

ESSAYS ON CONSUMER BEHAVIOR AND PRICING



Ammara Mahmood

Green Templeton College

*A thesis submitted in requirement for the degree of
Doctor of Philosophy*

Hilary 2014

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This dissertation is a collection of five essays examining different aspects of consumer and firm behavior in dynamic markets.

The first essay combines clickstreams of users at a major news website with Facebook activity data, to study if social networks complement or compete for online browsing time. This is the first empirical study to show that Facebook activity increases time spent on news sites. Online news consumption is a shared experience, as the activity of social network friends strongly influences the behavior of other network members. We also find that visitors' own browsing patterns are important predictors of online content consumption.

The second essay examines consumer attitudes to risk and uncertainty vis-à-vis their purchase and search decisions for air tickets online. Using a two-stage model of purchase incidence and carrier choice, we find that browsing experience, search costs and product characteristics are important predictors of purchase incidence. Implications for website managers are also discussed.

The third essay provides insights on the impact of customer heterogeneity and preference stochasticity on behavior based price discrimination. While customer heterogeneity intensifies competition, resulting in greater price discrimination, preference stochasticity reduces the incidence of price discrimination. Overall, the effect of preference stochasticity is more salient.

The fourth essay presents models of strategic interaction to analyze the impact of dominance and concentration on pricing strategies. We show that lack of market dominance is a sufficient condition for discounts to existing customers. We further test our predictions via an experiment with pricing professionals. The behavior of professionals confirms that price discrimination increases with market dominance and concentration; however, lack of dominance is not a sufficient condition for loyalty discounts. We contend that increasing competition is a more effective means of improving consumer welfare compared to regulating dominant firms.

The fifth essay considers the role of identity and customer type recognition in influencing pricing behavior in dynamic markets with symmetric and asymmetric players. When customer identity is detectable firms charge higher prices to repeat customers while new customers are offered lower prices. However, pricing behavior changes when information on customer type is available and this behavior varies with market structure. Age, education and experience of managers are also found to significantly influence pricing behavior.

To my parents.

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ABSTRACT

This dissertation is a collection of five essays examining different aspects of consumer and firm behavior in dynamic markets.

The first essay combines clickstreams of users at a major news website with Facebook activity data, to study if social networks complement or compete for online browsing time. This is the first empirical study to show that Facebook activity increases time spent on news sites. Online news consumption is a shared experience, as the activity of social network friends strongly influences the behavior of other network members. We also find that visitors' own browsing patterns are important predictors of online content consumption.

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The fourth essay presents models of strategic interaction to analyze the impact of dominance and concentration on pricing strategies. We show that lack of market dominance is a sufficient condition for discounts to existing customers. We further test our predictions via an experiment with pricing professionals. The behavior of professionals confirms that price discrimination increases with market dominance and concentration; however, lack of dominance is not a sufficient condition for loyalty discounts. We contend that increasing competition is a more effective means of improving consumer welfare compared to regulating dominant firms.

The fifth essay considers the role of identity and customer type recognition in influencing pricing behavior in dynamic markets with symmetric and asymmetric players. When customer identity is detectable firms charge higher prices to repeat customers while new customers are offered lower prices. However, pricing behavior changes when information on customer type is available and this behavior varies with market structure. Age, education and experience of managers are also found to significantly influence pricing behavior.

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1 Introduction

Technological advances are influencing consumer and firm behavior across markets. Consumers are today spending considerable time online, engaging with social networks, consuming and sharing content and making purchases. Due to the low costs involved in gathering readily available information and the influence of social networks, consumer behavior in these online markets differs from traditional channels. While information on prices and product attributes is becoming widely available to customers, marketing firms and data intermediaries are simultaneously recording and analyzing information on consumer purchase and search patterns. Firms are now investing significant resources in customer recognition technologies and the widespread adoption of customer recognition has created new opportunities for customer targeting, such as price discrimination based on purchase timing (e.g. via yield management pricing algorithms) and past purchase history (e.g. sign up discounts for new customers). It is estimated that around 91% of marketers of successful brands base marketing strategies on customer behavior data (Roger and Sexton, 2012).

In today's dynamic markets the relation between firms and consumers is becoming increasingly complex, on the one hand, the consumer is influencing firm behavior, and on the other hand, informed businesses are shaping consumer behavior. Because firms can now quickly respond to market signals, there is a constant need for

businesses to better understand consumer behavior in order to appropriately meet customer needs. This dissertation aims to shed light on some of these current issues by presenting an empirical analysis of consumer behavior in online markets and experimentally examining the pricing behavior in markets with customer recognition. The results presented in this study have relevance for managers as well as policy makers across a variety of industries, such as online content, travel sales, retail, utilities and other subscription markets.

The main contribution of this dissertation is presented in Chapters 2, 3, 4, 5 and 6. Each chapter is a self-contained 'research paper' with an introduction, overview of relevant literature, methodology and conclusion. The first two papers, in Chapters 2 and 3 examine how social networks and price uncertainty influence consumer behavior in dynamic online channels. Chapter 2 explores how the activity at social network sites impacts the actions of users at third-party content websites. Because social network members primarily connect to share content like videos, news, music, images and information, one of the areas that has been most impacted by the rise of these networks is the search and consumption of online content. Online content represents, directly and indirectly, a significant portion of economic activity online, and supports the online advertising market worth billions of dollars. However, despite its economic significance, content consumption, has not received much attention in the academic literature. I use data from a panel of Facebook users registered with a major news website to jointly model website visitation (traffic) and the number of pages viewed over time (readership) at the news website (a third-party website independent of Facebook). I test whether users' actions while on Facebook, and their friends' actions at the news website can help predict traffic and readership.

This study could not have come at a more appropriate time, as the influence of social networks continues to grow, news sites can increase visits by increasing visibility in users social networks. In contrast to the common perception that social networks compete with content sites for browsing time, I show that time spent on online social networking sites actually increases the likelihood of visiting content websites. This is one of the first studies to highlight the complementary role of social media and the need for increasing visibility in user's social networks. Furthermore, it appears that online news consumption is a shared experience; site visitors seem to be following links from their social network peers and visit the site more often if their friends have also visited the site. However, visitors that follow links from friends seem to be engaged in directed search and view fewer articles compared to visitors in an explorative search mode who visit the home page in search of news. I also find that visitor's own browsing patterns are important predictors of online content consumption.

This study has important implications for managers of content sites. Given the importance of ad impressions, managers can increase traffic flow to content sites by increasing presence on Facebook and other social networking sites. Since social network members follow the activity of their friends, content providers could make the activity of friends more visible to network members. The proliferation of Facebook pages for newspapers in recent years appears to be a step in the right direction.

Chapter 3 examines how price uncertainty affects consumer search and purchase behavior for airline tickets at E-commerce websites. This is an ideal context to study the impact of extreme price uncertainty emanating from complex yield management pricing strategies on consumer search behavior. The low effort and cost of online search, enables customers to easily obtain updated information on prices and availability,

making the Internet increasingly important in the airline industry. I model the decision to continue searching versus buying using a dynamic two-stage model of purchase incidence and carrier choice. The model is calibrated on a unique data set of online consumers visiting one of the largest online European travel agents, and includes extensive details regarding consumers' pre-purchase behavior at the website.

I find that the current and the expected value of the available travel alternatives, browsing experience, and search effort are all important predictors of consumer purchase behavior. These findings concur with models of inter-temporal choice as consumer expectations about the future are informed by past experiences. Based on the findings of this study, purchase conversion rates at online travel sites could be improved if websites take measures to increase involvement when customers are actively searching. For instance, travel sites could display special offers or recommend flights to customers who frequently change their travel dates as targeting active customers could be more profitable than sending weekly email alerts to all customers. From a website managers perspective even small increments in purchase conversion rates can result in considerable growth in sales revenues.

The second half of this dissertation empirically verifies the impact of customer recognition technologies on pricing behavior. There is limited consensus in the literature on behavior based price discrimination (BBPD) regarding the outcome of customer recognition on pricing strategies in competitive markets. While experiments are commonly used in the industrial organization literature to test pricing behavior, they are also gaining popularity in the marketing literature. However, experimental validation of conflicting theories of BBPD has been lacking. Since detailed data on pricing is not always accessible, controlled experiments are a powerful means of testing

the validity of causal factors in isolation, revealing the behavioral motivations for agent's decisions, as well as providing internal validity. Through a series of studies presented in Chapters 4, 5 and 6, I show that customer characteristics, market structure and availability of information influence pricing strategies, however, the direction of the effect does not always confirm theoretical models. The main contribution of these chapters is to empirically identify why pricing behavior varies across markets.

Chapter 4 explores whether differences in pricing strategies can be attributed to customer characteristics. Building on the theoretical advances in the literature on BBPD, this chapter focuses on the interaction between changing consumer preferences (stochasticity) and customer type (value heterogeneity). The primary motivation of this study is to analyze whether, preference stochasticity and customer heterogeneity provide sufficient incentives for sellers to reward customer loyalty. I develop a novel experimental design to model stochastic brand preferences in a two period heterogeneous market, with observable purchase histories. Experimental findings shed light on pricing practices across industries, when preferences are stable and customers are homogeneous (e.g., utilities), new customers are offered lower prices and excessive competition between firms results in lower prices. When preferences change over time (for example in the airline industry and motor insurance), similar prices are offered to existing and new customers. However, given preference stochasticity, customer heterogeneity is not sufficient to ensure profitable price discrimination, consequently, there is no difference in the prices offered to existing and rival's customers. These results dispel the findings of several existing studies on BBPD (e.g., Shin and Sudhir, 2010; Chen and Percy, 2010), highlighting the need to develop richer models incorporating customer and firm characteristics.

Furthermore, by using real buyers in the study, I find evidence that customers exhibit loyalty in their purchase patterns. Buyers also appear to have a strong aversion for add on charges and appear to focus more on the base price. This finding helps explain the popularity of obfuscation strategies in online channels and the rising trend of showing prices inclusive of all charges.

Chapter 5 examines whether dominance and market power could provide a reasonable explanation for loyalty discounts. The chapter first develops models of price discrimination with symmetric duopolies, asymmetric duopolies and multiple firms. The analytical model predicts that small firms in asymmetric markets are most likely to implement a customer retention strategy. Secondly, a controlled lab experiment is conducted to test the validity of the analytical model. To gain real world insights into the impact of market structure on price discrimination, pricing professionals are recruited as experimental subjects.

In contrast, to conventional wisdom, I find that compared to dominant firms in asymmetric markets, symmetric duopolies are more aggressive while firms competing against multiple competitors are the least aggressive with regards to price discrimination. From a policy and regulatory perspective, it appears that customer welfare is better served under asymmetric markets compared to symmetric markets. Based on the experimental evidence, it is also prudent to allow free entry into markets rather than regulating the dominant firm.

Chapter 6 is an extension of the study presented in Chapter 5, and examines the role of *identity* and customer *type* recognition in influencing pricing behavior in dynamic markets with symmetric and asymmetric players. Using a subject pool of marketing and pricing professionals, I show that when customer identity is

distinguishable, firms charge higher prices to repeat customers while new customers are offered lower prices. However, pricing behavior changes when information on customer type is available, and this behavior varies with market structure. Dominant firms in asymmetric markets adopt a more aggressive pricing strategy while symmetric players are mostly unaffected by additional information.

With greater information on consumer willingness to pay, some customers are priced out of symmetric markets. However, in asymmetric markets there is greater market coverage as small firms safeguard existing customers from being poached away by the dominant rival. This suggests that customer data protection and privacy laws are necessary to ensure customer welfare is not compromised as firms invest to improve targeting capabilities.

I also find that age, education and experience of managers influence their pricing behavior. This Chapter highlights the need to develop richer models of managerial prices to account for individual level heterogeneity and contextual factors in pricing decisions.

Finally, a brief outline of the key findings and implications for businesses, regulators and policy makers are presented in the concluding chapter. The predictions although wide-ranging in nature, contribute significantly to the current understanding of the role of social networks in defining consumption patterns, the impact of price uncertainty on consumer search behavior and the determinants of behavior based price discrimination.

2 Friends or Foes: How Does Social Network Activity Affect News Consumption?

2.1 Introduction¹

Social networks like Facebook and Twitter are today an integral part of people's lives. The economic significance of social networks is now becoming clear for many online and offline businesses. Because social network members primarily connect to share videos, news, music, images, and other private or public information, one of the areas that has been most impacted by the rise of these networks is the search and consumption of online content. Online content can be informational or aimed at pure entertainment though it often serves both purposes. Content represents, directly and indirectly, a significant portion of economic activity online, and supports the flourishing online advertising market with global advertising spend in excess of \$100 billion in (E-Marketer, 2012).

Among companies whose business models revolve around content provision, news websites are facing some of the most significant challenges. Falling online advertising prices, difficulty to charge for content (after years of giving it away for free), reduced readership of their offline arms, competition from a variety of information (and entertainment) sources, a shift in consumers towards more informal

¹Based on joint work with Professor Catarina Sismeiro.

sources of information, are all factors that play a role in news websites' demise. Because anyone, anywhere, can become a content producer and share it online via social platforms, including specialized ones like Pinterest for images and YouTube for videos, there is a growing debate on the role social networks are playing in the troubles of news websites.

Some authors suggest that the main impact of social media is the business stealing effect due to competition for digital users' time. Li and Bernoff (2011) report that the widespread use of social media has been “sucking up online time” from other media and online content sites. Statistics seem to confirm this contention. In December 2011 Facebook users spent, on average, 423 minutes on Facebook and only 12 minutes on news websites (Mitchell et al., 2012a). Other survey studies find that social media websites now account for a quarter of time spent online (e.g., Nielsen, 2011) and drive little traffic to news websites (approximately a third of online browsers log-in directly to news organizations and only 9% of online news consumers follow recommendations from Facebook and other social media sites (Mitchell et al., 2012a). Though social networks could serve as a platform that directs traffic towards news websites, through user recommendations and content sharing, the amount of traffic originating from social media seems insignificant.

Despite the relevance of this evidence, most is either survey-based or simply anecdotal. To the best of our knowledge, no empirical work using actual online browsing activity attempts to determine the impact of a user's social network activity on that same user's online content consumption outside the social network. In addition, little is known on how the activities of friends in social network impact users' online content consumption. For example, if my Facebook friends recommend a news article,

will I be more likely to visit the news website or is the headline-like information enough? If I do visit the news website, will that recommendation impact the number of articles I read from that content provider? Will my behavior at the news site change?

These very important questions need to be addressed, especially considering that today many news websites survive on their advertising revenue. 81.5% of news websites' revenue is derived from advertising and the remaining from subscriptions (Clemons et al., 2002). Ad revenue depends on the number of available impressions, which in turn depend on website traffic and page views. Interestingly, today many news websites are pushing their readers to register using their Facebook accounts, and to allow users the easy embedding of news article recommendations and news feeds on their Facebook pages. On one hand, such registration gives news websites access to a rich set of personal information (what users post and reveal on their personal pages) that could help the selling of premium, targeted ads. On the other hand, news posted on Facebook (or seen through Facebook news feeds) can either direct people to the news website or compete with an actual visit (for instance stories shared via applications like the Social Reader allow users to read and share stories without leaving Facebook). Visits to the news website are what produce the potential ad impressions sold to advertisers. Thus, the impact of social network sites on online content consumption is not yet clear.

This chapter aims to bridge this knowledge gap. Using actual clickstreams of users on a major news website, together with data on users' social network activities and the actions of their friends online, we study if social networks complement or compete with online content businesses. This is a research question that has not been formally explored using clickstream data. We use data from a panel of Facebook users registered

with a major news website to jointly model website visitation (traffic) and the number of pages viewed over time (readership) at the news website (a third-party website independent of Facebook). We then test whether users' actions while on Facebook, and their friends' actions at the news website, can help predict traffic and readership. In our model, we account for individual heterogeneity and for possible endogeneity, while simultaneously controlling for potential confounding effects including daily unobserved factors that could influence a user's decision and that of his friends.

Our results highlight that news consumption and Facebook activity seem to be complementary. We find that users active on Facebook in a given day are also more likely to visit news websites to consume content. In addition, news consumption by Facebook friends directs traffic to the focal news website: visitors are four times more likely to visit the news website if their friends have also visited it on that day. Hence, our results suggest that online news consumption is a shared experience, as the activity of social network friends strongly influences the behavior of other network members. Our results also indicate that visitors following links from active friends seem to be engaged in directed search and, as a result, view fewer articles (conditional on site visit) compared to visitors in an explorative search mode who visit the home page in search of news as they are still deciding what to read. However, the net effect of friends' actions is positive: given the strong positive impact on the likelihood of site visit, the average page views unconditional on a visit taking place is positively influenced by friends' actions. These results are robust to possible endogeneity bias, temporal effects, and individual heterogeneity.

Our study also suggests that visitor's own browsing patterns are important predictors of online content consumption. We find that it is important for content sites

to remain salient in users' minds as the probability of site visits declines the longer the time visitors stay away from the website. In addition, users reading specialized content like Sports news, Local news, and TV related content are more likely to return to the site.

Our results have important implications for content websites. Contrary to previous research, we find that news websites might have something to gain from Facebook registrations, beyond the obvious advantage associated with the collection of personal information and the possibility of selling premium-targeted ads. Content consumption and Facebook activity seem complementary, and the gain in traffic due to Facebook recommendations more than compensates the more directed search (and fewer page views), that might follow such recommendations. As a result, incentivizing Facebook users to share articles online might lead to significant changes in metrics, and some might not appear positive (e.g., the average page views amongst users). It is then important to monitor both the likelihood of site visit and the number of pages viewed at the site when comparing users registered using their Facebook accounts and those who are not registered.

The chapter is structured as follows. Section 2.2 gives an overview of related literature, Section 2.3 describes the data used in the study, and Sections 2.4 and 2.5 outline the modeling approach and the performance of alternative specifications. Section 2.6 presents the main results and Section 2.7 concludes with our discussion of the results and model findings.

2.2 Literature Review

Since the 1960s researchers have tried to understand how individuals interact, how they influence each other in a social context, and how this interaction and influence might have an impact on purchase decisions and market performance of a variety of products. Though it is not always easy nor immediate to identify and measure peer influence and its effects (e.g., Aral and Walker, 2011; Nair et al., 2010), it is now well documented that consumers influence each other offline and online (Watts and Dodds, 2007). This influence is visible, for example, in product adoption and diffusion and even in the formation of product ratings, demonstrating the forms of peer influence (e.g., Godes and Silva, 2012; Moe and Trusov, 2010; Dellarocas et al., 2007; Chevalier and Mayzlin, 2006; Van den Bulte and Lilien, 2001).

The recent rise in importance of online communities and online social networks has generated an added interest into the area of social interaction and peer influence. Few recent studies in the marketing literature have used online social network data to identify the role of influential users (Trusov et al., 2010).

The impact of brand promotion Agarwal and Hosanagar (2012), and the phenomenon of social advertising (Tucker, 2012). Surprisingly, however, it is not yet clear how the actions of an individual in an online social network might influence product performance in the market, or whether such actions are predictive of such performance.

The lack of research in this area is probably due to the difficulty in obtaining data on what an individual does while visiting online social networks. Much of what individuals do and share is kept private and not visible to researchers outside the

individual's network. Many of the existing studies rely on self-reported data or on small-scale experiments conducted in an artificial environment. Rishika et al. (2013) is an exception. In their work, the authors study the effect of customers' participation in a firm's social media efforts on the intensity of the relationship between the firm and its customers. The authors find that a firm's social media efforts lead to an increase in the frequency of customer visits and customer profitability. However, the "social network" information in this study is limited to participation in the firm's social media efforts. The private actions of social network users are not used to explain the performance of the third party firm. In addition, content websites are not studied.

Content websites pose specific challenges because they directly compete with social media for the time of online users. Online content businesses and online social media have long faced a troubled relationship. According to the literature on "displacement effects," alternative media are substitutes for an individual's time. Because users are subject to time constraints, association with one medium reduces the consumption of the other medium (Kayany and Yelsma, 2000; Robinson et al., 1997; James et al., 1995). As a result, social network activity should have a business stealing effect. On the other hand, online social networks are also an ideal place for users to share information and links to other websites. Because of such sharing, online social network users could be more likely to visit and interact with third party content websites, and this "promotional" hypothesis would be in contrast to the displacement effects typically discussed in the literature. Stephen and Toubia (2010) find, for example, that in the context of social commerce shops that are more accessible from other shops in the network generally enjoy higher commission revenues. In their

context, the network added economic value (due to incoming links) despite potential competition. In the context of online content, such an effect could also be possible.

News websites and Facebook (one of the most popular social networks in the world) are a good example of how these competing effects are possible because they provide both information and entertainment to users. Understanding the impact that social networks might have on the visitation of news websites is essential. On one hand, the time consumers spend online browsing social networks has increased significantly in the past years and, on the other hand, news websites are highly dependent on the total number of page views to produce advertising revenues. To understand the possible effects, consider that if my Facebook friends post links to articles from news websites, I can decide that the headline-like information provided is enough and reduce my visits to the website (displacement effects). Or, instead, I can follow the link and this resulting visit can be in addition to the visits I would normally make to that website (promotional effect), or it can substitute visits I was planning to make anyway (in which case we would find no effects at all on visitation).

Previous studies on the link between social network and content consumption are mostly survey based (e.g., Li and Bernoff, 2011) and often provide contradicting results depending on the methodology used and data employed (e.g., De Waal and Schoenbach, 2010; Nguyen, 2010; Lee and Leung, 2008; Tewksbury, 2006; Dimmick et al., 2004). Studies have shown that public endorsement of content serves as a site navigation tool and affects readers' attitudes towards content (see Johnson et al., 2004; Hallahan, 1999), and recommendations for online news (including 'most read' and 'most emailed' stories or the inclusion in Google News) affect individual patterns of news consumption even at external websites (e.g., Jeon and Esfahani, 2013; Thorson,

2008). However, none of these studies analyze actual behavioral data from online social networks, irrespective of whether such behavior is private or public. Berger and Milkman (2012) are a notable exception who use unique data set of nearly 7,000 New York Times articles and examine what type of content is more likely to be shared by examining which articles make it to the newspaper's 'most emailed' list. The authors experimentally manipulate the emotions aroused by content to test the impact of arousal on the extent to which content is shared. While this article focuses on social transmission and type of content the study provides limited insight into the impact of an individual user's social activity and content consumption.

To the best of our knowledge, the relation between social network activity and content consumption through online content websites has not been empirically validated, nor studied using behavioral data tracked from actual websites. As a result, it is yet unclear how the activity of users while visiting social network websites can drive or prevent these same individuals or their friends from consuming content at third party websites. We bridge this gap in the literature by exploring how an individual's own social network activity and friend's news consumption affects visitation and consumption behavior at an external news site.

There are several points of departure between our work and existing work on social effects. Firstly, whereas extant studies consider product sales or the consumption of recreational content (i.e. online videos on YouTube), our study focuses on news websites that have both an informational and an entertainment role. Secondly, our focus is on Facebook networks formed due to exogenous factors and even the result of offline ties. This type of network differs from product-related networks or the networks at a site like YouTube studied in previous research.

In product-based networks users with similar interests follow each other or are assigned by the website as being part of a “network” of interests (these are endogenous networks). As noted by Trusov et al. (2010) there are numerous dissimilarities between exogenous and endogenous networks in terms of the number of people involved, the motives for connections, the nature of interactions, and the revenue-generating models. It is interesting to note that despite the weak ties in endogenous social networks, consumers respond to positioning of products and peer effects. This raises hitherto unanswered questions of how exogenous networks (e.g., of actual offline friends) influence the consumption of online content.

Finally, and most importantly, our motivation is not to develop an understanding of the structure of the network (i.e., determine influential users or study size and shape of the network). Instead, we care about the relation between the consumption of online news and: (1) the actions of a user while on Facebook, and (2) what that user’s Facebook friends do while visiting the news website.

2.3 Data

We obtained data from a leading European newspaper with an online and an offline presence (the second largest newspaper in its country of origin in terms of readership and circulation). We monitored the activity of a panel of online users who registered with the news website using their Facebook accounts (when registering, users also gave consent to the news website to view part of their actions while on Facebook). We collected the browsing activity of these users from March 1st, 2012 to March 31st, 2012 while visiting the news website. To ensure we only studied users with an interest in the focal website, and not those who visited the website by accident, we followed previous research on online browsing behavior and included in the panel users who

made at least two website visits during the month of March. Also following previous research, we define a page view as starting a new site visit whenever the user has been idle for more than thirty minutes at the site (see Bucklin and Sismeiro, 2003).

In addition, users needed to make their first visit to the site during the first seven days of March (we placed no restriction on when the second, or subsequent visits, should take place). We made these restrictions to guarantee we observed enough of the visitation stream of each user and to allow for the initialization of cumulative variables used during estimation (for a similar approach see the work of Sismeiro and Bucklin, 2004).

For each visitor we recorded the daily number of visits and pages viewed, whether the visitor viewed the home page or not, and the content categories viewed in each day.² We collected this information from the news website servers. We also had access to Facebook friendship information for those users in the panel. We know the number of friends, whether friends are registered with the news website and, if registered, their identification number. This information allowed us to monitor the activity of a visitor's friends while at the focal news site. Because the purpose of this study is to understand the influence of social network activity on content consumption, we included in the panel those individuals with at least one Facebook friend also registered with the news website. Finally, we were also able to obtain visitors' general profile data (e.g., age and gender), and part of their Facebook activity. Though we do not have access to a visitor's daily posts and comments, we know whether they have

² The news site divides content into distinct categories that correspond to specific areas of the website. We condense the category data for more meaningful analysis. For example, we grouped all sections related to local news for different cities and regions of the country into one category called Local News. Table 2.1 provides further information on the categories considered.

liked a Facebook page or website in a given day, and when they liked it (we call this a “page like”). Researchers seldom have access to such detailed information.

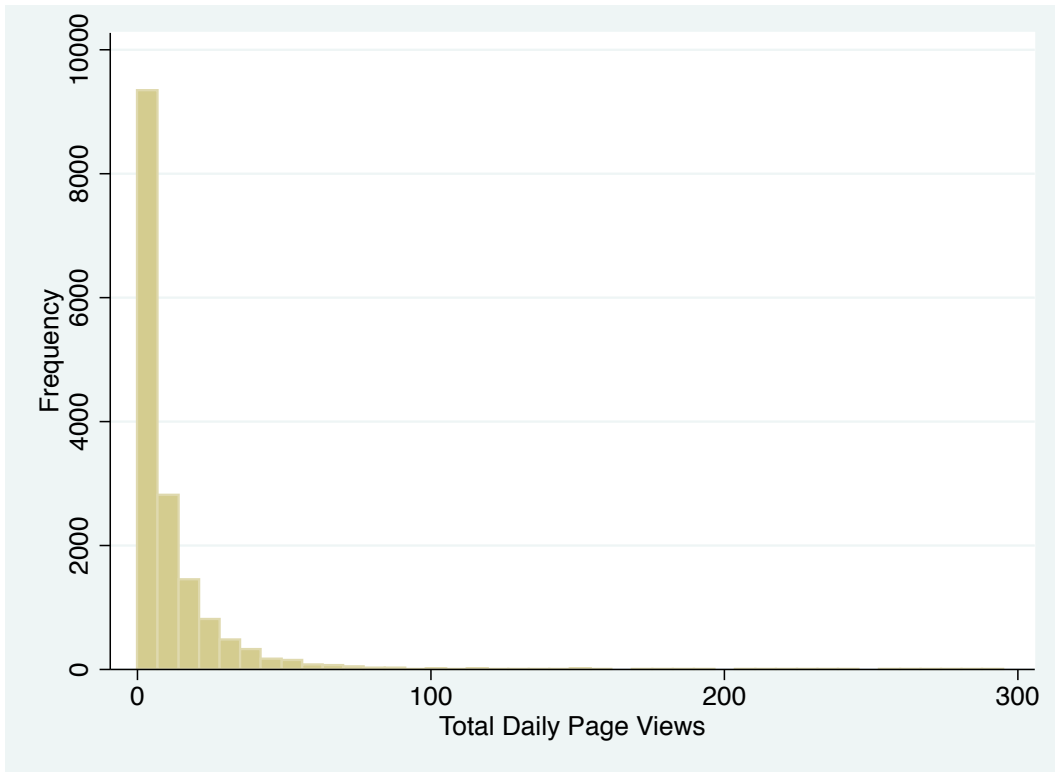
Our final dataset comprises the actions of 1,562 site visitors during the month of March 2012.³ The first week of data is used for initialization and we used the remaining three weeks of data (8th March till 31st March) for model estimation. There are 35,926 daily individual observations in our estimation sample that correspond to 15,864 website visits. Given the frequency of visits, we found that the one-week initialization period provided a reasonable time window to capture previous site visits and across-visit dynamics needed to initialize key variables. Table 2.1 summarizes the browsing behavior over the three-week estimation period.

On average visitors viewed five pages per day though the number of page views is highly skewed.⁴ Figure 2.1 presents the distribution of daily page views across Facebook users. As it can be seen from Figure 2.1 a significant number of visitors only request a single page in a day with some heavy users requesting several pages. It is very typical of visitors to news websites to request only one page (typically the Home Page of the website) as most visitors simply read news headlines without reading the full articles (shallow readers). We note that the more a user visits the site, and the higher the number of pages viewed, the more ad exposures (i.e., impressions) the website can sell to advertisers. Hence, site visits and page views are key determinants of news websites' revenue.

³ We also collected from the company's servers overall traffic data on users who registered with the website using their email accounts instead of their Facebook accounts. We use the daily traffic to the website by these registered users to control for temporal variability in news interest due, for example, to special events that might attract interest of users and their friends to the website. We present further details on this variable in the results section.

⁴ To ensure we do not inflate the total page views by automatic refreshes made by the browser, we remove the number of browser refreshes from total page views.

Figure 2:1: Distribution of Page views



Not all visitors visited the site on a daily basis: some visitors made multiple visits to the website during a single day whereas others took several days to return. On average visitors made about 0.6 visits to the news website in a given day, though there were instances in which visitors visited the site 11 times. Site visitors also varied in their inter-visit patterns. We computed the time since last visit as the time in days since an individual's last visit to the news site (Table 2.2 illustrates the distribution of inter-visit times across site visitors). On average visitors returned to the site about four days after their last visit. About 45% of all visits have an inter-visit time of one day, whereas 78% of all visits occur within five days, and only 3% of visits occur with a gap of more than 15 days.

The type of navigation and content consumed at the site also differs significantly across visitors. For example, whereas some site visitors visited the home page in search for content, other visitors directly visited news articles without going through the home page (these are likely visitors who were sent links or viewed the recommendations of articles while online). About 90% of the visits to the site included home page views, and on average visitors visited the home page twice during a site visit. This seems to confirm that home pages tend to be the preferred navigation tool for users to find content and the latest news (Mitchell et al., 2012b). We further breakdown the page views of visitors by category. The most popular categories were Local News, Sports and TV News; we grouped the remaining very fragmented categories into the category “Other News.”

Table 2.3 presents the details of the visitors' Facebook profiles. The majority of visitors in our sample are male (78%) with an average age of 39 years (this demographic profile maps well with the readership audience of the newspaper). Visitors to the site had on average 424 friends, with a minimum of five friends and a maximum of 1,000. On average visitors had a total of 178 “page likes” though not all visitors actively liked Facebook pages during the period under analysis.

During the study period, we also monitored whether visitors liked Facebook pages (visitors provided consent to collect this information during the registration phase) and, for each visitor included in our panel, we monitored whether their Facebook friends also visited the focal news website in any given day. We built a daily dummy of “page like” activity that takes the value of one if the visitor had been active liking pages on a given day, and takes the value zero otherwise. We also built a daily dummy for

“friend activity” that takes the value of one if friends had been active on the focal news website on a given day, and zero otherwise.

Table 2.3 also presents the details on visitors' Facebook actions during the last three weeks of March (our estimation sample period). Considering the summary statistics of these variables, we conclude that, during the last three weeks of March, visitors liked on average 0.13 new Facebook pages per day (there was an average gap of 2.39 days in between like activities) and that friends made an average of 0.15 visits per day to the focal news site.

2.4 Modeling Approach

Our objective is to understand the impact social networks might have on the consumption of online content. To do so we propose to use a random effects flexible Poisson Hurdle model to study simultaneously (1) the decision to visit the news website in a given day, and (2) the amount of daily content consumed once at the website (which in our case we measure by the number of pages viewed). These two dependent variables are of great managerial significance. Advertising is the main source of revenue for most content providers and ad-related revenue opportunities are directly proportional to the traffic and page views a site is able to generate. It is for this reason that content providers routinely monitor these key variables and wish to understand the factors driving site visits and page view decisions. However, to the best of our knowledge, ours is the first study to use a flexible joint modeling approach that incorporates individual level heterogeneity, social network activity, and browsing at the website to explain site visit and online content consumption.

2.4.1 Random Effects Poisson Hurdle Model

Because not all visitors are active every day at the news website, daily count of page views by individual visitors are typically characterized by excessive zeros (more zeros than Poisson models can accommodate) and over dispersion (mean different from its variance, though the Poisson model requires variance and mean to be the same). Excessive zeros and over dispersion in count data is common and if not correctly modeled can lead to incorrect inferences (Ridout et al., 1998). Poisson Hurdle and zero inflated models provide a flexible way to model such data (see Atkins et al., 2013; Hilbe, 2011; and Zeileis et al., 2007, for details on zero inflated and Poisson Hurdle models).

We propose a random effects Poisson Hurdle model to jointly study the visit and page view behavior of website visitors. The model has two components: the hurdle component to study the daily site visitation decision and the truncated count model to study the page view decisions once a visitor is at the site. We allow the two decisions (site visit and page views) to be correlated over time, and we jointly estimate the two components (these could be fit independently for computational flexibility, though we report the results from a joint estimation). We further account for individual differences via a random effects specification.

We define p_{it} as the probability that visitor i does not pass the hurdle on day t and does not visit the website, that is:

$$P(Y_{it} = 0) = p_{it}$$

where Y_{it} represents the daily count of page views for visitor i on day t (when a visitor does not visit the website in a given day, the variable takes the value zero). If visitor i

passes the hurdle (i.e., visits the website), we model the probability that visitor i views y_{it} (non-zero) pages on day t using a truncated Poisson process such that:

$$P(Y_{it} = y_{it}) = (1 - p_{it}) \cdot g(Y_{it} = y_{it}) \quad 2.1$$

where $g(\cdot)$ is a zero truncated Poisson process. We can rewrite eq. (2.1) as:

$$P(Y_{it} = y_{it}) = (1 - p_{it}) \cdot \frac{e^{-\mu_{it}} \mu_{it}^{y_{it}} / y_{it}!}{1 - e^{-\mu_{it}}}$$

Where μ_{it} is the individual and time-dependent parameter of the Poisson distribution. Following (Wang et al. 2009; Wang et al., 2007), we adopt a logit specification for the hurdle component of the model and we define the attractiveness of a visit to the site as follows (for $i = 1, \dots, 1562$ and $t = 1, \dots, 23$):

$$V_{it} = \alpha_i z_{it} + u_{it} \quad 2.2$$

where z_{it} is a vector of covariates for the hurdle model, α_i is the corresponding vector of coefficients, and the error term u_{it} has an i.i.d extreme value distribution. We make the site visitation decision a function of individual characteristics, individuals' activity while on social network sites, the browsing activity of network members, and exogenous temporal factors influencing news generation and interest.

Given a visit to the site, non zero-page views follow a truncated Poisson distribution such that:

$$\log \mu_{it} = \beta_i x_{it} + v_{it} \quad 2.3$$

where x_{it} is the vector of covariates, β_i the corresponding vector of coefficients, and v_{it} an error term potentially correlated with the error term of the logit model. We define the

number of page views as a function of user browsing behavior, individual specific social network activity, and the activity of network friends.

We capture correlation and temporal dependence among the within-site page view and the site visit decision by allowing for individual random effects. That is, we adopt a random effects specification for α_i and β_i . Given the panel structure of the data, such a generalized mixed model (GLMM) (Alfò and Maruotti 2010; Breslow and Clayton, 1993) can capture individual-specific variability and the possible non-independence in observations (e.g., high demand for content at one occasion by a site visitor could imply high content consumption on the next visit by that same visitor).

We allow for correlated error structures across the two model components (e.g., it is possible that a higher likelihood of site visit is associated with a higher number of page views once the visitor is at the site). It should be noted that in GLMM. We assume that the error terms u_{it} and v_{it} follow a joint distribution such that:

$$\begin{bmatrix} u_{it} \\ v_{it} \end{bmatrix} \sim N(0, A(\emptyset))$$

where the variance-covariance matrix $A(\emptyset)$ is defined as:

$$A(\emptyset) = \begin{pmatrix} \sigma_u^2 & \rho\sigma_u\sigma_v \\ \rho\sigma_u\sigma_v & \sigma_v^2 \end{pmatrix}$$

Note that σ_u^2 is the variance for the site visit decision (logit model) and for identification purposes is set to 1; σ_v^2 is the variance of the page view model (zero truncated Poisson), and ρ is the correlation term which is estimated in our model.

The log-likelihood can then be defined as:

$$LL = \sum_{i=1}^{1,562} \sum_{t=1}^{23} \log \int_{\nu} p_{it}^{d_{it}} [(1 - p_{it})g(Y_{it} = y_{it})]^{1-d_{it}} . d\theta \quad 2.4$$

where d_{it} takes the value 1 if visitor i does not visit the site on day t , and zero otherwise. Note that each individual's contribution to the likelihood is the product of the probability of crossing the hurdle and then selecting y_{it} pages to view (when a visit to the site occurs) times the probability of no visit taking place (when no site visit occurs in a day). Due to the inclusion of individual specific random effects we need to integrate over the distribution of random effects.

2.4.2 Estimation

We use a hierarchical Bayesian approach to estimate simultaneously the Poisson Hurdle model. We allow for visit and page view behavior of users to be correlated over time and estimate the covariance between the Poisson count model and the logit visit model. We sample β_i and α_i from a normal distribution with an inverse Wishart as priors for the parameters of the distribution (mean and variance-covariance) of the random coefficients. No closed form solutions exist for the integral over the random effects distribution, hence we use the Markov Chain Monte Carlo (MCMC) sampling to generate draws from the posterior densities of model parameters (for a discussion of Bayesian estimation of such Poisson Hurdle models using GLMM (see Draper, 2008). We use 50,000 iterations for burn-in and a further 100,000 iterations to determine the posterior distribution of parameters and we check the MCMC chains for convergence using standard methods in Bayesian estimation.

2.5 Model Comparison

To determine the final model specification we tested for the inclusion of variables sequentially and compared model performance in-sample using the deviance

information criterion (DIC).⁵ We tested the two parts of the model separately as well as simultaneously and kept only those variables that improved model fit. For all variables that might have a non-linear effect we also considered logarithmic and quadratic functional forms. We present as our final results the best fitting specification for each variable (e.g., the quadratic specification seemed to best describe the effect of “time since last visit” on visit behavior, and that was the specification adopted). We also tested variables not reported in the final results including total number of Facebook likes in March for each individual, average gap between Facebook like activity, total daily page views by Facebook friends, news categories viewed by Facebook friends, and lagged page views. These variables did not provide an improvement in fit (details available from the authors upon request). Care was also taken to capture consumer heterogeneity in browsing and visit behavior. The final results presented allow for individual random effects and for daily effects (via day-specific dummy variables). Variables like age, gender, and size of the social network, which could capture observed heterogeneity, did not improve fit and were not included in the final model.

To control for the effects of external factors that could influence both the actions of visitors and their friends, we add as a control variable the total number of page views by registered visitors (users who registered with the news website without using their Facebook accounts and hence are not included in our panel). This variable accounts for variations in popularity or interest for the website that is due to external factors (e.g., specific events that might increase the interest of certain news) that could lead to an increase in probability of site visitation or an increase in page requests by all users.

⁵ See appendix for detailed description of variables.

We estimate four alternative specifications of the Poisson Hurdle model: (1) Intercept only (base model), (2) No Facebook (includes individual browsing behavior variables but excludes Facebook-related variables), (3) Own Facebook (adds the activity of users on Facebook), and (4) Full Facebook (also adds the activity of Facebook friends while at the news site). Note that in all models, except for the Intercept Only model, we incorporate several control variables including the total number of page views by registered users (“Registered User Browsing Activity”) and daily dummy variables that flexibly account for temporal effects. All models allow for heterogeneity via a random effects specification.

Of all the models estimated the Full Facebook specification is the best fitting in-sample: the DIC of the Full Facebook model is 103,811.0 compared to 111,508.4 for the Own Facebook model, 111,507.6 for the No Facebook model, and 115,149.9 for the Intercept Only model. (In the next section we will present the final variables kept after testing for each model specification).

To compare the models in holdout we re-estimated the four alternative model specifications after removing the last two days of data from the original sample (these correspond to the two last days of March 2012). We then built a holdout sample that included the page views and visit information made by 1,559 site visitors during the days excluded from estimation.⁶ For each estimated model we predicted the number of page views and the likelihood of site visit. Table 2.4 presents a summary of the holdout model performance when predicting page views. Comparing the holdout model

⁶ We removed three visitors with no activity prior to the last two days in March. After their visits to the website during the first week of March (the initialization period) these three visitors returned to the website only on the two last days used for holdout. While we could predict page views and site visitation for these users using the population means of the parameters, though the overall performance results do not present any significant variation from the ones presented here which exclude these visitors.

performance one can see that the Full Facebook model (which includes own Facebook activity and the activities of Facebook friends) has the lowest mean squared error (MSE) and outperforms all other models. The proposed final model predicts an average 3.0 page views per visit, which closely corresponds to the actual average number of page views. Models without any Facebook information and models that do not consider friends' activities perform worse out-of-sample and tend to over-predict individual page views.

The proposed model is also able to mimic closely the actual distribution of page views. Figure 2.2 maps the distribution of the predicted page views onto the distribution of actual page views. As one can see, the actual and predicted values are very close to each other.

Figure 2:2: Distribution of Predicted Page Views

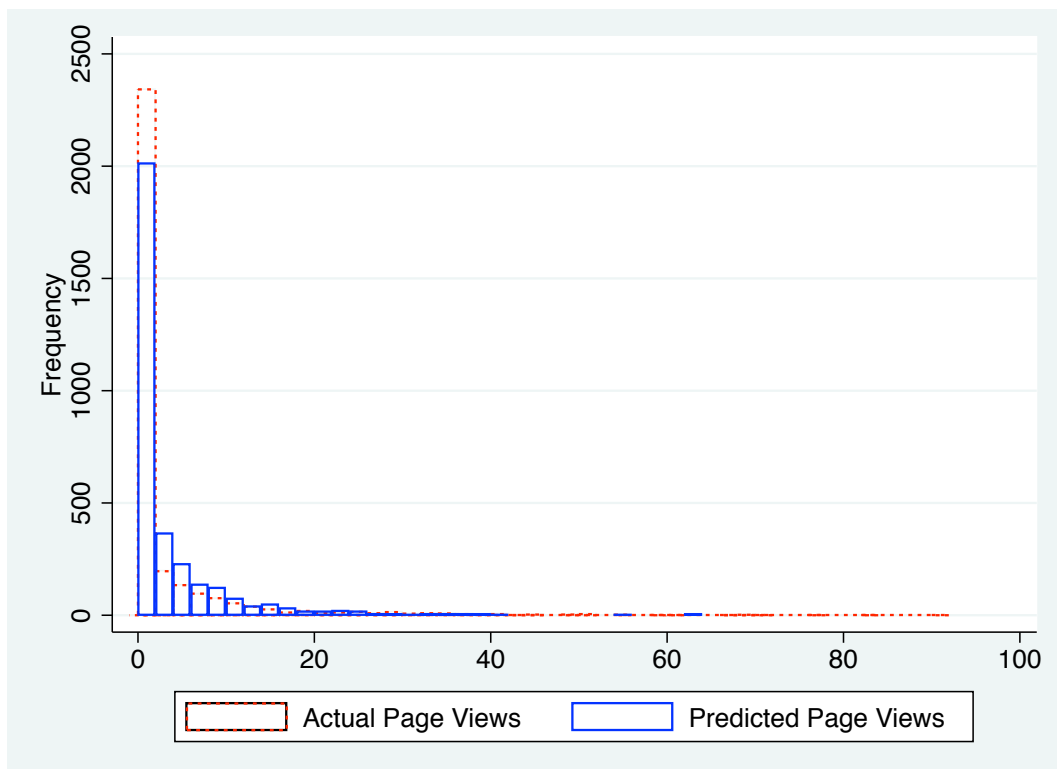
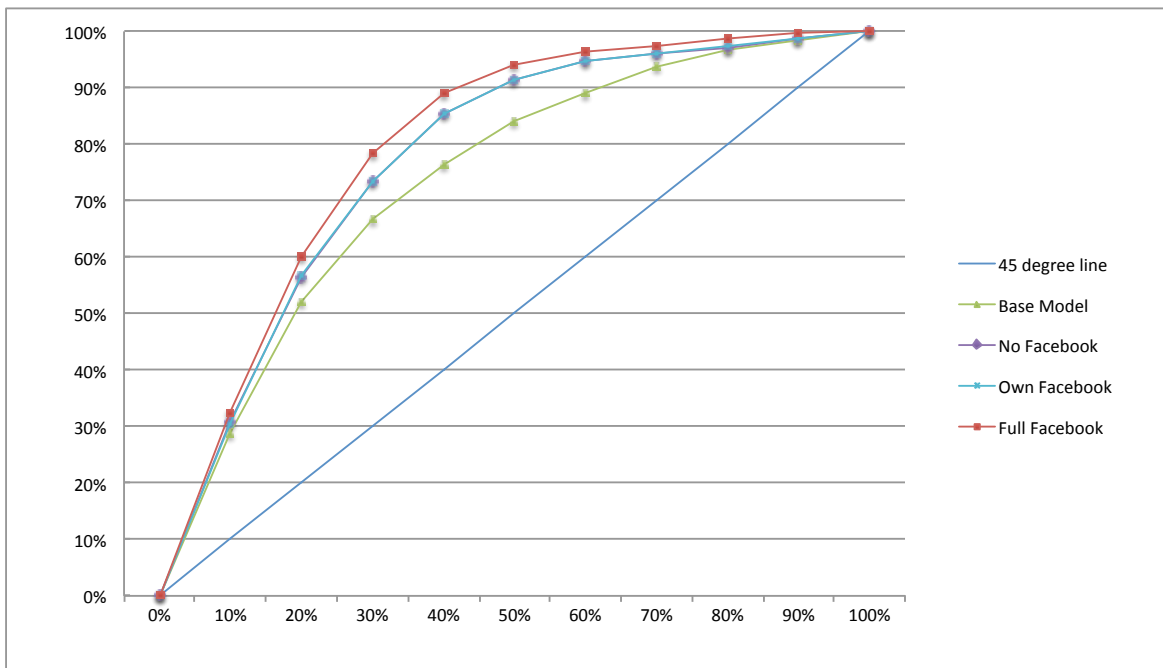


Figure 2.3 presents the holdout lift charts when predicting site visitation for the “Full Facebook”, “No Facebook”, “Own Facebook”, and the “Intercept Only” model specifications. To create the charts we sorted the holdout observations by predicted visit probabilities. We then took 10% of all (holdout) observations with the highest predicted probability and computed the percentage of actual visits associated to these observations. We repeat this procedure for 20% of the observations, 30%, and so on. We then plotted the fraction of visits that each model would have been able to capture at different targeting percentages. As we can see from the graphs, the lift line of the Full Facebook model is always above the others: this is the best model in predicting whether a user will visit the site or not in a given day (considering the holdout sample).

Figure 2:3: Out-of-Sample Lift Charts



Hence, the best fitting model in- and out-of-sample is the Full Facebook model. It jointly models site visits and page views at the news site as a function of (1)

the user's actions at the news site, (2) the user's actions whilst on Facebook, and (3) the actions at the news website of the user's Facebook friends (i.e., the news consumption of friends). We further note that jointly estimating the two dependent variables provide better fit, and the two dependent variables are positively (and significantly) correlated (Table 2.5 provides the details of the variance-covariance structure of the final joint model). This means that an unexpected positive shock that increases the likelihood of visitation will also likely mean an increase in the average number of page views, once a visit takes place (i.e., in a given day a higher likelihood of site visitations is associated with a higher expected number of page views).

2.6 Results

Table 2.6 presents the posterior means and 95% probability interval for the hierarchical parameters of the included variables and for each model specification (in the previous section we explained the variable selection process). The parameters presented correspond to the population level means.

2.6.1 Social Networks and Their Impact on News Consumption

Detailed analysis of the results suggests that when users are active on Facebook they are also more likely to visit the focal news website (the coefficient of daily like activity in the logit component of the model is positive and its 95% probability interval does not cover zero). This implies that the decision to visit the news website is positively related to the user's social network activity on a specific day. This impact is substantial. We simulate the impact of Facebook activity and find that, when someone is active on Facebook on a given day, the median increase of daily visit probability is about 22% (we report median values because these are less influenced by the extreme

values of some observations and better represent the central tendency in this type of data characterized by an excessive number of zeros).

In addition, considering the Poisson component of the model, our results further suggest that daily like activity also has a positive impact on the number of articles read. On days in which users are active on Facebook, they are not only more likely to visit the news site; they will also read more articles once they are at the site. Through simulation we find that the median number of articles read when a visitor is active on Facebook is 7.15, versus 6.23 when visitors are not active. Hence, our results suggest that social networks do not necessarily divert traffic from news providers nor do they necessarily reduce content consumption.

The estimated impact of friends' actions on site visitation provides additional evidence of this promotional effect: when Facebook friends are active on the news website, a user is more likely to visit the website (positive effect of friends' actions on the probability of site visitation).⁷ By simulating the impact of friends' actions on visit probability we find that a visitor is four times more likely to visit the website when his friends are active compared to when they are not (the median change in visitation likelihood is 422%, which corresponds to a median absolute change in visit probabilities of 0.81; see Table 2.7). It is likely that this positive effect on site visitation is due to article recommendations made by friends and to the links friends add to their timeline as they read news articles.

⁷ The heightened interest for the news website due to specific events (e.g., Olympic Games or an election) could affect simultaneously a user and his friends causing a spurious connection between a user and a friend's actions. We control for the general attractiveness of news to all users by including in the model the number of page views requested by other users who registered using an email account and did not provide their Facebook info. As expected, this variable has a positive coefficient and captures significant variance in the data serving as a good time-variant control. Our results are robust to the inclusion of this control variable.

However, with regards to page views, the actions of friends have the opposite effect. Visitors tend to request fewer pages from the website when their friends are active compared to when they are inactive (from Table 2.7 we can see that the impact of friends' actions on the page view model is negative and the 95% probability interval does not include zero). We also simulated the impact of friends' actions on page views and find that visitors view about two fewer pages when their friends are active compared to when they are not, which corresponds to a reduction of one third in page views (median change of page views of -2.39). We note that this negative effect is conditional on a visit taking place. Because the impact of friends' actions on site visitation is positive and strong, the net effect on page views, unconditional on a visit taking place, could also be positive.

To further explore this possibility we predict page views unconditional on site visitation and simulate what would happen if friends were active on the news website on a given day. Table 2.7 reports the unconditional median change in page views due to friends' activities. As we can see from the table, when friends are active the significant increase in visit probability leads to a net positive effect on page views: we find that an increase in friends' activities has a positive net increase in page views (almost two more page views per day). This positive net effect is due to an increase in traffic to the website, despite the more directed navigation once at the site. These effects are also likely due to the recommendations and posts of friends on Facebook, though a better understanding of this result is required.

To fully understand these results one needs to consider that the amount of content consumed (as measured by the number of pages viewed) is dependent on whether the visitor is in a directed search or explorative mode. For instance, in the

context of online commerce, previous work has noted that consumers in explorative mode spend more time before making a purchase (e.g., De Nie, 2012; Janiszewski, 1998). Similarly, in the context of online content consumption, visitors in explorative mode tend to visit the news website home page and scan for the most recent and hottest topics, and are willing to try new links and even return to the home page to further search for available content. Thus, visitors are likely to request more pages and read more articles as they are exposed to further stimuli. In contrast, visitors engaged in directed search are likely to view fewer pages and quickly navigate to articles of interest, remaining focused in their site visits. Those who receive a link to a specific article, and as a result do not start navigation through the website homepage, are also more likely to be in directed search and are less exposed to the stimuli of news headlines.

Hence, if friends who are active on the news site post and send links about the articles in a given day, users will be more likely to visit the website but, contrary to those who visit the home page (and are more likely to be in explorative mode), view fewer pages once at the site on a given day. This result would explain the sign and significance of the parameters in Table 2.6. To confirm this hypothesis, we have also included in the model a dummy for home page views and an interaction of the home page dummy and the friends' activity. From the results in Table 2.6 we can see that users who go through the home page also view more articles on average (indicating an explorative mode). In addition, the interaction term has a positive impact on page views. This suggests that, for those visitors who visit the homepage, the negative impact of friends' activity is less pronounced. Users seem to be directed by their friends to specific articles (and have no need to go through the home page) and that the negative impact on

page views (in a given site visit) is a result of article recommendations that lead to more directed searches.

To see the impact of these effects we computed the changes in page views due to friends' activities online, with and without home page visitation (see Table 2.8 for the results). On average, when there are no home page views and no friends' activity at the site, the daily median page views per user are 1.74. If that user visits the home page (and hence is more likely to have been in explorative mode) then the median page views is 7.24, without friends' activities. If friends are active the median page views is 6.10 for those visiting the home page and 1.16 for those who skip the homepage. On average, and even after controlling for home page visits, friend activity negatively impacts the number of pages viewed conditioned on a site visit. This suggests that friend activity results in “directed content consumption” and that individuals are more likely to limit their viewing to recommended news and content shared by friends. The experience with online news content appears to be a shared experience that can be affected by the browsing patterns of others. Our empirical study provides evidence supporting user dependence on the content recommendation of other users and positive spillover effect generated by social networks over news websites.

2.6.2 Individual Behavior and News Consumption

We find that including time-variant variables, capturing previous navigation at the news site significantly improves model performance compared to an intercept only model. For example, individuals who allow a long period to pass in between their visits are less likely to visit the site (the more time that passes without visiting the site the less likely users are to return to the news site). In addition, visitors who visit the site repeatedly in a day are more likely to return to the site the following day. This means

that once users stay away from the news website for a while they might forget and lose the habit of visiting the website for their daily news, which in turn indicates that it is important to remain salient in users' minds and be part of their daily choice for news consumption.

Our results also support theories of involvement and selective exposure (see Dutta-Bergman, 2004) whereby a high level of involvement in a particular subject area is positively associated with information seeking related to that subject. Visitors who read categories like Sports, Local News, and check TV related content are more likely to return to the site. Knowing that visitors are not shallow visitors, that is, knowing that they are reading specialized content and not simply browsing for headlines while at the home page, helps predict future visits to the site. The results also suggest that Facebook registered users follow the behavior of other registered news readers: the number of page views of other registered users, when included in the model, have a positive impact on site visit and content consumption. These results have particular relevance to news site managers, since the type of content influences individual visit behavior, it could answer questions like “how” to integrate optimally” with users social networks.

2.6.3 Results Robust to Endogeneity Correction

Social network data poses challenges for researchers wishing to identify causal effects. According to Hartmann et al. (2008) the primary confounding factors that can lead to incorrect inference are (1) endogenous group formation, (2) correlated unobservables, and (3) simultaneity. Just as in Nair et al. (2010), we avoid the problem of endogenous group formation because in our study “social groups” are defined by Facebook connections, a third party website not related to the focal news website under analysis. The use of panel data in our study also mitigates the problem of endogenous

group formation, as actions have a temporal structure and we can account for individual unobserved heterogeneity and for differences in the network impact over time. We further account for possible correlated unobservables by including a control variable that reflects the daily actions of other registered users not part of the focal agent's reference group (this is similar to the approach of Nair et al., 2010 who consider the behavior of agents not in the focal agent's reference group to control for such unobservables). Finally, we include daily effects (as daily dummies) to further account for possible unobservable factors influencing daily online news consumption. These corrections and controls mitigate the first two challenges.

However, the final challenge is far more complex to resolve. In social interaction models it is difficult to disentangle whether the focal agent's behavior influenced other members of the group, or whether the activity of other members influenced the focal agent's actions. To account for this possible endogeneity and simultaneity in the activities of friends and the focal user, we re-estimate the model using a two stage instrumental variable approach to correct for endogeneity. In the first stage we regress the friend activity dummy variable on a set of instruments using a binary logit specification. We use lagged page views and average page views by registered users as instruments and control for factors that might impact an individuals' social network such as age, number of Facebook friends, number of Facebook likes, and average time in between likes to give a measure of Facebook activity. We then used the predicted value of friend activity in the final model as a covariate.

We observe no significant difference in our results despite introducing controls for the possible endogeneity due to the simultaneity of actions between friends (results available from the authors upon request).

2.7 Conclusion

The purpose of this research has been to establish a link between social network activities and the visitation and use of content websites. There has been significant discussion regarding the role of social networks on websites whose business models rely on content provision. On one hand, such businesses fear the competition from social networks, as users' time seems to be increasingly channeled to alternative social forms of content sharing. On the other hand, because social networks are now so prevalent in users' lives, there seems to be no alternative than to engage with these networks.

News websites provide a good example of this dilemma. In recent years, news websites have pushed for the registration of visitors using a Facebook account instead of the traditional registration with the site. Despite the obvious benefit of collecting rich personal information from user profiles and social interactions, allowing the selling of premium targeted ads; it is not clear what the net effect is of this new policy. Social networks compete for a user's time and the headline-like news available at social network news feeds (the result of users sharing and reading articles) could be enough for most users in terms of information gathering. This would in turn deter users from visiting the news website causing a reduction in the number of visits and in the number of available impressions for sale to advertisers.

Previous research has relied on survey data to study the behavior of social network users within the network and little research exists that studies the impact of the network on the individual's behavior on third party websites. In addition, little research has focused on online content providers and their users. The purpose of this study has been to establish the impact of a visitor's social network activity and their friends'

actions online on the visitation of a content website and on content consumption. More specifically, we focus on two elements of browsing behavior at a leading news website: (1) a user's decision to visit the content website, and (2) the amount of content consumed. These variables capture some of the key decisions users make in terms of their demand for content and have a direct bearing on the revenue generated by content providers.

We adopt a flexible modeling approach and jointly model the visit and page view decision using a random coefficients Poisson Hurdle model (estimated using a hierarchical Bayesian approach). We allow for site visit and content consumption decisions to be correlated (visitors who are more likely to visit the website may also read more news and consume more content) and correct for potential temporal variation and endogeneity. We fit the proposed model on detailed browsing data from a panel of 1,562 Facebook users who are registered with a leading newspaper website and have visited the website during the month of March 2012. Our findings provide valuable insights regarding the dynamics of visitors' content consumption and the interrelation between demand for content and social network activity.

Based on actual browsing patterns of consumers of online content and their exogenous social network ties, we conclude that social network activity and content consumption are complements. In contrast to conventional wisdom, our results suggest that actively participating in social networking sites increases the likelihood of visiting the content website and increases content consumption. We also find that the activity of friends strongly influences the behavior of network members. Visitors are more likely to visit the content website when their friends have also visited the website, suggesting that the sharing of news and news recommendations play an important role in attracting

traffic. However, the navigation within the site exhibits a directed search as users with active friends request fewer pages once they are at the site. The net effect of friends' actions is nevertheless positive: the significant increase in traffic increases overall average page views and these results are robust to possible endogeneity biases.

Our findings have several implications for content managers. Given the importance of ad impressions for website managers, managers can increase traffic flow to the content website by targeting active social network users and making article recommendation easy and seamless (once social network users are online and active, they are also more likely to visit the content website and read more articles). Many websites seem to be adopting this policy by requiring Facebook users to register by default with the website Facebook page and app to be able to read articles recommended by friends. This provides an additional intake of registered users. In addition, many news websites are prominently promoting Facebook registration on their websites.

Finally, given that social network members follow the activity of their friends, content providers could endeavor to make the activity of friends more visible to network members by making articles read by Facebook users automatically visible on their news feed, news website and by making the article recommendation process easier. Indeed, this is a trend we observe in many news websites in which Facebook apps post (by default) the articles read on the news feeds. More and more news websites today are making the news consumption of Facebook users more visible to site visitors and recommendations seamless through the proliferation of Facebook like buttons.

Despite the relevance of our findings, our research suffers from certain limitations. For example, we do not observe the actual article recommendations by users and we infer this activity. Hence, we are unable to incorporate the visitor's decision to recommend articles. In addition, typical news websites provide users with a variety of recommendations generated from multiple sources. Recommendations taking into account what similar users have read recently, and what are the most emailed and most commented on articles are only some examples. We cannot compare the effectiveness of these recommendations to that of friends in increasing traffic and readership at the site, as we do not have data on these alternative forms of article recommendations. Future research could explore the differential impact of generic recommendations and recommendations of friends from social networks. We note that generic recommendations and the impact of endogenous networks (i.e., those inferred or created by the content website itself) have been considered in extant literature (e.g., Oestreicher-Singer and Sundararajan, 2012), and future research could use clickstream data on browsing in tandem with information on content recommendations to understand whether social recommendations are preferred over generic ones.

Similarly, our results suggest an increase in site traffic to the website under consideration, however, this increase in traffic might be the result of an increase in the demand for content or merely a redirection of traffic from other content sites. Future research could explore whether there are certain content sites that benefit from social networks more than others or whether social networks lead to an overall increase in content consumption across all content sites.

While our results briefly shed light on the importance of the type of content in driving site visits, future research could explore what type of content is more likely to

be shared and which headlines are more likely to be clicked-through on their site versus on Facebook; for example, do we find teaser-like headlines to be more clickable but less sharable?

In this research we have also not considered metrics of network centrality and network influence. Future research could also explore how influential users affect the flow of traffic to content providers and how one can identify the most influential users with respect to traffic generation. If certain users who share news stories are more influential in channeling traffic to content sites, then managers could target these focal network members with the latest news updates. Similarly, content sites could encourage greater content consumption by highlighting the stories read by focal network members.

List of Tables

Table 2:1: Summary Statistics of Browsing Behavior (Estimation Sample)

	Mean	Std. Dev	Min	Max
Page Views	4.98	13.20	0	295
Site Visits	0.59	0.83	0	11
Inter-visit Time (in days)	3.72	4.05	1	28
Home Page Views	1.97	7.49	0	295
Page Views for Local News	0.38	1.84	0	146
Page Views for Sports News	0.37	3.21	0	162
Page Views for TV News	0.69	3.54	0	71
Page Views for Other News	0.40	2.43	0	108

Note: All variables are daily variables.

Table 2:2: Frequency of Inter-visit Time (in days)

Day	No. of Observations	% of Observations	Cumulative % of Observations
1	16,141	44.93	44.93
2	4,728	13.16	58.09
3	3,077	8.56	66.65
4	2,198	6.12	72.77
5	1,756	4.89	77.66
6	1,427	3.97	81.63
7	1,202	3.35	84.98
8	1,000	2.78	87.76
9	848	2.36	90.12
10	682	1.90	92.02
11	519	1.44	93.46
12	425	1.18	94.65
13	363	1.01	95.66
14	316	0.88	96.54
15	285	0.79	97.33
>15	959	2.67	100

Table 2:3: Summary Statistics for Facebook Profiles and Activity

	Mean	Std. Dev.	Min	Max
Facebook Profile				
Gender	0.22	0.41	0	1
Age	38.61	13.17	16	80
Total Number of Likes	178.29	137.93	0	551
Total Number of Friends	424.36	293.45	5	1,000
Facebook Activity (During the Last Three Weeks of March)				
Daily Like Dummy	0.13	0.34	0	1
Daily Friend Activity Dummy	0.15	0.35	0	1

Table 2:4: Out-of-Sample Predictive Performance - Unconditional Page Views

	Mean Predicted Page Views	Mean Squared Error	Normalized Mean Squared Deviation
Base Model	4.52	68.92	2.92%
No Facebook	3.25	50.95	2.51%
Own Facebook	3.27	50.18	2.49%
Full Facebook	3.01	46.14	2.39%

Note: 3.06 is the average observed page views.

Table 2:5: Variance-Covariance of the Poisson Hurdle Model

	Posterior Mean	Confidence Interval
Covariance between site visit and page views	0.68	[0.60, 0.75]
Page view variance	0.71	[0.68, 0.73]

Table 2:6: Comparison of Results

Model Component/Variable	Base Model	No Facebook	Own Facebook	Full Facebook
Count Model - Page views				
Intercept	1.849*** [1.780, 1.897]	0.360*** [0.153, 0.556]	0.333*** [0.140, 0.562]	0.447*** [0.235, 0.661]
Home Page Views		1.439*** [1.362, 1.516]	1.448*** [1.357, 1.520]	1.400*** [1.312, 1.511]
Facebook Like Activity			0.124*** [0.078, 0.173]	0.138*** [0.090, 0.185]
Facebook Friend Activity				-0.405** [-0.569, -0.229]
Facebook Friend Activity* Home Page Views				0.219*** [0.068, 0.377]
Registered User Browsing Activity		0.008* [-0.001, 0.018]	0.008 [-0.009, 0.011]	0.002 [-0.008, 0.011]

Table 2.6: (Cont'd)

Model Component/Variable	Base Model	No Facebook	Own Facebook	Full Facebook
Logit Model - Visit Decision				
Intercept	-0.345*** [-0.443, 0.234]	-152.467*** [-191.153,-111.487]	-155.769*** [-195.603, -111.843]	-140.953*** [-189.315, -92.348]
Facebook Like Activity			0.357*** [0.239, 0.455]	0.330*** [0.217, 0.456]
Facebook Friend Activity				12.447*** [11.438, 13.942]
Inter-visit time		-0.408*** [-0.445, -0.371]	-0.408*** [-0.446, -0.366]	-0.400** [-0.447, -0.352]
Inter-visit time Squared		0.020*** [0.018, 0.023]	0.020*** [0.018, 0.023]	0.020*** [0.017, 0.023]
Lag Visits in a Day		0.425*** [0.342, 0.496]	0.426*** [0.337, 0.505]	0.353*** [0.257, 0.444]
Lag Page Views for Local News		0.353*** [0.213, 0.482]	0.354*** [0.229, 0.495]	0.323*** [0.187, 0.483]
Lag Page Views for Sports News		0.278*** [0.149, 0.431]	0.307*** [0.164, 0.473]	0.260*** [0.151, 0.473]
Lag Page Views for TV News		0.223** [0.057, 0.385]	0.220*** [0.048, 0.386]	0.110 [-0.316, 0.083]
Lag Page Views for Other News		0.244*** [0.130, 0.380]	0.230*** [0.113, 0.352]	0.225*** [0.074, 0.361]
Registered User Browsing Activity		7.112*** [5.204, 8.943]	7.276*** [5.216, 9.148]	6.554*** [4.336, 8.890]
DIC	115,149.900	111,507.600	111,458.400	103,811.000

Note: ‘***’ imply significance at the 0.1%, ‘**’ at 1% and ‘*’ implies significance at the 5% level. In the interest of space we do not report estimates for the daily dummies included in the model. In addition, we only report the population averages of the estimated coefficients. See Appendix for variable description.

Table 2:7: Median Change in Page Views and Site Visit Due to Friends' Activity

	Absolute Change	Relative Change
Visit Probability	0.81	4.22
Conditional Page Views (given a site visit)	-2.39	-0.33
Unconditional Page Views	1.66	3.37

Table 2:8: Median Predicted Page Views Conditional on a Visit Taking Place

	When friends are inactive	When friends are active
When visitors do not view the home page	1.74	1.16
When visitors view the home page	7.24	6.10

Note: Computed for the estimation sample and considering the four alternative scenarios; medians are reported to minimize the impact of extreme values.

2.8 Appendix

Table 2:9: Variable Description

Variable	Description
Friend Activity	Indicator variable taking value of 1 if Facebook friend visited news website
Like Activity	Indicator variable taking value of 1 if visitor liked a new page on Facebook on a given day
Page views	Number of pages viewed at the news site in given day
Site visit	Indicator taking the value of 1 if a visit is made to the news site
Page views – registered users	Total daily page views of users registered via their email addresses
Lag activity	Number of pages viewed on last visit
Inter visit time	Time in days between subsequent visits to the site
Friend match	Indicator variable taking the value of 1 if individual sees the same category as Facebook friend
Size of friend network	Number of friends on Facebook

3 To Buy or Not to Buy? Choice Under Uncertainty

3.1 Introduction¹

Revenue management (or yield management) systems are today the standard pricing mechanism in many markets characterized by perishability and capacity constraints (Desiraju and Shugan, 1999). These include markets for air travel, hotel bookings, and car rentals, all of significant economic impact not only offline but especially online. Travel related online businesses have historically accounted for 40% of the revenue from e-commerce (Combes and Patel, 1997) and recent studies also confirm that the Internet is the most frequently used medium for travel research with 84% of leisure and 79% of business travelers booking online (Traveler's, 2010). It is expected that one third of the world's travel sales are expected to be completed online by the end of 2012 (Sileo et al., 2011). The growing importance of online search and online purchase, is likely due to online search efficiencies. Because it is simple and economical to search for alternatives over the web, customers can easily obtain updated information on prices and available alternatives, even when prices and availability change continuously as a consequence of the use of revenue management systems (Desiraju and Shugan, 1999). Uncertainty regarding prices and product availability at each moment in time, until the product or service is purchased or booked, results in a

¹ Based on joint work with Professor Catarina Sismeiro.

greater need for frequent information gathering. As a result, a medium with lower search costs that allows constant and easy access to information on prices and availability is bound to gain importance.

From the researcher's perspective a key advantage of the Internet is that consumer search behavior can be easily tracked, as each request for price quotes and product availability can be registered almost effortlessly. With this study we intend to exploit such detailed information to study the impact of uncertainty regarding prices and availability on consumers, in an industry dominated by revenue management systems.

We contribute to the literature on revenue management by investigating; (1) how do consumers cope with the extreme uncertainty caused by such systems, as prices and available flight options change dynamically during the day? (2) Whether consumers form expectations and learn over time, adapting to the existing market conditions? (3) What is the impact of search effort on purchase?

Although studies in the context of frequently purchased consumer goods and consumer durables have studied how uncertainty and the number of product alternatives available impact choice and purchase incidence (e.g., Zhang et al., 2012), little is known on how consumers cope with the extreme levels of volatility that characterize markets dominated by revenue management systems (Desiraju and Shugan, 1999).

To study these issues, we jointly model search and purchase behavior using a novel and detailed panel data from a large online travel agent (OTA). We use a flexible modeling approach to estimate a two-stage dynamic model to study the within-site purchase and search behavior, and draw inferences regarding customer preferences. We model site visitor's decision to make a purchase now or to continue searching and, conditional on purchase incidence, the choice of airline carrier. By including covariates

capturing what a visitor is exposed to during browsing and the actions taken while searching the site, we study the impact of price uncertainty and product availability on search and incidence decisions, while accounting for individual-level differences in search and buying preferences. We allow for the value of current options and expected future value of travel options to influence the decision to buy now or continue searching. We assume that consumers have dynamic price expectations regarding ticket prices, whereby sophisticated consumers update their expectations based on observed prices. We test for alternative models of expectation formation, including temporally rising prices and hedonic price expectations. Finally, unlike previous models of search we account not only for individual level heterogeneity, but also correct for potential endogeneity bias.

Our empirical findings suggest that consumers search in order to resolve uncertainty, which is consistent with existing theories of consumer search (Lanzetta, 1963; Stigler, 1961). Our dynamic two-stage model indicates that price uncertainty and the number of options available, influence the decision to buy versus continued search. Greater price variability in the options presented to browsers, all else constant, leads to more search and the postponing of a purchase, a result similar to findings of previous research, that also holds in the context of markets with extreme price uncertainty. On the other hand, the greater the number of options available to site visitors (while controlling for price dispersion), the greater the likelihood that a purchase will take place. That is, when the available choice set is large, consumers appear more confident and search less, irrespective of price uncertainty. This result is consistent with the view that consumers might experience additional utility simply from having multiple items in the choice set (Kahn et al., 1987; Broniarczyk et al., 1998), in addition to a potential “variety effect”

(Ratner et al., 1999). This is also in agreement with the view that larger assortments might influence preferences by creating a perception of freedom of choice (Brehm, 1972). This increased menu of choices reducing search time is also consistent with classic rational search models as more choice would lower the perceptions of “uncertainty” and reduce the benefits from additional search.

In addition, consumers appear to use current and previous prices to form expectations of future prices and dynamically update their expected value of future options (and the greater the expected value of future options the greater the likelihood of continuing search, whereas the greater the value of current options, the greater the likelihood of buying now). We also observe that price expectations strictly based on product characteristics are unlikely to hold in this market.

Our results also suggest that search effort impacts a consumer’s decision to search, and that the type of search is revealing of consumer’s motivation to buy. Site visitors are more likely to make a purchase the more actively they search within a short time span (session) and the more actively they change travel dates in search for alternatives with a better fit to their needs (revealing a form of strategic adaptation as prices and product availability is discovered during search). In contrast, customers that exit the website before completing a purchase and that frequently adjust their route (within a short time span) have a lower likelihood of ever making a purchase on subsequent visits. This type of search behavior is probably revealing of less motivated buyers or buyers not yet sure of their travel plans.

Finally, we find that pre-purchase search behavior is a key determinant of purchase outcomes and that ignoring search behavior can lead to misleading inferences. For example, excluding pre-purchase behavior from those site visitors who do not

eventually purchase from the OTA, compromises the model's predictive power. Hence, in the context of online search for travel related products, ours is one of the first papers to highlight the need to include all browsers in a model of search and purchase, whether or not browsers are also purchasers.

The remainder of the chapter is organized as follows. Section 3.2 summarizes the relevant literature and Section 3.3 provides an overview of the air-travel industry and the type of price and product uncertainty in this market. Section 3.4 presents the rich dataset used, and in Section 3.5 we present the model and key modeling assumptions. Section 3.6 summarizes the estimation approach. Finally, our main findings are presented in Section 3.7 and in Section 3.8 we provide our conclusions and propose areas for future research.

3.2 Literature

Pricing under revenue management regimes is a complex phenomenon constrained by two factors “perishability” and “capacity” constraints (Desiraju and Shugan, 1999). Considering the case of air-travel, perishability stems from the fact that once a flight departs the seats can no longer be sold. Capacity constraints on the other hand, arise from the physical limitations on the number of people who can be accommodated on a single aircraft. The combination of perishability and capacity constraints has driven airlines to adopt complex revenue management pricing systems to profitably fill each aircraft to capacity (Wardell, 1989). The basic idea of these systems is to continuously monitor demand (through for example centralized booking systems, which are at the center of the technology development) and adjust pricing to maximize the yield of each seat, each room or even each car (Boyd and Bilegan, 2003). These revenue management strategies introduce significant temporal price variation. For

example, in the case of air travel, if the likelihood of selling a ticket at full price increases the number of seats available at lower fares decrease and hence prices increase. Research in operations management finds that in a normal day, fares can be updated up to 200,000 times in a travel agent's computerized reservation system (Hopper, 1990).

For a specific flight prices can change as often as seven times during a single day (Etzioni et al., 2003). Previous evidence shows that these systems have led to significant increases in profitability that far outweigh their cost (Davis, 1994).

Because the algorithms behind these systems are so vital, existing research in the field of revenue management has thus far focused on the optimal pricing strategy of firms and their demand forecast (e.g., Perakis and Sood, 2006; Dana, 1999). However, most of this work has assumed that consumers arrive as a stochastic process. For instance, Ben-Akiva (1987) and Sa (1987) forecast demand for flights using regression and time series models based on advanced and historical bookings data. Recent developments in the literature include choice-based revenue management models, whereby discrete choice models are used to forecast consumer demand (e.g., Ferguson et al., 2011; Vulcano et al., 2010; Talluri and Van Ryzin, 2005). However, these models assume that customer are myopic, and strategic waiting in response to price uncertainty has largely been ignored.

Boyd and Bilegan (2003) note that the main challenge for revenue management systems is to effectively use the information contained in consumer purchase requests, as eventually airlines would like to charge each customer their willingness to pay. Similarly, Elmaghraby et al. (2003) stress the importance of understanding consumer behavior in revenue management “an important element that is largely missing, both in

most of the academic literature and price optimization software, is the consideration of strategic customer behavior” (p.1298).

The need to understand the role of price volatility becomes even more pressing in light of evidence in the search literature, that suggests that the more uncertain a consumer is concerning the true value of product attributes, the more the consumer will search to resolve the uncertainty (e.g., Mehta et al., 2003; Urbany, 1986; Stigler, 1961). According to traditional models of consumer search, price uncertainty increases the marginal utility of search as the likelihood of finding a lower price increases (Ratchford, 1982). A key limitation of the extant literature is the breadth of industries studied: most research has been conducted in the context of frequently purchases consumption goods (e.g., Gauri et al., 2008; Fox and Hoch, 2005; Urbany et al., 1996) and durable goods markets (e.g., Sobel, 1984). Very few studies look at services and other more complex products subject to extreme price variability.

Researchers have commonly used the spatial price dispersion across available alternatives as measures of price uncertainty (Stigler, 1961). However, temporal price variation has also been noted to influence consumer search behavior. For instance, Bell and Bucklin (1999) and Erdem and Keane (1996) focus on the role of temporal price changes on the price expectations for frequently purchased consumer goods. Though temporal price variation is an important market force in these industries (e.g., promotional activity or price decreases due to the sequential introduction of new product generations), the level of price changes and price uncertainty is not as extreme as in the case of revenue management. Similarly, Lemieux and Peterson (2011) study the impact of purchase deadlines for consumers searching for rental trucks and show that high levels of price uncertainty are likely to increase search duration when the

deadline is distant, however, once deadlines draw near consumers are less reactive to price uncertainty.

Another potential source of uncertainty could be regarding the availability of product options. Extant research highlights the importance of product variety and the size of the choice set as important determinants of consumer search. Having multiple items in the choice set results in greater utility (Kahn et al., 1987; Broniarczyk et al., 1998), in addition to a potential “variety effect” (Ratner et al., 1999). Hence, large assortments might influence preferences by creating a perception of freedom of choice (Brehm, 1972) which would lower the perceptions of “uncertainty” and reduce the benefits from additional search. Due to the capacity constraints in the airline industry only a limited number of seats are available in a given fare class, therefore, seats available in one search request may no longer be available on a subsequent search. While most studies on consumer search are limited to spatial and temporal uncertainty, we extend extant research by also considering the impact of product availability.

Compared to offline markets, consumers can search online stores with little time and effort, in addition, online commerce can track website visitors and observe their search behavior, something that had been either difficult or too expensive to engage in offline channels. Previous research highlights that purchase behavior is sensitive to browsing experience, there is evidence that purchase conversion is influenced by page design (Mandel and Johnson, 2002), number of pages requested and time spent at the site (Sismeiro and Bucklin, 2004), and frequency of site visit (Moe and Fader, 2004). Our detailed data set on browsing behavior controls for factors like frequency of site visit and past experience with the site.

The richness and growing availability of clickstream data sets has led to the proliferation of studies estimating consumer search cost distributions. However, for most studies data is often at a different level at which theory has been developed or aggregated in some way. This poses specific problems as authors need to develop a link between the different level of analyses and impose strong assumptions in order for their structural models to hold at all levels, including the one at which data is collected. For instance, Koulayev (2010) estimates demand for hotels by estimating a structural model of sequential online search on a data set from an aggregator site that records clicks on hotel links. The key modeling assumption is that by clicking on a hotel, consumers reveal a preference for that hotel. However, this can be a misleading assumption as consumers may click in order to gather more information and does not indicate necessarily a preference and much less an actual booking.

Similarly, Santos et al. (2012) empirically test alternative search models using individual level visit data. However, the authors only have access to final transaction prices, which could to some extent explain why the authors find no relation between price and search behavior.

Furthermore, most search models using clickstream data sets assume that utility maximizing consumers are aware a-priori of the distribution of prices, and decide to stop or continue search if the marginal benefits of search outweigh the marginal costs of additional search (e.g. Kim et. al, 2010). These assumptions are reasonable in the durable goods industry with limited uncertainty, though not so in a context with extreme uncertainty. According to Morgan and Manning (1985), sequential search models are optimal if customers have perfect recall and have no time preference, this makes traditional sequential models problematic in markets with high price volatility and

limited recall. Furthermore, Lemieux and Peterson (2011), note that a sequential search model may not always accurately capture consumers search behavior. For instance, information search may be driven by a sense of urgency (Ariely and Zakay, 2001) or attempting to reduce uncertainty.

In addition, while most studies have focused on homogenous product with limited price variation across sellers and time, in contrast, we expect to see a stronger relation between price and consumer choice for the highly volatile market for air travel. In the context of air travel Nair et al. (2010), analyze the determinants of consumer's choice of travel website, browsing time and purchase based on final transaction prices. Since the authors only have access to final prices they are unable determine the impact of prices observed during search on purchase outcomes.

Through our study we aim to bridge these gaps in the literature. We contribute to the literature on revenue management and consumer search behavior by modeling prices and options observed during search for a dynamic product category subject to high levels of spatial and temporal uncertainty.

3.3 Data

We analyze site centric browsing and purchase behavior of users registered with one of the largest European travel operators and its subsidiaries.² We identify repeated search behavior by site visitors over the period December 1st, 2005 - April 30th, 2006. The data includes customers³ logging into the main OTA website and customers directed from price comparison sites, shop bots and search engines. Lack of across OTA data is not a limitation as there is evidence of limited across site search. Smith and

² In addition to the main travel website, the OTA operates price comparison sites which direct online traffic to the main ticketing website.

³ We use customers, consumer and visitor interchangeably.

Brynjolfsson (2001) in their study of online shop bots show that 70% of consumers repeatedly visit a single site. According to Comscore data, only 27% customers visited more than one store in 2002 and 33% customers visited more than one in 2004 (Santos et al., 2012).

Customers visiting the OTA can search for departure cities, arrival cities and travel dates. We define the combination of route,⁴ travel dates and number of travelers as a single search request. After consumers request a flight the search engine displays the available flights. Consumers then have the option to select a flight and checkout, redefine the search criteria or exit the website. Every time consumers change the trip specification a new search request is generated.

The size of the data set required considerable effort in synchronizing the consumer specific data with the extensive flight information from the search engine. We removed all searches with incoherent search fields (e.g., departure dates after arrival dates) and instances where consecutively requested destinations were more than 400 miles apart.⁵ For such requests we could not determine if mistakes had been made or if a consumer simply changed travel plans. To ensure that we observe all the search activity related to a specific booking, we considered flights searched during the month of March 2006, reserving the initial three months of online activity for variable initialization and search behavior in April 2006 for predictive analysis. In addition, we excluded the booking activity of travel agents to avoid biases arising from their bulk purchasing activity (1.1% of all bookers were travel agents).

⁴ For round trips, a route is a combination of arrival and departure cities.

⁵ In the European context 400 miles is a significant distance.

In addition, we select twelve domestic routes,⁶ which generate 90% of all domestic flight requests (domestic routes are those for which departure and arrival city are within the primary country of activity of the OTA website under analysis).⁷ We included 8 airlines in our final estimation sample.⁸ Not all carriers operated on each route and the number of carriers for a given itinerary changed across time depending on seat availability.

On average consumers had a choice between 2.6 airlines, with a minimum of 2 and a maximum of 4 carriers operating on a particular route. Air travel is a complex product with flights operating several times a day, including each flight option displayed to a customer in a choice model is not trivial. In the interest of tractability we combine the flights operated by an airline into one option. On average 2.2 different flights were displayed for each carrier.⁹ The final price per carrier was computed as the average price across all flights operated by the carrier.¹⁰ Table 3.1 presents the average price across carriers and their market share. Carriers 5 and 6 have the highest market share and most frequently enter a consumer's consideration set.

The final data set comprises of 18,136 search requests generated by 5,087 site visitors. 2,776 site visitors made at least one purchase during the period under analysis. As is the case with online search data, our data is limited in terms of demographic

⁶ A route is defined as a combination of departure and arrival city pairs.

⁷ The OTA we study sells more than 40 different routes. However, the bulk of the business is concentrated around the top 12 routes for which information was collected. By focusing on domestic flight we avoid currency conversions and we do not need to include the information of connecting flights, which could influence substantially the quality of the product. Furthermore, we minimize country specific effects because residents of a single country predominantly book domestic flights.

⁸ We removed carriers that were never purchased during the period under analysis. Since the excluded carriers were part of the consumers' consideration set, these carriers were used to compute variables measuring price variability and options for each search request.

⁹ A maximum of 15 flights were displayed for a carrier while 20% of the time a single flight was operated by a given carrier.

¹⁰ For round-trips, we first computed the average price for each leg of the journey and then computed the sum for the two legs to arrive at the final price per carrier.

information about customers (Brynjolfsson et al., 2004). This is not a serious limitation as our focus is on identifying consumer search preferences and we can distinguish customers on the basis of their observed search behavior.

3.3.1 Spatial and Temporal Price Variation

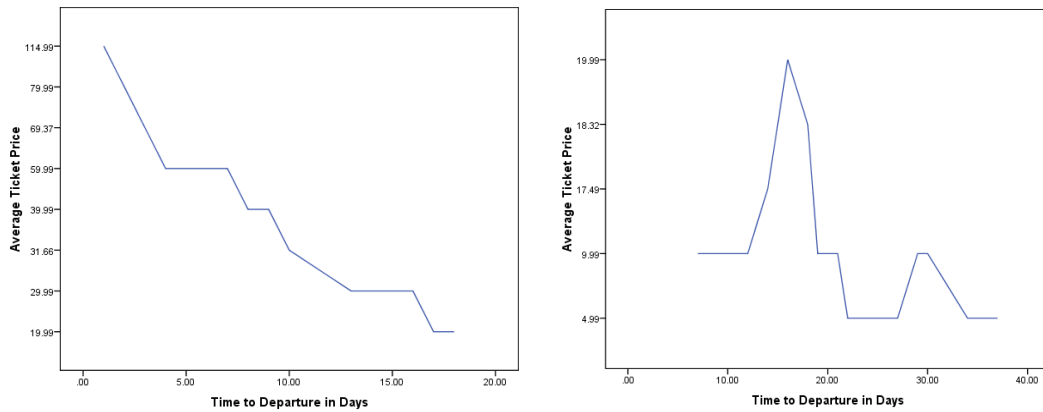
In this section we highlight the nature of price uncertainty across time and across carriers stemming from the revenue management systems in the context of air travel.

Temporal Price Variation

It is commonly believed that tickets purchased in advance are cheaper unless there are any last minute deals.¹¹ In reality, revenue management systems cause pricing patterns that are far more complex than what conventional wisdom leads us to believe. Many firms now limit last minute deals (sometimes offering these through very specialized channels) just because last minute travels tend also to be business travels and hence less price sensitive. To demonstrate this point, Figure 3.1 plots the average posted prices over time for flights operating on two domestic European routes with a set departure date. Figure 3.1 dispels the traditional view that prices always increase as the departure date approaches. In fact, ticket prices do not follow a deterministic trend, making it difficult for consumers to make precise predictions about future prices. Figure 3.1 also highlights that prices may be more volatile for some flights compared to others depending on the particular supply and demand conditions, but that prices do change significantly over time till the departure date. It is this significant price variability over time that could lead consumers in the market for air travel to act strategically.

¹¹ We conducted experiments with 30 MBA students at Yale SOM, and asked them to plot the relation between price and days till departure for flights from New York to L.A. The vast majority of respondents plotted upward sloping graphs as they expected prices to rise closer to the departure date. A few respondents also indicated a drop in prices due to last minute deals.

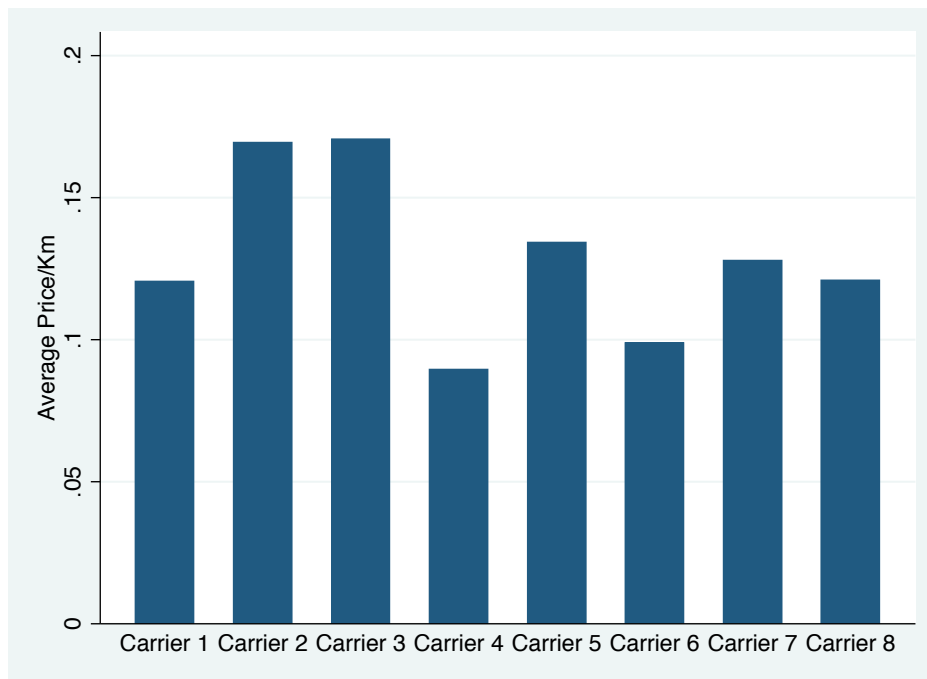
Figure 3:1: Temporal Price Variation



Spatial Price Variation

In addition to the temporal variation in prices, within a given website customers need to resolve the additional uncertainty associated with different carriers offering different prices for the same travel itinerary. Based on the carriers included in our estimation sample we observe that at a given search occasion customers on average observe a standard deviation of 28 Euros for a flight on a particular date on a given route. Figure 3.2 shows the variation in average price (adjusted for distance) across airlines 15 days prior to departure. Despite controls for time to departure and distance we observe that the average price for some carriers is lower when compared to others. Hence, customers who search for air travel online face both spatial and temporal price variation.

Figure 3:2: Average Price/Km for Flights with 15 Days to Departure



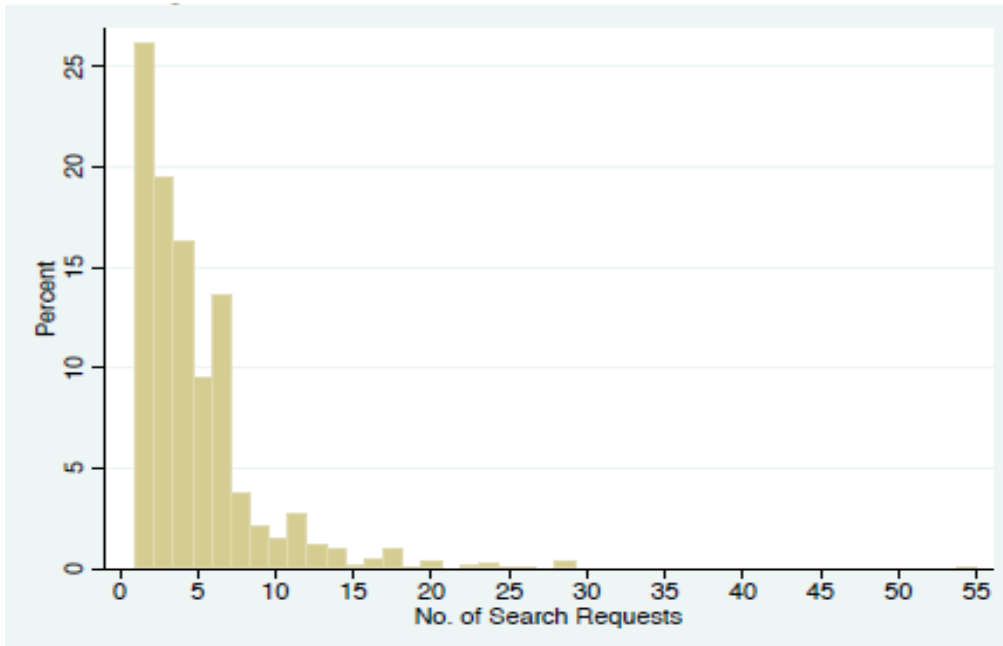
3.3.2 Search Behavior

The data reveals that most site visitors exited or made a purchase after 4.9 search requests. Visitors who made no purchase exited after 3.9 search requests on average while customers who purchased at least once made search 5.2 requests on average (see Table 3.2).

Since we cannot observe the actual time site visitors spent searching we decompose search into search sessions to get a better understanding of how actively customers searched. In line with previous literature on consumer browsing behavior, a new search session begins if a request is made after an idle period of 30 minutes or more (Sismeiro and Bucklin, 2004; Catledge and Pitkow, 1995). Table 3.2 summarizes the search behavior of all visitors and purchasers at the website. Table 3.2 highlights the fact that on average purchasers searched more actively within a session compared to all

visitors. There is also evidence of consumer heterogeneity in the amount of search, while approximately 25% of the sample made 2 search requests, a few customers made more than 10 search requests (see Figure 3.3).

Figure 3:3: Distribution of Number of Search Requests



Visitors in our sample on average started 3 new search sessions, which means that on average customers searched for over 1.5 hours. Within each session customers made 3.87 requests on average. We also find that 50% of repeat search takes place on the same day. The data indicates that customers were aware of the variability in prices and changed dates to find better deals; 70% of the visitors did not change route, while only 7% of visitors did not change dates.

The data also reveals that customers do not always purchase the lowest price option available. Approximately 56% of the purchase occasions consumers purchased at the lowest session price. This is inline with observed industry behavior, according to

Sileo et al. (2011), 60% of airline customers purchase at the lowest price. This pattern highlights the need to focus on pre-purchase behavior to understand how in addition to price sensitivity, the search environment, search effort and flight characteristics influence consumer preferences.

3.4 Modeling Approach

We adopt a flexible modeling approach and use our individual level data on both observed choice sets and search behavior to inform our model of pre-purchase and purchase behavior. At a given search occasion we assume that site visitors are looking for a flight which is a combination of a specific route and travel date. Site visitors are aware of the most suitable flight in terms of flight characteristics and may have carrier preferences but are uncertain about the price and availability. Unlike traditional sequential search models (e.g., Kim et al., 2010) site visitors do not decide whether they will search for an additional carrier, rather consumers are looking to resolve price and availability uncertainty. In addition, site visitors vary in terms of their flexibility for date and route preferences and the amount of search they are willing to undertake. Our random coefficients approach allows us to capture this heterogeneity.

We model a site visitor's decision to make a purchase, as a two-stage process. In the first stage, the visitor has the option to (1) make a purchase, (2) make another search request at the website or another website. The hierarchy of the decision tree is purely analytical; the consumer could make the brand choice decision before deciding to purchase and vice versa.

It should be noted that the two-stage model approach is a modeling preference, which allows us to breakdown the search decision, and product choice decision. We

also tested an alternative one-stage model which models the decision to search vs. purchase while controlling for carrier characteristics via carrier preference dummies. The results of this one stage model are presented in Table 3.8 in the appendix. The results for the key variables are similar to the two-stage model, lending further credibility to our findings. In this chapter we will focus on the two-stage approach even though a binary model of search yields the same results.

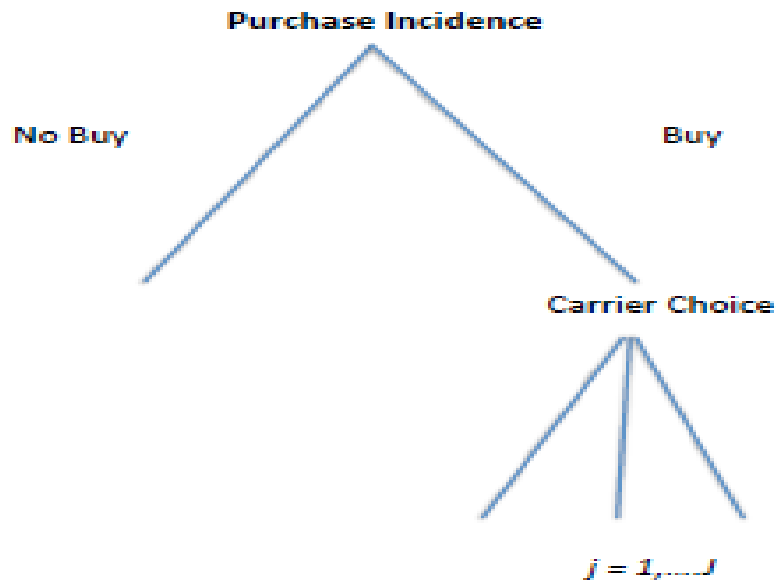
Visitors decide based on the information gathered, future price expectations, search effort and flight characteristics. In the second stage, given the decision to make a purchase, visitors decide which airline to choose. The two-stage decision process can be summarized in Figure 3.4. By jointly estimating the choice and incidence decisions we avoid the problem of endogenous choice sets, as we estimate carrier choice conditional on the decision to purchase. Since, prices in the airline industry change frequently, options searched in one search may no longer be available in the next search, therefore, a consideration set approach is not feasible.

The purchase probability of carrier j at occasion t is given by

$$P_t^h(j) = P_t^h(j|purchase) \cdot P_t^h(purchase) \quad 3.1$$

Whereby, the probability that visitor h chooses carrier j at search occasion t is the product of the probability of purchase incidence and the conditional carrier choice probability. We describe the two stages in greater detail in the following sections.

Figure 3:4: Two Stage Decision Process



3.4.1 Purchase Incidence

At a given occasion t visitor h 's indirect utility of making a purchase is defined as:

$$V_{ht} = U_{ht} + e_{ht} \quad 3.2$$

We assume that the outside option has a utility of zero. Visitors continue searching if the utility from buying now is greater than the utility from postponing purchase (i.e. $U_{ht} < 0$). We further assume the error term e_{ht} has an extreme value i.i.d distribution, which gives us the following closed form expression for the probability of purchase:

$$P_t^h(\text{Purchase}) = \frac{\exp(V_{ht})}{1 + \exp(V_{ht})}$$

Where U_{ht} has the following specification:

$$U_{ht} = \lambda_{h1}IV_{ht} + \lambda_{h2}EIV_{ht+1} + \delta_{ht} + s_{ht} + \gamma_{ht} \quad 3.3$$

The indirect utility of buying now, U_{ht} is based on the category value of purchase IV_{ht} , expected future utility of buying later EIV_{ht+1} , uncertainty δ_{ht} , search effort s_{ht} , and observed heterogeneity γ_{ht} .

Since consumers are looking for the best available flight, the decision to purchase now vs. later depends on the current and future category value. IV_{ht} is the inclusive value parameter which captures the attractiveness of making a purchase based on carrier specific characteristics and price. Formally, $V_{ht} = \ln \sum_j e^{u_{hjt}}$, where u_{hjt} is the deterministic component of the utility of visitor h 's indirect utility of carrier j at occasion t . In addition, we assume a visitor's decision to buy now vs. later depends on his expected future utility. The term EIV_{ht+1} denotes the expected future value of purchasing at occasion $t + 1$. Analogous to IV_{ht} , EIV_{ht+1} is similar to the inclusive value term, except the utility is based on future price expectations. Formally, $EIV_{ht+1} = \ln \sum_j e^{E(u_{hjt+1})}$ we describe the future price expectations in detail in section 3.4.2. We expect current category value to have a positive impact on purchase incidence while higher expected future value is likely to result in a delay in purchase.

We consider the following specification for price and availability uncertainty (δ_{ht})

$$\delta_{ht} = \mu_1^h \sigma_{ht} + \mu_2^h n_{ht} \quad 3.4$$

In line with common practice in the search literature (e.g., Lemieux and Peterson, 2011; Urbany, 1986) we define spatial uncertainty as the standard deviation of

ticket prices for each search request captured by σ_{ht} . While the parameter n_{ht} is the average number of flight options for each carrier displayed to customers after each request.¹² Punj and Staelin (1983) find that the amount of information influences consumer search decisions. We posit that consumers search in order to expand their choice set, therefore, the more options visitors are displayed is likely to affect the amount of search.

A visitor's decision to search may also depend on underlying search costs. In the context of online search for air travel the main search costs include the time spent browsing and the effort involved in changing the search criteria, i.e. changing route and date. Therefore, we account for individual level heterogeneity in search costs by including the following search actions taken by individuals:

$$s_{ht} = \sigma_1^h Sess_{ht} + \sigma_2^h Req_Sess_{ht} + \sigma_3^h \Delta Date_{ht} + \sigma_4^h \Delta Route_{ht} \quad 3.5$$

Search sessions (*Sess*)¹³ allows us to better understand the temporal element of search. Site visitors who allow considerable time to pass between their searches experience temporal price variation. When customers return after thirty minutes the variability in prices may increase the degree of uncertainty and may deter purchase. We therefore expect most purchases to result within a single search session. We use the number of search requests made within a session (*Req_Sess*), as a measure of a visitors involvement in the search process.¹⁴ The more searches made without idle time indicates a high opportunity cost of time and such visitors might have higher costs of search compared to visitors who devote more time to search. We also include variables

¹² We also included the total number of flight options as a covariate, however the average options provide better fit.

¹³ A new search session begins after an idle period of thirty minutes.

¹⁴ Sismeiro and Bucklin (2004) also divide consumer search into similar session in their study of online browsing

capturing whether site visitors changed route or travel dates while searching ($\Delta Date_{ht}$ and $\Delta Route_{ht}$). These variables capture the strategic response of customers to the information displayed during search. We expect casual browsers with low search costs to change their route more frequently as they do not have concrete travel plans, while changing travel dates suggests are indicative of flexible travellers looking for cheaper alternatives and may be willing to devote more time to search.

In addition, individual characteristics, previous experience, environmental variables and time availability have been noted to influence patterns of consumer search (e.g., Urbany et al., 1989; Beatty and Smith, 1987; Lanzetta, 1963). We capture the observed heterogeneity in search behavior by including the following covariates

$$\gamma_{hjt} = \rho_1^h Experience_{ht} + \rho_2^h Trip_{ht} + \rho_3^h Day_Req_{ht} + \rho_4^h OTA_{ht} + \sum_{i=1}^{11} \rho_{5i}^h Route_{hti} \quad 3.6$$

Where:

$Experience_{ht}$	= 1 if prior booking experience within the past (July 2004 till February 2006), 0 otherwise, ¹⁵
$Trip_{ht}$	= 1 if customer is searching for a round trip, 0 otherwise,
Day_Req_{ht}	= 1 if customer searched between 8 a.m and 6 p.m, 0 otherwise,
OTA_{ht}	= 1 if customer was directed from the main travel agency website, 0 otherwise,
$Route_{hti}$	= Dummies indicating route requested
$\rho_1 - \rho_{5i}$	= Parameters to be estimated

¹⁵ We use the bookings database to determine if the customer has made a purchase at the OTA. If the customer makes a purchase for the first time during the period under analysis the variable is updated to 1 for all subsequent search requests.

Observed differences in consumer behavior is a more accurate control for consumer heterogeneity than demographics, as it is likely that customers within a household may exhibit considerable variation in search behavior. Another advantage of our observed heterogeneity variables is the fact that they change over time. For instance, if at one occasion a consumer searches during the day and on the next occasion logs on during the night; we are able to account for such variability in search behavior.

3.4.2 Carrier Choice

At each search occasion the visitor has the option to select between several differentiated airline carriers ($j = 1 \dots 8$). Following principles of utility maximization we expect the flight with the highest utility to be chosen. The total utility from a particular carrier is the sum of the deterministic component and an unobserved component such that:

$$v_{hjt} = u_{hjt} + \epsilon_{hjt} \quad 3.7$$

The unobserved component of utility denoted by i.i.d error term ϵ_{hjt} . Which gives us the following conditional choice probability of carrier j being selected at occasion t .

$$P_t^h(j|purchase) = \frac{\exp(v_{jt}^h)}{\sum_j \exp(v_{jt}^h)}$$

We consider the following specification for flight characteristics which influence consumer's carrier choice:

$$u_{hjt} = \xi_j^h + \beta_1^h P_{hjt} + \beta_2^h Flight_Duration_{hjt} + \beta_3^h Flex_Time_{hjt} \quad 3.8$$

Carrier choice depends on consumers' inherent preference for carriers measured by carrier specific fixed effects ξ_j^h , the average price of the carrier P_{hjt} , and carrier characteristics. We include the average ticket price for each carrier operating on the searched route and date as a measure of expected expenditure in the carrier choice utility. In addition, consumers may select different carriers based on the journey time, to capture this effect we include a measure of the average flight duration for each carrier ($Flight_Duration_{hjt}$).¹⁶ We also include a flight time dummy $Flex_Time_{hjt}$ to capture the convenience of the flight, for instance consumer's might prefer flights during the day as it is easier to commute to the airport, as opposed to flights in early in the morning or late at night. Table 3.3 provides summary statistics for variables used in the model.

We further define the expected future utility at time $t + 1$ as follows:

$$E(u_{hjt+1}) = \xi_j^h + \beta_1^h E(P_{hjt+1}) + \beta_2^h E(Flight_Duration_{hjt+1}) + \beta_3^h E(Flex_Time_{hjt+1}) \quad 3.9$$

We assume that consumers only form expectations regarding prices for the flights they have observed. Therefore, $E(Flight_Duration_{hjt+1}) = Flight_Duration_{hjt}$ and $E(Flex_Time_{hjt+1}) = Flex_Time_{hjt}$, i.e. carrier characteristics do not change across time.¹⁷ Thus, at a given search occasion consumers decide whether they would purchase the available options at P_{hjt} or whether they would wait for $E(P_{hjt+1})$ in the future,

¹⁶The variable is computed, as the total time taken for the journey, for round trips this variable is the sum of the travel time for both legs of the journey.

¹⁷Zhang et. al. (2012) make similar simplifying assumptions regarding feature and display for packaged goods, and only allow consumers to form expectations regarding future prices.

given that flight characteristics remain the same. We outline alternative models of expectation formation in the following section.

3.4.3 Price Expectations

Following Zhang et al. (2012), we model expected future price as a reference price that influences the purchase incidence decision. We assume that visitors expectations of future prices are informed by past experience and information gathered during search. In this respect future price expectations capture consumer response to the temporal variation in prices. We compare three alternative methods of expectation formation; 1) expectations with learning, (2) rising price expectations and (3) hedonic price expectations.

3.4.3.1 Price Expectations with Learning

We assume that consumers search in order to learn about the price process and they update their expected price after every search request t , where $t = 1, \dots, T_h$. T_h denotes the number search requests for each individual.¹⁸ As search progresses consumers update their price expectations such that:

$$E(P_{hjt+1}^{learn}) = \alpha E(P_{hjt-1}^{learn}) + (1 + \alpha)P_{hjt} \quad 3.10$$

For each search request $E(P_{hjt+1}^{learn})$ is computed as the weighted average of the price expectation in the last request and the current price where α is the weight assigned to prior price expectations.¹⁹ Previous research on browsing behavior notes that future browsing behavior is dependent the last decision and not the entire browsing history (see for instance, Montgomery et al., 2004) in line with these finding we model price

¹⁸ It should be noted that price expectations are made for each trip, when a consumer searches a new trip after making a booking t is set to 0. Hence, T_h is the number of search requests made for a particular trip by visitor h .

¹⁹ We use grid search to estimate the optimal value of α .

recall as a first order Markov process. At the initial search request we assume consumers have some beliefs about the price of a ticket based on past booking experience. Since we cannot trace each consumers past bookings, we use the OTA's extensive bookings database to form initial price expectations. We express booking prices as a function of time till departure, seasonality, weekend, routes and carrier specific effects.

$$P_{jt'}^{book} = \omega_0 + \omega_1 \text{Departure}_{jt'} + \omega_2 \text{Weekend}_{jt'} + \sum_{i=1}^{11} \omega_{2+i} \text{Month}_{ijt'} + \omega_{14} \text{Carrier}_{jt'} + \sum_{k=1}^{11} \omega_{15+k} \text{Route}_{kjt'} \quad 3.11$$

Where $t' = 1 \dots T'$ is the occasion at which a booking for carrier j was made. We estimate the coefficient vector based on information on transaction prices for flights booked in July 2004 till April 2006. A total of 145,829 bookings were used to estimate the coefficients of the price equation. The reference price for each user at the first search occasion is taken as the predicted value ($E(P_{hj1}^{learn}) = \widehat{P}_{j1}^{book}$). The initial price expectation allows customers to have a prior belief about the prices before they begin the search process.²⁰

3.4.3.2 Rising Price Expectations

It is a common belief that airlines charge higher prices for tickets purchased only a few days prior to departure as the demand for these customers is relatively inelastic (Carlton and Perloff, 2005) and the cheapest seats are the ones to be sold first (Pender and Baum, 2000). To incorporate these rising price expectations we assume that consumer expectations are drawn from a truncated normal distribution, where the truncation point is set as the current price for each carrier observed by the visitor.

²⁰ Predicted prices were also used to define the initial price expectation for the first time a carrier appeared in search results. For instance, if carrier 2 appeared for the first time on search occasion 3, the initial price expectation is defined by the predicted value.

$$E(P_{hjt+1}^{rise} | P_{hjt}) = f(\overline{P_{hjt}}, \sigma_j, P_{hjt}) \quad 3.12$$

Where:

$$f(\overline{P_{hjt}}, \sigma_j, P_{hjt}) = \frac{\phi(\overline{P_{hjt}}, \sigma_j^2)}{1 - \phi(P_{hjt}, \sigma_j^2)}$$

At every occasion consumers expect prices to increase in future, such that $E(P_{hjt+1}^{rise}) > P_{hjt}$.²¹ It should be noted that while consumers expect prices to increase in future, they are sophisticated enough to adjust their price expectations downwards if they see a decline in the price. For instance, if a visitor saw a price of \$50 at occasion $t = 1$, he would expect that at $t = 2$ the expected price would be greater than \$50, i.e. $E(P_{hj2}^{rise}) > \$50$. However, if at $t = 2$ the observed price was \$30, the visitor will adjust his expectation such that $E(P_{hj3}^{rise}) > \$30$. For each carrier the moments of the distribution were based on the mean of all searched prices and the standard deviation in observed prices.²²

3.4.3.3 Hedonic Price Expectations

Models of consumer search often assume that consumers know the distribution of prices prior to search (e.g., Kim et al., 2010; Weitzman, 1979). We test the validity of such hedonic price expectation in our empirical model. We assume that visitors have prior knowledge about the relation between price and flight attributes based on their past booking experience. Using past booking prices we predict expected prices. Based on based on the relation between prices and flight characteristics (prices time till

²¹Koulayev (2010) makes a similar assumption regarding price expectations for ordered search results for hotels. In Koulayev's (2010) model consumers cannot observe the prices on the second page, therefore, they make an assumption regarding the prices on the next page of results, before deciding whether to click or not.

²² We used the extensive bookings database to compute the moments but did not find any statistical difference between the two measures.

departure, seasonality, weekend, routes and carrier specific effects) consumers can determine the expected future price of the flights they have observed in the current search request.

$$E(P_{hjt+1}^{rational}) = \widehat{P}_{jt}^{book}(Departure, Weekned, Month, Carrier, Route)$$

3.13

3.4.4 Estimation

We use a hierarchical Bayesian approach to simultaneously estimate the incidence and choice models. We use the Markov Chain Monte Carlo (MCMC) sampling to generate draws from the posterior densities of model parameters. For the random coefficients distributions, we use the normal distribution as the prior and the inverse Wishart distribution for the variance. Our choice of hyper parameters is based on weak priors allowing the data to drive the results. The simultaneous estimation approach ensures that covariance is allowed among the incidence and brand choice parameters. We use 10,000 iterations for burn in and an additional 1,000 iterations to determine the posterior distribution of parameters.

3.4.5 Endogeneity

The error term ϵ_{hjt} in the carrier choice equation (eq. 3.7) may contain unobserved factors that influence prices and consumer choice. The presence of endogeneity can seriously bias estimates of discrete choice models (see Andrews and Currim, 2009), for a discussion of the importance of accounting for endogeneity in disaggregate multi stage models of demand). In the case of airlines, factors like seasonal demand or fuel price hikes might affect the price, while these factors would have been observed by air carriers when setting price, the researcher needs to account for the impact of these unobservables on price. Another source of endogeneity could be that the

error term includes flight characteristics such as the choice of the airport, which may be positively correlated with the price variable due to factors like airport taxes. We use a two stage instrumental variable approach; in the first stage we regress P_{hjt} on a set of instruments Z_{jt} and flight characteristics X_{jt} i.e.,

$$P_{hjt} = \phi_{0j} + \phi_{1j}Z_{hjt} + \phi_{2j}X_{hjt} + v_{hjt} \quad 3.14$$

The instrument Z_{hjt} is the mean price of all other available carriers, while X_{hjt} included flight characteristics not been included in the final choice model to account for any omitted variable bias. X_{hjt} includes weekend dummy, days till departure, journey distance month and route dummies.

In the second stage the predicted price \widehat{P}_{hjt} is inserted in equation 3.8, such that the carrier choice utility is defined as:

$$u_{hjt} = \xi_j + \beta_1^h \widehat{P}_{hjt} + \beta_2^h Flight_Duration_{hjt} + \beta_3^h Flex_Time_{hjt} \quad 3.15$$

The predicted price is free form any endogeneity bias arising from the correlation between unobserved factors and the error term. Ours is one of the few papers that accounts for endogeneity in multi-stage decision models.

3.5 Empirical Results

In this section we report the main empirical findings and compare the predictive ability of the proposed model. We estimate several alternative benchmark models to arrive at the best fitting model. We estimate a base model with no search, alternative specifications of the price expectation function (constant reference prices, expectations with learning, rising price expectations, hedonic expectations), a model calibrated on the entire sample of site visitors and a model calibrated on a sub sample of purchasers.

Table 3.4 presents a comparison across the various model specifications. In addition, we also test an alternative one-stage model with carrier intercepts to test the robustness of our two-stage model. The results of the one stage model are included in the appendix and we find no significant difference in the findings from the one stage model.

Comparison of in sample fit based on Bayesian Information Criterion (BIC) across the three expected price specifications suggests that the model with consumer learning best explains the observed search behavior. The weight attached to current session prices (α) was estimated as 0.7, indicating that consumers give more weight to current prices when forming expectations. It is not surprising that the model with price expectations based on the value of product attributes is the worst performing in terms of fit. Due to the uncertain prices in the airline industry, prices seldom conform to straight forward price rules, therefore, expectations that link future prices to flight characteristics is the least accurate model.

Comparison of the base model and the full search models highlights that ignoring consumer pre-purchase behavior results in poor in sample fit and an underestimation of the impact of price (see Table 3.4). To check the robustness of our results we re-estimate the full search model on a subset of purchasers. Due to the differences in sample size we cannot directly compare the purchaser only and visitor model, therefore, we conduct tests of predictive ability of the two models in hold out samples.

Out of Sample fit

To test the out of sample predictive ability of our proposed model we use the data on consumer search from February and April 2006. The hold out sample includes

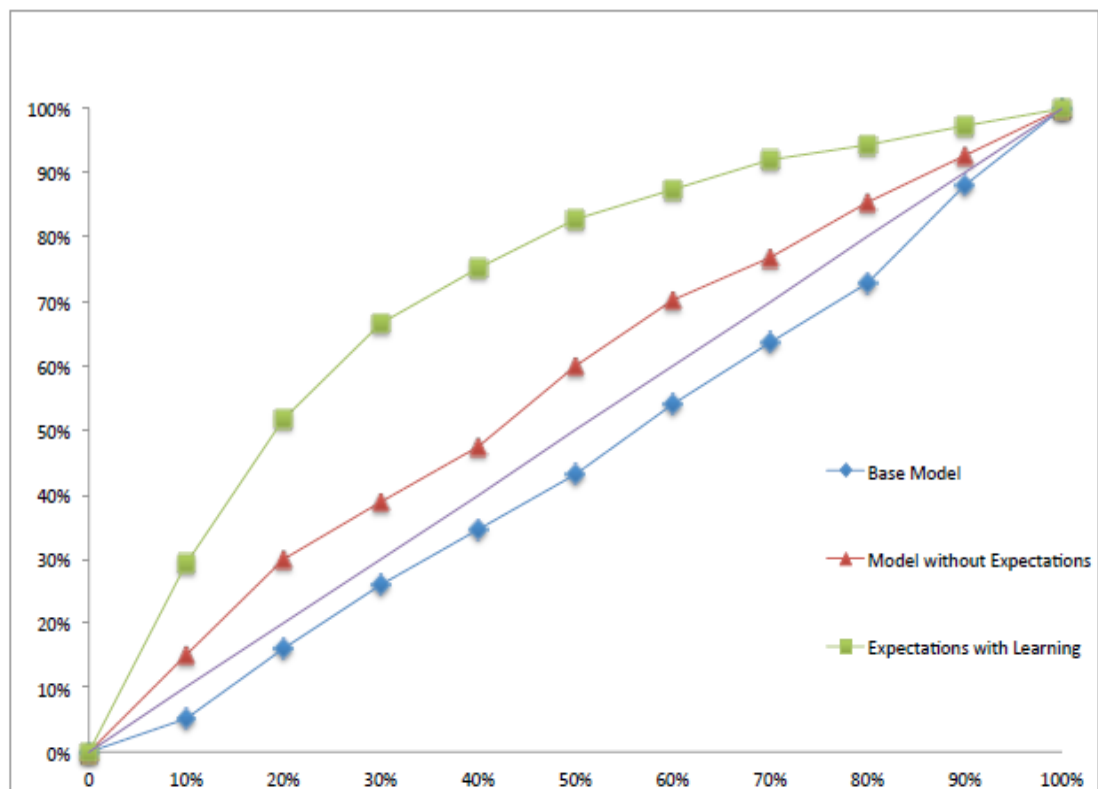
2,840 search requests and 757 purchases generated by 1,126 site visitors. Table 3.5 presents a summary of the predictive accuracy for the hold out sample. According to Table 3.5, the full search model calibrated on all site visitors correctly predicts purchase incidence approximately 78% of the time, while the model calibrated on purchasers has a hit rate of 58% and the model without search is the worst performing with a hit rate of 28%. Similarly, the visitor model is more accurate than the purchaser model in predicting purchase incidence compared to the base model and the model calibrated on a subset of purchasers.

Based on out of sample hit rates we conclude that the full model (including both purchasers and visitors who do not make a purchase), has greater predictive power. The superior predictive ability of our preferred model highlights that the behavior of non-purchasers contains valuable information, which can enable firms to better predict purchase incidence. Ours is the first studies to suggest that in the absence of data on non-purchasers only a conditional analysis of consumer pre-purchase behavior can be performed.

We further test the ability of our proposed model to accurately target customers. Figure 3.5 presents lift charts for the full search model (model with learning), model without future price expectations and the base model. To create the charts we sorted the purchase probabilities for all holdout visitors, as predicted by the models. We took the 10% of all (holdout) visitors with the highest predicted probability and predicted how many would make a purchase. This procedure was then repeated for 20% of the visitors, 30%, and so on. We then plotted the fraction of online purchases that each model would have been able to capture at different targeting percentages. Our proposed modeling approach, the full search model, outperformed both the base model and the model

without future price expectations in terms of lift. The lift lines corresponding to the full search model outperform the other specifications. Figure 3.5 shows that by targeting the best 30% of all holdout web site visitors we are able to capture about 67% of online buyers if we use the full search model. The base model performs poorly and only captures 26% of buyers. This suggests that including search in the model is essential to accurately predict consumer behavior. We find further evidence that consumers form future price expectations, as the model without future category value only captures 57% of online buyers.

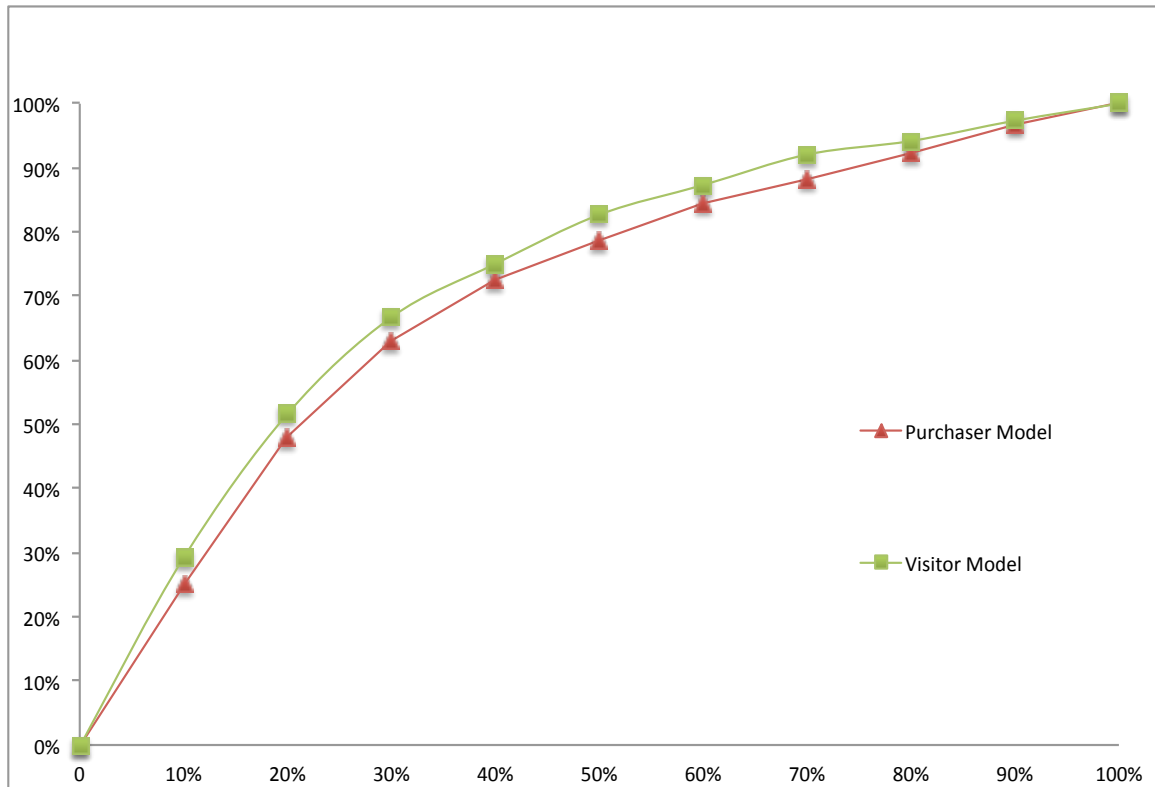
Figure 3:5: Lift Charts for Purchase Prediction (Comparison of Model with Search and Without Search)



Similarly, we find that casual site visitors contain valuable information that can help inform web site managers to better target customers. Figure 3.6 compares the

performance of the proposed model estimated on all site visitors and a purchaser only sample. Again the model calibrated on all site visitors performs better than the conditional purchaser only model.

Figure 3:6: Lift Charts for Purchase Prediction (Comparison of Model calibrated on Purchasers and Visitor)



In the following sub sections we present an overview of the main results for purchase incidence and carrier choice based on the full search model with learning.

3.5.1 Purchase Incidence

The final estimates and confidence intervals for the preferred model are presented in Table 3.6 column 2. Overall the estimated parameters have the expected signs. Visitor actions are significantly impacted by current and future category value. When consumers expect higher future utility they are likely to forgo purchase on the

current search occasion. On average we find that consumers current category attractiveness measured by the inclusive value parameter has an estimated coefficient of 1.04 while future category attractive has a coefficient of approximately -0.10. This suggests that a decline in current prices have a greater impact on current purchase incidence compared to an equally large discount in the future. This behavior is consistent with theories of discounted utility, as consumers value a gain at present more than a gain in the future.

In concurrence with the widely accepted view that consumers search more in the presence of uncertainty (e.g., Lanzetta, 1963; Urbany et al., 1989), the negative coefficient for standard deviation in observed prices indicates that consumers tend to search more when there is greater spatial variation in prices. Despite the control for the number of available flight options, variance in prices encourages search to reduce uncertainty.

While customers are averse to the variation in prices, greater variety reduces the need to invest time in search as visitors feel more confident regarding their purchase decision. Brehm (1972) notes that larger assortments might influence preferences by creating a perception of freedom of choice that could reduce uncertainty regarding availability of options. Another possible explanation could be the “variety effect”, whereby, consumers obtain additional utility from a large choice set which makes them more likely to make a purchase (Ratner et al., 1999; Broniarczyk et al., 1998; Kahn et al., 1987). This finding is consistent with search theory as the ability to sample a large number of products at the same time would resolve uncertainty and reduce the duration of search as the primary motivation for search is to resolve uncertainty.

Our results also suggest that search effort is an important determinant of purchase incidence. We find that the number of 30 minute search sessions started by a visitor has a negative impact on purchase incidence. This is an interesting finding which suggests that customers who return to the website repeatedly over time may have low search costs and spend more time searching. We regard this as proclivity for temporal search. However, the number of searches within a session has a positive impact on incidence. This implies that repeated searches within a short span of time are evidence of targeted information gathering, we regard such behavior as evidence of spatial search. Furthermore, the search actions taken while searching also determine purchase incidence. Date changes appear to be indicative of serious purchase intent as visitors appear to alter travel plans to find better prices. On the other hand, visitors who frequently change their destination appear to be casual browsers without concrete travel plans and are less likely to purchase. Comparing the magnitude of the effect of route and date changes we find that date changes have a larger impact on purchase incidence than route changes.

We contend that spatial search is reflective of visitors with high search costs, while temporal search is a characteristic of visitors with low search costs. This is a powerful result for OTA's who can improve purchase conversion by targeting visitors engaged in active spatial search.

Our results suggest that search behavior is affected by observed consumer heterogeneity. Customers searching for round trips tend to search more as they spend time finding the best flight option for both legs of the journey. While customers directly visiting the OTA are less likely to book a flight, perhaps customers are more confident about purchase decisions when they are directed from price comparison websites. The

dummy for search during the day is positive and significant; this implies that customers with serious purchase intent log on during the day (between 8 am and 6 pm). This is valuable information for OTAs; by introducing price variation across times of the day OTAs could take advantage of the difference in purchase incidence by timing of search. In line with Nair et al. (2010a) we find that prior purchase behavior at a site is a determinant of current purchase; consumers with previous purchase experience at the website are more likely to purchase again, hence site loyalty is an important determinant of purchase incidence.²³

We also tested the impact of time till departure on search behavior, but found no evidence that customers are affected by the time constraint. This suggests that customers normally start search when they are certain about their travel plans and there is no evidence that customers who start searching in advance will search more than customers who begin search closer to the date of departure.

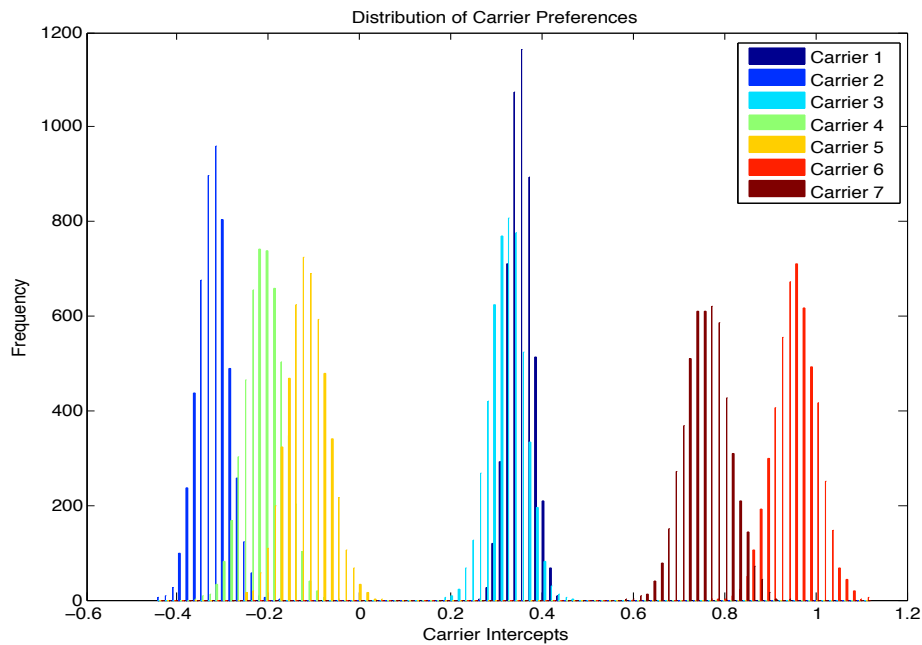
3.5.2 Carrier Choice

There is considerable variation in the estimates for the carrier dummies, this implies that some airlines are preferred over others; Figure 3.7 shows the distribution of consumer preferences for the various carriers. Carriers 2, 4 and 5 were generally quite unpopular amongst site visitors while Carrier 6 and 7 are normally preferred. This suggests consumers place great importance to carrier quality in addition to price and other observed flight characteristics.

²³ In line with earlier studies of revenue management, which suggest that airline customers normally fall into two categories, business and leisure (e.g., Dana, 1998), we tested for the impact of trip type on purchase incidence, but found no difference in search patterns across the two groups. We specifically tested whether the behavior of leisure customers (i.e. customers searching for flights on weekends and customers traveling with children), behaved differently from business travelers. However, we found these variables to be insignificant and were dropped from the final model. Number of passengers also did not influence search behavior.

In accordance with our expectation, when prices are high there is a greater financial risk associated with purchase, hence customers are less likely to purchase when prices are high (Punj and Staelin, 1983). Comparison of the price coefficient across various models in Table 3.6 reveals that consumer price sensitivity is underestimated when search is not modeled. While the coefficient on price is positive but insignificant in the purchaser only model highlighting the fact that including all site visitors in the estimation sample improves model reliability.

Figure 3:7: Distribution of Carrier Intercepts



We also find that customers prefer short journey times as indicated by the negative coefficient on the flight duration parameter. However, carriers with arriving and departing flights operating during different timings of the day are not preferred.

3.6 Conclusion

We present a joint analysis of consumer search and purchase behavior for a product categorized by high levels of price uncertainty. Complex revenue management

pricing algorithms introduce uncertainty in prices across time and across airlines, as a result consumer search behavior in such dynamic environments is likely to differ from behavior in more stable industries. However, little is known about the impact of revenue management pricing on consumer behavior. Ours is one of the few studies that attempt to understand the impact of this spatio-temporal price uncertainty on consumer purchase behavior. We apply a flexible modeling approach to a rich data set on the browsing and purchase behavior of a large panel of customers visiting a leading European OTA. Our two stage model of incidence and choice uses covariates based on information gathered and consumer actions at the website to answer how consumers cope with the significant price uncertainty, how consumers form their expectations, and how search effort impacts purchase.

Our dynamic two stage model confirms that uncertainty results in greater search, we find that spatial price variation makes visitors less confident about the purchase decision resulting in greater search, while the more options available to customers the more confident they are about the decision and less time is spent searching. In order to cope with this price uncertainty forward-looking consumers use observed prices to dynamically update their price expectations. These price expectations in turn determine the anticipated future utility of travel options. When expected future value is high consumers are more likely to wait and continue searching, however, when expected future value is low consumers are more likely to make a purchase. However, in line with theories of discounted utility visitors place greater value on current utility compared to future utility. Consumer search costs as reflected by the investment in search effort are also important determinants of purchase incidence. In line with existing studies (e.g., Moe and Fader, 2004), consumers are more likely to make a purchase the

more actively they search, however, once customers exit the website there is a lower chance of making a purchase on subsequent visits. Customers who change dates frequently are more likely to purchase at the website while customers who change routes do not exhibit serious purchase intent. Our detailed data coupled with a flexible modeling approach allows us to account for heterogeneity in customer behavior as well as possible endogeneity. Our empirical results also highlight that the behavior of non-purchasers includes important information that can help improve purchase conversion. In the context of online search for travel related products, ours is one of the first studies to highlight the need to incorporate visitors who do not purchase in a model of search. Tests of out of sample predictive power conclude that the full search model calibrated on all site visitors has greater predictive power compared to models estimated on a sample of purchasers.

Our within site analysis of consumer information search has managerial relevance for OTAs in particular and online businesses in general. While researchers are often limited by the availability of data, OTAs have access to detailed browsing and purchase data. OTAs can use their extensive database to incorporate the search behavior of non-purchasers to better predict purchase incidence as proposed by our research. In addition to improvements in prediction, managers can use our findings to identify the determinants of a consumer's decision to continue or abandon search. We find that consumers are less likely to purchase in the presence of price variation across carriers, OTAs could alter the flights displayed to customers to reduce the price variation across carriers. From a website managers perspective improvements in forecasting and even small increments in purchase conversion can result in considerable growth in sales revenues.

Furthermore, our findings regarding frequency of search have important implications for OTAs. Our results suggest that consumers who actively search within a short span of time are more likely to purchase while purchase likelihood declines when customers resume search after a thirty-minute interval. Currently, OTAs do not target customers while they are actively browsing, instead follow up emails and weekly newsletters with special offers are sent to encourage repeat visit. According to our findings conversion rates can be improved if websites take measures to increase customer involvement during the time they are actively searching. For instance, OTA could display special offers or recommend flights to customers who frequently change their travel dates. Since travel is not an impulse purchase, customers start active search once they are certain of their plans, therefore targeting active customers could be more profitable for OTAs than sending weekly email alerts to all customers.

Our study has certain limitations. Our existing analysis focuses on a single product category, however OTAs sell several complimentary product categories. It would be insightful to explore how consumer search influences basket choice decisions. While Nair et al., 2010) study consumer basket choice across travel portals, their analysis is limited as they do not observe the impact of prices observed during search. Future research could incorporate basket choice in a multi-stage model of within site search. Another limitation of the present study is the lack of information regarding consumer behavior at competitor sites. By augmenting the existing data set with details on consumer behavior at other sites, a more holistic model accounting for both within and across site search could be calibrated.

List of Tables

Table 3:1: Prices and Market Share Across Airlines

Carrier	Frequency of Availability	Average Price	Market Share %
Carrier 1	4,022	123.49	15.74
Carrier 2	718	100.42	4.05
Carrier 3	1,593	128.73	5.93
Carrier 4	721	57.17	5.04
Carrier 5	9,861	134.67	24.09
Carrier 6	5,179	117.69	25.55
Carrier 7	856	100.46	4.24
Carrier 8	6,544	131.25	15.35

Table 3:2: Summary of Search Behavior

	All Visitors		Purchasers only	
	Mean	Std. Dev	Mean	Std. Dev
Search Requests	4.90	3.81	5.22	4.01
Search Sessions	3.04	2.32	3.58	2.44
Requests per Session	3.87	2.96	4.14	3.07
Date Changes	2.67	3.32	3.64	3.39
Route Changes	0.48	1.23	0.57	1.37
Purchases	2.76	3.30	3.76	3.33

Table 3:3: Summary Statistics for Covariates

Variable	Mean	Std. Dev	Min	Max
Standard dev. in Prices	24.20	30.41	0	866
Flight Options	2.36	1.13	1	15
Days to Departure	13.36	8.67	1	31
Price	125.45	56.47	18	975
Flight Duration	2.39	0.83	1	5
Day Flight	0.20	0.40	0	1
Previous Experience	0.08	0.50	0	15
Round Trip	0.58	0.49	0	1
Day Request	0.58	0.50	0	1
OTA	0.15	0.36	0	1

Note: All search effort variables are presented in Table 3.2

Table 3:4: In Sample Performance

	Hedonic Expectations	Rising Price Expectations	Expectations with Learning	Sample of Purchasers	Base Model
Log-Likelihood	-44,122.00	-44,079.00	-44,045.00	-43,337.00	-47,355.00
BIC	-44,288.70	-44,245.70	-44,211.70	-43,176.07	-47,433.45
Parameters	34	34	34	34	16
Observations	18,136	18,136	18,136	12,917	18,136

Note: Due to the fewer number of observations in the sample of Purchasers, the model calibrated on Purchasers is not comparable to the models calibrated on all site Visitors. We conduct out of sample tests to compare the predictive ability of the model calibrated on Purchasers and all site Visitors.

Table 3:5: Out of Sample Hit Rate

	Base Model	Full Search Model – All Visitors	Full Search Model – Purchasers Only
Purchase Hit Rate (%)	26.76%	80.30%	37.30%
Overall Hit rate (%)	27.46%	77.68%	57.99%

Note: We use a 0.5 probability cutoff, i.e. a purchase is predicted when the probability is at least 0.5

Table 3:6: Comparison of Full Search Model and Benchmark Models

	Base Model -No Search (1)	Full Search Model – All Visitors (2)	Full Search Model – Purchasers Only (3)
Incidence Parameters			
Inclusive Value	0 .726 [0.7253, 0 .7266]	1.043 [1.0377, 1.0469]	0.9 58 [0.9512, 0 .9653]
Expected Future Value		-0.097 [-0.1014, -0.0924]	-0.155 [-0.1608, -0.1478]
Standard Dev. in Prices		-0.045 [-0.0500, -0.0401]	-0.059 [-0.0670, -0.0505]
Flight Options		0.609 [0.6049, 0.6140]	0.626 [0.6187, 0.6343]
Requests per Session		0.082 [0.0778, 0.0876]	0.136 [0.1271, 0.1444]
Search Sessions		-0.166 [-0.1700, -0.1605]	-0.163 [-0.1719, -0.1555]
Date changes		0.217 [0.2127, 0.2211]	0.059 [0.0518, 0.0669]
Route changes		-0.060 [-0.0640, -0.0552]	-0.039 [-0.0464, -0.0315]
Previous Experience	0.867 [0.8657, 0.8673]	0.069 [0.0645, 0.0730]	0.101 [0.0937, 0.1084]
Round Trip	0.011 [0.0098, 0.0114]	-0.326 [-0.3308, -0.3215]	-0.051 [-0.0589, -0.0431]
Day Request	-0.655 [-0.6553, -0.6539]	0.105 [0.1007, 0.1094]	0.105 [0.0974, 0.1120]
OTA	0.067 [0.0661, 0.0676]	-0.073 [-0.0778, -0.0692]	-0.057 [-0.0648, -0.0495]
Intercept	1.283 [1.2825, 1.2836]	-2.575 [-2.5790, -2.5706]	-1.448 [-1.4540, -1.4406]
Choice Parameters			
Price	-0.001 [-0.0020, 0.0004]	-0.011 [-0.0177, -0.0040]	0.0 04 [-0.0095, 0.0170]
Flight Duration	0.022 [0.0209, 0.0224]	-0.300 [-0.3053, -0.2954]	-0.450 [-0.4578, -0.4416]
Day Flight	-0.084 [-0.0845, -0.0828]	-0.115 [-0.1202, -0.1097]	-0.106 [-0.1140, -0.0973]

Note: In the interest of space we exclude the Route dummies and Carrier intercepts from the table. 95% confidence interval reported in [].

3.7 Appendix

Table 3:7: One Stage Demand Model

	Full Search Model with logit specification – All Visitors
Expected Future Value	0.005*** [0.0034, 0.0072]
Standard Dev. in Prices	-0.028*** [-0.0310 -0.0250]
Flight Options	0.778*** [0.7076, 0.8487]
Requests per Session	0.082*** [0.0778, 0.0876]
Search Sessions	-0.231*** [-0.2693, -0.1930]
Date changes	0.406*** [0.3749, 0.4379]
Route changes	-0.123*** [-0.1850, -0.0614]
Previous Experience	0.067*** [-0.0368, 0.1717]
Round Trip	-0.129 [-0.5822, 0.3234]
Day Request	0.105** [0.1007, 0.1094]
OTA	-0.123 [-0.2728, 0.0263]
Price	-0.011*** [-0.0135, -0.0086]
Flight Duration	-0.422 [-0.3053, -0.2954]
Day Flight	-0.184 [-0.3473, -0.0198]
Carrier 1 Dummy	1.312*** [1.0620, 1.5624]
Carrier 2 Dummy	1.045*** [0.5564, 1.5335]
Carrier 3 Dummy	1.645*** [1.1413, 2.1487]
Carrier 4 Dummy	1.447*** [0.9297, 1.9634]
Carrier 5 Dummy	1.086*** [0.7929, 1.3788]
Carrier 6 Dummy	0.939*** [0.7488, 1.1297]
Carrier 7 Dummy	1.909*** [1.5391, 2.2796]
Carrier 8 Dummy	0.569 [0.3917, 0.7453]
Intercept	-4.855*** [-5.7799, -3.9297]
Log likelihood	-9,010.837

Note: Route dummies excluded from the table in the

4 How do Customer Characteristics Impact Behavior Based Price Discrimination? An Experimental Investigation

4.1 Introduction

Customer recognition is widely prevalent today. Purchase behavior is recorded across several competitive industries ranging from air travel, financial services, and utilities to online retailers. Customer recognition technologies have enabled firms to distinguish customers based on their purchase histories, allowing for personalized marketing and targeted pricing. Such price discrimination based on past purchase behavior is regarded as “behavior-based price discrimination” (BBPD).

In light of the popularity of BBPD, a growing body of literature has emerged (see Fudenberg and Villas-Boas, 2006, for a comprehensive review of models of BBPD). According to Esteves (2009), extant literature on BBPD is primarily concerned with two questions: Firstly, what are the profit and welfare implications of BBPD in competitive markets? Secondly, when is price discrimination profitable? There is a general consensus in the literature that personalized pricing in the presence of competition leads to intensified competition and a decline in profits (e.g., Zhang, 2011; Esteves, 2010; Musalem and Joshi, 2009; Ulph and Vulkan, 2000; Shaffer and Zhang, 1995). Despite the academic evidence rendering BBPD unprofitable, we observe widespread price discrimination based on customer history across competitive industries

(e.g., subscriptions markets, retail and utilities). Another prominent theme in the literature suggests that in competitive markets the dominant strategy is to offer discounts to poach competitor's customers and extract profits from existing customers (e.g., Esteves, 2010; Pazgal and Soberman, 2008; Villas-Boas, 2004; Fudenberg and Tirole, 2000; Villas-Boas, 1999). Examples of such acquisition strategies are easy to find, for instance, it is common for insurance companies to charge high renewal rates to existing customers and offer low sign up rates to new customers. However, we also observe customer recognition being used to give preferential treatment to existing customers. For instance, supermarkets use the vast amount of loyalty card information to offer rewards to existing customers. Such differences in pricing strategies across competitive markets raises concerns regarding the practicality of theoretical models of BBPD.

While theory concerning BBPD is sophisticated and well developed, there is a lack of empirical validation of predictions. Likewise, there is limited understanding of the behavioral mechanisms that drive the pricing behavior we observe in real markets. A large number of existing studies on BBPD are based on restrictive assumptions like customer homogeneity and preference stability. These assumptions may not hold in real markets. For instance, it is well established that customers are heterogeneous in terms of the value they generate. The 80/20 rule is commonly applied to segment customers, as a small group of customers often generate greater value for businesses than the large majority of customers (Schmittlein et al., 1993). Similarly, studies on consumer behavior suggest that consumer preferences are labile and can change over time. For instance, a customer may like Coca Cola but over time he may prefer Pepsi. While Kahn et al. (1986) suggest customer preferences shift at random and mimic markov

processes, other researchers note that preference shifts occur due to environmental factors, cuing (e.g., Frederick et al., 2009; Wang et al., 2009) and product attributes (e.g., Bawa, 1990; Lattin, 1987; McAlister and Pessemier, 1982).

Preference stochasticity has received some attention in the literature on BBPD. Caminal and Matutes (1990) and Fudenberg and Tirole (2000) are amongst the few studies that consider the impact of stochastic preferences on BBPD, however, their assumption of preference independence across time does not provide a realistic depiction of consumer behavior. Chen and Percy (2010) account for this shortcoming, the authors rationalize both loyalty and switching incentives as functions of stochastic yet correlated preferences and price commitment. They find that given future price commitment, rewarding loyalty is a dominant strategy only when preferences change over time.

Another notable exception is Shin and Sudhir (2010), the authors extend models of BBPD to include both preference stochasticity and value heterogeneity. Shin and Sudhir (2010), find that in the presence of preference stochasticity¹ and customer heterogeneity, a customer retention strategy will be adopted, whereby, high value existing customers are offered low prices. In the absence of these conditions it is in the firm's interest to adopt a customer poaching strategy.

Building on the recent theoretical advances in the literature on BBPD, this chapter empirically tests the impact of *preference stochasticity* and *value heterogeneity* on pricing strategies when customer recognition is possible. We aim to contribute to the understanding of the interaction between customer characteristics and the decision to

¹ It should be noted that preferences across the two periods are correlated such that observing a customer's Period 1 provides some indication of the possible future preferences.

price discriminate based on purchase history. We conduct the first experimental study that tests whether preference stochasticity and heterogeneity provide the requisite conditions for loyalty rewards. Given the difficulty of observing customer characteristics in secondary data, our controlled laboratory experiment simulates a dynamic two period market with customer recognition, while simultaneously allowing for value heterogeneity and stochastic brand preferences. An experimental setting is particularly suited,² as it controls for confounding factors (e.g., differences in willingness to pay, asymmetric information, differences in costs of production), facilitating the determination of causal factors in isolation and providing internal validity.

Laboratory experiments have a long tradition of studying price competition (e.g., Morgan et al., 2006; Baye and Morgan, 2004; Dufwenberg and Gneezy, 2000; Abrams et al., 2000). Existing experimental studies on price discrimination find that sellers discriminate between customers when given the option (e.g., Shaw and Vulkan, 2012). Furthermore, there is experimental evidence suggesting that price discrimination in competitive markets can be efficient (Bayer, 2010). However, existing experimental studies on price discrimination do not consider the possibility of customer recognition through repeated interaction between buyers and sellers. Mahmood and Vulkan (2013) is a notable exception, and experimentally investigates the role of market structure and information on BBPD. Our study is also related to experiments on price competition in spatial markets (e.g., Orzen and Sefton, 2008; Selten and Apesteguia, 2005).

² Experimental studies are increasingly being used to better understand competition and pricing in oligopolistic markets (e.g., Dufwenberg and Gneezy, 2000; Grether and Plott, 1984).

Our results suggest that sellers choose to price discriminate when given the option. Participants discriminate in 79% of the pricing decisions and in line with extant literature, price discrimination results in a customer acquisition strategy. However, the difference in prices to existing and new customers is influenced by customer characteristics. While customer heterogeneity intensifies competition and increases price discrimination, preference stochasticity softens competition and reduces discrimination. Similarly, aggressiveness in pricing also varies with customer characteristics; the highest premium is charged when heterogeneous customers have stable preferences, followed by homogenous customers with stable preferences, in contrast, when customers switch exogenously the difference in price to existing and new customers declines. Furthermore, when preference stochasticity is combined with value heterogeneity, we observe the smallest difference in the prices offered to existing and new customers, indicating that exogenous customer switching has a greater impact on pricing strategy compared to value heterogeneity. We also find evidence of loyalty amongst buyers and an aversion for add on charges.

The behavior of experimental subjects highlights that differences in observed pricing strategies across industries could be attributed to differences in customer characteristics. For example, in the case of utilities, customer preferences are fairly stable over time; as a result companies offer better rates to new customers who sign up. While in the airline industry, preferences are mobile and similar incentives are offered to existing and new customers.

The remaining chapter is organized as follows. Section 4.2 outlines the testable hypotheses emerging from extant literature. Section 4.3 presents the experimental

design and procedures. Section 4.4 analyses the key results of the experiment and Section 4.5 outlines the main conclusions of the study.

4.2 Testable Implications

In this section we outline hypotheses regarding the interaction between preference mobility and customer heterogeneity derived from two period dynamic duopoly models of behavior based price discrimination.

H1: Price discrimination results in lower prices and profits in Period 2

$$P_1 > P_2 \Rightarrow \pi_1 > \pi_2$$

A dominant theme in the literature on BBPD suggests that customer recognition results in intensified competition between sellers in Period 2 (e.g., Zhang, 2011; Esteves, 2010; Musalem and Joshi, 2009; Ulph and Vulkan, 2000; Shaffer and Zhang, 1995). Since the competitive effects of price discrimination outweigh the surplus extraction effect, we expect prices and profits to decline over time.

H2: Prices and Profits vary with customer characteristics

$$P^{\text{Mobility}} > P^{\text{Het. \& Mob.}} > P^{\text{Heterogeneity}}$$

We expect pricing behavior to vary with customer characteristics. Stochastic preferences are likely to have a competition softening impact as exogenous customer switching eases the pressure on sellers to offer large discounts to induce customer switching (see Shin and Sudhir, 2010). As a result we expect prices to be higher with preference mobility, compared to the case with homogenous customers and stable preferences. In contrast, when buyers are heterogeneous but preferences are stable, we expect an increase in competition as sellers offer discounts to attract high type

customers. On the other hand, when customers are heterogeneous and preferences are mobile, the two effects work in opposite directions; while sellers compete to attract the high type customers in Period 2, preference mobility dampens competition. Therefore, customer heterogeneity reduces prices while preference mobility results in higher prices.

H3: Price discrimination results in customer acquisition

$$\text{Price Discrimination} \Rightarrow P_{\text{Existing}} > P_{\text{New}}$$

In line with extant literature (e.g., Fudenberg and Tirole, 2000; Villas Boas, 2006; Pazgal and Soberman, 2010), we expect customer recognition to result in customer-poaching behavior, whereby new customers are offered lower prices compared to existing customers.

H4a: Preference stochasticity reduces price discrimination while customer heterogeneity increases price discrimination

$$\text{Discrimination}_{\text{Mobility}} < \text{Discrimination}_{\text{Heterogeneity}}$$

H4b: The effect of preference stochasticity dominates the effect of customer heterogeneity

$$\text{Discrimination}_{\text{Het. \& Mob.}} < \text{Discrimination}_{\text{Heterogeneity}}$$

In line with Chen and Percy (2010), we hypothesize that exogenous customer switching due to preference stochasticity softens competition and firms discourage switching by offering similar prices to new and existing customers. However, we expect

customer heterogeneity to have the opposite impact. Since high type customers are more valuable, firms offer discounts to new high type buyers, while making up for lost profit by charging higher prices to existing buyers. Therefore, we expect limited price discrimination when customer preferences are mobile, and greater price discrimination when customers are heterogeneous.

Overall, we expect preference mobility to have a stronger influence on the decision to price discriminate compared to heterogeneity. This is due to the fact that when high type existing buyers exogenously move to the competitor, sellers will make efforts to retain these buyers by lowering prices to existing customers compared to the case with heterogeneity alone.

Table 4.1 summarizes the theoretical predictions regarding the implication of value heterogeneity and preference stochasticity on pricing.

4.3 Experiment

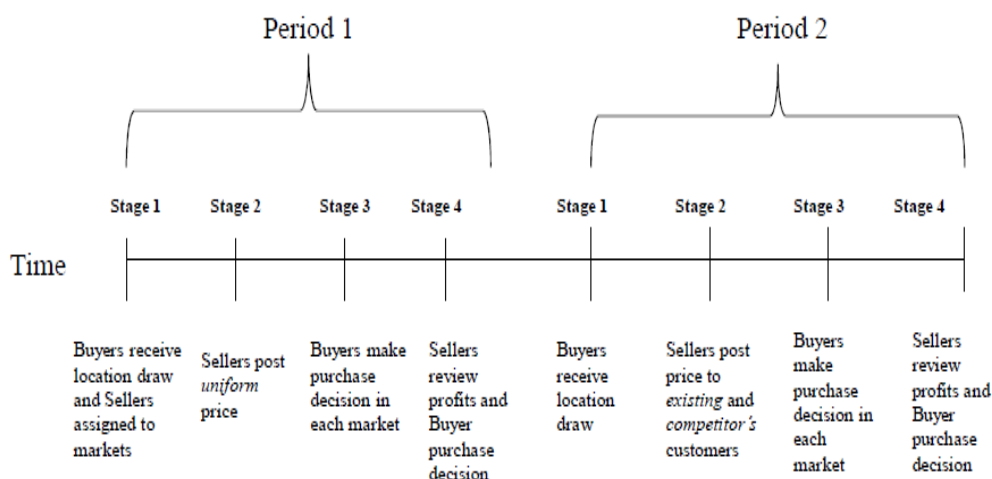
4.3.1 Experiment Design

In accordance with dynamic models of BBPD, we model competition in a two period duopolistic market with profit maximizing sellers (A and B) located at opposite ends of a linear market. To ensure ex-ante symmetric competition, half of the customers are located close to seller A and the other half are closer to seller B. Buyers are per period utility maximizers, with inelastic unit demand. Buyers receive a random draw for their location relative to the location of sellers. If a buyer located close to seller A buys from seller B transportation costs are incurred however, purchase from seller A is free

of charge.³ The location of buyers is crucial in our design and represents intrinsic brand preferences. Transportation charges can also be interpreted as switching costs as buyers need to pay an additional cost to buy from the less preferred seller. Furthermore, we assume complete market coverage, i.e., if a buyer did not purchase from seller A, she most certainly purchased from seller B.

At the beginning of Period 1 sellers are unaware of the location/preference or type of buyers, and can only offer uniform prices. Sellers only have the option to price discriminate in the second period, once sellers know location/preference and buyer type. Figure 4.1 outlines the experimental stages.

Figure 4:1: Stages in the Experiment



The experiment has four treatments, which test the differential impact of preference stochasticity and customer heterogeneity on pricing strategies. The details of the treatments are presented below.

³ It should be noted that delivery charges do not imply that some customers will get the product before the others; in our design all buyers will receive the product at the same time. However, they can either get it without paying additional charges or might have to pay additional charges. Hence, time value considerations for buyers are not a concern.

Base Case

In the Base Case buyers are homogenous and purchase a single unit, while stable brand preferences imply constant delivery/transportation costs across the two periods. The Base Case replicates markets such as utilities and cable television where consumers are similar in their purchase habits and preferences for different firms are stable from one period to another. Preference stability in our context implies that a consumer does not experience an exogenous shock that would change his brand preferences, e.g. if a consumer prefers Toyota over Honda in Period 1 he will continue to prefer Toyota in Period 2. The only reason the person would switch brands would be due to a price discount from Honda.

Heterogeneity

To analyze the impact of value heterogeneity on pricing strategy, we introduce two customer types: *high* and *low*. High type buyers purchase 5 units of the product, while low type buyers are restricted to purchasing only 1 unit of the product. Buyers are randomly assigned high and low types and are evenly distributed across the market to ensure symmetric competition between sellers. Sellers are unaware of the type of new customers and can only learn about the type of their existing customers after observing Period 1 purchases. Hence, there is asymmetric information regarding buyer type at the beginning of Period 2.⁴

Mobility

We introduce exogenous customer switching by allowing transportation costs to change

⁴ Asymmetric information regarding buyer types is the key driver of the results presented in Shin and Sudhir (2010).

across periods. In Period 2 there is a 50% probability that a buyer close to seller A does not move, and a 50% probability he could move closer to seller B and pay a delivery charge to purchase from seller A. A customer with stochastic preferences faces exogenous shocks that result in changes in the preference structure, such that someone who preferred Toyota to Honda may prefer Honda in Period 2. The probability of remaining in the seller's turf has been computed from Shin and Sudhir (2010), based on their equilibrium results. The exact probabilities based on the paper are 45% however, to ensure subjects understand the instructions we model movement in and out of the turf to be equally likely. The aim of the study is to test the behavioral implications of the theory; therefore, we test if the behavior holds under stronger conditions. Pilot studies reveal that subjects had no difficulty understanding the concept of mobility when the probability was set at 50%.

Preference stochasticity can also be conceptualized as a scenario where inherent preferences remain constant but the state space (as defined by delivery charge) change exogenously. This interpretation is consistent with Stigler and Becker (1977) who suggest that changes in behavior can be explained by state contingent preferences, such that every time states change, consumer preferences also appear change.

In our design preferences are related across periods, as 50% of the Period 1 customers are likely to stay with the seller in Period 2. Therefore, this situation differs from an uninformative scenario where the preferences were completely independent with no relation to Period 1 purchase behavior.

Het. & Mob.

In the final treatment, we introduce both customer value heterogeneity and preference mobility to study how the customer characteristics interact to influence pricing strategy.

Table 4.2 provides a summary of the experiment design.

4.3.2 Experiment Procedure

The experiment was conducted at Oxlab facilities at the Said Business School, University of Oxford from the 8th June to till the 21st of June 2011. Experimental sessions were advertised to registered Oxlab participants and Said Business School MBA and MFE students. Treatments were administered between subjects and a total of 90 participants took part in the experiment. 58 participants enacted the role of sellers while 32 participants played the role of buyers. To avoid any contextual effects, participants were randomly assigned to play the roles of buyers and sellers. While existing studies use automated buyers, by including real buyers in our study to allow for strategic action on the part of buyers enabling us to draw inferences regarding buyer behavior.

Each participant was seated at a computer terminal displaying preliminary instructions (see Appendix for instructions). Further instructions were read out aloud to participants. Prior to the start of the actual experiment participants played a trial round to familiarize themselves with the rules and procedures. Once all participants indicated they understood the rules, the actual experiment began.

Sellers and buyers interacted to play a 2 period sequential game. Each market comprised of 2 sellers and 4 buyers. To economize on subjects, buyers participated in multiple experimental markets. Since all sellers were selling to the same group of

buyers we were able to control for buyer heterogeneity across markets. Pilot studies also revealed that buyer involvement increased when buyers participated in multiple markets compared to a single market.

For the sake of simplicity marginal costs were set to zero and sellers were informed that buyers have a valuation of £50 for the experimental product. Transportation costs were set at 20% of reservation prices (i.e., a delivery charge of £10 for the distant seller). Other experimental studies on spatial competition specify similar ratios for reservation prices and transportation costs (e.g., Selten and Apestegua, 2005).

At the start of Period 1, sellers were prompted to enter a uniform price. After reviewing the offer price in each market and the associated delivery charges, buyers selected a seller from every market (buyers purchased 1 unit in the Base Case and Mobility and 1 or 5 units (depending on their type) in the Heterogeneity and Het. & Mob, treatments). All trades were conducted via computer terminals and no communication between participants was allowed. At the end of trading in Period 1 the following information was displayed to sellers:

- Own and competitor's offer price
- Delivery charges for each buyer
- Buyers who purchased from the seller and the competitor
- Total profit for the period

Once sellers had reviewed the information they proceeded to Period 2. In Period 2 sellers were prompted to set two prices: i) prices to their existing buyers and ii) prices for new buyers (buyers who had purchased from the competing seller in Period 1). Once sellers posted prices, buyers made the purchase decision. In Mobility and Het. & Mob.,

buyers also reviewed their updated delivery charges for Period 2. Furthermore, in Heterogeneity and Het. & Mob., buyer types changed across rounds to ensure that sellers did not memorize the identity of the high type buyer in subsequent rounds. After buyers made their selection, sellers reviewed the summary and proceeded to the next round. With the exception of two experimental sessions 20 rounds were played in each session.⁵

In line with established practice in the experimental literature (e.g., Morgan et al., 2006), we control for repeated game effects and learning by randomly shuffling sellers across markets in every round. After every round participants competed with a different seller. Participants were only provided information regarding their earnings for the current period; the absence of cumulative earning feedback further mitigated any learning effects. This allows us to treat data from every round as an independent observation.

At the end of the 20 experimental rounds, the total payoff from the experiment was displayed. Two participants were then randomly selected and were privately paid in cash, after which the experiment ended. The conversion rate for experimental earnings for the Base Case and Mobility was set at set at: £1 per 100 units of experimental money earned for sellers and £0.5 per 100 units of experimental money for buyers. For Heterogeneity and Het. & Mob., the conversion rate for sellers was set at £0.33⁶ per 100 units of experimental money and £0.167 per 100 units of experimental money for

⁵ Due to technical difficulties one session of the Heterogeneity and Mobility treatment was stopped after 8 rounds and a session of the Base case was stopped after 13 rounds.

⁶ Treatments 2 and 3 include heterogeneous buyers who purchase 5 units, therefore, The existence of high type buyers who could purchase 5 units meant that sellers were selling to 12 buyers compared to treatments with 4 buyers purchasing a single unit. Therefore, resulting profit for sellers and budgets for buyers were much higher in treatments with heterogeneity. Hence, the conversion rate was scaled down to ensure participants earned the same expected payoff from across treatments.

buyers. The conversion rates were set to equalize the expected earnings for each treatment. Participants earned £17 on average and experimental sessions on average lasted an hour and ten minutes.

4.4 Results

In this section we present the main findings of the experimental study.

4.4.1 Average offer prices and profits are lower when sellers price discriminate

We find that customer recognition results in lower prices in Period 2 compared to Period 1. Overall the average offer price in Period 2 (the average is computed over price to existing buyers and the price offered to new buyers) is lower than the price offered in Period 1 ($M = 18.83$). Based on a two-sample means comparison test the difference is statistically significant ($diff = 4.80$, $t\text{-value} = 20.18$). This result holds across all treatments as illustrated by Table 4.3. Other experimental studies also report a decline in prices when participants engage in personalized pricing (see, Shaw and Vulkan, 2012).

We also regress the average Period 2 price on seller's decision to price discriminate (the indicator variable takes on a value of 1 if sellers choose to discriminate and 0 otherwise), customer characteristics (captured through treatment dummies) and controls for possible feedback effects (we include Period 1 price, Period 1 market share, measured by number of customers in Period 1, and competitor's price in Period 1). We further account for participant heterogeneity and estimate a mixed effects regression model with participant random effects and round dummies to control for possible learning effects. Our results confirm that discrimination has a significant

negative impact on Period 2 prices, despite controls for treatments effects, learning and feedback effects (see Table 4.4, column 1).

Due to the decline in Period 2 prices, profits in Period 2 are also lower compared to Period 1 profits (see Table 4.5). Overall the average profit per seller in Period 2 ($M = 17.54$) is lower than the average profit earned by sellers in Period 1 ($M = 20.15$) and the difference is statistically significant ($diff = 2.60$, $t\text{-value} = 3.43$) based on a two sample means comparison test. For all treatments Period 2 profits are significantly lower than Period 1 profits. This result is in line with the prediction of Fudenberg and Tirole (2000), as aggressive discounts to acquire new buyers results in a decline in Period 2 prices and profits. Thus, participant behavior confirms *H1*, as price discrimination results in a decline in prices and profits.

4.4.2 Prices and profits vary with customer characteristics

Our results suggest that Period 1 prices vary with customer characteristics ($F_{3,244} = 30.29$, $p < 0.00$),⁷ similarly, in Period 2, customer characteristics influence the price offered to new customers ($F_{3,244} = 39.46$, $p < 0.00$) and existing customers ($F_{3,244} = 68.15$, $p < 0.00$). Average offer price in Period 1 is highest in the Base Case, followed by Mobility, Het. & Mob. and Heterogeneity. While in Period 2 prices are highest under Mobility, followed closely by Base Case, Het. & Mob. and Heterogeneity (see Table 4.3).

We also find that, profits are sensitive to customer characteristics. Analysis of the profits across treatments reveals that Period 2 profits are highest under Mobility ($M = 22.58$), followed closely by the Base Case ($M = 16.47$). While price discrimination in

⁷ Based on a one way ANOVA.

the Base Case is as profitable as charging uniform prices under stochastic preferences, the underlying driver of profit under the two cases is different. In the Base case, sellers extract surplus from existing buyers in Period 2. In contrast, when preferences are stochastic sellers do not discount prices in Period 2 and charge higher uniform prices to both existing and new buyers.

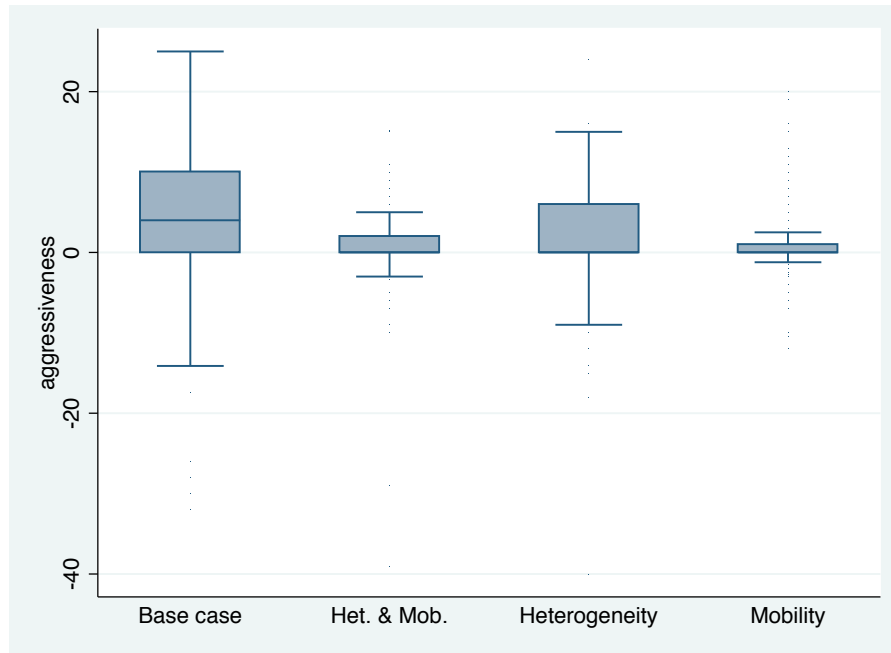
However, under conditions of buyer heterogeneity the competitive effect of price discrimination dominates the surplus extraction effect, resulting in lower profits ($M = 10.21$). Even though in our design customer heterogeneity increases market size (sellers compete to sell 12 units when the market has high type buyers compared to 4 units with homogenous buyers), competition increases as sellers attempt to attract high type buyers in both periods. Orzen and Sefton (2008) in their study of spatial competition also find greater competition in larger markets.⁸ Thus we only find partial support for *H2*.

4.4.3 Sellers engage in customer poaching

For all treatments pooled together the average offer price to existing buyers is lower ($M = 15.57$) than the price offered to new customers ($M = 12.58$, see Table 4.3). Parametric tests reveal that the difference is statistically significant ($diff = 2.90$, t -value = 11.63). This result is in line with mainstream of models of BBPD, (e.g., Zhang, 2011; Pazgal and Soberman, 2008; Villas-Boas, 2004; Fudenberg and Tirole, 2000; Chen, 1997). Thus, experimental subjects exhibit customer-poaching behavior, confirming *H3*.

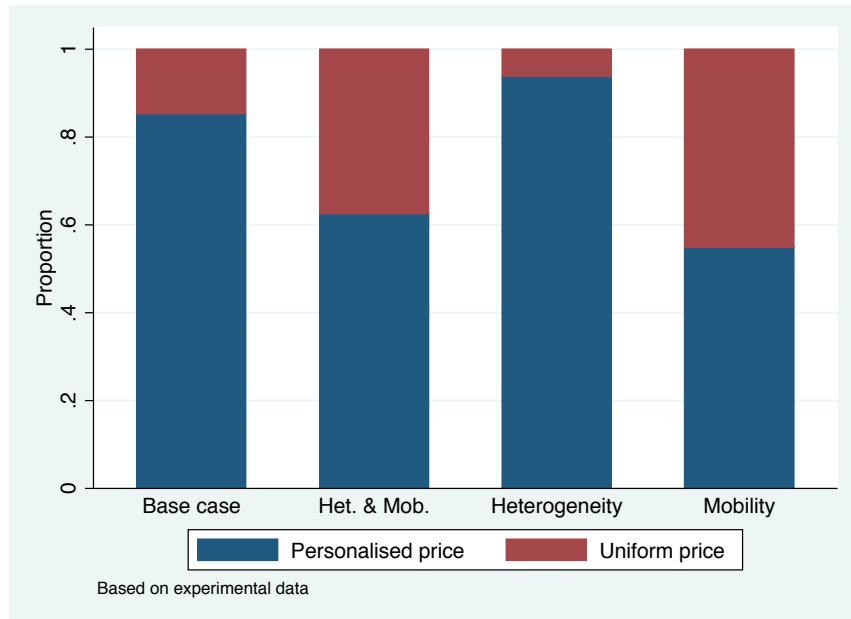
⁸ In their experiment higher valuation is signifies a larger market.

Figure 4:2: Aggressiveness in Poaching Across Treatments



While sellers adopt a customer acquisition strategy, the degree of aggressiveness varies with customer characteristics. Figure 4.2, plots the distribution of the aggressiveness (Price to Existing Customers - Price to New Customers) in prices across treatments. In the Base case (homogenous buyers with stable preferences) the difference in price to existing and new buyers is most pronounced, (*diff* = 6.26, *t-value* = 10.30), followed by Heterogeneity (*diff* = 3.31, *t-value* = 4.37). However, when preferences are stochastic the average difference in prices falls (*diff* = 1.48, *t-value* = 5.63). It is interesting to note that the difference is smallest when both heterogeneity and preference mobility are jointly introduced (*diff* = 1.22, *t-value* = 2.68).

Figure 4:3: Seller Preference for Price Discrimination in Period 2



When high value customers can move exogenously sellers reduce the gap between new and existing customers to ensure high value existing customer do not switch. Thus, the most aggressive pricing strategy is adopted under the Base Case where buyers are substitutable (all buyers generate the same value) and there is no exogenous customer switching.

This result is further strengthened by our regression analysis of the aggressiveness in pricing. Table 4.4 (column 2) suggests that after controlling for Period 1 feedback, round effects and individual effects the aggressiveness in pricing strategy is reduced when preferences are mobile, while combining heterogeneity with preference mobility results in the least aggressive discriminatory behavior.

4.4.4 Preference stochasticity reduces price discrimination while heterogeneity increases price discrimination

We observe that discriminatory behavior varies significantly across treatments ($F_{3,244} = 32.78, P < 0.00$). In line with *H4a*, sellers price discriminate in 85% of the pricing decisions in the Base Case (see Figure 4.3), however, when preferences are mobile, the incidence of price discrimination falls to 45% as there is a probability that buyers might switch without incentives. In contrast, customer heterogeneity increases the incidence of price discrimination to 94% (the difference is statistically significant compared to the Base Case, $diff = -8.5\%$, $z\text{-value} = -2.21$)⁹ as sellers attempt to attract new high type buyers. When preference stochasticity and heterogeneity are jointly introduced the incidence of discrimination falls to 62%, and the difference in the incidence of discrimination is statistically significant ($diff = 31.3\%$, $z\text{-value} = 5.86$) compared to Heterogeneity.

We further model the decision to set a uniform vs. personalized price as a mixed effects logit model with participant random effects, controls for feedback effects from Period 1 and round specific effects. The results are presented in (Table 4.4, column 3). The key variable of interest is the indicator for preference mobility. Introducing preference stochasticity reduces the incidence of price discrimination irrespective of customer heterogeneity, as the treatment dummy for preference mobility is negative and significant. However, introducing heterogeneity has a positive impact on the incidence of price discrimination. Overall, the negative effect of preference stochasticity outweighs the positive effect due to customer heterogeneity. Hence, we find evidence supporting *H4b*.

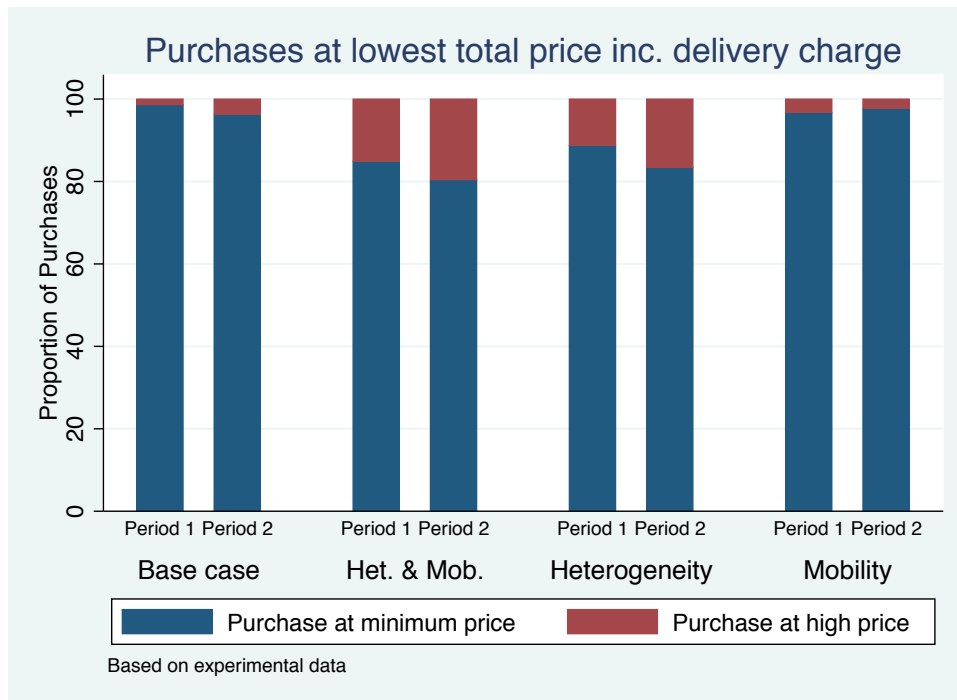
⁹ Based on a comparison of proportion test.

4.4.5 Buyer behavior

The use of real buyers in our experiment (instead of computerized buyers) provides valuable insights into buyer behavior. Buyers in our experiment behaved in line with our expectations and adhered to the principals of utility maximization while simultaneously exhibiting loyalty to their preferred seller.

Buyers purchased the cheapest option (inclusive of any applicable delivery charges) on 90% of the purchase occasions. Figure 4.4 summarizes buyers' purchase decisions across periods and treatments. Comparison of purchase price excluding delivery charges reveals that buyers selected the lower offer price 80% of the time in Period 1 and 72% of the time in Period 2 (the difference is statistically significant, $diff = 6.88$, $z\text{-value} = 6.12$). We do not find any statistically significant difference in buyer purchase behavior across treatments. It appears that buyers were focusing more on the offer prices exclusive of add on charges (i.e., delivery cost). A possible explanation for this behavior can be found in (Morwitz et al., 1998) who suggest that incase of partitioned prices customer pay greater attention to the base price and relatively little importance is given to add on charges. Such differences in attention they argue can result in biases when retrieving price information.

Figure 4:4: Proportion of Purchases at Minimum Price Across Treatments



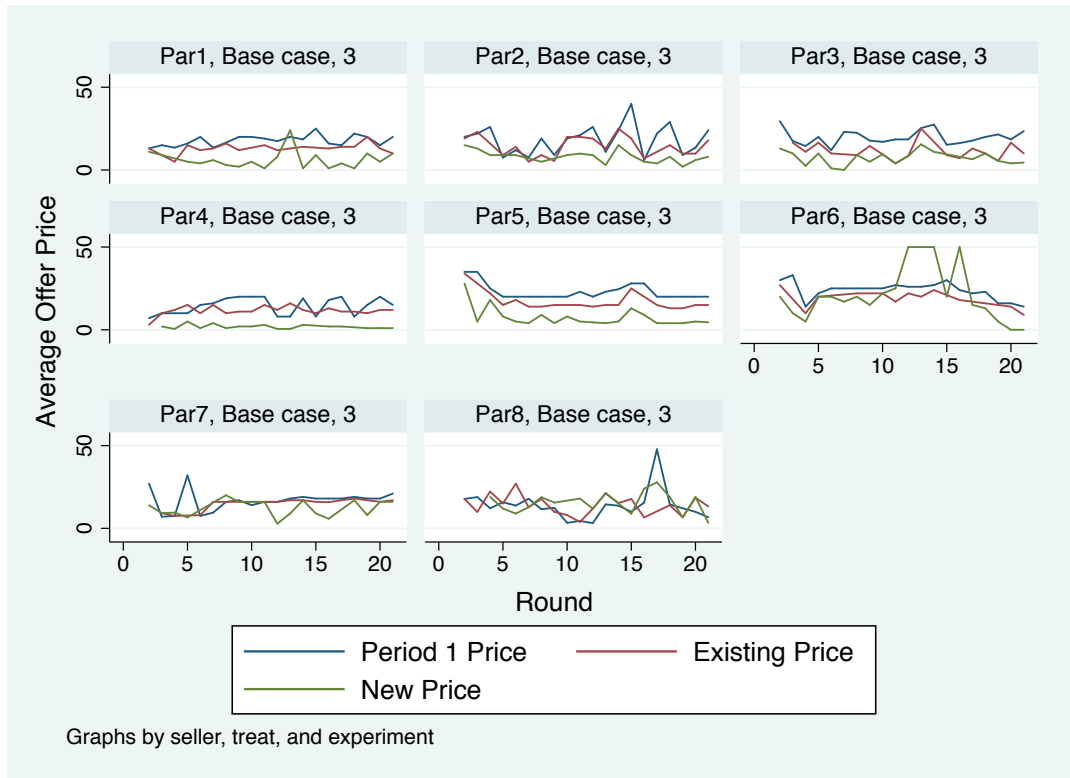
With regards to buyer loyalty we note that 63% of the purchases in Period 2 were made from Period 1 sellers and this pattern was similar across treatments. The Proportion of repeat purchases in the Base Case, Mobility, Heterogeneity and Het.& Mob., accounted for 67% , 66%, 55% and 59% respectively.

Buyer purchase decisions also reveal that buyers avoided paying delivery charges; across all purchases buyers paid delivery charges in only 22% of the purchase occasions. This proportion is stable across periods. The fact that buyer behavior was stable across treatments suggests that observed differences in pricing behavior across treatments was not a reaction to variation in buyer behavior, further strengthening our experimental findings

4.4.6 Robustness Checks

Our main concern when analyzing the experimental results is the possible presence of reinforcement learning among experiment participants: as it may take considerable amount of time for participants to fully appreciate the workings of markets and therefore their decisions may be sub-optimal in the initial rounds of the experiment. This affects the treatment of individual rounds as independent observations in the analysis. To confirm the robustness of the results we plot the offer prices for participants across rounds for a randomly selected experimental session. Figure 4.5 illustrates that prices set by a random seller does not exhibit a deterministic relation with round. It appears, participants were reacting to the strategy of their competitor in each subsequent round, and no learning effects were observed. We also plotted offer prices across rounds for other experiment participants and found no significant relation between the prices offered and the round played. These plots can be made available upon request. Hence, we are confident that by shuffling competitors across rounds we have been able to mitigate possible learning effects across rounds.

Figure 4:5: Individual Offer Price Across Rounds



4.5 Discussion and Conclusion

We present one of the first experimental studies on behavior based price discrimination (BBPD). Through our experiment we study how customer heterogeneity and stochastic brand preferences influence firm pricing. We not only empirically validate theoretical findings on BBPD but also attempt to explain why some firms offer discounts to new customers while other firms adopt uniform pricing strategies.

Given the widespread popularity of customer recognition technologies, it is not surprising that experimental sellers choose to discriminate between existing and new customers. Our study corroborates the findings of extant literature, as customer recognition results in increased competition and a decline in prices and profits. From a

policy perspective BBPD is unlikely to raise antitrust concerns as markets become more competitive and consumers benefit from lower prices. In accordance with Fudenberg and Tirole (2000), we find that in the absence of exogenous customer switching and value heterogeneity, price discrimination results in discounts to poach rival's customers.

However, the main contribution of this study lies in highlighting the influence of customer characteristics on pricing behavior. We observe that customer heterogeneity intensifies discrimination and aggressiveness, resulting in lower prices and profits compared to the commonly considered scenario with homogenous customers and stable preferences. Even though in our experimental setup, heterogeneity resulted in an expansion of the market, we find sellers competing more aggressively for high type customers by offering large discounts to new customers. However, when heterogeneity and preference stochasticity are jointly introduced we find no significant difference between prices offered to existing customers and rival's customers. This indicates that exogenous customer switching has a greater impact on pricing behavior compared to customer heterogeneity.

While extant literature is not unanimous regarding the impact of stochastic preferences on BBPD,¹⁰ we find that sellers are more likely to offer uniform prices when customer preferences change over time. Our findings rationalize price guarantees schemes, whereby firms offer to match rival's prices. Examples of such behavior can be found in the airline industry. Since brand preference for travel is stochastic, airlines

¹⁰ Shin and Sudhir (2010) expect profitable poaching while Chen and Percy (2010) find changing preferences to be pre-requisite for loyalty rewards.

offer similar rewards to existing customers and competitor's customers irrespective of customer heterogeneity. Recently, three of the six major airlines in the US joined together their frequent flyer reward schemes, and customers now earn the same rewards if they travelled on any rival airline. Similarly in markets where switching is common, firms ensure new and existing customers are offered the same price, for example, Barclay card matches renewal premiums with lowest switching premiums.

Furthermore, the use of real buyers in our study enabled us to gain insights into buyer behavior.

However, our results are limited. In our model switching costs are exogenous, Caminal and Matutes (1990) highlight that the ability to commit to future prices endogenizes switching costs, which can alter the equilibrium price dynamics and overall profitability. Therefore, we leave empirical analysis of price commitment to future research.

Perhaps more importantly, we find that value heterogeneity and preference stochasticity do not provide the requisite conditions that make loyalty rewards feasible. Therefore, future research could explore other behavioral customer characteristics that would rationalize a customer retentions strategy. For instance, research on social preferences could shed light on the proliferation of loyalty reward schemes. According to Gouldner (1960) “norm of reciprocity” exchange relationships are reciprocated because individuals feel obligated to provide a benefit to others in return for any favors that they may have received. Therefore, when a firm offers discounts to its customers they feel indebted to return to the firm and a virtuous cycle is created, whereby rewards to existing customers strengthens customer ties which results in greater profitability and

benefits for customers (see Kumar and Shah, 2004, for more details on the dynamics of reciprocity). Future research could explore if reciprocity and considerations of fairness influence buyer and seller behavior.

Thus far the literature on BBPD has assumed consumers have inelastic demand, recently theoretical advances consider BBPD in markets with elastic demand and find that BBPD with elastic demand has a market expansion effect (e.g., Esteves and Reggiani, 2014). Future research could look at the behavioral implications of such demand expansion and explore how sellers react to elastic demand.

As Fudenberg and Villas-Boas (2006) state research on BBPD has so far just uncovered the “tip of the iceberg”, there is much work to be done on this topic in the future. An experimental study of BBPD we believe is a step in the right direction.

List of Tables

Table 4:1: Implication of Behavioral Customer Characteristics for Pricing

Behavioral Characteristics	Relevant Literature	Prediction	Relevant Industries
Homogenous Customers & Constant Preferences	Fudenberg and Tirole (2000)	$P_{Existing} > P_{New}$ $P_1 > P_2$	Utilities
Homogenous Customers & Stochastic Preferences	Chen and Pearcy (2010)	$P_{Existing} < P_{New}$ $P_1 = P_2$	Airlines, Restaurants
Heterogeneous Customers & Constant Preferences	Shin and Sudhir (2010)	$P_{Existing} > P_{New}$ $P_1 > P_2$	Subscription Markets
Heterogeneous Customers & Stochastic Preferences	Shin and Sudhir (2010)	$P_{Existing} < P_{New}$ $P_1 > P_2$	Supermarkets

Table 4:2: Experiment Design

Variables	Base Case	Mobility	Heterogeneity	Het. & Mob.
Delivery charges	Constant	Change	Constant	Change
Heterogeneity	All buyers buy 1 unit	All buyers buy 1 unit	50% buy 1 unit and 50% buy 5 units	50% buy 1 unit and 50% buy 5 units
No. of Periods	2	2	2	2
No. of rounds	0	20	20	14
No. of Markets	0	1	10	10
No. Participants	6	24	18	22

Table 4:3: Comparison of Average Prices across Periods

	Price in Period 1	Price in Period 2	Existing Customers	New Customers
Base Case	22.40 (9.85)	16.46 (10.72)	18.76 (10.26)	14.32 (12.27)
Heterogeneity	17.08 (9.36)	9.35 (5.43)	10.48 (5.50)	8.47 (7.24)
Mobility	19.57 (7.64)	16.70 (6.70)	17.26 (6.78)	16.16 (7.14)
Heterogeneity & Mobility	14.82 (9.46)	10.65 (7.55)	11.11 (7.46)	10.22 (8.19)
All Treatments	18.83 (9.32)	14.03 (8.50)	15.11 (8.47)	13.05 (9.41)

Note: Period 2 price is the average across the price offered to new and existing customers.
Standard deviation is in parenthesis

Table 4:4: Determinants of Second Period Pricing

Dependent Variable	Average Price in Period 2 (1)	Existing Price – New Price (2)	Indicator for Discrimination (3)
Period 1 Price	0.394*** (0.023)	0.015 (0.033)	-0.007 (0.021)
Competitor's Period 1 Price	0.204*** (0.029)	-0.060** (0.031)	0.025 (0.019)
Discrimination Dummy	-1.423*** (0.423)		
No. of Existing Customers	0.328*** (0.254)	-0.061 (0.269)	-0.215 (0.162)
Mobility Dummy	0.964 (1.332)	-3.712*** (1.068)	-1.675*** (0.502)
Heterogeneity Dummy	-4.582** (1.564)	-2.830** (1.259)	1.312** (0.703)
Het. & Mob. Dummy	-2.308 (1.445)	-4.115*** (1.176)	-1.001** (0.571)
Seller Random Effects	4.611** (0.108)	2.842** (0.333)	1.156** (0.186)
Constant	2.589* (1.507)	6.352*** (1.384)	3.181*** (0.786)
Log likelihood	-2,996.621	-3,043.556	-416.091
No. of Observations	1,000	1,000	1,000

Note: Standard deviation is in parenthesis, *** significant at 1%, ** significant at 5% and * significant at 10%

Table 4:5: Comparison of Average Profits across Periods

	Mean Profit in Period 1	Mean Profit in Period 2
Base Case	24.44 (23.26)	16.46 (10.72)
Heterogeneity	18.61 (20.12)	10.21 (11.04)
Mobility	20.69 (17.10)	22.57 (24.58)
Heterogeneity & Mobility	15.46 (17.62)	12.28 (15.07)
All Treatments	20.15 (19.67)	17.54 (21.65)

Note: Standard deviation is in parenthesis, *** significant at 1%, ** significant at 5% and * significant at 10%

4.6 Appendix

4.6.1 Instructions for both buyers and sellers (announced at the beginning of all treatments and displayed on welcome screen)

Thank you for participating in our experiment Following is an outline of the experiment and you will be provided with further instructions.

You are about to participate in an experimental market where you will either buy or sell the experimental good. The experiment consists of a trial trading session and 20 experimental trading sessions. The experiment is expected to last for an hour. The trial trading session is designed to give you experience for trading sessions in which you can earn money, so it is in your interest to take it seriously and familiarize yourself with the trading mechanism.

Experimental subjects can be either buyers or sellers. Every trading session consists of two periods. Every trading session has 2 sellers (A and B) and 4 buyers.

Buyers can either be close to seller A or seller B. Buyers will have to pay delivery charges based on their distance from sellers. If buyers purchase from the distant seller they will have to pay a delivery charge to get the products delivered, however, delivery is free from the seller close to them. Note that all buyers will get the product at the same time irrespective of the delivery charge.

Sellers will set the price for the product and buyers will then determine which seller they would like to purchase from. At the end of the first period the profits of the seller and savings of the buyers will be computed.

In the second period sellers will again post prices for the same experimental product. Sellers will now have the option to post different prices to different customers. Buyers will again make purchases from the seller of their choice.

Your earnings from the experiment depend on your performance in the game. At the end of the experiment the total profit will be computed, and two participants will be randomly selected to receive a payment. £100 experimental is equivalent to £0.4; therefore, randomly selected participants could earn up to £50.

4.6.2 Instructions for the screen when all participants are logging on

You are about to participate in a market for pens. You will enact the role of a buyer or a seller. Every trading market has 2 sellers and 4 buyers.

Buyers will have to pay delivery charges based on their distance from sellers. If buyers purchase from the distant seller they will have to pay a delivery charge to get the product delivered, however, delivery is free from the close by seller.

Every trading round consists of two periods.

Sellers will set the price for the product and buyers will then determine which seller they would like to purchase from. At the end of the first period the profits of the seller and surplus of the buyers will be computed.

In the second period sellers will again post prices for the same experimental product. sellers will now have the option to post different prices to customers. buyers will again make purchases from the seller of their choice.

At the end of the round the total prices and profits will be computed and the monetary rewards will be determined based on your performance in each round.

The round number and period number will be displayed on the screen.

4.6.3 Instructions displayed for Base case

4.6.3.1 Instructions for sellers

You are a seller in the market for the Experimental Product. The market consists of 1 competitor and 4 buyers. Take account of the following information when setting prices:

There are zero costs of production.

Buyers will pay a maximum of £50 for the product. You cannot charge a price greater than £50.

2 buyers are situated close to you (they pay no delivery charge) and two buyers are situated close to your competitor (they will have to pay a delivery charge of £10 if they buy from you)

o Delivery charges will be displayed only after buyers have made their purchase decision in Period 1.

Your payoffs will be calculated as follows

Payoff = Posted price * Number of buyers who purchase from you

Note: There will be 20 such experimental rounds and you will be paired with a different seller in each round

2.2 Instructions for buyers

You will participate in 5 markets and purchase 1 Experimental Product in each market.

You have £50 to spend on the purchase of the experimental product in each period.

You will participate in each market for 2 periods.

Delivery charges can be either £0 or £10 and will be constant across periods

Your payoffs will be calculated as follows:

Pay off = £50 --Price paid to seller -Delivery charge

Sellers in each market will change after every round

Note: There will be 20 such experimental rounds

5 Does Lack of Market Dominance Result in Loyalty Rewards? An Experimental Investigation

5.1 Introduction¹

Recently, at a Safeway supermarket in Denver USA, a pack of bottled water was priced at \$2.71 for customer A, while customer B was charged \$3.69 for the same pack (Clifford, 2012). Customer A had not purchased the bottled water in the past and was charged a lower price, while customer B who had purchased the water at previous shopping trips was charged a higher price. Price discrimination based on consumers' past purchase history is regarded as behaviour based price discrimination (BBPD). Rigby (2011) predicts that store recommendations and customized price offers will be the norm in the future.

While BBPD is widely prevalent across competitive markets, pricing strategies vary across markets. For instance, it is common practice amongst mobile operators to create high switching costs for existing customers; in contrast, banks often offer existing customers preferential lending rates. Given the popularity of BBPD, a growing literature

¹ Based on joint work with Professor Nir Vulkan.

studying price discrimination in dynamic models of strategic interaction has emerged (see Fudenberg and Villas-Boas, 2006 for a detailed survey). Equilibrium outcomes in these models are dependent on specific modeling assumptions and diverge in their predictions regarding the impact of BBPD on prices and consumer welfare. For instance, market outcomes vary with assumptions regarding market dominance (e.g., Chen, 2008), consumer preferences (e.g., Chen and Percy, 2010), switching costs (e.g., Shaffer and Zhang, 2000; Chen, 1997) and customer heterogeneity (e.g., Shin and Sudhir, 2010; Gehrig et al., 2007). As noted by Amaldoss et al. (2008), theoretical models of strategic interaction are well developed in the literature; however, the empirical validation of theoretical predictions is limited.

Through this study we aim to reconcile differences in observed pricing behavior across industries by comparing the effect of market concentration (number of firms) and market dominance (size of firms) on pricing strategies. We present stylized models of dynamic strategic interaction across symmetric duopoly markets, asymmetric duopoly markets and markets with multiple symmetric firms, to address the following questions; How do market dominance and competitiveness impact prices? Are small firms more likely to offer loyalty discounts or do large firms extract surplus from existing customers? Does an increase in the number of firms incentivize price discrimination?

We show that given rational customers with stable preferences, in equilibrium, symmetric competitors will offer discounts to new customers, while asymmetric competition provides sufficient conditions for small firms to offer loyalty rewards. Based on our proposed model of dynamic competition, aggressiveness in pricing (difference in price to new and existing customers) decreases when markets become more competitive and market dominance is positively correlated with aggressive

customer poaching. We test our theoretical predictions by conducting an experiment with a representative subject pool of marketing and pricing professionals from diverse industries. An experimental setting is particularly suited to our study² as it allows us to control for confounding factors (e.g., strategic customer behavior, asymmetric information and differences in costs of production) enabling us to determine the impact of causal factors in isolation and providing internal validity. Since detailed data on pricing is difficult to come by, through a controlled laboratory experiment we can not only replicate real world pricing scenarios but can also observe the strategic interaction among experimental participants. The use of marketing professionals allows us to draw on the experience and expertise of professional price setters to better understand how competition affects the decision to price discriminate. Since the experimental tasks closely mimic real world scenarios faced by professionals we observe they are quick to understand the experiment and act strategically.

Based on the behavior of our expert subject pool, we find that an increase in competition reduces the prevalence of price discrimination. Participant behavior is consistent with the practice of sign up discounts in concentrated markets (e.g., cable television) and the proliferation of loyalty reward schemes in competitive industries (e.g., retail). Similarly, the aggressiveness³ in pricing strategy varies with market dominance. We observe that symmetric duopolists adopted the most aggressive poaching strategy with discounts to new customers and high premiums to existing customers. In contrast to popular wisdom, dominant firms in asymmetric markets were not as aggressive in their pricing. Small firms in the asymmetric and multiple firm

² Experimental studies are increasingly being used to better understand competition and pricing in oligopolistic markets (e.g., Dufwenberg and Gneezy, 2000; Grether and Plott, 1984).

³ We define the difference in price to existing and new customers as a measure of price aggressiveness, details are outlined in Section 4.

markets adopted the least aggressive strategy and discouraged customer switching by offering similar prices to existing and new customers. Our results have useful policy implications; our findings suggest that government regulation targeting dominant firms may not protect consumers from high prices. Based on our findings competition authorities could encourage competition in markets to increase customer participation rather than legislating against dominant firms in asymmetric markets.

The remainder of this chapter is organized as follows: Section 5.2 summarizes the developments in the literature on BBPD, Section 5.3 presents the analytical model while Section 5.4 outlines the main hypothesis to be tested, Section 5.5 outlines the experimental procedure and design, Section 5.6 presents the findings of the experimental study and Section 5.7 presents a discussion of the key findings and policy implications.

5.2 Literature Review

Over the past decade a diverse literature has emerged studying price discrimination in markets with customer recognition. Most studies consider price discrimination in symmetric duopoly markets, where each firm has sufficient market power and therefore acts strategically in response to rival's pricing strategy. A dominant theme in the literature is that customer recognition coupled with constant consumer preferences results in intense competition to attract new customers through switching discounts, while consumer surplus is extracted from existing customers (e.g., Chen and Zhang, 2009; Pazgal and Soberman, 2008; Fudenberg and Tirole, 2000). However, practitioner perspective and academic literature diverge on whether current or new customers should be rewarded. The theoretical literature fails to explain the phenomenon of loyalty reward schemes, which have been popular for over two decades.

Recently a few studies outline the necessary conditions for profitable loyalty rewards. For instance, Chen and Percy (2010) introduce price commitment and preference stochasticity to show that loyalty rewards can be profitable. Whereas Shin and Sudhir (2010) suggest that customer stochasticity and heterogeneity are pre-requisites for profitable customer retention strategies.

Equilibrium outcomes have also been noted to depend on assumptions regarding market dominance. Shaffer and Zhang (2000) consider asymmetry in a duopoly model and find that asymmetric switching costs are sufficient to make a customer retention strategy profitable. However, not all models of asymmetric competition suggest profitable loyalty rewards. For instance, Chen (2008) considers an asymmetric market where the firm with the stronger brand eliminates competition by adopting an aggressive poaching strategy. In contrast, Gehrig et al. (2006) find that the smaller firm engages in aggressive customer poaching to gain market share. Gehrig et al. (2006) also study the relation between market dominance and BBPD, however, in their model the smaller firm engages in aggressive customer poaching to expand its market share. Both Gehrig et al. (2006) and Shaffer and Zhang (2000), consider price discrimination in static games, that provide no insights into the dynamics of competition across the two periods. Building on the extant literature on BBPD, we present an analytical model that shows that lack of market dominance in an asymmetric market provides incentives to protect its existing customers from the predatory dominant firm.

While the literature on BBPD in the context of duopolies is fairly well developed, strategic interaction between multiple firms has received limited attention. According to Fudenberg and Villas-Boas (2006), with multiple firms the implications for the profitability of firms are less obvious. Taylor (2003) contends that with more

than two firms, each firm faces the threat of customer poaching from at least two rival firms, this increase in price competition could result in prices being set below cost to attract new customers, while some rents may be extracted from existing customers.

Thus, the impact of BBPD on prices and consumer welfare is dependent upon specific modeling assumptions. The difficulty in obtaining detailed pricing data at the industry level makes empirical validation of theoretical predictions difficult. Furthermore, extant research on BBPD has not considered how the incentives for price discrimination change when market structure changes. In order to compare price discrimination across size and number of firms, we extend Fudenberg and Tirole's (2000) dynamic model of strategic interaction with homogenous products to competition with asymmetric and multiple firms. Through our experimental study we contribute to the existing literature on BBPD by not only testing the validity of theoretical predictions but we also provide insights on how real world pricing experts react to dominance and competition.

Our chapter also contributes to the experimental literature on pricing in competitive markets. There has been a long tradition of using experiments to study price competition (e.g., Mahmood 2013; Morgan et al., 2006; Baye and Morgan, 2004; Dufwenberg and Gneezy, 2000; Hoggatt et al., 1976; Smith, 1962). Dufwenberg and Gneezy (2000) show that competition intensifies as the number of players increases in a Bertrand oligopoly game. Similarly, Dufwenberg et al. (2007) find that anti-competitive price floors in Bertrand models foster competition and may lead to lower prices under conditions of duopoly, but not so with multiple firms. Hence, there is experimental evidence suggesting alteration in pricing behavior as market dominance and

concentration change. However, these studies focus on static markets where customer recognition is not possible.

Mahmood (2013) experimentally examines price competition in a dynamic two period market with customer recognition. While Mahmood (2013) focuses on the impact of customer characteristics (heterogeneity and preference stochasticity), on pricing in symmetric duopolistic markets with student subjects, we consider the impact of dominance and competition on pricing with professional participants in a controlled experiment.

5.3 Theoretical benchmarks

In this section we briefly outline equilibrium predictions from three different models that underlie our experimental design. We consider two period models of dynamic competition between strategic forward looking symmetric, asymmetric and multiple symmetric firms. Firms are assumed to be located in a market of unit length and strategically set prices across two periods to maximize total profits subject to per unit cost of production c .⁴ Following Fudenberg and Tirole (2000), in Period 1 firms cannot distinguish between customers and therefore, can only charge a uniform price to all customers. In Period 2 firms learn about consumer preferences based on Period 1 purchase behavior and in light of this information firms have the option to discriminate between existing and new customers. Consumers are assumed to be rational utility maximizers with inelastic unit demand and constant preferences over time. The main source of customer heterogeneity is the intrinsic preference for a firm (horizontal differentiation), which is defined in terms of consumer location in the market.

⁴ Costs of production are identical across firms.

Customers are assumed to face a per unit transportation cost of t . In this section we present analysis of prices, details of profit can be found in Appendix A.

5.3.1 Symmetric Duopoly

Following Fudenberg and Tirole (2000), two symmetric firms A and B are located at opposite ends of a market of unit length. Given customer recognition we expect the two firms to engage in behavior based price discrimination in period 2. Firms maximize the following profit functions across the two periods:

$$\pi^A = (P_1^A - c)x + \delta[(P_2^{AA} - c)\alpha + (P_2^{BA} - c)(\beta - x)] \quad 5.1$$

$$\pi^B = (P_1^B - c)t(1 - x) + \delta[(P_2^{BB} - c)(1 - \beta) + (P_2^{AB} - c)(x - \alpha)] \quad 5.2$$

Where P_1^A and P_1^B are Period 1 prices, P_2^{AA} and P_2^{BB} are prices offered to existing customers and P_2^{BA} and P_2^{AB} are prices offered to new customers by firm A and B respectively. Firm A's Period 1 market share is defined by x , while firm B's market share is $(1 - x)$, and α denotes the location of A's existing customer indifferent between switching to B in Period 2. Similarly β denotes the location of B's existing customer indifferent between remaining loyal to firm B and switching to firm A in Period 2. Lastly, δ is the discount rate. Due, to the dynamic nature of the game, Period 2 prices depend on market share in Period 1. Solving the model by backwards induction we first optimize the pricing strategy in Period 2.

$$P_2^{AA} = c + \frac{t(1 + 2x)}{3}, P_2^{BA} = c + \frac{t(3 - 4x)}{3},$$

$$P_2^{AB} = c + \frac{t(4x - 1)}{3}, P_2^{BB} = c + \frac{t(3 - 2x)}{3}$$

5.3

The above expressions for Period 2 prices show that the loyalty premium increases with the inherited market share from Period 1, while the poaching price offered to rival's customers decreases with the inherited market share. Thus, if firms have a large inherited market share they offer discounts to new customers to encourage switching and simultaneously make up for the lost profit by extracting consumer surplus from existing customers. The larger the Period 1 market share the more aggressive the pricing strategy in Period 2.

We solve for Period 1 prices assuming firms set prices to maximize total profits. This results in a symmetric equilibrium where

$$P_1^A = P_1^B = c + \frac{t(\delta + 3)}{3}$$

5.4

Both firms have equal market share in the first period i.e., $x = 0.5$. This equilibrium outcome is similar to the equilibrium in a single period game, as both firms try to maximize Period 1 market share to ensure profitable discrimination in Period 2. Consequently, Period 2 equilibrium prices are:

$$P_2^{AA} = P_2^{BB} = c + \frac{2t}{3}$$

$$P_2^{BA} = P_2^{AB} = c + \frac{t}{3}$$

5.5

In Period 2 customer recognition results in customer poaching behavior; firms offer discounts to new customers and charge higher prices to existing customers. Due to the competitive effect of customer poaching we observe that prices decline in Period 2 ($P_1^A > P_2^{AA} > P_2^{BA}$). Furthermore, in line with Fudenberg and Tirole (2000), we expect a decline in profits across time due to the competitive effects of customer poaching.

5.3.2 Asymmetric Duopoly

In this model we consider competition between a large firm and a small firm. We assume the large firm (A) is located in the center of the market while the small firm (B) is located at the end of the market. The market can be viewed as being divided between customers loyal to the large firm and a competitive segment where customers may switch between the two firms. We set the mass of the loyal segment equal to l , such that $0 < l < 1$. Firms compete over the $1 - l$, segment of switchers.⁵ The dominant firm maximizes its profits over the competitive and loyal segment, while the small firm only maximizes profits over the competitive segment. Total profits are as follows:

⁵ Bouckaert et al. (2008) use a similar set up to define asymmetric competition.

$$\begin{aligned} \pi'^A = & (P_1'^A - c)(l + (1 - l)x') + \delta[(P_2'^{AA} - c)(l + (1 - l)\alpha') \\ & + (P_2'^{BA} - c)(\beta' - x')] \end{aligned} \quad 5.6$$

$$\begin{aligned} \pi'^B = & (1 - l)[(P_1'^B - c)t(1 - x') + \delta[(P_2'^{AA} - c)(1 - \beta') + (P_2'^{AB} - c)(x' - \alpha')] \end{aligned} \quad 5.7$$

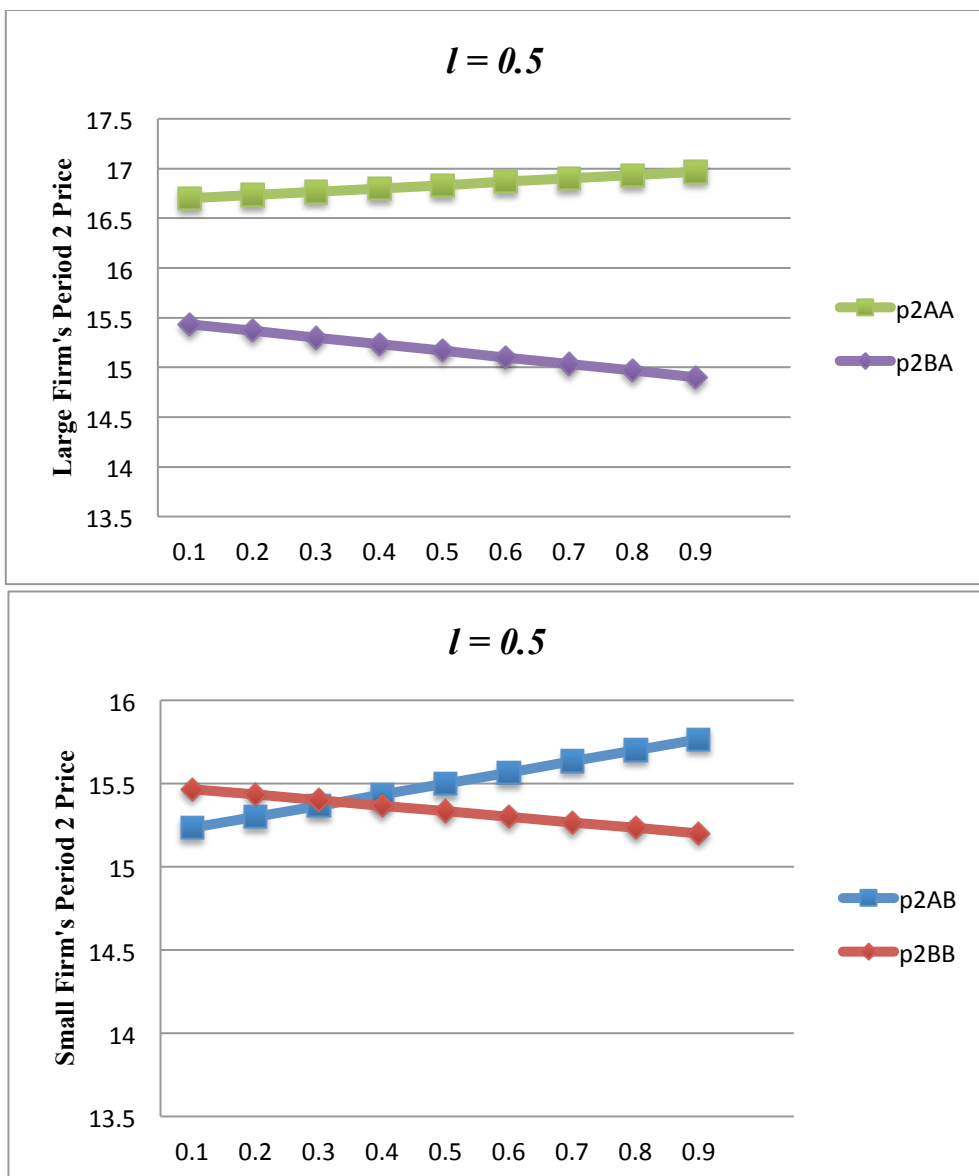
The description of prices and market share is similar to the symmetric duopoly market. Solving the model by backwards induction we first optimize the pricing strategy in Period 2.

$$\begin{aligned} P_2'^{AA} = c + \frac{t(2x'(1 - l) - 3l - 1)}{3(l - 1)}, P_2'^{BA} = c + \frac{t(3 - 4x')}{3} \\ P_2'^{AB} = c + \frac{t(4x'(l - 1) - 3l + 1)}{3(l - 1)}, P_2'^{BB} = c + \frac{t(3 - 2x')}{3} \end{aligned} \quad 5.8$$

Similar to the symmetric case, Period 2 prices are dependent on Period 1 market share. For the large firm the price charged to existing customers is also positively related to the size of the loyal segment; for the large firm the higher the market share in Period 1 (both in the loyal segment (l) and the switching segment ($1 - x'$)) the higher the price charged to existing customers. Figure 5.1 illustrates the relation between price to existing customers and Period 1 market share given the size of the loyal segment $l = 0.5$. In contrast, the price charged to new customers declines with Period 1 market share, i.e., when the large firm has a large share of the competitive segment it expands its market share in Period 2 by offering discounts to new customers. For the small firm

price to existing customers has a positive relation with the small firm's Period 1 market share ($1 - x'$). However, the price to new customers declines with the small firm's Period 1 market share but increases with the size of the large firm's loyal segment (l). Given x' is large ($x' > 0.3$) the price charged to existing customers is lower than the price charged to new customers and the gap rises as the small firm's Period 1 market share declines (see Figure 5.1). Thus, the small firm offers discounts to existing customers to ensure its small customer base is not poached away.

Figure 5.1: Relation between Period 2 prices and size of loyal segment



Solving for Period 1 prices results in the following equilibrium prices:

$$P_1^A = \frac{t(\delta + 3)}{3(1-l)} - \frac{tl(81 + 36\delta - 17\delta^2)}{3(1-l)(27 - 11\delta)} + c$$

$$P_1^B = \frac{t(\delta + 3)}{3(1-l)} - \frac{tl(81 + 48\delta - 5\delta^2)}{3(1-l)(27 - 11\delta)} + c$$

5.9

Our analytical model suggests that in Period 1 despite its large inherited customer base the dominant firm sets lower prices compared to the smaller firm i.e., $P_1^A < P_1^B$. While firm A's customers are better off in the asymmetric market compared to the symmetric market, the small firm's customers are worse off as the small firm charges higher price compared to the symmetric case ($P_1^A < P_1^A$ and $P_1^B > P_1^B$). Consequently, in Period 1 the dominant firm captures more than half of the competitive segment. Finally Period 2, prices are:

$$P_2^{AA} = c + \frac{2t}{3(1-l)} \left[1 + \frac{3l(9 - 2\delta)}{27 - 11\delta} \right] > P_2^{AA}$$

$$P_2^{BB} = c + \frac{2t}{3(1-l)} \left[1 - \frac{3l(9 - 2\delta)}{27 - 11\delta} \right] < P_2^{BB}$$

$$P_2^{BA} = c + \frac{t}{3(1-l)} \left[1 - \frac{9l(3 + \delta)}{27 - 11\delta} \right] < P_2^{BA}$$

$$P_2^{AB} = c + \frac{t}{3(1-l)} \left[1 + \frac{9l(3 + \delta)}{27 - 11\delta} \right] > P_2^{AB}$$

5.10

Given $\delta > 0.45$ (i.e. the future is not heavily discounted), the dominant firm will adopt a customer acquisition strategy in Period 2 as it attempts to increase its

market share in the competitive segment. The dominant firm earns extraction profits by charging a high loyalty premium to customers in the switching and captive segments. Due to the large firm's high price to existing customers the small firm avoids discounts to induce customer switching in the competitive segment. In contrast the small firm engages in a customer retention strategy (given l is sufficiently large) to protect its existing customers from being poached by the dominant firm. By keeping Period 2 prices low the small firm will also encourage the dominant firm's customers to switch resulting in a decline in the dominant firm's market share in Period 2 from Period 1 ($x' > \alpha + \beta - x'$).

5.3.3 Multiple Firms

We assume that four identical firms A, B, C and D are located at equal intervals in the market such that each firm competes with at least two neighboring firms, one on the right and one on the left. Each firm maximizes the following profit function:

$$\pi^{ii} = (P''_1{}^i - c)x'' + \delta[(P''_2{}^{iexist} - c)\alpha'' + (P''_2{}^{inew} - c)(\beta'' - x'')] \quad 5.11$$

for i = A, B, C & D

F.OCs and assuming symmetry we get:

$$P''_2{}^{iexist} = c + \frac{t}{4} - \frac{2tx''}{3}$$

$$P''_2^{inew} = c + \frac{t}{4} - \frac{4tx''}{3} \tag{5.12}$$

In equilibrium each firm adopts a customer acquisition strategy, whereby price offered to new customers is lower than the price to existing customers ($P''_2^{inew} < P''_2^{iexist}$).

Period 1 prices given rational buyers are:

$$P''_1^A = P''_1^B = P''_1^C = P''_1^D = c + \frac{t(\delta + 3)}{12} \tag{5.13}$$

All firms equally share the market in Period 1, which implies that $x'' = 0.25$.

The resulting Period 2 equilibrium prices are:

$$P''_2^{iexist} = c + \frac{t}{6} < P_2^{AA}$$

$$P''_2^{inew} = c + \frac{t}{12} < P_2^{AB} \tag{5.14}$$

Equilibrium with multiple firms results in lower period 2 prices compared to the duopoly scenario case. In addition, compared to the symmetric duopoly scenario the gap between price to new and existing customers is reduced and multiple small firms adopt a less aggressive pricing strategy.

5.4 Testable Implications

In this section we present hypotheses based on Nash equilibrium predictions from models of BBPD presented in Section 5.3.

Our theoretical models suggest that pricing behavior is sensitive to firm size (dominance) and competition (number of firms). We expect the average prices to be higher in the asymmetric duopoly market and lowest in the multiple firm markets. In the asymmetric market the large firm exploits its dominant position by charging a high price to customers, while the small firm also benefits from the large rivals high prices, as it does not have to drop prices extensively to gain market share. In the symmetric market due to the increased competition in Period 2 both firms offer discounts resulting in a drop in the average price level. Finally with multiple firms each firm competes for a smaller share of the market resulting in lower average prices compared to duopolistic markets. According to Stole (2007) with “all-out” competition, price discrimination lowers prices and profits, therefore, we hypothesize that offer prices will be highest in the asymmetric duopoly market followed by the symmetric duopoly market and lowest in the multiple firm market

H1: Prices vary across markets

$$Price_{Asymmetry} > Price_{Symmetric-Duopolist} > Price_{Multiple Firms}$$

Given stable customer preferences and sufficient market dominance (i.e., $x \geq 0.5$, and $x' > 0.5$ & $l \geq 0.3$) we expect dominant firms in symmetric and asymmetric markets to extract surplus from existing customers. In addition, we expect large firms to expand market share by attracting competitor’s customers to switch by offering lower prices. Based on the analysis above we expect large firms in the asymmetric market and symmetric market to engage in customer poaching:

H2: Firms with market power engage in customer poaching

- $Price^{Symmetry_{Existing\ Customers}} > Price^{Symmetry_{New\ Customers}}$
- $Price^{Dominant-Asymmetry_{Existing\ Customers}} > Price^{Dominant-Asymmetry_{New\ Customers}}$

With forward looking firms we expect small firms in asymmetric markets to adopt a customer retention strategy. The smaller the size of the competitive segment (i.e. $l \geq 0.3$) the small firm protects its share of existing customers from switching to the dominant firm. Similarly, when the competitive segment is small the gains to the small firm of encouraging customer switching decline. Only a small proportion of the market will switch. On the other hand, due to its high captive share of the market the large firm charges a high price to existing customers and the small firm can encourage the large firm's existing customers in the competitive segment to switch without significant price discounts. Therefore, we expect forward-looking small firms to offer loyalty rewards to existing customers:

H3: Small firms in asymmetric markets adopt a customer retention strategy

$$Price^{Small-Asymmetry_{Existing\ Customers}} > Price^{Small-Asymmetry_{New\ Customers}}$$

We expect the degree of aggressiveness in price discrimination to vary across markets. We define aggressiveness as the premium charged to existing customers over and above the price charged to new customers in Period 2. Based on the analysis in the previous section, we expect the large firm to offer low prices to rival's customers to increase market share in the competitive segment, while simultaneously compensating for lost profit by charging high loyalty premiums to its existing customers. While symmetric duopolists will also adopt an aggressive pricing strategy, the symmetry in the market will limit the price differential, as firms need to ensure their existing customers

do not switch. Similarly, in the multiple firm market each firm has a smaller share of the total market and risks losing its market share to multiple rivals. Therefore as competition increases, aggressiveness declines.

H4: Aggressiveness increases with market dominance

$$Aggressiveness_{Asymmetry-Dominat} > Aggressiveness_{Symmetric Duopolist} > Aggressiveness_{Multiple Firms}$$

5.5 Experiment

5.5.1 Experiment Design

We employ a within subjects design with three market scenarios; symmetric duopoly, asymmetric duopoly and multiple firms. The order in which participants played the game was randomized to control for possible reference effects. Each market comprised of two periods, participants were given a 24-hour window to set Period 1 prices, after which participants were matched and provided feedback on Period 1 outcomes. Thereafter participants were asked to make Period 2 decisions after which the market scenario was complete. While we had intended to complete each session in a week, due to the busy schedule of some participants the deadlines were extended and the experiment lasted a total of four weeks.⁶ The markets are defined as follows:

- **Symmetric duopoly**

⁶ 26 participants completed all three market scenarios, 10 participants completed 2 scenarios and 8 participants completed only one scenario. We conducted detailed drop out analysis (see Widaman, 2006 for details) on the responses of participants who completed all scenarios and those who completed only one or two scenarios. Based on t-tests for prices entered by participants we find no statistically significant difference in the responses of either group of participants. In addition statistical analysis for participants who completed all scenarios was compared to the results of all participants and no difference in behavior was observed (details of comparison tests can be requested from the authors). Therefore, we do not suspect any systematic difference in the behavior of participants who dropped out before completing all three scenarios.

The market is modeled as a linear city with two sellers A and B located at opposite ends of the city. A-priori there are equal number of customers close to each seller.⁷

- **Asymmetric duopoly**

The market is modeled as a linear city with the large seller located in the center of the market and the small seller located at the end of the city. 75% of the market is closer to the large seller, while only 25% of the customers are in close proximity to the small seller.

- **Multiple Small firms**

The market is modeled as a circular city, with four sellers located at equal intervals. Each seller is conveniently located for 25% of the market.

5.5.2 Procedure

Participants were recruited from alumni networks and executive MBAs of two leading UK based Business Schools and members of professional pricing societies. We recruited professionals⁸ with at least one year experience in setting prices and promotional activities in competitive industries like fast moving consumer goods, telecoms, banking, retail, utilities and consulting. Subjects were invited to share their real world experience and contribute to academic research. Participants actively responded through email and appeared sufficiently motivated to facilitate the understanding of pricing in dynamic markets.

⁷ Geographical proximity can be interpreted in terms of store loyalty.

⁸ Frechette (2011) defines professionals in experimental contexts as people working in an industry where the game under study is relevant.

45 participants took part in the experiment. 34 participants completed the duopoly and asymmetry scenarios while 39 participants completed the multiple firm scenarios (see Table 5.1 for details). 88% of the participants were men and 84% had an MBA degree. Around 58% of participants stated they belonged to large firms with over 1,000 employees and 73% of the participants belonged to industries with high competition. 54% of respondents stated that pricing and promotions were important for their industry. 53% of the respondents stated their firm followed a pricing strategy similar to their competitor, while 33% noted that their firm had an innovative pricing strategy. Based on the participant profiles we are confident that recruited participants were familiar with price setting in competitive scenarios.

Our experimental setting mimics naturally occurring pricing scenario familiar to participants so that the strategic interaction occurs endogenously. To accommodate the busy schedule of working professionals we conducted all experimental sessions online. Online correspondence with participants has been gaining popularity due to its convenience, especially for specialist subject pools (e.g., Artinger and Vulkan, 2013, accommodate the busy schedule of entrepreneurs with an online experiment). Horton et al. (2011) present a detailed discussion regarding the merits of online platforms and note that online experiments in addition to eliminating travel costs and providing convenience to participants, mitigate any demoralization that may occur in a lab setting due to knowledge regarding other participants or experimenter effects. Similarly, Buhrmester et al. (2011) find no difference in the data collected from online sources and data obtained via traditional methods.

Participants were sent emails with instructions regarding the competitive scenario and the rules of the game (detailed instructions can be found in section 5.9,

Appendix B). Participants were informed that they were taking part in a two period game with one (three) competitors and their primary task was to set prices in each period to maximize profits. Participants were informed that 2,000 customers were evenly distributed across the 20-mile market with 100 customers at each unit interval. Since real world markets seldom have homogenous customers, we make markets more realistic by allowing for customer heterogeneity such that 50 customers had a high willingness to pay of £50 while the other 50 customers at each mile interval had a willingness to pay of £25 our proposed. However, it should be noted that in the experimental framework willingness to pay does not generate an incentive for discriminatory pricing when customers have the same size because of the symmetric two-point support with each point equally likely and each point equidistant from the mean value. Therefore, we do not expect seller behavior to be altered by the willingness to pay.

Sellers were informed that buyers incurred transportation costs to travel to the store. The location of buyers is crucial in our design and represents their intrinsic preference for a particular seller.⁹ Other spatial price experiments have also defined buyer preferences in terms of transportation costs (e.g., Mahmood and Vulkan, 2013; Orzen and Sefton, 2008; Selten and Apesteguia, 2005).

To ensure buyers made rational purchase decision we use robot buyers programmed to minimize expenditure.

Participants were informed that they would be competing against randomly matched experiment participants. Once participants made Period 1 pricing decisions, emails with feedback on Period 1 market share, competitor's Period 1 market share,

⁹ The experimental product was defined as electronic brush heads and was selected because the retail prices were in the range of prices outlined in the experiment.

Period 1 own price, competitor's Period 1 price and Period 1 profit were sent out the following day.

In Period 2, sellers had the option to personalize prices based on buyer's behavior in Period 1. Participants were asked to set prices for existing customers and new customers. It took 3-4 days to complete a session as participants set prices on day 1 and waited for all participants to complete the scenario after which participants were matched.

In week 1 all participants were asked to play a trial round. To learn about the competitive nature of the game, participants were also given the option to play against a computer simulated competitor each week. Once participants had understood the rules of the game they proceeded to make actual pricing decisions. Participants played the game only once. While other experiments often play multiple rounds to ensure equilibrium play, it has been noted that multiple round games can result in repeated game effects such as increased cooperation amongst participants (see Pearce, 1992; Friedman, 1977). Furthermore, we expect the outcome of the experiment to reflect a market in equilibrium as participants have significant real world experience in setting prices.

Experimental sessions lasted around half an hour. At the end of the game two randomly selected participants were made payments based on their performance in the game. Every £1 earned in the game was worth 5p in the real world. The two selected participants earned £264 and £227.¹⁰

¹⁰ Only participants who had completed all experimental scenarios were short listed to receive payment.

5.6 Results

In this section we outline the main findings of our experimental study.

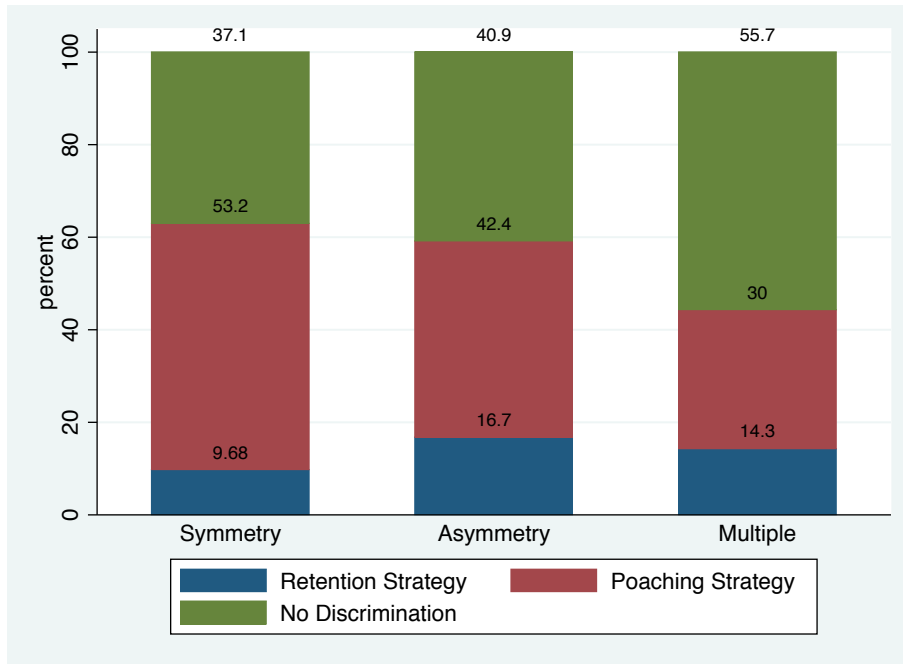
5.6.1 Determinants of Price Discrimination

We find that the proportion of participants engaged in price discrimination declines with the number of firms ($z = 2.21, p < 0.03$)¹¹ and there appears to be no significant difference in the incidence of discrimination between symmetric and asymmetric duopoly markets (see Figure 5.2). This result suggests that when multiple small firms compete for the same customers, the incentive to poach competitor's customers declines. Since each firm's market dominance is diluted firms are unable to earn extraction profits to compensate for lost profits from aggressive poaching.

Comparison of small and large firms in the asymmetric market also strengthens the notion that price discrimination depends on ex-ante market dominance. We find that the large firms engage in more price discrimination compared to small firms ($z = 2.44, p < 0.02$). According to Figure 5.3, 56.3% participants assigned the role of small firms in the asymmetric scenario do not discriminate between customers. In contrast, 73.5% participants assigned the role of dominant firms in an asymmetric market engage in discrimination.

¹¹ Based on the Wilcoxon signed rank test

Figure 5:2: Price Discrimination Across Markets



We further analyze the pricing behavior to determine the factors influencing the decision of participants to discriminate between existing and new customers. Using a binary logit specification we regress discrimination (the dependent variable takes the value of 1 if the price to existing customers is different from the price offered to new customers and 0 otherwise) on dominance (an indicator taking the value of 1 if the firm has a dominant position compared to the rival in asymmetric markets) and number of firms (an indicator taking value 1 in the multiple firm market and 0 otherwise). In addition we control for Period 1 price, competitor’s Period 1 price and Period 1 market share. We also allow for observed and unobserved heterogeneity in participants by including individual level factors like age (indicators for age groups 30-40, and greater than 40), education (indicator taking value of one if participant holds an MBA degree), firm size (indicator taking value of one if firm has greater than 1000 employees), industry background (indicator taking a value of one if industry is growing) and pricing

strategy (whether the participants firm adopts an innovative strategy or follows industry practice. Table 5.2 presents regression results.¹² We find that the incidence of discrimination declines in the market with multiple competitors. Despite controls for individual level effects we observe that small firms in asymmetric markets and small firms in multiple firm markets engage in less discrimination compared to firms in a dominant position. We observe that none of the observed individual characteristics influence price discrimination, however 40% of the observed variance in behavior can be explained by participant level heterogeneity.

5.6.2 Prices and theoretical benchmarks

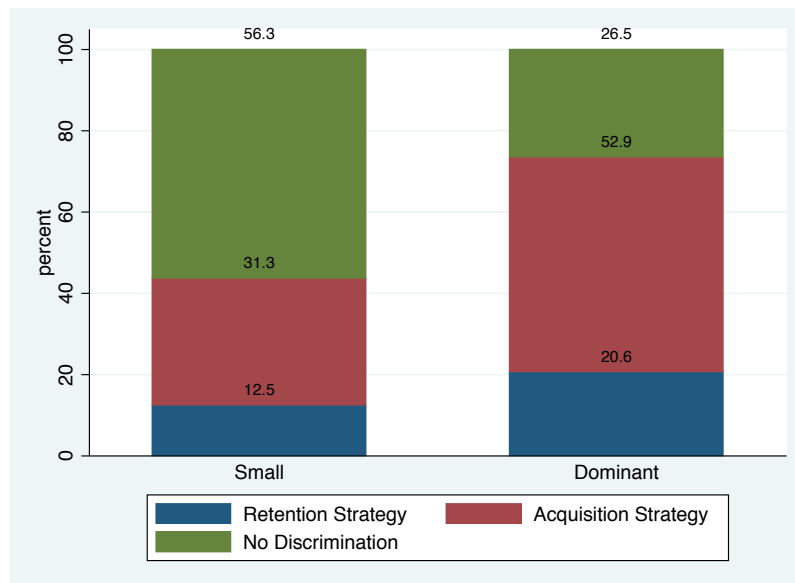
5.6.2.1 Prices vary with market dominance

Table 5.3 provides a comparison of offer prices across the three market conditions and Nash equilibrium predictions. We consider equilibrium predictions with myopic ($\delta = 0$) and forward-looking ($\delta = 1$) firms. The behavior of practitioners seems to be closer to the equilibrium predictions for forward-looking firms. However, across all market scenarios experimental participants set prices higher than the prices predicted by theory. This could indicate that participants did not behave strategically, however, we observe that prices decline in the second period when sellers compete to expand market share in line with Fudenberg and Tirole (2000). The fact that participants set prices higher than equilibrium highlights important elements of pricing in real markets. While pricing experts act strategically, they are mindful of profits and maintain a premium above the equilibrium predictions.

We find that pricing behavior differs with market structure. While there is no statistically significant difference in average Period 1 prices across scenarios, prices

vary across scenarios in Period 2. Based on a one-way ANOVA prices to existing customers differ across scenarios ($F_{2,106} = 3.01, p < 0.06$). Prices offered to existing customers are the lowest for the multiple firm scenarios, followed by the asymmetric scenario, while the symmetric duopolists offer the highest prices to existing customers.

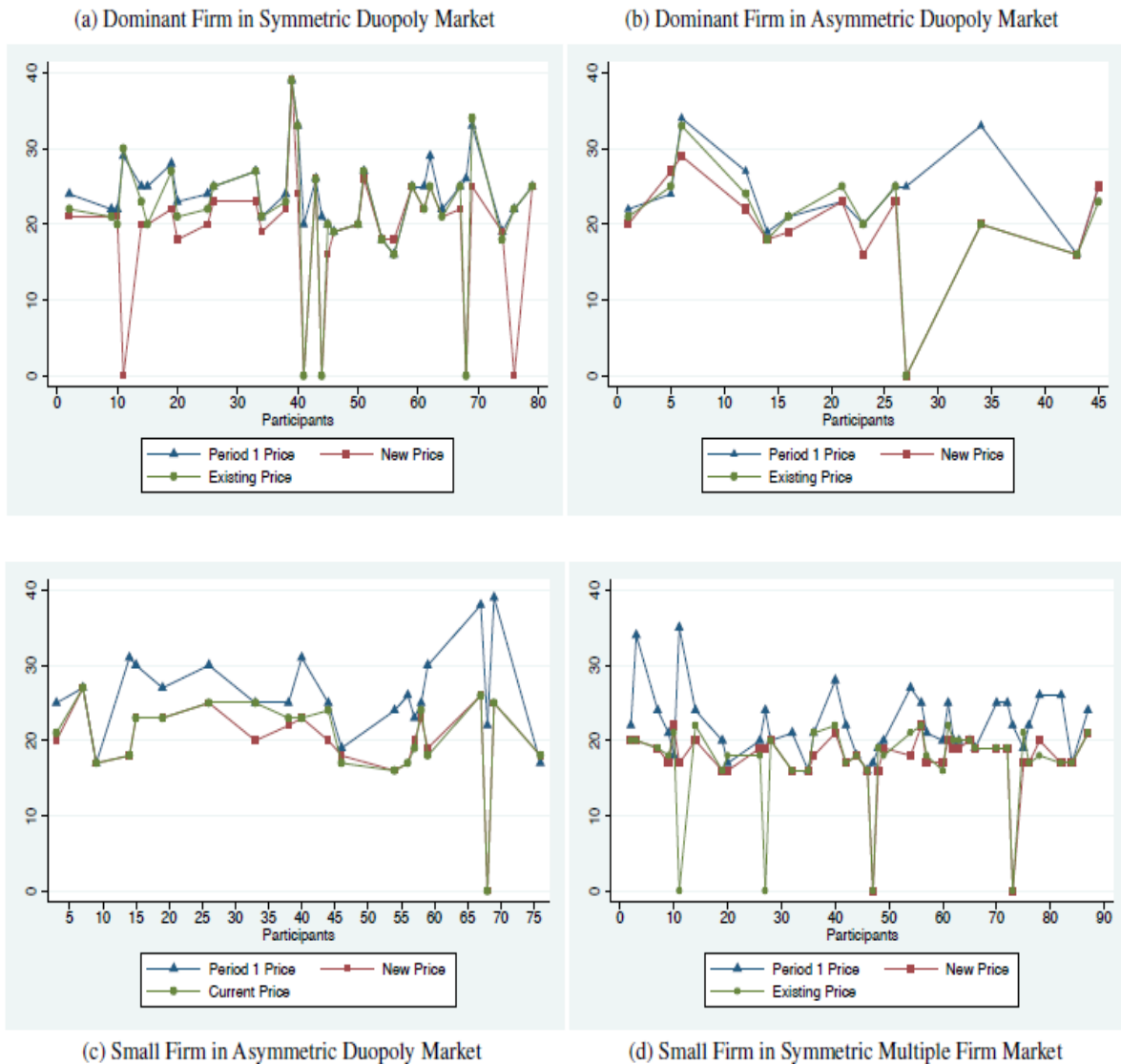
Figure 5.3: Price Discrimination Across Firm Size



Competition between multiple small firms results in lower offer prices compared to the duopoly markets ($diff = 4.27, t = 2.79, d.f = 28$). Similarly, market structure influences prices offered to new customers ($F_{2,398} = 6.19, p < 0.01$). However, new customers are on average offered the same price in the symmetric duopoly scenario and the multiple firm scenario ($diff = 0.07, t = 0.06, d.f = 28$). Figure 5.3 also highlights that few participants set low prices in the symmetric duopoly scenario, while the majority of participants offered similar prices to new and existing customers in the multiple firm scenario. Our results, concur with *H1*, as prices on

average drop with increased competition, however the impact of dominance is on average not significant in duopoly markets.

Figure 5:4: Offer Prices across Markets



5.6.2.2 Dominant firms engage in customer poaching while small firms offer uniform prices

Table 5.4 provides a comparison of average prices offered to existing and new customers across market scenarios. In line with *H2*, customer recognition by the

dominant firm results in lower prices for new customers and higher prices for existing customers. According to Table 5.4, competition between multiple small firms results in no significant difference between prices offered to existing and new buyers. To better understand participant behavior, we compare the percentage of participants that offered discounts to existing customers (retention strategy), percentage that offered discounts to new customers (acquisition strategy) and the proportion of participants that offered both groups the same price (no discrimination). We report the findings in Figure 5.2. When competition is symmetric, participants adopt a poaching strategy and offer discounts to new customers and charge high prices to their existing customers. Similarly, there is greater customer poaching under the asymmetric scenario, however, the incidence of discrimination decreases. While in duopolistic markets majority of participants adopt a poaching strategy (53% in the symmetric market and 42% in the asymmetric market), in the multiple firm scenario only 30% adopt a poaching strategy and 58% of the time old and new customers are offered similar prices. Hence, when market share is diluted participants are less likely to pay customers to switch. Our results are in line with Bouckaert et al. (2008), in Period 2 dominant firms expand market share by offering discounts to competitor's customers, whereas the smaller firms protect market share. Figure 5.3 also shows that prices to exiting customers are above the price offered to existing customers in most instances for firms with market dominance (i.e. large firm in the asymmetric market and the symmetric duopolists).

To confirm whether customer acquisition is dependent on market structure, we regress customer acquisition (the dependent variable takes a value of one if price to existing customers is greater than the price offered to new customers and zero otherwise) on market type, firm size, controls for Period 1 own and competitor strategy.

In addition, we also include variables for age, industry, education, firm size and participant random effects. See Table 5.5. In line with our predicted hypothesis, we observe that compared to the symmetric scenario there is less customer acquisition in markets with multiple firms. Similarly, we observe that small firms in asymmetric markets are less likely to engage in customer acquisition. In addition, we observe that pricing strategy is also dependent on the managerial characteristics. Participants belonging to large firms are more likely to engage in customer poaching further strengthening our findings that customer acquisition is dependent on market dominance.

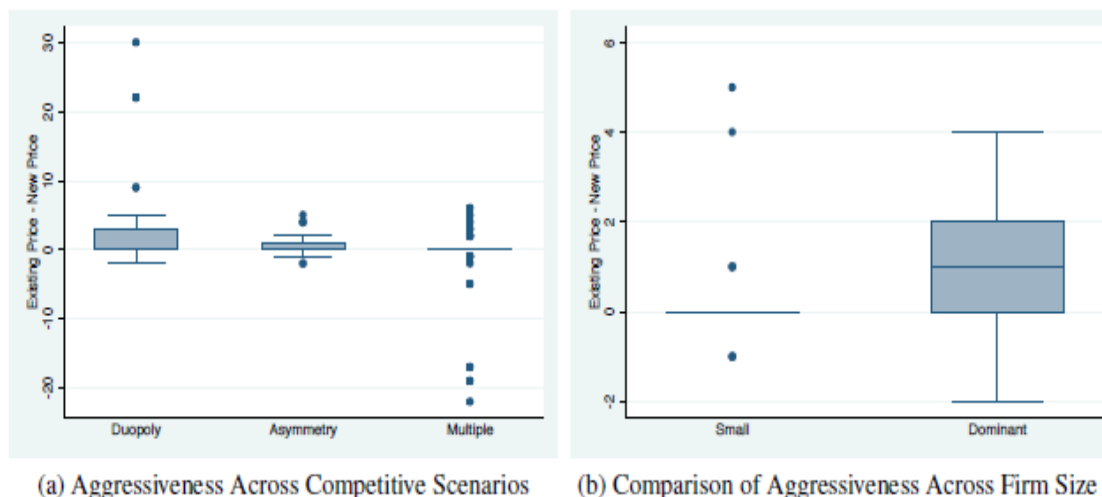
5.6.2.3 Dominant firms are more aggressive than small firms

We measure aggressiveness as the difference between the price offered to existing and new customers. Figure 5.5a shows the box plot for aggressiveness across scenarios and Figure 5.5b presents the average aggressiveness across firm size in the asymmetric scenario.

We find that aggressiveness in pricing behavior varies across market scenarios ($F_{2,106} = 5.35, p < 0.01$). The maximum observed difference in prices to existing and new customers is under the symmetric duopoly scenario followed by the dominant firm in the asymmetric scenario. It is also interesting to note that the price offered to existing customers in Period 2 is similar to the price offered to customers in Period 1 (see Figure 5.5a) while in all other market conditions the prices in Period 2 are almost always below prices in Period 1. Based on our sample of participants the most aggressive poaching is practiced when firms have ex-ante equal market dominance, while dominant firms in asymmetric markets are not as aggressive as theory predicts. Furthermore, in the asymmetric scenario in the face of the dominant participant's aggressive poaching strategy the small participant offers similar prices to both existing and new customers.

Hence, our experimental results do not support *H4*. We find that sellers operating in a symmetric duopoly market are the most aggressive followed by dominant firms in an asymmetric market, while multiple small sellers are the least aggressive.

Figure 5:5: Comparison of Aggressiveness Across Markets



We further analyze the reasons for the aggressiveness using mixed model regression analysis with participant random effects on data pooled across competitive scenarios. The results are presented in Table 5.6. Our results confirm economic theory (e.g., Fudenberg and Tirole, 2000) as the primary motivation behind customer poaching appears to be an expansion of market share. If competitor's Period 1 prices are high participants engage in aggressive customer poaching to retain market share in Period 2.

5.7 Discussion and Conclusion

We contribute to the literature on BBPD by conducting a controlled experiment that explores the interaction between the size of firms and number of firms in markets with customer recognition. Through our experiment we study BBPD in a number of common market scenarios that define many industries (e.g., subscription markets, retail,

insurance, telecommunications and utilities). Our sophisticated subject pool of pricing professionals highlights the significance of purchase history when setting prices. We find that pricing and marketing professionals set prices above those predicted by theory. This suggests that professionals do not sacrifice profits by under cutting their rivals. However, the prevalence of price discrimination varies with market competitiveness. Firms in duopolistic markets are more likely to discriminate compared to firms competing against multiple competitors. Participants choose to discriminate approximately 62% of the time in duopolistic markets, and only 44% of the time in markets with multiple firms.

Our findings support theoretical models of BBPD, whereby customer recognition results in customer poaching. While the number of competitors reduces the prevalence of customer poaching, competition increases the proportion of participants adopting a customer retention strategy. This result helps explain why industries with few similar sized firms attract new customers by offering discounts, for instance, Sky a dominant cable operator, was offering customers gift vouchers upon signing up for their services. On the other hand, in industries with multiple competitors competing for the same pool of customers, like fashion retailers similar prices are offered to new and existing customers.

Furthermore, participant behavior suggests that pricing behavior varies with market dominance. For instance, in asymmetric markets, large firms are more likely to extract surplus from their existing customers and offer poaching discounts to new customers while smaller firms offer similar prices to new and existing customers. However, lack of market power is not a sufficient condition to ensure loyalty rewards as predicted by our theoretical framework.

Contrary to economic theory and conventional wisdom, the observed difference in prices to existing and new customers is on average greater for symmetric duopolists compared to the dominant firm in the asymmetric scenario. This suggests that when firms have equal ex-ante market dominance they act strategically by offering large discounts to rivals customers to expand market share, while simultaneously making up for lost profit by extracting surplus from their existing customer base. On the other hand, the dominant firm in asymmetric markets already has an ex-ante larger market share compared to the small rival and therefore, earns profits from the existing customer base with less incentive to offer steep discounts to new customers.

From a policy perspective BBPD is unlikely to raise antitrust concerns as markets become more competitive and consumers benefit from lower prices when firms have the ability to price discriminate. However, there have been instances where dominant firms have been accused of abusing their power by charging high prices to their existing customers while simultaneously encouraging rival's customers to switch. For instance, the Swedish telecommunications company, Teliasonera was referred to competition authorities for aggressive customer poaching and forcing customer switching. Our sample of pricing experts highlight that symmetric firms are more likely to be aggressive in terms of their pricing compared to dominant firms. Therefore, existing customers might be more disadvantaged in markets with equal sized competitors with sufficient market power compared to a single dominant firm with asymmetric market power. Since we observe that multiple firm markets are the least aggressive, encouraging entry in subscription markets might be a better policy than regulating dominant firms.

There are however certain limitations of our study. We consider customers with constant preferences, in real subscription markets the preferences of customers are volatile and customers may act strategically. Therefore, it would be useful to run the experimental study with real life buyers who are allowed to change preferences over time. Furthermore, the current study does not allow for the possibility of endogenizing customer recognition. If firms were given the choice to invest in customer recognition technologies we expect to see different competitive dynamics. Future research can explore these areas in more detail.

Controlled experiments are particularly useful in comparing behavior across models of strategic interaction. This is particularly useful in the context of models of behavior based price discrimination, where theory is well developed but sensitive to modeling assumptions and the question is not whether assumptions are right or wrong, rather which features explain real world pricing strategies. We hope this study will encourage further interest in experimental validation of models pricing strategies in the presence of customer recognition.

List of Tables

Table 5:1: Participant Breakdown

Scenarios	No. of Participants
Symmetric Duopoly	34
Asymmetric Duopoly	34
Multiple Firms	39
Total	45

Table 5:2: Determinants of Discrimination

	Parameter	Std. Error
Period 1 Price	-0.051	0.068
Competitor's Period 1 Price	-.040	0.068
Period 1 Market Share	-.0005	.0007
Dummy Small Firm	-1.509*	0.829
Dummy Multiple	-1.414**	0.768
Large(>1000 employees)	-0.950	0.695
Age 30-40	0.601	0.932
Age > 40	0.331	1.020
MBA	0.404	0.865
Growing Industry	0.004	0.650
Innovative Pricing	-0.515	0.663
Constant	3.571	3.670
ρ	0.317**	0.217
σ^2	0.423**	1.000
LL	-67.464	
N	107	

Note: * denotes significance at the 10% level, ** denote significance at the 5% level, *** denote significance at the 1% level.

Table 5:3: Average Prices Across Market Scenarios

	Experiment Outcome	Nash eq. $\delta = 1$	Nash eq. $\delta = 0$
Symmetric Duopoly Period 1 Price	23.51 (4.48)	15.667 (0)	15.50 (0)
Symmetric Duopoly - Existing Price	20.97 (7.41)	15.333(0)	15.333(0)
Symmetric Duopoly - New Price	18.94 (8.20)	15.167(0)	15.167(0)
Asymmetric -Dominant- Period 1 Price	23.22 (4.44)	15.292 (0)	15.50 (0)
Asymmetric -Dominant- Existing Price	20.76 (5.71)	16.104 (0)	16.00 (0)
Asymmetric -Dominant- New Price	19.65 (5.28)	14.958 (0)	15.17 (0)
Asymmetry-Small - Period 1 Price	24.04 (6.47)	16.042 (0)	15.50 (0)
Asymmetric Small - Existing Price	20.00 (5.60)	15.229 (0)	15.67 (0)
Asymmetric Small - New Price	19.69 (5.37)	15.708 (0)	15.5 (0)
Multiple Firms - Period 1 Price	23.50 (4.89)	15.17 (0)	15.13 (0)
Multiple Firms - Existing Price	17.29 (6.83)	15.08 (0)	15.08 (0)
Multiple Firms - New Price	18.30 (4.15)	14.96 (0)	14.96 (0)

Note: Standard deviation in (parenthesis).

Table 5:4: Comparison of Prices offered to Existing vs. New Customers

	Existing Customers	New Customers	Customer Poaching
Symmetric Duopoly	20.97 (7.41)	18.94 (8.20)	t =-2.58**, d.f=31
Asymmetry Duopoly	20.76 (5.71)	19.65 (5.28)	t =-2.33**, d.f=33
Multiple Firms	17.29 (6.83)	18.30 (4.15)	t=-1.15, d.f=38

Note: Standard errors in (parenthesis), 't' denotes t-value.

Table 5:5: Factors Influencing Customer Acquisition

	Parameter	Std. Error
Period 1 Price	-0.149	0.134
Period 1 Market Share	-0.002*	.001
Dummy Small Firm	-4.042**	1.766
Dummy Asymmetry	1.123	1.077
Dummy Multiple	1.460	0.926
Large	1.548**	0.798
Age 30-40	0.517	1.036
Age > 40	0.752	1.087
MBA	-.428	.928
Growing Industry	-0.034	0.682
Innovative Pricing	1.247*	0.665
Constant	-5.531	3.447
ρ	0.069	0.332
σ^2	-1.413	5.163
LL	-40.134	
χ^2	0.416	
N	107	

Note:* denotes significance at the 10% level, ** denote significance at the 5% level, *** denote significance at the 1% level.

Table 5:6: Determinants of Aggressiveness

	Parameter	Std. Error
Period 1 Price	-0.217	0.161
Period 1 Market Share	-0.609	2.077
Competitor's Period 1 Price	0.396***	0.140
Dummy Size	-1.077	1.248
Dummy Asymmetry	1.151	1.751
Dummy Multiple Firms	-4.163***	1.378
Age 30-40	-0.516	1.574
Age > 40	-1.004	1.701
MBA	-0.210	1.407
Innovative Pricing	0.145	1.077
Constant	0.639	5.595
x^2	0.046	
R^2	0.239	
N	107	

Note: *** denote significance at the 10% level, ** denote significance at the 5% level, *** denote significance at the 1% level.

5.8 Appendix A

5.8.1 Symmetric Duopoly

Customer utility from purchase from A and B is defined as follows:

$$U_A = v - tx - P^A \tag{5.15}$$

$$U_B = v - t(1 - x) - P^B \tag{5.16}$$

We solve the equilibrium prices by backward induction. Starting the analysis in Period 2, there are two indifferent customers, customer located at α who purchased from firm A in the first period and is indifferent between switching to firm B or staying

with firm A. The second indifferent customer is located at β , purchased from firm B in the first period and is indifferent between staying with firm B or switching to firm A. We define the indifference conditions as follows:

- Indifference condition for Firm A's Period 1 customer

$$P_2^{AA} + t\alpha = P_2^{AB} + t(1 - \alpha) \quad 5.17$$

- Indifference condition for Firm B's Period 1 customer

$$P_2^{BA} + t\beta = P_2^{BB} + t(1 - \beta) \quad 5.18$$

Based on the location of the customers second period demand is the sum of demand from existing customers $\alpha, (1 - \beta)$, and demand from new customers $((\beta - x), (x - \alpha))$.¹³ Thus second period profit of the firms can be defined as:

Firm A

$$\pi_2^A = (P_2^{AA} - c)\alpha + (P_2^{BA} - c)(\beta - x) \quad 5.19$$

Firm B

$$\pi_2^B = (P_2^{BB} - c)(1 - \beta) + (P_2^{AB} - c)(x - \alpha) \quad 5.20$$

Considering the interior solution optimal prices in Period 2 are as follows:

$$\begin{aligned} P_2^{AA} &= c + \frac{t(1 + 2x)}{3}, P_2^{BA} = c + \frac{t(3 - 4x)}{3}, P_2^{AB} = c + \frac{t(4x - 1)}{3}, P_2^{BB} \\ &= c + \frac{t(3 - 2x)}{3}, \end{aligned} \quad 5.21$$

The second period profits are symmetric and are defined as follows:

¹³ In Period 1 firm A's market share is defined by x , while firm B's market share is defined as $(1-x)$

$$\pi_2^A = \pi_2^B = \frac{5t(2x^2 - 2x + 1)}{9}$$

5.22

We now turn to first-period competition. In the first period the myopic customers will only maximize current utility, therefore, the indifferent customer located at x will face the flowing trade off in Period 1:

$$P_1^A + tx = P_1^B + t(1 - x)$$

However, since firms are forward looking, they will set prices in Period 1 to ensure that total profits are maximized. Therefore, the total profits will be the sum of the first period and the discounted value of the second period profits, where the discount rate $\delta < 1$.

$$\pi^A = (P_1^A - c)x + \delta[(P_2^{AA} - c)\alpha + (P_2^{BA} - c)(\beta - x)]$$

5.23

$$\pi^B = (P_1^B - c)t(1 - x) + \delta[(P_2^{BB} - c)(1 - \beta) + (P_2^{AB} - c)(x - \alpha)]$$

5.24

Solving the necessary first order conditions in terms of P_1^A and P_1^B reveals a symmetric equilibrium where

$$P_1^A = P_1^B = c + t$$

5.25

Both firms have equal market shares in the first period i.e., $x = 0.5$.

Substituting the value of x in Period 2 prices we get:

$$P_2^{AA} = P_2^{BB} = c + \frac{2t}{3}$$

$$P_2^{BA} = P_2^{AB} = c + \frac{t}{3}$$

5.26

Period 1 and Period 2 profits are symmetric

$$\pi_1^A = \pi_1^B = \frac{t}{2}$$

5.27

$$\pi_2^A = \pi_2^B = \frac{5t}{18}$$

5.28

5.8.2 Asymmetric Duopoly

Customer utility along the competitive segment is defined as follows:

$$U_A = v - tx' - P^A$$

$$U_B = v - t(1 - x') - P^B$$

5.29

While utility of the loyal customers is defined as

$$U_A = v - tx'_l - P^A$$

5.30

Starting in Period 2 we solve the model by backwards induction and only consider interior solutions where both firms remain in the market. Similar to the symmetric market the indifferent switching customers will be located in the $1 - l$, segment of the market. Firm A's existing customers indifferent between switching to firm B will be located at α' , while firm B's existing customers indifferent between switching to firm A will be located at β' .

- Indifference condition for Firm A's customer

$$P_2'^{AA} + ta' = P_2'^{AB} + t(1 - a')$$

- Indifference condition for Firm B's customer

$$P_2'^{BA} + t\beta' = P_2'^{BB} + t(1 - \beta')$$

Based on the location of the customers second period demand is the sum of demand from existing customers $(\alpha, 1 - \beta)$ and demand from new customers $((\beta - x), (x - \alpha))$, where x' is the Period 1 market share of the dominant firm A in the competitive segment. Thus second period profit of the firms can be defined as:

Firm A

$$\pi_2^A = (P_2'^{AA} - c)(l + (1 - l)a') + (P_2'^{BA} - c)(1 - l)(\beta' - x') \quad 5.31$$

Firm B

$$\pi_2^B = (1 - l)[(P_2'^{BB} - c)(1 - \beta') + (P_2'^{AB} - c)(x' - \beta')] \quad 5.32$$

Solving the F.O.C.s with respect to Period 2 prices we get the following interior solution for Period 2 prices.

$$P_2'^{AA} = \frac{t2x'(l - 1)3a - 1}{3(l - 1)}, P_2'^{AB} = \frac{t[4x'(l - 1) - 3l + 1]}{3(l - 1)}$$

$$P_2'^{BA} = \frac{t(3 - 4x')}{3}, P_2'^{BB} = \frac{t(3 - 2x')}{3} \quad 5.33$$

We now turn to first-period competition. Myopic first-period indifferent consumers only consider the current period prices offered by the two firms. The indifferent customer located at x' faces the following trade off:

$$P_1^A + tx' = P_1^B + t(1 - x')$$

Forward-looking firms will maximize total profits given the discount rate δ .

$$\pi'^A = (P_1'^A - c)(l + (1 - l)x') + \delta[(P_2'^{AA} - c)(l + (1 - l)a') + (P_2'^{BA} - c)(\beta' - x')] \quad 5.34$$

$$\pi'^B = (P_1'^B - c)t(1 - x') + \delta[(P_2'^{BB} - c)(1 - \beta') + (P_2'^{AB} - c)(x' - a')] \quad 5.35$$

Solving for Period 1 prices results in the following:

$$P_1'^A = \frac{t(\delta + 3)}{3(1 - l)} + \frac{tl(81 + 36\delta - 17\delta^2)}{3(1 - l)(27 - 11\delta)} + c \quad 5.36$$

$$P_1'^B = \frac{t(\delta + 3)}{3(1 - l)} - \frac{tl(81 + 48\delta - 5\delta^2)}{3(1 - l)(27 - 11\delta)} + c \quad 5.37$$

Dominant firms charge a higher price than symmetric firms $P_1'^A < P_1^A$.

In contrast the small firm is able to charge a higher price compared to the duopoly scenario

$$P_1'^B > P_2^B$$

The competitive segment market share for the dominate firm can be defined as:

$$x' = \frac{t}{2(1 - l)} - \frac{3l(9 - 7\delta)}{2(1 - l)(27 - 11\delta)} \quad 5.38$$

Substituting the value of x we get the following Period 2 prices:

$$P_2'^{AA} = c + \frac{2t}{3(1-l)} \left[1 + \frac{3l(9-2\delta)}{27-11\delta} \right] > P_2^{AA}$$

$$P_2'^{BB} = c + \frac{2t}{3(1-l)} \left[1 - \frac{3l(9-2\delta)}{27-11\delta} \right] < P_2^{BB}$$

$$P_2'^{BA} = c + \frac{t}{3(1-l)} \left[1 - \frac{9l(3+\delta)}{27-11\delta} \right] < P_2^{BA}$$

$$P_2'^{AB} = c + \frac{t}{3(1-l)} \left[1 + \frac{9l(3+\delta)}{27-11\delta} \right] > P_2^{AB}$$

5.39

The resultant market share in the competitive segment for the dominant form is:

$$\alpha + \beta - x' = \frac{1}{2(1-l)} - \frac{15l(3-\delta)}{3(1-l)(27-11\delta)}$$

5.40

Period 1, profit for the two firms is:

$$\pi_1^A = \left[t + \frac{t(4l(81-99\delta-80\delta^2))}{9(27-20\delta)} \right] \left[\frac{1}{2} - \frac{9l}{27-20\delta} + l \right]$$

5.41

$$\pi_1^B = \left[t + \frac{t(2l(81-198\delta-80\delta^2))}{9(27-20\delta)} \right] \left[\frac{1}{2} + \frac{9l}{27-20\delta} \right]$$

5.42

Four Firms

In this section we analyze the equilibrium prices for a market with multiple equal sized firms. The indifferent existing customer for firm B is located at

$$P_2''^{Bexist} + t\alpha_2 = P_2''^{Cmew} + t\left(\frac{1}{4} - \alpha_2\right)$$

$$\alpha'' = \alpha_1 + \alpha_2 = \frac{(P_2''^{Anew} - P_2''^{Bexist}) + (P_2''^{Cnew} - P_2''^{Bexist})}{2t} + \frac{1}{4} \quad 5.43$$

$$P_2''^{Bnew} + t\left(\frac{1}{4} - \beta_1\right) = P_2''^{Aexist} + t\beta_1$$

$$P_2''^{Bnew} + t\left(\frac{1}{4} - \beta_2\right) = P_2''^{Cexist} + t\beta_2$$

$$\beta'' = \beta_1 + \beta_2 = \frac{(P_2''^{Bnew} - P_2''^{Aexist}) + (P_2''^{Bnew} - P_2''^{Cexist})}{2t} + \frac{1}{4} \quad 5.44$$

Imposing a symmetric equilibrium, all firms offer the same price to new and existing customers

$$P_2''^{Anew} = P_2''^{Bnew} = P_2''^{Cnew} = P_2''^{Dnew}$$

$$P_2''^{Aexist} = P_2''^{Bexist} = P_2''^{Cexist} = P_2''^{Dexist}$$

$$\pi''_2 = (P_2''^{iexist} - c)\alpha + (P_2''^{inew} - c)(\beta - x'') \quad 5.45$$

$$P_2''^{iexist} = c + \frac{t}{4} - \frac{2tx''}{3}, P_2''^{inew} = c + \frac{t}{4} - \frac{4tx''}{3} \quad 5.46$$

Price offered to new customers is lower than the price to existing customers.

Indifferent customer for firm B in Period 1 N

$$P_1''^B + tx_A'' = P_1''^A + t\left(\frac{1}{4} - x''\right)$$

5.47

$$P_1''^B + tx_B'' = P_1''^C + t\left(\frac{1}{4} - x_B''x_B'''\right)$$

5.48

$$x_1'' = x_A'' + x_B'' = \frac{\left((P_1''^A - P_1''^B) + (P_1''^C - P_1''^B)\right)}{2t} + \frac{1}{4}$$

5.49

$$\pi_B'' = x_1''(P_1''^B - c) + \delta[P_2''^B\alpha'' + P_2''^{Bnew}\beta'']$$

5.50

Maximize subject to prices.

$$P_1''^A = P_1''^B = P_1''^C = P_1''^D = c + \frac{t}{4}^{14}$$

5.51

$$\pi_1^i = \frac{t}{16}$$

5.52

All firms equally share the market in Period 1, which implies that $x = 0.25$.

5.9 Appendix B

5.9.1 Instructions

Week 1: Introductory E-mail

Thank you for participating in our experiment. In this experiment you will be participating in a series of price setting scenarios. You are the pricing and promotion expert for Astra supermarket; located in town X. Astra deals in a wide range of products, including groceries, electronics, apparel, insurance and financial services.

Every week you will be making pricing and promotion decisions for Astra under different scenarios. You will be making important pricing and promotion decisions,

¹⁴ Despite the dynamic game, the first period equilibrium is similar to the equilibrium in a static one period model without BBPD.

which will impact the profitability of your store and in, turn your earnings. Your pay is directly proportional to the profit earned by your firm.

The price-setting task will be straightforward and will only take 5- 10 minutes or longer depending on how long it takes you to arrive at a decision. You will have a 24-hour window to submit your decision. After you set the prices, details of your earning and performance will be provided through email once all other participants have made their decisions.

The first week is the trial week to familiarize you with the procedure. The actual experimental sessions will commence the following week.

Each week your earnings from the experiment will be recorded. At the end of the experiment 2 random participants will be selected to receive a payment based on their performance in the price setting experiment. We expect selected participants to earn around £200 at the end of the experiment.

Week 2: Scenarios

Symmetry

Astra's main competitor is Beta mart, which has a product selection identical to Astra. In addition, the same wholesaler supplies to both supermarkets and charges identical wholesale prices to both supermarkets.

Due to town planning regulations stores can only locate on the outskirts of the city.

- Astra is located at the west end of the town while Beta mart is located on the east end.
- The distance between the two stores is 20 miles
- You will be setting the prices across 2 periods. You must decide on the optimal price and promotion for each product category taking into account costs and competitor strategy.

Symmetric Competition



5.9.2 Asymmetry

You are in charge of the pricing and promotion of Giant (Townsend) supermarket, located in Town X. There is one other competing supermarket Townsend (Giant) supermarket, in Town X. Townsend (Giant) is a relatively small (large) store compared to Giant (Tonwsend) supermarket. Despite its small size Townsend has a product selection, which is identical to Giant supermarket. In addition the wholesaler supplying Giant supermarket and Townsend is the same and due to government regulation charges the same wholesale prices.

- Due to its large size Giant is located in the center of the town while Townsend is located on the east end
- The distance between the two stores is 10 miles
- Giant is conveniently located for 2/3rd of the customers while the remaining 1/3rd find Townsend is closer

Asymmetric Market



Four Firms

You are in charge of the pricing and promotion of A mart, located in Town X. There are 3 other supermarkets; B, C and D, in Town X. All 4 supermarkets have identical product selection. The wholesaler supplying the supermarkets is the same and due to government regulation charges the same wholesale prices.

- All stores are 5 miles apart



- Each supermarket is conveniently located for 1/4th of the town's population
- You will be setting price across 2 periods. You must decide on the optimal price and promotion for each product category taking into account costs and competitors strategy.

Period 2/ Next Day Email

Welcome to period 2 of the experiment Welcome to period 2 of the experiment.

Customers in have now made purchases for electronic brush heads. Following is the detail of the market sales:

— Customers bought from you @ a price of £——

— Customers bought from your competitor: Beta mart @ a price of £——

Your market share in period 1 was: ——

Your total profit is £——

The sales department has compiled a database of the customers who purchased from you. In addition you have purchased detailed customer data from a market research firm. The detailed market analysis enables you to distinguish between customers based on their purchase behavior.

Based on this information you learn that customers in the market vary in their valuation for the product you sell. The market research firm identifies 2 distinct customer segments:

Existing customers:

— Customers purchased from Astra mart in the period 1. Purchase behavior in conjunction with survey data shows that these are low- type customers who will not be willing to pay more than £30 for brush heads

New customers:

—— Customers did not purchase from Beta mart. Due to data privacy you cannot access willingness to pay information for these customers. This segment comprises of the remaining high and low type customers that did not purchase from you in period 1.

Additionally, the survey data on store preferences suggests that while customers have a liking for a particular store they could consider switching if they find the product at a suitable price.

In period 2 you again need to set prices in order to maximize sales in light of your performance in the previous period. One option is to offer different prices to different customer segments.

You can send personalized discount coupons to customers, would you choose to offer different prices to the different customer segments?

a) Yes b) No

What is the price (including any discount) you will set to Existing customers?

What is the price (including any discount) you will set to New customers?

6 How Does Customer Information Affect Pricing Strategies?

6.1 Introduction¹

Customer recognition is widely prevalent today, with firms investing greater resources than ever before to track consumer behavior. Information on consumer behavior gives firms the opportunity to implement “micro-segmentation and customer management strategies” (Shin and Sudhir 2010, p.1). For instance, Catalina, a US based marketing company that tracks billions of purchases each year has gone as far as using a shopper’s in store location to refine offers. Similarly with the growing popularity of “big data” on the Internet more and more firms are able to offer personalized prices and promotions. Firms are essentially collecting two types of information: firstly, firms identify whether a customer is making a repeat purchase or is new to the firm. Shy and Stenbacka (2013) regard this as *identity recognition*. Secondly, firms are interested in collecting information on the willingness to pay of customers; we call this *type recognition*.

The recent rise in the collection and use of consumer information has raised new questions and concerns regarding the impact of information on market dynamics and consumer welfare. A growing body of literature in the field of marketing and economics

¹ Based on joint work with Professor Nir Vulkan.

examines price discrimination in imperfectly competitive markets (see Esteves, 2009 for a review), however, the profit and welfare implications of price discrimination are dependent on the specific modeling assumptions (i.e., assumptions regarding market structure, customer heterogeneity and preferences). There is a lack of empirical research on pricing behavior that can reconcile the often diverging findings of analytical models. Similarly, little is known about the impact of information on price discrimination and customer welfare. For instance, information on customer types could increase consumer welfare by ensuring more customers are served in equilibrium, however, it could also result in greater surplus extraction and customers being worse off.

This study addresses this gap in the literature. To the best of our knowledge we conduct the first empirical study that inspects the effect of customer type recognition and identity recognition on behavior based price discrimination. In a controlled experimental setting with a representative pool of professional pricing experts, we test how the availability of information influences pricing behavior. By using a subject pool of professionals we are able to not only test the role of identity and type recognition on pricing behavior, but also gain insights into the underlying incentives for the actions of pricing experts. In addition, we ascertain the role of external factors like industry background, firm size age and education of pricing experts, in affecting pricing strategies.

In our experimental setting, we consider both horizontally and vertically differentiated customers, while information about customer valuations and purchase history is manipulated across treatments. We further explore the relationship between customer information and market structure, we specifically test if dominant firms adopt

more aggressive pricing strategies or if market coverage increases when type recognition is possible in symmetric markets.

Based on the behavior of our expert subject pool, we find that price discrimination increases with customer type recognition across both symmetric and asymmetric markets. However, the aggressiveness in the pricing behavior varies with market dominance, as dominant firms in asymmetric markets extract the greatest surplus from existing high type customers. We also find that customer recognition does not necessarily serve the interests of customers, as type recognition results in higher prices in Period 2 and some customers are priced out of the market.

The remainder of this chapter is organized as follows: Section 6.2 presents the developments in the literature on BBPD, Section 6.3 outlines the experimental procedure and design, Section 6.4 presents the findings of the experimental study and Section 6.5 presents a discussion of the key findings and policy implications.

6.2 Literature Review

A key feature of models with customer recognition is the ability of firms to classify customers based on purchase history into two groups: existing/loyal customers and new/competitor's customers (e.g., Fudenberg and Tirole, 2000; Shaffer and Zhang, 2000; Villas-Boas, 1999). Customer recognition coupled with homogenous consumers and constant preferences is noted to result in intense competition to attract new customers through switching discounts, while consumer surplus is extracted from existing customers (e.g., Chen and Zhang, 2009; Pazgal and Soberman, 2008; Chen and Iyer, 2002; Fudenberg and Tirole, 2000). Most studies of behavior based price discrimination (BBPD) assume consumers are horizontally differentiated, (i.e.

customers differ in terms of their preference for stores), however, in reality consumers also differ in their willingness to pay. Some customers may be high type and have a high willingness to pay, while others may have a low willingness to pay. Although customer type heterogeneity has been considered in monopoly models of third degree price discrimination (e.g., Thisse and Vives, 1988), the analysis of vertical differentiation competitive markets with identity recognition is lacking.

Shin and Sudhir (2010) is a notable exception, the authors extend two period models of BBPD and consider a market with both vertical and horizontal differentiation between customers. The authors show that given sufficient preference mobility and customer value heterogeneity, firms offer lower prices to loyal high type customers compared to new customers. Thus, equilibrium outcomes depend on customer information, as type recognition in addition to identity recognition results in profitable customer retention.

According to Stole (2007), the ability to segment consumers is an important determinant of price discrimination. Any additional information on customer types that aids in customer segmentation is expected to result in greater price discrimination. In the context of pricing for Netflix, Shiller (2013) finds that the availability of detailed web browsing data for Netflix customers greatly improves profitability of first-degree price discrimination. Similarly, Esteves (2010) indicates that access to information can alter the equilibrium in markets with customer recognition. According to Esteves (2009), the profitability of price discrimination depends on the type of information available, and not all information results in a prisoner's dilemma. For instance, with customer type recognition firms can extract greater surplus from high type customers

without pricing low type customers out of the market, consequently profits increase with information.

Therefore, we expect participants to use the additional information on customer types to set personalized prices for existing customers and draw inferences about the type of new customers. For instance, if the proportion of new customers comprises of more low type customers sellers would be likely to set different prices for existing and rivals customers. We further contend that the ability to discriminate on the basis of customer type will impact consumer welfare. When firms use additional information to improve customer targeting based on willingness to pay, it is expected to result in greater market coverage, compared to the partial information condition. Therefore, we hypothesize that type recognition in addition to identity recognition is mutually beneficial for customers and firms.

Extant literature on price discrimination with customer recognition mostly considers symmetric duopoly markets, however, equilibrium outcomes have been shown to depend on market dominance. For instance, Chen (2008) finds that in asymmetric markets, the stronger brand eliminates competition by adopting an aggressive poaching strategy. In contrast, Gehrig et al. (2006) find that the smaller firm engages in aggressive customer poaching to gain market share. Shaffer and Zhang (2000) also consider asymmetry in a duopoly model and find that asymmetric switching costs are sufficient to make a customer retention strategy profitable. In a controlled experimental setting Mahmood and Vulkan (2013), also find that BBPD varies with market dominance. However, the relationship between market dominance and the use of customer information has not been explored thus far. Since market power is a prerequisite for price discrimination, we expect dominant firms to engage in greater

customer poaching when information on customer type is available. In contrast, the small firm in the asymmetric market is likely to protect market share in the second period by offering discounts to existing high type customers, to ensure they do not switch to the dominant firm.

This chapter also contributes to the experimental literature on pricing in competitive markets (e.g., Mahmood, 2013; Mahmood and Vulkan, 2013; Morgan et al., 2006; Baye and Morgan, 2004; Dufwenberg and Gneezy, 2000; Hoggatt et al., 1976). We extend this literature by testing if the behavior of symmetric firms differs from the pricing strategy of asymmetric firms when more customer information is available. By considering the interplay between market structure and customer information we aim to provide a better understanding of observed pricing behavior.

6.3 Experiment Design

6.3.1 Experiment

Experiments not only provide a means of testing theoretical predictions but also allow for additional behavioral insights. Our experimental setup simulates behavior in two period models of dynamic competition between strategic forward-looking firms. Firms are located in a market of unit length and strategically set prices across two periods to maximize total profits. Consumers are assumed to be rational per period utility maximizers, with inelastic unit demand and constant preferences. Following Fudenberg and Tirole (2000), in Period 1 firms are unaware of customer preferences and, can only charge a uniform price to all customers. In Period 2 firms learn about consumer preferences based on Period 1 purchase behavior, in light of this information firms have the option to discriminate between existing and new customers (*identity recognition*). We further assume there are two types of customers; high type customers

have a higher willingness to pay and low type customers who have a lower willingness to pay, and firms can distinguish existing customer on the basis of willingness to pay (*type recognition*).

We employ a between subjects' information manipulation and divide participants into two information conditions: *full information* and *partial information*. In the full information treatment, participants are able to distinguish both the identity and type of customers, i.e., participants can price discriminate between existing high and low type customers as well as new customers. In the partial information treatment participants are not given information on customer type and could only discriminate between existing and new customers. In addition, participants play two market scenarios; symmetric duopoly and asymmetric duopoly. The markets are defined as follows:

- **Symmetric duopoly**

The market is modeled as a linear city with two sellers A and B located at opposite ends of the city. A-priori there are equal number (50%) of customers close to each seller.²

- **Asymmetric duopoly**

The market is modeled as a linear city with the dominant seller located in the center of the market and the small seller located at the end of the city. 75% of the market is closer to the dominant seller, while only 25% of the customers are in close proximity to the small seller.

Each week participants were asked to participate in a different market scenario and the order was randomized to control for any reference effects. In addition, to ensure

² Geographical proximity can be interpreted in terms of store loyalty.

participants realized the difference between existing and new customers we made the game last for two periods. Where the first period served to educate participants about the market and personalization was allowed in the second period.

6.3.2 Procedure

Participants were recruited from leading UK Business School alumni networks, executive MBAs and members of professional pricing societies. We recruited professionals³ with at least one year experience in setting prices and promotional activities in competitive industries like fast moving consumer goods, telecoms, banking, retail, utilities and consulting. Subjects were invited to share their real world experience and contribute to academic research. Participants actively responded through email and appeared sufficiently motivated to facilitate the understanding of pricing in dynamic markets.

A total of 60 participants were randomly assigned to the full information condition while 68 participants were given only partial information about the type of their existing customers. A total of 62 subjects participated in the symmetric duopoly scenario and 66 subjects participated in the asymmetric duopoly scenario. Table 6.1 presents a breakdown of experiment participants.

83% of the participants were men and 82% had an MBA degree. Around 51% of participants stated they belonged to large firms with over 1,000 employees and 70% of the participants belonged to industries with high competition. 60% of respondents stated that pricing and promotions were important for their industry. 45% of the respondents stated their firm followed a pricing strategy similar to their competitor, while 38% noted

³Frechette (2011) defines professionals in experimental contexts as people working in an industry where the game under study is relevant.

that their firm had an innovative pricing strategy. We are fairly confident that recruited participants were familiar with price setting in competitive markets.

Our experimental setting follows a naturally occurring pricing scenario familiar to participants so that the strategic interaction occurs endogenously. To accommodate the busy schedule of working professionals we conducted all experimental sessions online. Horton et al. (2011) note that online experiments are convenient for participants as they not only to eliminate travel costs, but also mitigate any demoralization that may occur in a lab setting due to knowledge of other participants or experimenter effects. In addition, there have been no reported differences between data collected in online experiments and data collected via traditional methods (Buhrmester et al., 2011).

Participants were sent weekly emails with instructions regarding the competitive scenario and the rules of the game (detailed instructions can be found in Section 6.6 Appendix). Participants were informed that their primary task was to set prices that would maximize profits in a two period game with a randomly matched participant. Participants were matched within the information conditions, i.e. a participant assigned to the full information condition only played against other participants in the full information condition.

Our experimental setting allowed for both vertical and horizontal differentiation amongst customers. Participants were informed that 2,000 customers were evenly distributed across the 20-mile market with 100 customers at each unit interval, buyers incurred transportation costs to travel to the store. The location of buyers is crucial in our design and represents their intrinsic preference for a particular seller. Other spatial

price experiments have also defined buyer preferences in terms of transportation costs (e.g., Mahmood, 2013; Orzen and Sefton, 2008; Selten and Apesteguia, 2005).

We use robot buyers who were programmed to minimize per period expenditure, i.e., buyers were rational. We mimic real markets with partial coverage and allow customers the option to not purchase.

Once participants made Period 1 pricing decision, emails with feedback on Period 1 market share, competitor's Period 1 market share, Period 1 own price, competitor's Period 1 price and Period 1 profit were sent out the following day.

In Period 2, sellers had the option to personalize prices based on buyer's behavior in Period 1. In Period 2, participants assigned to the partial information condition were asked to set two prices; (1) price for existing buyers and (2) price for new buyers. Participants in the full information condition were given the option of setting three different prices; (1) price to high type existing buyers, (2) price to low type existing buyers and (3) price to new buyers. Once all participants had submitted the Period 2 prices, participants were contacted in the following week with a request to participate in a different market condition.

To ensure participants fully understood the rules of the experiment, in week 1, all participants were asked to play a trial round. Furthermore, participants were given the option to play against a computer-simulated competitor each week. Once participants understood the rules of the game they proceeded to make actual pricing decisions. Participants played the game only once. By allowing subjects to play only once we were able to control for reputation effects and prevent collusive behavior. Our aim is not to test convergence to the Nash equilibrium, rather to provide insights into

pricing behavior based on professional experience; therefore we do not play the game repeatedly.

Experimental sessions lasted around half an hour. At the end of the game two randomly selected participants were made payments based on their performance in the game.⁴

6.4 Results

In this section we outline the main findings of our experimental study.

Since the experimental tasks closely mimic real world scenarios faced by professionals, we find evidence of strategic price setting behavior however, the prices offered to existing and new customer remain significantly higher than theoretical predictions (see Table 5.3). Based on nonparametric tests across both information conditions prices to new customers were significantly higher than equilibrium ($z = 8.33$, $p < 0.00$)⁵ similarly, the price to existing customers is also significantly higher than the equilibrium prediction ($z = 5.96$, $p < 0.00$).⁶ Table 6.2 compares average prices across periods and information conditions.

6.4.1 Identity recognition results in customer poaching

Comparison of the average price offered to new and existing customers reveals that participants engage in strategic customer poaching when customer recognition is possible. Figure 6.1 plots the offer prices across market scenarios. In line with the models of BBPD (e.g., Fudenberg and Tirole, 2000) participants offer lower prices to

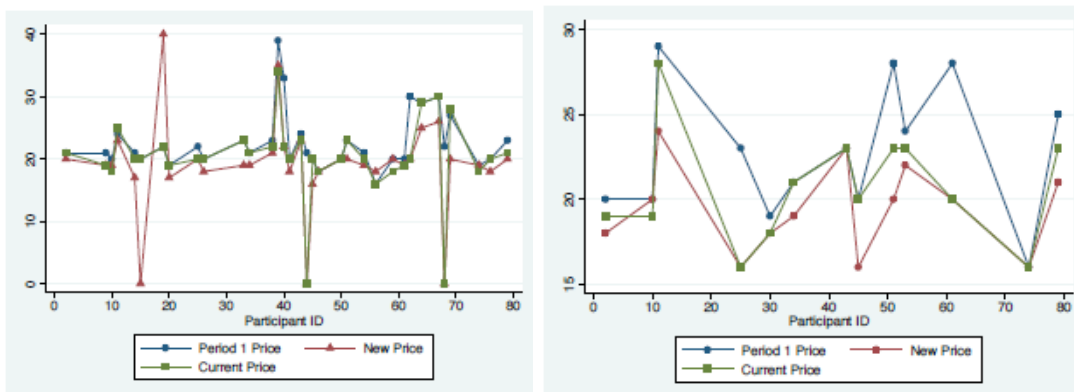
⁴ Every £1 earned in the game was worth 5p in the real world. The two selected participants earned £227 and £264.

⁵ Based on sign rank test.

⁶ Based on sign rank test.

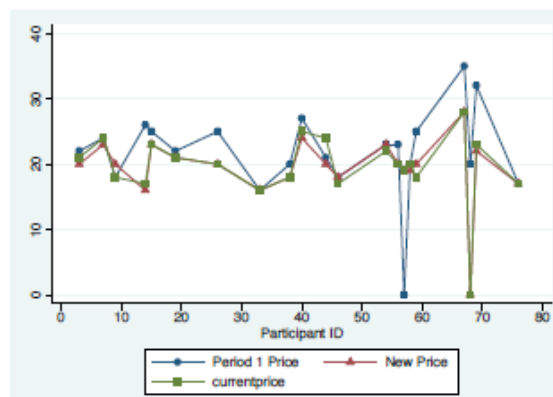
new customers and higher prices to existing customers (see column 3, Table 6.3). Dominant firms in asymmetric markets reported the largest gap in offer prices to new customers and existing customers; while for small firms there is very limited difference in the price to existing and new customers (see column 3, Table 6.3).

Figure 6:1: Offer Prices Across Markets with Full Information



(a) Symmetric Duopoly

(b) Asymmetric Duopoly Dominant



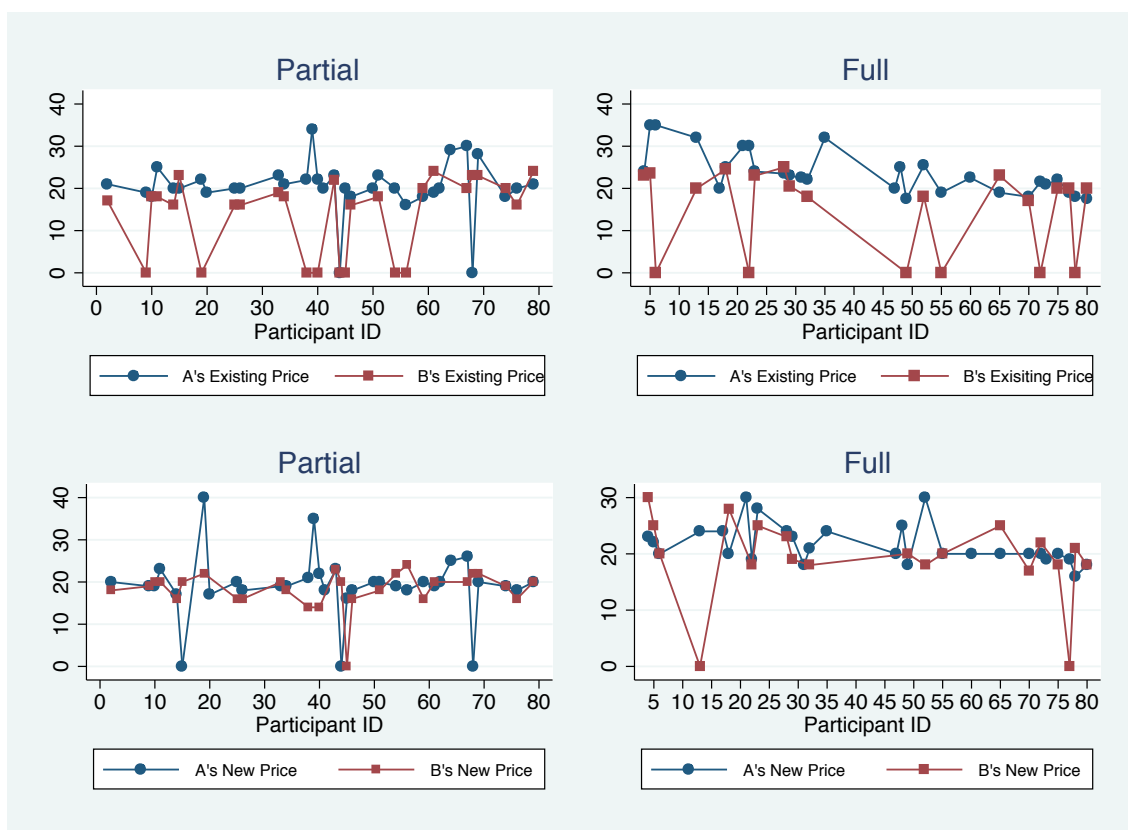
(c) Asymmetric Duopoly Small

In contrast to the commonly applied symmetric equilibrium solutions (see Fudenberg and Tirole, 2000), we do not find evidence of symmetric strategies by participants. Figure 6.2 plots the Period 2 prices of randomly matched participants in the symmetric duopoly scenario. Figure 6.2 illustrates that there were significant differences in the prices offered by participants assigned to the same market. Despite the same

incentives, there are very few instances when participants set similar prices, implying that pricing strategy is dependent on participant heterogeneity.

We also note that offer prices are substantially higher than marginal cost (£15)⁷, suggesting that while managers compete to gain market share they are mindful of profit maximization and avoid driving prices down to costs. Similarly, we do not find evidence of customer retention amongst small firms (see Mahmood and Vulkan (2013), for a detailed discussion on the relation between market dominance and price discrimination).

Figure 6:2: Period 2 Equilibrium in Symmetric Duopoly Markets



⁷ The difference between second period price and marginal cost is significant based on a sign rank test ($z = 5.77, p < 0.00$).

6.4.2 Price discrimination increases when both customer type and identity are recognizable

Our results suggest that managers react to information differently; Figure 6.2 shows that the overlap between participant A and B's price declines when participants have information on both customer identity and type. An increase in information available to participants results in greater variation in the pricing strategy of professionals.

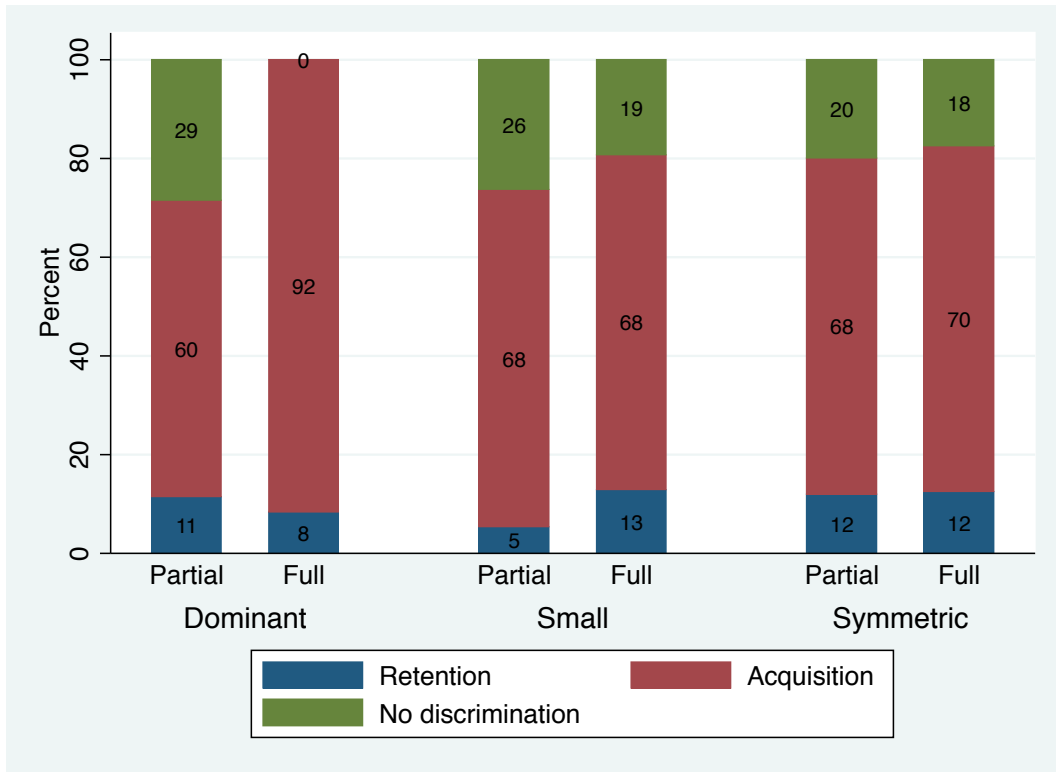
Customer type recognition also influences the decision to discriminate based on customer identity. Across both symmetric and asymmetric markets price discrimination increases from 63% to 78% (the difference is statistically significant based on two sample Wilcoxon rank-sum test ($z = -1.86, p < 0.06$)). To better understand participant behavior, we compare the percentage of participants that offered discounts to existing customers (retention strategy), percentage that offered discounts to new customers (acquisition strategy) and the proportion of participants that offered both groups the same price (no discrimination). We report the findings in Figure 6.3. When competition is symmetric, 70% of the participants in the partial information condition adopt an acquisition strategy. Similarly, there is customer poaching under the asymmetric scenario, however, the incidence of discrimination varies with market dominance; the dominant firm participants adopt an acquisition strategy 60% of the time with identity recognition while 68% of the small firm participants adopt an acquisition strategy. When participants in the symmetric duopoly market were given full information on customer type, there is no notable difference in the pricing strategy. However, the dominant firms react very strongly to the additional information, and increase customer acquisition by 30%. In contrast, the small firm participants increase customer retention

from 5% to 13%, while the proportion of participants adopting an acquisition strategy remains unaffected. Thus, the reaction to additional information varies with market structure. There is overall an increase in price discrimination across both symmetric and asymmetric markets. Whereas dominant firms show a significant increase in customer acquisition, small firms move towards retaining customers.

We further analyze the pricing behavior to determine the factors influencing the decision to price discriminate. Using a binary logit specification we regress discrimination (the dependent variable takes the value of 1 if the participant offers different prices to existing and new customers in Period 2, and 0 otherwise),⁸ an indicator for firm size, information dummy, controls for individual characteristics (like participant age, industry background, education and firm size) and participant random effects. The results are presented in Table 6.4.

⁸ We compute this variable across the two information conditions and market scenarios.

Figure 6:3: Price discrimination across firms

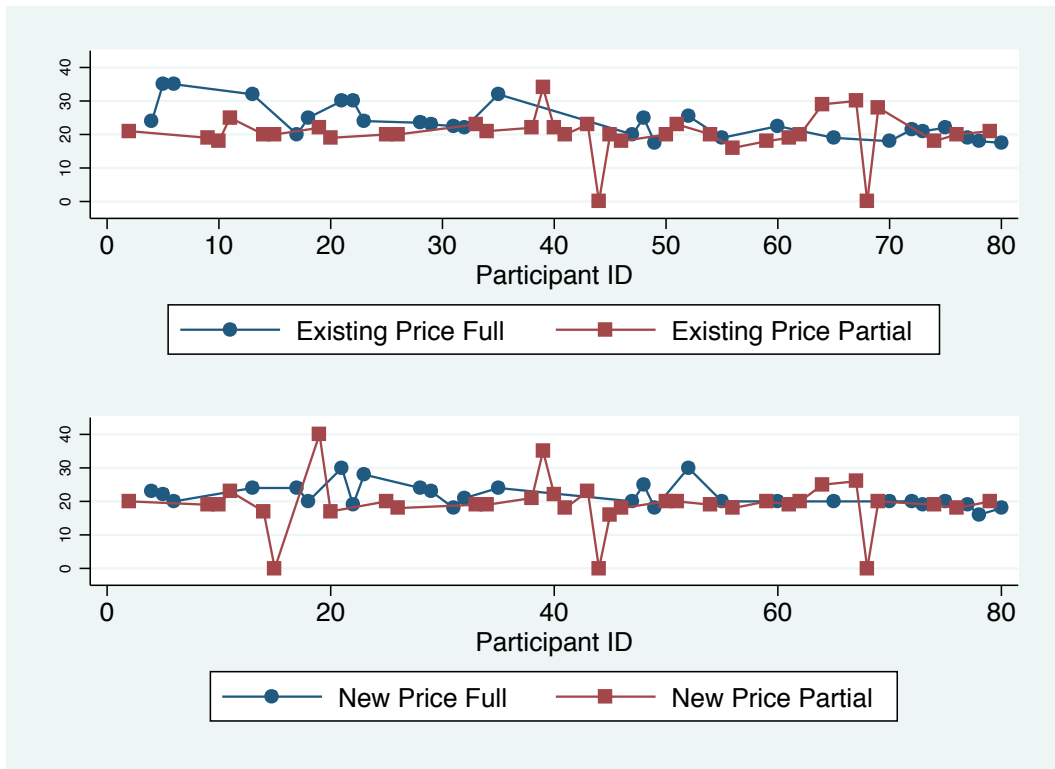


We find that price discrimination is positively related to the amount of information; participants increase discrimination under the full information condition compared to the partial information condition. It is interesting to note that participants in the middle age group engage in more discrimination compared to younger managers in the 20-25, age group. Professionals from large firms are also more likely to engage in price discrimination compared to smaller firms. These results hold despite controls for Period 1 market share and Period 1 pricing behavior. Thus, there is evidence that the decision to discriminate is dependent on the experience as well as information available to managers.

6.4.3 No significant difference in price levels across information conditions

We also analyze the price levels across the two information conditions. Figure 6.4 plots Period 2 prices across the two information conditions. We find no significant difference in the offer prices between the full information and partial information condition. Similarly, the price to existing customers was similar across the two treatments. While participants charged lower prices to low type customers, and high prices to high type customers, the average offer price remained the same across the two conditions. Due to the asymmetry in type recognition participants were unaware of the type new customers, since the average value of new customers did not change across the information conditions we observe no difference in prices.

Figure 6:4: Comparison of offer prices across information conditions-Duopoly

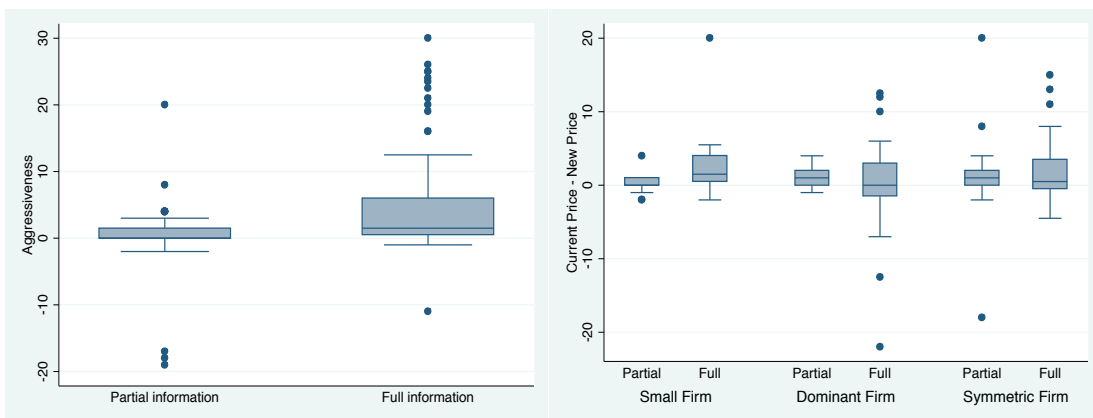


6.4.4 Aggressiveness in pricing increases with type recognition

We define aggressiveness as the premium charged to existing customers over and above the price charged to new customers. For the full information condition we compute the price to existing customer as the average of the price charged to high and low type customers. Pricing behavior of experts reveals that aggressiveness in pricing behavior is conditional on the availability of information and market dominance.

The average aggressiveness increases when type recognition is possible; in addition, there is greater variance in the price differential charged to existing and new customers (see Figure 6.5). Figure 6.5 also illustrates that the impact of information is not identical across markets. Small firm participants report the least difference in prices to existing and new customers; in contrast, dominant firm participants use the additional information to extract surplus from existing high type customers, whereas the aggressiveness of symmetric firms falls in the intermediate range.

Figure 6.5: Comparison of Aggressiveness Across Firms



(a) Breakdown by Information Condition

(b) Breakdown by Firm Size

We further test for the significance of the price differential to existing customers and new customers (see Table 6.3). In the symmetric duopoly market, we observe that the price differential was insignificant with partial information and increased to 2.09 when participants were given the ability to discriminate based on customer type. Similarly, for the small firm in the asymmetric market the gap increased from 0.19 to 3.18 (significant at the 5% level).

However, for the dominant firm in the asymmetric market the gap between price to new customers and average price to existing customers became small and insignificant in the full information treatment.

6.4.5 Customer Recognition has a mixed impact on customer welfare

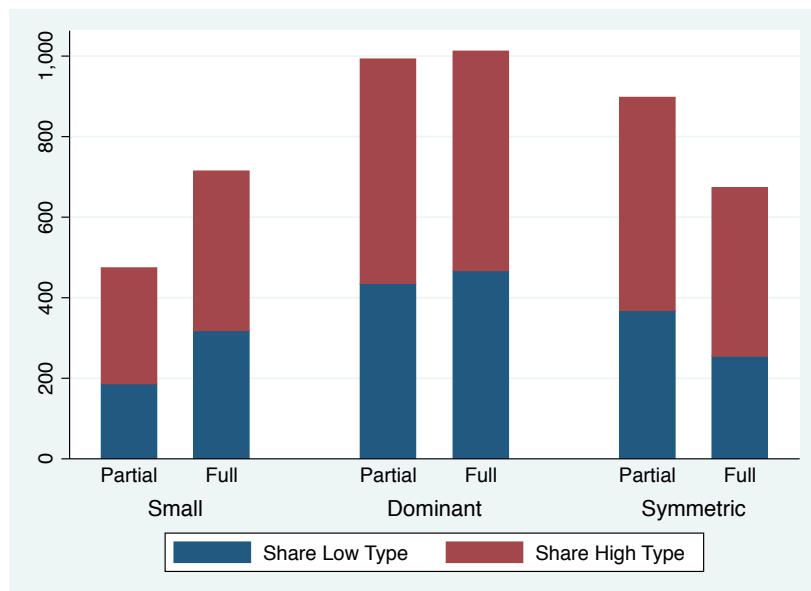
In order to determine the impact of customer information on consumer welfare we compare the market coverage across the full information and partial information conditions. Figure 6.6 compares the market share across information conditions and market structure. Figure 6.6 shows that full information on customers type and identity do not result in greater market coverage compared to the partial information condition. More importantly, the impact of information on market coverage varies with market structure. Though the average market share declines when both customer type and identity are identifiable in the symmetric market, the market share increases in asymmetric markets.

The lower market coverage in symmetric markets can be explained by the higher prices under the full information treatment compared to the partial information treatment. Table 6.2 summarizes the average prices across the two treatments. When participants are allowed to discriminate by customer type, the price to existing and new

customers is on average higher than the partial information treatment. Thus, information about customer types not only results in greater surplus extraction from existing customers, but also reduces the competitive pressure of customer poaching.

In the asymmetric market availability of customer type information results in a substantial increase in the market share of the small firm and a marginal increase in the share of the dominant firm. Small firm participants on average lower the price offered to new customers, resulting in more customers being served. The large firm on the other hand, offers higher prices in the full information condition. As a result there is no significant change in the dominant firm’s market share. Furthermore, compared to the symmetric firms dominant firms do not increase prices by a large margin and are therefore able to maintain their market share.

Figure 6:6: Comparison of Market Share Across Information Conditions



Therefore the impact of information on customer welfare is dependent on the market structure. While customers in asymmetric markets are better off with increased

customer recognition, some customers may be priced out of the market in symmetric markets.

6.5 Discussion and Conclusion

This chapter contributes to the literature on BBPD by presenting a controlled experiment that explores the role of *customer identity* and *type recognition* on pricing behavior. Our specialist subject pool engages in strategic pricing behavior and behavior is susceptible to customer recognition; identity recognition results in customer poaching and additional information on customer types increases the incidence of price discrimination. However, the impact of information on pricing behavior varies with market dominance.

Participants select an acquisition strategy approximately 68% of the time in symmetric markets and as small firms in asymmetric markets, while dominant firms chose to discriminate 60% of the time. The behavior of experimental subjects helps explain the growing investments in personalization technologies and investment in improving customer recognition. Across both symmetric and asymmetric markets we observe that participants engage in greater price discrimination when they have additional information on customer types. Thus, firms are more likely to use additional information to personalize prices (e.g., the increase in couponing in supermarkets).

However, the behavior differs across markets. Dominant players register the greatest increase in customer acquisition, with 90% of participants choosing acquisition, followed by symmetric players who select an acquisition strategy 70% of the time, while there is no change in the incidence of customer acquisition amongst small firm participants.

Similarly, aggressiveness in pricing increases with type recognition and also varies with market dominance. Dominant firm participants adopt the most aggressive pricing strategy followed by symmetric participants and small firm participants. Our results are consistent with the practice of big insurance providers like AA charging existing customers higher premiums while offering discounts to new customer, on the other hand, smaller providers offer similar benefits to new and existing customers.

Our results also shed light on the implications for consumer welfare. We observe that the increased price discrimination results in lower market coverage in symmetric markets. With greater information on consumer willingness to pay some customers are priced out of the market. However, in asymmetric markets there is greater market coverage as small firms safeguard existing customers from being poached away by the dominant rival. This suggests that customer data protection and privacy laws are necessary to ensure customer welfare is not compromised as firms invest to improve targeting capabilities.

While experiments have traditionally been particularly useful in comparing behavior across models of strategic interaction, our experiment provides additional insights on external factors that may influence the strategic behavior of firms. We find that pricing behavior is dependent on managerial characteristics like age and experience. Even though managers act strategically, they do not drive prices down to cost. The fact that managerial pricing behavior departs from theoretical predictions highlights the need to develop models that account for the behavioral motivations of pricing strategies. We hope that our study will generate more interest in the development of richer analytical models of behavior based price discrimination, which can better explain the phenomenon of loyalty rewards.

Our study also has a few limitations. For instance, we do not consider the additional costs of acquiring information. If costs of acquiring information are too high firms may be discouraged from engaging in price discrimination or the aggressiveness in pricing may increase to makeup for lost profit. The current study does not test the case when firms are unable to segment customers on the basis of past purchase history. It would be interesting to compare the uniform pricing scenario with the partial and full information conditions, to determine whether identity or type recognition is more profitable. We leave future research to fully explore these outstanding issues.

List of Tables

Table 6:1: Number of Participants

	Total Participants	Symmetric Duopoly	Asymmetric Duopoly
Partial Information	68	34	34
Full Information	60	28	32
Total	128	62	66

Table 6:2: Average Offer Prices

	Period 1 Price	New Price	Existing Price	Low Existing	High Existing
Symmetry –Partial	22.71 (4.66)	19.05 (7.66)	20.26 (6.37)		
Symmetry –Full	24.17 (5.05)	21.60 (3.52)	23.69 (5.22)	20.96 (2.68)	26.43 (2.68)
Asymmetry Dominant – Partial	21.85 (6.82)	19.38 (5.26)	19.57 (5.46)		
Asymmetry Dominant – Full	22.38 (7.97)	22.14 (6.42)	22.47 (7.35)	19.14 (5.13)	25.81 (10.88)
Asymmetry Small – Partial	22.76 (3.94)	19.46 (2.63)	20.69 (3.32)		
Asymmetry Small – Full	23.37 (7.73)	17.90 (6.67)	21.09 (3.09)	19.72 (2.49)	22.45 (4.50)

Note: Standard deviation in (parenthesis).

Table 6:3: Impact of information on customer poaching

	New Price	Current Price⁹	New Price - Current Price
Symmetric- Partial	19.06	20.26	diff = 1.21*, t= 1.38
Symmetric – Full	21.61	23.70	diff = 2.09***, t = 2.26
Dominant – Partial	19.46	20.69	diff = 1.23***, t =2.71
Dominant – Full	22.14	22.48	diff = 0.33, t = 0.20
Partial Small firms	19.38	19.57	diff = -0.19, t = 0.70
Full Small firms	17.91	21.09	diff = 3.18**, t = 1.78

Note: * denote significance at the 10% level, ** denote significance at the 5% level, *** denote significance at the 1% level.

Table 6:4: Determinants of Discrimination

	Estimate	Std. Error
Period 1 Price	0.0075	0.061
Period 1 Market Share	-0.001	0.001
Full Information	1.603***	.542
Dominant firm	1.201***	.508
Age- 30-40	1.358***	.610
Age > 40	1.298*	.727
Education-MBA	-1.377**	.665
Industry- Growing	-1.024**	.520
Pricing strategy-		
Innovative	0.058	.443
Constant	1.267	2.006
N	128	
Log-likelihood	67.579	
ρ	0.0001	0.001
σ_u	0.002	.432

Note: * denote significance at the 10% level, ** denote significance at the 5% level, *** denote significance at the 1% level.

⁹ For the full information condition the Current price is the average of the price to existing high and low customers

6.6 Appendix

6.6.1 Week 1: Introductory E-mail

Thank you for participating in our experiment. In this experiment you will be participating in a series of price setting scenarios. You are the pricing and promotion expert for Astra supermarket; located in town X. Astra deals in a wide range of products, including groceries, electronics, apparel, insurance and financial services. Every week you will be making pricing and promotion decisions for Astra under different scenarios. You will be making important pricing and promotion decisions, which will impact the profitability of your store and in, turn your earnings.

Your pay is directly proportional to the profit earned by your firm. The price-setting task will be straightforward and will only take 5- 10 minutes or longer depending how long it takes you to arrive at a decision. You will have a 24-hour window to submit your decision. After you set the prices, details of your earning and performance will be provided through email once all other participants have made their decisions.

The first week is the trial week to familiarize you with the procedure. The actual experimental sessions will commence the next week. Please treat this experiment as if this were the real experiment as this will give you practice for sessions in which you can earn money. Each week your earnings from the experiment will be recorded. At the end of the experiment 2 random participants will be selected to receive a payment based on their performance in the price setting experiment.

We expect selected participants to earn around £200 at the end of the experiment.

6.6.2 Symmetry

Astra's main competitor is Beta mart, which has a product selection identical to Astra. In addition, the same wholesaler supplies to both supermarkets and charges identical wholesale prices to both supermarkets. Due to town planning regulations stores can only locate on the outskirts of the city. • Astra is located at the west end of the town while Beta mart is located on the east end. • The distance between the two stores is 20 miles • You will be setting the prices across 2 periods. You must decide on the optimal price and promotion for each product category taking into account costs and competitor strategy.

This week you have been asked to set the price for the 8 pack of electronic brush heads manufactured by brand A, available exclusively at supermarkets. You will be setting the price of brush heads across 2 periods. You must decide on the optimal price and promotion for each product category taking into account costs and competitor strategy. A randomly selected experiment participant will simultaneously set the price for Townsend mart. You can only find out the price set by your competitor when the market sales figures are compiled. You expect that the target market for electronic brush heads in town X in period 1, comprises of no more than 2,000 customers. • Customers are evenly distributed across the west and east ends of the town. Approximately, 100 customers live per square mile. For the sake of simplicity you can assume that half of the town's population has a high willingness to pay for brush heads while the other half has a low willingness to pay. • High type - 1,000 target customers will not pay more than £50 • Low type- 1,000 target customers will not pay more than £25 You cannot differentiate between high and low type customers. However, you do know that both high and low type customers are evenly spread across the city. Such that

there are approximately 50 high type customers and 50 low type customers in every square mile. Customers are rational and would always try to purchase the product that results in the lowest expense. For customers the decision to select a store depends on the price as well as the transport costs they incur to travel to the store.

- The average transportation cost including time, fuel costs and public transport fares is estimated as 50p/mile.

Assuming that at a given purchase occasion a consumer only purchases a single pack of brush heads. The revenue from the sale of packs of brush heads can be computed as follows

$$\text{Profit} = (\text{Price} - \text{Wholesale price}) * \text{No. of units sold}$$

Where Wholesale price = £15 Your task is to set the optimal price that will maximize profits.

6.6.3 Period 2/ Next Day Email Welcome to period 2 of the experiment

Welcome to period 2 of the experiment. A quick reminder, last period you set the price for electronic brush heads at Astra mart in two markets.

Following are the details of the Market

- High type - 1,000 target customers will not pay more than £50
- Low type- 1,000 target customers will not pay more than £25

- The average transportation cost including time, fuel costs and public transport fares is estimated as 50p/mile.

- Where Wholesale price = £15
- Competitor Beta mart is located 20 miles away on the east end of the town

Customers in have now made purchases for electronic brush heads. Following is the detail of the market sales:

--- Customers bought from you @ a price of £-----

--- Customers bought from your competitor: Beta Mart @ a price of £-----

Your market share in period 1 was: -----

Your total profit is £-----

The sales department has compiled a database of the customers who purchased from you. In addition you have purchased detailed customer data from a market research firm. The detailed market analysis enables you to distinguish between customers based on their purchase behavior. Based on this information you learn that customers in the market vary in their valuation for the product you sell.

The market research firm identifies 3 distinct customer segments:

Existing customer with a low willingness to pay:

----- Low-type customers purchased from Astra mart in the period 1. Purchase behavior in conjunction with survey data shows that these are low- type customers who will not be willing to pay more than £25 for brush heads

Existing customer with a high willingness to pay:

----- High-type customers purchased from Astra mart in the period 1. Purchase behavior in conjunction with survey data shows that are high-type customers who will not be willing to pay more than £50 for brush heads

New customers:

----- Customers did not purchase from Giant supermarket. Due to data privacy you cannot access willingness to pay information for these customers. This segment comprises of the remaining high and low type customers that did not purchase from you in period 1. Additionally, the survey data on store preferences suggests that while customers have a liking for a particular store they could consider switching if they find the product at a suitable price.

In period 2 you again need to set prices in order to maximize sales in light of your performance in the previous period. One option is to offer different prices to different customer segments.

You can send personalized discount coupons to customers, would you choose to offer different prices to the different customer segments?

a) Yes

b) No

- What is the price (including any discount) you will set to Existing customer with a low willingness to pay?
- What is the price (including any discount) you will set to Existing customer with a high willingness to pay?

7 Conclusion

With the advent of new technologies the relation between firms and consumers is becoming increasingly complex. While information on prices and product attributes is becoming widely available to customers over mediums like the Internet, marketing firms and data intermediaries are simultaneously recording and analyzing information on consumer purchase and search patterns. The relation between consumers and firms is bilateral, on the one hand, consumer behavior influences firm strategies and on the other hand the actions of firms influence consumer behavior. The primary motivation of this body of work has been to contribute to an understanding of the influence of technological advancements such as the rise of social networks, low search costs in online channels and customer recognition on consumer and firm behavior. I combine rigorous analysis of large data sets with experimental methods to draw a number of novel conclusions regarding firm and customer behavior in dynamic markets.

The first half of the dissertation examines consumer behavior using detailed clickstream data sets in consumer search and purchase behavior. Chapter 2 developed an understanding of content consumption at online news websites. On one hand, the time consumers spend online browsing social networks has increased significantly in the past years and, on the other hand, news websites are highly dependent on the total

number of page views to produce advertising revenues. Despite the economic salience of online content, academic interest in consumption and search for online content has been limited. This is the first study that links an individual's online news consumption with his own Facebook activity and social network friend's news consumption. Contrary to common perception I find a complementary role between social networks and online content consumption. It appears that news consumption is a shared experience, as network members appear to follow recommendations from their Facebook friends.

Based on the analysis in Chapter 2, news websites can positively benefit from increased visibility in social networks. Indeed, this is a trend we observe in many news websites in which Facebook apps post (by default) the articles read on the news feeds. More and more news websites today are making the news consumption of Facebook users more visible to site visitors and recommendations seamless through the proliferation of Facebook like buttons. In addition, any websites seem to be adopting this policy by requiring Facebook users to register by default with the website providing not only details on consumer likes and preferences but the preferences of their friends. These emerging trends highlight the need for future research on the role of social recommendations in generating demand for content.

Chapter 3 extends models of consumer search to industries with high levels of spatial and temporal uncertainty. Using a dynamic two-stage model of site visit and carrier choice, the impact of information gathered during search, price expectations and search costs on search behavior of online customers visiting one of the largest European online travel agents is examined. I find that conversion rates could be improved if websites take measures to increase involvement when customers are actively searching.

Travel sites could display special offers or recommend flights to customers who frequently change their travel dates as targeting active customers could be more profitable than sending weekly email alerts to all customers. From a website managers perspective even small increments in purchase conversion can result in considerable growth in sales revenues.

Based on the findings of Chapter 3, online travel agents (OTAs) could display special offers or recommend flights to customers who frequently change their travel dates. OTAs could also change the layout and the design of their websites to encourage greater involvement. Since travel is not an impulse purchase, customers start active search once they are certain of their plans, therefore targeting customers at the website could be more profitable for OTAs than sending weekly email alerts. Since customers also exhibit a preference for variety, travel websites could strike deals with more airlines to increase options available to customers, as this can have a positive impact on purchase.

The second half of the dissertation focused on the pricing behavior in competitive markets. This thesis presented three experimental studies that empirically tested models of behavior based price discrimination. While experiments are commonly used in the industrial organization literature to test pricing behavior, experimental validation of behavior price discrimination has vastly been ignored. Through a series of studies I show that customer characteristics, market structure and availability of information influence pricing strategies, while the direction of the effect may not always confirm theoretical models.

Chapter 4 explores whether differences in pricing strategies can be attributed to customer characteristics. I develop a novel experimental design to test if stochastic brand preferences and customer heterogeneity provide sufficient conditions for loyalty rewards. Experimental findings highlight that preference mobility has a stronger impact on pricing behavior compared to customer heterogeneity. When preferences are stable and customers are homogeneous, for example in utilities, the increase in competition results in lower prices and discounts to poach rival's customers. However, introducing preference mobility mitigates competition and results in a decline in price discrimination between existing and new customers. This scenario helps explain pricing in the airline industry where several airlines are joining together to offer new and existing customers similar prices and rewards. More importantly, preference stochasticity combined with customer heterogeneity does not provide sufficient incentives for firms to offer discounts to existing customers and firm continue offering uniform prices. These results dispel the findings of several existing studies on behavior based price discrimination (e.g., Shin and Sudhir, 2010; Chen and Percy, 2010), highlighting the need to develop richer models incorporating customer and firm characteristics.

Chapter 5 analyses the role of market structure as a possible factor influencing pricing behavior. I present stylized models of strategic interaction in symmetric duopoly, asymmetric duopoly and multiple firm markets to compare the impact of firm size and number of firms on pricing strategies given customer recognition. I formally test whether small and dominant firms differ in their pricing strategies in markets with customer recognition. To gain real world insights pricing professionals are recruited as experimental subjects. While dominant firms engage in customer poaching, in contrast

to theoretical predictions small firms do not offer loyalty discounts. Results suggest that compared to dominant firms in asymmetric markets, symmetric duopolists are more aggressive while firms competing against multiple competitors adopt the least aggressive pricing strategy. In light of these findings I contend that increasing competition could be a more effective means of improving consumer welfare compared to regulating dominant firms.

Finally, Chapter 6 investigates the role of customer information in BBPD discrimination. In particular, the chapter explores how managers use information about customer valuations and purchase history in their pricing decisions, and how the use of information is affected by market dominance. Based on the behavior of the expert subject pool, I find that price discrimination increases with customer type recognition across both symmetric and asymmetric markets. However, the aggressiveness in the pricing behavior varies with market dominance with dominant firms in asymmetric markets extracting the most surplus from their high type customers. I also find that customer recognition does not necessarily serve the interests of customers as type recognition results in customers being priced out of the market.

The factors considered in this thesis, namely customer characteristics, market structure and information do not provide the pre-requisite conditions for loyalty rewards. Research on social preferences may be another avenue that could shed light on the underlying behavioral mechanisms that have resulted in the proliferation of reward schemes. It has been observed that when subjects interact repeatedly or if there is a possibility of acquiring reputation subjects exhibit cooperative behavior or punish each other. Future research could explore these areas in greater detail.

Experiments are a convenient means of testing and developing theoretical models of behavior based price discrimination. I hope that this research will create interest in further experimental investigation of behavior based price discrimination.

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