

STRATEGIC PLATFORMS IN THE DIGITAL AGE

by

Mark Thomas Bender

B.A. Economics, History, Washington and Jefferson College, 2009

M.A. Economics, University of Pittsburgh, 2011

Submitted to the Graduate Faculty of

Joseph M. Katz Graduate School of Business, Department of Marketing, in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

University of Pittsburgh

2016

UNIVERSITY OF PITTSBURGH
JOSEPH M. KATZ GRADUATE SCHOOL OF BUSINESS
DEPARTMENT OF MARKETING

This dissertation was presented

by

Mark Thomas Bender

It was defended on

April 28, 2016

and approved by

Dissertation Co-Advisor: Dr. Tansev Geylani, Associate Professor of Business Administration,
Katz Graduate School of Business

Dissertation Co-Advisor: Dr. Esther Gal-Or, Glenn Stinson Chair in Competitiveness, Professor
of Business Administration and Economics, Katz Graduate School of Business

Dr. J. Jeffery Inman, Associate Dean for Research and Faculty, Albert Wesley Frey Professor of
Marketing and Professor of Business Administration, Katz Graduate School of Business

Dr. R. Venkatesh, Professor of Business Administration and Area Director, Katz Graduate
School of Business

Dr. Kannan Srinivasan, H.J. Heinz II Professor of Management, Marketing, and Information
Systems, Tepper School of Business

Dr. Kaifu Zhang, Assistant Professor of Marketing, Xerox Junior Faculty Chair, Tepper School
of Business

Copyright © by Mark Thomas Bender

2016

STRATEGIC PLATFORMS IN THE DIGITAL AGE

Mark Thomas Bender, Ph.D.

University of Pittsburgh, 2016

Platforms, or intermediaries that serve two distinct user groups in a market, are becoming increasingly common in ecommerce and digital marketing since the advent of web 2.0. This dissertation examines the role of three platforms that facilitate marketing interactions between two distinct user groups. In the first essay, *Daily Deal Websites as Matchmakers*, I examine the role that daily deal websites (e.g., Groupon, LivingSocial) serve in matching consumers and vendors. Specifically, I am interested in how competition between multiple platforms may segment both sides of the markets and allow each daily deal website to play the role of matchmaker. However, I also show that segmenting both sides of the market is difficult and this may explain the demise of many of these websites. In the second essay, *Crowdfunding as a Vehicle for Raising Capital and for Price Discrimination*, I investigate an entrepreneur's optimal decision to set instruments available in a crowdfunding (e.g., Kickstarter, Indiegogo) campaign (campaign goal and funder reward). I find that conditional upon market conditions, consumers' interest in the proposed product, and the entrepreneur's need to fund the product through crowdfunding, that the entrepreneur may choose to set his instruments to either raise capital or to price discriminate. In the third essay, *Setting Artist Royalties on Music Streaming Platforms*, I investigate how a streaming platform (e.g., Spotify, Apple Music) may choose to set its royalty to attract artists to the platform. I explore when the streaming platform may choose to exclude high valuation artists.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS	ix
1.0 GENERAL INTRODUCTION.....	1
2.0 DAILY DEAL WEBSITES AS MATCHMAKERS.....	5
2.1 INTRODUCTION	5
2.2 MODEL	14
2.3 ANALYSIS.....	23
2.3.1 Full Segmenting Equilibrium with Both Populations of Consumers Segmented.....	30
2.3.2 Partial Segmenting Equilibrium with Only One of the Two Consumer Populations Segmented	34
2.3.2.1 Partial Segmenting Equilibrium with $R_H < R_L$	35
2.3.2.2 Partial Segmenting Equilibrium with $R_H > R_L$	41
2.3.3 Recommendations to Facilitate Segmentation.....	45
2.4 CONCLUDING REMARKS.....	49
3.0 CROWDFUNDING AS A VEHICLE FOR RAISING CAPITAL AND FOR PRICE DISCRIMINATION	51
3.1 INTRODUCTION	51
3.2 MODEL	60
3.3 ANALYSIS.....	68
3.3.1 Pledge Behavior of the High Valuation Consumers	68
3.3.2 The Entrepreneur’s Choice of the Campaign Goal and Reward.....	72

3.3.3	Price Discrimination with Crowdfunding	81
3.3.4	Maximization of Platform.....	85
3.4	CONCLUDING REMARKS.....	89
4.0	SETTING ARTIST ROYALTIES ON MUSIC STREAMING PLATFORMS	92
4.1	INTRODUCTION	92
4.2	MODEL	98
4.3	ANALYSIS.....	105
4.3.1	Platform Streams Both Types of Artists’ Music.....	107
4.3.2	Platform Streams Only One Type of Artist’s Music	114
4.3.2.1	Platform Streams Only Low Valuation Artists’ Music	114
4.3.2.2	Platform Streams Only High Valuation Artists’ Music	120
4.3.3	Comparing Royalties	121
4.4	CONCLUDING REMARKS.....	126
	APPENDIX A: PROOFS FOR “DAILY DEAL WEBSITES AS MATCHMAKERS”	128
	APPENDIX B: PROOFS FOR “CROWDFUNDING AS A VEHICLE FOR RAISING CAPITAL AND FOR PRICE DISCRIMINATION”	140
	APPENDIX C: PROOFS FOR “SETTING ARTIST ROYALTIES ON MUSIC STREAMING PLATFORMS”	148
	BIBLIOGRAPHY	155

LIST OF FIGURES

Figure 2.1. Segmenting Equilibrium.....	24
Figure 2.2. The Graph of $LB_{(L>H)}$ vs β	39
Figure 2.3. The Graph of $UB_{(H>L)}$ vs β	44
Figure 2.4. Values of $\frac{d(1+r)}{1+m}$ Supporting Partial Segmenting Equilibria	46
Figure 3.1. Summary of Variables	67
Figure 4.1. Depiction of Continuum of Fan Base for Each Artist	101
Figure 4.2. Utility that Fans Receive by Subscribing to the Streaming Platform.....	103
Figure 4.3. How Streaming Platform Pays Artists.....	104

LIST OF TABLES

Table 2.1. Extreme Values of c Required to Support Segmentation of all Three Populations	33
Table 3.1. Optimal Choice of Sharing Rule α	88

ACKNOWLEDGEMENTS

This dissertation is dedicated to my family and friends who have provided encouragement throughout the last five years. They have delivered meals to me in my office, kept me sane, provided voices of reason, given me an outlet to discuss my research, and most importantly, been great friends.

I thank my two advisors, Dr. Tansev Geylani and Dr. Esther Gal-Or, for their limitless support and gracious guidance. When I spent an entire night/day/week/month constructing and solving a model only to end up with seemingly uninterpretable results, I could count on Esther to help me navigate around the issue. Tansev made sure that I remained on track and was always available to discuss any issue or idea that I had during my time in the program. I am honored to have had the opportunity to have such fantastic mentors, and words cannot describe my gratitude.

I want to recognize the members of my committee: Dr. Jeff Inman, Dr. R. Venkatesh, Dr. Kannan Srinivasan, and Dr. Kaifu Zhang. They have exerted time and effort on my behalf, to mold me into a better scholar and to enhance my dissertation, and for that I am truly grateful. I would also like to thank present and prior faculty in the Department of Marketing in the Joseph M. Katz Graduate School of Business whom I have not yet named: Dr. Rabikar Chatterjee, Dr. Nicole Verrochi Coleman, Dr. Cait Lamberton, Dr. Vanitha Swaminathan, Dr. Eugenia Wu, and Dr. Andrew Stephen. They introduced me to marketing, attended my presentations, and provided

advice inside and outside of class. The essays in my dissertation originated as nascent ideas during coursework and each faculty member has shared wisdom that shaped my dissertation in one way or another.

I would not be here if it was not for my undergraduate advisor Dr. Yongsheng Wang, who first encouraged me to turn a term paper into a full-fledged essay. His guidance paved a path for me to find success in academia. I would finally like to thank Carrie Woods, Chris Gursky, and Chris Fedor for their support in the doctoral office. Carrie made sure that I was constantly on track so that I could worry less about administrative details and more about my research.

1.0 GENERAL INTRODUCTION

This dissertation consists of three essays which investigate the decisions of strategic platforms in the digital age and their consequences on the two sides of the markets that they serve. Bringing together two distinct user groups that provide each other with network benefits, Groupon, LivingSocial, Kickstarter, Indiegogo, Spotify, and Apple Music are just a few prominent examples of digital platforms that have integrated themselves into the lives of consumers and the minds of managers. While these platforms play a different role within their respective markets, they all serve a purpose in bridging the gap between producers and consumers. The important functions that these disruptive platforms play in the marketplace can be seen in the following numbers: Groupon has 53.9 million active customers, Kickstarter has been used to generate over \$2.25 billion dollars, and Spotify has over 30 million paid subscribers and 75 million active listeners.¹ In fact, according to Van Alstyne et al. (2016), in 2014 three of the world's five largest firms were running platform business models.

Platforms face unique dilemmas when choosing how to market their services because they seek to attract two distinct user groups that provide each other with network benefits. Consider the following illustrative example of this dilemma. Spotify sets two distinct prices: the subscription fee that it charges consumers and the royalty that it gives to artists that have chosen to stream their content through the platform. When determining the optimal price for each user group, Spotify needs to be aware of the network benefits that each user group provides to the

¹ Statistics as of April 1, 2016. See Groupon Works (2016), Kickstarter (2016), and Spotify (2016a).

other party. Artists gain every time Spotify is able to secure an additional consumer because that consumer may generate additional revenue for an artist through streaming royalties. From the consumers' perspective, the more artists that opt to distribute their music through Spotify, the deeper the catalog to which the consumers have access and the more valuable the service. If Spotify is able to get distribution rights to a specific artist, Spotify may be able to lure that artist's fans to the platform. These considerations all play a role in the decisions being made by Spotify, the artists, and the consumers. The essays in this dissertation provide novel insight into how digital platforms are changing the way producers are marketing their products to consumers, how consumers are buying these products, and how the platforms are creating value for all involved in the exchange.

The first essay in my dissertation is titled "Daily Deal Websites as Matchmakers." Daily deal websites operate as intermediaries (platforms) by selling vendor deals to consumers. I investigate whether these websites can act as matchmakers between vendors and consumers by segmenting each side of the market. Such segmentation ensures an improved match between vendors and consumers in terms of the quality provided by the former and the willingness to pay for quality of the latter. Specifically, while one intermediary can potentially match relatively high quality vendors with high willingness to pay consumers, the other can match the opposite profiles of vendors and consumers. My results suggest that such segmentation can be attainable if platforms focus on selling products and services in categories with more frequent purchases, in new product markets, and in categories for which it is relatively easy for consumers to detect and disseminate quality information. However, I also show that segmentation can fail altogether, in which case platforms are completely undifferentiated and compete fiercely in prices. This

difficulty in segmenting both sides of the market may explain the demise of many daily deal websites.

The second essay in my dissertation is titled “Crowdfunding as a Vehicle for Raising Capital and for Price Discrimination.” Crowdfunding campaigns are traditionally used as a means for entrepreneurs to raise capital to fund the development of new products. I show that crowdfunding may serve an additional purpose of acting as a platform to allow entrepreneurs to successfully implement price discrimination. The entrepreneurs’ ability to implement such price discrimination depends on the extent to which they are eager to raise capital through the crowdfunding campaign in comparison to the eagerness of contributors in the campaign to ensure that the product becomes a reality. Specifically, I show that enhanced consumer surplus extraction through price discrimination is feasible when the total surplus that the project generates is relatively small, when the pool of potential contributors in the campaign is relatively small, and when the extent of heterogeneity in the consumer population is relatively high. In contrast, when both the development and the financing costs from traditional funding sources are relatively high the capacity of crowdfunding to serve as a price discrimination device is hampered. I provide insights regarding the entrepreneur’s choice of the funder reward and campaign goal, two tools that can enable her to achieve the dual objective of raising funds and implementing price discrimination. In an extension, I allow for the platform to strategically set the sharing rule and conduct numerical calculations to help us observe such a decision.

The third essay in my dissertation is titled “Setting Artist Royalties on Music Streaming Platforms.” In this essay I investigate how a digital streaming platform in the music industry (e.g., Spotify, Apple Music) sets its royalty to entice artists to stream their music on the platform. These streaming platforms offer artists a percentage of the platform’s revenue and

divide it between the artists on the platform based upon each artist's streaming share.

Accounting for competition between a streaming platform and digital store, my analysis shows that it may be profitable for the artist to stream her music through a streaming platform if the streamer shares enough of its revenue to make up for cannibalization that occurs when the artist streams her music. I allow artists to have differing valuations and show that the platform may need to set a higher royalty if it wants to stream content from both the high valuation and low valuation artists than if it only desires to stream music from low valuation artists. When this happens, the streaming platform may find it optimal to exclude high valuation artists from the platform and only host music from low valuation artists. However, this is not always the case as additional artists make the streaming platform more valuable which can give the platform a better bargaining position to attract other artists while offering a low royalty. My results may also generalize to other digital content industries with streaming platforms (e.g., movie, television, book, video game).

Chapter 2.0 contains my essay "Daily Deal Websites as Matchmakers. Chapter 3.0 includes my essay "Crowdfunding as a Vehicle for Raising Capital and for Price Discrimination. Chapter 4.0 consists of my essay "Setting Artist Royalties on Music Streaming Platforms."

2.0 DAILY DEAL WEBSITES AS MATCHMAKERS

2.1 INTRODUCTION

Daily deal websites, such as Groupon, Living Social, and Local Flavor, are websites that sell deals on services or products. Consumers who visit these websites and purchase such deals are given gift certificates or vouchers to later redeem with a specific vendor who has entered into an agreement with the daily deal website. Daily deal websites are platforms that seek to attract and match vendors and consumers in a two-sided market. Consumers visit these platforms because they provide a vehicle to learn more about a specific product or service without having to pay full price for it. Vendors, oftentimes mom and pop shops seeking to expand their business, sell deals through these platforms because the platforms have a vast reach due to large consumer subscription bases. Their hope is that upon having a good experience with the service, these consumers will return in the future to purchase the service again at full price.

Daily deal websites offer their services to consumers with no usage or subscription fees in order to build a consumer base. Having built consumer bases to which vendors want access, these websites are able to keep a fraction of the revenue made from each deal sold on their website. It has been noted that the fraction of revenue that daily deal websites keep for themselves can reach upwards of 50% (Bice 2012). However, selling through daily deal

websites introduces risks to the vendors. One such risk is the fact that deals may attract consumers who have no intention of making a repeat purchase at full price. A second risk is related to the heterogeneity in the vendor and consumer populations. With vendors offering products of different quality and consumers having different willingness to pay for higher quality, a mismatch between vendors and consumers types may limit the ability of vendors to extract surplus from consumers. In this paper we explore the possibility that daily deal websites may reduce the second type of risk by segmenting both the vendor and consumer markets. At such a segmenting equilibrium the platforms can increase the likelihood of correct matches between vendors and consumers. In addition, by reducing the likelihood of a mismatch daily deal websites can create additional value that a price discount offered directly by the vendors would not be able to achieve.

In our model there are two daily deal websites (platforms). We assume that the vendor population consists of mom and pop stores that are differentiated by their quality. Similarly, the consumer population is differentiated by their willingness to pay for higher quality. Vendors cannot distinguish between high and low willingness to pay consumers, and consumers cannot distinguish between high and low quality vendors. Further, prior to trying a service by purchasing a deal offered on a platform the consumer faces additional uncertainty regarding the extent to which the service of the vendor is indeed beneficial. This uncertainty could be the result of a consumer's idiosyncratic tastes that are unrelated to quality, such as her preference for spiciness or a specific item on a restaurant's menu. Uncertainty regarding the benefit could also stem from doubts of the consumer regarding the trustworthiness of the vendor. After purchasing the deal and trying the service, the consumer may find that the quality of the provided service is inconsistent with the full price that the vendor charges for it. Mom and pop stores may renege on

quality because of unexpected budgetary constraints or financial distress (e.g., to be able to pay off a loan). Inconsistency between pricing and the actual quality delivered may lead to distrust of the vendor and lack of satisfaction by the consumer.

In addition, consumers are further differentiated by their reasons for using daily deal websites. We assume that there are two segments of consumers each with different goals. Information seekers are interested in finding a suitable vendor for the purpose of patronizing him in the future. On the other hand, one time shoppers are interested in making only one purchase in a given product category for which the daily deal websites offer “deals”.

We explore the possible existence of a segmenting equilibrium whereby each platform specializes in matching different segments of vendors and consumers (information seekers and one time shoppers). Specifically, while one platform matches high quality vendors with high willingness to pay consumers in both the information seeking and one time shopper populations (high quality “matchmaker”), the competing platform matches the opposite profiles of vendors and consumers (low quality “matchmaker”). This possible matching of different segments of the populations results in vertically differentiated platforms. In contrast to traditional models of vertical product differentiation, at a segmenting equilibrium platforms are differentiated not because they actively choose to offer different qualities of service. Rather, when different segments of the vendor population self-select to be represented by different platforms, part of consumers’ uncertainty regarding quality is alleviated, and quality differentiation between platforms endogenously arises. Put differently, it is the selection of platforms by the different segments of the vendor and consumer populations and not the active choice of quality by the platforms themselves that generates the vertical differentiation between the platforms.

When a segmenting equilibrium exists, a consumer can benefit from a deal offered by a platform in three different ways. First, she knows that the platform she selects represents, on average, merchants that offer qualities more likely to be consistent with her willingness to pay for quality. Choosing to buy the deal from the “correct” platform (i.e., representing either high or low quality vendors) provides her information about the average quality of the vendor without having to incur any additional costs of searching online or consulting with friends and relatives. Second, after visiting the mom and pop vendor and experimenting with his service she can verify whether the vendor is trustworthy, in sense that the full price he charges is consistent with the observable attributes of quality he offers. Quality information available from other sources can be outdated and not as reliable as the actual utilization of the vendor’s services. And third, she can determine whether the service offered by the vendor is compatible with her idiosyncratic tastes that are unrelated to quality. Reviews offered by other consumers may reflect their own idiosyncratic preferences which do not necessarily coincide with the tastes of the consumer herself. These three pieces of information are all obtained by purchasing the deal (at a significant discount in comparison to the full price) from the platform.

We identify three distinct types of segmenting equilibrium. The first one is a full segmenting equilibrium in which all three populations (vendors, information seekers, and one time shoppers) are segmented by the platforms and the high quality platform sells deals at a higher price than the low quality platform. However, for this equilibrium to exist it is necessary that information seekers are highly skeptical about the benefit they are likely to derive, either because of compatibility issues or because of suspicions regarding the honesty of vendors. When this equilibrium exists it is characterized by fierce price competition between platforms because

information seekers become very price sensitive when their odds of finding a suitable vendor are very small.

We also identify two different partial segmenting equilibria in which only the vendor and information seeker populations are segmented. In the first partial segmenting equilibrium, the high quality platform offers lower priced deals than the low quality platform. The entire one time shopper population visits the high quality platform because they are guaranteed a higher quality product at a lower price. This equilibrium exists when the reward high quality vendors expect from repeat purchases by consumers is much higher than the reward low quality vendors can expect. This added benefit from repeat purchases that is derived by high quality vendors is relatively big when there is a large population of information seekers and when the full market price is a steep function of quality. However, we find that for this equilibrium to exist the steepness of the quality-price schedule should exceed the average willingness to pay for higher quality in the consumer population. In fact, when the size of the information seeker segment is only moderate, this steepness of the price schedule should exceed even the highest valuation of quality among consumers, a requirement that is unlikely to hold for the continued existence of this vendor market. Moreover, this equilibrium exists only if more than 50% of the population consists of information seekers. Such a requirement is inconsistent, however, with reports suggesting that most consumers who use deals have no intention of returning to the vendors that offer them to make purchases at full price (see for example Dholakia 2011).

In the other partial segmenting equilibrium, the high quality platform offers deals at higher prices than the low quality platform. In addition, the price differential between the platforms is such that all one time shoppers visit the low quality platform. To sustain this equilibrium, the portion of the consumer population that consists of information seekers should

be sizable, yet not too large, and the market quality-price schedule should be relatively flat. In our model, the market price schedule is flat when it is relatively inexpensive for vendors to make improvements in quality and when it is easy for consumers to detect and disseminate quality information about vendors. Of all the three segmenting equilibria, the partial segmenting equilibrium of the second kind, the one with high quality platforms offering deals at higher prices than the low quality platforms, is the most attainable given that its existence depends on reasonable values of the parameters of the model.

When the probability that information seekers can find a suitable vendor is not too small and when the steepness of the quality-price schedule is moderate, segmentation may fail altogether. In the absence of segmentation, platforms are not differentiated and random matching of vendors and consumers arises. Random matching leads, however, to fierce (undifferentiated price) competition between platforms, an outcome that hurts the platforms. The possible non-existence of a segmenting equilibrium and the undifferentiated competition between the platforms, can explain, to some extent, the poor performance of many daily deal websites.²

To reduce such intense competition and provide services not only as sellers of deals but as matchmakers daily deal websites should identify product categories for which profitable segmentation might be possible. Given that the second type of partial segmentation is the most reasonable among the three types we consider, platforms should focus on selling deals from product categories that are likely to support this type of equilibrium. Specifically, product categories for which the market quality-price schedule is relatively flat. This is the case for

² One of the more prominent daily deal websites, Amazon Local, shut down its business in December 2015 following the 2014 closure of another major daily deal website, Google Offers (La Monica 2015). Living Social, another major player in the daily deals space, announced in October 2015 that it was laying off 20% of its staff (Lunden 2015). Even Groupon, the biggest player in the deals industry, has been struggling with its own economic difficulties (Kharif and Katz 2015).

categories where small investments are sufficient to improve the perceived quality of the service by consumers. This property may be true for restaurants, where higher quality can be the result of better (and marginally more expensive) ingredients, but may not be true for dentistry, where higher quality is the result of additional training or investment in new technology. In addition, a flatter quality-price schedule is more likely when it is easier for consumers to detect and disseminate quality information. Once again, this should hold for restaurants, where quality is more experience based, as opposed to medical doctors or auto mechanics where quality is more credence based. Similarly, we expect consumers to be able to more easily detect and disseminate quality information in categories where purchases are frequent (such as yoga classes) as opposed to categories where purchases are infrequent (such as laser eye surgery or mechanics).

Further, our findings suggest that this second type of partial segmentation is more likely to occur when the portion of information seekers in the consumer population is sizable. Therefore, to be able to segment the market and increase profits, daily deal websites need to search for product categories where consumers are actively seeking information to learn about their preferences, with the aim of returning to suitable vendors. This is more likely to be the case in categories with more frequent purchases (e.g., restaurants versus laser eye surgery).³ It is also more likely to hold in new product markets. For example, the market for barre classes (the latest fitness craze) is likely to exhibit sizable levels of information seekers attempting to determine if they like this type of workout.⁴

³ For example, in a Groupon sponsored case study, Briosio Fresh Pasta's owner credits his company's success on Groupon to the deals having created repeat customers (Groupon 2016a).

⁴ In a Groupon sponsored case study, Pure Barre's owner credits her company's success on the daily deal website to the deals' ability to generate many new customers immediately, about fifty percent who became permanent members (Groupon 2016b).

Our study contributes to several streams of research. The first is the literature on platform competition in two-sided markets. Much of this literature has investigated competition between horizontally differentiated platforms (Gabszewics et al. 2002; Armstrong 2006; Hagiu 2009, Gal-Or et al. 2012). One exception is a study by Brown and Morgan (2009) who investigate whether two platforms can coexist in equilibrium when one offers superior service than the other. In our paper, however, vertical differentiation between the platforms arises through self-selection by heterogeneous populations of consumers and vendors. The quality of the platform is not under its control. Rather, it is the segments of the consumer and vendor populations who choose to transact with the platform that determine its quality.

Our study is also related to the literature on market segmentation that is implied by quality differentiation (Mussa and Rosen 1978; Katz 1984; Schmidt-Mohr and Villas-Boas 2008). In this literature firms have full control over the qualities of the products they offer and consumers self-select among the vertically differentiated products offered by these firms. In order to support segmentation the firms need to satisfy only one incentive compatibility constraint related to self-selection by consumers. However, for platforms that seek to match vendors with consumers, there is an additional incentive compatibility constraint related to self-selection by vendors. We show that the additional vendor incentive compatibility constraint makes it harder for these platforms to implement an equilibrium in which both sides of the market are segmented.

Some of the comparative statics we conduct highlight the difference between the traditional models of vertical product differentiation in one sided markets and vertical differentiation between platforms that play the role of “matchmakers” between vendors and consumers. For instance, when the spread in consumer valuations of quality in the population

expands while the spread of qualities in the vendor population stays the same, price competition between platforms intensifies, as it becomes less important for consumers to identify an appropriate quality match. As a result, the platform that charges the lower price gains in market share. In contrast, in traditional models of vertical product differentiation in one sided markets, a bigger spread in consumer valuations leads to producers actively increasing the extent of quality differentiation between them, thus leading to alleviated price competition.

There is a growing literature that investigates various aspects of daily deal websites. Some of these are empirical (Byers et al. 2012; Dholakia 2011). Two analytical studies that have examined daily deal websites are Edelman et al. (2016) and Kumar and Rajan (2012). However, both are from the perspective of vendors. Unlike our paper, these studies have no strategic intermediary or intermediary competition. Two analytical studies of daily deal platforms that introduce a strategic intermediary are Subramanian and Rao (2016) and Shivendu and Zhang (2012). The former paper investigates whether it is in the platform's interest to advertise the number of deals sold. The authors demonstrate that doing so may signal the vendor's quality to inexperienced buyers. The latter paper investigates the discount rate on deals offered on platforms. Our study differs from these papers by introducing competition between two daily deal websites and by examining the impact of this competition on the profitability of the platforms.

2.2 MODEL

We model an environment where mom and pop stores use daily deal websites to promote their services.⁵ The objective of the websites is to encourage consumers to purchase the services at reduced prices in order to acquire information about unknown vendors. The vendors hope that based upon their early experience, consumers will return to purchase their services at full price. Hence, vendors use the daily deal websites as platforms to increase consumer awareness of their service offerings. We model, therefore, a two sided market in which platforms act as intermediaries in an attempt to attract and match consumers and unknown vendors. It is possible that daily deal websites will also contract with large companies and chains in an effort to advertise their own services and grow their user base. However, we seek to model the more common case of these daily deal websites featuring deals from smaller local businesses and mom and pop shops (Dholakia 2011, Kumar and Rajan 2012).

Even for a specific geographic region, there is often a multitude of vendors who offer a certain service for sale (e.g. roofing, Italian dinner, massage, etc.). Given their large number, it is many times the case that consumers are not aware of all vendors and have difficulty in distinguishing among them in terms of the quality of service they provide. We model this environment by assuming that there exists a continuum of vendors within a specific service category that are uniformly distributed based upon quality along the interval $[0, \bar{q}]$. Vendor q

⁵ For expositional convenience, we will limit the firm side of the market to service providers, which we will refer to as vendors throughout this paper.

sells a service of quality q ; however, the quality of each vendor is private information available only to the vendor himself.

Because there is a continuum of vendors, each vendor is a price-taker and no single vendor has the power to set a price. This assumption is realistic in that mom and pop stores that utilize daily deal websites have little market power and find themselves in competition amongst many other vendors selling a similar service. We also assume that a vendor, whose service quality is q , incurs a cost of $C(q) = dq, d > 0$.

Gal-Or (2013) borrows from Shapiro (1983) to model a similar competitive environment in which price taking firms offer products of different quality. Both studies demonstrate that in such an environment, prices exceed marginal cost in order to sustain equilibrium where firms do not have incentives to “milk” their reputation (once established) by offering minimal quality, and thus saving on cost. They demonstrate, in particular, that if cutting promised quality can be detected by consumers with a lag of one period the equilibrium price is determined according to the function $p(q) = C(q) + rC(q)$ where r is the interest rate the vendors use to discount future profits. Under normal circumstances, the rent $rC(q)$ ensures that a vendor, after establishing himself as a vendor of quality q (for example by offering trials via daily deal websites as in our environment) has an incentive to maintain it. The interest rate r reflects the length of the period it takes consumers to detect and disseminate information about a cut in promised quality by a firm. If this period is long, then the interest rate r (and therefore the rent $rC(q)$) has to be larger to support honest behavior. A longer period may be the result, for instance, of infrequent use of the product by consumers, thus translating to a higher value of r . A more detailed summary of the model discussed in Gal-Or (2013) can be found in Appendix A.

In our case, this formulation yields $p(q) = d(1 + r)q$. As in these two earlier studies, consumers are wary of “fly by night vendors” that offer very low quality (i.e., quality zero). This price schedule guarantees that a vendor that offers the observable quality q has no incentive to cut quality to the minimum level of zero offered by such vendors in order to save on costs. The rent $p(q) - C(q) = drq$ that this vendor earns ensures that he has the incentive to establish and maintain his reputation as a vendor of quality q . Note that this rent increases when r is higher, implying that if it takes longer for consumers to detect “dishonesty” on the part of vendors, rents have to be higher in order to support “honest” behavior. For instance, if a restaurant has the established reputation of only using organic ingredients, this rent has to guarantee that the restaurant does not have an incentive to “cut corners” by using non-organic ingredients instead. If it is more difficult for consumers to detect such a deviation from the established reputation the value of r is likely to be higher.

In spite of the fact that the quality-price schedule ensures that the vendor does not have an incentive to “milk” his reputation, we will allow in the model for the possibility that the vendor might face unforeseen circumstances that force him to reduce quality due to unexpected financial distress. This possibility will contribute to uncertainty consumers may face regarding the benefit they are likely to derive when using the services of a vendor.

There are two daily deal websites that act as intermediary platforms between the consumers and vendors; these platforms compete for both the vendor and the consumer business. The platforms are uninformed about vendor quality and about consumer willingness to pay for quality. Each platform sells deals to consumers at price⁶ R_i for $i \in \{H, L\}$. Groupon, for instance,

⁶ Deals are usually offered in the form of discounts or gift certificates. Our formulation that platforms set the actual prices of deals can be interpreted as them offering gift certificates to guarantee the final discounted price of the service.

can sell deals that offer a discount on the prices charged by the vendors in a specific category. It can strategically choose this discount to be either higher or lower than the discount offered for deals in this category sold by competing platforms. We assume that each platform has full control over its own deal price R_i . Industry analysts have argued that daily deal merchant agreements favor the platform and give the vendor little room to negotiate, especially for small (unknown) vendors (Agrawal 2011). Platforms have complete price setting power in our model because they operate on a national level, but the vendors with whom they contract are often specific to a geographic area. Further, platforms have large consumer subscription bases and mom and pop vendors can only reach these consumers using the platforms. For its services, each platform takes a share of the revenue; this share is denoted by $1 - \alpha$ and we will assume it to be the same for each vendor and platform. In Appendix A we demonstrate that segmentation can become more easily supported when each platform can strategically choose its share of revenues and $\alpha_H \neq \alpha_L$. For simplicity, we assume that platforms incur no cost.

There is a continuum of consumers who are uniformly distributed based upon their willingness-to-pay for quality along the interval $[\underline{\theta}, \bar{\theta}]$, where $\underline{\theta} \geq 0$. The parameter θ of the consumer determines her willingness to pay for quality. If consumer θ has complete confidence of the benefit she can derive from consuming the service of vendor q , her gross utility is equal to $a + \theta q$. However, before trying the service by purchasing the deal offered on the platform the consumer is likely to face uncertainty regarding the extent to which the service of the vendor is indeed beneficial. This uncertainty may be tied to attributes of the service that are unrelated to the quality offered by the vendor. For instance, if the vendor is a restaurant operator the consumer's utility may be affected by the appeal of the serviced food (spiciness, specific menu items) and the restaurant's ambiance to her tastes. In addition, uncertainty regarding the benefit

may also be the result of the vendor possibly renegeing on quality because of unexpected budgetary constraints or financial distress (e.g., to be able to pay off a loan). Specifically, after purchasing the deal and trying the service of the vendor the consumer can verify whether the full price $p(q)$ charged by the vendor is actually consistent with the observable attributes of quality this vendor offers⁷. Inconsistency between pricing and the actual quality delivered may lead to distrust of the vendor and lack of satisfaction by the consumer. Such inconsistency may increase, in particular, doubts about other unobservable attributes of the service. We model the existence of uncertainty by introducing the parameter c to measure the extent to which consumers are confident regarding their benefit. We assume that before purchasing the deal the consumer assigns probability c to the event that she will derive the benefit $a + \theta q$ when buying the service from vendor q . She assigns the probability $(1 - c)$ to the event that she will derive no benefit from the vendor's service either because she doesn't find the vendor's service compatible with her tastes or because of doubts about the vendor's trustworthiness.

Before trying the service, the consumer's net expected utility depends on whether she will buy directly from the vendor at the full price $p(q)$ or from the platform at the reduced prices R_H or R_L . Specifically, in equations (2.1) and (2.2) we express the consumer's net expected payoff when buying a deal via platform i or directly from the vendor, respectively:

$$u_1(\theta) = c(a + \theta q) - R_i, \tag{2.1}$$

$$u_2(\theta) = c(a + \theta q) - d(1 + r)q. \tag{2.2}$$

The parameter a measures the consumer's basic willingness to pay for the service that is unrelated to its quality when she is perfectly certain that the purchase of the service is beneficial

⁷ While the price schedule $p(q)$ ensures that a vendor of type q has no incentive to cut quality under normal circumstances, mom and pop vendors may face unforeseen circumstances of financial distress because of their limited access to capital markets.

to her (i.e., when $c = 1$). We assume this parameter to be sufficiently big to ensure that the net payoff of the consumer is positive even when paying full price for the service and irrespective of the quality provided by the vendor. Consumers can purchase at most one deal for a given service from either one of the platforms.

In addition to the heterogeneity of the consumers in terms of their willingness to pay for higher quality, consumers differ also in terms of their interest in acquiring information about vendors for the purpose of guiding their future purchasing decisions. In this regard, we assume two different segments. The first segment consists of consumers who seek to learn about the service offered by a given vendor in order to determine whether they will continue to buy the service from him in the future. In contrast to the information seeking segment, the second segment consists of one-time shoppers who buy the service only once by using the daily deal websites with no intention of ever buying the service again for full price. We assume that a fraction β of all consumers consists of information seekers and a fraction $(1 - \beta)$ consists of one-time shoppers.⁸

We consider an infinite horizon environment where in each period a new vendor from the vendor population arrives and seeks to be represented by one of the platforms. Similarly, a new group of consumers with characteristics as described above arrives and considers buying a deal from one of the platforms. Each information seeker continues to sample vendors from one of the platforms until she finds a suitable vendor that she is confident about the service he provides (i.e., a vendor that is compatible with her tastes and that charges an honest price consistent with the level of quality he offers). This last event happens with probability c . Specifically, after experimenting with the service, if an information seeking consumer finds a suitable vendor, she

⁸ We may think of these one-time shoppers as individuals who purchase a deal while on a trip, have no need to make future purchases from a category (e.g., concert from an out of town group), or are bargain hunters.

returns to buy the service directly from him in every future period. Otherwise, she continues to sample vendors from the same platform. We assume that the initial experimentation with a given vendor fully reveals to the consumer both his quality q and whether this is a suitable vendor. If an information seeking consumer judges the vendor as unsuitable she never buys the service from him again, and instead, chooses to sample another vendor from the same platform.⁹

We designate by m the common interest rate considered by consumers in discounting future benefits derived from purchasing the service. Hence, an information seeking consumer of type θ derives the following expected utility when obtaining a deal from platform i , denoted by $EU_i^l(\theta)$:

$$EU_i^l(\theta) = c[a + \theta * E[q|\text{consumer } \theta \text{ visits platform } i]] - R_i + \frac{c}{m}E[a + \theta q - d(1 + r)q]|\text{consumer } \theta \text{ visits platform } i] + \frac{1-c}{1+m}EU_i^l(\theta). \quad (2.3)$$

The first term of (2.3) measures the expected net benefit of the consumer from the initial purchase via the platform. The second term measures the present value of the expected net benefit when the consumer finds the sampled vendor suitable and returns to buy the product in perpetuity directly from him in future periods. The third term in (2.3) captures the possibility that the consumer does not find the sampled vendor suitable and samples, therefore, another vendor from the platform (happens with probability $(1 - c)$). In this case, she waits another period before she can sample the second vendor, implying that her future expected utility is discounted by one period (multiplied by $1/(1 + m)$). The value of the interest rate m reflects the frequency of consumption of the service by information seekers, where lower frequency leads to a bigger value of m . As a result, the benefit from repeat purchases in the future that is derived by

⁹ When continuing to sample, each information seeker compares the payoff she can obtain from the two platforms. This comparison yields the same choice whenever it is made, given that the environment is stationary.

information seekers is smaller. Note that with segmentation of the vendor population consumers can improve their estimate of the average quality offered via each platform. The conditional expected quality terms in (2.3) capture the updating of the information that is facilitated at a segmenting equilibrium.

One-time shoppers visit daily deal websites with a sole interest of obtaining a service at a reduced deal price. These consumers have no intention of making a repeat purchase at full price. A one-time shopper of type θ receives the following expected utility when visiting platform i , denoted ¹⁰ $EU_i^D(\theta)$:

$$EU_i^D(\theta) = c[a + \theta * E[q|\text{consumer } \theta \text{ visits platform } i]] - R_i. \quad (2.4)$$

Because of our focus on small mom and pop vendors we assume that before consumers choose the platform they are unaware of the vendor's existence, and therefore, do not have access to any information regarding the vendor's quality. This is the reason that in (2.3) and (2.4) the consumer has to calculate the expected quality she is likely to encounter by choosing a given platform. We also assume that the consumer does not search for direct information about a vendor's quality (e.g., by asking friends or searching online) once they learn of his existence via his advertised deal. There are three possible reasons for why such a direct search may be of limited value to the consumer. First, the information she gets from this search may be outdated, as mom and pop vendors may face financial distress that forces them to lower quality in order to save on costs. Such a possibility is not necessarily reflected in old online reviews. Second, such reports and reviews of quality may be colored by the idiosyncratic preferences of the report

¹⁰ Note that the parameter c for one time shoppers could be higher than that for information seeking consumers, because one time shoppers are not interested in a possible long term relationship with a given vendor. Although such consumers may still incur disutility because of incompatibility of the vendor with their tastes or because of the vendor's dishonesty, this possible disutility may not be as high as it is for information seekers. To simplify the analysis we assumed c to be the same for the two types of consumers.

writers. These preferences do not necessarily coincide with those of the consumer herself. Lastly, if platforms are successful in segmenting the vendor population, the consumer can already estimate the average quality she can expect when buying a deal from either platform. If the consumer has to incur additional search cost to obtain more precise information than the average quality measure, it may not be worthwhile for her to incur this cost, given the noise included in such reports (i.e., idiosyncratic preferences and outdated experiences of report writers).

Note that in our model consumers learn about the existence of the vendor only after visiting the platform. The consumer can assess the complete characteristics of the vendor, including the full price he charges, only after purchasing the vendor's deal and using his services. In particular, we assume that the deal itself does not provide useful information about horizontal attributes of the vendor or the full price he is charging. Indeed, Groupon's or Living Social's deals can include only vague information about the full prices charged by featured vendors. Ads may state, for instance, \$15 for \$30 worth of Italian cuisine, \$12 for \$25 to spend on a dinner (see Groupon and Living Social for such deals in the Restaurants category). These statements do not specify full prices of different items on the menu, and as a result, are of limited informational value to consumers. Similarly, the advertised deal is unlikely to communicate whether the vendor is compatible with the subjective tastes of the consumer (e.g., for the spiciness of food or the restaurant's ambiance). This is the reason consumers in our model are uncertain of whether the service of the vendor will be beneficial to them. (The parameter c in our formulation captures the degree of confidence of the consumer about such a benefit.)

The timing of the game is as follows. First, each platform simultaneously sets a deal price R_i . Second, given the knowledge of R_i , a vendor that seeks to be represented by a platform decides whether to sell his "trial" service through platform H or platform L . Simultaneously,

consumers choose whether to buy a deal from platform H or platform L . After trying the service and verifying the service's quality and compatibility, an information-seeking consumer who finds the service suitable returns in future periods to make subsequent purchases directly from the vendor at full price. If she does not find the service suitable, she samples another vendor from the same platform.

2.3 ANALYSIS

We seek to characterize an equilibrium in which high q -type vendors and high θ -type consumers self-select to transact with platform H and low q -type vendors and low θ -type consumers self-select to transact with platform L . We will refer to such an equilibrium that segments the markets as a segmenting equilibrium. Figure 2.1 depicts a segmenting equilibrium as defined above.¹¹ At the segmenting equilibrium vendors of type $q > q^*$ and consumers of type $\theta > \theta^*$ choose platform H and vendors of type $q < q^*$ and consumers of type $\theta < \theta^*$ choose platform L .

¹¹ The designation of the platforms is without any loss of generality. We could also solve for the opposite arrangement in which high (low) q -type vendors and high (low) θ -type consumers interact with platform L (H).

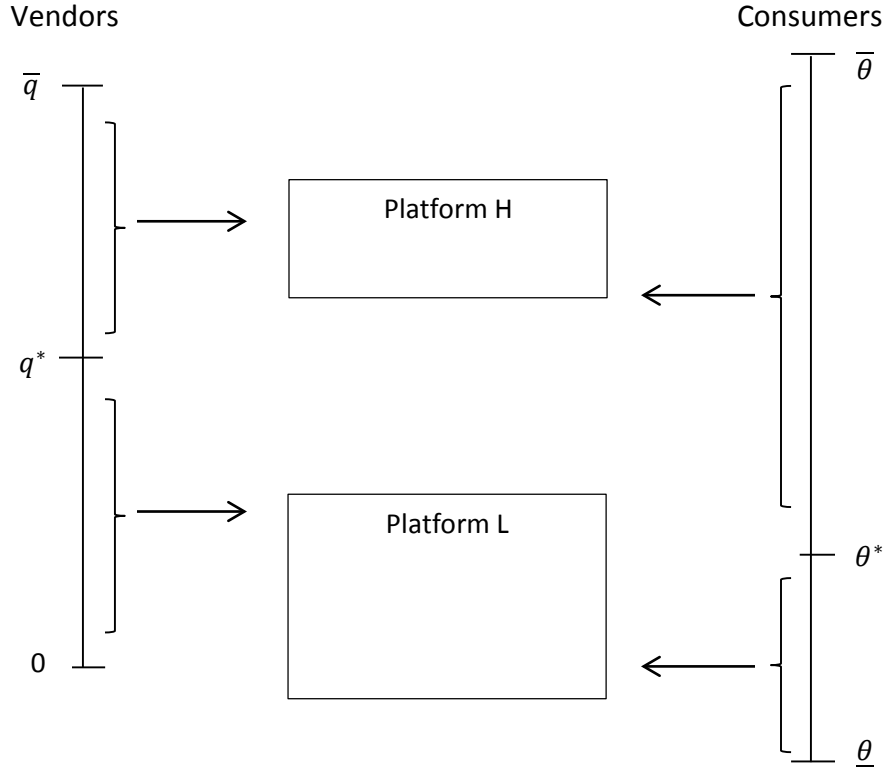


Figure 2.1: Segmenting Equilibrium

We start by analyzing the choice of the consumers between the two platforms. At a segmenting equilibrium, consumers know that platform H offers deals for vendors of relatively high quality ($q > q^*$) and platform L offers deals for vendors of relatively low quality ($q < q^*$). They use this information to update their expected net utility when buying from each platform. For the information seeking consumers the expected net utilities are:

$$EU_H^I(\theta) = c[a + \theta * E[q|q > q^*]] - R_H + \frac{c}{m} E[a + \theta q - d(1+r)q|q > q^*] +$$

$$\frac{1-c}{1+m} EU_H^I(\theta),$$

$$EU_L^I(\theta) = c[a + \theta * E[q|q < q^*]] - R_L + \frac{c}{m} E[a + \theta q - d(1+r)q|q < q^*] +$$

$$\frac{1-c}{1+m} EU_L^I(\theta).$$

As pointed out earlier, information seekers use the platforms to obtain information about vendors. Because of the segmentation of the vendor population they know that platform H represents, on average, higher quality vendors and platform L represents lower quality vendors. They use this information in calculating the average quality of vendors serviced by each platform. This average quality is $\frac{q^*+\bar{q}}{2}$ for H and $\frac{q^*}{2}$ for L . Solving for EU_H^I and EU_L^I from the above two expected utility expressions we obtain:

$$EU_H^I(\theta) = \frac{1+m}{c+m} \left[c \left[a + \theta \left(\frac{q^*+\bar{q}}{2} \right) \right] - R_H + \frac{c}{m} \left[a + \left(\frac{q^*+\bar{q}}{2} \right) (\theta - d(1+r)) \right] \right], \quad (2.5)$$

$$EU_L^I(\theta) = \frac{1+m}{c+m} \left[c \left[a + \theta \frac{q^*}{2} \right] - R_L + \frac{c}{m} \left[a + \frac{q^*}{2} (\theta - d(1+r)) \right] \right]. \quad (2.6)$$

From (2.5) and (2.6) we can calculate the utility gain that an individual of type θ receives from visiting platform H as opposed to visiting platform L :

$$\Delta^I(\theta) \equiv EU_H^I(\theta) - EU_L^I(\theta) = \frac{1+m}{c+m} \left[\frac{c(m+1)\theta\bar{q}}{2m} - (R_H - R_L) - \frac{c\bar{q}d(1+r)}{2m} \right]. \quad (2.7)$$

From (2.7), it is clear that the utility gain of buying from H rather than L is increasing in θ . Hence, segmentation of the information seeking consumers might be possible if there exists a θ^{I^*} -type inside the support $[\underline{\theta}, \bar{\theta}]$ such that $\Delta^I(\theta^{I^*}) = 0$. For types $\theta < \theta^{I^*}$ $\Delta^I(\theta) < 0$ and for $\theta > \theta^{I^*}$ $\Delta^I(\theta) > 0$, implying that the information seeking consumers self-select the platforms as predicted at a segmenting equilibrium. Solving the equation $\Delta^I(\theta) = 0$ for θ in (2.7) yields:

$$\theta^{I^*} = \frac{2m(R_H - R_L)}{c(m+1)\bar{q}} + \frac{d(1+r)}{m+1}. \quad (2.8)$$

One-time shoppers have no intention of a repeat purchase. Therefore, they seek to maximize their net expected utility when buying the service only once via one of the platforms as follows:

$$EU_H^D(\theta) = c[a + \theta * E(q|q > q^*)] - R_H, \quad (2.9)$$

$$EU_L^D(\theta) = c[a + \theta * E(q|q < q^*)] - R_L. \quad (2.10)$$

Constructing the difference in the net utility from visiting platform H as opposed to platform L , we obtain:

$$\Delta^D(\theta) \equiv EU_H^D(\theta) - EU_L^D(\theta) = \frac{c\theta\bar{q}}{2} - (R_H - R_L). \quad (2.11)$$

Segmentation of the one-time shoppers is feasible if there exists θ^{D*} such that $\Delta^D(\theta^{D*}) = 0$.

Because the function $\Delta^D(\theta)$ is increasing in θ , consumers of type $\theta < \theta^{D*}$ will choose platform L and those of type $\theta > \theta^{D*}$ will choose H . Solving the equation $\Delta^D(\theta) = 0$ yields:

$$\theta^{D*} = \frac{2(R_H - R_L)}{c\bar{q}}. \quad (2.12)$$

Comparing the expressions derived for θ^{I*} and θ^{D*} in (2.8) and (2.12) we notice that whereas θ^{I*} depends on the values of the parameters d , r and m , θ^{D*} does not. The parameters d , r and m are all related to the consequences of repeat purchase by consumers. The term $d(1 + r)$ in (2.8) measures the steepness of the full price schedule and the parameter m is the interest rate the consumer uses to discount her expected benefit from repeat purchases. Because one-time shoppers do not intend to ever buy the service again for full price, the values of these parameters do not affect their behavior. The values of both θ^{I*} and θ^{D*} increase when the gap $(R_H - R_L)$ increases, as more consumers opt to purchase the relatively cheaper deal from L . Note also that the value of θ^{I*} increases when $d(1 + r)$ increases. When $d(1 + r)$ is high purchasing high quality service is much more expensive than low quality service, when the consumer returns to the same vendor and pays full price for the service. Factoring this higher price differential implies that more consumers will choose to experiment with the deal offered by the low quality platform, and θ^{I*} increases.

For simplicity, define x as the fraction of information-seeking consumers who visit platform L , namely $x \equiv \frac{\theta^{I^*} - \theta}{\theta - \underline{\theta}}$. Therefore, $1 - x$ is the fraction of information-seeking buyers who visit platform H . Similarly, define y as the fraction of one-time shoppers who visit platform L , namely $y \equiv \frac{\theta^{D^*} - \theta}{\theta - \underline{\theta}}$. Hence, $1 - y$ is the fraction of one-time shoppers who visit platform H .

With knowledge of consumer strategies, vendors seek to maximize their own profits by choosing whether to sell a deal through platform H or platform L . A vendor of quality q receives the expected profit of $E\pi_H(q)$ and $E\pi_L(q)$ by selling through platform H and platform L , respectively, expressed by the following equations.

$$E\pi_H(q) = \beta(1 - x) \left[\alpha R_H - dq + \frac{cdrq}{r} \right] + (1 - \beta)(1 - y) [\alpha R_H - dq], \quad (2.13)$$

$$E\pi_L(q) = \beta x \left[\alpha R_L - dq + \frac{cdrq}{r} \right] + (1 - \beta)y [\alpha R_L - dq]. \quad (2.14)$$

The first term in both (2.13) and (2.14) is profits from information seekers and the second term is profits from one-time shoppers. The profits from information seekers accrue both from the vendor's share of the deal ($\alpha R_i - dq$) and the expected profits from repeat purchases $\frac{cdrq}{r}$.

The per period rent that accrues to vendor q when selling his product for full price is

$(1 + r)dq - dq = drq$. However, the vendor can expect this rent to be repeated in perpetuity if

a consumer finds the service of the vendor suitable (i.e., if she finds that the vendor is honest with its price for the quality of the service he offers and if she finds the service compatible with her tastes). Hence, the expected net present value from repeat purchases by a satisfied

information seeker amounts to $\frac{cdrq}{r}$. The profits from one-time shoppers accrue only from the vendor's share of the deal.

In order to focus on the informational benefits of daily deal websites, we have assumed that no consumers in the population are directly familiar with the vendors unless they use the services of the platforms. This explains why there are no terms in (2.13) and (2.14) that capture profits that accrue from informed consumers who buy directly from the vendors without the assistance of the platforms.¹² Essentially, (2.13) and (2.14) represent the additional profits that the vendor can expect from consumers who are completely uninformed.

As with the consumer population, in order to ensure the existence of segmentation of the vendor population, there should be a vendor of quality q^* in the support of the vendor population $[0, \bar{q}]$ such that this vendor is indifferent between the two platforms. All vendors of quality $q < q^*$ should prefer platform L and those of quality $q > q^*$ should prefer platform H . Designating by $\Delta\pi(q)$ the added profits of a vendor of type q when transacting with H rather than L , we obtain from (2.13) and (2.14) that:

$$\begin{aligned} \Delta\pi(q) \equiv E\pi_H(q) - E\pi_L(q) = qd[\beta(1-c)(2x-1) + (1-\beta)(2y-1)] - \\ \alpha[(\beta x + (1-\beta)y)R_L - (\beta(1-x) + (1-\beta)(1-y))R_H]. \end{aligned} \quad (2.15)$$

The value of q^* satisfies the equation $\Delta\pi(q^*) = 0$. Note that the vendor of quality q takes the values θ^{I^*} , and θ^{D^*} as given when calculating the added benefit he derives from platform H and L (and therefore x and y as given). Hence, it is only the first term of (2.15) that depends upon the vendor's own quality level. In particular, the sign of the coefficient of q in this term $[\beta(1-c)(2x-1) + (1-\beta)(2y-1)]$ determines whether the function $\Delta\pi(q)$ is increasing or decreasing in q . To ensure the existence of a segmenting equilibrium where high q -types transact with H , the function should increase in q , implying the following result.

¹² If we allowed such consumers to exist, our results would not be affected as long as their proportion is sufficiently small as compared to that of deal redeemers. During deal periods this is likely to happen (Fenn 2010).

Lemma 2.1. *To ensure segmentation of vendors:*

(i) $\frac{\partial \Delta\pi(q)}{\partial q} > 0$, implying that $\delta \equiv [\beta(1-c)(2x-1) + (1-\beta)(2y-1)] > 0$, and

(ii) $q^* > 0$ implying that

$$\gamma \equiv [(\beta x + (1-\beta)y)R_L - (\beta(1-x) + (1-\beta)(1-y))R_H] > 0. \quad (2.16)$$

We assume that the conditions given in Lemma 2.1 hold when deriving the three segmenting equilibria below.

Finally, in Lemma 2.2 we derive the objective functions of the platforms, assuming that they use the same interest rate r as vendors in discounting future profits.

Lemma 2.2. *The objective functions of the platforms can be expressed as follows:*

$$EV_H = \frac{1}{r} \left[\frac{1+r}{r+c} \beta(1-x)R_H + (1-\beta)(1-y)R_H \right] (1-\alpha), \quad (2.17)$$

$$EV_L = \frac{1}{r} \left[\frac{1+r}{r+c} \beta x R_L + (1-\beta)y R_L \right] (1-\alpha). \quad (2.18)$$

The platforms choose their fees R_H and R_L to maximize their respective objective functions. Note that the expected payoffs of the platforms in (2.17) and (2.18) increase as c declines. When the probability of finding a suitable vendor c declines, information seekers are more likely to continue sampling from the platform before finding a good match. As a result, the platform can expect to obtain more revenues from them.

In addition, from (2.17) and (2.18), we observe that a change in the deal price of a given platform has counteracting effects on its profits. On the positive side, it raises its markup, but on

the negative side, it reduces the demand by shifting the indifferent consumer in (2.8) and (2.12) in favor of the competing platform, thus affecting the values of x and y . Note that even though platforms do not charge consumers any subscription fees their profits depend on their market shares among consumers ($1 - x$ and $1 - y$ for H and x and y for L). When consumers sign up with one of the platforms they end up choosing to purchase a “trial” product from one of the vendors represented by this platform. Such purchases constitute the source of revenues of the platform.

2.3.1 Full Segmenting Equilibrium with Both Populations of Consumers Segmented

Next we investigate whether a segmenting equilibrium can arise when both the population of information seekers and the population of one time shoppers are segmented, namely $0 < x < 1$ and $0 < y < 1$. If both populations are segmented it necessarily means that $R_H > R_L$. If $R_H < R_L$ all one time shoppers choose platform H and $y = 0$. Note that in (2.12) if $R_H < R_L$ then $\theta^{D^*} < 0$, and because $\underline{\theta} \geq 0$ it follows that $y = 0$. Because platform H is cheaper and represents, on average, higher quality vendors it is clear that all one time shoppers will choose it when $R_H < R_L$. Assuming that a fully segmenting equilibrium exists $R_H > R_L$ and consumers and vendors can infer that the platform that offers the better deal (lower price) represents the vendors of lower average quality. Equipped with these inferences they choose the platform as explained earlier. Assuming indeed that both populations are segmented, we optimize (2.17) and (2.18) with

respect to R_H and R_L to obtain the following solution for the fees¹³ expressed in terms of the market shares x and y .

$$R_H = \frac{c\bar{q}(\bar{\theta}-\underline{\theta})\left[\frac{\beta(1+r)}{r+c}(1-x)+(1-\beta)(1-y)\right]}{2\left[\frac{\beta(1+r)m}{(r+c)(m+1)}+(1-\beta)\right]},$$

$$R_L = \frac{c\bar{q}(\bar{\theta}-\underline{\theta})\left[\frac{\beta(1+r)}{r+c}x+(1-\beta)y\right]}{2\left[\frac{\beta(1+r)m}{(r+c)(m+1)}+(1-\beta)\right]}. \quad (2.19)$$

Substituting (2.19) back into the expressions for x and y derived from (2.8) and (2.12), yields a system of two equations in x and y as unknowns. Solving it yields:

$$x = s \frac{m}{m+1} + \frac{1}{(\bar{\theta}-\underline{\theta})} \left[\frac{d(1+r)}{m+1} - \underline{\theta} \right],$$

$$y = s - \frac{\underline{\theta}}{\bar{\theta}-\underline{\theta}}, \text{ where} \quad (2.20)$$

$$s \equiv \frac{\{(\bar{\theta}+\underline{\theta})\left[\frac{\beta(1+r)}{r+c}+(1-\beta)\right] - \frac{\beta(1+r)}{r+c}\left(\frac{2d(1+r)}{m+1}\right)\}}{3(\bar{\theta}-\underline{\theta})\left[\frac{\beta(1+r)m}{(r+c)(m+1)}+(1-\beta)\right]}.$$

In Lemma 2.3 we state conditions that have to be satisfied by the market shares x and y to ensure segmentation of the vendors when both populations of consumers are segmented.

Lemma 2.3. *To ensure segmentation of vendors when both populations of consumers (i.e., information seekers and one time shoppers) are segmented it is necessary that:*

$$(i) \quad 0 < x < \frac{1}{2}, \quad \frac{1}{2} < y < 1, \text{ and}$$

$$(ii) \quad \frac{(1+r)}{(r+c)} \left(\frac{\beta}{1-\beta} \right) > \frac{(2y-1)}{(1-2x)} > \text{Max} \left\{ (1-c) \left(\frac{\beta}{1-\beta} \right), \frac{\left[\frac{1+r}{r+c} + \frac{(1-\beta)}{2\beta} \right] \left(1 + \frac{1+r}{r+c} \right)}{\left[\frac{1}{2} \left(1 + \frac{1+r}{r+c} \right) + \frac{1-\beta}{\beta} \right]} \left(\frac{\beta}{1-\beta} \right) \right\}.$$

¹³ In all of the three equilibria, in their maximizations platforms take into account the fact that both information seekers and one time shoppers react to their deal prices (i.e., they use (2.8) and (2.12) to obtain the expressions $\frac{\partial x}{\partial R_L} = -\frac{\partial x}{\partial R_H} = \frac{2m}{c(m+1)\bar{q}(\bar{\theta}-\underline{\theta})}$ and $\frac{\partial y}{\partial R_L} = -\frac{\partial y}{\partial R_H} = \frac{2}{c\bar{q}(\bar{\theta}-\underline{\theta})}$).

According to Lemma 2.3 to ensure segmentation of the vendor as well as the two consumer populations, it is necessary that platform H obtains the bigger market share among information seekers and platform L obtains the bigger market share among one time shoppers. In addition, the ratio $(2y - 1)/(1 - 2x)$ has to fall in the interval specified in part (ii) of the Lemma. The numerical calculations we conduct in Table 2.1 illustrate that it is very difficult to satisfy the conditions of Lemma 2.3 for reasonable values of the parameters of the model. Only if the parameter c assumes a very small value it is possible to sustain such an equilibrium. For instance, when $\underline{\theta} = 2, \bar{\theta} = 10$, the maximum value that c can assume is 0.05. When the spread of θ values is larger, the value of c can be bigger but still rather small (when the interval of θ values is $(2,20)$ $c_{max} = 0.07$ and for the interval $(2,30)$ $c_{max} = 0.09$).

A very small value of c implies that there is a very small probability for a consumer to find a suitable vendor. Hence the consumer may have to sample many vendors from a given platform before finding a good match. For $c = 0.05$, the consumer has to sample, on average, 20 vendors ($1/c$) before finding a suitable vendor. Because consumers anticipate a bigger number of repeated purchases from the platforms when c declines they become more price-sensitive, and competition in price between the platforms intensifies. Indeed, in (2.8) and (2.12) a smaller value of c implies that consumers are much more responsive to the price differential $R_H - R_L$. Intensified price competition generates higher powered incentives for platforms to achieve segmentation in order to alleviate such competition. Our numerical calculations illustrate that the value of c has to be extremely small for segmentation of the three different populations – vendors, information seekers, and one time shoppers – to be feasible.

TABLE 2.1: Extreme Values of c Required to Support Segmentation of all Three Populations

$\bar{q} = 3, r = 0.1, m = 0.15, \text{ and:}$					
$(\underline{\theta}, \bar{\theta}) =$	(2, 10)	(2, 20)	(2, 30)	(2, 100)	(2, 1000000)
c cannot exceed:	0.054	0.082	0.091	0.103	0.108
At $c = 0.05$, in order to support segmentation:	$0.727 < d < 2.405$ $0.266 < \beta < 0.413$	$0 < d < 5.172$ $0.235 < \beta < 0.548$	$0 < d < 7.533$ $0.235 < \beta < 0.574$	$0 < d < 24.013$ $0.235 < \beta < 0.605$	$0 < d < 229543$ $0.235 < \beta < 0.617$

The difficulty of obtaining segmentation when there are three different populations to be segmented is related to the incentive compatibility conditions. The segmentation of each additional population implies that one more incentive compatibility constraint has to be satisfied. In traditional models of vertical product differentiation, producers have full control over the qualities they choose, and a single incentive compatibility condition that determines the choice of consumers constrains the producers. For platforms matching vendors with consumers there are multiple incentive compatibility conditions constraining the platforms. In particular, with full segmentation there are three incentive compatibility conditions related to self-selection by information seekers, by one time shoppers, and by vendors, thus making segmentation according to quality more difficult to obtain.

2.3.2 Partial Segmenting Equilibrium with Only One of the Two Consumer Populations Segmented

In view of the difficulty of obtaining segmentation of the three different populations, next we investigate the possible existence of a segmenting equilibrium with only one of the two consumer populations being segmented. Because information seekers have more to gain from segmentation given that their objective in purchasing the deal is to find a good fit with a vendor for long term consumption, we explore the possible existence of an equilibrium with only information seekers being segmented and one time shoppers all choosing the same platform.

When $R_H < R_L$ this platform is H and when $R_H > R_L$ this platform is L . We refer to this type of

equilibrium as partial segmenting equilibrium.¹⁴ Although one time shoppers have different valuations of quality, just as information seekers, at this type of equilibrium they end up always choosing the platform that offers them the better deal in terms of price, even when this platform represents, on average, lower quality vendors.

2.3.2.1 Partial Segmenting Equilibrium with $R_H < R_L$. In this case, because $R_H < R_L$ it follows from (2.12) that $y = 0$. Substituting $y = 0$ in the objective functions of the platforms yields:

$$\begin{aligned} EV_H &= \frac{1}{r} \left[(1 - \alpha) R_H \left[\frac{(1+r)}{(r+c)} \beta (1 - x) + (1 - \beta) \right] \right], \\ EV_L &= \frac{1}{r} \left[(1 - \alpha) R_L \frac{(1+r)}{(r+c)} \beta x \right]. \end{aligned} \quad (2.21)$$

Optimizing (2.21) with respect to fees yields the following solution for R_H and R_L expressed in terms of x :

$$\begin{aligned} R_H &= \frac{\bar{q}(\bar{\theta} - \underline{\theta})c(m+1)}{2m} \left[(1 - x) + \frac{(1-\beta)(r+c)}{\beta(1+r)} \right], \\ R_L &= \frac{\bar{q}(\bar{\theta} - \underline{\theta})c(m+1)}{2m} x. \end{aligned} \quad (2.22)$$

Substituting for R_H and R_L from (2.22) back into the expressions for x derived from (2.8) yields an equation that can be solved for x as follows:

$$x = \frac{\bar{\theta} - 2\underline{\theta}}{3(\bar{\theta} - \underline{\theta})} + \frac{d(1+r)}{3(m+1)(\bar{\theta} - \underline{\theta})} + \frac{(1-\beta)(r+c)}{3\beta(1+r)}. \quad (2.23)$$

¹⁴ One-time shoppers can only be segmented when $R_H > R_L$. From Lemma 2.3 if they are segmented, $x < y$. This inequality is impossible when $0 < y < 1$ and $x = 1$. The latter would be necessary for one-time shoppers to be segmented and information seekers not to be segmented.

In Proposition 2.1 we derive conditions that the parameters of the model should satisfy in order to support segmentation of both the population of vendors and the population of information seekers when $R_H < R_L$.

Proposition 2.1.

(i) *A partial segmenting equilibrium with $R_H < R_L$ exists if:*

$$\frac{\bar{\theta} + \underline{\theta}}{2} < LB_{(L>H)} < \frac{d(1+r)}{m+1} < UB_{(L>H)}, \quad (2.24)$$

where $LB_{(L>H)}$ and $UB_{(L>H)}$ are as given in Appendix A,

and $\beta > \frac{1}{2-c}$.

(ii) *The size of the feasible region that supports the equilibrium expands as β and*

$(\bar{\theta} - \underline{\theta})$ increase and as c decreases.

(iii) *At such an equilibrium $x > \frac{1}{2}$ and $y = 0$.*

Recall that the full market price is given by $p = d(1+r)q$ and that m is the interest rate used by consumers. Therefore, $d(1+r)/(m+1)$ represents the slope of the full market price schedule as discounted by consumers. According to part (i) of Proposition 2.1 a partial segmenting equilibrium with $R_H < R_L$ exists only if this slope lies in the interval indicated in (2.24). This interval is nonempty provided that $\beta > 1/(2-c)$, namely if a sufficiently big portion of the population of consumers consists of information seekers.

Moreover, it is easy to show that the size of the interval increases as β and $(\bar{\theta} - \underline{\theta})$ increase and as c declines. Hence, as the size of the population of information seekers and the heterogeneity of consumers increase (heterogeneity increases when the spread $\bar{\theta} - \underline{\theta}$ increases)

or when the probability of finding a suitable vendor decreases; there is a larger set of values of the price steepness that can support segmentation of the two populations when $R_H < R_L$. Note also that as c declines there is a longer interval of β values that can support segmentation. For instance, when $c = 0.5$ $\beta > 2/3$, but when $c = 0.2$ $\beta > 5/9$. As mentioned earlier, a smaller value of c implies from (2.8) and (2.12) that consumers become more sensitive to the price differential between the platforms. For a smaller c , consumers are less likely to find a suitable vendor, implying that they may have to sample a bigger number of vendors from a given platform before finding the right match. As a result, they become more sensitive to the price differential $|R_H - R_L|$ when choosing between the platforms. When consumers become more price sensitive, platforms have a stronger incentive to achieve segmentation in order to alleviate price competition, thus making segmentation more likely.

The lower bound of the interval in (2.24) ensures that the condition of Lemma 2.1 is valid, namely that segmentation of vendors is feasible. The upper bound ensures that $x < 1$, namely that information seekers are segmented as well. From Part (iii) of the Proposition, $x > 1/2$, namely platform L obtains a bigger share of the information seekers than platform H . However, because platform H charges the lower fee the entire population of one time shoppers chooses platform H ($y = 0$).

Note that interval (2.24) implies that a segmenting equilibrium with $R_H < R_L$ exists if the reward to high quality vendors from repeat purchases by information seekers is very high. This reward is high when the size of the segment of information seeking consumers (β) is big and when the market price schedule is sufficiently steep ($d(1 + r)/(m + 1)$ is bigger than the lower bound of interval (2.24)). When the reward from future purchases is large, high quality vendors distinguish themselves from low quality vendors by agreeing to offer customers a better

introductory deal via the platform that represents them. Low quality vendors have no incentive to mimic this behavior because they do not expect a very high reward from information seekers who return to purchase their service again, given the significant steepness of the market price schedule (bigger than the average valuation for quality in the population).

In spite of agreeing to offer customers a better introductory deal, the high quality platform actually attracts a smaller fraction of the information seeking consumers than the low quality platform ($x > 1/2$). Given that this type of equilibrium is supported only when $d(1 + r)/(m + 1)$ is relatively large information seekers anticipate paying a much higher price for higher quality when purchasing the service again for full market price. More of them choose, therefore, to experiment with the platform that is known to represent low quality vendors. Even though this platform charges them a high initial deal price, if they return to the selected vendor they can expect to pay a much lower full price when they purchase the service a second time. In contrast, all one-time shoppers buy the deal from the high quality platform because they have no concern about future payments. Given that the high quality platform offers a better deal, and on average, represents higher quality vendors, all one-time shoppers choose to transact with H .

To illustrate how high the reward to quality should be in order to support segmentation, in Figure 2.2 we depict the relationship between the lower bound on the steepness of the quality contingent price schedule ($LB_{(L>H)}$) and the share of the population that consists of information seekers (β).

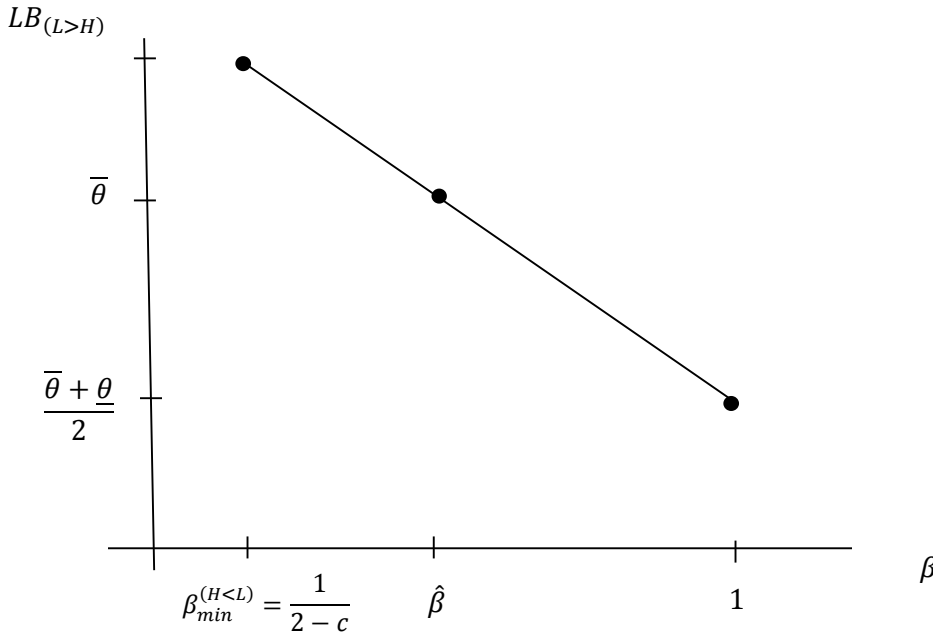


Figure 2.2: The Graph of $LB_{(L>H)}$ vs β ¹⁵

According to this Figure, the discounted market price should reward vendors for higher quality at a rate that exceeds the average valuation of consumers for improved quality (higher than $(\bar{\theta} + \underline{\theta})/2$). Moreover, when the size of the population of information seekers is relatively small but is still in the feasible region, namely $1/(2 - c) < \beta < \hat{\beta}$, the reward to higher quality has to exceed even the highest possible valuation of quality among consumers (higher than $\bar{\theta}$). As discussed earlier a very steep quality-price schedule arises when the cost of offering higher quality is relatively high (big values of d) or when it is more difficult for consumers to detect and disseminate information about vendors who cut quality below their established reputation (big

¹⁵ Illustrates that extremely high rewards to quality are necessary to support segmentation when $R_H < R_L$. See Appendix A for the value of $\hat{\beta}$.

values of r). Increased cost of high quality or difficulty of detecting deteriorated quality raises the temptation of the vendors to “milk” their reputation, thus requiring higher rents to ensure that they offer their promised quality at the equilibrium. However, it is very unlikely that the required price would exceed the maximum amount consumers are willing to pay for improved quality. To support segmentation with $R_H < R_L$, however, the steepness of the market price may sometimes have to exceed this maximum level $\bar{\theta}$. Consider, for instance, the case that $c = 0.5$ and $r = 0.1$. In this case $\beta_{min}^{(H<L)} = 0.67$ and $\hat{\beta} = 0.77$. Hence, more than two thirds of the population of consumers has to consist of information seekers. As mentioned before, based upon recent reports (Dholakia 2011) such a large population of information seekers is unlikely. Moreover, when $0.67 < \beta < 0.77$, the steepness of the price-quality schedule has to exceed the maximum valuation for improved quality among consumers in order to support segmentation. When $\beta > 0.77$ this required steepness is not as extreme but is still higher than the average valuation in the population.

It is worthwhile to note one interesting comparative statics result that is unique to the two sided market we consider. The result relates to changes in the extent of heterogeneity in the population of consumers. We find that increasing the spread $(\bar{\theta} - \underline{\theta})$ for a fixed mean valuation of quality $(\bar{\theta} + \underline{\theta})/2$ in the population of consumers (mean preserving spread), leads to intensified price competition between the platforms and a decline in the market share of platform L among information seekers (x decreases). As the spread of consumer valuations increases while the spread in the vendor population remains the same (still distributed over $(0, \bar{q})$), the importance of finding a good quality match to consumers declines as the relative spread in quality in comparison to the spread in consumer valuations declines. This forces platforms to compete more aggressively, and when price competition intensifies, it is the lower priced

platform that gains in market share, namely platform H (this comparative statics result is reversed if the spread in qualities in the vendor population increases while the spread of valuations among consumers stays the same). Note that in traditional models of vertical product differentiation (one sided markets), producers unambiguously benefit from increased consumer heterogeneity because such increased heterogeneity leads to greater product differentiation and alleviated price competition. In two sided markets it is the heterogeneity of one side of the market relative to the heterogeneity of the other side that determines the extent of price competition between the platforms.

2.3.2.2 Partial Segmenting Equilibrium with $R_H > R_L$. We now consider the possible existence of a segmenting equilibrium with the entire population of one time shoppers choosing platform L ($y = 1$), which can only happen if $R_H > R_L$. Substituting into the objective of the platforms $y = 1$ yields:

$$\begin{aligned}
 EV_H &= \frac{1}{r} \left[\beta \frac{(1+r)}{(r+c)} (1-x)(1-\alpha)R_H \right], \\
 EV_L &= \frac{1}{r} \left[\left[\beta \frac{(1+r)}{(r+c)} x + (1-\beta) \right] (1-\alpha)R_L \right].
 \end{aligned} \tag{2.25}$$

Optimizing with respect to the fees yields:

$$\begin{aligned}
 R_H &= \frac{(1-x)\bar{q}(\bar{\theta}-\underline{\theta})c(m+1)}{2m}, \\
 R_L &= \frac{\left[x + \frac{(1-\beta)(r+c)}{\beta(1+r)} \right] \bar{q}(\bar{\theta}-\underline{\theta})c(m+1)}{2m}.
 \end{aligned} \tag{2.26}$$

Substituting the expressions for the fees from (2.26) back into x as derived from (2.8) yields an equation with x as unknown. Solving it yields:

$$x = \frac{(\bar{\theta}-2\underline{\theta})}{3(\bar{\theta}-\underline{\theta})} - \frac{(1-\beta)(r+c)}{3\beta(1+r)} + \frac{d(1+r)}{3(m+1)(\bar{\theta}-\underline{\theta})}. \tag{2.27}$$

In Proposition 2.2 we derive conditions on the parameters of the model that are necessary to support segmentation of both the population of vendors and the population of information seekers when $R_H > R_L$.

Proposition 2.2.

(i) *A partial segmenting equilibrium with $R_H > R_L$ exists if:*

$$0 < T^* < \frac{1-\beta}{\beta} < \left(\frac{1+r}{r+c}\right) \left[1 - \frac{m\bar{\theta}}{(m+1)(\bar{\theta}-\underline{\theta})}\right], \quad (2.28)$$

where T^* defines a positive lower bound on the value of the ratio $\frac{1-\beta}{\beta}$, and

$$LB_{(H>L)} < \frac{d(1+r)}{(m+1)} < UB_{(H>L)} < \frac{\bar{\theta}+\underline{\theta}}{2}. \quad (2.29)$$

where $UB_{(H>L)}$, and $LB_{(H>L)}$ are as defined in Appendix A.

(ii) *The size of the region that supports the equilibrium expands as $\bar{\theta}$ increases, $\underline{\theta}$ decreases, and c declines.*

(iii) *At this equilibrium $x < \frac{1}{2}$ and $y = 1$.*

According to part (i) of Proposition 2.2, to support equilibrium with $R_H > R_L$ and $y = 1$, it is necessary that the fraction of the consumer population who are information seekers is sizable, yet not too big. The upper bound on the ratio $(1 - \beta)/\beta$ in (2.28) implies that β has to be sufficiently big. Given that the degree of success of segmentation depends on the size of the population that can be segmented, it is necessary that the size of the population of information seekers exceeds a certain critical level. However, in contrast to the equilibrium characterized in Proposition 2.1 when $R_H < R_L$, in Proposition 2.2 the reward to high quality has to be relatively

modest to support equilibrium with $R_H > R_L$. The requirement for this modest reward leads the lower bound T^* on the ratio $(1 - \beta)/\beta$ in (2.28) (upper bound on β), and to the upper bound on the slope of the full market price schedule $UB_{(H>L)}$ in (2.29), which is less than $(\bar{\theta} + \underline{\theta})/2$. In fact, the upper bound on this slope is much smaller than the lower bound on the slope that supports the segmenting equilibrium with $R_H < R_L$ (i.e., $LB_{(H<L)}$). Similar to the result reported in Proposition 2.1, here as well, the size of the region that supports segmentation expands as the heterogeneity in the consumer population increases (i.e., $\bar{\theta}$ increases, $\underline{\theta}$ decreases) and the probability of finding a suitable vendor (c) declines.

According to part (iii) of the Proposition, at the equilibrium with $R_H > R_L$, platform H commands a larger share of information seekers than platform L ($x < 1/2$). When information seekers face a relatively flat quality contingent price schedule, they are encouraged to experiment using the deal offered by the high quality platform in spite of the higher price deal that this platform charges. Because they can expect to pay only marginally more for higher quality service if they decide to purchase the service again, they have a stronger incentive to experiment via the platform that represents the higher quality vendors. In contrast to the results reported in Proposition 2.1, segmentation in Proposition 2.2 is achieved with the deal price more correctly representing the quality of the set of vendors that self-select to transact with the platforms. The vendors that offer, on average, higher quality command also a higher price for the deal they offer to consumers via the platform.

To illustrate how flat the quality contingent price schedule should be in order to support the segmentation described in Proposition 2.2, in Figure 2.3 we depict the relationship between $UB_{(H>L)}$, the upper bound on the slope of the schedule, and β , the portion of the population that comprises of information seekers.

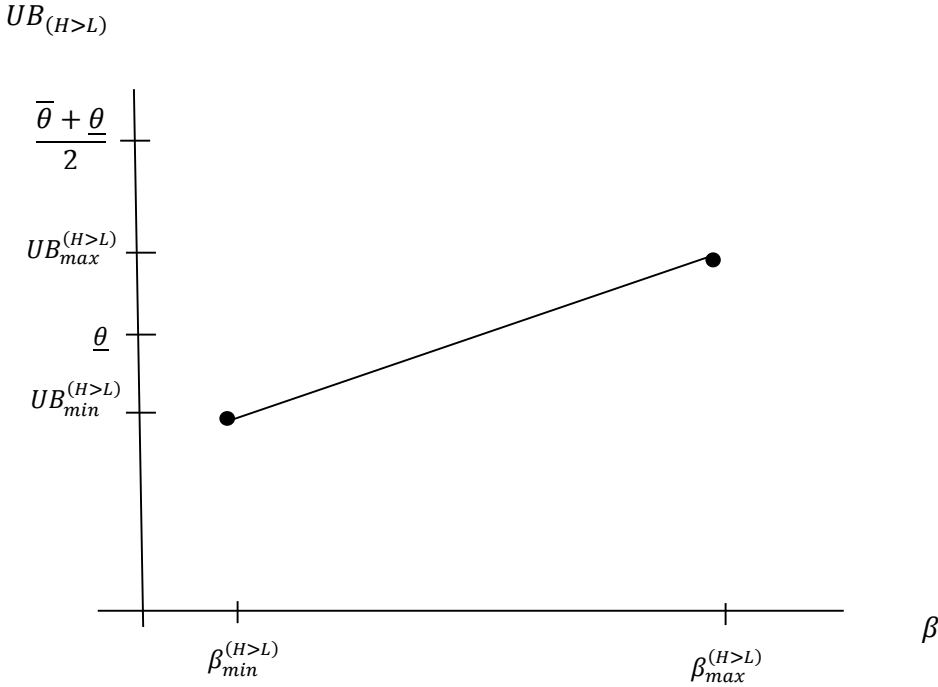


Figure 2.3: The Graph of $UB_{(H>L)}$ vs β ¹⁶

According to Figure 2.3 the slope of the price schedule has to be smaller than the average valuation for improved quality in the population of the consumers. When β is relatively small, this slope has to be extremely small. In particular, in the neighborhood of $\beta_{min}^{(H>L)}$, the reward to higher quality (as measured by the slope of the price schedule) that vendors receive has to be even smaller than the lowest valuation for quality among consumers (lower than $\underline{\theta}$) in order to support this type of segmentation. Note that the partial segmenting equilibrium with $R_H > R_L$ exists for intermediate values of β . This set of feasible β values expands as c declines. For example, for $\alpha = 0.5, \bar{\theta} = 10, \underline{\theta} = 2, \bar{q} = 3, r = .10, m = .15, d = 1$, and $c = 0.5$, the feasible

¹⁶ Illustrates that a very flat quality contingent price schedule is necessary to support segmentation when $R_H > R_L$. See Appendix A for the values of $UB_{max}^{(H>L)}$, $UB_{min}^{(H>L)}$, $\beta_{max}^{(H>L)}$ and $\beta_{min}^{(H>L)}$.

region of β values that supports this equilibrium is $0.42 < \beta < 0.47$. For the same set of parameter values and $c = 0.2$ the feasible region of β expands to $0.27 < \beta < 0.46$.

As in the partial equilibrium described in Proposition 2.1, in the partial equilibrium characterized in Proposition 2.2 the intensity of price competition between the platforms depends on the relative heterogeneity in the two sides of the market. As before, intensified competition increases the market share of the platform that offers the lower priced deal, which is platform L at the partial segmenting equilibrium with $R_H > R_L$.

2.3.3 Recommendations to Facilitate Segmentation

From Propositions 2.1 and 2.2 partial segmenting equilibria exist only when the slope of the quality contingent price schedule is significantly high or low, respectively. The required big $d(1+r)/(m+1)$ value necessary to support the equilibrium in Proposition 2.1 and the small $d(1+r)/(m+1)$ value necessary to support the equilibrium in Proposition 2.2 are needed to ensure either very high or very low rewards to quality. In Proposition 2.3 we state that under moderate rewards to quality, segmentation of this type cannot exist.

Proposition 2.3.

For intermediate values of the discounted slope of the market price schedule $\frac{d(1+r)}{m+1}$ in the interval $(UB_{(H>L)}, LB_{(H<L)})$ partial segmenting equilibria do not exist.

An inspection of the bounds imposed on $d(1+r)/(m+1)$ in (2.24) and (2.29) yields that $UB_{(H>L)} < LB_{(H<L)}$ implying that there is a nonempty interval of $d(1+r)/(m+1)$ values that cannot support this type of segmentation. (See Figure 2.4 for a visual representation of

Proposition 2.3.) The size of the interval of nonexistence is smaller as β increases or as c declines. Hence, when a bigger share of the population of consumers consists of information seekers and when the probability of finding a suitable vendor decreases (c declines), it is more likely that a partial segmenting equilibrium can arise (either in the form of $R_H < R_L$ or $R_H > R_L$).

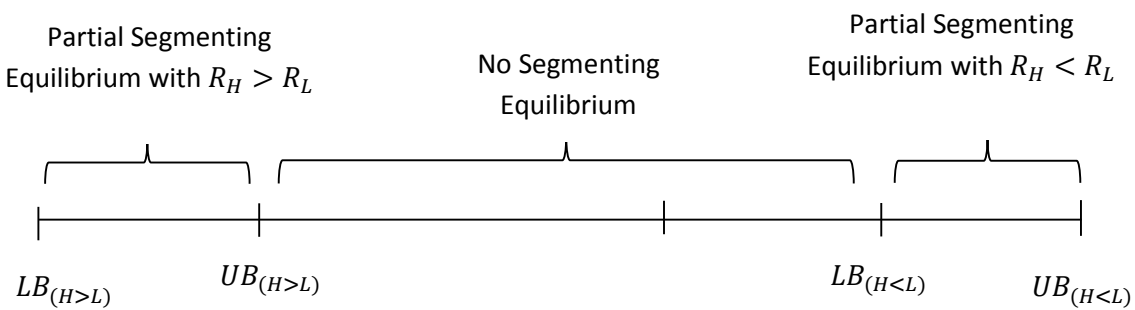


Figure 2.4 – Values of $\frac{d(1+r)}{m+1}$ Supporting Partial Segmenting Equilibria

Of the three types of equilibria we have considered it seems like the one characterized in Proposition 2.2 is the most likely to arise. The full segmenting equilibrium with both information seekers and one time shoppers being segmented requires unrealistically low values of the parameter c . Such low values imply that consumers have to frequently sample vendors in the same category from a given platform before being able to find a suitable vendor, and that platforms are forced to charge very low prices, as a result. In particular, when c approaches zero, $R_H = R_L = 0$ in (2.19), (2.22), and (2.26). The partial segmenting equilibrium with $R_H < R_L$ is equally unlikely. This type of equilibrium requires an unrealistically large portion of the consumer population to consist of information seekers. As well, it also requires a very steep price

quality schedule, so much so, that the required steepness may even exceed the highest willingness to pay for quality among consumers. Because markets where prices exceed consumer willingness to pay normally collapse, this type of segmentation is unlikely as well.

Sustaining the partial segmenting equilibrium with $R_H > R_L$ requires more reasonable values of the parameters. The portion of the population that consists of information seekers should be sizable, yet not too large, and the required steepness of the quality-price schedule should be relatively small in comparison to the willingness to pay for higher quality in the consumer population. Viable markets normally have this latter characteristic. In the context of our model, a relatively flat quality price schedule arises in markets where offering higher quality is not extremely more costly for vendors than offering low quality (i.e., d is small) and consumers can easily detect and disseminate information about vendors who choose to lower quality below their established reputation (i.e., small r). Consumers can easily detect and disseminate quality information in categories where purchases are frequent and where quality is experience based as opposed to credence based (e.g., restaurants, fitness classes, and salon services vs. medical doctors and auto mechanics). Note that because the two platforms offer at the equilibrium deals at different prices, consumers and vendors can infer which platform represents, on average, higher quality vendors.

If segmentation fails, the platforms are not differentiated and the matching of consumers to vendors is completely random. With random matching, platforms compete fiercely on deal prices, and marginal cost pricing implies that $R_H = R_L = 0$. With segmentation, the platforms are vertically differentiated and they can charge positive deal prices. However, this vertical differentiation is not the result of platforms actually having control over the quality of the service they provide. Instead, the differentiation is the result of different segments of the vendor and

consumer populations choosing to interact with different platforms. In traditional models of vertical product differentiation, producers have full control over the qualities of the products they offer. In order to support segmentation they need to satisfy only one incentive compatibility constraint related to self-selection of the differentiated products by consumers. For intermediaries that seek to match vendors with consumers there are, in fact, two separate incentive compatibility conditions that constrain the ability of the platforms to implement segmentation. It is not only the choice of consumers but that of the vendors as well that has to be incorporated in ensuring the segmentation of each side of the market. The additional self-selection constraint of the vendors makes it more difficult to implement equilibrium with vertically differentiated platforms. It is important, therefore, for the platforms to carefully select the categories of service that can support the partial segmentation characterized in Proposition 2.2.

It is noteworthy that the segmentation in our model is attained even though platforms have a single instrument at their disposal to generate differentiation: the price each of them charges for the deal. If additional instruments were available, we conjecture that the range of parameter values that could support segmentation would expand. One such instrument is a different sharing rule of the profits between the platform and the vendor (different values of α selected by the platforms). In Appendix A we demonstrate, indeed, that it becomes easier for the platforms to implement segmentation when sharing rules are chosen strategically.

2.4 CONCLUDING REMARKS

We offer a characterization of segmenting equilibrium in a two sided market where daily deal websites assume the role of platforms. In the segmenting equilibrium, platforms provide information to vendors and consumers about the type of populations they serve. The use of daily deal websites can reduce, therefore, the risk of mismatch between consumers and vendors in a given product category. When segmentation exists, platforms can generate positive profits by charging for the added informational benefits that they bestow on each side of the market. However, as is clear from recent reports in the trade press, daily deals are not necessarily profitable for intermediaries that offer them. In this paper, we argue that one possible reason for this unfortunate outcome may be related to the failure of platforms to implement an equilibrium in which they offer differentiated products/services to consumers. In the absence of differentiation, segmentation of vendors and consumers is not feasible, and random matching of the two populations arises. Such random matching leads to intense price competition between the platforms and zero profits. This may explain the recent demise of the daily deal industry, including the exit of the daily deal websites Google Offers and Amazon Local, and large employee layoffs of the industry leaders Groupon and Living Social.

We characterize three distinct patterns of segmenting equilibria. One of these equilibria, the full segmenting equilibria, allows all three populations (one time shoppers, information seeking consumers, and vendors) to be segmented. It is characterized by the high quality platform selling deals at higher prices than the low quality platform. The other two equilibria are partial segmenting equilibria in which the vendor and the information seeking populations are segmented, but the entire one time shopper population visits the low price platform.

Considering the market conditions that need to be satisfied for each the three types of segmenting equilibrium, we argue that the partial segmenting equilibrium with the high quality platform charging the higher deal price is the most likely to arise. To sustain this equilibrium, daily deal websites must consider product categories with sizable, yet not too large information seeking populations, and categories characterized by relatively flat quality-price schedules. We posit that new product categories and product categories with frequent purchases are likely to satisfy the requirement of having sizable information seeking populations. We also argue that a product category has a relatively flat quality-price schedule if the cost of improved quality for vendors is not extremely high, if consumers make frequent purchases in the category, and if it is relatively easy for consumers to detect and disseminate quality information.¹⁷

¹⁷ Interestingly enough, Groupon's newest CEO, Rich Williams, has stated that it is in his company's best interest to focus on specific categories, such as high frequency local categories (Groupon, Inc. 2016)

3.0 CROWDFUNDING AS A VEHICLE FOR RAISING CAPITAL AND FOR PRICE DISCRIMINATION

3.1 INTRODUCTION

Online crowdfunding provides an alternative way for entrepreneurs to finance the development and production of new products without the need of traditional financial intermediaries. While crowdfunding has been around since the first entrepreneur solicited friends and family for funding, the Internet has expanded the accessible “crowd” from friends and family to individuals all over the world. Allowing these consumers-turned-investors to support the development of a product that they like, crowdfunding platforms bring together entrepreneurs looking to finance a product with individuals who have funds to provide to the project. Many entrepreneurs utilize crowdfunding to finance new product ideas because traditional financial intermediaries such as banks and venture capitalists find their ideas to be too risky. However, as crowdfunding gains in popularity, entrepreneurs who would have traditionally sought funding from these intermediaries look instead to the crowd to finance a project.

While several types of crowdfunding exist (reward, patronage, lending, and equity), our focus is on reward based crowdfunding. (For more information on the other types of crowdfunding see Mollick (2014).) This is the model used by the leading creative project crowdfunding website Kickstarter. Reward based crowdfunding taps consumers for funding, as

opposed to traditional investors, through the design of the reward and the promise of a new product. An important reason why reward based crowdfunding has been successful is the existence of high valuation consumers who wish to ensure that their preferred products are produced and become available on the market. Entrepreneurs that use the services of crowdfunding platforms employ campaign goals to motivate such consumers to make pledges. These consumers are aware that unless the campaign goal to finance their preferred product is reached the product might never be produced. Crowdfunding campaigns also offer pecuniary rewards (e.g., a digital download of a crowdfunded album's first single) that further incentivize contributions from hopeful consumers. When the early pledges of such consumers in the campaign exceed the reward that the entrepreneur promises to pay them when the project is complete, these consumers with higher valuation for the product pay de-facto a higher price for it than those having lower valuation. Hence, crowdfunding has the potential to serve as a price discrimination device. This was likely the case for the team behind the movie Blue Mountain State who was able to use crowdfunding to raise \$40 from each of 836 backers in exchange for the digital download of the movie and some small product affiliated gifts (Falconer 2015).

However, the primary goal of crowdfunding campaigns is for entrepreneurs to raise capital to fund the development of new products. Many times campaigns offer entrepreneurs the opportunity to save significant amounts in financing costs. As a result, entrepreneurs may end up providing very generous rewards to funders in order to incentivize them to submit high pledges in the campaign. If, as a result, funders' pledges fall short of such generous rewards, high valuation consumers end up paying a lower (rather than a higher) price in comparison to low valuation consumers. In such instances, crowdfunding fails as a price discrimination device. In this research we investigate conditions under which a crowdfunding campaign can, indeed, be

used as a device to extract additional surplus from high valuation consumers. We also examine the entrepreneur's choice of the pecuniary funder reward and campaign goal, two instruments that the entrepreneur can use to achieve the dual objective of raising funds to finance the project while successfully implementing price discrimination between high valuation and low valuation consumers.

Our model consists of two stages. In the first stage, the entrepreneur chooses the two instruments of the campaign: the campaign goal and the funder reward geared towards incentivizing high valuation consumers to pledge in the campaign. In the second stage, high valuation consumers, that we also refer to as "fans of the product," strategically decide if and how much they wish to contribute to the campaign. We assume that only when the total funds raised in the campaign exceed the campaign goal can the entrepreneur and platform keep the contributions of funders. Otherwise, all contributions are returned to funders. (This is the rule used by Kickstarter.) High valuation consumers choose their pledges strategically in response to the two instruments of the campaign, the campaign goal and the pecuniary funder reward, selected in the first stage. In their decision, they also consider their expected surplus from consuming the product and the possibility to "free ride" on contributions or other funds that might become available to the entrepreneur both in and out of the campaign.

At the completion of the campaign, if the aggregate contributions exceed the campaign goal and if the total funding the entrepreneur can raise (consisting of contributions from funders and the loan the entrepreneur can procure from outside funding sources) is sufficient to cover the development cost of the project, the product may be produced and sold to the consumer population. If the product is produced, the entrepreneur distributes the pecuniary reward to the high valuation consumers who contributed to the campaign.

We find that when the entrepreneur is very eager to raise funds through the crowdfunding campaign her ability to implement price discrimination between high and low valuation consumers is hindered. She is more eager to raise such funds when the total surplus from completion of the project is significant or when both the development cost of the project and financing costs through traditional funding sources are high. In this case, the entrepreneur offers a more generous funder reward in order to encourage higher pledges from fans of the product. However, such a high reward limits the ability of the entrepreneur to successfully extract extra surplus from fans of the product.

In contrast, when high valuation consumers value the product significantly higher than the price they anticipate to pay for it (namely, when their anticipated consumption benefits are high), they are highly motivated to contribute to the campaign as is, and the entrepreneur can cut the reward offered. This increases the entrepreneur's ability to use crowdfunding as a means to extract additional surplus from fans of the product in comparison to uniform pricing. In addition, the importance of generating capital from high valuation consumers declines when the entrepreneur is more likely to raise funds from other possible participants in the campaign. While this allows the entrepreneur to offer fans a smaller reward, it does not necessarily enhance her ability to use crowdfunding for price discrimination purposes. When fans of the product anticipate that contributions from others are more likely, they have a stronger incentive to "free ride" on such contributions by reducing their pledges.

The entrepreneur can optimally choose the level of the campaign goal to supplement the choice of pecuniary funder reward. In this regard, the entrepreneur weighs two counteracting effects. On the one hand, lowering the campaign goal raises the odds that the less demanding goal can be reached and that contributions raised in the campaign can be retained by the

entrepreneur. On the other hand, a low campaign goal implies that fans are less motivated to submit high pledges as they anticipate that the less demanding goal can be easily reached by contributions raised from others. In addition, a lower campaign goal implies that a bigger share of the development costs has to be financed via costly traditional funding sources.

We demonstrate that the entrepreneur has an incentive to raise the goal when the pool of funders outside of the fan group is relatively small or when it becomes more expensive to fund the product through outside funding (borrowing from a bank). In such instances, it becomes more important for the entrepreneur to highly motivate fans and obtain a bigger share of the development cost from the crowdfunding campaign. In contrast, when the entrepreneur can keep a bigger share of the campaign's contributions, she is more determined for the campaign to be successful, and lowers, therefore, the campaign goal in order to increase the likelihood of a successful campaign. However, even when lowering the campaign goal the entrepreneur does not necessarily lower it to ensure that the goal can always be met. Instead, the entrepreneur finds it optimal to risk an unsuccessful campaign in order to more highly motivate high valuation consumers to submit high pledges, thus saving on capital costs.

Of particular interest, we also find that the entrepreneur will always set the campaign goal below the level that allows her to completely cover the development cost of the product. As a result, the entrepreneur chooses to sometimes procure a portion of the development costs via traditional funding (i.e., a loan from the bank). While raising the campaign goal can help the entrepreneur to motivate more aggressive pledge behavior it also exposes her to the risk of a failed campaign when funds are insufficient to meet the more demanding goal. Given that the entrepreneur can also use the funder reward as an instrument to motivate funders and given that a

traditional outside funding source is available to the entrepreneur, she chooses the goal to be strictly lower than the level that allows her to cover the entire development cost.

Our research also illustrates the difference between crowdfunding and traditional vehicles that have been suggested in the literature in order to implement price discrimination. In this literature, the success of vendors to segment the market and practice price discrimination primarily depends on the extent of heterogeneity in the consumer population. With crowdfunding, while the success of price discrimination still depends on the extent of heterogeneity among consumers, it also depends on a variety of other variables. These variables determine how eager the entrepreneur is to obtain funding from the campaign to finance the project in comparison to how eager fans are to ensure that the product becomes a reality. Successful price discrimination between high and low valuation consumers is more likely with crowdfunding if fans are relatively more eager for the product to become available than the entrepreneur is about covering most development costs from the campaign. In our model, fans are more eager when they do not expect a large pool of other contributors, and therefore have fewer opportunities to free ride on such contributions. The entrepreneur is less eager when the new venture generates a relatively small total surplus. In this case, the entrepreneur has reduced incentives to motivate fans to contribute, and therefore, offers them only a modest reward. This permits her to extract greater surplus from high valuation consumers via their early contributions. In contrast, the entrepreneur becomes more eager to obtain funding from the campaign (thus hampering her ability to use crowdfunding to price discriminate) when both the development cost of the project and the financing costs through traditional funding sources are relatively high.

For their service of bringing together the entrepreneur and funders, the crowdfunding platform retains a fraction of the contributions raised in a successful campaign. In an extension

we allow the platform to strategically choose the sharing rule taking into account how such a choice will affect the instruments of the campaign selected by the entrepreneur, and ultimately, the overall contributions raised in the campaign. We demonstrate that the platform faces a tradeoff in choosing the sharing rule. On the positive side, increasing the share of the contributions that the entrepreneur retains can benefit the platform because the entrepreneur is more likely to set a lower campaign goal and a larger reward to funders in this case. The lower campaign goal increases the likelihood of a successful campaign and a larger reward motivates higher pledges from strategic funders. On the negative side, a bigger share promised to the entrepreneur implies that the platform retains a smaller portion of the contributions.

Our numerical calculations show that the platform's optimal sharing rule increases as the donations from altruistic donors decreases or the development cost of the project increases. In both instances, pledges from the strategic funders become more important. By raising the entrepreneur's share of the total contributions, the platform provides higher powered incentives to the entrepreneur to raise the funder reward, which motivates the strategic funders to pledge at higher levels.

Our research is related to several streams of literature. First is the literature on price discrimination. This literature examines different devices that can be used to price discriminate between segments of consumers such as coupons (e.g., Narasimhan 1984), bundling (e.g., Adams and Yellen 1976), and quality pricing (Mussa and Rosen 1979). We introduce in this paper a novel device that can help entrepreneurs to benefit from price discrimination while raising funds for their projects. Crowdfunding is most similar to advance purchase discounts (e.g., Dana 1998, Nocke et al. 2011) typically used in pricing of service products (e.g., in hotel industry) in that both use time as the means to segment the consumers. The main difference

between the two is in the segment that pays the higher price. In advance purchase discounts consumers who buy late pay higher prices because they have higher valuations. In crowdfunding, however, high valuation consumers whose early campaign contributions exceed the campaign reward effectively pay higher prices than those who wait for the product to become available on the market.

Another related literature is on fundraising of a discrete public good (e.g., Cadsby and Maynes 1999, Menezes et al. 2001, Palfrey and Rosenthal 1984 and 1988) in which case these goods are provided only if a distinct funding threshold is met. In our paper, as well, there is a funding goal which must be met before the entrepreneur receives the funders' contributions. It can then use these contributions to develop the product. However, in our paper the funding goal is set endogenously by the entrepreneur, whereas in this literature it is often exogenously determined by the cost of the good. As well, the entrepreneur can set an additional campaign incentive (i.e., campaign reward) to further motivate funders to contribute to the campaign.

There is an emerging literature on crowdfunding. Most of the research in this area, however, is empirical (e.g., Agrawal et al. 2015, Mollick 2014, Ward and Ramachandran 2010). The empirical literature supports the claim that individuals who contribute to campaigns are strategic and pay attention to various campaign variables when choosing to contribute. For instance, Mollick (2014) provides evidence that perceived project quality affects the success of the campaign.

Belleflamme, Lambert and Schwienbacher (2014) and Hu, Li, and Shi (2015) are two analytical papers that explore crowdfunding. Belleflamme et al. (2014) compare two forms of crowdfunding. In one type funders are consumers who pre-order the product and in the other the funders may not be interested in consuming the product but give funds in exchange for a share of

future profits. Our model is more similar to the prior type of crowdfunding. However, in our model instead of pre-ordering the product, high valuation consumers make pledges in the hopes that they receive the reward set by the entrepreneur and that they can purchase the product when it becomes available on the market. This reward is conditional on the campaign goal being met and the product being produced. While in Belleflamme et al. (2013), the entrepreneur has one instrument, the pre-ordering price, to influence participation in the crowdfunding, in ours she has two instruments to motivate funders, the crowdfunding campaign goal and funder reward. Similar to our study, in Belleflamme et al.'s pre-ordering case the entrepreneur is able to price discriminate between crowdfunders (consumers who pre-order the product) and other consumers who buy the product when it is available on the market. However, in their study, the entrepreneur is always able to extract extra surplus from consumers who pre-order because of additional utility such consumers derive from the sheer act of being contributors in the campaign. The focus of this paper is on examining conditions under which the profit extracted via the pre-ordering scheme is higher than when the entrepreneur chooses profit sharing in the crowdfunding campaign. In contrast, in our setting even when high valuation consumers are attracted to the campaign the entrepreneur cannot necessarily extract extra surplus from them. Our focus is on deriving conditions of the crowdfunding environment that can facilitate such additional surplus extraction from high valuation consumers. We incorporate, therefore, several relevant features of such campaigns that are not considered in this earlier paper. They include, the strategy of setting the campaign goal, consideration of outside funding to supplement funds raised in the campaign, uncertainty regarding the level of contributions, and the price paid by the entrepreneur to the platform running the campaign.

Hu, Li, and Shi (2015) examine the manner in which a project creator offers different product options in a crowdfunding campaign. Each of the product alternatives in Hu et al. (2015) corresponds to a different level of reward that the creator offers in exchange for a particular pledge level requested from buyers. The authors find that price discrimination with a menu of products can be more profitable than uniform pricing. A novel finding of their paper is that in comparison to a traditional product line design setting, the qualities of the products are less differentiated in crowdfunding. We also examine the possibility that crowdfunding can facilitate price discrimination. However, we focus on investigating whether the need of entrepreneurs to raise funds in the campaign may limit their ability to practice price discrimination. We incorporate, therefore, in the model, development costs of the project and financing costs from traditional funding sources in order to evaluate how the instruments of the campaign (funding reward and campaign goal) and the entrepreneur's ability to practice price discrimination depend upon such costs. In contrast to the product line design in Hu et al. (2015), in our setting there is only one basic product and one reward level. Price discrimination is successful if fans of the product, via their early pledges, pay de-facto a higher price than low valuation consumers.

3.2 MODEL

Consider an entrepreneur with an idea for a new product. The entrepreneur seeks funding to cover the development cost K of the new product. To this end, she tries to raise capital for her project by tapping the crowd on a platform. When creating the crowdfunding campaign, the entrepreneur has two strategic decisions she must make. First, she must set a campaign goal F for the aggregate contributions. Only if aggregate contributions exceed this goal is the campaign

considered successful. If these contributions fall short of the goal, the campaign is declared unsuccessful and they are returned to the funders.

Second, the entrepreneur makes the strategic choice of the level of the promotional funder reward Δ to be awarded to funders whose contribution exceeds a certain predetermined threshold. The funder reward corresponds to the future transfer of funds between the entrepreneur and the funders if the new product is successfully developed. Given that many rewards in crowdfunding campaigns are tied to the production of the product (e.g., a digital copy of the first single on an album) we assume that the funder reward is given to backers only after production occurs. We also assume that concerns regarding her reputation prevent the entrepreneur from renegeing on the promised reward once the product is produced. Indeed, empirical evidence shows that most entrepreneurs deliver on their promised rewards upon successful production of their products (Mollick 2014).

In order for production to take place, the entrepreneur must raise enough funds to cover the cost K of developing the product. If the funds available to the entrepreneur exceed the development cost, the entrepreneur incurs the development cost and the product is produced. Products produced are sold to consumers and rewards are distributed to backers of the crowdfunding campaign. Without loss of generality we assume that other than the development cost K , the entrepreneur incurs no additional production costs.

We allow for the entrepreneur to have access to traditional sources of funding in addition to funds raised in the crowdfunding campaign. Increasingly entrepreneurs are utilizing crowdfunding websites to finance only part of the development cost of their projects, hoping that successful campaigns attract traditional investors to complete the investment necessary to cover the entire cost of the projects (Geigner 2013). To account for this possibility, we consider an

environment where the entrepreneur may have access to funding sources other than the crowd. We model the possible outside funding source that is available as a lender that may provide funds to the entrepreneur at an interest rate s .

We assume that when the entrepreneur approaches the lender with news of a successful crowdfunding campaign, she can definitely secure funds from the lender to cover the shortfall between the contributions collected in the campaign and the development cost. In contrast, a failed campaign may be perceived as a risky investment. Such a failure may raise a “red flag” regarding the managerial skills of the entrepreneur. Her failure to attain the goal of the campaign may be interpreted by the lender as inability to set realistic objectives. Therefore, an entrepreneur who approaches the lender with news of a failed campaign faces uncertainty regarding her ability to obtain funding from the lender. We model this uncertainty by assuming that following a failed campaign the lender approves a loan to the entrepreneur with probability $q < 1$. In case of a failed campaign, however, the entrepreneur has to secure a loan of $\$K$ because she cannot keep any portion of the contributions when the goal of the campaign is not met.

In addition, we assume that raising sufficient capital to cover the development cost of the product does not necessarily guarantee that the product will become a reality. Because entrepreneurs may run into difficulties while developing the product or may make poor estimates of the cost of the project, it is sometimes the case that an entrepreneur is unable to introduce the product in the marketplace or may be unable to deliver the promised quality level (e.g., may have to renege on certain features) even after she collects sufficient funds to cover its anticipated cost. An investigative article found that out of the top 50 projects on Kickstarter, at the time of the article 15 projects had not been delivered to their backers as promised (Pepitone 2012). Therefore, we introduce a probability that is associated with the technical success of the product

which we denote by $p < 1$. This probability is known to the entrepreneur, consumers who plan to pledge in the campaign, and the platform.

If the entrepreneur is able to develop and produce the product, she sells it as a monopolist. This assumption is reasonable as many crowdfunding projects are for new products that are intended to ultimately serve niche markets: an electric skateboard, a 3D printer pen, a farm-to-table organic restaurant, etc. The entrepreneur's new product appeals to two types of consumers. The first type consists of n high valuation consumers (or fans of the product) having the reservation price r_H . The bulk of the market is comprised of consumers who have much lower valuation for the product. There are m consumers in the second group and their valuation is $r_L < r_H$. We assume that if the product is successfully developed the entrepreneur finds it optimal to set the price of the product at r_L because the segment of low valuation consumers is so big, that it makes it profitable for the entrepreneur to set the price to ensure that the entire market is covered (i.e., all $n + m$ consumers are served). We assume that the low valuation segment of consumers is unaware of the campaign. In Appendix B we relax this assumption and allow for a portion of these consumers to be aware of the campaign.

High valuation consumers (fans of the product) are aware that the campaign exists and are interested in contributing to the campaign because they expect to receive a positive consumption surplus if the product is produced. The fans choose their contribution level D_i (or D at the symmetric equilibrium) strategically to maximize their expected payoff. This expected payoff depends upon the fans' expected surplus from consuming the product and the promotional funder reward Δ that they receive if they make a pledge and the product is successfully developed. The expected payoff depends also on the threshold total contribution level F and any expected contributions from other funders which together determine the likelihood of the

successful completion of the project. Because all fans share the same valuation in our formulation, the entrepreneur chooses a single minimum threshold that entitles funders to receive the pecuniary reward. The entrepreneur sets it equal to the pledge level selected by high valuation consumers at the equilibrium, D . Any pledge equal to or above this threshold is eligible for the reward.

We assume that there is uncertainty regarding the total contributions raised in the campaign. Specifically, contributions may exceed the aggregate contributions of the fans. The pool of contributors outside of the fan group may consist of different types of individuals. They may be altruistic individuals who want to help entrepreneurs cultivate their dreams without having any actual interest in the specific product or reward. They may be funders who like the idea of the project without actually planning to become consumers of the product. Examples may include environmentalists supporting “green” projects even if they do not plan to be consumers of the final product when it becomes available. They may also be future consumers (out of the pool of the m lower valuation consumers) who have a marginally higher valuation than the price r_L they anticipate to pay for the product when it becomes available in the market. Therefore, such consumers each provide only a small amount in the campaign. This amount does not qualify them for the higher pecuniary reward Δ , but may qualify them for a smaller symbolic reward, such as being included in the “early backers of the product club” or receiving a “thank you” letter. We designate the aggregate level of such random donations by x , and assume that x is stochastically determined according to a uniform distribution over the support $[0, \bar{X}]$.

Indeed, in reality, we can observe many contributions to campaigns that are individually so small that they fall short of any threshold level that would qualify the contributors for any pecuniary reward. It is also quite common for contributors in campaigns to opt to receiving no

reward for their contributions. Indiegogo is one crowdfunding website that facilitates inferring some information regarding the size of the segment of funders who do not anticipate receiving any significant reward in return for their contribution. This website posts the pledge level submitted by each funder as well as the number of funders who opt to receive no reward for their contributions. Based on information regarding two campaigns that were ongoing on October 9, 2015, this segment of non-reward motivated contributions is quite significant. In the case of Dipper Audio Necklace that was 63% funded on this day, about 40 out of a total of 128 funders (about 30%) made contributions in which they did not anticipate any pecuniary reward. In the case of Wine Down SF that was 48% funded on this day, 10 out of 62 backers (about 16%) did not expect any such reward.

Notice that in addition to raising funds and thereby saving on capital costs, the crowdfunding campaign can enable the entrepreneur to price discriminate between fans of the product and lower valuation consumers. Because pledges are paid with certainty in the campaign and the reward is paid only with some probability if the product becomes available in the market, price discrimination can be implemented if $(D - p\Delta) > 0$, namely if the pledge exceeds the expected future reward paid upon completion of the product. In this case, high valuation consumers pay de-facto a higher price than low valuation consumers (i.e., they pay in expectation $D + p(r_L - \Delta)$ whereas the lower valuation consumers pay in expectation pr_L).

The crowdfunding platform is tasked with bringing together funders and entrepreneurs. For its service of bringing together the two populations, the platform keeps a percentage of the aggregate contributions. We designate by α the percentage of the aggregate contributions that the entrepreneur can keep. (For campaigns on Kickstarter, this is between 90-92% including 5%

Kickstarter fee and 3-5% processing fees). Figure 3.1 summarizes all of the variables used in our model.

We model the crowdfunding campaign as a two stage game. In the first stage, the entrepreneur sets the levels of the campaign goal F and the funder reward Δ . In the second stage, high valuation consumers decide how much to pledge D_i and nature determines the realization of random donations x . At the completion of the campaign if the aggregate funds raised (i.e., high valuation consumers' pledges and random donations) exceed the campaign goal, and if the total funding the entrepreneur can raise (including the possible loan the entrepreneur can get from the lender) are sufficient to cover the development cost K , the product has the potential to be produced. Once sufficient funds are raised, the product will be produced with probability p . If the product becomes available, it is sold to $m + n$ consumers at the price r_L , and the reward Δ is distributed to contributors in the campaign whose contribution exceeded the minimum pledge level selected by the entrepreneur. In an extension we later consider a third stage that precedes the other two in which the platform first chooses the sharing rule α .

Variable	Definition
r_H	Valuation of the product for high valuation consumers
r_L	Valuation of the product for low valuation consumers
n	Number of high valuation consumers in the market
m	Number of low valuation consumers in the market
x	Random donations raised through the campaign
K	Development cost of the new product
q	Probability that the entrepreneur can borrow funds from an outside lender given a failed campaign
p	Probability that a successfully funded product is actually produced; also referred to as probability of technical success
s	Interest rate on funds borrowed from outside lender
α	Share of contributions raised through the crowdfunding campaign that the entrepreneur keeps
D_i	Contribution by high valuation consumer i
Δ	Funder reward set by entrepreneur
F	Campaign goal set by entrepreneur

Figure 3.1: Summary of Variables

3.3 ANALYSIS

3.3.1 Pledge Behavior of the High Valuation Consumers

To obtain subgame perfect equilibrium, we start by considering the second stage when high valuation consumers (fans of the product) choose their pledges. Fans are aware of the fact that the entrepreneur has access to an outside funding source and consider this when choosing how much to pledge. They know, therefore, that as long as the crowdfunding campaign is successful ($(\sum_{i=1}^n D_i + x) \geq F$), the entrepreneur will be able to secure any additional funds needed to cover the development cost of the project through outside funding. However, fans know that with probability $(1 - p)$, the entrepreneur may not be able to produce the product as planned. This exposes the fans to the risk of losing their investment (pledge) without obtaining the promised benefits from consumption of the product and the funder reward. Additionally, because fans know that the project may be fully funded even when the crowdfunding campaign is unsuccessful (with probability q when $(\sum_{i=1}^n D_i + x) < F$), they may have muted incentives to contribute to the campaign, as they expect positive odds for the product to be available even in the absence of their contributions. Specifically, they anticipate that with some probability the project will be executed even when they reduce their contributions and the goal of the campaign is not met. (We assume that the entrepreneur's expected benefit from producing the product always exceeds the incurred financing and development costs $[p(n + m)r_L - K(1 + s)] > 0$).

The above discussion leads to the following expression for the expected utility of high valuation consumer i when choosing his pledge:

$$EU_i = \int_{F-D_i-\sum_{j \neq i} D_j}^{\bar{x}} (p(r_H - r_L + \Delta) - D_i) f(x) dx + pq \int_0^{F-D_i-\sum_{j \neq i} D_j} (r_H - r_L) f(x) dx. \quad (3.1)$$

The first integral of (3.1) is the expected net payoff of the fan when the goal of the campaign is met. With probability p the product is produced as planned and the fan receives the funder reward Δ and proceeds to buy the product yielding a consumption net benefit of $r_H - r_L$. However, the fan must pay his pledge D_i upfront, when the goal of the campaign is met, even if the product is never produced. The second integral is the high valuation consumer's net payoff when the campaign fails, in which case he can benefit from consuming the product with some probability pq that is strictly less than one (q is the probability that the entrepreneur can receive funding from the outside source given a failed campaign and p is the probability that the product will be produced given sufficient funding). High valuation consumer i chooses his pledge level D_i to maximize (3.1). Fans face a tradeoff when choosing D_i . A higher pledge level increases the probability that the campaign will be successful and the product will be produced, but decreases fan i 's welfare when the campaign is successful.

Note that in modeling the behavior of high valuation consumers we assume that they have the freedom to optimally set their pledge level. Essentially we assume that the crowdfunding platform follows a Name Your Own Price (NYOP) model instead of a Posted Price (PP) model, where the pledge level necessary to receive a certain reward would be dictated by the entrepreneur. The reason we make this assumption is that it is consistent with the mechanics of Kickstarter in which after selecting a reward the funder gets to choose his exact contribution level. Additionally, one can observe that there is heterogeneity in the pledge levels

As the surplus from consumption $r_H - r_L$ increases, fans increase their pledge in order to raise the probability that they will be able to consume the product in the future (we refer to this as the “consumption effect”). As the funder reward Δ increases, fans pledge more to increase the probability that they will be able to receive the bigger reward. The increase in the pledge level in both of these instances depends, however, on the probability p that the product will be produced because funders receive no consumption or reward benefits when the product is not produced. When the campaign goal F increases, the likelihood of a successful campaign declines, and it is less likely that the product will be produced. Fans try to reverse this possibility by increasing their pledge. We refer to the effect of changes in the levels of the instruments Δ and F as the “instrument effect”. Note that in our environment the effect of either instrument on the pledge behavior of strategic funders is identical. The pledge function depends simply on the sum of the two instruments. When either the maximum level of random donations \bar{X} increases or the number of high valuation consumers n increases each high valuation consumer has stronger incentives to “free ride” on the contributions of other funders, thus reducing his willingness to pledge himself (we refer to this as the “free riding effect”). The comparative statics we obtain from (3.2) would remain unchanged if we assumed that the pledge level is set by the entrepreneur instead of chosen optimally by high valuation consumers (see Appendix B.)

3.3.2 The Entrepreneur's Choice of the Campaign Goal and Reward

In the first stage the entrepreneur chooses the three campaign instruments F , Δ , and the minimum threshold level to qualify for Δ in order to maximize her expected profit. When choosing these instruments, the entrepreneur tries to attain the dual objective of motivating more aggressive pledge behavior by fans and of aligning more closely the payments of different consumer groups with their willingness to pay for the product. By offering high valuation consumers the opportunity to submit pledges in the campaign the entrepreneur can extract additional surplus from these fans. With this objective of surplus extraction, it is optimal for the entrepreneur to set the minimum pledge level that qualifies for the reward Δ at the level D , the symmetric equilibrium pledge of fans derived in (3.2).

Whenever aggregate contributions exceed the campaign goal F , the entrepreneur is able to keep her fraction of the revenue from the campaign (given the equilibrium pledges of fans this fraction amounts to $\alpha(nD + x)$). The actual execution of the project takes place, however, only when the entrepreneur is able to raise enough money to cover the development cost K . As mentioned earlier, because successful campaigns are interpreted by outside investors positively we assume that if the goal of the campaign is met the entrepreneur can raise any remaining funds necessary to cover the development cost K through an outside funding source at interest rate s . In addition, recall that with probability q the product may still be produced even after a failed campaign. Given the equilibrium pledge strategy D of each fan, the expected profit of the entrepreneur can be expressed by the following piecewise profit function:

$$E\pi_E = \tag{3.3}$$

$$\left\{ \begin{array}{ll} \omega + \int_{F-nD}^{\frac{K}{\alpha}-nD} [p(n+m)r_L + (\alpha(nD+x) - pn\Delta - K) - s(K - \alpha(nD+x))] f(x)dx & \text{if } F < \frac{K}{\alpha} \\ \quad + \int_{\frac{K}{\alpha}-nD}^{\bar{x}} [p(n+m)r_L + (\alpha(nD+x) - pn\Delta - K)] f(x)dx & \\ \omega + \int_{F-nD}^{\bar{x}} [p(n+m)r_L + (\alpha(nD+x) - pn\Delta - K)] f(x)dx & \text{if } F \geq \frac{K}{\alpha} \end{array} \right.$$

where $\omega = q \int_0^{F-nD} [p(n+m)r_L - (1+s)K] f(x)dx$.

The expected profit expression depends on whether the campaign goal is set below or above K/α , which we refer to as the gross-cost of the project. The first term ω appears in the expected profits of the entrepreneur irrespective of whether the campaign goal is set below or above the gross-cost of the project. It measures the expected payoff of the entrepreneur when the campaign fails. In this case, if the lender is willing to make a loan to the entrepreneur (happens with probability q) the entrepreneur will cover the development cost by borrowing the entire funds from the lender at an interest rate s . She will earn, therefore, the difference between expected revenues $p(n+m)r_L$ and the overall cost of $(1+s)K$ of financing the project.

The remaining terms depend on whether the entrepreneur chooses the campaign goal below or above the gross-cost of the project K/α . If the goal is chosen below the gross-cost two possibilities may arise. The first possibility is that the campaign is successful but insufficient funds are available to cover the entire cost of the project. In this case, the entrepreneur has to borrow the shortfall $(K - \alpha(nD+x))$ and pay the interest rate s on these funds. The second term of the expected profits when $F < K/\alpha$ corresponds to this possibility. The second possibility is that the campaign has raised sufficient funds to cover the entire development cost,

in which case the entrepreneur does not need to borrow any additional funds. The third term of the expected profits when $F < K/\alpha$ corresponds to this possibility. Note that the product will be produced as promised with probability p irrespective of whether sufficient funds to cover the entire cost have been raised in the campaign, implying that the entrepreneur has to pay the funder reward in each of these two possibilities only when the product is indeed produced. When the goal is chosen above the gross-cost of the project, whenever the campaign is successful it also generates sufficient funds to cover the entire development cost. As a result, the entrepreneur does not need to borrow any additional funds in this case. The second term of the expected profits when $F \geq K/\alpha$ corresponds to this event.

The entrepreneur chooses the instruments Δ and F to maximize her expected profit in (3.3) subject to the constraint that the optimal pledge strategy of each strategic funder is given by (3.2). A higher campaign goal F encourages fans to contribute more to the campaign in order to increase the likelihood of reaching the higher goal as well as extracting additional surplus from the fans. However, this higher goal decreases the probability of a successful campaign and thus the potential for the entrepreneur to earn profits by selling the product in the market.

Similarly, a larger reward Δ incentivizes fans to make more aggressive pledges but reduces the profit of the entrepreneur when she is able to produce the product. A larger Δ may help the entrepreneur extract surplus from high valuation consumers because it induces the fans to contribute more to the campaign, however a larger Δ can effectively decrease the realized price that fans must pay for the product because it results in a larger transfer of funds from the entrepreneur to the high valuation consumers.

We first derive the optimal funder reward Δ for a fixed value of F and calculate the elicited pledge D^* given the optimal funder reward Δ . (Both the funder reward Δ and aggregate

pledges from fans nD^* are fully characterized in Appendix B.) It is interesting that the expression for the optimal funder reward remains the same irrespective of whether the campaign goal is set above or below the gross-cost of the development. Because the funder reward has to be paid to fans if the product becomes available in either of these two cases, the entrepreneur chooses its value to be the same regardless of whether $F < K/\alpha$ or $F \geq K/\alpha$. We report comparative statics for the optimal value of the funder reward Δ in Proposition 3.1.

Proposition 3.1. *For a fixed value of F , the optimal value of the funder reward Δ :*

- (i) Increases when the total surplus generated by the project (as measured by the difference between the expected total willingness to pay of consumers and the development cost, $p(nr_H + mr_L) - K$) is bigger and when either the maximum level of random donations \bar{X} or the gap in valuations $r_H - r_L$ are smaller.*
- (ii) Increases when the campaign goal F is raised and when the interest rate s increases.*
- (iii) Increases with the sharing rule α .*

When the project generates a larger surplus the entrepreneur is more highly motivated to execute the project, and therefore, offers a larger reward to fans in order to ensure that sufficient capital to cover the development cost becomes available. In this case, the entrepreneur has greater interest in raising enough capital to produce the product than extracting surplus from the high valuation consumers, which limits her ability to price discriminate (i.e., a larger Δ reduces the effective price premium paid by the fans for the product, $D - p\Delta$).

In contrast, when the entrepreneur expects high levels of random donations, the relative importance of fans in generating capital declines, and the entrepreneur offers them a smaller

reward. Even though the entrepreneur offers high valuation consumers a smaller reward her ability to use crowdfunding to price discriminate is hindered because fans have a stronger incentive to free ride on contributions by others.

Similarly, when the benefit that fans derive from the product ($r_H - r_L$) is higher, they are highly motivated as is, and the entrepreneur cuts the reward offered to fans who pledge. This again leads to favorable conditions for extracting consumer surplus from high valuation consumers, thus enhancing the entrepreneur's ability to price discriminate.

Raising the campaign goal requires the entrepreneur to raise the funder reward in order to provide extra incentives to fans to increase their contribution and ensure that the more demanding goal is met. This result demonstrates the two counteracting effects on the ability of the entrepreneur to extract surplus from fans when raising the campaign goal. From (3.2) raising the goal motivates fans to pledge more aggressively. However, given that it also reduces the likelihood that the more demanding goal can be met it requires the entrepreneur to reward high valuation consumers more generously in order to reduce the likelihood of a failed campaign.

As the interest rate s increases, the entrepreneur increases the reward because it becomes costlier to finance the project through loans. The entrepreneur is intent, therefore, on raising more funds in the crowdfunding campaign by providing extra rewards to fans who contribute. This result demonstrates that the need to finance the product weakens the ability of the entrepreneur to use crowdfunding as a device to successfully implement price discrimination between high and low valuation consumers.

The effect of the sharing rule α on the funder reward is implied by the fact that when the entrepreneur is entitled to a bigger share of the product's revenue she is more highly motivated to increase the likelihood that the project is executed. As a result, she offers fans a more generous

reward to ensure that they submit higher pledges. However, a higher α means also that the entrepreneur can keep a larger share of each of the contributions made by high valuation consumers. Hence, in spite of the higher reward associated with a bigger value of α , surplus extraction might actually improve when α increases (i.e., $\alpha D - p\Delta$ might be bigger.)

Having established the optimal funder reward as a function of F as given in Proposition 3.1, we now turn to the derivation of the optimal campaign goal F . We start by considering the region $F \geq K/\alpha$. After substituting Δ and nD^* back into the objective of the entrepreneur (3.3), we take the derivative of the entrepreneur's expected profits when $F \geq K/\alpha$ with respect to F and obtain:

$$\frac{\partial E\pi_{|F \geq \frac{K}{\alpha}}}{\partial F} = \frac{-(1-\alpha)[(1-q)(p(nr_H + mr_L) - K) + Ksq - (1-\alpha)F + \bar{X}]}{\bar{X}(2n+2-\alpha)} = - \frac{(1-\alpha)[\bar{X} + nD^* - F]}{\bar{X}} < 0. \quad (3.4)$$

The last inequality follows because $\bar{X} + nD^* - F > 0$ is necessary to ensure that there is a positive probability that the campaign is successful for some realization of the random variable x . Proposition 3.2 is a direct result of the sign of (3.4).

Proposition 3.4. *The entrepreneur will never find it optimal to set the campaign goal F above the gross-cost threshold K/α .*

Recall that F and Δ are substitutable instruments in affecting the pledge of a high valuation consumer in (3.2) because the equilibrium pledge depends on the sum of these two variables. However, raising the campaign goal in the region $F \geq K/\alpha$ in order to motivate more aggressive pledge behavior may be risky for the entrepreneur because a higher goal reduces the probability of a successful campaign and the likelihood that the product is ever produced. Hence,

in this region the entrepreneur is more inclined to utilize the instrument Δ to motivate higher pledges while keeping the campaign goal as low as possible (i.e., $F = K/\alpha$.)

Next we consider the region $F < K/\alpha$. Designating by $E\pi(F)$ the expected payoff of the entrepreneur as a function of the campaign goal, it is easy to see from the objective function of the entrepreneur in (3.3) that:

$$E\pi(F)_{|F < \frac{K}{\alpha}} = E\pi(F)_{|F \geq \frac{K}{\alpha}} - \frac{\alpha s \left(\frac{K}{\alpha} - F\right)^2}{2\bar{X}}. \quad (3.5)$$

Taking the derivative of the right hand side of (3.5) with respect to F while using (3.4) yields that

$$\frac{\partial E\pi_{|F < \frac{K}{\alpha}}}{\partial F} = \frac{-(1-\alpha)[(1-q)(p(nr_H + mr_L) - K) + Ksq - (1-\alpha)F + \bar{X}]}{\bar{X}(2n+2-\alpha)} + \frac{\alpha s}{\bar{X}} \left(\frac{K}{\alpha} - F\right). \quad (3.6)$$

Differentiating the right hand side of (3.5) with respect to F , once again, yields:

$$\frac{\partial^2 \left(E\pi_{F < \frac{K}{\alpha}} \right)}{\partial F^2} = \frac{(1-\alpha)^2}{\bar{X}(2n+2-\alpha)} - \frac{\alpha s}{\bar{X}}. \quad (3.7)$$

This second order derivative of the profit function is negative if $T \equiv 2\alpha(1 + s + ns) - \alpha^2(1 + s) - 1 > 0$, in which case the objective of the entrepreneur is a concave function of F .

This latter condition for concavity is very likely to be satisfied for reasonable values of the parameters of the model. For instance, if the sharing rule assumes a value of $\alpha = 0.9$

(Kickstarter's approximate payment including processing fees is between 8-10%) and the cost of borrowing is $s > 0.05$ (for risky loans), then $T > 0$ for all $n \geq 1$. Assuming that concavity holds we can set the derivative in (3.5) equal to zero and solve for F to obtain the solution:

$$F^* = \frac{(2n+2-\alpha)sK - (1-\alpha)[(1-q)(p(nr_H + mr_L) - K) + Ksq + \bar{X}]}{2\alpha(1+s+ns) - \alpha^2(1+s) - 1}. \quad (3.8)$$

This solution should satisfy the constraint that $nD^* \leq F^* \leq K/\alpha$ to ensure that it falls in the feasible region. The lower bound on F^* is necessary to ensure that the probability of a successful

campaign does not exceed 1 and the upper bound is necessary given the result reported in Proposition 3.2.

Proposition 3.3

(i) *The entrepreneur chooses the campaign goal $F = F^*$ at the interior of the region $(nD^*, K/\alpha)$:*

If either the development cost of the product or the maximum level of random giving is relatively high (when $K > K_{LB}$ or $\bar{X} > \bar{X}_{LB}$, where $K_{LB} \equiv$

$$\frac{\alpha \left\{ (1-q)p(nr_H+mr_L) - \bar{X} \left[(2n+1-\alpha) - \frac{(1-\alpha)^2}{\alpha s} \right] \right\}}{[1-\alpha q - \alpha q s]} \text{ and } \bar{X}_{LB} \equiv \frac{\alpha s(1-q)p(nr_H+mr_L) + sK(q\alpha s + \alpha q - 1)}{\alpha s(2n+1-\alpha) - (1-\alpha)^2} .$$

(ii) *The entrepreneur chooses the campaign goal $F = nD^*$:*

If either the development cost of the product or the maximum level of random giving is relatively low (when $K < K_{LB}$ or $\bar{X} < \bar{X}_{LB}$).

(iii) *The entrepreneur never chooses the campaign goal so that $F = K/\alpha$.*

When the development cost K is relatively high or when the maximum level of random donations \bar{X} is relatively high the entrepreneur chooses the campaign goal to be strictly smaller than K/α and bigger than nD^* , implying that the campaign may sometimes be unsuccessful (i.e., when $nD^* + x < F$) and even when it is successful the entrepreneur finances only part of the development cost with funds raised from the campaign and part with outside funding (i.e., when $F < nD^* + x < K/\alpha$). In this situation, the entrepreneur is willing to risk an unsuccessful campaign in order to receive additional funds from the high valuation consumers that can enable her to save on capital costs. Further, by raising the campaign goal (i.e., setting it over nD^*), she

can reduce the incidence of free riding by fans who may think their contributions are not needed for the campaign to be successful.

When the development cost K is very low or when the maximum level of random donations \bar{X} is relatively modest part (ii) of the Proposition states that the entrepreneur chooses F at the minimum feasible level to ensure that the campaign is always successful; specifically, because $F = nD^*$, $nD^* + x$ is always bigger than F . When K is relatively small there is no need to raise a lot of funds given the low level of development cost. As a result, the entrepreneur does not have to raise the goal above the minimum in order to motivate fans to raise their pledges. Similarly, when \bar{X} is relatively small, fans have reduced incentives to “free ride” on random donations, given that these donations are relatively small. As a result, high valuation consumers are motivated to submit high pledges even when the goal is set at the lowest possible level.

According to part (iii) of the Proposition the entrepreneur does not choose the goal so high to ensure that she never utilizes the outside funding source. Because of the availability of this source the entrepreneur is never so desperate to guarantee that the entire amount of the development cost is raised in the campaign. If we relaxed the assumption that outside funding is always available following a successful campaign it would be possible that the goal of the campaign would be set at the level of the gross cost requirement. However, according to Proposition 3.2 it would never exceed this level. (Related analysis and proof are available from the authors upon request.) A direct inspection of the expression derived for F^* in (3.8) yields the comparative statics reported in Corollary 3.1.

Corollary 3.1. *When $nD^* < F^* < K/\alpha$, the campaign goal is an increasing function of $K, s,$ and q and it is a decreasing function of $\bar{X}, nr_H + mr_L, p,$ and α .*

When more funds are required to execute the project (higher K) or when it becomes more expensive to finance the development cost with outside funding (higher s), the entrepreneur raises the goal in order to more highly motivate the high valuation consumers and obtain a bigger share of the development cost from the crowdfunding campaign. When the probability q of outside funds becoming available even after a failed campaign is higher the entrepreneur is less concerned about the consequences of raising the campaign goal. Even if this higher goal is not met outside funds are still likely to be available in this case. When the importance of fans to the entrepreneur declines because the random donations are more significant (\bar{X} is bigger) the entrepreneur reduces the campaign goal because motivating fans is less important to her in this case. When the total consumer surplus is bigger the entrepreneur increases the funder reward Δ in order to generate higher pledges from high valuation consumers. Given that Δ and F are substitute instruments in motivating the fans the entrepreneur can reduce the level of the campaign goal when $nr_H + mr_L$ increases or when the probability p that a funded campaign turns into a finished product increases. When the entrepreneur obtains a bigger share of the product's revenue (when α is bigger) she is more determined for the campaign to be successful. She reduces, therefore, the campaign goal in order to increase the likelihood that the lower goal is reached.

3.3.3 Price Discrimination with Crowdfunding

We have argued that crowdfunding may play a dual role for the entrepreneur. While serving the basic function of raising funds to finance the new venture it may also serve as an effective price discrimination device if it can facilitate extraction of additional surplus from high valuation consumers in comparison to uniform pricing. Enhanced surplus extraction arises at the

equilibrium if the expected funder reward $p\Delta$ falls short of the share of the equilibrium pledge of each fan that the entrepreneur can retain, namely αD^* . However, because of her need to raise capital it is unclear whether the entrepreneur can necessarily extract extra surplus from high valuation consumers. For instance, the team behind Coolest Cooler (a high tech cooler) promised to give backers who contributed \$165 their very own Coolest Cooler which had an estimated market price of \$300 (Grepper 2015). In Proposition 3.4 we assume that the conditions supporting an interior solution for F are valid (i.e., at $nD^* < F = F^* < K/\alpha$), and we investigate circumstances under which enhanced consumer surplus extraction is possible, namely the share that the entrepreneur keeps from a contribution is bigger than the reward she must pay to a fan, in case the project is successfully completed ($\alpha D^* > p\Delta$.)

Proposition 3.4. *The entrepreneur can extract additional surplus from fans of the product in comparison to uniform pricing provided that:*

$$p(1 - q)(r_H - r_L) > \frac{s\{\alpha[(1-q)p(nr_H + mr_L) + \bar{X}] - K[1 - \alpha q - \alpha qs]\}}{[2\alpha(1+s+ns) - \alpha^2(1+s) - 1]}, \quad (3.9)$$

where the right hand side of (3.9) is strictly positive.

The fact that the right hand side of (3.9) is positive implies that for crowdfunding to support price discrimination the extent of heterogeneity in the population, as measured by the gap in valuations ($r_H - r_L$) has to exceed a certain threshold. This extent of heterogeneity determines the high valuation consumer's net consumption benefit from submitting a pledge. Because another important objective of the campaign besides surplus extraction is to raise funds, fans of the project have to be especially enthusiastic about the product to enable the entrepreneur to extract additional surplus from them in comparison to uniform pricing.

implement price discrimination. In the literature on quality differentiation, for instance, the success of vendors to segment the market and practice price discrimination primarily depends on the extent of heterogeneity in the consumer population (the spread $r_H - r_L$ in our model). With crowdfunding, while the success of price discrimination still depends on the extent of heterogeneity among consumers, it also depends on a variety of other variables. These variables determine how eager the entrepreneur is to obtain funding from the campaign to finance the project in comparison to how eager fans are to ensure that the product becomes a reality. Successful price discrimination between high and low valuation consumers is more likely with crowdfunding if fans are relatively more eager for the product to become available than the entrepreneur is about covering most development costs from the campaign.

One example in which price discrimination was likely achieved was the campaign for the movie *Blue Mountain State*. In the campaign, the project creator offered funders a digital download of the movie as well as some small affiliated gifts in exchange for a contribution equal to or higher than \$40. Upon release, the movie retailed at a price of \$13. The project creator was likely able to price discriminate in this case because the movie was based upon a cult television series with a niche, yet eager fan base. On the other hand, the campaign for the Pono Music Player (a high-resolution portable digital music player) offered the music player in exchange for a \$300 contribution (PonoMusic Team 2015). Because the music player would later go on to retail at \$399, the entrepreneur probably had to entice the fans of the product to contribute by giving them a generous reward. This was possibly the case because the music player had high development costs and high financing costs given the risk facing startups in the digital music market that is dominated by big established companies such as Apple and Sony. It was also likely that fans of the product had only a marginally higher valuation for the product than the

bulk of the market that the Pono Music Player would eventually serve. In addition, because award-winning musician Neil Young provided the vision behind the campaign, it is likely that the fans anticipated to free ride on a large group of followers of the musician (in our model a big population of random funders).

3.3.4 Maximization of Platform

We provide an extension to our previous analysis by allowing the platform to strategically set the sharing rule α prior to the entrepreneur's decision to set her campaign instruments. Therefore, the platform sets the sharing rule while anticipating how such a choice affects the entrepreneur's and funder's strategies. Recall that α denotes the fraction of the contributions that the entrepreneur retains and $(1 - \alpha)$ is the fraction of the contributions that the platform keeps for providing the intermediation services of bringing the entrepreneur and funders together. Unlike the entrepreneur's expected profit, the functional form of the platform's expected profit is independent of whether the campaign goal is set above or below the gross-cost threshold. The platform's profit accrues only from its share of the campaign contributions, and therefore, its profit is positive only when the crowdfunding campaign is successful. The platform does not derive any additional profit from the actual execution of the project. In the event of an unsuccessful campaign, the contributions are returned to the funders and the platform receives no compensation.

Assuming that an interior solution for F exists, in the first stage the platform chooses the sharing rule α to maximize its profits which are given by the expression:

Table 3.1: Optimal Choice of Sharing Rule α

For this numerical analysis, the following parameters are fixed: $r_H = 2200$, $r_L = 200$, $n = 100$, $m = 1000$, $s = 0.1$, $q = 0.5$, and $p = 1$. Note that these parameters satisfy the conditions for $F = F^*$ in Proposition 3.3. For small values of α , there is no equilibrium for the entrepreneur's choice of F as either the condition $K/\alpha > nD$ or $nD + \bar{X} > K/\alpha$ is not satisfied. α^* is the value of α that maximizes the platform's profits. The values for F^* in the table are in thousands.

α	$K = 100,000$				$K = 110,000$			
	$\bar{X} = 10000$		$\bar{X} = 50000$		$\bar{X} = 10000$		$\bar{X} = 50000$	
	F^*	Platform Profits	F^*	Platform Profits	F^*	Platform Profits	F^*	Platform Profits
0.05	--	--	--	--	--	--	--	--
0.10	--	--	--	--	--	--	--	--
0.15	--	--	--	--	--	--	--	--
0.20	--	--	--	--	--	--	--	--
0.25	--	--	--	--	--	--	--	--
0.30	--	--	--	--	--	--	--	--
0.35	--	--	282.9	568	--	--	313.7	134
0.40	248.1	1932	244.9	993	274.6	471	271.5	770
0.45	218.9	3264	216.4	1135	242.2	2466	239.7	1030
0.50	196.2	3748	194.2	1138	216.9	3342	214.9	1100
0.55	178	3778	176.3	1071	196.7	3606	195	1071
0.60	163	3561	161.7	968	180.1	3527	178.7	989
0.65	150.6	3208	149.5	848	166.2	3251	165.2	879
0.70	140	2782	139.2	721	154.5	2864	153.6	755
0.75	131	2321	130.3	593	144.4	2416	143.8	625
0.80	123.1	1846	122.6	466	135.7	1939	135.2	495
0.85	116.3	1371	115.9	343	128.1	1449	127.7	366
0.90	110.2	902	110	224	121.3	959	121.1	240
0.95	104.8	444	104.7	110	115.4	474	115.3	118
	$\alpha^* = .53$		$\alpha^* = .47$		$\alpha^* = .56$		$\alpha^* = .50$	

have no associated development costs. Further research is necessary to address the implications of using different refund rules when the goal of the campaign is not met.

We model the outside funding source available to the entrepreneur in the form of a lender. We could have alternatively modelled it as a venture capitalist that obtains an equity share in return for the funds invested in the company. Whereas interest payment is the cost of borrowing from the bank in our formulation, the loss of equity is the cost of raising funds from a venture capitalist. In addition, in our framework, the lender's interest rate is determined exogenously and is independent of the contributions raised in the crowdfunding campaign. However, it is possible that the lender offers a lower interest rate to entrepreneurs who are able to raise a bigger share of the required capital through the crowdfunding campaign, possibly because the larger contributions serve as a signal of a project that is less risky to finance. Incorporating such considerations may be worthwhile extensions of our current investigation.

In our model we do not allow for any transmission of information between the entrepreneur and the funders or communication amongst the fans themselves. Fans may be self-incentivized to tell others about a project in order to encourage more contributions, so that the campaign goal is reached. Accounting for these social effects may be an interesting extension to the present study.

4.0 SETTING ARTIST ROYALTIES ON MUSIC STREAMING PLATFORMS

4.1 INTRODUCTION

Digital streaming platforms are rapidly changing the way individuals consume digital content. These streaming platforms provide a new way for content producers to reach consumers and have become significant players in various industries: music (Spotify, Apple Music, TIDAL), movie and television (Hulu, Netflix, Amazon Prime), book and magazine (Kindle Unlimited) and video game (Steam, GeForce NOW). Digital streaming platforms allow subscribers to access and stream a variety of content hosted by the platform for a flat fee as opposed to traditional retail channels which require consumers to buy individual units of content. These platforms must create a value proposition for content producers and consumers to attract both user groups to their platform. Like traditional platforms, users accessing digital streaming platforms gain from cross-network benefits. The more subscribers using a streaming platform, the more revenue the platform generates to be shared via royalties with content producers. Likewise, the more content producers on a platform, the more valuable the platform is for consumers because it provides subscribers with variety.

The focus of this paper is on digital streaming platforms (for convenience we will also refer to streaming platforms as “streamers”) in the music industry. While streaming platforms continue to grow in popularity and use, skeptics argue that streamers are decreasing consumers’

willingness-to-pay for content and question whether it is possible for content producers to be fairly compensated by the streamer. We investigate conditions for which it may be profitable for an artist¹⁸ to distribute her music through a streamer. We provide insight regarding the royalty that the streamer must set if it wants to lure artists to its platform. We explore the streamer's decision to potentially exclude artists with different valuations. Our research also investigates competition between a digital store selling copies of artists' music and the streaming platform that offers a variety of artists' music for its subscribers to stream.

Digital streaming platforms are currently in a stage of rapid growth. As of March 2016, Spotify claims to have over 30 million users who pay to subscribe to Spotify's premium service. On the other side of the market, Spotify offers over 30 million songs and has paid over \$3 billion in revenues to artists and labels (Spotify 2016a). In 2015, for first time in the United States, streaming revenues surpassed those of digital downloads and was the largest component of industry revenues (Friedlander 2016). Apple Music, another streaming platform that debuted in June 2015 had already amassed over 10 million paid subscribers as of January 2016 (Garrahan and Bradshaw 2016).

Because streaming platforms are relatively new, artists have not exactly figured out how these platforms fit into their business models. Some artists have come out in support of such services, while others have launched attacks against these streamers for devaluing their music. Bono, lead singer of Grammy award winning and diamond certified rock band U2, supported Spotify by saying "Spotify are giving up 70 percent of all their revenues to rights owners" and that "the greatest way you serve your songs is to get them heard" (Grow 2014). On the other hand, pop sensation Taylor Swift refused to distribute her music through Spotify, criticizing the

¹⁸ For the sake of convenience, we refer to these decision makers as artists. In reality, rights holders are not always the artists, and when this is the case, the rights holders make content distribution decisions.

platform with the following comment: “Everybody's complaining about how music sales are shrinking, but nobody's changing the way they're doing things. They keep running towards streaming, which is, for the most part, what has been shrinking the numbers of paid album sales”¹⁹ (Dickey 2016). Thom Yorke, lead singer of the Grammy winning and platinum certified alternative rock band Radiohead, casts his line in the debate and seemingly sides with Taylor Swift: “I feel like we as musicians need to fight the Spotify thing” (Dredge 2013). Other artists that have vocally refused to stream all or some of their content through streaming platforms include Prince, Adele, Garth Brooks, the Black Keys, Bob Seger, King Crimson, and the Traveling Wilburys.

In this research, we analyze the revenue sharing model used by Spotify and Apple Music to determine exactly what percentage of revenue a streaming platform needs to share with artists to entice artists of varying valuations to stream their music through the platform. Artists who stream their music through a streamer receive compensation determined by a simple formula. First, the streamer keeps a portion of its revenue for its service in bringing together consumers and artists. The remaining revenue is then shared with artists on the streaming platform. Each individual artist’s earnings from streaming her music on the platform is ultimately determined by her individual streaming share (how her streams on the platform compare to other artists’ streams on the platform).²⁰

We construct an analytical model to capture competition between a digital store (retailer) and streaming platform. An artist must decide whether to stream her music on the streaming platform and sell her music to consumers through the store or to only sell her music to consumers through the store. Each artist has her own fan base consisting of consumers who, due

¹⁹ It is worth noting that Taylor Swift has since distributed her music through Apple Music.

²⁰ For a more in depth look at how Spotify pays artists, see Spotify (2016b)

to budgetary constraints, must choose whether to buy their preferred artist's music from the store or subscribe to the streamer and gain access to the variety offered by the streamer (and potentially their preferred artist's music). If an artist chooses to stream her music through the streamer, she receives a share of the streamer's revenue based upon the established royalty and her streaming share. When an artist streams her music through the streamer she risks cannibalizing sales of her content through the store. Therefore, to entice artists to the streamer, the streaming platform must set an appropriate royalty (how much of its revenue it will share with artists) to ensure that an artist's expected profit from streaming music through the streamer exceeds her expected profit from withholding music from the streaming platform.

We also distinguish between high valuation and low valuation artists. High valuation artists (determined by the benefit that their fan base derives from consuming their music) expect a larger demand for music purchases before joining the streamer and thus risk cannibalizing more of their sales by streaming their music. Because of this, the streamer may need to increase her offered royalty to entice high valuation artists to the platform. Therefore, streaming platforms may instead find it beneficial to only curate music from low valuation artists. We characterize conditions for which this is more likely to be true.

However, because having more artists on the streaming platform increases its variety and makes the streamer more valuable for consumers (and thus attracts more consumers to the platform), a streaming platform may be able to offer a lower royalty when it hosts content from both high valuation and low valuation artists. In this scenario, the streamer will curate its selection to include music from both high valuation and low valuation artists because it can sell more subscriptions at a higher price and retain more of its revenue.

Our study contributes to several streams of research in the marketing and economics literature. The first is the literature on channel competition (for example, see Coughlan 1985). More specifically, we model channel competition for a digital product akin to Balasubramanian et al. (2015). Our model accounts for horizontal channel competition between a retailer (digital store) and streaming platform. Channel competition of this sort has been studied in Cattani et al. (2006) wherein the authors model competition between a producer selling her content directly to consumers and a retailer. In our model, artists do not sell their music directly to consumers but through a digital store. Given the determined royalty, artists in our study must first decide whether or not to stream their music through the streamer, which increases the value of the platform and cannibalizes sales of her music in the store.

Our research also contributes to the literature on platforms. Platform competition has been an increasingly studied area in the marketing and economics literature (see Rochet and Tirole 2003; Hagiu 2009; Gal-Or et al. 2012). To the best of our knowledge, our paper is the first to investigate competition between a service offered by a platform (with whom a producer could or could not be using to enhance her own profits) and a retailer (who sells the producer's product to consumers). By offering her product through the platform, a producer makes the platform more desirable to consumers. We also add to the literature by studying digital streaming platforms that share revenue with artists who use the platform. We do not believe that any prior research on platforms has studied revenue sharing platforms. However, Dana Jr. and Spier (2001) investigates revenue sharing in the video rental agency between a retailer and its suppliers. Unlike the royalties in our study, they consider an industry in which producers are paid an upfront fee for content and then given a share of the revenue. They also do not model the

supplier's decision to distribute content through the retailer and the competitive effects from doing so.

In digital content markets, streaming platforms effectively curate a content bundle to which they provide their subscribers access. A content producer must choose whether or not to add her content to the bundle and enhance the bundle's position against her own content. (See Venkatesh and Mahajan (2009) for a review of the literature on bundling.) One such paper that specifically considers the bundling of digital goods is Bakos and Brynjolfsson (2000). In their study they investigate competition between two bundlers and show that large bundles may provide significant advantage in obtaining upstream content. They limit their focus to pure bundling strategies in which a supplier can either sell the product or bundle the product. In our research, we investigate an environment more akin to mixed bundling; specifically, how licensing content through a streaming platform (bundler) impacts competition between the streaming platform (bundler) and a store that sells the content. In an article that studies competition between bundlers and individual content producers, Nalebluff (2000) argues that bundles may have competitive advantage over component counterparts. In his analysis, the component counterparts are owned by different producers and are substitutes to the components in the bundle. In our model, while the components serve as substitutes to the bundle, a producer must first decide if she will license her component to the bundle for consumers to access. This is what happens in the music industry when an artist (the producer) chooses whether she should stream her music (the component) through the streamer (the bundle) or only sell it in the store.

Research on digital streaming platforms is rather nascent. An empirical working paper by Wlömert and Papies (2016) provides evidence that paid subscription based streaming platforms in the music industry (specifically Spotify) may enhance revenues for artists. A working paper

by Aguiar and Waldfogel (2015) further proposes that Spotify may stimulate music sales. The authors show that 137 streams appear to reduce the sale of one track by 1 unit on average. However, after considering royalties in the industry, the revenue generated from the 137 streams should exceed the revenue lost from the cannibalized sale. Our research expands upon these empirical results in digital content markets and provides theoretical insight into why distributing content through streaming platforms may be profitable for artists. However, we also show that dependent upon the royalty set by the platform, high valuation artists may not be able to enhance their profits through streaming because they have a larger market to cannibalize when they stream their music through the platform.

In the next section we describe the model. We proceed with our analysis and discuss the results. Finally in the conclusion, we recap the main results and discuss potential extensions that we plan to consider in the future.

4.2 MODEL

We model an environment comparable to the digital music industry in which competition exists between a streaming platform and a store that sells music downloads. As such, when a copy of the music is sold, it is sold through a digital music store (retailer) and not directly by the artist. Indeed, this appears to hold true in the digital music industry in which Apple's iTunes is responsible for the majority of digital music sales (Crupnick 2015). Analysts have also been quick to blame the decline in digital sales at such stores to the rise in digital streaming platforms, thus our focus on competition between the streaming platform and the store.

The store is responsible for setting a single price at which she sells all music downloads, regardless of the artist. This assumption is based on the fact that iTunes sells all songs at standard prices.²¹ We denote this store price p . Similarly, the streaming platform is in charge of setting a subscription fee s . Consumers who pay this subscription fee have access to all music streamed by the platform.

We model a continuum of artists in the market, each with their own fan base. Each fan base is a continuum of consumers who individually decide whether to purchase their preferred artist's music from the store at price p or subscribe to the streaming platform for fee s and stream the music available. We assume that all consumers have a limited budget to spend on entertainment and as such cannot purchase music from the store and simultaneously subscribe to the streamer. This ensures an environment in which the artist risks cannibalizing sales of her music when she streams her music through the streaming platform.

Each artist's fan base is distributed uniformly along the unit interval (from $[0,1]$). A fan's location on this interval, denoted by x , determines her innate preference for either streaming the music offered by the platform or purchasing (and owning a copy of²²) her preferred artist's music from the store. We set the location of the streaming platform to 0 and the location of the store to 1 and assume consumers incur a linear transportation cost t . Therefore, a fan at location x incurs a cost tx from subscribing to the streaming platform or a cost $t(1 - x)$ from purchasing music from the store. The transportation cost t is a parameter that captures the

²¹ Artists do not have the option to set their own price on iTunes but must sell at one of three prices (\$0.99 is the most common pricing tier for songs. \$0.69 is reserved for classic songs. \$1.29 is the price for new releases).

²² There are benefits from buying content as opposed to streaming it. For one, consumers who buy music have the ability to burn the music to a compact disc and listen to it while off line. Streaming is more akin to leasing the content.

intensity of consumer preferences and as such is a measure of competition in the market. When t increases, a consumer's preference for either the streaming platform or the store intensifies.

An artist has the choice of streaming her music on the streaming platform and selling her music through the store or only selling her music through the store (withholding her music from the streamer).²³ There are two types of artists. A type i artist provides her fans with consumption benefit v_i , where $i \in \{H, L\}$, such that $v_H > v_L$. Therefore, fans of H (high) type (valuation) artists value the music from their preferred artists more than fans of L (low) type (valuation) artists and thus have a higher reservation price for music, all else equal. This also means that in assuming a standard price for all music, there is more demand to buy the high valuation artist's music from the store than there is to buy the low valuation artist's music.²⁴

There is a continuum of each type of artist with mass m_i . Having a continuum of artists prevents any single artist's decision to join the platform from having an effect on the store's and streaming platform's decisions to set prices. Indeed, prices are fairly sticky and there are over 26 million songs available for purchase in the iTunes store. While data on the number of artists in the music industry is not readily available, with over 26 million songs it is sensible that no single artist's decision to join the streaming platform will impact prices. We later restrict $m_H = m_L = 1/2$ to reduce the number of parameters in the model. This allows us to focus on the difference in valuations across types as opposed to the mass of each type. With this restriction we can interpret the mass of each type as the percentage of artists in the market that belong to a type.

²³ Artists do not make a decision on whether or not to sell their content from the platform. To the best of our knowledge, there are not any artists who stream their music but refrain from selling it.

²⁴ We use these differences in reservation price to make distinction regarding the artist's popularity. However, one could also consider more popular artists having a larger density of fans. For the sake of this analysis, we only consider popularity as a difference in reservation price. Future research may investigate differences in sizes of fan bases.

Figure 4.1 depicts the market when there is a continuum of artists and each artist has its own fan base.

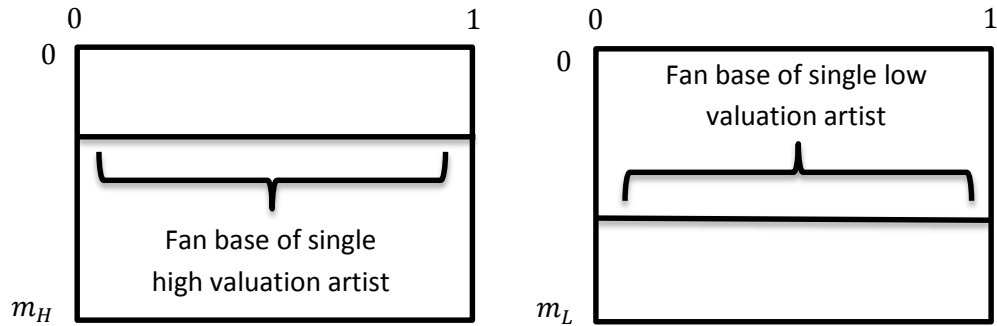


Figure 4.1. Depiction of Continuum of Fan Base for Each Artist

Streaming platforms provide value by offering variety and curating content. The variety benefit that a consumer receives from subscribing to the streamer is v_o . Because a streamer's value depends upon the amount of content available to stream on platform, we assume that this benefit is weighted by mass of artists served by the platform. Therefore, if the streamer hosts m_H high valuation artists and m_L low valuation artists, the platform provides benefit $(m_H + m_L)v_o$ to consumers. On the other hand if the platform chooses to only host low (high) valuation artists, then it provides benefit $m_L v_o$ ($m_H v_o$) to consumers. When we restrict $m_H = m_L = 1/2$ and the platform hosts music from both types, it offers variety benefit v_o . Therefore, it is sensible to assume $v_o > v_H > v_L$ because the variety benefit that the platform provides when hosting music from many artists (in fact, every other artist in the market) should exceed the value a consumer receives from the purchase of a single artist's music. Finally, because there is a continuum of

artists on the platform, any single artist's decision to join the platform has no impact on the variety benefit.

A consumer's total benefit from subscribing to the streaming platform depends upon whether or not the consumer's preferred artist streams music through the streamer. When an i type artist streams her music, her fans receive benefit αv_i in addition to the variety benefit from subscribing to the streamer, such that $\alpha < 1$. Fans subscribing to the streamer not only get the variety benefit from the curated content, but also the benefit from streaming their preferred artist's music. The benefit from streaming their preferred artist's music is reduced by α for several reasons. First, the fan does not own a copy of the music when she chooses to stream it; when she subscribes to the streaming platform it is as if she leases the music. However, fans who buy music through a store receive a digital copy of the content to own.²⁵ As well, streaming platforms often require the consumer to be connected to the Internet to access the content, and the stream may be interrupted by a dropped connection. Fans who buy music from the store are able to take a copy with them off line. Finally, the quality of the streamed music is determined by the Internet connection, and may sometimes be of lower quality than the download.

Given the framework aforementioned, the following expression represents the utility of a consumer located at x when she buys her type i preferred artist's music from the store:

$$u(x, i) = v_i - p - t(1 - x).$$

A fan who buys her preferred artist's music from the store receives benefit v_i , incurs transportation cost $t(1 - x)$, and pays store price p . The utility of a fan located at x when she subscribes to the streamer depends upon whether or not her preferred artist is on the streamer and

²⁵ Certain rights are bestowed upon consumers who purchase digital content. For instance, the consumer does not need to continue to pay for the right to access the content. Additionally, she may burn the content to a compact disc.

the mass of artists on the streaming platform. We summarize the streaming utility of a fan located at x with a type i preferred artist in Figure 4.2.

Is the preferred artist's music on the streamer?	What types of artists are on the streamer?	Streaming utility for fan located at x with type i preferred artist: $u(x, i) =$
Yes	Both types	$\alpha v_i + (m_H + m_L)v_o - s - tx$
No	Both types	$(m_H + m_L)v_o - s - tx$
Yes	Only low type	$\alpha v_i + m_L v_o - s - tx$
No	Only low type	$m_L v_o - s - tx$
Yes	Only high type	$\alpha v_i + m_H v_o - s - tx$
No	Only high type	$m_H v_o - s - tx$

Figure 4.2. Utility that Fans Receive by Subscribing to the Streaming Platform

The consumer receives benefit αv_i from subscribing to the platform when her preferred artist is on the platform. The variety benefit is dependent upon the mass of artists on the streamer. This mass is smaller when only one of the types of artists is on the streamer. Finally, a consumer who subscribes to the platform incurs transportation cost tx and pays subscription fee s .

If an artist chooses to stream her music through the streamer, the streaming platform shares a portion of its revenue with the artist. This is how streaming platforms such as Spotify and Apple Music compensate artists.²⁶ We define royalty as the percentage of revenue that the platform shares with all artists who stream their music and denote it as r , where $0 \leq r \leq 1$ (thus

²⁶ See Spotify (2016b) and England (2015).

the streamer retains $(1 - r)$ of its revenue). Once the streaming platform portions out the revenue to be shared, it pays each artist based upon that artist's streaming share. We distinguish an artist's streaming share as the number of streams she receives divided by the number of streams an average artist on the streaming platform receives. Therefore, an artist who is streamed less (more) than average will receive a smaller (larger) portion of the revenue appropriated for the artists. Figure 4.3 outlines how an artist is paid by the streaming platform:

$$\boxed{\text{Total revenue acquired by the streamer}} \times \boxed{\text{Royalty } r \text{ at which streamer shares revenue}} \times \boxed{\text{Artist's streaming share on the streamer}} = \boxed{\text{Artist's payout from streamer}}$$

Figure 4.3. How Streaming Platform Pays Artists

In defining the streaming share, we must also characterize the behavior of streaming platform subscribers. We assume that a subscriber on the platform will stream the entire library of music offered by the streaming platform. This simplifying assumption allows us to obtain distinguishable results and is more likely to hold when the opportunity cost of streaming more content is zero.²⁷

²⁷ In the Concluding Remarks, we consider extensions that relax this assumption. In reality, there is too much content on any given streaming platform for a subscriber to be able to stream it all under time constraints. Additionally, a subscriber is likely to stream her preferred artist's music more than she may stream other artist's music. Streaming platforms can aid in introducing fans of one artist to the music of another artist by improving recommendation algorithms. However, any of these considerations greatly complicate the current analysis.

We also denote the royalty that an artist receives every time her music is sold by the store as δ , where $0 < \delta < 1$ (thus the store retains $(1 - \delta)$ of each sale). For this study, we do not consider δ to be a strategic variable. This is because we assume that all artists sell their music through the store and δ is not set to entice artists to the store.²⁸ Additionally, our focus is on a streaming platform as an industry entrant and its ability to entice artists to the platform. We leave the store's decision to set δ for future research.

In the first stage of the game, the streamer sets a royalty r at which she will share revenue with artists on the platform. Then, artists decide whether or not to stream their music through the streamer. Finally, the platform and store set the subscription fee and store price simultaneously. Because no single artist has any impact on prices or the platform's variety benefit, the order that prices are set and an artist decides to stream her music is inconsequential and may be reversed.

4.3 ANALYSIS

We solve for a subgame perfect equilibrium by determining the optimal pricing strategies for the streaming platform and the store and the royalty needed to entice an artist to stream her music. To do so we calculate the expected profit of an artist when she streams her music and compare it to her expected profit when she withholds her music from the streamer.

We solve the game for three different environments. In the first environment the streaming platform streams music from both types of artists. In the second (third) environment, the streamer only streams music from low (high) valuation artists and excludes the other type. In

²⁸ This is more likely to be the case. Taylor Swift, who pulled her music off of Spotify (the streaming platform), did not pull her music off of iTunes (the digital store). Additionally, when Apple Music was released subscribers did not have access to every artist in iTunes' library (Welch 2015).

the first environment the platform offers more variety by hosting a larger mass of artists and thus provides consumers a greater variety benefit. We compare optimal strategies (store price, subscription fee, and royalty) across environments to gain a better understanding of the market for digital music in the presence of a streaming platform.

The store's and streamer's expected profits do not functionally differ across environments. In each environment the store sets a store price and the streamer chooses a subscription fee simultaneously to maximize expected profit. The store's expected profit $E\pi_r$ follows below:

$$E\pi_r = (1 - \delta)p[(1 - x_H^*)m_H + (1 - x_L^*)m_L]. \quad (4.1)$$

Because the store and streamer compete for a share of each artist's fan base, we make note of the consumer who is indifferent between buying their preferred artist's music from the store and subscribing to the streamer within each fan base. For a low valuation artist this indifferent consumer is located at x_L^* , and for a high valuation artist this indifferent consumer is located at x_H^* . We further describe the locations of the indifferent consumer within a fan base when we discuss each environment. Because preference is monotonic in consumer location we know that consumers to the left of the indifferent consumer choose to subscribe to the platform and consumers to the right of the indifferent consumer choose to buy their preferred artist's music from the store. Therefore, expected demand for the store is captured by the bracketed term in (4.1), or $(1 - x_H^*)m_H + (1 - x_L^*)m_L$. Notice that we multiply the store's demand from the fan base of an artist of each type by the mass of the corresponding type to get the total store demand.

The store seeks to maximize her expected profit by setting a single store price at which any artist's music can be purchased. Because demand for the store is decreasing in store price,

the store encounters a tradeoff when setting an optimal price. Finally, the store shares δ of each sale with the artist whose music was purchased, retaining $(1 - \delta)$ of the revenue for herself.

Similarly, the streaming platform's expected profit is denoted by $E\pi_p$ and follows:

$$E\pi_p = (1 - r)s[x_H^*m_H + x_L^*m_L]. \quad (4.2)$$

For the streamer, the bracketed term in (4.2), $x_H^*m_H + x_L^*m_L$, represents its total demand. The streaming platform sets a single subscription fee that maximizes its expected profit. As before, because demand for the streamer is decreasing in subscription fee, the streamer faces a tradeoff when setting an optimal fee. The streaming platform only retains a portion $(1 - r)$ of its revenues, sharing the rest as royalties. We later investigate the streamer's decision to set r such that she is able to entice artists to stream their music through her platform.

4.3.1 Platform Streams Both Types of Artists' Music

We first consider the environment in which the platform hosts content from both types of artists. Recall that in this environment, consumers are aware that both types of artists are on the streaming platform and expect a variety benefit of $(m_H + m_L)v_o$ when they subscribe. Because both types of artists stream their music, the indifferent consumer (located at x_i^*) in an i type artist's fan base is characterized by the following equality:

$$\alpha v_i + (m_H + m_L)v_o - s - tx_i^* = v_i - p - t(1 - x_i^*).$$

Solving the above equality for x_i^* reveals the demand for the streamer from an i type artist's fan base:

$$x_i^* = \frac{t + (m_H + m_L)v_o - (1 - \alpha)v_i + p - s}{2t}. \quad (4.3)$$

As such, $(1 - x_i^*)$ denotes the demand for the store from an i type artist's fan base. Because demand is a function of store price and subscription fee, we substitute (4.3) into (4.1) and (4.2) to solve for the prices that maximize expected profits. From (4.3) it is evident that a higher store price and lower subscription fee increases the demand for the streaming platform, and a lower store price and higher subscription fee increases the demand for the store.

Recall that store price and subscription fee are set simultaneously. Differentiating (4.1) and (4.2) with respect to store price and subscription fee and solving the resulting system of equations yields the following response functions:

$$p = \frac{3t - (m_H + m_L)v_o}{3} + \frac{(1 - \alpha)(m_H v_H + m_L v_L)}{3(m_H + m_L)}, \text{ and} \quad (4.4)$$

$$s = \frac{3t + (m_H + m_L)v_o}{3} - \frac{(1 - \alpha)(m_H v_H + m_L v_L)}{3(m_H + m_L)}.$$

A higher t is an indicator of more intense consumer preferences and as such reduces competition and allows the streamer and store to sustain higher prices. As consumers value variety v_o more, the streamer is able to charge a higher subscription fee but the store must offer a lower purchase price. When enhanced technology makes the streamer more effective at replicating the benefit from purchasing an artist's music, α increases. This increases the value that a platform offers fans and results in a higher subscription fee and lower store price. However, because $\alpha < 1$ an increase in valuation v_H or v_L has a more profound impact on the store and allows the store to charge a higher price while forcing the streamer to lower its subscription fee.

When we restrict the mass of each artist type such that $m_H = m_L = 1/2$, the store price given in (4.4) reduces to $p = [3t - v_o + (1 - \alpha)(v_H + v_L)/2]/3$. It is noteworthy that price is a function of horizontal and vertical preferences. The parameter t captures the intensity of horizontal preference for either the store or streaming platform. $v_o - (1 - \alpha)(v_H + v_L)/2$ is the

difference in benefit, on average, between the two outlets and thus captures the intensity of vertical preference.

When store price and subscription fee are set according to (4.4), the demand for the streaming platform from a fan base with an i type preferred artist is:

$$x_i^* = \frac{3t+(m_H+m_L)v_o-3(1-\alpha)v_i}{6t} + \frac{(1-\alpha)(m_Hv_H+m_Lv_L)}{3t(m_H+m_L)}. \quad (4.5)$$

Even after accounting for prices, demand for the streaming platform increases when consumers value variety v_o more or the effectiveness of streaming α is enhanced. This is because higher values of v_o or α strengthen the streamer's competitive position. The total demand for the streamer $x_H^*m_H + x_L^*m_L$ can be written as:

$$\left[\frac{3t+(m_H+m_L)v_o}{6t} - \frac{3(1-\alpha)v_H+3(1-\alpha)v_L}{12t} + \frac{(1-\alpha)(m_Hv_H+m_Lv_L)}{3t(m_H+m_L)} \right]. \quad (4.6)$$

An artist observes the streaming platform's royalty and is aware of the pricing strategies given in (4.4) when she decides whether or not she should stream her music. Recall that any single artist's decision to withhold her music from the streaming platform has no effect on the prices or variety benefit. However, her decision affects the utility that her fans receive from subscribing to the streamer. When a high valuation artist streams her music through the streamer, her fans receive benefit $\alpha v_H + (m_H + m_L)v_o$ from the platform; when she withholds her music from the streaming platform her fans only receive benefit $(m_H + m_L)v_o$ from the platform. When a high valuation artist withholds her music from the platform, the consumer in her fan base who is indifferent between subscribing to the streamer and purchasing her music from the store is located at \bar{x}_H^* such that:

$$(m_H + m_L)v_o - s - \bar{x}_H^* t = v_H - p - (1 - \bar{x}_H^*)t.$$

By removing her content from the platform, a high valuation artist makes the streaming platform less valuable to her fans and increases the demand for her music from the store (all else equal).

After accounting for the pricing strategies given in (4.4), the location of the indifferent consumer in a fan base of a high valuation artist who withholds her music is:

$$\bar{x}_H^* = \frac{3t + (m_H + m_L)v_o - 3v_H}{6t} + \frac{(1 - \alpha)(m_H v_H + m_L v_L)}{3t(m_H + m_L)} \quad (4.7)$$

As expected, the consumer who is indifferent between the streamer and store is located closer to the streamer (and thus the demand for the streamer is lower) when the artist withholds her music from the streamer. Thus, when an artist streams her music she cannibalizes sales of her content through the store. The extent of cannibalization is characterized by $(1 - \bar{x}_H^*) - (1 - x_H^*) = x_H^* - \bar{x}_H^* = 3\alpha v_H / 6t$. If we repeat the preceding analysis for a low valuation artist, we find that low valuation artists risk cannibalizing sales due to streaming by $3\alpha v_L / 6t$.²⁹ Because $v_H > v_L$, a high valuation artist risks cannibalizing more store sales than a low valuation artist by streaming her music.

A high valuation artist will only stream her music when the expected profit that she receives from streaming her music exceeds the expected profit that she earns when she withholds her music from the streamer and only sells it through the store. When an artist streams her music she earns a payoff from the streaming platform that is determined by the royalty, the streamer's revenues, and the artist's streaming share. An artist's fan base that opted for the streaming platform will always stream their preferred artist's music when it is on the streaming platform. A high valuation artist is guaranteed x_H^* streams and a low valuation artist is guaranteed x_L^* streams. We assume that every subscriber on the streaming platform will stream each artist's music resulting, on average, in an additional $m_H x_H^* + m_L x_L^*$ streams per artist.

²⁹ We denote the location \bar{x}_L^* of the indifferent consumer in the fan base of the low valuation artist who withholds her music from the streamer as:

$$\bar{x}_L^* = \frac{3t + (m_H + m_L)v_o - 3v_L}{6t} + \frac{(1 - \alpha)(m_H v_H + m_L v_L)}{3t(m_H + m_L)}$$

We denote a high valuation artist's expected profit from streaming her music as $E\pi_H^{Join}$ and her expected profit from withholding her music from the streamer as $E\pi_H^{Not Join}$:

$$E\pi_H^{Join} = \delta p(1 - x_H^*) + rs(m_H x_H^* + m_L x_L^*) \left[\frac{x_H^* + (m_H x_H^* + m_L x_L^*)}{m_H(x_H^* + m_H x_H^* + m_L x_L^*) + m_L(x_L^* + m_H x_H^* + m_L x_L^*)} \right],$$

and $E\pi_H^{Not Join} = \delta p(1 - \bar{x}_H^*)$. (4.8)

The expected profit for an artist who streams her music is the sum of her earnings from both the store and the streamer. The first term in $E\pi_H^{Join}$, $\delta p(1 - x_H^*)$, is the revenue she receives from the store. In the second term, $rs(m_H x_H^* + m_L x_L^*)$, is the revenue that the streamer shares with all artists. However, an individual artist earns an amount weighted by her streaming share:

$$\frac{x_H^* + (m_H x_H^* + m_L x_L^*)}{m_H(x_H^* + m_H x_H^* + m_L x_L^*) + m_L(x_L^* + m_H x_H^* + m_L x_L^*)}. \quad (4.9)$$

The numerator of the streaming share in (4.9) is the sum of streams an artist receives from her own fans that opt to subscribe to the platform x_H^* and the streams she receives, on average, from other subscribers ($m_H x_H^* + m_L x_L^*$). The denominator in (4.9) is the expected number of streams an average artist on the streaming platform receives; m_H artists are high valuation artists receiving $x_H^* + m_H x_H^* + m_L x_L^*$ streams and m_L artists are low valuation artists receiving $x_L^* + m_H x_H^* + m_L x_L^*$ streams. The denominator in (4.9) reduces to $(1 + m_H + m_L)(m_H x_H^* + m_L x_L^*)$.³⁰

When an artist withholds her music from the streamer, her profit accrues from sales at the store, $\delta p(1 - \bar{x}_H^*)$. Recall that by streaming her music she cannibalizes sales from the store ($\bar{x}_H^* < x_H^*$). Therefore, the streaming platform needs to offset the loss of store sales by setting a high enough royalty to ensure that the additional revenue she gets from streaming royalties exceeds the revenue she loses due to cannibalization. Because the streamer's expected profit is

³⁰ In reality, streaming share is the total number of streams for an artist divided by the total number of streams on the platform. Because we assume a continuum of artists and thus the total number of streams approaches infinity, we instead consider the expected streams of a particular artist divided by the expected streams of an average artist.

decreasing in royalty, when she wants to retain high valuation artists the streaming platform will set the lowest royalty that guarantees $E\pi_H^{Join} - E\pi_H^{Not Join} \geq 0$. We denote the royalty that is needed to guarantee both types of artists stream their music as r_{both} :

$$r_{both} = \frac{(x_H^* - \bar{x}_H)\delta p(1+m_H+m_L)}{s(x_H^*+m_Hx_H^*+m_Lx_L^*)}.$$

For the remainder of this study we restrict the mass of each type of artist such that $m_H = m_L = 1/2$. In this manner, the mass can also be interpreted as the portion of the artist population that belongs to each type. Using this restriction and the optimal pricing strategies derived earlier, the royalty needed to ensure that both types stream their music is:

$$r_{both} = \frac{3\alpha v_H \delta \left[3t - v_o + \frac{(1-\alpha)(v_H+v_L)}{2} \right]}{\left[3t + v_o - \frac{(1-\alpha)(v_H+v_L)}{2} \right] \left[3t + v_o + \frac{(1-\alpha)(v_L - 5v_H)}{4} \right]}. \quad (4.10)$$

In Appendix C we repeat the preceding analysis for a low valuation artist in this environment and calculate the royalty needed to convince a low valuation artist to stream her music. It is easily verifiable that the royalty needed to prevent a high valuation artist from withholding her music from the streamer (given in 4.10) is strictly greater than the royalty necessary to retain a low valuation artist (given in Appendix C). Therefore, when the streamer wants to host content from both types of artists it must set the royalty given in (4.10).

The numerator in (4.10) is the benefit that a high valuation artist receives if she withholds her music from the streamer. In other words, it is the lost revenue from cannibalizing her music sales when she also streams her music. The denominator in (4.10) is the artist's payoff from the streaming platform when she chooses to stream her music. Therefore, when the store's competitive position is strengthened, the streamer needs to set a higher royalty to convince high valuation consumers to stream their music. When the platform's competitive position is enhanced, the platform generates more shareable revenue and can decrease the royalty. We

conduct comparative statics on r_{both} to show how the parameters of the model affect the royalty needed to prevent an artist from withholding her music from the streamer.

Observation 4.1. *A higher royalty r_{both} is needed when v_H increases, when v_o decreases, or when t decreases and t is sufficiently large. The effects of α and v_L on royalty are ambiguous.*

Observation 4.1 is the result of differentiating r_{both} with respect to each parameter. For results that are not easily verifiable, calculations for Observation 4.1 can be found in Appendix C. When the value that fans derive from a high valuation artist's music v_H increases, a high valuation artist risks cannibalizing more store sales when she chooses to stream her music. Therefore, to offset this effect and entice her to stream her music, the streamer must offer a more generous (from the artists' perspective) royalty r_{both} . As consumers value variety v_o more, the streaming platform sells more subscriptions at a higher price. This strengthens the streamer's position as artists become interested in her revenue pool and thus she can offer a lower royalty r_{both} .

When consumers' preferences intensify (larger t), the store can increase its profit margin from each sale. This strengthens the position of the store and provides an additional incentive for the artist to refrain from streaming. However, more intense preferences also ease the rate of cannibalization from streaming because it becomes increasingly difficult to convince consumers who prefer purchasing music to instead subscribe to the streamer. When the intensity of preferences t is sufficiently large, the cannibalization easing effect dominates and an increase in t allows the streamer to offer a lower royalty r_{both} .

Streaming's effectiveness at replicating purchased music α has opposing effects on the royalty r_{both} . When α increases, an artist who streams her music risks cannibalizing more of her store sales. However, an increase in α allows the platform to sell more subscriptions at a higher price in order to grow her revenue to share with streaming artists. Additionally, when the low valuation artists become more valuable (v_L increases) the store is able to sustain a higher price for all music sales and high valuation artists worry more about cannibalization. However, the value of low type artists v_L also impacts a high valuation artist's position on the platform through its streaming share. As v_L increases there are fewer low valuation fans on the streamer and thus a high valuation artist ends up with a higher streaming share when she streams her music. This increases her potential earnings from streaming her music.

Having found the royalty r_{both} needed to entice any artist to stream her music when the streaming platform hosts content from both types of artists, we next consider the environment where the streaming platform only hosts music from one type of artist.

4.3.2 Platform Streams Only One Type of Artist's Music

In this section, we consider a streaming platform that hosts music from only one type of artist. Because the platform excludes an entire type of artists, the variety benefit and pricing strategies differ from those in the preceding section. The variety benefit that the streamer provides to subscribers is $m_i v_o$ when it hosts i type artists' music. Given that $m_H = m_L = 1/2$, the variety benefit is the same regardless of the type of artists that streams their music through the streamer.

4.3.2.1 Platform Streams Only Low Valuation Artists' Music. We consider the environment in which only low valuation artists stream their music. Indeed, this context may mimic reality in

the music industry. Examples of artists who have withheld their music from streaming platforms such as Spotify consist of very popular artists such as Taylor Swift, Adele, the Beatles, and AC/DC. In fact, Taylor Swift and Adele had the top selling albums in 2014 and 2015 respectively, and neither could be found on Spotify (Caulfield 2014, 2016).

Because high valuation artists do not stream their music in this environment, the location of the indifferent consumer in a high valuation artist's fan base is denoted x_H^* and characterized by the following equality:

$$\frac{v_o}{2} - s - x_H^* t = v_H - p - (1 - x_H^*)t.$$

Fans of high valuation artists do not receive benefit αv_H from subscribing to the platform. Because low valuation artists stream their music through the streaming platform, the location of the indifferent consumer in a low valuation artist's fan base is denoted x_L^* characterized by the following equality:

$$\alpha v_L + \frac{v_o}{2} - s - t x_L^* = v_L - p - t(1 - x_L^*).$$

Solving the first equality for x_H^* and the second equality for x_L^* reveals the demand for the streamer from a fan base for each type:

$$x_H^* = \frac{t + \frac{v_o}{2} - v_H + p - s}{2t}, \text{ and}$$

$$x_L^* = \frac{t + \frac{v_o}{2} - (1 - \alpha)v_L + p - s}{2t}.$$

The equations for x_H^* and x_L^* can be substituted in to the expected profit functions given in (4.1) and (4.2). Differentiating (4.1) and (4.2) with respect to store price and subscription fee and solving the resulting system of equations yields the following response functions:

$$p = \frac{3t - \frac{v_o}{2}}{3} + \frac{[v_H + (1 - \alpha)v_L]}{6}, \text{ and} \tag{4.11}$$

$$T\left(1 - \frac{q^*}{\bar{q}}\right) \geq \mu[(1-x)\beta + (1-\beta)(1-y)], \text{ and}$$

$$T\left(\frac{q^*}{\bar{q}}\right) \geq \mu[x\beta + (1-\beta)y]. \quad (\text{A.3})$$

Equation (A.3) guarantees that the capacity offered from vendors is sufficient to answer demand. Finally, while the first condition for segmentation of vendors from Lemma 2.1 stays the same as in the main text, the second condition changes when α_L and α_H may be different as follows:

$$\gamma \equiv [[\beta x + (1-\beta)y]\alpha_L R_L - [\beta(1-x) + (1-\beta)(1-y)]\alpha_H R_H] > 0,$$

and the solution for q^* is given as:

$$dq^* = \frac{[\beta x + (1-\beta)y]\alpha_L R_L - [\beta(1-x) + (1-\beta)(1-y)]\alpha_H R_H}{[\beta(1-c)(2x-1) + (1-\beta)(2y-1)]}. \quad (\text{A.4})$$

To maximize its profits platform H chooses the lowest possible sharing rule α_H that ensures the participation of a vendor of type \bar{q} , namely

$$\alpha_H = \frac{d\bar{q} [\beta(1-c)(1-x) + (1-\beta)(1-y)]}{R_H [\beta(1-x) + (1-\beta)(1-y)]}, \quad (\text{A.5})$$

where R_H , x , and y remain as derived in the main text. With this choice, all other vendors served by H obtain a strictly positive payoff, including a vendor of type q^* . Because of vendor of type q^* is indifferent between L and H , it follows that the sharing rule α_L guarantees a strictly positive payoff to vendor q^* , and therefore, to all other vendors $q \leq q^*$ as well. Hence, the participation constraint for vendor L is slack.

Platform L wishes to set α_L at the lowest possible level. However, it has to guarantee that sufficient capacity exists to serve demand. It lowers α_L until its capacity constraint is just binding. Substituting into (A.4) the expression derived for $\alpha_H R_H$ from (A.5), it follows from (A.3) that in order to exactly satisfy the demand from consumers:

$$\alpha_L = \frac{d\bar{q}}{R_L} \left[\frac{\beta(1-x)(1-c) + (1-\beta)(1-y)}{\beta x + (1-\beta)y} + \frac{\mu}{T} [\beta(1-c)(2x-1) + (1-\beta)(2y-1)] \right], \quad (\text{A.6})$$

Evaluating (B.1) at the symmetric equilibrium $D_i = D_j = D$ and solving it for D , we get the second stage equilibrium pledge strategy as given in (3.2) in the Lemma. Note the condition (B.1) is sufficient for maximization because $\frac{\partial^2 EU_i}{\partial D_i^2} < 0$.

Behavior of Fans if Crowdfunding Platform Used the Posted Price Model

If the entrepreneur dictated the pledge level D necessary to receive the reward Δ it would choose it at the highest level that induces the fan to participate in the campaign instead of simply waiting for the product to become available in the future. Specifically, D would satisfy the equation:

$(p(r_H - r_L + \Delta) - D) \left[\frac{\bar{X} - (F - nD)}{\bar{X}} \right] + qp(r_H - r_L) \left(\frac{F - nD}{\bar{X}} \right) = p(r_H - r_L) \left\{ \left[\frac{\bar{X} - (F - (n-1)D)}{\bar{X}} \right] + q \frac{(F - (n-1)D)}{\bar{X}} \right\}$, where the LHS of the above equation corresponds to the payoff of a fan who participates in the campaign and the RHS corresponds to his payoff if he stays out and waits for the product to become available. The above equation yields a quadratic equation in D . Solving it for D in terms of the two instruments Δ and F yields:

$$D = \frac{R + \sqrt{R^2 + 4np\Delta(\bar{X} - F)}}{2n}, \text{ where } R \equiv [F + np\Delta + (r_H - r_L)p(1 - q) - \bar{X}].$$

Similar to the comparative statics obtained from equation (3.2), it is easy to show that the “Posted Price” D is an increasing function of the instruments Δ and F (similar “instrument effect” as with NYOP) and a decreasing function of \bar{X} and n (similar “free riding” effect as with NYOP). Because the effect of the instruments of the campaign on the behavior of fans is qualitatively similar under both the NYOP and PP models, we do not anticipate that our predictions will be significantly affected. However, the simpler derivations under NYOP allow us to obtain closed form solutions for the optimal level of the instruments and to more clearly

$$\frac{\partial r_{both}}{\partial v_o} = -r_{both} \left[\frac{1}{(3t-T_2)} + \frac{1}{(3t+T_2)} + \frac{1}{\left[3t+T_2 - \frac{3(1-\alpha)(v_H-v_L)}{4}\right]} \right], \quad (C.2)$$

$$\frac{\partial r_{both}}{\partial v_H} = r_{both} \left[\frac{1}{v_H} + \frac{(1-\alpha)}{2(3t-T_2)} + \frac{(1-\alpha)}{2(3t+T_2)} + \frac{5(1-\alpha)}{4\left[3t+T_2 - \frac{3(1-\alpha)(v_H-v_L)}{4}\right]} \right], \quad (C.3)$$

$$\frac{\partial r_{both}}{\partial v_L} = \frac{(1-\alpha)r_{both}}{2} \left[\frac{1}{(3t-T_2)} + \frac{1}{(3t+T_2)} - \frac{1}{2\left[3t+T_2 - \frac{3(1-\alpha)(v_H-v_L)}{4}\right]} \right], \text{ and} \quad (C.4)$$

$$\frac{\partial r_{both}}{\partial t} = 3r_{both} \left[\frac{1}{(3t-T_2)} - \frac{1}{(3t+T_2)} - \frac{1}{\left[3t+T_2 - \frac{3(1-\alpha)(v_H-v_L)}{4}\right]} \right], \quad (C.5)$$

Constraints on the parameters in the model ensure that (C.2) is negative and (C.3) is positive. We expand upon the observation made by differentiating r_{both} with respect to t as given in (C.5), or alternatively:

$$\frac{\partial r_{both}}{\partial t} = 3r_{both} \left[\frac{2T_2(3t+T_4) - 9t^2 + T_2^2}{(9t^2 - T_2^2)(3t+T_4)} \right]. \quad (C.6)$$

Constraints on the parameters in the model ensure that the denominator in (C.6) is positive.

Therefore $\partial r_{both}/\partial t < 0$ when:

$$2T_2(3t + T_4) - 9t^2 + T_2^2 < 0.$$

Using the quadratic formula to find values of t such that $2T_2(3t + T_4) - 9t^2 + T_2^2 = 0$, we get $t = \frac{1}{3} \pm \frac{\sqrt{72T_2(T_2+T_3)}}{18}$. Because the above quadratic function is concave in t , and the vertical intercept is $2T_2T_4 + T_2^2$ (which is always positive), then $2T_2(3t + T_4) - 9t^2 + T_2^2 < 0$ only when $t > \frac{1}{3} + \frac{\sqrt{72T_2(T_2+T_3)}}{18}$. Thus, t must be sufficiently large to guarantee $\partial r_{both}/\partial t < 0$.

Because $T_2 > T_3$ and $v_H > v_L$, the numerator in (C.13) is always less than the numerator in (C.14) and the first term in the denominator in (C.14) is always greater than the first term in the denominator in (C.13). Therefore, to show that $r_{both} < r_{high}$ we need only to show that the second term in the denominator of (C.13) is also greater than the second term in the denominator of (C.14), or $3t + T_2 - \frac{3(1-\alpha)(v_H-v_L)}{4} > 3t + T_3$. We rewrite this inequality as

$$v_o > \frac{3}{2}(1-\alpha)v_H - \frac{v_L}{2}(3-4\alpha). \quad (\text{C.15})$$

The inequality in (C.15) is true for $\alpha > \frac{1}{3}$. It is also true for $v_o > \frac{3}{2}(v_H - v_L)$. Thus, $\alpha > \frac{1}{3}$ or $v_o > \frac{3}{2}(v_H - v_L)$ is sufficient to ensure $r_{both} < r_{high}$.

We can find total demand for the streaming platform in each environment. Using (4.4) and (4.5), the streamer's expected profit when she hosts music from both types of artists is:

$$E\pi_p^{both} = (1 - r_{both}) \left[\frac{3t+v_o}{3} - \frac{(1-\alpha)(v_H+v_L)}{6} \right] \left[\frac{3t+v_o}{6t} - \frac{(1-\alpha)(v_H+v_L)}{12t} \right].$$

$$E\pi_p^{high} = (1 - r_{high}) \left[\frac{3t+\frac{v_o}{2}}{3} - \frac{[(1-\alpha)v_H+v_L]}{6} \right] \left[\frac{3t+\frac{v_o}{2}}{6t} - \frac{[(1-\alpha)v_H+v_L]}{12t} \right].$$

Because $\frac{3t+v_o}{3} - \frac{(1-\alpha)(v_H+v_L)}{6} > \frac{3t+\frac{v_o}{2}}{3} - \frac{[(1-\alpha)v_H+v_L]}{6}$ and $\frac{3t+v_o}{6t} - \frac{(1-\alpha)(v_H+v_L)}{12t} > \frac{3t+\frac{v_o}{2}}{6t} - \frac{[(1-\alpha)v_H+v_L]}{12t}$, $E\pi_p^{both} > E\pi_p^{high}$ whenever $r_{both} < r_{high}$. Thus the streamer always prefers to host content from both types of artists when $r_{both} < r_{high}$.

Proof of Proposition 4.2

When a fan's valuation for high type artists is indistinguishable from a fan's valuation for low type artists, $v_H = v_L$. Using this equality, from (4.14) and (4.10):

$$r_{low} = \frac{3\alpha v_L \delta \left[3t - \frac{v_o}{2} + \frac{v_L + (1-\alpha)v_L}{2} \right]}{\left[3t + \frac{v_o}{2} - \frac{(v_L + (1-\alpha)v_L)}{2} \right] \left[3t + \frac{v_o}{2} - \left(1 - \frac{\alpha}{2}\right)v_L \right]}, \text{ and} \quad (\text{C.16})$$

- Cattani, K., Gilland, W., Heese, S., & Swaminathan, J. (2006). Boiling Frogs: Pricing Strategies for a Manufacturer Adding a Direct Channel that Competes with the Traditional Channel. *Production and Operations Management*, 15(1), 40-56.
- Caulfield, K. (2014). Taylor Swift's '1989' Beats 'Frozen' as Top Selling Album of 2014. *Billboard*. <http://www.billboard.com/articles/columns/chart-beat/6422411/taylor-swift-1989-beats-frozen-top-selling-album-2014>. Accessed 4 April 2016.
- (2016). Adele's '25' Rules as Nielsen Music's Top Album of 2015 in U.S. *Billboard*. <http://www.billboard.com/articles/columns/chart-beat/6835248/adele-25-top-album-of-2015-in-us>. Accessed 4 April 2016.
- Coughlan, A. (1985). Competition and Cooperation in Marketing Channel Choice: Theory and Application. *Marketing Science*, 4(2), 110-129.
- Crupnick, R. (2015). One Third of US Consumers Still Buy Music Downloads, Even as Streaming Gains Momentum. MusicWatch, Inc. <http://www.musicwatchinc.com/blog/one-third-of-us-consumers-still-buy-music-downloads-even-as-streaming-gains-momentum/>. Accessed 2 April 2016.
- Dana, J. D. (1998). Advance Purchase Discounts and Price Discrimination in Competitive Markets. *Journal of Political Economy*, 106(2), 395-422.
- Dana Jr., J. D., & Spier, K. E. (2001). Revenue Sharing and Vertical Control in the Video Rental Industry. *The Journal of Industrial Economics*, 49(3), 223-245.
- Dholakia, U. M. (2011). What Makes Groupon Promotions Effective for Businesses? Working Paper. Rice University, Houston TX.
- Dickey, J. (2014). Taylor Swift on 1989, Spotify, Her Next Tour and Female Role Models. *Time*. <http://time.com/3578249/taylor-swift-interview/>. Accessed 1 April 2016.
- Dredge, S. (2013). Thom Yorke Calls Spotify 'the Last Desperate Fart of a Dying Corpse'. *The Guardian*. <http://www.theguardian.com/technology/2013/oct/07/spotify-thom-yorke-dying-corpse>. Accessed 2 April 2016.
- Edelman, B., Jaffe, S., & Kominers, S. D. (2016). To Groupon or not to Groupon: The Profitability of Deep Discounts. *Marketing Letters*, 27(1), 39-53.
- England, L. (2015). Here's How Much Apple Music is Going to Pay Artists. *Business Insider*. <http://www.businessinsider.com/apple-is-going-to-start-paying-artists-per-stream-after-launch-2015-6?r=UK&IR=T>. Accessed 2 April 2016.
- Falconer, E. (2015). Blue Mountain State: The Movie. *Kickstarter*. <https://www.kickstarter.com/projects/773106364/blue-mountain-state-the-movie/description>. Accessed 11 October 2015.

- Fenn, D. (2010). Should Your Company Use Groupon to Increase Sales? CBS Money Watch. http://www.cbsnews.com/8301-505143_162-41841181/should-your-company-use-groupon-to-increase-sales/ . Accessed 23 February 2016.
- Friedlander, J. P. (2016). News and Notes on 2015 RIAA Shipment and Revenue Statistics. RIAA. <http://www.riaa.com/wp-content/uploads/2016/03/RIAA-2015-Year-End-shipments-memo.pdf>. Accessed 1 April 2016.
- Gal-Or, E. (2013). Game and Information Theory in Modern Managerial Economics. In C.R. Thomas and W.F. Shughart II (Ed.), *The Oxford Handbook of Managerial Economics* (pp. 129-154). Oxford: Oxford University Press.
- Gal-Or, E., Geylani, T., & Yildirim, T. P. (2012). The Impact of Advertising on Media Bias. *Journal of Marketing Research*, 49(1), 92-99.
- Gabszewicz, J. J., Laussel, D., & Sonnac, N. (2002). Press Advertising and the Political Differentiation of Newspapers. *Journal of Public Economic Theory*, 4(3), 317-334.
- Garrahan, M., & Bradshaw, T. (2016). Apple's Music Streaming Subscribers Top 10M. Financial Times. <http://on.ft.com/1RDDfNA>. Accessed 1 April 2016.
- Geigner, T. (2013). Crowd Funding: Also a Method for Proving Marketability to Investors. techdirt. <https://www.techdirt.com/articles/20130220/09261722038/crowd-funding-also-method-proving-marketability-to-investors.shtml>. Accessed 11 October 2015.
- Gibson, H. (2013). Nigel Godrich: What He Really Thinks About Spotify. The Guardian. <http://www.theguardian.com/music/2013/aug/22/nigel-godrich-really-thinks-about-spotify>. Accessed 3 April 2016.
- Grepper, R. (2015). Coolest Cooler: 21st Century Cooler that's Actually Cooler. Kickstarter. <https://www.kickstarter.com/projects/ryangrepper/coolest-cooler-21st-century-cooler-thats-actually>. Accessed 11 October 2015.
- Groupon (2016a). Briosio Fresh Pasta's Case Study. Groupon. <https://www.grouponworks.com/case-studies/making-money-with-groupon/briosio-fresh-pasta>. Accessed 17 December 2016.
- Groupon (2016b). Pure Barre's Case Study. Groupon. <https://www.grouponworks.com/case-studies/pure-barre>. Accessed 17 December 2016.
- Groupon, Inc. (2016). Q4 2015 Earnings Conference Call. NASDAQ. <http://www.nasdaq.com/aspx/call-transcript.aspx?StoryId=3890266&Title=groupon-s-grpn-ceo-rich-williams-on-q4-2015-results-earnings-call-transcript>. Accessed 17 February 2016.

- Groupon Works (2016). Effective Marketing, Measurable Results. Groupon Works. <https://www.grouponworks.com/benefits-of-advertising-with-groupon>. Accessed 7 April 2016.
- Grow, K. (2014). Bono Defends Spotify: 'Let's Experiment. Let's See What Works'. Rolling Stone. <http://www.rollingstone.com/music/news/bono-defends-spotify-lets-experiment-lets-see-what-works-20141107>. Accessed 1 April 2016.
- Hagiu, A. (2009). Two-Sided Platforms: Product Variety and Pricing Structures. *Journal of Economics and Management Strategy*, 18(4), 1011-1043.
- Hu, M., Li, X., & Shi, M. (2015). Product and Pricing Decisions in Crowdfunding. *Marketing Science*, 34(3), 331-345.
- Katz, M. L. (1984). Firm-Specific Differentiation and Competition among Multiproduct Firms. *Journal of Business*, 57(1) Part 2: Pricing Strategy, S149-S166.
- Kharif, O., & Katz, L. (2015). Groupon at Crossroads After Weak Forecast, Management Shakeup. Bloomberg. <http://www.bloomberg.com/news/articles/2015-11-03/groupon-names-williams-ceo-lefkofsky-resumes-as-chairman>. Accessed 12 November 2015.
- Kickstarter (2016). Stats. Kickstarter. <https://www.kickstarter.com/help/stats>. Accessed 8 April 2016.
- Kumar, V., & Rajan, B. (2012). Social Coupons as a Marketing Strategy: A Multifaceted Perspective. *Journal of the Academy of Marketing Science*, 40(1), 120-136.
- La Monica, P. R. (2015). Amazon Killing Off its Local Daily Deals Site. CNN. <http://money.cnn.com/2015/11/02/technology/amazon-local-daily-deals-groupon/>. Accessed 12 November 2015.
- Lunden, I. (2015). LivingSocial Lays Off 200, 20% of Staff, as it Shifts from Deals to Experiences. TechCrunch. <http://techcrunch.com/2015/10/14/livingsocial-lays-off-200-20-of-staff-as-it-shifts-from-deals-to-experiences/>. Accessed 17 February 2016.
- Menezes, F. M., Monteiro, P. K., & Temimi, A. (2001). Private Provision of Discrete Public Goods with Incomplete Information. *Journal of Mathematical Economics*, 35(4), 493-514.
- Milian, M. (2012). Rejected by VCs, Pebble Watch Raises \$3.8M on Kickstarter. Bloomberg Business. <http://go.bloomberg.com/tech-deals/2012-04-17-rejected-by-vc- Pebble-watch-raises-3-8m-on-kickstarter>. Accessed 11 October 2015.
- Mollick, E. (2014). The Dynamics of Crowdfunding: An Exploratory Study. *Journal of Business Venturing*, 29(1), 1-16.

- Mussa, M., & Rosen, S. (1978). Monopoly and Product Quality. *Journal of Economic Theory*, 18(2), 301-317.
- Nalebluff, B. (2000). Competing Against Bundles. In P. Hammond and G. Myles (Ed.), *Incentives, Organization, and Public Economics* (pp. 323-335). Oxford: Oxford University Press.
- Narasimhan, C. (1984). A Price Discrimination Theory of Coupons. *Marketing Science*, 3(2), 128-147.
- Nocke, V., Peitz, M., & Rosar, F. (2011). Advance-Purchase Discounts as a Price Discrimination Device. *Journal of Economic Theory*, 146(1), 141-162.
- Palfrey, T. R., & Rosenthal, H. (1984). Participation and Provision of Discrete Public Goods: A Strategic Analysis. *Journal of Public Economics*, 24 (2), 171-195.
- (1988). Private Incentives in Social Dilemmas: The Effects of Incomplete Information and Altruism. *Journal of Public Economics*, 35(3), 309-332.
- Parker, G. G., Van Alstyne, M. W., & Choudary, S. P. (2016). *Platform Revolution*. New York: W. W. Norton & Company.
- Pepitone, J. (2012). Why 84% of Kickstarter's Top Projects Shipped Late. CNNMoney. <http://money.cnn.com/2012/12/18/technology/innovation/kickstarter-ship-delay/index.html>. Accessed 11 October 2015.
- PonoMusic Team (2015). Pono Music – Where Your Soul Rediscovered Music. Kickstarter. <https://www.kickstarter.com/projects/1003614822/ponomusic-where-your-soul-rediscovered-music/description>. Accessed 11 October 2015.
- Rochet, J. C., & Tirole, J. (2003). Platform Competition in Two-Sided Markets. *Journal of the European Economic Association*, 4(1), 990-1029.
- Shapiro, C. (1983). Premiums for High Quality Products as Returns to Reputations. *Quarterly Journal of Economics*, 98(4), 659-680.
- Schmidt-Mohr, U., & Villas-Boas, J. M. (2008). Competitive Product Lines with Quality Constraints. *Quantitative Marketing and Economics*, 6(1), 1-16.
- Shivendu, S., & Zhang, Z. (2012). Deal or No Deal? : Advertising and Sampling Effects on Two-sided Daily Deal Platforms. Working Paper. University of California Irvine, Irvine CA.
- Spotify (2016a). About – What is Spotify? Spotify. <https://press.spotify.com/us/about/>. Accessed 1 April 2016.

- Spotify (2016b). How is Spotify Contributing to the Music Business? Spotify.
<https://www.spotifyartists.com/spotify-explained/>. Accessed 1 April 2016.
- Subramanian, U., & Rao, R. (2016). Leveraging Experienced Consumers to Attract New Consumers: An Equilibrium Analysis of Displaying Deal Sales to Sell Daily Deals. Forthcoming in *Management Science*.
- Venkatesh, R., & Mahajan, V. (2009). Design and Pricing of Product Bundles: A Review of Normative Guidelines and Practical Approaches. In V. R. Rao (Ed.), *Handbook of Pricing Research in Marketing* (pp. 232-257). Northampton, MA: Edward Elgar Publishing Company.
- Ward, C., & Ramachandran, V. (2010). Crowdfunding the Next Hit: Microfunding Online Experience Goods. Paper presented at the Workshop on Computational Social Science and the Wisdom of Crowds, Conference on Neural Information Processing Systems (December 6-11).
- Welch, C. (2015). Apple Hasn't Convinced The Beatles to Let You Stream Their Music. The Verge. <http://www.theverge.com/2015/6/8/8745963/the-beatles-apple-music>. Accessed 2 April 2016.
- Wlömert, N., & Papies, D. (2016). On-demand Streaming Services and Music Industry Revenues – Insights from Spotify's Market Entry. Forthcoming in *International Journal of Research in Marketing*.