Price Discrimination in Online Retail – Fact or Fiction?

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*ABSTRACT --* Are there particular demographic characteristics, specifically race, gender and economic status, which influence product pricing in the online retail marketplace? As e-commerce continues to expand and companies use more data to "personalize" the online shopping experience, the role of Big Data in both the shopping lifecycle and pricing transaction should be of interest to consumers. Our research and analysis attempt to uncover underlying themes or inferences in pricing differences based on gender, race, or economic status. We performed a one-way ANOVA test using eight shopping personas across 15 product categories and determined the few observed differences were persona-driven behavior rather than price discrimination based on gender or race, where much of the deviation for economic status was a result of more thorough checking for lower prices.

# INTRODUCTION

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HE tailored experiences our parents enjoyed when they frequented the bank or Saturday-shopped at the local hardware store are inimitable in today’s get-it-now and get-it-cheap online marketplace – or are they? Our maternal figures were likely treated differently from the paterfamilias, the affluent among them were probably favored over the penny-pinchers. Companies employing dynamic pricing techniques that mimic these Baby Boomer experiences would argue the consequential expansion of a seller’s market maximizes revenue and minimizes wasted inventory. Higher prices are charged to and paid by those who are most likely to be able to afford them. Customization and tailored experiences are an expectation. Opponents of the practice purport that any variation in pricing of a product across different demographic groups, whether disparate or otherwise, is a violation of civil rights. An ACLU class-action lawsuit filed in Jun. 2016 seeks to change the laws that limit investigation of the practice by journalists, academic researchers and scientists, which should ultimately lead to a level of transparency consumers now demand in their online transactions.

Our project hypothesis suggests that dynamic pricing, a.k.a.

price discrimination is alive and well in the online retail marketplace, specifically as it relates to race, gender or shopping behavior. Recognizing that time and resource constraints would hinder execution of a full-blown experiment, we designed an observational study that would mitigate the impacts of as many anticipated confounding variables as possible, including daily price changes, impacts based on geographic location of the shopper and secondary marketplace volatility. Our comprehensive study design included creation and testing of eight separate personas that combined race, gender and simulated shopping behaviors. We employed a control and compare framework to contrast the differences with and without treatment. Our control persona navigated shopping experiences on Amazon via Google Chrome incognito, a browser mode that allows a user to browse the internet in a state of pseudo-privacy without saving site visit activity. We tested pricing across 15 distinct product categories, gathering unique price points on three different days to randomize for daily price variability and sale events. We gathered a total of 405 separate price-point observations over a period of 14 calendar days.

Our study utilized the One-Way ANOVA statistical technique to evaluate differences in means among the groups tested, using Price as the dependent variable and Gender, Race, and Shopping Behavior as the independent variables. As with all parametric statistical exercises, our work began with tests of our underlying assumptions. All observations are independent of one another. Violations of the normality assumption were explored and validated using the Shapiro-Wilkes test for normality, which eliminated three product categories.

Our findings were consistent with our hypothesis, although the most statistically significant differences were limited and observed primarily in the shopping behavior dimension of our contrived personas. Shopping behavior saw significant differences across four of the 15 categories, race saw significant differences across 3 of the 15 categories and gender was the only categorical variable tested that did not see significant differences across any of the product types. Surprisingly, three of our selected product categories -- clothing, musical instruments and skin care -- did not experience a price change across either the days observed or the various personas used to access those prices.

Our research and analysis paper are organized as follows. We sought to explore relevant examples of dynamic pricing in multiple businesses, from the sharing economy to the wide world of professional sports. Our research briefly touches upon the stance our government and court systems are taking as businesses walk the fine ethical line of providing the right products to the right consumers at the right prices. We proceed with a description of our experiment design and step-by-step components of our statistical analysis. We summarize our findings as well as the limitations of our work, along with our recommendations for future efforts that would address these limitations.

# Supporting Research and Current Trends

While applications of dynamic pricing are as close as the nearest keystroke, perceptions of the practice are more wide-ranging than the industries utilizing the technique. Is it the hallmark of a consumer-centric organization and a personalized experience, providing greater access to consumption at the right price for unique individuals? Or do these initially well-intentioned supply-and-demand-balanced algorithms ultimately perpetuate bias and cultural sensitivity for the sake of profit?

First-degree price discrimination, being able to anticipate the exact price each and every unique consumer is willing to pay for a given product, is utopian by nature but well on its way to becoming a commonplace reality in this age of Big Data. Examples of price discrimination, a term used interchangeably with dynamic pricing, can be found in the margin-thin service industries of hospitality and travel, ridesharing, group fitness and even in professional sports ticketing.

In 2012, the travel-booking site Orbitz targeted Mac users with higher room rates than their PC-toting counterparts with a search discrimination strategy. Orbitz applied a new spin to an old game, not by not charging the two personas different rates for the same room – rather, they used a steering and sorting method that placed higher-priced options first for Mac users. The approach supported their internal research conclusions that Mac users are 40% more likely to book a four- or five-star hotel and they will spend as much as 30% more on the room expense.

Surge pricing at rideshare giant Uber, while in place for less than 10% of trips, is most often employed during peak weekend nights, holidays and during major entertainment/sporting events or inclement weather. The strategy is propelled by scarcity of supply, incidentally powered by the same motivations on the part of the driver as those who consume the product. Public perception appears to approve of this application of the science as a legitimate business need and Uber’s emergency event rate-capping (originally agreed to in a 2014 settlement with the New York attorney general) soothes the ire of the fairness naysayers.

San Diego-based startup Lymber recently launched a dynamic pricing algorithm for workout sessions in local gyms via an iOS app. Real-time supply-and-demand-based updates to pricing allow gym-goers to benefit from lower rates for off-peak sessions. This model lends strong support to the theory that dynamic pricing done right provides more consumers with access to a product or service at a price they are willing and able to pay.

Approximately one-fourth of NFL teams utilized some type of dynamic pricing model during the 2015 season – as of 2013, 21 of 30 MLB teams were pricing single-game tickets in this manner. Weather, pitching, winning streaks and consumer demand are influential factors in the price point determination. While the practice is generally accepted, not enough is known about the real revenue impacts and the true elasticity of the marketplace. Three Wharton professors built and evaluated a customer demand model for single game ticket sales using real data for an anonymous MLB franchise. Their experiment concluded that one of three optimal strategies could produce as much as a 14.3% improvement in overall revenue compared to a baseline strategy implemented by the same ball club – adoption of the practice in the league seems to support cognizance of the benefits.

Government has been passive and prudent in its stance on the matter, choosing guidance over positioning. The Federal Trade Commission’s Jan. 2016 Report “Big Data: A Tool for Inclusion or Exclusion?” describes the disparate impact litmus test, or a disproportionate adverse effect on a protected class, and provides texture around avoiding the pitfalls. The White House’s more-informational-than-solutional contribution to the dialogue appeared in Feb. 2015 with “Big Data and Differential Pricing”, suggesting that “if historically disadvantaged groups are more price-sensitive than the average consumer, profit-maximizing differential pricing should work to their benefit.” The FTC brief contains a much more robust and specific considerations section, challenging potential implementers of dynamic pricing strategies with hard-and-fast legal compliance questions and reinforcing responsibility up and down the information-sharing food chain.

Challenges to the constitutionality of dynamic pricing models in the court system to date have been largely unsuccessful, although a few hold promise. State-specific anti-discrimination laws, such as California’s Unruh Civil Rights Act, prohibit discrimination in e-commerce when such discrimination is based on sex, race, sexual orientation and several other personally identifying characteristics; however, the Unruh Act does not obstruct classifications of consumers based on financial or economic status, which are often deemed a proxy for protected class segmentation. Senate Bill 600 went into effect in January 2016 and expanded the protections provided by Unruh to citizenship, primary language and immigration status. In what will most assuredly be landmark litigation on the topic, the ACLU filed a lawsuit on Jun. 29 in U.S. District Court on behalf of academic researcher, computer scientist and journalist plaintiffs. The lawsuit questions the relevance of “exceeds authorized access” provisions of the 1986-enacted Computer Fraud and Abuse Act, specifically those limiting research and investigation of online practices, i.e. discrimination, through standard academic and journalistic techniques. On Mar. 31, a U.S. District Judge denied a bid by an Uber co-founder to dismiss a class action lawsuit that claims illegal coordination of high surge-pricing fares.While the risk to Uber’s dynamic pricing algorithm is deemed remote to date, the accusation of violations of antitrust regulations aren’t good for public sentiment as the popularity of sharing-economy based businesses continues to burgeon.

# RESEARCH AND ANALYSIS METHODOLOGY

The methodology and process for our research can be divided into three key parts: setup of the study, gathering the data, and the use of statistics. In the setup phase, we address the categorical variables used in the study, how we measured for a control group and how we accounted for any confounding variables that may affect the outcome of the experiment. For the data-gathering exercise, we provide details around the number of observations recorded along with performing normality tests on the data collected. Finally, we discuss the statistical methods chosen that best interpret the potential conclusions (if any) from completing the experiment.

## Structure and Setup of Observational Study

Our analysis primarily focuses on three factors that may or may not impact online prices: race, gender, and shopping behavior/economic status. The variable “Product Category” was also used for both the research as well as the analysis, mostly because certain products are more susceptible to price variability than others, while some products are more apt to stay at or very near the MSRP (Manufacturer’s Suggested Retail Price).

Instead of simply measuring differences between our chosen personas, good study design warranted the addition of a control group. Due to the nature of our hypothesis, we needed to locate one large online retail site and search for products without allowing the site to collect any information about our “control” persona. Amazon was chosen as the site to use as it is the largest online retailer in the world and we ensured that no cookies or web-browsing behavior were being tracked as we navigated the site in search of our selected products. The simplest way of performing this task was to utilize the “incognito” mode within the Google Chrome browser, which addresses both of these needs.

We took the following confounding variables into consideration during the setup of our research; accompanying proposed solutions to minimize the effects these factors are also included and may have factored into our overall results.

* *Daily Pricing Changes*: Depending on the type of product and its general lifecycle, as well as the timeframe in which a consumer is viewing online prices, the observed values can easily change daily and sometimes even hourly. To appropriately account for this, each persona was required to revisit the same website a total of three times to adjust for any potential price variability.
* *Pricing Based on Location*: To evaluate whether location played a role in price fixing and to ensure that US-based pricing did not shift based on the team member’s location, an online mechanism known as the $heriff Price Discrimination tool was initially utilized. It was determined that prices appearing on the same website were not impacted by location, specifically within the U.S.; therefore, location was not considered a confounding variable during the final analysis.
* *Secondary or Bidding Marketplaces*: Sites where bidding is encouraged for purchasing products or marketplaces that sell either factory-refurbished or secondhand products were widely avoided, as these prices not only tend to fluctuate more rapidly but are also lower-on-average in terms of cost, and could skew any potential results in favor of those team members who were to use these sites. The only exceptions were sites such as eBay where an option to immediately purchase the new product (i.e. “Buy It Now”) was available.

Including these confounding variables in our research helped us mitigate variability so the team could focus primarily on the main objectives at hand. This analysis is still considered an observational study and no inferences or insights can be conveyed to a larger population outside of the demographics utilized, the product categories used, and the websites chosen for observing prices.

## Gathering Data for Analysis

The first step in our project plan established structure, including the type of data to be collected and the process for collecting it. Second, each team member created new online personas via the web browser Google Chrome to be used for the sole purpose of browsing the internet in search of the predetermined list of designated products. Between the dates of June 16th, 2016 and June 29th, 2016, a total of 405 observations were gathered and recorded. These 405 observations consisted of:

* 8 personas – 4 different races, 2 genders, 2 levels of economic status/shopping behavior
* 15 product categories – Music, Audio Equipment, Men’s Grooming, Cameras, Bedding, Vehicle Electronics, Books, Lawn Equipment, Small Appliances, Toys, Clothing, and Skin Care
* 3 prices per product – Prices recorded on three different dates to account for variability or dynamic pricing

Before pursuing meaningful conclusions, the process of testing for normality was considered to better understand any abnormalities in the dataset. The results of the Shapiro-Wilkes Test for Normality are displayed below in Figure 1.1. Based on these results, (which exclude three categories where the price was equal across all observations), the number of product categories was reduced to 12 which were then considered for the next phase of the analysis.

*Figure 1.1: Shapiro-Wilkes Normality Test for Product Category Prices*

|  |  |  |
| --- | --- | --- |
| PRODUCT CATEGORY | W-VALUE | p-VALUE |
| Lawn Equipment | 0.68714 | 4.916e -06 |
| Vehicle Electroncis | 0.91017 | 0.02303 |
| Men’s Grooming | 0.90481 | 0.01726 |
| Office Gear | 0.74775 | 1.93e -05 |
| Small Appliances | 0.74525 | 1.767e -05 |
| Toys | 0.61111 | 2.794e -07 |
| Hiking Gear | 0.74408 | 1.696e -05 |
| Cameras | 0.78802 | 2.2e -16 |
| Books | 079203 | 9.991e -05 |
| Bedding | 0.81106 | 0.0002141 |
| Audio Equipment | 0.64235 | 6.727e -07 |
| Music | 0.85368 | 0.001364 |

## Statistical Methods Utilized

Because the hypothesis we are attempting to either reject or not reject is centered on more than one categorical variable, the primary statistical method selected for use was the One-Way ANOVA (Analysis of Variance) test. By choosing this test, we are able to perform multiple analyses to gain insight into the differences (if any) between the means of the prices observed and the categorical variable(s) we are testing. Additionally, due to the variability of prices between the selected product categories, separate ANOVA tests were performed for each type of product to determine a) whether the demographic variables experienced variances and b) whether certain products were either immune or highly impacted by pricing alone.

# Analysis and Results

The One-Way ANOVA Test was conducted for a total of 36 separate instances, with price always representing the dependent variable and the independent or categorical variable being either shopping behavior/economic status, gender, or race. In addition to running the default ANOVA test, other compatible methods and tests were run in conjunction to gain a better understanding of the variability and distribution within each product category, including Welch’s Variance-Weighted ANOVA Test, the Levene Test for Homogeneity of Variance, the Ryan-Einot-Gabriel-Welch (REGWQ) Method for comparison purposes, and residual diagnostics plots.

After performing all 36 tests, the overall results are displayed below in Figure 2.1, highlighting which categorical variable within each product category received a result that was considered “statistically significant” based on an alpha-value of 0.01. Essentially, this alpha value will explain that 99% of the time when attempting to conduct this test, the difference in means will be as or more extreme than the t-Statistic observed during the analysis. We selected 0.01 as the alpha value for this study to minimize the room for false errors as well as eliminate any possible “close calls” of p-Values that are at or around 0.05.

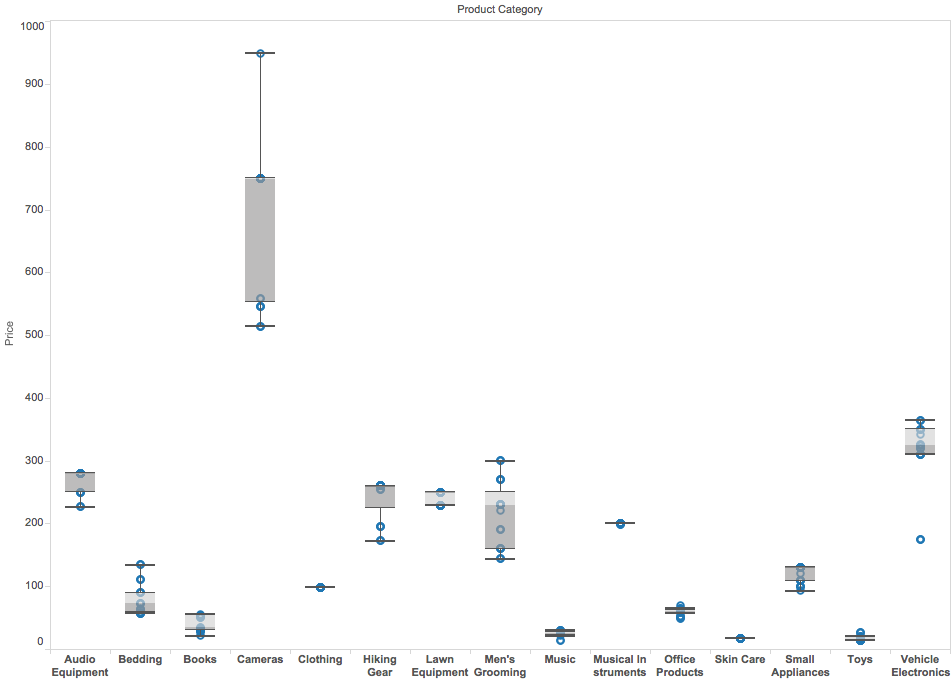
*Figure 2.1: ANOVA Test Results (f-Values) for Each Product Category by Shopping Behavior, Gender and Race; highlighted results received a p-Value of 0.01 or less.*

|  |  |  |  |
| --- | --- | --- | --- |
| **PRODUCT CATEGORY** | **SHOPPING BEHAVIOR** | **GENDER** | **RACE** |
| Audio Equipment | **2.43** | **2.37** | **17.17** |
| Bedding | **4.14** | **1.33** | **3.85** |
| Books | **21.57** | **3.96** | **2.76** |
| Cameras | **7.98** | **1.88** | **2.36** |
| Clothing | **0** | **0** | **0** |
| Hiking Gear | **0.58** | **4.79** | **2** |
| Lawn Equipment | **1.33** | **1.33** | **3,776,621** |
| Men’s Grooming | **3.55** | **3.27** | **2.8** |
| Music | **10.32** | **1.7** | **3.09** |
| Music Instruments | **0** | **0** | **0** |
| Office Gear | **6.15** | **0.41** | **3.44** |
| Skin Care | **0** | **0** | **0** |
| Small Appliances | **3.84** | **3.84** | **13.7** |
| Toys | **10.48** | **2.4** | **2.62** |
| Vehicle Electronics | **2.39** | **0.57** | **3.79** |

## Results by Product Category

For this analysis, 15 products and their respective product categories were observed, ranging from music and audio products to lawn equipment and children’s toys. The wide range of prices observed allowed us to analyze any noticeable differences not only between the personas we had selected, but the ways that various types of products are sold in the online marketplace. Figure 2.2, displayed below, shows a box and whisker plot for each product category and the range of prices observed.

*Figure 2.2: Box-and-Whiskers Plots of All Observed Prices by Product Category*



Of the 15 product categories observed during this analysis, only 3 products experienced no changes at all between any of the prices gathered by all 8 personas (clothing, musical instruments, and skin care). The apparent static pricing of these items is likely a function of the product type and the “newness” of the product itself. Often in the marketplace, certain manufacturers refuse to sell their items at a cost that differs from the MSRP. Several products were observed to have fairly wide ranges in price, with the Cameras category being the most widespread, although this can be expected as this product category was also the most expensive and more likely to have a wider price range. Other categories such as Men’s Grooming, Vehicle Electronics and Bedding also saw slightly wider ranges.

Even though the analysis of the product categories themselves is not the overall objective of this paper, it is important to note both the similarities and differences in pricing distribution for these products as well as to have an understanding of how certain products are sold within the online marketplace. Additionally, understanding the dynamic landscape of online pricing and the results obtained for the primary categories being analyzed (race, gender, economic status/shopping behavior) will provide more insight into how we interpret our overall findings.

## Results by Race

Similar to our shopping behavior/economic status results, only three of the fifteen product categories saw statistically significant results in differences between means where at least one group or race had a different average price compared to at least one other group being observed. However, no one race dominated the results.

When observing the results by product category, the Hispanic group was the race appearing most frequently to have differing mean prices; however, other races also saw different means compared to other categories.

For example, the Asian and Hispanic groups had the widest difference in mean prices for the Office Products category, as the Asian group had an average price of $63.65 while the Hispanic group received an average price of $54.55, a $9 difference. The Lawn Equipment product (Husqvarna Leaf Blower) was the other category with shared results, with the White and Hispanic groups having similar average prices ($229.00 for both, same as the control) and the Asian and Black having similar averages at $249.

## Results by Gender

Of the four categorical variables that were observed during this analysis, Gender received no "statistically significant" results in our ANOVA tests. Only two products, Books and Hiking Gear (both of which were more male-targeted in general), had f-Values that could be considered “significant” if the alpha-value was chosen to be 0.05.

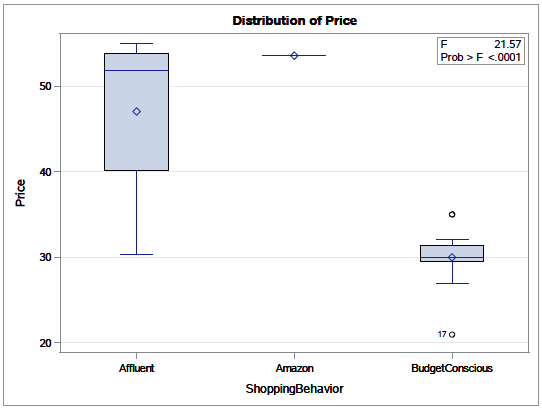
## Results by Shopping Behavior/Economic Status

Because the online shopping marketplace is so vast, there is seemingly no end to the websites a consumer can visit to find the right price for a product they are potentially willing to purchase. The economic status category you occupy (which likely coincides with your online shopping behavior of being more budget-conscious or “price indifferent”) generally has an impact on the final price that will ultimately make you click the “add to cart” button.

Overall, as is fairly typical with online retailers, if a consumer is willing to both spend the additional time needed to find a lower price for a product as well as trust the credibility of a lesser-known website, the likelihood of finding a lower price tends to be higher. However, only certain products or product categories may be susceptible to this kind of dynamic online pricing.

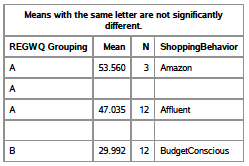
Of the 15 categories, the “books” category provides the best synopsis for the differences in shopping behavior. Below in Figure 2.3 is a box-and-whisker plot showing the price distribution for the observed small appliance, broken out by shopping behavior. In this instance, the control group (Amazon.com) was considered to be among the highest in terms of average price, with the “Affluent/Price Indifferent” groups covering a wider range of prices and the “Budget Conscious” group receiving an average price of 29.99, a difference of nearly $24 from the control group’s price. The results of this category in particular are interesting because Amazon is known for its prices in the books category; however, at least in this instance, several sites offered prices considerably lower than Amazon advertised pricing during the time of this study.

*Figure 2.3: Box-and-Whisker Plots for All Prices by Shopping Behavior*



The REGWQ Range Test, displayed in Table 2.4, shows us which groups are actually statistically significant from one another, with the mean price for the “budget conscious” category being over $23 lower than the control’s mean price.

*Table 2.4: REGWQ Results for “Small Appliances” by Shopping Behavior*



*The Product Category observed in the table is for Books. Using the REGWQ method, the is considered “statistically significant.” The control is significant from both the budget-conscious and affluent, the budget-conscious is significant from the control, and the affluent is significant from the control; however, the budget-conscious and affluent groups are not significant from each other.*

## Key Takeaways and Inferences

Even though there were some interesting and even statistically significant results based on the experiment conducted, it is difficult to make any clear assertions or draw solid conclusions without taking into consideration the current nature of online shopping as well as other factors that are more related to the product itself than the demographic composition of an online user. Below are a few key takeaways that may have affected several of the outcomes of the overall experiment:

* *The absence of demographic information requests during site registration*: Before attempting to shop online for certain sites, the intent was to register the created user’s email and information for the site in hopes that the information captured would alter products and prices listed; however, almost all websites accessed in our study did not request such information and typically only required shipping preferences, email frequency and address information. Web sites were not knowingly capturing this information and potentially using it from a pricing or even a marketing/targeting perspective.
* *The importance of the product and price variability*: With a multitude of products to choose from when conducting a pricing experiment, it became clear that the product a consumer is looking to purchase depends on two primary factors. First, the newness or uniqueness of a product returned certain prices, such as designer clothing. Second, the distribution of a product’s price can be attributed to stark differences in the product’s means. For example, the high price of the camera is associated with a higher likelihood of a wider range in price; however, the music album will not have as great a range because the average album is 40 times less expensive than the camera we chose to include in the research.
* *The need for more large-scale and timely experiments to draw firmer conclusions*: Overall, the time constraints placed on this particular experiment allowed for possible gaps in the analysis. A more thorough research attempt needed to be performed and could have given greater insight into price discrimination. Additionally, being able to perform this experiment on a much larger scale is crucial, considering large amounts of different products coupled with observing more websites to purchase these products, thereby allowing for a more rigorous approach to the analysis portion of the experiment.

When discussing any inferences that can be made from the experiment, we must be overly explicit around the caveats uncovered during the experiment as well the understanding that these results can not be applied to any larger population as this experiment was primarily an observational study and ultimately relied on several unknown or largely uncontrolled factors.

Overall, even though the experiment did provide significant results for 7 of the 45 individual ANOVA tests conducted, the inconsistencies of these results can be further attributed to a fundamental need to perform more advanced, thorough, and rigorous experiments that take the aforementioned caveats and confounding items into consideration in future experiment design work.

# Conclusions And Future Work

Our analysis uncovered evidence, albeit limited, that price discrimination is alive and well in the online retail space. Race, shopping behavior/economic status and product category all saw statistically significant results in differences between means where at least one group obtained a different average price compared to at least one other group being observed. Of the four categorical variables that were observed in our work, Gender received the least amount of statistically significant results in our ANOVA tests and does not appear to influence pricing in any of the categories tested.

The limitations of our work prompted us to consider future related areas of investigation. Cookies, which are utilized by browsers to track user behavior, provide insight into the history of a user’s price comparisons. Profiles/personas could capitalize on cookie storage and provide a deeper level of insight into price discrimination employed by a particular retailer. In short, the researcher will only use a browser with cookies from shopping with a specific persona and keep those cookies to reinforce the web site’s learning about them when they visit again. It will allow the researchers to observe the behavior programmed by various shopping web sites via the cookies rather than waiting for items to be in the shopping cart. This will answer the question: What influence do cookies have in pricing, specifically looking for pricing discrimination when a profile is represented in cookies? Comparison of affluent and budget conscious behaviors, race or gender would confirm or reject that online shopping of a particular style influences the prices found.

Finally, a possible improvement in study design would be to consider product stratification. Often, there are many levels of product capability in the market place. Audio Equipment, Men’s Grooming, Cameras, Vehicle Electronics, Lawn Equipment, Small Appliances, Clothing, and Skin Care are all products with wide ranges from simple and inexpensive to complex and pricey. Research could be enhanced by encouraging the personas to shop not just at a site that would appeal to their economic status but for specific products in their persona’s economic band, e.g. less expensive cameras for a budget-conscious shopper. This study design takes product stratification into account, then gives a clearer picture of discrimination based on based on gender or race.

Our dynamic pricing research supports that while ethical considerations remain front and center and cultural sensitivity to all matters discrimination-related remains high, balance-seeking is prevalent in many industries. In our quest to improve the efficiency of the online retailer space, policies that perpetuate society’s core values are the key to successful implementation. Transparency, justifiable math driven by a legitimate business need and active management of unintended impacts to low income or underserved populations are all critical cogs in the dynamic pricing machine.

# References

[1] D. Mattioli. On Orbitz, Mac Users Steered to Pricier Hotels. Wall Street Journal, 2012.

<http://www.wsj.com/articles/SB10001424052702304458604577488822667325882>.

[2] B. Gurley. A Deeper Look at Uber’s Dynamic Pricing Model. Above the Crowd, 2014.

<http://abovethecrowd.com/2014/03/11/a-deeper-look-at-ubers-dynamic-pricing-model/>.

[3] J. Van Grove. The Latest Craze in Fitness? Dynamic Pricing. San Diego Union-Tribune, 2016.

<http://www.sandiegouniontribune.com/news/2016/may/20/lymber-app-fitness-studios-san-diego-los-angeles/>.

[4 ] J. Xu, P. Fader, S. Veeraraghavan. “Evaluating the Effectiveness of Dynamic Pricing Strategies on MLB Single-Game Ticket Revenue.” *MIT Sloan Sports Analytics Conference 2015*. Feb. 2015.

<http://www.sloansportsconference.com/wp-content/uploads/2015/02/SSAC15-RP-Finalist-Evaluating-the-effectivness-of-dynamic-pricing2.pdf>.

[5] A. Friel. Taking Care in Using Consumer Data to Drive Dynamic Pricing of E-Commerce. Data Privacy Monitor, 2015.

<https://www.dataprivacymonitor.com/big-data-2/take-care-in-using-consumer-data-to-drive-dynamic-pricing-of-e-commerce/>.

[6] J. Fingas. ACLU sues US over law limiting data discrimination studies. Engadget, 2016.

<https://www.engadget.com/2016/06/29/aclu-sues-us-over-law-limiting-data-bias-studies/>

[7] E. Larson, P. Hurtado. Uber Surge-Pricing Antitrust Suit Green-Lighted by Judge. Bloomberg Technology, 2016.

<http://www.bloomberg.com/news/articles/2016-03-31/uber-antitrust-lawsuit-over-pricing-green-lighted-by-judge>.

[8] C. Duhigg. How Companies Learn Your Secrets. The New York Times, 2012. <http://www.nytimes.com/2012/02/19/magazine/shopping-habits.html>

[9] Turow, J., Feldman, L., & Meltzer, K. (2005). Open to Exploitation: America's Shoppers Online and Offline. A Report from the Annenberg Public Policy Center of the University of Pennsylvania, Retrieved from <http://repository.upenn.edu/asc_papers/35>

[10] H. Van De Mark. “Target Audience & Online Shopping Personae”. March 11, 2011. <http://www.gotgroove.com/ecommerce-blog/analysis-strategy/target-audience-online-shopping-personas/>

[11] A. Hannak, G. Soeller, D.Lazer, Al Mislove, C. Wilson. . Measuring Price Discrimination and Steering on E-commerce Web Sites, IMC '14 Proceedings of the 2014 Conference on Internet Measurement Conference Pages 305-318.

[12] J. Hu, H. Zeng, H. Li, C. Niu, Z. Chen. Demographic Prediction Based on User’s Browsing Behavior. WWW '07 Proceedings of the 16th international conference on World Wide Web Pages 151-160.

[13] R. Calo. Digital Market Manipulation. (August 15, 2013). 82 George Washington Law Review 995 (2014); University of Washington School of Law Research Paper No. 2013-27. Available at SSRN: <http://ssrn.com/abstract=2309703>.

[14] T. Wadhwa. How Advertisers Can Use Your Personal Information To Make You Pay Higher Prices. January 2014. <http://www.huffingtonpost.com/tarun-wadhwa/how-advertisers-can-use-y_b_4703013.html>

[15] J. Mikians, L. Gyarmati, V. Erramilli, N. Laoutaris. J. Mikians, L. Gyarmati, V. Erramilli, and N. Laoutaris. Crowd-assisted Search for Price Discrimination in E-Commerce: First results. CoNEXT, 2013.

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