ESSAYS ON CROWDFUNDING AND THE SHARING ECONOMY

by

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Abstract

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Information technology creates links that connect people, organizations, and resources together. My thesis is focused on modeling and studying the marketing strategies in two business models in the connected economy: online crowdfunding and the sharing economy.

Online crowdfunding allows creators to raise money from a large number of people (the “crowd”) to make their projects happen. In Chapter 2, I examine the product and pricing decisions in crowdfunding. Two key ways of how crowdfunding scenario differs from traditional list-price setting are identified. With crowdfunding, the fundraiser is more likely to offer a line of products, and the quality gap between products becomes smaller. In Chapter 3, I study the effects of video advertising in online crowdfunding. While a video ad helps improve the success rate of a crowdfunding project, I show that merely having a video is not enough. The length, stimulation level, and content of a video ad all have significant effects on the funding outcomes of a project. Together, these results contribute to a further understanding about the rising crowdfunding industry.

Sharing economy refers to the peer-to-peer based sharing of goods and services. Among all sectors of the sharing economy, short-term rental is becoming more and more popular and important. In Chapter 4, I empirically study the behaviors of hosts on Airbnb, the leading sharing economy platform. I compare the differences between professional hosts and amateur hosts, showing that amateur hosts tend to charge higher prices, provide better services but less information. These results can be helpful to the platform, hosts and the legislative authorities.
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Chapter 1

Introduction

Information technology creates links that connect people, organizations, and resources together. Nowadays, we get our innovative projects funded at Kickstarter, borrow money at Prosper, rent a property at Airbnb, and take a ride with Uber. While these new business models have dramatically affected our everyday life, they have also brought new opportunities and challenges to marketers. In this thesis, I study the implications of two new business models, online crowdfunding and the sharing economy, for marketers, consumers, and the platforms.

1.1 Online Crowdfunding

Online crowdfunding allows creators to raise money from a large number of people (the “crowd”) to make their projects happen. With the pass of the Jumpstart Our Business Startups (JOBS) Act in the United States in 2012, online crowdfunding has gained its legality, and investment in start-ups is no longer limited to the wealthy venture capitalists or private equities. Since then, online crowdfunding has been growing explosively, with over $34 billion raised via crowdfunding worldwide in 2015. Many successful campaigns have been funded with crowdfunding, for example, The Pebble E-Paper Watch, raised $10,266,845 in 37 days, Ouya, an open source game console, raised over $8.5 million in 29 days.

Crowdfunding distinguishes itself from traditional business models from several perspectives. First, almost all crowdfunding projects have a threshold called target, and the fundraising is successful only when the amount of money that the creators raised is equal to or above the target. In other words, nobody contributes unless the total funding reaches the predetermined target. Second, unlike traditional start-ups which are funded by a few large investors, a typical crowdfunding project is funded by hundreds of, or
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thousands of, small investors. These small investors are often unfamiliar with the creators and rely heavily on information on the project webpage when making their funding decisions. In Chapters 2 and 3, we explore how these unique features will affect several central marketing decisions, including pricing, product quality, and advertising.

Chapter 2 has been published as Hu et al. (2015). In this chapter, we investigate the product and pricing decisions when raising funds at a crowdfunding platform. More specifically, we study the optimal design of crowdfunding mechanisms in a two-period game where cohorts of backers arrive at a proposed project and make contribution decisions sequentially. Backers contribute to the project for products or services delivered in the future. We show that the fundraiser benefits from price discrimination when backer valuations are sufficiently heterogenous with disparate values and a dispersed distribution. Price discrimination, as an optimal selling mechanism, may appear either vertically, i.e., backers choose from a menu of different prices, or horizontally, i.e., sequential arrivals arriving in different periods are charged differently. The profit advantage of price discrimination is driven by the unique property of crowdfunding: the project is only successful when a threshold on the amount of contributions is met. Backers, instead of being separate individuals in the traditional list-price setting, are now tied together by a common goal of making the project successful. When quality decisions are endogenized, the fundraiser is more likely to offer a product line, and the quality gap between products becomes smaller in a crowdfunding setting, compared to the traditional list-price setting.

To further understand the unique product and pricing decisions in crowdfunding, we generalize the basic model in a number of directions. First, we consider non-economic motivations including the warm glow effect (i.e., backers gain utility from helping others) and the prestige effect (i.e., backers gain utility when making the most contribution). Second, we generalize the model to include time-varying valuations. Third, we extend the basic model to multiple backers by modeling two cohorts of backers. Fourth, to capture uncertainty, we model an uncertain number of backers. Finally, we model strategic delay and endogenous arrivals. The results show that our model is robust in these scenarios, and help explain real life phenomena such as overfunding.

To sum up, with online crowdfunding, the high-valuation consumers are willing to pay more to improve the success rate of the project. As it is easier to separate between high-valuation and low-valuation consumers, the seller is more likely to offer a line of different products with lower quality differentiation.

In Chapter 3, we empirically study the effect of video advertising in crowdfunding. Marketers are increasingly relying on videos to advertise their products. This research investigates how online video advertising affects the success rate of crowdfunding projects,
using a dataset of 8,327 music projects listed on the Kickstarter website. In the chapter, we analyze the content of the video advertising by measuring its duration, stimulation level, and perceived credibility. All other things being equal, we find a lower success rate for projects with longer videos, indicating the presence of the tedium effect (which increases in the length of the video). Moreover, the tedium effect was stronger when the creator had prior crowdfunding experience, but weaker when the project target was higher. Second, there existed an optimal level of stimulation. The project success rate was lower when the stimulation level was either too high or too low. Finally, the project success rate increased when the video advertising demonstrated higher credibility by including humans and/or instruments in the videos. The results offer functional guidelines for the optimal design of advertising in the digital age.

In short, the research not only shows that video advertising matters, it also shows how video advertising matters. It matters through (at least) the following three channels: the tedium effect, the optimal stimulation level and the effect of credibility.

1.2 The Sharing Economy

Sharing indeed is not something new. Offering someone a ride, accommodating a guest in your spare room, and running an array of errands for your friend are not revolutionary ideas. What is new here, in the rising “sharing economy”, is that you are no longer helping someone for free (Sundararajan 2016). Instead, you are providing these services for money. Today we can drive for Uber or Lyft, sell products directly on Etsy, provide a loan on Lending Club, or offer services on Upwork. The unstoppable rise of the sharing economy has changed our world. The market size for sharing economy was $15 billion dollars in 2013, and is expected to grow to $335 billion by 2025, according to a PwC report.

Among all sectors of the sharing economy, short term rental is becoming more and more popular and important. The rise of Airbnb, the leading online peer-to-peer rental sharing platform, has materially reshaped the rental and the hospitality industries. Now, owners could rent their properties online without having to resort to professional agents. As Airbnb CEO Brian Chesky wrote in his blog, most Airbnb hosts were “regular people renting the homes in which they live”. “They are teachers, artists, students, and retirees who love doing this”, Brian emphasized, “They didn’t provide just a place to stay. They are personally connected with the guests and offered them support in a time of need.” Airbnb’s unique business model of “peer-to-peer renting” appeared to be a great success: In 2016, Airbnb bookings increased to 129 million ‘room nights’, making it larger than
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any other hotel chain in the world. A more surprising number comes from Cowen Group, a Wall Street firm, expecting Airbnb to book a billion nights a year in 2025. Airbnb is particularly popular with young travelers who want to feel more like at home.

While Airbnb was created for ‘regular people’ to rent their homes, more and more people are running Airbnb as a professional business. These hosts spend several hours a day helping guests check-in, doing laundry and cleaning apartments for their next Airbnb guests. They manage a number of properties across the city and rely Airbnb as their sole source of income. Some owners even hire agents to help manage their properties. When staying in these professionally managed properties, you do not stay with the hosts. However, you can still get all the essential hotel services. From this perspective, to travelers, Airbnb is not much different from a hotel. In fact, nowadays, Airbnb is asked to pay hotel tax in many major cities, including San Francisco, Los Angeles and Paris.

In Chapter 4, using data from Airbnb and Zillow, we empirically study the differences between professional hosts and amateur hosts. We focus on the following factors: price, services, information and competition. The empirical results provide some interesting insights. First, compared with professional hosts, amateur hosts charge a higher price in average, and tend to provide superior services to the guests. This phenomenon supports the mere ownership effect and is a piece of evidence for the problem of effort limitation. Second, professional hosts post more photos and write longer descriptions, which proves their cost advantage obtained from economies of scale. Finally, professional hosts respond more effectively to competition. A potential explanation can be that amateur hosts are less informed about the competition than professional hosts are.

Overall, the results suggest that amateur hosts behave significantly different from professional hosts. They charge higher prices, put more effort, provide less information, implement more flexible cancellation policies and respond less strongly to competition. The platform and legislative authorities must take the differences into consideration when making their policies.
Chapter 2

Product and Pricing Decisions in Crowdfunding

Many hands make light work.
– English Proverb

2.1 Introduction

Cristian Barnett is a professional photographer living in Cambridge, England. Mr. Barnett was so fascinated with the arctic circle that in 2006 he started visiting the countries intersected by the circle. After seven years and a dozen trips to the arctic circle, he decided to create a book called Life on the Line, which would contain a selection of portraits he had taken over the years. In order to raise funds to pay for the design and printing of the books, Mr. Barnett launched the Life on the Line project on Kickstarter on November 26, 2013. (Figure 2.1) The funding period would expire on December 31, 2013, with a goal of £10,000. Every buyer who committed £30 or more would receive a signed copy of Life on the Line book. A buyer who committed £150 or more would receive a collector’s edition of the book, hardbound and in a slipcase, and signed with author’s personal dedication. Of course, the pledges would not be redeemed and the books would not be delivered unless the project reached the goal.

Kickstarter is one of the leading online non-equity crowdfunding sites that match people (the “crowd”) with projects. In such crowdfunding sites, creators raise funds from potential buyers to start their ventures and in return the creators offer products to the buyers.\(^1\) The creators are entrepreneurs like Cristian Barnett who may be designers,

\(^1\)In equity crowdfunding sites, funders are also investors for the creators’ financial endeavors. This
musicians, software developers, or any kind of inventors. Unlike in the conventional retail setting, here a buyer not only commits to purchasing the product, but also prepays to fund the project. A project will be successfully funded only if the total value of committed purchases exceeds a specified goal within a certain time. The crowdfunding industry has experienced tremendous growth in recent years. For example, Kickstarter has raised more than $800 million and supported more than 50,000 projects in the four years since its inception in 2009. With the passing in the US of the Jumpstart Our Business Start-ups Act in September 2013, the crowdfunding industry acquired legitimacy and is expected to lead a new era of entrepreneurship (Wortham 2013).

In this chapter we investigate the product and pricing decisions in crowdfunding. Creators often provide a line of products for buyers to choose from. Cristian Barnett, for example, offered multiple versions of his Life on the Line book, including a signed copy for £30 and a collector’s edition for £150. We monitored all the projects posted.

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2One reason that creators seek the crowdfunding platform is because private equity investors or venture capitalists seldom back entrepreneurs who are not able to show evidence of substantial sales. See, e.g., Cortese (2013).
on Kickstarter during the five days between November 14, 2013 and November 18, 2013. Among 457 newly launched projects, 448 (98 percent) contained more than one level of rewards and prices. A seller may design a menu of offerings (either with different qualities or in different quantities) when buyers have heterogeneous valuations (Moorthy 1984, Monahan 1984). A crucial consideration in menu design is incentive compatibility; that is, each type of consumers should be better off by choosing the option designed for them than by choosing any other options. Following the same logic, a creator may provide a menu of product and pricing options in a crowdfunding project to match different preferences of buyers. In addition, a creator needs to consider the project success rate anticipated. In the design of the menu for a crowdfunding project, how would the creator’s consideration of project success affect the optimal product line and pricing decisions?

To investigate how the adoption of a crowdfunding mechanism may affect product and pricing decisions, we propose and analyze a two-period model where a creator may offer a line of products or charge different prices over time to sequentially arriving buyers. The decisions of the earlier buyers are posted to the later arrivals. The buyers decide whether or not to purchase and which product option to choose according to their valuations. Since the project will not succeed unless the total purchases from all buyers meet the goal, the buyers are linked together by the common goal of project success. As a result, given two product options of similar or even identical quality but at different prices, a buyer with a high product valuation may choose the high-price option in crowdfunding to ensure the success of the project. This will be the case as long as a buyer perceives that other buyers may have low product valuations. Interestingly, this “over-pay” behavior can also improve buyer total surplus and hence the introduction of discriminatory pricing strategies, such as a menu, can be win-win for both the creator and buyers. This result is in stark contrast to the traditional situation where the low-price option would be generally preferred, given little or no difference in quality. Moreover, the buyers’ incentive to collaborate for the project’s success also affects the optimal product line design when quality decisions are endogenous. Compared to the traditional situation, a creator using a crowdfunding mechanism is more likely to offer a menu of product options, and the difference in quality between product options tends to be smaller.

We extend the main model in several directions. First, we consider buyers’ altruistic motivations such as warm glow, i.e., deriving positive utility from spending more money to support a project. We show that when buyers are altruistic, the main insights on offering a menu of options remain. Moreover, buyers are willing to contribute more to the projects than in the selfish setting. Second, we extend the base model to situations
where cohorts of buyers arriving in two periods can have different product valuations or different numbers of buyers. Our main findings about menus of options hold in both cases. Surprisingly, given all others the same, a creator’s profit can be lower when the chance of having a high-valuation buyer in the second period is greater. That is because the first high-valuation buyer, being more optimistic about the second buyer’s valuation, is more likely to consider free-riding. Third, we consider demand uncertainty in the number of buyers in each period. When we consider the possibility of no-show in one period, we find the results on the optimal menu prices to be the same. In addition, when two cohorts have uncertain number of buyers, we find that the pledged amount can exceed the target, resulting in commonly observed over-funding phenomenon. Finally, we extend the model by allowing the buyers to choose decision time. When the first buyer can choose to wait and decide later, we find that the first buyer would prefer not to wait, and our main results on menu strategy hold. When the creator offers the optimal menu strategy in the base model and two buyers both decide which period to enter, the creator’s profit can be even higher.

**Literature Review**

This chapter contributes to the extensive marketing literature of product line design. Moorthy (1984) provides a general framework for a monopoly seller’s product line design problem. The marketing literature has investigated how the product line design decisions may depend on market conditions such as the extent of horizontal differentiation (Desai 2001), the presence of private information (Balachander and Srinivasan 1994) and network externality (Jing 2003), the structure of the distribution channel (Villas-Boas 1998), and customization (Syam et al. 2005, Valenzuela et al. 2009). Consistent with this body of literature, this chapter provides new insights into product line design in an emerging business model.

Second, this chapter also contributes to the emerging literature on crowdfunding mechanisms. Research in public economics has extensively examined provision point mechanisms for improving the private provision of public goods (see, e.g., Varian 1994). The provision point mechanism and crowdfunding share the feature that a good will be provided only when the preset contribution level is reached. Otherwise, the parties are not bound to carry through and any monetary contributions are refunded. However, unlike the provision of public goods, a buyer in crowdfunding cannot benefit from a successfully funded project without pledging at a suggested price. Moreover, price decisions and the threshold (i.e., the provision point) are typically treated as exogenous in public economics.
The emergence of online crowdfunding in recent years has attracted the attention of academic researchers (Agrawal et al. 2013). Several papers have empirically investigated the herding behavior caused by asymmetric quality information and observational learning from early contributions (see, e.g., Agrawal et al. 2010, Freedman and Jin 2011, Zhang and Liu 2012, Mollick 2013). We isolate the effect of asymmetric information and study specific marketing decisions under the provision point mechanism, as compared to the conventional selling mechanism. The chapter yields new insights into how the crowdfunding business model may affect decisions about optimal product line and pricing.

A mechanism similar to crowdfunding is group buying where a seller offers promotional discounts to a sufficiently large number of committed purchasers. This mechanism has been used by companies like Groupon and LivingSocial. Existing theoretical research has examined many aspects of the group buying mechanism, including the ability to respond to market size uncertainty (Anand and Aron 2003), the use of informed consumers to enhance the valuation of uninformed consumers in their social networks (Jing and Xie 2011), and disclosure of the cumulative sign-up information to increase the success rates of the deal (Hu et al. 2013) and to signal a merchant’s high quality (Subramanian and Rao 2013). Empirical research has studied consumers’ sign-up behavior in group buying with multiple levels of thresholds (Kauffman and Wang 2001) and revealed two types of threshold-induced effects (Wu et al. 2013). While group-buying deals are often offered by established businesses, crowdfunding projects studied in this chapter are typically associated with new ventures. However, both mechanisms involve product sales, and the insights developed in this chapter can be applied to group buying for exclusively designed products and services.

Finally, our model is related to the pay-what-you-want (PWYW) selling scheme. In that scheme, buyers can choose to pay any price they wish. Like product design in crowdfunding, PWYW can be an effective price discrimination mechanism (Chen et al. 2012). An important factor for the success of PWYW is the buyer’s altruism and fairness concern (Kim et al. 2009, Chen et al. 2012, Gneezy et al. 2010). In this chapter, we also take into account similar behavioral considerations, such as the altruism and warm glow effect, and examine their influence on the crowdfunding design.
2.2 The Base Model and Analysis

In this section, we develop a two-period model to study the creator’s decisions and the buyers’ sign-up behavior. Online crowdfunding firms like Kickstarter allow creators to set a target for each project, and a project is deemed to be realized only when the total amount pledged exceeds the target. We start with a base model, which assumes an exogenously determined quality, to develop the unique insights into buyer’s behavior in crowdfunding. We will analyze the creator’s product line decisions in the next section.

2.2.1 Model Setup

Consider a simple two-period game where a risk-neutral creator adopts a sequential crowdfunding mechanism for selling products. The creator posts a proposed project, with specific product quality and price information, on a crowdfunding platform. The signup process expires after two periods. In each period $t$, one buyer arrives at the proposed project. We denote the buyer at time $t$ as $B_t$, with $t = 1, 2$. For the proposed project to succeed, both of buyers are required to sign up. Having both buyers to sign on to the project is necessary to model the coordination between buyers. In practice all crowdfunding projects require many buyers. There are many reasons why a project needs a certain number of buyers and a certain amount of funds to start. For instance, on the supply side, there may be economies of scale due to high initial setup costs. Most digital products fall in this category. On the demand side, the product may exhibit positive externality and it requires enough users for the product to be valuable enough.

Buyers may have different product valuations. To model this heterogeneity, we assume their valuations are i.i.d. with the following two-point distribution:

$$V_t = \begin{cases} H & \text{with probability } \alpha, \\ L & \text{with probability } 1 - \alpha, \end{cases}$$

where $H > L > 0$.

Upon arrival at the project in period 1, buyer $B_1$ realizes private product valuation, makes the purchase decision, and leaves the site. The creator observes and then announces the purchase decision of $B_1$. Then, buyer $B_2$ arrives at the project, realizes a private product valuation, observes the purchase decision of buyer $B_1$, and makes her own purchase decision. Both buyers are fully rational and make purchase decisions to maximize their own expected utility.

At the beginning of the game, the creator makes product and pricing decisions, and
posts them on a crowdfunding website. In addition, the creator decides the funding target, denoted by $T$. The creator commits to a provision point mechanism such that the project succeeds only if the total amount pledged reaches or exceeds $T$. Otherwise, the project fails. When making decisions, the creator knows the distribution of product valuations of two buyers, but does not know the exact realized valuations. The creator’s goal is to maximize the expected profit from the proposed project.\footnote{In reality, creators can have different goals. An entrepreneur is likely to concentrate on expected revenue and profit, but an artist may also want to reach a wide audience. We have chosen the profit-maximization framework so that our results will be directly comparable to existing work on product-line design.} We assume, without loss of generality, that there is no transaction cost associated with pledging or rewarding, and there is no time discounting over the sign up horizon.

Next we define alternative pricing strategies with the target endogenized to be consistent with the pricing strategy, and analyze their profitability.

### 2.2.2 Alternative Pricing Policies

**Uniform Pricing.** With uniform pricing strategy, the creator posts a single price $p$ for her product. Since the project succeeds only if both buyers sign up for the project and pay $p$, the creator can effectively set $T = 2p$. Price $p$ can take any positive value; however, given the two-point distribution of product valuations, the optimal price should be either $p = H$ or $p = L$. Thus, it suffices to consider the following two cases:

**Margin Strategy** ($H$). With this strategy, the creator sets the price at $p^H = H$ and the target at $T^H = 2H$: any target beyond $2H$ would doom the project to failure; any target in $(H + L, 2H]$ is equivalent to $2H$, which sells only to high-type buyers, consistent with the term of “margin strategy.” Under this strategy, a high-type buyer will sign up, but a low-type buyer will decline. This strategy has a success rate $s^H = \alpha^2$ and the creator has an expected profit $\pi^H = 2\alpha^2 H$.

**Volume Strategy** ($L$). With this strategy, the creator sets the price at $p^L = L$ and the target at $T^L = 2L$: any target below $2L$ is equivalent to $2L$, with only the low price being paid, consistent with the term of “volume strategy.” Under this strategy, both buyers will sign up, regardless of their types, and the project always succeeds; i.e., $s^L = 1$. The creator’s profit is $\pi^L = 2L$.

Compared to the margin strategy, the volume strategy gives the creator a higher chance of project success; however, given that the project succeeds, the volume strategy yields a lower margin.
INTERTEMPORAL PRICING (D). With this strategy, a creator sets different prices for different periods, denoted by \( p_t^D \) for period \( t, t = 1, 2 \). Following the same logic as before, given the two-point distribution of product valuations, the optimal price in each period must be either \( L \) or \( H \). That leads to two candidate strategies, either \((p_1^D, p_2^D) = (H, L)\) or \((p_1^D, p_2^D) = (L, H)\). The creator’s goal is \( T^D = H + L \): any target in \((2L, H + L)\) is equivalent to \( H + L \), which leads to different prices charged in different periods, consistent with the term of “intertemporal pricing strategy.” The success rate is \( s^D = \alpha \) and the creator’s expected profit is \( \pi^D = \alpha(H + L) \). Note that since the buyers arriving at different periods have the same distribution of product valuations, the creator is indifferent between these two intertemporal pricing strategies. However, as shown later in Section 2.4.2, the creator may prefer one type over another when buyers have different product valuations.

MENU PRICING (M). With this strategy, the creator posts a menu of two prices, a high price \( p_h^M \) and a low price \( p_l^M \), where \( p_l^M \leq L \leq p_h^M \leq H \). Unlike intertemporal pricing, the optimal prices in the menu may not be equal to the two valuation points \( H \) and \( L \) (see Lemma 1 below). The creator sets the target at the sum of the high and low prices, i.e., \( T^M = p_h^M + p_l^M \); any target in \((2p_l^M, p_h^M + p_l^M)\) is equivalent to \( p_h^M + p_l^M \), which requires at least one buyer to pay the high price.

The menu pricing strategy proposed here may not appear to be a valid menu because the same quality product has different prices. That is done intentionally in order to tease out a buyer’s incentive to overpay in crowdfunding. With the traditional selling mechanism, such a menu must not work because each buyer would always choose the lower price option. However, in crowdfunding, a buyer, who is also a funder, may choose the higher price if such a choice could substantially increase the likelihood of the project success. One buyer’s behavior affects another buyer’s expected utility; that is, positive externality arises through the common goal of project success.

We solve the optimal menu strategy with the backward induction method. In period 2, buyer \( B_2 \) observes the contribution of the earlier buyer \( B_1 \) and makes her own decision accordingly. Specifically, if \( B_1 \) has signed up at \( p_h^M \), \( B_2 \) always signs up at the low price \( p_l^M \leq L \), regardless of product valuations. On the other hand, if \( B_1 \) has signed up at \( p_l^M \), \( B_2 \) either pledges \( p_h^M \) or does not sign up at all: for \( B_2 \) to sign up at \( p_l^M \) is meaningless because the project will certainly fail. Hence, buyer \( B_2 \) should sign up at \( p_h^M \) if her product valuation is \( H \) and otherwise not sign up at all. Recall that the probability is \( \alpha \).

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\[^4\text{The price menu may not be far stretched from practice. Many projects contain levels with minute quality differences. For each of interpretation, one may consider a trivial quality for the price menu in this section.}\]
for the product valuation to be $H$.

Next we move back to the first period and consider buyer $B_1$. If her product valuation
is $L$, she always signs up at $p^M_l$. Otherwise, she can choose from two options. By choosing
the low-price option $p^M_l$, $B_1$ expects a larger surplus $H - p^M_l$ but a lower success rate at \( \alpha \). Alternatively, by choosing the high-price option $p^M_h$, the buyer expects a smaller surplus $H - p^M_h$ but a higher success rate at $1$. A high-type $B_1$ would prefer the high-price option $p^M_h$ over the low-price option $p^M_l$ if and only if the following incentive-compatibility (IC) condition is satisfied:

$$\alpha(H - p^M_l) \leq H - p^M_h. \quad (IC)$$

The creator decides the optimal menu of prices to maximize the expected profit, subject to the condition (IC). Analyzing the creator’s problem leads to the following lemma.

**Lemma 1 (Optimal Menu Strategy).** With the menu strategy, the creator’s optimal
prices are $p^M_h = (1 - \alpha)H + \alpha L$, $p^M_l = L$ and the optimal target is $T^M = (1 - \alpha)H + (1 + \alpha)L$. The corresponding success rate is $s^M = \alpha(2 - \alpha)$, and the expected profit is $\pi^M = \alpha(2 - \alpha)((1 - \alpha)H + (1 + \alpha)L)$.

Lemma 1 indicates that with the menu pricing strategy, given all others are the same,
as long as the high price $p^M_h$ is low enough such that the (IC) condition is satisfied, a high-
type buyer $B_1$ prefers to pay the high price, even though a lower price option is available.
The amount of over-payment is $p^M_h - p^M_l = (1 - \alpha)(H - L)$, which increases with product
valuation gap $(H - L)$ and decreases with $\alpha$. Thus, when product valuation is more heterogenous between different types of buyers or when buyer $B_1$ is more pessimistic
about the product valuation of buyer $B_2$, a high-type buyer $B_1$ has a greater incentive
to overpay. With a larger gap $H - L$, a high-type buyer $B_1$ derives more utility from
the project and is thus more willing to take a sacrifice to ensure the project’s success.
Similarly, with a smaller $\alpha$, the risk of project failure is high, and thus the incentive
to overpay is higher. As $\alpha$ decreases from $1$ to a small value $\epsilon > 0$, the amount of
overpayment increases from $0$ to $(1 - \epsilon)(H - L)$, close to $H - L$.

When a high-type $B_1$ chooses price option $p^M_h$, this buyer enjoys a surplus of $\alpha(H - L)$.
Since the project is sure to succeed, the buyer $B_2$ will simply choose the low price $p^M_l = L$.
Otherwise, had the buyer $B_1$ chosen $p^M_l$, a high-type buyer $B_2$ would have to pay $p^M_h$
and incur a reduction of surplus $(1 - \alpha)(H - L)$. Thus, when the high-type buyer $B_1$
pays the higher price, the overpayment has a positive externality effect on the second
buyer’s surplus. Moreover, the size of the positive externality effect increases with the
high price option in the menu. Thus, the crowdfunding mechanism not only artificially
creates an externality effect among the decisions of buyers, but also determines the size of the externality effect endogenously.

2.2.3 Optimal Pricing Strategy

The creator determines the optimal pricing strategy by comparing the expected profits from each of the alternative pricing strategies. We summarize our analysis in the proposition below.

Proposition 1 (Optimal Pricing Strategy). The creator’s optimal strategy is

1. volume strategy, if $\frac{H}{L} \leq \frac{2-a^2}{a(2-a)}$;

2. menu strategy, if $\frac{2-a^2}{a(2-a)} \leq \frac{H}{L}$ and $\alpha \leq \frac{3-\sqrt{5}}{2}$, or $\frac{2-a^2}{a(2-a)} \leq \frac{H}{L} \leq \frac{1+a-a^2}{3a-a^2-1}$;

3. intertemporal strategy, if $\frac{1+\alpha-a^2}{3\alpha-a^2-1} \leq \frac{H}{L}$, and $1+\alpha-a^2 \leq \frac{3-\sqrt{5}}{2}$, or $\frac{1+\alpha-a^2}{3\alpha-a^2-1} \leq \frac{H}{L} \leq \frac{1}{2\alpha-1}$, or $\frac{1+\alpha-a^2}{3\alpha-a^2-1} \leq \frac{H}{L}$.

4. margin strategy, if $\frac{1}{2} \leq \alpha$ and $\frac{1+\alpha-a^2}{3\alpha-a^2-1} \leq \frac{H}{L}$.

Proposition 1 indicates that each of the four pricing strategies can be optimal within certain parameter subspaces. We illustrate the results in Figure 2.2. The vertical axis represents the ratio of high-type to low-type buyer’s product valuations ($H/L$); the horizontal axis represents the fraction of high-type buyers ($\alpha$) in the market. The figure shows that uniform pricing strategies are optimal in two extreme cases. Specifically, given the valuation of $L$, the volume strategy is optimal when buyers are unlikely to have high product valuation (i.e., small $\alpha$) or when high- and low-type buyers have a narrow valuation gap (i.e., $H/L$ is close to 1). Intuitively, it can be seen that if both buyers are very likely to have a low product valuation, then the creator should pursue volume strategy. The expected gain from targeting at high-valuation buyers only is not worth the risk that the project may fail. At the other extreme, if buyers are very likely to have a high valuation (i.e., large $\alpha$) and the valuation gap between high- and low-type buyers is large (i.e., large $H/L$), then the creator should go for margin strategy. In other words, if both buyers are very likely to have a high product valuation that is much higher than low valuation, the creator should pursue margin strategy. The gain from targeting on high-type buyers is large, and the risk is bearable.

Two types of discriminatory pricing strategy, namely the intertemporal and menu pricing strategies, are more profitable than the uniform pricing strategies when the fraction of high-type buyers ($\alpha$) is not very large and the valuation ratio ($H/L$) is large
enough, in other words, when buyers believe that others may have low product valuations and the product valuations are heterogeneous enough. The difference between these two discriminatory pricing strategies is the timing: while the same menu of two options exists in both periods with a menu pricing strategy, a unique option is available in each period with an intertemporal pricing strategy. It is important to note that, first, with our model, an optimal discriminatory pricing strategy degenerates into a uniform pricing strategy in the traditional selling setting. The intertemporal, or menu, pricing strategy becomes optimal with a crowdfunding mechanism because two buyers are linked by a common target. As a result, a high-type buyer may choose the high-price option to compensate for the small contribution from a low-type buyer. Second, the buyers can achieve coordination without any explicit interactions. In our model, self-interested buyers do not incorporate other buyers’ utilities into their objectives (as in Chen and Li 2013), nor do some buyers communicate with others to increase their valuations (as in Jing and Xie 2011).

Table 2.1 shows the target amount and project success rate for each type of pricing strategy. Specifically, the target amount increases in the order of volume strategy, menu strategy, intertemporal strategy, and margin strategy, and project success rate decreases in the same order. When the fraction of high-type buyers ($\alpha$) increases, the difference in the success rate between different strategies diminishes, but the difference in the target level remains large. A high target leads to a low project success rate, and vice versa.5

5Our model can be easily adapted to situations where a not-for-profit creator wants to maximize

---

Figure 2.2: Optimal Strategy with Different Values of $H/L$ and $\alpha$
Table 2.1: Success Rate and Target

<table>
<thead>
<tr>
<th></th>
<th>Success rate</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Volume strategy</td>
<td>1</td>
<td>2L</td>
</tr>
<tr>
<td>Menu strategy</td>
<td>2\alpha - \alpha^2</td>
<td>(1 - \alpha)H + (1 + \alpha)L</td>
</tr>
<tr>
<td>Intertemporal strategy</td>
<td>\alpha</td>
<td>H + L</td>
</tr>
<tr>
<td>Margin strategy</td>
<td>\alpha^2</td>
<td>2H</td>
</tr>
</tbody>
</table>

The next corollary summarizes the social welfare implications of discriminatory pricing strategies.

**Corollary 1 (Social Welfare).** The introduction of discriminatory strategies can improve creator and buyer surplus.

1. If \( \frac{2 - \alpha}{\alpha} < \frac{H}{L} < \max \{ \frac{3 - \sqrt{5}}{2}, \frac{1 + \alpha - \alpha^2}{3\alpha - \alpha^2 - 1} \} \), the introduction of menu strategy improves both creator and buyer surplus over the optimal strategy of the other three strategies.

2. If \( \frac{1}{2} \leq \alpha \) and \( \frac{(2 - \alpha)(1 + \alpha)}{5\alpha - 2 - \alpha^2} \leq \frac{H}{L} \leq \frac{1}{2\alpha - 1} \), the introduction of intertemporal strategy improves both creator and buyer surplus over the optimal strategy of the other three strategies.

Corollary 1 states that discriminatory pricing strategies can improve buyer surplus and social welfare. With discriminatory pricing strategies, the creator can serve more buyers. Margin strategy serves high-type buyers only, and volume strategy, though serving all buyers, is often not sustained as the optimal pricing strategy, because of low profitability. In contrast, with the menu and intertemporal strategies, creators can reach all high-type buyers and a fraction of low-type buyers and, at the same time, achieve high profitability.

**Discussions:** In a model without product quality differentiation, menu pricing strategy can be optimal in a crowdfunding mechanism. When buyers are sufficiently heterogeneous in product valuation, offering a menu of prices can help achieve a better balance between volume (or success rate) and margin. A unique insight is that a self-interested high-type buyer might be willing to pay extra to ensure the project’s success. Thus, by turning buyers into funders, the crowdfunding mechanism enhances coordination among different buyers. Moreover, menu pricing strategy, by choosing a proper level the success rate, subject to raising enough funds to cover setup costs in advance. The amount of fixed setup costs can become the exogenous target. Table 2.1 can be used as a guide for the optimal pricing strategy given the exogenous target. For example, if the exogenous target \( T \) falls in the range \((2L, (1 - \alpha)H + (1 + \alpha)L]\), the menu strategy maximizes the success rate.
of high-price option below $H$, moderates the high-type buyer’s sacrifice and optimizes the coordination incentive. Crowdfunding creates compatibility between the purchases of two buyers who share the common goal of project success. As a result, each buyer’s behavior has external effect on other buyers’ utilities. The extent of externality effect is regulated by the price difference.

The high-type buyer’s incentive to pay extra relies on the belief that the creator is committed to the provision point mechanism, i.e., the project will not be carried out unless the target is met. Although it is not the focus of this chapter, we have conducted formal analysis to validate that when a menu strategy is optimal, it is indeed an equilibrium outcome for the creator to make the commitment. Intuitively, lacking such a commitment would jeopardize the ability of the menu strategy to price discriminate among buyers. If a high-type buyer expects the creator to carry on the project even if the target is not met, there would be little incentive to pay extra.

2.3 Product Line Design

In this section, we extend the base model to allow the creator to offer two vertically differentiated products. We intend to explore how the crowdfunding mechanism may alter the optimal product line design, specifically, the optimal quality gap between product options. For the analysis of this problem, we modify the base model as follows. First, buyer’s valuations depend on the quality of the products. Specifically, we assume product valuation $V_h = QH$ for a high-type buyer, and valuation $V_l = QL$ for a low-type buyer. The base model can be seen as a special case, with the quality level fixed to $Q = 1$. Second, in keeping with the existing literature, we assume that the production cost is a function of quality. In particular, we assume that the unit production cost of a good with a quality level $Q$ is $Q^2/2$. This quadratic form is widely used in the marketing literature (see, e.g., Guo and Zhang 2012). Finally, to cover the development cost, we assume that the creator requires producing two units of products, which may be available in different qualities.

We denote the creator’s menu decision by $(Q_l^M, P_l^M)$ and $(Q_h^M, P_h^M)$. (To distinguish the product line model from the base model, we use capital letters here.) The creator’s funding target is $T^M = P_h^M + P_l^M$. Analysis of this model is similar to that of the base model. The major distinction is the IC condition that ensures self-selection by a high-type buyer $B_1$, which now becomes:

$$
\alpha(HQ_l^M - P_l^M) \leq HQ_h^M - P_h^M,
$$

(2.1)
where the buyer’s surplus hinges on quality, too. The creator’s expected profit is given by

$$\Pi_M = (\alpha^2 + 2\alpha(1-\alpha))\left(P_h^M + P_l^M - \frac{(Q_h^M)^2}{2} - \frac{(Q_l^M)^2}{2}\right),$$  \(2.2\)

subject to the IC condition (2.1) and \(P_l^M \leq LQ_l^M\). For given quality levels \((Q_h^M, Q_l^M)\), it is easy to see that the optimal prices are achieved when both inequalities are binding, i.e., \(P_h^M = HQ_h^M - \alpha(H - L)Q_l^M, P_l^M = LQ_l^M\).

The first order condition yields the optimal quality choices \(Q_h^M = H, Q_l^M = L - \alpha(H - L)\). We summarize the optimal, either interior or boundary, solution as follows.

**Proposition 2 (Optimal Product Line Design).** In the product line model,

1. if \(H \leq L \leq 1 + \frac{1 + \alpha}{\alpha}\), the optimal quality levels are \((Q_h^M, Q_l^M) = (H, \Delta)\), where \(\Delta \equiv L - \alpha(H - L) \leq L\), and the optimal prices are \((P_h^M, P_l^M) = (H^2 - \alpha(H - L)\Delta, L\Delta)\). The corresponding expected profit of the creator is

$$\Pi_M = \frac{\alpha(2 - \alpha)}{2} \left(1 + \alpha^2\right)H^2 - 2\alpha(1 + \alpha)HL + (1 + \alpha)^2L^2;$$

2. if \(H \geq L \geq 1 + \frac{1 + \alpha}{\alpha}\), the optimal quality levels are \((Q_h^M, Q_l^M) = (H, 0)\), and the optimal prices are \((P_h^M, P_l^M) = (H^2, 0)\). The corresponding expected profit of the creator is

$$\Pi_M = \frac{\alpha(2 - \alpha)}{2} H^2.$$

To see the effect of crowdfunding mechanism on product line design, we compare the results of this model with the traditional product line design problem without crowdfunding. In the traditional situation, the current model would have a different self-selection IC condition:

$$HQ_l^T - P_l^T \leq HQ_h^T - P_h^T,$$  \(2.3\)

where the superscript \(T\) specifies the traditional model. The creator’s goal here is to maximize his expected profit

$$\Pi_T = \alpha\left(P_h^T - \frac{(Q_h^T)^2}{2}\right) + (1 - \alpha)\left(P_l^T - \frac{(Q_l^T)^2}{2}\right),$$  \(2.4\)

subject to the IC condition (2.3) and \(P_l^T \leq LQ_l^T\). Similarly, the optimal prices are achieved when both inequalities are binding, i.e., \(P_h^T = HQ_h^T - (H - L)Q_l^T, P_l^T = LQ_l^T\).

We summarize the optimal solution to the traditional product design problem as follows, for purposes of comparison.

**Lemma 2.** In the traditional product line design problem, the optimal strategy is:
Chapter 2. Product and Pricing Decisions in Crowdfunding

1. if $\frac{H}{L} \leq \frac{1}{\alpha}$, $Q^{T}_{h} = H$, $Q^{T}_{l} = \frac{L-aH}{1-\alpha}$ and $P^{T}_{h} = \frac{H^{2}-(1+\alpha)HL+L^{2}}{1-\alpha}$, $P^{T}_{l} = \frac{(L-aH)L}{1-\alpha}$;
2. if $\frac{H}{L} \geq \frac{1}{\alpha}$, $Q^{T}_{h} = H$, $Q^{T}_{l} = 0$ and $P^{T}_{h} = H^{2}$, $P^{T}_{l} = 0$.

Comparing the quality differences between $(Q^{T}_{h} - Q^{T}_{l})$ and $(Q^{M}_{h} - Q^{M}_{l})$, we have:

**Proposition 3 (Less Differentiation in Crowdfunding).** Qualities are less differentiated in the crowdfunding scenario.\(^6\)

To understand Proposition 3, first note that in case of perfect discrimination, the creator knows each buyer’s true type and hence can supply products of quality $H$ to high-type buyers and products of quality $L$ to low-type buyers. When buyers hold private information on quality valuations, in order to satisfy the self-selection condition, the creator has to distort quality levels downwards. According to our analysis, in both traditional and crowdfunding settings, $Q^{T}_{h} = Q^{M}_{h} = H$. The downward quality distortion comes from the low-quality product, and is smaller in the crowdfunding setting, i.e., $Q^{T}_{l} < Q^{M}_{l} < L$.

We explain this result through IC conditions (2.1) and (2.3), together with objective functions (2.2) and (2.4). The low-quality option is associated with project success rate $\alpha$ in crowdfunding’s IC condition (2.1), but the associated success rate is 1 in the IC condition (2.3) of the traditional setting. The difference in the success rates is also reflected in the objective functions. Intuitively we can see that in crowdfunding, high-type buyers are concerned about both the success rate of the project and surplus from purchase. If a high-type buyer had deviated from the high-quality option and chosen the low-quality product, the buyer would experience a higher surplus from the option, but face a lower success rate. In light of this tradeoff, which itself deters deviation and does not exist in the traditional setting, the creator can afford to have a less downward distortion, i.e., to set the low-option quality $Q^{M}_{l}$ higher.

### 2.3.1 Strategy Comparison

We now evaluate the profitability of the menu strategy in comparison to three other strategies. As with the analysis in the base model, we consider three different strategies: margin strategy (H), volume strategy (L), and intertemporal strategy (D). For each strategy, we analyze the optimal quality level and corresponding profits. We summarize the results in the next lemma.

**Lemma 3.** When product qualities are endogenized, the creator’s optimal decisions under each of three strategies are as follows:

\(^6\)Unless otherwise specified, the monotonicity is in its weaker sense.
1. Margin strategy: \( Q^H = H, P^H = H^2 \) and \( \Pi^H = \alpha^2 H^2 \);

2. Volume strategy: \( Q^L = L, P^L = L^2 \) and \( \Pi^L = L^2 \);

3. Intertemporal strategy: \( Q^D_t = H, P^D_t = H^2, Q^D_{3-t} = L, P^D_{3-t} = L^2 \), where the solutions are symmetric for \( t = 1, 2 \). Moreover, \( \Pi^D = \frac{\alpha}{2}(H^2 + L^2) \).

In the intertemporal strategy, we can also measure the optimal quality gap, though only one product is offered in each period. It is easy to see that the optimal quality gap with the intertemporal strategy, \( H - L \), is also smaller than that in the traditional product design. The driving force is similar to what we explained for the menu strategy. We compare the profitability of the discriminatory strategies with the uniform pricing strategies, leading to the following proposition.

**Proposition 4.** For the profit comparison,

1. the menu strategy is more profitable than the volume strategy when
   \[
   \frac{H}{L} \geq \frac{-2\alpha^2 - \alpha^3 + \alpha^4 - \sqrt{4\alpha - 6\alpha^2 + \alpha^4 + 2\alpha^5 - \alpha^6}}{-2\alpha + \alpha^2 - 2\alpha^3 + \alpha^4}
   \]
   and is more profitable than the margin strategy when
   \[
   \frac{H}{L} \leq \min\left(\frac{1 + \alpha}{\alpha}, \frac{-2\alpha - \alpha^2 + \alpha^3 - \sqrt{-4 + 9\alpha^2 + 2\alpha^3 - 3\alpha^4}}{-2 + 3\alpha - 2\alpha^2 + \alpha^3}\right)
   \]
   or \( \alpha \leq \frac{2}{3} \);

2. the intertemporal strategy is more profitable than the volume strategy when \( \frac{H}{L} \geq \sqrt{\frac{2-\alpha}{\alpha}} \), and is more profitable than the margin strategy when \( \frac{H}{L} \leq \frac{1}{\sqrt{2\alpha-1}} \) or \( \alpha \geq \frac{1}{2} \).

Proposition 4 confirms that the same insight, obtained from Proposition 1 for the base model, applies to the generalization where the product qualities are endogenized. That is, discriminatory pricing strategies, either the intertemporal or menu pricing strategy, can be more profitable than the uniform pricing strategies with crowdfunding. Like Figure 2.2 in the base model, Figure 2.3 demonstrates the optimal product and pricing strategy under different market conditions. From Figure 2.3, we see again that the menu strategy or intertemporal strategy becomes optimal when the fraction of high-type buyers (\( \alpha \)) is not too large and the valuation differentiation between two types of buyers (\( H/L \)) is large enough. Again, these figures imply that no single marketing strategy dominates in all parameter spaces; instead, creators need to tailor their product and pricing strategies to the specific market conditions associated with their projects. Lastly,
it can be numerically shown that the intertemporal strategy is always dominated by other strategies when product quality is endogenous.

Our main insights about the high-type buyer’s behavior and implications for menu design have strong relevance to crowdfunding practices. Although high-type buyers may not be the majority, their contributions are critical to project success. To collect some empirical evidences, we monitored the progresses of all new projects launched on Kickstarter from 15:15 to 23:15 on January 15, 2014. There were a total of 60 such projects, 58% of them succeeded, and 95% of them posted a menu consisting of multiple levels of reward-price offers. On average, top 10% of buyers contributed 52.2% of the total pledged amount. There were a total of 8,754 buyers, 87.6% of them paid the exact prices as suggested. Thus, consistent with our results, a vast majority of consumers paid according to the menus. To explain why the rest 12.4% paid above the required amounts, we will extend the base model in next section to incorporate non-economic motivations.

## 2.4 Model Extensions

In this section we discuss a number of extensions to the base model. Analyzing these model extensions not only establishes the robustness of our results regarding product and pricing decisions in crowdfunding, but also further deepens our understanding of these issues. To simplify the discussion, we may concentrate on the menu strategy when...
similar insights are applicable to the intertemporal strategy.

2.4.1 Non-economic Motivations

The main model assumes that all buyers are self-interested and make decisions to maximize their own surpluses. However, for many crowdfunding projects, especially those posted by artists and not-for-profit organizations, the buyers can be influenced by non-economic or altruistic motivates (Mollick 2013). Here we consider two commonly examined forms of such motivations - warm glow and prestige effect - and examine the implications for product and pricing decisions. In both cases we add a term for non-economic motivation to a buyer’s utility function.

In the warm-glow model, a buyer’s utility function becomes

\[ U = (V - p) + \lambda \cdot p, \]

where \((V - p)\) is the economic surplus in the base model and \(p\) represents the amount the buyer contributes to the project. The parameter \(\lambda\) represents the significance of the warm glow effect. This formulation follows the previous literature on warm glow and altruistic motivation (see, e.g., Andreoni 1990).

We now examine the influence of the warm glow effect on the menu strategy. Suppose the creator sets the prices at \(p^M_w\) and \(p^M_l\). In order to motivate a low-type buyer to participate, we need to make sure that

\[ L - p^M_w + \lambda p^M_w \geq 0. \]

To ensure that a high-type buyer selects the high-price option, we need to ensure the following IC condition,

\[ H - p^M_w + \lambda p^M_w \geq \alpha (H - p^M_l). \]

Incorporating the above two constraints into the creator’s problem, we can solve for the optimal pricing strategy, which is summarized as follows:

**Proposition 5 (Warm Glow).** When buyers experience the warm glow effect, the optimal menu strategy is

\[ (p^M_w, p^M_l) = \left( \frac{(1 - \alpha)H + \alpha L}{1 - \lambda}, \frac{L}{1 - \lambda} \right), \]

which amplifies the optimal menu prices in the base model by a factor of \(\frac{1}{1 - \lambda}\).

Prestige effect is a discrete form of warm-glow effect based on relative contributions. When a creator offers several categories of contributions, those who choose the higher categories could experience the prestige value (Harbaugh 1998). Assume that a buyer’s additional utility from the prestige effect is \(u_p\). To motivate a high-type buyer to choose the high-price option, it is necessary to ensure that

\[ H - p^M_w + \zeta (p^M_w - p^M_l) \geq \alpha (H - p^M_l). \]

Given this revised IC condition, the buyer’s optimal pricing strategy is summarized as follows.

\[ (p^M_w, p^M_l) = \left( \frac{(1 - \alpha)H + \alpha L}{1 - \zeta}, \frac{L}{1 - \zeta} \right). \]
Proposition 6 (Prestige). When buyers experience prestige effect, the optimal menu strategy is \((p_h^{M_w}, p_l^{M_w}) = ((1 - \alpha)H + \alpha L + u_p, L)\).

The above propositions imply that, with either the warm glow or prestige effect, the parameter spaces under which a creator should adopt the menu strategy expand. Moreover, both the high-price option and the price gap increase. Intuitively, we can see that both effects increase the expected value of and the relative preference for the high-price option. Thus, both warm glow and prestige effects provide additional justifications for the creator to offer more than one option.

The base model considers one buyer in each period with the same distribution of valuation. Next we examine two alternative models. In one model two buyers have different valuations. In another model different number of buyers arrive in two periods.

2.4.2 Time-Varying Valuations

Two buyers arriving in different periods may not follow the same distribution of product valuations. For example, buyers with a special interest in certain types of project are more likely to search for such projects and arrive at them earlier; or a creator may share the proposed project with family and friends first, who may be willing to pay more to show their support. To consider such time-varying valuations, we assume that the buyers arriving at two periods follow different value distributions. Specifically, let \(\alpha_t\) be the probability that buyer \(B_t, t = 1, 2\), has high valuation \(H\). Then the creator’s expected profit is \(\pi^{H_h} = 2\alpha_1\alpha_2H\) with the margin strategy, and the expected profit is \(\pi^{L_h} = 2L\) with the volume strategy. With the intertemporal pricing strategy, the creator charges the high price during the period with the larger \(\alpha\), and the expected profit is \(\pi^{D_h} = \max(\alpha_1, \alpha_2)(H + L)\).

Lemma 4. With time-varying product valuations, the creator’s optimal menu strategy is \(p_h^{M_h} = (1 - \alpha_2)H + \alpha_2L, p_l^{M_h} = L\). The corresponding expected profit is \(\pi^{M_h} = (\alpha_1 + \alpha_2 - \alpha_1\alpha_2)((1 - \alpha_2)H + (1 + \alpha_2)L)\).

The proof is analogous to that of Lemma 1. A comparison of the expected profits with various pricing strategies leads to the following proposition.

Proposition 7. The menu pricing strategy is more profitable

1. than the volume strategy if \(\frac{2 - \alpha_1 - \alpha_2}{\alpha_1 + \alpha_2 - \alpha_1\alpha_2} < \frac{H}{L}\);

2. than the margin strategy if \(\frac{H}{L} \leq \frac{(1 + \alpha_2)(\alpha_1 + \alpha_2 - \alpha_1\alpha_2)}{3\alpha_1\alpha_2 + \alpha_2^2 - \alpha_1 - \alpha_2 - \alpha_1\alpha_2}\), or, \(\alpha_1\) and \(\alpha_2\) satisfy \(\alpha_1 + \alpha_2 - 4\alpha_1\alpha_2 - \alpha_2^2 + \alpha_1\alpha_2^2 \geq 0\).
3. than the intertemporal strategy if \( \frac{H}{L} \leq -\frac{\alpha + \alpha_2^2 - \alpha_1 \alpha_2}{\alpha - 2\alpha_1 \alpha_2 - \alpha_2^2 + \alpha \alpha_2^2} \), or, \( \alpha_1 \) and \( \alpha_2 \) satisfy 
\[
2\alpha_1 \alpha_2 + \alpha_2^2 - \alpha_1 \alpha_2^2 \leq \alpha, \quad \text{where } \alpha \equiv \min(\alpha_1, \alpha_2).
\]

Proposition 7 is consistent with the results for the menu pricing strategy in the base model. Interestingly, \( \alpha_1 \) and \( \alpha_2 \) have very different effects on the creator’s profit. Taking derivatives of \( \pi_{Mh} \) with respect to \( \alpha_1 \) and \( \alpha_2 \) respectively yields the following result.

**Corollary 2.** With time-varying product valuations, a creator following the menu strategy has the expected profit increasing in \( \alpha_1 \); increasing in \( \alpha_2 \) if \( \alpha_2 \leq \alpha_2^* \equiv \frac{H-2\alpha_1 H+L}{2(1-\alpha_1)(H-L)} \), and decreasing in \( \alpha_2 \) if \( \alpha_2 \geq \alpha_2^* \).

Though it is not difficult to see the first part of Corollary 2 that the creator’s expected profit increases in \( \alpha_1 \), the second part is intriguing. The latter implies that the buyer may gain more when buyer \( B_2 \)’s expected valuation \( \alpha_2 H + (1 - \alpha_2) L \) decreases. To understand that, recall that the creator’s expected profit hinges on both the success rate and the target, which equals \( p_{h}^{Mh} + p_{l}^{Mh} \). While a larger \( \alpha_2 \) increases the success rate, it can reduce the price \( p_{h}^{Mh} \) and hence the target: when \( \alpha_2 \) is large enough, expecting that \( B_2 \) has a greater chance of being a high type, \( B_1 \) may be reluctant to pay the high price, hoping that \( B_2 \) pays it instead. Namely, \( B_1 \) is more likely to free ride when \( \alpha_2 \) rises. With these forces, the effect of \( \alpha_2 \) on the creator’s profit is no longer monotonic.

Even after all the alternative pricing strategies are considered, the expected profit from the best pricing strategy may still decrease in \( \alpha_2 \). These results have implications for how creators manage the arrival sequence of buyers and their beliefs about product valuations of future buyers. Under some conditions, persuasive marketing campaigns to increase a buyer’s valuation in period 2 could backfire and reduce the creator’s profit. This implies that a creator may benefit from certain “demarking” efforts in the second period (see, e.g., Miklos-Thal and Zhang 2013, Gerstner et al. 1993, Pazgal et al. 2013).

### 2.4.3 A Two-Cohort Model

Instead of assuming one buyer in each period, we now consider a cohort of buyers arriving in each period \( t, t = 1, 2 \), but keep the assumption of identical value distributions. We let the size of the two cohorts be \( n_1 \) and \( n_2 \) respectively. As in the base model, here the valuation distributions \( V_t \) for both periods are i.i.d., following a two-point distribution, equal to \( V_t = H \) with probability \( \alpha \) and \( V_t = L \) with probability \( (1 - \alpha) \). We further assume that the project requires all buyers from both cohorts to participate.

The analysis of the margin strategy and volume strategy proceeds in the same way as in the base model, except that the targets are now \( (n_1 + n_2)H \) and \( (n_1 + n_2)L \),
respectively. The expected profits with these two strategies are \( \pi^H_c = \alpha^2(n_1 + n_2)H \) and \( \pi^L_c = (n_1 + n_2)L \), respectively. With the optimal intertemporal pricing strategy, the creator charges cohort 1 price \( H \) and cohort 2 price \( L \) if \( n_1 \geq n_2 \) (which is reversed if \( n_1 < n_2 \)), and the expected profit is \( \pi^{D_c} = \alpha(n_1H + n_2L) \).

With the menu pricing strategy, we generalize the argument made in the base model that the project is successful only if one buyer is of the high type. In the extended model, a project succeeds only when one cohort of buyers are of high type. Correspondingly, the target will be \( T^{M_c} = \max(n_1, n_2)p^{M_c}_l + \min(n_1, n_2)p^{M_c}_h \), where \( p^{M_c}_l \leq L, p^{M_c}_h \leq H \) are the menu prices offered in both periods. Since each buyer can pay anywhere between \( p^{M_c}_l \) and \( p^{M_c}_h \), the total contribution from the first cohort of buyers will be between \( n_1 p^{M_c}_l \) and \( n_1 p^{M_c}_h \). Suppose the first cohort has paid \( \lambda \in [n_1 p^{M_c}_l, n_1 p^{M_c}_h] \), and the remaining amount needed is \( T^{M_c} - \lambda > 0 \). The conditional success rate is then

\[
S^{M_c} = \begin{cases} 
1 & \text{if } T^{M_c} - \lambda \leq n_2 p^{M_c}_l, \\
\alpha & \text{if } n_2 p^{M_c}_l < T^{M_c} - \lambda \leq n_2 p^{M_c}_h.
\end{cases}
\]

The IC condition for cohort 1 can be written as \( n_1 H - (T^{M_c} - n_2 p^{M_c}_l) \geq \alpha(n_1 H - (T^{M_c} - n_2 p^{M_c}_h)) \).

Proposition 8. In the two-cohort model, the optimal menu strategy has a target \( T^{M_c} = \max(n_1, n_2)p^{M_c}_l + \min(n_1, n_2)p^{M_c}_h \), and an expected profit \( \pi^{M_c} = \alpha(2 - \alpha)T^{M_c} \), where

1. \( p^{M_c}_h = \min(H, (1 - \alpha)(H - L)\frac{n_1}{n_2} + L) \) and \( p^{M_c}_l = L \), if \( n_1 \geq n_2 \);

2. \( p^{M_c}_h = (1 - \alpha)H + \alpha L \) and \( p^{M_c}_l = L \), if \( n_1 \leq n_2 \).

It can be shown that the optimality of the menu pricing strategy, as well as the intertemporal strategy, is sustained in similar parameter spaces to the base model. However, the two-cohort model extension leads to the following new insights:

(i) The menu pricing strategy requires one of the two cohorts of buyers to have high valuations. The creator should target the higher price at the smaller cohort, thus reduce the effectiveness of the menu pricing strategy as a price discrimination mechanism.

(ii) If \( n_1 > n_2 \), price \( p^{M_c}_h \) is higher, and the second cohort of buyers find it harder to free ride on the contributions from the first cohort. The high price \( p^{M_c}_h \) increases in this case because the first cohort’s surplus depends not only on individual surplus \( H - p^{M_c}_h \), but also on the portion of buyers contributing \( p^{M_c}_l \). Since the first cohort is less sensitive to \( p^{M_c}_h \), the creator increases the high price in the menu, and that hurts the second cohort.
In summary, in above two subsections, the optimality of the menu pricing strategy, as well as the intertemporal strategy, is sustained in similar parameter spaces. Additional insights arise from the changed incentives to free ride on another cohort’s contributions. A second cohort that is larger or whose product valuations are expected to be higher could create greater free-riding incentives for the buyers in the first cohort, and consequently make it more challenging for the creator to discriminate buyers through a menu strategy.

2.4.4 Uncertainty in Number of Buyers

We now examine the implications of demand uncertainty. We first consider the possibility of no-show in one period, followed by uncertain number of buyers in two cohorts.

No-Shows. Suppose that in the first period, buyer $B_1$ shows up with probability $\theta$. Conditional on the arrival of buyer $B_1$, the IC condition of the menu strategy remains $H - p_h^M \geq \alpha (H - p_l^M)$, then the optimal menu prices are the same as in Lemma 1. Next, suppose that in the second period, buyer $B_2$ shows up with probability $\theta$. In this case, the project may still fail even if buyer $B_1$ has contributed $p_h^M$. The IC condition becomes $\theta (H - p_h^M) \geq \alpha \theta (H - p_l^M)$, which is equivalent to the original (IC) condition. Hence the optimal menu prices remain the same as in Lemma 1. In both cases, the project success rate and the creator’s expected profit under the menu strategy shrinks by a factor of $\theta$.

Since the profits under other pricing strategies are also reduced by the same factor $\theta$, the parameter spaces where each pricing strategy is optimal remain the same. Therefore the presence of demand uncertainty in the form of no show does not change the main results obtained in the base model.

Uncertain number of buyers and overfunding. To consider the uncertain number of buyers in a two-cohort model, we suppose that the number of buyers in the first period a constant $n_1$ and the number of buyers in the second period $N_2$. We let $N_2$ follow a two-point distribution: with probability $\beta$, $N_2 = n_2^H$ and with probability $1 - \beta$, $N_2 = n_2^L$. Consider the case that $n_1 \leq n_2^L < n_2^H$. Consistent with the base model, to induce a high-valuation first cohort to pay the high price to ensure success, the creator sets the target $T^{Mo} = n_1 p_h^{Mo} + n_2^L p_l^{Mo}$ for a menu $(p_l^{Mo}, p_h^{Mo})$. Further assume that $n_2^H$ is large enough such that even if the first cohort has low valuation and chooses to pay $p_l^{Mo}$, the project can succeed when $N_2 = n_2^H$, i.e., $(n_1 + n_2^H)p_l^{Mo} \geq T^{Mo}$. Then, the IC condition for the first cohort is $n_1 (H - p_h^{Mo}) \geq (\alpha + (1 - \alpha)\beta)n_1 (H - p_l^{Mo})$, which yields the optimal pricing strategy $p_h^{Mo} = (1 - \alpha)(1 - \beta)H + (\alpha + \beta - \alpha\beta)L$, $p_l^{Mo} = L$.

When the first cohort has high valuation and $N_2 = n_2^H$, the creator collects $n_1 p_h^{Mo} + n_2^H p_l^{Mo}$, which exceeds the target $T^{Mo}$. Here the target is set ex ante and the first cohort
of buyers make pledge decisions before knowing the actual size of the second cohort. Overfunding occurs in equilibrium when the second cohort turns out to be large. The same phenomenon occurs for the case $n_2^L \leq n_1 \leq n_2^H$ and the cases when the size of the first cohort is random. Overfunding is commonly observed in crowdfunding. For example, among the 60 projects we tracked on Kickstarter, the creators on average collected 27% more than the targets.

The base model assumes that each buyer arrives at the site at an exogenously determined time and makes the sign-up decision at arrival. In reality, the buyer who arrives early may choose to postpone the decision. If both buyers are fully informed of the posting, they may simultaneously choose the decision times. We examine these two possibilities in next two extensions.

### 2.4.5 Strategic Delay

Here we extend the base model by allowing buyer $B_1$ to postpone the decision, and analyze how buyer $B_1$’s timing of the decision may affect the creator’s optimal product and pricing strategy.

**Proposition 9.** In a sequential crowdfunding model with an endogenous timing decision, the first buyer always makes the sign-up decision in the first period, and the optimal product and pricing decisions are identical to those in the base model.

The underlying logic for the above proposition is as follows. First, a low-type buyer $B_1$ is indifferent between waiting or making the decision immediately because the creator sets a price that fully extracts the surplus from a low-type buyer. Postponing the decision to the second period will not improve the expected surplus. To break the tie, we assume that a low-type buyer $B_1$ always purchases at $p^M_H = L$ in the first period.

Now consider a high-type buyer $B_1$. If this buyer chooses to postpone the purchase decision, in period 2 there will be two buyers in the market, $B_1$ and $B_2$. Since zero contribution is posted in period 1 and a low-type $B_1$ never postpones the decision, buyer $B_2$ can correctly infer that $B_1$ must be of the high type. Such inference will not affect a low-type $B_2$, who will always purchase at $p^M_H = L$. However, if $B_2$ is a high-type buyer, then $B_2$ may purchase at $p^H_M$ with certain probability, say, $0 \leq \gamma_2 \leq 1$. Furthermore, if $B_1$ postpones the decision, in the second period $B_1$ will purchase at $p^M_H$ with some probability $0 \leq \gamma_1 \leq 1$. Given the belief on $\gamma_1$ and $\gamma_2$, the expected surplus of $B_1$ from postponing the decision is $\gamma_1(H-p^M_H)+(1-\gamma_1)\gamma_2\alpha(H-p^M_l) \leq \gamma_1(H-p^M_H)+(1-\gamma_1)\alpha(H-p^M_l) = H-p^M_H$, with the inequality strict when $\gamma_2 < 1, \gamma_1 < 1$. Thus, regardless of $B_2$’s choice, it is a dominant strategy for $B_1$ to pay $p^M_H$ in the second period, i.e., to choose $\gamma_1 = 1$. In
other words, even if \( B_1 \) postpones the sign-up decision, the expected surplus is \( H - p^M_h \), which is identical to the payoff from making the sign-up decision immediately in the first period. In summary, there is no incentive for a high-type \( B_1 \) to postpone the sign-up decision.

### 2.4.6 Endogenous Arrivals

Now we further extend the base model by adding before the two-period model a period 0 when two buyers decide which period to enter. The sequence of move is as follows: 1) Buyers simultaneously decide which period to enter; 2) Buyer(s) entering in period 1 choose a price option; 3) Buyer(s) entering in period 2 observe decisions made in period 1 and choose a price option. Here we assume the creator adopts the optimal menu strategy specified in Lemma 1. We limit our attention to a symmetric equilibrium where a buyer’s strategy depends on the buyer’s type only.

First, both types of buyers choosing to enter in period 2 is an equilibrium outcome. For low-valuation buyers, since their surpluses would be fully extracted, they are indifferent between entering in periods 1 and 2. Now consider a high-valuation buyer. Given the other buyer enters in period 2, the high-valuation buyer does not gain from deviating to enter in period 1. If this buyer pays \( p^M_h \) with probability \( \gamma \in [0,1] \) in period 1, the expected surplus will be \( \gamma(H - p^M_h) + (1 - \gamma)\alpha(H - p^M_l) \), which is maximized at \( \gamma = 1 \). That is, a high-valuation buyer will still pay \( p^M_h \) in period 1. Intuitively, regardless of which period she enters, the high-valuation buyer does not know the contribution made by the other buyer. Therefore, the high-valuation buyer does not have incentive to deviate to entering in period 1.

Next we consider other possible pure-strategy symmetric equilibria:

- Both low- and high-valuation buyers enter in period 1. This is not an equilibrium because a high-valuation buyer is strictly better off by waiting until period 2. We fix one buyer who follows the strategy of always entering in period 1 and consider if the other buyer has any incentive to deviate. For a high-valuation buyer who enters in period 1, she would optimally pay \( p^M_h \) earning surplus \( H - p^M_h \), because she cannot observe the contribution made by the other buyer who also enters in period 1. However, if she deviates to period 2, her expected surplus is higher at \( H - \alpha p^M_h - (1 - \alpha)p^M_l \), because she can free ride when the other buyer in period 1 is a high type and has paid \( p^M_h \).

- Low-valuation buyers enter in period 2 and high-valuation buyers enter in period 1. For the same reason as above, this strategy is not an equilibrium.
• Low-valuation buyers enter in period 1 and high-valuation buyers enter in period 2. If no one pays in period 1, both buyers will know that the other buyer is a high-valuation buyer. Then in period 2, the only symmetric equilibrium is in mixed-strategies, with each high-valuation buyer chooses $p_h^M$ with probability $\gamma$ such that $\gamma(H - p_l^M) = H - p_h^M$. Solving this yields that $\gamma = \alpha$. Therefore, each high-valuation buyer optimally chooses $p_h^M$ with probability $\alpha$ and $p_l^M$ with probability $1 - \alpha$, which results in an expected surplus of $H - p_h^M$. If a high-valuation buyer deviates and enters in period 1, by the same analysis as described above, the expected surplus is also $H - p_h^M$. Thus, high-valuation consumers are indifferent between deviating or not. This validates another equilibrium of endogenous sequencing.

In summary, there are two symmetric equilibrium strategies for the game with endogenous arrivals. In one equilibrium, both types of buyers enter in period 2. In this equilibrium, the creator expects a higher profit than in the base model under the same menu strategy as specified in Lemma 1. In another equilibrium, low-valuation buyers enter in period 1 and high-valuation buyers enter in period 2. In this equilibrium, the creator can be worse off than in the base model, but can still achieve higher profits than under the optimal uniform strategies because a high-valuation buyer can be induced to pay the high price option $p_h^M$ with some probability.

### 2.4.7 Simultaneous versus Sequential Models

Sequential mechanism assumes that two buyers arrive at the proposed project at different periods and that the second buyer can observe the first buyer’s decision. This is a common feature of all of the well-known crowdfunding and group-buying sites. An alternative format is a simultaneous setting where each of the two buyers makes decisions without knowing the other’s action. The two buyers may arrive at the project and make sign-up decisions simultaneously, or they may arrive and make decisions sequentially, but the second buyer is not informed of the first one’s decision. In essence, simultaneous and sequential settings are two alternative information management mechanisms. The simultaneous mechanism is not commonly observed in practice, but it has been studied in the literature (see, e.g., Hu et al. 2013).

For margin and volume strategies, the creator’s optimal prices and profits remain the same. We show that the intertemporal strategy is dominated by the other strategies in the simultaneous model. To avoid confusion, we use superscript “$\sim$” to denote strategies in the simultaneous model.
Lemma 5. The intertemporal strategy is dominated by other strategies in the simultaneous model.

Due to Lemma 5, our analysis focuses on the menu strategy.

Proposition 10. In the simultaneous model,

1. if \( \frac{H+L}{2\alpha H} \geq 1 \), the optimal menu strategy is \( p_h^M = (1-\alpha)H+\alpha L, \ p_l^M = L \). The optimal strategy induces a pure strategy equilibrium of buyers, in which high-type buyers always choose \( p_h^M \). The corresponding expected profit is \( \pi^M = 2\alpha(H - \alpha H + L) \);

2. Otherwise, the optimal menu strategy is \( p_h^M = \frac{H^2+L^2}{2H}, \ p_l^M = L \). The optimal strategy induces a mixed strategy equilibrium of buyers, in which high-type buyers choose \( p_h^M \) with probability \( \gamma = \frac{H+L}{2\alpha H} \). The corresponding expected profit is \( \pi^M = \frac{(H+L)^2}{2H} \).

Comparing Proposition 10 with Lemma 1, we obtain the following profitability comparison under different information structures.

Corollary 3. \( \pi^M \geq \pi^c \), with the inequality strict when \( \alpha > 0 \).

Corollary 3 shows that when the creator offers the menu strategy, disclosing cumulative purchase information is worse off than no disclosure.\(^8\) This insight is similar to that of Varian (1994). In both sequential and simultaneous settings, the creator prices exactly at the same levels (i.e., \( p_h^M = p_h^\tilde{M}, \ p_l^M = p_l^\tilde{M} \)). In the sequential menu setting, a high-type later arrival \( B_2 \) may free-ride the purchase made by the earlier arrival. This buyer will always pay the low price if the first buyer \( B_1 \) has already paid the high price in the first period. However, in a simultaneous setting, where the previous contribution cannot be observed, such free-riding does not occur and the creator’s expected profit will be higher. This result is in contrast to Hu et al. (2013), where sequential information disclosure is more profitable. This is because in Hu et al. (2013), each consumer makes one unit of purchase and a price is fixed exogenously; as a result, such a free-riding incentive by paying “less” after knowing the other’s contribution does not exist.

Proposition 10 also shows that creator’s profit can be higher under a mixed-strategy equilibrium of buyers. If \( \alpha > \frac{H+L}{2H} \), the buyers are more likely to be of the high type. When a buyer expects the other one to have a high product valuation, she will have a greater incentive to choose the low-price option. Interestingly, the creator can deter such

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\(^8\)Sequential mechanism can out-perform simultaneous mechanism in alternative model formulations. For example, if buyers experience the warm-glow effect discussed in Section 2.4.1, the free-riding incentive is diminished, and a sequential mechanism can lead to better outcomes (see, e.g., Romano and Yildirim 2001).
behavior and gain more by allowing the buyers to play mixed strategies. Of course, in reality, it may not be easy to induce the buyers to do so.

Next, in the simultaneous setting, we compare the menu strategy with the other three strategies and obtain the following corollary.

**Corollary 4.** In the simultaneous setting, the optimal strategy is

1. volume strategy, if \( \frac{H}{L} \leq \frac{1}{\alpha} \);

2. menu strategy, if \( \frac{1}{\alpha} \leq \frac{H}{L} \) and \( \frac{1}{2} \leq \alpha \leq \frac{1}{2} + \frac{1}{2\alpha - 1} \);

3. margin strategy, if \( \alpha > \frac{1}{2} \) and \( \frac{H}{L} \geq \frac{1}{2\alpha - 1} \).

Different information management mechanisms (simultaneous versus sequential) may have implications on product line design, too. We let the creator decide the product qualities in the simultaneous setting and summarize the results in Proposition 11.

**Proposition 11.** In the simultaneous setting, when quality is endogenized,

1. if \( \alpha H \leq L \), the creator’s optimal decision under the menu strategy is

\[
\begin{align*}
(Q^M_h, Q^M_l) &= \left( H, \frac{L - \alpha H}{1 - \alpha} \right), \\
(P^M_h, P^M_l) &= \left( \frac{(1 - \alpha + \alpha^2)H^2 - \alpha(1 + \alpha)HL + \alpha L^2}{1 - \alpha}, \frac{(L - \alpha H)L}{1 - \alpha} \right).
\end{align*}
\]

The corresponding expected profit is

\[
\Pi^M = \frac{\alpha((1 - \alpha + \alpha^2)H^2 - 2\alpha HL + L^2)}{1 - \alpha};
\]

2. otherwise, the optimal menu strategy reduces to offering a single product.

Given our emphasis on product-line and pricing decisions, \( \alpha H \leq L \) is the more relevant case. Surprisingly, the creator’s optimal product decisions are exactly the same as in the traditional model. In other words, the optimal quality levels in the simultaneous setting, as shown in the above proposition, are identical to those of the traditional setting shown in Lemma 2. Hence, the optimal quality gap for the product line is greater in the simultaneous setting than that in the sequential setting (i.e., \( Q^M_h - Q^M_l \geq Q^M_h - Q^M_l \)). As discussed earlier, a free-riding incentive exists in the sequential setting, but not in the simultaneous setting. In the absence of free riding, the creator extracts more surplus from high-type buyers in the simultaneous setting. Here the creator keeps the low-option product quality \( Q^M_l \) lower to sustain a sufficiently high price \( P^M_h \) for the high-option product.
Although the optimal quality levels in simultaneous setting are identical to those in the traditional setting, the optimal prices are different. Specifically, $P_{\tilde{M}} = P_T$, $P_{\tilde{M}} - P_T = (H - L)(L - \alpha H) \geq 0$. In other words, the optimal price of a high-quality product is higher in simultaneous crowdfunding than in the traditional setting, even though the same levels of product quality are offered. This difference is caused by the nature of the crowdfunding mechanism. In addition to the original forces that lead to product differentiation in the traditional model of product line design, here the buyers can also be persuaded to pay more to meet the common goal of project success.

2.5 Conclusion

Crowdfunding is emerging as a popular platform on which thousands of entrepreneurs can raise initial funds and sell innovative products. This chapter studies how this new business model may affect a creator’s product and pricing decisions on the basis of a two-period game where cohorts of buyers arrive at a crowdfunding project and make sign-up decisions sequentially. Our results contribute some unique insights to the literature on product line design. In crowdfunding, even when product options are virtually the same, high-type buyers may still choose the high-price option. This result is unique to the crowdfunding mechanism, where tacit coordination among buyers is necessary to ensure the project success. Moreover, the incentive for a high-valuation buyer to coordinate with other buyers in that way is shaped by the creator’s pricing decisions. When the value of the inferior option decreases, the high-valuation buyer’s coordinating incentive will diminish. Our analysis also shows that the crowdfunding mechanism can change the optimal product line design. Compared to the traditional setting where a creator produces products before selling to individual consumers, crowdfunding leads to a smaller quality gap in a product line.

This chapter provides a number of considerations that will be useful to both entrepreneurs who are interested in adopting the crowdfunding model and to managers of crowdfunding platforms. First, the optimal product and pricing decisions should depend on market characteristics. Specifically, depending on the distribution of buyers’ product valuations, a creator may choose a volume strategy, a margin strategy, an intertemporal strategy, or a menu strategy. Second, when the market consists of a low or moderate fraction of high-type buyers and a moderate level of valuation heterogeneity, it is optimal to offer a menu of options. Product-line structure tends to be tighter with crowdfunding. Therefore, when an entrepreneur moves from the crowdfunding stage to large-scale production and retailing, even if the market condition remains the same, the product line
design should evolve. Third, creators should be cautious about any marketing activities that may change the mix of buyers arriving at the projects over time. The belief about the valuations of buyers that arrive at the project at a later time has substantial implications for the sign-up behavior of earlier arrivals, as well as for the creator’s product and pricing decisions. Under some conditions, the later arrival of a group of high-valuation buyers can encourage free-riding behavior.

Crowdfunding as an emerging area deserves more attention in future research. Theoretical analysis may investigate alternative mechanisms. For example, virtually all the crowdfunding sites adopt the sequential mechanism. Alternatively, a creator may arrange for the buyers to make decisions simultaneously under which buyers do not know others’ sign-up decisions. Our analysis indicates that the main results are similar in both sequential and simultaneous situations. However, offering a menu of product options tends to be more profitable in the simultaneous than in the sequential setting. Another important feature of crowdfunding is buyers’ uncertainty towards the quality of products as well as the creator at the time of decision. Future research may investigate possible mechanisms to alleviate such information asymmetry. Empirical researchers should also find crowdfunding a fruitful area for future work. Many hypotheses can be generated from the existing literature in public economics and the current research regarding project designs and dynamics of sign-up decisions. These hypotheses can be tested with a large number of projects that are posted online and observed publicly.

2.6 Appendix

Proof of Lemma 1. Similarly to the traditional product line design problem, the creator maximizes her profit when the IC condition is binding, and \( p_i^L = L \). This gives that \( p_h^M = (1 - \alpha)H + \alpha L \). Furthermore, the deal succeeds when at least one consumer has the high valuation, so the success rate is \( s^M = 1 - (1 - \alpha)^2 = \alpha(2 - \alpha) \). The part on the profit function follows immediately.

Proof of Corollary 1. Since all costs are zero in the base model, it suffices to consider the valuations of buyers served. With the margin strategy, the social welfare (W) is \( W^H = 2\alpha^2H \); with the volume strategy, the welfare is \( W^L = 2(\alpha H + (1 - \alpha)L) \); with the intertemporal strategy the welfare is \( W^D = \alpha((1 + \alpha)H + (1 - \alpha)L) \); and under the menu strategy the welfare is \( W^M = \alpha(H + (1 - \alpha)L) + (1 - \alpha)\alpha(L + H) \). A simple calculation yields that \( W^H < W^D < W^M < W^L \). As for buyer surplus, denoted by \( CS \), we have \( CS^L = 2\alpha(H - L) \), \( CS^H = 0 \), \( CS^M = \alpha(H - L) \) and \( CS^D = \alpha(H - L + H - p_h^M) + \alpha(1 - \alpha)\).
\( \alpha(H - p_h^M) \) where \( p_h^M < H \). We have \( CS^H < CS^D < CS^M < CS^L \).

Without introducing the menu strategy, the volume strategy dominates whenever \( \frac{H}{L} \leq \frac{2-\alpha}{\alpha} \). Hence in the rest part \( \frac{H}{L} \geq \frac{2-\alpha}{\alpha} \), the menu strategy improves social welfare over the local optimal strategy. A similar argument holds for buyer surplus as well. The claim that the menu strategy is the dominating strategy when \( \frac{2-\alpha}{\alpha} < \frac{H}{L} < \frac{3-\sqrt{5}}{2} \) or \( \frac{2-\alpha}{\alpha} < \frac{H}{L} < \frac{1+\alpha-\alpha^2}{3\alpha-\alpha^2-1} \) follows from Proposition 1.

Proof of Proposition 3. If \( \frac{H}{L} \leq \frac{1}{\alpha}, (Q_h^T - Q_l^T) - (Q_h^M - Q_l^M) = \frac{\alpha^2(H-L)}{1-\alpha} > 0 \). If \( \frac{1}{\alpha} \leq \frac{H}{L} < \frac{1+\alpha}{\alpha} \), \( (Q_h^T - Q_l^T) - (Q_h^M - Q_l^M) = \Delta > 0 \). If \( \frac{H}{L} \geq \frac{1+\alpha}{\alpha} \), \( (Q_h^T - Q_l^T) - (Q_h^M - Q_l^M) = 0 \).

Proof of Lemma 3. With the margin strategy, the creator charges high-type buyers their valuations, i.e., \( P^H = HQ^H \). His expected profit is \( \Pi^H = 2\alpha^2 (HQ^H - (Q^H)^2/2) \). Taking the first order derivative with respect to \( Q_M \) solves the problem.

With the volume strategy, the creator charges \( P^L = LQ^L \), so that both buyers make purchases. Then \( \Pi^L = 2(LQ^L - (Q^L)^2/2) \), whose maximum can be solved by the first order condition.

Last, let us consider the intertemporal strategy. The creator sells to high-type buyers in one period (and without loss of generality, let us suppose it is period 1), and to buyers of any type in the other period (period 2). In period 1, the creator prices at \( HQ^D \), and in period 2 at \( LQ^D \). Then his expected profit is \( \Pi^D = \alpha(HQ^D + LQ^D - (Q^D)^2/2 - (Q^D)^2/2) \). Again, the first order conditions give us the solution.

Proof of Lemma 4. The IC condition is now \( \alpha_2(H - p_h^{M_h}) \leq H - p_h^{M_h} \), together with the individual rationality \( p_l^{M_h} \leq L \). When both inequalities are binding, the creator maximizes her profit. The success rate is \( 1 - (1 - \alpha_1)(1 - \alpha_2) = \alpha_1 + \alpha_2 - \alpha_1 \alpha_2 \), and this proves the lemma.

Proof of Corollary 2. Taking derivatives of \( \pi^{M_h} \) with respect to \( \alpha_1 \) and \( \alpha_2 \) yields that \( \partial \pi^{M_h} / \partial \alpha_1 = (1 - \alpha_2)^2 H + (1 - \alpha_2^2) L \geq 0 \) and \( \partial \pi^{M_h} / \partial \alpha_2 = (1 - 2\alpha_1 - 2\alpha_2 + 2\alpha_1 \alpha_2) H + L + 2(1 - \alpha_1) \alpha_2 L \), which is no less than zero when \( \alpha_2 \leq \frac{H - 2\alpha_1 H + L}{2(1 - \alpha_1)(H - L)} \), and is less than zero otherwise.

Proof of Proposition 8. When \( n_1 \geq n_2 \), \( T^{Mc} = n_1p_h^{Mc} + n_2p_l^{Mc} \) and the IC condition is \( n_1 H - n_1p_l^{Mc} - n_2p_h^{Mc} + n_2p_l^{Mc} \geq \alpha n_1 (H - p_h^{Mc}) \). The creator maximizes her profit when \( p_l^{Mc} = L \) and the IC condition is binding, which gives \( p_l^{Mc} = L \) and \( p_h^{Mc} = (1 - \alpha)(H - L) \). However, we need the additional constraint \( p_h^{Mc} \leq H \) here. Moreover, we have the success rate being \( \alpha(2 - \alpha) \), and this proves the first part.
When $n_1 \leq n_2$, $T^{Me} = n_1 p_i^{Me} + n_2 p_h^{Me}$. The first cohort pays either $n_1 p_h^{Me}$ or $n_1 p_i^{Me}$, but never anything between them. If the first cohort pays $n_1 p_h^{Me}$, the conditional success rate is 1; if the first cohort pays within $[n_1 p_i^{Me}, n_1 p_h^{Me})$, the success rate is $\alpha$. The first cohort cannot pay less than $n_1 p_i^{Me}$ as long as $p_i^{Me} \leq L$. Now the IC condition becomes $n_1 H - n_1 p_h^{Me} \geq \alpha(n_1 H - n_1 L)$, and this immediately verifies the second part.
Chapter 3

What Makes an Effective Online Video Advertisement?

3.1 Introduction

In 2015, Google launched the Unskippable Labs experiments. In one experiment, Google compared three different versions of the Gomez Family video ads - a short 15-second cut, a medium 30-second cut, and a long cut with 2:17 runtime. It turned out that the 30-second ad had the highest view-through rate (VRT)\(^1\). This finding suggests that advertisers may want to shorten their video ads, “The average length of ads on the YouTube Ads Leaderboard in 2014 averaged three minutes - an increase of 47% vs. 2013. And none of the top ads in 2014 and 2015 were under a minute.”

Viewership is moving online. As spending on online video ads has risen 43% year on year, money spent on television ads has grown only 2.6%, while print has fallen 4.9% (Haynes 2016). According to eMarketer, in 2015, U.S. online video advertising spending was $7.46 billion - and it is expected to reach $14.77 billion in 2019. As viewership moves online, viewer’s preferences, behaviors, and attitudes toward video ads are rapidly changing (Paasch 2016). For advertisers, the challenge is to “create content that communicates with viewers and makes them want to tune in”. Despite the rapid growth in online video advertising budgets, academic research has been lagged behind and provides little advice on making an effective video advertisement. In this research, we contribute to the literature on video ads by (i) showing the downside of having a lengthy video ad, (ii) quantifying the optimal stimulation level of a video, and (iii) demonstrating content of the video that helps communicate credibility and trust.

\(^1\)https://www.thinkwithgoogle.com/articles/unskippable-video-advertising-ad-recall-brand-favorability.html
We also contribute to the analysis of visual information. Prior research on video advertising has focused on identifying its effectiveness using controlled experiments, but has focused less on the automatic analysis of the visual information. In this case, analyzing videos is costly, time consuming and limited to small scales. We contribute to the area by proposing several effective visual data analysis tools, and apply them to a large number of videos. While these techniques are new and immature, they open up the world of video analysis in a digital age.

Finally, we provide a new understanding of the crowdfunding industry. We choose Kickstarter, the leading online crowdfunding site, as our empirical context. Online crowdfunding is a novel environment that allows creators to raise money from a large number of people (the “crowd”) to make their projects happen. Besides its commercial success, less is known about the crowdfunding mechanism. In this research, by analyzing the effectiveness of crowdfunding videos, we provide insights into the communication strategies in online crowdfunding.

We conduct logistic regression analysis to investigate the relationship between video design measures and projects’ success rate. After controlling for project-specific and creator-specific factors, our results show that, all other things being equal, first, the success rate of a project is adversely affected by the length of its advertising video. This is consistent with the well-documented tedium effect, which proposes that over the time of an advertising campaign, viewers increasingly come to feel bored and then discount the advertising. Moreover, we find that this tedium effect hinges on both project and creator characteristics. Specifically, the tedium effect is weaker for projects with bigger targets, but is stronger if the creators have prior crowdfunding experiences. Second, the visual stimulation level of a video and the project success rate follow an inverted-U-shape relationship. From each video we extract a number of frames and measure the stimulation level of the video by the dynamic change of image gray scales. We find that the highest project success rate is associated with an intermediate level of stimulation. When a video provides either a low or a high level of stimulation, buyers may feel less satisfied and are less likely to support the project. Finally, the project success rate is higher when the advertising video features the creators and/or musical instruments, which can trigger a sense of credibility\(^2\). A typical buyer does not have prior interactions with the creators. It is therefore important for the video to make the personal connection between the two parties. Similarly, showing the musical instruments generates a sense of realness for buyers. Moreover, merely having a video is not enough. A good video needs to have the

\(^2\)We study music projects in the chapter, and in the Appendix, we generalize the results to the technology category as well to show robustness.
ideal length, have the right level of stimulation, and be perceived as credible (usually by way of presenting the creators and their activities/instruments).

**Literature**

Advertising is the central focus of this chapter. As one of the most important topics in marketing, advertising has been studied extensively. Empirical research has shown robust evidence that television advertising increases sales of consumer packaged goods (Lodish et al. 1995). Since advertising campaigns on television are expensive, a large body of research has examined the optimal amount of exposure (Tellis 1997). To address this question, quantitative researchers have estimated the wear-in and wear-out effects when an advertisement is repeated multiple times (e.g., Pechmann and Stewart 1988). Consumer psychologists generally follow a different paradigm and investigate the tedium effect (e.g., Rethans et al. 1986) and level of processing (Nordhielm 2002). Unlike the past research that focuses on print and television advertising, this chapter studies online videos as an emerging form of advertising. This chapter is among the recent efforts using large-scale field data to test and extend the advertising theories developed in consumer psychology. For example, Sahni (2015) uses online field experiments to study the effect of temporal spacing between advertising exposures. Goldfarb and Tucker (2011) use a large scale field experiment to study the interactive effect of targeting and obtrusiveness of online advertising on advertising effectiveness.

More specifically, we analyze a large number of online videos using automatic methods, which contributes to the emerging stream of research that seeks insights from a variety of big data (e.g., Liu et al. 2016). While the existing research has studied text data extensively, much less has been done concerning visual data. Traditionally, research on the effect of imagery was limited to psychological measurements (e.g., Unnava and Burnkrant 1991; Scott 1994). Only in recent years have researchers started to develop and apply quantitative methods to study visual data. For example, Ghose et al. (2012) use image classification methods to extract location-based variables from satellite images. Xiao and Ding (2014) apply principle component analysis to study the facial features in print advertising. Teixeira et al. (2014) use a facial emotion analysis software to measure the “entertainment level” when consumers view advertisements, and show that entertainment has an inverted-U-shape relationship to purchase intent.

We further apply the recent computer science methods to analyze visual data, a large set of Kickstarter videos. In addition to some features that are potentially important to video advertising - length, visual complexity, color composition, picture complexity.
In this research, we limit our attention to three most important video design measures: duration, stimulation level, and perceived credibility for each video based on the existing behavioral literature (Jalali and Papatla 2016; Pieters et al 2010). Duration captures the length of the video, stimulation level reflects how rapidly the screen changes over time, and perceive credibility is measured by content of the video that conveys credibility to the audience.

This chapter uses online crowdfunding as the empirical context to study video advertising, and thus contributes to the emerging literature on crowdfunding. An extensive review of the crowdfunding industry and related areas of research is available in Agrawal et al. (2014). Although the Internet has expanded the boundaries of reach, Agrawal et al. (2015) show that the geographic effect still exists in crowdfunding. Similarly, Lin and Viswanathan (2016) show the home bias effect in crowdfunding. Mollick and Nanda (2016) address the question of whether or not crowds and experts have similar preferences. Hu et al. (2015) study the optimal product and pricing decisions in crowdfunding, and Mollick (2014) uses Kickstarter data to show that the projects with a video have higher success rates. This chapter not only recognizes the value of video, but also extends Mollick (2014) by investigating specific features of video design such as video length, stimulation level, and credibility. We also examine the interactions between video advertising and text descriptions of new products or services.

3.2 Industry Background and Conceptual Development

The online crowdfunding industry matches prospective buyers/funders (the “crowd”) with creators. We collected data from Kickstarter, a leading online crowdfunding platform where creators raise funds from potential buyers in order to initiate their new projects. In return, the creators offer products (e.g., an album) or services (e.g., access to a concert) to be delivered on a future date. The creators are entrepreneurs who can be industrial designers, musicians, software developers, or writers. Unlike the conventional business model, here a buyer not only commits to purchasing the product or service, but also prepays to fund the project. A project will be successfully funded if and only if the total value of committed purchases exceeds a pre-specified target within a pre-specified time period (e.g., a month). The crowdfunding industry has experienced tremendous growth in recent years. For example, Kickstarter has raised more than $2.3 billion and supported more than 104,000 projects since its inception in 2009. Yet disappointment is
also common: more than 185,000 projects on Kickstarter were unsuccessful, leading to an overall success rate of just 36% (www.kickstarter.com).

For a typical Kickstarter project, the sellers (called the “creators”), like De La Soul, design offerings, choose prices (e.g., a digital album for pledges of $15 or more, a CD and a bonus track for $25 or more, etc.), and set a funding target. When potential buyers arrive at the project site, they watch a video followed by a paragraph of project description before making their buying decisions. Crowdfunding sites provide an ideal setting to study the effect of online video advertising on consumer decisions for a number of reasons. First, crowdfunding platforms provide us with a direct measure of video effectiveness, the funding outcome, which allows us to monetize the value of video ads. This measure seems more relevant than traditional measures such as video-through rate, ad completion rate, or ad abandon rate. Second, most crowdfunding campaigns launch a video; in our dataset, 81.9% of the projects have a video, providing us with a large number of videos to study the effect of video ads. (Videos are also commonly observed in other crowdfunding sites such as Indiegogo and Patreon.) Third, an online crowdfunding site is a fairly closed environment where the potential buyers learn about the projects within the site. We are able to gather virtually all the key information presented to the buyers. Relative to other purchase environments (e.g., supermarkets), there are fewer external and unobservable factors that could affect the buyer decisions in crowdfunding. Finally, the buyer decision journey is simpler. Once the potential buyers arrive at a crowdfunding site, they browse the projects and make decisions within a short period of time. The projects they have interacted with are virtually independent from each other. In comparison, the decision journeys in traditional purchase settings are much more complex, often making it difficult to isolate the advertising effect on sales from the effects of many other factors.

Figure 3.1 shows a typical Kickstarter project page. Too Many Zooz, a New York band that had spent a great deal of time playing music in subway stations, asked for $100,000 to help it complete its debut album. The crowdfunding campaign was launched on January 12, 2016. The project page contained a video, a product description, a menu of rewards and prices, and a target, as well as the number of backers and the amount of money pledged so far. By February 11, 2016, the project successfully raised $102,010 from 2,766 backers.

Like Too Many Zooz, many crowdfunding projects used a video to communicate with potential buyers and supporters. It is generally agreed that posting a video will increase the success rate. In an industry study, Davidson (2013) found that 48% of Kickstarter projects that had a video were successful, while only 26% of projects that did not have a
video achieved their funding goals. However, not all the advertising videos were designed in the same way, nor did they make the same impact on potential buyers. In the rest of this section, we discuss three well-researched factors in the advertising literature: video length, stimulation level, and credibility. We also discuss related theories and develop relevant hypotheses for empirical testing.

### 3.2.1 Tedium Effect and Video Length

Empirical evidence has shown a non-trivial relationship between the effect of advertising and the amount of ad exposures measured by the length and/or number of repetitions (Tellis 1997). In fact, excessive exposures may be counter-productive, reducing the
overall effectiveness of advertising. This interesting phenomenon has attracted a great
deal of attention from researchers in consumer psychology and communication. In this
literature, the most prominent theory is conceptualized as a two-factor model with a
positive learning factor and a negative tedium factor. The two-factor model was first
introduced by Berlyne (1970), and later generalized and applied to advertising and con-
sumer marketing (Nordhielm 2002; Rethans et al. 1986; Pechmann and Stewart 1988).
In the context of crowdfunding, a longer video can provide more information about the
band (for example) and its music. Learning about the musicians and their stories can
reduce uncertainty about their products or services, and build buyers’ confidence in prod-
ucts and future delivery. These effects should be monotonic. Longer videos should lead
to more information, and thus to higher purchase likelihood. However, after the video
length reaches a saturation point, the incremental learning from additional frames typi-
cally diminishes. As a result, the overall positive learning effect is a concave function of
video length.

The second factor hypothesizes a negative tedium (or counter-argumentation) effect. After watching a segment of video, viewers will start experiencing a continuous decrease
in interest toward the music project, likely due to boredom. The negative process can also
arise from an increasing tendency for counter-argumentation. In our empirical setting,
when viewing videos, potential buyers may gradually get a feeling of boredom; they may
also look for evidence that the musicians are not worth funding or are unlikely to fulfill
their promises. If a potential buyer feels bored or finds counter-argumentation evidence,
a strong negative effect will emerge, leading the buyer to disregard the positive learning
and leave the project.

Combining the effects of both factors, we are presented with two opposing processes
when potential buyers are exposed to an ad. The positive learning effect dominates the
negative tedium effect at the beginning; however, after a period of video time, the positive
learning effect gradually “crowds out” and the negative tedium effect takes over. Overall,
the effect of video advertising initially increases with the amount of exposure, and then
decreases with the amount of exposure after reaching a threshold level. We summarize
the above discussion in the following hypothesis.

**Hypothesis 1.** Above a certain threshold, the length of a project’s video advertising has
a negative relation with the project’s success rate.

We now extend the two-factor model by introducing two moderating factors in our
empirical setting. First, some music projects request more funds than others. If a project
is larger in scale, the information value - and hence the positive learning effect - becomes
greater. At the same time, a larger project can be more exciting and have a weaker
tedium effect. As a result, while the negative relation hypothesized in H1 will still exist,
it should be weaker for larger projects.

**Hypothesis 1.1.** *The negative relation hypothesized in H1 is weaker for music projects requesting more funds.*

Another moderating factor is the “newness” of the creators. Some musicians had
posted crowdfunding projects before, so they are not new to buyers. Online videos are
a means to help consumers evaluate creators as well as their projects. When buyers al-
ready have some prior knowledge about creators, they can learn about their new projects
faster. As a result, the positive learning effect saturates more quickly. Moreover, when
the musicians and their projects are not fresh to buyers, the boredom effect should be
stronger. Therefore, we expect that consumers will be less patient when watching videos
produced by experienced creators.

**Hypothesis 1.2.** *The negative relation hypothesized in H1 is stronger if the creators have prior crowdfunding experiences.*

### 3.2.2 The Role of Stimulation in Video Advertising

The emotional experience of pleasant arousal produced by visual stimuli is central to
the effect of video advertising. However, an excessive amount of visual stimulation will
lead to disequilibrium that viewers strive to avoid. There is general agreement in the
literature that the stimulation level obtained and the affective response to stimulation
by a viewer follows an inverted-U-shape curve (Berlyne 1970), with an intermediate level
of stimulation perceived as the most satisfying. This optimum point is often referred
to as the optimal stimulation level (OSL), and the framework is proposed as the OSL
theory by Hess (1955). In the context of crowdfunding, we propose that prospective
buyers develop an affective response to the video ad; moreover, the affective response to
the video affects the buyers’ attitude toward the project. There exists an intermediate
level of stimulation at which the buyer’s response to the project is most positive. We
summarize this in the next proposition.

**Hypothesis 2.** *A project’s success rate is higher when the project’s video has an in-
termediate level of stimulation, and lower when the video has a lower or higher level of
stimulation.*

We can extend the OSL literature in the following two ways. First, it is worth noting
that the OSL literature does not specify the exact optimum level. As we estimate a
model with field data, the parameter estimates would yield useful implications for this optimum point. Second, we can extend the OSL theory by identifying the moderating factors. Similar to Hypothesis 1.1, when a crowdfunding project has a bigger target, the optimal stimulation level should be higher. Such projects are expected to have longer videos and convey more information, and thus a low stimulation level can be more detrimental.

Hypothesis 2.1. The optimal stimulation level should be higher for projects with bigger targets.

3.2.3 Effect of Credibility in Video Ads

The credibility of advertisers and their claims plays a central role in advertising effectiveness. Prior research in marketing (e.g., Erdem and Swait 2004; Brinol et al 2004) suggests that credibility increases “the probability of inclusion of a brand in the consideration set, as well as brand choice conditional on consideration”. The quest for credibility can be particularly important for crowdfunding projects. In traditional marketplaces, consumers make their purchase decisions based on product inspection, consumption experiences, word of mouth, and expert reviews. These information sources are largely unavailable for crowdfunding projects. In online crowdfunding, products are not available yet, and creators are typically not established in the market. As a result, consumers - acting as buyers as well as funders - have to make decisions based on their trust in the creators. As stated in Fredman (2015), “Creators are only as reliable as their promises. And those promises don’t always deliver.” To communicate credibility, the creators need to establish a personal connection with potential buyers and create a sense of realness. In online crowdfunding, project videos are often the first and primary channel for the creators to establish credibility for potential buyers. Therefore, we expect the level of credibility communicated in the video ad to have a positive effect on project outcomes. We summarize the above discussions in the next hypothesis.

Hypothesis 3. A crowdfunding project with a higher level of credibility in its video ad is more likely to succeed.

In the next section, we describe the data collected to test the hypotheses.

3.3 Data: Measurement and Preliminary Analysis

We developed a Python program to automatically scrape data from Kickstarter. The dataset contains all completed projects (both successful and unsuccessful) in the music
category in three major U.S. markets: New York, Los Angeles, and Texas. We choose to focus only on the projects in the music category, the largest single category with most videos at Kickstarter. Projects in the music category are also relatively homogeneous with smaller within-category differences. As a robustness check, we analyze the technology category in the Appendix, and show that our main results are not qualitatively altered.

Our dataset includes 8,327 projects from April 2009, when Kickstarter was introduced, to December 2015, when we collected the data. We collected virtually all the information about the projects that potential buyers could access on Kickstarter when making their funding decisions. The variables describe the projects, the creators, communications between them, and project outcomes. Table 3.1 provides summary statistics for some simple variables.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Video (Dummy)</td>
<td>8,327</td>
<td>0.819</td>
<td>0.385</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Success (Dummy)</td>
<td>8,327</td>
<td>0.536</td>
<td>0.499</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Target ($)</td>
<td>8,327</td>
<td>17,404.15</td>
<td>346,258.300</td>
<td>1</td>
<td>21,474,836</td>
</tr>
<tr>
<td>Project Duration</td>
<td>8,327</td>
<td>36.149</td>
<td>14.864</td>
<td>1</td>
<td>92</td>
</tr>
<tr>
<td>Word Count</td>
<td>8,327</td>
<td>465.337</td>
<td>361.181</td>
<td>16</td>
<td>6,546</td>
</tr>
<tr>
<td>Menu Length</td>
<td>8,327</td>
<td>8.978</td>
<td>5.636</td>
<td>0</td>
<td>73</td>
</tr>
<tr>
<td>Creator Experience</td>
<td>8,327</td>
<td>0.195</td>
<td>0.396</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Positive</td>
<td>8,327</td>
<td>0.028</td>
<td>0.012</td>
<td>0.000</td>
<td>0.111</td>
</tr>
<tr>
<td>Negative</td>
<td>8,327</td>
<td>0.006</td>
<td>0.006</td>
<td>0.000</td>
<td>0.057</td>
</tr>
<tr>
<td>Price</td>
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<td>128.096</td>
<td>357.935</td>
<td>0</td>
<td>10,000</td>
</tr>
<tr>
<td>Fund Pledged</td>
<td>8,327</td>
<td>4,864.492</td>
<td>12,359.450</td>
<td>0</td>
<td>600,874</td>
</tr>
</tbody>
</table>

**Project Outcome**

We measure project outcome by a dummy variable (“Success” in Table 3.1), indicating whether or not the project succeeded by raising enough funds to meet the target. For the projects listed in Kickstarter, their outcomes are “all or nothing”: if the amount of funds pledged for a project is below its target, regardless of its closeness to the target, the creators will receive nothing. Therefore, the creators’ primary goal is to reach their targets. As shown in Table 3.1, among the 8,327 projects, 4,466 of them successfully reached their goals (all others failed), leading to a 53.6% success rate. The success rate for the music category is higher than that in most of the other categories; the average success rate for all Kickstarter project was 36% (www.kickstarter.com).
Chapter 3. What Makes an Effective Online Video Advertisement?

Project outcome can be measured using a number of other approaches. For instance, one can measure project outcome by the total amount of funds pledged for each project. Figure 3.2 plots the amount of funds pledged as a percentage of target for all of the projects. The distribution of results is skewed in both the below- and above-target areas, with a large mass in the interval slightly above one (at the target). Based on how project successes are judged in practice and the irregular distribution of funds pledged, we choose to measure the project outcome using the indicator variable. This measure is commonly adopted in the literature (e.g., Mollick 2014).\(^3\)

Next we describe the explanatory variables for the crowdfunding projects.

**Projects and offers**

First, each project has a *target amount of funds* that the creator is requesting for the project. If the pledged fund for a project fails to meet the target, then the project is deemed unsuccessful and all of the pledged funds are returned to the buyers. The targets

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\(^3\)All of the main results hold in the regression analyses using the logarithm of the total amount pledged as the dependent variable.
vary significantly among the projects, ranging from $1 to $21,474,836, as shown in Table 3.1. Targets are also skewed in distribution, with an average of $17,404, and a median target of $5,000. In the regression analysis we take log-transformation of the target.

Second, each project specifies a *Project Duration*, the number of days within which the project remains valid and can continue accepting fund pledges. For example, if a project ran from March 30, 2015, to May 2, 2015, then the project duration is equal to 33 days. A project is closed automatically after reaching the end of its project duration. In our data, Kickstarter allowed a maximum of 90 days for project durations. Most of the projects (i.e., about 80% in our data sample) had durations of between 30 and 60 days, with an average duration of 36 days.

Third, most projects offer multiple levels of rewards and/or recognitions. Hu et al. (2015) suggest that a well-designed menu of offerings can help creators improve their project success rates. We include the variable Menu Length in Table 3.1 to measure the number of different rewards in the form of products or services offered to buyers. In our data, two projects offered no rewards, 478 projects offered one single reward, and the remaining 7,847 projects offered at least two levels of rewards. On average, each project offered about eight levels of rewards.

Fourth, the *Price* variable indicates the median price of the offerings in the menu. As discussed above, most projects have multiple offerings, each associated with a price. For example, consider a project which offers four products at prices $15, $30, $50, and $100, then the median price is ($30 + $50)/2 = $40. The average price is $128. The two projects that do not offer any rewards have prices equal to zero.

Finally, we construct a number of indicator variables for the music genres, following the classifications used by Kickstarter: Blues, Chiptune, Classical Music, Country & Folk, Electronic Music, Faith, Hip-Hop, Indie Rock, Jazz, Kids, Latin, Metal, Music (for those without a specific genre), Pop, Punk, R&B, Rock, and World Music.

**The Creators**

For the project creators, we measure their experiences in Kickstarter and their social connectivity. We constructed a dummy variable, *Experience*, to indicate whether or not the creator of a project had previous experience posting projects on Kickstarter. In our data, 19.5% of creators had prior experiences with Kickstarter. Past research on offline ventures shows that experienced entrepreneurs are more likely to succeed (Roure and Maidique 1986). Thus, buyers may perceive a higher success rate with more experienced creators. However, buyers on Kickstarter may also have the tendency to support newer,
Chapter 3. What Makes an Effective Online Video Advertisement?

Communications with potential buyers

We use a dummy variable Video to indicate whether or not a project has a video. In our data, 81.9% of the projects have a video ad. The information contained in project descriptions and video ads requires further analysis. The techniques - especially the methods used to analyze the videos - are fairly complex. Thus, we use a separate section to describe them.

In the next section, we introduce additional variables that measure the design of each video ad. We also conduct text analysis of the project description.

3.4 Video, Audio and Text Analysis: Methods and Preliminary Results

In this section, we explain marketing communications through video ads and product description in crowdfunding. We introduce the methodologies we used to extract the relevant information from the videos and texts, and provide some preliminary results.

3.4.1 Video Duration

We use the variable Video Duration to measure the length of a video in number of minutes. The blue bars in Figure 3.3 show the histogram of video duration for all the projects with videos (in number of seconds). The video duration ranges from 1 second to 2,089 seconds (close to 35 minutes long), with an average duration of 201 seconds (close to 3.5 minutes). There was only one project that has a one-second video (basically an uploaded picture).

As an initial evidence for or against the two factor model, the orange lines in Figure 3.3 plot the success rates of the projects and their video lengths. It shows that that the average success rate is small for short videos, becomes relatively higher for medium-length videos, and drops lower for long videos. Specifically, among all the projects with videos, the average success rate is 45.2% for those with video duration shorter than 70 seconds, 62.4% for those with video duration between 70 and 190 seconds, and 57% for
those with video duration longer than 190 seconds. This pattern is consistent with what we propose in Hypothesis 1.

### 3.4.2 Visual Stimulation Level

To assess the role of an advertising video’s stimulation level in its effectiveness, we need to provide a measure of stimulation level. While measuring video duration is straightforward, defining and quantifying the stimulation level is not simple. To the best of our knowledge, the marketing literature does not have a standard method to quantify the stimulation level of a video ad. As discussed in Section 3.2, stimulation is caused by the change of visual stimulus. We thus propose that a video should be viewed as a series of frames; we operationalize the stimulation level of a video as the average of the stimulation levels over the duration of a video, and the level of stimulation at a particular point \( t \) of the video increases with the extent of difference between two consecutive frames located before and after this point \( t \). As far as we know, this is the first automatic measure of visual stimulation level.

We calculate the difference in stimulation level between two frames as follows. First,
we read color images as 3D arrays, and average the red-green-blue (RGB) channels to obtain an intensity measure. In other words, we convert color images into grayscale. Although the conversion is not essential, it significantly simplifies the problem and reduces the computational overhead (and our results are not qualitatively altered with other transformations). For example, for a color pixel (49, 15, 14), the grayscale value of the pixel will be converted to \((49 + 15 + 14) \div 3 = 26\). Second, we normalize the image scores from the interval \([0, 255]\) to \([0, 1]\). For an image with \(n\) pixels of value \(x_1, \cdots, x_n\) shown at time \(t\), we normalize them through the following transformation:

\[
x'_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}
\]

where \(x_{\max} = \max\{x_1, \cdots, x_n\}\), \(x_{\min} = \min\{x_1, \cdots, x_n\}\), and \(x'_i\) is the normalized grayscale value for the pixel \(x_i\). The normalization compensates for possible exposure difference. For instance, if we take videos of the same object in the early morning and in the afternoon, the two videos will look quite different. Normalization reduces such exposure-induced differences between images. Third, we calculate the pixel level distance between the images, where the distance is defined as the Manhattan norm, \(d(x_i, y_i) = \|x_i - y_i\|\). The difference between the images is the sum over the absolute distance of every pair of pixels, i.e., \(d(X,Y) = \sum_{i=1}^{n} d(x_i, y_i)\). This aggregation assumes that the sizes of images are the same, which is always true for different frames from the same video. Part of the algorithm is adapted from http://stackoverflow.com/questions/189943/how-can-i-quantify-difference-between-two-images.

The algorithm calculated distance score is consistent with our intuition. To illustrate this, we include two examples in Figure 3.4. In the first set of images, a musician is playing a guitar without any changes of background. In contrast, in the second set of images, the background changes completely from one setting to another. The image distance of the first video is equal to 0.176, which is much smaller than that of the second video (equal to 1.04). In these two sets of images, clearly the difference in distance scores reflects the extent of the changes between two images.

We calculate the stimulation level score in the following way. For a given video of duration \(T\), we divide it into 10 equal-distanced clips and take the frame in the middle of each clip \(^4\). In other words, we extract 10 frames at times \(\frac{T}{20}, \frac{3T}{20}, \cdots, \frac{19T}{20}\). We denote these 10 frames by \(F_1, F_2, \cdots, F_{10}\). The stimulation level score is then the average distance

\(^4\)One concern with this calculation is that, the distance between two frames are different in different videos. As a robustness check, we also constructed stimulation level with equal-distanced frames in all videos, and the results are not qualitatively altered.
Example 1 – low difference: Distance between the above two image frames \[ d = 0.17608. \]

Example 2 – high difference: Distance between the above two image frames \[ d = 1.16550. \]

Figure 3.4: Examples of image distance between consecutive frames - that is\(^5\),

\[
\text{stimulation score} = \frac{1}{9} \sum_{i=1}^{9} d(F_i, F_{i+1})
\]

where \( d(\cdot, \cdot) \) is the distance function introduced earlier. The stimulation score is maximized when the video changes its scenes quickly and significantly, and is minimized when its images are relative stable and predictable over time.

The idea of stimulation level is similar to the entertainment level defined by Teix-

\(^5\)The stimulation level of a video ad is usually constant over its duration. The results would remain the same if we choose only the first or last few frames to construct the stimulation measure.
eira et al. (2014). While there may be some correlation between stimulation level and entertainment level, they are different measures because (1) the entertainment level is calculated from viewers’ facial expressions when watching an advertisement video, whereas the stimulation level is based on the video itself, and (2) most crowdfunding videos are not designed to entertain consumers, rather, the goal is to inform consumers about the project.

In the data, the stimulation score ranges from 0 to 1.51, with an average score of 0.435. To visualize the relation between the stimulation level and project success rate, we plot the stimulation score and product success rate in Figure 3.5.

The figure shows an inverted-U-shape curve: when the stimulation level is either low or high, the projects have lower success rates. When the stimulation level fall in an intermediate range (stimulation score from 0.5 to 1), the projects have higher success rates. These results are consistent with the conceptual discussions and support Hypothesis 2 in Section 3.2.

### 3.4.3 Video Image Recognition

To assess the effect of credibility in video ads, we need specific measures of credibility. Erdem and Swait (2004) assert that “credibility is broadly defined as the believability of
Chapter 3. What Makes an Effective Online Video Advertisement?

an entity’s intentions at a particular time and is posited to have two main components: trustworthiness and expertise.” For the majority of the crowdfunding projects studied, neither the musicians nor their music are well established to the potential buyers. To convey trustworthiness and expertise for musical consumption, we believe that the video ads should provide visual content about the musicians (as the creators) and their instruments (as their tools)\(^6\).

Recognizing images in a large number of videos can be a daunting task for humans. Our dataset includes more than 6,800 videos, with the total length of videos running to around 400 hours. In this study, we use convolutional neural network (CNN), a recently emerged machine learning technique, to recognize the content of the video frames. While CNNs are relatively new to marketing, they are based on neural networks which have been used in marketing to predict consumer choice (West et al. 1997; Bentz and Merunka 2000). This technique is mature and reliable, and has achieved classification accuracy of 94% (Simonyan and Zisserman 2015; Markoff 2014).

CNN Variables

Rather than working on images directly, the algorithm we use works on images. We first extract three frames from the beginning, middle, and end of each video (i.e., video frames at times \(\frac{T}{6}, \frac{T}{2}, \frac{5T}{6}\)). We then extract features from these images. Then, using the CNN algorithm, we extract two features from project videos: Human and Instruments. Human is a dummy variable that is set to 1 when the video features human beings, and Instruments is a dummy variable indicating whether the video contains any of the following instruments: guitar, wind instruments, piano, bass, and banjo (these are used because they are considered the most popular instruments for music projects).

Based on our video image analysis, in our data, a video had (on average) a 78.5% chance of including human beings, and a 27.3% chance of featuring one of the common musical instruments.

3.4.4 Controlling for Audio Content

Videos provide not only visual content, but audio content as well. If the audio content is not orthogonal to the visual content, our estimates of video related variables could be biased. In this section, we follow the standard computer science and acoustic approach to

---

\(^6\) Myers et al (2009) suggest that self-disclosure of personal information adds credibility to the information, Erdem and Swait (1998) show that higher investments help signal credibility. Here visual information about the musicians could serve as self-disclosure of personal information, and instruments can be viewed as investments already made by the musicians.
control for audio content. These measures are not our own contribution; we refer readers to Giannakopoulous and Pikrakis (2014) for detailed technical descriptions.

Digital audio signals are sampled from natural sound. Let $x_i(n), n = 1, \ldots, L$ be the sequence of audio samples of the $i$th frame, where $L$ is the length of that frame. First, we calculate the average zero crossing rate ($ZCR$) of the audio content, which is based on the rate of sign-changes during each audio frame. More precisely,

$$Z_i = \frac{1}{2L} \sum_{n=1}^{L} ||\text{sign}[x_i(n)] - \text{sign}[x_i(n - 1)]||$$

and $ZCR$ is the average of $Z_i$ over all frames. $ZCR$ could be interpreted as a measure of the “noisiness” of a signal, which usually exhibits higher values in the case of noisy signals. $ZCR$ has been frequently used in acoustic studies for speech detection, speech-music discrimination and music genre classification (Panagiotakis and Tziritas 2005).

The second measure we construct is the short-term energy ($Energy$) of the audio content, which is computed according to the following equation.

$$E_i = \frac{1}{L} \sum_{n=1}^{L} x_i^2(n)$$

$E_i$ is averaged over the frames to obtain the Energy measure. Energy reflects the power of an audio file, and it is expected to change rapidly over the file. We use another measure, $Entropy$, to capture the rapid change of the energy. For each frame, it has various sub-frames, and for each sub-frame $j$, we calculate its sub-frame energy value

$$e_j = \frac{E_{\text{Subframe}_j}}{\sum_k E_{\text{Subframe}_k}}$$

and the entropy of that frame is

$$H(i) = -\sum_{j=1}^{K} e_j \log_2 e_j$$

and we further average $H(i)$ over all frames to obtain the entropy measure. Energy and Entropy are used for genre classification and emotion detection (Giannakopoulos et al 2007).

We then apply discrete Fourier transformation (DFT) of the signal and obtain spectral coefficients of an audio frame, $X_i(k), k = 1, \ldots, FL$. Using the spectral coefficients, we calculate two measures, Spectral Centroid ($Brightness$) and Spectral Entropy. Spectral
Centroid is defined as
\[ C_i = \frac{\sum_{k}^{F^L} kX_i(k)}{\sum_{k}^{F^L} X_i(k)} \]

Research has shown that higher values of spectral centroid correspond to brighter sounds, and hence we call it *Brightness*. Spectral Entropy is analogous to Entropy and we omit the details here. Together, these frequency domain measures are also proven effective in genre classification, emotion detection, and speech-music discrimination (Misra et al. 2004).

As mentioned above, these measures could be used for different audio analysis tasks ranging from speech-music classification to emotion detection. Since a typical video in our data comprises both speech, music, and a mixture of emotions, we do not train a model to classify the audio content (which is not the focus of our research). We simply take these measures as controls of the audio content of a video.

### 3.4.5 Sentiment Analysis of Project Description

A project description is always included in the project page. A typical buyer views both the video and product description before making the purchase decision. The communications through the text and video can substitute for each other or be complementary in attempting to persuade the buyer. Thus, it is necessary to account for the text information when studying the effect of videos. A thorough content analysis of the product description text will require developing and testing a unique dictionary for the music industry through supervised learning. Since our primary focus is on the effect of video ads, we limit the text analysis to word count and simple sentiment analysis (commonly conducted in the literature). First, we use the variable *Word Count* to denote the number of words in the project description as a proxy for the amount of text information. As shown in Table 3.1, the number of words ranges from 16 to 6,546, with an average of 465 words. Since this measure has a large magnitude, we divide it by 100 to normalize it, and use the normalized measure in subsequent analysis.

Second, we adopt sentiment analysis to study the sentiment expressed in the project description. It is a natural language processing (NLP) methodology used in computer science to extract and analyze subjective information from the data. In marketing, sentiment analysis has been used to study social network data (Schweidel and Moe 2014) and online communities (Homburg et al. 2015). The prior literature suggests that the frequency of positive and negative words capture the tone of a text. Following this tradition, we use positive and negative word lists compiled by Hu and Liu (2004) and Liu et al. (2005) (https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html).
lists include 2,006 positive words (e.g., fine, smile, etc.) and 4,783 negative words (e.g., disadvantage, reject, etc.), covering most “sentiment words” in English. Positive and Negative are the fractions of positive and negative words in a descriptive text. They are normalized numbers. These measures have been proved to be effective in prior research (Chen et al. 2014).

3.5 Analysis Results

In this section, we present the results of our main analysis. Since the dependent variable (project success) is a binary variable, we use logistic regression to estimate the effect of video ads on project success rate. In the regression analysis, we control for genre fixed effects by including the genre dummies. In relating our results to the hypotheses presented in Section 3.2, we provide initial evidences from the entire population of music projects, but the evidences are not definitively causal ones.

We first present the regression results regarding the effect of video duration and stimulation level to test Hypotheses 1 and 2. The results are shown in Table 3.2.

Table 2 shows that, all other things being equal, first, the projects that ask for more money (bigger Targets) are less likely to succeed (p-value < .01). A bigger target is often associated with a lower chance of success because the project requires more buyers to participate. Second, the more products/services offered in the menu (a larger Menu Length), the more likely the project would succeed (p-value < .01). This is consistent with the findings of Hu et al. (2015), which suggests that a well-designed menu with multiple options helps the creators obtain more funds by providing a better price discrimination mechanism. Third, the projects with longer durations (Project Duration) are less likely to succeed (p-value < .01). This result is also found by Mollick (2014), saying that longer durations may lead to a sign of the lack of confidence. Another possible reason is that longer durations reduce early buyers’ incentive to contribute (Hu et al. 2013). Finally, creators with prior experiences on Kickstarter perform worse than

---

7While a project with a bigger target has a lower success rate, on average it attracts more funds. This is consistent with the finding in Zhang and Liu (2012).
### Table 3.2: Logistic regression results

<table>
<thead>
<tr>
<th></th>
<th>Success</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Video</td>
<td>0.730***</td>
<td>(0.073)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Video Duration</td>
<td>-0.072***</td>
<td>(0.014)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stimulation</td>
<td>3.136***</td>
<td>(0.443)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stimulation - Squared</td>
<td>-1.908***</td>
<td>(0.414)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ZCR</td>
<td>1.889</td>
<td></td>
<td>(2.491)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>-10.905***</td>
<td>(1.527)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entropy</td>
<td>0.340</td>
<td></td>
<td>(0.264)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brightness</td>
<td>-8.628***</td>
<td>(2.090)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spectral Entropy</td>
<td>0.847***</td>
<td>(0.255)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log(Target)</td>
<td>-0.616***</td>
<td>(0.028)</td>
<td>-0.647***</td>
<td>(0.029)</td>
<td>-0.647***</td>
</tr>
<tr>
<td>Project Duration</td>
<td>-0.017***</td>
<td>(0.002)</td>
<td>-0.016***</td>
<td>(0.002)</td>
<td>-0.017***</td>
</tr>
<tr>
<td>Menu Length</td>
<td>0.142***</td>
<td>(0.007)</td>
<td>0.131***</td>
<td>(0.007)</td>
<td>0.119***</td>
</tr>
<tr>
<td>Creator Experience</td>
<td>-0.308***</td>
<td>(0.064)</td>
<td>-0.303***</td>
<td>(0.065)</td>
<td>-0.325***</td>
</tr>
<tr>
<td>Price</td>
<td>-0.0002</td>
<td>(0.0001)</td>
<td>-0.0001</td>
<td>(0.0001)</td>
<td>-0.0002</td>
</tr>
<tr>
<td>Word Count</td>
<td>0.269***</td>
<td>(0.019)</td>
<td>0.247***</td>
<td>(0.019)</td>
<td>0.244***</td>
</tr>
<tr>
<td>Word Count - Squared</td>
<td>-0.009***</td>
<td>(0.001)</td>
<td>-0.008***</td>
<td>(0.001)</td>
<td>-0.008***</td>
</tr>
<tr>
<td>Positive</td>
<td>-5.977***</td>
<td>(2.087)</td>
<td>-5.978***</td>
<td>(2.105)</td>
<td>-8.489***</td>
</tr>
<tr>
<td>Negative</td>
<td>-46.797***</td>
<td>(4.506)</td>
<td>-44.833***</td>
<td>(4.540)</td>
<td>-47.958***</td>
</tr>
<tr>
<td>Genre Fixed Effects</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>8,327</td>
<td>8,327</td>
<td>6,822</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-4,604.044</td>
<td>-4,552.383</td>
<td>-3,664.352</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>9,262.088</td>
<td>9,160.767</td>
<td>7,398.704</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note:* *p<0.1; **p<0.05; ***p<0.01
first-time creators (p-value < .01). This seems to suggest that buyers are more willing to support a musician’s first album (perhaps due to the idea that they are supporting the fulfillment of a lifelong dream, rather than just the continuation of a career). However, this result may be specific to the music category in Kickstarter; in the appendix, we conducted the same analysis on the technology category, and the results show that experienced creators are more likely to succeed.

**Effect of text advertising on project success rate: Length and valence of project description**

The results in column (1) of Table 3.2 show a quadratic relation between the number of words in a project’s description and its success rate. As already supported in the literature, our data also shows that longer text descriptions are associated with higher success rates, but the marginal effect is decreasing (p-value < .01). On the one hand, bringing more details about a project can reduce buyers’ perceived uncertainty and risk toward that project. Longer text also represents more effort on the part of the creators. On the other hand, the marginal effect of word description is decreasing as the number of words grows. Additional content included is secondary and helps less in resolving uncertainty.

The regression results show that sentiment - especially negative sentiment in the product description - is significantly related to a project’s success rate. Specifically, positive (negative) valence of the project description text is positively (negatively) correlated with project success rate. Moreover, the effect of negative valence is much more salient than that of positive valence (p-value < .01 for the effect of negative valence, coefficients of negative valence three times larger than that of positive valence). This result is consistent with the psychological theory that emotional feelings resulting from exposure to advertising can affect attitude toward the brand; moreover, positive and negative feelings make independent contributions (Edel and Burke 1987).

**Effect of video advertising on project success rate: Effect of a video**

In our data, the project success rate was 58.3% for the projects with a video, and 32.4% for those without a video - a stark 26% difference. From column (2) of Table 3.2, we see that after controlling for all other observable factors, posting video still has a significant

---

8After controlling for the target of the project, experienced creators are not significantly different from new creators in video length or stimulation level.
relationship with project success (p-value < .01). The coefficient of the video effect is 0.731; in the logistic regression, to quantify the effect of a video on project success rate, we will need to know the value of other variables. For instance, for a project with a target of $1,000, and all other variables being equal to the mean values of the sample, the model predicts a success rate of 65.3% without a video and 80.2% with a video, a lift of 15% points. All other things being equal, if we change the target to $10,000, then the predicted success rate will be 29.8% without a video and 47.7% with a video, a lift of 18% points.

Although we cannot claim a causal relationship, the results clearly suggest that those projects without a video are much less likely to succeed. This is consistent with what Kickstarter suggests: “Rule #1 for Kickstarter videos: make one! There are few things more important to a quality Kickstarter project than video. Skipping this step will do a serious disservice to your project.” (Mollick 2014)

**Effect of video advertising on project success rate: Length of video**

According to the two-factor model, lower success rates are associated with either very short or very long video ads, and higher success rates are associated with medium-length video ads. Although the plot in Figure 3.3 shows such a pattern, in the regression, we only see that the project success rate is adversely affected by the length of the video (Column 3, coefficient=-0.001, p-value < .01) \(^9\). One possible reason is the left truncation in our data: we have a very small number of projects with very short videos. Among 6,822 projects with videos, there are only 90 projects with a video shorter than or equal to 30 seconds. (When we rerun a logistic regression only on the projects with video duration of 120 seconds or less, we observe a positive relationship between video duration and project success rate. For these 1,745 projects, the coefficient of duration is 0.00676, p-value < .01; for the remaining 5,077 projects, the coefficient of duration is -0.00158, p-value < .01.) Overall, our results are consistent with Hypothesis 1. The results provide clear evidence that is consistent with the tedium process; without the tedium process, the coefficient of duration could not be negative.

\(^9\)We also tried to fit a model with a nonlinear effect of video duration, which turns out to be insignificant. By contrast, in our robustness check, we do see a nonlinear effect of duration with the technology category. Please refer to the Web Appendix for more details.
Effect of video ads on project success rate: Stimulation level of video

Column (3) of Table 3.2 is the regression of success on video characteristics, including only projects with a video. It shows that the impact of video stimulation level on the likelihood of project success has a significant linear effect (mean 3.1, p-value < .01) and a significant nonlinear effect (mean −1.9, p-value < .01). Thus, the results provide strong evidence for Hypothesis 2 (i.e., increasing stimulation level increases the video ad’s effectiveness up to a point, but decreases it thereafter). Those project videos with either a low or a high stimulation level have lower success rates. 10

The above result holds after we controlled for other elements known to influence the success rate of a project. While the estimates are not casual, they suggest that optimal stimulation level is around 0.78. For practical implications for video design, one would need to resort to our definition of stimulation level and infer the corresponding specifications for the video images.

So far we have discussed the main effects of video duration and stimulation level. These effects may depend on project and creator characteristics. Next, we discuss the effects of project size and creators’ past crowdfunding experiences.

Effect of video ads on project success rate: Interaction with project size

As we have discussed in Section 3.2, when considering a large project, potential buyers may value the information more, and are less likely to feel bored when watching its video ad. Project size can be defined by the price of offerings or the total target set by the creators. Since the majority of Kickstarter projects have multiple offerings (and prices), it is not easy to identify a unique price for each project and use that for analysis. For instance, how would one compare a project with two prices ($5 and $100) to another project with a single price ($20)? In contrast, each project has a unique target that can be readily used for analysis. In our data, the median target level is $5,000. We follow a median split strategy and divide our sample of 6,822 projects into two types: we create a

\[10\]

In an alternative specification, we divide the videos based on their stimulation level and include only the linear term of stimulation level. There are 5,102 videos with stimulation level lower than 0.7 and for this segment of videos, the coefficient for stimulation level is 1.802 (p-value < .01). For the remaining 1,720 videos, the coefficient for stimulation level is not significant. This suggests that, at first, an increase in stimulation has a positive effect on project success; however, after reaching a certain threshold, it has little impact on project success.
dummy variable, \( \text{Large} (Y = 1) \), to indicate the projects that call for more than $5,000.\(^{11}\) Since many projects call for exactly $5,000 dollars, only 43.5% of the projects qualify as large ones (see Figure 3.6).

We then run the logistic regression including the interaction between project size and duration, as well as the interaction between project size and video stimulation level. The results are summarized in Table 3.3 below.

Table 3.3 shows that the interaction between project size and video duration is positive and significant (p-value < .01), thereby supporting Hypothesis 1.1 (i.e., for projects with bigger targets, the tedium effect is weaker and buyers value longer videos). In addition, the interaction between project size and stimulation level is positive and significant, supporting Hypothesis 2.1 and implying that the optimal stimulation level could be higher when buyers evaluate large projects. Together, these two results suggest that those musicians who crowdfund for a bigger funding target may consider making a longer advertising video with a higher level of stimulation.

\(^{11}\)The results are not qualitatively altered when we use the continuous variable target instead of using the dummy variable large.
Table 3.3: Does the effect of a video ad depend on project size?

<table>
<thead>
<tr>
<th></th>
<th>Success</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Video Duration</td>
<td>$-0.078^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
</tr>
<tr>
<td>Stimulation</td>
<td>3.029$^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.433)</td>
</tr>
<tr>
<td>Stimulation - Squared</td>
<td>$-1.840^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.405)</td>
</tr>
<tr>
<td>Large</td>
<td>$-0.955^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
</tr>
<tr>
<td>Video Duration × Large</td>
<td>0.052*</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
</tr>
<tr>
<td>Stimulation × Large</td>
<td>0.510**</td>
</tr>
<tr>
<td></td>
<td>(0.236)</td>
</tr>
<tr>
<td>Observations</td>
<td>6,822</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>7,606.811</td>
</tr>
</tbody>
</table>

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01
**Effect of video ad on project success rate: Interaction with creators’ prior crowdfunding experience**

Some creators are more experienced than others. On Kickstarter, if a creator has created some projects before, these projects will be displayed on that creator’s personal page. Earlier we discussed the negative main effect of creator experience, indicating that buyers prefer to support those musicians launching their first crowdfunding projects. In Section 3.2, we also posited that creators’ prior experience may change the buyers’ preference for the design of the video ad; specifically, the need for information is lower and the tedium effect develops faster due to familiarity.

Table 3.4: Does the effect of a video ad depend on the creator’s crowdfunding experience?

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Video Duration</strong></td>
<td>−0.072***</td>
<td>−0.049***</td>
<td>−0.072***</td>
<td>−0.048***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.016)</td>
<td>(0.014)</td>
<td>(0.016)</td>
</tr>
<tr>
<td><strong>Stimulation</strong></td>
<td>3.136***</td>
<td>3.132***</td>
<td>3.093***</td>
<td>3.065***</td>
</tr>
<tr>
<td></td>
<td>(0.443)</td>
<td>(0.443)</td>
<td>(0.447)</td>
<td>(0.447)</td>
</tr>
<tr>
<td><strong>Stimulation - Squared</strong></td>
<td>−1.908***</td>
<td>−1.900***</td>
<td>−1.904***</td>
<td>−1.894***</td>
</tr>
<tr>
<td></td>
<td>(0.414)</td>
<td>(0.414)</td>
<td>(0.414)</td>
<td>(0.414)</td>
</tr>
<tr>
<td><strong>Experience</strong></td>
<td>−0.325***</td>
<td>0.120</td>
<td>−0.428**</td>
<td>−0.024</td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
<td>(0.146)</td>
<td>(0.166)</td>
<td>(0.200)</td>
</tr>
<tr>
<td><strong>Video Duration × Experience</strong></td>
<td>−0.131***</td>
<td></td>
<td>−0.136***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td></td>
<td>(0.038)</td>
<td></td>
</tr>
<tr>
<td><strong>Stimulation × Experience</strong></td>
<td></td>
<td>0.200</td>
<td>0.312</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.293)</td>
<td>(0.296)</td>
<td></td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>6,822</td>
<td>6,822</td>
<td>6,822</td>
<td>6,822</td>
</tr>
<tr>
<td><strong>Log Likelihood</strong></td>
<td>−3,664.352</td>
<td>−3,658.072</td>
<td>−3,664.118</td>
<td>−3,657.514</td>
</tr>
<tr>
<td><strong>Akaike Inf. Crit.</strong></td>
<td>7,398.704</td>
<td>7,388.145</td>
<td>7,400.236</td>
<td>7,389.028</td>
</tr>
</tbody>
</table>

*Note:* *p<0.1; **p<0.05; ***p<0.01

To test this hypothesis, we incorporate the interaction between creator’s experience and video duration as well as the interaction with video stimulation level into our logistic regression analysis. We summarize the results in Table 3.4.

The results in Table 3.4 show that all the main effects of duration and stimulation level remain after incorporating the interaction with creator experience. The results also show that the interaction between video duration and creator experience is negative and significant (p-value < .01), suggesting that, all other things being equal, buyers are
likely to prefer shorter videos when evaluating projects posted by experienced creators. It is worth noting that in our data, the average video length of the projects posted by experienced creators is not significantly different from those posted by their inexperienced counterparts (p > .1). Thus, our results suggest that projects might benefit from abridged versions of videos.

The interaction between video stimulation level and creator experience is positive but not statistically significant. The optimal level of stimulation in a video does not seem to depend on buyers' familiarity with the creators.

Effect of video advertising on project success rate: Interaction with text advertising

We have shown that a project’s success rate is positively related to Word Count, the number of words in the project description. Other than the video ad, text information in the project description can be another important source for prospective buyers to learn about a project or its creators. However, the relationship between video ad and project description is unclear. On the one hand, these two information channels can be substitutes. Both the videos and texts provide project information, and there is likely information overlap and repetition. If a project has a lengthy project description, then the video information can become redundant, making the information less valuable and increasing the chance that buyers become bored. On the other hand, these two information channels may complement each other. If creators can use the videos to develop an emotional connection with potential buyers and establish credibility for their projects, then buyers may place more value on the related text information. To estimate the relationship, we include the interaction between video information and text information in the logistic regression, and show the results in Table 3.5.

The results in Table 3.5 show that, first, the interaction between video length and word count is not significant. Thus, it is unclear how a longer project description may interfere with the effect of video duration. Second, the interaction between video stimulation level and word count is negative and significant (p-value < .01). Recall that word count has a positive relationship with project success rate. The result then suggests that after experiencing a low-stimulation video, buyers may find a long project description more receptive. Alternatively, after experiencing a high-stimulation video, prospective buyers would be less likely to be influenced by a long project description. It is worth noting that the magnitude of the interaction effect can be significant. For instance, if stimulation level is equal to 1, then the coefficient for Word Count will be reduced by half. This
Table 3.5: Does the effect of a video ad depend on length of project description?

<table>
<thead>
<tr>
<th></th>
<th>Success</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td><strong>Video Duration</strong></td>
<td>−0.072***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
</tr>
<tr>
<td><strong>Stimulation</strong></td>
<td>3.136***</td>
</tr>
<tr>
<td></td>
<td>(0.443)</td>
</tr>
<tr>
<td><strong>Stimulation - Squared</strong></td>
<td>−1.908***</td>
</tr>
<tr>
<td></td>
<td>(0.414)</td>
</tr>
<tr>
<td><strong>Word Count</strong></td>
<td>0.244***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
</tr>
<tr>
<td><strong>Word Count- Squared</strong></td>
<td>−0.008***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td><strong>Video Duration × Word Count</strong></td>
<td>−0.003</td>
</tr>
<tr>
<td><strong>Stimulation × Word Count</strong></td>
<td>−0.117***</td>
</tr>
<tr>
<td>Observations</td>
<td>6,822</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>7,398.704</td>
</tr>
</tbody>
</table>

*Note:* *p<0.1; **p<0.05; ***p<0.01
effect is significant because the number of words in a product description can reach several thousand.

**Effect of video ads on project success rate: credibility factors**

As described in Section 3.4, we create two variables from the video content - Human and Instrument - for 6,822 projects with videos. We run logistic regressions on project success with respect to each of these two variables, separately and together. We summarize the estimation results in Table 3.6. The coefficients of Human and Instruments are both significant and positive (p-value < .01 in all cases), suggesting that those projects with videos featuring humans and/or instruments have higher success rates.

Table 3.6: The effects of using humans and/or instruments in video ads on project success

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human</td>
<td>0.391** (0.156)</td>
<td>0.365** (0.156)</td>
<td></td>
</tr>
<tr>
<td>Instrument</td>
<td>0.207*** (0.062)</td>
<td>0.200*** (0.063)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>6,822</td>
<td>6,822</td>
<td>6,822</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-3,661.221 -3,658.827 -3,656.086</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>7,394.441 7,389.653 7,386.172</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note:* *p<0.1; **p<0.05; ***p<0.01

These results support Hypotheses 3 on video ads credibility. They provide evidence that the content of the projects’ video ad affects the funding decisions made by the potential buyers. We manually went through a large number of videos, and found that almost all humans featured in the videos are the project creators. When they are featured in the videos, these creators develop a personal connection with potential buyers, making them feel like they have a real and credible relationship with the musicians. Our result is also consistent with the suggestions provided in Kickstarter’s official blog: “And don’t be afraid to put your face in front of the camera and let people see who they’re giving money to. We’ve watched thousands of these things, and you’d be surprised what a difference this makes.”

12Musical instruments are the essential elements of music making and performance. Therefore, showing the instruments in the video ads should enhance the perceived credibility of the musical projects. This feature is unique to the music category. Moreover,

12Source: [https://www.kickstarter.com/blog/how-to-make-an-awesome-video](https://www.kickstarter.com/blog/how-to-make-an-awesome-video).
due to technical constraints, we are not able to confirm through the programming that the creators actually played the instruments in each video (although manual inspection of several hundred videos indicates that the musicians were indeed playing the instruments). Our results confirm that the projects featuring instruments in a video are associated with a higher success rate.

Overall, the musicians who feature instruments in their videos are more likely to succeed in crowdfunding. In addition, the coefficient of Human is greater than that of Instrument. This indicates that when establishing credibility to improve the project success rate, it is more effective if one can achieve that through personal connection with the performers than through the connection with real objects.

### 3.6 Conclusion

This chapter examines the effect of video ads on the success rates of online crowdfunding projects. We extract more than 6,000 videos and analyze multiple features of them. Our regression analyses control for many project-specific factors, such as menu of offer, price, targets, as well as creator-specific factors such as past crowdfunding experience. Our results show that, all other things being equal, first, longer videos are associated with lower success rates. This result indicates that the tedium effect of the two-factor model is significant in online video ads. Second, an intermediate level of stimulation is related to the highest project success rate. In comparison, the project success rate is lower when the stimulation level is either higher or lower. Thus, there exists an optimal stimulation level (OSL) for online video ads. Third, the project success rate is higher when the online video features the creators (musicians) and their instruments; this indicates that credibility is an important consideration in video advertising for crowdfunding because the creators rely solely on their videos to make a personal connection with prospective buyers. Together, these findings suggest that while having a video is critical for successful communication, merely having a video is not sufficient. Creators must pay attention to the design of the videos.

This empirical study not only provides evidence to suggest that the advertising theories developed from analyzing traditional media (such as print) still hold with respect to emerging online video media, but also extends these theories in the context of crowdfunding. Specifically, in our research, the tedium effect is weaker when a project has a big target, but stronger when the creators have prior crowdfunding experiences on Kickstarter. In addition, the optimal stimulation level is higher when a project has a bigger target. These results are not only theoretically intriguing, but also managerially useful.
for entrepreneurs interested in crowdfunding for their next projects.

Our research successfully analyzes a large number of online videos. These results support the idea that we can take advantage of publicly available online videos for academic research in marketing. Our research also has several limitations. First, we only focus on the duration, optimal stimulation level and content features of the videos. Future research may further use new techniques to extract additional features from online videos to gain further insights. For instance, future research may develop new methods to study the emotional aspects of video ads. In another direction, further research could examine the effect of video in other business contexts (e.g., online travel and hospitality industry websites—video design may alter consumers’ search and purchase behaviors on these websites). Second, we do not further identify causal relationship, but present correlational evidence from the crowdfunding industry. Future research may consider the possibility of conducting online field experiments to formally test causal effects in video ads. Such research would benefit practitioners as well as academic researchers. Third, there are alternative explanations that we cannot rule out. For example, consumers may prefer humans in the video because human faces reduce the psychological distance between the creators and the viewers. Lab experiments can be a good way to understand the underlying mechanism.

3.7 Appendix: Robustness Checks on The Technology Category

In the research we focused on the music category. While the music category has many strengths (e.g., small within-category differences, sufficient observations), it also has its own weakness. For example, in the music category, the video itself can be part of the product. The creators may include a song in the video, which is part of the final product. It is possible that the unique feature of the music category limits the generalizability of the results. To overcome the limitations and check the robustness the results, we further replicate the analysis in Kickstarter’s technology category.

The data includes all technology projects in the following six US states: California, Illinois, Massachusetts, New York, Texas, and Washington. It comprises all completed projects in these states from the inception of Kickstarter to March 6, 2017. Together, we have 6,958 observations, among which 5,291 projects have a video. This projects studied here are slightly fewer than the music projects studied in the chapter.

Since all the variables used here are essentially the same variables we use in the chapter
(except for the CNN variables, which will be discussed in detail later), and we omit the description of the variables. First, we replicate the main regression to examine the main effect of video length and visual stimulation on the final outcome of the projects.

Table 3.7 summaries the logistic regression results of the technology category (with the same control variables used in the chapter). Unlike with the music category, here we include the nonlinear term of Duration in the regression as well (when modeling only the linear effect, the coefficient of Duration is not significant). The non-video related control variables are omitted.

Table 3.7: Logistic regression results

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Success</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Video</td>
<td>1.333***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.120)</td>
<td></td>
</tr>
<tr>
<td>Video Duration</td>
<td></td>
<td>0.115**</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td></td>
</tr>
<tr>
<td>Video Duration - Squared</td>
<td>-0.011**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>Stimulation</td>
<td></td>
<td>3.377***</td>
</tr>
<tr>
<td></td>
<td>(0.600)</td>
<td></td>
</tr>
<tr>
<td>Stimulation - Squared</td>
<td></td>
<td>-1.452***</td>
</tr>
<tr>
<td></td>
<td>(0.461)</td>
<td></td>
</tr>
<tr>
<td>ZCR</td>
<td></td>
<td>2.490</td>
</tr>
<tr>
<td></td>
<td>(4.810)</td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td></td>
<td>-5.556***</td>
</tr>
<tr>
<td></td>
<td>(2.038)</td>
<td></td>
</tr>
<tr>
<td>Entropy</td>
<td></td>
<td>0.626**</td>
</tr>
<tr>
<td></td>
<td>(0.272)</td>
<td></td>
</tr>
<tr>
<td>Brightness</td>
<td></td>
<td>1.002</td>
</tr>
<tr>
<td></td>
<td>(2.281)</td>
<td></td>
</tr>
<tr>
<td>SpectralEntropy</td>
<td></td>
<td>-0.486</td>
</tr>
<tr>
<td></td>
<td>(0.537)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>6,958</td>
<td>5,291</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-2,955.908</td>
<td>-2,563.795</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>5,963.815</td>
<td>5,195.589</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
The linear effect of video length is positive and significant, whereas the nonlinear effect of video length is negative and significant, thereby suggesting an inverted-U-shape effect of video length. Moreover, the estimates imply an optimal length of around five minutes for the technology category. This is much longer than that of the music category. This suggests that relative strength of the two factors - the learning effect and the tedium effect - actually hinges on the exact product category being considered. For the technology category, the learning effect is relatively stronger and the tedium effect is relatively weaker. One possible explanation is that, there is more information uncertainty with technology products, and much of this uncertainty can be addressed in the video. Buyers desire more information from the video.

The effects of Stimulation are similar. In Table 3.7, the coefficient of Stimulation is positive and significant, whereas the coefficient of Stimulation-Squared is negative and significant, again supporting the optimal stimulation level theory. Unlike with the music category, the OSL is also larger in the technology category, with a mean 1.16. Again, the OSL is context dependent.

Next, we examine the effect of project size on the effectiveness of video ads and the results are presented in Table 3.8.

From Table 3.8, we see that the interaction between Stimulation and Project Size is still positive and significant, whereas the interaction between Duration and Project Size is positive but not significant. As discussed before, the learning effect is relatively stronger and the tedium effect is relatively weaker in the technology category, and most videos are shorter than the optimal length. Therefore, the effect of project size on the two-factor model is not significant. Also, we have fewer observations in the technology category.

The effects of the creator’s past crowdfunding experience on video ads are replicated, the results are summarized in 3.9.

For the technology category, we do not observe a significant substitution or complement effect between visual information and text information, suggesting that the exact relationship may be context dependent.

Finally, we examine the effect of perceived credibility on a project’s success rate. Again, we use humans as a proxy of the credibility of the projects. However, unlike music projects, technology projects do not feature musical instruments, and we shall not use them as a proxy of credibility. Instead, we resort to a similar tool in technology, computers (including both desktops and laptops), and use them as a measure of credibility. Creators often use computers to show the software or programs they developed, and this brings credibility to the project. Still, these measures are obtained using the same CNN
Table 3.8: Does the effect of a video ad depend on project size?

<table>
<thead>
<tr>
<th></th>
<th>Success</th>
</tr>
</thead>
<tbody>
<tr>
<td>Video Duration</td>
<td>0.040</td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
</tr>
<tr>
<td>Stimulation</td>
<td>2.942***</td>
</tr>
<tr>
<td></td>
<td>(0.577)</td>
</tr>
<tr>
<td>Large</td>
<td>-1.795***</td>
</tr>
<tr>
<td></td>
<td>(0.253)</td>
</tr>
<tr>
<td>Video Duration - Squared</td>
<td>-0.007</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>Stimulation - Squared</td>
<td>-1.522***</td>
</tr>
<tr>
<td></td>
<td>(0.458)</td>
</tr>
<tr>
<td>Video Duration × Large</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td>(0.042)</td>
</tr>
<tr>
<td>Stimulation × Large</td>
<td>0.770**</td>
</tr>
<tr>
<td></td>
<td>(0.311)</td>
</tr>
<tr>
<td>Observations</td>
<td>5,291</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-2,725.750</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>5,523.501</td>
</tr>
</tbody>
</table>

*Note:* *p<0.1; **p<0.05; ***p<0.01
Table 3.9: Does the effect of a video ad depend on the creator’s crowdfunding experience?

<table>
<thead>
<tr>
<th></th>
<th>Success</th>
</tr>
</thead>
<tbody>
<tr>
<td>Video Duration</td>
<td>0.144***</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
</tr>
<tr>
<td>Stimulation</td>
<td>3.412***</td>
</tr>
<tr>
<td></td>
<td>(0.617)</td>
</tr>
<tr>
<td>Experience</td>
<td>0.923***</td>
</tr>
<tr>
<td></td>
<td>(0.259)</td>
</tr>
<tr>
<td>Video Duration - Squared</td>
<td>$-0.011^*$</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
</tr>
<tr>
<td>Stimulation - Squared</td>
<td>$-1.441^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.462)</td>
</tr>
<tr>
<td>Video Duration $\times$ Experience</td>
<td>$-0.105^{**}$</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
</tr>
<tr>
<td>Stimulation $\times$ Experience</td>
<td>$-0.197$</td>
</tr>
<tr>
<td></td>
<td>(0.322)</td>
</tr>
</tbody>
</table>

Observations 5,291
Log Likelihood $-2,561.259$
Akaike Inf. Crit. 5,194.517

*Note:* *p<0.1; **p<0.05; ***p<0.01
techniques. As can be seen from Table 3.10, the effects of both human and computers are significantly positive, thereby supporting the effect of credibility.

Table 3.10: The effects of featuring humans and/or computers in video ads on project success

<table>
<thead>
<tr>
<th></th>
<th>Success</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Human</td>
<td>0.531***</td>
<td>0.543***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.093)</td>
<td>(0.093)</td>
<td></td>
</tr>
<tr>
<td>Computer</td>
<td>0.199***</td>
<td>0.221***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.077)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>5,291</td>
<td>5,291</td>
<td>5,291</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>−2,547.112</td>
<td>−2,560.437</td>
<td>−2,543.022</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>5,164.223</td>
<td>5,190.873</td>
<td>5,158.044</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
Chapter 4

Professional vs. Amateur Hosts on Airbnb

4.1 Introduction

Noam Ben-Ami, a software engineer living in San Francisco, decided to stay in an Airbnb property on a trip to Portland, Oregon. After that journey, he made the following comment to describe this Airbnb experience: “It was in a small room in a basement in Oregon. I woke up to a loud grinding noise above me. Groggily, I walked up the stairs to the kitchen, where the home’s owner was grinding fricking wheat by hand to make me scones. Those scones were served with preserved Oregon strawberries, which are amazingly fresh and still amazingly properly preserved. It was charming and unexpected and so Portlandia. I was really sad when she stopped hosting folks as I’d have made her my go-to place for all my trips to PDX (Portland International Airport).” Clearly, Airbnb is offering something that has never been offered by typical rental places or hotels. Namely, you can stay with the hosts and have a great experience with them: listening to their stories, trying new food, and getting to learn about the place from them.

Consistent with Noam’s experience, Airbnb insists it is not a hotel. As Airbnb CEO Brian Chesky wrote on his blog, most Airbnb hosts were “regular people renting the homes in which they live”. “They are teachers, artists, students, and retirees who love doing this”, Brian emphasized, “They didn’t provide just a place to stay, they are personally connected with the guests and offered them support in a time of need.” Airbnb’s unique business model of “peer-to-peer renting” appeared to be a great success: In 2016, Airbnb bookings increased to around 129 million “room nights”, making it larger than any other hotel chain in the world. A more surprising number comes from Cowen Group,
a Wall Street firm, expecting Airbnb to book a billion nights a year in 2025. Airbnb is particularly popular with young travelers who want to feel more like at home.

Today, more and more hosts are running Airbnb as a professional and serious business. These hosts spend several hours a day helping guests check-in, doing laundry and cleaning apartments for their next Airbnb guests. They manage a number of properties across the city and rely on Airbnb as their sole source of income. Some owners even hire agents to help manage their properties. When staying in these professionally managed properties, you do not stay with the hosts. However, you can still get all the essential hotel services. From this perspective, to travelers, Airbnb is not much different from a hotel. In fact, nowadays, Airbnb is asked to pay hotel tax in many major cities, including San Francisco, Los Angeles and Paris.

This new trend is more or less beyond Airbnb’s original intent. It has actually re-defined the sharing platform. In fact, the same phenomenon has affected other sharing economies as well. Etsy is filled with not only artists, but also professional sellers. To them, selling on Etsy is just the same as selling on EBay or Amazon. Uber service is not only provided by individuals who spend a few hours of spare time a day, but also by drivers who drive throughout the day. To them, driving for Uber is nothing different from driving for a taxi company. What does it imply when more and more people are running a professional business on these sharing economies platforms?

In this chapter, we are interested in understanding the Airbnb’s fast-changing business model by analyzing the behaviors of its hosts. Would amateur hosts running small-scale business behave substantially differently from the professional hosts running comparatively large-scale business? If so, what are the differences and what are the underlying causes? To answer these questions, in this chapter, we resort to economic and psychological theories to investigate and analyze the behavioral differences between different types of hosts, and use data to test the implications of the differences. More specifically, we focus on the following key issues:

1. **Price.** Do professional hosts charge higher or lower price compared with amateur hosts?

2. **Services.** Do professional hosts provide better or worse services?

3. **Information.** Do professional hosts provide more or less information to guests?

4. **Competition.** Do different types of hosts respond differently to competition?

While it is not surprising that amateur hosts may behave differently from professional ones, it has long been challenging to quantify these effects because, in traditional rental
markets, small property owners usually do not manage their own properties directly. As for Airbnb, while much of Airbnb’s business is based on “regular” people offering extra rooms or beds, there are yet another group - hosts with multiple listings or whole homes for rent. For example, an analysis of global Airbnb listings in 2014 revealed that hosts offering multiple listings made up of over 40% of the company’s business (Grothaus 2015). Most of these hosts are professional hosts and running Airbnb as a business. Therefore, Airbnb provides us with data on property listings managed by different types of hosts, which enables us to make the comparison.

Economic and psychological theories provide several insights into the hosts’ incentives to price, provide services and information, and respond to competition. First, amateur hosts are subject to the mere ownership effect, which asserts that they are likely to put more value on their own properties. The professional hosts, by contrast, own or manage the properties for the purpose of transaction, and are less likely to be biased. Hence, amateur hosts are likely to charge higher prices for the same listing. Second, professional hosts manage more properties than amateur hosts do. The more properties a host manages, the less effort he or she could put on a property. Therefore, professional hosts are more prone to provide inferior services. Third, in terms of information disclosure, hosts with lower disclosure cost may have stronger incentives to disclose their property information (Jovanovic 1982). Because of specialization and economies of scale, professional hosts may have increased cost efficiency over amateur hosts in providing information. When this advantage outweighs the effort limitation described above, professional hosts may disclose more information about a property than amateur hosts do. Finally, the hosts may strategically behave when faced with competition from other nearby properties. Thus, there may be a correlation between price, service provision, information disclosure and the type of hosts. These theories are used to guide the specification of our empirical models.

To achieve our goals, we collected data from Airbnb, the largest online peer-to-peer property rental platform, and Zillow, a real estate database firm. To measure the effects of host types on price, service, information and competition, we use linear regression models. The empirical results provide some interesting insights. First, compared with professional hosts, amateur hosts, whose business scale is relatively small, charge a higher price in average, and at the same time, they tend to provide superior services to the guests. This phenomenon supports the mere ownership effect and is a piece of evidence for the problem of effort limitation. Second, professional hosts post more photos and write longer descriptions, which proves their cost advantage obtained from economies of scale. Finally, professional hosts respond more effectively to competition. A potential
explanation can be that amateur hosts are less informed about the competition.

The rest of the chapter is organized as follows. In Section 4.2, we review the related literature. We review the theories and propose some testable implications in Section 4.3. Section 4.4 provides a description of the data. Empirical analysis is performed and analyzed in Section 4.5. Section 4.6 concludes the chapter.

4.2 Literature

This chapter is related to the following three literature streams: the sharing economy (or peer-to-peer markets), the real estate industry, and the differences between amateur entrepreneurs with small-scale business and professional entrepreneurs with large-scale business.

First, our work is within the context of the emerging literature on the peer-to-peer firms. A number of studies have empirically investigated the roles and functions of peer-to-peer markets. For example, Einav et al. (2016) view the primary function of the peer-to-peer markets as “making it easy for buyers to find sellers and engage in convenient, trustworthy transactions”. Hall and Krueger (2015) analyze the supply side of the sharing economy using data from Uber, and show the pricing pattern facilitates part-time and variable hours. Zervas et al. (2015) compare the online rating systems of Airbnb and TripAdvisor, showing that, in average, properties receive higher ratings on Airbnb. Using a difference-in-difference approach, Zervas et al. (2016) investigate the impact of Airbnb on the hotel industry, and estimate that the causal impact is in the 8% - 10% range. There are also analytical models of the sharing economy. For example, Jiang and Tian (2016) develop a model to examine the strategic and economic impact of product sharing among consumers, and find that transaction costs in the sharing market have a non-monotonic effect on the firm’s profits, consumer surplus, and social welfare. Tang et al. (2016) study the coordination of supply and demand in on-demand platforms using price, wage, and payout ratio.

In addition, this chapter focuses on the Airbnb platform for short-term peer-to-peer rental, which is closely related to the real estate industry. While the real estate literature is more interested in selling instead of renting houses, it provides us with insights that could also be applied to the rental market. Another difference between the real estate market and Airbnb is that, almost all properties are managed by agents in the real estate market, whereas many properties are managed by owners directly at Airbnb. Among studies on the real estate market, Tucker et al. (2012) show the effect of authenticity in home sales. Carrillo (2008) studies the effect of visual information in real estate listings,
and show that it may facilitate the search and matching process between home buyers and sellers. Similar results are also obtained by Benefield et al. (2012).

This chapter compares amateur hosts running small-scale business with professional hosts running large-scale business. Small business owners themselves are the business, and perform all the important tasks (Churchill and Lewis 1983). Small business owners usually value personal satisfaction, achievement, and a flexible lifestyle more than wealth creation (Walker and Brown 2004). Carland (1995) shows that small business owners are more risk averse than entrepreneurs. In the real estate market, professional managers are known to offer expertise covering consumer and media research (Horsky 2006), and they may be better informed about the market (Levitt and Syverson 2008). After initial investigation in the literature, we would like to examine the effect of different types of hosts on Airbnb, the unique peer-to-peer rental market.

### 4.3 Theories and Testable Implications

In social psychology, the mere ownership effect asserts that, owners would evaluate an object more favorably merely because they own it (Beggan 1992). This is in line with the endowment effect and loss aversion, which show an increment in value accruing to an object perceived by its owner. In the case of Airbnb, an owner of a property is likely to perceive it more valuable than others do, which will lead to a higher listed price.

Research has also shown the boundary of loss aversion (Novemsky and Kahneman 2005). A key idea is that exchanges of goods that are given up “as intended” do not exhibit loss aversion. If this idea also applies to the mere ownership effect, we shall expect that professional hosts, who take their properties as business vehicles, should not exhibit the mere ownership effect. Their properties are rented “as intended”. The amateur owners, however, rent their own homes to travelers and are much more likely give their properties a higher valuation.

The above discussions lead to the following hypothesis about pricing Airbnb properties.

**Hypothesis 1.** *All other things being equal, amateur hosts who run small-scale business charge higher prices than professional hosts who run large-scale business do.*

The service level is likely to be different between professional hosts and amateur hosts. First, hosts have capacity constraints. While amateur hosts can hardly use up their capacity, the professional hosts can easily use up their limited resources. For example, when multiple inquiries are directed to the same host, he or she may not be able to
answer all of them in a timely fashion. Second, the service cost itself may also be a convex function of scale for an individual, which is commonly assumed in the literature. The convex nature of the cost function makes it increasingly costly to manage an additional property, as the number of properties grows. Third, the existing literature also suggests that flexibility as a key competitive advantage of small businesses (Kuratko et al. 2001), which enables them to apply effective practices to improve the quality of services.

To overcome the resources limitations, when their businesses scale up, Airbnb owners may hire professional agents to help them manage their properties. The service offered can include cleaning the property, giving keys to guests, answering questions from the guests etc. This would partially help the owners break through resources limitations. However, at the same time, this gives rise to a potential moral hazard problem. The agents are usually paid a small fraction of the revenue but bear almost all the costs associated with providing the services. Therefore, there is a misalignment of incentives between owners and agents, with the agents providing services at suboptimal levels.

Finally, the service level affects the reputation of a host, which is reflected by his or her overall reviews and ratings. The performance of a host with large-scale business is defined by all the reviews he or she receives, and hence the marginal effect of a given rating is smaller for him or her. In this sense, small hosts with small-scale business need to put more effort for a higher return.

**Hypothesis 2.** All other things being equal, amateur hosts who run small-scale business provide better services.

Similarly, amateur hosts who run small-scale business are likely to implement more flexible cancellation policies. Airbnb allows its hosts to choose among the following cancellation policies: flexible, moderate, and strict. For example, under the flexible cancellation policy, guests could get full refund one day prior to arrival; under the strict cancellation policy, however, guests could only get 50% refund up until one week prior to arrival. If a host implements a flexible cancellation policy, he or she will encounter more cancellations and bear the cost of rescheduling and looking for new guests. Therefore, implementing a flexible cancellation policy will increase the (per night) service effort needed. For the same reasons described above, we have the following hypothesis.

**Hypothesis 3.** All other things being equal, amateur hosts who run small-scale business implement more flexible cancellation policies.

Every coin has two sides. On the negative side, in the discussion above, we suggest that professional hosts who run large-scale business would provide inferior service. On
the positive side, because of specialization, these professional hosts may possess advanced knowledge and expertise that typical amateur hosts do not have. We exclude such concern in the analysis of service effort, because knowledge and expertise do not help much to serve the guests. For example, professional hosts are not much more efficient than amateur hosts to clean the properties. However, this difference can be significant in the case of information provision.

Unlike chain hotels with reliable and trusted brand names, Airbnb properties are generally unknown to guests. As guests are unfamiliar with Airbnb properties, information provided by the hosts - the photos and the property description - plays a key role in resolving the uncertainties. Would different types of hosts differ in information provision? Being better informed about consumer needs and market characteristics, professional hosts are more efficient to provide the information. In addition, professional hosts also have access to more resources and benefit from the economies of scale. For example, professional hosts could use the same camera kit to take photos of multiple properties, or develop advanced skills to compose informative descriptions of a number of listings. From this perspective, professional hosts who run large-scale business may have a cost advantage over the amateur hosts who run small-scale business. Therefore, they may provide richer and better information about Airbnb listings.

Thus, the overall effect of professional hosts on information provision remains unclear to us. When the effect of resources limitation dominates the cost advantage, professional hosts provide less information, and vice versa. Therefore, we come up with the following two hypotheses.

Hypothesis 4a. All other things being equal, amateur hosts who run small-scale business provide more information than that professional hosts who run large-scale business do.

Hypothesis 4b. All other things being equal, amateur hosts who run small-scale business provide less information than that professional hosts who run large-scale business do.

Finally, we examine the effect of competition on different host types. Competition has its clear economic consequences. In the presence of competition, part of the profits will be competed away, while the cost of providing services and supplying information remain the same. Consequently, a host’s effort is compromised when faced with competition (The same insight has been documented in Guo and Zhao (2009), though in a different setting).

While host behavior is likely to be affected by competition, amateur hosts who run small-scale business may react differently from professional hosts who run large-scale business. The amateur hosts typically do not have the time or effort to monitor the
volatile market, and are thus less informed about the state of the local rental market. In this way, they tend to be ignorant, and thus underreact to competition simply because they are not aware of it.

We summarize the above discussions in the next hypothesis.

**Hypothesis 5.** All other things being equal, professional hosts who run large-scale business put less effort on properties faced with competition.

### 4.4 Data and the Airbnb Platform

Most of our data is collected from Airbnb. Founded in the August of 2008, Airbnb is now one of the largest sharing networks in the world. It describes itself as “a trusted community marketplace for people to list, discover, and book unique accommodations around the world - online or from a mobile phone or tablet.” With its more than 2 million listings worldwide, Airbnb has hosted more than 60 million guests since its inception.

Airbnb has a pretty standard platform business model. It facilitates the exchange between “hosts” and “guests”. Airbnb does not own any properties itself, and everyone could list his or her properties on the platform. It gains its revenue from the following two ways: (1) a 3% service fee from the host for each reservation which covers the cost of the process and (2) a 6-12% service fee charged to guests when booking a property.

In this study, we combine information collected from Airbnb with the rental price information collected from Zillow. For Airbnb, we collected the one-shot listing data in November 2015 in four major cities in the United States: New York, San Francisco, Miami, and Chicago. We hired an RA to scrape the consumer facing data directly from the Airbnb platform. The cities are in different geographic areas that represent different markets. In addition to Airbnb, we also collected data from Zillow, an online real estate database. This data complements the Airbnb data and tells us the features of a neighborhood rather than a single listing. From Zillow, we collected the rental price data of all available ZIP codes of September 2016. We then removed Airbnb listings that are not matched with Zillow data or have missing variables (e.g., listings that have no ratings yet). This gives us a clean set of 32,320 Airbnb properties, or 86.7% of the original data.

Airbnb provides an unusually attractive environment for comparing the effects of professional and amateur hosts. Unlike other markets such as the real estate market, amateur hosts - or the “ordinary people”, do not need any knowledge to list their properties on the platform. In addition, the effort that hosts put into a property can be observed or inferred from the listed information, which enables us to make inferences conveniently.
Although the data is comprehensive, there are a few flaws and limitations. First, the
data does not specify how professional a host is. We inferred his or her professionality
based on the number of properties that the host manages, which will be discussed in
detail later. There is no independent check of the host information. Second, as discussed
above, many listings have missing variables or do not match the Zillow data.\footnote{We use Zillow Rental Index (ZRI) to measure the local rental price. The data is only available in
certain areas.} We removed
these listings from the original dataset for estimation. The omission is acceptable because
we still have enough observations for estimation (13.3\% of the original observations are
removed due to incompleteness).

**Variables**

For each property, the variable that we are interested in is **Professionality**, how profes-
sional its host is. This is inferred from the number of listings that its host manages. The
idea is that, when a host manages a great number of properties, he or she is likely to run
Airbnb as a professional business and relies on it as his or her sole source of income; if
the host manages only a single property, he or she is more likely to take it as a part-time
job or side business.

We take the logarithm of the number of properties a host manages because it has a
heavy tail. On Airbnb, each host is represented by a unique number (or ID). We went
through our entire dataset to find out the number of listings managed by a same host.
For example, if Properties equals 3, then the host of the property is managing three
listings at the same time, and the Professionality variable is set to log 3.

Below we describe how the other variables in our data are quantified.

- **Price:** The listed per night price of the property, measured in USD. In the follow-up
  empirical analysis, we take the logarithm of Price and constructed another variable
  LogPrice.

- **Amenities:** Airbnb creates a list of 24 standard amenities and 5 safety features
  for hosts to select for their properties. The amenities and safety features include
  the followings: Kitchen, Internet, TV, Essentials, Air-Conditioning, Washer, Dryer,
  Free Parking on Premises, Wireless Internet, Cable TV, Breakfast, Pets Allowed,
  Family/Kid Friendly, Suitable for Events, Smoking Allowed, Wheelchair Accessible,
  Elevator in Building, Heating, Indoor Fireplace, Buzzer Wireless Intercom, Door-
  man, Pool, Hot Tub, Gym, Smoke Detector, Carbon Monoxide Detector, First Aid
  Kit, Safety Card, and Fire Extinguisher.
• **Review Ratings:** Review Rating is a central component of Airbnb’s trust system, beyond self-supplied information. Unlike other major online platforms such as Amazon and TripAdvisor, Airbnb only displays the average of all ratings on the listing webpage rather than discloses the specific rating attached to each individual review. The rating is composed of the following breakdown categories, according to Airbnb’s official webpage.²

  - **Overall Experience.** What was your guest’s overall experience?
  - **Cleanliness.** Did your guests feel that your space was clean and tidy?
  - **Accuracy.** How accurately did your listing page represent your space?
  - **Value.** Did your guest feel your listing provided good value for the price?
  - **Communication.** How well did you communicate with your guest before and during their stay?
  - **Arrival.** How smoothly did their check-in go?
  - **Location.** How did guests feel about your neighbourhood?

²https://www.airbnb.ca/help/article/1257/how-do-star-ratings-work

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**Figure 4.1: Reviews and Ratings at Airbnb**

<table>
<thead>
<tr>
<th>Summary</th>
<th>Accuracy</th>
<th>Communication</th>
<th>Cleanliness</th>
<th>Location</th>
<th>Check In</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emmanuel was the best. Extremely communicative and welcoming. My boyfriend and I had a great time in New York. One note I will say is that the bed is more on the firm side so be aware of that if you have particular preferences. I would definitely stay here again.</td>
<td>⭐⭐⭐⭐⭐</td>
<td>⭐⭐⭐⭐⭐</td>
<td>⭐⭐⭐⭐⭐</td>
<td>⭐⭐⭐⭐⭐</td>
<td>⭐⭐⭐⭐⭐</td>
<td>⭐⭐⭐⭐⭐</td>
</tr>
<tr>
<td>December 2016</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Summary</th>
<th>Accuracy</th>
<th>Communication</th>
<th>Cleanliness</th>
<th>Location</th>
<th>Check In</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>This place is awesome. It is exactly what we needed. Emmanuel is the best host ever. He is so sweet and kind. Gave us places where we should go and options for food around the neighborhood. Answered all our questions and his place is so cozy and his attitude is so positive that you feel like you’re at home. It’s nice and warm in there, the heater works</td>
<td>⭐⭐⭐⭐⭐</td>
<td>⭐⭐⭐⭐⭐</td>
<td>⭐⭐⭐⭐⭐</td>
<td>⭐⭐⭐⭐⭐</td>
<td>⭐⭐⭐⭐⭐</td>
<td>⭐⭐⭐⭐⭐</td>
</tr>
<tr>
<td>December 2016</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Each category uses a five-star rating with 0.5 increments. These categories correspond to different aspects of a listing: some guests care more about services (e.g., cleanliness) whereas others care more about the intrinsic characteristics of the property (e.g., location). While the intrinsic characteristics cannot be changed by hosts, better services can always be provided to improve the other ratings. To capture the service level provided by the hosts, we average service-related ratings, i.e.,

\[
\text{Service} = \frac{\text{Cleanliness} + \text{Accuracy} + \text{Communication} + \text{Arrival}}{4}
\]

- **Photos:** Among all self-provided information, photos are critical for a listing. Unlike the unverifiable text information, the photos serve as a better means for guests to assess the value of the property. Airbnb suggests that “You need at least one photo in order to list a space, but we recommend you upload at least 10 - enough to show potential guests a thorough view of the space they’ll get to use if they stay with you.” In the present research, the variable Photos represents the number of photos attached to a single listing, as a proxy of the amount of information that a host provides to guests.

- **Text Length:** Like photos, descriptions of a property can also be posted by the host. The variable Text Length represents the number of characters in the text description, as another measure of the amount of information provided.

- **Competition:** Competition matters. A host’s behavior is likely to be affected by the competition from other Airbnb listings. Airbnb does not directly provide us with information on competition. It is calculated based on the location (i.e., latitude and longitude) of the listed properties. Namely, competition refers to the number of other Airbnb listings within half-mile distance from the focal listing. Since the original variable is large, it is then normalized to mean 1 in follow up studies.

- **ID:** At the time when the data was collected (November 2015), hosts could choose, at their own will, whether or not to provide their verified ID to the platform. Providing verified ID later became a prerequisite for listing a property on the platform. In this study, we use Verified ID to represent that a host voluntarily provided his or her ID completing the listing procedure.

- **Zillow Rent Index (ZRI):** The Zillow Rent Index (ZRI) represents the house rental price of September 2016. It tracks the monthly median rent in particular
geographic regions by ZIP code. The ZIP code data is then matched with the location of the Airbnb listings to create a ZRI for each listing. This data will later be used in the study to control the endogenous price effect.

- **Property, Room and Bed Types:** Each Airbnb property belongs to one of several property types - e.g., Apartment, House, Loft, Condominium, Bed and Breakfast, Cabin, and Dorm. For this research, we construct two dummies that stand for apartment and house respectively. As regards room types, there are three types: namely Entire Home/Apt, Private Room and Shared Room. As regards bed types, there are Real Bed, Airbed, Couch, and several smaller types. All these three variables are treated as fixed effects in this research.

- **Capacity:** This variable captures how many people that a property could accommodate. As we do not observe the size of the property, this variable is used as a proxy of the size.

- **Minimum Stay:** Hosts could set the minimum number of nights that a guest has to stay. Similarly, maximum stay can also be set. However, this feature is rarely used and is thus excluded from the study.

- **Cancellation Policy:** Airbnb allows hosts to choose amongst three standardized cancellation policies (Flexible, Moderate, and Strict) that we will enforce to protect both guests and hosts alike. For example, under the Flexible cancellation policy, guests could get full refund for cancellation made one day prior to arrival. Hosts could also adopt a Super Strict cancellation policy. However, this policy only applies to special circumstances and is by invitation only (only less than 0.1% percent of the properties deploy the super strict cancellation policy).

Table 4.1 presents selected summary statistics for the key variables in the dataset. Note that Competition is normalized to mean 1 by dividing 313.3, the average number of Airbnb neighbors a property has within half-mile distance.

### 4.5 Empirical Analysis

In this section, we study the behavior differences between different types of hosts on the Airbnb platform. When studying their behaviors, we focus on the following dimensions: price, service, information, and competition. While most features of a property (location, size etc.) are exogenous and are not affected by its hosts, the first three dimensions
Table 4.1: Data Summary

<table>
<thead>
<tr>
<th>Statistic</th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Photos</td>
<td>32,320</td>
<td>14.809</td>
<td>10.642</td>
<td>1</td>
<td>197</td>
</tr>
<tr>
<td>Text Length</td>
<td>32,320</td>
<td>1761.07</td>
<td>1507.72</td>
<td>3</td>
<td>27530</td>
</tr>
<tr>
<td>Reviews</td>
<td>32,320</td>
<td>19.214</td>
<td>28.951</td>
<td>0</td>
<td>413</td>
</tr>
<tr>
<td>Capacity</td>
<td>32,320</td>
<td>2.837</td>
<td>1.557</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>Price</td>
<td>32,320</td>
<td>134.568</td>
<td>175.821</td>
<td>4</td>
<td>8,400</td>
</tr>
<tr>
<td>ID</td>
<td>32,320</td>
<td>0.740</td>
<td>0.439</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>ZRI</td>
<td>32,320</td>
<td>3.242</td>
<td>1.410</td>
<td>0.530</td>
<td>6.482</td>
</tr>
<tr>
<td>Service</td>
<td>32,320</td>
<td>4.625</td>
<td>0.428</td>
<td>1.000</td>
<td>5.000</td>
</tr>
<tr>
<td>Minimum Stay</td>
<td>32,320</td>
<td>2.508</td>
<td>2.890</td>
<td>1</td>
<td>180</td>
</tr>
<tr>
<td>Competition</td>
<td>32,320</td>
<td>1.000</td>
<td>1.027</td>
<td>0.000</td>
<td>5.522</td>
</tr>
</tbody>
</table>

(price, service, and information) are with the hosts’ capacity. In addition, competition from other properties can directly affect a host’s behavior.

**Pricing Decisions**

Pricing is one of the most important decisions that a host has to make. As discussed in Section 4.3, the price charged to guests may be affected by the types of hosts. Amateur hosts who run small-scale business are more inclined to charge higher prices than professional hosts who run large-scale business. We adopt the following empirical specification to test that hypothesis.

\[
\log(\text{Price}_i) = \beta_0 + \beta_{\text{Professionality}_i} + \beta_{\text{Service}_i} + \beta_{\text{Photos}_i} + \beta_{\text{ZRI}_i} + \gamma X_i + \epsilon_i
\]

where *Professionality* is the independent variable that we are interested in. Recall that Professionality is the logarithm of the number of properties that the same host manages. When a host manages a great number of properties, he or she is more likely to run Airbnb as a professional business, and is less likely to be biased by the mere ownership effect. Hence, we expect $\beta_H$ to have a negative sign here.

In the empirical model above, Service captures the service effort that a host puts into the property, and Photos, the number of photos that a host posts, captures the amount of information provided. Moreover, $\text{ZRI}_i$, the Zillow Rent Index, captures the rental price of the local neighborhood and reflects the location value of the neighborhood. $X_i$ includes all the property specific control variables such as the amenities and property types. Location fixed effects are also included. $\epsilon_i$ is the error term.
Then, we use OLS to estimate the models, and the results are presented in Table 4.2.

<table>
<thead>
<tr>
<th></th>
<th>Log Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Professionality</td>
<td>−0.015***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>Service</td>
<td>0.077***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>Photos</td>
<td>0.003***</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
</tr>
<tr>
<td>Text Length</td>
<td>−0.000001***</td>
</tr>
<tr>
<td></td>
<td>(0.000000)</td>
</tr>
<tr>
<td>ZRI</td>
<td>0.139***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
</tr>
</tbody>
</table>

Observations: 32,320
R²: 0.622
Adjusted R²: 0.621
Residual Std. Error: 0.311 (df = 32242)
F Statistic: 688.474*** (df = 77; 32242)

*Note: *p<0.1; **p<0.05; ***p<0.01

The results presented in Table 4.2 provide several insights. The coefficient of Professionality is negative and significant, implying that, when a host manages a large number of properties, he or she is likely to charge lower prices. This observation is consistent with H1: due to the mere ownership effect, amateur hosts running small-scale business value their own properties more than that others do. Regarding professional hosts running large-scale business, their properties are originally intended for rent, and thus they are less likely to be affected by the mere ownership effect, and hence their prices are lower.

The other results in Table 4.2 are straightforward: the host is likely to charge a higher price when better services or more information is provided, or when the property is located in an expensive community. These results are consistent with our expectations, despite that there is no causal relationship between.

**Service Effort**

As discussed in Section 4.3, professional hosts who run large-scale business have more properties to manage but have limited resources, and thus in average they may put less effort into a property than that amateur hosts who run small-scale business do.
To test this theory, we use service rating as a proxy for service effort. Recall that the service level is the average of the four service related component ratings, namely Cleanliness, Accuracy, Communication, and Arrival (i.e., check in). The service level in each component is between 1 and 5, with 0.5 increments. The empirical specification we use to predict the service effort takes the following form.

\[ \text{Service}_i = \beta_0 + \beta_{H}\text{Professionality}_i + \beta_P\log\text{Price}_i + \beta_RZRI + \gamma X_i + \varepsilon_i \]

Then, we estimate the model and present the results in Column (1) of Table 4.3.

<table>
<thead>
<tr>
<th></th>
<th>Service</th>
<th>Strictness</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Professionality</td>
<td>-0.090***</td>
<td>0.222***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Log Price</td>
<td>0.134***</td>
<td>-0.032**</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>ZRI</td>
<td>-0.031***</td>
<td>0.029***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Observations</td>
<td>32,320</td>
<td>32,320</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.112</td>
<td>0.149</td>
</tr>
<tr>
<td>Adjusted (R^2)</td>
<td>0.110</td>
<td>0.148</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

Column (1) of Table 4.3 shows that amateur hosts who run small-scale business put significantly more service effort than that professional hosts who run large-scale business do. We further tested the effect of host types on each individual component of the service rating (e.g., cleanliness) and the results remained the same. These results support Hypothesis 2, suggesting that, amateur hosts who run small-scale business will put more effort into managing a property.

The service effort to manage a property is also reflected by its cancellation policy. If a listing has a flexible cancellation policy, guests will cancel their bookings more frequently. Consequently, more effort, such as rescheduling and searching for new guests, is required. However, the property with a flexible cancellation policy could attract more guests. For amateur hosts who run small-scale business, they have enough time and effort to deal with these problems, and are therefore more likely to implement the flexible cancellation policy. To test this hypothesis, we encode a new dependent variable, Strictness. It equals to 1 when the cancellation policy is flexible, 2 for moderate cancellation policy,
and 3 for all other cancellation policies (strict, super strict, non-refund). The results are summarized in Column (2) of Table 4.3.

The results show that amateur hosts who run small-scale business do implement more flexible policies, thereby the results support Hypothesis 3. Together, these results clearly indicate the differences in service provision between the two types of hosts in the Airbnb rental market.

### Information Disclosure

The effect of host types on the provision of information is unclear based on the existing analysis. On the one hand, amateur hosts who run small-scale business tend to provide more information because they have more effort (allocated to each property). On the other hand, professional hosts who run large-scale business tend to provide more information because they can benefit from their expertise and knowledge as well as the economies of scale. In other words, professional hosts who run large-scale business have lower information disclosure costs. The exact sign of the coefficient of Professionality hinges on the combination of the two forces. To explore the relationship, we choose the number of photos and the length of text descriptions that a host posts on the listing webpage as the dependent variables to examine the effect. The results are presented in Table 4.4.

**Table 4.4: Owner types and information disclosure**

<table>
<thead>
<tr>
<th></th>
<th>Photo (1)</th>
<th>Textlength (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Professionality</td>
<td>1.029***</td>
<td>62.146***</td>
</tr>
<tr>
<td></td>
<td>(0.108)</td>
<td>(15.513)</td>
</tr>
<tr>
<td>Log Price</td>
<td>2.537***</td>
<td>−15.186</td>
</tr>
<tr>
<td></td>
<td>(0.168)</td>
<td>(24.133)</td>
</tr>
<tr>
<td>ZRI</td>
<td>−0.634***</td>
<td>−43.312***</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(8.709)</td>
</tr>
<tr>
<td>Observations</td>
<td>32,320</td>
<td>32,320</td>
</tr>
<tr>
<td>R²</td>
<td>0.217</td>
<td>0.191</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.215</td>
<td>0.189</td>
</tr>
</tbody>
</table>

*Note:* *p<0.1; **p<0.05; ***p<0.01

In Table 4.4, for both dependent variables, the coefficients of Professionality are positive and significant, showing that amateur hosts who run small-scale business provide
less information than that professional hosts who run large-scale business do. This finding is in favor of Hypothesis H4b. Here, the advantage requires through expertise and economies of scale overcomes the effort limitation.

The role of competition

In section 4.3, we hypothesized that professional hosts running large-scale business respond more effectively to competition because (1) competition reduces the profitability of a property and return on effort and (2) professional hosts are informed about competition whereas amateur hosts are usually unaware of the level of competition. To test this hypothesis, we use service, photos, and text length as our dependent variables, assuming that proving more services or more information requires more effort. The results are presented in Table 4.5 below.

<table>
<thead>
<tr>
<th>Table 4.5: How different types of agents respond to competition</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Service</td>
</tr>
<tr>
<td>(1)</td>
</tr>
<tr>
<td>---------------------------------------------------------------</td>
</tr>
<tr>
<td>Professionality</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Competition</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Log Price</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>ZRI</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Professionality $\times$ Competition</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>$R^2$</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

From Table 4.5, we can see that the effect of competition varies for different types of hosts: In the case of service, the coefficient of the interaction between professionality and competition is negative and significant. Meanwhile, the competition main effect is not significant. In other words, amateur hosts are rather “immune” to competition, whereas professional hosts respond to competition by putting less effort. These results provide
direct support for Hypothesis 5, suggesting that professional hosts are more aware of the market conditions.

The effect of competition on information provision, however, is not significantly different between the two types of hosts. This is potentially because posting photos and writing descriptions are one-shot decisions, and the cost is more related to the skills and expertise that the host possesses.

4.6 Concluding Remarks

In this chapter, we study the behavioral differences between amateur hosts who run small-scale business and professional hosts who run comparatively large-scale business in the rental industry. The comparison is hard in the typical rental markets where the vast majority of properties are managed by professional agents. We overcome this problem by using listing data from the Airbnb platform, a peer-to-peer property rental website, on which hosts could easily manage their properties without having to resort to professional agents. The analysis results suggest that, first, compared with professional hosts who run large-scale business, amateur hosts who run small-scale business tend to charge higher prices, thereby it reflects the mere ownership effect. Second, professional hosts who run large-scale business put less effort to provide service, potentially because their effort is spread too thin. Third, in contrast to the second result, professional hosts running large-scale business post more photos and write longer descriptions. This is possibly because they have advanced knowledge and expertise about the rental market. Besides, they can also benefit from the economies of scale. Finally, being better informed about the market and faced with the challenge of allocating limited effort to a large number of properties, professional agents respond more effectively to competition - they put much less effort when faced with competition. Together, these results help us gain a preliminary understanding about the behaviors of different types of hosts in the online peer-to-peer property rental market.

This chapter provides several considerations that could be helpful to Airbnb hosts, the Airbnb platform and the legislative authorities. First, a host needs to know the potential benefits and risks when he or she wishes to scale up and run Airbnb as a professional business. Second, when implementing policies, the platform should be cautious about the differences between different types of hosts. Third, the legislative authorities may take the differences between professional and amateur hosts into consideration when regulating the platform - in particular, whether or not to view Airbnb as a professional hotel business.
The work also has its limitations. In the data, we only observe the supply side (i.e., hosts), but do not observe the characteristics and behaviors of individual consumers. The differences between professional and amateur hosts managed properties may be also affected by the consumers that they target. For example, the amateur hosts managed properties may attract more leisure travellers and young people, who value the experiences of staying with the hosts. By contrast, the professional hosts managed properties may attract business travellers. Subsequently, these consumers may have different characteristics, and the hosts should implement different marketing strategies on them.

A possible way to overcome the limitation is to obtain more data on individual consumers. Also, it may help to dig deep into the reviews to see if there are any differences in consumer perception between the two types of properties.
Bibliography


Davidson N. 2013. Your Kickstarter is 85% more likely to succeed with a video. https://mwpdigitalmedia.com/blog/without-a-video-your-kickstarter-project-will-probably-fail/.


Jalali NY, Papatla P. 2016. The palette that stands out: Color compositions of online curated visual UGC that attracts higher consumer interaction. *Quantitative Marketing and Econ.*, 14(4), 353-384.


Zervas, G., Proserpio, D., and Byers, J. 2015. A first look at online reputation on Airbnb, where every stay is above average. Working Paper, Boston University Questrom School of Business.


