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Essays on Consumer Behavior and Analytics

A Dissertation submitted in partial satisfaction of the requirements
for the degree Doctor of Philosophy

in

Management

by

Prabhanjan Kumar Didwania

Committee in charge:

Professor Karsten Hansen, Chair
Professor Rajesh Gupta
Professor Wendy Liu
Professor Kanishka Misra

2022

The Dissertation of Prabhanjan Kumar Didwania is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

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2022

DEDICATION

I would also like to dedicate my dissertation to my parents Dr. Anjani Kumar and Sneh Didwania, and my brother Dr. Maruti Kumar Didwania. Their guidance and unconditional love have helped me immensely throughout this long journey. I would not be anywhere without their continued support in shaping me into the individual I am today.

Additionally, I would like to dedicate my work to lecturers (Jeff Klaas & Magnus Felke), and friends for their continued encouragement through the ups and downs of completing my research.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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Chapter 1, in part, will be submitted for publication. Hansen, Karsten; Didwania, Prabhanjan. The dissertation author was the secondary investigator and author of this paper.

Chapter 2, in part is currently being prepared for submission for publication of the material. Didwania, Prabhanjan. The dissertation author was the primary investigator and author of this paper.

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ABSTRACT OF THE DISSERTATION

Essays on Consumer Behavior and Analytics

by

Prabhanjan Kumar Didwania

Doctor of Philosophy in Management

University of California San Diego, 2022

Professor Karsten Hansen, Chair

The first chapter of my dissertation is joint work with Professor Karsten Hansen. This chapter examines gender differences in grocery retail shopping. We used consumer transaction data over the length of 12 years to find that the typical female consumer is less concentrated in choice of retail outlet, product category, brand choice and is more responsive to promotions than male shoppers. The findings are confirmed in both the “raw data” and regression analysis (including other demographic factors). The second chapter is a solo authored paper. Chapter 2 examines consumer behavior in response to manipulations of an increasingly popular price framework, called ‘drip pricing’. Our research is the first to provide insights through the manipulation (salience, magnitude, and type) of its two primary elements:

the base price and surcharges. We conduct eight field experiments on a popular travel platform to document causal effects on the search and purchase process. My findings confirm the importance of the headline price as an ‘anchor’ in this framework; additionally, its removal led to higher quality tickets purchased but leading to reduced quantity in tickets sold. When surcharge information is shrouded, customers are not information seeking and did not seek price information and made purchases based on the most pertinent data. Consumers are more sensitive to changes in fees at lower prices and are responsive to variations in the type of surcharge. Additionally, customers are responsive to taxes rather than fee surcharges.

INTRODUCTION

Whether the context is a bartering or cash economy, a supplier's main motive is to sell a good or service in the most efficient manner. This primarily is driven by marketing, which is promoting or advertising to potential customers to sell goods. As firms get a better gauge of their customers' behaviors, they may vary their marketing practices towards different demographic segments. For many years, researchers have replicated sales practices in the laboratory setting to get a sense of the customer thought process. With the rise in 'big data' technology, however, firms can now collect data on customers (demographic) and their browsing activity throughout the purchase process. This led to the creation of 'Quantitative Marketing' – where researchers and firms use massive amounts of digital data to improve engagement, revenue, and retention. This new approach uses economics, statistics, and data science (and more recently, machine learning). The plethora of public and private datasets help quantitative marketing researchers to confirm previous hypotheses and provide insights that once were thought to be nearly impossible to produce. This holds for offline (brick and mortar) stores and rapidly growing online platform markets.

In this dissertation, I aim to provide insights into consumer behavior by using big data and large-scale field experiments in the retail (offline) and online platform setting. In chapter 1, we examined gender differences in grocery retail shopping using data provided by AC Nielsen. Our findings suggest that female shoppers are less concentrated in choice of product, brand and retail outlet while purchasing across a larger set of product categories than men. Also, these shoppers are more responsive to promotional deals and engage in new product trial than their male counterparts. In chapter 2, I examine the consumer behavior to 'drip pricing', an increasingly popular price technique that online platforms are using to increase profits. In conjunction with an online tourism platform, I ran a series of eight field experiments which manipulated it's two primary elements: headline price and surcharges. Our findings suggest that the headline price plays a role in comparison while limiting the quality of goods purchased but increasing the total quantity. Furthermore, customers react differently when surcharges are shrouded versus completely transparent and to the type presented. Both chapters are of interest to marketers with the second for policymakers who aim to curb the negative effects of misleading price frameworks.

CHAPTER 1

The aim of this research to understand the difference between genders in shopping behavior. Using a large-scale consumer transactional database over the length of 12 years, we examine gender differences in a traditionally female dominated activity – grocery retail shopping. The typical female shopper is (a) less concentrated in her choice of retail outlet, (b) relies on a larger set of product categories, (c) is less concentrated in her choice of product or brand within a category, (d) is more likely to respond to promotional deals and is more likely to engage in new product trial than the typical male shopper. These differences manifest both in the raw data and when comparing "similar" males and female shopper through a regression with background demographics.

Introduction

Over the course of an individual's life, interests and activities vary and evolve in a unique manner. While this evolution varies from person to person, there are aspects that an individual has no control over, such as gender. While gender does not determine the arc of a human's life, it is non-controversial that in all cultures – past and present – many realized outcomes are, on average, different for males and females.

A large stream of literature in social science documents differences in gender at the societal level across important domains, such as education, income, and professional positions of power. While the gender gap has decreased over the last couple of decades in the United States, there still a exists a glaring disparity between genders. As of 2010, American women earned 81 percent of what males earned and only 24 percent of CEOs in the United States were women[1], regardless of major strides in education.[2]

Previous literature has examined the underlying causes of these observed differences – such as cross-country variations in economic development and women rights in areas such as property, voting, education, and labor force participation (see Geddes and Lueck 2002, Doepke and Tertilt 2009, Doepke et al. 2012). An interesting finding also suggests that patrilocality and concerns for women's "purity" led to increased gender inequality and favoritism towards males (Jayachandran 2015). At the individual level, extensive research in psychology shows that biological and social factors contribute to produce gendered self-concepts impacting individual cognition and behavior (Wood and Eagly 2015). In this biosocial framework, gender identity (beyond biological sex) emerges from a complex interaction of biological factors and cultural roles ascribed to males and females (Wood and Eagly 2012, 2013). Extensive evidence from economics and psychology, in conjunction, suggests that social/cultural norms play a significant role in observed gender differences in outcomes.[3]

In this paper we wish to conduct a large-scale empirical analysis of systematic gender differences in a traditionally female dominated activity – grocery retail shopping. Although our focus is on a specific activity and in a somewhat narrow domain of grocery shopping, there are several aspects of our analysis that makes it appealing for broader insights on the psychology of gender (Eagly et al. 2005).

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[1] Highlights of Women's Earnings in 2009 https://www.bls.gov/opub/reports/womens-earnings/archive/womensearnings_2009.pdf
[2] Number of bachelor's degrees earned in the United States from 1949/50 to 2028/29, by gender https://www.statista.com/statistics/185157/number-of-bachelor-degrees-by-gender-since-1950/
[3] It is important to note that many gender differences found in individual research (and popularized in popular press) don't hold up when subjected to careful meta-analysis (see Eagly and Wood 2015 for a review).

First, as previously mentioned, grocery shopping is an activity traditionally ascribed to women in most societies. Although industry reports suggest that men (at least in the US) are increasingly sharing the responsibility, women continue to dominate food purchases and meal planning in joint households.[4]

Second, marketing literature suggests systematic gender differences in shopping attitudes, product choices, and responses to marketing stimuli (Zeithaml 1988, Fischer and Arnold 1990, Mazumdar and Papatla 1995). Men perceive shopping as a burden and are primarily motivated by convenience while, women view the shopping process as a leisure activity; often shopping to express their love for others and are motivated by the emotional and social interaction aspects of shopping (Hart et al. 2007, Sit et al. 2003, Zhou et al. 2007). This literature also suggests that females are more involved and seek detailed product-specific information, while spending more time in stores before making decisions (Fischer and Arnold 1994, Clevaland et al. 2003).

Differences in motivations and goals identified in the literature may also translate into overall satisfaction with an individual shopping trip, and in fostering long-term loyalties towards a brand or retailer. For example, industry surveys suggest that women have a complex set of shopper loyalty requirements that depends on satisfaction with a range of operational, consultative, and emotional factors. Male shopper loyalty on the other hand was found to depend primarily on the ability of a sales associate to get them in and out of the store quickly.[5]

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[4] "The New Grocery Shopper", https://www.npd.com/wps/portal/npd/us/news/press-releases/more-men-are-grocery-shopping-but-they-do-so-grudgingly/, NPD Report (2014).
[5] "He Buys, She Shops: A Study of Gender Differences in the Retail Experience", https://bakerretail.wharton.upenn.edu/wp-content/uploads/2015/04/He_Buys_She_Shops_fall_2007_exec_summary.pdf, report by Verde/Wharton Baker Center

There are several aspects of our work that distinguishes it from previous research. First, our focus on utilitarian grocery products. This allows us to abstract away from social aspects of shopping and intricacies associated with high involvement shopping decisions (e.g. fashion, gifts) considered in previous work. Most importantly, previous work has primarily relied on observational or cross-sectional surveys. Our analysis utilizes purchase histories from a commercial database from a large number of consumers observed over several years and across all product categories sold in supermarkets. This database provides key advantages – the data are not self-reported measures but are tracked and carefully logged by optical scanners. Additionally, the data is extremely comprehensive, covering **all** aspects of supermarket shopping (trips, prices, promotions, basket sizes, detailed product information etc.) and represents demographically balanced set of US households across all 50 US states.

Our large sample size allows us to carefully zero in on the effect of gender in purchase decisions: Using household data to identify gender effects is generally impossible for multiple-member households since we do not observe which household member shops – only what is purchased. However, in our database, we observe more than 11,000 single males and approximately 28,000 single females over many years (2004-2016). Together these shoppers make a total of 71,793,108 transactions. This provides us with a clean strategy to identify the effect of gender on purchase decisions.[6] We rely on these data to construct several theoretically relevant metrics such as purchase concentration, propensity to try new products, price-promotion sensitivity, and the use of multiple store shopping. Although somewhat related, each of these measures capture distinct psychological phenomena. For example, purchase concentration (e.g.,

[6] Of course, we are limited to estimating gender effects for individuals living in single households.

percent of total spending in yogurt were allocated to a single product) captures aspects of variety seeking behavior amongst existing options while, the propensity to try new products measures aspects of novelty in unfamiliar situations (e.g., trying a new brand of yogurt).

Although we have no prior hypotheses regarding differences in variety seeking across gender, industry reports and previous research suggest that females tend to engage in more complex information search about products. Given the traditional role of females in grocery shopping, we expect females to be more savvy shoppers which in turn may manifest in more promotional product purchases than their male counterparts.

The downside of the consumer panel data used in this analysis is that we are limited by the set of demographic predictors and by the detail for those that are provided. Hence, we are unable to design meaningful scales to elicit attitudes and other psychological traits pertinent to the exercise. Instead, our approach is to evoke "reveled preference"" arguments where gender differences in shopping behaviors are ascertained by the observed shopping patterns of households.

Our results show that females spread their purchases across a larger number of retail outlets and have much broader product portfolios (i.e., regularly purchase in a much larger number of product categories). Within a product category (e.g., detergent, ice-cream) we find that single males display significantly higher levels of repeated buying behavior compared to females. The effect sizes for purchase concentration are quite dramatic and manifest in virtually all product categories sold in supermarkets. We also find that female shoppers are consistently

more sensitive to promotional deals that male shoppers. In addition, across thousands of new product introductions during our data period we find females to display significantly higher propensity to try new products compared to males. All effects are found both in the raw gender differences in the data and when demographic controls (e.g., income, and age) are used.
The rest of the paper is organized as follows. We describe the data in the next section, empirical setup in the Section 3, present our findings in Section 4 and discuss those results in the last section.

Data Source

Our empirical analysis relies on an extensive consumer panel dataset provided by ACNielsen. The database contains information on each store visit including date of purchase, identification of the retail outlet, and the total amount spent for each individual shopping transaction. Furthermore, the database contains detailed information on every product in the shopping basket, such as the product description (brand name, size, fat content, etc.), number of units purchased, price paid, and indicators for any promotion or coupon usage. Nielsen provides panel households with in-home optical scanners. Panelists are expected to scan the barcode of the items purchased, enter the quantity amount, enter the price paid (unless store is in the Nielsen POS system) and self-report coupon value, provided that they received a promotion on the item. Over the past several decades, these types of data have become one of the most important tools for understanding consumer buying behavior in the CPG industry and has sprawled a vast academic literature in marketing.

Nielsen randomly recruits households across fifty-two major US markets and nine census divisions. According to Nielsen, the panel set retains about 80% of active panelists from year to year. None of the panelists are forced dropped, meaning that households opt out of the program on their own.[7]

ACNielsen provides a comprehensive list of demographics on its panelists. At the end of a panel year, households are asked to fill in a questionnaire to provide this information. These metrics include income, size, residence type, household composition, location (such as zip code, county, market), presence of household items (kitchen, television, and internet) and information on household members (occupation, education, age, race). For this single member household analysis, we will use income, education, and age as demographic factors of analysis.

The data used in this paper is a subset of purchase histories of 168,783 demographically balanced households from 2004 – 2016. The households stay in the panel for an average of 4 years. Households in the Nielsen panel differ in terms of both size (number of members) as well as composition: Joint households (both female and male heads), single female (no male household head) and single male (no female household head).

For the objectives of this paper, we look only at single member households – single head households with no other members (i.e., living alone). We removed households where identifiers were reused to reduce inconsistencies in the data. This leaves us with a panel dataset of 43,031 households. Given the large sample size, we can isolate the behavior of males and females,

[7] Information provided by NielsenAC in the Kilts Center – University of Chicago Guide and Handbook

which to the best of our knowledge has not been studied before using data of this scale. Throughout the analysis, we will refer to households (panelists), as single member households, unless otherwise noted.

As previously mentioned, we will limit our analysis to grocery store shopping instances. This allows us to reduce endogenous effects of social shopping and the purchase of luxury items. We introduce a series of restrictions to reduce potential outliers in transactions. First, we remove those households with irregular activity to grocery stores. This analysis does not account for infrequent and abnormally high grocery store visits[8]. For the purposes of this analysis, the minimum number of trips will be 11 (i.e. panelists that take less than 11 trips in a panel year – amounting to less than 1 trip a month) and a maximum of 182 (i.e. panelists that take more than a trip to the grocery store every two days). Additionally, we examined transactions that had registered some paid for amount purchased goods. According to NielsenAC, trips that do not record an amount paid, represent transactions where the panelist received items for free. Items that are free to panelists may not truly identify their interests or needs for purchase. After accounting for these factors, we will analyze the behaviors for a total of 39,834 households; with 11,494 being single male panelists and 28,340 being female. These households took a combined 9,633,172 trips and 71,793,108 purchases during their participation period in the panel. A demographic breakdown for the sample of single households is provided in Figure 1, respectively.

[8] According to Statistica, from 2006 to 2016, on households took on average 1.85 trips a week or 96 total trips in a year

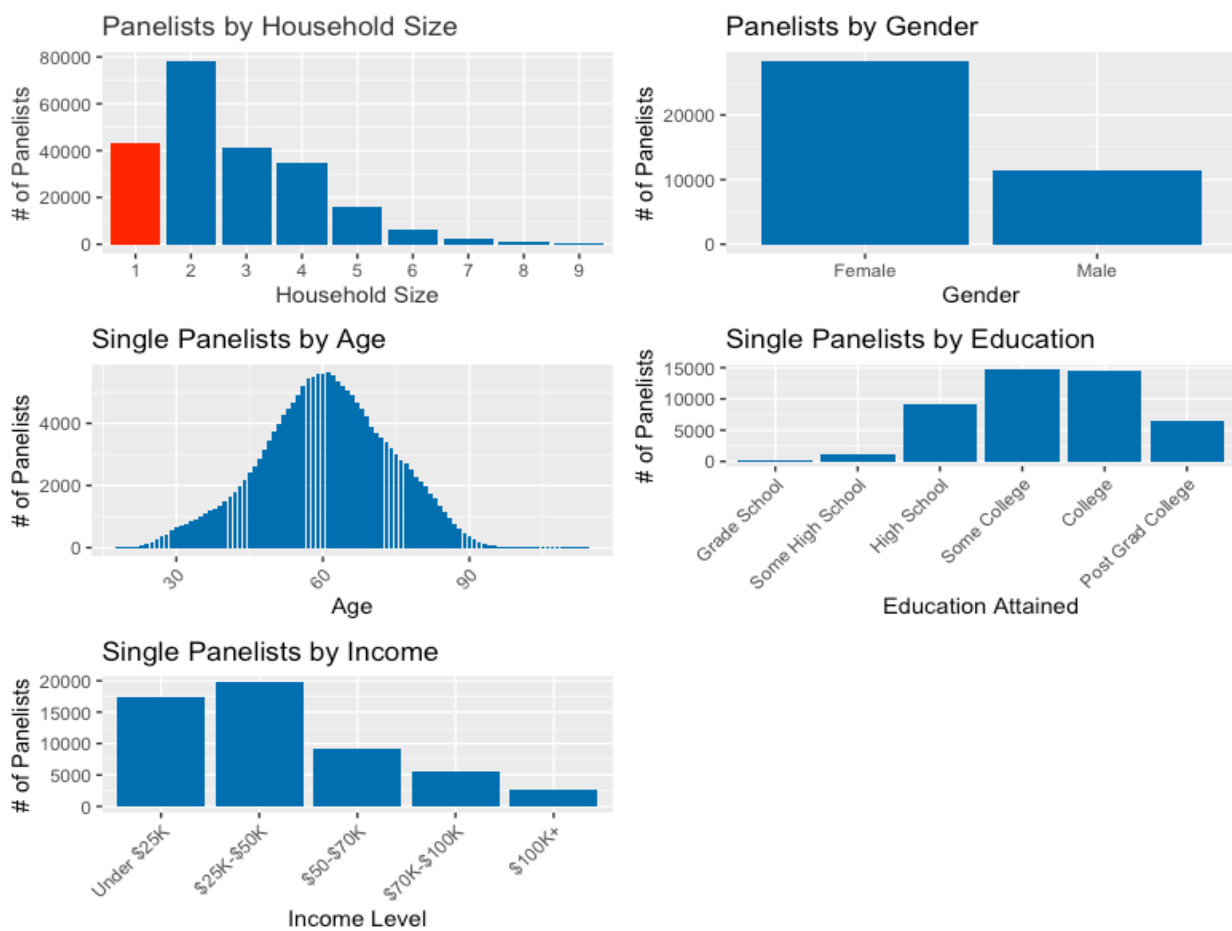


Figure 1: Panelists Demographic Breakdown – (a) households by number of members (single member in red to represent our set of interest) (b) single households based on gender of head (c) single households age distribution (d) single households by education attained and e) single households by income bracket

Empirical Setup

Purchase behavior in panel data set can be analyzed at different levels of aggregation. The most granular level is a single product (or "UPC"). This is a unique product of a certain size, flavor, brand etc., produced by a certain manufacturer. Products are then organized in product categories (called modules) meant to capture shopping goals. These product categories are then organized as product groups consistent with higher order shopping goals. These product groups are make-up departments, which are the primary classifications between product groups at a store. For example, “Canned Peaches” and “Canned Pears” are two product categories contained in the product group “Canned Fruit” which are located in the “Dry Grocery” department.

To analyze gender differences in purchase behavior, we construct several theoretically relevant metrics. Our goal to measure aspects of purchase behavior that summarize different levels of the shopper’s engagement in the purchase decision.

- **Store Choice**. Previous research has shown that while females are in general more loyal to other individuals compared to males, males are more loyal to groups and organizations such as companies and even brands (Melnyk et.al 2009). We investigate this by focusing on measures of store loyalty such as the percent of total expenditures allocated to the shopper’s favorite store (where favorite store is defined as the store where the shopper spends the most money). This is a simple of how much of a favorite, the favorite store is: the higher this number is, the more loyal the decision maker is to his/her favorite store.

- **Number of Categories Purchased.** Previous research has argued that females are more motivated by assortment seeking and impulse buying (Noble et. 2006, Tifferet and Herstein (2012)). One implication of this is that females have “wider” preferences, i.e., they make purchases in a larger number of product categories compared to men. We analyze this by comparing the count of the total number of product groups and UPCs in which a household has ever made a purchase for males and females.

- **Purchase Concentration in Individual Product Categories.** Another implication of the hypothesis expressed above is that females should be less loyal to their most favorite choice option in a category. To explore this, we calculate purchase concentration measures defined as the percent of total household expenditure in a category that is allocated to a single UPC.

- **Promotion:** Based on gender differences in information processing strategies, Meyers-Levy and Maheswaran (1991) argues that females are more sensitive to the details of message claims. Similarly, Mazumdar and Papatla (1995) and Phillip and Suri (2004) argue that females are more sensitive to promotional deals. On the hand, other research (e.g., Noble et. 2006) has argued that males are more motivated to engage in price comparison shopping. We test among these explanations by focusing on each shopper's promotional spending ratio, i.e., the percent of total expenditures in a category that were allocated to promotional items.

- **New Product Trial.** To investigate gender differences in new product trial – an indicator of a shopper's openness and desire to try new experiences – we calculate the percent of a shopper's overall purchases in a product group that are "new to the market"" products.

Throughout the following results and analysis, we run regressions to examine the effect of demographics on the dependent variables of interest. The demographic factors that used in our analysis is income, education, and age. Age is numerical (birth year for panelists are provided), education as categorical and income as ordinal. This is modeled by the following equation:

$$y\ (outcome\ of\ interest) = \beta_o + \beta_{age} + \beta_{income} + \beta_{education} + \beta_{gender}$$

Gender is a dummy representing male or female panelists. Length in panel factors into the regression analysis, when looking at outcome variables that are over the length of the panelists stay in the panel.

Results

Store Choice

In the first step of the shopping process, the customer makes the decision of whether to make a trip to the grocery store. In the data, there is statistically, yet not large difference, across genders in yearly shopping trips: on average, single females (55.38) make less trips than males (62.22). To understand the effect of gender compared to other demographic variables, we run the regression discussed above. The gender difference is larger in this scenario; 8.01 trip difference yearly between males and females.

The next step in the decision-making process requires choosing the retailer the consumer shops at. Males and females, on average, shop at the same number of retailers in an average panel year (3.65 and 3.30, respectively). This finding is consistent with regression results and may be in part due to the number of retailers available in close proximity to the panelist. The number of retailers near the panelist cannot be determined from the dataset as Nielsen only provides the first three digits of a store’s zip code.

A stronger measure of loyalty may be to examine activity at the customers top retailer. We investigate this by calculating a simple store concentration measure, CR-B1: the fraction of a household's overall budget spent at that household's favorite store. The larger this number, the more loyal the household is to that store. Figure 2 shows the average gender and regression differences on this measure. The average difference is 3.46% with a similar difference of around 3.6% when controlling for demographic factors. As a further robustness check, we re-ran the analysis using an alternative measure of concentration, the Herfindahl-Hirschman Index (HHI). This is a measure used in economics to measure the degree of firm concentration in an industry.[9] This leads to very similar conclusions, with on average, 67.4% of males total spending occurring at their top store (also shown in Figure 2). We conclude that there is clear evidence for single males being more concentrated in their grocery spending across stores than single females. This is consistent with previous findings arguing the males are more loyal to organizations and brands and are less interested in exploring a variety of stores.

[9] HHI is calculated as the sum of the square of each firm's marketshare. In our application it is the sum of the squares of the share of spending in each store for each household. The higher the number, the more concentrated is the household's spending on one store.

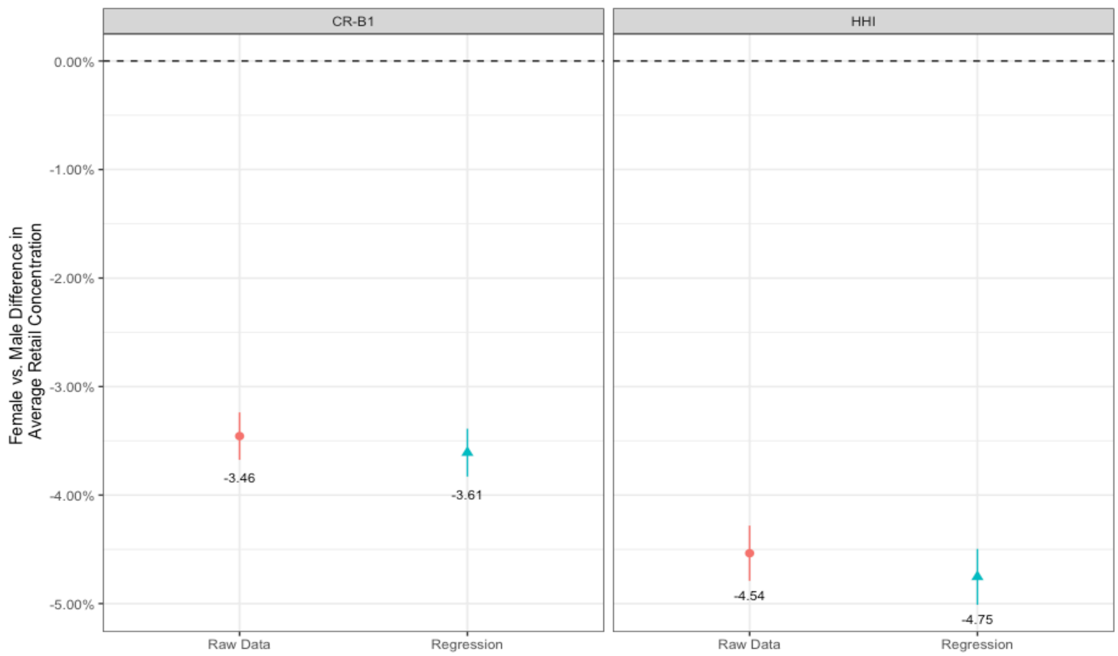


Figure 2: Female Shoppers are Less Concentrated in Retail Outlet Choices. Calculated by two methodologies – CR-B and HHI. “Raw Data” is the direct gender difference, while “Regression” is the gender effect from a regression of the dependent variable on gender and other demographics. Vertical lines are 95% confidence intervals

Breadth of Purchases

The previous section, the highest level of the shopping hierarchy, showed that males are more concentrated in their store choice than females. In the next step of the decision-making process, we examine in-store department and product categories that are chosen by each panelist. The question of interest is: are females more diverse in terms of the set of product categories they regularly use?

The highest level of product distinction is at the department level shopping. Products that serve a similar purpose are placed in the same department level group. Nielsen defines 10 departments, for the list of grocery store products. Figure 3 shows the fraction of spending by gender in each department. Women tend to spend more across most departments; while alcoholic beverages, frozen foods and packaged meats show larger fractional spending for males. In the data, there is nearly no difference between the number of departments visited between the two genders.

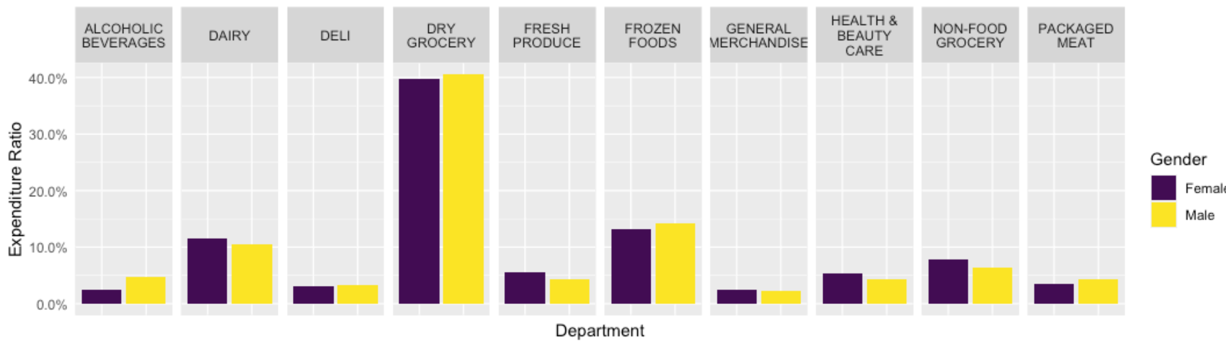


Figure 3: Female Shoppers are More Diverse in their Spending Across Departments. Expenditure ratio is proportion of spending in the specific department compared to total spending by genders over the length of the panel. Purple represents female and yellow represents male single households

What about the next level? Are they also more diverse in terms of the set of product categories they regularly use? In the purchase database there are over 1,000 individual product categories covering all aspects of shopping goals. Of all departments, dry grocery has the highest number of product groups, which also dominates total spending by both genders. Amongst these product groups, how many of these does the typical household use? More importantly, does the average number of categories depend on the gender of the decision maker?

Figure 4 shows the answer. In the second to left most chart, we calculated the average gender difference in the number of categories in which a household has ever made a purchase (we can call this “trial”). We see that female shoppers on average have tried over 48 categories more than male shoppers on average per year. This difference changes slightly when we run a regression of number of categories on gender and additional demographics. Rather than study category trial (i.e., have a household ever had a purchase in a certain category?), we can consider an alternative measure: The number of product categories of which a household is a regular

”user”, i.e., does the household buy in the category on a regular basis? We defined households as a user of a category if they have made at least 5 purchases in the category. This doesn't change the overall finding: Female households are on average users in a larger number of categories than male households (on average 18 more categories) (left most chart in Figure 4)

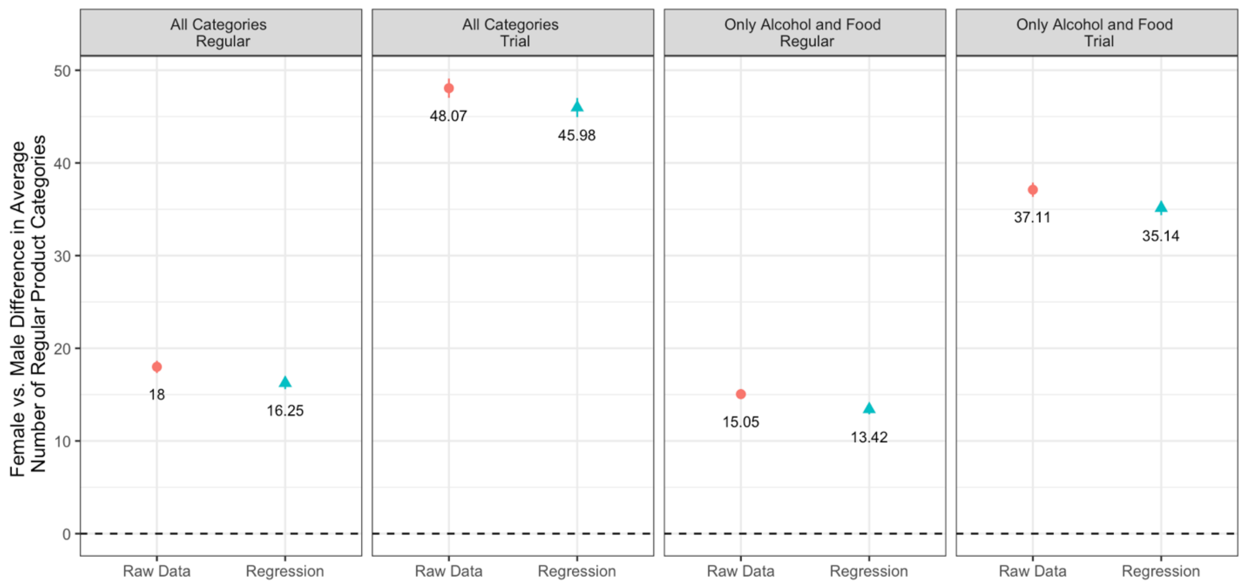


Figure 4: Female Shoppers Have Wider Purchase Breadth. Females shop across more product categories in both trial (at least one purchase) and regular (at least 5 purchases) (food and alcohol as well).

A potential criticism of this analysis is the possibility that there simply are more product categories that are uniquely targeted towards women than there are for men, e.g., feminine hygiene products, make-up and beauty care products etc. To investigate this point, we repeated the analysis including only food and alcohol product categories. As shown on the right two plots in Figure 4, we still find substantial gender differences: The average single female household is a user of 72 food and alcohol categories in an average year, while the average male household is a user of 15 fewer regular categories. We conclude this section by noting that the finding that female households have "wider" preferences - that is relying on a larger set of product categories

- is consistent with the finding above that they also spread their total expenditure over a wider set of stores compared to male shoppers.

Within Category

In the previous two sections, we showed that females are more diversity in store choice and range of department/product category selection. Suppose we go one step deeper and investigate the most granular level of purchasing, UPCs. UPCs are codes that help identify the vendor and unique product (different UPCs for products with the same brand, group or size). There is a statistically large difference between genders; females on average purchase 129 more upcs than males in an average panel year.

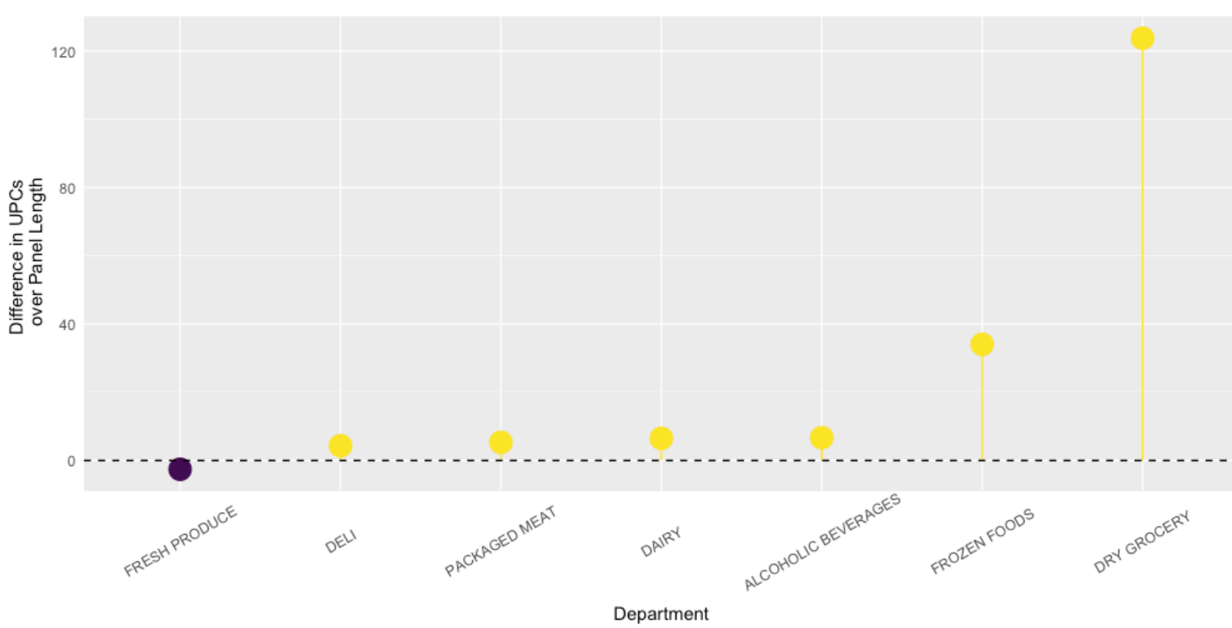


Figure 5: Female Shoppers are Less Concentrated in Their Shopping Behavior Within Departments. The products used in this analysis are in product categories where the customer is a regular user.

Figure 5 shows that females purchases are more diverse in their regular product selection across most departments. The largest difference is exhibited amongst dry grocery products; women tend to buy 123 more upcs than men.

Is it then also the case that female shoppers show more loyalty to a good in their shopping history within this product category? For example, do female users of canned fruits buy a more diverse set of products than male users in the same group? To investigate this, we calculated a concentration measure similar to the one used in the retail store analysis (CR-B1). Specifically, for each shopper, we calculated the spending on the shopper's top choice in each category as a fraction of the total spending on products in that category. The higher this fraction is, the more loyal the shopper is to his/her favorite product. We perform this calculation at both the detailed product level (UPC) and at the higher brand level in Figure 6.

We conclude that for single males are more loyal with product categories to certain products and brands they purchase. This is consistent with findings in the literature and the previous section.

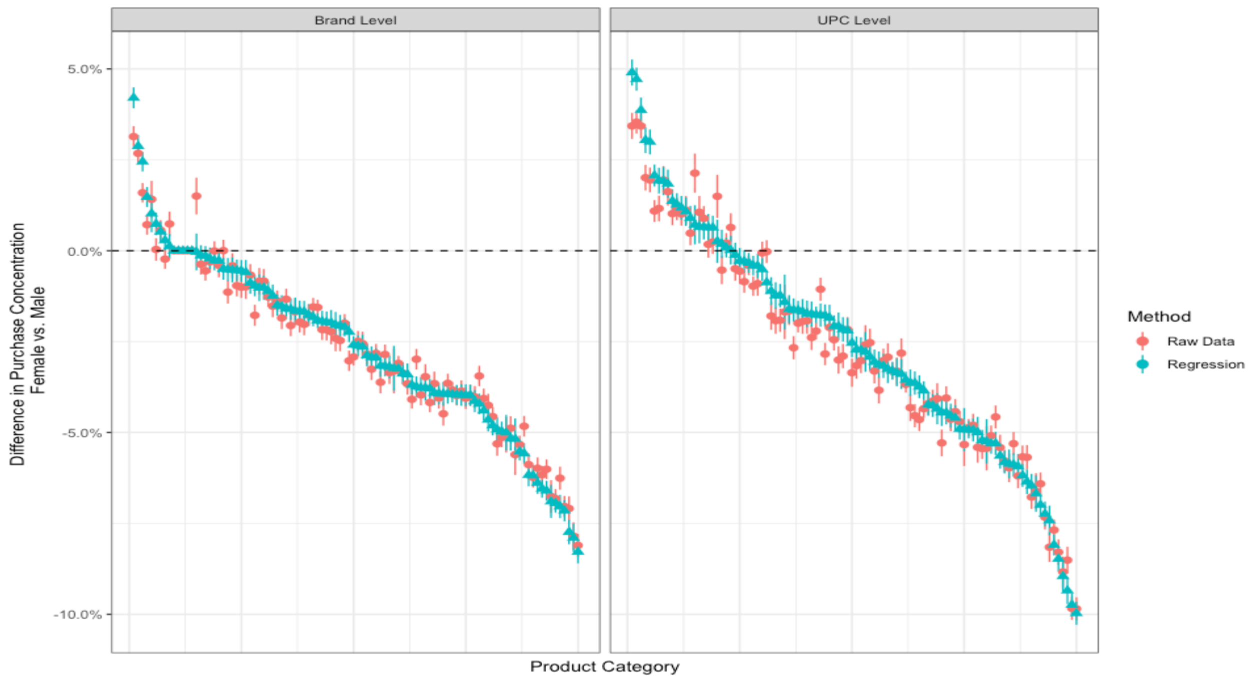


Figure 6: Female Shoppers Have Lower Purchase Concentration. Results for the top 100 product categories purchased.

Promotional Spending

The sections above have shown that no matter what level of the purchase hierarchy one analyses, female shoppers show more diversity of choice than male shoppers. One interpretation that emerges from this is that the female shopper is more engaged in the shopping decision and display more sophisticated behavior than male shoppers. If this is correct, we should also expect to see female shoppers being more sensitive to shopping deals.

To explore this idea, we calculated the fraction of promotion on total spending on items on for each department for each shopper (Figure 1.7). Promotional expenditure ratio is the fraction of a household's total promotion saving by how much is spent in the department. Across all departments, women are more promotional sensitive than men.

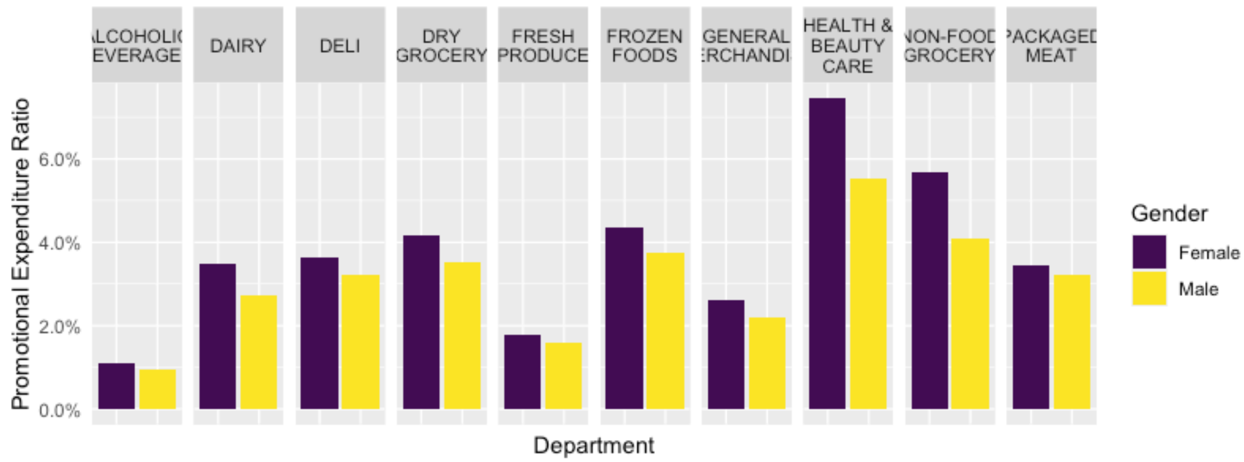


Figure 7: Female Shoppers Spend more on Promotion across all food and alcohol departments. The products used in this analysis are in product categories where the customer is a regular user.

We use the same 100 product categories as we used above (and again - for each household - we only use categories where the household was a regular user). The results, shown in Figure 1.8, are remarkable: female shoppers are more promotion sensitive in their shopping decisions in **most categories**. Again, we see considerable heterogeneity in effect sizes across categories.

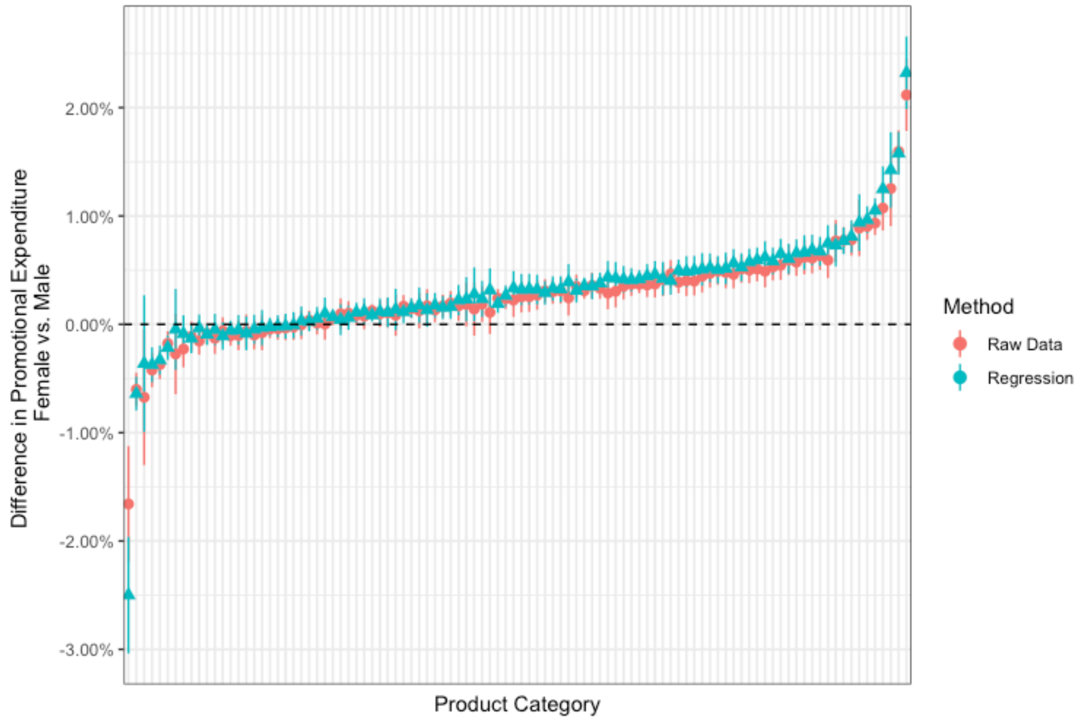


Figure 8: Female Shoppers are More Promotion Sensitive. Results for 100 product categories, "Raw Data" is the direct gender difference, while "Regression" is the gender effect from a regression of the dependent variable on gender and other demographics. Vertical lines are 95% confidence intervals for the regression gender effects.

New Product Purchases

In this section, we explore whether male and female shoppers differ in the extent to which they engage in new product trial. If the findings from the previous sections are consistent with this metric, we should expect female shoppers to engage in higher amounts of new product trial. We carried out this analysis at the product group level over five years (2004-2009). This was done to ensure enough new product entry from which purchase trials can be made while being able to identify new products in a shorter time period.[10] For each shopper we then

[10] It is a non-trivial task to identify new products in the data - we do not have a file that directly specifies the date of introduction of a product. We defined new products in the market as products that had observed sales after the third year in the data but had no sales in the first three years of the data.

calculated the percent of all product purchases that were of products new to the product group. We then compared the resulting trial ratios for male and female shoppers. The results are shown in Figure 9. We see an extremely consistent pattern: In most product groups female shoppers are engage in significantly more, new product trial than men. This is so both in the raw data and when controlling for background demographics.

The effect sizes in Figure 1.9 may seem small - they are not: The baseline new product trial levels are quite small, i.e., most households do not purchase a lot of newly introduced products. The average trial percentage across households varies from less than 1% for some categories up to 10%. The overall average across categories and household is around 2.5%. This means that the relative effects sizes are massive: On average across all product groups, female shoppers engage in 22.5% more new product trial than male shoppers. Then 10 product groups with the biggest effects have effects from 39% to 47%.

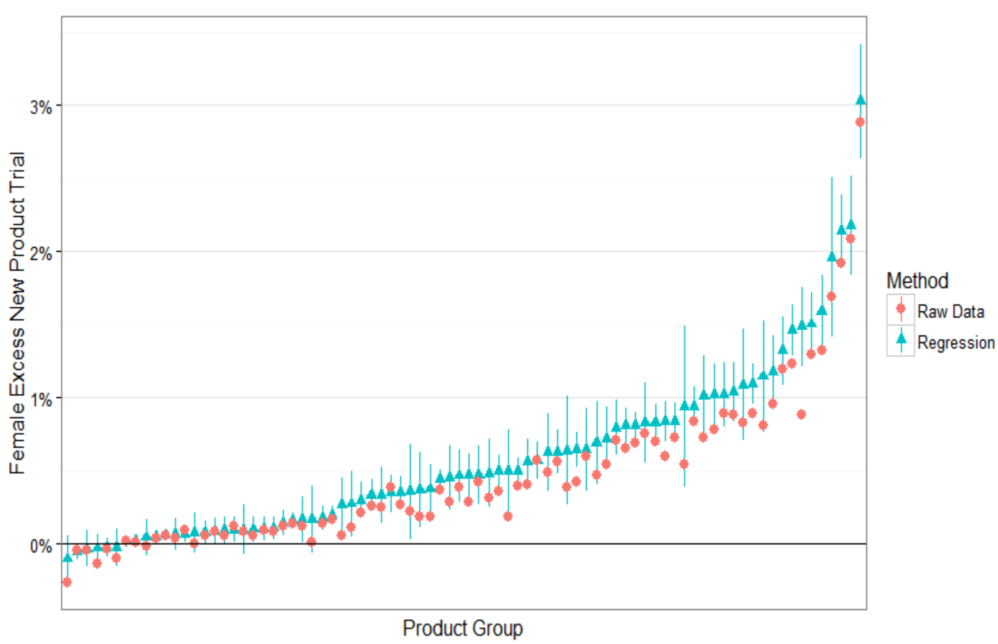


Figure 9: Female Shoppers Have Higher New Product Trial. Results for 83 product groups, N=2,688-19,590. "Raw Data" is the direct gender difference, while "Regression" is the gender effect from a regression of the dependent variable on gender and other demographics.

Discussion

Using a large-scale database containing more than 71 million transactions on nearly 40,000 single-person households over the length of 12 years, we have provided evidence for large and systematic differences in shopping habits between single female and male shoppers. The findings suggest similar conclusions to those based in the literature of psychology, economics, and gender studies. Our findings highlight differences at each of the various steps of the shopping process; retailer/store selection, breadth of purchases across departments and product categories, within category purchases at the UPC and brand level, promotional spending, and new product trial.

At the highest level of the shopping process, we found that typical female shopper tends to make more shopping trips on average per year, which may be explained by women view the shopping process as a leisure activity even at for groceries (Hart et al. 2007, Sit et al. 2003, Zhou et al. 2007) Men are found to be more concentrated in the choice of retailers than women. This is consistent with the findings in Melnyk et. al 2009, which suggested that males are more loyal to companies and brands.

Within the store setting, our findings suggest that women spend more of their budget across many grocery store departments while men spent higher amounts on frozen food, prepackaged meat and alcoholic beverages. Higher spending in these departments suggest that men spend less time in food preparation and settle for options where foods are prepackaged and consequently less healthy. This difference may provide insights into gender disparities in health consciousness and more importantly, the convenience in the shopping process, as discussed in

(Hart et al. 2007, Sit et al. 2003, Zhou et al. 2007). A further dive found that women made purchases across more product categories than males in both trial (all categories where a customer made a purchase) and regular (purchases greater than 5 items for a category). This finding held consistent when examining on food and alcohol categories – removing for distortion due to a higher number of categories just targeted towards women. This is consistent with previous findings (in Noble et al 2006 and Tifferet and Herstein 2012) which suggested that females are motivated by assortment seeking and impulse buying.

The findings presented in Noble et. al 2006 and Tifferet and Herstein 2012 also suggest that women should be more diverse in their product selection within category. To explore this finding, we examined the most granular level of purchases – UPC. Females tend to buy higher amount of UPCs regularly across most departments. At the product category level, the conclusions are similar – women are less loyal to their favorite choice within a product category. This finding also holds for brands within a category.

At the product level, previous research suggests that females are more sensitive to details in messaging (Meyes-Levy and Maheswaran (1991)) and promotional deals (Mazumdar and Paptala (1995), Phillip and Suri (2004)). In our findings, we find that women tend to spend more on promotion across all departments. For regular product categories, women tended to respond to promotional deals at a higher rate than men. An additional finding, we look examine is a customer's desire to try new products or experiences. Our calculation over the 5-year period suggests that women are more likely to engage in new product trial than men.

The analysis presented in this paper is unique as it examines a large number of transactions for households across all shopping behavior. The gender differences in shopping behavior were manifest both in the raw data and through a regression with background demographics. While we have limited demographic information, the data is the next best alternative to information from a credit card company, etc. These findings are consistent with males and females different in decision process engagement when it comes to grocery shopping in psychology and gender studies literature.

Chapter 1, in part, will be submitted for publication. Hansen, Karsten; Didwania, Prabhanjan. The dissertation author was the secondary investigator and author of this paper.

CHAPTER 2

Recent years have witnessed a meteoric rise in the use of online platforms to conduct daily tasks. These firms maximize profits by presenting lower upfront prices and adding surcharges later in the purchase process. This technique, known as drip pricing, is rapidly increasing in popularity despite limited knowledge outside its general effectiveness. Our research is the first to provide insights through the manipulation (salience, magnitude, and type) of its two primary elements: the base price and surcharges. We conduct eight field experiments on a popular travel platform to document causal effects on the search and purchase process. Our findings confirm the importance of the base price ‘anchor’ (previous laboratory studies); its removal led to higher quality tickets selected in search with further shrouding in the purchase funnel leading to reduced quantity in tickets sold. When surcharges were shrouded, customers did not seek price information and purchased tickets based on the total amount presented. When total prices and quantity of goods is high, customers purchased at a higher rate than when surcharges were transparent. Consumers with higher transparency were sensitive to changes in fees at lower prices, but responsive to variations in the type (taxes vs. fees) of surcharge. Our research is of particular interest to industry and policymakers, who aim to strike a balance in protecting the interests of billions of consumers and of the largest platforms in the world.

Introduction

“Airbnb will tell you it’s 150 a night and you when you go to checkout for 2 nights it’s $1,987”

– Twitter User @greg_ramirez21 (May 17, 2021)

"Is it me or is Airbnb no longer a realistic alternative to a hotel?!? These prices are ludicrous!!! And with all the extra fees lawd!!! 250 a night really hot like dang near 500 a night... what I miss"

– Twitter User & NFL Player @camjordan94 (May 19, 2021)

These are just a few of the complaints levied against Airbnb on the addition of unavoidable surcharges at the checkout step. Frustrations were felt across all types of customers, from the common man to one of the highest paid NFL players, as evidenced above. Due to the backlash, Airbnb released a statement detailing information on their fees with news they had formed an internal team "with the objective of making pricing even more transparent and easy for hosts and guests to navigate". This begs the question - how does a $100 billion company lack proper insights of their pricing practices?

Platforms and customers are eternally engaged in a 'tug-of-war'; firms aim to maximize profit and retention with users targeting the best 'value' for goods and services. As a result, platforms manipulate the presentation of prices in hopes of capitalizing on customer inattention and miscalculation. Airbnb, like most online platforms, institutes a pricing practice called 'drip pricing'. Customers are shown a low upfront base price with surcharges added at later steps in the purchase process. Despite its prevalence (e.g., Uber/Lyft, Stubhub/Ticketmaster, Priceline/AirBnB/Vrbo), limited field research has been conducted on the detailed aspects of this framework. Current literature only examines its effectiveness relative to other pricing techniques in increasing profits (Ahmetoglu et. al, 2014, Huck and Wallace, 2015).

Drip pricing can be primarily explained as a two-part process. In the initial steps, customers are presented a *'headline (base) price',* which is a fraction of a good's actual price (typically inaccurate representation). At later steps, the 'true' price is revealed with the addition of mandatory '*dripped surcharges'* The framework's effectiveness is explained by two pyschology theories: 'anchoring and adjustment' (Tversky and Kahneman, 1974) and 'endowment effect' (Kahneman et al, 1991). The 'anchoring and adjustment theory' suggests that unsophisticated customers 'anchor' to pricing information that is most pertinent and visible (base price). Buyers fail to adjust price notions with the addition of surcharges, spending more than they have mentally calculated. The endowment effect suggests that customers who have proceeded to the surcharge step, experience 'loss aversion' and feel the need to complete a transaction despite an increase in the total price due to fear of missing out on the good.

It is common for platforms to manipulate the amount and presentation of the headline (base) price. Most ticketing and travel platforms provide the lowest headline price ('from price') for a certain category of good. Deeper in the purchase funnel, headline prices are further revealed (which are limited). Some platforms outright hide the 'from' price, forcing customers to proceed deeper into the purchase funnel for base price information. At checkout, firms 'drip' surcharges that vary in amount and type. Surcharges typically go to the supplier (cleaning, resort fee), platform (order, ticket fee) or government (state and federal sales tax). Firms further obscure surcharges by manipulating the number of fees and the presented saliency. An example breakdown is provided in Figure 1. The headline price is under the 'subtotal' section, and the surcharges contained in the 'total charges' section.

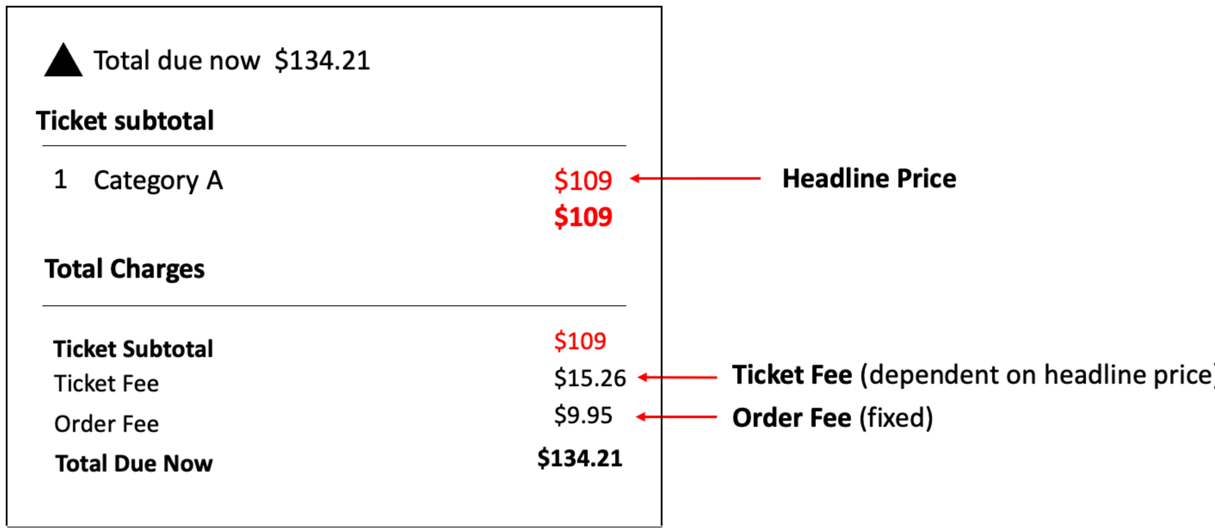


Figure 10: Example of Drip Pricing Breakdown - At the checkout page, the user is introduced to the total price. In the example above, $109 represents the headline price, the 'ticket fee' is linearly related to the headline price and the 'order fee' which is a constant $9.95 per order.

Global trade commissions have aimed to tackle drip pricing by notifying companies that their pricing frameworks are misleading. In 2012, the United States FTC warned '22 hotel operators that their online reservation sites may violate the law by providing a deceptively low estimate of what consumers can expect to pay for their hotel rooms'. (FTC, 2019) The Australian Competition Commission (ACCC, 2015) and European Commission (Boffey, 2018) has acted against AirBnB. In recent years, action has been taken against ticketing agencies, such as Stubhub. (Harris and Bouras, 2020)

Our research aims to initiate a deeper and mechanistic understanding of headline prices and surcharges. We accomplish this by conducting eight field studies on a tourism platform. In the first two studies, we varied the salience of the "from" price across the initial steps to understand the role of the anchor. Studies 3 and 4 examined how customers react to minimal increases in fees when presentation is obfuscated versus transparent. In studies 3-6, we varied the fee and total amount (low, high) in different saliency situations (low, high). In studies 7 and 8, headline prices were lowered, with the difference added as a tax or fee surcharge (total was constant). Our goal is to provide firms a better understanding of this framework so they can improve practices while increasing revenue and user retention. For policymakers we want to provide better insights into consumer behavior to help regulate this pricing method moving forward.

In the next section, we review the literature on drip pricing and related areas. Section 3 describes the data, platform setup and important metrics. Section 4 provides setup, results, and analysis for each study. In the last section, we provide a general discussion of our findings and implications for firms and policymakers.

Previous Literature

Existing literature on drip pricing examines its impact as a whole; its ability to increase revenue (consistent across most studies) due to increases in the quality of goods purchased (Blake et. al (2021), Dertwinkel-Kalt et. al (2019), Siem et. al (2017)). Drip pricing draws parallels to 'partitioned pricing' – a technique that presents surcharges in conjunction with the base price (comprehensive review in Greenleaf et. al 2016 and Abraham et. al 2018). Add-on pricing is a similar framework, where firms advertise a low price for product but aim to sell 'add-ons' that enhance the base good (optional).

We split our examination of the previous literature into two major categories: headline price (salience and amount) and surcharges (salience, amount, and type). While both parts are interdependent, we aim to examine previous findings that can help form hypotheses for the unique studies conducted in this paper.

Headline Price

The argument that describes the effectiveness of the base price is the ‘anchoring and adjustment theory’ (Tversky and Kahneman, 1974). The findings are confirmed in laboratory studies by Morovitz et. al (1998), Lee and Han (2002), Finkelstein (2009). Other studies suggest that the anchor leads customers to select suboptimal, higher priced goods which they select in follow-up visits (Santana et. al (2020), Blake et. al (2021), Dertwinkel-Kalt et. al (2019), Siem et. al (2017)). There are no experiments (laboratory and field) that examine the common practice of manipulating its saliency across steps.

The firm conducted two studies (1-2) where the ‘from’ price (anchor) is hidden. In the first the anchor was removed in search, decreasing the ‘time’ a buyer anchors to the ‘from’ price. The anchor was effectively removed in study 2 (search and product page). In the last two studies (7-8), all headline prices were reduced with difference added as a surcharge (fee vs. tax), similar to Brown et. al (2010) and Hossain and Morgan (2006). Their studies, run in a price portioned ebay auction, show that a reduction in anchor price and equivalent increase in shipping charges led to higher revenue for suppliers despite declines in transaction volume.

Dripped Surcharges

The effectiveness of dripped surcharges is attributed in part to the afore mentioned 'endowment effect' (Kahneman et al, 1991). Firms most commonly manipulate surcharges through presentation, amount, and type of surcharge. Due to reduced screen space on mobile devices, platforms minimize price information to increase click-through rates. This is accomplished by only showing the total price, with a drop-down menu that a user must open to view 'dripped' charges. Given that drip pricing inherently reduces price salience, shrouding fees is the next level of obsfucation. There are no prior tests (field and laboratory) that examine how customers behave in such a context. Gabriax and Laibson (2006) and Ellison (2005) examined the effect of 'shrouding' add-on prices - i.e. when they are 'unobserved'. The consumer is not explicitly told that the add-on is needed for the good they are purchasing. In relation to drip pricing, the findings suggest that myopic customers that will not seek out information on the addition of fees, thus benefiting the firm. We test the phenomenon of firms by 'forcing' customers into being myopic through varying saliency in studies 3 and 4.

In studies 3-8, we manipulate the magnitude (low and high) of different fees charged at checkout. The previously described experiments examine situations where the total price remained constant. Findings are consistent, in the laboratory (see Greenleaf and Abraham for review) and field settings (Chetty et al. (2009), Taubinsky and Rees-Jones (2018), Hossain and Morgan (2006), Brown et. al (2010)); on average, customers do not properly account for increases in fees, leading to higher revenues. To our knowledge, Brown et. al (2010) is the only field study that examines the effect of changing the surcharge amount and total price (low, high) with a fixed headline price. Their results show that customers are less sensitive to increases in shipping costs than the headline price. In the context of our studies, we compare changes in ‘ticket and order’ fees (studies 3-5) (high, low) and in both surcharge saliency situations (low, high).

In the final two studies (7 and 8), we examined the effect of decreasing the headline price and adding the difference as a part of the surcharge, keeping the total price fixed (similar to Hossain and Morgan (2006), as previously mentioned). Most previous work examines ‘dripped’ fees with no field studies contrasting the relative effect of different types of surcharges. Few laboratory studies examine the difference lies in the intention of the surcharge. They suggest that customers are more accepting of governmental taxes than superfluous fees (Bambauer-Sachse and Mangold (2010), Schindler et al. (2005)). In studies 7-8, we examine the effectiveness between dripped fees and taxes.

Data Source

The studies presented in this paper were conducted on an online platform where customers buy entertainment tickets for a specific travel destination. The platform sells tickets from attraction owners and has large multi-market competitors (e.g., Ticketmaster, Stubhub, etc.) with limited direct. All direct competitors use drip pricing, making it difficult to compare pricing across platforms due to high search costs (Baye and Morgan, (2009), Huck and Wallace (2010)). The surcharge breakdown closely resembles Figure 1. The headline price is set by the supplier with a variable “ticket fee” and fixed “order fee” collected by the platform.

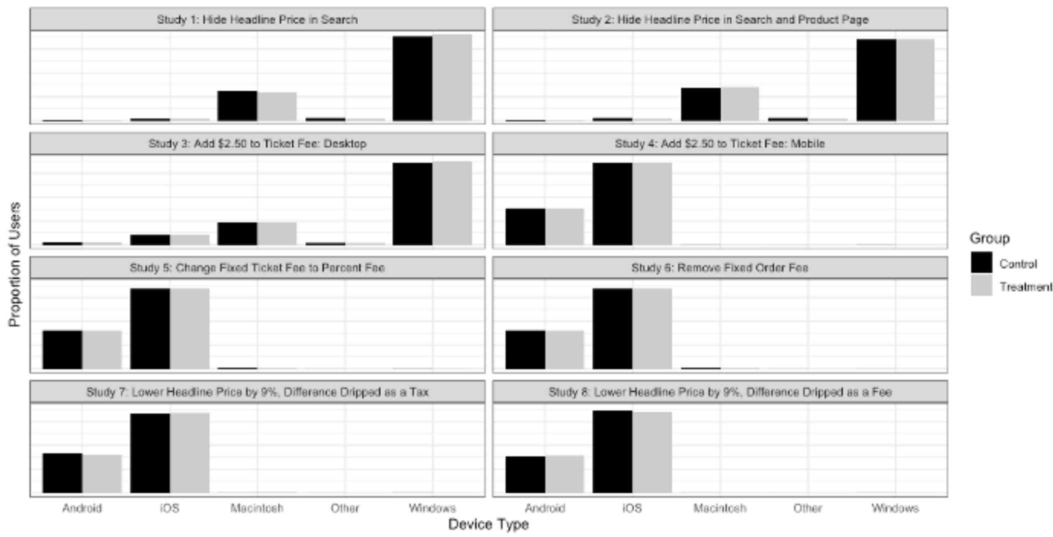
For our field studies, subjects were randomly selected from the general traffic to the platform. Users were then excluded if they had visited the site within the last thirty days. A short summary of tests (descriptions and total users) is included in Table 1. To show randomization was correctly performed, Figure 2 shows the distribution of two pre-study covariates: hour of first visit and device type.

Table 1: All Studies Summarized

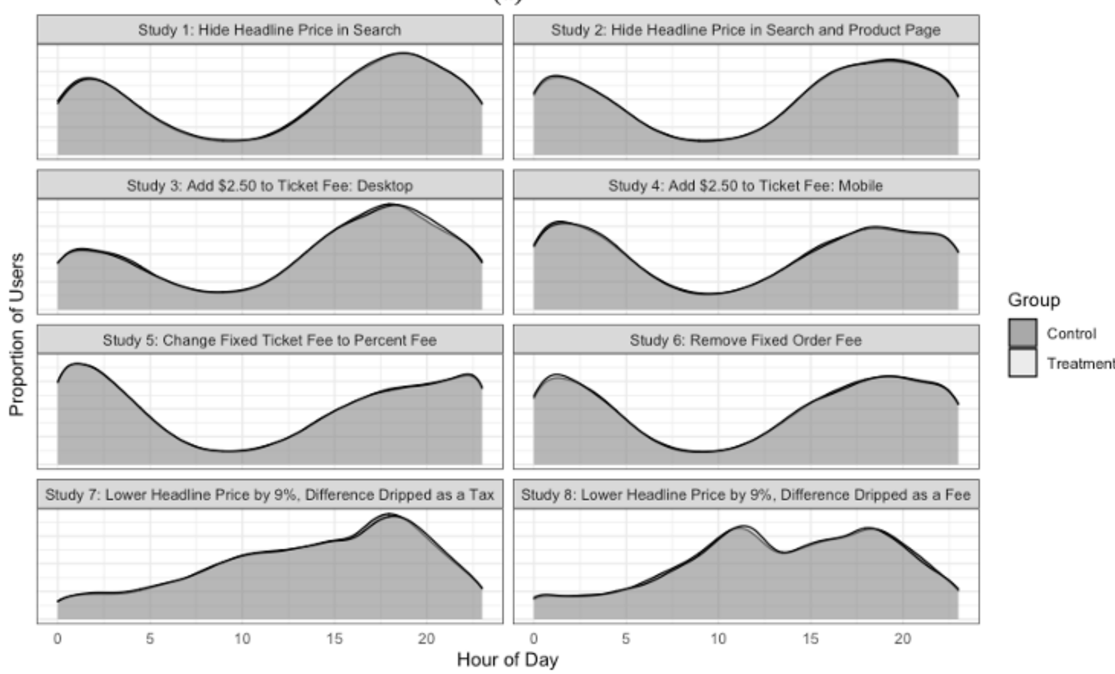
Study Name	Device	Description	Length	Control Size	Treatment Size
Study 1: Hide Lowest Headline Price in Search	Desktop	In search, from price is hidden	7 days	10,821	10,791
Study 2: Hide Lowest Headline Price in Search and Product Page	Desktop	In search AND product page, the from price is hidden	13 days	66,762	67,509
Study 3: Add $2.50 to Ticket Fee	Desktop	Added $2.50 to ticket fee for select options (salient presentation) total price changes	7 days	42,709	43,090
Study 4: Add $2.50 to Ticket Fee	Mobile	Added $2.50 to ticket fee for select options (non-salient presentation) total price changes	7 days	49,538	49,170
Study 5: Fixed Ticket Fee to Percent Fee	Mobile	Ticket fees are switched from fixed to a percentage of the headline price; total price changes	27 days	435,165	435,809
Study 6: Remove Fixed Order Fee	Mobile	$9.95 fixed order fee removed; total price changes	6 days	53,389	54,687
Study 7: Lower Headline Price by 9%, Difference Dripped as a Tax	Mobile	Headline prices lowered by 9% and dripped as a tax surcharge; total cost remains the same	3 days	27,750	28,232
Study 8: Lower Headline Price by 9%, Difference Dripped as a Fee	Mobile	Headline prices lowered by 9% and dripped as apart of order fee; total cost remains the same	3 days	18,989	19,174

We collected clickstream data (page, session, and transaction information) for each customer. Web activity was linked on a “cookie” stored in the user's browser - if a customer made multiple visits to the platform without its removal, the data tracks all visits. If the “cookie” is cleared from the browser, there is no way to link sessions. The users were primarily first-time visitors with limited session-based identifiers (location, device type and time). Session location (Table 2) and relative booking time are heavily dependent on the device type (i.e., mobile users are primarily last minute and in-market, desktop are 30+ days from visiting and out of market). Product attributes, such as event popularity and rating, are highly correlated with price.

Figure 3 describes purchase funnel for a typical user. Step 1 represents the homepage and various landing pages. Most visitors enter at this point and are referred to as ‘search entry’. At this step, users enter a date of interest for attending an entertainment option. At step 2, the search results of the query are presented. In search, the “from” price is displayed next to all event options. Step 3 is the product page, where available times for the selected option are presented with the “from” price. Visitors who enter at this point, are called ‘product entry’ users. Unlike ‘search entry’, these users are aware of the specific product they are viewing before entering the platform. The proportion of user entry type by study is provided in Table 3. At Step 4, headline prices for all ticket types are available for the selected entertainment option. Once the ticket is chosen, the customer is directed to checkout (Step 5) where the ‘true’ pricing breakdown (*with surcharges*) is revealed for the first time (Figure 1). In Step 6, the customer completes the transaction.



(a)



(b)

Figure 11: Randomization Tests – Pre-variate (device type (a) and time hour (b)) distributions across for the control and treatment. Across all studies, the distributions were similar – ensuring randomization worked.

Table 2: Proportion of Users by Location in Each Study

	In Market Users (%)		Out of Market Users (%)		In and Out of Market Users (%)	
	Control	Treatment	Control	Treatment	Control	Treatment
Study 1: Hide Headline Price in Search	3.11	2.92	96.07	96.23	0.82	0.85
Study 2: Hide Headline Price in Search and Product Page	4.67	4.86	90.25	89.94	0.83	0.8
Study 3: Add $2.50 to Ticket Fee - Desktop	3.51	3.34	95.66	95.81	0.83	0.85
Study 4: Add $2.50 to Ticket Fee - Mobile	11.33	11.31	85.97	85.88	2.7	2.81
Study 5: Change Fixed Ticket Fee to Percent Fee	14.65	14.64	80.63	80.68	4.72	4.68
Study 6: Remove Fixed Order Fee	5.3	5.41	92.61	92.65	2.09	1.94
Study 7: Lower Headline Price by 9%, Difference Dripped as a Tax	10.74	10.63	87.58	87.52	1.68	1.86
Study 8: Lower Headline Price by 9%, Difference Dripped as a Fee	13.92	13.46	83.62	83.53	2.46	3.01

Table 3: Proportion of Entry of Users by Study

	Search Page Entry		Product Page Entry	
	Control	Treatment	Control	Treatment
Study 1: Hide Headline Price in Search	92.96	93.2	7.04	6.8
Study 2: Hide Headline Price in Search and Product Page	79.39	80.15	20.61	19.85
Study 3: Add $2.50 to Ticket Fee - Desktop	63.81	63.13	36.19	36.87
Study 4: Add $2.50 to Ticket Fee - Mobile	13.42	15.18	86.58	84.82
Study 5: Change Fixed Ticket Fee to Percent Fee	76.19	76.21	23.81	23.79
Study 6: Remove Fixed Order Fee	79.39	80.15	20.61	19.85
Study 7: Lower Headline Price by 9%, Difference Dripped as a Tax	72.58	72.29	27.42	27.71
Study 8: Lower Headline Price by 9%, Difference Dripped as a Fee	70.54	70.54	29.46	29.46

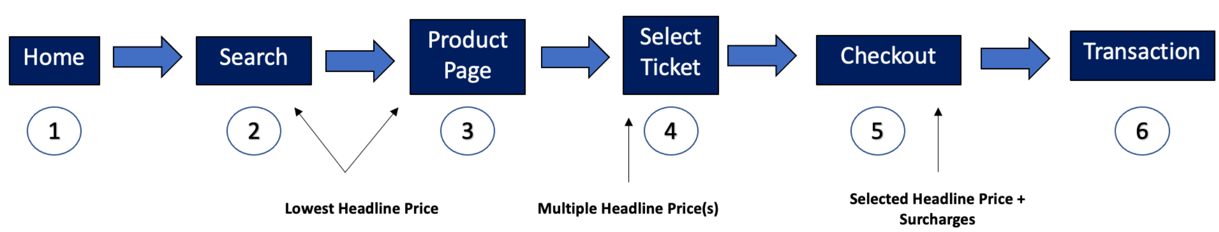


Figure 12: Page Flow for Platform - The customer starts at the homepage, where they select a general product category for a specific date. This leads to the search results page. Once a product is selected in search, the user visits the product page.

To provide context of the tickets sold, we provide a distribution of the headline prices (Figure 4), from prices for all options (also the top 30) (Figure 5), and the number of tickets per order (Figure 6) purchased for a two-year period, 2018- 2020. Most available tickets are priced in the \$50 - \$100 range, the 'lowest headline price' has a median of around \$50 and nearly 60% of orders contain two tickets.

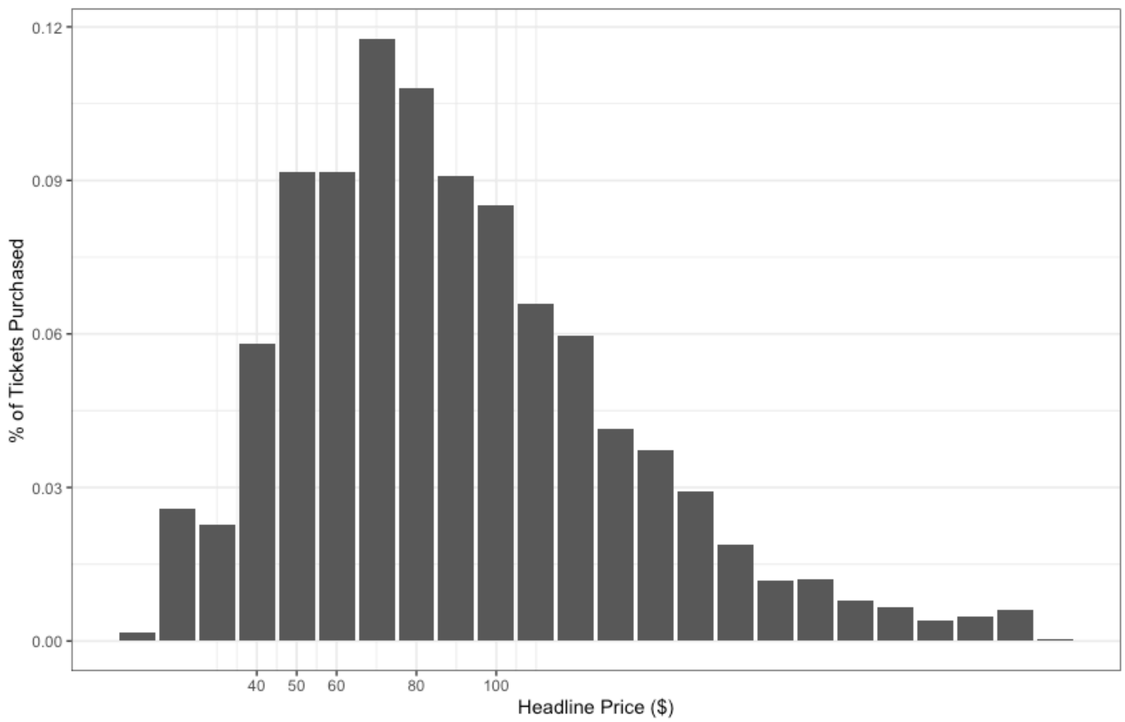


Figure 13: Distribution of Purchased Tickets by Headline Price (Less than \$250)

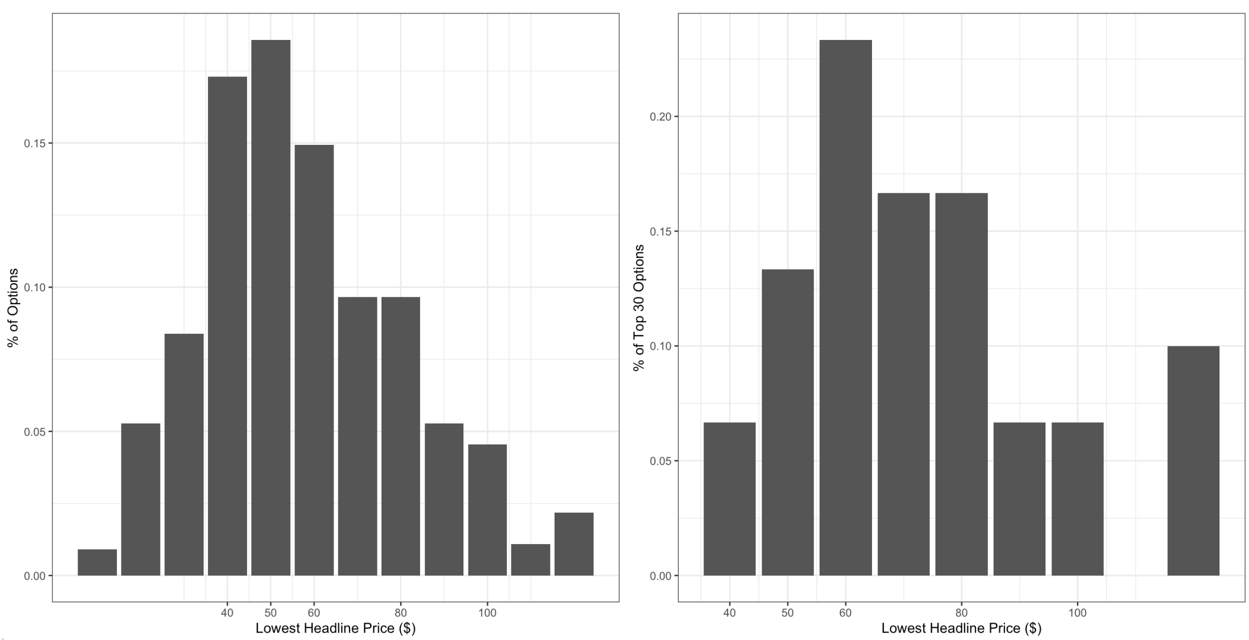


Figure 14: Distribution of Options by Lowest Headline Price: For Options Less than \$125 (left) and for top 30 options (right)

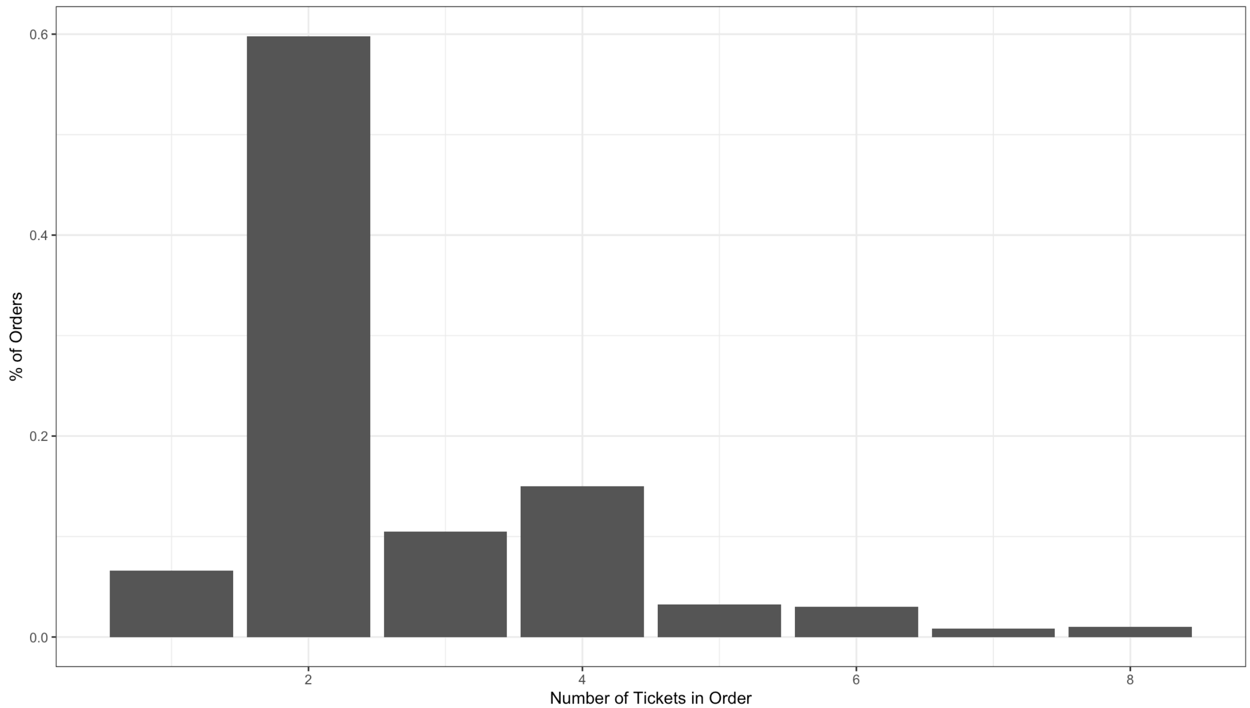


Figure 15: Distribution of Tickets in Order: For Orders Less than 9 Total Tickets

Important Metrics

There are notable limitations to our analysis due to the context being studied. Step by step conversion rates decrease further into the purchase funnel with a large drop off at checkout. This coupled with the fact that we have no demographic information for visitors, limits the analysis that can by conducted. As a result, our paper shows aggregate causal effects ('diff' model) to compare conversion rates and revenue between the control and treatment. At the request of the firm, we calculate the rate of change in the conversion rate and revenue. For metrics such as tickets sold or change in headline prices, we present the difference (treatment – control).

For this analysis, we focus on three parts of the potential purchase process: 'before first checkout', 'at first checkout', and 'after first checkout'. After checkout behavior is limited in this context as the platform as high bounce rates after the first visit. Table 4 contains statistics on revenue, orders placed, tickets purchased and average headline price (search and product page entry included). The difference in overall conversion (proportion of total users that transacted) is included alongside the step-by-step conversions in Table 5 and Figure 7. These are calculated as the proportion of users of the previous step that made it to the subsequent page. Table 6 displays the metrics about the distinct number of products viewed and the difference in the rate of users who did not view a product; for checkout visitors, the average number viewed before the first checkout and after the checkout visit. Additionally, we find the value of the average price (weighted) of the products viewed. Similarly in Table 7, we look at the rate of change users who did not visit checkout, bounce rate at first checkout, the proportion of the lowest cheapest ticket within an option selected and the values of the items added to checkout.

At checkout, we can identify detailed pricing information of the selected ticket. Table 8 and Figure 8 shows the price breakdown of the ticket types added to checkout. We provide the difference in checkout conversion rate and purchase metrics (revenue, tickets, and headline price) based on the

Table 4: Rate of Change in Entertainment Revenue, Difference in Headline Price, Number of Tickets and Orders of Items Purchased

	Revenue (%)	Orders	Tickets	Headline Price ($)	Revenue (%)	Orders	Tickets	Headline Price ($)	Revenue (%)	Orders	Tickets	Headline Price ($)
Study 1: Hide Headline Price in Search	5.98	65	178	-1.33	1.68	30	85	-2.45	34.66	35	93	5.58
Study 2: Hide Headline Price in Search and Product Page	0.8	-54	-246	2.67	-2.69	-168	-500	2.96	7.87	114	254	1.98
Study 3: Add $2.50 to Ticket Fee - Desktop	-1.85	-2	-3	-3.28	-14.22	-10	-47	-4.71	27.34	8	44	-0.49
Study 4: Add $2.50 to Ticket Fee - Mobile	32.88	-19	227	3.45	23.38	-16	108	2.18	52.09	-3	119	5.68
Study 5: Change Fixed Ticket Fee to Percent Fee	6.31	334	4046	-1.56	4.37	209	3252	-2.05	7.27	125	794	-0.65
Study 6: Remove Fixed Order Fee	3.18	171	401	-3.19	4.32	148	333	-4.47	0.98	23	68	-0.56
Study 7: Lower Headline Price by 9%, Difference Dripped as a Tax	20.23	68	143	9.2	24.51	69	134	9.28	12.12	-1	9	8.96
Study 8: Lower Headline Price by 9%, Difference Dripped as a Fee	1.03	-41	-63	-1.16	-4.93	-36	-72	-3.18	12.12	-5	9	2.25

Table 5: User Funnel - Rate of Change in Conversion between steps (and overall)

	Overall (%)	Search to Product Page (%)	Product to Select Ticket Page (%)	Select Ticket to Checkout (%)	Checkout (%)
Study 1: Hide Headline Price in Search	3.95 (0.2)	8.13* (0.08)	-2.71 (0.1)	1.78 (0.1)	-2.41 (0.12)
Study 2: Hide Headline Price in Search and Product Page	-1.6 (0.04)	7.82* (0)	57.69* (0.82)	-30.06* (0.67)	-2.42 (0.05)
Study 3: Add $2.50 to Ticket Fee - Desktop	-2.56 (0.24)	-2.15 (0.08)	5.42 (0.08)	-9.22 (0.97)	-6.95 (0.68)
Study 4: Add $2.50 to Ticket Fee - Mobile	-5.57 (0.34)	-1.41 (0.03)	5.94 (0.06)	1.01 (0.05)	-9.22* (0.69)
Study 5: Change Fixed Ticket Fee to Percent Fee	1.76* (0.02)	0.09 (0)	-1.26 (0.01)	1.29 (0.01)	0.84 (0.01)
Study 6: Remove Fixed Order Fee	18.45* (0.35)	-0.19 (0)	-5.52* (0.15)	1.8 (0.05)	7.42* (0.26)
Study 7: Lower Headline Price by 9%, Difference Dripped as a Tax	8.65* (0.41)	1.64 (0.02)	0.74 (0.03)	-0.54 (0.02)	6.05 (0.28)
Study 8: Lower Headline Price by 9%, Difference Dripped as a Fee	-6.52 (0.39)	-0.86 (0.01)	6.02 (0.32)	5.57 (0.29)	-11.02* (0.59)

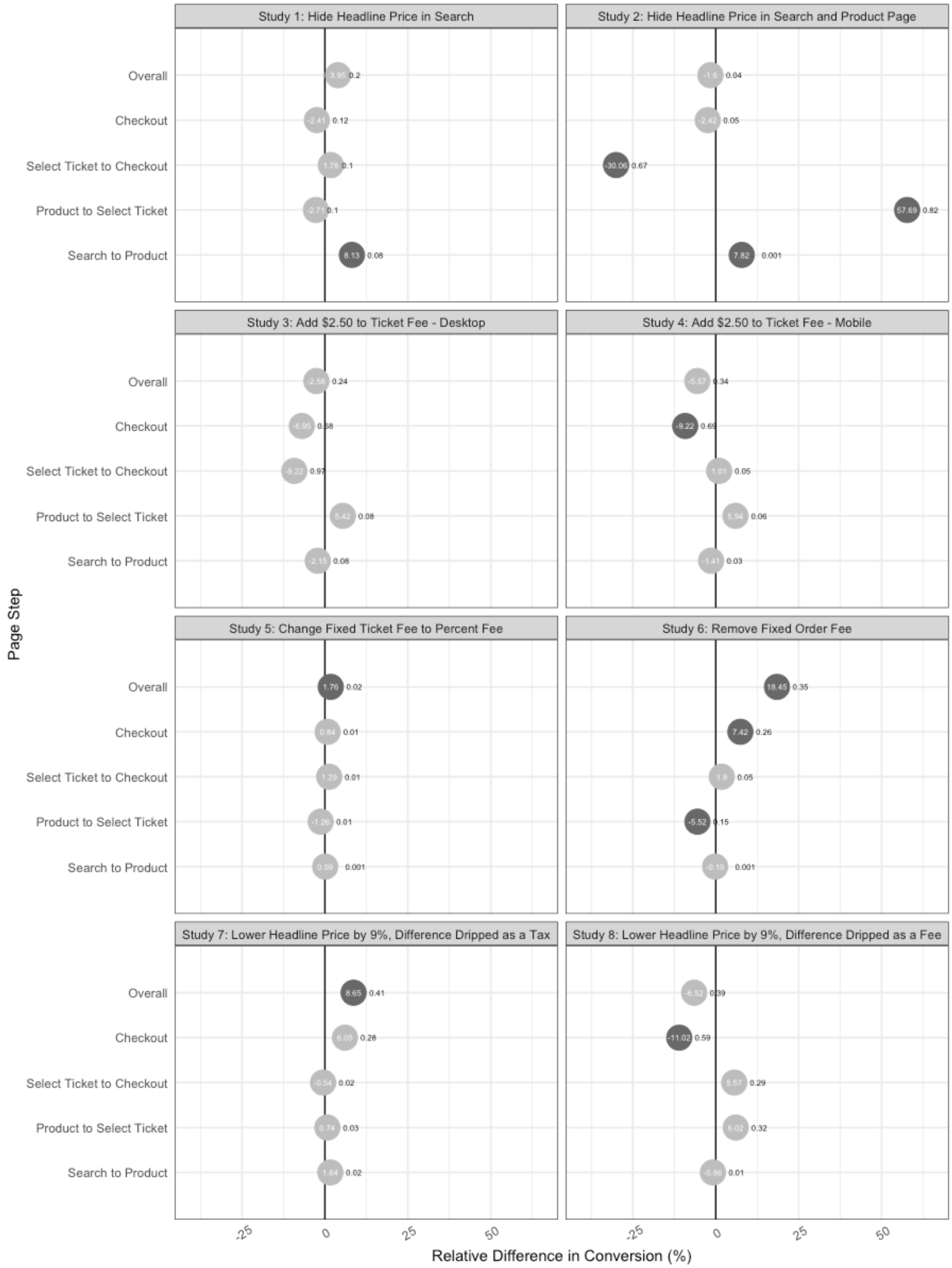


Figure 16: Step by Step Conversion - Relative change in conversion shown in points with standard error written to the right the data point. Darker points show significant difference between treatment and control

Table 6: View Statistics – Difference in No Checkout Users, Before Checkout and After Checkout, Difference in Headline Price

	Average Product Pages Viewed		Users - No Products Viewed (%)	Products Viewed - No Checkout Users		Products Viewed Before First Checkout		Products Viewed After First Checkout		Difference in Average Product Headline Price ($)	
	Control	Treatment		Control	Treatment	Control	Treatment	Control	Treatment	All Viewed	First Viewed
Study 1: Hide Headline Price in Search	2.75	3.02	-11.87* (0.21)	2.07	2.26	1.86	2.08	2.48	2.7	1.78	4.27
Study 2: Hide Headline Price in Search and Product Page	2.29	2.46	-12.15* (0.12)	1.68	1.76	1.8	1.87	2.36	2.46	1.01	2.05
Study 3: Add $2.50 to Ticket Fee - Desktop	1.78	1.73	-1.11 (0.01)	1.3	1.31	1.41	1.38	1.47	1.45	-0.37	0.07
Study 4: Add $2.50 to Ticket Fee - Mobile	1.94	2.02	0.57 (0.01)	1.39	1.4	1.42	1.49	1.42	1.58	0.11	0.39
Study 5: Change Fixed Ticket Fee to Percent Fee	2.48	2.46	-0.47 (0)	1.76	1.75	1.88	1.88	2.07	2.07	0.01	-0.33
Study 6: Remove Fixed Order Fee	2.27	2.29	1.02 (0.01)	1.7	1.71	1.73	1.78	1.9	1.93	0.08	0.55
Study 7: Lower Headline Price by 9%, Difference Dripped as a Tax	2.34	2.29	-1.73 (0.03)	1.72	1.67	1.8	1.84	1.99	1.9	0.77	0.18
Study 8: Lower Headline Price by 9%, Difference Dripped as a Fee	2.25	2.29	1.25 (0.02)	1.71	1.72	1.96	2	2.12	2.02	0.06	-0.62

Table 7: No Checkout Rate, Cheapest Ticket Added to Checkout Rate and Difference in Headline Price

	No Checkout Users (%)	Cheapest Ticket added to Checkout	Difference in Average Product Headline Price ($) - All	Difference in Average Product Headline Price ($) - First
Study 1: Hide Headline Price in Search	-1.24* (0)	-1.95 (0.04)	-2.24	-1.79
Study 2: Hide Headline Price in Search and Product Page	-0.7* (0)	-0.77 (0.01)	0.3	0.06
Study 3: Add $2.50 to Ticket Fee - Desktop	0.06 (0)	11.47* (0.43)	-0.84	-2.12
Study 4: Add $2.50 to Ticket Fee - Mobile	0.28 (0)	-3.83* (0.09)	0.64	1.18
Study 5: Change Fixed Ticket Fee to Percent Fee	-0.1 (0)	0.28 (0)	1	1.03
Study 6: Remove Fixed Order Fee	0.01 (0)	-0.07 (0)	-0.85	-0.91
Study 7: Lower Headline Price by 9%, Difference Dripped as a Tax	-0.35 (0)	-2.3* (0.03)	2.36	1.97
Study 8: Lower Headline Price by 9%, Difference Dripped as a Fee	-0.73 (0)	0.35 (0.01)	0.02	0.29

Table 8: User Ticket Value added to First Checkout; Average Headline Price & Ticket Quantity

	Difference (%)	Change in Headline Price ($)	Change in Mean Ticket Quantity	Difference (%)	Change in Headline Price ($)	Change in Mean Ticket Quantity	Difference (%)	Change in Headline Price ($)	Change in Mean Ticket Quantity	Difference (%)	Change in Headline Price ($)	Change in Mean Ticket Quantity	Difference (%)	Change in Headline Price ($)	Change in Mean Ticket Quantity	Difference (%)	Change in Headline Price ($)	Change in Mean Ticket Quantity
Study 1: Hide Headline Price in Search	-15.42 (2.29)	1.15	0.03	13.99 (1.87)	0.13	0.13	0.56 (0.08)	-0.09	-0.17	-5.43 (0.4)	0.47	-0.36	5.4 (0.38)	0.03	0.09	0 (0)	-5.63	-0.22
Study 2: Hide Headline Price in Search and Product Page	-2.33 (0.15)	-0.97	0.18	3.63 (0.21)	-0.23	-0.25	1.96 (0.11)	0.22	-0.05	-6.59* (0.21)	0.01	0.07	-0.19 (0.01)	0.03	-0.03	2.38* (0.04)	0.5	0.01
Study 3: Add $2.50 to Ticket Fee - Desktop	10.5 (1.44)	0.12	0	25.67 (3.64)	-0.42	-0.15	-19.88 (2.68)	-0.52	0.29	0.32 (0.03)	-0.54	0	-23.85 (6.15)	-0.64	-0.03	-3.08 (1.14)	-6.57	1
Study 4: Add $2.50 to Ticket Fee - Mobile	-11.95* (0.99)	0.67	0.07	6.12 (0.54)	-0.08	-0.05	11.47 (1.08)	-0.42	0.26	-5.06 (0.42)	0.5	0.2	1.35 (0.2)	0.17	0.15	27.61 (7.21)	2.7	-0.02
Study 5: Change Fixed Ticket Fee to Percent Fee	-1.94 (0.06)	-0.51	-0.09	-1.82 (0.04)	-0.03	0.01	2.32 (0.06)	-0.09	-0.04	-0.12 (0)	0.03	-0.04	-0.35 (0.01)	-0.01	-0.07	0.66 (0.01)	2.7	0.02
Study 6: Remove Fixed Order Fee	-11.26 (0.97)	-1.31	0.04	-0.79 (0.05)	0.42	0.16	6.23 (0.4)	-0.49	-0.1	0.69 (0.03)	-0.72	0.02	-3.65 (0.16)	0.06	0.01	2.16 (0.07)	-3.76	0.05
Study 7: Lower Headline Price by 9%, Difference Dripped as a Tax	-10.34 (1.27)	-1.16	-0.14	-14.34 (1.64)	-0.43	-0.1	1.19 (0.11)	0.47	0.13	-9.12* (0.65)	-0.41	-0.1	-3.51 (0.25)	0.11	-0.19	9.29* (0.62)	-5.11	0.12
Study 8: Lower Headline Price by 9%, Difference Dripped as a Fee	1.25 (0.16)	-1.04	-0.02	18.35 (2.34)	-0.14	-0.33	-10.46 (1.25)	0.54	-0.33	-4.5 (0.32)	0.15	0.14	3.29 (0.26)	-0.12	0.03	-0.28 (0.02)	1.63	0

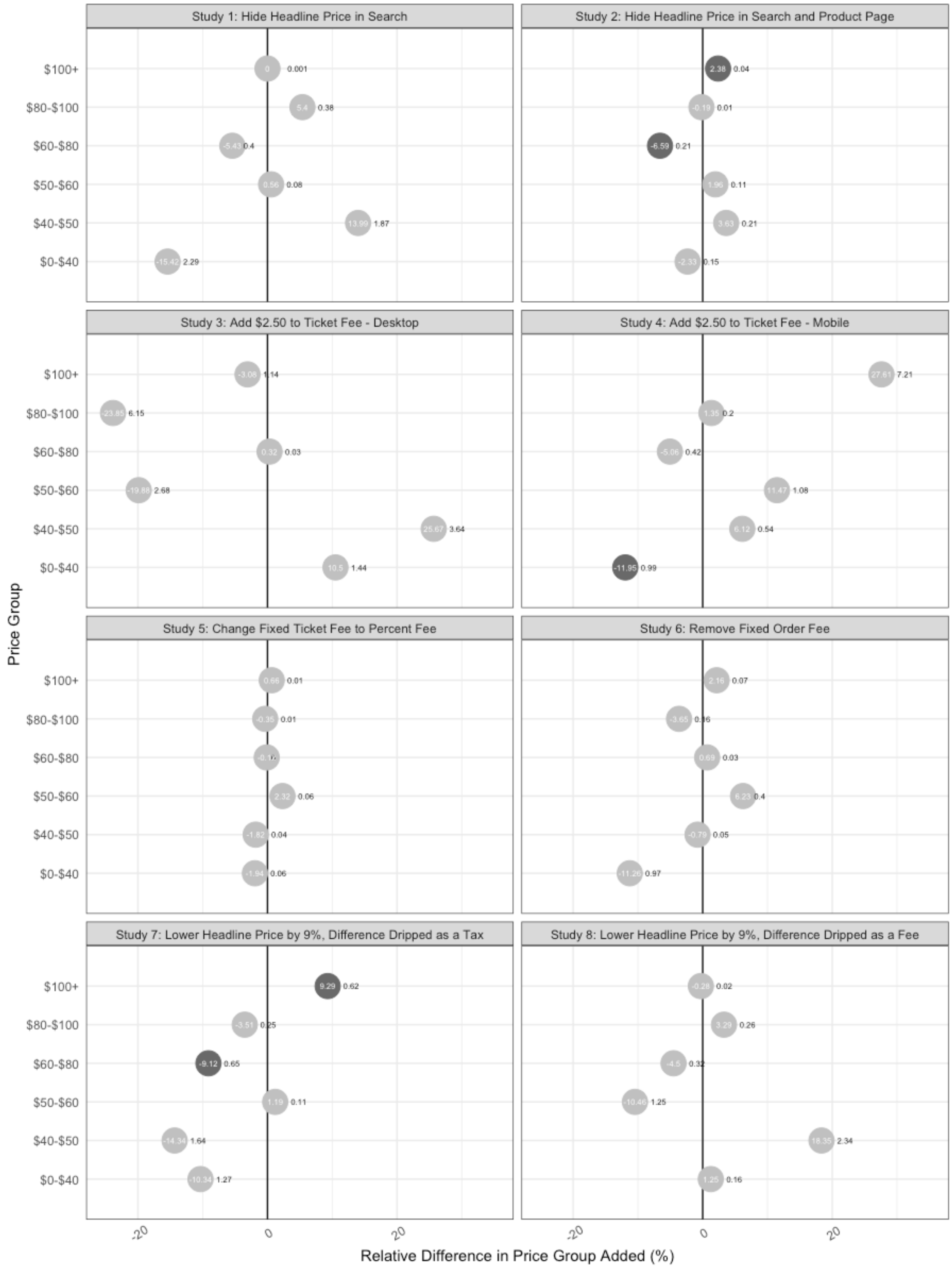


Figure 17: Tickets Added to Checkout: Relative change in tickets added to checkout shown in points with standard error written to the right the data point. Darker points show significant difference between treatment and control

headline price of the tickets added to the cart (Table 9 and Figure 9). The base price is split into six major price categories; $0-40, $40-50, $50-60, $60-80, $80-100 and $100+, a grouping used to vary the item fee structure in Study 5. For studies 3-6 we provide checkout conversion based on the control fixed fee amount in Table 10. Specifically for study 5, which is a large-scale study varying the ticket fee, we calculate the checkout conversion, bounce rate, and purchase metrics across dollar amount differences in the fee (Table 11). In Tables 12 and 13, we examine the behavior of users after the first checkout (bounce rate and successive pages). For studies 3 and 4 we examined the addition of fees on *select* options. The numbers presented in the table for these studies were for customers who interacted with those specific options.

For the first two studies (1-2) and the last two studies (7-8), initial step conversion is crucial, as customers are affected by changes to the headline price. Studies 3 - 6 (varying surcharge transparency and amount) focus primarily on customer behavior at checkout. Each of these studies saw mostly consistent initial step conversion and product page views before first checkout, as expected.

In the remaining sections, we will provide a description, results and a discussion comparing similar studies. The pairings are as followed: anchor salience (studies 1-2), surcharge salience (studies 3-4), low salience fee manipulation (study 5), high salience fee changes (study 6) and anchor/type of surcharge manipulation (study 7-8). In the discussions for studies 5 and 6, we provide comparisons to salience similar studies, studies 4 and 3, respectively.

Table 9: Checkout Conversion Difference, Change in Average Headline Price, Change in Tickets Purchased & Change in Revenue by Price Group at First Checkout

	Difference (%)	Change in Headline Price ($)	Change in Tickets Purchased	Revenue Difference (%)	Difference (%)	Change in Headline Price ($)	Change in Tickets Purchased	Revenue Difference (%)	Difference (%)	Change in Headline Price ($)	Change in Tickets Purchased	Revenue Difference (%)	Difference (%)	Change in Headline Price ($)	Change in Tickets Purchased	Revenue Difference (%)	Difference (%)	Change in Headline Price ($)	Change in Tickets Purchased	Revenue Difference (%)	Difference (%)	Change in Headline Price ($)	Change in Tickets Purchased	Revenue Difference (%)
Study 1: Hide Headline Price in Search	-41.21* (11.59)	0.93	-25	-21.7	26.91 (6.41)	0.48	39	61.13	-6.73 (1.43)	0.58	-16	-17.53	-15.14 (2.06)	0.48	-68	-20.35	-4.16 (0.44)	-0.6	48	18.44	-5.38 (0.44)	-4.78	-12	-3.74
Study 2: Hide Headline Price in Search and Product Page	-23.66* (2.62)	-1.21	-131	-25.2	-14* (1.48)	-0.23	-54	-9.69	-19.34* (1.58)	0.22	-69	-11.37	0.5 (0.03)	0	-5	-0.32	-6.63* (0.29)	0.05	-84	-6.95	-5.38* (0.18)	0.66	82	3.13
Study 3: Add $2.50 to Ticket Fee - Desktop	15.9 (4.58)	-0.33	7	20.18	44.13 (12.87)	-0.72	27	56.28	-19.9 (5.33)	-0.27	-25	-29.42	-2.74 (0.56)	1.77	24	47.66	16.69 (8.68)	7.21	4	37.02	-62.5* (47.22)	10.34	-9	-79.95
Study 4: Add $2.50 to Ticket Fee - Mobile	-22.05 (4.21)	2.92	-13	6.67	-1.58 (0.29)	-0.54	33	28.19	-24.28 (4.3)	0.04	2	5.97	-5.18 (1.02)	-2.47	73	75.85	0 (0)	-1.52	11	33.58	51.5 (33.77)	17.73	4	69.72
Study 5: Change Fixed Ticket Fee to Percent Fee	23.4* (1.48)	-0.46	516	12.35	7.53 (0.46)	-0.26	66	0.4	2.64 (0.13)	-0.29	346	10.89	0.02 (0)	-0.2	364	3.15	0.62 (0.02)	0.22	92	1.23	-6.25* (0.17)	-1.5	144	3.4
Study 6: Remove Fixed Order Fee	5.16 (0.9)	-1.7	-18	-22.41	5.07 (0.75)	0.48	72	20.74	28.94 (3.6)	-0.47	61	31.18	20.18 (1.85)	-1.85	53	2.18	6.9 (0.55)	-0.26	8	-2.14	6.75 (0.46)	-5.56	125	10.44
Study 7: Lower Headline Price by 9%, Difference Dripped as a Tax	-15.98 (4.34)	-1.83	-8	-1.77	40.54* (9.66)	-2.41	46	56.54	-2.72 (0.51)	-1.17	0	6.58	-3.73 (0.53)	-1.19	-32	-3.2	1.58 (0.19)	4.2	28	37.29	16.03* (1.3)	-5.71	43	21.73
Study 8: Lower Headline Price by 9%, Difference Dripped as a Fee	-24.4 (5.96)	-1.32	-8	5.99	-4.52 (1)	-1.63	-18	-7.6	-2.24 (0.44)	0.14	43	75.63	-11.28 (1.39)	-3.17	41	30.93	-13.8 (1.81)	1.1	-44	-17.06	-7.32 (0.83)	-13.93	-39	-9.58

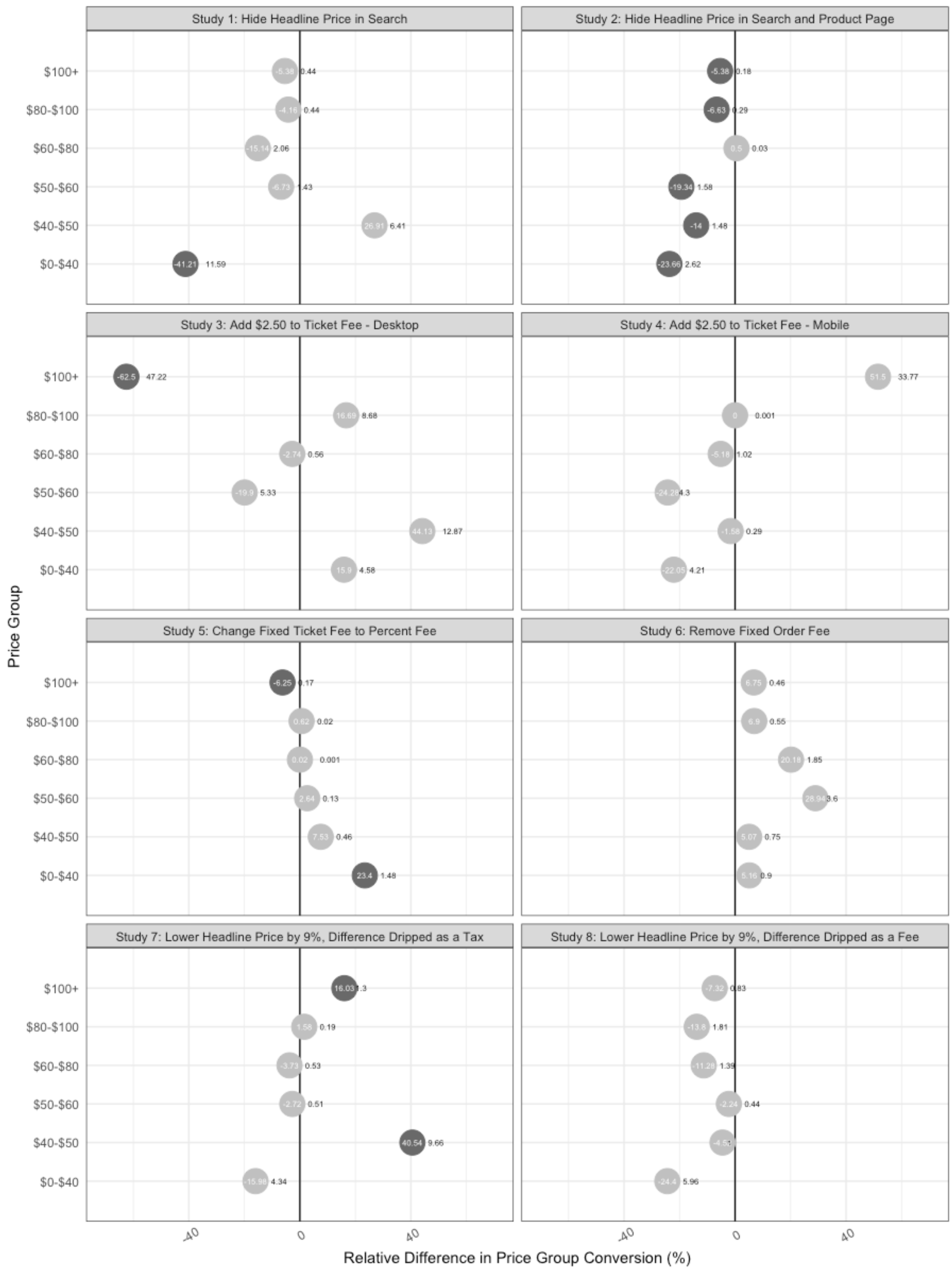


Figure 18: Price Group Checkout Conversion: Relative change in checkout conversion shown in points with standard error written to the right the data point. Darker points show significant difference between treatment and control

Table 10: Fixed (Control Fee) by Study – Change in Revenue, Change in Headline Price and Change in Tickets Purchased

		Revenue (%)	Headline Price ($)	Tickets
Study	**Fee Type**	**Difference (%)**	**Difference ($)**	**Difference**
Study 3: Add $2.50 to Item Fee - Desktop	**5.95**	11.63	-3.28	14
	7.95	-20.42	7.58	-26
	9.95	-0.44	-4.18	9
Study 4: Add $2.50 to Item Fee - Mobile	**5.95**	-23.99	7.21	-68
	7.95	85.91	5.31	89
	9.95	33.5	0.02	206
Study 5: Change Fixed Item Fee to Percent Fee	**7.95**	-3.44	4.7	-64
	9.95	5.17	-1.94	292
	12.45	9.12	-0.2	1268
	14.95	4.34	-2.62	1424
Study 6: Remove Order Processing Fee	**7.95**	82.55	18.27	18
	9.95	20.75	0.64	116
	12.45	0.36	-5.83	120
	14.95	3.23	-4.88	172

Table 11: Study 5 – Change in Checkout Conversion & Bounce Rate based on Fee Difference Treatment vs. Control

Fee Difference ($) (Treatment - Control)	Average Headline Price ($)	Checkout Conversion Rate (%)	Bounce Rate (%)
-5	29.43	79.59* (15.84)	-24.67* (3.52)
-4	39.04	27.35* (4.06)	-26.84* (3.13)
-3	43	14.42* (0.79)	-6.09* (0.28)
-2	51.37	4.42 (0.23)	6.67 (0.39)
-1	59.81	3.56 (0.13)	-0.25 (0.01)
0	74.16	-3.48 (0.15)	7.03 (0.3)
1	72.9	-2.81 (0.21)	1.33 (0.08)
2	76.31	-8.79* (0.43)	6.24 (0.35)
3	76.5	-9.45 (0.96)	-8.62 (0.89)
4	94.93	1.09 (0.08)	12.06* (0.67)
5	109.37	-11.73 (1.24)	-8.03 (0.88)
6	120.4	0.2 (0.03)	-4.34 (0.56)
7	127.07	-12.69 (1.41)	-2.77 (0.32)
8	136.59	-21.04* (1.81)	0.17 (0.02)

Table 12: Change in Bounce Rate at First Checkout by Price Group

	< $40	$40-$50	$50-$60	$60-$80	$80-$100	$100+
Study 1: Hide Headline Price in Search	119.57* (52.29)	-14.19 (4.11)	14.24 (4.23)	6.26 (1.12)	-32.79* (7.24)	16.29 (1.99)
Study 2: Hide Headline Price in Search and Product Page	-17.88* (2.26)	-0.49 (0.07)	-3.06 (0.36)	3.73 (0.26)	-8.74 (0.6)	-2.64 (0.11)
Study 3: Add $2.50 to Ticket Fee - Desktop	35.25 (9.4)	-47.08* (17.17)	66.5* (18.35)	39.07* (7.75)	85.63 (35.88)	181.32* (132.88)
Study 4: Add $2.50 to Ticket Fee - Mobile	9.77 (1.73)	18.68 (3.03)	7.15 (1.47)	1.81 (0.31)	-0.04 (0.01)	38.88 (16.83)
Study 5: Change Fixed Ticket Fee to Percent Fee	-11.17* (0.61)	2.09 (0.1)	3.97 (0.19)	0.49 (0.01)	-1.59 (0.06)	2.6 (0.06)
Study 6: Remove Fixed Order Fee	-15.02 (2.17)	-4.89 (0.59)	-13.69 (1.52)	-7.06 (0.5)	-1.11 (0.1)	8.79 (0.54)
Study 7: Lower Headline Price by 9%, Difference Dripped as a Tax	11.38 (2.34)	-13.76 (2.74)	-13.48 (2.18)	-1.54 (0.2)	-8.17 (1.1)	-3.13 (0.28)
Study 8: Lower Headline Price by 9%, Difference Dripped as a Fee	36.95 (10.92)	22.76 (5.58)	39.09 (9.58)	28.5* (4.38)	-2.36 (0.35)	6.64 (0.72)

Table 13: Post First Checkout Behavior – Last Page Visited

	Payment	Return to Select Ticket	Return to Product Page	Return to Search	New Product Page	New Select Ticket	New Checkout	New Payment
Study 1: Hide Headline Price in Search	-3.29 (0.29)	-40 (356.74)	18.67 (26.76)	-1.37 (0.7)	40.69 (28.2)	-18.02 (7.25)	3.02 (0.5)	2.06 (0.36)
Study 2: Hide Headline Price in Search and Product Page	-7.67* (0.26)	-15.09 (56.68)	-4.94 (2.17)	-0.74 (0.2)	-30.33 (13.36)	36.47* (5.02)	13.1* (1.06)	-3.01 (0.25)
Study 3: Add $2.50 to Ticket Fee - Desktop	14.65 (3.1)	-2.25 (7.51)	-29.79 (44.04)	-1.79 (2.61)	-12.2 (11.68)	-26.22 (49.67)	10.56 (3.19)	-8.94 (2.6)
Study 4: Add $2.50 to Ticket Fee - Mobile	-8.58 (1.41)	159.42 (913.41)	13.81 (5.51)	-9.87 (34.25)	-27.59 (15.68)	13.14 (12.32)	12.43 (2.06)	-6.33 (1.93)
Study 5: Change Fixed Ticket Fee to Percent Fee	1.16 (0.03)	6.43 (4.13)	-5.69 (0.47)	6.45 (4.55)	4.89 (0.65)	-0.62 (0.07)	-1.71 (0.05)	1.42 (0.08)
Study 6: Remove Fixed Order Fee	11.88* (0.81)	-35.2 (63.22)	0.34 (0.07)	14.14 (34.18)	2.29 (0.65)	-7.91 (3.38)	-11.45* (0.96)	1.84 (0.46)
Study 7: Lower Headline Price by 9%, Difference Dripped as a Tax	3.46 (0.35)	-16.29 (38.29)	4.81 (1.78)	21.71 (59.72)	-13.78 (7.98)	-20.2 (12.42)	6.5 (0.58)	-2.48 (0.61)
Study 8: Lower Headline Price by 9%, Difference Dripped as a Fee	-6.52 (0.62)	103.37 (404.86)	-13.2 (6.15)	28.09 (126.76)	0.75 (0.46)	1.63 (1.26)	21.03 (3.36)	-13.72 (3.79)

Experiments

Study 1: Hide Headline Price in Search & Study 2: Hide Headline Price in Search and Product Page

In the first study, we varied the salience of the ‘from’ price in search (Figure 10). This study was conducted on 21,612 desktop users (10,791 in treatment, 10,821 in control), over the length of eight days. In the control, the ‘from’ price was displayed in search. In the treatment, this price was removed. ‘Search entry’ treatment users were not exposed to a headline price until the product page (step 3). ‘Product entry’ treatment users were shown the ‘from price’ for a specific product upon entry but eventually navigated to the search page.

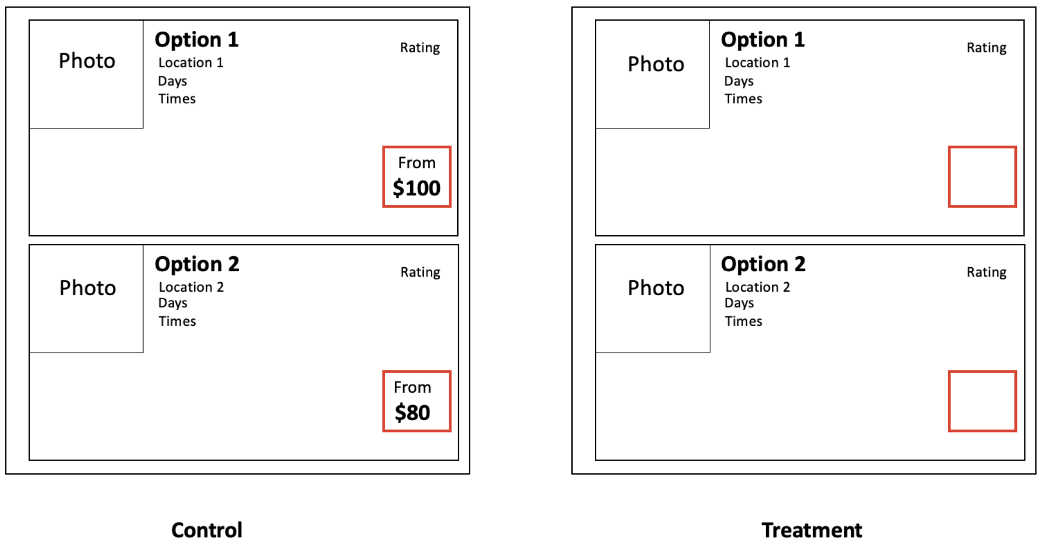


Figure 19: Hide Headline Price in Search: For study 1, we examined the effect of removing the lowest headline price for options in search. The diagram shows a mockup of search page results. In the control (left), the lowest headline price is shown. In the treatment (right), the headline price is hidden, and no pricing information is shown.

The second study is an extension of the first, as we removed the ‘from’ price in both the search and product pages. This study was conducted on ~134,271 desktop users (67,509 in treatment, 66,762 in control), over the length of fourteen days. Treatment users did not see an anchor; all headline prices were presented in the next step. Control users were shown the from price provided in search and product page as shown in Figure 11.

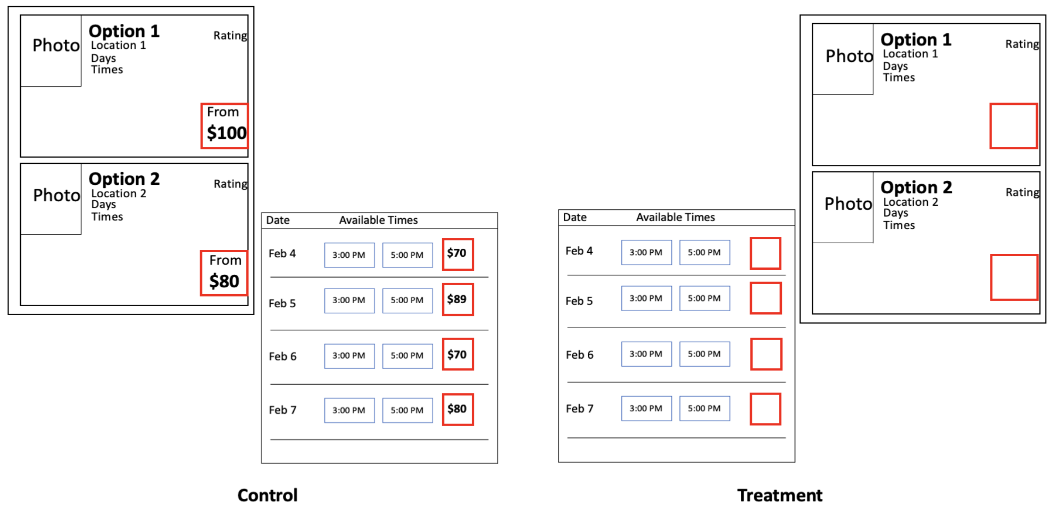


Figure 20: Study 2 - Hide Headline Price in Search and Product Page: We examined the effect of removing the headline price for options in search and the product page. The diagram shows a mockup of search page results (far left) and product page (second from left).

Results

In study 1, revenue was 5.98% higher for the treatment driven by an increase in tickets (178). The numbers were lower for study 2, with a 0.8% increase despite less tickets (246) purchased but being $2.67 higher in value. Treatment 'search entry' users produced more revenue in study 1 (1.68%) but in study 2, this segment experienced a relative decrease in revenue (2.69%), driven by 500 less tickets purchased. Treatment 'product entry' users in study 1 produced 34.66% more revenue; purchasing more tickets (58) that were $5.58 higher in value. In study 2, this difference dropped to 7.87%, with an increase in tickets purchased (254) but only $1.98 higher in value.

The overall conversion rate for both studies were not significantly different. For study 1, only the 'Search to Product Page' rate was significantly higher for the treatment (8.13%). For study 2, the treatment converted significantly better for 'Search to Product Page' (7.82%) and

‘Product to Select Ticket’ (57.69%). However, conversion was higher for the control at the ‘Select Ticket to Checkout’ step (30.06%). ‘Checkout Conversion’ was not significantly different for both studies.

The treatment visited more unique product pages for ‘non-checkout’ and ‘checkout’ users in both studies (before and after first checkout). For Study 1, this group viewed options, on average, \$1.78 and \$4.27 higher for the first product. This value was lower in study 2, with treatment users viewing products \$1.01 higher (\$2.05 for the first). A significantly much higher proportion of control users did not reach the product age in both studies (11.87% and 12.15%, respectively). This led to significantly higher rate of control visitors not reaching checkout for both studies (1.24%, 0.70%)

The price of the items added to checkout were not significantly different between conditions in Study 1. However, in study 2, the control added a significantly more \$60-\$80 (6.59%) tickets. The treatment added more \$100+ (2.38%) tickets. In first study, the <\$40 price group experienced a significantly higher conversion for the control (41.21%). In study 2, all groups except for one (\$60-\$80), saw the control perform significantly better than the treatment. At the \$100+ ticket group, the treatment purchased more tickets (82), despite the control converting at a higher rate (5.38%) – suggesting that orders with higher number of tickets converted significantly better.

Post checkout behavior was insignificant for study 1. In study 2, of the users who visited ‘first checkout’ a higher proportion of control users completed payment (7.67%). Of the users who continued in the purchase process, a significantly larger proportion of treatment users visited the select ticket page (36.47%) and checkout (13.10%) with new tickets.

Discussion

In the first two studies, we aim to understand the role of the from price on the purchase process. In the first study, we hid the anchor in search while Study 2 this was extended to the product page as well; effectively removing the anchor. Once the customer reaches the select ticket page, he/she views multiple base prices, with no option holding prominence over the other.

As expected, in both studies there was markedly higher conversion for the treatment the initial step. Further removal of the anchor led to increased conversion until customers were presented all headline prices. At this step, customers dropped off at a significantly higher rate highlighting the importance of the anchor; they are not as blindsided with the introduction of prices presented to them later in the purchase process. Despite being misleading the anchor provides them some level of pricing information. It's removal however led more customers to view more products and checkout at a higher rate, benefitting the firm.

Customers viewed more distinct options in both studies despite increases in search costs. In the study 1 (higher search costs), search click option was on average $4 higher. For study 2 (highest search costs), the differences in price were less but still positive. Higher search costs led to increased difficulty in comparison. When removed search, customers had to navigate between search the product page of interest. When this was extended to the product page, search costs increased even further as to compare the pricing information required six total steps. This is evident when examining ‘product entry’ users; in the case where the from price was removed in just search – revenue increased by over 34%. When there was no anchor, the revenue difference was not as high, despite further anchor obfuscation. However, it is worth noting that customers who entered deeper into the purchase funnel did produce higher revenue.

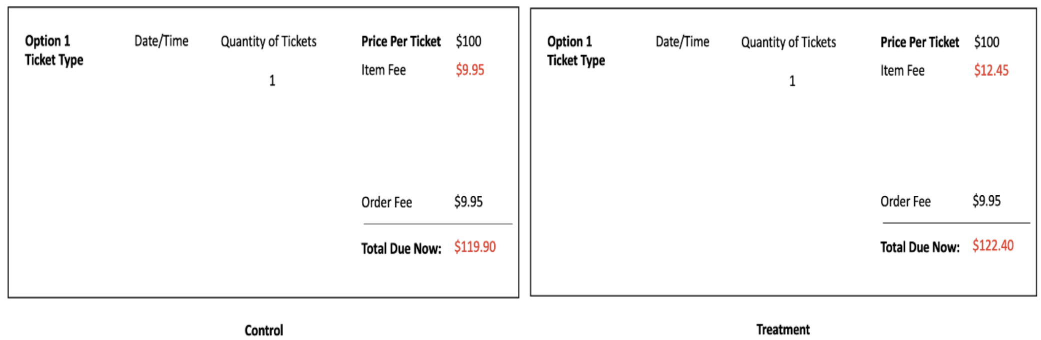
Customers with no anchor added tickets in the highest price group at a significantly higher rate, but a lower rate in the $60-$80. For the top thirty options (based on revenue), the “from” price (anchor) primarily falls into this range (Figure 5b). This suggests that the anchor may limit the addition of expensive tickets when present. There was no such effect when the anchor was removed in search.

When there is no anchor, conversion at checkout favors the control for almost all price groups, except $60-$80. At the highest price group (most revenue, we find that despite the control transacting at a higher rate, the treatment purchases 82 more tickets suggesting the average number of tickets purchased in the are higher per order. Without the anchor, customers may not focus on higher total prices/fees but rather in completing the transaction – generating a kind of ‘quantity effect’. Conversion is significantly less at the lowest-priced tickets when hidden in just search - which may suggest that for the cheaper valued options, customers may be more sensitive to the length of anchor presentation.

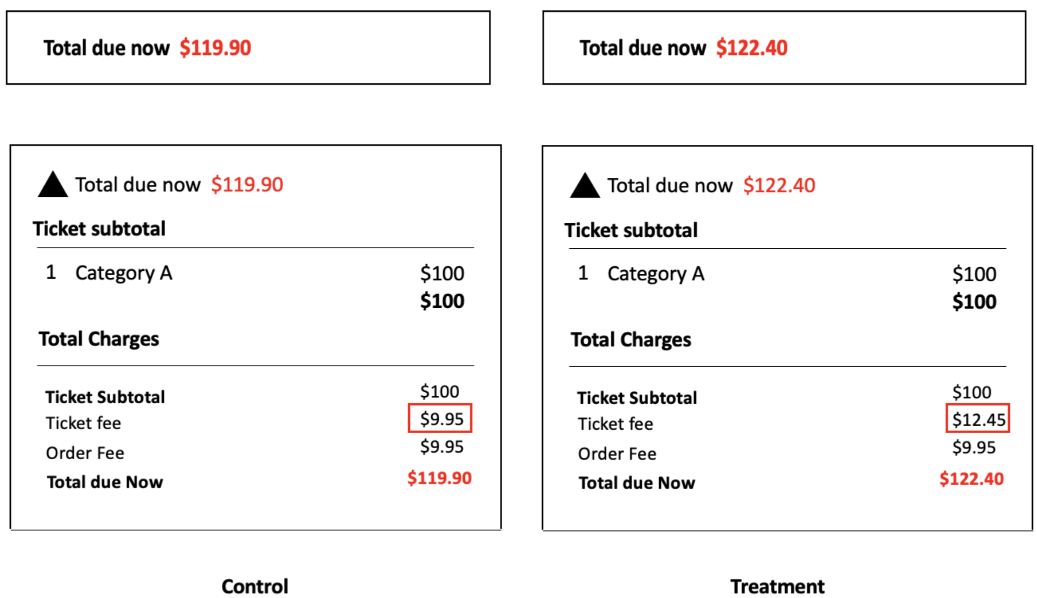
In conclusion, the lack of a posted anchor price forced customers to proceed deeper in the purchase funnel. In the initial stages of the purchase process, the anchor helps as a point of comparison between options, decreasing overall search costs for customers. Once the headline prices were revealed, a substantial number of customers bounced from the platform. The removal of the anchor led customers to add more expensive options to checkout. This suggests the from price hampers platforms from selling more expensive tickets, which is where the highest fees are charged. When there was no anchor was present, customers consistently converted less across most of the price groups - as they were not as ‘anchored’ to the item elect. This highlights the importance of the anchor as presented in the literature, as customers were more attentive to the added surcharges. Higher ticket orders converted better than lower quantity – suggesting headline price saliency did not affect consumers with high total prices. For customers entering in the beginning of the purchase funnel, in both studies, the number and price of tickets counteracted to produce near null revenue effects. However, those entering in the middle, the reduced transparency reduced comparison with other options, increasing revenue for both studies, as search and comparison costs were higher.

Study 3 and 4: Add $2.50 to Ticket Fee (Desktop and Mobile) - Select Options

Studies 3 and 4 examined the addition of $2.50 per ticket to the pre-existing fixed ‘ticket fee’ for select options (Figure 12). There were three fixed fee levels in the control: $5.95, $7.95 and $9.95. The total amount due increases by $2.50 per ticket for the treatment ($8.45, $10.45 and $12.45) (Table 14). Study 3 examined the effect on desktop (85,799 users; 42,709 in control and 43,090 in treatment) while Study 4 looked at it on mobile (99,248 users; 49,538 in control and 49,170 in treatment). Each study was concurrently run over seven days. There were differences in the salience of surcharges across device types. Desktop users saw all surcharges in a transparent manner (Figure 12a). In mobile, upon initial inspection, the price breakdown is hidden with only the total cost line item displayed. The customer must click on the price to reveal the surcharge breakdown (Figure 12b)



(a)



(b)

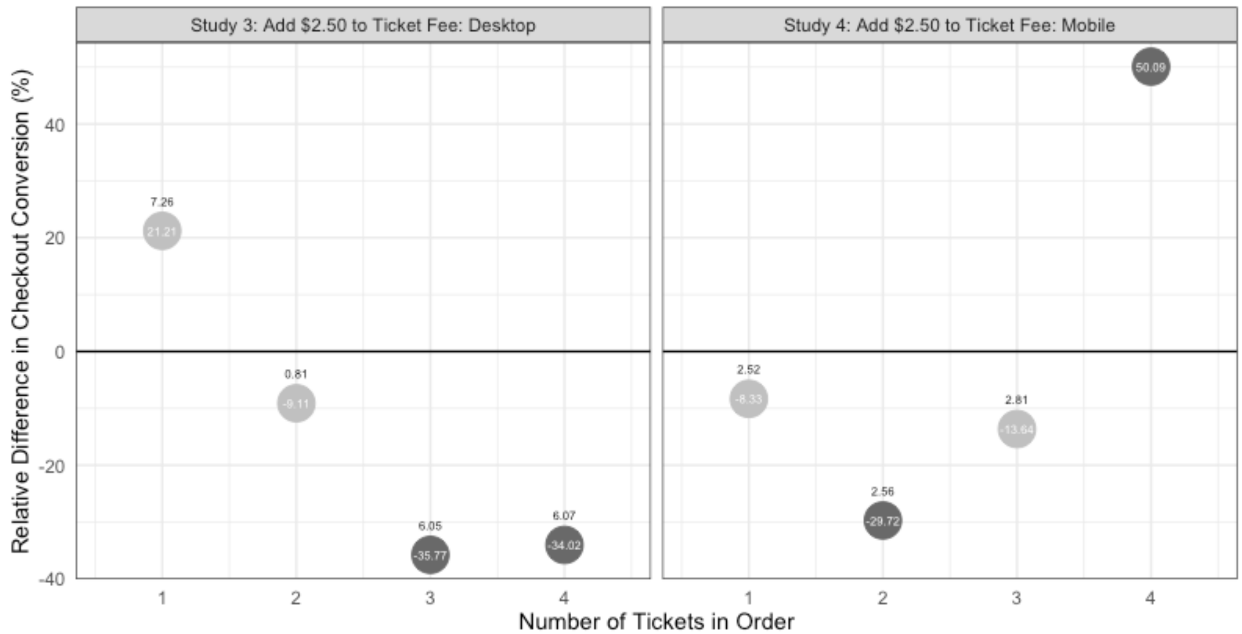
Figure 21: (a) Study 3: Add $2.50 to the Ticket Fee Desktop: In the treatment (right), the ticket fee is $2.50 per ticket higher than the control (left) for the same ticket being purchased.

Table 14: Study 3 and 4: Add $2.50 to Ticket Fee - For 56 total options, the fee was increased by $2.50

No. of Products	Control Ticket Fee	Treatment Ticket Fee	% increase in Ticket Fee
8	$5.95	$8.45	42%
6	$7.95	$10.45	31.44%
42	$9.95	$12.45	25.13%

Results

For the desktop study, the treatment produced less revenue (1.85%), due to opposite forces - search (-14.22%) and product (27.34%) entry users. In the mobile test, the treatment outperformed the control by 32.88%; both for search (23.38%) and product (52.09%) entry users. The large differences are primarily due to increases in the number of tickets purchased (227), despite a decline in orders purchased (19). This is explained by a significant rise in the conversion rate across the number of tickets purchased by each group (provided in Figure 13b). While conversion is significantly higher for the control group at two tickets, the treatment experiences a significantly large rise at four.



(a) (b)

Figure 22: Add $2.50 to Item Fee - Conversion by Number of Tickets Added to First Checkout

Most selected options had $9.95 ticket fees in the control. This group experienced a minimal change in revenue (0.44%) on desktop but on mobile a 33.5% increase (for the treatment) – in conjunction with overall revenue numbers. Revenue for other fee groups are available in Table 10.

The conversion across steps was not significantly different for both studies. There were no ‘overall conversion’ differences in fee groups for the desktop study. At checkout, the control performed better across all fee groups in both settings. For the select shows where the fee was manipulated, the view statistics are relatively the same between both groups, as expected.

For checkout customers on desktop (salient condition), there was a significantly much higher number of users leaving the platform upon their visit to checkout in the treatment – not seen on mobile. Of the items being added to checkout, the control added significantly higher amounts of the cheapest ticket than the treatment in mobile (3.83%), while this was flipped on desktop (11.47%). This led to a significant increase in < $40 tickets added by the control on mobile. Most values of tickets for where the $2.50 fee was added were for headline prices $40-$80. None of these price groups experienced significant difference in conversion at checkout for the desktop study. On mobile, only the $50-$60 group saw the control perform significantly better than the treatment (24.28%). The open rate of the surcharges menu in checkout (on mobile) is equivalent (0.46%) for the treatment and control. Due to the analysis being around a limited number of select shows, we cannot track post-checkout behavior differences.

Discussion

Current literature suggests that with greater price salience, customers should better assess a change in fees. With an increase in fees customers should convert less and we should expect a decline in total purchases. We compare a relative increase in fees for salient (desktop) vs. non-salient (mobile) cases. Despite common belief, we find in the transparent situation there is a minimal decline in revenues numbers due to a small change in order quantity. In the non-salient situation, revenue increased drastically, despite an expected decline in orders. The minor decline in total revenue still increases profits for the firms as they collect from surcharges. In both studies there was some variation in the ticket values added to checkout. While these values played some role in revenue differences, we focus on the change in tickets primarily for our analysis.

On desktop, the increase in $2.50 led a large decline in revenue for search entry customers, while those who entered through a specific product page produced over 27% more revenue. This suggests that customers entering deeper in the funnel may be less sensitive to increases in dripped surcharges. Sensitivity to surcharges is apparent in the most salient case, users across most headline ticket price. groups on desktop bounced at a higher rate after viewing the fee structure than those with the original item fee.

In mobile, the revenue is much more pronounced despite a decline in total orders. Further inspection of the sales data shows that a small number of customers interested in purchasing high quantity of tickets (8+ tickets) were included in the treatment. These high-ticket customers were unique to this group; no users added more than 8 tickets to checkout in the control. If we remove these sales from our analysis, the change in revenue is still in favor of the treatment by 15.66%. The most common ticket amounts are two and four tickets. In the mobile setting, checkout conversion was significantly higher for the less fee situation for two tickets. However, at four tickets the treatment (added fee) had a much higher conversion rate (Figure 13b).

The proportion of users who opened the surcharge menu on mobile the rate was the same (0.46%), across both groups, despite increases in the total amount. This suggests that customers do not seek out surcharge prices when this information is obfuscated, at least in the case when there is a small change in the fee amount. They make decisions based on the information readily available to them or completely disregard them (consistent with Morowitz et. al (1998)), which in this case is the total amount.

Our findings may suggest that customers might be making miscalculations of surcharge amount when only the total price is present. For example, if a visitor was purchasing two tickets of a headline price of $100 (control item fee of 9.95), the control would pay $229.85, while the treatment would face a total price of $234.85 ($5 difference). We should expect that rational customers would be equally affected at higher ticket values with the same rate. For four tickets, the difference would be 10 dollars with total amounts being $449.75 and $459.75. This finding is like that found in Study 2 at the $100+ ticket group, where decreased headline price salience led to a 'quantity effect' of higher ticket orders converting better. When the surcharges are transparent, there was no difference in conversion for two tickets. Three and four ticket orders saw the control perform significantly better as expected with an increase in fee amount.

In general, we find increases in dripped surcharge value leads to more profit for the firm despite minimal increases in revenue. When there is decreased salience of the surcharges, we find that customers may in fact have issues accounting for increases in fees when the total amount is large. Additionally, these visitors are more attentive to the total price and are not information seeking on fees. In more salient pricing breakdowns, customers are not as sensitive to minimal increases to fees if they are entering the platform deeper into the purchase process.

Study 5: Change Fixed Ticket Fee to Percent Fee

Study 5 (Figure 14) examines the effect of changing the ticket fee, from a fixed product dependent to a percentage of the headline price. In the control, there are four primary fixed fees - $7.95, $9.95, $12.45, and $14.95. In the treatment, the ticket fee is a percent value of the headline price (dollar amounts displayed for both) (Table 15). This test was conducted on mobile across ~870,000 total users; 435,165 in the control and 435,809 in the treatment, over 27 days. Like in Study 4, the fee structure is obfuscated, and the customer must click on the total to reveal surcharges.

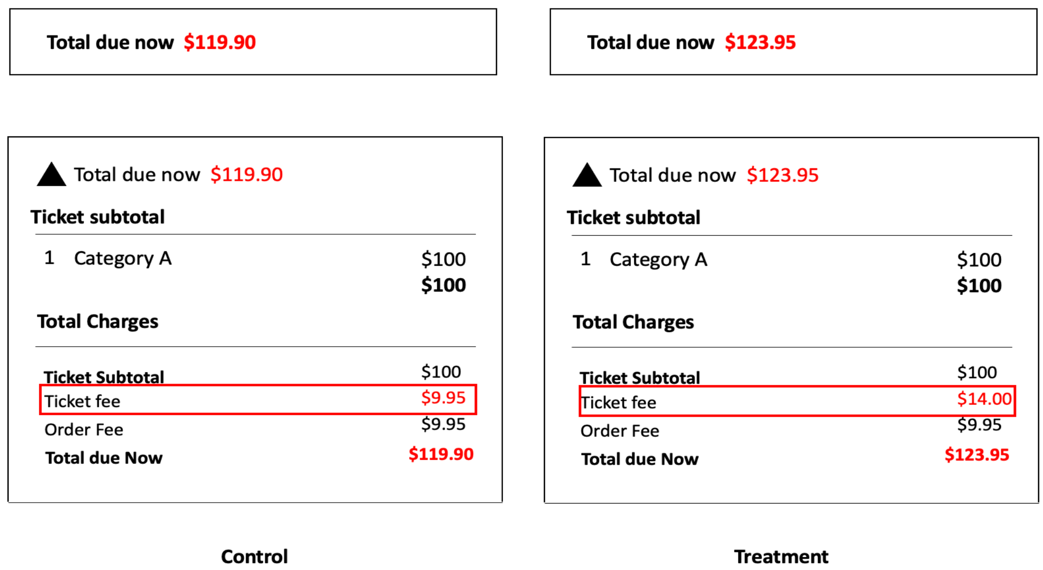


Figure 23: Study 5: Change Fixed Ticket Fee to Percent Fee - In the treatment (right), the ticket fee is based on the headline price selected, while in the control (left) the ticket fee is based on the product selected.

Table 15: Study 5: Change Fixed Ticket Fee to Percent Fee - The percentage of the headline price the ticket fee amounts to as a function of the headline price. The dollar amount range is also provided in the last column. The control fee group of $7.95 has 15 options, $9.95 has 72 options, $12.45 has 49 options and $14.95 has 15 options

Headline Price	Ticket Fee Percentage	Ticket Fee Dollar Amount
$0-40	27%	$0-10.8
$40-50	25%	$10-12.5
$50-60	22%	$11-13.2
$60-80	18%	$10.8-14.4
$80-100	15%	$12-$15
$100+	14%	$14+

Results

The treatment outperformed the control by producing 6.31% more revenue with 4046 more ticket purchases. For 'search entry' users - the revenue difference favored the treatment by 4.37% and for 'product page entry' users by 7.27%. The average headline price of the tickets purchased was $1.56 less for the treatment. For all fixed fee options except for $7.95 (-3.44%), the treatment outperforms the control. For each of these groups, the headline price purchased by the treatment is lower than the control (over $2 for the $9.95 and $14.95, groups).

The overall conversion for the treatment was significantly better (4.63%). All conversion steps experience no significant change in conversion, as expected. There were no differences in the items viewed or the value of the items added to checkout.

A deeper breakdown of the price groups shows the treatment performs significantly better for the < $40 price group (23.40%) with the control (11.17%) bouncing from the platform at a significantly higher rate. At the $100+ price group, the control performed significantly better (6.25%).

For the ticket fee difference (treatment-control, Table 11/Figure 15), we calculated the checkout conversion and bounce rates. We find the treatment converting significantly better at the lowest groups (-$5 to $1) (treatment was lower than the control in most of these cases) with the bounce rate being significantly higher for the control. The average headline prices for these groups were $74 and below. There were only two fee difference groups, where the fee was higher in the treatment and the conversion was significantly different ($2, $8) in favor of the control. At checkout, the open rate of the surcharges menu is (1.12% and 1.23%) higher for the treatment.

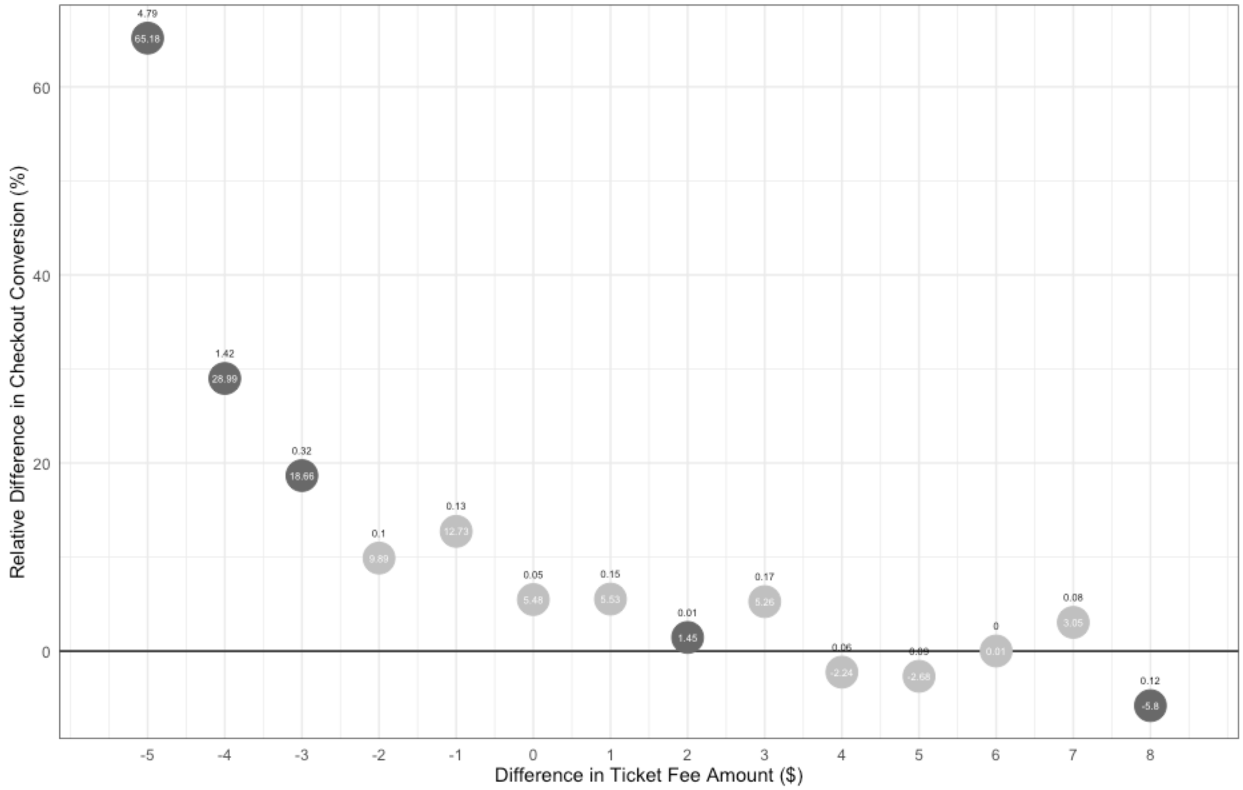


Figure 24: Study 5: Change Fixed Item Fee to Percent Fee – Change in Conversion rate in ticket fee amount across conditions (treatment - control). Conversion rate change inside point; standard error located above. Darkened points show significant difference between both groups

Discussion

We varied the ticket fee as the surcharges were obfuscated like in study 4. Due to the scale of the experiment, we able to examine the conversion rate across fee groups and the change in fee amount. The largest changes in fees occurred in the lowest (<$40) and highest ($100+), where fees were decreased/increased in the treatment. Overall behavior was consistent with what we expect – a decline in fee amount led to a decrease in total price, and an increase in conversion (and vice versa). This finding is new to study 5, because we lacked a proper sample size in study 4.

There is a range from \$2 to \$7, where there is little significant change in conversion. It is understandable for customers to not process large differences in value for \$2 or lower changes it might be negligible (as shown in previous studies). However, when the fee difference is \$4 higher in the treatment, there is no checkout conversion change, unlike when the control is higher (-\$4). This is because headline prices range from \$70 - \$100 for the increased fee, compared to ~\$40 for the other situation. Our findings suggest that customers follow a demand effect in the less salient surcharge scenario. However, as the fee increases to much higher values, despite the increase in headline price – there is a 'tipping point' where customers do not convert significantly better – which in this study was \$8. While it may be enticing for firms to increasing dripped fees as high as possible, they must be wary of a point where customers do not convert, despite the fee being nearly the same proportion of the headline price.

Like study 4, we find that despite changes in fees, there is nearly no difference in the rate of customers opening the surcharge menu. When surcharges are obfuscated, rather than comprehending the breakdown, customers make decisions based on the posted price. Furthermore, the 'quantity effect' explained in study 4 is evident at the \$100+ ticket group. Despite a significant decline in conversion for the treatment, this group purchased more tickets leading to an increase in revenue when compared to the control. This can be attributed to increases in the total price as described in our previous analysis. Also like study 3 and 4, we find that customers who entered later in the purchase process produced higher revenue than 'search' entry.

Study 6: Remove Fixed Order Fee

Study 6 examines the effect of removing a fixed $9.95 order fee. (Figure 16) The control was charged a $9.95 order fee on each order containing an entertainment option. In the treatment, the order fee was removed. This reduced the total order value by $9.95, regardless of the of ticket(s) purchased. The test was run over six days on mobile for nearly 108,076 users (53,389 in control and 54,687 in treatment).

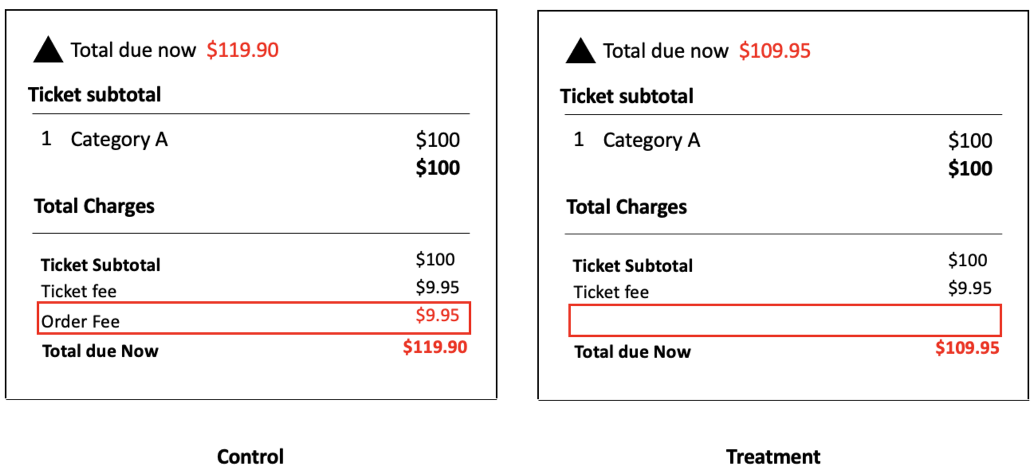


Figure 25: Study 6: Remove Fixed Order Fee - In the treatment (right), the $9.95 is removed on all orders that included an entertainment ticket. This made all orders in the control $9.95 higher assuming the same tickets were being purchased

Results

The treatment produced 3.18% more revenue than the control. Treatment search entry users accounted for a 4.32% increase, while product page entry differences were minimal at 0.98%. The treatment group purchased items $3.19 lower in value but bought 171 more orders (401 more tickets). Amongst all item fee groups, the revenue and total tickets purchased favored the control. In the highest fee groups (12.95 and 14.95), the treatment purchased tickets that were $5.83 and $4.88, less than the control.

The overall conversion rate was significantly higher for the treatment (18.45%). We find a significant increase for the 'Product Page to Select Ticket' in favor of the control, which was not expected. At checkout, the treatment converted at a significantly higher rate (7.42%). As expected, there was no significant difference in the prices of the tickets added to the checkout. The < $40, $40-$50, $80-$100, $100+ (two highest and lowest groups) tickets experienced no significant difference of checkout conversion. The treatment converted significantly better for the $50-$60 (28.94%) and $60-$80 (20.18%). For single checkout users, the treatment performed significantly better (11.88%), with the control bouncing at a higher rate at checkout across price groups. Post checkout behavior shows a significant number of users in the control (11.45%) visited the checkout again.

Discussion

In this study, the firm looked at the effect of removing a fixed order fee of $9.95 (transparent), independent of the amount of items purchased. Given the online nature of the platform, from the customer's point of view, an order fee is a frivolous surcharge that goes directly to the platform. The study was run on mobile but prices were fully displayed to the customer, as in Study 3. We should expect that the removal of fee is purely a demand effect, the average order would be $9.95 lower when the fee was removed. The platform implements such a fee in hopes of increasing revenue from inattentive customers, who do not fully account for the 'commission' like surcharge to purchase from the platform. The removal of the fee led to a minimal increase in revenue which probably leads to for a loss in profit for the firm ($9.95 was a directly goes to firm).

As expected, conversion was not drastically different between the initial steps. The control significantly converted at a higher rate from the product page to select checkout page – which made have muted revenue numbers slightly. There was no significant difference in the price group of items added to checkout. At checkout, however, the treatment performed significantly better compared to the control at the middle price groups. This is of particular interest for the lowest groups as a $9.95 order fee is a substantial proportion of the total price. Like in study 3, we find that customers, when provided full surcharge transparency, are not as responsive to prices at lower transparency conditions (total price just displayed). These low-price ticket customers may be more perceptible to the ‘endowment as they are primarily last-minute purchasers, who may feel a time constraint to book the cheapest tickets as a fear of ‘missing out’. At the highest levels, the $9.95 total fee is a smaller proportion of the total amount, leading to insignificant differences in conversion. Regardless, on average, the treatment performed better across all groups. At the highest worth groups, $80-$100, $100+, the control on average purchased more expensive tickets since more orders transacted in the treatment that were lower in value.

Although we find some similarities in the findings of study 3 (due to the value), consumer behavior can also be tied to the change in the type of fee. The order fee is a processing fee that is paid to the firm, which the customer may try to avoid by going to a competing platform. Previous work (see previous literature section) in the laboratory setting suggests that customers are sensitive to the type of surcharge. We will further examine provide further analysis for the difference in studies 7 and 8.

Study 7: Lower Headline Price by 9%, Difference Dripped as a Tax & Study 8: Lower Headline Price by 9%, Difference Dripped as a Fee

Study 7 explores the effect of a 9% decrease in the headline price and the addition of the difference as a tax surcharge. This 9% difference was added as an 'entertainment tax' surcharge (Figure 17) at checkout. The 'total' cost faced at checkout is the same in both conditions. The test was performed over three days on mobile with 55,982 users (27,750 in the control and 28,232 in the treatment). Study 8 was similar to Study 7; instead of dripping the difference as a separate 'entertainment tax' the platform adds the 9% difference to the existing 'order fee.' (Figure 18) The test was conducted over three days on mobile with ~38,000 users (18,989 users in the control and 19,174 users in the treatment).

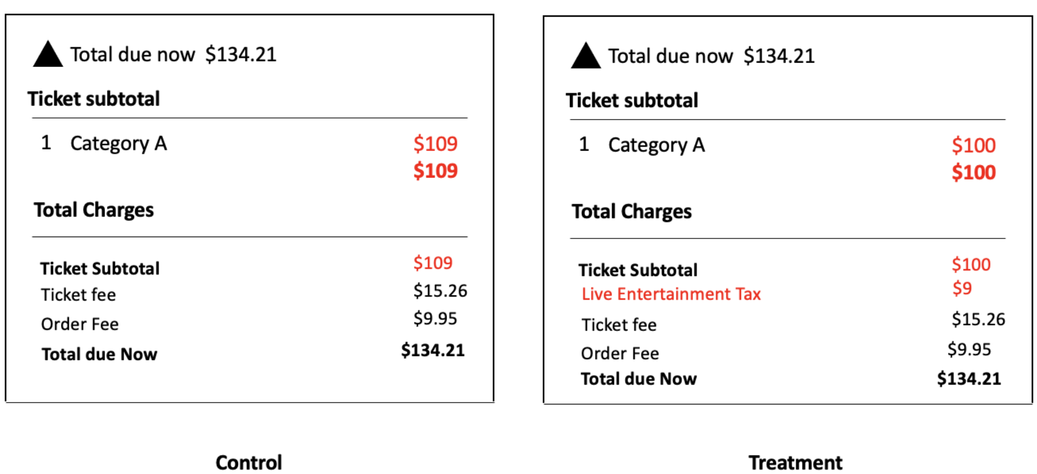
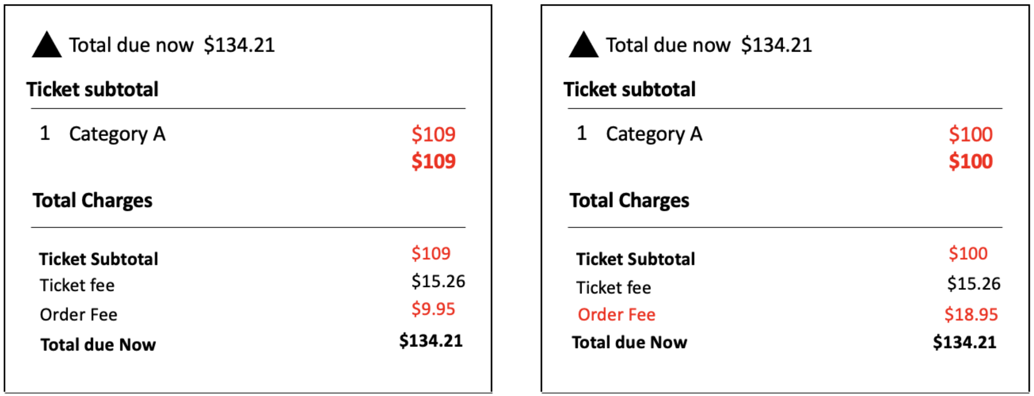


Figure 26: Study 7: Lower Headline Price by 9%, Difference Dripped as a Tax - In the control (left), the customer views a headline price that is 9% higher than the treatment (right). The 9% difference is added as a "Live Entertainment Tax" surcharge in the treatment. The total amount associated with an order is the same, regardless of the condition.



Control **Treatment**

Figure 27: Lower Headline Price by 9%, Difference Dripped as a Fee - In the control (left), the customer views a headline price that is 9% higher than the treatment (right). The 9% difference is added as a part of the pre-existing "Order Fee" surcharge in the treatment.

Results

Revenue was 20.23% higher for the treatment in the tax situation (study 7) and only 1.03% in the fee study (study 8). The difference between studies is attributed to an increase in purchased tickets (143) that were $9.20 higher in value for the tax study. There were differences in 'search entry' user behavior; the treatment produced 24.51% more revenue in the tax study, while the control performed 4.93% better in the fee situation. Treatment 'product entry' users produced 12.12% more in both studies.

The overall conversion was significantly higher for the treatment in only the tax situation. The 9% decrease in headline price did not lead to significant changes in stepwise conversion initially across both studies. On average, the number of products viewed did not vary drastically amongst groups for both studies. This in turn did not affect the proportion of customers who visited the checkout page.

In the tax study the control added a significantly higher rate of $60-80 tickets (9.12%) while the treatment had a significantly higher proportion of $100+ tickets added (9.29%). There was no significant difference in the items added to checkout for the fee situation.

At checkout in the tax study, for the $40-50 (40.54%) and $100+ (16.03%), the treatment experienced significantly higher conversion. The increase in ticket sales for the $100+ tickets led to a 21.73% increase in revenue - in conjunction with the headline price 'increase'. A $5.71 decline in the headline price favors the treatment because the presented headline price in this group is $9 (or more) less than the control for the same ticket. In the fee study, there was no significant difference amongst price groups in the items added or the conversion at the first checkout. It is worth noting, at the highest worth group, $100+, the control group purchased tickets almost $14 more expensive than the treatment, driving a 10% decline in revenue for these items. There is no substantial difference in bounce rate at first checkout or in post-checkout behavior.

Discussion

In the last two studies presented, we examine the effect of a two-part manipulation: reducing the headline price and the addition of the difference as a tax vs. a fee. In the control setting, 9% of the headline price is a tax (unknown to the consumer), while in the treatment the amount is added as a fee or tax. As with the first two studies presented, we should expect some initial step conversion increases that should stay consistent between both studies. Additionally, at checkout we should expect rational consumers to have similar conversion despite the change in surcharges type.

Overall conversion in the tax study favored the treatment significantly but across both studies the conversion between each step stayed relatively similar. The treatment expectedly performed better across most steps in both studies. One important thing to note, however, for tax analysis a significantly higher amount of $100+ tickets were selected, which is not seen in the fee condition. Despite this difference, results across both studies suggest that a 9% decline in the headline price did not amount to a significant difference in stepwise conversion.

At checkout, conversion rates in the tax study were not significantly different across price groups except the $100+ (most of the revenue produced). Concurrently, in the fee study, no group experienced significant difference, but across all groups, the control condition outperformed the treatment leading to an overall difference in checkout conversion. The findings suggest that despite the percent increase in dripped surcharges, at higher prices, customers converted better when the increase was framed as a tax. In the fee condition, regardless of price, customers were wary of the increased surcharge amount when dripped as a part of the order fee.

The headline price (inclusive tax) of items purchased in the $100+ group were 5.71 lower for the treatment. If customers' perceptions of the total price were tied to the total price, we would expect an over $9 decline for the treatment. This difference in added ticket price and higher conversion rate, helped drive up revenue in this group by over 21%. In the fee condition, behavior was consistent at this highest price group, as tickets were $13.93 less. Across all other price groups in both studies, we find that the 9% decrease in headline price led customers to purchasing higher quality tickets on average, similar to previous work in partitioned pricing (Chetty et. al (2009)) and drip pricing (Blake et. al (2021), Dertwinkel-Kalt et al. (2019)).

In summary, a 9% decline in headline price did not significantly increase the number of customers to checkout, which may be due to the prominence of the from price. When reaching checkout, we find at the highest headline prices, customers may in fact be more sensitive to the type of surcharge, as taxes are more accepted than an equivalent rise in fees. Customers in the tax study in this group purchased tickets of higher quality, helping to increase revenue numbers. This was not seen in the fee condition at the highest group where ticket quality on average declined. As in previous studies, we find that customers who entered deeper in the funnel were not sensitive to changes in the surcharge presented or the increased amount.

Conclusion

We aimed to understand the importance of the anchor and surcharges in the drip pricing framework. This was accomplished by manipulating the salience (between steps) and magnitude of the anchor price. For surcharges we varied the salience (high vs. low), magnitudes (high vs. low) and type (fees vs. taxes).

Our first two studies highlight the importance of the anchor in providing customers with pricing information. Despite its relative inaccuracy, customers use the from price as a point of comparison between options as it decreased overall search costs. With reduced exposure to the anchor (study 1), customers proceeded deeper into the purchase funnel, helping to boost revenue. In no anchor situations – a large segment of potential customers left the platform when headline prices were presented (select ticket). Despite this drop-off, a significantly higher number of visitors visited checkout where they converted at a lower rate but purchased higher valued tickets. This in turn help firms produce more profit as higher priced options typically have large surcharge amounts. In the last two studies, we decreased the headline price which had mixed results in customers adding higher priced items to checkout. Our findings are unique as no previous field studies have shown the anchor's role in search comparison as well as limiting revenue in the drip pricing context.

In the next four studies (3-6), we examine how customers respond to changes in fee amount in different surcharge saliency conditions. Studies 3 and 4 show that a minimal increase in the fee, in both saliency conditions, led declines in conversion, as expected. However, revenue varied drastically; in the transparent condition, customers saw only a small decline in total revenue – with profits for the firm minimally increasing. In the low surcharge saliency scenario, there was an overall increase in revenue, despite a small decline in orders. Customers 'anchored' to the total price; the only information readily available to them. When given the opportunity, they did not seek out the pricing breakdown despite changes in total cost. When the total price was higher and more tickets were in an order, customers converted at a higher rate, despite the increase in fee (quantity effect) This may be due to a series of factors such as the endowment effect or miscalculation of added surcharges at higher values. These findings were further confirmed by study 5, which examined fee changes across a range of ticket values with low surcharge salience. As expected, we find customers follow a demand effect, but at high headline prices there is a "tipping point" where customers become sensitive to added surcharges despite the proportion minimally increasing. In study 6, we decreased the fee amount (by $9.95, compared to $2.50 in study 3) in a salient fee case. We find that lower-priced tickets converted at similar rates despite removal of a high fee amount, potentially due to the 'endowment effect'. Despite an increase in total volume of tickets, increase in revenue did not counter the potential profit loss for the firm.

In the last series of studies, we examined the effect of reducing the posted headline prices and increasing the surcharge amount as a part of tax vs. a fee. At checkout, we found resounding differences; despite the similar change in headline price and total dripped surcharges, the tax situation led to a large increase in revenue, conversion and quality purchased for higher priced tickets. The fee situation showed a consistent decline across all groups. Customers were more accepting of a required tax than a fee that goes directly to the platform. Across all studies we found that customers who entered the purchase funnel later produced more revenue and converted better despite the increase in fee amount or type. These customers were relatively unaffected and despite being a small portion of the traffic, helped boost revenue throughout.

There are a few takeaways from our analysis of the anchor that can be beneficial for both firms and policymakers. For firms, removal of misleading upfront anchors pushes customers to continue deeper into the purchase funnel. Removal of the anchor completely helps to increase the value of good purchased, but bounce rates increase for customers when headline prices are higher than expected (increased surcharge profits). For daily use platforms, anchor removal is probably not beneficial for long term user retention. Decreases in the anchor price may have similar effects if the change is high – as shown in previous work as well. On the other hand, policymakers should be wary of limited price information as its removal increases search costs for the customer. However, both parties may find common ground in changes to the base price if the value is more representative of the average price of tickets. As a result, we believe checkout conversion may increase for higher priced tickets, thus benefitting the firm and reducing the relative size of surcharges charged at later steps.

Our results around fee manipulations suggests firms should be able to minimally increase fees without changes in consumer conversion rates. While less salient cases may seem intuitively more appealing to platforms, customer sensitivity is dependent on the presented information. Firms can capitalize on user inattentiveness when total prices are very high, if the added fees are not exorbitantly high ('quantity effect'). In less salient cases, customers are least sensitive to fees at low prices, potentially due to loss aversion. Policymakers may find potential value by limiting the amount of charged surcharges based on the base price of the tickets being sold in such scenarios. Furthermore, firms may find it beneficial to partition taxes that do not seem frivolous or intended for profit (e.g. order, product fees). This is common accepted practice in many platforms that policymakers may support in lieu of added unnecessary charges.

With the increase in the implementation of drip pricing, it is apparent that this technique is not going to disappear. It is important for policymakers and firms find a common understanding of drip pricing to limit its harmful effects while still protecting the livelihood of platforms. Our studies act as a first step towards a deeper dive into this pricing technique and provide firms and policymakers a lot of insights on both the anchor and surcharges parts of drip pricing. Moreover, our findings add to the limited but expanding number of field experiments in areas such as anchoring, salience, and the shrouding of price information.

Chapter 2, in part is currently being prepared for submission for publication of the material. Didwania, Prabhanjan. The dissertation author was the primary investigator and author of this paper.

REFERENCES

Abraham, A. T., & Hamilton, R. W. (2018). When Does Partitioned Pricing Lead to More Favorable Consumer Preferences?: Meta-Analytic Evidence. Journal of Marketing Research, 55(5), 686–703.

Ahmetoglu, G., Furnham, A. and Fagan, P. (2014). Pricing practices: A critical review of their effects on consumer perceptions and behaviour. Journal of Retailing and Consumer Services, 21, 696–704.

Airbnb. (2021, May 19). Fee transparency on Airbnb. Retrieved February 16, 2022, from https://news.airbnb.com/fee-transparency-on-airbnb/

Australian Competition and Consumer Commission. (2015, November 2). Airbnb and eDreams give undertakings to ACCC for improved pricing practices. Retrieved January 10, 2022, from https://www.accc.gov.au/media-release/airbnb-and-edreams-give-undertakings-to-accc-for-improved-pricing-practices

Bambauer-Sachse S. and Mangold S. (2010) ,"Does a Marketer’s Responsibility For a Surcharge Moderate Price Partitioning Effects?", in NA - Advances in Consumer Research Volume 37, eds. Margaret C. Campbell, Jeff Inman, and Rik Pieters, Duluth, MN : Association for Consumer Research, Pages: 333-339

Baye M. and Morgan J., “Search Costs, Hassle Costs, and Drip Pricing: Equilibria with Rational Consumers and Firms,” March 2019. Working Paper

Blake, T., Moshary S., Sweeney K., Tadelis S.(2021) Price Salience and Product Choice. Marketing Science 40(4):619-636.

Boffey, D. (2018, July 16). Airbnb warned it breaches EU rules over pricing policy. The Guardian. Retrieved January 10, 2022, from https://www.theguardian.com/technology/2018/jul/16/airbnb-eu-pricing-accommodation-fees-charges

Brynjolfsson E., Smith MD (2001) Consumer decision-making at an Internet shopbot: Brand still matters. J. Indust. Econom. 49(4):541–558.

Chetty R., Looney A., Kroft K. (2009) Salience and taxation: Theory and evidence. Amer. Econom. Rev. 99(4):1145–1177.

Cleveland, M., Babin, B.J., Laroche, M., Ward, P. and Bergeron, J. (2003), Information search patterns for gift purchases: a cross-national examination of gender differences. Journal of Consumer Behaviour, 3: 20-47.

Dertwinkel-Kalt M , Köster M , Sutter M (2019) To buy or not to buy? Shrouding and partitioning of prices in an online shopping field experiment. Working paper 7475, CESifo, Munich.

Doepke M., Tertilt M., Women's Liberation: What's in It for Men?, *The Quarterly Journal of Economics*, 124(4): 1541–1591

Doepke M., Tertilt M., Voena, A., The Economics and Politics of Women's Rights Annual Review of Economics 2012 4:1, 339-372

Eagly, A. H., Beall, A. E., & Sternberg, R. J. (Eds.). (2005). *The psychology of gender*. Guilford Press.

Eagly, A. H., & Wood, W. (2012). *Social role theory.* In P. A. M. Van Lange, A. W. Kruglanski, & E. T. Higgins (Eds.), *Handbook of theories of social psychology* (p. 458–476). Sage Publications Ltd.

Eagly, A. H., & Wood, W. (2013). The nature–nurture debates: 25 years of challenges in understanding the psychology of gender. *Perspectives on Psychological Science, 8*(3), 340–357.

Ellison G (2005) A model of add-on pricing. Quart. J. Econom. 120(2):585–637.

Ellison G., Ellison SF (2009) Search, obfuscation, and price elasticities on the Internet. Econometrica 77(2):427–452.

Finkelstein A (2009) E-z tax: Tax salience and tax rates. Quart. J. Econom. 124(3):969–1010.

Fischer, Eileen, and Stephen J. Arnold. "More than a labor of love: Gender roles and Christmas gift shopping." *Journal of Consumer Research* 17.3 (1990): 333-345.

Fisher, Eileen, and Stephen J. Arnold. "Sex, gender identity, gender role attitudes, and consumer behaviour." *Psychology and marketing* 12.2 (1994): 163-182.

FTC warns hotel operators that Price quotes that exclude 'resort fees' and other mandatory surcharges may be deceptive. (2019, February 28). Retrieved February 19, 2022, from https://www.ftc.gov/news-events/press-releases/2012/11/ftc-warns-hotel-operators-price-quotes-exclude-resort-fees-other

Gabaix X., Laibson D (2006) Shrouded attributes, consumer myopia, and information supression in competitive markets. Quart. J. Econom. 121(2):505–539.

Geddes, R., & Lueck, D. (2002). The Gains From Self-Ownership and the Expansion of Womens Rights. *American Economic Review, 92*(4), 1079-1092.

Greenleaf EA, Johnson EJ, Morowitz VG, Shalev E (2016) The price does not include additional taxes, fees, and surcharges: A review of the research on partitioned pricing. J. Consumer Psych. 26(1):105–124.

Harris, K., & Bouras, E. (E. (2020, February 18). Drip pricing: StubHub enters into $1.3M consent agreement with competition bureau. Lexology. Retrieved January 10, 2022, from https://www.lexology.com/library/detail.aspx?g=108d4033-809c-4efb-9f39-8662a3ec868e

Hart, C., Farrell, A., Stachow, G., Reed, G., & Cadogan, J., (2007) Enjoyment of the Shopping Experience: Impact on Customers' Repatronage Intentions and Gender Influence, The Service Industries Journal, 27:5, 583-604

Hossain T., Morgan J. (2006) … Plus shipping and handling: Revenue (non) equivalence in field experiments on eBay. Adv. Econom. Anal. Policy 6(2):1–30.

Huck, S., Wallace, B. (2015). The impact of price frames on consumer decision making: Experimental evidence, unpublished working paper.

Jayachandran, S. (2015). The Roots of Gender Inequality in Developing Countries. *Annual Review of Economics, 7*(1), 63-88. doi:10.1146/annurev-economics-080614-115404

Kahneman D, Knetsch JL, Thaler RH (1991) Anomalies: The endowment effect, loss aversion, and status quo bias. J. Econom. Perspect. 5(1):193–206.

Mazumdar, Tridib, and Purushottam Papatla. "Gender difference in price and promotion response." *Pricing Strategy & Practice* 3.1 (1995): 21.

Melnyk, Valentyna, Stijn MJ Van Osselaer, and Tammo HA Bijmolt. "Are women more loyal customers than men? Gender differences in loyalty to firms and individual service providers." *Journal of Marketing* 73.4 (2009): 82-96.

Meyers-Levy, Joan, and Durairaj Maheswaran. "Exploring differences in males' and females' processing strategies." *Journal of Consumer Research*18.1 (1991): 63-70.

Morowitz VG, Greenleaf EA, Johnson ET (1998) Divide and prosper: Consumers' reactions to partitioned prices. J. Marketing Res. 35(4):453–463.

Noble, Stephanie M., David A. Griffith, and Mavis T. Adjei. "Drivers of local merchant loyalty: Understanding the influence of gender and shopping motives." *Journal of Retailing* 82.3 (2006): 177-188.

Phillip, Marissa V., and Rajneesh Suri. "Impact of gender differences on the evaluation of promotional emails." *Journal of Advertising Research* 44.04 (2004): 360-368.

Rella, E. (2021, May 20). Internet rips into Airbnb for high prices, hidden fees: 'These Prices Are Ludicrous'. Retrieved February 16, 2022, from https://www.entrepreneur.com/article/372427

Sit, J., Merrilees, B. & Birch, D. (2003) Entertainment-seeking shopping centre patrons: the missing segments. International Journal of Retail and Distribution Management, 31, 80–94.

Taubinsky D., Rees-Jones A. (2018) Attention variation and welfare: Theory and evidence from a tax salience experiment. Rev. Econom. Stud. 85(4):2462–2496.

Tifferet, Sigal, and Ram Herstein. "Gender differences in brand commitment, impulse buying, and hedonic consumption." *Journal of Product & Brand Management* 21.3 (2012): 176-182.
Sampson, H. (2021, May 25). Airbnb is taking a closer look at fees after a social media backlash. The Washington Post. Retrieved January 10, 2022, from https://www.washingtonpost.com/travel/2021/05/25/airbnb-fees-cleaning-hotels/

Santana S., Dallas S., Morwitz V (2020) Consumer Reactions to Drip Pricing. Marketing Science 39(1):188-210.

Schindler, R. M., Morrin, M., & Bechwati, N. N. (2005). Shipping charges and shipping-charge skepticism: Implications for direct marketers' pricing formats. Journal of Interactive Marketing, 19(1), 41–53.

Seim K., Vitorino MA, Muir DM (2017) Drip pricing when consumers have limited foresight: Evidence from driving school fees. Working paper, Yale School of Management, New Haven, CT.

Sheng, S., Bao, Y., & Pan, Y. (2007). Partitioning or bundling? Perceived fairness of the surcharge makes a difference. Psychology & Marketing, 24(12), 1025–1041.

Sullivan, M. W. (2017). Economic analysis of hotel resort fees, Report Federal Trade Commission.

Wood, W., & Eagly, A. H. (2015). Two traditions of research on gender identity. *Sex Roles: A Journal of Research, 73*(11-12), 461–473.

Zeithaml, Valarie A. "Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence." *The Journal of Marketing* (1988): 2-22.

Zhou, L., Dai, L., & Zhang, D. (2007). Online shopping acceptance model-A critical survey of consumer factors in online shopping. *Journal of Electronic commerce research*, *8*(1).