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Essays on Price Discrimination and Information Disclosure

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Economics

by
Liuna Issagholian
May 2019

Accepted by:
Dr. Mathew Lewis, Committee Chair
Dr. F. Andrew Hanssen
Dr. Tom Lam
Dr. Christy Zhou

Abstract

The first chapter of this dissertation deals with different cash-back rebates in the new-automobile market. In the automotive industry, manufacturers use different types of cash-back rebates to attract buyers to their brands. In this chapter, I mainly focus on the use of "conquest cash" and "loyalty cash" which enable manufacturers to discriminate price among different groups of customers. The conquest cash and loyalty cash are based on consumers' purchase history. The purpose of conquest cash is to poach the rival manufacturers' customers, whereas the loyalty cash lowers prices for the manufacturer's customers. Moreover, I examine "college-graduate" discounts and "military" discounts which manufacturers use to practice price discrimination on certain demographic groups of customers. I empirically investigate the factors associated with greater use of these offers in the U.S. auto industry and compare these patterns to predictions from the theoretical literature. The theoretical studies include product differentiation and brand preferences as plausible reasons to explain price discrimination by purchase history. My results suggest that manufacturers' market share impacts the manufacturers' decision for customer poaching and customer retention. However, the manufacturers'market share does not determine the use of college-graduate and military discounts.

The second chapter examines how competition affects information disclosure on Airbnb. Airbnb accommodates lodging for travelers by matching hosts and guests in an online platform. Hosting on this platform has been getting popular in recent few years. Similar to other online platforms, sharing photos, description of a product, and reviews of previous users are possible ways to attract customers. It is possible that as the competition among Airbnb's listings increases, hosts change the description of their listings. Theoretical papers include different relationships between competition and information disclosure. I use publicly available data of Airbnb's listings in San Fransico and its surrounding cities to examine whether an increase in the number of listings impacts hosts' information disclosed about the quality of listing. My findings suggest that on average a higher number of listings increases the number of words in the description of listings.

Dedication

This dissertation is dedicated to Travis for his unconditional love and kindness.

Acknowledgments

I would like to thank my advisor, Dr. Mathew Lewis. His innumerable hours of feedback helped me become an independent researcher. I will be greatly indebted to him for his incredible patience, extensive knowledge, and helpful guidance. I appreciate all the mentorship I got from one of my committee members Dr. Tom Lam who never stopped inspiring me to learn new skills. I am grateful for the valuable comments of other members of my dissertation committee Dr. F. Andrew Hanssen and Dr. Christy Zhou. Also, I have benefited from the valuable suggestions of the participants of the Clemson University IO workshop.

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Chapter 1

Cash-Back Rebates in New-Automobile Market

1.1 Introduction

Firms may use different types of customers' information such as purchase history, age, and military membership as a tool to implement their pricing strategy. Using such information can help firms to segment the customers into different groups and offer different prices to each group. For instance, grocery chain stores offer loyalty cards to the customers who shop there regularly. Cell phone carriers often use special prices and promotions to induce their rivals' customers to change their carriers. A lot of clothing brands offer special discounts to military members and college students.

In the new-automobile market, manufacturers frequently offer lower prices to their returning customers, known as loyalty cash, and also offer discounts to their rivals' customers, known as conquest cash. Besides, military discount and college-graduate discount are other types of common discounts in this market. Although in recent years such cash rebates have become more popular among automobile manufacturers, their nature has not been studied carefully.

Different cash-back rebates in the new-automobile market can be explained by third-degree price discrimination. The theoretical literature of third-degree price discrimination is focused on customer segmentation based on the differences in demand elasticities. The lower prices are offered to price-sensitive customers and higher prices are available to a less elastic group of customers.

Customer segmentation may also happen based on customers' past purchasing decision which the literature refers to it as price discrimination by purchase history. The literature explains this particular type of price discrimination by product differentiation and switching cost. Fudenberg and Tirole (2000) find that firms with similar market shares poach each others' customers, whereas a lower market share firm poaches its competitor's customers more aggressively. Shaffer and Zhang (2000) explain if two firms have customers with similar brand loyalty, both firms should poach their competitors' customers, whereas firms with lower brand loyalty should pay their own customers to stay and their competitors should pay to switch. Chen and Pearcy (2010) describe that high intertemporal brand preference leads firms to poach rivals' customers, whereas lower intertemporal brand preference leads the firms to pay their own customers to stay. These studies suggest that firms should pay lower prices to a group of customers who have weak preferences, and it can be either firm's customers or its rivals' customers.

In this chapter, I empirically study the automobile manufacturers' decision to use cash-back rebates as their price setting strategy. My primary focus is on conquest and loyalty cash-back rebates. This chapter is the first to empirically study the automobile manufacturers' decision to use conquest and loyalty cash. Results from the theoretical literature are used to motivate a variety of empirical tests. Following the insights of Fudenberg and Tirole (2000), I investigate whether manufacturers with lower market share are more likely to use conquest offers. Based on the predictions of Shaffer and Zhang (2000) and Chen and Pearcy (2010), I examine whether the use of conquest and loyalty rebates differs between groups of manufacturers (domestic versus foreign) or vehicle types (luxury versus non-luxury) that are likely to experience different levels of customer loyalty or brand preference intensity. For example, sellers in luxury car segments may face customers with stronger brand preference and less price-sensitivity. Domestic and foreign manufacturers may also cater to different types of customers and respond by utilizing different types of rebates.

My results suggest that one percentage point increase in market share for foreign manufacturers decreases the probability of offering loyalty cash by 0.31 percentage point. However, one percentage point increase in market share for domestic manufacturers increases the probability of offering loyalty cash by 0.36 percentage point. Moreover, one percentage point increase in market share for non-luxury brands increases the probability of offering conquest cash by 0.40 percentage point, whereas one percentage point increase in market share for luxury brands decreases the probability of offering conquest cash by 0.17 percentage point.

The empirical results suggest that it is possible as the market share of foreign manufactures increases, these manufacturers may get customers with higher brand loyalty and do not need to offer loyalty cash to their customers. On the contrary, higher market share domestic manufactures may acquire customers with lower brand loyalty and offer loyalty cash to keep their high market share. Luxury brands with higher market share may get customers with strong preferences who are less likely to switch when offered conquest cash, whereas non-luxury brand automobiles are relatively similar to each other and may be able to substantially increase sales by offering discounted prices to rivals' customers.

In section 1.2, I describe the theoretical models of third-degree price discrimination with the emphasis on the literature of price discrimination by the purchase history. I explain the application of cash-back rebates in the automobile market in section 1.3. Section 1.4 describes data and develops an empirical strategy. Section 1.5 provides the results, and the last section concludes.

1.2 Third-Degree Price Discrimination

Economists have been studying price discrimination for many decades.[1] The main idea behind price discrimination is to charge different prices to buyers based on their willingness to pay. The literature traditionally describes a setting in which a monopolist firm can practice price discrimination. However, a more recent approach to this matter explains the possibility of price discrimination in an oligopoly market.

Corts (1998) and Holmes (1989) describe a context in which firms in an oligopoly setting can practice third-degree price discrimination. Corts (1998) outlines that competing firms may or may not agree on recognizing strong market and weak market. Robinson (1933) defines the strong market as the less elastic group of customers, whereas the weak market is the more elastic group of customers. In other words, the strong market has customers with higher brand preference compared to the weak market. If all firms agree on the weak market, as Corts describes the market shows best-response symmetry. In a different scenario, the competing firms may not assign the same groups as their weak and strong markets. Corts (1998) calls this setting a market with best-response asymmetry.

Firms may divide customers into the weak and strong markets, and offer a different price to each segment based on customers' preferences revealed by their previous purchase. In this setting, the firms only know about the preference of customers

[1]The history goes back to the researches done by Pigou (1920) and Robinson (1933).

over their product versus their rivals' product, and they cannot exactly identify the consumer's location (Armstrong (2006)). Therefore, firms can employ purchase history as a criterion for price discrimination. Such customer segmentation is a type of third-degree price discrimination which literature refers to as behavior-based price discrimination or price discrimination by purchase history. Customers who do not have a strong preference for any firms' products are offered lower prices to either stay with their current firm or switch to the competitors.

Chen (1997) is the first paper which describes "paying customers to switch" in a theoretical framework. Chen infers that customers face a switching cost in a repeated purchase market, and customers who switch firm are offered lower prices. Shaffer and Zhang (2000) explain that depending on firms' relative brand loyalty, firms may pay to switch or pay to stay. According to these authors, if both firms have customers with similar brand loyalty, both firms poach each others' customers. However, if firms face dissimilar brand loyalty, the firm with lower brand loyalty should offer lower prices to its customers, and the other firm should poach rival's customers. Chen and Pearcy (2010) describe the price discrimination based on purchase history as a matter of intertemporal brand preference. If price commitment was feasible in the long run, firms with lower preference dependence pay to stay. According to Chen and Pearcy (2010), customer poaching would happen if customers were locked in with a high switching cost.

Fudenberg and Tirole (2000) explain poaching prices when customers' preferences towards differentiated products are fixed over time. These authors find that poaching occurs based on firms' market share in the previous period. Two firms with a similar market share in the last period would both poach each others' customers. However, firms with different market shares may behave differently. The firm with a lower market share would poach more aggressively.

Following Fudenberg and Tirole (2000), Esteves (2014) studies a special case which firms know in advance about their own customers' intention of switching. Therefore, the firm's own customers can be divided into two groups: the first group is the customers who are not interested in switching and the second group who are willing to switch to the rivals. Her model is based on loyalty offers designed for the second group of customers. Before switching, the firm uses a loyalty discount to make the switching less attractive.[2] The rest of theoretical papers are extensions of either Chen (1997) model or Fudenberg and Tirole (2000) approach to price discrimination based on purchase history (Villas-Boas, 1999; Chen and Iyer, 2002; Pazgal and Soberman, 2008; Esteves, 2014; Amorim and Esteves, 2016).

The theoretical papers provide different interpretations to explain price discrimination based on purchase history. However, these studies mainly focus on customer poaching and do not incorporate the role of market share as a reason to explain the possibility of both paying to stay and paying to switch. Moreover, this literature has not been broadly tested empirically in different markets. Therefore, the lack of empirical work and integration of market share in these studies urge more work in this area. The goal of this chapter is to fill the gap between the theoretical works and empirical framework in the new-automobile market.

One of the empirical papers which examine price discrimination based on purchase history is Mahmood (2014). This paper examines the decision of competing firms to practice purchase history price discrimination in an experimental setting. The author finds that poaching new customers does occur when customers have homogeneous preferences. However, heterogeneity in preferences intensifies price discrimination. Unlike Chen and Pearcy (2010), Mahmood's results suggest that loyalty rewards

[2] The theoretical model explained by Esteves (2014) does not occur in many markets. For instance, in the new-automobile market, customers do not let their current manufacturer know that they plan to switch to a different manufacturer.

cannot be a dominant strategy when customers obtain heterogeneous preferences.

1.3 Institutional Background

Automobile manufacturers compete fiercely with each other to attract new customers and retain the old ones. To stand out against their competitors, the manufacturers use new features, novel platforms, modern technology, and offer different types of discounts and financing options.

Discounts in the form of cash-back rebates are used frequently by manufacturers in the new-automobile market. These offers are available for purchasing, leasing, and financing new cars. Such rebates can be categorized into two groups: general cash back and conditional cash back (Kelly Blue Book 2018).[3] The general cash back is a type of discount which any type of customer can use. However, customers who are eligible for conditional discounts should meet specific condition and criteria. Customers can use general cash back and typically one conditional offer at the time of purchase.

The goal of this paper is to explain the factors which drive automobile manufacturers to apply conditional offers based on the existing theoretical work on third-degree price discrimination. Specifically, my primary focus is to examine conquest cash and loyalty cash offers. I also investigate on two relatively common conditional offers, college-graduate and military discounts.[4]

Conquest cash and loyalty cash are designed based on customer recognition by the purchase history. The loyalty cash rewards the returning customers, and conquest cash entices rivals' customers to switch. Manufacturers target these offers to their

[3] Retrieved from `https://www.kbb.com/car-news/all-the-latest/conditional-rebates-knowing-what-to-ask-can-save-you-money/2100004474/` on 3.1.2018.

[4] There are other types of rebates such as uber driver discounts which are less common among manufacturers.

weak market, which may be the manufacturers' customers or rivals' customers. In other words, if a manufacturer finds its customers as the weak market, it is more likely to offer them loyalty cash, whereas if the manufacturer considers its rivals' customers as the weak market, the manufacturer uses conquest cash.

College-graduate and military discounts are not offered based on the purchase history of the customers. These types of discounts are available for customers with certain demographic characteristics. College-graduate discounts are typically available for customers who graduate from college within the last two years or would graduate within the next six months. The recent college graduates should provide a proof of source of income to show their ability to pay for the finances. This group of customers usually have a limited credit history. Military discounts are offered to the United State's active and reserve military members, military veterans, retires, honorable discharged or disabled military members, or their spouse. The manufacturers employ college-graduate and military discounts because recent college graduates and military members are considered as the weak market to them.

The customers find out about the cash rebates during their search process in the automobile market. Specifically, they obtain such information from their direct visit to dealerships, online search, and advertisement.[5,6] During the customers' visit to dealerships,a salesperson is allowed to ask customers the type of current car that the potential customers acquire. This way the dealerships can gather information about the customers' purchase history with a negligible cost by just asking for customers' current car registration.[7] Additionally, the salesperson may ask the customers

[5]Busse et al. (2006) examine the pass-through rate of different cash rebates. They find that customers receive 70 to 90 percent of customer cash. Conquest and loyalty cash are considered as customer cash promotions.

[6]The online offers can be typically found on websites such as kellybluebook.com, edwards.com, or on the manufacturer's website.

[7]Identifying the purchase history in different markets might be a costly process. For instance, in online markets, firms set up "cookies" in their website to track down their visitors' behavior through

about their demographic features such as education, occupation, income, and military status which assist the dealerships in classifying the customers within different groups. To be eligible for college-graduate discounts, the customers should present a proof of graduation, and for military discounts, the customers should have either a military identification or a proof of military affiliation. Based on this information, the customers are offered conquest cash or loyalty cash, military and college graduate discounts issued by manufacturers.

Although the average amount of conquest and loyalty cash, college-graduate and military discounts during different months tend to be relatively constant, their availability may vary slightly among manufacturers within different cities and months.[8] The content and the value of college-graduate and military discounts are usually constant, whereas the content and the values of conquest cash and loyalty cash change in their specificity. Typical loyalty cash offered by a make lists the eligible model years, and sometimes includes the exact nameplate which qualifies for loyalty offer. For instance, Audi offers loyalty cash to returning customers of the model year 2005 or newer. Conquest offers may target all nameplates or only specific nameplates manufactured by the rivals. Some conquest offers include an only particular eligible segment for conquest cash. For instance, Nissan offers conquest cash on Nissan Titan to current owners of Chevrolet Silverado.

Manufacturers use the cash-back rebates on different methods of payment: purchase, lease, and finance. Some of the offers on lease and purchase may not be the same as for finance. Moreover, there are some conquest and loyalty offers specific to leasing, which allows a leasee to return the automobile a few months before the

the time, or pay a third party to sell them such information (Acquisti and Varian (2005); Varian (2001); Taylor (2004)).

[8]As Table 1.4 suggests, conquest and loyalty cash, and college-graduate and military discounts do not follow any seasonality.

maturity date of the lease. These types of offers, which are known as pull-ahead offers or early turn-in, can be in the form of both conquest and loyalty offers. If such early turn-in offers are part of loyalty cash, the manufacturers typically wave the remaining last three lease payments. For instance, Ford offers three-month early turn-in on Focus, one of its nameplates. Similarly, for conquest offers, a manufacturer pays the remaining last few payments up to a certain amount to encourage the rivals' customers to terminate their lease contract earlier and switch firm. For instance, Porsche offer "Welcome to Porsche" credit to the rivals' customers who end their lease earlier than the maturity date and switch from competing manufacturers to Porsche.

Table 1.1 presents the makes which offer conquest and loyalty cash, college-graduate and military discounts from December 2017 to April 2018 in six selected cities.

1.4 Data and Empirical Strategy

I gather data for this chapter from different sources including Automotive News website, usnews.com and Kelly Blue Book webpage.[9] The data on cash-back rebates are collected for December 2017 through April 2018 from Automotive News website where provides data for 33 makes, excluding exotic automobile manufacturers.[10] The cash-back rebates consist of purchasing, leasing, and financing new cars. Most of the nameplates available in this period were nameplates with the model year of 2017 and 2018. Therefore, I limit the data to model years 2017 and 2018.[11] I use the United State Census' divisions of sub-regions to select data for rebates available in six cities

[9] https://cars.usnews.com/cars-trucks/rankings and https://www.kbb.com are retrieved 3.1.2018

[10] Exclusions are Alfa Romero, Maserati, Rolls-Royce, McLaren, Bentley, and Tesla.

[11] In my sample, there were small number of nameplates from model years 2014-2016, and 2019.

of Chicago, Kansas City, Houston, Jacksonville, Boston, and New York City. These cities are the most populated cities in their sub-region.

Manufactures which use the cash-back rebates, may not apply them to all trims of a particular nameplate. I assign zero to the trims with no offers, and one to the trims, which have these offers. In my dataset, only 10% of loyalty offers and 9% of conquest offers to vary among trims. Such variation is even less among college graduate and military discounts, 2.5% and 2.8% respectively. Subsequently, I aggregate the offers for all types of purchase, lease, and finance methods on different trims for a given nameplate, and take the average of offers within the trims. Therefore, my dependent variable is a fraction of each of these offers within trims of a nameplate.

To construct market share, I access the nation-wide sales number from Automotive News website.[12] The sales data used in this chapter are on an aggregated level for all trims, and all model years. I use narrowly defined 23 segments provided by usnews.com to calculate the market share. Figure 1.1 illustrates the average market share within the segments. I define the market share for the previous period as twelve months before a month which offers are applied. Therefore, the market share is based on an average of sales number among these twelve months. For instance, for offers in December 2017, I first calculate the average sales number from December 2016 to November 2017, then I define market share within the segment based on the average sales number.

I use manufacturer's suggested retail price (MSRP) for the base models as the price of nameplates, and I web-scrape it from usnew.com.[13] Car characteristics are

[12]For market share calculation, having sales number on zip-code level provided by registration data would be ideal which I do not access such data.

[13]In automobile market, there are three types of price: invoice price, manufacturer's suggested retail price (MSRP), and negotiated price. Invoice price is the price which the dealers pay to manufactures, and MSRP is the suggestive price from manufacturers to dealers. The dealers can add a markup amount to MSRP, and sell at higher prices. Ultimately, the negotiated price is the actual transacted price paid by buyers after negotiating with the dealers. For nameplates which the

collected from Kelly Blue Book webpage. All characteristics reflect the base model, and they include horsepower, wheelbase, curb weight, and cost per mile. Cost per mile is calculated based on the average consumption of relevant fuel in city and highway. For cars consuming gasoline, cost per mile is calculated by dividing the nation-wide average of monthly gasoline price on a mile per gallon (MPG). For electric cars, cost per mile is calculated in two steps. The first step is converting miles per gallon gasoline equivalent (MPGe) to miles per kilowatt-hours (MPK), and second, dividing the nation-wide average of monthly electricity price by MPK. For hybrid cars, an average cost per mile for gasoline and electric is calculated (U.S. Energy Information Administration 2018).[14]

The summary statistics are shown in Table 1.2 and it exhibits that the loyalty cash is the most popular cash-back rebate compared to conquest cash, college-graduate and military discounts. In this chapter, these offers are not mutually exclusive. In other words, there are nameplates which possess all of these four offers. The number of observations for the monetary value of conquest and loyalty cash in Table 1.2 is not equal to the number of entire samples. Such difference occurs because the amount of some of these offers is not observable to me for several reasons. First, some of the manufacturers do not specify the amount of the offer in my data source. Second, as mentioned in Section 3, some of the offers are specific to leasing in the form of early turn-in and pull-ahead. Third, some conquest and loyalty offers are directly mailed to the customers. Therefore, sub-samples available for the dollar value of conquest cash and loyalty cash do not include all observations.

To examine the influence of market share on the probability of offering the

prices were not available on usnews.com, I acquire the prices from jdpower.com.

[14]The nation-wide average of monthly gasoline price and the nation-wide average of monthly electricity price are from the U.S. Energy Information Administration. Retrieved from `https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=pet&s=emm_epmr_pte_nus_dpg&f=m` and `https://www.eia.gov/electricity/monthly/epm_table_grapher.php?t=epmt_5_3` on 2.1.2018.

cash-back rebates I use

$$
\begin{aligned}
offer_{nymvct} =& \alpha + \beta_1 market\ share_{nt-1} + \beta_2 price_{ny} + \beta_3 make\ year_n \\
&+ \beta_4 X_{nym} + \gamma_m + \zeta_v + \theta_c + \nu_t + \epsilon_{nymvct}
\end{aligned}
\tag{1.1}
$$

where $offer_{nymvct}$ can be the probability of offering loyalty cash, conquest cash, college-graduate discount, and military discount. In other words, I have four dependent variables. These offers are available on nameplate n for model year y, produced by make m, with vehicle class v offered in city c and month t. Although endogeneity may be a concern in models where price is a function of market share, my specification does not have the price level as its outcome variable. My focus is on the differences between prices which different groups of customers pay. In addition, following Fudenberg and Tirole (2000), I use the *market share* of the previous period which also reduces the potential for reverse causality. *Make Year* refers to the name plate's production year of 2017 or 2018, and it is equal to one if the make year is 2017. X is product characteristics. To control for average differences across makes, vehicle classes, cities and months on the propensity to offer rebates, I include make fixed effect γ_m, vehicle class fixed effect ζ_v, city fixed effect θ_c, and time fixed effect ν_t.[15]

The likelihood of offering the cash-back rebates may vary based on customers' preferences for manufacturers. Moreover, the effect of market share may depend on the manufacturers' origin (domestic versus foreign), and type of brand (luxury versus non-luxury). Employing such segmentation, the likelihood of offering the conditional

[15] I assign nine groups of vehicle classes including small cars, midsize cars, large cars, compact SUVs, large SUVs, compact pickup trucks, full-size pickup trucks, cargo van, and minivans for vehicle class fixed effect.

offers can be estimated as

$$\begin{aligned} offer_{nymvct} =&\alpha + \beta_1 market\ share_{nt-1} + \beta_2 foreign_m \times market\ share_{nt-1} \\ &+ \beta_3 price_{ny} + \beta_4 make\ year_n + \beta_5 X_{nym} + \gamma_m + \zeta_v + \theta_c + \nu_t + \epsilon_{nymvct} \end{aligned} \tag{1.2}$$

and

$$\begin{aligned} offer_{nymvct} =&\alpha + \beta_1 market\ share_{nt-1} + \beta_2 luxury_m \times market\ share_{nt-1} \\ &+ \beta_3 price_{ny} + \beta_4 make\ year_n + \beta_5 X_{nym} + \gamma_m + \zeta_v + \theta_c + \nu_t + \epsilon_{nymvct}. \end{aligned} \tag{1.3}$$

In model (1.2), *foreign* is a binary variable which is equal to one if the manufacturer is either Asian or European. In model (1.3), *luxury* is a binary variable which is equal to one if the nameplate is categorized as a luxury brand by usnews.com. Based on usnews.com, the luxury segments are luxury sport cars, small luxury cars, luxury midsize cars, large luxury cars, luxury subcompact SUVs, luxury compact SUVs, luxury midsize SUVs, and large luxury SUVs. The interaction term between market share and foreign manufacturere in (model 1.2) captures differences between domestic and foreign manufacturers in the impact of market share on the likelihood of using the conditional offers. Similarly, the interaction term between market share and luxury brand in model (1.3) captures differences between luxury and non-luxury brands in the impact of market share on the likelihood of using the conditional offers.

1.5 Results

In this section, first I report results related to conquest and loyalty offers. Second, I present results for the descriptive analysis of college-graduate and military discounts.

1.5.1 Offering Conquest or Loyalty Cash

In this section, first, I examine the impact of market share on the likelihood of offering conquest and loyalty cash. Second, I analyze whether foreign and domestic manufacturers use these rebates differently. Third, I investigate the simultaneous use of conquest and loyalty offers.

Columns (1) and (2) of Table 1.5 presents the results of the model (1.1) which examines how within-segment market share affects the use of loyalty and conquest cash. A consistent relationship between market share and rebates is not clear when examining all cars, but this is a result of the fact that different makes use these rebates differently.

I estimate models (1.2) and (1.3) which their results are reported in columns (3) to (6) of Table 1.5. Model (1.2) includes the impact of manufacturers' origin on market share which drives manufacturers' decision to offer loyalty or conquest cash. According to columns (3) and (4) of Table 1.5, domestic manufacturers with higher market share are more likely to offer loyalty cash, whereas higher market share for foreign manufacturers lowers the probability of offering loyalty cash. In other words, higher domestic market share manufacturers view their customers as the weak market and offer them lower prices. The difference in the likelihood of offering loyalty cash by foreign and domestic manufacturers may be explained by brand preferences. The consumers shape their preferences by gaining information about manufacturers' product after experiencing it. Following Chen and Pearcy (2010), customers of foreign manufacturers may adopt higher preference dependency over time compared to domestic customers. In contrast, market shares do not significantly impact the use of conquest cash by foreign or domestic manufacturers.

I examine model (1.3) to study how the relationship between market share and the likelihood of offering conquest or loyalty cash differs depending on the brand type (luxury versus non-luxury). Estimates from model (1.3) are shown in columns (5) and (6) of Table 1.5. Based on these columns, higher market share non-luxury brands are more likely to poach the rivals' customers, while luxury brands with higher market share are less likely to offer conquest cash. Within non-luxury brands, the nameplates are more similar to each other and therefore these cars are considered as more substitutable to customers. On the other hand, a lower likelihood of offering conquest cash by luxury brands with higher market share may be explained by the strong preferences of luxury brand customers. According to Fudenberg and Tirole (2000), aggressive poaching occurs due to having a relatively lower market share. However, my results imply that in the automobile market, the higher market share of non-luxury brands indeed increases the likelihood of poaching. There is no evidence that the relationship between market share and loyalty cash differs across manufacturers' brand type.

As a robustness check, I estimate models (1.2) and (1.3) for each month separately. The results are reported in Table 1.12 to Table 1.16, and confirm the results of the entire sample. Also, I examine models (1.2) and (1.3) for the dollar amount of conquest or loyalty cash as the outcome variable, and the results of these estimations are reported in Table 1.6.

Furthermore, I divide my sample into four sub-samples of luxury foreign, luxury domestic, non-luxury foreign, non-luxury domestic to examine the likelihood of offering conquest or loyalty cash in each of these groups. The results are shown in Table 1.7. Among luxury foreign and luxury domestic manufacturers, on average, market share does not significantly impact the use of conquest or loyalty cash. Among non-luxury foreign manufacturers, higher market share lowers the probability of offering loyalty cash to the returning customers, whereas higher market share among non-luxury domestic manufacturers increases the probability of offering loyalty cash. These results may be explained by brand preference. Customers of non-luxury foreign manufacturers are more loyal compared to customers of non-luxury domestic manufacturers. Although non-luxury foreign and non-luxury domestic manufacturers are more likely to offer conquest cash as their market share increases, this impact is not significant for non-luxury foreign brands.

I also estimate specifications without manufacturer fixed effects to examine whether foreign and domestic manufacturers differ in their overall use of conquest or loyalty cash. The results in Table 1.8 suggest that on average Asian and European manufacturers are less likely to use either loyalty or conquest offers. By avoiding the practice of price discrimination based on purchase history, foreign manufacturers resist a comprehensive competition which leads all manufacturers to compete in offering lower prices. Corts (1998) describes a situation where all competing firms engage in offering a lower price and calls it an all-out competition. My results do not show such all-out competition in offering conquest and loyalty cash in the automobile market.

Table 1.9 shows the likelihood of offering conquest or loyalty cash by foreign and domestic manufacturers conditioned on the type of brand. Based on columns (1) and (3) in Table 1.9, non-luxury European manufacturers are less likely to offer loyalty rebates which suggest that these manufacturers consider their customers as the strong market. A similar trend occurs for Asian luxury manufacturers. Results in columns (5) and (7) reveal that the lower probability of offering loyalty cash in

Asian manufacturers is driven by its luxury brands. It is possible that customers of Asian luxury brands and European non-luxury brands shape strong brand loyalty. Therefore, such customers may be considered as already locked-in customers and need no extra incentives to choose the same manufacturer.

Some makes offer simultaneous conquest and loyalty offers for the same vehicles.[16] These types of offers can be used to rank the amount paid by different customers.[17] For instance, Cadillac offers a higher dollar amount for conquest cash over loyalty cash. This may mean even though Cadillac's returning customers are offered a discounted price, they probably negotiate less and are ready to pay a relatively higher price compared to the rivals' customers who are encouraged to switch by Cadillac's conquest cash.

In light of this, I also examine the factors which drive makes' decision on applying different dollar values to these simultaneous offers. After dropping zero and missing values for conquest and loyalty offers, 47% of nameplates in the subsample have larger conquest offers than loyalty offers. After calculating the ratio of the dollar amount of conquest offer to the dollar amount of loyalty offer, I define a binary variable called net conquest which equals one if the dollar amount of conquest offer exceeds its loyalty offers and zero otherwise.

Table 1.10 and Table 1.11 describe the impact of manufacturers' market share and origin on the net conquest respectively. Asian manufacturers with higher market share are less likely to offer a lower discount to their customers compared to the discounts they offer to their rivals' customers. Additionally, based on Table 1.11, on average it is less likely for Asian manufacturers to offer a higher amount of conquest cash relative to loyalty cash when both rebates are offered concurrently on a

[16]Table 1.3 lists manufacturers which use simultaneous offers.

[17]In some cases, the amount of conquest and loyalty offers on a given nameplate is the same.

nameplate.

1.5.2 Offering College Graduate or Military Discounts

Table 1.17 exhibits the results of the model (1.1), (1.2) and (1.3) which examine how within-segment market share impacts the possibility of offering college graduate and military discounts by manufacturers. The market share and these rebates do not show any consistent relationships. Such relationship does not exist even among a different group of manufacturers and vehicle types.

Manufacturers use college graduate and military discounts to compete with each other to attract college graduates and military members to their brand. Since college graduates and military members are elastic groups of customers, they are more likely to buy lower-priced nameplates. Therefore, on average, lower-priced nameplates within their segment are more likely to have these discounts. This descriptive analysis reveals that product differentiation and market share are not correlated with the likelihood of offering these discounts.

I also investigate whether domestic and foreign manufacturers offer college graduate and military discounts differently. For this purpose, I estimate specifications without manufacturers fixed effects, and the results are reported in Table 1.18. According to these results, the origin of the manufacturers does not explain the likelihood of offering college graduate and military discounts.

As a robustness check, I estimate models (1.1), (1.2) and (1.3) for five months separately. The results are reported in Tables 1.19 to 1.23, and confirm that there is no clear relationship between market share with college graduate and military discounts.

1.6 Conclusion

In this chapter, my focus is conquest and loyalty offers used by automobile manufacturers in the U.S. new-automobile market. Even though the economists have been studying the new-automobile market closely, the use of these two specific types of cash-back rebates has not been examined empirically. These offers are part of manufacturers' pricing strategy which is built on customer recognition.

This chapter is the first empirical work which utilizes the insight of the theoretical literature of price discrimination by purchase history to examine the likelihood of offering conquest or loyalty rebates by manufacturers in the automobile market. My results suggest that the existing theoretical papers cannot fully explain how manufacturers' market share impacts the application of cash-back rebates to retain their own customers and poach their rivals' customers.

My findings imply that differentiated products and market share affect the manufacturers' decision to apply conquest cash and loyalty cash. Higher market share foreign manufactures and higher market share luxury brands are less likely to offer loyalty cash and conquest cash respectively. Moreover, higher market share domestic manufacturers are more likely to offer loyalty cash and higher market share non-luxury brand are more likely to offer conquest cash. Moreover, my findings do not show any consistent relationship between the likelihood of offering college-graduate and military discounts with manufacturers' market share. My hope is that future work with more data will provide us with a better understanding of the nature of these offers in the automobile market.

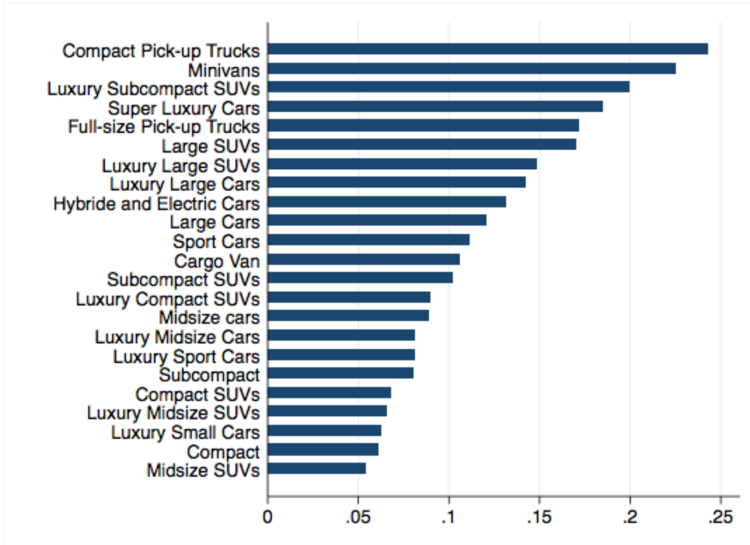

Figure 1.1: Average of Market Share within Segment in Previous Period

Table 1.1: Conditional Offers by Makes

Offers	**Makes**
Conquest Cash	Acura, Audi, BMW, Buick, Cadillac, Chevrolet, Chrysler, Dodge, Fiat, Ford, Genesis, GMC, Hyundai, Jeep, Kia, LandRover, Lexus, Lincoln, Mazda, Mitsubishi, Nissan, Porsche, Ram, Volvo
Loyalty Cash	Acura, Audi, BMW, Buick, Cadillac, Chevrolet, Chrysler, Dodge, Fiat, Ford, Genesis, GMC, Hyundai, Infiniti, Jaguar, Jeep, Kia, LandRover, Lexus, Lincoln, Mazda, Mini, Mitsubishi, Nissan, Porsche, Ram, Toyota, Volvo
College-Graduate Discount	Acura, BMW, Chrysler, Dodge, Ford, Genesis, Honda, Hyundai, Jeep, Kia, Lexus, Lincoln, Mini, Mitsubishi, Nissan, Porsche, Ram, Subaru, Toyota, Volkswagen
Military Discount	Acura, Audi, Chrysler, Dodge, Fiat, Ford, Genesis, Honda, Hyundai, Jeep, Kia, Lexus, Lincoln, Mazda, Mitsubishi, Nissan, Porsche, Ram, Toyota, Volkswagen

Notes: This table includes the list of makes which use the conditional offers in Decmeber 2017 to April 2018 in six cities of Boston, Chicago, Houston, Jacksonville, Kansas City, and New York City.

Table 1.2: Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Offering General Cash-Back	0.422	0.474	0	1	13,429
Offering Loyalty	0.651	0.459	0	1	13,429
Offering Conquest	0.321	0.449	0	1	13,429
Offering College-Graduate Discount	0.394	0.485	0	1	13,429
Offering Military Discount	0.528	0.494	0	1	13,429
Dollar Amount Offered as Loyalty	443.8	641.4	0	5,000	12,065
Dollar Amount Offered as Conquest	300.8	595.6	0	5,000	10,941
Market Share	0.101	0.1	0.0002	0.889	13,429
Price	37,789	2,2076	11,990	164,900	13,429
Model Year 2017	0.485	0.5	0	1	13,429
Foreign	0.692	0.462	0	1	13,429
Luxury	0.398	0.49	0	1	13,429
Horsepower	242.5	87.1	78	565	13,429
Wheelbase	112.7	57.7	73.7	2,018	13,429
Curb Weight	3,774	777	1,984	6,129	13,429
Cost per Mile	0.110	0.030	0.017	0.324	13,429

Notes: Summary Statistics are based on the offers available from December 2017 to April 2018 in six cities of Boston, Chicago, Houston, Jacksonville, Kansas City, and New York City. Offering loyalty, conquest, college graduate and military discounts are the fraction of these rebates among different trims of a nameplate.

Table 1.3: Magnitude of Simulataneous Offers

Make	**Conquest = Loyalty**	**Loyalty < Conquest**	**Loyalty > Conquest**
Acura	34.29%	65.71%	0
Audi	2.13%	58.51%	39.36%
Buick	6.67	92.22%	1.11%
Cadillac	0	98.63%	1.37%
Chevrolet	7.87%	73.03%	19.1%
Chrysler	0	86.36%	13.64%
Dodge	0	100%	0
Fiat	12.16%	87.84%	0
Ford	4.55%	6.82%	88.64%
GMC	24.14%	51.72%	24.14%
Genesis	71.43%	17.86%	10.71%
Hyundai	47.06%	52.94%	0
Jeep	16.67%	83.33%	0
Kia	100%	0	0
Land Rover	58.33%	41.67%	0
Lexus	52.5%	15%	32.5%
Lincoln	24.27%	48.54%	27.18%
Mazda	83.55%	16.45%	0
Nissan	33.33%	50%	16.67%
RAM	0	78.57%	21.43%
Volvo	0	100%	0

Notes: Some makes use simultaneous conquest and loyalty offers for a given nameplate. This table lists all three possible simultaneous offers based on their dollar amount from December 2017 to April 2018 in six cities of Boston, Chicago, Houston, Jacksonville, Kansas City, and New York City.

Table 1.4: Summary Statistics of Conditional Offers by Month

Offers by Month	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Offering Loyalty in December	0.635	0.463	0	1	2,772
Offering Conquest in December	0.328	0.45	0	1	2,772
Offering College Graduate Discount in December	0.438	0.492	0	1	2,772
Offering Military Discount in December	0.519	0.493	0	1	2,772
Offering Loyalty in January	0.646	0.463	0	1	2,739
Offering Conquest in January	0.305	0.444	0	1	2,739
Offering College Graduate Discount in January	0.397	0.485	0	1	2,739
Offering Military Discount in January	0.547	0.494	0	1	2,739
Offering Loyalty in Febuary	0.654	0.458	0	1	2,652
Offering Conquest in Febuary	0.325	0.452	0	1	2,652
Offering College Graduate Discount in Febuary	0.384	0.482	0	1	2,652
Offering Military Discount in Febuary	0.53	0.494	0	1	2,652
Offering Loyalty in March	0.671	0.452	0	1	2,674
Offering Conquest in March	0.354	0.46	0	1	2,674
Offering College Graduate Discount in March	0.359	0.476	0	1	2,674
Offering Military Discount in March	0.531	0.494	0	1	2,674
Offering Loyalty in April	0.648	0.462	0	1	2,592
Offering Conquest in April	0.293	0.439	0	1	2,592
Offering College Graduate Discount in April	0.389	0.485	0	1	2,592
Offering Military Discount in April	0.514	0.496	0	1	2,592

Notes: This table includes summary statistics of conquest and loyalty offers from December 2017 to April 2018 in six cities of Boston, Chicago, Houston, Jacksonville, Kansas City, and New York City. Offering loyalty, conquest, college graduate and military discounts are the fraction of these rebates among different trims of a nameplate.

Table 1.5: Loyalty and Conquest Offers and Market Share

	(1) Offering Loyalty	(2) Offering Conquest	(3) Offering Loyalty	(4) Offering Conquest	(5) Offering Loyalty	(6) Offering Conquest	(7) Offering Loyalty	(8) Offering Conquest
Market Share	-0.040	0.145	0.355**	0.291	0.046	0.395**	0.381*	0.616*
	(0.114)	(0.149)	(0.158)	(0.331)	(0.189)	(0.168)	(0.200)	(0.308)
Price/100,000	-0.056	0.021	-0.040	0.027	-0.059	0.011	-0.045	0.020
	(0.074)	(0.062)	(0.075)	(0.061)	(0.072)	(0.054)	(0.075)	(0.053)
Make Year	0.036	0.063***	0.036	0.063***	0.036	0.063***	0.036	0.063***
	(0.021)	(0.015)	(0.021)	(0.015)	(0.021)	(0.015)	(0.021)	(0.015)
Foreign x Market Share			-0.665***	-0.246			-0.566**	-0.389
			(0.170)	(0.318)			(0.250)	(0.327)
Luxury x Market Share					-0.193	-0.560**	-0.067	-0.743
					(0.174)	(0.240)	(0.189)	(0.443)
Luxury x Foreign x Market Share							-0.230	0.389
							(0.236)	(0.526)
Horsepower/1000	-0.341	-0.563*	-0.522	-0.630**	-0.316	-0.489*	-0.501	-0.547**
	(0.290)	(0.323)	(0.311)	(0.297)	(0.274)	(0.246)	(0.302)	(0.218)
Wheelbase/1000	-0.539***	-0.013	-0.542***	-0.014	-0.537***	-0.008	-0.539***	-0.011
	(0.035)	(0.027)	(0.037)	(0.027)	(0.035)	(0.025)	(0.038)	(0.025)
Curb Weight/1000	0.034	0.074*	0.039	0.076*	0.033	0.070*	0.039	0.069**
	(0.040)	(0.039)	(0.038)	(0.039)	(0.039)	(0.034)	(0.037)	(0.032)
Cost per Mile	0.350	0.300	0.427	0.328	0.371	0.362	0.438*	0.402*
	(0.265)	(0.262)	(0.250)	(0.265)	(0.270)	(0.240)	(0.245)	(0.228)
Make FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,429	13,429	13,429	13,429	13,429	13,429	13,429	13,429
R^2	0.606	0.590	0.610	0.590	0.607	0.593	0.610	0.594

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are clustered at segment level.

Table 1.6: Dollar Value of Loyalty and Conquest Offers and Market Share

	(1) Loyalty Amount	(2) Conquest Amount	(3) Loyalty Amount	(4) Conquest Amount	(5) Loyalty Amount	(6) Conquest Amount
Market Share	-120.777	255.194	-12.451	260.309	26.608	686.990
	(352.073)	(616.320)	(273.315)	(239.507)	(464.602)	(470.175)
Price/100,000	307.500	37.468	286.614	3.332	287.356	31.896
	(181.859)	(121.611)	(172.005)	(113.964)	(177.692)	(113.665)
Make Year	-101.859***	64.298**	-101.661***	65.619**	-101.467***	64.671**
	(30.586)	(25.821)	(30.784)	(25.241)	(30.675)	(25.317)
Foreign x Market Share	-271.818	-468.555			-55.167	-717.766
	(384.942)	(675.531)			(443.918)	(465.407)
Luxury x Market Share			-610.231*	-621.600	-356.778	-910.811
			(347.479)	(375.250)	(537.643)	(711.975)
Luxury x Foreign x Market Share					-488.512	591.441
					(545.204)	(783.792)
Horsepower/1000	-943.047**	-637.906	-789.260	-418.317	-863.356*	-542.439
	(446.787)	(501.798)	(459.652)	(432.093)	(481.200)	(439.268)
Wheelbase/1000	-298.461***	7390.528*	-290.907***	6978.699	-289.553***	7193.753*
	(92.873)	(3804.049)	(96.206)	(4134.170)	(92.794)	(3632.036)
Curb Weight/1000	87.222**	7.014	82.741*	2.467	87.401**	-2.662
	(41.074)	(65.728)	(42.083)	(65.513)	(40.113)	(63.506)
Cost per Mile	-48.012	-1166.108***	-24.200	-1122.458***	-10.312	-1069.250***
	(504.731)	(361.003)	(479.181)	(331.468)	(468.382)	(315.102)
Make FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle Class FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,065	10,941	12,065	10,941	12,065	10,941
R^2	0.587	0.475	0.588	0.476	0.589	0.478

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are clustered at segment level.

Table 1.7: Loyalty and Conquest Offers and Market Share Conditioned on Type

	Luxury Foreign		**Luxury Domestic**		**non-Luxury Foreign**		**non-Luxury Domestic**	
	Offering Loyalty	Offering Conquest	Offering Loyalty	Offering Conquest	Offering Loyalty	Offering Conquest	Offering Loyalty	Offering Conquest
Market Share	0.053	0.111	-0.003	-0.370	-0.482***	0.044	0.431*	0.836**
	(0.184)	(0.148)	(0.072)	(0.234)	(0.091)	(0.026)	(0.229)	(0.280)
Price/100,000	-0.069	-0.147	0.163	2.682	-0.094	0.007	0.928	0.821
	(0.176)	(0.108)	(0.726)	(1.614)	(0.147)	(0.016)	(0.640)	(0.875)
Make Year	0.075	0.097**	0.001	0.210*	0.001	0.001	0.049	0.101**
	(0.046)	(0.033)	(0.024)	(0.107)	(0.019)	(0.007)	(0.049)	(0.034)
Horsepower/1000	-0.727	-0.086	0.270	-11.461***	-0.668	-0.017	-1.592**	-1.693***
	(0.657)	(0.485)	(0.541)	(1.458)	(0.390)	(0.095)	(0.535)	(0.462)
Wheelbase/1000	-1.968	-2.565	3.358	-0.664	-0.541***	-0.027***	3.931	3.005
	(2.122)	(2.149)	(7.141)	(17.202)	(0.020)	(0.008)	(6.074)	(7.214)
Curb Weight/1000	-0.080*	-0.037	-0.040	-0.909***	0.062	0.006	0.030	0.197**
	(0.041)	(0.043)	(0.050)	(0.167)	(0.048)	(0.007)	(0.079)	(0.080)
Cost per Mile	4.147*	0.945	1.429	46.583***	1.493**	0.015	0.098	0.167
	(2.214)	(1.322)	(2.214)	(11.545)	(0.583)	(0.199)	(0.398)	(0.308)
Make FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.526	0.152	0.935	0.522	0.613	0.277	0.802	0.566
Observations	4,493	4,493	858	858	4,802	4,802	3,276	3,276
R^2	0.542	0.315	0.390	0.576	0.782	0.769	0.377	0.589

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are clustered at segment level.

Table 1.8: Loyalty and Conquest Offers and Origin

	(1) Offering Loyalty	(2) Offering Conquest	(3) Offering Loyalty	(4) Offering Conquest	(5) Offering Loyalty	(6) Offering Conquest	(7) Offering Loyalty	(8) Offering Conquest
Make Year	0.039	0.038	0.037	0.039	0.042	0.038	0.041	0.039
	(0.040)	(0.033)	(0.040)	(0.033)	(0.040)	(0.033)	(0.039)	(0.033)
Asian	-0.254*	-0.317**	-0.248*	-0.311**	-0.138	-0.297	-0.132	-0.291
	(0.139)	(0.147)	(0.139)	(0.148)	(0.137)	(0.186)	(0.133)	(0.186)
European	-0.219	-0.333**	-0.218	-0.326**	-0.399*	-0.327	-0.417*	-0.322
	(0.164)	(0.122)	(0.161)	(0.123)	(0.218)	(0.216)	(0.208)	(0.219)
Luxury	-0.034	-0.048	-0.029	-0.039	0.144	-0.001	0.145*	0.005
	(0.142)	(0.095)	(0.146)	(0.097)	(0.085)	(0.195)	(0.079)	(0.201)
Luxury x Asian					-0.417**	-0.078	-0.426**	-0.074
					(0.182)	(0.227)	(0.173)	(0.229)
Luxury x European					0.106	-0.041	0.127	-0.038
					(0.248)	(0.256)	(0.235)	(0.261)
Horsepower/1000	-0.363***	-0.682***	-0.573***	-0.971**	-0.272	-0.672***	-0.503*	-0.963**
	(0.116)	(0.240)	(0.194)	(0.375)	(0.202)	(0.231)	(0.259)	(0.365)
Wheelbase/1000	-0.266*	0.347***	-0.273**	0.330***	-0.365***	0.339***	-0.357***	0.322***
	(0.130)	(0.091)	(0.127)	(0.085)	(0.129)	(0.095)	(0.086)	(0.090)
Curb Weight/1000	0.032	-0.010	0.027	-0.004	0.032	-0.008	0.035	-0.001
	(0.048)	(0.045)	(0.052)	(0.065)	(0.047)	(0.045)	(0.044)	(0.061)
Cost per Mile	0.263	0.960	0.689	1.285*	0.224	0.967	0.658	1.289*
	(0.398)	(0.846)	(0.574)	(0.728)	(0.358)	(0.872)	(0.487)	(0.746)
Make FE	No	No	No	No	No	No	No	No
Vehicle Class FE	No	No	Yes	Yes	No	No	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,429	13,429	13,429	13,429	13,429	13,429	13,429	13,429
R^2	0.075	0.149	0.090	0.158	0.126	0.150	0.145	0.159

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are two-way clustered at make and segment level.

Table 1.9: Loyalty and Conquest Offers Conditioned on Origin by Type

	non-Luxury				**Luxury**			
	(1) Offering Loyalty	(2) Offering Conquest	(3) Offering Loyalty	(4) Offering Conquest	(5) Offering Loyalty	(6) Offering Conquest	(7) Offering Loyalty	(8) Offering Conquest
Make Year	0.011	-0.007	0.008	-0.008	0.096	0.108*	0.096	0.113*
	(0.046)	(0.033)	(0.044)	(0.033)	(0.064)	(0.056)	(0.067)	(0.052)
Asian	-0.139	-0.290	-0.125	-0.282	-0.547**	-0.376**	-0.562**	-0.378
	(0.155)	(0.187)	(0.135)	(0.188)	(0.172)	(0.155)	(0.174)	(0.231)
European	-0.405*	-0.316	-0.412*	-0.310	-0.272	-0.368**	-0.285	-0.364
	(0.218)	(0.217)	(0.200)	(0.212)	(0.178)	(0.156)	(0.178)	(0.226)
Horsepower/1000	-0.466**	-0.899**	-1.070**	-1.449**	-0.506	-0.557	-0.603	-0.978**
	(0.215)	(0.338)	(0.364)	(0.653)	(0.538)	(0.381)	(0.666)	(0.322)
Wheelbase/1000	-0.377**	0.308***	-0.390***	0.306***	4.900	3.495	4.769	-2.964***
	(0.152)	(0.084)	(0.075)	(0.093)	(4.243)	(5.584)	(7.920)	(0.476)
Curb Weight/1000	0.050	0.019	0.044	0.006	-0.068	-0.064	0.008	0.037
	(0.084)	(0.050)	(0.074)	(0.071)	(0.113)	(0.074)	(0.132)	(0.103)
Cost per Mile	-0.025	0.999	0.673	1.496*	3.848	1.178	4.381	2.567
	(0.210)	(0.955)	(0.401)	(0.715)	(3.695)	(2.133)	(3.714)	(2.311)
Make FE	No	No	No	No	No	No	No	No
Vehicle Class FE	No	No	Yes	Yes	No	No	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.690	0.393	0.690	0.393	0.592	0.211	0.592	0.211
Observations	8,078	8,078	8,078	8,078	5,351	5,351	5,351	5,351
R^2	0.092	0.114	0.139	0.131	0.170	0.158	0.175	0.176

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are two-way clustered at make and segment level.

Table 1.10: Net Conquest and Market Share

	(1) Net Conquest	(2) Net Conquest
Market Share	0.445	0.369
	(0.335)	(0.398)
price/100,000	-1.213*	-1.254*
	(0.650)	(0.691)
Make Year	0.027	0.027
	(0.033)	(0.034)
Asian x Market Share	-2.847**	-3.093
	(1.312)	(1.948)
European x Market Share	-0.410	-1.570
	(0.750)	(1.405)
Luxury x Market Share		0.157
		(0.549)
Asian x Luxury x Market Share		0.641
		(1.864)
European x Luxury x Market Share		1.622
		(1.474)
Horsepower/1000	0.700	0.649
	(0.855)	(0.884)
Wheelbase/1000	8.269	8.370
	(8.473)	(8.843)
Curb Weight/1000	-0.182*	-0.176
	(0.095)	(0.112)
Cost per Mile	-0.715	-0.760
	(0.420)	(0.452)
Make FE	Yes	Yes
Vehicle Class FE	Yes	Yes
City FE	Yes	Yes
Month FE	Yes	Yes
Observations	2,327	2,327
R^2	0.648	0.649

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are clustered at segment level.

Table 1.11: Net Conquest and Origin

	(1) Net Conquest	(2) Net Conquest	(3) Net Conquest	(4) Net Conquest
Make Year	0.013	-0.012	0.018	-0.010
	(0.044)	(0.043)	(0.044)	(0.044)
Asian	-0.619***	-0.640***	-0.604***	-0.664***
	(0.096)	(0.088)	(0.109)	(0.092)
European	-0.130	-0.123	0.058	0.044
	(0.143)	(0.129)	(0.122)	(0.097)
Luxury	-0.078	0.001	0.006	0.003
	(0.099)	(0.062)	(0.204)	(0.117)
Asian x Luxury			-0.037	0.121
			(0.215)	(0.157)
European x Luxury			-0.436	-0.343
			(0.258)	(0.201)
Horsepower/1000	0.697	0.378	0.460	0.048
	(0.928)	(0.793)	(1.056)	(0.915)
Wheelbase/1000	-3.708	10.315	-1.656	12.805
	(7.097)	(9.180)	(7.622)	(9.535)
Curb Weight/1000	-0.035	-0.312***	-0.019	-0.304**
	(0.102)	(0.109)	(0.116)	(0.115)
Cost per Mile	-1.475***	-0.767**	-1.545***	-0.967***
	(0.415)	(0.281)	(0.431)	(0.259)
Make FE	No	No	No	No
Vehicle Class FE	No	Yes	No	Yes
City FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	2,327	2,327	2,327	2,327
R^2	0.399	0.510	0.412	0.524

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are two-way clustered at make and segment level.

Table 1.12: Loyalty and Conquest Offers in December and Market Share

	(1) Offering Loyalty	(2) Offering Conquest	(3) Offering Loyalty	(4) Offering Conquest	(5) Offering Loyalty	(6) Offering Conquest
Market Share	0.471*	0.423	0.209	0.399*	0.489**	0.847**
	(0.227)	(0.460)	(0.129)	(0.197)	(0.181)	(0.375)
Price/100,000	-0.108	-0.005	-0.139	-0.039	-0.121	-0.011
	(0.100)	(0.070)	(0.098)	(0.080)	(0.097)	(0.083)
Make Year	-0.018	0.016	-0.017	0.016	-0.018	0.013
	(0.020)	(0.019)	(0.021)	(0.019)	(0.021)	(0.019)
Foreign x Market Share	-0.635**	-0.470			-0.455*	-0.813*
	(0.255)	(0.470)			(0.243)	(0.400)
Luxury x Market Share			-0.341	-0.689**	-0.061	-1.284***
			(0.244)	(0.271)	(0.340)	(0.445)
Luxury x Foreign x Market Share					-0.769	2.096*
					(0.774)	(1.035)
Horsepower/1000	-0.458	-0.880**	-0.230	-0.643**	-0.408	-0.744***
	(0.394)	(0.334)	(0.333)	(0.270)	(0.406)	(0.236)
Wheelbase/1000	2.198	0.809	1.704	0.643	2.288	1.074
	(3.865)	(4.163)	(3.663)	(3.795)	(3.823)	(4.129)
Curb Weight/1000	0.035	0.110	0.030	0.100	0.034	0.089
	(0.053)	(0.065)	(0.052)	(0.059)	(0.055)	(0.055)
Cost per Mile	0.394	0.297	0.350	0.309	0.406*	0.393
	(0.254)	(0.475)	(0.244)	(0.431)	(0.229)	(0.383)
Make FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle Class FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,772	2,772	2,772	2,772	2,772	2,772
R^2	0.772	0.723	0.770	0.726	0.774	0.731

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are clustered at segment level.

Table 1.13: Loyalty and Conquest Offers in January and Market Share

	(1) Offering Loyalty	(2) Offering Conquest	(3) Offering Loyalty	(4) Offering Conquest	(5) Offering Loyalty	(6) Offering Conquest
Market Share	0.707*	0.351	0.267	0.502**	1.270***	1.064**
	(0.354)	(0.491)	(0.290)	(0.195)	(0.358)	(0.387)
Price/100,000	0.019	0.100	-0.039	0.070	0.002	0.080
	(0.108)	(0.067)	(0.092)	(0.054)	(0.084)	(0.057)
Make Year	0.043*	0.063***	0.043*	0.063***	0.041	0.061***
	(0.024)	(0.017)	(0.024)	(0.018)	(0.024)	(0.018)
Foreign x Market Share	-1.198***	-0.290			-1.773***	-1.035**
	(0.382)	(0.506)			(0.378)	(0.415)
Luxury x Market Share			-0.757**	-0.830***	-1.588***	-2.006***
			(0.289)	(0.293)	(0.213)	(0.316)
Luxury x Foreign x Market Share					1.637***	2.112***
					(0.301)	(0.356)
Horsepower/1000	-1.491**	-0.795**	-1.072**	-0.604**	-1.300***	-0.557**
	(0.602)	(0.343)	(0.497)	(0.270)	(0.410)	(0.209)
Wheelbase/1000	2.315	2.045	1.064	1.991	2.208	1.897
	(4.008)	(3.413)	(3.159)	(2.906)	(4.144)	(3.354)
Curb Weight/1000	0.073	0.053	0.070	0.044	0.057	0.034
	(0.061)	(0.054)	(0.054)	(0.048)	(0.050)	(0.042)
Cost per Mile	1.040**	0.701**	0.960**	0.744**	1.114**	0.793***
	(0.411)	(0.307)	(0.432)	(0.286)	(0.433)	(0.239)
Make FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle Class FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,739	2,739	2,739	2,739	2,739	2,739
R^2	0.754	0.737	0.749	0.743	0.765	0.755

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are clustered at segment level.

Table 1.14: Loyalty and Conquest Offers in Febuary and Market Share

	(1) Offering Loyalty	(2) Offering Conquest	(3) Offering Loyalty	(4) Offering Conquest	(5) Offering Loyalty	(6) Offering Conquest
Market Share	0.314	0.280	-0.069	0.464**	0.634*	1.017**
	(0.310)	(0.528)	(0.237)	(0.206)	(0.367)	(0.434)
Price/100,000	0.069	0.108	0.036	0.085	0.070	0.095
	(0.065)	(0.068)	(0.056)	(0.058)	(0.064)	(0.058)
Make Year	0.029	0.059***	0.028	0.059***	0.028	0.058***
	(0.030)	(0.018)	(0.030)	(0.018)	(0.030)	(0.019)
Foreign x Market Share	-0.676**	-0.191			-1.202***	-0.990**
	(0.317)	(0.521)			(0.364)	(0.432)
Luxury x Market Share			-0.132	-0.743**	-0.832***	-1.995***
			(0.251)	(0.324)	(0.287)	(0.370)
Luxury Foreign x Market Share					1.320***	2.188***
					(0.342)	(0.381)
Horsepower/1000	-0.512*	-0.768*	-0.294	-0.616*	-0.439*	-0.547**
	(0.272)	(0.377)	(0.231)	(0.308)	(0.220)	(0.203)
Wheelbase/1000	3.304	1.386	2.510	1.456	3.007	1.059
	(2.781)	(3.277)	(2.516)	(2.839)	(3.106)	(3.272)
Curb Weight/1000	-0.007	0.075	-0.007	0.067	-0.014	0.056
	(0.037)	(0.056)	(0.036)	(0.049)	(0.033)	(0.040)
Cost per Mile	0.471*	0.534**	0.380	0.566**	0.523*	0.659***
	(0.272)	(0.255)	(0.281)	(0.241)	(0.300)	(0.213)
Make FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle Class FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,652	2,652	2,652	2,652	2,652	2,652
R^2	0.734	0.731	0.731	0.736	0.739	0.749

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are clustered at segment level.

Table 1.15: Loyalty and Conquest Offers in March and Market Share

	(1) Offering Loyalty	(2) Offering Conquest	(3) Offering Loyalty	(4) Offering Conquest	(5) Offering Loyalty	(6) Offering Conquest
Market Share	0.399**	0.050	-0.093	0.023	0.490*	0.089
	(0.187)	(0.220)	(0.239)	(0.126)	(0.244)	(0.229)
Price/100000	-0.022	-0.125	-0.041	-0.127	-0.017	-0.125
	(0.068)	(0.090)	(0.067)	(0.088)	(0.070)	(0.091)
Make Year	0.075***	0.058**	0.076***	0.058**	0.075***	0.058**
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Foreign x Market Share	-0.725***	-0.048			-1.029***	-0.122
	(0.244)	(0.216)			(0.317)	(0.246)
Luxury x Market Share			0.075	-0.005	-0.230	-0.101
			(0.221)	(0.160)	(0.187)	(0.281)
Luxury x Foreign x Market Share					0.671**	0.176
					(0.252)	(0.317)
Horsepower/1000	-0.137	0.084	0.060	0.098	-0.132	0.090
	(0.232)	(0.235)	(0.195)	(0.212)	(0.225)	(0.245)
Wheelbase/1000	-0.563***	-0.012	-0.555***	-0.011	-0.569***	-0.013
	(0.018)	(0.015)	(0.019)	(0.017)	(0.018)	(0.016)
Curb Weight/1000	-0.006	-0.013	-0.011	-0.014	-0.011	-0.015
	(0.028)	(0.029)	(0.032)	(0.028)	(0.028)	(0.029)
Cost per Mile	0.337	-0.052	0.214	-0.059	0.345	-0.045
	(0.200)	(0.246)	(0.236)	(0.233)	(0.226)	(0.242)
Make FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle Class FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,674	2,674	2,674	2,674	2,674	2,674
R^2	0.814	0.776	0.810	0.776	0.815	0.776

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are clustered at segment level.

Table 1.16: Loyalty and Conquest Offers in April and Market Share

	(1) Offering Loyalty	(2) Offering Conquest	(3) Offering Loyalty	(4) Offering Conquest	(5) Offering Loyalty	(6) Offering Conquest
Market Share	0.271*	0.419	-0.055	0.554**	0.365	1.091**
	(0.134)	(0.295)	(0.200)	(0.208)	(0.227)	(0.411)
Price/100000	-0.068	0.066	-0.073	0.056	-0.057	0.084
	(0.065)	(0.102)	(0.068)	(0.089)	(0.067)	(0.089)
Make Year	0.071***	0.101***	0.071***	0.104***	0.070***	0.103***
	(0.025)	(0.015)	(0.024)	(0.016)	(0.025)	(0.016)
Foreign x Market Share	-0.501**	-0.287			-0.749**	-0.969**
	(0.210)	(0.324)			(0.274)	(0.432)
Luxury x Market Share			0.144	-0.513	-0.158	-1.092**
			(0.202)	(0.339)	(0.219)	(0.522)
Luxury x Foreign x Market Share					0.528*	1.177**
					(0.267)	(0.561)
Horsepower/1000	-0.049	-0.825*	0.046	-0.687*	-0.076	-0.810**
	(0.236)	(0.445)	(0.225)	(0.391)	(0.228)	(0.354)
Wheelbase/1000	0.278	-0.099	-0.425	-0.745	0.143	-0.506
	(2.103)	(3.645)	(1.938)	(3.242)	(2.196)	(3.817)
Curb Weight/1000	0.001	0.115*	0.006	0.118**	-0.000	0.111**
	(0.032)	(0.058)	(0.032)	(0.054)	(0.031)	(0.050)
Cost per Mile	0.160	0.343	0.084	0.390	0.172	0.497*
	(0.193)	(0.344)	(0.204)	(0.314)	(0.206)	(0.289)
Make FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle Class FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,592	2,592	2,592	2,592	2,592	2,592
R^2	0.806	0.710	0.804	0.712	0.807	0.718

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are clustered at segment level.

Table 1.17: College Graduate and Military Discounts and Market Share

	(1) Offering Col. Grad. Discounts	(2) Offering Military Discounts	(3) Offering Col. Grad. Discounts	(4) Offering Military Discounts	(5) Offering Col. Grad. Discounts	(6) Offering Military Discounts	(7) Offering Col. Grad. Discounts	(8) Offering Military Discounts
Market Share	0.243*	-0.053	0.144	0.036	0.370*	-0.085	0.166	-0.059
	(0.136)	(0.067)	(0.123)	(0.091)	(0.194)	(0.078)	(0.112)	(0.066)
Price/100000	-0.127**	-0.122**	-0.131**	-0.118**	-0.133**	-0.121**	-0.141**	-0.120**
	(0.055)	(0.044)	(0.055)	(0.043)	(0.053)	(0.044)	(0.054)	(0.043)
Make Year	0.008	-0.005	0.008	-0.005	0.008	-0.005	0.008	-0.005
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Foreign x Market Share			0.167	-0.150			0.362	-0.037
			(0.266)	(0.089)			(0.336)	(0.114)
Luxury x Market Share					-0.284	0.071	-0.065	0.210**
					(0.203)	(0.061)	(0.195)	(0.099)
Luxury x Foreign x Market Share							-0.461	-0.282
							(0.358)	(0.224)
Horsepower/1000	-0.509	-0.260	-0.463	-0.301	-0.472	-0.269	-0.430	-0.315
	(0.387)	(0.238)	(0.420)	(0.255)	(0.369)	(0.248)	(0.419)	(0.275)
Wheelbase/1000	-0.485***	-0.007	-0.484***	-0.008	-0.482***	-0.008	-0.479***	-0.007
	(0.030)	(0.016)	(0.030)	(0.016)	(0.029)	(0.017)	(0.029)	(0.016)
Curb Weight/1000	0.003	0.046**	0.002	0.047**	0.001	0.047**	0.002	0.049**
	(0.037)	(0.020)	(0.038)	(0.019)	(0.035)	(0.020)	(0.036)	(0.021)
Cost per Mile	0.457	0.105	0.438	0.123	0.488	0.097	0.452	0.105
	(0.332)	(0.271)	(0.350)	(0.270)	(0.313)	(0.270)	(0.319)	(0.256)
Make FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,429	13,429	13,429	13,429	13,429	13,429	13,429	13,429
R^2	0.841	0.916	0.841	0.917	0.842	0.916	0.842	0.917

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are clustered at segment level.

Table 1.18: College Graduate and Military Discounts and Origin

	(1) Offering Col. Grad. Discounts	(2) Offering Military Discounts	(3) Offering Col. Grad. Discounts	(4) Offering Military Discounts	(5) Offering Col. Grad. Discounts	(6) Offering Military Discounts	(7) Offering Col. Grad. Discounts	(8) Offering Military Discounts
Make Year	0.042**	0.032	0.044**	0.035*	0.041**	0.032	0.044*	0.035*
	(0.019)	(0.020)	(0.019)	(0.017)	(0.019)	(0.021)	(0.023)	(0.018)
Asian	0.265	0.270	0.267	0.273	0.357	0.329	0.367	0.334
	(0.212)	(0.221)	(0.196)	(0.204)	(0.237)	(0.242)	(0.220)	(0.227)
European	0.165	0.066	0.159	0.056	0.379	0.114	0.384	0.121
	(0.244)	(0.237)	(0.241)	(0.231)	(0.302)	(0.273)	(0.278)	(0.267)
Luxury	-0.137	-0.300*	-0.196	-0.339**	0.153	-0.149	0.110	-0.180
	(0.184)	(0.148)	(0.168)	(0.145)	(0.325)	(0.304)	(0.315)	(0.295)
Luxury x Asian					-0.372	-0.231	-0.397	-0.239
					(0.378)	(0.353)	(0.364)	(0.346)
Luxury x European					-0.485	-0.170	-0.512	-0.201
					(0.411)	(0.398)	(0.393)	(0.387)
Horsepower/1000	-0.291	-0.022	-0.501	-0.361*	-0.281	0.001	-0.474	-0.338*
	(0.351)	(0.038)	(0.523)	(0.177)	(0.362)	(0.114)	(0.505)	(0.174)
Wheelbase/1000	-0.195	0.038	-0.156	0.085	-0.186	0.022	-0.161	0.069
	(0.142)	(0.167)	(0.115)	(0.118)	(0.143)	(0.160)	(0.118)	(0.116)
Curb Weight/1000	0.070	0.046	0.197*	0.158**	0.085	0.051**	0.222*	0.171***
	(0.072)	(0.035)	(0.106)	(0.056)	(0.068)	(0.022)	(0.115)	(0.060)
Cost per Mile	-1.958**	-1.161***	-1.757**	-0.541	-1.861**	-1.131**	-1.691*	-0.517
	(0.745)	(0.231)	(0.765)	(0.630)	(0.884)	(0.405)	(0.867)	(0.671)
Make FE	No	No	No	No	No	No	No	No
Vehicle Class FE	No	No	Yes	Yes	No	No	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,429	13,429	13,429	13,429	13,429	13,429	13,429	13,429
R^2	0.090	0.157	0.110	0.187	0.117	0.164	0.140	0.195

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are two-way clustered at make and segment level.

Table 1.19: College Graduate and Military Discounts in December and Market Share

	(1) Offering Col. Grad. Discounts	(2) Offering Military Discounts	(3) Offering Col. Grad. Discounts	(4) Offering Military Discounts	(5) Offering Col. Grad. Discounts	(6) Offering Military Discounts
Market share	0.126	-0.064	0.393**	-0.127	0.142	-0.140
	(0.142)	(0.128)	(0.184)	(0.094)	(0.138)	(0.098)
Price/100000	-0.194***	-0.201***	-0.195***	-0.198***	-0.211***	-0.199***
	(0.061)	(0.060)	(0.068)	(0.059)	(0.065)	(0.057)
Make Year	-0.016*	-0.002	-0.017*	-0.002	-0.015	-0.002
	(0.009)	(0.007)	(0.009)	(0.007)	(0.009)	(0.007)
Foreign x Market Share	0.209	-0.023			0.454	0.032
	(0.283)	(0.116)			(0.345)	(0.120)
Luxury x Market Share			-0.353*	0.124	-0.057	0.232
			(0.189)	(0.105)	(0.198)	(0.175)
Luxury x Foreign x Market Share					-1.054	-0.350
					(0.676)	(0.419)
Horsepower/1000	-0.289	-0.267	-0.290	-0.280	-0.226	-0.293
	(0.256)	(0.271)	(0.213)	(0.282)	(0.253)	(0.311)
Wheelbase/1000	0.818	-1.495	1.193	-1.575	0.931	-1.545
	(2.137)	(1.285)	(2.299)	(1.360)	(2.010)	(1.323)
Curb Weight/1000	-0.019	0.064**	-0.025	0.066**	-0.020	0.068**
	(0.045)	(0.026)	(0.044)	(0.028)	(0.045)	(0.031)
Cost per Mile	0.245	-0.141	0.307	-0.157	0.259	-0.159
	(0.297)	(0.168)	(0.259)	(0.170)	(0.265)	(0.165)
Make FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle Class FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,772	2,772	2,772	2,772	2,772	2,772
R^2	0.890	0.952	0.890	0.952	0.892	0.952

Notes: Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are clustered at segment level.

Table 1.20: College Graduate and Military Discounts in January and Market Share

	(1) Offering Col. Grad. Discounts	(2) Offering Military Discounts	(3) Offering Col. Grad. Discounts	(4) Offering Military Discounts	(5) Offering Col. Grad. Discounts	(6) Offering Military Discounts
Market share	0.181	0.085	0.347	-0.050	0.116	0.024
	(0.144)	(0.107)	(0.214)	(0.084)	(0.137)	(0.072)
Price/100000	-0.139***	-0.082	-0.142***	-0.088*	-0.148***	-0.081
	(0.042)	(0.048)	(0.040)	(0.048)	(0.041)	(0.050)
Make Year	0.013*	0.003	0.012*	0.003	0.013*	0.003
	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
Foreign x Market Share	0.101	-0.189*			0.422	-0.119
	(0.290)	(0.100)			(0.391)	(0.149)
Luxury x Market Share			-0.261	0.045	0.147	0.171
			(0.220)	(0.068)	(0.221)	(0.150)
Luxury x Foreign x Market Share					-0.742	-0.194
					(0.447)	(0.314)
Horsepower/1000	-0.458	-0.327	-0.448	-0.284	-0.448	-0.347
	(0.385)	(0.278)	(0.333)	(0.263)	(0.409)	(0.305)
Wheelbase/10000	1.965	-0.603	2.196	-0.864	2.156	-0.586
	(2.013)	(1.173)	(2.069)	(1.274)	(1.907)	(1.161)
Curb Weight/1000	-0.025	0.049***	-0.028	0.051**	-0.024	0.051**
	(0.044)	(0.017)	(0.043)	(0.018)	(0.046)	(0.020)
Cost per Mile	0.407	0.125	0.445	0.097	0.421	0.118
	(0.380)	(0.270)	(0.341)	(0.268)	(0.340)	(0.260)
Make FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle Class FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,739	2,739	2,739	2,739	2,739	2,739
R^2	0.864	0.951	0.864	0.951	0.866	0.951

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are clustered at segment level.

Table 1.21: College Graduate and Military Discounts in Febuary and Market Share

	(1) Offering Col. Grad. Discounts	(2) Offering Military Discounts	(3) Offering Col. Grad. Discounts	(4) Offering Military Discounts	(5) Offering Col. Grad. Discounts	(6) Offering Military Discounts
Market share	0.150	0.053	0.351	-0.088	0.064	-0.009
	(0.148)	(0.111)	(0.215)	(0.085)	(0.127)	(0.064)
Price/100000	-0.147***	-0.086*	-0.145***	-0.092*	-0.155***	-0.084*
	(0.044)	(0.046)	(0.040)	(0.046)	(0.044)	(0.048)
Make Year	0.007	-0.024**	0.007	-0.024**	0.007	-0.024**
	(0.007)	(0.011)	(0.007)	(0.011)	(0.008)	(0.011)
Foreign x Market Share	0.144	-0.167			0.500	-0.123
	(0.280)	(0.104)			(0.369)	(0.129)
Luxury x Market Share			-0.260	0.079	0.185	0.173
			(0.217)	(0.069)	(0.206)	(0.158)
Luxury x Foreign x Market Share					-0.799*	-0.135
					(0.426)	(0.318)
Horsepower/1000	-0.440	-0.339	-0.449	-0.299	-0.432	-0.360
	(0.390)	(0.280)	(0.332)	(0.265)	(0.414)	(0.309)
Wheelbase/10000	1.711	-0.947	2.001	-1.189	1.976	-0.940
	(1.712)	(1.045)	(1.727)	(1.180)	(1.559)	(1.064)
Curb Weight/1000	-0.020	0.056***	-0.023	0.057***	-0.019	0.057***
	(0.042)	(0.017)	(0.041)	(0.018)	(0.045)	(0.019)
Cost per Mile	0.405	0.151	0.448	0.119	0.395	0.140
	(0.396)	(0.307)	(0.356)	(0.304)	(0.355)	(0.299)
Make FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle Class FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,652	2,652	2,652	2,652	2,652	2,652
R^2	0.915	0.930	0.915	0.930	0.917	0.930

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are clustered at segment level.

Table 1.22: College Graduate and Military Discounts in March and Market Share

	(1) Offering Col. Grad. Discounts	(2) Offering Military Discounts	(3) Offering Col. Grad. Discounts	(4) Offering Military Discounts	(5) Offering Col. Grad. Discounts	(6) Offering Military Discounts
Market share	0.154	0.002	0.390*	-0.105	0.107	-0.081
	(0.153)	(0.108)	(0.181)	(0.094)	(0.101)	(0.077)
Price/100000	-0.097	-0.126**	-0.095	-0.129**	-0.103	-0.126**
	(0.107)	(0.051)	(0.102)	(0.052)	(0.108)	(0.052)
Make Year	0.015*	0.000	0.015*	0.000	0.016*	-0.000
	(0.008)	(0.006)	(0.008)	(0.006)	(0.008)	(0.006)
Foreign x Market Share	0.175	-0.115			0.518	-0.029
	(0.277)	(0.106)			(0.339)	(0.170)
Luxury x Market Share			-0.274	0.076	0.110	0.221
			(0.189)	(0.073)	(0.214)	(0.140)
Luxury x Foreign x Market Share					-0.714*	-0.232
					(0.391)	(0.320)
Horsepower/1000	-0.474	-0.241	-0.498	-0.216	-0.461	-0.262
	(0.601)	(0.250)	(0.537)	(0.237)	(0.613)	(0.275)
Wheelbase/10000	-0.513***	-0.000	-0.513***	0.001	-0.505***	0.000
	(0.015)	(0.009)	(0.013)	(0.009)	(0.015)	(0.010)
Curb Weight/1000	0.007	0.050**	0.007	0.049**	0.012	0.052**
	(0.037)	(0.018)	(0.034)	(0.019)	(0.038)	(0.021)
Cost per Mile	0.670*	0.114	0.732**	0.086	0.675**	0.096
	(0.361)	(0.303)	(0.315)	(0.301)	(0.325)	(0.291)
Make FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle Class FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,674	2,674	2,674	2,674	2,674	2,674
R^2	0.877	0.935	0.878	0.935	0.879	0.935

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are clustered at segment level.

Table 1.23: College Graduate and Military Discounts in April and Market Share

	(1) Offering Col. Grad. Discounts	(2) Offering Military Discounts	(3) Offering Col. Grad. Discounts	(4) Offering Military Discounts	(5) Offering Col. Grad. Discounts	(6) Offering Military Discounts
Market share	0.139	0.102	0.426**	-0.007	0.137	0.022
	(0.087)	(0.085)	(0.195)	(0.092)	(0.091)	(0.073)
Price/100000	-0.044	-0.114**	-0.046	-0.116**	-0.065	-0.120**
	(0.072)	(0.051)	(0.067)	(0.052)	(0.071)	(0.051)
Make Year	0.015**	0.011	0.016**	0.011	0.016**	0.011
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Foreign x Market Share	0.167	-0.203			0.527	-0.044
	(0.270)	(0.119)			(0.336)	(0.178)
Luxury x Market Share			-0.378*	0.016	0.018	0.133
			(0.202)	(0.081)	(0.134)	(0.081)
Luxury x Foreign x Market Share					-0.854**	-0.324
					(0.333)	(0.244)
Horsepower/1000	-0.517	-0.335	-0.502	-0.290	-0.450	-0.322
	(0.470)	(0.265)	(0.425)	(0.253)	(0.469)	(0.266)
Wheelbase/10000	2.498	-0.413	2.598	-0.715	2.682	-0.325
	(1.767)	(1.040)	(1.883)	(1.211)	(1.652)	(1.018)
Curb Weight/1000	-0.024	0.051***	-0.026	0.053***	-0.022	0.052***
	(0.045)	(0.016)	(0.043)	(0.017)	(0.045)	(0.017)
Cost per Mile	0.554	0.303	0.630**	0.279	0.576*	0.290
	(0.339)	(0.378)	(0.297)	(0.378)	(0.297)	(0.359)
Make FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle Class FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,592	2,592	2,592	2,592	2,592	2,592
R^2	0.881	0.929	0.882	0.929	0.884	0.929

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors in parenthesis are clustered at segment level.

Chapter 2

My Words Against Yours: Case Study of Descriptions of Airbnb's Listings in San Francisco

2.1 Introduction

The existence of online markets expands the possibility of the transaction of wide ranges of experience goods. The experience goods can be defined as goods or services which their quality is unknown to consumers before consumption. Just like any other markets, information in experience good markets is invaluable. The buyers in online markets rely on the information which is part of product description and pictures provided by sellers. Although sellers voluntarily disclose some information about quality to attract the buyers, the precision and amount of information may not be adequate or accurate.

Airbnb is one of the online platforms which travelers can book accommodation as an experience good. This platform is one of the well-known players of sharing economy, and presents itself as "... a trusted community marketplace for people to list, discover, and book unique accommodations around the world — online or from a mobile phone or tablet". The users of this platform are divided into hosts and guests. Hosts are the providers of accommodation and guests are seekers of accommodation.[1]

New listings in different cities join the platform every day. Airbnb serves in more than 191 countries and has accommodated more than 60 million guests during recent years. The description of listings on Airbnb is a way for hosts to share information about their listing. As the number of listings in a given neighborhood or city increases, the competition among listings is expected to increase which may affect the amount of information disclosed by hosts.

The importance of information in the market place has been known to economists. Stigler (1961) and Akerlof (1978) show that asymmetric information leads to market power. Salop (1976) mentions that markets with imperfect information can be described as monopolistic competition rather than perfect competition. Cheong and Kim (2004) show that if information disclosure is costly in an oligopoly environment, no firm will reveal any information as the number of competing firms increases. Hotz and Xiao (2013) explain a model which includes product differentiation with multi-dimensional attributes and heterogeneous customers. They conclude that firms decide not to disclose information because disclosure may change demand elasticities and increase price competition between competing firms. Levin et al. (2009) compare costly information disclosure in duopoly market and cartels. Their findings show that a cartel is expected to reveal more information compared to a duopoly environment. Clinch and Verrecchia (1997) and Board (2009) explain that likelihood of disclosure decreases as the intensity of competition increases, whereas Stivers (2004) show that

[1]There are three ways of hosting on Airbnb; hosting the extra, hosting for an acquaintance as a co-host, and organizing experience. My main focus in this chapter is the first group of hosts.

increase in a number of competitors or intensity in competition among current sellers results in higher disclosure.

According to these theoretical papers, the impact of competition on information disclosure does not follow a clear direction which highlights the necessity of more empirical work in different settings. Jin (2005) examines how competition impacts disclosure incentives among health maintenance organizations. Her findings show that in a highly competitive market, the disclosure rate is low, and voluntary disclosure is a way for firms to differentiate their product. Jin and Leslie (2003) examine the impact of restaurants hygiene grade cards as a measure of revealing information on the quality of restaurants. Their empirical findings show that the grade cards reduce the search cost which causes an increase in competition. Lewis (2011) examines the impact of information disclosure on automobile auction at eBay and finds that disclosure occurs selectively. He adds that the cost of the disclosure can impact the amount of disclosure and the price which seller sets.

In this chapter, I empirically estimate how competition among Airbnb's listings in San Francisco and its surrounding cities impacts information disclosure about the quality of listings. Heterogeneity among Airbnb's listings is high, and it is plausible that information disclosure differentiates listings for guests. Therefore, I expect to see more information disclosure as the number of competing listings increases. The revealed information is measured by the number of words in listings description provided by the hosts, and competition is based on the proximity of same room type listings.

My empirical results suggest that an increase in the number of listings within five miles affects the number of words hosts use to describe their listings. These results are stronger and more statistically significant for private rooms than for entire house/apartment listings. A higher number of private rooms within half a mile adds on average 2 words to the description. Additional private room listings in further distances have a smaller impact on the description. Even though this marginal effect is relatively minor, it shows the positive effect of competition on the amount of information revealed by hosts. Section 2.2 describes data and develops an empirical strategy. In section 2.3, I provide the descriptive results. The last section concludes and describes possible work for the future.

2.2 Data and Empirical Startegy

To get data for Airbnb's listings, I web-scrape publicly available listings from the platform. I need to fill in a destination, check in and check out dates, and the number of guests to get the listings available in this platform. I choose San Francisco in California as the destination city because it is one of the top tourist attractions in the United States. The data are gathered on January 14th of 2017 for check in and check out dates of Friday, February 3rd to Sunday, February 5th of 2017.[2] Although I use San Francisco as the destination, Airbnb includes listings in the surrounding cities in the Bay Area. In my dataset, 53% of the listings are located in San Francisco. Table 12 in the Appendix presents the frequency of listings in the surrounding cities. Moreover, I enter one person for the number of guests, and the results include listings with at least one guest.

I possess features which can be categorized into two groups; listing's characteristics and host's characteristics. Listing's characteristics include information about listing's location, type of room, type of property, having instant-booking option, guests capacity, number of bedrooms and bathrooms, allowing guests to have infants

[2] I pick this date because it was part of a dataset which I already had for a different project. January 14th includes the highest number of listings for the early February check-in and check-out date.

and children, allowing guests to have a pet, and allowing guests to smoke.[3] Host's characteristics are whether a host speaks at least a foreign language, whether a host has at least a pet, and type of cancelation policy which a host sets.

Entire house or apartment, private room, and shared room are three room types available on Airbnb. I drop the shared rooms since they are less than 5% of the listings in my dataset. Property types for Airbnb's listings are versatile. I limit my dataset to the listings with property types including apartment, condominium, house, guesthouse, and loft. These property types consist 92% of my dataset which makes the number of observations to 3,026 listings. The rest of the dataset has either unspecified property types or less conventional property types.[4] Hosts can choose flexible, moderate, and strict cancelation policies for a short-term stay. These policies specify the portion of refund a guest can get within specified days of the trip. The summary statistics of San Francisco's listings are shown in Table 2.1.

Although I access to coordinates of each listing, this information is not accurate. Due to privacy issues, Airbnb does not provide the exact coordinates. However, these coordinates provide a relatively good idea where the listings are located. I use geo-mapping to determine the neighborhoods for listings in San Francisco based on the coordinates. I merge the neighborhoods' data with information provided by https://www.walkscore.com which includes walking, transit and biking scores for different San Francisco's neighborhoods.[5] Each of these scores is scaled between 0 to 100

[3]Instant booking is an option which a guest can book a listing without getting approved by a host.

[4]Less conventional property types include boat, bungalow, cabin, camper/RV, cave, chalet, dorm, serviced apartment, tent, townhouse, treehouse, and villa. I exclude listings which are bed and breakfast, boutique hotels and hostels to focus on hosts who do not provide accommodation as a full-time and professional job.

[5]In San Francisco's neighborhoods, safety and walkability can vary by block to block. Therefore, https://www.walkscore.com assigns a score based on sub-neighborhoods. For instance, Mission neighborhood in walkscore.com is divided into smaller sub-neighborhoods. Unfortunately, there is no unified definition for such sub-neighborhoods available. Therefore, I rely on the scores on the neighborhood scale.

where 100 is the highest score. The walking score is based on an average of ratings given to categories such as dining and drinking, groceries, shopping, errands, parks, schools, culture, and entertainment. The transit score measures the availability of public transportation based on its type and proximity. The biking score evaluates the availability of bike lanes and road connection.

To examine the effect of competition on information disclosure in San Francisco's listings I use

$$Word\ Count_{lp} = \alpha + \beta_1 Competition_{lp} + \beta_2 X_l + \beta_3 Z_l + \beta_4 N_l + \gamma_p + \epsilon_{lp} \tag{2.1}$$

where *Word Count* is the number of words used in listing's description written by a host for listing l with property type p and it is a proxy for information discloure.

Competition in the specification (1) is the variable of interest which measures the number of listings within a certain distance. The variable of interest is calculated for less than half a mile, one mile, and five miles. For listings in San Francisco, I do not use listings beyond five miles because the width of San Francisco is measured as maximum 12 miles. To calculate the number of listings within a certain distance, I divide the listings based on their room types. In other words, for a given listing as a private room, I count the number of private room listings in the certain distance, and for a given listing as an entire house or apartment, I count the number of entire house or apartment listings in the certain distance. I use Vincenty distance to calculate the distance between two coordinates. The Vincenty distance considers the ellipsoidal feature of the earth which provides a relatively accurate measure for a distance between two locations. From calculating the Vincenty distance, I get a matrix which shows how far a listing is from other listings and I count the number of listings within half a mile, one mile, and five miles as an estimate for competition.[6] Although the heterogeneity among listings of the same room type is quite significant, the number of listing can be a relative measure for competition for each listing with the same room type.

X, Z, and N are listing's, host's, and neighborhood's characteristics respectively. To control for average differences across property types on listing's description, I include property type fixed effect γ_p.

Moreover, to examine the impact competition on information disclosure with a given room type in San Francisco and surrounding cities, I use

$$Word\ Count_{lpc} = \alpha + \beta_1 Competition_{lpc} + \beta_2 X_l + \beta_3 Z_l + \gamma_p + \zeta_c + \epsilon_{lpc} \tag{2.2}$$

where *Word Count* is the number of words used in the listing's description written by a host for listing l with property type p in city c. Besides property fixed effects, I include city fixed effect ζ_c to control for average differences across cities on an amount of listing's description.

2.3 Results

In this section, first, I focus on listings in San Francisco's neighborhoods to examine whether there are any differences in listings' descriptions among different neighborhoods. Furthermore, I investigate how the number of competing listings in San Francisco impacts the information disclosure via listing's description. Second, I examine whether competition influences information revealed by hosts in San Francisco and its surrounding cities.

[6] I use python's package of geopy to calculate Vincenty distance.

Table 2.2 includes the average of word count for listings in San Fransico's neighborhoods. It is obvious that there are variations in listings' descriptions within neighborhoods for private room listings and entire place listings. Results in Table 2.3 shows the effect of the neighborhood's characteristics on the amount of information revealed in the description of listings. Neighborhood's characteristics are walking score, transit score, and biking score. Based on the results in Table 2.3, the walking score has a statistically significant effect on the listing's description for private room and entire house/apartment listings. In other words, a higher walking score is correlated with more words in listing's description for both room types. This may be interpreted as hosts sharing proximity of their listings with famous attractions or suggesting nearby local places to their guests within walking distance.

I examine model (2.1) to study the impact of competition on the listing's description in San Francisco. The results are presented in Table 2.4 and Table 2.5 for private room and entire house/apartment listings respectively. According to Table 2.4, a higher number of competitors within half a mile, one mile, and five miles increases the number of words used by hosts in the description. Moreover, the increase in the number of competitors for further distances has a smaller impact on the number of words in listing's description used by hosts. For private rooms in San Francisco, a higher number of listings may lead to information disclosure which can be interpreted as hosts' attempt to differentiate their listing's compared to their rivals'. Table 2.5 is specific to the entire house/apartment listings in San Francisco. Although the results in Table 2.5 are similar to the results for private room listings, they are not statistically significant.

The results of the model (2.2) are shown in Table 2.6 and Table 2.7 for private rooms and entire house/apartment for listings in San Francisco and its surrounding cities. The results are similar to the listings which are located in San Francisco. In other words, for private rooms, the number of competitors has a statistically significant effect on the description of listings, whereas such relationship is not statistically significant for the entire house/apartment listings.

2.4 Conclusion and Future Work

Given the increasing growth of online platforms to accommodate lodging for travelers, it is crucial to understand different aspects involved in such markets. The suppliers in online markets may not always have the incentives to reveal all information about their listings. As a result, information asymmetries can exist in these markets. This chapter shows whether competition among Airbnb's hosts may change their incentives to share information about their listings.

I measure information provided by hosts with the number of words used in the listing's description. I examine the impact of competition on information disclosure for listings with two different room types. My empirical results suggest that higher number of listings for private room type increases the number of words in listing's description, whereas the amount of description in entire house/apartment room type is not affected by the number of same room type listings.

There are a few caveats in this study which should be addressed in future work. First, the number of words may not be a sufficient measure for information disclosure on this platform. Combination of the number of words and number of pictures may provide a better compliment for providing information. Second, having a similarity measure which compares more similar listings with each other can be invaluable. In other words, having more detailed information about listings based on blocks in metropolitan areas or size and architecture style of listings can group listings more subtly. Finally, having more data for different cities of Airbnb's listings can lead us to a better understanding of information disclosure and competition in this platform. Moreover, comparison of incentives among Airbnb's hosts and its competing platforms such as booking.com, homeaway.com, etc. may be helpful to study information disclosure in different online platforms.

Table 2.1: Summary Statistics of Listings in San Francisco

Variable	Mean	Std. Dev.	Min.	Max.	N
Private Room:					
Word Count	326.01	347.562	1	2,456	813
Number of Listings in Half a Mile	25.301	14.561	0	61	813
Number of Listings in One Mile	87.203	45.905	3	100	813
Number of Listings in Five Miles	743.523	76.655	460	812	813
Price	163.61	482.746	38	10,000	813
Instant Booking	0.239	0.427	0	1	813
Person Capacity	2.091	0.809	1	9	813
Extra Language	0.322	0.468	0	1	813
Number of Bathrooms	1.146	0.388	0	3	813
Number of Bedrooms	1.018	0.181	0	4	813
Host Owning a Pet	0.26	0.439	0	1	813
Allows Children	0.594	0.491	0	1	813
Allows Infants	0.514	0.5	0	1	813
Allows Pets	0.093	0.291	0	1	813
Allows Smoking	0.044	0.206	0	1	813
Allows Events	0.058	0.234	0	1	813
Entire House/Apartment:					
Word Count	372.04	388.327	1	3,386	779
Number of Listings in Half a Mile	28.657	18.830	0	86	779
Number of Listings in One Mile	96.067	52.546	1	195	779
Number of Listings in Five Miles	717.415	77.983	354	778	779
Price	320.92	437.88	60	10,000	779
Instant Booking	0.213	0.41	0	1	779
Person Capacity	4.077	2.255	1	16	779
Extra Language	0.24	0.427	0	1	779
Number of Bathrooms	1.288	0.588	0	8	779
Number of Bedrooms	1.454	1.037	0	10	779
Host Owning a Pet	0.094	0.292	0	1	779
Allows Children	0.809	0.394	0	1	779
Allows Infants	0.742	0.438	0	1	779
Allows Pets	0.117	0.321	0	1	779
Allows Smoking	0.021	0.142	0	1	779
Allows Events	0.056	0.231	0	1	779

Notes: This table includes summary statistics of Airbnb's listings in San Francisco based on room type which are available on January 14th of 2017 for check in and check out dates of Friday, February 3rd to Sunday, February 5th of 2017.

Table 2.2: Average Word Count for San Francisco's Listings by Room Type

Neighborhoods	Private Room	Entire Apartment/House
Bayview	160	441.556
Bernal Heights	329.462	433
Castro and Upper Market	382.454	436.905
Chinatown	74.5	857.633
Civic Center	72.25	378.8
Cow Hollow	380.222	170.917
Crocker Amazon	88.6	257.6
Diamond Heights	196.333	—
Excelsior	290.2381	542.643
Financial District	96.167	323.75
Glen Park	310	464
Haight Ashbury	322.128	468.464
Inner Richmond	383.214	351.706
Inner Sunset	291.733	278.364
Lakeshore	190	105
Lower Nob Hill	220.25	263.609
Marina	365.75	269.444
Mission	400.706	370.033
Nob Hill	268.233	236.632
Noe Valley	390.107	396.196
North Beach	190.727	317.727
Ocean View	245.476	306.417
Outer Mission	345.75	367.067
Outer Richmond	283.211	444.5
Outer Sunset	269	383.964
Pacific Heights	375.333	280.143
Parkside	253.133	446.938
Potrero Hill	300.333	353.8
Presidio Heights	394.2	353.25
Russian Hill	366.8	219.36
Seacliff	274	615
South of Market	241.642	243.986
Tenderloin	235.133	152
Twin Peaks	229.9	385.444
Visitacion Valley	170.667	618.5
West Twin Peaks	721.269	338.526
Western Addition	391.339	454.634

Notes: This table includes average word count based on room types for listings in San Francisco's neighborhoods which are available on January 14th of 2017 for check in and check out dates of Friday, February 3rd to Sunday, February 5th of 2017.

Table 2.3: Word Count by Room Type in San Francisco's Neighborhoods

	Word Count in Private Room	Word Count in Entire House/Apartment
Walking Score	3.277**	3.377*
	(1.585)	(1.961)
Transit Score	-0.606	-2.221
	(1.260)	(1.405)
Biking Score	0.642	-2.166*
	(0.966)	(1.255)
Property FE	Yes	Yes
Observations	813	779
R^2	0.027	0.033

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. In parenthesis, robust standard errors are reported.

Table 2.4: Word Count in Private Room in San Francisco

	(1) Word Count	(2) Word Count	(3) Word Count
Number of Listings in Half a Mile	2.145**		
	(0.897)		
Number of Listings in One Mile		0.823***	
		(0.318)	
Number of Listings in Five Miles			0.528***
			(0.154)
Instant Booking	-9.749	-7.812	0.626
	(25.982)	(26.300)	(26.455)
Person Capacity	32.936*	34.128**	35.233**
	(17.037)	(17.192)	(17.288)
Cancellation Policy	136.235***	135.860***	136.193***
	(15.478)	(15.521)	(15.488)
Extra Language	21.773	22.536	23.059
	(23.254)	(23.195)	(23.266)
Walking Score	0.455	0.409	0.217
	(1.522)	(1.514)	(1.587)
Transit Score	-0.946	-1.150	0.015
	(1.202)	(1.225)	(1.149)
Biking Score	-0.481	-0.752	-0.965
	(0.910)	(0.892)	(0.931)
Property FE	Yes	Yes	Yes
Observations	813	813	813
R^2	0.196	0.198	0.202

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. In parenthesis, robust standard errors are reported. These regressions include the number of bedrooms and bathroom, host owning a pet, allowing children and infant, allowing a pet, allowing smoking, allowing events.

Table 2.5: Word Count in Entire House/Apartment in San Francisco

	(1) Word Count	(2) Word Count	(3) Word Count
Number of Listings in Half a Mile	1.184		
	(0.971)		
Number of Listings in One Mile		0.432	
		(0.387)	
Number of Listings in Five Miles			0.213
			(0.171)
Instant Booking	4.437	6.105	8.153
	(28.308)	(28.176)	(28.911)
Person Capacity	25.944**	25.724**	26.192**
	(10.126)	(10.197)	(10.396)
Cancellation Policy	103.482***	103.726***	104.423***
	(15.282)	(15.281)	(15.547)
Extra Language	90.566***	91.382***	90.602***
	(32.436)	(32.462)	(32.350)
Walking Score	2.390	2.470	2.475
	(2.039)	(2.073)	(1.985)
Transit Score	-3.201**	-3.424**	-2.218
	(1.415)	(1.576)	(1.391)
Biking Score	-1.918	-2.054*	-2.394*
	(1.224)	(1.232)	(1.248)
Property FE	Yes	Yes	Yes
Observations	779	779	779
R^2	0.120	0.120	0.120

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. In parenthesis, robust standard errors are reported. These regressions include the number of bedrooms and bathroom, host owning a pet, allowing children and infant, allowing a pet, allowing smoking, allowing events.

Table 2.6: Word Count in Private Room in San Francisco and Surrounding Cities

	(1) Word Count	(2) Word Count	(3) Word Count	(4) Word Count
Number of Listings in Half a Mile	1.698**			
	(0.705)			
Number of Listings in One Mile		0.613**		
		(0.257)		
Number of Listings in Five Miles			0.341***	
			(0.079)	
Number of Listings in Ten Miles				0.003
				(0.041)
Instant Booking	-11.205	-10.852	-5.151	-10.698
	(17.181)	(17.166)	(17.279)	(17.258)
Person Capacity	31.024***	31.597***	30.902***	30.517***
	(10.440)	(10.532)	(10.493)	(10.417)
Cancellation Policy	95.510***	95.108***	95.648***	97.709***
	(9.200)	(9.259)	(9.186)	(9.273)
Extra Language	40.766***	40.454***	39.842***	41.046***
	(15.164)	(15.197)	(15.084)	(15.182)
City FE	Yes	Yes	Yes	Yes
Property FE	Yes	Yes	Yes	Yes
Observations	1,673	1,673	1,673	1,673
R^2	0.174	0.175	0.179	0.171

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. In parenthesis, robust standard errors are reported. These regressions include the number of bedrooms and bathroom, host owning a pet, allowing children and infant, allowing a pet, allowing smoking, allowing events.

Table 2.7: Word Count in Entire House/Apartment in San Francisco and Surrounding Cities

	(1) Word Count	(2) Word Count	(3) Word Count	(4) Word Count
Number of Listings in Half a Mile	0.412			
	(0.768)			
Number of Listings in One Mile		-0.018		
		(0.254)		
Number of Listings in Five Miles			0.142	
			(0.125)	
Number of Listings in Ten Miles				-0.171***
				(0.061)
Instant Booking	-9.949	-10.432	-7.109	-9.295
	(20.153)	(20.074)	(20.527)	(20.022)
Person Capacity	17.127***	17.028***	17.168***	17.179***
	(6.186)	(6.201)	(6.235)	(6.172)
Cancellation Policy	88.067***	88.283***	88.460***	86.648***
	(10.302)	(10.337)	(10.430)	(10.442)
Extra Language	66.802***	66.115***	66.728***	64.659***
	(20.351)	(20.499)	(20.372)	(20.231)
City FE	Yes	Yes	Yes	Yes
Property FE	Yes	Yes	Yes	Yes
Observations	1,353	1,353	1,353	1,353
R^2	0.111	0.111	0.112	0.114

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. In parenthesis, robust standard errors are reported. These regressions include the number of bedrooms and bathroom, host owning a pet, allowing children and infant, allowing a pet, allowing smoking, allowing events.

Appendices

Appendix A Conquest Cash and Loyalty Cash by Type

Table 8: Summary Statistics of Conquest and Loyalty Offers by Type

Offers by Type	Mean	Std. Dev.	Min.	Max.	N
Offering Loyalty on Luxury Foreign Cars	0.526	0.499	0	1	4,493
Offering Conquest on Luxury Foreign Cars	0.152	0.35	0	1	4,493
Offering Loyalty on Luxury Domestic Cars	0.935	0.185	0	1	858
Offering Conquest on Luxury Domestic Cars	0.522	0.472	0	1	858
Offering Loyalty on non-Luxury Foreign Cars	0.613	0.482	0	1	4,802
Offering Conquest on nonLuxury Foreign Cars	0.277	0.447	0	1	4,802
Offering Loyalty on non-Luxury Domestic Cars	0.802	0.327	0	1	3,276
Offering Conquest on non-Luxury Domestic Cars	0.566	0.442	0	1	3,276

Notes: This table includes summary statistics of loyalty and conquest offers based on their types of brand and origin from December 2017 to April 2018 in selected cities. Offering loyalty and offering conquest are the fraction of these rebates among different trims of a nameplate.

Appendix B Conquest Cash and Loyalty Cash within Makes

Table 9: Conquest Cash and Loyalty Cash by Makes

Offers	Makes
Neither **Conquest nor Loyalty**	Honda, Mercedes-Benz, Smart, Subaru, Volkswagen
Only **Loyalty**	Infiniti, Jaguar, Mini, Toyota
Only **Conquest**	—
Both **Loyalty and Conquest**	Acura, Audi, BMW, Buick, Cadillac, Chevrolet, Chrysler, Dodge, Fiat, Ford, GMC, Genesis, Hyundai, Jeep, Kia, Land Rover, Lexus, Lincoln, Mazda, Mitsubishi, Nissan, Porsche, Ram, Volvo

Notes: This table includes the list of makes which use conquest cash and loyalty cash in Decmeber 2017 to April 2018 in six cities of Boston, Chicago, Houston, Jacksonville, Kansas City, and New York City.In this table, some of the makes which use both conquest and loyalty offers have specific nameplates which have only conquest offers, and only loyalty offers. For instance, both Hyundai and Lincoln offer conquest and loyalty cash on their nameplates; however, Hyundai offers only conquest cash on nameplate Kona with model year 2018, and Lincoln offers only loyalty cash on nameplate Navigator with model year 2018.

Appendix C All Listings in San Francisco by Neighborhoods

Table 10: Number of Listings in San Francisco's Neighborhoods

Neighborhoods	Private Room	Entire Apartment/House
Bayview	22	9
Bernal Heights	39.462	38
Castro and Upper Market	44	21
Chinatown	2	30
Civic Center	4	5
Cow Hollow	9	12
Crocker Amazon	5	5
Diamond Heights	3	—
Excelsior	21	14
Financial District	6	16
Glen Park	8	10
Haight Ashbury	39	28
Inner Richmond	28	17
Inner Sunset	15	11
Lakeshore	5	2
Lower Nob Hill	16	23
Marina	16	27
Mission	92	61
Nob Hill	30	19
Noe Valley	28	46
North Beach	11	22
Ocean View	21	12
Outer Mission	28	15
Outer Richmond	19	18
Outer Sunset	46	28
Pacific Heights	15	28
Parkside	15	16
Potrero Hill	21	25
Presidio Heights	5	4
Russian Hill	20	25
Seacliff	2	1
South of Market	53	71
Tenderloin	15	17
Twin Peaks	10	9
Visitacion Valley	12	4
West Twin Peaks	26	19
Western Addition	62	71

Notes: This table includes number of listings based on room types for listings in San Francisco's neighborhoods which are available on January 14th of 2017 for check in and check out dates of Friday, February 3rd to Sunday, February 5th of 2017.

Appendix D All Listings in San Francisco and Surrounding Cities

Table 11: Summary Statistics of Listings in San Francisco and Surrounding Cities

Variable	Mean	Std. Dev.	Min.	Max.	N
Private Room:					
Word Count	295.421	299.616	1	2,456	1,673
Number of Listings in Half a Mile	16.69	13.923	0	61	1,673
Number of Listings in One Mile	56.117	46.002	0	180	1,673
Number of Listings in Five Miles	526.051	274.745	20	884	1,673
Number of Listings in Ten Miles	904.341	303.036	69	1,401	1,673
Price	124.219	341.177	25	10,000	1,673
Instant Booking	0.213	0.409	0	1	1,673
Person Capacity	2.082	0.854	1	10	1,673
Extra Language	0.332	0.471	0	1	1,673
Number of Bathrooms	1.118	0.364	0	3.5	1,673
Number of Bedrooms	1.019	0.282	0	10	1,673
Host Owning a Pet	0.298	0.457	0	1	1,673
Allows Children	0.632	0.482	0	1	1,673
Allows Infants	0.553	0.497	0	1	1,673
Allows Pets	0.106	0.308	0	1	1,673
Allows Smoking	0.05	0.217	0	1	1,673
Allows Events	0.062	0.24	0	1	1,673
Entire House/Apartment:					
Word Count	341.305	337.488	1	3,386	1,353
Number of Listings in Half a mile	18.945	18.5	0	86	1,353
Number of Listings in One Mile	63.038	56.337	0	196	1,353
Number of Listings in Five Miles	500.004	282.591	12	806	1,353
Number of Listings in Ten Miles	784.617	286.185	60	1,141	1,353
Price	271.709	364.507	50	10,000	1,353
Instant Booking	0.189	0.392	0	1	1,353
Person Capacity	4.054	2.4	1	16	1,353
Extra Language	0.275	0.447	0	1	1,353
Number of Bathrooms	1.292	0.632	0	8	1,353
Number of Bedrooms	1.483	1.113	0	10	1,353
Host Owning a Pet	0.128	0.334	0	1	1,353
Allows Children	0.794	0.405	0	1	1,353
Allows Infants	0.724	0.447	0	1	1,353
Allows Pets	0.13	0.337	0	1	1,353
Allows Smoking	0.022	0.147	0	1	1,353
Allows Events	0.071	0.257	0	1	1,353

Notes: This table includes summary statistics of listings in San Francisco and its surrounding cities based on room type which are available on January 14th of 2017 for check in and check out dates of Friday, February 3rd to Sunday, February 5th of 2017.

Appendix E Frequency of Listings by Cities

Table 12: Frequency of Listings in San Francisco and Surrounding Cities

Cities	**Frequency**
Alameda	1.39
Albany	1.06
Belvedere Tiburon	0.23
Berkeley	7.44
Brisbane	0.43
Burlingame	0.76
Corte Madera	0.30
Daly City	3.07
El Cerrito	0.69
El Sobrante	0.30
Emeryville	0.59
Greenbrae	0.07
Hillsborough	0.03
Kensington	0.40
Kentfield	0.20
Larkspur	0.26
Mill Valley	2.71
Millbrae	0.66
Muir Beach	0.03
Oakland	17.48
Orinda	0.40
Pacifica	1.12
Piedmont	0.20
Point Richmond	0.07
Richmond	1.59
San Anselmo	0.03
San Bruno	1.20
San Francisco	52.64
San Leandro	0.40
San Mateo	0.89
San Pablo	0.23
San Quentin	0.03
San Rafael	0.96
Sausalito	0.56
South San Francisco	1.12
Stinson Beach	0.36
Tiburon	0.13

Notes: This table includes the frequency of Airbnb's listings in San Francisco and its surrounding cities which are available on January 14th of 2017 for check in and check out dates of Friday, February 3rd to Sunday, February 5th of 2017.

Appendix F Average Word Count by Cities

Table 13: Average Word Count for San Francisco and Surrounding Cities by Room Type

Cities	Private Room	Entire House/Apartment
Alameda	225.233	249.25
Albany	270.4	231.857
Belvedere Tiburon	203.75	255.333
Berkeley	302.919	300.539
Brisbane	178.25	445.375
Burlingame	356.333	481.25
Corte Madera	339	331.2
Daly City	203.2	268.087
El Cerrito	394.177	408.5
El Sobrante	263.429	233.5
Emeryville	302.083	233.167
Greenbrae	194	796
Hillsborough	–	48
Kensington	185.5	271.75
Kentfield	201.333	293.667
Larkspur	64	376.857
Mill Valley	312.514	356.467
Millbrae	315.083	229.875
Muir Beach	–	302
Oakland	277.280	296.198
Orinda	264.571	184
Pacifica	294.263	367.933
Piedmont	51	262.5
Point Richmond	45	468
Richmond	207.432	259.455
San Anselmo	347	–
San Bruno	171.45	201.933
San Francisco	325.730	371.432
San Leandro	165.833	119.2
San Mateo	235.429	194.167
San Pablo	106.333	367
San Quentin	–	59
San Rafael	274.923	274.125
Sausalito	249.75	327.385
South San Francisco	260.130	233.909
Stinson Beach	–	432.182
Tiburon	223	256

Notes: This table includes average word count based on room types for listings in San Francisco and its surrounding cities which are available on January 14th of 2017 for check in and check out dates of Friday, February 3rd to Sunday, February 5th of 2017.

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