Learning about product demand using Crowdfunding

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ABSTRACT
Do entrepreneurs use crowdfunding to learn about the demand for their entrepreneurial product? Crowdfunding serves not only as a financial tool for entrepreneurs but also as an informational tool to run experiments and gather information about the quality of their idea, while also gaining marketing benefits. In this paper, I present a model of Bayesian learning in which an entrepreneur is uncertain about the demand curve and updates her belief when information from the realized sales of her crowdfunding campaign arrives. I focus on the pricing decision of a forward-looking entrepreneur in an oligopoly environment who faces uncertainty about the true value of demand parameters. Different price choices provide different degree of information about these parameters. For instance, setting a higher price reveals more information about the slope parameter than setting a lower price. Therefore, an entrepreneur's pricing decision under crowdfunding is based on a trade-off between current profits and learning about demand of its product that can report higher future profits. Using Kickstarter data, I investigate the presence of concerns for learning in crowdfunding market. I find that less experienced entrepreneurs set higher prices than more experienced ones who are assumed to have less uncertainty on market demand parameters. Entrepreneurs with more experience, offer more discounts on their product to benefit from the marketing effects of crowdfunding platforms. I also show that entrepreneurs with more innovative and novel products have more concerns for market demand learning relative to marketing benefits.

1. Introduction

Crowdfunding is the process of funding a project or venture by raising small amounts of money from a large number of people. In general, it is an open call to provide financial resources. This financing method for entrepreneurs, has grown rapidly and attracted great attention. Crowdfunding platforms are internet-based two-sided markets that link fundraisers to backers to fund a campaign or project by typically many funders. Crowdfunding platforms can be categorized into three different groups. Investment-based platforms such as Prosper marketplace or Crowdcube where the fundraisers offer interest payments or equity in return for fund. Donation-based platforms such as GoFundMe where the funders do not have monetary incentives to fund a campaign.

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Reward-platforms on the other hand, enable entrepreneurs to raise funds by preselling their product to the potential future customers.

On reward-based crowdfunding platforms, entrepreneurs launch a campaign, introduce their new product and ask for a specified minimum payment in exchange for the new product that will be delivered in the future. So, the entrepreneur sets a price for the first versions of her new product and observes the demand at the end of the campaign. Preselling a product through these platforms is a credible way to test the market for a new product in the early stages of the production. It provides the entrepreneur with information about the demand of the product and she learns about consumer preferences. Entrepreneurs observe demand from backers and then update their belief about the preferences of their future customers. These platforms can also be used as a powerful marketing tool to introduce their product to the crowd and affect the new product diffusion process through advertising and word-of-mouth. Thus, crowdfunding platforms value goes beyond the financing value and provides the entrepreneur with market demand information and also marketing benefits.

In this paper I use a dataset from the world's largest crowdfunding platform, Kickstarter to explore whether entrepreneurs make their pricing decisions such that they get early feedback on the market and mitigate their uncertainty about the demand of their product. This paper considers how an entrepreneur improves her learning about the demand curve by choosing a price for her crowdfunding campaign. It explores the entrepreneur's pricing decision to affect the learning process. I first study whether the entrepreneurs make their campaign decisions such that they can get more informative signals from the realized sale. Therefore, the value of crowdfunding platforms for entrepreneurs can go beyond financing the project. To show the existence of learning benefits, I show the deviations of entrepreneurs pricing from the myopic profit maximizing pricing strategies. I then explore the heterogeneity in entrepreneurs' concerns for learning. Less experienced entrepreneurs or the ones with more innovative projects tend to have higher demand uncertainty and thus care more about learning benefits relative to marketing benefits. I expect entrepreneurs with higher degrees of uncertainty to care more about learning the demand while making their campaign decisions.

Entrepreneur may have uncertainty about both time-invariant demand parameters and *i.i.d* demand shocks while for the latter she cannot learn to reduce her uncertainty. In this paper I focus on concerns for learning about the price sensitivity parameter and the product specific quality parameter which are assumed to be time-invariant. Different price choices reveal different degrees of information about demand parameters through the accuracy of observed signal from realized demand. Different prices affect the variance of the signals and thus affect the speed of learning about demand parameters. These effects bring up a trade-off between current period profit and learning motives since entrepreneurs can actively affect the learning process by choosing different prices.

The importance of this empirical question is that it provides information on entrepreneurs willingness to pay for information and marketing benefits. In general, it can be very difficult to get information on this willingness to pay. But the pricing decision and its deviation from the standard profit maximizing choice, give us information about this willingness to pay. Antonovitz and Roe (1990) develop a theoretical model of a competitive firm under uncertainty and introduce a measure of a firm's willingness to pay for information. The value of information to a firm is formulated using a Bayesian approach which compares the expected utility levels from myopic choices and choices based on additional information. In general, it can be very difficult to get empirical evidences on this willingness to pay.

There are some empirical challenges to answer this empirical question and identify firms' concern for learning about demand. Typically, the marginal cost is unobservable such that concern for learning can be confounded with marginal cost. To alleviate this concern, I have considered digital games products since they have negligible marginal costs. Ideally, as researchers, I would like to observe pricing decisions and quantity sold for different levels of demand uncertainty to investigate how concerns for learning affect the pricing decisions. I have considered experience and product novelty to be related to level of uncertainty about demand. There are some alternative explanations for the pattern of pricing for different experience or novelty levels. Experienced entrepreneurs might have access to other financial sources that affects the pricing decision. To mitigate this problem, I have presented my analysis within unfunded projects to make sure experienced entrepreneurs have not raised any money on their previous campaigns. However, I cannot rule out the possibility of having more access to other financial sources.

The main contribution of this paper is to empirically show the entrepreneurs concerns for learning and their use of crowdfunding platforms to mitigate the uncertainty about the demand of a new product in the early stages of the production. This paper contributes to the literature on structural models of active learning where firms actively make their decisions to affect the process of learning about market demand. Rothschild (1974) constructs a theoretical model of optimizing firms who do not know the demand of their product. they argue that a firm who does not know the consequences of charging a specific price, can set this price and observe the market outcome. However, this experimentation to learn about the demand curve is costly. Thus, firm's optimal pricing decision under demand uncertainty should consider the value of information from gained from a particular price against the cost of not charging the myopic optimal price. Cyert et al. (1978) also analyses investment decisions that produce information as well as profits or losses. A two-period optimal investment policy with Bayesian learning is studied to show the optimal investment decision changes under concerns for learning. Harpaz et al. (1982) study the effect of learning from experience on the output decisions of a perfectly competitive firm faced with the demand uncertainty. They present a Bayesian framework for expectations formation and demand forecasting by a perfectly competitive firm. They show that through output experimentation, the firm will deviate from the myopic sequential policy to actively affect the learning process and will tend to overproduce. Cyert and DeGroot (1987) illustrate a trade-off between the current period's reward and the information that affects the future rewards. Since some decisions are more informative than the others, the optimal decision is changed to affect the process of learning. Balvers and Cosimano (1990) propose an active learning model which relates the speed of learning to the firm's price and explores the possible impact of optimal decisions on the learning process. I add to this literature by introducing an active learning model and empirically documenting the presence of this motive in crowdfunding platform.

This paper also contributes to a very recent empirical literature on structural models of competition where firms learn about demand. Huang et al. (2019) develop a dynamic pricing model for products with demand uncertainty where a forward-looking firm learns about the demand through an initial assessment which improves future profit. Jeon (2021) develops a dynamic oligopoly model where firms do not know the true demand parameters but form and update beliefs based on the available information. Then empirically shows that strategic incentives increase both the level and the volatility of investment and that learning intensifies strategic incentives of firms.

Huang et al. (2022) empirically examine how firms learn to set prices in a new market. They find that experienced retailers are initially better-informed, and also that the learning process is faster when sale information is more accurate.

This paper also contributes to the marketing literature on product diffusion and word-of-mouth effect. I introduce a marketing channel into the model as another forward-looking motive for entrepreneur. The product diffusion and word-of-mouth literature studies the effect of consumers' pas experience on their future purchases and also the effect of word-of-mouth on the new products growth curves. This channel brings up an incentive for entrepreneur to use crowdfunding platforms as a marketing tool. Dodson Jr and Muller (1978) develop a model of the diffusion process through advertising and word-of-mouth. Their model incorporates the interaction between buyers and other potential buyers and the effect of external information such as advertising on the diffusion process of a new product. They present the effect of word-of-mouth and advertising on the shape of the new product growth curve. All these papers show the potential of crowdfunding platform as a marketing channel to affect the future purchases and the product diffusion process. Zhao et al. (2013) also studies the effect of consumer learning from online reviews, their own past experiences and others people experiences on their purchases. Their findings confirm that more positive reviews and more numerous reviews affect other consumers choice. Gardete (2016) investigates the role of learning in DRAM manufacturing industry and develops an oligopoly model of competition in which firms decide about their production and capacity. the authors find that that both firms and customers benefit from the learning dynamics. More related to my paper, Beier et al. (2019) explore how firms use reward-based crowdfunding campaigns in their marketing strategies. They show that beside financial objectives, the reward-based crowdfunding is used as a powerful marketing tool for already established and experienced enterprises. So, even for an experienced entrepreneur who already knows her market and has access to other financial resources, crowdfunding is used as a marketing tool.

I also contribute to the literature on informational roles of crowdfunding. Da Cruz (2018) investigates the presence of passive learning in crowdfunding and empirically shows that crowdfunding reduces the entrepreneur's uncertainty about the demand. They investigate if entrepreneurs use the information acquired during crowdfunding in their post campaign decisions. However, the concerns for learning and price experimentation is not studied. Xu (2018) also shows that crowdfunding gives early feedback to entrepreneurs about the market demand. Using Kickstarter data, they show that entrepreneurs use the information from the crowdfunding to make their future decisions. These two papers explore the presence of passive learning and show that the crowdfunding feedback have real option value. Since the real informational value of the crowdfunding affects the profitability of the project in the future, the findings of these two papers open a new avenue for research on the presence of active learning in crowdfunding platforms. I add to this literature by providing evidences that entrepreneurs take these informational values into account and make their pricing decision in crowdfunding campaign such that they can actively affect this learning process.

Although the literature has investigated the role of learning about the demand in the crowdfunding, as far as I know, this is the first paper that studies how entrepreneurs' concern about learning is reflected in their pricing decision. I model the trade off between crowdfunding campaign's profit and the cost of acquiring more information about the demand and then empirically investigate the presence of active acquisition of information by entrepreneurs from crowdfunding campaigns. To do so, I propose a theoretical framework for a forward-looking entrepreneur who is uncertain about the demand of her entrepreneurial product and competes with other entrepreneurs in an oligopoly environment. The model incorporates the possibility of concerns for future profit. The entrepreneur launches a crowdfunding campaign, sets a price for the new product , observes the sales and then updates her belief about the demand curve in a Bayesian updating framework. I then compare the actual pricing behavior to myopic profit maximizing price. As firms get more experienced, the uncertainty about the market demand, especially the price elasticity parameter becomes smaller and the effect of concerns for learning on pricing decision becomes negligible. Thus, the value of marketing benefits relative to learning benefits increase. The heterogeneity in pricing decision of entrepreneurs based on their experience shows the presence of concerns for learning which decrease by experience. To rule out the alternative explanation of potential financial spillovers from previous projects, I explore the change in pricing decision by experience within unfunded projects. I provide evidence that less experienced entrepreneurs set higher prices than more experienced entrepreneurs who are assumed to have less uncertainty on market demand parameters. Experienced entrepreneurs offer more discounts on their products which confirms the higher value of marketing benefits relative to learning benefits. I also show that entrepreneurs with more innovative and novel products have more concerns for market demand learning relative to marketing benefits.

2. Data

Kickstarter is the largest reward-based crowdfunding platform founded in April 2009. As of July 2021, Kickstarter has raised nearly $6 billion from 20 million backers to fund different projects in different categories such as art, video games, technology, etc. To launch a campaign, entrepreneurs create a project page on Kickstarter website, introducing the details of their innovative project. They offer a reward to the potential backers and then set a funding goal. In most of the categories that involve introducing a new product, the entrepreneurs offer their product as reward and set a minimum price on it. For example, in the video games category, entrepreneurs set a price on their final product and offer a version of this final product as reward to backers. If the funding goal set by the entrepreneur is met before the campaign deadline, the entrepreneur gets all the funding raised and should deliver the final product (rewards) on a prespecified estimated delivery date. If the funding goal is not met by the end of the campaign, entrepreneur gets nothing and backers are not charged. Figure 1 shows a sample kickstarter project. This project has reached more than 40% of its funding target and 19 days is left until the end of the campaign.

I use the Kickstarter relational database Li (2019) which includes almost all the projects that were posted from May 2009 to Jan 2019. These data describe the projects in details including their category, location, launch time, deadline, product description, price, fund raised, number of backers and whether they met their target. For the purpose of my analysis I only include projects in digital games category. The reason for choosing this category is that the identification strategy that I use in this paper is based on the condition that the marginal costs of the product is negligible. Entrepreneurs may offer different versions of the same product for different prices. In categories such as technology that entrepreneur produces a physical product, different versions might be related to different quantities that can result in second-degree price discrimination. However in the digital games category, different versions of a game are mostly the same game in different digital formats, or with different technical support

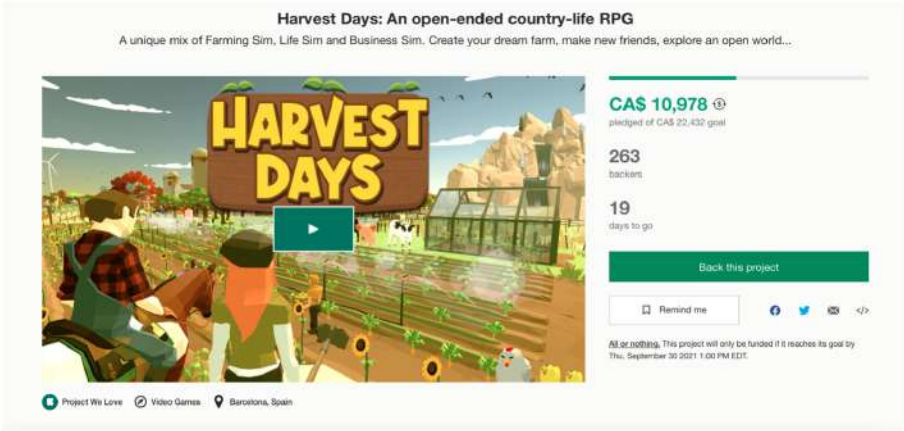


Figure 1. Example of a Kickstarter project

levels. Thus, using the digital games category alleviates the problem of versioning and price discrimination. I use the average price of different versions as the price for product and the summation of backers for each version as the total number of buyers. Text analysis of the descriptions of different versions of each product can be a next step to this research to make a more accurate weighted price for each product. Backers can also pay more than the specified price for a product. However, I do not use the data on payments and instead, I only use the data on number of consumers who choose to buy the product. The number of these consumers reflect the demand of the product since their willingness to pay is at least as large the specified price. The working sample contains 31,562 different projects from which 13,213 met their funding goal. There are 22,295 different entrepreneurs that means some entrepreneurs have launched more than one project in this category.

I create experience measure for entrepreneurs as the number of their previous projects in the same category at Kickstarter. The entrepreneurial experience is considered to be related to the entrepreneur's level of demand uncertainty. As the entrepreneurs introduce more products in the same category, they get a better evaluation of the market demand for their new product. More than 4,000 entrepreneurs have launched more than one project in Kickstarter. Following Xu (2018), I create a Novelty score for each product that might be also related to the degree of demand uncertainty. I calculate the The Bigram text similarity score between the description of two projects. The Bigram algorithm compares two strings and calculates a score, valued between 0 and 1. Higher score means higher similarity between two descriptions. I then define one minus the mean of this similarity score for each products compared to other products as the Novelty Score of the product. The calculation of the novelty score can be improved by more extensive text analysis to get the measure in more specific groups of the product. In this paper, my main focus is on the experience measure which is assumed to be related to the level of demand uncertainty associated with the entrepreneur. I introduce this simple measure of novelty to represent the uncertainty associated with the nature of the product. Thus, Experience and Novelty measures are assumed to capture the uncertainty from the entrepreneur side and the product side respectively. Table 1 shows the summary statistics for the main variables.

Figure 2 shows the distribution of the logarithm of price in the data. It shows the variation in prices among digital game projects. The entrepreneur cannot set a reward tier higher than $10,000 and also a backer cannot pay more than $10,000 to back a sin-

Table 1. Kickstarter – Digital Games – May 2009 to Jan 2019 – Summary Statistics

	Number of Projects(Observations)=31,562				
Variable	Mean	St. Dev.	Median	Min	Max
Price($)	289.69	503.80	110.44	.55	10,000
Number of Buyers	412.69	2,349.61	46	0	219,382
Funding Goal($)	45,264.85	892,934.4	8,396.9	.76	1.00e+08
Successful (Dummy)	.41	.49	0	0	1
Entrepreneur's Experience	2.22	4.11	1	1	83
Novelty Score (0-1)	.63	.05	.62	.42	1
Has Video (Dummy)	.78	.40	1	0	1
Staff Picked(Dummy)	.13	.34	0	0	1

gle project. I have converted all the prices in other currencies to US dollar. The main source of price dispersion is product differentiation. In the absence of demand uncertainty, products with higher demand and less competition should have higher prices. In this paper, I am interested in demand uncertainty as another potential source of price dispersion. In fact, demand uncertainty has an ambiguous effect on pricing pattern. Since the marginal cost for this specific category of projects is negligible, a part of the variation in prices for similar projects can be associated with entrepreneurs experimenting the market demand. Experienced entrepreneurs typically face lower demand uncertainty especially when introducing products in the same category. Figure 3 shows the pricing pattern of projects for different levels of entrepreneurial experience and also shows the pricing pattern of projects by their novelty score. Although both diagrams are noisy, The level of prices decrease when entrepreneurs get more experienced and introduce more products. If learning and testing out the market demand is not present, the pricing behaviour of entrepreneurs should be independent of their previous projects. For the novelty score, the pattern in figure 3 is unclear. The presence of concerns for learning and marketing benefits have different effects on price dispersion. To study the effect of concerns for learning on pricing decision, the deviation of chosen price from the optimal full-information myopic price is a more accurate measure which I explore in next sections.

Considering both concerns for learning and marketing benefits, I expect entrepreneurs to offer larger discounts when their incentives for marketing benefits is larger and their demand uncertainty is negligible. If concerns for learning decrease, then their effect on pricing pattern also disappear. Thus, the pure effect of marketing benefit results in offering larger discounts to introduce the first versions of the product to a larger crowd. More specifically, I expect to see larger discounts associated with more experience and less novelty score.

There are other possible explanations for the relationship between experience or novelty and price dispersion. First, more experienced entrepreneurs might have lower marginal costs. I have only included the digital games category to make sure negligible marginal costs for the product. More experienced entrepreneurs might have access to alternative source of funding. To mitigate this financial effect, I have also presented my analysis within the unfunded projects to make sure entrepreneurs have not raised any money on their previous projects at Kickstarter. However, I cannot rule out the

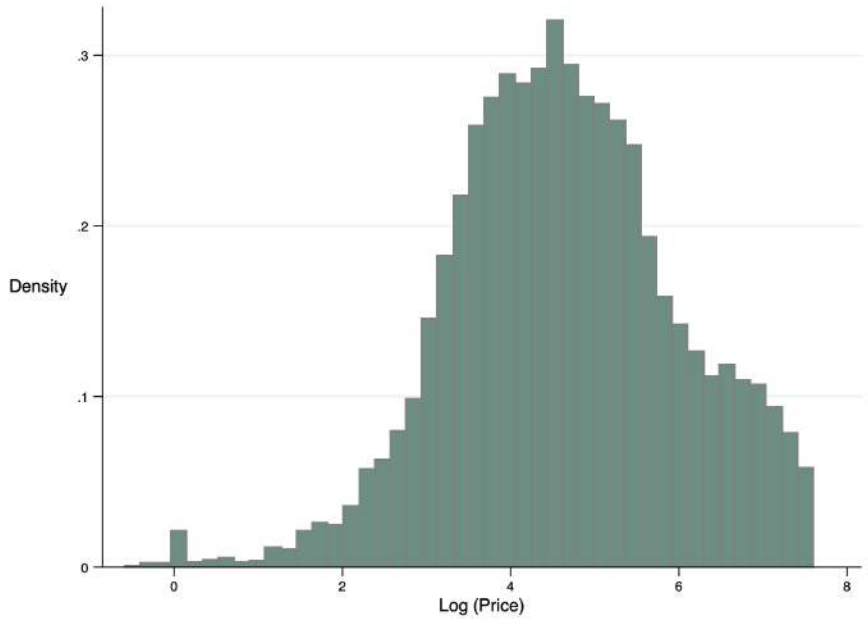
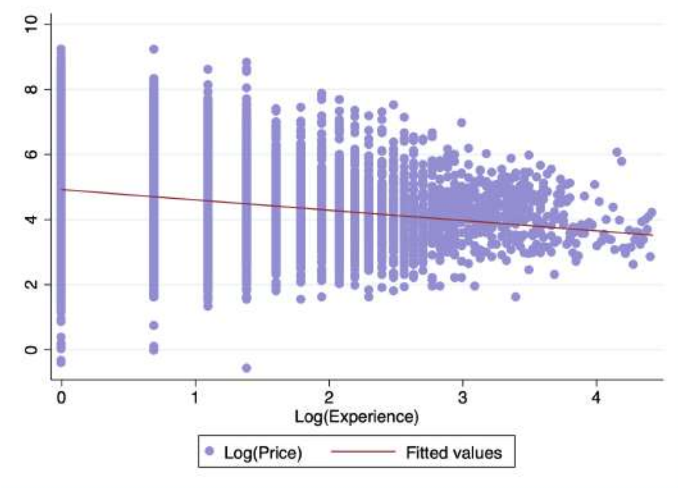
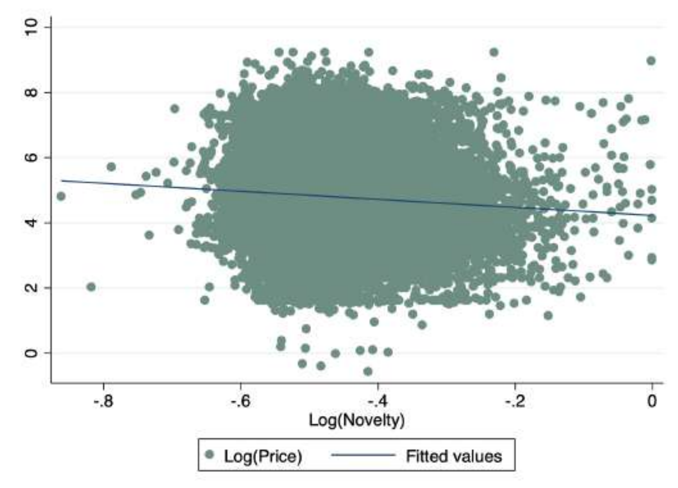


Figure 2. Distribution of the logarithm of price

possibility that entrepreneurs with multiple Kickstarter projects to have more access to other financial sources compared to less experienced ones. More experienced entrepreneurs might have other products in the same market which are competing with this new product and they internalize the cannibalization effect. Based on Kickstarter policy, entrepreneurs cannot launch multiple campaigns at the same time or launch a second project before fulfilling the first one. So, the cannibalization effect is not present in this specific market. More novel products have more distant competitors which implies higher prices. The standard logit model presented in this paper can be extended to a nested logit or BLP demand model for future research.



(a) $log(price)$as a function of $log(Experience)$



(b) $log(price)$as a function of $log(Novelty)$

Figure 3. This figure shows the pricing pattern of projects for different levels of entrepreneurial experience and also shows the pricing pattern of projects by their novelty score.

3. Theoretical Framework

3.1. Basic Framework

I focus on the pricing decision of an entrepreneur in an oligopoly environment who is uncertain about the demand curve of her new product. This uncertainty is expressed in the form of a prior belief about parameters of the demand curve. The uncertainty can be mitigated using a campaign launch in the crowding platform, as realized sales provide the entrepreneur with the information about the demand curve. I first propose a basic model where the firs do not have forward-looking motives and only care about the financial benefits of crowdfunding period. I then add concerns for learning about the demand parameters to the model and investigate the effect of this motive on pricing decision. I then introduce concerns for marketing into the model as an additional forward-looking motive that may confound with learning motives. Although this channel is not the main focus of this paper, I need this to make sure learning channel is not confounding with marketing benefits. At last, I investigate the pricing decision under learning and marketing motives to get the implications of theoretical model for price pattern.

I propose a two-period model where the first period is the crowdfunding campaign and the second period is after the product launch. The timing of the model is as follows:

- **Start of t=1:** the entrepreneur launches a campaign, sets a price for the new product based on her belief about the demand and her concern for learning about the demand curve.
- **End of t=1:** the product demand is realized and the entrepreneur observes the quantity sold, which provides a noisy signal about the parameters in the demand curve. The entrepreneur updates her belief about the demand curve using Bayesian updating.
- **Start of t=2:** the entrepreneur sets the retail price based on the updated belief about the demand.

Considering one special category of products, I consider a market populated by backers who choose among several differentiated products. Then the product demand is modeled as a logit demand system. I assume each backer chooses among the available products on that day. Each product is available during a prespecified period of time which is on average 30 days. Each entrepreneur is competing with all other products which are available during her campaign. The utility of consumer i from purchasing product j in crowdfunding period and retail period are:

$$
\begin{aligned}
t = 1: \quad & U_{ij1} = \alpha_j - \beta p_{j1} + \xi_{j1} + \epsilon_{ij1} \\
t = 2: \quad & U_{ij2} = \alpha_j - (\beta + \kappa) p_{j2} + \xi_{j2} + \epsilon_{ij2}
\end{aligned}
$$

α_j is the quality of product j which is the average valuation consumers assign to all unobserved product attributes. p_j is the price of product j and β reflects the price sensitivity of backers. ξ_{j1} is i.i.d normally distributed with mean 0 and variance σ_ξ^2. ξ_{j2} is also normally distributed and independent from ξ_{j1} and prior beliefs. However, ξ_{j2} has nonzero mean to allow for change in the quality of product j over time and also account for different types of consumers in each of the two periods. κ is normally distributed with nonzero mean to allow for the change in price sensitivity of consumers over two periods. κ is also independent from prior beliefs. Since the crowdfunding period and retail period can have different types of consumers, nonzero mean ξ_{j2} and κ let the demand parameters to vary over the two periods. What is important is that the quality and price sensitivity parameters in retail period are related to these parameters in crowdfunding period so that the realized demand from crowdfunding period contains information about the demand curve of the retail period.The fact that α_j and β are constant between the two periods, introduces the incentive for learning. Finally, ϵ_{ij} is an idiosyncratic demand shock that follows independent standard Gumbel distributions. It captures both the taste heterogeneity and also the noisy signal of consumers about the true quality of product. I assume all the campaigns have the same duration of T days. The market share of product j can be written as:

$$s_{j1} = \frac{1}{T}\sum_{r=1}^{T}\frac{exp(\alpha_j - \beta p_{j1} + \xi_{j1})}{1 + \sum_{k_r} exp(\alpha_{k_r} - \beta p_{k_r 1} + \xi_{k_r 1})}$$

where T is the duration of product availability and k_r is the set of projects which are available on the *r-th* day of duration T. For two different projects that are launched in the same day, their competitors are the same which means all the denumerators in the market share equations are the same. Normalizing the utility of outside option to zero, The following equation can be written:

$$log(s_{j1}) - log(s_{01}) = \alpha_j - \beta p_{j1} + \xi_{j1} \quad \xi_1 \sim N(0, \sigma_\xi^2)$$

s_{01} is the market share for outside option. If the entrepreneur does not have any forward-looking concerns, she solves the following profit maximization problem:

$$Max_{p_{j1}} \quad (p_{j1} - mc)Q_{j1}$$

p_{j1} is the crowdfunding price and $Q_{j1} = M_1 s_{j1}$ is the quantity. M_1 is the market size and s_{j1} is the market share. For this logit demand system, it is straightforward to show that the optimal price has the following expression:

$$\begin{aligned} F.O.C[p_{j1}] : s_{j1} - \beta_1 s_{j1}(1 - s_{j1})(p^*_{j1} - mc) = 0 \\ \rightarrow p^{myopic}_{j1} = \frac{1}{\beta_1(1 - s_{j1})} + mc \end{aligned}$$

3.2. Pricing Decision Under Concerns for Learning

In presence of concerns for learning, the entrepreneur has uncertainty about demand parameters α and β. This uncertainty mitigates in a Bayesian updating framework. entrepreneur's prior belief about coefficients are assumed to be normally distributed:

$$\begin{aligned} \alpha_{j1} \sim N(\mu_{\alpha j1}, \sigma^2_{\alpha j1}) \\ \beta_1 \sim N(\mu_{\beta 1}, \sigma^2_{\beta 1}) \end{aligned}$$

The entrepreneur observes $log(s_{j1}) - log(s_{01})$. The entrepreneur observes s_{j1} since she knows market size, and observes its own quantity sold. To observe s_{01}, the entrepreneur needs to know the total quantity sold of all the products. This information is available in the online platform which makes it possible for the entrepreneur to observe $log(s_{j1}) - log(s_{01})$ from the realized quantities sold. Thus, the realized demand at the end of period one provides the entrepreneur with two noisy signals $z_{\alpha j}$ and $z_{\beta j}$ about the demand parameters:

$$z_{\alpha j} = log(s_{j1}) - log(s_{01}) + \beta_1 p_{j1} = \alpha_j - (\beta - \beta_1)p_{j1} + \xi_{j1}$$

$$z_{\beta j} = \frac{log(s_{j1}) - log(s_{01}) - \alpha_{j1}}{-p_{j1}} = \beta - \frac{\alpha_j - \alpha_{j1}}{p_{j1}} - \frac{\xi_j}{p_{j1}}$$

Since the prior beliefs about the unknown parameters are normally distributed, the two signals are also normally distributed:

$$z_{\alpha j} \quad \sim N(\alpha_j - (\beta - \mu_{\beta 1})p_{j1},\ p_{j1}^2 \sigma_{\beta 1}^2 + \sigma_\xi^2)$$

$$z_{\beta j} \quad \sim N\left(\beta - \frac{\alpha_j - \mu_{\alpha j1}}{p_{j1}},\ \frac{\sigma_{\alpha j1}^2 + \sigma_\xi^2}{p_{j1}^2}\right)$$

The firm updates its belief about the parameters in a Bayesian fashion. define $\lambda_{\alpha j}$ and $\lambda_{\beta j}$ as the speeds of learning of entrepreneur j about two unknown parameters:

$$\lambda_{\alpha j} = \frac{\sigma_{\alpha j1}^2}{\sigma_{\alpha j1}^2 + p_{j1}^2 \sigma_{\beta 1}^2 + \sigma_\xi^2}$$
$$\lambda_{\beta j} = \frac{p_{j1}^2 \sigma_{\beta 1}^2}{\sigma_{\alpha j1}^2 + p_{j1}^2 \sigma_{\beta 1}^2 + \sigma_\xi^2}$$

The posterior beliefs about unknown parameters are normally distributed with the following means and variances:

$$\mu_{\alpha j2} = \mu_{\alpha j1} + \lambda_{\alpha j}(z_{\alpha j} - \mu_{\alpha j1})$$

$$\sigma_{\alpha j2}^2 = \sigma_{\alpha j1}^2 - \lambda_{\alpha j1}^2(\sigma_{\alpha j1}^2 + p_{j1}^2 \sigma_{\beta 1}^2 + \sigma_\xi^2)$$

$$\mu_{\beta j2} = \mu_{\beta 1} + \lambda_{\beta j}(z_{\beta j} - \mu_{\beta 1})$$

$$\sigma^2_{\beta j2} = \sigma^2_{\beta 1} - \lambda^2_{\beta j}(\sigma^2_{\beta 1} + \frac{\sigma^2_{\alpha 1} + \sigma^2_{\xi}}{p^2_{j1}})$$

$$\begin{aligned} \rightarrow \alpha_{j2} &\sim N(\mu_{\alpha j2}, \sigma^2_{\alpha j2}) \\ \beta_{2j} &\sim N(\mu_{\beta j2}, \sigma^2_{\beta j2}) \end{aligned}$$

The updating rules illustrate how the learning process can converge to the true values of the utility parameters. Based on the equations for the speeds of learning, if the variance of the signal decrease which means the signal is more accurate and informative, the learning process becomes faster. Moreover, if the uncertainty about the parameter is higher, the speed of learning is also higher which means it is difficult to mitigate small uncertainties. Speed of learning is the weight of the surprise in the updating rules.Higher λ s mean the the entrepreneur puts higher weight on the new information when updating her belief.

The equations for both signals show that the distributions of the signals are affected by entrepreneur's pricing decision. Higher prices increase the variance of the signal $z_{\alpha j}$ which reduce the speed of learning about the intercept parameter. On the other hand, higher prices decrease the variance of the signal $z_{\beta j}$ and increases the speed of learning about the slope parameter. The intuition behind this is that conditional on a specific intercept, if the entrepreneur is uncertain about the slope, higher prices increase the distance between potential demand curves which makes it easier to learn the true parameter. Larger prices increase the effect of slope uncertainty on signal for the intercept parameter. On the other hand, larger prices reduce the effect of intercept uncertainty on the signal for the slope parameter. The levels of uncertainty and the chosen price determine the speeds of learning about demand parameters. Thus, entrepreneurs can actively affect the learning process by choosing the price.

A price-setting entrepreneur is able to obtain information by choosing a price that increases the spread between potential demand curves. This consideration determines whether incentives to learn induce setting lower or higher prices. In a linear demand curve with known intercept and unknown slope, setting higher prices increases the spread between quantities observed from potential demand curves. Thus, higher prices provide more information about the demand curve as it is easier to infer the true slope from observed quantity. However, in a linear demand curve with known slope and unknown intercept, potential demand curves are all parallel lines and choosing different prices does not affect the spread between potential curves. Thus, learning about intercept when slope is known is irrelevant of the price. In the logit demand system where $log(s_{j1}) - log(s_{01})$ is a linear function of price, The same discussion remains valid as entrepreneur's incentive for learning about demand can be seen as learning about $log(s_{j1}) - log(s_{01})$.

I assume that active entrepreneurs engage in price competition.The entrepreneur's objective is to maximize the expected profit of the two periods. The optimal price for the second period is the myopic price that maximizes expected profit:

$$Max_{p_{j2}} \quad E_2[(p_{j2} - mc)Q_{j2}]$$

For this logit demand system, it is straight forward to show that the optimal price has the following expression:

$$F.O.C[p_{j2}] : E_2[s_{j2} - \beta_{2j}s_{j2}(1 - s_{j2})(p^*_{j2} - mc)] = 0$$
$$\rightarrow p^*_{j2} = \frac{E_2[s_{j2}]}{E_2[\beta_{2j}s_{j2}(1 - s_{j2})]} + mc$$

p_{j2} is the retail price and $Q_{j2} = M_2 s_{j2}$ is the retail quantity. s_{j2} is retail period's market share and the belief of entrepreneur about the market share is a function of posterior belief about demand parameters. M_2 is the retail period's market size. The expectation is taken over the posterior belief of entrepreneur about demand parameters. In the crowdfunding pricing decision, each entrepreneur recognizes the impact that current price has not only on the current profit, but also on the next period's profit through the learning process. The entrepreneur chooses the optimal price for the first period based on the following optimization problem:

$$Max_{p_{j1}} \quad E_1[(p_{j1} - mc)Q_{j1} + \delta E_2[(p_{j2} - mc)Q_{j2}]]$$
$$s.t: \; p^*_{j2} = \frac{E_2[s_{j2}]}{E_2[\beta_{2j}s_{j2}(1 - s_{j2})]} + mc$$

$Q_{j1} = M_1 s_{j1}$ and M_1 are the crowdfunding period's quantity and market and $Q_{j2} = M_2 s_{j2}$ and M_2 are the retail period's quantity and market. The expectations are taken over the belief of entrepreneur about the demand parameters. Substituting the retail price in the expected profit equation:

$$Max_{p_{j1}} \quad M_1 E_1[(p_{j1} - mc)s_{j1}] + \delta M_2 E_1[\; \frac{E_2[s_{j2}]}{E_2[\beta_{2j}s_{j2}(1 - s_{j2})]} E_2[s_{j2}] \;]$$

The optimal solution to the optimization problem is as follows:

$$F.O.C[p_{j1}] : E_1[s_{j1} - \beta_1 s_{j1}(1 - s_{j1})(p^*_{j1} - mc)] + \delta \frac{M_2}{M_1} \frac{\partial}{\partial p_j} EV_2 = 0$$

$$p^*_{j1} = \frac{E_1[s_{j1}]}{E_1[\beta_1 s_{j1}(1 - s_{j1})]} + mc + \frac{\delta \frac{M_2}{M_1} \frac{\partial}{\partial p_{j1}} EV_2}{E_1[\beta_1 s_{j1}(1 - s_{j1})]}$$

EV_2 is the expected continuation value which is a function of the crowdfunding period's price. To evaluate the effect of experimentation on the entrepreneur's pricing decisions, I compare the optimal experimenting price with the optimal price when the impact of learning is ignored. An entrepreneur who ignores the effect of learning will solve the following problem:

$$Max_{p_{j1}} M_1 E_1[(p_{j1} - mc)s_{j1}]$$

The optimal solution to the optimization problem is as follows:

$$F.O.C[p_{j1}] : E_1[s_{j1} - \beta_1 s_{j1}(1 - s_{j1})(p_{j1}^{myopic} - mc)] = 0$$

$$p_{j1}^{myopic} = \frac{E_1[s_{j1}]}{E_1[\beta_1 s_{j1}(1 - s_{j1})]} + mc$$

In the absence of concerns for learning, I expect the difference in the myopic optimal price and the observed price in the data to be independent of price and only depend on exogenous variables. If entrepreneur is concerned about learning, the deviation from myopic pricing systematically depend on the chosen price.

$$p_{j1}^* - p_{j1}^{myopic} = \delta \frac{M_2}{M_1} \frac{\partial}{\partial p_{j1}} EV_2$$

The difference between the myopic price and the experimenting optimal price is $\delta \frac{M_2}{M_1} \frac{\partial}{\partial p_{j1}} EV_2$. Since $\delta \frac{M_2}{M_1}$ is positive, $\frac{\partial}{\partial p_{j1}} EV_2$ determines whether the incentive to learn generates under- or over-pricing. This is consistent with the previous discussion about the effect of price on two signals. If resolving the uncertainty about parameter β is more important to entrepreneur, the experimenting optimal price will be greater than the myopic price. Since the only channel that current price affects future's profit is through the learning process, if $\frac{\partial}{\partial p_{j1}} EV_2 > 0$, higher prices produce more information and increase the expected continuation value of the product. On the other hand, if entrepreneur values an accurate signal about parameter α relative to parameter β, the optimal experimenting price will be lower than the myopic price. More specifically, I can decompose the $\frac{\partial EV_2}{\partial p_{j1}}$ into four terms:

$$\frac{\partial EV_2}{\partial p_{j1}} = \frac{\partial EV_2}{\partial \mu_{\alpha j2}} \frac{\partial \mu_{\alpha j2}}{\partial p_{j1}} + \frac{\partial EV_2}{\partial \sigma_{\alpha j2}^2} \frac{\partial \sigma_{\alpha j2}^2}{\partial p_{j1}} + \frac{\partial EV_2}{\partial \mu_{\beta j2}} \frac{\partial \mu_{\beta j2}}{\partial p_{j1}} + \frac{\partial EV_2}{\partial \sigma_{\beta j2}^2} \frac{\partial \sigma_{\beta j2}^2}{\partial p_{j1}}$$

The following terms capture the effect of first period price on the distribution of posterior belief:

$$\begin{aligned}\frac{\partial \mu_{\alpha j2}}{\partial p_{j1}} = & \frac{-p_{j1}\sigma_{\beta 1}^2 \sigma_{\alpha_{j1}}^2}{(\sigma_{\alpha j1}^2 + p_{j1}^2 \sigma_{\beta 1}^2 + \sigma_{\xi}^2)^2} (\alpha_j + \xi_{j1} - \mu_{\alpha_{j1}} - (\beta - \mu_{\beta 1}) p_{j1}) \\ & + \frac{\sigma_{\alpha_{j1}}^2}{\sigma_{\alpha j1}^2 + p_{j1}^2 \sigma_{\beta 1}^2 + \sigma_{\xi}^2} (-(\beta - \mu_{\beta 1}) + 2\sigma_{\beta_1}^2 p_{j1})\end{aligned}$$

$$\begin{aligned}\frac{\partial \sigma_{\alpha j2}^2}{\partial p_{j1}} = & \frac{-2p_{j1}\sigma_{\beta 1}^2 \sigma_{\alpha_{j1}}^2}{(\sigma_{\alpha j1}^2 + p_{j1}^2 \sigma_{\beta 1}^2 + \sigma_{\xi}^2)^2} \frac{\sigma_{\alpha_{j1}}^2}{\sigma_{\alpha j1}^2 + p_{j1}^2 \sigma_{\beta 1}^2 + \sigma_{\xi}^2} (\sigma_{\alpha j1}^2 + p_{j1}^2 \sigma_{\beta 1}^2 + \sigma_{\xi}^2) \\ & + 2\sigma_{\beta 1}^2 p_{j1} \frac{\sigma_{\alpha_{j1}}^4}{(\sigma_{\alpha j1}^2 + p_{j1}^2 \sigma_{\beta 1}^2 + \sigma_{\xi}^2)^2} = 0\end{aligned}$$

$$\frac{\partial \mu_{\beta j2}}{\partial p_{j1}} = \frac{2p_{j1}\sigma^2_{\beta 1}(\sigma^2_{\alpha j1} + p^2_{j1}\sigma^2_{\beta 1} + \sigma^2_{\xi}) - 2p^3_{j1}\sigma^4_{\beta 1}}{(\sigma^2_{\alpha j1} + p^2_{j1}\sigma^2_{\beta 1} + \sigma^2_{\xi})^2}\left(\beta - \mu_{\beta_1} - \frac{\alpha_j - \mu_{\alpha j1}}{p_{j1}} - \frac{\xi_{j1}}{p_{j1}}\right)$$
$$+\frac{p^2_{j1}\sigma^2_{\beta 1}}{\sigma^2_{\alpha j1} + p^2_{j1}\sigma^2_{\beta 1} + \sigma^2_{\xi}}\left(\frac{(\alpha_j - \mu_{\alpha_{j1}})}{p^2_{j1}} - \frac{2(\sigma^2_{\alpha j1} + \sigma^2_{\xi})}{p^3_{j1}}\right)$$

$$\frac{\partial \sigma^2_{\beta j2}}{\partial p_{j1}} = \frac{1}{p^2_{j1}}\frac{2p_{j1}\sigma^2_{\beta 1}(\sigma^2_{\alpha j1} + p^2_{j1}\sigma^2_{\beta 1} + \sigma^2_{\xi}) - 2p^3_{j1}\sigma^4_{\beta 1}}{(\sigma^2_{\alpha j1} + p^2_{j1}\sigma^2_{\beta 1} + \sigma^2_{\xi})^2}(\sigma^2_{\alpha j1} + p^2_{j1}\sigma^2_{\beta 1} + \sigma^2_{\xi})$$
$$-2\frac{p^4_{j1}\sigma^4_{\beta 1}}{(\sigma^2_{\alpha j1} + p^2_{j1}\sigma^2_{\beta 1} + \sigma^2_{\xi})^2}\frac{\sigma^2_{\alpha j1} + \sigma^2_{\xi}}{p^3_{j1}}$$
$$= \frac{2\sigma^2_{\beta 1}(\sigma^2_{\alpha j1} + \sigma^2_{\xi})^2}{p_{j1}(\sigma^2_{\alpha j1} + p^2_{j1}\sigma^2_{\beta 1} + \sigma^2_{\xi})^2}$$

If the entrepreneur's uncertainty about parameter β is negligible and $\sigma_{\beta 1}$ is close to zero, then all the above derivatives are equal to zero, Thus $\frac{\partial}{\partial p_{j1}} EV_2 = 0$ and learning concerns do not affect the pricing decision. This shows that as entrepreneurs get more experienced and learn about the price sensitivity parameter, the effect of concerns for learning on pricing decision disappears, even if the entrepreneur still wants to learn the product specific quality parameter. Resolving uncertainty about price sensitivity parameter reduces the effect of concerns for learning on pricing.

3.3. Pricing Decision Under Concerns for Learning and Marketing

Beside financial and learning objectives, crowdfunding platforms are used as a powerful marketing tool for entrepreneurs to introduce their product. Entrepreneurs use crowdfunding platforms not only as a source of finance, but also to learn about the market demand and ensure a ready market before the product launch and also use the platform to boost the image of the brand and engage customers in experiencing the product. This effect can come from different channels through which advertising affect the market demand. Different models of product diffusion have studied the effect of advertising, trial of new customers and word-of-mouth on the new product growth. The positive effect of crowdfunding market share on retail period demand will introduce an incentive for entrepreneurs to offer more discounts. Larger discounts are consistent with entrepreneurs trying to sell the product to a larger crowd and benefit from the higher product diffusion in the second period.

For example in the special case of digital games, larger crowdfunding market shares are associated with more new customers trials and these experienced customers are willing to suggest the product to their peers or they can also buy the higher quality version in the retail period. All these marketing channels give the entrepreneurs incentive to sell the first versions of their product at a lower price and induce a larger product diffusion.

It is important to take the marketing channel into account as an additional forward-looking motive that affects the pricing decision in the crowdfunding period. Although this channel is not the main focus of this paper, it should be taken into account since it generates an under-pricing incentive for entrepreneurs and I do not want to confound learning about demand with this channel. The positive effect of crowdfunding market share on second period's market shares can be modeled in different ways. As the entrepreneur gets more experienced, The financial and learning value of the crowdfunding platforms decrease and the entrepreneur takes advantage of selling the first versions of the product at a lower price. To introduce the concerns for marketing benefits in the model, I consider the effect of first period's market share on the second period's purchase decision. The utility of consumer i from purchasing product j in both periods are:

$$
\begin{aligned}
t = 1: &\quad U_{ij1} = \alpha_j - \beta p_{j1} + \xi_{j1} + \epsilon_{ij1} \\
t = 2: &\quad U_{ij2} = \alpha_j - (\beta + \kappa) p_{j2} + \xi_{j2} + \psi(s_{j1}) + \epsilon_{ij2}
\end{aligned}
$$

$\psi(.)$ is an increasing function of first period's market share that captures the positive effect of selling the first versions of the product to a larger crowd. This term introduces the marketing benefits of the crowdfunding campaign into the model and creates incentives for offering larger discounts in the first period. The entrepreneur chooses the optimal price for the first period based on the following optimization problem:

$$
Max_{p_{j1}} \quad M_1 E_1[(p_{j1} - mc)s_{j1}] + \delta M_2 E_1\Big[\; \frac{E_2[s_{j2}]}{E_2[\beta_{2j} s_{j2}(1 - s_{j2})]} E_2[s_{j2}] \; \Big]
$$

To see the effect of marketing benefits on offering larger discount, I solve the profit maximization problem for a fully informed entrepreneur. Assuming that a fully experienced entrepreneur knows the demand parameters and has unbiased beliefs about market shares, I can drop the expectations from the objective function and get the pricing strategy when marketing channels exist. Thus, for a fully experienced entrepreneur:

$$
Max_{p_j} \quad M_1 (p_j - mc) s_j + \delta M_2 \; \frac{1}{\beta(1 - s_{j2})} s_{j2}
$$

The optimal solution to the optimization problem is as follows:

$$
F.O.C[p_j] : s_j - \beta s_j (1 - s_j)(p_j^* - mc) + \delta \frac{M_2}{M_1} \frac{\partial}{\partial p_j} \frac{s_{j2}}{\beta(1 - s_{j2})} = 0
$$

$$
p_j^* = \frac{1}{\beta(1 - s_j)} + mc + \frac{\delta \frac{M_2}{M_1}}{\beta^2 s_j (1 - s_j)} \frac{\partial}{\partial p_j} \frac{s_{j2}}{(1 - s_{j2})}
$$

The marketing channel implies that $\partial s_{j2} / \partial s_j > 0$. The deviation from myopic pricing for a fully informed experienced entrepreneur who does not have concerns for learning is as follows:

$$
p_{j1}^* - p_{j1}^{myopic} = \frac{\delta \frac{M_2}{M_1}}{\beta^2 s_{j1}(1 - s_{j1})} \frac{\partial}{\partial p_{j1}} \frac{s_{j2}}{(1 - s_{j2})}
$$

$$\frac{\partial s_{j2}}{\partial s_{j1}} > 0 \ , \ \frac{\partial s_{j1}}{\partial p_{j1}} < 0 \quad \rightarrow \frac{\partial s_{j2}}{\partial p_{j1}} < 0$$
$$\Rightarrow \frac{\partial}{\partial p_{j1}} \frac{s_{j2}}{(1 - s_{j2})} < 0$$
$$\Rightarrow p^*_{j1} < p^{myopic}_{j1}$$

Based on above discussions, if both learning and marketing concerns are present, as entrepreneur gets more experienced and $\sigma_{\beta 1}$ converges to zero, the effect of learning concern on pricing disappears and the marketing benefits gives under-pricing incentives. The difference between optimal and myopic prices in the full model is:

$$p^*_{j1} - p^{myopic}_{j1} = \delta \frac{M_2}{M_1} \frac{\partial}{\partial p_{j1}} EV_2$$

$$\frac{\partial EV_2}{\partial p_{j1}} = \frac{\partial EV_2}{\partial \mu_{\alpha j2}} \frac{\partial \mu_{\alpha j2}}{\partial p_{j1}} + \frac{\partial EV_2}{\partial \sigma^2_{\alpha j2}} \frac{\partial \sigma^2_{\alpha j2}}{\partial p_{j1}} + \frac{\partial EV_2}{\partial \mu_{\beta j2}} \frac{\partial \mu_{\beta j2}}{\partial p_{j1}} + \frac{\partial EV_2}{\partial \sigma^2_{\beta j2}} \frac{\partial \sigma^2_{\beta j2}}{\partial p_{j1}}$$
$$+ \frac{\partial EV_2}{\partial \psi(s_{j1})} \frac{\partial \psi(s_{j1})}{\partial s_{j1}} \frac{\partial s_{j1}}{\partial p_{j1}}$$

In presence of marketing benefits, if $\sigma_{\beta 1}$ converges to zero, the first four terms in the above equation converge to zero.

$$\sigma_{\beta 1} \rightarrow 0 \Rightarrow \frac{\partial EV_2}{\partial p_{j1}} \rightarrow \frac{\partial EV_2}{\partial \psi(s_{j1})} \frac{\partial \psi(s_{j1})}{\partial s_{j1}} \frac{\partial s_{j1}}{\partial p_{j1}}$$

$$\frac{\partial EV_2}{\partial \psi(s_{j1})} > 0, \ \frac{\partial \psi(s_{j1})}{\partial s_{j1}} > 0, \ \frac{\partial s_{j1}}{\partial p_{j1}} < 0,$$
$$\Rightarrow \sigma_{\beta 1} \rightarrow 0 \Rightarrow \frac{\partial EV_2}{\partial p_{j1}} < 0$$

In presence of both forward-looking concerns, as uncertainty about price sensitivity parameter decrease, $\frac{\partial}{\partial p_{j1}} EV_2$ converges to a negative value which translates into offering larger discounts. This negative value corresponds to the marketing benefits of offering larger discounts. A simple numerical example in Appendix A shows that as $\sigma_{\beta 1}$ converges to zero, the optimal first period's price decrease.

3.4. Comparing predictions of different models

If entrepreneurs are only concerned about the financial role of the crowdfunding, they choose the myopic optimal price to maximize the profit in the crowdfunding period. If concerns for learning is present, $\delta \frac{M_2}{M_1} \frac{\partial}{\partial p_{j1}} EV_2$ is the deviation from myopic price which converges to zero as uncertainty about demand parameters decrease. Thus, if learning is the only forward-looking concern, I expect less innovative or more experienced entrepreneurs to choose prices closer to myopic price. Concerns for learning about the demand parameters bring up experimentation and explains different pricing strategies based on the level of uncertainty about different parameters. If the entrepreneur knows the β parameter and $\sigma_{\beta 1}$ is close to zero, learning about the product quality -α_j- does not have any effect on optimal price since $\delta \frac{M_2}{M_1} \frac{\partial}{\partial p_{j1}} EV_2$ converges to zero.

Based on signals about demand parameters, If β is known, then the signal for unknown parameter α_j does not depend on price:

$$\sigma_{\beta 1} = 0,\ \beta = \mu_{\beta 1}:\ z_{\alpha j} = \alpha_j + \xi_{j1} \quad \sim N(\alpha_j,\ \sigma_\xi^2)$$

However, if β is unknown, concerns about learning α_j result in under pricing strategy. For a fixed $\sigma_{\beta 1}$, lower prices reduces the effect of $(\beta - \beta_1)$ on $z_{\alpha j}$ and also reduces the variance of $z_{\alpha j}$ which leads to a more accurate signal about the α_j parameter:

$$z_{\alpha j} = \alpha_j - (\beta - \beta_1) p_{j1} + \xi_{j1} \quad \sim N(\alpha_j - (\beta - \mu_{\beta 1}) p_{j1},\ p_{j1}^2 \sigma_{\beta 1}^2 + \sigma_\xi^2)$$

Concerns about learning the price sensitivity of consumers -β- result in over pricing strategy. For a fixed $\sigma_{\alpha_{j1}}$, larger prices reduces the effect of $(\alpha_j - \mu_{\alpha_{j1}})$ on $z_{\beta j}$ and also reduces the variance of $z_{\beta j}$ which leads to a more accurate signal about the β_j parameter :

$$z_{\beta j} = \beta - \frac{\alpha_j - \alpha_{j1}}{p_{j1}} - \frac{\xi_j}{p_{j1}} \quad \sim N\left(\beta - \frac{\alpha_j - \mu_{\alpha j1}}{p_{j1}},\ \frac{\sigma_{\alpha j1}^2 + \sigma_\xi^2}{p_{j1}^2}\right)$$

If entrepreneurs are fully informed and have marketing incentives, they tend to offer larger discounts to increase the market share in the crowdfunding period. Thus, in the full model where both learning and marketing concerns are present, as the entrepreneurs get more experienced and get closer to fully informed situation, I expect the informational value of the crowdfunding to decrease and the marketing value play a more important role. Thus, I expect more experienced entrepreneurs or less innovative ones to offer larger discounts since they have already reduced their uncertainty about the β parameter. As the concerns for learning about the β parameter decrease, the concerns for learning about the α_j becomes irrelevant of the price and thus the marketing channel results in setting lower prices.

To summarize, in presence of learning and marketing values, entrepreneurs pricing decisions varies from myopic profit maximization price. This variation comes from two different sources: First, the chosen price affects the signal that entrepreneur receives about the market demand. Thus, entrepreneurs set different prices based on their concerns about learning the demand parameters. This price experimentation affects thee retail period profit through the learning channel. Second, the chosen price affects the number of consumers who buy the first version of the product and help the product diffusion. This marketing channel rationalizes offering more discounts on the first versions of the products to induce larger product diffusion. As entrepreneurs get more experienced, the uncertainty on the demand parameters especially on the price sensitivity parameter β becomes extremely small and additional learning is unnecessary. At this point where the uncertainty about β is negligible, concerns for learning about product specific quality α_j does not affect the pricing strategy. Concerns for learning about β encourages setting higher prices while marketing purposes encourage the entrepreneur to offer larger discounts on the first versions of the product in the crowdfunding period. Thus, experienced entrepreneurs tend to set lower than optimal myopic prices while the inexperienced entrepreneurs who have more learning concerns choose relatively higher prices. This is the main prediction of the theoretical framework to be tested in the next section. One challenge is separating the learning effect from financing effect for experienced entrepreneurs. Successful funded project may give an entrepreneur the ability to offer more discounts in her future projects both because she has less concerns for learning and the capital she raised. To alleviate this problem, I also examine the change in pricing strategy for only unfunded projects all of which received no money in Kickstarter. I also expect entrepreneurs with more innovative and novel products to have higher concerns for learning due to higher demand uncertainty. Thus, they will offer less discount compared to entrepreneurs with less innovative products.

As mentioned before, There are other possible reasons alternative to learning and marketing motives. I have considered category with negligible marginal cost and also presented the analysis within unfunded projects to mitigate the financial channels. However, I cannot rule out the possibility that entrepreneurs with multiple Kickstarter projects might be less financially constrained. Based on Kickstarter policy, entrepreneurs cannot have multiple campaigns at the same time and the cannibalization effect is not present in this specific market. More novel products have more distant competitors which implies lower discounts. Considering a nested logit or BLP demand model can be a future approach to extend this paper.

4. Empirical Analysis

4.1. Reduced Form Evidence

Based on the theoretical benchmark, I expect the informational value of crowdfunding decrease as entrepreneur gets more experienced. This should result in a relative increase in marketing value and thus setting lower prices. Novelty score also captures the uncertainty associated with the product. To test this prediction I run the following reduced form regression:

$$log(Price_j) = \theta_0 + \theta_1 log(Experience_j) + \theta_2 log(Novelty_j) + \theta_3 X_j + \nu_j \qquad (1)$$

$log(Price_j)$ is the logarithm of the actual price set for product j and $log(Experience_j)$ is the logarithm of experience. If product j is the n^{th} product launch of an entrepreneur, then the experience associated with this project is n. $log(Novelty_j)$ is the logarithm of Novelty score for each product and X_j is the vector of project characteristics that can affect the pricing decision. θ_1 and θ_2 the parameter of interest which I expect to be negative. Since both $Experience$ and $Novelty$ are both proxies for demand uncertainty, the signs of one of the coefficients can be the opposite to the expected. Thus, I first make separate regressions with $log(Experience)$ and $log(Novelty)$ as independent variables. I then estimate a regression with both proxies included together. Table 2 shows the estimation results for equation 1 with only $log(Experience_j)$ as the main independent variable. To make sure offering lower prices is not driven by previous projects funding, I run the same regression within unfunded projects all of which entrepreneurs received no money. This rules out the alternative explanation that more experienced entrepreneurs can offer lower prices since they have raised money on their previous projects.

The coefficient of $log(Experience_j)$ is negative and statistically significant. This result shows that as entrepreneurs become more experienced, they set lower prices for the first version of their product. Offering lower price can be associated with the raised capital from previous projects. To rule out the financial spillover from entrepreneur's experience, I run the same regression within unfunded projects from which entrepreneur received no financial benefits. Columns 4-6 show the estimation result within unfunded projects. If concerns for future profits are not present and crowdfunding has only financial benefits, the pricing pattern should be independent of demand uncertainty. Entrepreneur's experience captures the uncertainty associated with the entrepreneur. As the demand uncertainty resolves for entrepreneur, she offers lower prices to benefit from the marketing benefits of the crowdfunding setting.

Based on the prediction from theoretical model in previous section, larger prices provide more accurate signal about learning the price sensitivity parameter and as the uncertainty about this parameter resolves, the effect of learning on price pattern disappears and marketing effect becomes relatively more important. Thus, as entrepreneur gets more experienced or if they offer less innovative products, the level of demand uncertainty is lower and I expect to see a larger discount consistent with marketing benefits. An important implication from the model is that higher prices are more informative for learning the β parameter and as the uncertainty about β decrease, learning about product specific quality parameter becomes irrelevant for pricing. Thus, results presented in table 2 are consistent with the main prediction of the structural model that is if uncertainty about demand becomes negligible, then the learning effect disappears and marketing channel results in offering larger discounts. I also use the structural model to calculate the myopic optimal price and then calculate the discount that each entrepreneur offers. I then present the results with discount as the main dependent variable to test the mentioned implications of the theoretical model.

In table 2, $Not\ Competing\ Price$ is the average price of the products which ended in the last month. These products are not competitors while sharing the same cost structure. The effect of this variable on price decision is positive and statistically significant. $Competitor\ Has\ Video$ is the average of $HasVideo$ dummy variable for the competitors. The results show the positive effect of this variable on price. However, the coefficient of $Competitor\ Staff\ Picked$ is not statistically significant. The coefficients of variables $Staff\ Picked$ and $Has\ Video$ are positive and statistically significant as expected. In the following regression tables I report these variables as Control Variables since they are not the focus of my analysis.

Table 3 shows the estimation results for equation 1 with both $log(Experience_j)$ and $log(Novelty_j)$ as the main independent variables. The coefficient of $log(Experience_j)$ is negative and statistically significant. The coefficient of $log(Novelty_j)$ is also negative and statistically significant. I expect entrepreneurs with more innovative projects to have higher demand uncertainty and thus have more concerns for learning. However, the reduced form regressions of pricing pattern do not reflect the discount pattern offered by entrepreneurs. This shows the need to calculate the myopic optimal price for each entrepreneur and investigate the discount pattern by demand uncertainty. The more innovative entrepreneurial products in this market might have lower perceived product specific quality (α_j) resulting in lower optimal price. These results motivate the calculation of deviation from optimal price for each product.

Table 2. Pricing Pattern by Entrepreneur's Experience

	All			Unfunded		
log(Price)	(1)	(2)	(3)	(4)	(5)	(6)
Log(Experience)	-.3160951***	-.197868***	-.1636278***	-.3671699***	-.2843795***	-.248915***
	(.0102565)	(.0104754)	(.0105394)	(.0267328)	(.0259936)	(.0259755)
NotCompeting Price		.0007825***	.0002568***		.0007209***	.000216***
		(.0000526)	(.0000607)		(.0000639)	(.0000739)
Competitor Has Video		1.104969***	.33552***		1.113579***	.4353464**
		(.0951076)	(.1293548)		(.1231196)	(.1723331)
Competitor Staff Picked		-.0493094	-.2305502		-.1297075	-.2203029
		(.1127307)	(.1471571)		(.173566)	(.210947)
Staff Picked		.4527649***	.4489545***		.585477***	.5963647**
		(.0204896)	(.0203651)		(.0384391)	(.0381783)
Has Video		.4617277***	.4546753***		.5025238***	.4907324**
		(.0171882)	(.0171041)		(.023661)	(.0235993)
Country FE	NO	YES	YES	NO	YES	YES
Category FE	NO	YES	YES	NO	YES	YES
Time FE	NO	NO	YES	NO	NO	YES
Observations	31,562	31,549	31,549	18,342	18,335	18,335

[Note] This Table shows pricing pattern based on entrepreneur's experience. More experienced entrepreneurs set lower prices for the first version of their products. Columns 1-3 are the estimation results for all the products. Columns 4-6 show the estimation results for only unfunded products to make sure financial channel does not drive the results.

Table 3. Pricing Pattern by Entrepreneur's Experience and Product's Novelty

	All			Unfunded		
log(Price)	(1)	(2)	(3)	(4)	(5)	(6)
Log(Experience)	-.1636278***		-.1635449***	-.248915***		-.2463626***
	(.0105394)		(.0105295)	(.0259755)		(.0259734)
Log(Novelty)		-.7586504***	-.7558256***		-.7778689***	-.7548052***
		(.0922006)	(.09185)		(.1278308)	(.1275424)
Controls	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Observations	31,549	31,549	31,549	18,335	18,335	18,335

[Note] This Table shows pricing pattern based on entrepreneur's experience and product's novelty. More experienced entrepreneurs set lower prices for the first version of their products. Entrepreneurs with more innovative products also set lower prices. This result motivates the calculation of the deviation from myopic optimal price to study the discount pattern by demand uncertainty.

4.2. Structural Evidence

Based on the theoretical framework, and using product-level Kickstarter database to compare actual pricing behavior to theoretical benchmark for myopic pricing. I then investigate the heterogeneity of pricing strategy among entrepreneurs with different experience levels. To calculate the optimal myopic price , I estimate the parameters in the logit demand system. The estimated true demand parameters may not correspond to each entrepreneur's belief. That is, I allow each entrepreneur to have biased beliefs about demand parameters, but I assume that the aggregate bias is zero when we average these idiosyncratic biases over entrepreneurs. Following Balvers and Cosimano (1990) and Shen and Liu (2014), I assume unbiased prior belief about the demand parameters. This assumption allows me to calculate the difference between actual price and optimal myopic price for each entrepreneur.

I use the detailed product-level data on Kickstarter projects from 2009 to 2019. Since I do not have the daily data on product sales, I calculate the market share of each product using the total sales for each product weighted by the number of days each two products are competing with each other. For example, if the duration of campaign for product j is 30 days and overlaps with product k's campaign for 10 days, the weight of product k's sales is 1/3 in calculating the market share for product j. I also assume that backers who enter the market are willing to support a project (zero outside option).[1].

Since product prices can be endogenous , I use the average price of the products in the same category which ended in the last month as instrument. I choose these products because they are not competing with each other while sharing the same cost structure. The identification assumption relies on the no time or serial correlation in the unobservables. This is in the spirit of Hausman-Nevo, but I look at the time dimension rather than geographic dimension. I also use the competitors characteristics as instruments for the price. I construct the competitors characteristics weighted by the number o days that they are competing with each other.

The estimation results of the logit demand model where β is assumed homogeneous are presented in Table 4. The price coefficient is negative as expected and highly significant. Columns 1-4 present OLS results which show the positive coefficient for price confirming the endogeneity problem. Columns 5-8 show the demand estimation result using mentioned instrumental variables. $Staff\ Picked$ is a dummy variable that shows if the project is featured by Kickstarter staff. This variable is observable to buyers and affect the demand of the product. The coefficient for this variable is positive and statistically significant. $HasVideo$ is also a dummy variable that shows if the project page has a video introducing the product. The coefficient for this variable is also positive and statistically significant. In the following regression tables, I only report these variables as Control Variables since they are not the focus of my analysis.

Assuming negligible marginal cost for digital games, I calculate the optimal myopic full-information price using the market shares and the estimated price coefficient. The on average unbiased beliefs about parameters and the market shares are important assumptions for this calculation. The myopic price is calculated using the following equation:

[1]To calculate the market share for product j, consider all the projects $j_1, j_2, ..., j_n$ which have at least one day overlap with product j's campaign duration. $d_1, d_2, ..., d_n$ are the number of days each of these products are competing with product j. I have calculated these overlaps using start and end date of each campaign. The market share for product j is the product j's total quantity sold q_j divided by the summation of other competing products' total quantities sold weighted by the overlaps $q_j + \sum_{k=j_1}^{k=j_n} q_k d_k$

Table 4. Logit Demand Estimation

	OLS				IV			
log(s)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price	.0001851***	.0001086***	.0002502***	.0001333***	-.0021254***	-.0012483***	-.0021206***	-.0054053***
	(.000026)	(.0000219)	(.0000261)	(.0000216)	(.0001197)	(.0001948)	(.0001425)	(.0008302)
Staff Picked		2.406023 ***		2.430907***		2.514867***		2.903726***
		(.0298039)		(.0294492)		(.03541)		(.088674)
Has Video		.91974***		.9383008***		1.034384***		1.355555***
		(.0262029)		(.0258525)		(.0323533)		(.0780038)
Country FE	NO	NO	YES	YES	NO	NO	YES	YES
Category FE	NO	NO	YES	YES	NO	NO	YES	YES
Time FE	NO	NO	YES	YES	NO	NO	YES	YES
Observations	29002	29002	29002	29002	29002	29002	29002	29002

[a]This Table shows the Logit demand estimation results. The dependent variable is the logarithm of market share. The coefficient of price is negative and statistically significant.

$$p_j^{myopic} = \frac{1}{\hat{\beta}(1-s_j)}$$

$$log(p_j^{myopic}) = -log(\hat{\beta}) - log((1-s_j) + e_j \qquad e_j \sim N(0, \sigma_e^2)$$

I estimate the logit demand for four different groups of entrepreneurs: Inexperienced entrepreneurs, entrepreneurs with 1 campaign launch experience, entrepreneurs with 2 experiences and entrepreneurs with more than 2 product launches experiences. Table 5 shows the estimation results. Price coefficients are negative and statistically significant.I then recalculate the optimal myopic price using heterogeneous price coefficients. I also estimate the logit demand for 5-quantiles of the Novelty score to account for heterogeneity in the demand parameters by product novelty. Table 6 shows the estimation results. Price coefficients are negative and statistically significant. These heterogeneous demand estimations can deal with some of the alternative explanations to the relationship between entrepreneur's and price or the relationship between product's novelty and price. I then recalculate the optimal myopic price using these heterogeneous price coefficients. These estimations deal with the probable heterogeneity in the demand elasticity for different levels of experience or novelty. Figure 4 shows the distribution of $log(p_j^{myopic}) - log(p_j^{actual})$ for homogeneous and heterogeneous demand estimations. The gray histogram shows the distribution for all the projects. The pink histogram shows the same distribution which is calculated using heterogeneous β s based on different experience levels and blue histogram shows the distribution of this difference which is calculated using heterogeneous β s based on different novelty score levels. Based on this figure, accounting for heterogeneity in demand parameter does not make a significant change in the distribution of $log(p_j^{myopic}) - log(p_j^{actual})$. This sensitivity analysis shows that the deviation from myopic full-information price still exists even after allowing for heterogeneous price elasticity. The positive values of $log(p_j^{myopic}) - log(p_j^{actual})$ show under pricing and offering discount.

To test the prediction of the model on discount pattern, I run the following regression with the calculated $log(p_j^{myopic}) - log(p_j^{actual})$ as dependent variable to test the hypothesis of experienced entrepreneurs offering more discounts relative to their profit maximizing myopic price. $discount_j$ is the ratio of the optimal myopic price -which

Table 5. Logit Demand Estimation (Different Entrepreneurial Experience Levels)

Experience	All	1	2	3	≥ 4
log(s)	(1)	(2)	(3)	(4)	(5)
Price	-.0054053***	-.0051756***	-.0032846**	-.0029681	-.0034348*
	(.0008302)	(.0009358)	(.0013272)	(.0020157)	(.0021165)
Controls	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Observations	29002	20176	3776	1532	3518

NoteThis Table shows the Logit demand estimation results for four groups of entrepreneurs based on their experience. The dependent variable is the logarithm of market share. The coefficient of price is negative and statistically significant in all columns.

Table 6. Logit Demand Estimation (Different Product Novelty Levels)

Novelty 5-Quantiles	Q1	Q2	Q3	Q4	Q5
log(s)	(1)	(2)	(3)	(4)	(5)
Price	-.0051162**	-.0017312*	-.004491**	-.0056913	-.0044881*
	(.001882)	(.0009514)	(.0012793)	(.0016655)	(.0010744)
Controls	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Observations	5697	5806	5839	5877	5768

NoteThis Table shows the Logit demand estimation results for four groups of entrepreneurs based on their experience. The dependent variable is the logarithm of market share. The coefficient of price is negative and statistically significant in all columns.

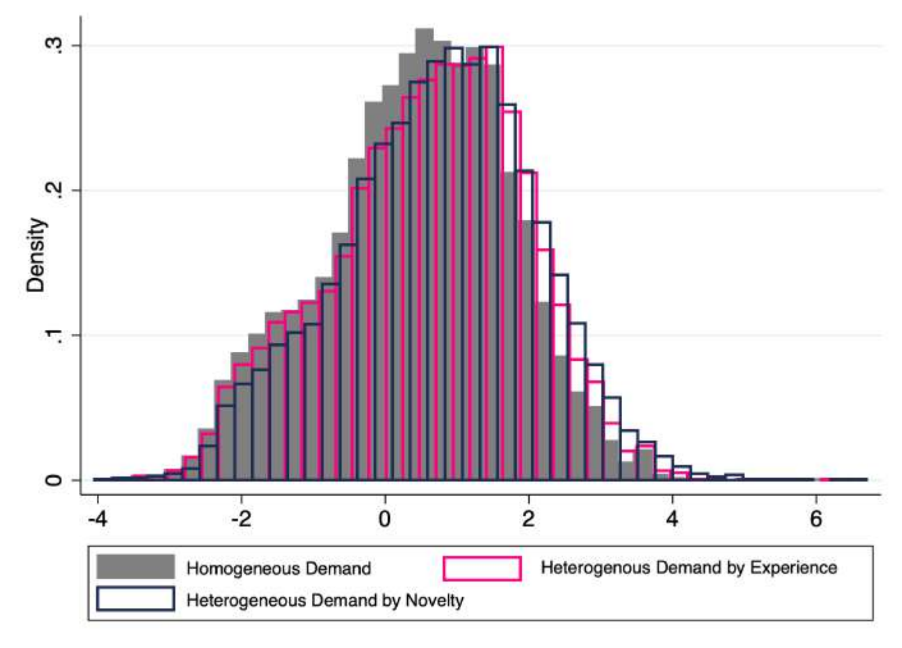


Figure 4. The distribution of $log(p_j^{myopic}) - log(p_j^{actual})$ for homogeneous and heterogeneous demand estimations

Table 7. $log(p_j^{myopic}) - log(p_j^{actual})$ Pattern by Entrepreneur's Experience

	All			Unfunded		
log(Discount)	(1)	(2)	(3)	(4)	(5)	(6)
Log(Experience)	.5517287***	.4306463***	.3965086***	.738725***	.6586266***	.6229815***
	(.010317)	(.0105571)	(.0106238)	(.026761)	(.0260519)	(.0260373)
Controls	NO	YES	YES	NO	YES	YES
Time FE	NO	NO	YES	NO	NO	YES
Observations	31,554	31,547	31,547	18,339	18,334	18,334

Note This Table shows the $log(p_j^{myopic}) - log(p_j^{actual})$ pattern based on entrepreneur's experience. More experienced entrepreneurs offer more discount for the first version of their products. Columns 1-3 are the estimation results for all the products. Columns 4-6 show the estimation results for only unfunded products to make sure financial channel does not drive the results.

is calculated using the estimated demand parameters- over the observed price in the data. Entrepreneurs with more innovative projects are also expected to have more concerns for learning and thus offering less discounts relative to their myopic optimal price.

$$log(discount_j) = log(p_j^{myopic}) - log(p_j^{actual})$$

$$log(discount_j) = \gamma_0 + \gamma_1 log(Experience_j) + \gamma_2 log(Novelty_j) + \gamma_3 X_j + \kappa_j \qquad (2)$$

Table 7 shows the estimation results for equation 2 with only $log(Experience_j)$ as the main independent variable. In this regression, p^{myopic} is calculated with the heterogeneous βs for different experience levels. I expect the coefficient of experience γ_1 to be positive confirming that the experienced entrepreneurs offer more discount to benefit from marketing values of the crowdfunding campaign. To make sure offering lower prices is not driven by previous projects funding, I also run the same regression within unfunded projects to make sure results are not driven by the financial channel. coefficient of $log(Experience_j)$ is positive and statistically significant. This result shows that as entrepreneurs become more experienced, they offer more discounts for the first version of their product to sell the trial versions to a larger crowd. columns 4-6 show the estimation results within unfunded projects and confirm that even entrepreneurs who have not raised money from their previous projects change their pricing strategy and offer more discounts. The fact that less experienced entrepreneurs set higher prices can be rationalized by concerns for learning about market demand since learning about price elasticity is associated with setting higher prices.

I run the regression in equation 2 with only $log(Novelty_j)$ as the main independent variable to explore the discount pattern of entrepreneurs based on their Novelty score. In this regression, p^{myopic} is calculated with the heterogeneous βs for different novelty levels. I expect the θ_2 to be negative confirming that entrepreneurs with higher demand uncertainty offer less discount to resolve their uncertainty through learning channel. Table 8 shows the estimation results. Parameter of interest is negative and statistically significant. This result shows that entrepreneurs with higher demand uncertainty offer less discount on their products suggesting higher concerns for learning relative to marketing benefits.

I run the regression in equation 1 with both $log(Experience_j)$ and $log(Novelty_j)$ as the main independent variable to explore the discount pattern of entrepreneurs based

Table 8. $log(p_j^{myopic}) - log(p_j^{actual})$ Pattern by Product's Novelty

log(Discount)	(1)	(2)	(3)
Log(Novelty)	-.0190161	-.3592741***	-.4775254***
	(.10004978)	(.0954175)	(.0971859)
Controls	NO	YES	YES
Time FE	NO	NO	YES
Observations	31,534	31,527	31,527

Note This Table shows the $log(p_j^{myopic}) - log(p_j^{actual})$ pattern based on product novelty score. More innovative products are associated with higher demand uncertainty and concerns for learning encourages the entrepreneur to offer less discount.

Table 9. $log(p_j^{myopic}) - log(p_j^{actual})$ Pattern by Entrepreneur's Experience and Product's Novelty

	All			Unfunded		
$log(p_j^{myopic}) - log(p_j^{actual})$	(1)	(2)	(3)	(4)	(5)	(6)
Log(Experience)	.3097529***	.1999779***	.1672604***	.3530775	.2797883**	.2463107*
	(.0107093)	(.0110271)	(.0111018)	(.0277125)	(.027112)	(.0271177)
Log(Novelty)	-.0948915***	-.3894694***	-.4804696***	.0273302	-.2775078***	-.3503686***
	(.0987847)	(.0949392)	(.0968382)	(.1356334)	(.130721)	(.1331445)
Controls	NO	YES	YES	NO	YES	YES
Time FE	NO	NO	YES	NO	NO	YES
Observations	31,534	31,527	31,527	18,326	18,321	18,321

Note This Table shows the $log(p_j^{myopic}) - log(p_j^{actual})$ pattern based on entrepreneur's experience and product novelty. Columns 1-3 are the estimation results for all the products. Columns 4-6 show the estimation results for only unfunded products to make sure financial channel does not drive the results.

on their Novelty score. In this regression, p^{myopic} is calculated with the heterogeneous βs for different novelty levels. I expect θ_1 to be positive and θ_2 to be negative. Table 9 shows the estimation results. Although the magnitude of θ_1 is considerably less than the coefficient in Table 7, θ_1 is positive and θ_2 is negative as expected. This result shows that entrepreneurs with higher demand uncertainty offer less discount on their products suggesting higher concerns for learning relative to marketing benefits.

One of the alternative explanations for the effect of novelty on price is that the more novel products have more distant competitors that implies smaller discounts.Considering a nested logit or a BLP demand model can be a potential approach for next research.

5. Conclusion

In this paper I develop a theoretical framework to study the presence of concerns for learning in crowdfunding platform. Beyond financial benefits for entrepreneurs, crowdfunding has additional advantages for entrepreneurs and provides them with market demand information and also marketing benefits through advertising and word-of-moth. I focus on the pricing decision of an entrepreneur in an oligopoly environment who is uncertain about the demand curve of her new product. If entrepreneurs only care about the financial role of the crowdfunding, they choose the myopic profit maximizing price. If they are fully informed and have marketing incentives, They tend to offer lower prices to increase the market share in the crowdfunding period. Concerns for learning about the demand parameters bring up experimentation and explains different pricing strategies based on the level of uncertainty about market demand.

Concerns about learning the price elasticity result in over pricing strategy. If the entrepreneur knows the price elasticity, learning about the product quality parameter does not have any effect on optimal price. As the entrepreneurs get more experienced and uncertainty about price elasticity resolves, the informational value of the crowdfunding decreases and the marketing value plays a more important role. Thus, I expect more experienced entrepreneurs to set lower prices since they have already resolved their uncertainty about the price sensitivity parameter and thus care more about the marketing values. I also expect entrepreneurs with more innovative products to have higher demand uncertainty and thus have more learning concerns compared to marketing concerns.

In presence of learning and marketing values, entrepreneurs pricing decisions varies from myopic profit maximization price. Using Kickstarter data, I explore the deviation of the actual prices from the myopic profit maximization prices. The deviation from myopic profit maximizing price shows the learning and marketing roles of crowdfunding platforms. The heterogeneity in pricing behaviour among entrepreneurs with different experience levels, shows the presence of concerns for learning which resolve with getting more experienced.

I find that less experienced entrepreneurs set higher prices than more experienced entrepreneurs who are assumed to have less uncertainty on market demand parameters. Experienced entrepreneurs offer more discounts on their products which confirms the higher value of marketing benefits relative to learning benefits. I also show that entrepreneurs with more innovative and novel products offer lower discounts and have more concerns for market demand learning relative to marketing benefits.

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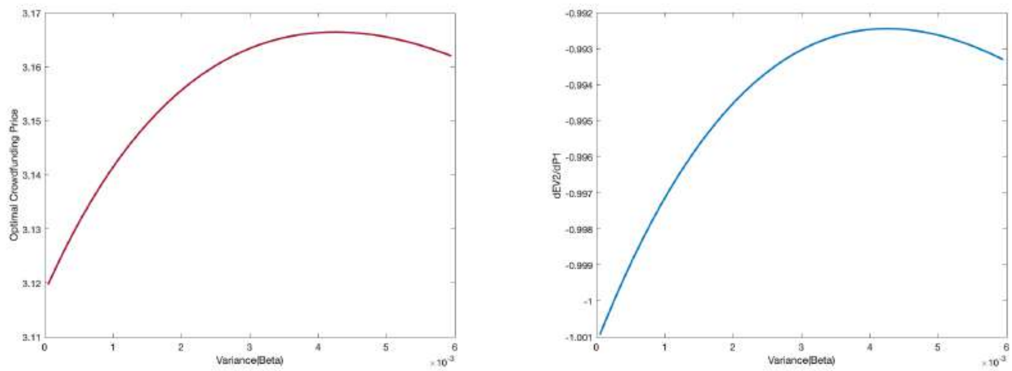
6. Appendices

Appendix A. Numerical example



(a) p_1 as a function of σ^2_β

(b) $\frac{\partial EV_2}{\partial p_1}$ as a function of σ^2_β

Figure A1. This figure shows a numerical example of pricing decision under concerns for learning and marketing. The beliefs about parameters update in a Bayesian fashion and marketing benefit $\psi(s_1)$ enters as a linear increasing function in utility function. $\mu_{\alpha_{j1}} = 20$, $\mu_{\beta_1} = 3$, $\sigma^2_{\alpha j1} = 0.01$, $\sigma^2_\xi = 0.25$, $\sum_{-j} exp(U_{-j}) = 200$, $\xi_{j1} = 0.1$ and $\psi(s_1) = 10s_1$. In this example, as uncertainty about the demand parameter β decrease, the $\frac{\partial EV_2}{\partial p_1}$ also increase which is consistent with the prediction of the model which incorporates marketing benefits along with concerns for learning. In this example, lower demand uncertainty is associated with offering larger discounts. This is consistent with the predictions that concerns for learning about β gives incentives for choosing larger prices to get a more accurate signal and also consistent with offering larger discounts when these concerns for learning disappear.