Essays on Emerging Digital Platform Policies

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Abstract

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This dissertation focuses on emerging policies and strategies on different digital platforms. In three different contexts, the charitable crowdfunding, the streaming media, and the knowledge sharing platform, I study the impact of platform's policies and how the platforms should design their policy. In the first essay, I study the effect of match funds on income inequality on an educational crowdfunding platform. I build a structural model to characterize utility of donation for donors. I find that people prefer to contribute to projects with match offers, and those high-poverty projects can benefit the most from match offers. In the second essay, I investigate the content producing policies for streaming media companies. I build an analytical model and maximize the customer engagement to find optimal policies. I find that the coverage intervals of products should overlap to reach optimal profit, and products should be placed closer where the density of customers is higher. In the third essay, I examine the effect of auditions and voice features on a payment-based knowledge sharing platform. I extract voice features leveraging natural language processing techniques and construct an aggregated demand model to estimate the effects. I find that audition can boost demand, especially for those highly relevant auditions. Voice features also play important roles in attracting customers, and I also provide several related suggestions for live contributors.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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Chapter 1. INTRODUCTION

Digital platforms are still growing at a high speed in past few years. Accompanying their growth, platforms design and implement various policies to attract customers and boost demand. My studies focus on these emerging policies on different digital platforms. To be specific, I study the impact of match funds on charitable crowdfunding platforms, the optimal content producing strategies for streaming media companies, and the effect of auditions and voice features on knowledge sharing platforms.

In Chapter 3, I study how match offers can affect the donation process of projects on an educational crowdfunding platform. The United States has the highest level of inequality of any rich OECD country, and past studies indicate a lack of effective policies and spending on behalf of low-income families (Smeeding 2005). In this study, I examine the effect of "*match funds*" on income inequality on an educational crowdfunding platform. Match funds are adopted by donation-based crowdfunding platforms such that institutional donors commit to match the contribution of individual donors at a given rate. It is not only a popular fundraising strategy to activate collaboration among donors but also a policy that can be initiated by the fundraising platform to possibly address the issue of income inequality. Our context highlights the provision of poverty information for educational projects in the crowdfunding platform to understand whether match funds work better for fundraising projects that support low-income families. I first perform a reduced-form study to find that match funds effectively help projects to reach the fundraising goals. More importantly, match funds work better for projects that support low-income families. To understand the mechanisms underlying such discoveries, I devise a structural model to understand individuals' fund allocation decisions. I find that people prefer to support projects with match offer than those without. Generally speaking, match offer has greater benefits when being applied to high-poverty projects. This merit mainly comes from a higher donation probability of high-poverty projects, whereas the average donation amount has no salient difference. Further analyses show that it is the experienced donors who strictly prefer projects with match funds. New donors do not show particular interest in match funds and may even prefer projects without match funds. My discoveries have implications for policymaking, platform design, and fundraising managers who struggle to best utilize promotional strategies to improve fundraising performance.

In Chapter 4, I strive to find the best policy to produce contents for streaming media companies. Streaming media companies have changed how contents are consumed, produced, and delivered. This research develops a theoretical model on optimal content policies for streaming media companies in order to maximize customer engagement. I have the following interesting findings. First, in contrast to the results in prior literature that firms produce just enough products without overlapping product coverage intervals, we show that overlapping coverage intervals and placing products closer can be a better policy for engagement-based firms. Second, under engagement-based model, more contents are produced when the value of the contents is large to the customers or the profit margin in selling content is less than a certain threshold. Third, on learning the distribution of its customers, the media firm will always overlap product coverage intervals and place programs closer when the distribution density is higher. Additionally, in facing the tradeoffs of content quality and quantity, the firm should use a higher-quality and low-variety policy for high density clusters but a lower-quality and high-variety policy for low density clusters. Furthermore, when customers consume multiple shows in a period, a better policy is to produce TV shows or series with multiple episodes rather than individual movies. This study contributes to the literature on digital media, and the results provide interesting and insightful implications for streaming companies.

In Chapter 5, I investigate the impact of auditions and voice features on a payment-based knowledge sharing platform. Paid knowledge has become a new trend in knowledge sharing platforms. Experts on the platforms make money by giving lectures to audience in the community. Although some studies have been carried out on demand estimation of knowledge products, little attention has been paid to the effectiveness of audition as well as the content and voice features it contains. Leveraging a unique dataset from one of the largest payment-based knowledge sharing platforms in China, we conduct an aggregated demand estimation model and extract various voice features from the audition using techniques from natural language processing and signaling processing. I conclude that audition can indeed boost the consumer demand especially with highly relevant audition content. Suggestions offered for practitioners that it is better to give shorter speech with rich information, and the duration of one piece of audio should not be too long. Noise-free, soft, but full-of-variety voice is preferred by consumers. And female voice shows a small advantage in attracting demand. My findings contribute to the emerging literature of knowledge product as well as the impact of voice in online marketplace.

Chapter 2. LITERATURE REVIEW

In this section, I review the literature in relevant fields of my studies. Section 2.1 provides the related literature in inequality, crowdfunding, and match funding. Section 2.2 shows the related literature in digital media, consumer engagement, subscription models, and product assortment. Section 2.3 reviews the related studies on online knowledge sharing, product sampling, voice features and user behavior.

2.1 MATCH FUNDING AND INEQUALITY

2.1.1 *Inequality*

According to extant literature, charitable giving is highly influenced by the degree of inequality (Bekkers and Wiepking 2011; Fehr and Schmidt 1999). Donations are higher in time periods (Schwartz 1970) and states with more poverty (Abrams and Schmitz 1984; Amos 1982). Fehr and Schmidt (1999) and Bolton and Ockenfels (2000) propose the inequality aversion theory – donors incur disutility from inequality which motivates altruism in turn. Some studies also argue that donors wish to make the distribution of wealth more equal to improve social justice (Furnham 1995; Todd and Lawson 1999). Moreover, inequality can increase charitable giving by eliciting empathy of donors towards fundraisers (Duquette and Hargaden 2021). Andreoni and Rao (2011) shows that communication between donors and fundraisers which improves empathy of donors can help charitable campaigns become more successful. Besides, the effect of inequality can also be related to donors' consideration on reputation. Contributing to charitable projects is usually viewed as a positive and prosocial behavior that can improve the reputation of donors, and this reputation effect is greater when donation reduces inequality (Brickman and Bryan 1975).

Different from the above-mentioned works, my first study focuses on the effect of inequality under match funding strategy. I directly analyze the effectiveness of match funds by comparing donor preferences towards high-poverty and low-poverty projects with match funds.

2.1.2 *Crowdfunding*

A large and growing body of literature has investigated the mechanisms of crowdfunding. Previous studies have investigated how project-related factors (Mollick 2014; Doosti and Tan 2018) and fundraiser-related factors (Mollick 2014; Burtch et al. 2015) impact fundraising performance. Individual funding behaviors are also studied from the perspective of rational and irrational herding (Zhang and Liu 2012; Burtch et al. 2013), home bias (Lin and Viswanathan 2016), and the deadline effect in the fundraising process (Kuppuswamy and Bayus 2018). Another stream of works has looked at information control policy, i.e., whether to hide a certain piece of information for public consumption (Burtch et al. 2015; Burtch et al. 2016; Zhou et al. 2021; Zhou et al. 2019), fundraising mechanism design (Xiao et al. 2017), and user retention (Xiao and Yue 2021).

These studies cover four types of crowdfunding platforms: donation-based, reward-based, lending-based, and equity-based (Hemer 2011). Our research falls into the category of donation-based crowdfunding or charitable crowdfunding. In particular, my first essay is related to a stream of works looking at how early contributions affect other donors' subsequent charitable giving behavior. Multiple studies have found that projects that gain large support from the very beginning stage have a higher chance of success (Bøg et al. 2012; Burtch et al. 2013; Koning and Model 2017). On the other hand, Burtch et al. (2013) observe the crowding-out effect among contributors on a crowdfunding platform that supports online journalism, consistent with predictions in the economics literature (Andreoni 1989; 1990). Tan et al. (2016) examine the reputation, peer effects, and popularity effects leveraging a dataset with individual donation records. They find that while peer effects are significantly positive, leaders (i.e., early donors) may be attracted to unpopular projects, taking the edge of the network effects. These works discuss how an individual's contribution is possibly affected by the contribution of others, which is highly related yet still different from our study.

My first study is also related to crowdfunding literature in terms of platform design (Kenney and Zysman 2016; Allon and Babich 2020; Chen et al. 2020). Crowdfunding platforms can employ proper campaign designs and pricing strategies to boost backers' contribution (Alaei et al. 2016; Zhang et al. 2021; Burtch et al. 2021). Van Alstyne et al. (2016) argue that the success of online platforms hinges on the value they created for different user groups. In a two-sided market like crowdfunding, both demanders and suppliers of funds are essential user groups that derive positive network externality from each other (Kenney and Zysman 2016; Allon and Babich 2020). We contribute to the studies of platform design by showing how demanders and suppliers of funds are affected by the promotional strategy of match offers differently.

Out of all the past literature, my first study is most closely related to Song et al. (2022). Song et al. (2022) also investigate the DonorsChoose platform, and they categorize donor motivation into altruistic and egoistic to predict the acts of giving. They adopted a neoclassical consumer theory to model the utility toward different motivations of charitable giving and maximizes the overall utility under budget constraints to estimate individual preference (Barnett and Serletis 2009). This theory is considered the best developed formal theory of rationality. My first study follows this neoclassical economics idea to reveal donors' preference in charitable projects with and without matched funds.

2.1.3 *Match Funding*

My first study is also related to the studies of match funding, which is also termed "leadership donations" in the economics literature (Karlan and List 2007). Formally, a match offer is defined as a conditional commitment by a leadership donor to match the contributions of others at a given rate, up to the maximum amount the leadership donor is prepared to give (Rondeau and List 2008, p264). When the leadership donors are the government, match offers become government grants, which has been shown to crowd out the individual provision of charitable giving both theoretically (Warr 1982; Roberts 1984) and empirically (Abrams and Schmitz 1978; Steinberg 1986). Further, Schiff (1985) offers empirical evidence that government spending will crowd out individual giving, only if it is in the form of a substitute of individual donations, such as direct cash transfers to the needy. Other types of government spending, such as those on social services, will even encourage individual giving. Match funding is also a prevalent corporate social responsibility (CSR) activity performed by corporations. Many companies offer matching subsidies to match the charitable contributions of their employees as an employee benefit to foster their willingness to donate (Meier 2007) and enhance their loyalty (Lee et al. 2013). In addition, companies conduct cause-related marketing by matching the charitable contributions of their customers or linking charitable giving to the customers' purchase of the company's products or services (Varadarajan and Menon 1988). The rise of social media further provides opportunities for corporations to build a positive image (Porter and Kramer 2006) when they roll out matching campaigns that are open to the public, especially when such campaigns are virally spread on social media.

Regarding the impact of match offers, no conclusive results have been reached. On the one hand, much of the prior research has found match funding to have a positive impact on individual contributions (Eckel and Grossman 2003; Eckel and Grossman 2008; Chen et al. 2005; Meer

2017). For example, Eckel and Grossman (2003; 2008) find the advantage of match offers in encouraging donations, compared to rebate subsidies with a theoretical equivalent price. Chen et al. (2005) reveal that match offers could increase the response rate of online donors. On the other hand, the evidence on the crowding-out effect of match funding should not be neglected (Huck and Rasul 2011; Null 2011). For instance, Huck and Rasul (2011) find that the match offer is dominated by the lump-sum leadership gift alone. Needless to say, some works find a null effect from match offers (Karlan et al. 2011; Rondeau and List 2008). For example, Rondeau and List (2008) find that the matching gift is not useful at all, in stark contrast with the efficacy of the lump-sum seed money unconditionally given to the charities. In addition, there are many studies with mixed results (Karlan and List 2007; Meier 2007; Huck et al. 2015). A summary of the inconclusive results is presented in Table 2.1.

Table 2.1. Summary of Match Funding Literature

Literature	**Matching Scheme**	**Results**	**Methodology**	**Context**
Eckel and Grossman (2003)	1:4 and 1:3	Contributions are significantly higher with matching subsidies than with rebate subsidies.	Lab experiment	–
Eckel and Grossman (2008)	1:4 and 1:3	Matching grants have up to three times greater impact on donations than rebate subsidies with a theoretical equivalent price.	Field experiment with mailings	Minnesota Public Radio
Chen et al. (2005)	VCM (voluntary contribution mechanism), seed money, premium (gift offered to donors), and 1:1 matching	With similar gift size across mechanisms, seed and matching schemes generate a significantly higher user click-through response rate than premium and VCM schemes.	Web-based online field experiment	Internet Public Library website
Meer (2007)	1:1	Although matches increase giving, they do not appear to crowd out giving to similar ones.	Natural experiment	Crowdfunding platforms
Meier (2007)	1:4 and 1:2	Immediate positive effect of match funding in the short run, whereas contributions decline after the termination of the program.	Field experiment with mailings	Social funds at a university
Karlan and List (2007)	1:1, 2:1, and 3:1	Match offer increases both the individual contribution and the donation probability, but only among some but not all groups of potential donors. A larger match	Field experiment with mailings	A liberal nonprofit organization focusing on civil liberties

		ratio has no additional impact relative to a smaller match ratio.		
Karlan et al. (2011)	1:1 and 1:3	The matches have an almost null effect on individual contributions in general. A small match ratio can be more effective than the larger one due to donor heterogeneity.	Field experiment with mailings	An organization focusing on civil justice issues
Rondeau and List (2008)	1:1	The matching gift does not increase contributions, whereas the lump-sum seed money has a significant positive impact.	Field experiment with mailings and lab experiment	Sierra Club supporting K-12 education
Huck and Rasul (2011)	1:1 and 1:2	Match funding partially crowds out the actual donation given, excluding the match. Simply announcing a lead gift without match funding is the best strategy for charities.	Field experiment with mailings	Bavarian State Opera benefiting children
Huck et al. (2015)	1:1, 1:2, nonlinear matching, and fixed gift matching	A nonconvex matching scheme with fixed gifts has a positive impact on individual contributions, but the pure lead gift is still the optimal strategy if viable.	Field experiment with mailings	Bavarian State Opera benefiting children
Null (2011)	Various cases for three charities	Donors tend to simultaneously contribute to multiple charities even with different matching rates, which is evidence of warm glow utility.	Lab experiment	–

As pointed out by Levitt and List (2007), the impact of match offers is highly contextual, and investigations are needed for different contexts. Extant studies have investigated the traditional contexts such as mail-in appeals (Karlan and List 2007; Karlan et al. 2011; Huck and Rasul 2011), door-to-door fundraising (Landry et al. 2010), and radio fundraising (Shang and Croson 2009). My first study follows Levitt and List's (2007) call to further examine the impact of match offers in an innovative fundraising context – the charitable crowdfunding platform. Among the previous studies on match offers, Meer (2017) is most relevant to our work in that it shares the same context of donation-based crowdfunding. He concludes that match offers encourage donations to the focal project without crowding out charitable contributions to other similar projects. My work is different from Meer's by focusing on the impact of match funds on income inequality. I leverage a neoclassical structural model to formulate donor utilities toward projects with and without match funds and in regions with different poverty levels, and then relate their preferences to donation probability and donation amount.

2.2 Streaming Media and Product Assortment

2.2.1 *Digital Media*

Prior researches have studied the digitization of various media such as music (Danaher et al., 2014), video and movie (Waldfogel 2009), and books (Hao and Fan 2014). The transformation from physical product to digital product induces new issues in management and thus becomes an important stream of literature. Fan et al. (2007) give suggestions on when digital media should sell programs online or offer advertising options with respect to the content quality and access cost. Hao and Fan (2014) compare the two pricing models of e-book industry – agency model and wholesale model, and then analyze the underlying mechanisms as well as the social welfare. Hashim et al. (2019) analyze the cannibalization effect that occurs between digital rentals and offline DVD purchases. Among the abundant literature of digital media, research on streaming media is the most relevant to our current study. Datta et al. (2018) show that adoption of streaming vastly raises consumption from users in the very early stage, and the behavior of music discovery gradually grows as well. Ananthakrishnan et al. (2016) uncover the salient substitution effect between streaming channel and conventional paid channel. However, these studies all focus on the consumer behavior on the demand-side, the strategy of streaming firms has not garnered much attention especially on the product assortment planning and personalization. My second essay helps to answer this crucial question by considering the streaming media platforms who make their own movies and shows.

2.2.2 *Consumer Engagement*

Consumer engagement, as an important customer-centric measure to evaluate the effectiveness of marketing, has long been investigated in the literature of consumer relationship management (Pansari and Kumar 2017; Kumar and Reinartz 2016). After forming satisfying relationships and emotional bonds with a firm, consumers will contribute to the revenue of the firm by direct purchase, referring and offering feedbacks (Pansari and Kumar 2017). Consumer engagement is essential to the profitability of firms. Bolton and Lemon (1999) suggest that evaluations of the fairness of the exchange affects overall satisfaction, leading to different levels of purchase behavior. Therefore, many researchers have designed and evaluated various strategies considering the factor of consumer loyalty for firms to gain higher profit and better revenue management (Caminal and Matutes 1990; Caminal and Claici 2007; Chen and Pearcy 2010). For example, Caminal and Matutes (1990) assumes that firms can lower the switching cost for loyal consumers, by pre-committing a future price discount. Chen and Pearcy (2010) develops a dynamic pricing strategy to lure consumers to switch brand as well as to retain them by offering rewards. My second study contributes to the stream of consumer engagement literature by coming at it from another angle, that is, product assortment planning and personalization. I model consumer engagement and involves it in the objective function of profit maximization.

2.2.3 *Subscription Models*

Differentiated subscription pricing based on user types and usage has been investigated as a pricing strategy to improve profits (e.g., Sundararajan 2004, Cachon and Feldman 2011). The advantages of subscription pricing over pay-per-use pricing are manifold: First, the reasons for customers to choose subscription include overestimation of usage and avoiding the hassle of multiple payments (Cosgrove and Linhart 1979; Garfinkel and Linhart 1979). Thus, customers are willing to pay even more than under the pay-per-use scheme. Second, subscription pricing with usage constraints reduces the uncertainty in demand which benefits the firm (Randhawa and Kumar 2008). Moreover, prior literature suggests that subscription pricing fits consumers with homogenous usage better (Bhargava and Gangwar 2016). And under subscription pricing scheme, which is similar to the advance-purchase pricing (e.g., DeGraba 1995, Xie and Shugan 2001), customers are more homogeneous towards the product value relative to the situation of pay-per-use, which resembles the spot market. There is large body of literature comparing subscription pricing with the pay-per-use pricing. Fishburn and Odlyzko (1999) establish a duopolistic model where one firm adopts subscription pricing, while the other implements pay-per-use pricing. Cachon and Feldman (2011) build a queueing-based model to compare these two pricing strategies in the presence of congestion. Although the literature on subscription model is well-established, all of them adopt a traditional profit-driven setting, which is not suitable for streaming media firms. In real business scenarios, streaming media cares more about long-term user growth and uses a flat subscription pricing, encouraging users to consume as much content as possible. Thus, my model does not incorporate the pricing of subscription model, but use an exogenous unit price since our focus is long-term customer engagement and satisfaction. With the simplification, my second essay generates insightful results on optimal policy of product assortment.

2.2.4 *Product Assortment*

Product differentiation and assortment literature originates from Hotelling's (1929) horizontal differentiation model, in which firms are located in an attribute space and individuals are uniformly distributed in the same space. The objective of product assortment problem is to find the number of products, their locations and the pricing strategy in equilibrium, as well as the resulting consumer welfare (Kök et al. 2015). Lancaster (1966, 1974, and 1979) extends Hotelling's model and provides solutions for optimal product differentiation in a locational model. Gaur and Honhon (2006) study assortment planning and inventory management using a location choice model. The study generalizes the Lancaster model by considering stochastic demand and non-uniform consumer preferences, and, nevertheless, retains the property of equally-spaced product locations. Mendelson and Parlakturk (2008) study the competition between a firm that chooses a set of product configurations and another firm which adopts a make-to-order mass customization strategy. Several studies focus on vertically differentiated market in which products have different quality levels (Mussa and Rosen 1978, Moorthy 1988, Krishnan and Zhu 2006), and others incorporate both dimensions (Neven and Thisse 1987, Cremer and Thisse 1991, Ferreira and Thisse 1996, Lacourbe et al. 2009). For example, Lacourbe et al. (2009) extends the early studies with both dimensions and examines the product assortment for a monopolist firm with both variable and fixed costs. Numerous studies have attempted to answer more specific questions of product assortment, including consumer substitution behavior, shelf space allocation, consumer's perception of variety, and demand learning under uncertainty (Sauré and Zeevi 2013). However, very little is known about optimal product assortment and personalization in streaming media. Given the never out-of-stock industrial attribute, the omnipresent subscription-based pricing and self-producing contents, streaming media firms are inherent different from traditional firms and thus need to make different assortment plans. Besides, I also examine the strategy and the corresponding improvement in consumer surplus when firms can leverage user data to learn consumer tastes.

To summarize, my second study fills the literature gap in several aspects. First, prior literature on digital media focuses on content pricing and consumer behavior transformation, but ignores the product/content development decisions. Second, prior studies with subscription model are all based on short-term profit maximization, while mine is in light of consumer engagement and satisfaction, thus more practically suitable to the context of streaming media firms. Lastly, I also contribute to the product assortment literature in operations management. Streaming media firms with never out-of-stock products, focus on customer engagement, and subscription-based pricing, are inherently different from traditional firms. My model, based on the horizontal differentiation model, is tailor-made to the streaming media firms and thus generates some insightful findings.

2.3 Online Knowledge Sharing

2.3.1 *Online Knowledge Sharing*

Online knowledge sharing platforms allow users to contribute content, ask and answer questions, vote for others' answers, and follow other users. Prior studies on online knowledge sharing mainly focus on contributors' performance (Jin et al. 2020), quality control of Q&A (Ravi et al., 2014; Adamic et al., 2008), and social network in the community (Gray et al., 2013).

Many recent studies investigate the payment-based knowledge sharing platforms, as the concept of "pay for knowledge" springs up. Several papers examine the consumer payment decisions on the platforms (Jin et al. 2019, Cai et al. 2018, Shi et al. 2020). Jin et al. (2019) conduct an aggregated demand estimation model (BLP) to examine the various factors of consumer decisions. They find the gap in consumer purchase decisions on pre- and post-broadcast markets. Cai et al. (2018) concentrate on the payment behavior from the perspective of customers' continued use intention. Consumer satisfaction is another central issue analyzed by many researchers (Fu et al. 2020, Zhang et al. 2019). Fu et al. (2020) investigate how consumers on the platform form satisfaction from their initial and post-usage expectation, based on expectation-confirmation theory. Zhang et al. (2019) examine the factors of customer satisfaction on paid knowledge. They find significant customer heterogeneity in their willingness to pay. Specifically, expertise customer with rich domain knowledge are less sensitive to the price. Spillover effect also exists in paid knowledge communities. According to Yan et al. (2017), the financial incentives on the paid knowledge sharing activities can motivate users' free sharing behavior, whereas no impact has been found in users' knowledge seeking behavior.

However, no prior research pay attention to the impact of free sampling on consumers' decision-making process, especially for audio-based paid contents. My third study plans to fill this gap by examining the voice features of the free audition.

2.3.2 *Product Sampling*

Product sampling has long been identified as an effective marketing technique (Jain et al. 1995, Montoya et al. 2010). On the one hand, offering free samples can mitigate consumers' pre-purchase uncertainty to persuade them to make periodic purchase for products like daily necessities (Jain et al. 1995). Information goods can offer free trials of certain period or basic version to consumers and persuade them to purchase complete version (Lee and Tan 2013, Niculescu and Wu 2010). On the other hand, product sampling also leverages the concept of signaling effect (Spence 1973). Consumers who do not receive free samples can also benefit from a lower level of asymmetry information, because only high-quality products prefer to offering free samples for consumers to experience (Lin et al. 2019, Liu et al. 2022).

There are three kinds of product sampling, offline sampling of physical goods (e.g. Jain et al. 1995, Montoya et al. 2010), online sampling of information goods (e.g. Lee and Tan 2013, Niculescu and Wu 2014), and online sampling of physical goods (e.g. Lin et al. 2019, Liu et al 2022). Our research belongs to the second kind, online sampling of information goods (i.e. contributors provide audio-based audition to potential consumers). Nevertheless, my research focus is not standardized information good like software, e-book, electronic music, etc. In my research context, the knowledge offered by contributors are the products, whose quality depends on the expertise and expressive ability of contributors. In other words, the consumers experience a higher uncertainty level on knowledge market. Thus, I expect that audition can play an important role in the customer decisions, and the effect can be moderated by the quality of audition. Different from previous studies, my third essay analyzes the voice features of free audition, since consumers can judge the quality of paid content based on the audio pieces.

2.3.3 *Voice Features and User Behavior*

The influence of voice cues has already studied in various domains including psychology (Mileva et al. 2020), politics (Tigue et al. 2012, Klofstad 2016) and marketing (Peterson et al. 1995). For example, Kendall (2009) shows that silent pause is a powerful signal of the speaker's confidence, while Guyer et al. (2019) finds that speech rate can enhance the perceived confidence level. Klofstad (2016) argues that lower pitch is more favorable in political voting, while in another study, it has been found that higher pitch can effectively grab the attention of audience thus female is more advantageous in this regard (Rodero et al. 2017).

The discipline concerned with voice cues is called paralinguistics (Schuller and Batliner 2013). Different from linguistics which focuses on the language structure, phonetics, and grammar, paralinguistics answers questions related to three phenomena, personality, emotion and affect. Personality includes long-term characteristics of a person (i.e., age, gender, confidence, etc.), while emotion denotes the short-term states (i.e., angry, happy, nervous, etc.). Affect is somewhere in between, a broader concept including persistent mood, interpersonal stances, and attitudes (Picard 1997). To automatically extract paralinguistic phenomena from speech, the classic method is to extract time-domain and frequency-domain low-level descriptors (LLDs) using signaling processing techniques (Schuller et al. 2011). These LLDs include fundamental frequency, loudness, voice quality related descriptors, etc. Then, we can take functions of those LLDs to generate higher level features capturing dynamics in the speech. After that, machine learning algorithms like classification methods and Hidden Markov Model (HMM) can be applied. Recent development of deep learning solves the problem from a different perspective by escaping the extraction of LLDs. For example, Lee et al. (2009) apply the convolutional deep belief networks (CDBNs) to raw spectrograms of speech data and generate high level features from the hidden layers for speech recognition tasks. My third study takes the first step to extract meaningful LLDs and involves it in the empirical model to find the impact of voice features. We leave the extraction of deep learning features for future research.

Chapter 3. MORE THAN DOUBLE YOUR IMPACT: AN EMPIRICAL STUDY OF MATCH OFFERS ON CHARITABLE CROWDFUNDING PLATFORMS

Crowdfunding is an emerging fundraising phenomenon defined as "a collective effort by individuals who network and pool their money together, usually via the Internet, to invest in or support the efforts of others" (Ordanini et al. 2011, p444). In 2020, 178,000 crowdfunding campaigns were launched worldwide, projecting a transaction value of $940 million, with $480 million raised in the United States. The predicted annual growth rate of crowdfunding market size is as high as 3.3% by 2025 (Statista 2021). Four types of crowdfunding (i.e., reward-based, equity-based, lending-based, and donation-based) dominate the market, and this study focuses on donation-based crowdfunding, where backers (or donors) make charitable contributions without expecting tangible returns. Through online donation-based crowdfunding platforms, schools, free software developers, environmentalist groups raise donations for charitable projects and causes; even government agencies resort to crowdfunding to raise funds for public facilities (Cason and Zubrickas 2019). As an example, the donation-based crowdfunding platform DonorsChoose has raised more than one billion dollars for more than one million projects, attracting over four million supporters and benefiting at least 624 thousand teachers by the end of 2020 (DonorsChoose 2021a).

Despite the success of donation-based crowdfunding, sustaining and encouraging charitable contributions is challenging (Althoff and Leskovec 2015). According to statistics reported by Nonprofit Source,[1] 62% of donors that support charitable projects on crowdfunding platforms are

[1] Nonprofit Source is an SEO agency for nonprofits. Its website is https://nonprofitssource.com/.

new. Our dataset further suggests that 70.7% of donors make only one charitable donation on DonorsChoose. This is due to the relatively high transaction cost of giving on the crowdfunding platform; instead of having nonprofit organizations distribute the funds among the needy, donors need to select their preferred charitable projects proactively and make donations (Alaei et al. 2016).

One potential solution to stimulate contributions on charitable crowdfunding platforms is utilizing the promotional strategy of match offers. A match offer is a widely adopted strategy in traditional charitable giving, whereby fundraisers partner with leadership donors to facilitate matching funds (Riganto 2018). Leadership donors can be wealthy individuals or organizations who commit to matching individual donations at a certain rate (Karlan and List 2007; Rondeau and List 2008).[2] For example, Google provided one million dollars in matching funds for DonorsChoose in 2015 and launched a 1:1 matching initiative, along with a promotional social media campaign with the hashtag #ForEveryKid (AndroidGuys 2015).

However, the academic effort dedicated to understanding match offers on online fundraising platforms is not on par with its rapid growth (Meer 2017). On the one hand, the existing works on the efficacy of match funding in stimulating individual donations find inconclusive results. Some studies found evidence that match funding can increase average individual contributions (Eckel and Grossman 2003; Eckel and Grossman 2008; Chen et al. 2005; Meer 2017), whereas others came to the opposite conclusion (Huck and Rasul 2011; Null 2011). This can be ascribed to different research contexts and heterogeneous populations (Levitt and List 2007), necessitating the study of match offers systematically in the context of charitable crowdfunding platforms. On the other hand, prior studies on traditional fundraising channel overlook the economic status of the

[2] When the leadership donors are corporations, such match offers are corporate social responsibility (CSR) activities that allow companies to boost their public image (Porter and Kramer 2006) and enhance employee loyalty (Lee et al. 2013).

beneficiaries, which is an important factor of donation contributions. It has been found that donations are significantly higher when facing higher degree of inequality (Bekkers and Wiepking 2011; Schwartz 1970; Abrams and Schmitz 1984; Amos 1982). To understand the interplay between match offer and poverty level of charitable projects can help platforms analyze the social value of match offer strategy.

Our study is designed to answer these questions: *(1) How do donors evaluate charitable projects with and without match offers differently? (2) How does the interplay of match offer and poverty level of charitable projects affect donors' preference? (3) Do such preferences differ between new donors and experienced donors?*

We leverage public data from DonorsChoose, a donation-based crowdfunding platform focusing on the education sector, to answer the above questions at an individual level, a market level, and a transaction level. DonorsChoose is ideal for this research purpose because it introduced match offers in 2007 and publicized donation transaction data for all the crowdfunding projects both before and after match offers were introduced. We perform a Heckman control function model and find that match funding can help the charitable projects reach the fundraising goal more easily. More importantly, match funds work better for projects that support low-income families. To analyze the underlying mechanisms, we devise a neoclassical model to identify donors' fund allocation decisions. We first analyze donors' differential preference toward matched and unmatched projects, and then incorporate the interplay between match offer and poverty level in our model. To be specific, we aggregate individual charitable contributions monthly after the introduction of match offers when individuals face the option of both matched and unmatched charitable projects. We then formulate a donor's utility function and solve the utility maximization problem to compare the donation preference between projects with different matching and poverty conditions.

Our results show that, on average, donors derive higher utility from contributing to matched projects than unmatched projects. After accounting for the different exposure of matched and unmatched projects, an average donor has a higher probability (13.6%) of donating to matched projects as compared to her probability of donating to unmatched projects (7.7%); the average donation amount is also larger for matched projects. Generally speaking, match offer has greater benefits when being applied to high-poverty projects. This merit mainly comes from a higher donation probability of high-poverty projects, whereas the average donation amount has no salient difference. Further analyses show that it is the large and experienced donors who strictly prefer projects with match funds. New donors do not show particular interest in match funds and may even prefer projects without match funds.

Last, we verify our discoveries using a transaction-level analysis. A transaction-level analysis provides direct evidence regarding the changes in average contribution size; more importantly, it allows us to account for the possibly systematic difference between charitable projects with and without match offers. Our transaction-level analysis reveals that the average donation amount increases for matched projects, corroborating our findings regarding donor preference.

Our study makes a substantial contribution to the existing studies on crowdfunding. The majority of past works on crowdfunding focus on the fundraising outcome and patterns of the fundraising process (Agrawal et al. 2015; Mollick 2014; Kuppuswamy and Bayus 2018; Vismara 2018). This study takes a unique perspective to directly investigate donor preference under the influence of the match offer, an emerging strategy to encourage donations on crowdfunding platforms. Unlike inherent project attributes, such as location, fundraising goal, and project type, match offers are sponsored by leadership donors and facilitated by the crowdfunding platform. As such, the match offer is a promotional strategy that can be easily implemented and utilized.

We also contribute to the policy to solve inequality in charitable giving context. Past studies indicate a lack of effective policies and spending on behalf of low-income families (Smeeding 2005). Although people tend to give more to those in higher degree of inequality, it is still hard for policy makers to speculate the flow of donations and confirm the help to those in urgent need. Our research is among the first to analyze the effectiveness of match funds when being applied to high-poverty and low-poverty projects on online charitable crowdfunding platforms. Our findings indicate that the match offer can not only serve as a promotional strategy for platforms, but also a useful strategy tool to mitigate the inequality issue in online charitable giving context.

This study also extends the existing works on charitable giving in economics. Economists have spent over four decades exploring the effect of match offers (e.g., Karlan and List 2007). Prior studies mainly focused on traditional fundraising channels such as door-to-door fundraising and mail-in solicitations (Landry et al. 2010; Karlan and List 2007; Huck et al. 2015; Karlan et al. 2011). Our focus on individual funds allocation allows a holistic picture of donation preference free from selection issues, setting our study apart from existing project-level analyses (Meer 2017). Besides, existing works mostly focus on the retention and behavior of experienced donors rather than new donors without historical donation records (Song et al. 2022; Xiao and Yue 2021). Our research adds to this body of literature by examining match offers in the context of online crowdfunding. We enrich the understanding of donor heterogeneity by highlighting the distinctive donation patterns of new donors.

3.1 HYPOTHESIS DEVELOPMENT

We combine the literature on crowdfunding and match funding to develop testable hypotheses regarding the effect of match funding in the donation-based crowdfunding market. Although match offers have long been studied, the charitable crowdfunding market is a very different context to be investigated since the impact of match offer is context-dependent (Levitt and List 2007). For one thing, crowdfunding requires donors to contribute to charities proactively, while traditional fundraising is mostly based on passive solicitations (Karlan and List 2007; Rondeau and List 2008). For another, crowdfunding features small projects with detailed budgetary information and highlights the transparency of funding progress. Given these differences, the efficacy of match offers needs to be examined empirically in the context of donation-based crowdfunding platforms (Meer 2017).

3.1.1 *Match Funds*

As mentioned in the literature review, there are inconclusive results on the impact of match offer (Eckel and Grossman 2003; Chen et al. 2005; Meer 2017; Huck and Rasul 2011; Null 2011). However, the extra funding from leadership donor can still help the projects to reach the fundraising goal and become successful. According to Huck and Rasul (2011), although the match funds demotivate individual contributions, the overall donation amount including the match funds is higher. Therefore, we propose our hypothesis regarding project success as follows.

***H1a**: Projects with match funds are more likely to reach the pledging goal than projects without.*

However, the higher probability of project success does not proclaim whether individual contributions are increased or decreased by match funds. We also focus on individual contributions of donors and propose the corresponding hypotheses. As we discussed in the literature review, prior studies have identified a mostly positive effect of match funding, enabled by a signaling effect (Vesterlund 2003) or the lowered price of giving as a result of the match funding (Eckel and Grossman 2008; Karlan and List 2007). The signaling effect takes place when the prospective donors are uncertain about the quality of the projects and leverage leadership donors' choices as signals for high-quality projects (Andreoni 2006a). As such, matched projects are preferred because they are deemed to be better in quality. Such a prediction is consistent with the theory of herding, where subsequent individuals may imitate the behavior of early decision-makers (Zhang and Liu 2012). The price of giving, defined as "the amount a donor needs to give in order to provide one dollar of the charity's output" (Meer 2014, p113), may also drive donors to prefer matched projects. With match offers, the price of giving is effectively lowered because a unit-dollar donation results in charitable contributions greater than one dollar. As a result, donors derive a higher benefit from contributing to matched projects. We hypothesize that prospective donors will increase their contributions as reflected in donation probability and average donation amount when charitable projects are eligible for match offers in H1b.

H1b*: Individuals are more likely to contribute to charitable projects with match offers than to projects without. Similarly, they contribute a larger amount to projects with match offers than to those without.*

Negative evidence has also been discovered that match offers lead to crowding out (Huck and Rasul 2011; Null 2011). Specifically, when donors care more about the beneficiaries due to altruistic motivations, the supplemented funds from leadership donors reduce the need for a donor to make charitable contributions. Since matched projects are already supported by leadership donors who will likely help projects reach the fundraising goals, individual donors that are more altruism-oriented may choose to support unmatched projects (or give relatively less to matched projects) to enable a wider coverage of funds (Andreoni 1990). Below, we propose hypothesis H1c that opposes the prediction of H1b.

H1c*: Individuals are less likely to contribute to charitable projects with match offers than to projects without. Similarly, they contribute a smaller amount to projects with match offers than to those without.*

3.1.2 *Match Funds and Inequality*

Inequality is usually considered an important factor of charitable giving (Bekkers and Wiepking 2011; Fehr and Schmidt 1999). Donors give more when the beneficiaries are in higher poverty conditions according to inequality aversion theory (Fehr and Schmidt 1999; Bolton and Ockenfels 2000) and due to the consideration of reputation and empathy (Duquette and Hargaden 2021; Andreoni and Rao 2011). However, there is a lack of research on the interplay between inequality and match funds, and we refer to the theory of warm-glow and altruism to make our hypotheses.

According to Andreoni (1989; 1990), donors make donations out of two reasons: altruism, to help others; and warm-glow, to gain utility from their own donation actions. Donors are likely to be more altruistic when they donate to high poverty projects, as those beneficiaries are in urgent need of money (Bekkers and Wiepking 2011). In this case, donors care more about the amount obtained by the beneficiaries, so they express more enthusiasm to matched projects. However, for low poverty projects, donors would focus more on their personal impact instead of the benefits to fundraisers. For example, they may want to have a sense of completing an obligation. Since the leadership donor donates half of the fundraising goal, it is hard for individual donors to feel a large personal impact for matched projects. In this way, the warm-glow effect lowers the donation probability for low poverty projects if they receive match offers. However, if the altruism level of donors is not significantly higher when facing high-poverty projects, the impact of match funds would not be more salient. Thus, we propose the opposing hypotheses as follows.

***H2a**: High-poverty projects benefit more than low-poverty projects from match funds.*

***H2b**: High-poverty projects benefit no more than low-poverty projects from match funds.*

3.1.3 *Donor Heterogeneity*

Donor heterogeneity has always been a critical topic in fundraising (Landry et al. 2010). Karlan and List (2007), in their field experiment, identify the spatial heterogeneous treatment effect. They find that match offers associated with a political campaign are effective in "red" states, whereas such an effect was barely observed in "blue" states. Other than donors' political orientation, their past donation experience is a key characteristic. Landry et al. (2010) ran a door-to-door fundraising drive to show that previous donors are more likely to give and contribute more than those who have never given before. Huck et al. (2015) claim that donors are heterogeneous with respect to the valuation of leadership donations. More related to our study, Karlan et al. (2011) show that warm-list donors tend to be positively influenced by a match offer, whereas the cold-list donors remain unaffected or adversely affected. This categorization features donors' past donation intensity, or engagement level, which reflects the momentum of giving.

We highlight donors' prior charitable giving experience as the source of heterogeneity and predict individual preference over matched and unmatched projects. Compared to new donors, experienced donors have a higher level of momentum of giving. Past studies suggest that donors with a higher momentum are more susceptible to the influence of match offers (Landry et al. 2010; Karlan et al. 2011). This possibly results from the altruistic motivation that drives more supply of funds when the price of giving is low. Donors with a higher level of momentum are more likely those who give for the concerns for the beneficiaries. They would prefer to give to projects with matched offers than those without because contributing to matched projects ultimately results in more charitable funds supply. When one's charitable giving is considered together with the impact they generate with the match offers, the price of giving takes effect to drive contribution to matched projects. Donors with a lower level of momentum, on the other hand, are possibly less driven by such an altruistic motivation. As such, they have a lesser tendency to choose matched projects.

A counterargument can be made that new donors are more attracted to match offers. As we have mentioned, new donors with a lower level of momentum are more likely driven by private benefit, rather than the concerns for the beneficiaries' welfare. They may be more attracted to match offers because contributing to match offers also result in private benefits such as the joy of giving with someone else (the leadership donor) rather than by oneself. The private benefit can also simply be a higher sense of impact. As an individual donor, participating in matched projects triggers the contribution of a leadership donor. This positive externality increases individuals' sense of impact, making them feel good about their good deeds. This could be of particular interest for new donors, who are, in turn, more likely to give to matched projects. Thus, we propose the two opposing hypotheses as follows.

H3a: *New donors are less likely to respond positively to match funds than experienced donors.*

H3b: *New donors are more likely to respond positively to match funds than experienced donors.*

3.2 DATASET

3.2.1 *Research Setting*

For this research, we use an open dataset obtained from DonorsChoose.org (DonorsChoose 2020). DonorsChoose.org is a donation-based crowdfunding platform for public school teachers in the United States to raise money for school supplies. This website was founded in 2000, and it has raised over $800 million for more than 1.9 million projects as of the beginning of 2021. It also has great coverage, with at least one project launched for 85% of all public schools in the United States (DonorsChoose 2021b).

The fundraising scheme on DonorsChoose is all-or-nothing, which means that donations can only be given to teachers if the project is completed. If a project fails to reach its fundraising goal, all the donations are refunded to donors as credit for future donations. If a project reaches its fundraising goal, no more donations can be received, and a DonorsChoose volunteer orders the supplies through online shopping platforms, which are then delivered directly to the teacher’s classroom. A thank-you email written by the teacher will always be sent to all donors regardless of their donation amounts.

In October 2007, the website launched match offers, with funds provided by large companies and organizations. Fundraisers can apply for match offers and obtain subsidies for half of their fundraising goals when the match ratio is 1:1. Notice that all the match offers were dollar-for-dollar during the time window of our study. Other match ratio schemes were adopted later, which is beyond the scope of our study. Projects with match offers are labeled with a conspicuous mark, as shown in Figure 3.1. The matching policy for these projects is as follows: for every dollar a donor gives to the project, another dollar will be given by the company that provides the offer.

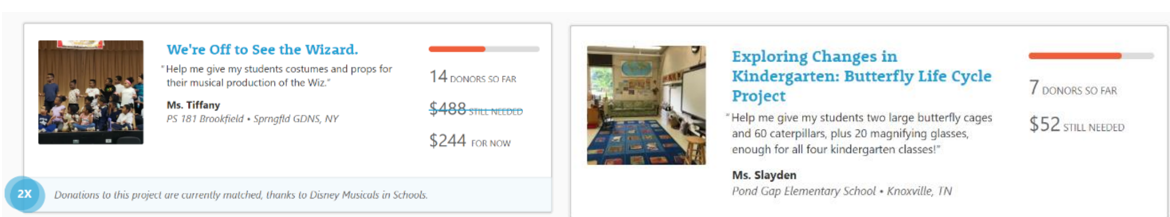


Figure 3.1. Projects with match offer and without match offer

Our dataset includes information of all 99,798 projects and 301,054 donations between November 5th, 2005 and September 5th, 2009. In our dataset, 71,305 (~71.45%) of projects started after the launch of match offers. Among all projects starting after match offers launched, 14,963

(~20.98%) are associated with match offers. Figure 3.2 shows the percentage of projects with different poverty levels. The majority of projects (67.37%) are of highest poverty, while 21.12% projects are of high poverty. Moderate and low level projects take 9.68% and 1.83% of all projects. In our paper, we redefine project poverty to two levels: high and low. High level projects are those tagged with highest or high level poverty in our data, and low level projects are those tagged with moderate and low level poverty in our data.

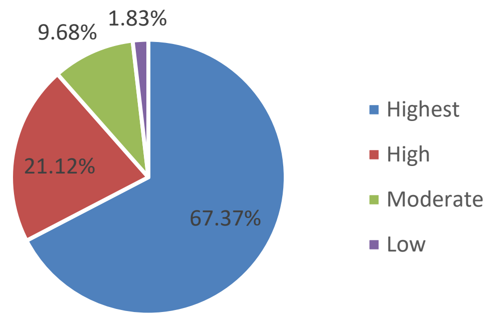


Figure 3.2. Percentage of different donors

We also include the individual income tax dataset from the IRS (International Revenue Service) of the United States (IRS 2019). This dataset includes the population statistics and the adjusted gross income (AGI) of U.S. households at a zipcode level from 2005 to 2009. We combine this income data with the donation dataset from DonorsChoose in our individual- and market-level models.[3] In our dataset, 117 (~0.12%) out of 97,987 donors gave over 5% of the average income of their zipcode area, indicating unusual donation motivations. These records are considered outliers, given their extreme donation patterns, and are excluded from our analyses.

[3] Donor location in DonorsChoose data is either at zipcode level or state level. If the zipcode of a specific donor is offered, we directly used the average adjusted gross income (AGI) of that zipcode region to approximate the donor income. If only state information is provided, we calculated the average AGI of the whole state by summing up the total AGI of each zipcode region and dividing by the population of the state.

3.2.2 *Model-free Evidence*

We introduce some model-free evidence to compare donation behavior before and after the introduction of match offers. Figure 3.3 shows the number of donation transactions each month. We observe a remarkable increase in donor contributions around October 2007 when the match offers were introduced. Since no other policy changes took place at that time, we expect this change to be a consequence of match offers. The patterns suggest that match funding can encourage the supply of funds on crowdfunding platforms. In Figure 3.4, we summarize success rate of projects in different groups. According to whether the project is matched or not and the poverty level of the project, we can categorize all projects into four groups. Figure 3.4 indicates that receiving match offer raises success rate, and project with high poverty level are more likely to succeed.

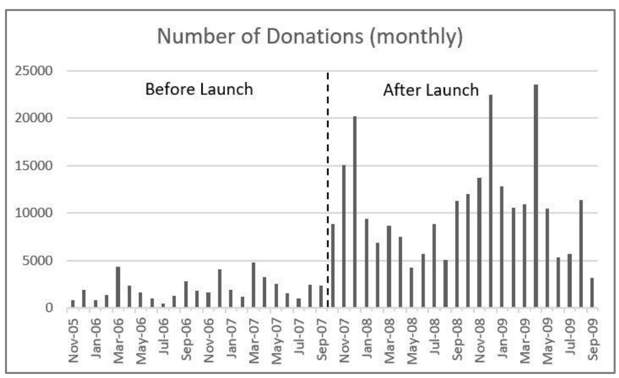


Figure 3.3. Number of donation transactions over time

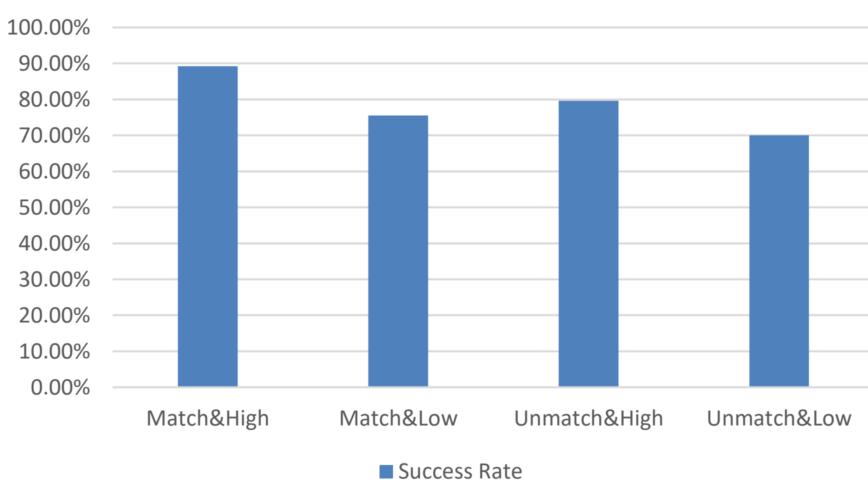


Figure 3.4. Donation to different projects by heterogeneous donors

3.3 EMPIRICAL ANALYSIS

In this section, we first perform a reduced-form study using Heckman control functions to analyze the effectiveness of match funds on project success. Then we perform a utility maximization model to investigate donors' preference between projects with match offers and those without match offers. Specifically, we infer donor preference from their fund allocation decisions after accounting for their exposure to matched/unmatched projects. We then extend our model to compare the impacts of match offers on projects with different poverty conditions. We categorize projects into matched and high poverty, matched and low poverty, unmatched and high poverty, and unmatched and low poverty ones. Donors' preference towards these projects can help us uncover different donation mechanisms when donors are facing projects with different poverty conditions.

3.3.1 *Reduced-form Analysis*

We first conduct a reduced-form analysis on the impact of match offers on project. We use a Probit model to describe how various factors affect the success rate of the project. To be specific, the attributes we include in the model are: *Match* which indicates if the project receives match offer, *High* which indicates if the project is of high poverty level, an interaction term between *Match* and *High* which captures the effect of match offer on high poverty projects, *Objective* which is the objective amount of the project, *Duration* of the project, other control variables including $SchoolChar_j$ and $ProjectChar_j$ (excluding poverty information) in Table A.2 in Appendix A. The result of this Probit model is in column (1) of Table 3.1, and it shows that project with high poverty and match offers are more likely to succeed. Also, match offers raise the success rate for high poverty projects.

However, the result above may suffer from selection bias, as projects receiving match offers may be those who cannot attract enough donors and need the help of match offers to succeed. Thus, we leverage a Heckman selection model to address this problem. We build the Heckman Control Function to be another Probit model predicting the probability that a project would receive match offers. We use all variables in the Probit model except *Match* and *Match*High* in the Heckman Control Function. To satisfy the exclusion restriction, we also add another variable *MatchProp* representing the proportion of projects with match offers at the time that the focal project starts in the Control Function. The result of our Heckman model is in column (2) of Table 3.1. The main findings of the Probit model in column (1) carries over. However, the effect of match offer soars from 0.148 to 1.582, showing that the true impact of match offer is large. The *InvMillsRatio* in the Heckman model is negative and significant, which indicates that projects that are more unlikely to success tend to apply for and receive match offers. This strong selection bias leads to a downward biased estimate of *Match* in our simple Probit model. In short, our reduced-form analysis shows that match offers help projects succeed, and projects of high poverty are more likely to succeed. Moreover, high poverty projects can also benefit from match offers. This implies that match offer can help both high and low poverty projects. In the following subsections, we build a utility maximization model to explore the effect of match offers more rigorously.

Table 3.1. Reduced-form Results on Success Rate

	(1)		(2)	
Variables	Coefficient	Std. Error	Coefficient	Std. Error
Probit				
Intercept	0.893^{***}	(0.036)	0.550^{***}	(0.040)
Match	0.148^{***}	(0.049)	1.582^{***}	(0.067)
High	0.271^{***}	(0.016)	0.220^{***}	(0.016)
*Match*High*	0.270^{***}	(0.052)	0.124^{***}	(0.053)
Objective	-0.0008^{***}	(0.00002)	-0.0008^{***}	(0.00002)
Duration	0.00009	(0.00009)	0.001^{***}	(0.0001)
InvMillsRatio	/		-0.829^{***}	(0.025)
Heckman Control Function				
Intercept	/		-2.016^{***}	(0.058)

High	/	0.326***	(0.022)
Objective	/	0.0001***	(0.00001)
Duration	/	-0.003***	(0.0002)
MatchProp	/	5.29***	(0.069)

*Note. standard errors are in brackets. *p < 0.1; **p < 0.05; ***p < 0.01.*

3.3.2 *Utility Maximization Model*

Following the neoclassical consumer preference model (Barnett and Serletis 2009; Song et al. 2022), we consider the individual donation decision process to be a utility maximization problem with a budget constraint on a monthly basis. Specifically, we construct balanced panel data with each donor's monthly contribution to both matched and unmatched projects. If a donor does not make any charitable contribution in a given month, the contribution is set to be zero.

Since matched projects only take up a small portion of the total demand of funds, they have limited visibility to donors. It is likely that many donors were not aware of matched projects or matched projects that still seek funds. To account for individual donors' different levels of exposure to matched projects, we propose the following component to capture the probability that a donor is aware of matched projects that are still active (fundraising goals not reached) as follows:

$$\Pr\left(A_{it}=1\right)=\frac{\exp\left(\boldsymbol{z}_{it}^{T}\boldsymbol{\gamma}\right)}{1+\exp\left(\boldsymbol{z}_{it}^{T}\boldsymbol{\gamma}\right)}. \tag{3.1}$$

In the equation above, $\boldsymbol{z}_{it}$ denotes the vector of variables that can potentially influence donors' awareness of available matched projects. This vector $\boldsymbol{z}_{it}$ includes the total number of matched projects at a given month ($Demand_m$), the total number of unmatched projects at a given month ($Demand_u$), whether a donor has donated to matched projects before (*MatchBefore*), the length of time from the last donation in months (*Recency*), the quadratic term of time from last donation ($Recency^2$), and a constant term. The number of matched projects directly affects donors' exposure; the number of unmatched projects also affects this process because users have limited cognitive capacity. Users who contributed to matched projects before are more likely to notice the emergence of matched projects. Similarly, users who have higher recency are more likely to visit the platform, hence have higher exposure. Note that new donors have no value for *Recency*; we replace the missing value with the number of months since the platform's establishment (112 months).

Next, we derive a donor's utility function given that the donor is aware of available matched projects. The utility function consists of three components – the utility from donating to matched projects, unmatched projects, and purchasing the outside goods. Below we present the utility maximization problem to solve for donors' optimal fund allocation plan.

$$\max_{\boldsymbol{d}_{it}} \mu_{it} = \max_{\boldsymbol{d}_{it}} \left(\mu_{it}^{m} \cdot \mu_{it}^{u} \cdot \mu_{it}^{o} \right)$$

$$\text{s.t. } d_{it}^{m} + d_{it}^{u} + d_{it}^{o} - Income_{it} = 0 \text{ (Budget Constraint)} \tag{3.2}$$

$$\text{and } d_{it}^{m} \geq 0,\ d_{it}^{u} \geq 0,\ d_{it}^{o} \geq 0 \text{ (Non-negativity Constraint).}$$

In the problem above, *i* represents the donor, and *t* represents the time at a monthly level. The total utility is set to be a Cobb-Douglas utility function. Specifically, μ_{it} denotes the total utility donor *i* derives at time *t*, and μ_{it}^{q} denotes the specific utility that donor *i* gains from the expenditure for *q* at time *t*. Here $q \in \{m, u, o\}$ refers to different ways for donor *i* to spend money: *m* corresponds to matched projects, *u* corresponds to unmatched projects, and *o* corresponds to the outside option. Since expenditure in each option exhibits a diminishing return, donor *i* allocates her income across these three options. The allocation is represented by the vector of $\boldsymbol{d}_{it}$, which consists of d_{it}^{m}, d_{it}^{u}, and d_{it}^{o}. $Income_{it}$ is the budget of donor *i* at time *t*. As we do not have income data of each donor, we approximate the budget of a donor with the average monthly adjusted gross income (AGI) of the donor's zipcode region (IRS 2019).[4] We only include the data after the launch of match offers since donors had no option for matched projects before then.

We model the utility that donor *i* obtains from spending d_{it}^{q} in option *q* at time *t* as:

$$\mu_{it}^{q} = \left(d_{it}^{q} + 1\right)^{\alpha_{it}^{q}}. \tag{3.3}$$

Here the coefficient α_{it}^{q} represents the relative preference of donor *i* at time *t* on option *q*. We normalize the utility coefficient of the outside option α_{it}^{o} to 1, and the interpretation of α_{it}^{q} is relative to other ways of spending the income. To break down the determinants of α_{it}^{q} where $q \in \{m, u\}$, we have:

$$\alpha_{it}^{q} = \boldsymbol{x}_{it}^{T}\boldsymbol{\beta}_{q} + \varepsilon_{it}^{q}, \text{ where } \varepsilon_{it}^{q} \sim N\left(0, \sigma_{q}^{2}\right), \tag{3.4}$$

where $\boldsymbol{x}_{it}$ includes donors' characteristics which can affect their preferences on the option *q*: the number of days since the donor's first visit to the crowdfunding website (*Tenure*), the logarithm of the number of historical donations (*log(DntNum)*), the logarithm of the average historical donation amount (*log(DntAvg)*), a dummy variable indicating whether the donor is a new donor or not (*NewDonor*), the ratio of high poverty projects out of all projects the donor has donated to (*HighPovertyRatio*), and a constant term. β_{q} represents the coefficient for the option *q* and ε_{it}^{q} is the error term whose variance depends on the option *q*. It is important to note that the purpose of the individual-level analysis is to understand donors' relative preference of matched and unmatched projects over the outside good. As such, no project-level characteristics are included in the formulation of α_{it}^{q}. In the transaction-level analysis, which will be introduced later in the

[4] The IRS income dataset only offered the AGI of the whole year; thus, we divided it by 12 months to obtain the monthly AGI used for estimation in our model. Notice that when the donor's location is not provided in the DonorsChoose dataset, we set the utility from the outside option to be zero for identification (Song et al. 2022).

robustness check part, more characteristics will be controlled to identify the effect of our interest. With the above specification, we can solve the optimization problem in Equation (3.2). Using Karush-Kuhn-Tucker conditions (Boyd and Vandenberghe 2004), we find that the optimal allocation of funds should satisfy the following conditions:

$$\left(\frac{\partial \mu_{it}}{\partial d_{it}^{o}} - \frac{\partial \mu_{it}}{\partial d_{it}^{q}}\right) d_{it}^{q} = 0 \ \forall i,t,q \text{, and } \frac{\partial \mu_{it}}{\partial d_{it}^{q}} \leq \frac{\partial \mu_{it}}{\partial d_{it}^{o}} \ \forall i,t,q:\ d_{it}^{q} = 0\,. \tag{3.5}$$

The above conditions indicate that when a donor allocates a positive amount to option *q*, her marginal utility from option *q* needs to be equal to her marginal utility from the outside option. If the donor allocates nothing to option *q*, her marginal utility from this choice should be less than or equal to her marginal utility from the outside option. Given the specified utility functions in Equation (3.3), we can derive the likelihood of observing d_{it}^{q} as follows:

$$p\left(d_{it}^{q}\right) = \begin{cases} \dfrac{1}{\sigma_q}\varphi\left(\dfrac{1}{\sigma_q}\left(\dfrac{d_{it}^{q}+1}{d_{it}^{o}+1} - \boldsymbol{x}_{it}^{T}\boldsymbol{\beta}_q\right)\right), & d_{it}^{q} > 0; \\ \Phi\left(\dfrac{1}{\sigma_q}\left(\dfrac{1}{d_{it}^{o}+1} - \boldsymbol{x}_{it}^{T}\boldsymbol{\beta}_q\right)\right), & d_{it}^{q} = 0. \end{cases} \tag{3.6}$$

Here $\varphi(\cdot)$ and $\Phi(\cdot)$ are the probability density function and cumulative distribution function of standard normal distribution. Then, the likelihood function for donor *i* at month *t* can be written as follows:

$$L_{it} = \begin{cases} \Pr\left(A_{it} = 1\right) \cdot p\left(d_{it}^{m}\right) \cdot p\left(d_{it}^{u}\right), & d_{it}^{m} > 0; \\ \Pr\left(A_{it} = 1\right) \cdot p\left(d_{it}^{m}\right) \cdot p\left(d_{it}^{u}\right) + \Pr\left(A_{it} = 0\right) \cdot p\left(d_{it}^{u}\right), & d_{it}^{m} = 0. \end{cases} \tag{3.7}$$

Specifically, when a positive amount is allocated to matched projects ($d_{it}^{m} > 0$), the donor must have observed matched projects and made the decision of contributing d_{it}^{m} to matched projects and d_{it}^{u} to unmatched projects. When no funds are allocated to matched projects ($d_{it}^{m} = 0$), the donor either observed matched projects and chose not to contribute ($\Pr(A_{it}=1)\cdot p(d_{it}^{m})\cdot p(d_{it}^{u})$) or did not notice the existence of matched projects and only observed unmatched projects ($\Pr(A_{it}=0)\cdot p(d_{it}^{u})$). We use maximum likelihood estimation (MLE) to estimate this model. In the next subsection, we use the estimated parameters to recover the monthly donation probability and average donation amount to test our hypotheses.

3.3.3 *Results on Donor Preference*

The result of our model is shown in Table 3.2. We first observe that donors' characteristics have similar impacts on matched and unmatched projects. New donors tend to have higher donation preferences, and *Tenure* has slightly negative effects on donors' donation preferences, which implies that relative new donors have stronger incentive to donate. We also notice that new donors have stronger donation motivations when facing unmatched projects (0.051 > 0.043). This supports hypothesis H3b, that is, new donors prefer unmatched projects. *log(DntNum)*, and *log(DntAvg)* exert positive effect on utility coefficient, which shows that more experienced and more generous donors have higher donation preferences. Donors with higher *HighPovertyRatio* are more likely to donate to matched projects, but the effect is not significant in the case of unmatched projects.

Next, to compare donors' preference between matched and unmatched projects, we draw the empirical probability density functions (p.d.f.) of donors' mean utility coefficients as shown in Figure 3.5. The empirical p.d.f. indicates that donors prefer matched projects to unmatched projects, and our calculation also shows that the average mean utility coefficient of matched projects (-0.0217) is higher than that of unmatched projects (-0.0279). Notice that most mean utility coefficients of both matched and unmatched projects in Figure 3.5 are negative, indicating a negative marginal utility of charitable giving for most donors. This is reasonable since charitable giving is an occasional act rather than a regular act. Donors are making charitable contributions without any tangible returns, and the majority of people do not make charitable contributions on a monthly basis. Specifically, if we observe positive average mean utility coefficients, donors should be making charitable contributions more frequently than twice a month. As such, the values of mean utility coefficients are of less relevance because they may change as we alter the time interval of data aggregation. Instead, the comparison between utility coefficients α_{it}^{q} 's is the key to testing our hypotheses.

Table 3.2. Donor preferences on projects with/without match offer

Variables	Coefficient	Std. Error
Awareness		
Intercept	-5.000***	(0.070)
Demand$_m$	3.330***	(0.054)
Demand$_u$	-0.033***	(0.003)
MatchBefore	0.860***	(0.035)
Duration	-0.123***	(0.004)
Duration^2	0.001***	(0.00004)
Match Preference		
Intercept	-0.052***	(0.001)
Tenure	-0.0001***	(0.00002)
log(DntNum)	0.012***	(0.00026)
log(DntAvg)	0.005***	(0.00018)
NewDonor	0.043***	(0.00094)
HighPovertyRatio	0.002***	(0.00056)
σ_m	0.018***	(0.00017)
Unmatch Preference		
Intercept	-0.042***	(0.0002)
Tenure	-0.0002***	(0.000005)
log(DntNum)	0.008***	(0.00007)
log(DntAvg)	0.002***	(0.00005)
NewDonor	0.051***	(0.00024)
HighPovertyRatio	-0.0002	(0.00013)
σ_u	0.016***	(0.00004)

Note. standard errors are in brackets. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

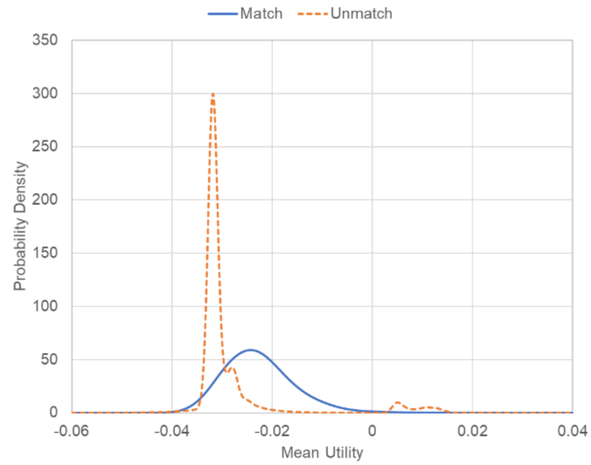


Figure 3.5. Empirical p.d.f. of the mean utility coefficients for projects with/without match offer

Since negative utility leads to no donation and only positive utility translates to donations, both the mean and the variance of utility coefficients are important to donation preference. To test the first and the second hypotheses, we use the mean utility coefficients and the variances σ_m^2 and σ_u^2 to calculate the monthly donation probability and the average donation amount for donors in Table 3.3. As for monthly donation probability, $\Pr\left(\alpha^q > 0\right)$, an average donor has a higher probability (13.6%) of donating to matched projects as compared to her probability of donating to unmatched projects (7.7%). As for the expected donation amount conditional on the acts of giving, $\mathbb{E}\left(\alpha^q \mid \alpha^q > 0\right)$, an average donor makes a greater monthly donation to matched projects (0.009) than to unmatched projects (0.007). According to the nature of the Cobb-Douglas utility function, the conditional expected donation amount is relative to the outside goods. In other words, our results show that donors will contribute nearly 1% of their total income to both matched and unmatched projects. This is consistent with the charitable giving statistics in the U.S. that people give 2% – 5% of their gross income to charities (Philanthropy Roundtable 2021). This result indicates that matched projects are more popular as compared to unmatched projects at an average level, and our empirical estimation supports hypothesis H1b.

Table 3.3. Donation Probability and Average Donation for Different Project Types

Donation Types	Average Donation Probability	Average Donation Amount Conditional on Non-Zero Contributions
Match	0.136	0.009
Unmatch	0.077	0.007

Note. Average donation probability equals $\frac{1}{|S|}\sum_{(i,t)\in S}\Pr\left(\alpha_{i,t}^{q}>0\right)=\frac{1}{|S|}\sum_{(i,t)\in S}\left(1-\Phi\left(-\frac{\boldsymbol{x}_{i,t}^{T}\cdot\boldsymbol{\beta}_{q}}{\sigma_{q}}\right)\right)$*, and average donation amount equals* $\frac{1}{|S|}\sum_{(i,t)\in S}\mathbb{E}\left(\alpha_{i,t}^{q}\mid\alpha_{i,t}^{q}>0\right)=\frac{1}{|S|}\sum_{(i,t)\in S}\left(\boldsymbol{x}_{i,t}^{T}\cdot\boldsymbol{\beta}_{q}+\sigma_{q}\cdot\varphi\left(-\frac{\boldsymbol{x}_{i,t}^{T}\cdot\boldsymbol{\beta}_{q}}{\sigma_{q}}\right)\Big/\left(1-\Phi\left(-\frac{\boldsymbol{x}_{i,t}^{T}\cdot\boldsymbol{\beta}_{q}}{\sigma_{q}}\right)\right)\right)$ *for* $q\in\{m,u\}$*, where* $\varphi(\cdot)$ *and* $\Phi(\cdot)$ *are probability density function and cumulative distribution function for standard normal distribution.*

The estimated parameters of the awareness equation are all significant and consistent with our expectations. Specifically, the demand for matched projects positively affects the awareness process, and the demand for unmatched projects has negative impact on it. This is intuitive as people have limited cognitive capacity to notice the existence of charitable projects, given the large number of them. Donors who have contributed to matched projects are significantly more likely to notice the existence of matched projects because they likely know how to use the filter on DonorsChoose.org to identify such projects. The estimation of the awareness process demonstrates the effectiveness and the necessity to control for the awareness of available matched projects.

3.3.4 *Extended Analysis with Poverty Conditions*

In this subsection, we extend our model to investigate the impact of match offers on projects with different poverty conditions. Specifically, we treat projects with highest or high poverty level to be high poverty projects, and those with moderate or low poverty level to be low poverty projects. Then, in the utility maximization problem, potential donors have five options to spend money on instead of three in our basic model:

$$\max_{\boldsymbol{d}_{it}}\mu_{it}=\max_{\boldsymbol{d}_{it}}\left(\mu_{it}^{mh}\cdot\mu_{it}^{ml}\cdot\mu_{it}^{uh}\cdot\mu_{it}^{ul}\cdot\mu_{it}^{o}\right)\tag{3.8}$$

$$\text{s.t. } d_{it}^{mh} + d_{it}^{ml} + d_{it}^{uh} + d_{it}^{ul} + d_{it}^{o} - Income_{it} = 0 \text{ (Budget Constraint)}$$

$$\text{and } d_{it}^{mh} \geq 0, d_{it}^{ml} \geq 0,\ d_{it}^{uh} \geq 0, d_{it}^{ul} \geq 0,\ d_{it}^{o} \geq 0 \text{ (Non-negativity Constraint).}$$

In our extended model, the donation options are: *mh* which represents matched and high poverty projects, *ml* which represents matched and low poverty projects, *uh* which represents unmatched and high poverty projects, and *ul* which represents unmatched and low poverty projects. After similar derivation using Karush-Kuhn-Tucker conditions, we can get the likelihood function of our extended model as follows:

$$L_{it} = \begin{cases} \Pr\left(A_{it}=1\right)\cdot p\left(d_{it}^{mh}\right)\cdot p\left(d_{it}^{ml}\right)\cdot p\left(d_{it}^{uh}\right)\cdot p\left(d_{it}^{ul}\right), & d_{it}^{mh}+d_{it}^{ml}>0; \\ \Pr\left(A_{it}=1\right)\cdot p\left(d_{it}^{mh}\right)\cdot p\left(d_{it}^{ml}\right)\cdot p\left(d_{it}^{uh}\right)\cdot p\left(d_{it}^{ul}\right)+\Pr\left(A_{it}=0\right)\cdot p\left(d_{it}^{uh}\right)\cdot p\left(d_{it}^{ul}\right), & d_{it}^{mh}=d_{it}^{ml}=0. \end{cases} \quad (3.9)$$

The result of our extended model is presented in Table 3.4. The effect of most donors' attributes on their awareness of matched offers and utility coefficients are consistent with our basic model. We further notice that donors with higher *HighPovertyRatio* tend to prefer high-poverty projects over low poverty projects. In Figure 3.6, we draw the graph of coefficients and their standard deviations for four different donation options to compare them in a more explicit way. We find that in most cases, the coefficients of high-poverty projects are higher than that low poverty projects for both matched and unmatched projects. The figure on *NewDonor* also clearly shows that new donors prefer unmatched projects, which again supports hypothesis H3b.

Table 3.4. Donor preferences on projects with/without match offer × high/low poverty level

Variables	Coefficient	Std. Error
Awareness		
Intercept	-4.930^{***}	(0.070)
Demand$_m$	3.310^{***}	(0.054)
Demand$_u$	-0.035^{***}	(0.003)
MatchBefore	0.881^{***}	(0.035)
Duration	-0.128^{***}	(0.004)
Duration^2	0.002^{***}	(0.00004)
Match + High Poverty		
Intercept	-0.057^{***}	(0.001)
Tenure	-0.000005	(0.00002)

log(DntNum)	0.011***	(0.00026)
log(DntAvg)	0.004***	(0.00018)
NewDonor	0.043***	(0.00097)
HighPovertyRatio	0.003***	(0.00059)
σ_{mh}	0.019***	(0.00016)
Match + Low Poverty		
Intercept	-0.077***	(0.003)
Tenure	-0.0001***	(0.00005)
log(DntNum)	0.009***	(0.00067)
log(DntAvg)	0.003***	(0.00057)
NewDonor	0.023***	(0.00262)
HighPovertyRatio	-0.010***	(0.00154)
σ_{ml}	0.027***	(0.001)
Unmatch + High Poverty		
Intercept	-0.046***	(0.00026)
Tenure	-0.0002***	(0.00001)
log(DntNum)	0.009***	(0.00008)
log(DntAvg)	0.002***	(0.00005)
NewDonor	0.053***	(0.00027)
HighPovertyRatio	0.001***	(0.00015)
σ_{uh}	0.017***	(0.00005)
Unmatch + Low Poverty		
Intercept	-0.062***	(0.00072)
Tenure	-0.0003***	(0.00001)
log(DntNum)	0.009***	(0.00018)
log(DntAvg)	0.0006***	(0.00013)
NewDonor	0.035***	(0.00062)
HighPovertyRatio	-0.007***	(0.00032)
σ_{ul}	0.023***	(0.00017)

Note. standard errors are in brackets. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

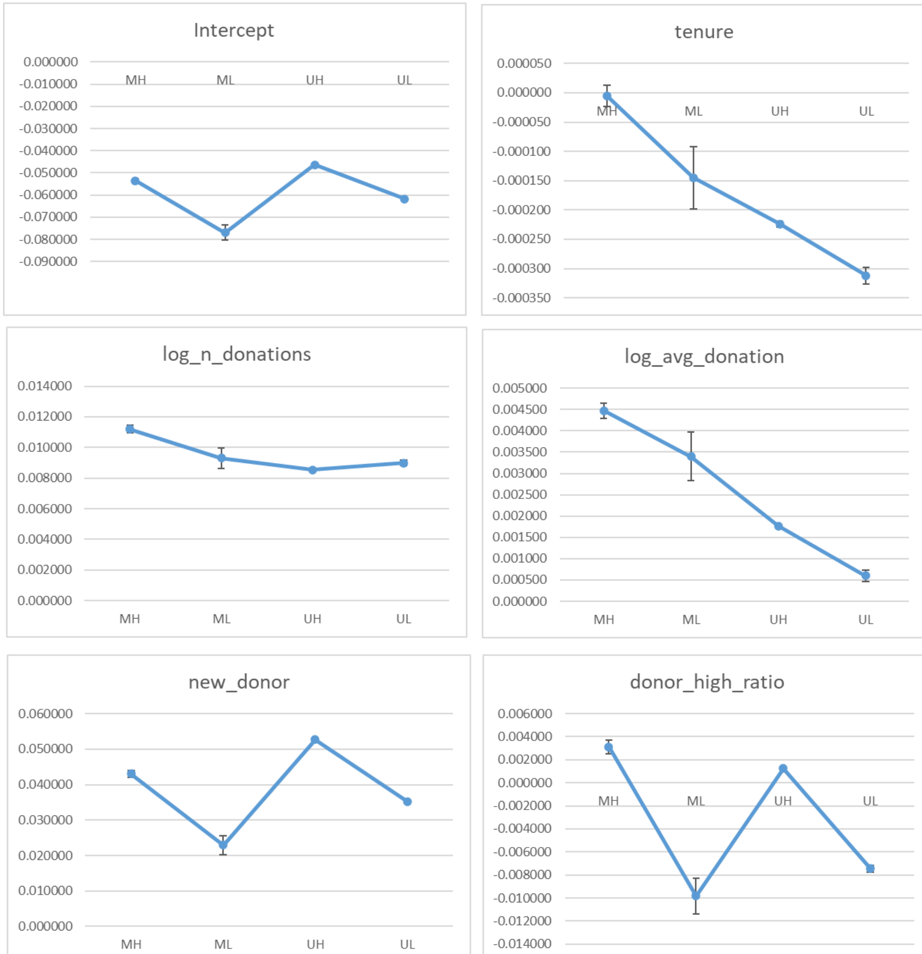


Figure 3.6. Coefficients and their standard deviations for four different donation options

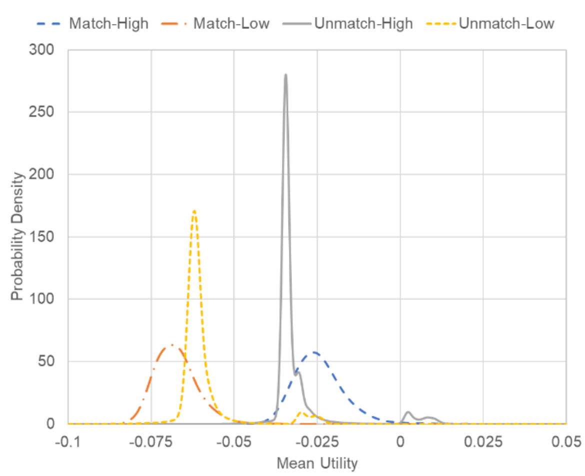


Figure 3.7. Empirical p.d.f. of the mean utility coefficients for project types with different match offer and poverty conditions

Furthermore, we draw the empirical p.d.f. of donors' mean utility coefficients in Figure 3.7 to directly compare four donation options. We also calculate the average mean utility coefficients of donors for four different donation options, and we find that donors prefer matched high-poverty projects the most (-0.0226), then unmatched high-poverty and unmatched low poverty projects (-0.0306 and -0.0590), and matched low poverty projects the least (-0.0648). This finding supports our hypothesis H2a, as high-poverty projects benefit from match offers, while low poverty projects are slightly harmed by match offers. As mean utility coefficients are not accurate enough to describe donors' preference, we also consider the variances of different options and derive the monthly donation probabilities and average donation amounts in Table 3.5 to perform more detailed analysis.

Table 3.5. Donation Probability and Average Donation for Different Project Types

Project Types	Match	Unmatch
High Poverty	DP = 0.128, DA = 0.009	DP = 0.069, DA = 0.007
Low Poverty	DP = 0.010, DA = 0.009	DP = 0.012, DA = 0.007

Note. DP = Donation Probability; DA = Donation Amount.

Average donation probability equals $\frac{1}{|S|}\sum_{(i,t)\in S}\Pr\left(\alpha_{i,t}^{q}>0\right)=\frac{1}{|S|}\sum_{(i,t)\in S}\left(1-\Phi\left(-\frac{\boldsymbol{x}_{i,t}^{T}\cdot\boldsymbol{\beta}_{q}}{\sigma_{q}}\right)\right)$*, and average donation amount equals* $\frac{1}{|S|}\sum_{(i,t)\in S}\mathbb{E}\left(\alpha_{i,t}^{q}\mid\alpha_{i,t}^{q}>0\right)=\frac{1}{|S|}\sum_{(i,t)\in S}\left(\boldsymbol{x}_{i,t}^{T}\cdot\boldsymbol{\beta}_{q}+\sigma_{q}\cdot\varphi\left(-\frac{\boldsymbol{x}_{i,t}^{T}\cdot\boldsymbol{\beta}_{q}}{\sigma_{q}}\right)\Big/\left(1-\Phi\left(-\frac{\boldsymbol{x}_{i,t}^{T}\cdot\boldsymbol{\beta}_{q}}{\sigma_{q}}\right)\right)\right)$ *for* $q\in\{m,u,mh,ml,uh,ul\}$*, where* $\varphi(\cdot)$ *and* $\Phi(\cdot)$ *are probability density function and cumulative distribution function for standard normal distribution.*

We find that matched high-poverty project has the highest donation probability and average donation amount, which indicates that match offers can effectively help high-poverty projects attract more donors and receive more donations. The average donation amounts for matched projects are higher than unmatched ones for both high-poverty and low poverty projects. However, the donation probability for matched low poverty projects is the lowest, even lower than unmatched low poverty projects. This is an interesting phenomenon, as one would expect matched offer to help projects gain notices from potential donors. We refer to the studies of Andreoni (1989;

1990) regarding warm-glow effect to explain this result. To be specific, donors make donations out of two reasons. One reason is to help others, which is called altruism, and the other reason is to feel that their actions have large impacts, which is called warm-glow effect. In our context, donors are more altruistic when they donate to high-poverty projects, as those beneficiaries are in urgent need of money. In this case, donors care more about how much money the beneficiaries can get, so they express more enthusiasm to matched projects. However, for low poverty projects, donors focus more on their personal impact instead of the benefits to fundraisers. For example, they may want to have a sense of completing an obligation. Since the leadership donor donates half of the fundraising goal, it is hard for individual donors to feel a large personal impact for matched projects. In this way, the warm-glow effect lowers the donation probability for low poverty projects if they receive match offers. Thus, we find that match offer helps high-poverty projects but can harm low-poverty projects, which again supports our hypothesis H2a.

3.4 Robustness Check

To complement and verify existing discoveries, we conduct a robustness check at the transaction level to compare the donation amount for matched and unmatched projects. The findings at the individual-level and market-level both show that match offers can increase donors' charitable contributions. These analyses focus on the average effect of match offers at an aggregate level, where project-level characteristics cannot be accounted for. We conduct this robustness check at the transaction level to include project-level characteristics and the selection process for a project to be a matched project.[5]

[5] Since the approval and assignment of match offers are not visible to the researchers, the selection process for a project to be a matched project can be influenced by unobservable features that also influence the donation amount. To put it simply, projects with match offers may be different from those without match offers in a systematic way. This leads to endogeneity issues that will resulting in biased estimation of the effect of match offers.

Specifically, we develop a simultaneous equation model to incorporate both the donation amount equation and the matching selecting equation. We allow these two equations to have correlated error terms as the selection process may affect the estimation of the effect of match offers. Below we introduce the donation amount equation in Equation (3.10) and the matching selection equation in Equation (3.11).

For the donation amount equation, we use the donation amount as the dependent variable. Besides the match offer dummy, we also include other variables that may affect the donation amount. The main model is specified as follows:

$$\begin{aligned}\log(Donation_{ijt}) = {} & \beta_0 + \beta_1 Launch_t + \beta_2 Launch_t \times Match_j + \beta_3 \log(Objective_j) + \beta_4 \log(Duration_j) \\ & + \beta_5 \log(CumDonors_{jt}) + \beta_6 CumProp_{jt} + \beta_7 \log(DaysLeft_{jt}) + \beta_8 \log(ProjectNum_{jt}) \\ & + \beta_9 Controls_{ijt} + \varepsilon_{ijt}\end{aligned} \tag{3.10}$$

In this model, i represents donor i, j represents project j, and t represents the time point when donor i contributes to project j. Since each donor only donates once to a specific project, time subscript t is redundant given i and j. *Match* indicates whether project j is matched, and *Launch* indicates whether match offers have launched on the platform. As a match offer exists only after its availability on the platform, we include the interaction term of *Match* and *Launch* but not *Match* itself. Other covariates include the fundraising goal *Objective*, the cumulative completed proportion *CumProp*, the cumulative number of donors *CumDonors*, the length of the fundraising period *Duration*, and the number of days before the fundraising deadline *Daysleft*. We also add *ProjectNum*, the number of projects on the platform at the time point of the donation, to control for the intensity of competition. Other control variables are represented by the vector *Controls* to include (i) the characteristics of school ($SchoolChar_j$), (ii) the characteristics of projects ($ProjectChar_j$), (iii) the characteristics of donors ($DonorChar_{it}$) ($CumProject_{it}$ and $AvgDonations_{it}$ are added in logarithm form), and (iv) dummy variables of months ($MonthDummy_t$). The details of the variables are presented in Table A.2 in Appendix A. Logarithms are taken after adding one to all continuous variables.

For the matching selection equation, we allow $Match_j$ to be the dependent variable and model the selection process of match offers as follows:

$$\begin{aligned} Match_j^* = \alpha_0 + \alpha_1 \log(Objective_j) + \alpha_2 \log(Duration_j) + \alpha_3 MatchProp_j \\ + \alpha_4 SchoolChar_j + \alpha_5 ProjectChar_j + u_j \end{aligned} \tag{3.11}$$

$$Match_j = 1(Match_j^* > 0) \tag{3.12}$$

$$\begin{pmatrix} u_j \\ \varepsilon_{ijt} \end{pmatrix} \sim N(\mathbf{0}, \Omega), \Omega = \begin{pmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{pmatrix} \tag{3.13}$$

In Equation (3.11), $Match_j^*$ is a latent variable that dictates the probability for a project to be matched. We consider the fundraising goal, duration, characteristics of the school, and characteristics of the project as factors in the selection process of match offers. We add $MatchProp_j$, the proportion of matched projects at the time when the focal project is posted, to measure the difficulty of receiving a match offer for the project. Here u_j is an unobservable term to capture other features of the project (e.g., quality). The selection process is captured as a Probit model, and u_j and ε_{ijt} are assumed to follow a bivariate normal distribution with mean zero and variance Ω, as described in Equation (3.13). Note that the selection process illustrated by Equations (3.11)-(3.13) only exists for projects posted after the launch of match offers.

We employ maximum likelihood estimation (MLE) to estimate parameters in our model and report the results in Table 3.6. Our finding shows that match offers have a positive and significant effect on the donation amount. Specifically, a match offer leads to a 57.3% boost in the donation amount for a project. This result concurs with our main findings at the individual and market levels that donors are more likely to be encouraged by the match offer and contribute a larger amount.

The negative and significant correlation coefficient ρ indicates that unpopular projects are more likely to receive a match offer. It seems that fundraisers are more willing to apply for match offers if their projects are not attractive. In the meanwhile, the leadership donors prefer projects that have a more difficult time reaching their goals. The takeaway of this robustness check is that matched projects are generally less likely to be successful than unmatched projects, if no match offers are provided. Given people's strict preference for matched projects, our results at the individual-level and market-level are preserved due to the potential underestimation of the effect of matched offers. Under an ideal context where project quality is identical across matched and unmatched projects, match offers are expected to be more effective in stimulating donations.

Table 3.6. Impact of match offers at the transaction level

Variable	Coefficient	Std. Error
log(Donation)		
Launch	0.086***	(0.026)
Launch × Match	0.573***	(0.009)
log(Objective)	0.178***	(0.004)
CumProp	-0.974***	(0.011)
log(CumDonors)	0.141***	(0.005)
log(Duration)	0.080***	(0.008)
log(DaysLeft)	-0.062***	(0.002)
log(ProjectNum)	-0.277***	(0.043)
log(DonorCumProject)	0.045***	(0.001)
log(DonorAveDonations)	0.330***	(0.002)
DonorCompleteRatio	-0.839***	(0.007)
Constant	5.544***	(0.363)
Controls	√	
Match		
log(Objective)	0.231***	(0.012)
log(Duration)	-0.125***	(0.029)
MatchProp	6.254***	(0.076)
Constant	-3.329***	(0.169)
Controls	√	
Variance-Covariance Matrix		
ρ	-0.481***	(0.003)
σ	0.955***	(0.002)

Note. t or robust t-statistics are in brackets. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

3.5 Conclusions

Facing a large number of projects on charitable crowdfunding platforms, donors bear relatively high transaction costs of giving to scrutinize potential projects to fund. This challenges the platforms to encourage continuous contributions from donors. Although match offers have long been applied to encourage charitable giving in various fundraising channels such as mail-in appeals and door-to-door solicitations, the application of match offers in crowdfunding market stays largely underdeveloped. Given that crowdfunding has gain growing importance as a new channel to bring people's effort together for social good, systematic studies are needed to understand how and when match offers can help overcome these challenges.

In this study, we examine the impact of match offers as a promotional strategy and particularly focus on the effectiveness of match offer on projects with different poverty conditions. We find that match offer can significantly help the projects to reach the fundraising goal, especially for those with a high-poverty level. Moreover, match offers effectively increase donors' donation probability and average donation amount due to a higher utility they derive from contributing to projects with match offers. Generally speaking, match offer has greater benefits when being applied to high-poverty projects. This merit mainly comes from a higher donation probability of high-poverty projects, whereas the average donation amount has no salient difference. We also discover that new donors are more attracted to unmatched projects, possibly due to the obligations they have to fill when they join the platform. Our work at the transaction level compares the donation amount for matched and unmatched projects and further verifies the robustness of the aforementioned findings.

Our research contributes to multiple streams of literature. First, we extend and enrich the body of crowdfunding studies by investigating how match offers, which we theorize about as the price of giving, affect users' donation preference. Instead of focusing on project-level factors, we scrutinize donors' fund allocation decisions by developing a model that considers donation decisions to be a utility maximization problem. We further account for the awareness component, which is prominent in crowdfunding, given the large number of projects available. This model captures the underlying preference for matched and unmatched projects, enabling estimation of both estimated donation probability and donation amount. The granularity of our estimation allows us to generate insightful conclusions (e.g., donors' expected donation amount as compared to their income) that were not able to be obtained from the traditional project-level analysis.

Second, we contribute to the studies on platform design and governance in the emerging literature of platform economy in general (Kenney and Zysman 2016; Allon and Babich 2020; Chen et al. 2020) and the literature of crowdfunding platform design in particular. We demonstrate the effectiveness of match funding and the remarkable benefits when being applied to high-poverty projects. Match offers encourage more donors to make contributions to people in urgent need on the online crowdfunding platform, leading to a more favorable outcome at a society level. Match offers are essentially a system design that allows the objective of leadership donors to align with that of the educators, answering the emerging calls to better understand platform design and governance in online crowdfunding market (Allon and Babich 2020; Chen et al. 2020).

Last but not least, this study adds to the economics literature of charitable giving in terms of donor heterogeneity. We reveal the distinctive preference of new donors, which was largely neglected in the extant literature. Our results show that new donors are likely driven by very different motivations as compared to experienced donors. In the innovative fundraising channel of charitable crowdfunding, new donors strictly prefer unmatched projects over matched projects. Moreover, different from extant studies using survey or experiment data to explore donor behaviors, we leverage a neoclassical structural model to format donor utility from different types of projects and to examine the heterogeneous preferences. This method allows more flexible control of the awareness process and the fund allocation process. It can be applied to many other giving contexts to derive more comprehensive insights regarding donation probability and donation amount.

Our findings also generate substantial practical implications and insights for different stakeholders in the crowdfunding market. For third-party organizations who seek social responsibility, our results confirm that match offers are not only a marketing strategy to build a positive social image for the leadership donor but also a promotional strategy to increase individuals' charitable contributions. By sponsoring match offers, the leadership donors can make a real difference for those who need help through their philanthropic acts. For charitable crowdfunding platforms, our study demonstrates the importance of offering matching funding by collaborating with leadership donors. As match offers bring more benefits to high-poverty projects, this measure results in more donations to people in urgent need. Moreover, since experienced donors are more attracted to projects with match offers, the platform should spend more marketing efforts on experienced donors to accelerate fundraising success.

This study is subject to some limitations which point out our future research directions. First, we do not observe donors' donation behaviors outside of DonorsChoose. As a result, we only see their allocation of funds within this platform. Second, we do not have specific donor demographics information such as age, income, and gender, which may affect donors' donation patterns. Our model focuses on the average preference between matched and unmatched projects, which is at a high level, and we would leave it for future works to examine how individual-level demographic factors play a role in crowdfunding donors' donation preference. We hope that our paper paves the way for future studies to continue examining strategies that can improve the fundraising performance and efficiency in donation-based crowdfunding markets.

Chapter 4. CONTENT PROLIFERATION AND NARROWCASTING IN THE AGE OF STREAMING MEDIA

Streaming media companies such as Netflix, Hulu, and Amazon Prime Video have changed how contents are consumed, produced, and delivered. Traditional broadcasting business requires large investment into a few mainstream contents in order to please the mass audience (Lobato 2019), and consumers can only do their best to find programs that suit their tastes, even if not perfectly. In contrast, the streaming media model, charging subscription fees periodically, allows customers to choose what they like from a myriad of programs in the library and consume as much as they want. The great success of streaming technology can be told from statistics. As of 2020, total Netflix subscribers grew to around 167 million worldwide (Statista 2020). Part of the success is attributed to the popularity of the original content. Streaming companies have invested heavily on content, with over $120 billion spending on original content in 2019 alone (Bridge 2020). More importantly, streaming companies have advanced their capabilities in applying learning algorithms on collected data to develop as many different types of contents for as many micro-targeted audience groups as possible (Novak 2017). Netflix has identified around 2,000 taste communities among its worldwide users (Adalian 2018), and the company has thrived by offering contents to these micro taste clusters rather than broad demographics.

Our research is motivated by the recent development in the streaming media industry and the growing importance of economics of data (e.g., Jones and Tonetti 2020, Farboodi and Veldkamp 2020). First of all, the current streaming business model has largely departed from the traditional, short-term profit-focused model, employed by cable and satellite providers and based on tiered subscription and video-on-demand transactions. In contrast, steaming companies focus on customer engagement in order to retain existing customers and grow new markets (Patel 2019a).

Most of the stream services adopt simple, flat subscription pricing model, often encouraging viewers to consume as much content as possible, which aims to maximize customer engagement and experience (Dumaine 2020). Under this type of business model, data collected from their customers can create the feedback loop, making the firms more productive and generating increasing returns (Patel 2019b, Jones and Tonetti 2020). This is notably different from prior literature on differentiated subscription pricing schemes based on user types and usage levels, whose goals are single-period profit maximization (e.g., Cachon and Feldman 2011). The departure from the traditional business model to engagement-driven paradigm provides motivation to develop our model based on a different objective function in analyzing streaming media companies.

Second, under the engagement-based competition, streaming companies realize content development is the core capability that matters in the long run. Industrial practitioners suggest that the top priority for streaming media companies is to enrich contents in their library in order to improve user experience, retaining existing customers and attracting new customers (Phillips 2019). Therefore, decisions regarding content investment are critical as they affect these firms' long-term success and competitive advantages.

Furthermore, with ample customer data, streaming media companies have unparalleled opportunities to tailor and narrowcast their contents to different customer taste communities (Adalian 2018). There are many tradeoffs in making content development decisions. For example, streaming companies may prioritize their resources in order to satisfy large taste clusters. As a result, companies may over-produce shows on mainstream contents while ignoring other, smaller viewing communities (Wright 2019). This may lead to a gap in user experience among different customer segments and harm the diversity of contents. These issues call for rigorous studies on alternative content development policies.

The purpose of this research is to study the optimal content policies for streaming media companies and examine the implications of our proposed policies. Specifically, we attempt to address the following research questions: What is the optimal content policy for a streaming company? Will a shift from profit-driven to engagement-driven lead to content proliferation? How can the company leverage the information on consumer distribution to optimize its content offerings to different customer clusters?

Our model is based on product assortment model with horizontal differentiation (Lancaster 1966; Lancaster 1974; Gaur and Honhon 2006), in which products are located in an attribute space and individuals follow various distributions in the same space. We derive several interesting findings. First, in contrast to the results in prior literature that firms produce just enough products without overlapping product coverage intervals, we show that overlapping coverage intervals and placing products closer can be a better policy for engagement-based firms. Second, engagement-based model produces more contents when the value of the contents is large to the customers or the profit margin in selling content is less than a certain threshold. Third, on learning the distribution of its customers, the media firm will always overlap product coverage intervals and place programs closer when the distribution density is higher. Additionally, in facing the tradeoffs of content quality and quantity, the firm should use a higher-quality and low-variety policy for high density clusters but a lower-quality and high-variety policy for low density clusters. Furthermore, when customers consume multiple shows in a period, a better policy is to film TV shows or series with multiple episodes rather than individual movies. Our research contributes to the literature on digital media, and, to the best our knowledge, is one of the first to study content production policies for streaming media companies. Our results provide interesting and insightful implications for streaming companies.

4.1 THE MODEL

4.1.1 *Model Setup*

We now construct model for a media company with heterogeneous viewers in a single time period. The company aims to determine the optimal number of programs and their differentiation in the continuous viewer preference space. The assumptions in our model are similar to those of Lancaster (1966, 1974) and Gaur and Honhon (2006). Specifically, the shows have different genres, such as action, science fiction, or comedies. But they are of same price and are only horizontally differentiated in the product space $\Theta = [0,1]$.

The model considers proportion of consumers buying products in a period. Every consumer makes a one-time choice in this period. The fixed cost of every product is K. All products can be represented by a vector of product specifications **b** and each product belongs to the product space, with $\mathbf{b} = (b_1, b_2, \dots, b_n)$, $b_1 < b_2 < \cdots < b_n$ and $b_j \in \Theta$. The total number of products is n. For consumers, we assume that their preferences of products are independently and identically distributed, following a uniform distribution on [0,1]. For a consumer who is located on x_i, a product located exactly at x_i will give her the highest utility Z, which we also name it as her base utility. Denote the price of each product as p. A product at the location b_j will provide a consumer located at x_i a disutility of $\alpha|x_i - b_j|$, where $\alpha \in \mathbb{R}^+$ is a positive real number representing the sensitivity of deviation from her most preferred product, and $|x_i - b_j|$ is the distance for a consumer from her ideal choice x_i. Therefore, the utility the consumer located at x_i gets from product j is:

$$U_{ij} = Z - p - \alpha\left|x_i - b_j\right|. \quad (4.1)$$

We here define the *coverage interval* for product b_j as the region within which consumers have a nonnegative utility for that product. Based on the condition that $U_{ij} \geq 0$, we can derive the coverage interval for product b_j as $\left[b_j - l, b_j + l\right]$, where $l = \frac{Z-p}{\alpha}$, and the range of the interval is *2l*. For those consumers located with this interval, they can potentially purchase b_j because their utility is nonnegative in consuming the product.

However, a consumer located within a coverage interval of a product does not necessarily purchase that product, for she will only do it if she can earn the highest utility compared to other products. Here, we define the *first-choice interval* for product j. The consumers who are located within the first-choice interval of product b_j will select it as their first choice. If the coverage interval of product b_j overlaps that of b_{j-1}, the left neighboring product of b_j, then the lower bound of the first-choice interval of b_j is $b_j^- = \frac{b_{j-1}+b_j}{2}$. If there is no overlap between the coverage intervals of b_j and b_{j-1}, the lower bound of the first-choice interval for b_j is $b_j^- = b_j - l$. Considering both situations, b_j^- should equal to the higher value of $\frac{b_{j-1}+b_j}{2}$ and $b_j - l$, whichever is closer to b_j, i.e. $b_j^- = max\left\{\frac{b_{j-1}+b_j}{2}, b_j - l\right\}$. Similarly, we can define the upper bound of the first-choice interval for b_j. Using the notation $b_0 = -\infty$ and $b_{n+1} = +\infty$ for products that are outside the product space, we can define the first-choice interval, $\left[b_j^-, b_j^+\right]$, for product j as follows:

$$b_j^- = max\left\{\frac{b_{j-1}+b_j}{2}, b_j - l\right\},$$

$$b_j^+ = min\left\{\frac{b_j+b_{j+1}}{2}, b_j + l\right\}.$$

We denote ω_j as the total number of consumers for product b_j and $\omega_j = \int_{b_j^-}^{b_j^+} f(x)dx$, where $f(x)$ is the distribution of consumers within the product space. If $f(x)$ follows a uniform distribution on $[0,1]$, $\omega_j = b_j^+ - b_j^-$.

4.1.2 *The Benchmark Model*

We first examine a transaction-based model for a firm that charges consumers a price *p* for each program. The model serves as a benchmark for further analysis. The firm's objective function can be written as:

$$\Pi_T = \sum_{j=1}^{n} p\omega_j - nK, \tag{4.2}$$

where consumers follow a uniform distribution on $[0,1]$, i.e., $\omega_j = b_j^+ - b_j^-$, and *K* is the cost of a program, which we assume to be the same for all programs. Please note that we assume a relative short period for the decision-making process, and each consumer consumes a single product or has a single viewing during the period. We will relax this assumption later one.

The firm solves the product assortment problem of $b_j \in \Theta$ for each product, and finds the optimal product number *n*. Since the cost and revenue for each product are the same, in order to have a positive profit, $p\omega_j - K > 0$ has to be satisfied. Since $\omega_j = b_j^+ - b_j^- \leq 2l, K < 2pl$ must be satisfied. In order to solve the product assortment problem and find the optimal product number, we can allow the firm to first estimate the initial number of products to offer. We can define a *base number of products*, $\tilde{n}_T$, as the maximum number of products such that each product occupies the whole market of its coverage interval, and it can be computed as the integer of the division of the product space range by the product coverage interval. For the benchmark model, the base number of products can be computed as follows:

$$\tilde{n}_T = \left\lfloor \frac{1}{2l} \right\rfloor.$$

We solve the profit maximization problem and compare the optimal number of products with base number of products. The result leads to Lemma 1. All proofs are in Appendix B.

LEMMA 1. *If each product covers its whole coverage interval, the optimal number of products* n^* *is at least as large as the base number of products* $\tilde{n}_T$, *i.e.,* $n^* \geq \tilde{n}_T$.

Lemma 1 suggests that if $n^* \geq \tilde{n}_T$ does not hold, e.g., letting $n^* = \tilde{n}_T - 1$, we can always introduce another product to capture the unmet demand and increase profit. With Lemma 1, we can further derive some properties regarding product assortment. One of the properties we want to examine is whether the products' coverage intervals overlap or not. To explore this property, we define the distance between two neighboring products as $d(j, j+1) = b_{j+1} - b_j, \forall j = 1, \ldots, n-1$, and we can derive the following results:

LEMMA 2. *For the transaction-based model, there exists an optimal solution as follows:*

(i) The coverage intervals of all neighboring products do not overlap with each other, and each product has the same first-choice interval, i.e., $\left[b_j^-, b_j^+\right] = \left[b_j - l, b_j + l\right]$ for $j = 1, \ldots, n$.

(ii) All products are evenly spaced at $\Theta = [0,1]$, *i.e.,* $d(j, j+1) = 2l,\ j = 1, \ldots, n-1$.

(iii) If $K < (1 - 2\tilde{n}_T l)p$, *then optimal number of products is* $n^* = \tilde{n}_T + 1$. *If* $K \geq (1 - 2\tilde{n}_T l)p$, *then optimal number of products is* $n^* = \tilde{n}_T$.

This result comes directly from Gaur and Honhon (2006) and we restate it here in order to compare it with engagement-based model. The Lemma suggests that a profit-maximizing firm will evenly space all the products along the product space [0,1]. The intuition is that the firm only cares about whether a consumer segment is covered by any products. There is no need for the firm to locate another product within an overlapping coverage interval, as each product contributes the same amount of revenue. Since all the programs' first choice intervals, being the same as the coverage intervals as there are no overlaps among them, all equal to $2l$, the products will be evenly spaced. The firm can simply locate products adjacently and produce as many products as possible to cover all the consumers. Thus, the first-choice interval of each product is just its coverage interval, that is $b_j^+ - b_j^- = 2l$. The firm can derive the initial number of products by dividing the product space by the first-choice interval, which is $\tilde{n}_T = \left\lfloor \frac{1}{b_j^+ - b_j^-} \right\rfloor = \left\lfloor \frac{1}{2l} \right\rfloor$. However, the firm may face the problem of whether to add another product when the uncovered part of the space within [0,1] is less than the length of a single first-choice interval. Introducing an extra product incurs a cost of *K*, but also generates a revenue of $(1 - 2\tilde{n}_T l)p$. Thus, the optimal number of total programs depends on this cost-benefit tradeoff. When $K < (1 - 2\tilde{n}_T l)p$, the revenue exceeds the cost, and the firm will choose to produce an additional program. When $K \geq (1 - 2\tilde{n}_T l)p$, the cost of introducing an extra program exceeds the revenue it generates, and the firm will not bother to produce it.

From Lemma 2, we can easily see that the optimal number of products increases in α, consumers' sensitivity to product mismatch, and price *p*, but decreases in consumers' base utility *Z*. When consumers' sensitivity to product mismatch, i.e., α, increases, the utility decreases quickly if the offered product is different from a customer's most preferred product. This leads to a narrower first-choice interval, which requires more programs to satisfy customers. Otherwise, there will be gaps between the first-choice intervals, and the consumers located in the gaps will simply not buy any programs. We can also see that with either an increase of consumers' base utility *Z* or decrease of price *p*, the first-choice interval for a product expands as consumers are more likely to satisfy with the product because of a high base utility or lower product price. Therefore, the firm is able to cover all consumers with fewer products.

4.1.3 *Engagement-Based Model*

In contrast to the transaction-based model, firms have been using business models that value customer engagement and retention (Patel 2019a). Prior study shows that engagement depends on customer satisfaction and emotional connectedness (Pansari and Kumar 2017), and, instead of maximizing short term profits, firms are increasingly becoming customer-obsessed and aim to maximize customer experience in order to retain existing customers (Dumaine 2020). Metrics such as monthly active users (MAU) and daily active users (DAU) are widely used to driver a company's valuation (Gallagher 2018). The content provider can adopt a subscription price model similar to Netflix and customers can consume contents without worrying about the marginal cost to pay for each content. Thus, a consumer i's utility has become $U_{ij} = Z - \alpha\left|x_i - b_j\right|$ when she watches content j. We formulate the following objective function to maximize the long-term value of customer satisfaction with the goal of retaining exiting customers and signing up new ones:

$$\Pi_E = \sum_{j=1}^{n} r \int_{b_j^-}^{b_j^+} U_{ij} f(x_i) dx_i - nK, \tag{4.3}$$

where $f(x_i)$ is the density function of consumer distribution, and we here assume $f(x_i) = 1$ for a uniform distribution. The parameter r is a valuation multiplier to measure the effect of consumer satisfaction on firm value as customer retention and acquisition are direly tied to customer experience and satisfaction. We assume that a medium firm will not introduce a new product unless the value it generates is at least as large as the product cost, i.e., $K \leq r \int_{b_j^-}^{b_j^+} U_{ij} dx_i = r\,Z^2/\alpha$.

Similar to the benchmark model, the firm here needs to solve the product assortment problem and find out the optimal product number. The firm can start by finding out its base number of products. From the utility function, we can derive that the coverage interval for each product is $\frac{2Z}{\alpha}$

. Thus, we find the base number of products by dividing the product space range by the coverage interval:

$$\tilde{n}_E = \left\lfloor \frac{1}{2Z/\alpha} \right\rfloor = \left\lfloor \frac{\alpha}{2Z} \right\rfloor.$$

Similar to the logic of Lemma 1, we can see that the optimal number of products is at least the base number of products, $\tilde{n}_E$. When the number of products is less than $\tilde{n}_E$, we can always introduce another product to capture the unmet demand. This will increase the objective function provided that the cost condition $K \leq r\, Z^2/\alpha$ is satisfied.

To solve Problem (3), we first solve the product assortment problem and find out the optimal distribution of the products for a given product number. Then, the firm optimizes to solve the product number. In order to derive the optimal policy, we examine two cases: (1) the optimal product number is less than or equal to the base number of products $\tilde{n}_E$, (2) the optimal product number is great than the based number. We can have the following results regarding the policy:

PROPOSITION 1. *For a given product number in the engagement-based model, it is optimal to evenly space all the products. Specifically, (i) when the optimal product number is less than or equal to the base number of products, i.e., $n^* \leq \tilde{n}_E$, there are no overlaps of the coverage intervals among all products; (ii) when the optimal product number is greater than the base number of products, i.e., $n^* > \tilde{n}_E$, product coverage intervals overlap and the overlap intervals are the same.*

From the above results, we can see that, similar to the benchmark model, the products in the engagement-based model are evenly spaced. It is clear that when the optimal product number is less than or equal to the base number of products, i.e., $n^* \leq \tilde{n}_E$, overlaps between product coverage intervals are not necessary as this will leave some customers unserved and lower the objective function. However, overlaps will happen when the optimal number of products is greater than the base number, i.e., $n^* \leq \tilde{n}_E$, and the overlap intervals have the same width. The properties from

Proposition 1 are largely driven by the assumption that customers follow a uniform distribution. Later, we relax this assumption and will check whether the results will change under a more general distribution.

The results form Proposition 1 provide important properties that will be helpful to solve the optimal product number problem. We first examine whether the optimal product number can equal to the base number of products. Then, we investigate the case that there are more products than the base number $\tilde{n}_E$. The following proposition summarizes the results regarding the optimal number of products:

PROPOSITION 2. *For the engagement-based model, (i) when the production cost K is large enough, i.e.* $K > \frac{rZ^2}{\alpha} - \frac{r(2Z(\tilde{n}_E+1)-\alpha)^2}{4\alpha(\tilde{n}_E+1)}$, *the optimal number of products equals to the base number of products, i.e.* $n^* = \tilde{n}_E$ *; (ii)when the production cost K satisfies the condition* $K \leq \frac{rZ^2}{\alpha} - \frac{r(2Z(\tilde{n}_E+1)-\alpha)^2}{4\alpha(\tilde{n}_E+1)}$, *the optimal number of products is* $n^* = \delta + 1$, *and the overlap intervals are* $\frac{2Z}{\alpha} - \frac{1}{\delta+1} \geq 0$ *, where* $\delta = \left\lfloor \frac{\sqrt{r\alpha/K+1}-1}{2} \right\rfloor$.

Proposition 2 suggests, first, that production cost is a major driver in determining the optimal number of products and the assortment policy. When $K > \frac{rZ^2}{\alpha} - \frac{r(2Z(\tilde{n}_E+1)-\alpha)^2}{4\alpha(\tilde{n}_E+1)}$, which means introducing another program is more costly than the value it creates, the optimal number of products should equal to the base number of products, $\tilde{n}_E$. When $K \leq \frac{rZ^2}{\alpha} - \frac{r(2Z(\tilde{n}_E+1)-\alpha)^2}{4\alpha(\tilde{n}_E+1)}$, it is optimal to have more products than the base number of products, $\tilde{n}_E$, and we will have products' coverage intervals overlapped. We can understand the condition more clearly by splitting the benefits into two parts. The first part, $\frac{rZ^2}{\alpha}$, is the maximum possible benefits by introducing a new product, and the second part, $\frac{r(2Z(\tilde{n}_E+1)-\alpha)^2}{4\alpha(\tilde{n}_E+1)}$, is the benefit loss due to overlaps of product coverage intervals and extensions of product coverages beyond the specified product space of $\Theta = [0,1]$.

Second, when the production cost is lower than a certain level, i.e. $K \leq \frac{rZ^2}{\alpha} - \frac{r(2Z(\tilde{n}_E+1)-\alpha)^2}{4\alpha(\tilde{n}_E+1)}$, the firm will produce more products, and the optimal number depends largely on the ratio of $r\alpha/K$, which can be viewed as the benefit versus cost of introducing a product. The firm value of introducing a product increases in either the valuation multiplier r, or customer taste heterogeneity α, but decreases in the production cost K. It is easy to understand that with a higher valuation of current customer engagement level the firm has more incentives to product more products. Meanwhile, if customer heterogeneity is higher, the firm needs to produce more contents in order to tailor the contents to the customers with different preferences.

Thus, the policy for engagement-based firm on content personalization is quite different from that in the benchmark model. In the transaction-based model, the firm focuses on whether customers are all served by the different products, and it just needs to produce enough different programs to cover all customers with a nonnegative utility. It is always suboptimal to overlap the coverage intervals for the products. On the other hand, for the engagement-focused model, it can be optimal to space the products closer and overlap the coverage intervals as the firm's objective function depends on level of customer value or utility in consuming the content, not just whether they consume or not. In other words, how satisfied the customers are in viewing the contents also matters.

4.2 Comparison of the Policies

In this section, we compare the product policies between the two models. Specifically, we want to examine whether a focus on customer engagement leads to more products. As we have already derived the optimal number of products under the two different models, it is straightforward to compare the number of optimal products. We now derive the following result in comparing the number of products in both models:

PROPOSITION 3. *When* $\sqrt{r\alpha/K+1} > 1 + \frac{p-K}{pl}$*, the engagement-based model produces no less contents than the transaction-based model; otherwise, the engagement-based model produces no more contents than the transaction-based model.*

The left-hand side of the condition in Proposition 3 represents the value of the contents in the engagement model, which increases in the value multiplier r and consumer heterogeneity α, and decreases in production cost K. On right-hand side, the term $(p-K)/pl$ represents the profit margin of the transaction model. To better understand the proposition, we draw a graph (Figure 4.1) with x-axis as $r\alpha/K$ and y-axis as $(p-K)/pl$. C1 is the region where the engagement-based model produces more content while C2 is the opposite. We can clearly see two distinct patterns: (i) When the value of the contents is large for the engagement model and profit margin for transaction model is small, engagement model produces more contents. (ii) When the profit margin for the contents is large in the transaction model and the value of content is not high in the engagement model, transaction model produces more content.

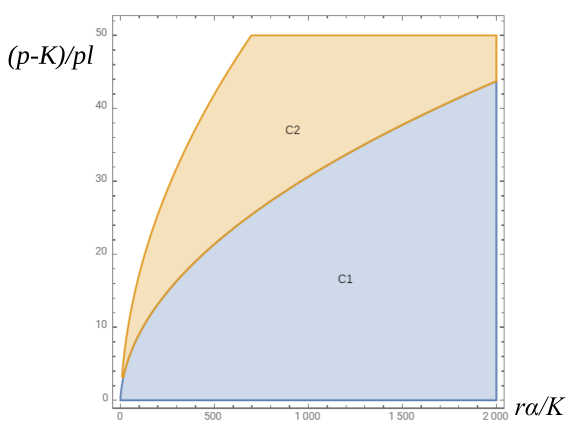
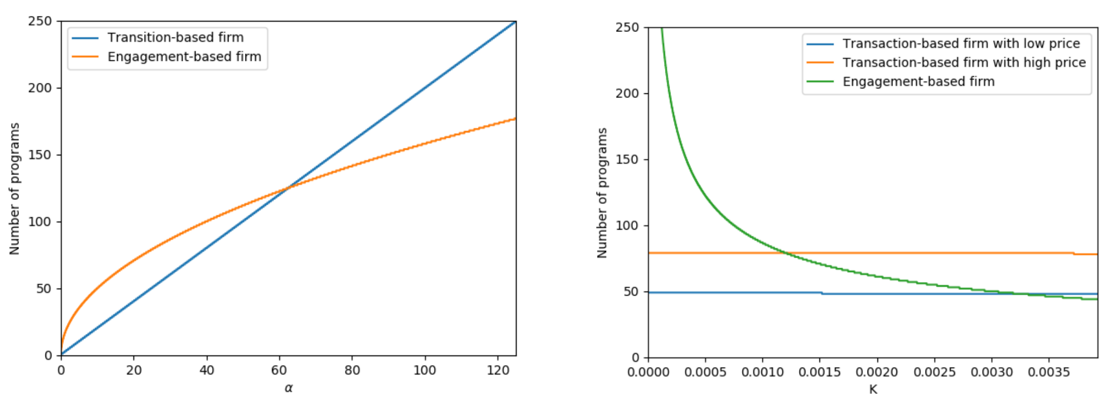


Figure 4.1. Comparing engagement model and transaction model

We further investigate the effects of customer heterogeneity α and product cost K on the number of programs. In Figure 4.2(a), we observe that the program number increases in customer heterogeneity in both models. But there are two differences. First, the effect of heterogeneity on program number is linear for the transaction model while the effect is nonlinear for the engagement model. In the former case, heterogeneity determines the program coverage interval, with a smaller interval for a higher heterogeneity, which directly affects the program number. In the latter case, program number is more complicated, affected by coverage interval as well as the overlaps between coverage intervals. Second, when heterogeneity is not too high, the effect of the overlaps dominates. While a program can cover a reasonable range of customers if α is not too big under the transaction model, which leads to a relatively small program number, the engagement model produces more programs because the programs have coverage overlaps. But when heterogeneity is high, the heterogeneity effect becomes more dominant as the firm under the transaction model has to produce enough programs as each covers a small range because of high heterogeneity. At the same time, under the engagement model, the coverage interval is relatively large because customers do not need to pay for each program directly.



(a). Optimal product number and α (b). Optimal product number and K

Figure 4.2. Optimal product numbers for the two models

Figure 4.2(b) presents the situation with the change of production cost per program *K*. Compared to the rapid decrease in the number of programs for the engagement model, the number of programs is almost fixed, decreasing by only one when the production cost is above a certain threshold. This is due to the fact that the number of programs is based on the trading off between consumer welfare and production cost. The higher the production cost, the less programs the firm will offer. However, under the transaction model, program number is almost fixed even when production cost changes as long as the cost satisfies the condition that the firm's profit level is not negative.

4.3 LEARNING CUSTOMER DISTRIBUTIONS

In this section, we assume that over time the streaming company has learned the distribution of its customers in terms of their tastes, which follow a continuous, unimodal probability distribution *F* with the support of [0,1]. The mode x^* is uniquely defined, the density function is strictly increasing on $[0, x^*]$ and strictly decreasing on $[x^*, 1]$. Without loss of generality, we let $b_k < x^* \leq b_{k+1}$ and $\frac{b_k+b_{k+1}}{2} \leq x^*$.

For engagement-based firms, the optimization problem is in the same form but more difficult to solve because the first-choice intervals of neighboring products can have different overlap sizes. It is hard to determine where to place every product and the optimal number of products. Nevertheless, we can still find a necessary condition of optimal product assortment and build a numerical algorithm to solve it.

The intuition of the algorithm is: Suppose the firm adds programs one at a time from the left side of product space Θ. Every program should be settled at a place which makes cumulative density from the lower bound of first choice interval to the highest utility point be the same as cumulative density from the highest utility point to the upper bound of first choice interval. The reason for this settlement of programs is also intuitive. If a program is settled at an optimal place, moving it a little should not offer additional benefits to the firm. If the firm moves the program a little to the right, then the utility loss experienced by every customer from the lower bound of first choice interval to the highest utility point equals to the utility gain earned by every customer from the highest utility point to the upper bound of first choice interval. To make sure the firm cannot be better off, the net utility gain should be zero (otherwise there exist additional gain by moving the program a little to the right or left). We prove the following Lemma, which is useful for us to find an algorithm to solve the optimal assortment problem.

LEMMA 3. *A necessary condition that* $b_j, j = 1 \dots n$, *is the optimal product location in product space* $\Theta = [0,1]$ *is that* $\int_{max\{0,b_j^-\}}^{b_j} f(x)dx = \int_{b_j}^{min\{b_j^+,1\}} f(x)dx$.

Based on the above necessary condition of optimal assortment proposed in Lemma 3, we develop Algorithm 1. In addition, we also propose the following properties regarding the optimal policy.

PROPOSITION 4. *The optimal product policy with unimodal distributed customers has the following properties: (i) The coverage intervals of all neighboring products overlap with each other. (ii) Products spacing decreases for* $(b_1, b_2, \dots, b_{k+1})$ *and increases for* $(b_{k+1}, b_{k+2}, \dots, b_n)$.

Property (i) states that all neighboring coverage intervals are overlapped with each other. Property (ii) states that the lengths of the overlapping intervals first increase and then decrease in the product space, following the increase and decrease of unimodal density. Proposition 4 indicates that engagement-based firms always produce overlapped programs after learning the customer distribution. This is because there always exists a point with higher density along the customer space. Therefore, the firm can always space the products a little more apart, lowing the average customer utility, at low density regions, but space the products a little closer in order to increase the average utility at high density regions. In this way, because of the density difference, the overall utility of customers is maximized.

ALGORITHM 1. NUMERICAL OPTIMAL ASSORTMENT STRATEGY

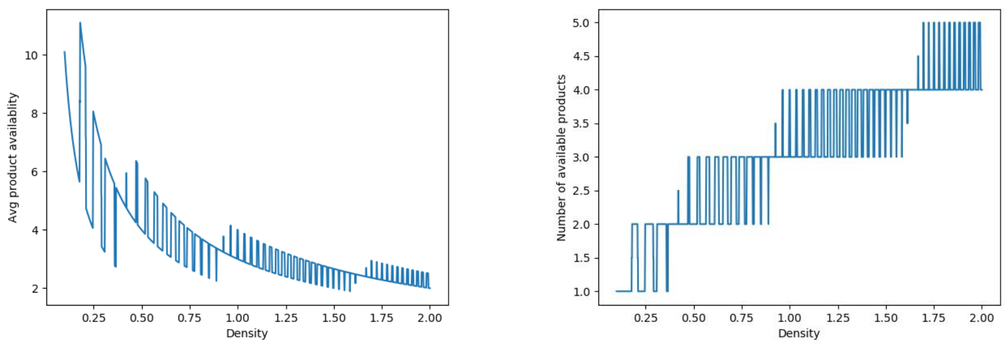
Input: Sensitivity of deviation, α; Highest utility, Z;
Production cost per unit, K
Consumer distribution cdf, $F(x)$
Left-most product location of breakeven, x_{start}
Right-most product location of breakeven, x_{end}

Initialization: $\pi^* \leftarrow 0$

while b_1 in $[x_{start}, x_{start} + 2Z/\alpha]$ **do**:
$j \leftarrow 0$, $b_1^- \leftarrow max\{0, b_1 - Z/\alpha\}$,
while $b_{j+1} < x_{end}$ **do**:
$j \leftarrow j + 1$
$b_j^+ \leftarrow min\left\{F^{-1}\left(2F(b_j) - F(b_j^-)\right), b_j + Z/\alpha, 1\right\}$
$b_{j+1} \leftarrow 2b_j^+ - b_j$, $b_{j+1}^- \leftarrow b_j^+$
End
$\pi \leftarrow$ consumer satisfaction minus production cost for $\{b_i\}_{i=1}^{j}$
if $\pi > \pi^*$then:
$\pi^* \leftarrow \pi$, $n^* \leftarrow j$, $b_{list}^* \leftarrow \{b_i\}_{i=1}^{j}$
End

Return: Optimal 'profit' π^*
Optimal product number, n^*
Optimal product locations, b_{list}^*

We illustrate the results with a numerical example and compare two measures: (i) average product availability, and (ii) number of available choices. We define the average product availability as the average number of products per customer at different density levels. For every customer, her available choices are the products that can give her positive utility. To calculate average product availability at a certain density level, we find the number of available products for the customer at this density level, and then divide it by the number of customers (i.e., customer density in this case). We consider a triangle distribution with the highest density of 2 at 0.5 in the product space, and set $Z = 0.7$, $\alpha = 50$, and $K = 0.001$. The results are shown in Figure 4.3.



(a) Average program availability with density (b) Number of choices with density

Figure 4.3. Content Availability and Choices

The numerical results suggest that average product availability decreases in customer density, though there are local fluctuations due to the fact that change of product numbers is not continuous over the customer and product space. On the other hand, as shown in Figure 4.3(b), product choices increase with customer density due to the more overlaps of program coverage intervals. While customer clusters with higher densities can have more program choices, low density clusters benefitted from a higher average of products per customer. To an extent, this phenomenon is consistent with the economy of agglomeration effect in economic geography (Krugman 1991).

We try to qualify the benefits of learning customer distribution by comparing the result to the one that the firm does not know the customer distribution and uses a uniform distribution for approximation. The first difference after the firm has gained information on customer distribution is that overlaps between adjacent products increase in density then decrease when density is lower over Θ for unimodal distribution, while overlaps are the same under uniform distribution. The reason is that the firm, after learning customer distribution, would optimally adjust program spacing with customer densities and overlap more where consumers are denser to increase average utility among those customers. Another difference is that there will always be overlaps between adjacent products for a unimodal, or even a multimodal, distribution, while it is possible not to have overlaps among product coverage areas under uniform distribution assumption.

We conduct numerical experiments to compare the two practices. As shown in Figure 4.4, first of all, the firm always produces less programs after learning customer distributions. This is due to the reason that the firm can place the programs more strategically after learning customer distribution rather than producing equal number of programs for different clusters with varying densities. In addition, we can see that, in general, program number increases in consumer heterogeneity represented by α, and decreases in production cost K. Further, the gap of optimal number of programs between the two practices enlarges with both α and K. Figure 4.5 shows that consumer surplus is higher when the firm learns the true customer distribution, which is the triangle distribution in this analysis. Not surprisingly, consumer surplus decreases in both α and K. Finally, the improvement in consumer surplus is higher with a larger customer heterogeneity, i.e., a larger α. On the other hand, the improvement of consumer surplus does not seem to be very sensitive to the change of product cost K.

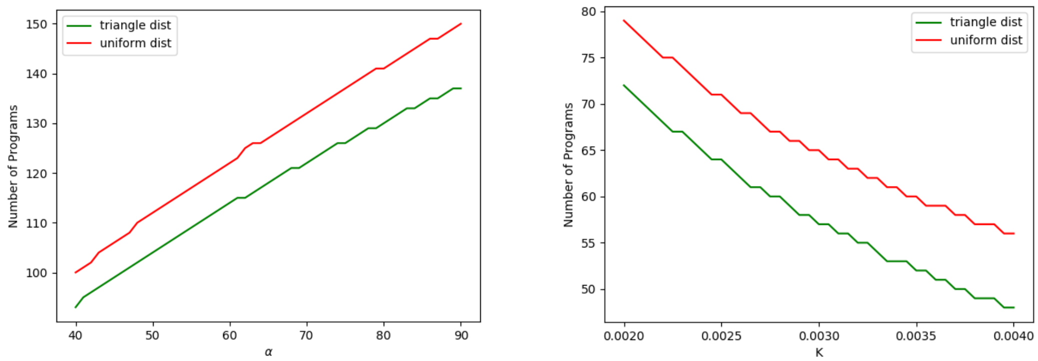


Figure 4.4. Change of Program Numbers after Learning Customer Distribution

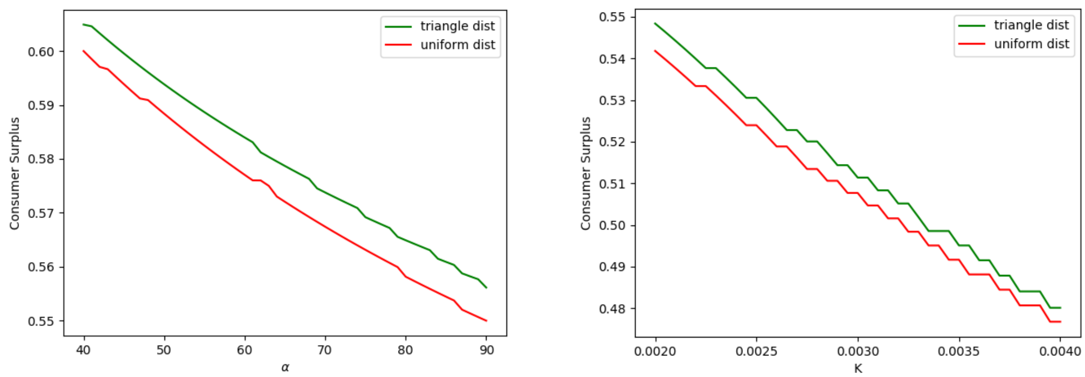


Figure 4.5. Change of Consumer Surplus after Learning Customer Distribution

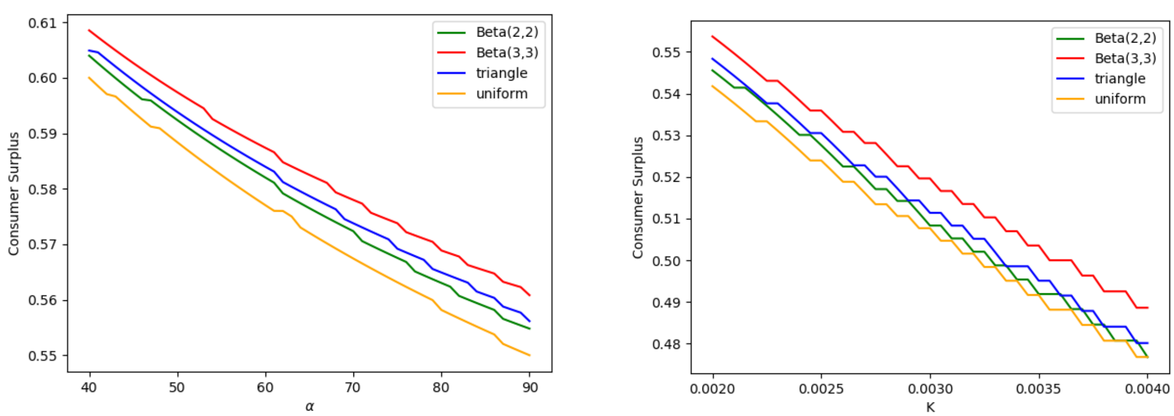


Figure 4.6. Change of Consumer Surplus under More Different Distributions

We conduct numerical studies using more general Beta distributions and the results are shown in Figure 4.6. Our results confirm that the result, i.e., customers receiving higher consumer surplus after the firm learns the customer distribution, is robust even though we change customer distributions. We choose a general Beta distribution with symmetry, and our results suggest that the firm provides higher consumer surplus under such a distribution than assuming customers are distributed evenly. Our result also shows that when the peak density becomes higher, the improvement of consumer surplus is even bigger. The implication is that when consumers are distributed more unevenly, learning their distribution and understanding their specific clusters is more valuable.

4.4 Extensions

4.4.1 *Endogenous Quality*

We further consider the situation where the quality of programs is endogenized and firms can provide programs of different quality levels to different customers. Meanwhile, we model the cost to be a convex function of quality, $K = cq^{\theta}$ $(\theta > 2)$, to reflect the fact that marginal cost is increasing. We assume that the streaming company learns customer clusters as in previous section. The distribution of customer is a continuous probability distribution F with the support of [0,1]. The streaming company can divide customers into multiple segments with consumers distributing evenly within the segment, and we denote s as the segment range. The company can then treat customers in each segment as uniformly distributed, but with different ranges for different segments, and then optimize both the number of programs and program quality. We denote s as the range for each customer segment.

We now derive the optimal policy for an engagement-based streaming company for the following problem:

$$\Pi_Q = \sum_{j=1}^{n} r \int_{b_j^-}^{b_j^+} U_{ij} f(x_i) dx_i - nK, \tag{4.4}$$

where $U_{ij} = Z - \alpha|x_i - b_j| = q - \alpha|x_i - b_j|$, $K = cq^{\theta}$ ($\theta > 1$), and $f(x_i)$ is the density function for uniformly distributed customers on the segment. Customers' highest possible utility Z is a function of quality, e.g., $Z = \tau q$. Without loss of generality, we can simply normalize $\tau = 1$. In addition to the program number *n*, we have another decision variable, quality q. The optimal number of programs and quality are demonstrated in Proposition 5.

PROPOSITION 5. *With the endogenous quality, the optimal strategy of streaming media firm on a customer segment with range s is as follows: the optimal product number* $n^* \in \left\{ \left\lfloor \frac{\alpha s\theta}{4}\left(\frac{\alpha sc\theta^2}{4r}\right)^{\frac{1}{\theta-2}} \right\rfloor, \left\lfloor \frac{\alpha s\theta}{4}\left(\frac{\alpha sc\theta^2}{4r}\right)^{\frac{1}{\theta-2}} \right\rfloor + 1 \right\}$ *,and the optimal quality is* $\left(\frac{r}{n^*\theta c}\right)^{\frac{1}{\theta-1}}$.

First of all, there is a tradeoff between optimal program quality and quantity as we can easily derive that $\frac{\partial q^*}{\partial n^*} < 0$. As the optimal quality increase, optimal product number or variety decreases. This is intuitive. When product number increases, overlapping area would become larger, and the firm can afford to sacrifice the quality a little bit. Second, the optimal product number increases in customer fit sensitivity α. When customer fit sensitivity α increases, the coverage of a product shrinks and the utility of a program declines quickly as the customers are located further away. Therefore, the firm needs to produce more programs to satisfy the customers. Third, the results also show that optimal product number increases in segment range s, i.e. $\frac{\partial n^*}{\partial s} > 0$, while the optimal quality decreases in segment range s, i.e. $\frac{\partial q^*}{\partial s} < 0$. Consider a crowded, high-density community with more homogeneous taste, which should have a small segment range s and a small taste variance. In such a community, the results suggest that an optimal policy is to produce fewer programs, i.e. low-variety, but higher quality. On the other hand, in a wider segment with a large s, indicating a more heterogeneous taste, the results suggest a lower-quality and high-variety content policy. In other words, in a crowded taste community where tastes are more homogeneous, the firm can just produce a handful big budget shows to satisfy the customers. On the other hand, when tastes are more diverse and difficult to identify, the firm is better off to try more varieties with moderate budgets in order to satisfy the different micro taste groups within the community.

4.4.2 *Multiple Viewings*

In this section, we consider the situation where the consumer can watch multiple programs during a period and aim to solve the assortment model. We assume that a consumer watch *m* programs during a period as consumers' marginal utility of viewing decreases. This assumption can be justified as consumers marginal utility decreases with the viewing quantity and *m* is reached when the marginal utility reaches zero. Consumers will rank all the available programs and will watch the first ranked program first. We can define the *m*-th ranked interval $\left[b_{j,m}^{-}, b_{j,m}^{+}\right]$ for a program j, which is the *m*-th ranked choice for a consumer, as follows:

$$b_{j,m}^{-} = max\left\{\frac{b_{j-m}+b_j}{2}, b_j - l\right\},$$

$$b_{j,m}^{+} = min\left\{\frac{b_j+b_{j+m}}{2}, b_j + l\right\}.$$

Thus, the firm's objective function can be written as:

$$\Pi_M = \sum_{l=1}^{m}\sum_{j=1}^{n} r\int_{b_{j,m}^{-}}^{b_{j,m}^{+}} U_{ij} f(x_i)dx_i - nK, \tag{4.5}$$

where $U_{ij} = Z - \alpha\left|x_i - b_j\right|$, and $f(x_i)$ is the density function of unimodal distributed customers.

We consider two production policies of the media firm. The first policy is to produce TV shows or series with multiple episodes, but at the same horizontal location. The second policy is to produce differentiated movies which are all horizontally differentiated products in terms of their horizontal locations. Therefore, under the second policy, the media firm will produce more varieties of shows in comparison to the first policy. We can derive the following result:

PROPOSITION 6. *In the engagement-based model, when a customer watches multiple programs during a period,* $\Pi_M^* = m\Pi_E^*$*, and the media firm is better off to produce TV shows with at least* m *episodes than individual movies.*

The intuition behind Proposition 6 is as follows: The optimal assortment plan in single-viewing setting is the best solution based on the trade-off between consumer welfare and production cost. In a multi-viewing setting, it is optimal for the firm to duplicate this assortment plan multiple times, given a specific consumer distribution and production cost. In contrast, if the firm adopts the second policy to produce all differentiated movies, either consumer utility decreases or the total number of products is suboptimal. Based on the results of Proposition 6, we can relax the single-viewing assumption and extend the results to multi-viewing setting by simply duplicating the optimal content policy derived in the single-viewing setting.

4.5 DISCUSSIONS AND MANAGERIAL IMPLICATIONS

Our results suggest that for engagement-based firms, overlapping product coverage is essential for achieving optimal profit. This is a major departure from prior literature, as we are the first to derive this property to the best of our knowledge. The reason of this phenomenon is that engagement-based firms maximize customer satisfaction with the cost constraint rather than the short-term profit they get from transaction fee. Thus, for engagement-based firms, overlapping product coverage greatly increases the utility of customers near the bound of first-choice interval and increases profit. The overlapping phenomenon also contributes to the fact that engagement-based firms produce more contents than transaction-based firm when the value of contents is relatively large, as in this case engagement-based firms would have larger incentive to produce more product aiming at increasing customer utility.

While it is optimal to evenly space all products when the true customer distribution is unknown, learning customer clusters increases the optimal profit of the firm and results in unevenly overlaps. Facing a unimodal customer distribution, the firm should produce more contents and thus inducing larger product overlaps where customer density is higher. The uneven overlap of contents is another major finding of our research, and it is robust to the specification of customer distribution as the algorithm we use to find optimal assortment of contents can be used on any unimodal distribution. Though the numerical results are mainly derived on a triangle distribution, the comparison of triangle and Beta distribution shows that for any unimodal distribution, results should be similar with that of a triangle distribution. The analysis on triangle and Beta distribution also implies that the benefit of learning customer clusters is larger when the peak of customer distribution is higher and the proportion of population around the peak is larger. In other words, the benefit of learning is higher when customer distribution is more uncertain. Moreover, the uneven overlapping result can be further extended to multimodal distribution with the same intuition: Firms should produce more where customer density is higher.

In Proposition 5, we only show the result for $\theta > 2$, as when $\theta \leq 2$ the optimal product number is 1. The reason is that $\theta \leq 2$ indicates that the marginal cost of improving quality is not increasing very rapidly. In this case, the firm would have large incentive to improve product quality but show no interest in creating more products. As a result, if the firm decides to produce, it will only create one product with extremely high quality to cover all or almost all customers. On the other hand, when θ is large enough ($\theta > 2$), the firm would produce more products. In general, there exists a threshold of θ above which our results in Proposition 5 will hold. Under our model setup, the threshold happens to be 2, while other setups can lead to different threshold values. For example, if we let Z be a concave function of q, the effect is equivalent to decreasing θ in our model. As a result, the threshold of θ will be larger than 2, but it still exists. In short, the results in Proposition

5 are general since the threshold exists as long as θ is an indicator of marginal cost of improving quality.

Our study can also provide essential managerial implications to streaming media companies. It is important for these firms to realize that they need to shift from the previous transaction-based model to the engagement-based model, as we show that the latter model is more appropriate for subscription-based streaming companies. The product strategies and policies we derive for engagement-based model can be used by streaming companies to maximize their profit. The focus of the best policy for streaming companies is to raise the overall utility so that the overall consumer surplus which is a proxy for customer satisfaction is high. Companies can benefit from the overall customer satisfaction, as it transforms directly into subscriptions.

Another point where streaming firms can benefit from our research is how to generate content for different customer segments. In general, companies should give priority to large customer segments. The tactics should be to provide more programs available for a large segment to reduce misfits so that viewers can easily find programs that suit their tastes and obtain high utility. If the firm is considering different types of programs with different budget constraints, it should make sure that the big budget programs appeal to the larger customer base. On the contrary, for niche customers who are located in small segments, a practical strategy is to provide programs with relatively lower budget. However, this strategy might create some negative consequences and need to be examined carefully by the company, as niche customers may complain about the low quality of the product and thus the firm risks losing these customers.

4.6 CONCLUSIONS

With the boom of data technology, streaming media companies show their competitive strength in content production, taking the advantage of the innovations of algorithms and subscription-based business model. However, much of the research up to now largely focuses on the demand-side analysis as well as technical methods in recommendation systems. Some research analyzes the pricing of subscription model, but no prior work attempts to tackle the problem of product personalization for streaming media firms who are ambitious in producing their own contents. Moreover, with the widely spreading phenomenon, content proliferation, it is still inconclusive whether the content production of streaming firms is biased in favor of the major audience, while ignoring the niche audience.

In this study, we develop a model to explore optimal content differentiation policies of streaming media companies. Our model is an extension of product assortment model originated from Hotelling (1929) and adapted by Lancaster (1974) and Gaur and Honhon (2006). Aware of the uniqueness in subscription-based pricing and self-producing contents of the streaming media firm, we develop a new-stylized objective function which considers consumer utility and production cost simultaneously. To examine the impact of learning algorithms, we assume various distributions of customer tastes and compare the optimal policies with that facing the uniformly distributed customers.

Our model, based on maximizing customer engagement and learned customer tastes, yields insightful results on media company's policies on content development. The results suggest that the engagement-based firm tends to locate products closer, different from the traditional firm who always pursues the non-negative utility for all customers. Further analyses demonstrate that focusing on customer engagement can, in general, lead to more content creation, with large-value contents for the engagement model and small profit margin for transaction model. Besides, an algorithm is offered to find the optimal product differentiation policy with learned customer tastes. Leveraging a numerical analysis, we find that the policy does not seem to cause over-production of contents for the high-density customer cluster. In contrast, the policy benefits low density customer clusters in terms of content provision, consistent with the idea of narrowcasting. With the learning algorithms, both the engagement-based firm and the customers enjoy a welfare surge. Furthermore, we develop an extension of the model and endogenize product quality. We find that the firm tends to use a policy with higher quantity and less content for more crowded clusters while implementing a policy with lower quality and more contents at niche clusters.

Our work contributes to the literature of media digitalization with emphasis on the supply-side production strategy as the first attempt. The results provide a deeper insight into the impact of consumer engagement by incorporating customer utility in the objective function of product differentiation problem. Additionally, we add to the product differentiation literature by devoting substantial efforts to optimal policy of the emerging streaming media firms. We find a new type of agglomeration effect due to data and algorithms under the focal context. The insights gained from this study may be of assistance to the content programing of streaming media firms, especially when they adopt algorithms to learn customer tastes. For example, with a non-uniform distribution, the firm should always produce some contents with overlapped features. Programs should be offered more at crowded genres without largely ignorance on the sparse genres.

We also recognize some limitations in our research. First, our work has not offered analytical solution to the optimal policy with learned customer tastes. Numerical cases may lead to certain bias in the analysis even though we examine the results with a wide range of parameters. Second, we haven’t considered the heterogeneity in consumers’ usage frequency. Specifically, we assume all consumers will be charged for a constant price for every view of programs, a compromise between realistic representation and mathematical tractability of the problem. In addition, product price is assumed to be exogenous in our model, in line with the seminal papers of Lancaster (1974) and Gaur and Honhon (2006). Future studies can attempt to generalize the subscription-based pricing with heterogenous consumer usage, as well as to endogenize the pricing decision. Lastly, we also see large opportunities in the current domain. For instance, the quality of programs can also be considered in the model, which is potentially correlated with production cost. We hope our work provides a starting point for future research in product differentiation of streaming media firms.

Chapter 5. THE ROLE OF VOICE IN CONSUMER DECISIONS: EVIDENCE FROM A PAYMENT-BASED KNOWLEDGE SHARING COMMUNITY

Knowledge has become a product or a service, which helps people obtain information efficiently and encourages high-quality content. The content of paid knowledge is more diverse nowadays, thanks to the development of live streaming technology. More and more applications emerge such as paid online courses, audio/video based live lectures and Q&A service. As reported, China's sharing knowledge transactions were 61 billion RMB in 2016, a 205 percent year-on-year increase. Among these emerging attempts, Zhihu Live, which launched in May 2016, became a big success with its large Q&A community. Until January 2017, over 1,500 Zhihu Live shows had been hosted. The average hourly rate of 737 knowledge-sharing speakers reached 10,980 RMB (around $1,591).

The economy of knowledge gives rise to the research questions regarding the operations in knowledge marketplaces. One of the most critical questions is how to generate higher demand under this context. Different from traditional e-commerce products, knowledge products have their distinctive characteristics by nature. For example, they are never out-of-stock, perishable, impossible to return, and lack standards. Thus, knowledge products bear the disadvantages of high uncertainty in quality, leading to the churn of risk-averse consumers.

To mitigate the issue, many payment-based knowledge-sharing platforms adopt product sampling, a common resolution in traditional marketing. For example, Zhihu Live allows consumers to get access to the first 5-30 audio-based audition of some of their recorded live broadcasts. It aims to attract potential purchasers and help consumers to make a better decision. Many prior studies, focusing on various contexts, show that product sampling is an effective means to mitigate information asymmetry problem with a signaling effect (Spence 1973, Lin et al. 2019, Liu et al. 2022). However, it is still unclear whether product sampling works in knowledge marketplaces with its highly uncertain quality. The quality of content fully depends on the expertise and expressive ability of contributors. In light of the large variety in quality on the market, the audition of an underperforming recorded live broadcast can even harm the consumer demand. Besides, it is also critical to find the definition of high quality, which can be highly subjective for most of the time. To understand what factors are included in a high-quality recorded live broadcast, it is also important to investigate the consumer preference towards audition content and voice features it contains. Hence, we propose our research questions as follows:

1) Can audition improve the demand of recorded live broadcasts?

2) How does the relevance of audition content to main topic affect the demand of recorded live broadcasts?

3) How do the voice features in audition affect the demand of recorded live broadcasts?

To answer the above questions, we conduct an aggregated demand estimation model (BLP) to analyze the mechanism of demand generation process in knowledge marketplace, leveraging a unique dataset from Zhihu Live. Zhihu Live is one of the largest payment-based knowledge-sharing platforms in China. It originates from the largest open knowledge sharing platform in China, Zhihu (i.e. an analogue of Quora). Experts in the knowledge sharing community utilize the opportunity to make money based on their knowledge and large fan base in the original community. With respect to the relevance of audition content to main topic, we use speech recognition technology to transform audio files into Chinese texts and compute the semantic similarity between audition texts and live subject as well as the description. To extract voice features, we adopt the traditional signaling process techniques to generate various low-level descriptors (LLDs).

By including these variables in our demand estimation model, we come up with several meaningful results. First, we find that the free audio-based audition can significantly improve the sales performance of online knowledge products, except for some extreme cases with highly disadvantageous voice features. Further, it is better to offer some topic-relevant information in the audition. Second, people bother to listen to long lectures in today's fast-paced life. Specifically, they prefer shorter speech with rich information, and the duration of one piece of audio should not be too long. Finally, noise-free, soft, but full-of-variety voice is preferred by consumers. And female voice shows a small advantage in attracting demand. We also conduct a counterfactual analysis to examine the impact of audition on demand and calculate the elasticities of voice features to check the sensitivity of demand to different voice features. We also check the robustness on non-VIP market since there exists VIP-free lives which can interfere results of our model estimation.

Our research contributes to several streams of literature. First, our work sheds light on the mechanism of demand generation process of knowledge products. Based on the framework of Jin et al. (2019), we only focus on the post-broadcast market, and take a further step in examining the impact of voice features. Second, our work offers new insights to the literature of product sampling by further examining content and voice features contained in the audition. Lastly, we make the first move in examining the impact of voice features on consumer demand, especially in knowledge marketplaces. Prior studies mainly consider the influence of voice features from the perspective of psychology and politics (Mileva et al. 2020, Tigue et al. 2012, Klofstad 2016). Only a few studies in marketing address the questions but only consider the context of phone call of consumer service center or offline salespersons (Peterson et al. 1995). Our findings provide insights for both the platform designers and knowledge contributors on how to operate paid knowledge marketplace successfully. Several suggestions have been offered including more relevant content of audition and special training of voice pattern.

5.1 RESEARCH CONTEXT

5.1.1 *Context*

Zhihu Live launched in May 2016, which is an extension of Zhihu, the largest online Q&A community in China. Since its establishment, the platform has invited many celebrities to give live speeches, such as Joseph E. Stiglitz, Buzz Aldrin, and Kaifu Li. Many experts in Zhihu community also hosted lives in area of their expertise. This is called knowledge monetization. And from the perspective of audience, the consumers on the platform, they believe these knowledge products can broaden their horizon and bring them more knowledge and techniques in work. Therefore, it becomes popular to pay for the knowledge, which is thought to be free in the past. It is important for us to investigate the decision process of customers and whether it is affected by the reputation of speakers.

Figure 5.1 shows the interfaces of Zhihu Live. The left figure is the feed list which shows the topic, speaker, category, review score, the number of participants, the number of “likes”, and whether it allows free trial. If entering the information page of a live, a customer can see the interface shown in the middle figure. There is more information of price, start time, number of reviews, duration, number of Q&A, number of documents and detailed introduction of speaker and live.

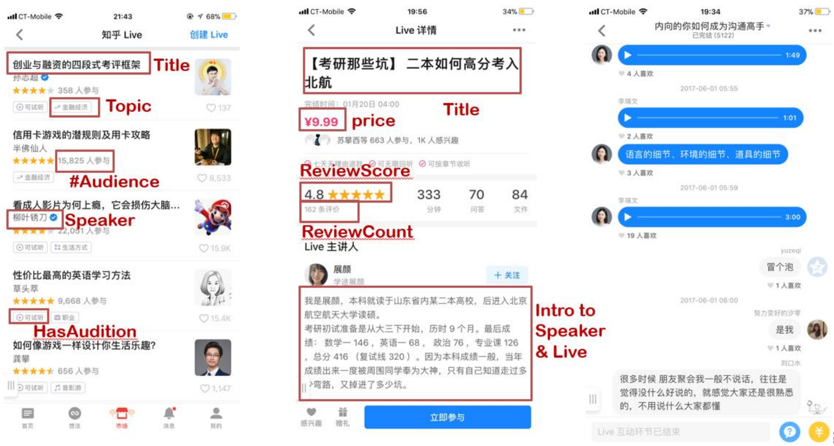


Figure 5.1. Interfaces of Zhihu Live

The right figure shows the interface within a live. The speaker can send pieces of audio, texts, pictures, videos and documents, while the audience can only send texts to communicate. Customers can choose to participant before or after the live ends, but cannot ask questions to the speaker if they enter after the live ends. However, customers may find it hard to decide before the live begins, because the interface can only provide an estimated review score according to the historical record of the speaker. On the other hand, customers who choose to participant after the live ends can refer to the reviews and ratings to make the decision. Besides, some of lives offer free audition to potential consumers, which are the first 5-30 pieces of messages of the live.

During our crawling period, Zhihu Live release its membership program. With an annual fee of about $30, a membership can listen to more than 1,000 past lives for free. Given the situation, it is hard for us to distinguish whether a consumer is a member or not. Thus, we conduct a robustness check in Section 5.3.5 and run our model only on non-VIP market (i.e., those lives not included in membership program).

5.1.2 *Data*

The data we crawled from Zhihu Live platform is from April 29, 2018 to September 26, 2018, including 6,149 lives and 2,469 speakers. Among those lives, 3,730 lives offer audio-based audition. Table 5.1 shows the description of variables in the dataset.

Table 5.1. Description of Variables

Variable	**Description**	**Mean**	**Std. Dev.**	**Min**	**Median**	**Max**
Weekly demand	Demand for the live aggregated in weeks.	28.71	841.578	0	2	60,182
Live Information						
Audio duration	The length of audio duration for the whole live, in unit of seconds.	61.97	40.710	55	59.29	692.94
Reply messages	Number of reply messages from the speaker to answer questions from the audience during the live. Before live broadcast, it takes zero.	20.16	28.709	0	10	374
Audio messages	Number of audio messages from the speaker during the live. Before live broadcast, it takes zero.	74.06	47.300	0	65	827
Attachment	Number of attached files from the speaker to facilitate the live content. Before live broadcast, it takes zero.	16.9	20.998	0	11	328
Price	The price of the live.	21.53	26.960	0.99	19.99	698.00
Like	Average number of likes during the week. Likes can be given before the live broadcast.	2,052.897	148.85	0	264	87,430.7
Review	Average number of reviews of the live during the week. Lives can only be reviewed after purchase.	108.55	384.917	0	36	21,125
Rating	Average review rating score of the live during the week. Lives can only be reviewed after purchase.	4.005	1.461	0	4.560	5.000
Review	Average number of reviews of the live during the week. Lives can only be reviewed after purchase.	71.52	150.22	5	31	3051
Dummy variables						
Audition	Whether the live has audition for free trial	3,052 Yes	3,097 No			
VIP	Whether the live is VIP-free.	1,505 Yes	4,644 No			
Refundable	Whether the live is refundable in 7 days.	3,168 Yes	2,981 No			
Topic	Which topic the live belongs to.	Internet (691) Sports (176) Healthcare (264) Business (131) Psychology (213) Travel (106) Education (1,097) Law (163) Lifestyle (489) Technology (290) Food (61) Job Market (798) Art (281) Finance and Economy (535) Design (189) Read and Write (226) Music, Movie and Game (439)				

5.2 EMPIRICAL MODEL

Since our dataset only includes aggregated data on live demand, we adopt an aggregated demand estimation model, BLP (Berry et al. 1995, Nevo 2001). In this section, we first introduce the variables of voice features we include in our empirical model and the theories behind them. Then, we present our model specification without and with voice features, followed by the estimation strategy.

5.2.1 *Variables of Voice Features*

The audio-based auditions contain useful information related to live content, and thus plays an important role to eliminate consumer uncertainty. In some auditions, contributors give a brief outline of the live content, while in other auditions the contributors talk about unrelated stuff such as causal talks to warm up the broadcast. How relevant the information offered in the audition is to the main topic of the live can potentially influence the evaluation from customers.

To find the relevance score of the audition content to the live description, we first leverage the speech recognition techniques of Keda Xunfei[6] to translate the audio files of audition into Chinese texts. Then, we translate each word in audition texts into word embedding vectors based on Tencent Embedding[7]. Tencent Embedding provides 200-dimension vector representation (i.e., embeddings) for over 8 million Chinese words and phrases, which are pre-trained on large-scale high-quality data. The training algorithm is directional skip-gram. The vectors capture the semantic meanings for Chinese words and phrases. After obtaining the word embeddings, we mean pool the vectors based on sentence level, then calculate the cosine similarity of paired sentence

[6] Keda Xunfei Speech Recognition: https://www.xfyun.cn/services/voicedictation
[7] Tencent Embedding: https://ai.tencent.com/ailab/nlp/zh/embedding.html

(i.e., audition text, live title/description). Similarities are both calculated between audition text and title, as well as audition text and description.

To derive voice features in our empirical model, we use a Python package Surfboard to extract LLDs (Lenain et al. 2020). The definition and explanation of our features can be found in Table 5.2. For RMS, we take the mean, standard deviation, minimum and maximum value in our model. For F0, we take the mean and standard deviation. Whereas for other LLDs, we only use the mean value to keep the simplicity of our model.

Table 5.2. Low Level Descriptors Extracted from Audition

LLD	**Definition and Explanation**
RMS (Root Means Square Energy)	The root means square of physical energy of the signal. RMS represents the intensity of the voice.
Loudness	The perceived intensity of the signal. The loudness measure is closer to human perception basically following a logarithmic representation of energy.
F0 (Fundamental Frequency)	The lowest and loudest frequency of the voice. Human ears can identify it as the specific pitch of the voice.
HNR (Harmonics-to-noise Ratio)	A measure quantifies the amount of additive noise in the voice signal. Often related to the quality of voice with respect to noise.
MFCCs (Mel-frequency Cepstral Coefficients)	A spectral representation of a voice based on a linear cosine transform of a log power spectrum on a nonlinear Mel scale of frequency. The Mel scale takes human hearing perception into account, where lower frequencies are resolved better by human hearing than higher ones. MFCCs are usually related to timbre of the voice.

5.2.2 *Model Specification*

As mentioned earlier, the platform allows consumers to make purchases both before and after the live broadcast. These two kinds of lives are inherently different: before live broadcast, consumers experience limited information on the quality and content of the live, whereas after live broadcast, consumers cannot communicate with the speaker in real time. Consumers have different pursuits towards these two kinds of lives. A typical demand growth trend of lives is like an S-curve, with a sharp surge just before the broadcast date and a gradual increase after then. Thus, we consider before and after broadcast lives as two separated markets. Our research only focuses on the after-broadcast market since audition can only be offered in after period.

We construct an aggregated demand model (BLP) at week level to analyze the impact of audition, since we only obtained aggregated data (Berry et al. 1995, Nevo 2001). The utility of consumer *i* from live *j* at time *t* can be presented in the following equations:

$$u_{ijt} = \alpha_i + \beta_i P_{jt} + X_{jt}\gamma + \xi_{jt} + \varepsilon_{ijt}, \tag{5.1}$$

$$\binom{\alpha_i}{\beta_i} = \binom{\bar{\alpha}}{\bar{\beta}} + \Sigma v_i,\, v_i \sim MVN(O, I), \tag{5.2}$$

where P_{jt} is the price of live *j* at time *t*, X_{jt} includes observable live features, ξ_{jt} is the unobserved characteristics of lives, and ε_{jt} is the idiosyncratic shock with independent and identically distribution (i.i.d.). Notice that X_{jt} can include, (i) $audition_{jt}$: whether live *j* offers audition at time *t*, (ii) control variables in Table 5.1, (iii) voice features in Table 5.2. In baseline model, we only include $audition_{jt}$ and control variables in X_{jt}, followed by the models with only relevance score and all the voice features.

We choose the intercept and price coefficient to be random, while others to be fixed, since consumers can have heterogeneity with respect to price. For identification, the utility of outside option is:

$$u_{it}^0 = \xi_{0t} + \varepsilon_{it}^0, \tag{5.3}$$

where ξ_{0t} is the unobserved utility of the outside option. We can normalize ξ_{jt} by subtracting ξ_{0t} from the former. Thus, ξ_{0t} can be normalized to 0.

5.2.3 *Model Estimation*

We use Nested Fixed Point (NFP), the common estimation approach, for BLP model estimation. The mean utility is the same for all the individual consumers and the market share for live *j* at time *t* can be written as Equations (5.4) and (5.5) respectively.

$$\delta_{jt} = \bar{\alpha} + \bar{\beta} P_{jt} + X_{jt}\gamma + \xi_{jt}, \tag{5.4}$$

$$s_{jt} = \int \frac{\exp\left(\delta_{jt} + [1, P_{jt}]\Sigma v_i\right)}{1 + \sum_{m=1}^{J} \exp(\delta_{mt} + [1, P_{mt}]\Sigma v_i)} f(v_i) dv_i, \tag{5.5}$$

Then, the parameters in our model can be separated into linear part $\theta_1 = (\bar{\alpha}, \bar{\beta}, \gamma)$, and non-linear part $\theta_2 = \Sigma$. To estimate the parameters, we optimize non-linear parameters θ_2 in the outer loop, while inner loop performs GMM estimation of linear parameters. In the outer loop, we use simulated market share, $\hat{s}_{jt}$, given in Equation (5.6), and contraction mapping to find mean utility δ_{jt}. In the inner loop, we use estimated mean utility to find ξ_{jt} and perform GMM estimation on ξ_{jt}.

$$\hat{s}_{jt} = \frac{1}{n_s} \sum_{i=1}^{n_s} \frac{\exp\left(\delta_{jt} + [1, P_{jt}]\Sigma v_i\right)}{1 + \sum_{m=1}^{J} \exp(\delta_{mt} + [1, P_{mt}]\Sigma v_i)}. \tag{5.6}$$

One common issue of demand estimation model comes from the endogeneity in product attributes. Thus, we construct a set of BLP-style instruments, including the average value of features of other products in the market, and the average value of features of other products under the same topic in the market. Furthermore, we also include a set of Villa-Boas-Winer style instruments, which are the lagged terms of endogenous variables (Zheng et al. 2016).

However, our live-week dataset contains many zero demand records, leading to zero market shares, which is not allowed in the estimation of BLP model. Therefore, we adopt the method proposed by Gandhi et al. (2014). They leverage a Bayesian approach and assume a Dirichlet prior for multinomial probabilities. Then, the optimal parameter for the prior distribution can be found using Maximum Likelihood Estimation (MLE) and the market shares can be approximated with non-zero posterior multinomial probabilities. In other words, we apply this method to add a small value to zero market shares and make sure our model can be well-estimated.

5.3 RESULTS

We discuss the model estimation results in this section by presenting three models: a basic model without speech related features in column (1), a model only with relevance score in column (2), and a model with all the voice features in column (3). The results are shown in Table 5.3.

5.3.1 *Impact of Audition*

The results of basic model in column (1) shows that audition has a significant and positive effect on the live demand. Results in column (2) and (3) demonstrate a negative coefficient for audition. However, this does not indicate a negative effect of audition. The reason is that we include relevance scores and voice features in column (2) and (3), and those features only takes non-zero values for lives with audition. For example, for a live with relevance scores with subject and description both larger than 0.535, the overall impact of audition is positive. The positive average effect of audition indicated by column (1) comes from the ability of auditions to reduce customers' uncertainty on the quality of lives and the signaling effect (Spence 1973, Liu et al. 2022). As the quality of lives on the platform has a wide range of variation, most customers hesitate to buy lives. However, auditions can help customers to get a better sense of what the live is about and if they like the way that the contributor presents in the live. Also, providing auditions as samples of the live is a signal of good quality in the literature of product sampling (Spence 1973, Liu et al. 2022).

As a result, auditions act as a sample of the live, thus signaling high quality of the live and attracting more customers to try the audition and buy the live.

The results in three models also show consistent pattern in audio related statistics of lives. Audio duration has a significantly negative impact on the live demand, whereas the number of attachment and audio messages manifest a positive effect. These results are intuitive. People are busy nowadays and do not have much time to listen to lives, so they want shorter lives with rich information offered. Besides, it is hard for them to locate useful information in longer audio pieces. Also, lives with more audio messages are those with rich contents or shorter average audio lengths, which also coincides with the effect of audio duration. Contributors can leverage our results when designing their lives to better cater customers' preference.

5.3.2 *Impact of Voice Features*

Both relevance scores of subjects and descriptions shows the same trend, that is, the more relevant the information offered in audition audio, the higher the demand will be generated. This is consistent with prior literature on consumer decisions. This is also an intuitive result, as more relevant content in the audition can reduce more uncertainty on the live quality and also signal higher quality of the live.

Table 5.3. Effects of Audition and Voice Features

	(1) Basic Model		(2) Relevance Score		(3) Speech Feature	
Variables	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Basic Features						
Audition	0.832^{***}	(0.275)	-1.991^{***}	(0.225)	-2.299^{***}	(0.202)
log(Audio_duration)	-0.404^{***}	(0.022)	-0.403^{***}	(0.021)	-0.394^{***}	(0.019)
log(Attachment)	0.128^{***}	(0.017)	0.148^{***}	(0.017)	0.135^{***}	(0.019)
log(Reply_message)	0.044	(0.047)	0.069	(0.048)	0.052	(0.046)
log(Audio_message)	0.277^{***}	(0.043)	0.288^{***}	(0.043)	0.278^{***}	(0.040)
Price	-0.445^{***}	(0.077)	-0.400^{***}	(0.076)	-0.408^{***}	(0.077)
log(Liked)	0.336^{**}	(0.139)	0.428^{***}	(0.141)	0.392^{***}	(0.141)
log(Review)	1.415^{***}	(0.033)	1.421^{***}	(0.032)	1.403^{***}	(0.026)

Rating	0.263***	(0.063)	0.330***	(0.063)	0.303***	(0.067)
Refundable	1.474***	(0.117)	1.309***	(0.121)	1.331***	(0.090)
Vip	-0.230	(1.773)	-1.706	(1.805)	-0.722	(1.967)
Constant	-21.539***	(0.782)	-22.587***	(0.789)	-22.287***	(0.830)
Topic_dummy	√		√		√	
Speech Features						
Relevance_subject	–		1.992***	(0.233)	0.815***	(0.459)
Relevance_description	–		1.735***	(0.265)	0.784***	(0.205)
RMS_mean	–		–		-13.432***	(3.436)
RMS_std	–		–		13.797***	(3.903)
RMS_min	–		–		10.647	(733.623)
RMS_max	–		–		1.090***	(0.763)
Loudness	–		–		-0.020	(0.019)
F0_mean	–		–		0.006***	(0.001)
F0_std	–		–		-0.002	(0.004)
HNR	–		–		-0.102***	(0.021)
MFCCs	–		–		√	
Non-linear Parameters						
Constant std	0.650 ***	(0.182)	0.650***	(0.174)	0.650***	(0.183)
Price std	0.311 ***	(0.048)	0.327***	(0.046)	0.311***	(0.049)

Note. Standard deviations are in brackets. **p < 0.1;* ***p < 0.05;* ****p < 0.01*

Results on voice features in column (3) generate more intuitions. First, the RMS energy shows a negative effect, while the impact of standard deviation of RMS energy is significantly positive. Loudness is insignificant mainly due to its impact has already been captured in RMS energy since they both focus on intensity of the speech. The result demonstrates that, on average, soft-spoken speech is preferable, but it should not be flat and without large variations. Consumers prefer enthusiastic voice with high variety but in small volume. Second, the fundamental frequency (F0) shows a significantly positive effect, but the absolute value is small. This indicates that in terms of voice pitch, consumers prefer female voice, but it is not the decisive factor. Finally, HNR shows significantly negative effect, which indicates that noisier audition is more disadvantage in attracting more demand. In general, we can conclude that customers prefer female voice with lower voice intensity and more variations. Our results can provide useful suggestions to contributors on how to present in their lives to attract more customers.

5.3.3 *Counterfactual Analysis on Audition*

The result from our aggregated demand model shows that audition can raise the utility of the customer to watch the focal live. However, this result does not directly tell us the impact of audition on demand. In this subsection, we conduct a counterfactual analysis to find out the influence of auditions on demand by simulating the case where no auditions exist.

The simulation is performed on all lives in our data, and we use the parameters found in our model with all voice features for accuracy. To simulate the case where no auditions exist, we set all characteristics related to auditions (including voice features) to zero for lives with auditions, and we leave other characteristics as they are. We then calculate the mean utility of lives in this new situation, and we simulate the unobserved characteristics of customers, v_i. Then we can calculate probabilities of simulated customers purchasing the lives and aggregate them to get simulated market share. We compare this new market share with the real market share in data to find out the impact of audition on projects with auditions and those without auditions. The result of our simulation is in Table 5.4.

Table 5.4. Simulated Impact of Auditions on Demand

	Mean	25%	Median	75%
Projects with audition	98.17%	54.82%	89.34%	132.66%
Projects without audition	-34.20%	-34.76%	-34.33%	-33.66%

The simulation result in Table 5.4 indicates that the impact of audition on demand is indeed huge. For many projects with auditions, having auditions almost double their demand. For projects without auditions, not having auditions while some other lives have auditions decreases their demand by more than 30%. This result shows that auditions play an important role in shaping the market of lives and building advantages for lives with auditions compared to those without them. We suggest that lives seriously consider providing an audition, as the impact of it on demand is large and not neglectable.

5.3.4 *Elasticities of Voice Features*

In this subsection, we explore the elasticities of voice features. We only calculate the own-voice-feature elasticities here to reflect how sensitive demand is to the change of different voice features. In our model, we can derive the own-speech-feature elasticity of a voice feature x_{jt}^k (the *k*-th entry of x_{jt}) following the approach in BLP (Berry et al. 1995) as follows:

$$\eta_{jt} = \frac{\partial s_{jt} x_{jt}^k}{\partial x_{jt}^k s_{jt}} = \frac{x_{jt}^k}{s_{jt}} \int \gamma^k s_{ijt} \left(1 - s_{ijt}\right) dF(v_i) \tag{5.7}$$

where s_{ijt} is the probability that individual i purchase live j:

$$s_{ijt} = \frac{\exp\left(\alpha_i + \beta_i P_{jt} + X_{jt}\gamma + \xi_{jt}\right)}{1 + \sum_{m=1}^{J} \exp\left(\alpha_i + \beta_i P_{mt} + X_{mt}\gamma + \xi_{mt}\right)} \tag{5.8}$$

We examine the elasticities of voice features which are significant in our results, and we summarize them by their average level in Table 5.5. We find that the absolute value of the elasticities of *RMS_mean* and *RMS_std* are low, while those of *F0_mean* and *HNR* are high, and the elasticities of relevance scores are moderate. This indicates that the demand of lives is more sensitive to voice pitch and noises and less sensitive to the volume of the voice. Our result can provide suggestions to live contributors on how to effectively boost their demand.

Table 5.5. Average own-voice-feature elasticities

Speech feature	Own-speech feature elasticity
Relevance_subject	0.807
Relevance_description	0.711
RMS_mean	-0.643
RMS_std	0.655
F0_mean	0.916
HNR	-0.877

5.3.5 *Robustness Check on Non-VIP Market*

In column (1) – (3) of Table 5.3, VIP is always insignificant, which indicates insignificant discrepancy between the demand structures of VIP-free lives and lives not included in VIP program. Thus, we conduct a robustness check to run our model only on Non-VIP market to eliminate the interference of demand from VIP-free lives.

The results are presented in Table 5.6 with three models in column (4) – (6). As we can see, the results are similar with respect to the impact of audition, audio duration, audio messages, and attachment. The number of reply messages is now significant after controlling for the VIP effect. For voice features, our results in whole market still carry over here, with respect to *RMS_mean*, *RMS_std*, *F0*, and *HNR*.

Table 5.6. Robustness Check on Non-VIP market

	(4) Basic Model		(5) Relevance Score		(6) Speech Feature	
Variables	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Basic Features						
Audition	0.914***	(0.038)	-2.292***	(0.095)	-2.457***	(0.098)
log(Audio_duration)	-0.440***	(0.020)	-0.414***	(0.018)	-0.412***	(0.019)
log(Attachment)	0.111***	(0.014)	0.133***	(0.014)	0.116***	(0.014)
log(Reply_message)	0.050***	(0.015)	0.027*	(0.015)	0.042***	(0.015)
log(Audio_message)	0.312***	(0.046)	0.284***	(0.045)	0.287***	(0.046)
Price	-0.512***	(0.086)	-0.433***	(0.094)	-0.471***	(0.090)
log(Liked)	0.314**	(0.021)	0.304***	(0.021)	0.358***	(0.021)
log(Review)	1.341***	(0.024)	1.363***	(0.024)	1.317***	(0.024)
Rating	0.301***	(0.015)	0.319***	(0.015)	0.326***	(0.015)
Refundable	1.748***	(0.041)	1.627***	(0.040)	1.546***	(0.041)
Constant	-21.298***	(0.252)	-21.814***	(0.257)	-21.954***	(0.250)
Topic_dummy	√		√		√	
Speech Features						
Relevance_subject	–		2.511***	(0.201)	1.084***	(0.248)
Relevance_description	–		1.523***	(0.177)	0.673***	(0.216)
RMS_mean	–		–		-13.658***	(3.105)
RMS_std	–		–		7.504*	(4.549)
RMS_min	–		–		-162.211	(713.280)
RMS_max	–		–		1.655***	(0.425)
Loudness	–		–		0.006	(0.017)
F0_mean	–		–		0.006***	(0.017)
F0_std	–		–		0.002	(0.100)
HNR	–		–		-0.020***	(0.021)
MFCCs	–		–		√	

Non-linear Parameters						
Constant std	0.763***	(0.195)	0.625**	(0.243)	0.697***	(0.217)
Price std	0.294***	(0.052)	0.252***	(0.064)	0.268***	(0.058)

Note. Standard deviations are in brackets. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

5.4 CONCLUSION

With the flourish of online live broadcast technology in recent years, everyone can make money by offering knowledge of their own expertise to the audience. The development of audio-based paid content has raised many critical research questions including the mechanism of demand generation (Jin et al. 2019). Our research takes a further step in examining the impact of audition and the impact of voice features in the audition on content demand.

Our research reveals several essential phenomena. First, we find that the free audio-based audition can significantly improve the sales performance of online knowledge products, except for some extreme cases with highly disadvantageous voice features. Our counterfactual analysis also shows the huge impact of audition on demand, encouraging more live contributors to provide auditions. Further, it is better to offer some topic-relevant information in the audition. Second, people bother to listen to long lectures in today's fast-paced life. Specifically, they prefer shorter speech with rich information, and the duration of one piece of audio should not be too long. Finally, noise-free, soft, but full-of-variety voice is preferred by consumers. And female voice shows a small advantage in attracting demand. From the analysis on elasticities of voice features, we find that demand is more sensitive to voice pitch and noises, while it is less sensitive to voice volume. We also check the robustness on non-VIP market since there exists VIP-free lives which can interfere results of our model estimation.

Our findings provide insights for practitioners from several perspectives. First, our work sheds light on the mechanism of demand generation in knowledge market with audio-based audition. Platform designers should consider offering audition to the underperforming contents. The content contributors should try to have a straightforward beginning in their speech which is more relevant to the topic. Besides, they should be cautious to the length of their speech as well as the duration of each audio piece. It will also be helpful to replace to advanced recording equipment to reduce the noise background in their speech if possible. They will also benefit from a soft voice full of variety after practice. The elasticities of different voice features also provide suggestions for content contributors to effectively boost the demand on their lives.

Our work still has some limitations for future improvement. First, we only include some of the low-level descriptors (LLDs) as the voice features in our model. We may include more emotional and personality-related voice features in the future. Besides, it will be helpful to extend our LLD-based features to deep learning features (Lee et al. 2009). Second, although we include the BLP-style instrument variables of audition in our empirical analysis, to mitigate the potential endogeneity issue, we also consider adding the supply-side of speaker features such as the number of followers, and the active level in knowledge sharing community. We hope our work provides a starting point for future research in voice features on various online platforms.

Chapter 6. CONCLUDING REMARKS

With the emerging growth of digital platforms, it becomes increasingly important to analyze the platform policies and designs. In this dissertation, I look into three related topics: match funding policy on online charitable crowdfunding platforms, product assortment on streaming media platforms, and free audition scheme on online knowledge sharing platforms.

My first essay aims to understand the effect of match funding on income inequality on a charitable crowdfunding platform. Match funding is a popular scheme which is adopted by donation-based crowdfunding platforms such that institutional donors commit to match the contribution of individual donors at a given rate. Our findings offer evidence that match offer can significantly help the projects to reach the fundraising goal, especially for those with a high-poverty level. Leveraging a structural model analysis, I find that match offers effectively increase donors' donation probability and average donation amount due to a higher utility they derive from contributing to projects with match offers. Regarding the impact on inequality, match offer has greater benefits when being applied to high-poverty projects. This merit mainly comes from a higher donation probability of high-poverty projects, whereas the average donation amount has no salient difference. I also discover that new donors are more attracted to unmatched projects, possibly due to the obligations they have to fill when they join the platform. My work at the transaction level verifies the robustness of the aforementioned findings by comparing the donation amount for matched and unmatched projects.

My second essay studies the best product assortment policy for streaming media companies. Streaming media companies leverage data and algorithms to self-program TV shows and movies to target various taste clusters. They also adopt subscription models and rely more on consumer engagement. This research develops a theoretical model on optimal content policies for streaming media companies in order to maximize customer engagement. I have the following interesting findings. First, in contrast to the results in prior literature that firms produce just enough products without overlapping product coverage intervals, we show that overlapping coverage intervals and placing products closer can be a better policy for engagement-based firms. Second, under engagement-based model, more contents are produced when the value of the contents is large to the customers or the profit margin in selling content is less than a certain threshold. Third, on learning the distribution of its customers, the media firm will always overlap product coverage intervals and place programs closer when the distribution density is higher. Additionally, in facing the tradeoffs of content quality and quantity, the firm should use a higher-quality and low-variety policy for high density clusters but a lower-quality and high-variety policy for low density clusters. Furthermore, when customers consume multiple shows in a period, a better policy is to produce TV shows or series with multiple episodes rather than individual movies. This study contributes to the literature on digital media, and the results provide interesting and insightful implications for streaming companies.

In my third essay, I investigate the impact of free auditions and voice features on a payment-based knowledge sharing platform. Experts on the platforms make money by giving lectures to audience in the community. Although some Fstudies have been carried out on demand estimation of knowledge products, little attention has been paid to the effectiveness of audition as well as the content and voice features it contains. Leveraging a unique dataset from one of the largest payment-based knowledge sharing platforms in China, we conduct an aggregated demand estimation model and extract various voice features from the audition using techniques from natural language processing and signaling processing. I conclude that audition can indeed boost the consumer demand especially with highly relevant audition content. Suggestions offered for practitioners that it is better to give shorter speech with rich information, and the duration of one piece of audio should not be too long. Noise-free, soft, but full-of-variety voice is preferred by consumers. And female voice shows a small advantage in attracting demand. My findings contribute to the emerging literature of knowledge product as well as the impact of voice in online marketplace.

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APPENDIX A

Table A.1. Summary Statistics

Variable	Definition	Mean	Std Dev	Min	Max	Median
Project Features						
Objective	Target of the goal to reach in U.S. dollars	457.760	637.627	17	35,135	354
Donors	Number of donors for each project	3.017	3.390	1	291	2
Duration	Project duration length in days	192.060	143.108	2	4,010	157
Complete	Whether the total donations reach the goal	0.814	0.389	0	1	1
Match	Whether the project is eligible for a match offer	0.150	0.357	0	1	0
Donation	Amount of each donation in U.S. dollars	101.839	202.358	0.010	21,847.750	42.500
ProjectNum	Number of ongoing projects on the platform at the time of each donation	12607.850	3059.602	3974	19183	12659
MatchProp	Proportion of matched projects when the project is posted	0.111	0.125	0	0.326	0.032
Donor Features						
CumProject	Number of projects that the donor donated to before	47.719	177.497	0	6,049	1
AvgDonations	Average donation amount that the donor donated before	84.137	184.792	0	20,717	12.750
CompleteRatio	Ratio of successful projects in all projects the donor contributed to before	0.436	0.471	0	1	0

Table A.2. Detailed Variables of Characteristics

Variable	Definition	Value of the Variable
SchoolChar	Characteristics of schools	
Charter	Whether the school is a charter school[8]	0 (93.20%), 1 (6.80%)
Magnet	Whether the school is a magnet school[9]	0 (87.99%), 1 (12.01%)
Area	The area type of the school	Urban (60.88%), Rural (8.64%), Suburban (20.00%), Other (10.50%)
ProjectChar	Characteristic of projects	
Poverty	The poverty level of students reached by a project	Highest (67.37%), High (21.12%), Moderate (9.68%), Low (1.83%)
Subject	Which subject a project primarily focuses on	Applied Learning (8.60%), Health & Sports (3.31%), History & Civics (6.27%), Literacy & Language (42.99%), Math & Science (23.09%), Music & The Arts (9.62%), Special Needs (6.12%)
Resource	Which type of resource the donation will be used for	Books (25.53%), Technology (24.47%), Supplies (39.56%), Trips (1.34%), Visitors (0.25%), Other (8.85%)
Grade	The grade level or age group of students reached by a project	Grades PreK-2 (34.46%), Grades 3-5 (30.61%), Grades 6-8 (17.75%), Grades 9-12 (17.17%)
MonthDummy	Which month the donation happened	From November 2005 to September 2009

[8] https://en.wikipedia.org/wiki/Charter_schools_in_the_United_States
[9] https://en.wikipedia.org/wiki/Magnet_school

APPENDIX B

B.1 Proof of Lemma 1

The length of coverage interval equals to $2l = \frac{2(Z-p)}{\alpha}$. If each product covers the whole coverage interval, the product space $\Theta = [0,1]$ can accommodate at most $\tilde{n}_T = \left\lfloor \frac{1}{2l} \right\rfloor = \left\lfloor \frac{\alpha}{2(Z-p)} \right\rfloor$ products. But it is possible that more products can generate higher profits, thus the optimal number of products n^* is at least as large as the base number of products $\tilde{n}_T$. i.e. $n^* \geq \tilde{n}_T$.

B.2 Proof of Lemma 2

We prove all three propertied together. First, to make positive profit, $K < \frac{2p(Z-p)}{\alpha}$ has to be held, which means that marginal cost is lower than marginal revenue.

Let the number of products be n. As $\tilde{n}_T = \left\lfloor \frac{\alpha}{2(Z-p)} \right\rfloor$, we know that when $n < \tilde{n}$, coverage of all products is at most $\frac{2n(Z-p)}{\alpha} < 1$. If overlaps exist, we can move all products to make sure that no overlap exists, and the coverage is exactly $\frac{2n(Z-p)}{\alpha}$, thus increasing revenue and leaving cost unchanged. So, no optimal assortment with $n < \tilde{n}_T$ can't have overlaps. For differentiations with no overlaps, noticing that：

$$1 - \frac{2n(Z-p)}{\alpha} \geq 1 - \frac{2(\tilde{n}_T - 1)(Z-p)}{\alpha} = 1 - \frac{2\tilde{n}_T(Z-p)}{\alpha} + \frac{Z-p}{\alpha} \geq \frac{Z-p}{\alpha}$$

we can always move those n products together and make them adjacent to each other with no overlaps. Then, as the place left uncovered is $1 - \frac{2n(Z-p)}{\alpha} \geq \frac{Z-p}{\alpha}$, we can add a new product which covers another $\frac{Z-p}{\alpha}$ that is not previously covered. As $K < \frac{2p(Z-p)}{\alpha}$, adding this new product can increase profit. So, no optimal solution has $n < \tilde{n}$.

When $n > \tilde{n}_T + 1$, $\tilde{n}_T = \left\lfloor \frac{\alpha}{2(Z-p)} \right\rfloor$, we know that $\frac{2(\tilde{n}_T+1)(Z-p)}{\alpha}$>1. This means that those n products can cover the whole product space, [0,1]. However, $\tilde{n}_T + 1$ products is enough to cover the whole product space when all products are evenly spaced along [0,1] with a distance of $b_{j+1} - b_j = \frac{2(Z-p)}{\alpha}$, $j = 1, \ldots, n-1$, so we can reduce n to $\tilde{n}_T + 1$, decreasing cost by $n - (\tilde{n}_T + 1)K$ while not decreasing revenue. So, no optimal solution has $n > \tilde{n}_T + 1$.

When $n = \tilde{n}_T$, the largest coverage of all intervals is $\frac{2(Z-p)}{\alpha}\tilde{n}_T \leq 1$. The largest coverage can only be reached by producing products with no overlaps. So, products with distance $b_{j+1} - b_j = \frac{2(Z-p)}{\alpha}$, $j = 1, \ldots, n-1$ is also a best assortment when $n = \tilde{n}_T$. When $n = \tilde{n}_T + 1$, the largest coverage of all intervals is 1. In this case, any assortments whose coverage is 1 is a best assortment when $n = \tilde{n}_T + 1$.We can also create an assortment of products with distance $b_{j+1} - b_j = \frac{2(Z-p)}{\alpha}$, $j = 1, \ldots, n-1$. In this assortment, these products are all in [0,1] (this is possible as $\frac{2\tilde{n}_T(Z-p)}{\alpha} \leq 1$) and can cover the whole product space. So, this assortment is also a best assortment when$n = \tilde{n}_T + 1$. As optimal solution can only have $n = \tilde{n}_T$ or $n = \tilde{n}_T + 1$, we have proved that there exists an optimal solution with distance $b_{j+1} - b_j = \frac{2(Z-p)}{\alpha}$, $j = 1, \ldots, n-1$, which also means that all neighbor products are adjacent and do not overlap with each other. So (i) and (ii) are proved.

Now we turn to prove (iii). When $n = \tilde{n}_T$, moving all products and produce another product $b_{\tilde{n}+1}$ can earn $(1 - \frac{2\tilde{n}_T(Z-p)}{\alpha})p$ more for the firm. So, when $K < (1 - \frac{2\tilde{n}_T(Z-p)}{\alpha})p$, $n = \tilde{n}_T + 1$ has the highest profit, while when $K \geq (1 - \frac{2\tilde{n}_T(Z-p)}{\alpha})p$, $n = \tilde{n}$ has the highest profit.

B.3 PROOF OF PROPOSITION 1

When $n \leq \tilde{n}_E$, that is, $\frac{2nZ}{\alpha} \leq 1$, the number of products is small enough so that we can place all the products within [0,1] without overlap. And the optimal differentiation should not have any overlaps, otherwise, we can move products to eliminate overlaps and increase the value of objective function.

When $n \geq \tilde{n}_E + 1$, that is, $\frac{2nZ}{\alpha} > 1$, the number of products is large enough to cover every point of [0,1] without "gaps" between neighbor first-choice intervals. We prove the proposition from three properties:

(1) The product coverage intervals must be overlapped, that is, $b_{j+1} - b_j \leq \frac{2Z}{\alpha}$, $j = 1,2,\ldots,n-1$.

As $\frac{2nZ}{\alpha} \geq 1$, if there exists a k such that $b_{k+1} - b_k > \frac{2Z}{\alpha}$, then there will exist an m, such that $b_m - \frac{Z}{\alpha} < 0$, $b_m + \frac{Z}{\alpha} > 1$, or $b_{m+1} - b_m < \frac{2Z}{\alpha}$. If $b_m - \frac{Z}{\alpha} < 0$ or $b_m + \frac{Z}{\alpha} > 1$, we can move all products on the left of b_{k+1} to the right until $b_{k+1} - b_k = \frac{2Z}{\alpha}$, or move all products on the right of b_k to the left until $b_{k+1} - b_k = \frac{2Z}{\alpha}$, thus increasing or decreasing b_m so that integrated consumer utility increases. If $b_{m+1} - b_m < \frac{2Z}{\alpha}$, we can move products between b_m and b_{k+1} to the right (if $m < k$) or between b_k and b_{m+1} to the left until $b_{k+1} - b_k = \frac{2Z}{\alpha}$. Then $b_{m+1} - b_m$ increases and integrated consumer utility increases. As $\frac{2nZ}{\alpha} \geq 1$, we can move products and eliminate all "gaps" between products (where $b_{k+1} - b_k > \frac{2Z}{\alpha}$) and increase integrated consumer utility. So, for the optimal assortment, there must exist $b_{j+1} - b_j \leq \frac{2Z}{\alpha}$ for all $j = 1,\ldots,n-1$. That is, product coverage intervals must be overlapped.

(2) All products are evenly spaced and the overlaps are the same width, that is, $b_{j+1} - b_j = \Delta$*,* $\Delta \geq 0$ *is a constant value,* $j = 1,2,\ldots,n-1$.

As $b_{j+1} - b_j \leq \frac{2Z}{\alpha}$, $j = 1,\ldots,n-1$, we have $b_j^+ = b_{j+1}^-$ and $b_j^+ - b_j = b_{j+1} - b_{j+1}^- = \frac{b_{j+1}-b_j}{2}$.

As $b_j \in [0,1]$, we have:

$$\sum_{j=1}^{n} r\int_{b_j^-}^{b_j^+} U_{ij} f(x_i)dx_i = \sum_{j=1}^{n} r\int_{b_j^-}^{b_j^+} \left(Z - \alpha\left|x - b_j\right|\right)dx$$

$$= r\int_{b_1^-}^{b_1}\left(Z - \alpha(b_1 - x)\right)dx + \sum_{j=1}^{n-1} r\left(\int_{b_j}^{b_j^+}\left(Z - \alpha\left(x - b_j\right)\right)dx + \int_{b_{j+1}^-}^{b_{j+1}}\left(Z - \alpha\left(b_{j+1} - x\right)\right)dx\right) + r\int_{b_n}^{b_n^+}\left(Z - \alpha(x - b_n)\right)dx$$

$$= r\int_{b_1^-}^{b_1}\left(Z - \alpha(b_1 - x)\right)dx + rZ(b_n - b_1) - \frac{r\alpha^2}{4}\sum_{j=1}^{n-1}\left(b_{j+1} - b_j\right)^2 + r\int_{b_n}^{b_n^+}\left(Z - \alpha(x - b_n)\right)dx$$

As $h(x) = x^2$ is a convex function, using Jensen's Inequality, we have:

$$\frac{1}{n-1}\sum_{j=1}^{n-1}(b_{j+1} - b_j)^2 \geq (\frac{1}{n-1}\sum_{j=1}^{n-1}(b_{j+1} - b_j))^2 = \frac{1}{(n-1)^2}(b_n - b_1)^2$$

So $\sum_{j=1}^{n-1}(b_{j+1} - b_j)^2 \geq \frac{1}{n-1}(b_n - b_1)^2$, and:

$$\sum_{j=1}^{n} r\int_{b_j^-}^{b_j^+} U_{ij} f(x_i)dx_i \leq r\int_{b_1^-}^{b_1}(Z - \alpha(b_1 - x))dx + r\int_{b_n}^{b_n^+}(Z - \alpha(x - b_n))dx + rZ(b_n - b_1) - \frac{r\alpha^2}{4(n-1)}(b_n - b_1)^2$$

The equality can only be reached when $b_{j+1} - b_j = \frac{1}{n-1}(b_n - b_1)$, $j = 1,\ldots,n-1$, because $h(x)$ is a strictly convex function. So, for an optimal assortment, $b_{j+1} - b_j = \Delta$, $\Delta \geq 0$ is a constant value, $j = 1,\ldots,n-1$. That is, product coverage intervals overlap with the same width.

(3) All products are symmetrically distributed, that is, $b_1 + b_n = 1$.

If $b_1 > \frac{Z}{\alpha}$ or $b_n < 1 - \frac{Z}{\alpha}$, we can decrease b_1 or increase b_n to increase integrated consumer utility, as overlapping must exist. If $b_1 = \frac{Z}{\alpha}$ and $b_n = 1 - \frac{Z}{\alpha}$, then $b_1 + b_n = 1$. If $b_1 \leq \frac{Z}{\alpha}$ and $b_n \geq 1 - \frac{Z}{\alpha}$, but $b_n - b_1 > 1 - \frac{2Z}{\alpha}$, then:

$$\sum_{j=1}^{n} r \int_{b_j^-}^{b_j^+} U_{ij} f(x_i) dx_i$$

$$= r \int_0^{b_1} (Z - \alpha(b_1 - x)) dx + Z(b_n - b_1) - \frac{r\alpha^2}{4} \sum_{j=1}^{n-1} (b_{j+1} - b_j)^2 + r \int_{b_n}^{1} (Z - \alpha(x - b_n)) dx$$

$$= \frac{rZ^2}{\alpha} - \frac{r}{2\alpha}((Z - \alpha b_1)^2 + r(Z - \alpha(1 - b_n))^2) + rZ(b_n - b_1) - \frac{r\alpha^2}{4} \sum_{j=1}^{n-1} (b_{j+1} - b_j)^2$$

When we keep all differences between adjacent specification of products the same (i.e., keeping $b_{j+1} - b_j$ constant), then $b_n - b_1$ is also a constant, and $b_1 + (1 - b_n)$ is a constant. As $h(x)$ is a convex function, using Jensen's Inequality, we have:

$$\frac{(Z - \alpha b_1)^2 + (Z - \alpha(1 - b_n))^2}{2} \geq (\frac{Z - \alpha b_1 + Z - \alpha(1 - b_n)}{2})^2 = \frac{(2Z - \alpha(b_1 + 1 - b_n))^2}{4}$$

So, we have:

$$\sum_{j=1}^{n} r \int_{b_j^-}^{b_j^+} U_{ij} f(x_i) dx_i$$

$$\leq \frac{rZ^2}{\alpha} - \frac{r}{4\alpha}(2Z - \alpha(b_1 + 1 - b_n))^2 + rZ(b_n - b_1) - \frac{r\alpha^2}{4} \sum_{j=1}^{n-1} (b_{j+1} - b_j)^2$$

As $h(x)$ is strictly convex, the equality can only be reached when $Z - \alpha b_1 = Z - \alpha(1 - b_n)$, which means that $b_1 + b_n = 1$. So, an optimal assortment should have $b_1 + b_n = 1$.

B.4 PROOF OF PROPOSITION 2

We first find the optimal assortment for every fixed *n*, then compare the optimal differentiation with different *n*, and finally find the optimal number of products and the optimal arrangement of products.

When $n \leq \tilde{n}_E$, that is, $\frac{2nZ}{\alpha} \leq 1$, there is no overlap among all product coverage intervals. Thus, every product offers an integrated consumer utility of $\frac{rZ^2}{\alpha}$. The maximization goal is $W(n) = n(\frac{rZ^2}{\alpha} - K)$.

When $n \geq \tilde{n}_E + 1$, that is, $\frac{2nZ}{\alpha} > 1$, the number of products is large enough to cover every point of [0,1] without "gaps" between neighbor first-choice intervals. We define *d* as the total length of all first-choice intervals, that is, $d = b_n^+ - b_1^-$. According to Proposition 2, the first-choice intervals must be adjacent or overlapped, that is, $1 \leq d \leq \frac{2nZ}{\alpha}$. Also, all products should be symmetrically distributed in [0,1]. Thus, the total benefits of all products can be separated to three parts: total benefits of all products ignoring benefit loss due to overlap, benefit loss due to overlap, and benefit loss due to excess beyond product space Θ. Thus, the maximization goal can be written as:

$$W(n,d) = r\left(\frac{nZ^2}{\alpha} - \frac{\alpha(\frac{2nZ}{\alpha} - d)^2}{4(n-1)} - \frac{\alpha(d-1)^2}{4}\right) - nK$$

Take the derivative of $W(n,d)$ with respect to *d*:

$$\frac{\partial W(n,d)}{\partial d} = \frac{r\alpha}{2}\left(\frac{\frac{2nZ}{\alpha} + n - 1}{n-1} - \frac{n}{n-1}d\right)$$

When $d = \frac{2Z}{\alpha} - \frac{1}{n} + 1$, the derivative equals to zero, and $W(n,d)$ achieves the maximum value. So, $W(n) = n\left(\frac{rZ^2}{\alpha} - K\right) - \frac{r\alpha(\frac{2nZ}{\alpha}-1)^2}{4n} = rZ - \frac{r\alpha}{4n} - nK$ is the maximization goal under this situation.

Thus, combining the analysis from first part, the maximization goal can be expressed as:

$$W(n) = \begin{cases} \frac{nrZ^2}{\alpha} - nK & when\, n \le \tilde{n}_E \\ rZ - \frac{r\alpha}{4n} - nK & when\, n \ge \tilde{n}_E + 1 \end{cases}$$

When $n \le \tilde{n}_E - 1$, $\Delta W = W(n+1) - W(n) = \frac{rZ^2}{\alpha} - K > 0$.

So, $W(\tilde{n}_E) \ge W(n)$, $n = 1,2,\ldots,\tilde{n}_E$.

When $n = \tilde{n}_E$, $\Delta W = W(n+1) - W(n) = \frac{rZ^2}{\alpha} - K - \frac{r\alpha(\frac{2(n+1)Z}{\alpha}-1)^2}{4(n+1)}$. The difference includes the benefit from the extra product and the loss from overlap and excess beyond product space Θ.

So, when $K > \frac{rZ^2}{\alpha} - \frac{r(2Z(\tilde{n}_E+1)-\alpha)^2}{4\alpha(\tilde{n}_E+1)}$, $\Delta W < 0$, the optimal number of products is $n = \tilde{n}_E$. Otherwise, $W(\tilde{n}_E + 1) > W(\tilde{n}_E) \ge W(n)$, $n = 1,2,\ldots,\tilde{n}_E$. Here, $K > (1 - \frac{(2Z(\tilde{n}_E+1)-\alpha)^2}{4Z^2(\tilde{n}_E+1)})\frac{rZ^2}{\alpha}$, $\frac{(2Z(\tilde{n}_E+1)-\alpha)^2}{4Z^2(\tilde{n}_E+1)}$ is the loss rate due to overlap and excess beyond product space Θ.

When $n \ge \tilde{n}_E + 1$, $\Delta W = W(n+1) - W(n) = \frac{r\alpha}{4n(n+1)} - K$. This benefit change is unrelated to Z. The reason is that, introducing another product can bring a certain amount of benefits, but also a larger benefit loss due to larger overlap. In the end, the benefit gain and benefit loss exactly offset to make the net increase of satisfaction unrelated to Z.

With the increase of n, the value of ΔW is decreasing from positive to negative. There are two values of n gives a ΔW very close to zero, thus are potential optimal number of products. They are $\left\lfloor \frac{1}{2}(\sqrt{\frac{r\alpha}{K}+1} - 1)\right\rfloor$ and $\left\lfloor \frac{1}{2}(\sqrt{\frac{r\alpha}{K}+1} - 1)\right\rfloor + 1$. Because $W\left(\left\lfloor \frac{1}{2}(\sqrt{\frac{r\alpha}{K}+1} - 1)\right\rfloor + 1\right) -$

$W\left(\left\lfloor\frac{1}{2}\left(\sqrt{\frac{r\alpha}{K}+1}-1\right)\right\rfloor\right)>0$ and $W\left(\left\lfloor\frac{1}{2}(\sqrt{\frac{r\alpha}{K}+1}-1)\right\rfloor+2\right)-W\left(\left\lfloor\frac{1}{2}\left(\sqrt{\frac{r\alpha}{K}+1}-1\right)\right\rfloor+1\right)<0$, the optimal number of products is $n=\left\lfloor\frac{1}{2}(\sqrt{\frac{r\alpha}{K}+1}-1)\right\rfloor+1\geq\tilde{n}_E+1$ when $K\leq\frac{rZ^2}{\alpha}-\frac{r(2Z(\tilde{n}_E+1)-\alpha)^2}{4\alpha(\tilde{n}_E+1)}$.

Now, the optimal number of products in both conditions has been solved.

In condition $K>\frac{rZ^2}{\alpha}-\frac{r(2Z(\tilde{n}_E+1)-\alpha)^2}{4\alpha(\tilde{n}_E+1)}$, all $\tilde{n}_E$ intervals should be adjacent without overlaps. And the optimal number of products is $n=\tilde{n}_E$ under this condition.

In condition when $K\leq\frac{rZ^2}{\alpha}-\frac{r(2Z(\tilde{n}_E+1)-\alpha)^2}{4\alpha(\tilde{n}_E+1)}$, according to Proposition 2, all products should be symmetrically placed with equal overlaps in [0,1]. As we know the optimal number of products is $n=\left\lfloor\frac{1}{2}(\sqrt{\frac{r\alpha}{K}+1}-1)\right\rfloor+1$, the total length of all first-choice intervals is $d=\frac{2Z}{\alpha}-\frac{1}{n}+1$. Thus, each overlap is $\frac{\frac{2nZ}{\alpha}-d}{n-1}=\frac{2Z}{\alpha}-\frac{1}{n}\geq 0$. And the distance between two neighbor products can also be calculated as $b_{j+1}-b_j=\frac{1}{n}\leq\frac{2Z}{\alpha}$.

B.5 Proof of Proposition 3

We define $2l$ as the coverage interval under the transaction-based model and $l=(Z-p)/\alpha$. The traditional firm's optimal number of products is n_1, which is the smallest integer satisfying $(1-2n_1 l)p\leq K$. This inequality means that it is not beneficial to introduce another product since the cost is not lower than income. So, $n_1=\left\lfloor\frac{1-\frac{K}{p}}{2l}\right\rfloor+1$. The customer-centric firm's optimal number of products is $n_2=\left\lfloor\frac{1}{2}\left(\sqrt{\frac{r\alpha}{K}+1}-1\right)\right\rfloor+1$. When $\frac{1-\frac{K}{p}}{2l}<\frac{1}{2}\left(\sqrt{\frac{r\alpha}{K}+1}-1\right)$, we have $n_1\leq$

n_2, which means that the optimal number of products of traditional firm is smaller than or equal to that of customer-centric firm. Solve the inequality, we can get the following condition,

$p(Z-p)\left(\sqrt{\frac{r\alpha}{K}+1}-1\right) > \alpha(p-K).$

Simplifying it, we get the condition in the Proposition.

Similarly, if $\frac{1-\frac{K}{p}}{2l} \geq \frac{1}{2}\left(\sqrt{\frac{r\alpha}{K}+1}-1\right)$, we can derive $n_1 \geq n_2$, which means that customer-centric firm can only produce at most the same number of programs as traditional firms.

B.6 Proof of Lemma 3

Suppose that the product number is n. Then similar with that of Proposition 2, we can prove that $b_{j+1} - b_j \leq 2L$, $j = 1, \ldots, n-1$. Thus for $2 \leq j \leq n-1$, $b_j^- = \frac{b_{j-1}+b_j}{2}, b_j^+ = \frac{b_j+b_{j+1}}{2}$. We first prove that the necessary condition is true for $2 \leq j \leq n-1$, then we prove that it is also true for j=1 and $j = n$.

For $2 \leq j \leq n-1$, given that the locations of other products are fixed, the necessary condition of b_j to be the optimal location of product j is that the integrated utility of customers on the interval which is affected by b_j is optimal. To be specific, the integrated utility of customers on $[b_{j-1}, b_{j+1}]$ should be optimal when the location of product j is optimal. This integrated utility is:

$$IU_j = \int_{b_{j-1}}^{b_j^-} (Z-\alpha(x-b_{j-1}))f(x)dx + \int_{b_j^-}^{b_j} (Z-\alpha(b_j-x))f(x)dx$$

$$+ \int_{b_j}^{b_j^+} (Z-\alpha(x-b_j))f(x)dx + \int_{b_j^+}^{b_{j+1}} (Z-\alpha(b_{j+1}-x))f(x)dx$$

As b_j is the optimal location, the derivative of integrated utility with respect to b_j should be 0. Noting that $b_j^- = \frac{b_{j-1}+b_j}{2}$, $b_j^+ = \frac{b_{j+1}+b_j}{2}$, the first order condition becomes:

$$0 = \frac{\partial IU_j}{\partial b_j} = \frac{1}{2}\left(Z - \alpha\left(b_j^- - b_{j-1}\right)\right) f\left(b_j^-\right) - \frac{1}{2}\left(Z - \alpha\left(b_j - b_j^-\right)\right) f\left(b_j^-\right) + Z \cdot f\left(b_j\right) - \alpha \int_{b_j^-}^{b_j} f(x)dx + \frac{1}{2}\left(Z - \alpha\left(b_j^+ - b_j\right)\right) f\left(b_j^+\right) - Z \cdot f\left(b_j\right) + \alpha \int_{b_j}^{b_j^+} f(x)dx - \frac{1}{2}\left(Z - \alpha\left(b_{j+1} - b_j^+\right)\right) f\left(b_j^+\right) \ = \alpha(\int_{b_j}^{b_j^+} f(x)dx - \int_{b_j^-}^{b_j} f(x)dx)$$

So the necessary condition of b_j to be the optimal location is $\int_{b_j^-}^{b_j} f(x)dx = \int_{b_j}^{b_j^+} f(x)dx$. As $0 \le b_j \le 1$, $j = 1, \dots, n$, it is obvious that $b_j^- > 0$ and $b_j^+ < 1$, so $\int_{max\{0,b_j^-\}}^{b_j} f(x)dx = \int_{b_j}^{min\{b_j^+,1\}} f(x)dx$.

For $j = 1$, similarly, b_1 is the optimal location for product 1 given that the locations of other products are fixed. The interval where customer's utility is affected by the choice of b_1 is $[max\{0, b_1^-\}, b_2]$, and the integrated utility on this interval is:

$$IU_1 = \int_{max\{0,b_1^-\}}^{b_1} (Z - \alpha(b_1 - x)) f(x)dx + \int_{b_1}^{b_1^+} (Z - \alpha(x - b_1)) f(x)dx + \int_{b_1^+}^{b_2} (Z - \alpha(b_2 - x)) f(x)dx$$

As $b_1^- = b_1 - L$, the first order condition aiming to find optimal b_1 is calculated differently under different conditions.

If $b_1 < L$, the first order condition becomes:

$$0 = \frac{\partial IU_1}{\partial b_1} = Z \cdot f(b_1) - \alpha \int_0^{b_1} f(x)dx + \frac{1}{2}(Z - \alpha(b_1^+ - b_1)) f(b_1^+) - Z \cdot f(b_1) + \alpha \int_{b_1}^{b_1^+} f(x)dx - \frac{1}{2}(Z - \alpha(b_2 - b_1^+)) f(b_1^+) = \alpha(\int_{b_1}^{b_1^+} f(x)dx - \int_0^{b_1} f(x)dx)$$

If $b_1 \ge L$, the first order condition becomes:

$0 = \frac{\partial IU_1}{\partial b_1} = Z \cdot f(b_1) - (Z - \alpha L)f(b_1 - L) - \alpha \int_{b_1-L}^{b_1} f(x)dx + \frac{1}{2}(Z - \alpha(b_1^+ - b_1))f(b_1^+) - Z \cdot$

$f(b_1) \quad + \alpha \int_{b_1}^{b_1^+} f(x)dx - \frac{1}{2}(Z - \alpha(b_2 - b_1^+))f(b_1^+) = \alpha(\int_{b_1}^{b_1^+} f(x)dx - \int_{b_1-L}^{b_1} f(x)dx)$

Summarizing first order conditions under different conditions, we find that the necessary condition of b_1 to be optimal is $\int_{max\{0,b_1^-\}}^{b_1} f(x)dx = \int_{b_1}^{b_1^+} f(x)dx$, which can also be written as $\int_{max\{0,b_1^-\}}^{b_1} f(x)dx = \int_{b_1}^{min\{b_1^+,1\}} f(x)dx$.

For $j = n$, we can prove that the necessary condition is also true using similar method as that we use to prove for $j = 1$.

So, the necessary condition for every b_j to be optimal is $\int_{max\{0,b_j^-\}}^{b_j} f(x)dx = \int_{b_j}^{min\{b_j^+,1\}} f(x)dx$.

As every b_j is optimal is also a necessary condition of locations of all products to be optimal, we conclude that $\int_{max\{0,b_j^-\}}^{b_j} f(x)dx = \int_{b_j}^{min\{b_j^+,1\}} f(x)dx$, $j = 1, \ldots, n$ is a necessary condition of optimal product locations in optimal assortment.

B.7 Proof of Proposition 4

We first prove (ii). From the proof of Algorithm 1, we get that the necessary condition for optimal product locations is $\int_{max\{0,b_j^-\}}^{b_j} f(x)dx = \int_{b_j}^{min\{b_j^+,1\}} f(x)dx$, $j = 1, \ldots, n$. As customers are unimodal distributed, $b_k < x^* \leq b_{k+1}$ and $\frac{b_k + b_{k+1}}{2} \leq x^*$, we know that $f(x)$ is increasing on $[max\{0, b_1^-\}, b_k^+]$ and decreasing on $[b_{k+1}, min\{1, b_n^+\}]$. So when $j \leq k$, we should have $b_j - max\{0, b_j^-\} \geq min\{1, b_j^+\} - b_j$, which indicates $d(j, j+1) > d(j+1, j+2)$ for $1 \leq j \leq k - 1$ and $d(1,2) \leq 2\, min\{b_1, L\}$. Similarly, when $j \geq k+1$, $b_j - max\{0, b_j^-\} \leq min\{1, b_j^+\} - b_j$

and it indicates that $d(j,j+1) < d(j+1,j+2)$ for $k+1 \le j \le n-2$ and $d(n-1,n) \le 2\,min\{1-b_n, L\}$. So (ii) get proved.

Following the proof of (ii), we find that $d(k,k+1) < d(k-1,k) <\ldots< d(1,2) < 2\,min\{L, b_1\} \le 2L$ and $d(k+1,k+2) < d(k+2,k+3) <\ldots< d(n-1,n) < 2\,min\{L, 1-b_n\} \le 2L$. These inequalities indicate that $b_{j+1} - b_j < 2L$ is true for $1 \le j \le n-1$, which is exactly what (i) states.

B.8 Proof of Proposition 5

We start from the profit function of the engagement-based company in the proof of Proposition 3:

$$W(n) = \begin{cases} \frac{nrZ^2}{\alpha} - nK & when\, n \le \tilde{n}_E \\ rZ - \frac{r\alpha}{4n} - nK & when\, n \ge \tilde{n}_E + 1 \end{cases}$$

Here $\tilde{n}_E = \left\lfloor \frac{\alpha}{2Z} \right\rfloor$. As the profit function above is calculated on a uniform distribution on [0,1], we can adapt the profit function to the following form for a segment with uniformly distributed customers and length s:

$$W(n,K) = \begin{cases} n\left(\frac{rZ^2}{\alpha s} - K\right) & when\, n \le \frac{\alpha s}{2Z} \\ rZ - \frac{r\alpha s}{4n} - nK & when\, n > \frac{\alpha s}{2Z} \end{cases}$$

As $K = cq^\theta, (\theta > 1)$ and $Z = q$, we can further simplify the profit function as:

$$W(n,K) = \begin{cases} n\left(\frac{r}{\alpha s}\left(\frac{K}{c}\right)^{\frac{2}{\theta}} - K\right) & when\, K \le c\left(\frac{\alpha s}{2n}\right)^\theta \\ r\left(\frac{K}{c}\right)^{\frac{1}{\theta}} - \frac{r\alpha s}{4n} - nK & when\, K > c\left(\frac{\alpha s}{2n}\right)^\theta \end{cases}$$

We can take partial derivative with respect to K as:

$$\frac{\partial W}{\partial K}(n,K)=\begin{cases} n\left(\frac{2r}{\alpha s\theta}c^{-\frac{2}{\theta}}K^{\frac{2-\theta}{\theta}}-1\right) & when\ K\le c\left(\frac{\alpha s}{2n}\right)^{\theta} \\ \frac{r}{\theta}c^{-\frac{1}{\theta}}K^{\frac{1-\theta}{\theta}}-n & when\ K> c\left(\frac{\alpha s}{2n}\right)^{\theta} \end{cases}$$

After checking the value of $W(n,K)$ and $\frac{\partial W}{\partial K}(n,K)$ on the boundary $K=c\left(\frac{\alpha s}{2n}\right)^{\theta}$, we find that they are both continuous functions. So $W(n,K)$ is continuous and differentiable with respect to K.

(1) When $\theta>2$, $\frac{\partial W}{\partial K}(n,K)$ is decreasing and we can find the optimal K as:

$$K^*(n)=\begin{cases} \left(\frac{2r}{\alpha s\theta}\right)^{\frac{\theta}{\theta-2}}c^{\frac{-2}{\theta-2}} & when\ n\le\frac{\alpha s}{2}\left(\frac{\alpha sc\theta}{2r}\right)^{\frac{1}{\theta-2}} \\ \left(\frac{r}{n\theta}\right)^{\frac{\theta}{\theta-1}}c^{\frac{-1}{\theta-1}} & when\ n>\frac{\alpha s}{2}\left(\frac{\alpha sc\theta}{2r}\right)^{\frac{1}{\theta-2}} \end{cases}$$

And the corresponding optimal profit function is:

$$W^*(n)=\begin{cases} \frac{n}{c^{\frac{2}{\theta-2}}}\left(\frac{\theta}{2}-1\right)\left(\frac{2r}{\alpha s\theta}\right)^{\frac{\theta}{\theta-2}} & when\ n\le\frac{\alpha s}{2}\left(\frac{\alpha sc\theta}{2r}\right)^{\frac{1}{\theta-2}} \\ \frac{1}{(nc)^{\frac{1}{\theta-1}}}(\theta-1)\left(\frac{r}{\theta}\right)^{\frac{\theta}{\theta-1}}-\frac{r\alpha s}{4n} & when\ n>\frac{\alpha s}{2}\left(\frac{\alpha sc\theta}{2r}\right)^{\frac{1}{\theta-2}} \end{cases}$$

We can find the derivative of $W^*(n)$ as:

$$\frac{dW^*}{dn}(n)=\begin{cases} \frac{1}{c^{\frac{2}{\theta-2}}}\left(\frac{\theta}{2}-1\right)\left(\frac{2r}{\alpha s\theta}\right)^{\frac{\theta}{\theta-2}} & when\ n\le\frac{\alpha s}{2}\left(\frac{\alpha sc\theta}{2r}\right)^{\frac{1}{\theta-2}} \\ \frac{r\alpha s}{4n^2}-c^{-\frac{1}{\theta-1}}\left(\frac{r}{n\theta}\right)^{\frac{\theta}{\theta-1}} & when\ n>\frac{\alpha s}{2}\left(\frac{\alpha sc\theta}{2r}\right)^{\frac{1}{\theta-2}} \end{cases}$$

We also check the value of $W^*(n)$ and $\frac{dW^*}{dn}(n)$ on the boundary $n=\frac{\alpha s}{2}\left(\frac{\alpha sc\theta}{2r}\right)^{\frac{1}{\theta-2}}$ and find that $W^*(n)$ is continuous and differentiable. Thus, we can find the optimal n if n is a continuous variable:

$$n_0 = \frac{\alpha s\theta}{4}\left(\frac{\alpha sc\theta^2}{4r}\right)^{\frac{1}{\theta-2}}$$

As n is actually a discrete variable, the optimal n should be:

$$n^* = \left\lfloor \frac{\alpha s\theta}{4}\left(\frac{\alpha sc\theta^2}{4r}\right)^{\frac{1}{\theta-2}} \right\rfloor or\ n^* = \left\lfloor \frac{\alpha s\theta}{4}\left(\frac{\alpha sc\theta^2}{4r}\right)^{\frac{1}{\theta-2}} \right\rfloor + 1$$

With the expression of n^* we can find the optimal K and finally derive the optimal quality as:

$$q^* = \left(\frac{r}{n^*\theta c}\right)^{\frac{1}{\theta-1}}$$

(2) When $\theta = 2$, $\frac{\partial W}{\partial K}(n, K)$ is constant and positive on $K \leq c\left(\frac{\alpha s}{2n}\right)^{\theta}$ and decreasing on $K > c\left(\frac{\alpha s}{2n}\right)^{\theta}$. So the optimal K is:

$$K^*(n) = \frac{r^2}{4n^2c}$$

And the corresponding optimal profit function is:

$$W^*(n) = \frac{r}{4n}\left(\frac{r}{c} - \alpha s\right)$$

As $W^*(n)$ is decreasing, the optimal n is $n^* = 1$ and the corresponding quality is $q^* = \frac{r}{2c}$.

(3) When $1 < \theta < 2$, $\frac{\partial W}{\partial K}(n, K)$ is increasing on $K \leq c\left(\frac{\alpha s}{2n}\right)^{\theta}$ and decreasing on $K > c\left(\frac{\alpha s}{2n}\right)^{\theta}$. As $\frac{\partial W}{\partial K}(n, 0) = -n < 0$, we need $\frac{\partial W}{\partial K}\left(n, c\left(\frac{\alpha}{2n}\right)^{\theta}\right) > 0$ to make sure that the optimal K is not 0. We can find the optimal K to be:

$$K^*(n) = \left(\frac{r}{n\theta}\right)^{\frac{\theta}{\theta-1}} c^{\frac{-1}{\theta-1}}$$

And the corresponding optimal profit function is:

$$W^*(n) = \frac{1}{(nc)^{\frac{1}{\theta-1}}}(\theta-1)\left(\frac{r}{\theta}\right)^{\frac{\theta}{\theta-1}} - \frac{r\alpha s}{4n}, \left(n < \frac{\alpha s}{2}\left(\frac{\alpha s c\theta}{2r}\right)^{\frac{1}{\theta-2}}\right)$$

We take derivative of $W^*(n)$ and find that it is decreasing in its domain. As the relationship between $\frac{\alpha s}{2}\left(\frac{\alpha s c\theta}{2r}\right)^{\frac{1}{\theta-2}}$ and 1 cannot be determined, the optimal n should be $n^* = 1$ or $n^* = 0$. When $n^* = 1$, the optimal quality is $q^* = \left(\frac{r}{\theta c}\right)^{\frac{1}{\theta-1}}$. When $n^* = 0$, the optimal quality is $q^* = 0$. We find that the results when $\theta = 2$ and when $1 < \theta < 2$ have similar form, so we merge (2) and (3) into one condition in the proposition.

B.9 PROOF OF PROPOSITION 6

According to the new objective function of multiple-viewing setting, the overall utility of all consumers consists of the utility obtained from each product in the *m*-th choice interval, $\int_{b_{j,m}^-}^{b_{j,m}^+} U_{ij} f(x_i) dx_i$. Since the *m*-th choice interval of product *j*, $\left[b_{j,m}^-, b_{j,m}^+\right]$, only depends on the locations of product *(j-m)*, project *j*, and product *(j+m)*, the utility obtained from product *j* is only related to the *m*-th product away from it. Thus, we can divide all products into *m* groups and do product assortment planning within each group. We index products from the leftmost one to the rightmost one in the product space. The first group of products consists of product 1, $m+1$, $2m+1$, …, $km+1$ (assuming that $km+1 \le n < (k+1)m+1)$), the second group consists of product 2, $m+2$, $2m+2$, …, $km+2$, etc. Now, we can consider the product assortment in each group as a new problem in the single-viewing setting. Since each group makes the same decision, it is equivalent to duplicating the optimal assortment in the single-viewing setting multiple times.

VITA

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