	Directly observed (nominal)
Delivery month	The month expected due date for delivering the perk	DeliveryM	Directly observed (ordinal)
Delivery year	The year expected due date for delivering the perk	DeliveryY	Directly observed (ordinal)

**Table 3**  
Variables of statistical tests.

Related strategy	Conceptual variable	Measurement	Variable label	Operationalization
Psychological pricing strategy	Pledge pricing's last digit	The last digit of the pledge price	Reward_price_last_digit	minMoney modulo (10) (continuous)
Bundle pricing strategy	Number of Pledged items	The number of items (rewards) included in a pledge.	Included	Directly observed (continuous)
Scarcity pricing strategy	Rate of limited pledges	Ratio between the number of limited rewards and number of all rewards in the project	Limited_percent	$\frac{\text{limited}(\text{yes,max})}{\text{number\_of\_pledges}}$ (continuous)
Scarcity pricing strategy	Pledges limited groups	Pledges with a limited amount are divided into 3 categories: No (was not limited), Yes (was limited but did not reach the maximum limit), Max (reached to the maximum limit)	Limited_group	Directly observed (nominal)
Scarcity pricing strategy	Pledges near a limited reward — before	Pledges that are before (one pledge above in the project funding tier's menu) a limited reward.	Before_limited	$\begin{cases} 1 & \text{if (next\_pledge\_limited)} \\ 0 & \text{else} \end{cases}$ (3) (binary)
Scarcity pricing strategy	Pledges near a limited reward — after	Pledges that are after (one pledge below in the project funding tier's menu) a limited reward.	After_limited	$\begin{cases} 1 & \text{if (previous\_pledge\_limited)} \\ 0 & \text{else} \end{cases}$ (4) (binary)
Penetration premium pricing strategies	Representative reward price ratio	Dividing the price of the representative reward by the mean of all representative rewards in all projects in the same category	Representative_reward_price_ratio	$\frac{\text{Representing\_pledge\_price}}{\text{mean\_Representing\_pledge\_price\_per\_category}}$ (continuous)
Anchoring pricing strategy	Profit from rewards up to 25\$	The profit that is raised from rewards whose prices are small or equal to \$25	Profit_up25	Sum (minMoney*sold) if (minMoney < 25) (continuous)
Anchoring pricing strategy	Number of pledges up to 25\$	Number of pledges that their price is small or equal to \$25	N	Count if (minMoney < 25) (continuous)

are overvalued when they are considered as loses and vice versa. For example, an item costs \$19.99 would be regarded as a gain comparing with \$20 (Manning and Sprott, 2009; Popescu and Yaozhong, 2007). Another example from the hospitality sector is when customers see a menu price with a “5” or “9” as its terminal digit, they might subconsciously believe they receive a discount. In contrast, a price with a final digit of “1” or “2” may be regarded as an attempt to squeeze more money from the customer (Carmin and Norkus, 1990; Kreul, 1982). Bhattacharya et al. (2012) used a random sample of more than 100 million stock transactions, and found excess purchases at all price levels one penny below round numbers. In the hotels sector, researchers conclude that psychological pricing contributes to the increased profitability (Dudu and Agwu, 2014; Boz et al., 2017; Nair, 2019; Bhattacharya et al., 2012; Collins and Parsa, 2006).

Systematic surveys confirm that in product pricing, the digits 0, 5 and 9 are more common than the other digits and that usually the digit 9 appears particularly often (el Sehity et al., 2005). In Kickstarter, most entrepreneurs price their rewards in round numbers in gaps of 5 or 10 (5, 10, 15, ...). Reward prices are integer numbers, and no fractions are allowed. To examine the dynamics of psychological left digit effect in crowdfunding, we will check prices ending with the digit 9, and other digits as well, to see whether these pledges were more popular, or if a project was more successful than others as a result of the psychological pricing effect. We are not aware of any studies on the left digit effect related to crowdfunding. We hypothesize the following:

**H1. Rewards priced with a 9 in the right-most digit will be more successful than others.**

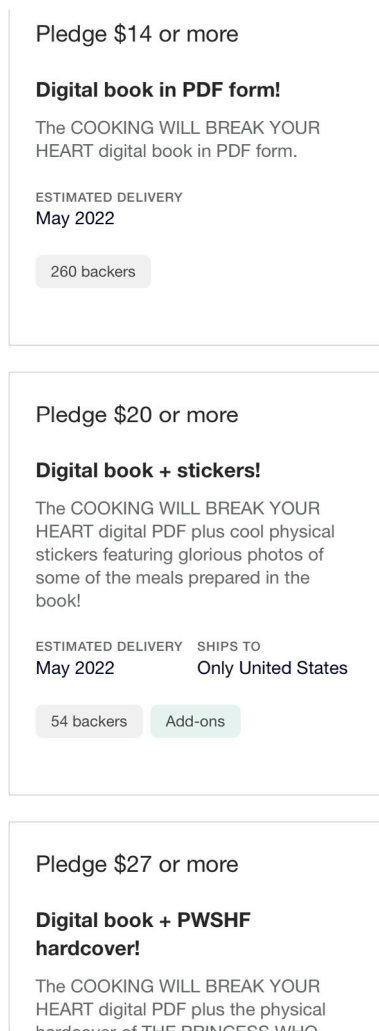


Fig. 1. An example of reward tiers in Kickstarter.

#### 4.2. QUESTION 2: Does bundle pricing strategy have a significant relationship with backers demand for pledges?

Product bundle pricing is a common pricing strategy, intended to increase profitability by bundling a set of products or services together. These products are marketed and priced as a whole to attract various consumers and to address wide range of needs (Rafiei et al., 2013). Many considerations dictate the pricing of a bundle and the goods it consists of, including segmented customer demand, product-specific costs, company's strategy, and competitor products (Yan and Bandyopadhyay, 2011; Hanson and Martin, 1990; Bulut et al., 2009; Bitran and Ferrer, 2007; Gürlér et al., 2009; Taleizadeh et al., 2017). In some cases, bundle pricing is also considered to be beneficial to consumers (Kim et al., 2009).

Myung et al. (2008) concluded that bundle pricing is the most important pricing factor compared to other strategies that were tested to affect consumers preferences; and Simon and Butscher (2001) demonstrated that using such a strategy may increase profitability by 10%–40%. There has been work showing its profitability in software sales (Lehmann and Buxmann, 2009) and electronic commerce (Ancarani et al., 2002; Ettl et al., 2019). Although many studies show that a bundle of products has a positive effect on consumers, Kaicker et al. (1995) claimed that consumers tend to avoid purchasing in bundles if they encounter multiple disappointments with regards to price compared with market prices for the individual products.

Mixed bundling strategy, i.e., selling products both in bundles and separately, is considered by Venkatesh and Mahajaim (1993) as a more profitable strategy than purely individual products or purely bundle pricing. Chu et al. (2011) suggested that while using mixed bundling strategy, pricing the bundles according to their size shows the best results in term of profitability, which was also bolstered by Lee et al. (2011), which demonstrated that when products are also sold separately, in addition to a bundle, pricing of the separate items may stir consumers into buying the bundle; when the additional product to the core product in the bundle is priced high, it encourages people to purchase the bundle.

In the crowdfunding setting, Peng et al. (2020) established that creating two sets of reward packages that differ by their content and size increases the chance for crowdfunding projects success. Thürriid and Kamleitner (2016) suggest, based on a small number of projects, that bundling products represents a core strategy entrepreneurs use to price rewards. According to them, bundling is a good strategy if the marginal cost of topping up a reward bundle is low for the initiator and if there are actual additional benefits readily and easily available. Potential drawbacks of this approach include fostering an opportunistic mindset in supporters. We will examine the effectiveness of bundling products in a pledge as a means of increasing sales. Thus, we hypothesize the following:

#### H2. Bundling products in a single reward will increase the reward's demand.

#### 4.3. QUESTION 3: Does scarcity pricing strategy significantly influence rewards' demand?

Researchers observe that a product's scarcity may generate a higher perceived value than its actual utility. By creating product scarcity — either deliberately or unintentionally — a seller can increase overall demand and grow their profits (Shi et al., 2020). Brock (1968), in association with their commodity theory, argued that scarcity enhances perceived value and desirability. According to Oruc (2015), product scarcity significantly affects variables related to sales, such as perceived value of the product, perceived exclusiveness and popularity, consumer competitive behavior, impulse buying, purchase behavior and intention and willingness to pay. However, they also point out that it may create an opposite response of frustration among consumers.

A particular strategy to create scarcity is using “limited editions” — a special version of an existing product, with some additional features that the regular version does not have (Yang et al., 2020). Balachander and Stock (2009) claimed that although this strategy offers a positive direct effect on profits of the seller, it may also have a negative effect by increasing price competition in the market. Bennett and Kottasz (2013) investigated this strategy's effect on price and valuation perceptions among art consumers, and found that sales can be increased by limiting the number of copies produced.

Yang et al. (2020) examined the above mentioned strategies in a crowdfunding setting, specifically Kickstarter. They concluded that setting a reward limit during the primary stages of the campaign, especially using limited-editions and discount offers, may benefit project success. Moreover, they found that adding a new limited edition reward as the campaign proceeds helps attract new pledges; and that exhausted rewards (i.e., all the limited version items have been given) may cause frustration and damage fundraising efforts.

We suggest that crowdfunding entrepreneurs may harness the effect of limited editions and scarcity to increase pledges and to stir backers to certain desirable pledges. This, by creating limited supply of rewards that are expected to be the most profitable or popular items. However, frustration over unavailability of desired rewards may create the opposite effect and reduce potential pledges to the project. Also, offering too many limited-edition rewards may create the opposite effect of the intended exclusivity. We will examine the effectiveness of limiting pledge as a means of increasing sales. We hypothesize the following:

#### H3. Limiting pledges will increase pledges' demand.

#### 4.4. QUESTION 4: Does market penetration/market skimming pricing strategy significantly affect crowdfunding project success?

Most crowdfunding projects consist of a brand new product or an existing product that has been modified or improved in some way. Before launching it, the product's cost and price are evaluated, comparing it to direct competitors and other products within the same general product category. Broadly, there are two widely-discussed pricing strategies when introducing products to new markets to promote sales and to increase profits:

**Market penetration pricing** This strategy intentionally charges low prices, helping entrepreneurs to discourage competition and take over a sizeable share of the market in order to increase the long-term revenue (Tellis, 1986; Kehagias et al., 2009; Noble and Gruca, 1999; Skripak, 2016; Nair, 2019).

**Market skimming** This pricing strategy attaches a perceived high value to a product by maintaining high price levels at the initial stage (Noble and Gruca, 1999; Tellis, 1986). By creating this image of high-quality or exclusive product it increases revenue and exploits brand loyalty (Huimin and Hernandez, 2011), helping to avoid competition in a specific quality and price category (Kehagias et al., 2009).

Redmond (1989) suggested that market skimming and penetration pricing differ in how many sellers are concentrated in the desired product market in the initial stages, while Noble and Gruca (1999) claim that skimming is generally used in markets with high levels of differentiation by firms with high production costs, and penetration pricing is used in elastic markets with low competition and low production costs. Dolan et al. (1996) recognize that cheaper products may go for penetration, while premium products will skim (though some differentiated between premium products that may aspire to good price/value ratio, and luxury products, for which high prices are a product feature Hinterhuber and Liozu, 2018).

As for Kickstarter projects, Chen et al. (2019a) claimed that if entrepreneurs create a high-quality, high-price category, they do not need multiple quality and price steps for rewards. Studies on menu-pricing in crowdfunding projects (Hu et al., 2015; Guan et al., 2020b,a) explored how menu pricing may offer to backers both economy and premium prices. We will examine the effect of these strategies on the mean/median reward price of a product category, and see its use to increase sales and fundraising effectiveness. This is widely studied in other economic markets, and as we believe the products marketed on crowdfunding platforms tend to be more unique, rather than mass-market, we hypothesize the following:

**H4. Market skimming/premium pricing strategy, expressed through the use of higher rewards prices compared to other projects in the same category, will increase pledge demand and project success.**

#### 4.5. QUESTION 5: Does the anchoring effect influence crowdfunding project success?

The anchoring effect is one of the most robust cognitive heuristics (Furnham and Boo, 2011) and was initially explained by Tversky and Kahneman (1974). According to them, values presented early can bias decision making when making subsequent judgments (e.g., the asking price in an eBay auction influences what people consider paying for it). In other words, human estimations are constructed in relation to an anchor value to which they are adjusted. A glimpse to a higher anchor may cause bias in the following estimations, which are expected to be exaggeratedly higher, and vice versa (Furnham and Boo, 2011; Teovanović, 2019)

Some evidence for the anchoring effect from the field of online retailing are of particular interest, since they suggested that even random numbers presented on websites could affect consumers willingness to buy. Dodonova and Khoroshilov (2004) supplied one of the first empirical evidence that anchoring affects bidders' behavior and decisions in online auctions, as consumers were more likely to purchase products when a higher reference price was present. Wu et al. (2008) determined that the effect is valid in such settings even when participants are not asked to make comparative valuation and that the influence may be reinforced when an anchor is presented multiple times. Other research found sellers have only a moderate ability to affect bid values via the advertised reference price (Wolk and Spann, 2008), but that anchors embedded in banner advertisements of a website significantly influenced participants willingness to pay (Wu and Cheng, 2011; Bogliacino and Cuntz, 2013). Koçaş and Dogerlioglu-Demir (2020) have also demonstrated that completely random numerical anchors that were used on marketing communications had an influence on consumers' price perceptions.

Some studies focused on applying this pricing strategy specifically in crowdfunding projects. Burtch et al. (2013) showed the published amount of previous donations is functioning as an anchor to the future backers, as long as donations details were public. Therefore, they suggested crowdfunding platforms in which default privacy settings of users may be altered, so as to allow promotion of larger contributions by revealing higher anchors and concealing lower donations from other potential backers. Liu et al. (2020) added that the disclosure of backers' donations may contribute to the campaign if the funding goal is high and have the opposite effect if the funding goal is relatively low.

When comparing between "point offer" strategy (a fixed price) with "adjustable point offer" (a fixed price or more) and "bolstering price offer" (a given price range, in which the lower end represents the minimal price), the latter was the most likely to raise higher backing amount (Kuo et al., 2020; Wu et al., 2008). Simons et al. (2017) claimed backers tend to choose the middle pricing category of the whole pricing range of a given project. However, they also indicated that too many pricing categories may confuse the backers and prevent them from finding the middle option. They also demonstrated how for the same project, changing the low and high pricing anchors managed to affect the number of pledges, since people tended to choose the middle pricing category.

Thus, we hypothesize that seeing a larger goal number will either make people go for a higher value reward, or will make them feel that a small pledge is "smaller", thus making it seem to be not a bid deal to pledge. We hypothesize the following:

**H5. Anchoring pricing strategy, expressed through the use of high fundraising goal price (the main number shown when seeing a Kickstarter project), will increase backers' donations.**

## 5. Methodology & analysis

We analyzed two sets of interrelated data: one with roughly 180,000 projects, and the other with over a million rewards (from those same projects). Since we have multiple rewards for one project, for the analysis of reward's data set, we used a Generalized Linear Mixed Model (GLMM) which is commonly used when repeated measurements are available for the same observational units or measurements (Breslow and Clayton, 1993). Random effects are used to capture underlying hidden effects among repeated observations for each individual measurement unit (here, rewards from the same project). The dependent variable is how many pledges were sold, therefore we use a log link function from the Poisson family to represent these effects. For the data analysis of the projects, we employ a General Linear Model (GLM). In cases where the dependent variable will be whether the project was successful or not we use the binomial family.

In analyzing the reward set, the variable that will be explained is, for each reward, the number of rewards sold. However, when we look

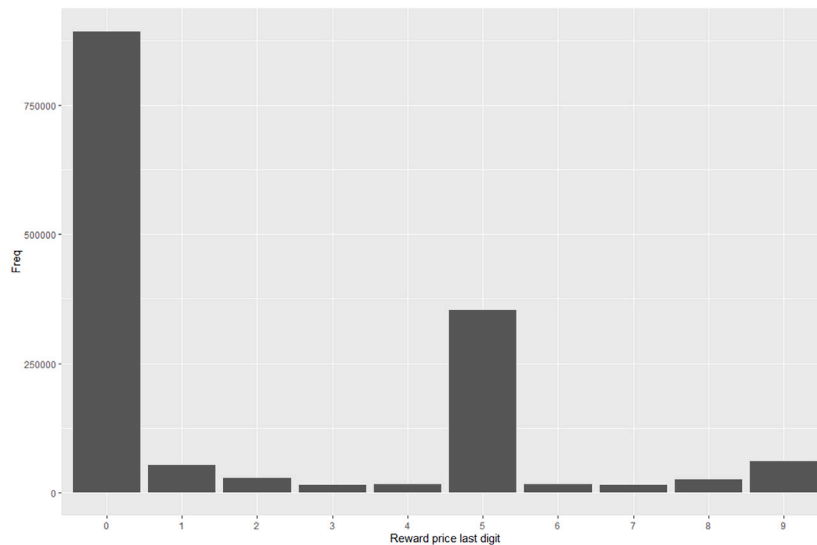


Fig. 2. For each digit, how many rewards were there with that digit as the value’s last digit (i.e., least significant digit).

at the set of projects, the explained variable will be the total number of rewards sold in the project, and another variable will be “succeeded” — did the project reach its funding goal or not.

In analyzing some of the strategies, we will use a *representing pledge* for each project, i.e., the pledge which sold the most. Using the representing pledge also helps to reduce the noise of very low-value/high-value pledges, when they do not represent well enough the value of the project’s sold rewards.

5.1. Analysis

We will show the analysis for each of our questions and hypotheses.

5.1.1. Q1: Psychological pricing strategy

As noted above, psychological pricing strategy targets human psychology to boost sales, mainly by choosing prices with particular final digits that make people perceive the price as low (e.g., 49 instead of 50). In order to better understand how this strategy works in Kickstarter, we examined the preponderance of the last digits (see distribution in Fig. 2).

Unsurprisingly, Fig. 2 shows that a vast majority of rewards were priced with “round” numbers — ending with 0 and 5. However, examining the profitability of the last digit choice (Fig. 3), we can see that the last digit 9 sells better than the rest of the options, and this is even more significant in successful projects.

To test the H1 hypothesis, we estimated a Poisson GLMM regression model (Poisson generalized linear mixed model), with fixed effects of pledge pricing’s last digit (between zero and nine) and random effects for the project identifier, with the number of rewards sold being the explained variable. The results of model estimation are presented in Table 4.

The results of model estimation confirmed that all last digits had significant fixed effect on number of sold pledges ( $p < 2e^{-16}$ ). The positive coefficient for the 9 digit (estimate = 1.118) suggests that the differences are in the hypothesized direction (higher sales in pledges which the last digit was 9). As can be seen from the table, the highest coefficient was awarded to the digit 9 when compared to the base group (the digit 0). Therefore, H1 is supported. In addition, the results confirmed that the digit 4 also has high coefficient compared to the rest of the last digits. This may indicate that backers may recognize the number 4 as a discount relative to the number 5 which is, as seen above, also very common on Kickstarter. The GLMM results confirm the observations from the graphs, that as Kickstarter has two common

Table 4

Results of Poisson generalized linear mixed model regression with psychological pricing strategy. N = 1 476 827; The DV was number of rewards sold; Baseline conditions for IVs were pledge pricing’s last digit zero; two tailed p values are reported; Random effects: Groups Name projId (Intercept). Variance 3.723.

Model term	Estimate	Std. error	Sig.
(Intercept)	0.5555574	0.0047331	$<2e^{-16}$ ***
1	0.1265782	0.0014054	$<2e^{-16}$ ***
2	0.7221561	0.0014867	$<2e^{-16}$ ***
3	0.8059878	0.0019322	$<2e^{-16}$ ***
4	1.0222269	0.0015446	$<2e^{-16}$ ***
5	0.6859048	0.0005668	$<2e^{-16}$ ***
6	0.7648929	0.0017584	$<2e^{-16}$ ***
7	0.8966342	0.0017756	$<2e^{-16}$ ***
8	0.7843684	0.0014125	$<2e^{-16}$ ***
9	1.1180771	0.0010122	$<2e^{-16}$ ***

\*\*\* $p < 0.001$ , \*\* $p < 0.01$ , \* $p < 0.05$ .

digits, 0 and 5, pricing with digits 9 and 4 (respectively), can be perceived as discounts of one price unit, and such priced items are the ones that add the highest marginal addition to sales.

To further examine this pricing strategy, we define for each project a representative reward — its best selling one (as stated above, this helps neutralize the noise caused by irrelevant rewards). We tested the *sold* feature (how many were sold) in projects with a representative reward from the following groups: pledges with prices of \$49 vs. \$50, \$99 vs. \$100, and \$24 vs. \$25 (the last one is the most popular pledge on Kickstarter, according to Kickstarter’s website). As can be seen in Table 5, for all groups, the representative reward priced one dollar less had a higher sale average.

5.1.2. Q2: Bundle pricing strategy

Bundle pricing strategy involves offering (or combining) two or more complementary products or services at a single price. Kickstarter pledges can include a number of products (see Fig. 4), which we use to analyze this strategy.<sup>5</sup> A histogram of the number of items in each bundle can be seen in Fig. 5, while Fig. 6 shows how the size of the bundle relates to the number of bundles sold.

<sup>5</sup> Some projects do not include a reward number for all rewards, and so we assume that rewards of gratitude (e.g., a “thank you” note), and empty “IncludedAmount” field have a single item.



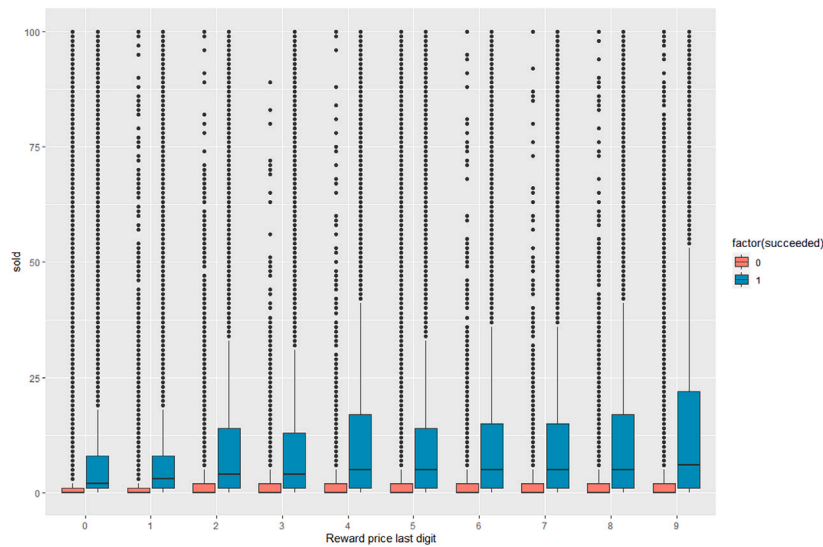


Fig. 3. How many items were sold of each reward, depending on their price's last digit and whether the project succeeded or not (box shows 25%–75% interval).

Table 5

Comparing how many rewards were sold for projects whose most sold pledge was \$24 vs. \$25; \$49 vs. \$50; and \$99 vs. \$100.

Model term	49 VS. 50		99 VS. 100		24 VS. 25	
	49	50	99	100	24	25
vars	49.00	50.00	99.00	100.00	24.00	25.00
n	586.00	13 943.00	743.00	9991.00	551.00	33 102.00
mean	<b>226.75</b>	<b>29.56</b>	<b>370.75</b>	<b>19.92</b>	<b>131.03</b>	<b>36.87</b>
sd	568.62	339.04	1946.23	398.86	420.36	219.89
median	<b>45.50</b>	<b>6.00</b>	<b>49.00</b>	<b>4.00</b>	<b>29.00</b>	<b>11.00</b>
trimmed	96.83	9.05	100.55	6.78	53.48	16.14
mad	63.01	7.41	68.19	5.93	35.58	14.82
min	0.00	0.00	0.00	0.00	0.00	0.00
max	5675.00	24 512.00	46 124.00	37 555.00	6200.00	20 159.00
range	5675.00	24 512.00	46 124.00	37 555.00	6200.00	20 159.00
skew	5.39	56.21	18.24	85.77	8.90	53.66
kurtosis	36.25	3710.86	410.95	7908.76	100.63	4130.67
se	23.48	2.87	71.40	3.99	17.90	1.20

Table 6

Parameter estimates, results of Poisson generalized linear mixed model regression with Bundle pricing strategy. N = 1 476 827; The DV was number of rewards sold; Baseline conditions for IVs were pledges that contained less than two products included in the price; two tailed p values are reported; Random effects: Groups Name projid (Intercept). Variance 3.944.

Model term	Estimate	Std. error	Sig.
(Intercept)	0.865069	0.004855	<2e <sup>-16</sup> ***
included2	0.233239	0.001343	<2e <sup>-16</sup> ***
included3	0.221265	0.001441	<2e <sup>-16</sup> ***
included4	0.034389	0.001652	<2e <sup>-16</sup> ***
included5	-0.636232	0.001489	<2e <sup>-16</sup> ***

\*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

To test the H2 hypothesis, we estimated a logistic regression model (Poisson generalized linear mixed model), with fixed effects of number of products included in the pledge price (The majority of projects include fewer than five products in their rewards, as can be seen in Fig. 5, so we decided to bucket together the rewards with 5 products and above) and random effects for the project identifier. The number of rewards sold was the explained variable, and the results are shown in Table 6.

The results of the model estimation confirm that the product's group — determined by the number of rewards in the bundle — has a significant fixed effect on number of sold pledges ( $p < 2e^{-16}$ ). The highest positive coefficient (estimate = 0.233) was awarded to pledges

that contain 2 items compared to the base group (pledges with a single item). The positive coefficient for 2–4 items suggests that the differences were in the hypothesized direction (higher sales in pledges which contain 2–4 items). Therefore, H2 is supported. By contrast, the group of 5 and above had a significant negative effect on number of rewards sold, leading to the conclusion that H2 is not supported for 5 rewards or more. Moreover, a decaying effect can be seen, as with every additional product up to 5 items, the number of units sold from that pledge increases, but the increase is smaller. A possible explanation for this is that the amount of money required for such a bundle begins to be too expensive for many potential backers, leading them to avoid such high-priced bundles (even if their value — payment per item — is still high).

### 5.1.3. Q3: Scarcity pricing strategy

Scarcity pricing strategy involves offering a limited number of rewards. In Kickstarter, an entrepreneur can create a limited run of an item (i.e., set a maximum number of rewards of a particular type), or simply offer early bird backers a reward, which becomes unavailable once the overall pledge reaches the maximum limit. Other backers are still able to see the reward, but they are not able to select it. We will use the “limited” feature to describe such pledges. Each pledge has three possible values: *max* — a limited reward that reached its maximum sales; *yes* — a limited reward that did not reach its maximum; and *no* — a reward that was not limited. For each project, we define a new feature, *limited percent*, which describes the number of limited pledges divided by the total number of pledges in a project ( $\frac{max+yes}{max+yes+no}$ ), and a histogram of the rewards can be seen in Fig. 7.

The H3 hypothesis was tested by estimating a logistic regression model (Binomial generalized linear model) with fixed effects of pledge's limited reward percent. The explained variable was the project's success (Table 7). We also fit a Poisson GLM model when the explanatory variable is, as before, percent of limited reward, while the explained variable is the number of rewards sold (Table 8).

The results confirmed that having a limited feature has a significant fixed effect on number of sold pledges ( $p < 2e^{-16}$ ). As can be seen from the tables, a positive coefficient was found for the percentage of limited rewards in both of our statistical tests. This means that limiting more rewards will increase sales or the chance of success. Therefore, it is important to ask if this means projects should limit all rewards, and what is the maximum number of limited rewards an entrepreneur should allow in their project. Attempting to answer this question, we created a density graph which illustrates the percentage of limited

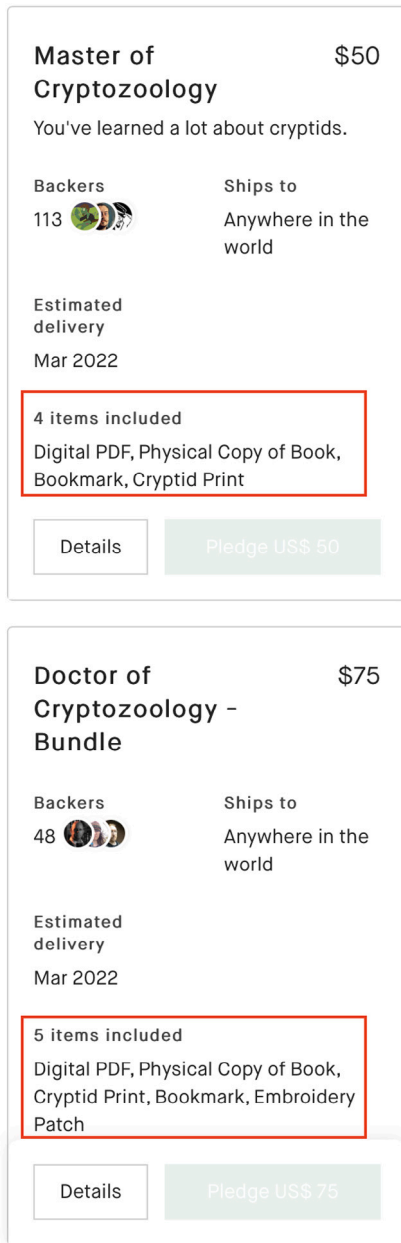


Fig. 4. Kickstarter bundle example.

Table 7

Parameter estimates, results of logistic regression with scarcity pricing strategy. Notes. N = 183942; The DV was project success ('0' failed, '1' succeeded); Baseline conditions for IVs was non-limited pledges; two tailed p values are reported.

Model term	Estimate	Std. error	Sig.
(Intercept)	0.011138	0.006373	0.0805
Limited percent	0.482732	0.014486	<2e <sup>-16</sup> ***

\*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

rewards for successful and unsuccessful projects (Fig. 8). Our graph illustrates the differences between successful and unsuccessful projects, and shows that projects whose share of limited rewards is between 0 and 0.1, as well as those with a share of above 0.9, are more likely to arise from the distribution of unsuccessful projects. Conversely, projects that limit rewards between 0.1 to 0.9 are more likely to be successful. As can also be seen from the graph, as the limited percent increases,

Table 8

Parameter estimates, results of Poisson regression with scarcity pricing strategy. Notes. N = 183942; The DV was the number of rewards sold; Baseline conditions for IVs was non-limited pledges; two tailed p values are reported.

Model term	Estimate	Std. error	Sig.
(Intercept)	4.4957876	0.0003189	<2e <sup>-16</sup> ***
Limited percent	0.9716073	0.0005808	<2e <sup>-16</sup> ***

\*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

Table 9

Parameter estimates, results of Poisson generalized linear mixed model regression with scarcity pricing strategy. Notes. N = 1 476 827; The DV was number of rewards sold; Baseline conditions for IVs was non-limited group of pledges; two tailed p values are reported; Random effects: Groups Name projId (Intercept) Variance 4.04 Std.Dev.2.01.

Model term	Estimate	Std. error	Sig.
(Intercept)	1.0429513	0.0049120	<2e <sup>-16</sup> ***
Limited Yes	-0.7057771	0.0006528	<2e <sup>-16</sup> ***
Limited Max	-0.5798167	0.0007184	<2e <sup>-16</sup> ***

\*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

Table 10

Parameter estimates, results of Poisson generalized linear mixed model regression with scarcity pricing strategy. Notes. N = 1 476 827; The DV was number of rewards sold; Baseline conditions for IVs was pledges that were not before (above in the page) a limited reward ; two tailed p values are reported; Random effects: Groups Name projId (Intercept) Variance 3.975 Std.Dev.1.994.

Model term	Estimate	Std. error	Sig.
(Intercept)	0.871905	0.004872	<2e <sup>-16</sup> ***
Before limited	-0.614867	0.000887	<2e <sup>-16</sup> ***

\*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

Table 11

Parameter estimates, results of Poisson generalized linear mixed model regression with scarcity pricing strategy. Notes. N = 1 476 827; The DV was number of rewards sold; Baseline conditions for IVs was pledges that were not after (below in the page) a limited reward ; two tailed p values are reported; Random effects: Groups Name projId (Intercept) Variance 4.002 Std.Dev.2.005.

Model term	Estimate	Std. error	Sig.
(Intercept)	0.8815857	0.0048991	<2e <sup>-16</sup> ***
After limited	-0.6225483	0.0007361	<2e <sup>-16</sup> ***

\*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

the gap between successful and unsuccessful projects is smaller. This indicates that it is beneficial to limit some of the rewards in the project, but not all of them, and probably not a very large percentage of them.

For a better understanding of limited rewards, we examined the results for each group (max, yes, no) in the rewards' data set. We applied a Poisson GLMM with fixed effects of pledge's limited group and random effects for the project identifier. The number of rewards sold was the explained variable (Table 9). The results confirmed that all groups had significant fixed effect on number of sold pledges (p < 2e<sup>-16</sup>). The table shows that "yes" and "max" had a negative effect compared to the base group ("no") on the number of rewards sold. The reason may be that when checking sales, there is a trade-off between the ability to sell and the limit on sales.

Our next objective was to examine the behavior that occurs in an environment of limited rewards, specifically whether rewards above and below the limited rewards will be more or less successfully sold. We applied a Poisson GLMM with fixed effects of pledges before or above a limited reward and random effects for the project identifier (Tables 10, 11).

This confirmed that rewards located near a limited reward had a significant fixed effect on the number of sold pledges (p < 2e<sup>-16</sup>). As can be seen from the tables, a negative coefficient was found for those rewards in both of our statistical tests. Thus, rewards near a limited

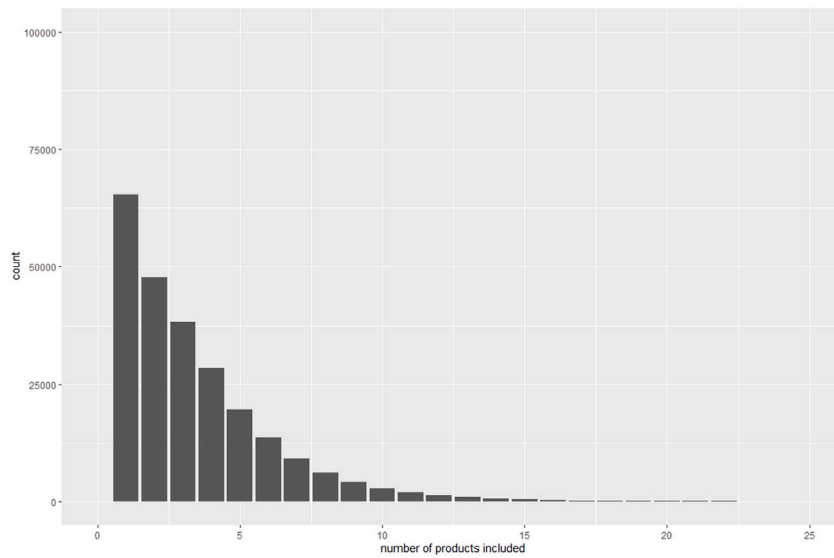


Fig. 5. How many items were included in each reward (a reward with more than one item is a bundle).

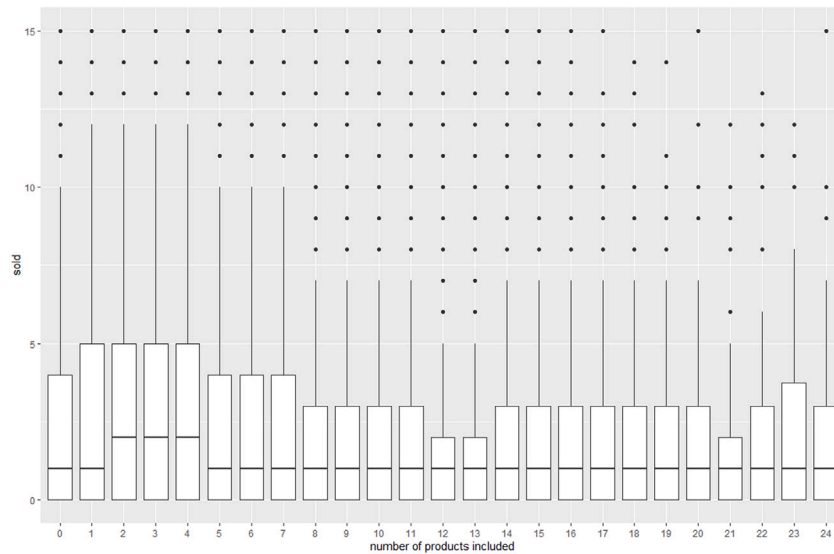


Fig. 6. How many rewards were sold, depending on the size of the bundle (i.e., how many items did the reward contain) (box shows 25%–75% interval).

reward sell less. This is surprising since we expected that if a reward was no longer available, people would be willing to move to adjacent rewards which are available. But it seems backers move to a completely different reward price (or give up).

5.1.4. Q4: Premium and penetration pricing strategy

Premium pricing (or skimming pricing) occurs when companies price their products high to convey the message that their products are high-value, luxurious, or premium. In contrast, penetration pricing (or economy pricing) involves charging very low prices for new products in order to increase sales quickly. Similarly, before launching a product on Kickstarter, the competition and other products prices in the same category matter to a project’s success. For each project, we added a new feature, *representative reward price ratio*, that divides the price of the representative reward by the mean of all representative rewards in all projects of the same category. We use this value to understand if a reward is priced very high or low compared to others in the category. Using the category allows us to understand what is the reward value that people backing projects in a particular category expect. Of course,

Table 12

Parameter estimates, results of logistic regression with the entry of a new product on Kickstarter pricing strategy. Notes. N = 183942; The DV was succeeded; The IVs was representative reward price ratio; two tailed p values are reported;.

Model term	Estimate	Std. error	Sig.
(Intercept)	0.1653262	0.0047499	<2e-16 ***
Representative reward price ratio	-0.0009467	-10.35	<2e-16 ***

\*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

there is still a level of variance within each category, and sometimes one can have very small and very large projects in the same category.

The H4 hypothesis was tested by estimating a logistic regression model (Binomial generalized linear model) with fixed effects of representative reward price ratio. The explained variable was “succeeded”, and results are presented in Table 12. We also fit a Poisson GLM model when the explanatory variable is the same, but the explained variable is the number of rewards sold (Table 13).

The results show the representative reward price ratio feature has a significant fixed effect on number of sold pledges and project success

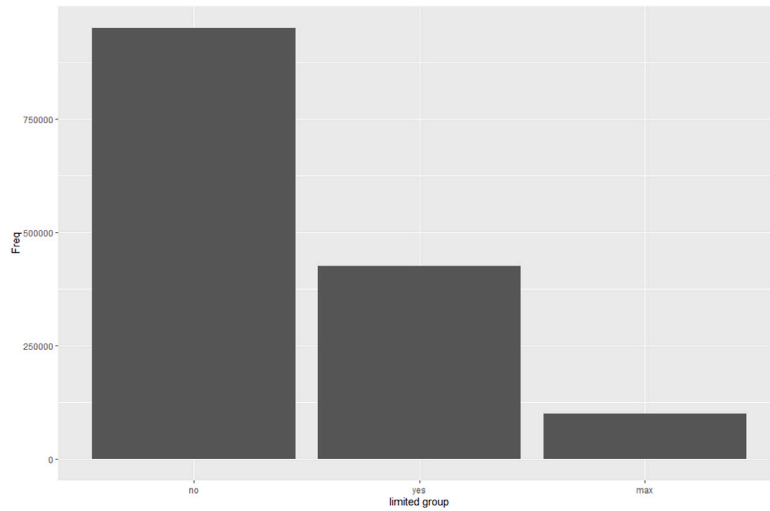


Fig. 7. How many rewards in our dataset were without any scarcity (i.e., no limit on the number of backers getting that reward), had scarcity, but it was not constrained (i.e., there was a limit on the number of backers, but it was not reached — the number of backers getting that reward did not reach the limit), or had scarcity and it was constrained (i.e., all of that reward sold and it could no longer be purchased).

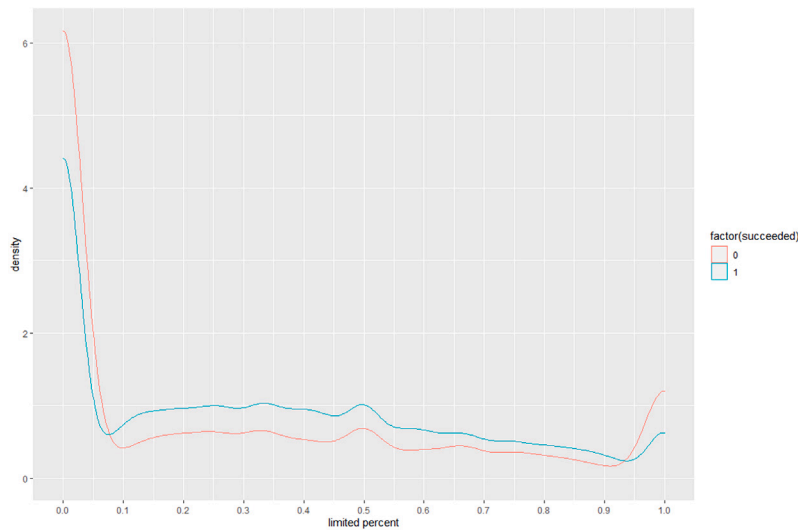


Fig. 8. Density of percent of successful/unsuccessful projects with each particular limited pledge percent value.

Table 13

Parameter estimates, results of generalized Poisson model regression with the entry of a new product on Kickstarter pricing strategy. Notes. N = 183942; The DV was total sold rewards; The IVs was representative reward price ratio; two tailed p values are reported.

Model term	Estimate	Std. error	Sig.
(Intercept)	4.8483777	0.0002100	<2e <sup>-16</sup> ***
Representative reward price ratio	-0.0044302	0.0000451	<2e <sup>-16</sup> ***

\*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

( $p < 2e^{-16}$ ). As can be seen from the tables, a negative coefficient was found for the representative reward price ratio in both of our statistical tests. This implies that choosing a higher price reward than the reward prices in the category will decrease sales or the chance of success. However, as the coefficient is small, this reduction is not quite definite. To help clarify it, we created a density graph which illustrates the representative reward price ratio for successful and unsuccessful projects in Fig. 9.

The density graph shows that unsuccessful projects are more likely to have reward prices less than 0.3 of the average market price, and

that successful projects have rewards prices above this level. As can also be seen from the graph, as the ratio increases, the gap between successful and unsuccessful is reduced, making it harder to predict whether the project will succeed or not. In particular, it seems hard to predict if projects with reward prices higher than the category’s mean will succeed. This implies that a new Kickstarter project might be better off with lower reward prices than those common in the same category, but not too low. This runs counter to our initial hypothesis.

There appears to be a relationship between the reward price and the goal price. Therefore, we examined a model that incorporates the interaction between the goal price and the representative reward price ratio. We estimate a logistic regression model (Binomial generalized linear model) with fixed effects of representative reward price ratio, goal, and their interaction. The explained variable was “succeeded”, and results are presented in Table 14.

Based on the results of the regression, it can be seen that as the ratio grew, the chance for the project’s success decreased. When looking at its interaction with the goal variable, it can be seen that the effect is reversed: the more both variables grew, the greater the chance of success. It seems the relationship between the goal price and the



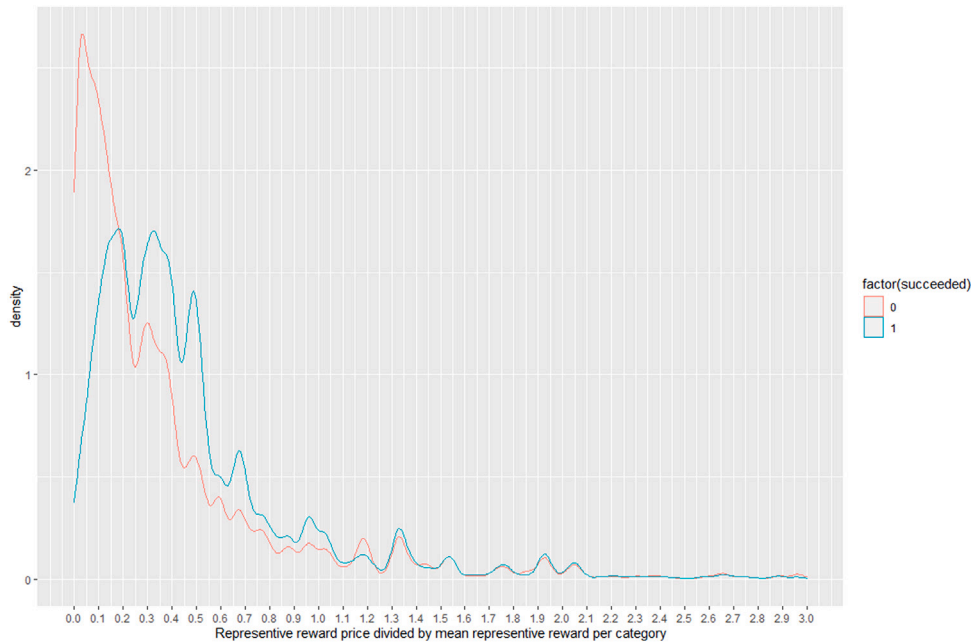


Fig. 9. Density of representative reward price ratio by successful and unsuccessful projects. Skewed distributions with right long tail as there are one or more outliers away from the majority of the data.

Table 14

Parameter estimates, results of logistic regression with the entry of a new product on Kickstarter pricing strategy. Notes. N = 183942; The DV was total sold rewards; The IVs was goal, representative reward price ratio and interaction between them; two tailed p values are reported.

Model term	Estimate	Std. error	Sig.
(Intercept)	2.766e-01	5.190e-03	<2e-16 ***
Representative reward price ratio	-4.361e-03	8.050e-04	6.05e-08 ***
goal	-5.997e-06	1.330e-07	<2e-16 ***
Representative reward price ratio:goal	6.368e-09	1.480e-10	<2e-16 ***

\*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

representative reward price ratio is crucial for setting prices relative to the accepted prices in the category.

5.1.5. Q5: Anchoring pricing strategy

Anchoring pricing strategy refers to the tendency to make decisions based primarily on the first piece of information presented. On Kickstarter, the goal price normally appears in the first part of the page, followed by the rewards, ordered by price. The best-selling reward on Kickstarter is \$25. Thus, we created a new variable: the profit that is raised from rewards whose prices are small or equal to \$25.<sup>6</sup>

The H5 hypothesis was tested by estimating linear regression model with fixed effects of goal and the number of rewards up to \$25. The explained variable was reward profit up to \$25, and results are presented in Table 15.

The results show that goal and number of rewards up to \$25 have a significant fixed effect on profit from rewards up to \$25 (p < 2e-16). As can be seen from the table, a positive coefficient was found for both independent variables. Profits tended to increase with a higher goal price, though it is difficult to deduce this using the model since the coefficients are very small. When we added the interaction variable in Table 16, the goal became negative, and its interaction with the number of rewards became positive. Based on these results, it is likely there is

<sup>6</sup> Technically, Kickstarter allows you to buy a low-priced reward and give more money for it. While this might somewhat skew our results, this is, as far as we know, not a common behavior observed on the platform.

Table 15

Parameter estimates, results of generalized linear model regression with the entry of a new product on Kickstarter pricing strategy. Notes. N = 183942; The DV was profit from rewards up to \$25; The IVs was goal and number of pledge up to \$25; two tailed p values are reported.

Model term	Estimate	Std. error	Sig.
(Intercept)	3.092e+02	2.767e+01	<2e-16 ***
Goal	3.629e-05	1.564e-05	0.0204 *
N	1.966e+02	8.009e+00	<2e-16 ***

\*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

Table 16

Parameter estimates, results of generalized linear model regression with the entry of a new product on Kickstarter pricing strategy. Notes. N = 183942; The DV was profit from rewards up to \$25; The IVs was goal and number of pledge up to \$25 and the interaction between them; two tailed p values are reported.

Model term	Estimate	Std. error	Sig.
(Intercept)	3.147e+02	2.768e+01	< 2e-16 ***
Goal	-9.500e-05	2.962e-05	0.00134 **
N	1.939e+02	8.026e+00	< 2e-16 ***
Goal:N	9.777e-05	1.873e-05	1.79e-07 ***

\*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

an interaction between number of rewards and goal, in that the higher the goal, the more rewards will be needed to increase the profit from rewards that their price is up to a cost of \$25.

6. Summary and discussion

Our results are summarized in Table 17. Broadly speaking, we have shown that:

- Projects succeed more if they price rewards with 9 or 4 as their last digit (probably due to a perception that these are lower prices).
- Bundling products together makes sense for few products (not more than 4).
- Having a significant number of limited quantity rewards is profitable, but they should not be too many out of the whole rewards.

**Table 17**  
Summary table.

Hypotheses	DV	IV	Results
H1. Pricing pledges with 9 left digit effect will increase their demand.	Number of rewards sold	Pledge pricing's last digit	H1 was supported, the differences were in the hypothesized direction: higher sales in pledges which the last digit was 9. The digit 4 had also high coefficient compared to the rest of the last digits.
H2. Bundle products in a pledge will increase pledges demand.	Number of rewards sold	Number of products in a pledge	H2 was supported, the differences were in the hypothesized direction: higher sales in pledges which contain 2–4 products. H2 was not supported for more than 4 products.
H3. Limiting pledges will increase pledges demand.	Succeeded/number of rewards sold	Limited percent	H3 was supported, the differences were in the hypothesized direction: higher sales or higher chances of success will come from limiting more rewards. However, not all rewards should be limited
	Number of rewards sold	Limited_group	Unlimited pledges sell better, there is a trade-off between the ability to sell and the limit on sales.
	Number of rewards sold	Pledges below or above a limited reward	Rewards in a limited reward environment resulted in lower sales.
H4. Market skimming/premium pricing strategy, expressed through the use of higher rewards prices with respect to project category, will increase pledge demand and project success.	Succeeded/number of rewards sold	Representative reward price ratio	H4 was not supported, the result obtained is in the opposite direction of our initial hypothesis: sales or success chances increase if the reward price is lower than the reward price in the category, meaning that penetration pricing is often better.
	Succeeded	Interaction between the goal price and the representative reward price ratio	Setting prices according to the accepted prices in a category depends critically on the interaction between the goal price and the representative reward price ratio.
H5. Anchoring pricing strategy, expressed through the use of high fundraising goal price will increase backers; donations.	Reward profit up to \$25	Goal and the number of rewards up to \$25.	H5 was supported, the differences were in the hypothesized direction: profits tend to increase with a higher goal price seen.
	Reward profit up to \$25	Interaction between the goal price and the number of rewards up to \$25	When the goal is higher, more rewards will be needed to increase the profit from rewards, which have a cost of \$25 or less.

- Pricing for luxury does not usually work, it is better to price one’s products slightly less than the category as a whole (but not too low).
- A higher goal price increases the number of rewards sold from those close (on the webpage) to the goal price itself. However, the increase in number of sales does not necessarily compensate for additional money that is needed.

6.1. Limitations

Like any research, this study has several limitations. First, data was extracted after campaigns were completed. A campaign page can be updated during the live period (and even following it). As a result, the actual launch values may differ from those we assumed in this study. For example, pledges can be added at any stage of the project, so it is difficult to determine whether a project that receives more pledges will be more successful or whether an entrepreneur will increase pledges to increase revenue as the project succeeds. It is our understanding that reward structure does not change very often, thus, despite this issue, our results are still meaningful.

Second, pricing strategies can be structured and arranged in many alternative ways, leading to different models and hypotheses, which can lead to different outcomes. There can be disputes about some of the assumptions in the study, for example, as noted above, the number of items in bundles may be only half of the story, because the price of the bundle may play an important role. While the identified results may be correct in small bundles, the difference in demand for large bundles may be related to the overall price of the bundle rather than the number of components they have. Similarly, the definition of premium/skimming price based on a category-wide reference reward value may be causing some relatively-cheap rewards to seem pricey (since it is part of a very pricy project), and vice versa.

Finally, our empirical analysis makes use of the data we were able to scrape. Of course, many aspects of crowdfunding success are not directly correlated with these attributes. Subjective factors such as creativeness, innovation, pitch and media quality can greatly affect success rates, and are beyond the scope of this research.

6.2. Discussion

This research is the first, to our knowledge, to combine an extensive dataset of Kickstarter projects with multiple pricing hypotheses. Generally, we show that pricing strategies that tend to work in “regular” markets seem to maintain their power in crowdfunding markets as well. On the one hand, this is not very surprising — there is no reason marketers’ techniques to grab people’s attention will cease to work. On the other hand, the very different market behavior, in which participants often perceive themselves as entrepreneurs and investors in novelty items, might have ended up with different patterns of behavior.

In light of psychological pricing, our results are consistent with other studies that conclude that psychological pricing increases profitability (Dudu and Agwu, 2014; Boz et al., 2017; Nair, 2019; Bhat-tacharya et al., 2012; Collins and Parsa, 2006). As for bundling products, Thüridl and Kamleitner (2016) conclude that bundles have an effect on sales but are specifically a good strategy if the marginal cost of creating a reward bundle is low for the initiator and if there are actual additional benefits readily and easily available. We conclude that bundles encourage consumption if the bundle consists of a few products (not more than 4). Similarly, in the real-world, Nair (2019) found that customers will be more pleased from bundling since they can benefit from all optional products at a much lower cost than buying those services individually.

Regarding scarcity, our findings suggest that not all rewards should be limited, and there is probably an optimal range that drives success. This provides empirical support to Yang et al. (2020) conclusions that

setting reward limits at the beginning of a campaign is beneficial. The number of limited reward tiers has an inverted U-shaped relationship with campaign performance, suggesting that having a moderate number of limited rewards is optimal. We add an unexpected finding that rewards near limited rewards sell less, and are not benefiting from the limited rewards being maxed out. This finding adds nuance to the understanding of how backers perceive scarcity effects, and will hopefully encourage further research into the psychology of backers in crowdfunding scenarios. With regard to penetration pricing strategy, according to Sewaid et al. (2021) and Chen and Liu (2023), setting a low crowdfunding price when committing to a high retail price enhances campaign performance. Similarly, in the real world, Nair (2019) highlights that penetration pricing is preferable as it can be advantageous in the long run due to the value customers associate with experiencing services. This aligns with our findings of pricing slightly below the category average, as it may also emphasize creating value for customers. In light of anchoring pricing strategy, studies like Burtch et al. (2013) and Liu et al. (2020) suggest that disclosing donation amounts can influence backer's behavior, serving as an anchor for future backers. They encourage promotion of larger contributions by revealing higher anchors and concealing lower donations from other potential backers. Our findings also seem to relate to this concept, where a higher goal price might make people feel that giving a small contribution is not a big deal.

Overall, our research findings provide valuable insights into the implementation of pricing strategies in crowdfunding campaigns. We add a layer of practicality to the marketing concept of known pricing techniques used for consumers by examining its effects in a crowdfunding context. In addition our research can offer valuable and creative insights to upcoming entrepreneurs and project leaders as they look for ideas to create rewards.

A promising avenue for future research would involve exploring campaign design strategies alongside the decision-making patterns of individual backers using backer subjective information to validate perceptions and decision mechanisms related to pricing strategies. It would try to see if different types of users (e.g., those identified by Ryu and Kim (2016)), react differently to these strategies. In addition, trying to suss-out different components of the bundling and the anchoring effects has a promising direction.

An additional intriguing future direction is trying to find novel pricing/reward patterns that do not exist in physical, real-world markets, but only in crowdfunding projects, particularly on online platforms. Moreover, potential platform differences (e.g., some platforms allow for fundraising) may have different patterns, enriching our understanding of how people adopt different pricing heuristics.

#### CRedit authorship contribution statement

**Bar Keisar:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Omer Lev:** Conceptualization, Methodology, Validation, Investigation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition.

#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Data availability

Data will be made available on request.

#### Acknowledgments

Bar Keisar was supported by Israeli Ministry of Science (MOST) grant #16588-3. Omer Lev was supported, in part, by the Israel Science Fund (ISF) grant #3152/20.

#### References

- Ancarani, F., Ancarani, Fabio, 2002. Pricing and the internet: Frictionless commerce or pricer's paradise? *Eur. Manag. J.* 20 (6), 680–687, URL: <https://econpapers.repec.org/RePEc:eee:eurman:v:20:y:2002:i:6:p:680-687>.
- Babaioff, M., Nisan, N., Leme, R.P., 2014. Price competition in online combinatorial markets. In: *Proceedings of the 23rd International Conference on World Wide Web (WWW)*. Seoul, Korea, pp. 711–722.
- Balachander, S., Stock, A., 2009. Limited edition products: When and when not to offer them. *Mark. Sci.* 28 (2), 336–355. <http://dx.doi.org/10.1287/MKSC.1080.0401>.
- Bennett, R., Kottasz, R., 2013. Attractiveness of limited edition artwork for first-generation newly affluent consumers. *Int. J. Arts Manag.* 15 (3), 21.
- Bhattacharya, U., Holden, C.W., Jacobsen, S., 2012. Penny wise, dollar foolish: Buy-sell imbalances on and around round numbers. *Manage. Sci.* 58 (2), 413–431. <http://dx.doi.org/10.1287/mnsc.1110.1364>.
- Bi, S., Liu, Z., Usman, K., 2017. The influence of online information on investing decisions of reward-based crowdfunding. *J. Bus. Res.* 71, 10–18.
- Bitran, G.R., Ferrer, J.-C., 2007. On pricing and composition of bundles. *Prod. Oper. Manage.* 16 (1), 93–108. <http://dx.doi.org/10.1111/J.1937-5956.2007.TB00168.X>, URL: <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1937-5956.2007.tb00168.xhttps://onlinelibrary.wiley.com/doi/10.1111/j.1937-5956.2007.tb00168.x>.
- Blythe, J., 2005. *Essentials of Marketing*. Pearson Education, Inc., Harlow, UK, URL: [www.pearsoned.co.uk/blythe](http://www.pearsoned.co.uk/blythe).
- Bogliacino, F., Cuntz, A., 2013. Price anchoring in online markets: An empirical assessment. *Revista Latinoam. Psicol.* 45 (2), 211–221. <http://dx.doi.org/10.14349/rlp.v45i2.1391>, URL: <https://doi.org/10.14349/rlp.v45i2.1391>, URL: <https://doi.org/10.14349/rlp.v45i2.1391>.
- Bouncken, R.B., Komorek, M., Kraus, S., 2015. Crowdfunding: The current state of research. *Int. Bus. Econ. Res. J. (IBER)* 14 (3), 407–416.
- Boz, H., Arslan, A., Koc, E., 2017. Neuromarketing aspect of tourism pricing psychology. *Tour. Manag. Perspect.* 23, 119–128, URL: [https://www.academia.edu/33490420/Neuromarketing\\_aspect\\_of\\_tourism\\_pricing\\_psychology](https://www.academia.edu/33490420/Neuromarketing_aspect_of_tourism_pricing_psychology).
- Brassington, F., Pettit, S., 2005. *Principles of Marketing*. FT Prentice Hall London, NY.
- Breslow, N.E., Clayton, D.G., 1993. Approximate inference in generalized linear mixed models. *J. Am. Statist. Assoc.* 88 (421), 9–25.
- Brock, T.C., 1968. Implications of commodity theory for value change. *Psychol. Found. Attitudes* 243–275. <http://dx.doi.org/10.1016/B978-1-4832-3071-9.50016-7>.
- Bulut, Z., Gürler, Ü., Şen, A., 2009. Bundle pricing of inventories with stochastic demand. *European J. Oper. Res.* 197 (3), 897–911. <http://dx.doi.org/10.1016/J.EJOR.2006.09.106>.
- Burtch, G., Ghose, A., Wattal, S., 2013. An empirical examination of users' information hiding in a crowdfunding context. In: *Proceedings of the 34th International Conference on Information Systems (ICIS)*. Milan, Italy, pp. 343–361.
- Cardon, M.S., Stevens, C.E., 2009. The discriminant validity of entrepreneurial passion. In: *Academy of Management Proceedings*, Vol. 1. pp. 1–6. <http://dx.doi.org/10.5465/ambpp.2009.44244277>.
- Carmin, J.A., Norkus, G.X., 1990. Pricing strategies for menus: Magic or myth? *Cornell Hotel Restaur. Adm. Q.* 31 (3), 44–50. <http://dx.doi.org/10.1177/001088049003100312>.
- Chen, Y., Liu, B., 2023. Advertising and pricing decisions for signaling crowdfunding product's quality. *Comput. Ind. Eng.* 176, 108947.
- Chen, M., Liu, Z., Ma, C., 2019a. Early bird or versioning: Which pricing strategy is better for creators in reward-based crowdfunding? *Asia Pac. J. Mark. Logist.* 32 (3), 769–792. <http://dx.doi.org/10.1108/APJML-12-2018-0529>.
- Chen, M., Liu, Z., Ma, C., Gong, X., 2019b. A distinctive early price in reward-based crowdfunding. *Electron. Commer. Res.* 21 (2), 347–370. <http://dx.doi.org/10.1007/S10660-019-09356-5>, URL: <https://link.springer.com/article/10.1007/s10660-019-09356-5>.
- Chen, X.P., Yao, X., Kotha, S., 2009. Entrepreneur passion and preparedness in business plan presentations: A persuasion analysis of venture capitalists' funding decisions. *Acad. Manag. J.* 52 (1), 199–214. <http://dx.doi.org/10.5465/AMJ.2009.36462018>, URL: <https://journals.aom.org/doi/abs/10.5465/amj.2009.36462018>.
- Chu, C.S., Leslie, P., Sorensen, A., 2011. Bundle-size pricing as an approximation to mixed bundling. *Amer. Econ. Rev.* 101 (1), 263–303. <http://dx.doi.org/10.1257/AER.101.1.263>.
- Collins, M., Parsa, H., 2006. Pricing strategies to maximize revenues in the lodging industry. *Int. J. Hosp. Manag.* 25 (1), 91–107.
- Colombo, M.G., Franzoni, C., Rossi-Lamastra, C., 2015. Internal social capital and the attraction of early contributions in crowdfunding. *Entrep.: Theory Practice* 39 (1), 75–100. <http://dx.doi.org/10.1111/etap.12118>, URL: <https://www.kickstarter.com/projects/>.
- Cumming, D.J., Leboeuf, G., Schwenbacher, A., 2014. Crowdfunding models: Keep-it-all vs. All-or-nothing. *SSRN Electron. J.* <http://dx.doi.org/10.2139/ssrn.2447567>, URL: <https://papers.ssrn.com/abstract=2447567>.

- Dodonova, A., Khoroshilov, Y., 2004. Anchoring and transaction utility: Evidence from on-line auctions. *Appl. Econ. Lett.* 11 (5), 307–310. <http://dx.doi.org/10.1080/1350485042000221571>, URL: <https://www.tandfonline.com/action/journalInformation?journalCode=rael20>.
- Dolan, R.J., Doan, R.J., Simon, H., et al., 1996. *Power Pricing*. Simon and Schuster.
- Du, S., Peng, J., Nie, T., Yu, Y., 2020. Pricing strategies and mechanism choice in reward-based crowdfunding. *European J. Oper. Res.* 284 (3), 951–966. <http://dx.doi.org/10.1016/J.EJOR.2020.01.021>.
- Dudu, O., Agwu, M., 2014. A review of the effect of pricing strategies on the purchase of consumer goods. *Int. J. Res. Manag. Sci. Technol.* 2 (2), 88–102.
- el Sehity, T., Hoelzl, E., Kirchler, E., 2005. Price developments after a nominal shock: Benford's law and psychological pricing after the euro introduction. *Int. J. Res. Market.* 22 (4), 471–480. <http://dx.doi.org/10.1016/j.ijresmar.2005.09.002>.
- Ettl, M., Harsha, P., Papush, A., Perakis, G., 2019. A data-driven approach to personalized bundle pricing and recommendation. *Manuf. Serv. Oper. Manag.* 22 (3), 461–480. <http://dx.doi.org/10.1287/msom.2018.0756>.
- Furnham, A., Boo, H.C., 2011. A literature review of the anchoring effect. *J. Soc.-Econ.* 40 (1), 35–42. <http://dx.doi.org/10.1016/j.socrec.2010.10.008>.
- Gerber, E.M., Hui, J.S., Kuo, P.-Y., 2012. Crowdfunding: Why people are motivated to post and fund projects on crowdfunding platforms. In: *Proceedings of the International Workshop on Design, Influence, and Social Technologies: Techniques, Impacts and Ethics*.
- Guan, X., Deng, W.J., Jiang, Z.Z., Huang, M., 2020a. Pricing and advertising for reward-based crowdfunding products in E-commerce. *Decis. Support Syst.* 131, 113231. <http://dx.doi.org/10.1016/J.DSS.2019.113231>.
- Guan, L., Mu, Y., Xu, X., Zhang, L., Zhuang, J., 2020b. Keep it or give back? Optimal pricing strategy of reward-based crowdfunding with a hybrid mechanism in the sharing economy. *Int. J. Prod. Res.* 58 (22), 6868–6889. <http://dx.doi.org/10.1080/00207543.2019.1685711>, URL: <https://www.tandfonline.com/doi/abs/10.1080/00207543.2019.1685711>.
- Gürler, Ü., Öztop, S., Şen, A., 2009. Optimal bundle formation and pricing of two products with limited stock. *Int. J. Prod. Econ.* 118 (2), 442–462. <http://dx.doi.org/10.1016/J.IJPE.2008.11.012>.
- Hanson, W., Martin, R.K., 1990. Optimal bundle pricing. *Manage. Sci.* 36 (2), 155–174. <http://dx.doi.org/10.1287/MNSC.36.2.155>.
- Hinterhuber, A., Liozu, S.M., 2018. Thoughts: premium pricing in B2C and B2B. *J. Revenue Pricing Manag.* 17 (4), 301–305. <http://dx.doi.org/10.1057/S41272-018-0138-0>, URL: <https://link.springer.com/article/10.1057/s41272-018-0138-0>. 2018 17:4.
- Hobbs, J., Grigore, G., Molesworth, M., 2016. Success in the management of crowdfunding projects in the creative industries. *Internet Res.* 26 (1), 146–166. <http://dx.doi.org/10.1108/IntR-08-2014-0202>.
- Hoegen, A., Steininger, D.M., Veit, D., 2018. How do investors decide? An interdisciplinary review of decision-making in crowdfunding. *Electron. Mark.* 28 (3), 339–365.
- Hossain, M., Oparaocha, G.O., 2017. Crowdfunding: Motives, definitions, typology and ethical challenges. *Entrep. Res. J.* 7 (2).
- Hu, M., Li, X., Shi, M., 2015. Product and pricing decisions in crowdfunding. *Mark. Sci.* 34 (3), 331–345. <http://dx.doi.org/10.1287/mksc.2014.0900>.
- Huimin, M., Hernandez, J.A., 2011. Price skimming on a successful marketing strategy: study of ipad launching as apple's innovative product. In: *Proceedings of the 8th International Conference on Innovation & Management*. Japan, pp. 389–393.
- Kaartemo, V., 2017. The elements of a successful crowdfunding campaign: A systematic literature review of crowdfunding performance. *Int. Rev. Entrep.* 15 (3), 291–318.
- Kaicker, A., Bearden, W.O., Manning, K.C., 1995. Component versus bundle pricing: The role of selling price deviations from price expectations. *J. Bus. Res.* 33 (3), 231–239. [http://dx.doi.org/10.1016/0148-2963\(94\)00072-M](http://dx.doi.org/10.1016/0148-2963(94)00072-M).
- Kehagias, J., Skourtis, E., Vassilikopoulou, A., 2009. Plaiting pricing into product categories and corporate objectives. *J. Prod. Brand Manag.* 18 (1), 67–76. <http://dx.doi.org/10.1108/10610420910933380>.
- Khosro, I., Ahmed, R.R., Ahmed, J., 2014. Pricing strategies in pharmaceutical marketing. *Pharma Innov.* 3 (7, Part A), 13.
- Kim, J., Bojanic, D., Warnick, R., 2009. Price bundling and travel product pricing practices used by online channels of distribution. *J. Travel Res.* 47 (4), URL: [https://scholarworks.umass.edu/htm\\_faculty\\_pubs/4](https://scholarworks.umass.edu/htm_faculty_pubs/4).
- Koçaş, C., Dogerlioglu-Demir, K., 2020. The 1 in 1,000,000: Context effects of how numbers cue different kinds of incidental environmental anchoring in marketing communications. *J. Bus. Res.* 109, 536–544. <http://dx.doi.org/10.1016/j.jbusres.2019.01.027>.
- Kreul, L.M., 1982. Magic numbers: psychological aspects of menu pricing. *Cornell Hotel Restaur. Adm. Q.* 23 (2), 70–75.
- Kunz, M.M., Bretschneider, U., Erler, M., Leimeister, J.M., 2017. An empirical investigation of signaling in reward-based crowdfunding. *Electron. Commer. Res.* 17 (3), 425–461. <http://dx.doi.org/10.1007/s10660-016-9249-0>.
- Kuo, Y.F., Lin, C.H., Hou, J.R., 2020. The effects of anchoring on backers' pledge in reward-based crowdfunding: evidence from Taiwanese market. *Internet Res.* <http://dx.doi.org/10.1108/INTR-05-2020-0260>.
- Kuppuswamy, V., 2018. A review of crowdfunding research and findings. In: *Handbook of Research on New Product Development*. Edward Elgar Publishing, pp. 361–373. <http://dx.doi.org/10.4337/9781784718152.00028>.
- Lee, H.C., Tsai, D.C., Wu, M.D., 2011. The dilemma of mixed bundles: The effects of price, brand, and content preference on music CD bundle choices. *J. Retail. Consum. Serv.* 18 (5), 455–462. <http://dx.doi.org/10.1016/J.JRETCONSER.2011.06.010>.
- Lehmann, S., Buxmann, P., 2009. Pricing strategies of software vendors. *Bus. Inf. Syst. Eng.* 1 (6), 452–462. <http://dx.doi.org/10.1007/S12599-009-0075-Y>.
- Lev, O., Oren, J., Boutilier, C., Rosenschein, J.S., 2015. The pricing war continues: On competitive multi-item pricing. In: *Proceedings of the 29th Conference on Artificial Intelligence (AAAI)*. Austin, Texas, pp. 972–978.
- Liu, J., Liu, X., Shen, H., 2020. Reward-based crowdfunding: The role of information disclosure. *Decis. Sci.* 53 (2), 390–422. <http://dx.doi.org/10.1111/dec.12486>, URL: <https://www.kickstarter.com/projects/getpebble/pebble-e-paper-watch-for-iphone-and-android>.
- Liu, X., Wang, J., Zhu, J., 2022. Pricing and observational learning in crowdfunding: The moderate effect of target. *J. Manag. Sci. Eng.* 7 (1), 146–158.
- Lu, C.-T., Xie, S., Kong, X., Yu, P.S., 2014. Inferring the impacts of social media on crowdfunding. In: *Proceedings of the 7th ACM International Conference on Web Search and Data Mining (WSDM)*. pp. 573–582, doi:<https://dl.acm.org/doi/10.1145/2556195.2556251>.
- Manning, K.C., Sprott, D.E., 2009. Price endings, left-digit effects, and choice. *J. Consum. Res.* 36 (2), 328–335. <http://dx.doi.org/10.1086/597215>.
- Mitra, T., Gilbert, E., 2014. The language that gets people to give: Phrases that predict success on kickstarter. In: *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW)*. pp. 49–61.
- Mollick, E., 2014. The dynamics of crowdfunding: An exploratory study. *J. Bus. Ventur.* 29 (1), 1–16. <http://dx.doi.org/10.1016/j.jbusvent.2013.06.005>.
- Mollick, E., 2018. Crowdfunding as a font of entrepreneurship: Outcomes of reward-based crowdfunding. *Econ. Crowdfunding: Startups Portals Invest. Behav.* 133–150.
- Moritz, A., Block, J.H., 2016. Crowdfunding: A literature review and research directions. In: *FGF Studies in Small Business and Entrepreneurship*. Springer, pp. 25–53. [http://dx.doi.org/10.1007/978-3-319-18017-5\\_3](http://dx.doi.org/10.1007/978-3-319-18017-5_3), URL: [https://link.springer.com/chapter/10.1007/978-3-319-18017-5\\_3](https://link.springer.com/chapter/10.1007/978-3-319-18017-5_3).
- Myung, E., McCool, A.C., Feinstein, A.H., 2008. Understanding attributes affecting meal choice decisions in a bundling context. *Int. J. Hosp. Manag.* 27 (1), 119–125. <http://dx.doi.org/10.1016/J.IJHJM.2007.07.014>.
- Nagle, T.T., Hogan, J., Zale, J., 2016. *The Strategy and Tactics of Pricing: New International Edition*. Routledge.
- Nair, G.K., 2019. Dynamics of pricing and non-pricing strategies, revenue management performance and competitive advantage in hotel industry. *Int. J. Hosp. Manag.* 82 (October 2018), 287–297. <http://dx.doi.org/10.1016/j.ijhm.2018.10.007>.
- Ng, I.C., 2009. A demand-based model for the advance and spot pricing of services. *J. Prod. Brand Manag.* 18 (7), 517–528. <http://dx.doi.org/10.1108/10610420910998244>.
- Noble, P.M., Gruca, T.S., 1999. Industrial pricing: Theory and managerial practice. *Mark. Sci.* 18 (3), 435–454. <http://dx.doi.org/10.1287/mksc.18.3.435>.
- Oruc, R., 2015. *The Effects of Product Scarcity on Consumer Behavior: A Meta-Analysis (Ph.D. thesis)*. Europa-Universität Viadrina Frankfurt.
- Peng, J., Zhang, J., Nie, T., Zhu, Y., Du, S., 2020. Pricing and package size decisions in crowdfunding. *Transp. Res. E* 143, 102091. <http://dx.doi.org/10.1016/J.TRE.2020.102091>.
- Popescu, I., Yaozhong, W., 2007. Dynamic pricing strategies with reference effects. *Oper. Res.* 55 (3), 413–429. <http://dx.doi.org/10.1287/opre.1070.0393>.
- Rafeei, H., Rabbani, M., Razmi, J., Jolai, F., 2013. Product bundle pricing in the new millennium: A literature review. *Int. J. Adv. Manag. Sci.* 2 (3), 109–118.
- Redmond, W.H., 1989. Effects of new product pricing on the evolution of market structure. *J. Prod. Innov. Manag.* 6 (2), 99–108. [http://dx.doi.org/10.1016/0737-6782\(89\)90004-0](http://dx.doi.org/10.1016/0737-6782(89)90004-0).
- Rossi, M., 2014. The new ways to raise capital: an exploratory study of crowdfunding. *Int. J. Financ. Res.* 5 (2), 8.
- Ryu, S., Kim, Y.-G., 2016. A typology of crowdfunding sponsors: Birds of a feather flock together? *Electron. Commer. Res. Appl.* 16, 43–54.
- Seward, A., Garcia-Cestona, M., Silaghi, F., 2021. Resolving information asymmetries in financing new product development: The case of reward-based crowdfunding. *Res. Policy* 50 (10), 104345.
- Shi, X., Li, F., Chumnumpan, P., 2020. The use of product scarcity in marketing. *Eur. J. Mark.* 54 (2), 380–418. <http://dx.doi.org/10.1108/EJM-04-2018-0285>.
- Shneur, R., Vik, A.A., 2017. Crowdfunding success: A systematic literature review 2010–2017. *Balt. J. Manag.* 15 (2), 149–182.
- Simon, H., Butscher, S.A., 2001. Individualised pricing: boosting profitability with the higher art of power pricing. *Eur. Manag. J.* 19 (2), 109–114, URL: <https://ideas.repec.org/a/eee/eurman/v19y2001i2p109-114.html>.
- Simons, A., Weinmann, M., Tietz, M., vom Brocke, J., 2017. Which reward should I choose? Preliminary evidence for the middle-option bias in reward-based crowdfunding. In: *Proceedings of the 50th Hawaii International Conference on System Sciences*. pp. 4344–4353. <http://dx.doi.org/10.24251/hicss.2017.526>.
- Skrupak, S.J., 2016. *Fundamentals of Business*. Virginia Tech.
- Taleizadeh, A.A., Babaei, M.S., Niaki, S.T.A., Noori-daryan, M., 2017. Bundle pricing and inventory decisions on complementary products. *Oper. Res.* 20 (2), 517–541. <http://dx.doi.org/10.1007/s12351-017-0335-4>, URL: <https://link.springer.com/article/10.1007/s12351-017-0335-4>. 2017 20:2.



- Tellis, G.J., 1986. Beyond the many faces of price: An integration of pricing strategies. *J. Mark.* 50 (4), 146. <http://dx.doi.org/10.2307/1251292>.
- Teovanović, P., 2019. Individual differences in anchoring effect: Evidence for the role of insufficient adjustment. *Eur. J. Psychol.* 15 (1), 8–24. <http://dx.doi.org/10.5964/ejop.v15i1.1691>.
- Thaler, R.H., Sunstein, C.R., 2008. *Nudge: Improving Decisions About Health, Wealth, and Happiness*. Yale University Press.
- Thürriidl, C., Kamleitner, B., 2016. What goes around comes around? Rewards as strategic assets in crowdfunding. *Calif. Manage. Rev.* 58 (2), 88–110.
- Tian, Y., Zhang, Y., 2022. Pricing of crowdfunding products with strategic consumers and online reviews. *Electron. Commer. Res. Appl.* 54, 101169.
- Tietz, M., Simons, A., Weinmann, M., vom Brocke, J., 2016. The decoy effect in reward-based crowdfunding: Preliminary results from an online experiment. In: *Proceedings of the 37th International Conference on Information Systems (ICIS)*. pp. 1–11.
- Tversky, A., Kahneman, D., 1974. Judgment under uncertainty: Heuristics and biases. *Science* 185 (4157), 1124–1131. <http://dx.doi.org/10.1126/science.185.4157.1124>, URL: <https://science.sciencemag.org/content/185/4157/1124.abstract>.
- Venkatesh, R., Mahajaim, V., 1993. A probabilistic approach to pricing a bundle of products or services. *J. Mar. Res.* 30 (4), 494–508. <http://dx.doi.org/10.1177/002224379303000408>, URL: <https://journals.sagepub.com/doi/abs/10.1177/002224379303000408>.
- Wang, C., 2016. The promise of kickstarter: Extents to which social networks enable alternate avenues of economic viability for independent musicians through crowdfunding. *Soc. Med. + Soc.* 2 (3), <http://dx.doi.org/10.1177/2056305116662394>, URL: <https://journals.sagepub.com/doi/full/10.1177/2056305116662394>.
- Wolk, A., Spann, M., 2008. The effects of reference prices on bidding behavior in interactive pricing mechanisms. *J. Interact. Mark.* 22 (4), 2–18. <http://dx.doi.org/10.1002/dir.20118>.
- Wu, C.S., Cheng, F.F., 2011. The joint effect of framing and anchoring on internet buyers' decision-making. *Electron. Commer. Res. Appl.* 10 (3), 358–368. <http://dx.doi.org/10.1016/j.elerap.2011.01.002>.
- Wu, C.S., Cheng, F.F., Lin, H.H., 2008. Exploring anchoring effect and the moderating role of repeated anchor in electronic commerce. *Behav. Inf. Technol.* 27 (1), 31–42. <http://dx.doi.org/10.1080/01449290600874998>.
- Xu, A., Yang, X., Rao, H., Fu, W.T., Huang, S.W., Bailey, B.P., 2014. Show me the money! an analysis of project updates during crowdfunding campaigns. In: *Conference on Human Factors in Computing Systems - Proceedings*. Association for Computing Machinery, pp. 591–600. <http://dx.doi.org/10.1145/2556288.2557045>.
- Yan, R., Bandyopadhyay, S., 2011. The profit benefits of bundle pricing of complementary products. *J. Retail. Consum. Serv.* 18 (4), 355–361. <http://dx.doi.org/10.1016/J.JRETCONSER.2011.04.001>.
- Yang, L., Wang, Z., Hahn, J., 2020. Scarcity strategy in crowdfunding: An empirical exploration of reward limits. *Inf. Syst. Res.* 31 (4), 1107–1131. <http://dx.doi.org/10.1287/isre.2020.0934>.
- Zhang, Y., Tian, Y., 2021. Choice of pricing and marketing strategies in reward-based crowdfunding campaigns. *Decis. Support Syst.* 144, 113520.
- Zhao, Y., Harris, P., Lam, W., 2019. Crowdfunding industry—History, development, policies, and potential issues. *J. Public Aff.* 19 (1), e1921.