SMOOTHING INCOME OR NOT? HOUSEHOLDS' PAYMENT CHOICE BETWEEN CREDIT AND DEBIT AT POINT-OF-SALE

A Dissertation

by

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ABSTRACT

A basic element of consumer behavior can be observed through shopping trips. Today's consumers have access to different monetary instruments to pay for goods and services. In the U.S., debit cards and credit cards are the most widely used means of payment. Assessing consumer payment behavior for point-of-sale transactions is a good source of information on market opportunities for various stakeholders. This dissertation examines the effect of consumer and transaction characteristics on the use of different electronic payments. We employed non-parametric approaches and generalized linear models to investigate the influence of transaction value, income, and other socio-demographic factors on households' probability of using credit. Our research was undertaken for the U.S. census regions over a five-year period (2015 – 2019) for different income groups. The incorporation of multiple locations, years, and income groups allow us to identify the existence of heterogeneity among consumers and perform cross-state comparisons. These considerations add to the consumer payment literature and provide better and more targeted results to help with policy making. Our transaction value results provided evidence for income smoothing when the cost of the shopping trip increased and highlighted the importance of controlling for household effects and the proper construction of the expenditure variables. We found heterogeneities among households and strong evidence of consumer behavior differing across income groups. These results provide insights to merchants, the financial sector, and policy makers on sale potential, improving the payment technologies, and monetary policy decisions, respectively.

DEDICATION

To my loving parents.

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All other work conducted for the dissertation was completed by the student independently.

Disclaimer:

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The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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NOMENCLATURE

AD	Anderson-Darling
CHI	Chicago
DFW	Dallas-Fort Worth
DMA	Designated Market Area
GLM	Generalized Linear Models
HH	Household
HMS	Consumer Panel Dataset
KS	Kolmogorov-Smirnov
LA	Los Angeles
NYC	New York City
POS	Point-of-sale
SCF	Survey of Consumer Finances
UPC	Universal Product Code

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CHAPTER 1

INTRODUCTION

Technological development has transformed the money market over time. Consumers went from using only coins, to choosing between coins and banknotes, and later to choosing between currency and checks. Much later, electronic payments such as credit cards emerged as forms of payment. The growth of electronic payments, that is, from cash and check to debit and credit has substantially reduced the social cost of a country's payment system (Humphrey et al., 2001). In the U.S., the Federal Reserve System is the primary provider of payment mechanisms that are used for trade and commerce. The public uses cash and eligible financial institutions use electronic payment services (Wong & Maniff, 2020). Though these payment tools have no value of their own, they initiate the transfer of monetary value, and are referred to as "payment instruments" (Schreft, 2006).

The existence of a wide range of payment instruments is essential to support customers' needs in a market economy. The safe and efficient use of forms of money as a medium of exchange in retail transactions underpins the stability of the monetary system (World Bank, 2020). Understanding the factors that influence consumer behavior to purchase a good or service using a specific payment method is important as it: (1) helps the financial sector with marketing services to current and potential customers – finding out what consumers really want (Crowe et al., 2006); (2) allows merchants to provide preferred payment options to consumers which could increase sales (i.e., the company is more attractive to customers and has an improved reputation); (3) allows for cross-country comparisons (World Bank, 2020); (4) provides better insights into payment regulations across different geographic locations; (5) helps policy decision making, since payment choice has macroeconomic implications for default rates on consumer debt and future consumption growth (Schreft, 2006); and (6) helps identify how resource availability influence consumer decisions.

Consumers utilize payment methods based on convenience and personal cost (Grüschow et al., 2016). In the U.S., debit cards, credit cards and cash have been the leading payment instruments for the past decade. In more recent years, credit card use surpassed that of cash, accounting for about 25% of use between 2018 and 2020 compared to 24% use for cash (The Federal Reserve Bank of San Francisco, 2021). Moreover, almost 80% of the payments are non-cash payments, which means that people are adopting new technologies and are using different methods of payments. Access to and employment of electronic payments such as debit and credit cards have grown over the years to become the most frequently used financial instruments by households in the United States. Gerdes et al. (2020) reported growth in the percentage of households using electronic modes of payment from 5.1% per year by number from 2012-2015 to 6.7% per year by number from 2015-2018.[1] According to a 2020 World Bank report, 88.3% of transactions were cashless in 2017, an increase of 25% compared to 2015. The World Bank further indicated that high-income and OECD countries are more likely to use cashless payment when compared to other income group countries and regions. These instruments have been noted to

[1] See https://www.federalreserve.gov/paymentsystems/2019-December-The-Federal-Reserve-Payments-Study.htm

provide a safer, more efficient, and more inclusive provision of payment and settlement services (World Bank, 2020).

The interest in consumer behavior when choosing a particular payment option has grown lately. In the past, researchers looked at issues pertaining to money and the factors influencing consumption and saving. In the early 2000s, researchers highlighted the disconnect between macroeconomic aggregates and the transactions that underlie them. Schreft (2006) noted that payment methods also affect aggregate consumption, thus understanding the factors that influence how consumers behave in choosing a payment instrument is important. Innovations in payment methods also spurred research in consumer payment behavior with studies analyzing the "pay now or pay later" mentality of the choice between checks and debit cards at stores (Klee, 2008) versus credit card use (Gross & Souleles, 2002). Consumer spending is noted to increase with the evolvement of certain payment methods, such as credit and debit cards (Incekara-Hafalir & Loewenstein, 2009; Hirschman, 1979), except for low-income groups (Greenacre & Akbar, 2019). Thus, further propelling the need to understand the payment-choice area better.

Consumers are heterogeneous and may behave differently across income groups. This is especially the case in societies where uneven wealth distribution exists across families with different characteristics. According to Gregori & Katsingris (2012), higher-income consumers spend more in total and shop less often, implying that they spend more per shopping trip. Lower-income consumers prefer certain retail channels, like "dollar" stores, convenience stores, and deep discounters- whereas upper-income consumers tend to shop in warehouse club stores. With the growing size of low-income households relative to other consumer groups,[2] it is important to understand these consumers' shopping behaviors. Moreover, given financial constraint barriers and imperfect information, shopping practices may vary between different income groups. Therefore, understanding payment practices provide better avenues to suggest policies that can address any differences.

Changes to the banking sector and consumer demand have transformed the retail sector. Traditional brick-and-mortar grocery retailers are receiving increasing competition from online grocery retailers. However, grocery shopping in a brick-and-mortar store is still essential to Americans (Tighe, 2020). With consumers in constant search of convenient and cost-effective ways of payment, financial institutions continue to innovate the market. An increasingly competitive financial industry intensifies the development of proprietary services and products to serve existing customer needs and attract new clients, which drives card acceptance among merchants. A network externality is created from these relationships, and most merchants across the U.S. accept electronic payments at point of sale (Bounie et al., 2017). Thus, understanding the relationship between various factors that affect consumer choice of payment instrument is important as it can help sellers better prepare for providing the necessary payment methods and attract greater sales or prevent loss sales from potential consumers who are unable to transact.

Most businesses have migrated their payment options to account for more advanced payment instruments. Smart devices and apps are increasingly dominating the digital

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[2] American adults within the low-income tier rose from 16% in 1971 to 20% in 2015 (Pew Research Center, 2015).

commerce scene and have been used more recently with the Covid-19 pandemic. However, debit cards and credit cards are still the preferred choice of payment for Americans (The Federal Reserve Bank of San Francisco, 2021; Stavins, 2017).[3] Also, in recent years, credit card and debit card interchange/surcharge fees are generally covered by the merchant or retailer, which eliminates a transaction fee paid by the consumer.[4] These changes reduce the practical differences between using a credit card and a debit card. Therefore, other features of both forms of payments are emphasized in explaining consumer payment-choice decisions. Consequently, this study considers the technological advancement of payment choices by focusing on credit cards and debit cards to understand the factors influencing the choice of payment during POS transactions.

The payment-choice literature showed four key sets of factors that affect consumer behavior (1) consumer characteristics, (2) transaction characteristics, (3) payment method attributes, and (4) store features. For example, Stavins (2001) highlighted the role of socio-demographic factors on the probability of using various payment instruments, and Hayashi & Klee (2003) underscored technological factors on the propensity to use electronic payment systems while the role of elasticities was the core factor in Humphrey et al. (2001). Since payment instruments are used for transaction purposes, the type of transactions and their average value are noted to influence the types of payment

[3] See https://www.frbsf.org/cash/publications/fed-notes/2021/may/2021-findings-from-the-diary-of-consumer-payment-choice/

[4] Credit card surcharges are handled differently in each state. They are illegal in Colorado, Connecticut, Florida, Kansas, Massachusetts, New York; illegal with exemptions given to certain government entities in California, Maine, Oklahoma, and Texas; and legal in the remaining states.

instruments used (Humphrey et al., 2001). Moreover, studies showed that the size and location of the store affect payment type decisions (Bolt et al., 2010; Simon et al., 2010).

Though the amount of work done in the payments area has increased over the past couple of decades or so, some interesting issues remain. In this paper, we seek to address some of these issues. We were unable to investigate supply-side factors given some data limitations, and this paper consequently builds on the existing literature regarding the role of socio-demographic factors and transaction value on the probability of using a credit payment instrument. The paper contributes further to the literature by studying multiple locations and time periods in the United States. Beside Cohen & Rysman (2013), that examined consumer behavior in various metropolitan areas in the U.S., no other research has looked at major cities and states within the same study nor assess whether the factors identified are consistent across time. Additionally, our study adds to the literature by including consumer payment choice by income bracket (low, lower-middle, upper-middle, and high). Thus, we analyzed our data by location, time, and income group which accounts for the heterogeneity among consumers and allows for cross-state comparison. These considerations provide better and more targeted results to help with policy making.

Our paper places greater emphasis on the influence of transaction value and income type on the consumer payment choice. Thus, the principal research questions of this study are as follows:

- Does the monetary value of the in-store transaction affect the choice of payment method?
- Are higher-income families more prone to using a credit card?

- Are consumers funding their in-store POS purchases out of current income/wealth (debit card) or with borrowed funds (credit card)?
- Are there any systematic differences that exist across household-income types and regions that affect payment choice?

This study also seeks to investigate the effect of other factors on payment choice. These factors help explain any systematic differences that exist amongst household income types. Hence, we identify additional questions to address as follows:

- Does the choice of payment instrument depend on the time of month of the transaction?
- Which payment instrument is used more often for point-of-sale transactions?
- Do consumers generally pay using a single payment instrument?
- What demand-side factors influence choice of payment method between credit and debit?

To answer our research questions, we utilized a quantitative research methodology. We analyzed the effect of several head-of-household characteristics (for e.g., age, race, marital status, income, and education) and transaction characteristics (value and date of purchase) on the probability of using a credit card. We employed binary logit regression models with and without random household effects to estimate these results. The kernel distribution functions were also used to assess the relationship between transaction value and the different electronic payment types. We investigated these relationships across time (2015-2019) using scanner data from the Nielsen company for four designated market areas (DMAs)- Chicago, Dallas-Fort Worth, Los Angeles, and New York City, which represent all four U.S. census regions.

Since transaction value is a key focus of this study, we considered four different expenditure definitions to investigate its impact. These definitions include (i) the dollar value of the amount spent by the household for each shopping trip or total expenditure in its level form (*exp*), (ii) total expenditure in its logarithmic form (*log_exp*), (iii) total expenditure in its relative form (*rel_exp*)[5], and (iv) total expenditure in its normative form (*norm_exp*)[6].

Findings from our analysis showed a significant effect of transaction value and income type on the use of credit. Credit card use was generally affiliated with higher-valued transactions, indicating that consumers finance the bulk of their in-store purchases with borrowed funds rather than with their own wealth. We found that household effects were important in influencing the effect of transaction value on credit use. The estimated coefficients for *log_exp* and *rel_exp* were different without controlling for household effects, but quite similar once we controlled for them. This speaks to the importance of controlling individual effects and the proper construction of the expenditure variable in these estimations.

Though the holding of credit cards was more widespread among households at all income levels, our findings suggested that higher-income families were more likely to

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[5] Relative expenditure was derived by dividing total expenditure for each household by its average expenditure (see Chapter 4 for more details).
[6] Normative expenditure was calculated by dividing total expenditure for each household by the size of its household. In essence, total expenditure per household member (see Chapter 4 for more details).

utilize credit cards for a point-of-sale transaction than they were to use debit cards. We also found some systematic differences across households when we considered income groups and regions. There were greater similarities between the upper-middle and high-income households when compared to the lower-middle and low-income households. Generally, the low-income group was regularly different from the other income groups.

Some socio-demographic factors were found to increase the probability of credit use. For example, white and college-educated households were more likely to use credit. Surprisingly, those families with more individuals residing in the same home and those that worked longer hours were more prone to using their own funds for purchases. We also observed that most of the consumers used credit more often than debit for their point-of-sale transactions. Also, there was no strong relationship between the timing of the transaction and the use of a credit card, implying that consumers used credit and debit despite the week of the month.

Assessing the payment choice of credit and debit allowed for a better understanding of consumption behavior. Financial institutions can better target customers with its products based on their demographics and thus enhance the utility and convenience of the payment instruments to them. This facilitates a greater focus on customer satisfaction and provides incentives to influence customer loyalty. Also, with consumer preference toward credit and debit use growing over the recent years, and the onset of the Covid-19 pandemic which has resulted in an increase in online purchases, it is additionally pertinent to improve the security features of these cards. This relationship is possible as knowledge of risk adversely affects consumer confidence in online purchases and payments, given the fear of misuse of personal information (Yoon, 2002) and possible financial losses (Napitupulu & Kartavianus, 2014).

Further, the results by income group are useful for decision makers when undertaking social planning. Low-income households and non-whites were found to have the lowest probability of using a credit card, which can be partially attributed to financial constraints since these demographics are less likely to enjoy high personal credit scores. Future public policy governing financial credit bureaus can be designed to create more equity in making different payment instruments available to all demographic and social groups. This could also help alleviate food insecurity issues which increasingly challenge many lower-income Americans.

The findings from this paper provide signals to merchants on which payment type is preferred by consumers and the factors that influence their payment choice. This information is important as the firms are aware of the card holder characteristics and preference for payment. They can provide the technology to the consumers and if consumers are found to make purchases based on borrowed funds, they can increase marketing in hopes of consumers spending more monies at their stores.

In what follows, the literature review of the dissertation is provided in Chapter 2. We present the empirical research that is relevant to our research objectives as well as provide an overview of credit cards and debit cards. From the previous literature, we develop a conceptual framework and the hypotheses for this study. In Chapter 3, a description of the data used in the study and its source are presented. We explain the reasons for choosing the DMAs and an outline of why those areas are important for the generalization of our findings in the U.S. Chapter 3 also provides a discussion on the households and the variables found in the data. In Chapter 4, the methodology and models are presented. In this chapter, we discussed how we prepared the data and the various techniques employed to answer our research questions. The regional findings of the study are interpreted and presented in Chapter 5. In this chapter, we also provided a discussion of the findings considering the literature reviewed and our research hypotheses. Finally, we conclude the paper with Chapter 6 by providing a summary of the other chapters, discussing the limitations of our study, and highlighting areas for future research.

CHAPTER 2

LITERATURE REVIEW

The observed gap in the literature of studying the effect of transaction payment methods on the transactions that underlie them and innovations in payment methods have spurred research in consumer payment decisions (Schreft, 2006). This literature extends back to Kennickell & Kwast (1997) and Stavins (2001), both utilizing data from the Survey of Consumer Finances (SCF)[7] to estimate the effects of consumer characteristics on payment choice. The empirical literature highlights the use of other data from the Federal Reserve such as the Diary of Consumer Payment Choice and the Survey of Consumer Payment Choice, as well as other independent surveys and diary data. To the authors knowledge, there is one other study that used scanner data from the Nielsen company.

In the payment choice literature, much of the U.S. studies examined the factors that influence a consumer use of cash versus other payment means while others focused on electronic payment choices for different types of transactions such as point of sale (Greenacre & Akbar, 2019; Cohen & Rysman, 2013; Bounie & Francois, 2006; Stavins, 2001) and online shopping (Nguyen & Nguyen, 2020; Alarooj, 2019; Napitupulu & Kartavianus, 2014; Gu et al., 2009; Yoon, 2002). More recent studies have examined mobile payment apps and the potential for growth of these non-traditional modes of

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[7] The SCF is usually a triennial cross-sectional survey of U.S. families conducted by the Federal Reserve Board. It includes information on families' balance sheets, pensions, income, and demographic characteristics.

payment (Jung et al., 2020; Slade et al., 2015; Koenig-Lewis et al., 2015). However, since our paper is focused on point of sale (POS) transactions, we will concentrate on the literature for those types of payments, with an emphasis on electronic payment types.

Numerous stylized facts suggested that electronic card use is driven by behavioral factors (Zinman, 2009; Zinman, 2004). Consumer behavior is affected by decisions related to allocating current income and wealth between current and future consumption (time dimension to the decision problem); funding current purchases from current income or wealth, or with borrowed funds (financial-management dimension); and choosing which payment instruments to acquire and use at POS transactions (technology-adoption decision). All these elements contribute to the heterogeneity among consumers in how they pay. Other contributions to the literature highlighted transaction characteristics and supply-side factors such as the payment features and associated risks (Bagnall et al., 2016; Simon et al., 2010; Hayashi & Klee, 2003). Prior empirical evidence showed that a large share of consumers used a single payment method (known as single homing), such as debit or credit, to conduct most of their transactions (Stavins, 2017; Cohen & Rysman, 2013; Shy, 2013).

In this chapter, we focus on those studies with a similar objective to ours as outlined in chapter one. We present the papers under two main clusters. First, we discuss the findings from papers with a specific focus on cash versus non-cash payments and the factors that affect the choice of these payment instruments. In the U.S., debit cards, credit cards and cash have been the leading payment instruments for the past decade, so understanding the effect of cash as a payment choice is important to assess the changes in consumer behavior. Second, we review those studies that generally analyzed point of sale transactions with a greater focus on electronic payments. Third, we provide an overview of the payment methods- credit and debit and fourth, we outline a conceptual framework for our model development. From the conceptual framework, we derived the hypotheses for this study. Our research questions in section 2.5 are based on the literature of the other sections.

2.1. Empirical Literature Review

2.1.1. Cashless society

Numerous studies have looked at the factors influencing the choice between cash and electronic payment methods. Researchers found that consumers view cash payments as an inexpensive way to pay compared to paying with electronic payment cards (Bolt et al., 2010; Jonker 2007). As relates to consumer characteristics, Carow & Staten (1999) used a 1992 survey of consumer gasoline purchases to determine the factors that affect consumers' decisions about whether to use cash or noncash methods of payment in the U.S. A nested multinomial logit model suggested that middle-aged consumers with less education, lower income, and fewer credit cards were more likely to use cash compared to other groups in the sample. Similarly, Kennickell & Kwast (1997) using SCF data from 1995 found that more educated and younger people with higher incomes used more advanced methods of payments.

Bagnall et al. (2016) measured consumers' use of cash for seven countries by harmonizing payment diaries surveys in the subsequent years: 2009 (Canada), 2010

(Australia), 2011 (Austria, France, Germany, and the Netherlands), and 2012 (the United States). The authors found cross-country differences regarding the level of cash use but emphasized the role of cash particularly in low-valued transactions. The strongest effect on consumers' choice between cash and non-cash was obtained for transaction values, where the estimation results showed that the use of cash decreases with transaction value across all countries. Cash share was found to be higher in Austria and Germany compared to the other countries and was attributed to the following reasons: (i) payment card acceptance at the POS, (ii) structure of purchases, (iii) shoe-leather costs and opportunity costs, (iv) financial and non-financial incentives, (v) behavioral aspects of payment choice, and (vi) the size of the shadow economy.

A later study done by Chen et al., (2019) compared the cost of paying with cash to paying with cards using a regression discontinuity design approach on data from a 2013 Bank of Canada Method-of-Payments Survey. They found that a significant number of cash users switch to paying with debit or credit at transaction values marginally above $5 and $10. This was attributed to consumers not wanting the burden of receiving coins as change associated with the currency denomination structure.

Jonker (2007) used survey data for the Netherlands to analyze four groups of payers: cash, e-purse, debit card, and credit card. The probit regression results were similar to those conducted for the U.S., like Carow & Staten (1999) and Kennickell & Kwast (1997). Income and educational levels were significant factors in the choice of payment methods of consumers, with higher income and educational level being associated with the use of more modern payment options. The author also found that men have a higher chance of being a frequent cash or credit card user than women, but a lower probability of being a frequent debit card user. Furthermore, Jonker noted that location, in particular persons living in more urban areas, played a role in whether debit cards were used. Those living in a major city had a lower probability of being a frequent debit card user than people living in towns and villages.

Another study on Dutch consumers examined the effect of surcharge card payments on consumer payment behavior. Bolt et al. (2010) used consumer and retailer survey data and found that surcharging steers consumers away from using debit cards towards cash. Additionally, the authors noted that consumer demand for debit card services is affected by firm characteristics and the transaction amount. Dutch consumers were found to pay in cash at small stores since those shops traditionally often only accept cash. They also paid significantly more often in cash when the transaction amount was relatively low and used their debit card significantly more often when the transaction amounts were relatively high (also found in Bagnall et al., 2016).

Świecka & Grima (2019) used a consumer payment behavior survey to assess the factors influencing the choice of the payment instruments by consumers. They found that cash was preferred amongst the Polish consumers over non-cash payments, as it was noted to reflect ease of use and lower cost of transaction by the consumers. Świecka et al. (2021) also investigated when, where, and for what amount customers use different forms of payment in Poland. Their data-mining method of Random Forests showed that despite the development of innovative forms of payment, traditional forms, especially cash, still had a strong position in the Polish economy. Harasim & Klimontowicz (2017) also found that cash was mostly used in Poland. Cash was also found to play an important role in the Austrian economy (Rusu & Stix, 2017). Rusu & Stix indicated that cash payment represents over 80% of all the direct payment transactions, which has consistently been the trend in the past 20 years.

Advancement in technology has increased the number of payment methods and reduced the popularity of consumers using cash for in-store POS transactions. The findings from the cashless society literature still have relevance to policy makers and banking professionals in the U.S. and elsewhere. Yet, the cashless society literature hints at a general decline in cash payments over time, especially given the evolution of payment towards more technological means of payment. We also saw evidence to suggest that cash use in the U.S. is on the decline with greater emphasis being placed on electronic modes of payment for in-store and online transactions (Gerdes et al., 2020). Hence, we shift our focus to those studies that address electronic types of payment.

2.1.2. Electronic Payments

In more recent years, credit card use surpassed that of cash in the U.S., accounting for about 25% of use between 2018 and 2020 compared to 24% use for cash (The Federal Reserve Bank of San Francisco 2021). The use of cash at stores declined with the growing convenience of electronic payment machines at check out and the reduced cost to the consumer of using these modes of payment. There are numerous reasons why consumers may prefer to adopt cashless payment instruments. Studies have found that performance expectancy, facilitating condition, social influence, innovativeness, perceived technology security, and hedonic motivation were key in explaining this adoption (Rahman et al., 2020; Boonsiritomachai & Pitchayadejanant, 2017; Onaolapo & Oyewole, 2018; Sun et al., 2013). For example, the more consumers have knowledge and resources (facilitating conditions) necessary to use cashless payments, the more they would be willing to adopt cashless payments. Rahman and others noted that consumers are more willing to adopt cashless payments when their perceived benefits are higher.

Consumer perception on electronic payments was also explored by Thomas (2000). The author mentioned that though U.S. consumers' opinions of credit cards were more negative in 2000 than in 1977, there was greater use of the payment instrument. The negativity was due in part from an individual's perceptions of other consumers' difficulties rather than from the individual's own experiences. Cards were also viewed less positively by holders of three or more cards with an outstanding balance of more than $1,500. Nonetheless, more recently, six in ten payments were made with either a debit or credit card, with debit being used more often than credit (Foster et al., 2020; The Federal Reserve Bank of San Francisco 2021). Anecdotal evidence suggests that issuers have focused on the substitution of debit cards for cash and check for convenience reasons (Reosti, 2000), and empirical work shows that the rise in debit card use was largely owing to the expense of paper payments (Borzekowski et al., 2008; Scholnick et al., 2008; Chakravorti & Shah, 2003). In what follows, we further explore these empirical studies. For instance, Stavins (2001) highlighted the role of socio-demographic factors on the probability of using various payment instruments, and Hayashi & Klee (2003) underscored technological factors on the propensity to use electronic payment systems while the role of elasticities was a core factor in Humphrey et al. (2001).

One of the earlier empirical works was undertaken by Stavins (2001). Stavins employed weighted logit regression models on the 1998 SCF data to determine the effect of demographic characteristics (e.g., age, education, and income) on different electronic payment instruments (ATM card, debit card, credit card, direct deposits, direct payment, smart card, other electronic transfers, and internet). In general, the author found positive relationships for the effect of income, education, homeownership, gender, marital status, and job classification on the electronic payment types. Net worth and family size were noted to have a negative relationship, with the effect of family size being small. Age and business ownership had varying results. Young persons were found to have a positive relationship with debit use and a negative relationship with credit use. Location by U.S. Census region was also a significant variable in explaining the utilization of electronic payments. Consumers were found to adopt payment types based on network externalities, i.e., they use a certain payment type if others within their network are using it.

Borzekowski et al. (2008) also tested the effect of demand-side factors on debit card use by employing probit models. The paper used 2004 data from the Michigan Surveys of Consumers, and found that age, education, marital status, gender, and regional variation influenced the probability of using a debit card. Younger females with some degree of a college education living in the West or South were more likely to use a debit card. They also looked at elasticity and provided evidence on consumer price sensitivity to payment card fees at the POS. On average, a 1.8% fee on a debit card transaction is associated with a 12% decline in the likelihood of use.

Likewise, Zinman (2009) examined the factors that influenced the use of debit cards. The utilized data from the 1995-2004 SCF, and identified consumers holding a credit card, credit card limits and a consumer being a revolver as influential factors.[8] Debit use was shown to respond sharply to other implicit prices on credit card payments while consumers facing credit limit constraints were more likely to use debit than consumers who revolve but have ample available remaining credit. Zinman found similarities between debit and credit cards as relates to non-pecuniary dimensions, such as acceptance, security, portability, and time costs, but that the forms of payment differed based on pecuniary costs. The author noted that over one-third of debit use was driven by pecuniary cost minimization and since debit can be a strong substitute for credit, he accounted for debit–credit interactions but didn't find any change in the qualitative results.

Shy (2013) used transaction-level data from the 2012 Diary of Consumer Payment Choice to examine the payment choice of consumers among card types. In particular, the paper investigated homing behavior of card use and found that consumers concentrated the bulk of their transactions on a single type of card. The demographic-related findings were that single-homing on debit declined with age whereas single-homing on credit increased with age; single-homing on debit generally declined with education whereas single-homing on credit increased with education; high-income respondents were less

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[8] A revolver is someone who did not pay his/her most recent credit card balance in full and pays interest.

likely to single-home on debit and more likely to single-home on credit relative to low-income respondents; male respondents were less likely to single-home on debit and were more likely to single-home on credit relative to female; very-low-income respondents were more likely to single-home on prepaid cards than other income groups; and Latino respondents were more likely to single-home on debit and less likely to single-home on credit relative to non-Latino respondents. Though two-thirds of consumers had payment cards from different networks during the period 1994 to 2001, Rysman (2007) also found that most consumers practiced single-homing and only switched for small benefits.

Schuh and Stavins (2010) extended the investigation of payment choice to include payment fees and non-price payment characteristics (convenience, safety, privacy, etc.). Consumers were found to be satisfied with the existing speed of payments and improving either speed or security of payments was unlikely to change their payment behavior significantly. Stavins (2017) examined the effect of both supply-side and demand-side factors on consumer payment behavior. Technology, regulation, and cost were significant supply-side factors affecting payment behavior while on the demand side, consumer demographics and income, consumer preferences, and consumer assessments of payment method attributes were significant.

Ching and Hayashi (2010) estimated the effects of payment card rewards and consumer characteristics on payment choice (credit, PIN-debit, signature-debit, and check). They used the 2005/2006 study of Consumer Payment Preferences conducted by the American Bankers Association and Dove Consulting and found the effects of rewards to be statistically significant across five retail types – grocery, department, discount, drug, fast food. A removal of rewards was noted to increase the share of paper-based payment methods (i.e., cash and checks) by as much as 4 percentage points. The paper also showed that comfort and convenience were the most crucial perception variables. Technology adoption, race, gender, and age were statistically significant for credit payment type and grocery stores.

Hayashi and Klee (2003) posited that payment choices depend in part on consumers' propensity to adopt new technologies and in part on the nature of the transaction. To test the hypothesis, the authors analyzed the use of payment instruments (cash, check, credit card, and debit card) at the point-of-sale transactions for US consumers surveyed in 2001. The logit regression results indicated that consumers who use new technology or computers are more likely to use electronic forms of payment, such as debit cards and electronic bill payments. Particularly, the use of direct deposit is a significant predictor of electronic payment use. Furthermore, the results indicated that payment choice depends on the characteristics of the transaction, such as the transaction value, and the physical characteristics of the point of sale.

In a later study, a systematic investigation of factors that influenced payment choice at the point of sale was conducted by Klee (2008). Klee used grocery store scanner data from 3 months in 2001 and found that interest rate sensitivity, opportunity costs, transaction costs and other handling costs influenced consumer payment choices.

In the case of empirical work outside the U.S., Greenacre & Akbar (2019) investigated payment methods on low-income Australian consumers' spending behavior. The authors used grocery store sales data to assess the price elasticities of demand and found that the introduction of cashless debit cards resulted in the overall grocery market becoming more inelastic for low-income consumers. The researchers also noted that overall consumer expenditure in the trial area remained stable both before and after the introduction of the cashless card.

Simon et al. (2010) also studied Australian consumers' payment behavior and estimated the effect of price incentives on payment patterns using transaction-level data obtained from a diary survey. They discovered that the credit card holder's choice of payment instrument was related to the transaction amount and the store type. Debit cards were used more at petrol stations and supermarkets while credit cards' share of payments was largest for travel and insurance payments. As for demographics, debit card use was preferred by the young and tended to decrease in use for older age groups, but the authors did not find any noticeable decline for credit card use by older age groups. Furthermore, credit cards were used relatively more at higher income levels, while debit card use is highest for middle-income consumers. As for the influence of price incentives, revolvers tended to use debit cards more often than transactors. Moreover, participation in a loyalty program and access to an interest-free period tend to increase credit card use at the expense of alternative payment methods, such as debit cards and cash. Interestingly though, the authors mentioned that the pattern of substitution from cash and debit cards differed according to the price incentive.

Kosse and Jansen (2013) investigated whether having a foreign background, that is being a first-generation or second-generation migrant, influenced the choice between payment instruments in consumer point-of-sale transactions. They used a diary survey where both participants with a Dutch and a foreign background documented their daily purchases. The authors found evidence that foreign backgrounds affected the choice between payment instruments after migration to the Netherlands. First-generation migrants were more likely to use cash in the Netherlands which was consistent in their country of origin while second-generation migrants have similar payment habits as individuals with a Dutch background.

Humphrey et al. (2001) estimated a demand analysis model of payment choice (cash, debit card and check) for Norway over the period 1989-1995. They found that own-price, cross-price, and payment substitution elasticities were relevant factors in consumer use of the payment methods. Additionally, they mentioned that cash, credit card, and debit card were generally used for low-value transactions ($50) since they were used with higher frequency whereas checks or giro payments were used for higher average values (over $1000). The authors also noted that institutional differences play a role in the choice of payment instruments.

Pertinent to our study, Bertaut & Haliassos (2006) investigated the factors influencing the probability of credit card use and debit card use over time and across demographic groups in the U.S. Probit regressions were employed on several waves of the SCF data. They found that younger households are much more likely to use debit cards than are older households, reflecting the tendency of banks to issue debit cards to younger families that have not yet acquired the financial resources or established the credit history needed for issuance of a credit card. Higher education and HHs with higher incomes were also significantly more likely to use debit cards, except for those with incomes over

$100,000. Also, greater financial asset holdings were associated with a small but significant effect on debit card use.

A closely related paper to ours is Cohen and Rysman (2013). They exploited scanner data from the Nielsen company database to track payment choice for grocery purchases. They looked at three years, from 2006 to 2008, and 16 Designated Marketing Areas (DMAs). A multivariate linear probability model showed that households focused most of their expenditures on one or at most two of these instruments in choosing between using cash, a check, or a card, and they very rarely switched. One focus of the paper was the role of expenditure size in determining payment choice as they found that household heterogeneity had little effect on payment choice. Transaction size was an important determinant across and within households. Consumers were found to mostly use cash for the smallest transactions, and cards, and to a certain extent checks, for larger transactions.

2.1.3. Summary

The studies summarized above used a growing number of data sources, including surveys and diaries of consumer behavior conducted in the U.S. and elsewhere. The differentiated approach toward determining the factors that influence the choice of payment methods suggested a large degree of heterogeneity among consumers on how they pay. The payments literature show that the choice of payment method depends on various factors, such as consumer's demographics (e.g., age, gender), consumer's financial characteristics (e.g., holding a credit card, credit card limits), consumer technology adoption, transaction characteristics (e.g., the amount), location characteristics (e.g., the availability of a POS terminal), and cost structures or payment method attributes (e.g., charges for using cards).

Though the results differed somewhat across studies, consumer characteristics were found to have significance in explaining payment choice. In particular, the intensity of using various methods of payment is usually related to demographic factors, such as age, education, income, and gender (Shy, 2013; Simon et al., 2010; Borzekowski et al., 2008; Klee, 2008; Stavins, 2001). Generational influence exists where consumers tend to choose the payment method they grew up with. Thus, the older generation were "single-user" customers that used cash more, while members of the younger generation were found to use multiple payment types and adopt electronic forms of payment. Moreover, people pay differently, depending on their wealth and whether they make their purchase in a large chain supermarket or in a small bakery or grocery (Świecka & Grima, 2019). Supply-side factors such as convenience and cost were also relevant in the literature.

Research in the U.S. showed a shift from cash to electronic forms of payment. With changing data, consumer heterogeneity, and the evolution of payment instruments, researchers noted that more work needs to be done to understand not just how consumers make their payment choices, but why they pay as they do (Schreft, 2006). The existing literature does not provide definitive answers but helps to narrow down possible explanations. The identified factors can likely change over time due to changes in the cost structures for using electronic cards rather than checks or cash, the evolution of payment instruments, the macroeconomic environment, and changes in the global commerce such as the recent Covid-19 pandemic.

2.2. Gap & Contributions to the Literature

While there has been an increasing amount of work done in the payments area over the past couple of decades or so, some interesting issues remain. There is still a dearth of empirical work investigating the factors influencing consumers' choice of in-store payment method. Most studies examined multiple payment instruments and the factors influencing the likelihood of use of each instrument. Few research focused solely on electronic modes of payment (Zinman, 2009; Bertaut & Haliassos, 2006; Zinman, 2004; Stavins, 2001). Our research concentrates on the factors affecting consumer choice between credit card and debit card, which are the two most used payment instruments in the U.S. With the declining use of cash and check as a means of payment, more research work is required to assess why consumers choose the payment method debit over credit or vice versa. As such, policymakers and banking specialists can use this information to make informed decisions and to promote marketing of the payment systems to targeted users.

Consumer decision-making process encompasses many stages. When deciding on which payment instrument to use or whether to conduct a transaction, the consumer must consider whether the payment methods are accepted by the merchant. As Crowe et al. (2006) indicated, "the decision of how to pay starts with a choice between current and future consumption, continues through decisions on whether to borrow or use existing funds, which payment instruments to carry and, finally, which to use" (pg. 8). The existing research falls short of capturing all the layers of this decision-making process. Little is known about the latent factors of consumer payment behavior for in-store POS transactions. Most of the literature used survey data which was based on consumers' perception on payment instruments. This study, however, uses scanner data which allows us to consider both observed and latent consumer characteristics that affect consumer choice of payment instrument.

This paper contributes further to the literature by studying multiple locations, time periods and income groups in the United States. Moreover, with a large sample size that covers the largest metropolitan areas in the U.S. census regions, our findings can be generalized. Previous work that considered multiple locations and time include Bagnall et al. (2016) that examined consumer behavior in various countries while Greenacre & Akbar (2019) focused on low-income groups in Australia. The study conducted by Cohen & Rysman (2013) is the closest related to ours but did not look at separated models for the regions which allows for comparative analysis. To our knowledge, no research has looked at consumer behavior by income groups for major DMAs and regions in the U.S. nor assess whether the factors identified are consistent across time. Analyzing the data by income types and location accounts for the heterogeneity among consumers and allows for cross-region comparison. These considerations provide better and more targeted results to help with policy making.

2.3. Payment Instruments

This section provides a brief overview of retail payment instruments considered in this study– credit and debit. This provides context for the results in this paper. In modern commerce, debit cards serve as a payment device in lieu of cash and check (Borzekowski et al., 2008), whereas credit cards mostly replaced the installment contracts retail stores in earlier decades (Thomas, 2000). Both instruments allow for the convenience of cashless transactions and today are heavily used by American consumers for most transactions. Though debit cards emerged as a financial payment instrument after credit cards, their use spread quickly and have overtaken credit cards as the most prevalent form of electronic payment at the point of sale (see Figure 2.1).[9] A description of both payment types is presented below.

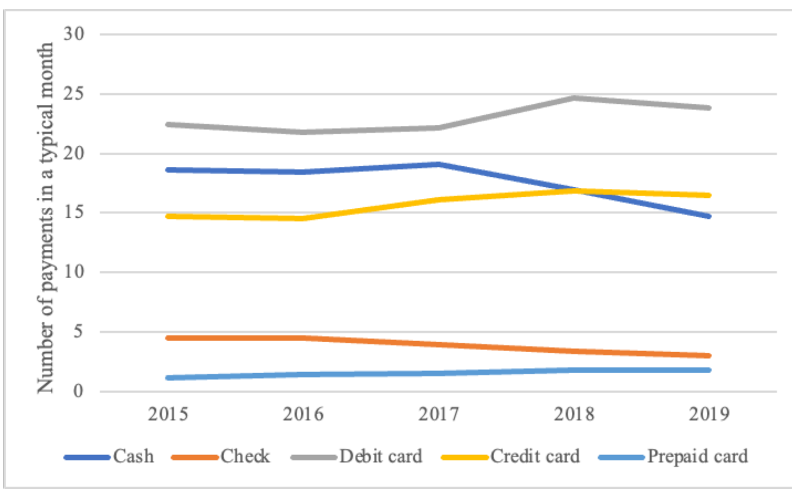

Figure 2.1: Payment method used by all incomes.

[9] Data sourced from the Survey of Consumer Payment Choice.

2.3.1. Credit Cards

Credit cards are one of the most frequently held financial instruments by U.S. households. About 75% of U.S. consumers adopted credit cards as a means of payment between 2015 and 2019 (Foster et al., 2020). Credit cards are generally obtained from banks, credit unions and other financial institutions. The cardholder does not necessarily need to have or maintain a checking account with the card-issuing bank. There are various types of credit cards that are issued. The major credit cards issued by financial institutions include Visa, Mastercard, American Express, and Discover.

Aside from credit cards being used as a means of payments, it can also be a source of revolving credit. Credit cards offer consumers the flexibility to defer payments to a future date thus allowing for the smoothing of income over time. In essence, cardholders borrow funds with which to pay for goods and services and are subject to pay interest and fees if unpaid balances are not made in full within a legal minimum grace period of 21 days. However, invoking a credit card's revolving credit option usually results in having to pay high interest rates not just on the existing balance and additional agreed-upon charges/fees but also on new charges made on the card. A credit card can also be used by cardholders to access cash through a line of credit or a cash advance from a bank teller or an automatic teller machine (ATM), for example.

Credit cards offer additional convenience of purchases over the telephone and the internet. Using credit cards for payments rather than for borrowing usually gives extra benefits or rewards, such as points or cash back. According to Foster et al. (2020), most credit cardholders (84%) reported that at least one of their cards offered rewards.

Consumers that use credit cards responsibly by paying off debts timely can also build a positive credit history and acquire a “good” credit score, which can be used for further borrowing. However, merchants pay higher fees for payments made with credit cards than for payments made with debit cards (Shy, 2013), which can affect the availability of payment options to consumers at stores. Since consumers are mostly unaware of the fees paid by the merchants, we do not expect this factor to influence their payment choice. However, rewards and incentive programs are more likely to affect consumer payment choice.

2.3.2. Debit Cards

A debit card is a payment card that is linked to the cardholder’s checking account. Money is deducted directly from the checking account when it is used. A debit card can be used for purchases, to obtain cash from an ATM or cash back added to a purchase at a store. Debit card transactions can either be made online, using a personal identification number (PIN), or offline using a signature and a process very similar to credit cards. Offline transactions are possible as the cards are issued by major card-payment processors such as Visa or Mastercard.

Debit cards do not allow over-borrowing, as funds are immediately withdrawn from the linked account or soon thereafter. This prevents overspending amongst impulsive shoppers and promotes budgeting. Overdrafts are sometimes available to debit card holders; however, these incur overdraft costs and penalties. ATM transaction fees may also be imposed by some banks on the user if withdrawing from another financial institution. Otherwise, debit card use does not have any consumer fees or charges.

Debit card use can also offer rewards. Customers with a checking account that offers rewards when purchases are made with a debit card (rewards checking account) may earn cash back on all the purchases. However, a monthly fee may be charged to the rewards checking accounts.

2.3.3. Credit & Debit Comparison

Credit and debit cards enjoy comparable levels of acceptability in today's financial market. Both cards look identical and have restrictions on financial resources. In credit cards, the consumer purchase values are constrained to a pre-qualified limit, whereas debit card users can only access the amount that is deposited into and available in the account. Moreover, debit and credit cards offer identical fraud protection (Zinman, 2009; Bertaut & Haliassos, 2006). However, credit and debit cards work in different ways. The income-smoothing and debt features of credit cards make it a better option for larger transaction value purchases. But if the credit card bill payment is late, it could be quite costly given interests and penalties. On the other hand, debit use draws on existing funds in a bank account and though it is not costly to hold or use, consumers may face financial constraints if they do not have sufficient funds.

Ownership of a credit card is typically based on the consumer's ability to obtain unsecured credit. This qualification depends on the applicant's credit score and other financial indicators. Debit cards however are easier to get, especially for individuals with poor credit as all they need is a bank account. Generally, consumers with low credit scores tend to have lower income and lower education levels than those with credit cards. Thus, we expect these consumers to use debit cards more.

> **Hypothesis 1:** Higher income households have a higher probability of using a credit card than lower income households.
>
> **Hypothesis 2:** More educated households have a higher probability of using a credit card than less educated households.

Debit cards might be more readily accepted by merchants as merchant's fees for accepting debit cards are lower compared to credit cards. Merchants may impose a minimum-purchase amount for the use of credit cards as a means of payment. Though some debit cards might receive some rewards, more often, credit cards are known for better reward incentives and can significantly affect payment choice (Simon et al., 2010; Ching & Hayashi, 2010). Thus, with credit and debit for the most part having similar features, we expect that the supply-side factor – rewards or card incentives – to influence payment choice.

2.4. Conceptual Payment-Choice Framework

The core assumption of the payment-choice framework is that each household makes rational decisions. A rational household chooses an option that maximizes benefits and minimizes any costs. The assumption that the household is a rational decision-maker has a long tradition in consumer behavior studies (Goldman and Johansson, 1978; Blattberg et al., 1978; Becker, 1965). Our framework is also based on consumers having a need to consume goods and services. The payment decision might be made before leaving the home if a shopping list is being used or at the point of sale for impulse-type buyers. Based on the payment choice literature, either timeframe is likely to be influenced by demand- and supply-side factors. In this study, we considered both household and transaction characteristics but did not directly test for supply-side effects given data constraints. However, we can make an indirect link between the transaction amount and credit card rewards. For example, if a consumer holds both credit and debit and the transaction amount is large, then we can expect the consumer to use credit not only because of the benefit from income smoothing, but also from the rewards program.

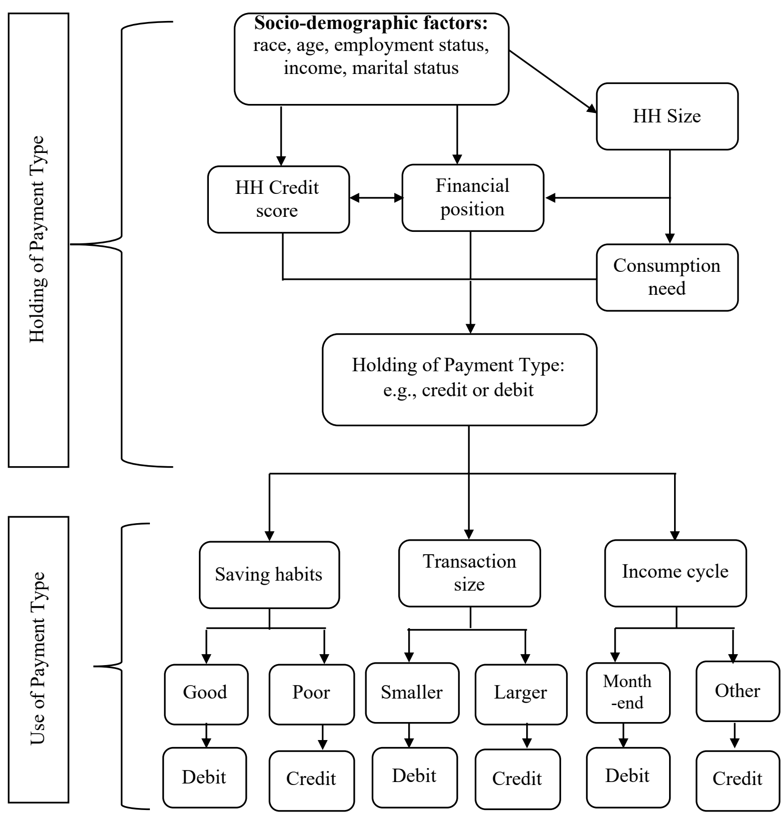

Figure 2.2: The household payment instrument choice conceptual framework.

Figure 2.2 illustrates the conceptual framework of our model of household payment choice. From the framework, socio-demographic factors such as age, marital status, race, gender, and employment status affect a household's credit score and financial position. As for age and marital status, capital accumulation generally follows a predictable life cycle where families commonly accrue wealth during their working years. Married people also have more because they can pool resources together and take advantage of economies of scale. Since the ownership of a credit card is based on the financial ability of the cardholder to repay any accumulated debt, we expect that there should be a positive relationship between the variables age and marital status with the utilization of a credit card.

> **Hypothesis 3:** A younger person is less likely to use a credit card than to use a debit card.
>
> **Hypothesis 4:** A head of household that is married has a greater probability of using a credit card than a debit card.

Along with the aforementioned factors, disparities in wealth exist among ethnic groups, worker effort, and between the sexes. Bhutta et al. (2020, September 28) highlighted considerable wealth gaps between white and non-white families throughout the wealth life cycle, with white persons being more likely to receive financial support from family such as inheritances. Merikull et al. (2021) noted that men have much more wealth than women in the top tail of the wealth distribution, while the gender differences in wealth are statistically insignificant in most of the lower wealth quintiles. This gap could be explained by men being less risk averse (Hallahan et al., 2004) and having higher investment participation rates (Hinz et al., 1997). Gender pay gaps are also noted to exist in the U.S. in favor of men (Buchholz, 2021; Blau & Kahn, 2000). Also, individuals that work longer hours are more likely to earn higher incomes, which can improve their creditworthiness score. Thus, the relationships between these variables and credit card use are given in the hypotheses below.

Hypothesis 5: Whites are more likely to utilize a credit card than non-whites.

Hypothesis 6: Males are more likely to utilize a credit card than females.

Hypothesis 7: Head of households that work longer hours per week are more likely to utilize a credit card than those working less hours per week.

The number of individuals residing in a home can also influence the financial assets of the head of household since greater expenditure is required when there are "more mouths to feed". Therefore, we expect large families to smooth income over a period.

Hypothesis 8: A household with more members has a higher probability of using a credit card than smaller-sized households.

The socio-demographic factors and household size determine consumption needs. The decision by the head of household to hold a specific type of financial instrument is determined by his/her consumption need, credit score and financial position (see Figure 2.2).

The use of a particular payment type is directly related to which payment instrument the consumer holds. Based on the literature, the consumer's ability to save (or financial assets), their income cycle (when they get paid), and the monetary value of the transaction are factors that influence payment-type use. If households save sufficiently, they might be more convinced to use a debit card. However, reward incentives might be an important factor that sways toward the use of credit cards. But if savings are low and families are holding both credit and debit cards, one would expect them to smooth their income with a credit card. The dollar value of a transaction also affects the choice of debit or credit. In the literature, larger transactions were affiliated with credit card payments which are attributed to the income-smoothing and borrowing features of credit, or the reward incentives associated with using a credit card.

> **Hypothesis 9:** The higher the monetary value of the transaction the more likely the consumer is to use a credit card than a debit card.

Despite consumers holding more than one form of payment instrument, some studies have shown that a large share of consumers used primarily a single payment method, such as debit or credit, to pay for most of their transactions (Stavins, 2017; Shy, 2013; Cohen & Rysman, 2013). This decision may be attributed to their preferences regarding the attributes associated with the card type, such as rewards. Thus, we can assume the following:

> **Hypothesis 10:** Households predominantly use one form of payment instrument.

The head-of-household income cycle can also affect the choice of payment. Individuals are usually paid on specific days such as month-end or at the end of the week for wage workers. It is expected that households are more likely to want to borrow outside of the week of payment and use their own savings upon being paid.

Hypothesis 11: Households that shop outside of month-end or the time in which they get paid are more likely to use a credit card than a debit card.

Since we hypothesize differences across household demographics and regions, we can expect the following hypothesis:

Hypothesis 12: Household income types and location have varying effects on credit and debit use.

2.5. Research Questions

Since our paper places greater emphasis on the influence of transaction value and the income type on the consumer payment choice, the main research questions that this study seeks to address for POS transactions are as follows:

- Does the monetary value of the in-store transaction affect the choice of payment method?
- Are higher-income families more prone to using a credit card?
- Are consumers funding their in-store POS purchases out of current income/wealth (debit card) or with borrowed funds (credit card)?
- Are there any systematic differences that exist across household-income types and regions that affect payment choice?

This study also seeks to investigate the effect of other factors on payment choice. These factors help explain any systematic differences that exist amongst household income types. Hence, we identify additional questions to address as follows:

- Does the choice of payment instrument depend on the time of month of the transaction?
- Which payment instrument is used more often for point-of-sale transactions?
- Do consumers generally pay using a single payment instrument?
- What demand-side factors influence choice of payment method between credit and debit?

CHAPTER 3

DATA

This chapter presents the data used in our study. In section 3.1, we first discussed how we determined which locations or areas in the U.S. to study and the significance of those areas for allowing generalization of our results. In section 3.2, we identified the source of our cross-section data, described the main variables used in the study, and discussed the frequency of these variables.

3.1. Location

In this study, we seek to investigate important research questions for the U.S. on the factors that influence consumer payment choice. Since our inferences are focused on explaining the wider population, we used data that is representative of the U.S. The United States Census Bureau defines four statistical regions (West, Midwest, South, and Northeast), with nine divisions that allows for incorporating geographic entities that represent major sections of the United States. The regional areas provide complete coverage of the U.S. through units that are similar in terms of historical development, population characteristics, and the economy (United States Census Bureau, 2013). Therefore, the Census Bureau region definition is not only widely used for data collection and analysis, but it provides for comparative statistical analysis.

The Nielsen home-scanned Consumer Panel (HMS) datasets provide geographic data by the region of the country in which a household is located (region codes). These region codes map to the U.S. Census Bureau regions, thus allowing us to conduct research that can be generalized for the U.S. population. According to the Nielsen DMA Rankings in both 2019 and 2020, the top five DMAs are New York, Los Angeles, Chicago, Philadelphia, and Dallas-Fort Worth. These DMAs also have a large population size and economy relative to others (see Figures 3.1 and 3.2). As such, we chose four of these important DMAs to represent each of the Census regions: Chicago (Midwest), Dallas-Fort Worth (South), Los Angeles (West), and New York City (Northeast).

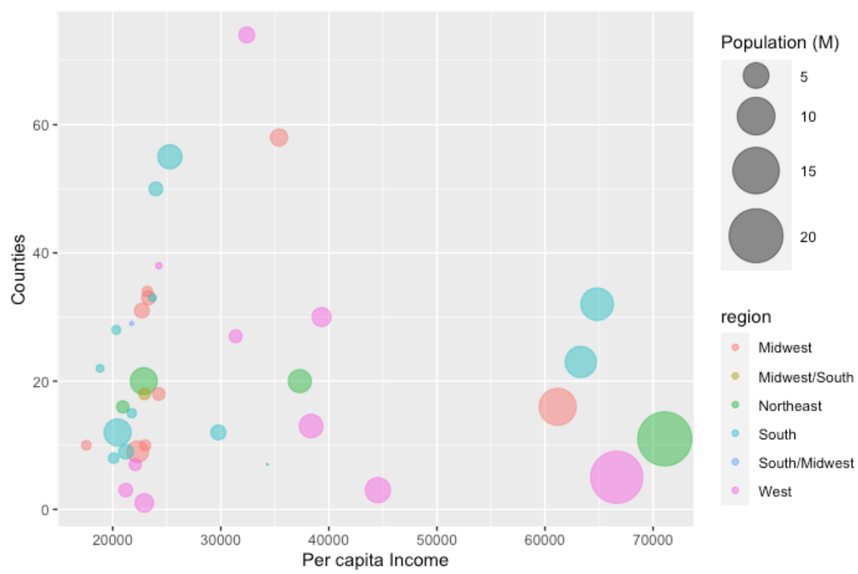

Figure 3.1: Relative Importance of Selected DMAs to other DMAs.

A brief description of each DMA is provided below as follows (see Figure 3.2 also):

- The *Chicago* metropolitan area is the third largest DMA in the Nielsen data, encompassing over 10,000 square miles. It includes the city of Chicago, and its suburbs of 16 counties in northeast Illinois, southeast Wisconsin, and northwest Indiana. The DMA has a population of about 9.7 million.

- The *Dallas–Fort Worth–Arlington* (DFW) metropolitan area is the fifth largest DMA in the Nielsen data, spanning just under 10,000 square miles. The DFW metropolitan statistical area is formed by combining two adjacent metropolitan statistical divisions into one metropolitan conurbation: the Dallas–Plano–Irving metropolitan division, and the Fort Worth–Arlington–Grapevine metropolitan division. This DMA has a population of about 7.6 million.
- The *Los Angeles* DMA spanned more than 30,000 square miles and covered five counties in California: Los Angeles, Riverside, Ventura, Orange and San Bernardino counties. This DMA is the second largest DMA in the Nielsen data and has a population of about 18.7 million.
- The *New York* DMA is the largest metropolitan area with a population of about 20.1 million, spanning over 13,300 square miles. The metropolitan area includes New York City (the most populous city in the United States), Long Island, and the Mid and Lower Hudson Valley in New York State; the five largest cities in New Jersey: Newark, Jersey City, Paterson, Elizabeth, and Edison, and their vicinities; and six of the seven largest cities in Connecticut: Bridgeport, New Haven, Stamford, Waterbury, Norwalk, and Danbury, and their vicinities.

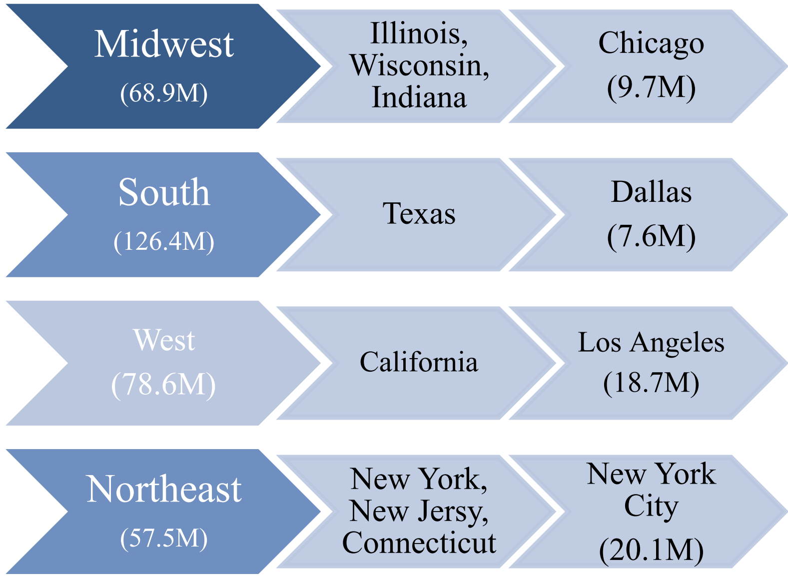

Figure 3.2: Selected DMAs and the Corresponding Region, State and Population.
Note: The 1st column represents regions, the 2nd column represents the state(s), and the 3rd column represents the DMA. Figures in parenthesis represent the population size.

3.2. Households

To assess consumer payment-choice behavior, we used scanner data from Nielsen's Consumer Panel Data. Although data is available from 2004, we chose to observe consumer payment behavior between 2015 and 2019 because the macroeconomic environment of the U.S. was relatively stable at that time. Data from the U.S. Bureau of Economic Analysis indicated an average real gross domestic product growth rate of 2.4%, with civilian unemployment rate ranging from 3.7% to 5.3% and averaging 4.4%. Against this backdrop, the annual rate of change in the consumer price index averaged 1.8%. Hence, we do not expect macroeconomic factors to influence payment choice in the analysis. However, there existed inequality in the distribution of the macroeconomic improvements which is reflected in the uneven income of families with different characteristics. These differences can explain the heterogeneity in consumer behavior by income type.

Table 3.1: Description of Variables Used from the Consumer Panel Dataset.

Variables	Description	Levels	Data
method_of_payment_cd	Method of payment used for the trip.	9	Cash, Check, Credit Card (5 types), Debit, Other
	Panelist Demographic Data		
Household_Size	Number of individuals residing in home.	9	Integer: min 1; max 9+
Household_Income	Range of total household income, estimated on annual basis.	16	Range: min <$5k; max $100k+
Age	The age range selected by the panelist of the head of household. Reported separately for male head and female head.	9	Range: min <25; max 65+
Marital_Status	Marital status of household heads.	4	Single, Married, Widowed, Divorced/Separated
Education	Highest degree earned by household head. Reported separately for male head and female head.	6	College (3 levels) or No college (3 levels from Grade to High school)
Race	Racial identity of the household.	4	White, Black, Asian, Other
Employment	Approximate number of hours per week. Reported separately for male head and female head.	3	Range: min <30; max 35+
Household_code	ID of household that made the purchase.	n.a	n.a
	Panelist Geographic Data		
dma	Indicates which of the Designated Market Area (DMA) of the panelist household.		
	Trips and Purchase Transactions Data		
trip_code	Unique identifier for trip.		
purchase_date	Date of purchase.		
retailer_code	ID code for the entire retail chain (not the individual store).		
store_code	ID code for each individual store		
store_zip3	First 3 digits of zip code of store where purchase was made.		
total_spent	Total expenditure for the trip, as entered by the consumer from the bottom of their receipt.		
total_price_paid	Total price paid for all units, before discounts.		
upc	UPC code of product – manufacturer assigned code.		

The Consumer Panel data tracks weekly UPC-level purchases of a panel of households from about 35,000 stores. According to Nielsen (2019), “the data describes when, where, and what the panelists purchase, and at what price."[10] The households' purchases include both food and non-food items. There are approximately 60,000 U.S. households included in the panel annually and the panelists are noted by Nielsen to be geographically dispersed and demographically balanced. However, the panel of households change over time as some panelists stay on the panel for several years, while others may join or drop off each year. Since the panelists change between years, we conducted our assessments on an annual basis, allowing us to make comparisons over time and test for robustness.

The HMS datasets also provide the panelists' geographic and demographic household information. In this study, the geographic variable of interest is the DMA code and the demand-side or demographic factors of interest include household size, income, age, gender, employment, education, marital status, and race, among others. We also considered the transaction variables such as total spent per shopping trip and the date of purchase or trip. Table 3.1 presents the description of all the variables from the Consumer Panel data that were used in our study. Some of these variables were grouped and transformed to create another variable. This is discussed in the next chapter (Chapter 4)

3.3. Regional Household Data

In this subsection we present diagrammatic illustrations of the descriptive findings for some of variables used in examining our research questions. The discussion is first

[10] The Nielsen Homescan panelists record all purchases from different outlet that are intended for personal or in-home by using in-home scanners or a mobile app.

provided by each DMA which is then followed by a regional summary of these key variables.

3.3.1. Chicago (CHI) DMA

In Figure 3.3, about two-thirds of the heads of households are 50 years old and over for the five-year period. This is not unusual since the information is reported for the head of the households. Figure 3.4 shows that the panelists were composed of mainly females (78%).

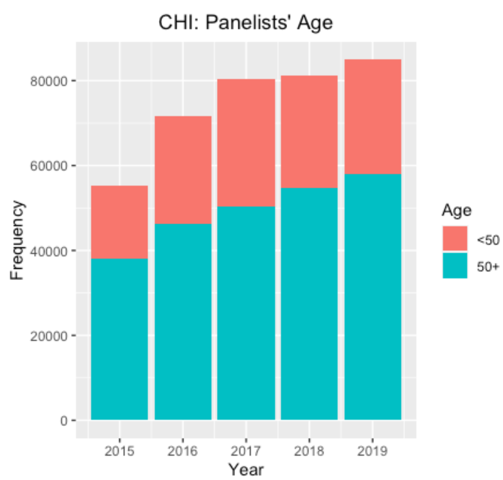

Figure 3.3: Panelists' Age in CHI.

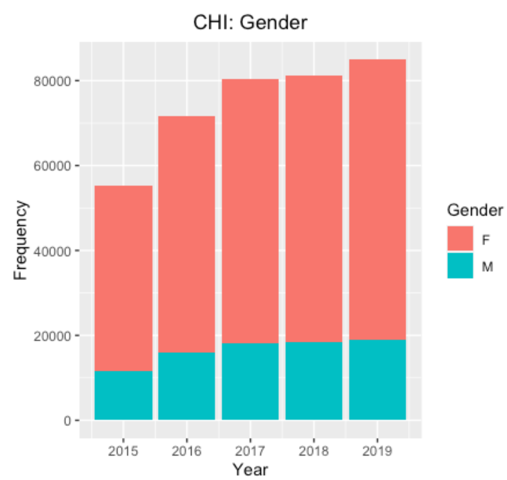

Figure 3.4: Panelists' Gender in CHI.

About 80% of the households' identified their ethnicity as White or Caucasian, while 10% identified as black or African American and the remaining 10% were split evenly between Asian and Other (see figure 3.5). The majority (70%) of the households' heads were married, whilst single and divorced households comprised about 14% and 11%, respectively (see figure 3.6).

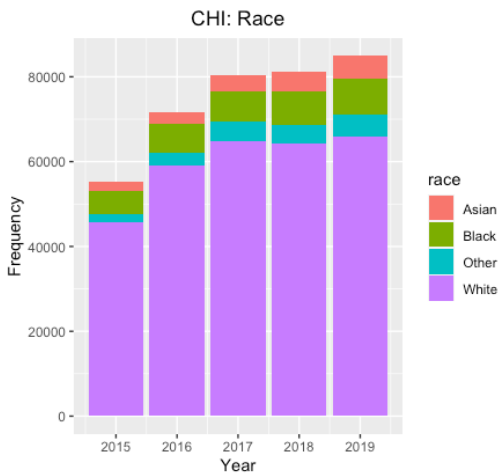

Figure 3.5: Panelists' Race in CHI.

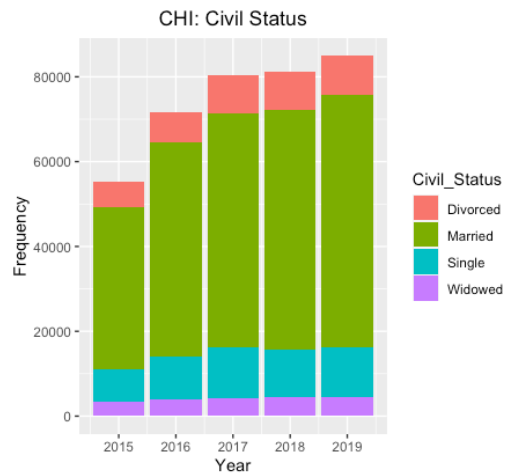

Figure 3.6: Panelists' Marital Status in CHI.

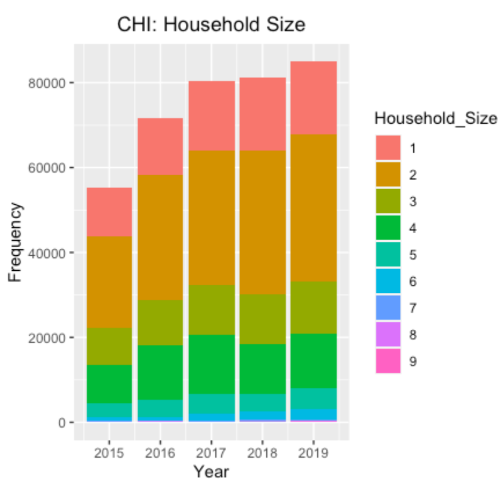

Figure 3.7: Individuals Residing in Home in CHI.

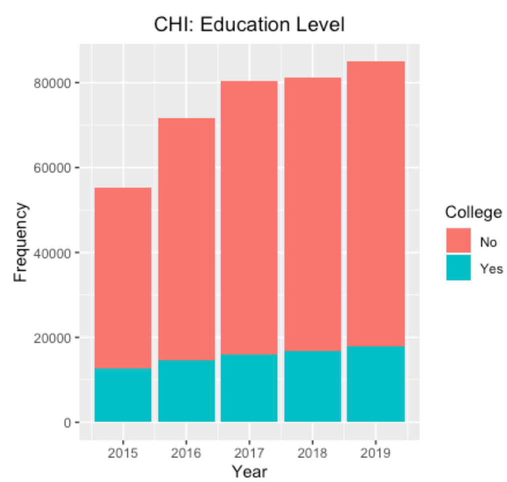

Figure 3.8: Panelists' Education Level in CHI.

From Figure 3.7, over 60% of the households comprised families of 2 or less members. Households with 3 and 4 members made up 14.8% and 16.2% of the sample, respectively. Very few households had over 5 members residing in the same home. About 20% of the head of households earned a college degree (see Figure 3.8).

The bulk of the head of households (68.4%) worked over 30 hours per week (see Figure 3.9). Of the remaining 31.6% of those households that worked less than 30 hours, about 77% were not employed for pay. Figure 3.10 on household income shows that the biggest income bracket was high income or an annual income above $100,000. However, most households were middle-income earners with lower-middle- and upper-middle income comprising 27% and 26%, respectively.

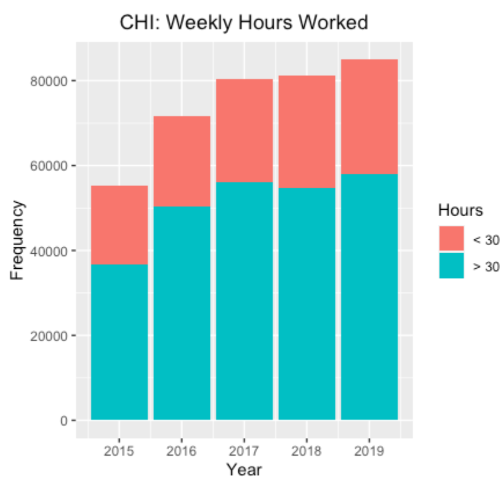

Figure 3.9: Frequency of Weekly Hours Worked in CHI.

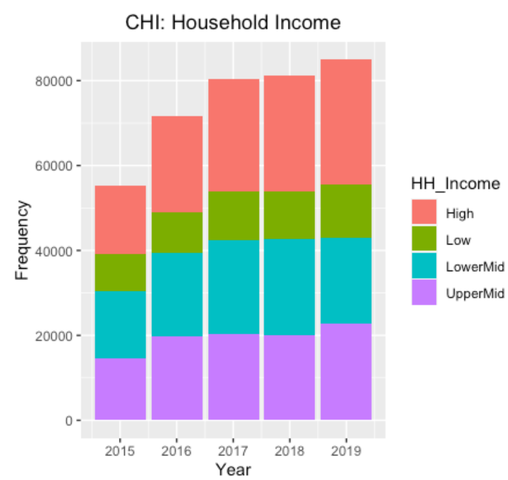

Figure 3.10: Number of Household Income Type in CHI.

3.3.2. Dallas-Ft. Worth (DFW) DMA

Like the metropolitan area of Chicago, the head of households in DFW were mostly above the age of 50 (see Figure 3.11). About two-thirds of the sample were females, though 2017 was an outlier year where the majority of the panelists (81%) were noted to be of male gender (see Figure 3.12).

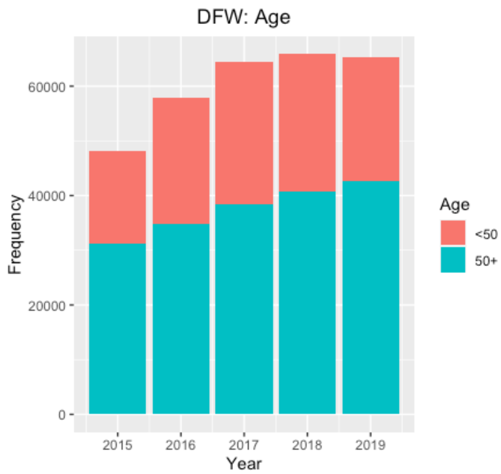

Figure 3.11: Panelists' Age in DFW.

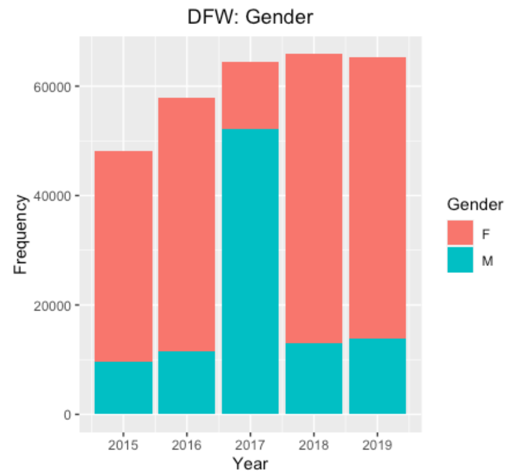

Figure 3.12: Panelists' Gender in DFW.

Whites or Caucasians comprised about 74.5% of the total sample compared with blacks or African Americans and Asians that were about 14.2% and 5%, respectively. The remaining 6.3% identified their household's ethnicity as other (see figure 3.13). From Figure 3.14, most of the households' heads were married (73.4%).

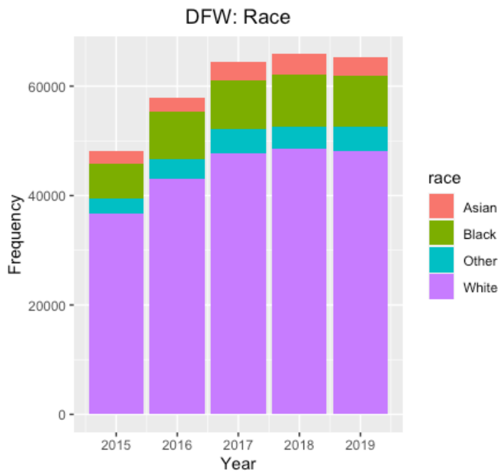

Figure 3.13: Panelists' Race in DFW.

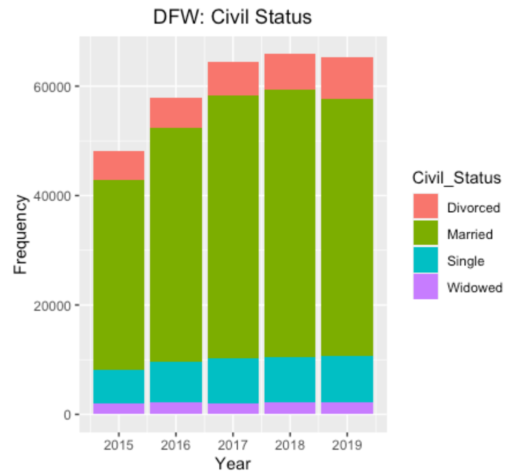

Figure 3.14: Panelists' Marital Status in DFW.

About 60% of the households comprised families of 2 or less members and those households with 3 and 4 members comprised about 16.7% and 14.8% of the sample, respectively (see Figure 3.15). Not many households had over 5 members residing in the same home. About 32% of the head of households earned a college degree (see Figure 3.16). Like Figure 3.12 on gender, there is an outlier in 2017 which makes the share significantly larger than that of Chicago. However, there seems to be a correlation between the household's gender and education level. This is expected as most of the households' heads are over 50 and would be affiliated with a time when the percentage of the U.S. population who have completed four years of college or more were mostly men (Statista, 2022).[11]

[11] https://www.statista.com/statistics/184272/educational-attainment-of-college-diploma-or-higher-by-gender/

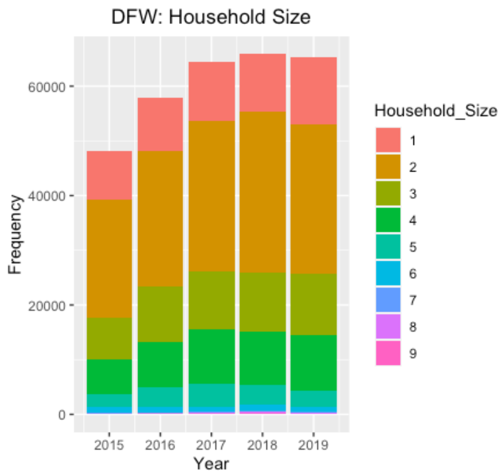

Figure 3.15: Individuals Residing in Home in DFW.

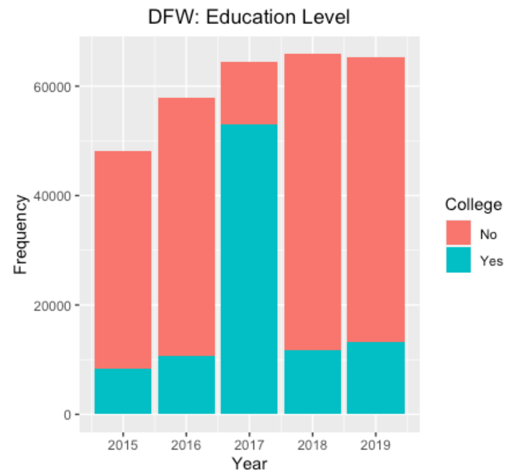

Figure 3.16: Panelists' Education Level in DFW.

Figure 3.17 shows that about 67.8% and 32.2% of the heads of households worked over 30 hours per week and less than 30 hours per week, respectively. About 26% of the sample were not employed and represent the biggest share of those working less than 30 hours. Figure 3.18 shows that most of the households were within the high-income bracket, earning above $100,000 whereas the lower-middle- and upper-middle income comprised about 26.5% and 27%, respectively.

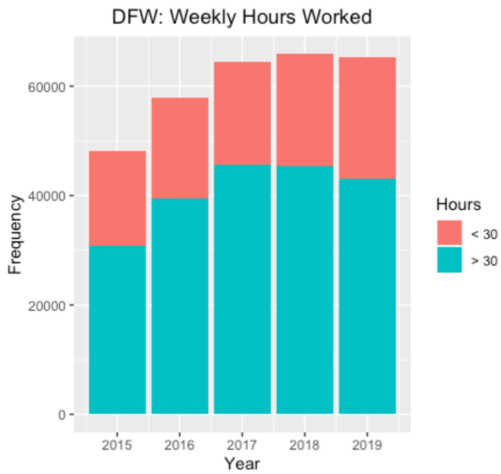

Figure 3.17: Frequency of Weekly Hours Worked in DFW.

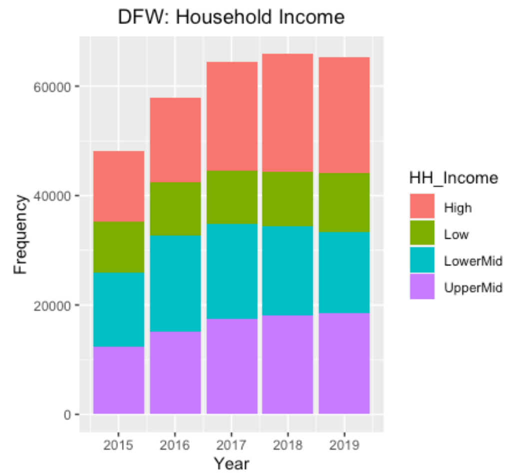

Figure 3.18: Number of Household Income Type in DFW.

3.3.3. Los Angeles (LA) DMA

From Figure 3.19, we see that most of the heads of households (62.8%) are 50 years old. The gender ratio was in favor of females, which represented about 78.2% of the sample (see Figure 3.20).

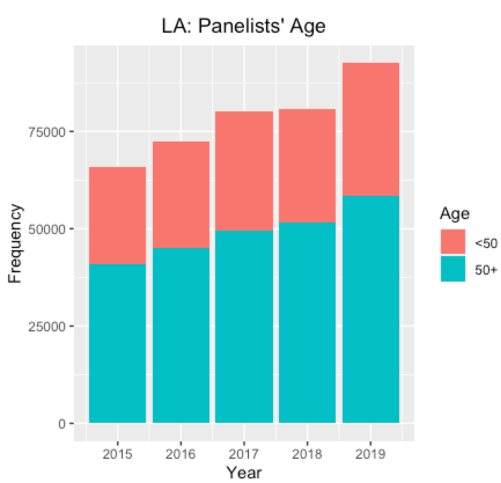

Figure 3.19: Panelists' Age in LA.

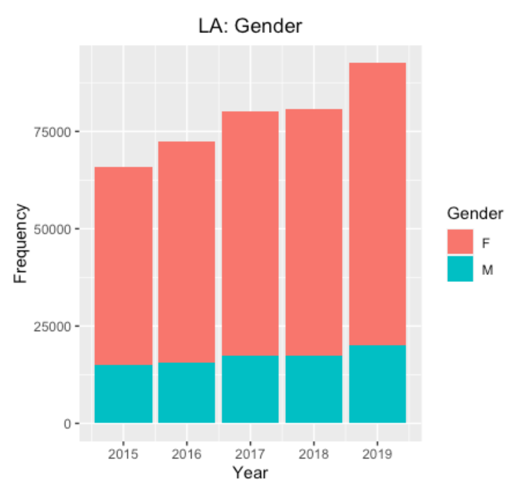

Figure 3.20: Panelists' Gender in LA.

In Figure 3.21, most of the households were identified ethnically as White or Caucasian (63.9%). The other categories were of Asian (16.4%), black or African American (9.1%), and Other (10.7%). Head of households were typically married (66.8% of the sample). Those single, divorced, and widowed comprised 17.1%, 11.5%, and 4.6%, respectively (see Figure 3.22).

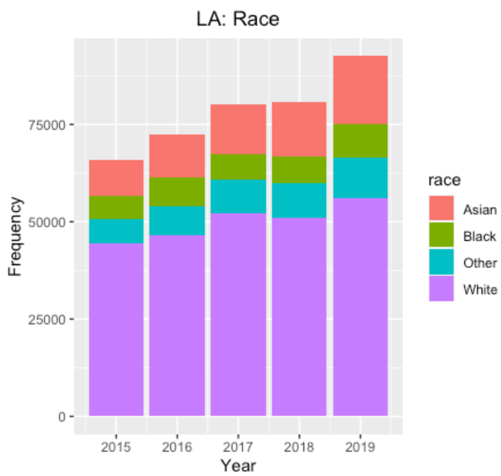

Figure 3.21: Panelists' Race in LA.

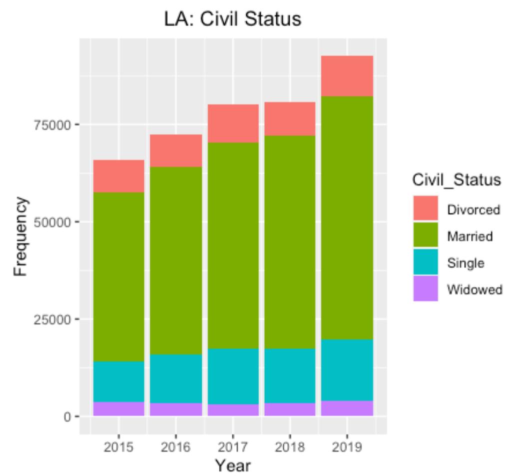

Figure 3.22: Panelists' Marital Status in LA.

From Figure 3.23, about 90% of the households comprised families of 4 or less members and 58.3% have 2 or less members residing in the same home. About 18% of the head of households earned a college degree (see Figure 3.24).

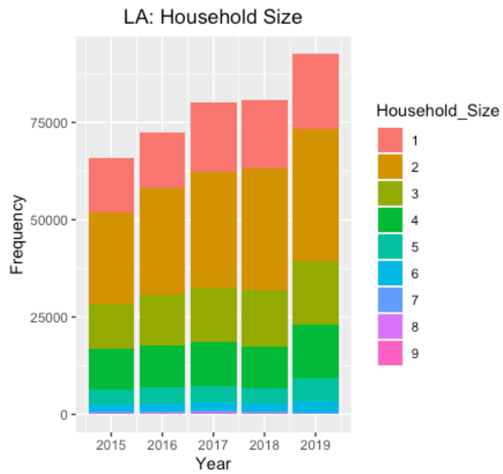

Figure 3.23: Individuals Residing in Home in LA.

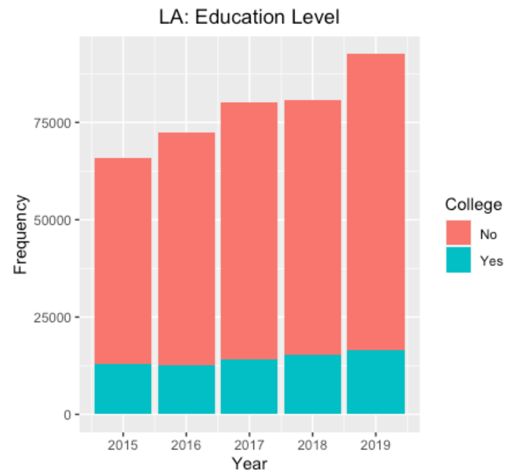

Figure 3.24: Panelists' Education Level in LA.

Most of the panelists (65%) worked over 30 hours per week (see Figure 3.25). About 27.6% of the head of the households did not report employment, which made up the bulk of those households working less than 30 hours per week. Figure 3.26 shows that 33.1% of the households were in the high-income bracket because they earned at least a six-digit annual income. However, most households were middle-income earners with lower-middle- and upper-middle income comprising 25.3% and 23.5%, respectively.

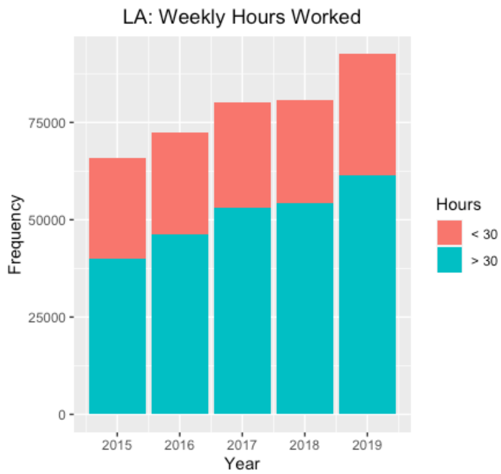

Figure 3.25: Frequency of Weekly Hours Worked in LA.

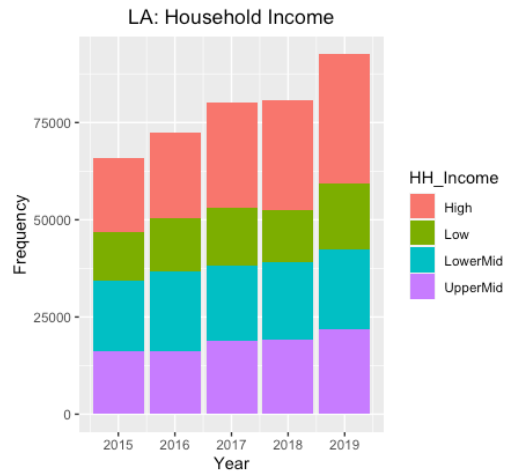

Figure 3.26: Number of Household Income Type in LA.

3.3.4. New York City (NYC) DMA

Figures 3.27 and 3.28 show that the households' heads in NYC were mostly female (74.7%) and above 49 years old (64%).

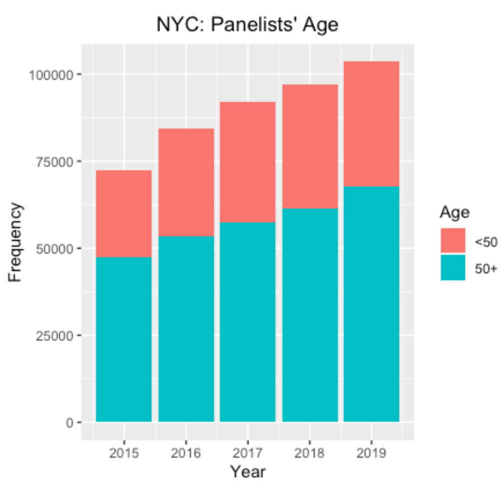

Figure 3.27: Panelists' Age in NYC.

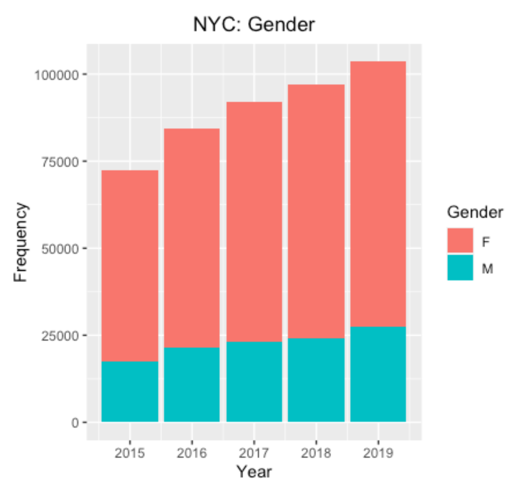

Figure 3.28: Panelists' Gender in NYC.

The majority of the households (73.3%) identified as white or Caucasian. The remaining share comprised 12.3% of black or African American households, 7% of Asian households, and 7.4% were classified ethnically as other (see figure 3.29). From Figure 3.30, most of the households' heads were married (64.3%).

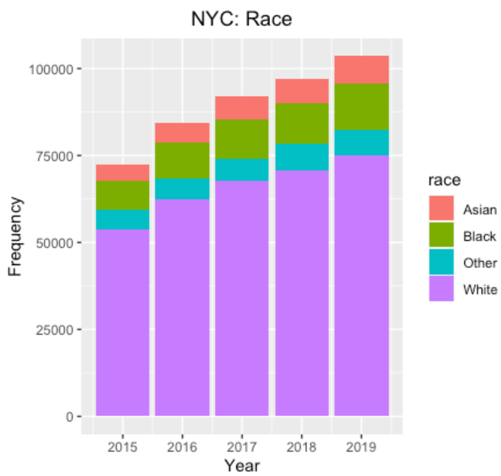

Figure 3.29: Panelists' Race in NYC.

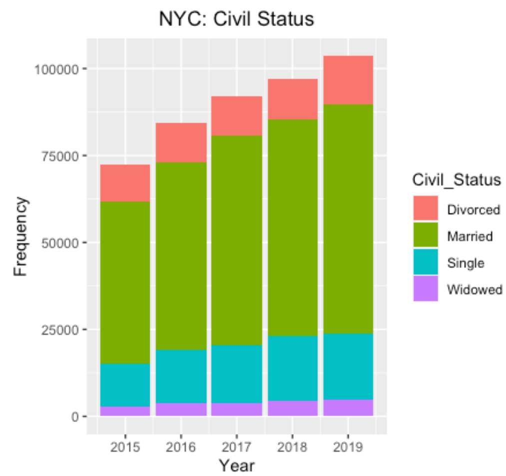

Figure 3.30: Panelists' Marital Status in NYC.

Figure 3.31 shows that households with more than 4 members comprised a small share of the total households (about 8%). About 59.4% of the households had at least 2 members and 32.9% of the households had 3 to 4 members residing in their home. The bulk of the head of households (79.5%) did not earn a college degree (see Figure 3.32).

Most heads of households (68.3%) worked over 30 hours per week (see Figure 3.33). Of the remaining households that worked less than 30 hours, about 78.5% were not employed for pay. Figure 3.34 shows that the largest income bracket was high income

(39.2%). However, most households were middle-income earners with lower-middle- and upper-middle income comprising 23.5% and 23.6%, respectively.

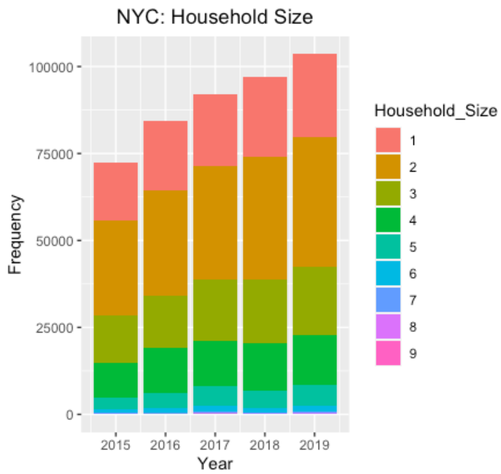

Figure 3.31: Individuals Residing in Home in NYC.

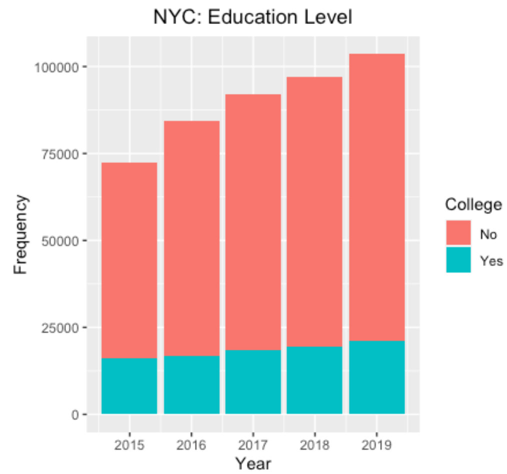

Figure 3.32: Panelists' Education Level in NYC.

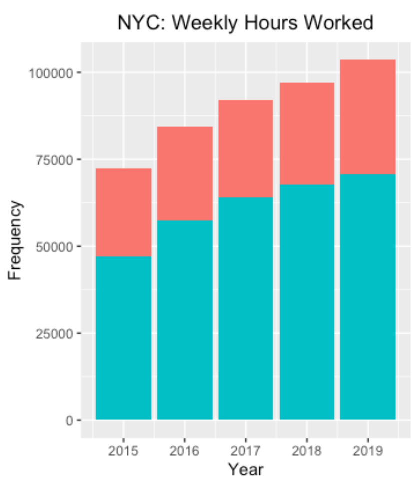

Figure 3.33: Frequency of Weekly Hours Worked in NYC.

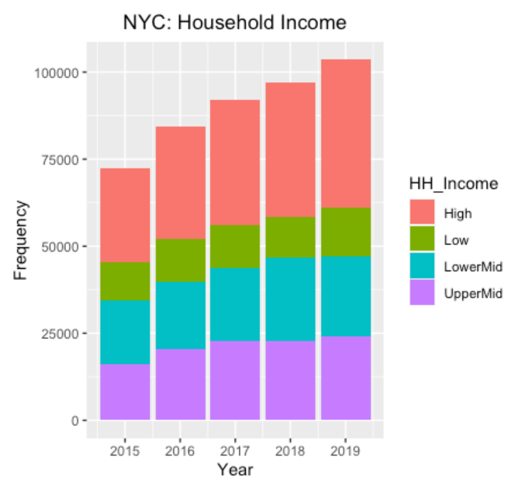

Figure 3.34: Number of Household Income Type in NYC.

3.3.5. Regional Data Summary

Most of the heads of households in all regions were female and above 50 years old. This age profile is consistent with the U.S. Census Bureau (2021) Current Population Survey[12] which shows growth in the head of households that are older but a decline in those that are younger. Also, across all the regions, females accounted for about three-quarter of the total panelists. This share is not surprising given the more recent shift towards women making up a larger share of the workforce. There is also a higher share of female head of household among single women from 18% in 1990 to 23% in 2019, and among married women from about 22% in 1990 to 46% in 2019 (U.S. Census Bureau 2020 American Community Survey and U.S. Census Bureau 1990 Decennial Census).

The bulk of the sample households was white, married, and without a college degree. Across the regions, white households as a share of the sample ranged from as low as 64% in Los Angeles to as high as 80% in Chicago. On average, 68.5% of the head of household was married. The share of single households increased over time which is in line with Census data where there is a rise in households with one person. The civil status statistics are reflected in the household size data where there was mainly one (1) or two (2) individuals residing in the same home. About 80% of the head of household in each DMA, except for DFW, did not earn a college degree.

[12] Source: U.S. Census Bureau, Current Population Survey, Annual Social and Economic Supplements, 1960 to 2021

Households generally worked for over 35 hours per week and earned income within the middle-income bracket. We also observed that a significant share (about 25%) of the sample did not work for pay whilst the fewest households fell within the low-income bracket in all DMAs.

Apart from the demographic characteristics of the panelist, we looked at the *purchase_date* variable to determine whether the panelists had any shopping patterns. The monthly share of purchases for each DMA is presented in Table 3.2, which shows that there is no seasonal shopping within the metropolitan areas as households have similar frequencies across all twelve months.

Table 3.2: Monthly Share of Transactions or Trips By DMA.

	Percent of Transaction by Month				
Month	**CHI**	**DFW**	**LA**	**NYC**	**Average**
1	8.20	8.37	8.25	8.41	8.27
2	7.86	7.85	7.91	7.96	7.87
3	8.97	8.70	8.90	9.10	8.86
4	8.49	8.35	8.54	8.57	8.46
5	8.59	8.53	8.74	8.65	8.62
6	8.19	8.27	8.19	8.16	8.22
7	8.38	8.50	8.39	8.36	8.42
8	8.41	8.58	8.38	8.15	8.46
9	8.02	8.16	8.15	8.08	8.11
10	8.28	8.15	8.25	8.32	8.23
11	8.21	8.19	8.10	8.21	8.17
12	8.40	8.36	8.20	8.04	8.32

CHAPTER 4

METHODOLOGY

In this study, we seek to determine (i) whether the monetary value of the consumer shopping basket affects the choice of payment, (ii) how households fund their in-store POS purchases, (iii) whether higher-income households are more likely to use borrowed funds for purchases, (iv) the demand-side factors that influence payment choice, and (v) whether there are systematic differences that exist across household income type and region that affects payment choice. These questions hint at a quantitative research methodology as we seek to categorize transaction features, calculate descriptive statistics, develop statistical models, test hypotheses, and generate inferences.

This chapter presents the procedures and methods used to answer our research questions. Specifically, we discuss our approach in sorting and filtering the data, the analysis of the distribution of the data using statistical tests and the kernel density functions, and the discrete choice empirical technique of the binomial logistic regression model. These methods are employed on selected designated market areas (DMAs) that fall under the four Census regions of the U.S. Census Bureau (see Chapter 3) and include: Chicago (Midwest), Dallas-Fort Worth (South), Los Angeles (West), and New York City (Northeast). These DMAs were chosen because of their size relative to the other DMAs. Robustness checks were undertaken at each step of our analysis which gives more reliable results that allows for the generalization of our inferences to the wider population. All data filtering, recoding, data analysis and visualization were done using RStudio 2021.09.1 Build 372.

4.1. Data Preparation

For this study, we are interested in examining consumer behavior between two payment choices: credit card and debit card. Therefore, we filtered the original data sourced from the Nielsen home-scanned Consumer Panel (HMS) datasets from 2015 to 2019. We conducted our assessments on each year since the panel of households were not consistent between years, allowing for comparisons over time and robustness checks. The data filtering process involved choosing a smaller part of the HMS datasets and using that subset in our analysis. First, we filtered the three HMS datasets (panelists, trips, and purchases) by *dma* and *store_zip3* (see Table 3.1 in Chapter 3 for a description of these variables), where applicable to obtain panelists information for each selected DMA. We then recoded or reclassified some of the variables in each of the subset DMA data to achieve our research objectives.

In the case of recoding the dependent variable, *payment*, all credit card payments, irrespective of type, were grouped under *"credit"*, check and debit were grouped under *"debit"*, while all other payment types such as cash and other unspecified forms were grouped as *"other"*. We further filtered the data using the reclassification of our dependent variable. For each household (HH_i), where $i = 1, \ldots, N$, we calculated the frequency of the transaction payment type as grouped above (x) as a percent of the sum of all the HH's transactions or observations (X), i.e.,

$$\frac{\sum_{t=1}^{T-k} x_i}{\sum_{t=1}^{T} X_i} \quad \forall i \text{ and } t = 1,2, \dots k, \dots T$$

where k are the trips affiliated with the use of another specific payment instrument and T are all the trips affiliated with the household despite the payment instrument used. We refer to the calculated ratios as p_1, p_2, p_3 where p_1 is for *"credit"*, p_2 is for *"debit"*, and p_3 is for *"other"*. Given the objective of our research, we focused on those households that used credit and debit cards at least 70% of the time. Thus, we subset the data by keeping only the households where $p_{i1} + p_{i2} \geq 0.7$. As we are interested in random household effects on our logistic regression, we dropped households with less than 10 transactions from this filtered sample. Having sufficient observations per household is important since the random effect estimator of our regression output could be numerically unstable.

A third sub-setting of the data was carried out. We normalized p_1 and p_2 for the remaining households, such that $p_{i1} + p_{i2} = 1$ and then categorized these normalized values into five groups based on the use of *"credit"* or p_1 as follows: [0,20], [20,40], [40,60], [60,80], [80,100]. That is, if a household used *"credit"* 20% of the time and *"debit"* the remaining 80% of the time, then that household was placed in the [0,20] group since it used a credit card 20% or less of the time. Similarly, if a household used *"credit"* 90% of the time and *"debit"* the remaining 10% of the time, then that household was placed in the [80,100] group since it used a credit card 80% or more of the time. This categorization is useful for the *"single-homing"* or *"multi-homing"* analysis, i.e., do households use mainly one type of payment system or multiple payment instruments? And if so, what are the factors that might influence such a decision?

We recoded some of the predictor variables and created new variables for our analysis. One such variable is the recoding of household income (*Household_Income*) from Table 3.1 to a categorical variable (*HH_Income*) with four income groups: low, lower-mid, upper-mid, and high. We use the recoded variable *HH_Income* in the remainder of this study. Table 4.1 shows the reclassification of the income variable.

Table 4.1: The Reclassification of Household Income.

Income Group	**Income Range (in U.S. dollars)**
Low	< 40,000
Lower-Mid	40,000 – 69,999
Upper-Mid	70,000 – 99,000
High	100,000+

Note: The data does not allow for grouping high income into 2 categories as 100,000+ is the last income category

We explored four different expenditure definitions to assess the impact of the monetary value of the consumer purchase basket of their payment choice. These are outlined as follows:

- Expenditure in its level form (*exp*) was the dollar value of the *total_spent* variable in the Consumer Panel Dataset,
- Expenditure in its logarithmic form (*log_exp*),
- Expenditure in its relative form (*rel_exp*) was found by dividing expenditure in its level form by the mean household expenditure, and
- Expenditure in its normative form was derived by dividing expenditure in its level form by the size of the household $\left({}^{exp}/_{HH\_size}\right)$.

Other variables were recoded to accommodate our logistic regression analysis. A frequency discussion of these variables is presented in Chapter 3. The analysis is conducted at the transaction level, and each transaction typically contains multiple items (UPCs). Table 4.2 describes the variables used in our methodological process.

Table 4.2: Description and Type.

Variables	Description	Variable Type
payment	Method of payment used per trip (1 = credit; 0 = debit)	Binary
HH_Income	Total annual household income categorized by: low, lower-mid, upper-mid, high	Categorical
exp	Total expenditure for the trip, as entered by the consumer from the bottom of their receipt	Continuous
log_exp	exp in its logarithmic form	Continuous
rel_exp	exp divided by the mean household expenditure	Continuous
norm_exp	exp divided by HH_Size	Continuous
HH_Size	Number of individuals residing in each household	Continuous
age	Age of household head (1 = > 49 years; 0 = other)	Categorical
marital_status	Marital status of household heads (1 = married; 0 = other)	Categorical
gender	Gender identification of household head (1 = male; 0 = female)	Categorical
education	Highest degree earned by household head (1 = college; 0 = no-college)	Categorical
race	Racial identity of the household (1 = white; 0 = other)	Categorical
purchase_day	Date of purchase, where 1= day < 7 or day > 23; 0=otherwise	Categorical
work	Approximate number of hours per week the female head is employed (1 = "> 30 hours"; 0 = other)	Categorical
HH_code	ID of household that made the purchase	Categorical

4.2. Data Analysis: Distributional Analysis

To understand the classification of our data we examined the distribution of the sample data and proportion statistics. This helps us to not only be able to identify essential concepts of statistical analysis but also to draw conclusions on the population (Sheats & Pankratz, 2002). With the data type and the distribution pattern of their values influencing the choice of statistical tests, we test whether the expenditure distribution for *debit* and the distribution for *credit* are the same for each income group. We adopted two nonparametric approaches to investigate our data: goodness of fit tests and the kernel density estimation. The nonparametric approach makes very minimal assumptions regarding the process that generated the data. We use these results to help us determine if there are any systematic differences or possible latent types in the income groups, such as credit constraints or budget consciousness.

The Kolmogorov-Smirnov (KS) test compares the equality of the probability distribution of two samples. It's null hypothesis states that the two sets of samples are drawn from the same probability distribution. Though the test doesn't assume a particular underlying distribution, it has commonly been used to test for normal distributed data. The Kolmogorov-Smirnov test statistic is defined as

$$D = \max_{1 \le i \le N} \left(F(Y_i) - \frac{i-1}{N}, \frac{1}{N} - F(Y_i) \right),$$

where F is the theoretical cumulative distribution of the continuous distribution being tested. Since the KS test tends to be more sensitive near the center of the distribution than at the tails, we adopted a second nonparametric goodness of fit test, the Anderson-Darling (AD) test, to confirm our test results. The AD test is a modification of the KS test, giving more weight to the tails than does the KS test. The AD test has a similar null and alternative hypotheses to the KS test and is defined as

$$A^2 = -N - S,$$

$$S = \sum_{i=1}^{N} \frac{(2i-1)}{N} \left[lnF(Y_i) + ln\big(1 - F(Y_{N+1-i})\big) \right].$$

Here, F is the cumulative distribution function of the distribution and Y_i are the ordered data. Both tests were applied to one of our key predictor variables, total expenditure (*exp*) across the different income types.

We continued looking at nonparametric estimation since both the KS and AD tests suggested that the expenditure distributions for credit and debit are different across the income groups. According to Cameron & Trivedi (2005), the estimation of a continuous density using a kernel density estimate is one of the better nonparametric approaches.[13] It provides a smoother density estimate than the histogram and can be used to conduct exploratory analysis of data across different groups.

The kernel density estimator generalizes the histogram estimate by using a different weighting function,

$$\hat{f}(x_0) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{x_i - x_0}{h}\right).$$

The weighting function, $K(\cdot)$, is the kernel function, and h is the smoothing parameter or the bandwidth. The density is estimated by evaluating $\hat{f}(x_0)$ at a wider range of values of x_0 than used in forming a histogram; usually evaluation is at the sample values $x_1, \ldots, x_N$. This also helps provide a density estimate smoother than a histogram (Cameron & Trivedi, 2005). The kernel function $K(\cdot)$ is a continuous function, symmetric around zero, that integrates to unity and satisfies other boundedness conditions.

We looked at the Kernel density across both payment types and the different income groups. We also plotted densities for different expenditure definitions. We considered expenditure in its level form (*exp*), expenditure in its logarithmic form (*log_exp*), and expenditure normalized for household size (*norm_exp*) and its logarithmic

[13] The kernel density estimation discussion borrows heavily from Cameron & Trivedi (2005).

form (*log_norm_exp*). We focused on various expenditure definitions to account for likely different household structures across income groups.

4.3. Regression Analysis

We discuss our estimation approach and econometric model specifications in this subsection. To study the contributing factors on the choice of payment methods, we employed a binomial logistic regression model. The logistic regression models the probability of outcome of a categorical dependent variable given all other independent variables. In this study, we have a two-category dependent variable, defined as a binary logistic regression. The logit link function makes the relationship between the dependent variable and predictor variables linear. In this subsection, we discuss how consumers make a rational decision and the generalized linear model employed for the empirical analysis.

4.3.1. The Binary Outcome

A binary outcome occurs when an agent is faced with two discrete alternatives. In this study, the household chooses between paying with a credit card for its shopping trip transaction or paying with a debit card. The dependent variable, y_i, is binary, taking on two values:

$$y_i = \begin{cases} 1 & \text{if payment made using a credit card,} \\ 0 & \text{if payment made using a debit card,} \end{cases}$$

and

$$y = \begin{cases} 1 & \text{with probability } p, \\ 0 & \text{with probability } 1 - p. \end{cases}$$

where the values 1 and 0 are chosen for simplicity and the predicted probability p determines the probability of the outcome, which needs to be constrained between zero and one. The rationality behind the choice between the two options can be explained by the random utility model.

4.3.2. The Random Utility Model

Under the random utility model, we assume that the agent/household makes a discrete choice among options to maximize his/her utility. In this study, the N households make a discrete choice between 2 payment instruments (c, d). The model assumes that each household chooses the option c if and only if the utility from using payment c is greater than the utility from using payment d, i.e., $U_{ic} > U_{id}$. We investigated households' choices and the factors influencing them in each of T time periods, where $T \in \{2015, 2016, 2017, 2018, 2019\}$. Therefore, household i in period t who chooses product c obtains utility U_{ict}. Since we do not observe this utility, we can model it as composed of utility from observed attributes (V_{ict}) and utility from unobserved attributes, ε_{ict}, which we treat as random and is distributed according to a type I extreme value distribution, $U_{ict} = V_{ict} + \varepsilon_{ict}$.

The probability that household, i, chooses alternative c in period t is given by:

$$P_{ict} = \Pr(U_{ict} > U_{idt}) = \int \mathbb{I}(\varepsilon_{idt} - \varepsilon_{ict} < V_{ict} - V_{idt}) f(\varepsilon_i) d(\varepsilon_i).$$

The difference of the two extreme values, $\varepsilon_{idt} - \varepsilon_{ict}$, follows a logistic distribution. The generalized linear models (GLMs) for categorical responses include logistic regression models.

4.3.3. The Generalized Linear Model (GLM)

The generalized linear models can analyze simultaneously the effects of several explanatory variables, which can be both categorical and continuous. GLMs have three components:

1. The ***random component*** identifies the response variable, Y, and its probability distribution. With the dependent variable being binary, we assume a binomial distribution for Y.
2. The ***linear predictor*** specifies the explanatory variables through a linear prediction equation, and
3. The ***link function*** denotes a function of $E(Y)$ that the GLM relates to the linear predictor. The $E(Y)$ connects the random component with the linear predictor function of the explanatory variables. The link function $E(Y) = log[\mu/(1-\mu)]$ models the log of an odds and like a probability, μ is between 0 and 1. A GLM that uses the logit link function is called a *logistic regression model*. This link function is most appropriate since our model has multiple explanatory variables, and the effects might be nonlinear rather than linear.

4.3.4. Logistic Regression Model

The binomial logistic regression model predicts the probability that an observation falls into one of two categories of a dichotomous dependent variable based on one or more independent variables. Our model looked at the effect of the predictor variables (see Table

4.2) on the probability of using a credit card and is based on the following assumptions: a dependent variable measured on a dichotomous scale, independent observations,[14] mutually exclusive and exhaustive dependent variable categories, a linear relationship with logit transformation of the response and the continuous predictors. Where appropriate, these assumptions were tested. Logistic regression was deemed sufficient to analyze and answer our research questions.

The logistic regression model form with multiple explanatory variables is generally given by

$$log\left[\frac{P(Y=1)}{1-P(Y=1)}\right] = \alpha + \beta_1 x_1 \ + \cdots + \beta_p x_p.$$

The random component for the (use of credit card, no-use of credit card) outcomes has a binomial distribution and a logit function, $log\left[\frac{\pi}{1-\pi}\right]$ or "$logit(\pi)$", is used for the link function of $\pi = P(Y = 1)$. Thus, the logit can be any real number and does not have the structural limitation of the linear probability model. Therefore, the coefficient of the explanatory variables can be positive (i.e., $\beta > 0$), which suggests that the $P(Y = 1)$ increases as the explanatory variable increases. The opposite is true for when the coefficient of the explanatory variables is negative.

We anticipated that some households may have a higher probability of using a credit card than other households. Household-specific random effects are incorporated into our models to account for these differences. Random effect models assist in controlling for unobserved heterogeneity when the heterogeneity is constant over time and

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[14] Violations of this assumption result in invalid statistical inference.

not correlated with the predictor variables. Therefore, for each of the five datasets in the metropolitan areas (i.e., the aggregated data and disaggregated data by income type), we built two (2) models, one with a household random effect and another without a household random effect. For each of these model specifications, we devised three (3) separate models based on the different definitions of expenditure (*exp*, *log_exp*, *rel_exp*). These models were considered for each year in the five-year period of this study. Thus, we ran 150 models for each DMA to determine the relationships between the independent variables and the probability of using a credit card. These models allowed us to check for robustness over time, DMA, and income group.

In the full specification of our generalized linear mixed model, the probability of household i using payment method j when making a transaction at DMA k in year t is defined as follows:

$$N_{ijkt} = log\left(\frac{p_{ijkt}}{1-p_{ijkt}}\right) = \theta_{kt} + \alpha_{jkt} + X_i\beta_{jkt} + C_{ij}\delta_{jkt} + \varepsilon_{ijkt} \qquad \textbf{\textit{(4.1)}}$$

where N_{ijk} is the proportion of use of credit card, X_i is a vector of HH characteristics (such as, age, race, gender, marital status, education, income, work, HH size), C_{ij} is a vector of transaction characteristics (such as, transaction value (*exp*, *log_exp*, *rel_exp*), and purchase date), θ_{kt} is the random household effect, α_{jkt} measures the overall mean from payment method j at DMA k and time t, and ε_{ijk} is the random error. The predictors as presented in Table 4.2 are a combination of quantitative and categorical variables.[15] *HH_code* was treated as random given the uncertainty in the panel composition changing

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[15] We exclude *norm_exp* as a predictor variable in our logistic model since we included *HH_Size*.

over the period. The predictor effects were assumed to have a linear and additive relationship with log odds of the outcome. Also, the random effect and residuals are assumed to be normally distributed with mean zero and with its respective finite variance. The sizes of the model parameters determine the strength and importance of the effects.

For the disaggregated DMA data by income group, we excluded the predictor variable *HH_Income* from the models. Also, for the models without the random effect, we omitted the random effect variable, θ_{kt} from equation 4.1. As noted above, we estimated six specifications of the binomial logit model that explains which payment method is chosen by the household as the most frequently used method for each income type. Three of these specifications were run without a household effect and the other three were regressed with a random household effect. The three specifications for the models with and without a random effect, are based on the expenditure definitions: *exp*, *log_exp*, and *rel_exp*.

For each independent variable, we analyzed the direction of the association of the predictor variable on the response variable of the different models for each year. A predictor is said to have a positive (negative) effect if there is a consistently positive (negative) relationship across all years and models. The explanatory variable results are inconclusive if there are both positive and negative relationships across the period and models.

4.3.5. Statistical Inference and Model Checking

Inferences about the parameters evaluate which explanatory variables are truly associated with the response variable Y, while adjusting for effects of other variables. Our test for multicollinearity in our additive models of with or without a random effect for households did not show any significant correlation coefficient (that is, a value greater than 10) among our variables (Vittinghoff et al., 2012). Moreover, since our sample size is large, multicollinearity becomes a lesser problem (de Jongh et al., 2014). Thus, we did not have problems of major potential collinearities.

For each explanatory variable we tested the hypothesis that its coefficient has no effect on the response variable of using a credit card or that the binary response variable is independent of the explanatory variable (i.e., $H_0: \beta = 0$). We checked whether the predictors were needed in the model by comparing the deviance values for that model and for a simpler model without those variables. The likelihood-ratio test compares the maximized log-likelihood (L_1) for the full model to the maximized log-likelihood (L_0) for the simpler model in which those parameters equal 0. The test statistic is determined by $2(L_1 - L_0)$, which was found in RStudio using the *Anova* function in the *car* package. It is important to note that studies have found that supply-side factors influence the payment instrument choice (Swiecka & Grima, 2019; Ching & Hayashi, 2010; Zinman, 2009). However, given the inability to identify store characteristics from the HMS data, we were unable to include these factors in our estimation model. Not being able to model these factors serves as a limitation in our approach.

CHAPTER 5

RESULTS

In this chapter, we present the descriptive statistics and the findings from the binomial logistic regression. In sections 5.1 to 5.4, we discussed the results for the data, distribution, and the logistic regression findings by region or DMA (CHI, DFW, LA, NYC) for the transaction value and income predictors. In section 5.5, we provide a comparative analysis discussion of the regional results while section 5.6 presents the results for the other predictor variables of the logistic regression output.

5.1. The Midwest Region: Chicago (CHI)

In this section, we discuss the results for the predictors income and expenditure for the metropolitan area Chicago in the Midwest region. This section comprises three main subsections. In subsection 5.1.1, we provide some descriptive statistics for the income groups and payment types with a special focus on expenditure. Subsection 5.1.2 discusses the expenditure densities and subsection 5.1.3 presents the expenditure and income results for the logistic regression analysis.

5.1.1. CHI Data Analysis

There were on average 74,683 observations or unique trip codes and 1033 unique households for the DMA of Chicago between 2015 and 2019. The households in Chicago spent an average of US$53.98 per trip (*total_spent*) and US$4.93 per item (*price_paid*). When shopping at retail stores, households in Chicago were found to use credit cards per trip more often than debit cards (see Figure 5.1 and Table A1 in Appendix A). From Table A1 we observe a difference of about 173 unique households using a credit card more than a debit card. As such, about 58.8% of the total unique households used a credit card to pay for the shopping trip transactions over the five-year period. This ratio remained relatively constant throughout this period (see Figure 5.1). However, from Table A1, credit cards were used for transactions with lower average total expenditure (*total_spent*) than debit cards (US$51.53 versus US$57.53) and for transactions with higher average price paid per item (*price_paid*) than a debit card (US$5.10 versus US$4.71).

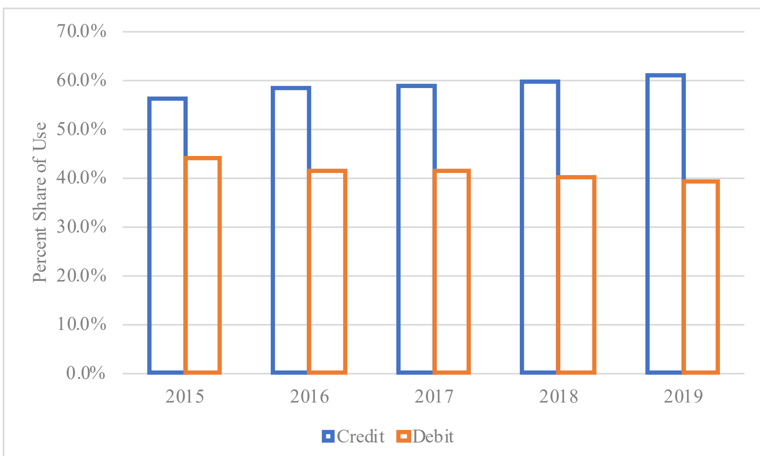

Figure 5.1: Share of Payment Instruments Used – CHI.
Note: The trend in payment instruments used for the sample data

The proportion analysis for the HHs that used a specific payment type during a shopping trip as a percent of their total transactions showed that most HHs revealed a preference toward a single type of payment instrument. About half of the HHs used a specific payment type at least 90% of the times and 80% of the HHs used a specific payment type at least 70% of the times. We found that only 6% of the HHs used a single payment instrument.

The largest share of households in Chicago fell within the high-income bracket (32.7%) followed by the lower-middle (26.9%), upper-middle (26.1%), and then low-income (14.3%). The share for each income type was similar when we disaggregated the data into credit and debit use only (see Table A1). The high-income households used a credit card more times than a debit card to pay for their transactions (71.1% versus 28.9%). All the other income categories used credit cards per trip more than debit cards except for low-income households where a more even distribution of electronic payment use was observed.

From Table 5.1, the three higher-income groups visited a similar number of unique retail chains (roughly 37) while low-income households visited the lowest number of unique retail chains (32). Low-income households also visited significantly fewer individual stores (601) compared to the other income groups (lower-middle-, high-, and upper-middle-income visited 832, 828, and 816 stores, respectively). Though the lower-middle income households shopped at the most stores (832), their total expenditure per trip was on average US$50.88, which was lower than the average for the upper-middle income (US$55.15) and the high-income households (US$59.59). The low-income group spent the least on each trip (US$45.05). The high-income consumers purchased the greatest number of products or UPCs (13,565) and spent the most on each shopping trip and per item (US$5.04) whilst the low-income households purchased the least number of unique products (7,097) and paid on average the least for each item (US$4.67). When we look at credit and debit use, the average total expenditure of all income groups was consistently higher when a debit card was used as a means of payment than a credit card, but the average price paid per item (*price_paid*) was higher for credit card use across all income groups (see Table A1).

Table 5.1: Selected Variables Count and Average Values by Income Type for CHI.

Income Type	Unique retailer code	Unique store code	Unique UPC	total_spent US$	price_paid US$
Low	32	601	7097	45.05	4.67
Lower-mid	37	832	12053	50.88	4.95
Upper-mid	36	816	11590	55.14	4.95
High	38	828	13565	59.59	5.04

5.1.2. CHI Distribution Analysis

The KS and AD test statistics indicate that the expenditure distributions across income type are not the same. The p-values of the KS and AD tests for all years are statistically significant, except for in 2015 where the KS test statistic for low-income households and both the KS and AD tests statistics for the lower-middle income households are insignificant (see Table A2). For the most part there are differences across the distributions, as such we observe the kernel densities for different expenditure definitions to identify any systematic differences across household type or region.

The density plots for the total expenditure distribution by payment type, debit, show that the densities for low- and lower-middle income groups are similar; while for credit, the densities for the mid- and high-income groups are similar (see Figures A1). The total expenditure density for the low-income group had the highest mode across all payment types and years. When we look at the densities for log expenditure, for both payment types, the densities for low- and lower-middle income groups are similar and are more left-modal while the densities for upper-middle- and high-income groups are similar and are mainly right-modal. From Figures A2, upper-middle and high-income groups display some semblance when we consider expenditure in its normalized form. This is the case for both debit and credit densities. For these groups, the credit normalized expenditure distribution seems to have a higher mode than the debit payment distribution. This difference seems to be less pronounced for the other income groups. In the case of the densities for both payment types for the logarithmic of normalized expenditure, the densities for low- and lower-middle income groups are more right-modal than the densities for upper-middle- and high-income groups. From these distributions, we observe that the upper-middle- and the high-income were similar whilst the lower-middle- and the low-income distributions show some likeness.

For the total expenditure densities by income type, credit payment type has a greater mode for all income types (see Figures A3). Similarly, the credit payment densities had a higher mode for normalized expenditure with an exception for the low- and lower-middle income groups in 2015 (see Figures A4). Regardless of the income group, the debit card densities for the log total expenditure and log normalized expenditure were left modal more than the credit card densities. We see similarities in the payment type densities in 2015 for the low- and lower-middle income groups. This is not surprising given the results from the KS and AD test statistics.

5.1.3. CHI Logistic Regression Analysis

CHI Predictor Results for Income and Expenditure

Table 5.2 presents the estimated coefficients of the categorical variable *HH_Income* and the different expenditure definitions (*exp*, *log_exp*, and *rel_exp*) on the probability of using a credit card. The estimated log-odds of all the income groups using a credit card are lower than the estimated log-odds for a high-income household with and without factoring for household random effects. The estimated log-odds of using a credit card generally increases as income increases for the models without random household effects. This result is similar for the random household effect models, except for some inconsistency between the middle-income groups where the upper-middle income group had a more negative coefficient estimate for *Model 1* in 2016 and 2019 and for *Model 3* in 2019. This discrepancy suggests that the lower-middle income group is more likely to use a credit card than the upper-middle income group. Low-income households were found to consistently have lower estimated log-odds in the probability of using credit cards.

In the case of a one unit increase in the different expenditure definitions on the log-odds of the probability of using a credit card, we found a positive association for all the random effects models for each year. For the random effects model, the effect on the log-odds of using a credit card for *log_exp* and *rel_exp* is similar, and much higher than *exp*. As for the models without a random household effect, expenditure in its level form (*exp*) and expenditure in logarithmic form (*log_exp*) indicate that the estimated probability of use of credit cards decreases as households spend more per transaction. However, the opposite is true for expenditure in its relative form (*rel_exp*). For the model without random household effects, we found that a one unit increase in *exp* and *log_exp* reduces the log-odds of using a credit card by about 0.025 and 0.165, respectively (see Table 5.2).[16]

Table 5. 2: Estimated Log-Odds of Income Categories and Expenditure Types for CHI.

The Midwest: Chicago														
Year	Model Type	Low Income		LowerMid Income		UpperMid Income		exp		log_exp		rel_exp		Observation
		Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	
2015	W/O HH	-1.328	<2E-16	-0.869	<2E-16	-0.584	<2E-16	-0.008	0.000					55284
	WITH HH	-10.444	0.000	-5.855	0.000	-3.945	0.002	0.035	<2E-16					55284
	W/O HH	-1.340	<2E-16	-0.874	<2E-16	-0.587	<2E-16			-0.075	0.000			55284
	WITH HH	-14.428	0.000	-8.727	0.000	-7.197	0.000			0.134	0.000			55284
	W/O HH	-1.317	<2E-16	-0.864	<2E-16	-0.580	<2E-16					0.059	0.000	55284
	WITH HH	-11.229	0.000	-6.258	0.000	-5.020	0.000					0.160	0.000	55284
2016	W/O HH	-1.092	<2E-16	-0.909	<2E-16	-0.767	<2E-16	-0.024	<2E-16					71757
	WITH HH	-11.160	0.000	-6.849	0.000	-6.184	0.000	0.018	0.000					71757
	W/O HH	-1.112	<2E-16	-0.917	<2E-16	-0.772	<2E-16			-0.174	<2E-16			71757
	WITH HH	-12.281	0.000	-6.182	0.000	-6.460	0.000			0.106	0.000			71757
	W/O HH	-1.056	<2E-16	-0.885	<2E-16	-0.751	<2E-16					0.036	0.000	71757
	WITH HH	-10.708	0.000	-5.976	0.000	-5.096	0.000					0.127	0.000	71757
2017	W/O HH	-1.058	<2E-16	-0.922	<2E-16	-0.811	<2E-16	-0.031	<2E-16					80359
	WITH HH	-12.779	0.000	-9.734	<2E-16	-8.565	0.000	0.022	0.000					80359
	W/O HH	-1.064	<2E-16	-0.920	<2E-16	-0.806	<2E-16			-0.182	<2E-16			80359
	WITH HH	-9.756	0.000	-8.023	0.000	-3.757	0.007			0.213	<2E-16			80359
	W/O HH	-1.013	<2E-16	-0.888	<2E-16	-0.792	<2E-16					0.046	0.000	80359
	WITH HH	-9.676	0.000	-7.435	0.000	-6.857	0.000					0.178	<2E-16	80359
2018	W/O HH	-10.702	<2e-16	-0.868	<2e-16	-0.773	<2e-16	-0.032	<2e-16					81126
	WITH HH	-10.083	0.000	-9.671	<2e-16	-8.637	0.000	0.027	0.000					81126
	W/O HH	-1.081	<2e-16	-0.873	<2e-16	-0.772	<2e-16			-0.197	<2e-16			81126
	WITH HH	-7.582	0.000	-6.762	0.000	-4.475	0.002			0.245	<2e-16			81126
	W/O HH	-1.033	<2e-16	-0.843	<2e-16	-0.756	<2e-16					0.043	0.000	81126
	WITH HH	-9.311	0.006	-7.393	0.000	-4.830	0.002					0.209	<2e-16	81126
2019	W/O HH	-0.944	<2e-16	-0.807	<2e-16	-0.807	<2e-16	-0.029	<2e-16					84889
	WITH HH	-5.756	0.000	-6.899	0.000	-6.978	0.000	0.022	0.000					84889
	W/O HH	-0.951	<2e-16	-0.810	<2e-16	-0.810	<2e-16			-0.190	<2e-16			84889
	WITH HH	-7.761	<2e-16	-11.922	<2e-16	-7.708	<2e-16			0.208	<2e-16			84889
	W/O HH	-0.919	<2e-16	-0.783	<2e-16	-0.789	<2e-16					0.050	0.000	84889
	WITH HH	-5.582	<2e-16	-5.843	<2e-16	-6.156	<2e-16					0.203	<2e-16	84889

Note: Model type includes (i) without household random effect (W/O HH) and (ii) with household random effect (WITH HH). Model 1 is expenditure in its level form (*exp*), Model 2 is expenditure in its log form (*log_exp*), and Model 3 is the relative expenditure (*rel_exp*).

Table 5.3 reports the log-odds effect for the three definitions of expenditure on the probability of credit card use by income type. Analysis of the disaggregated data by

[16] The average effect for each income bracket and model were determined by finding the mean of the estimate for each year, i.e., $\sum \frac{\beta_{it}}{n}$.

income category remained relatively consistent across the groups. There was a positive and significant relationship across all expenditure types for the random household effect models as well as the *rel_exp* model without random effects. The models without random effects showed both positive and negative relationships for *exp* and *log_exp*. The log-odds effects of expenditure types of *log_exp* and *rel_*exp on credit card use in the random effects models are the largest for the low-income group. The upper-middle- and high-income groups had similar average effects for both expenditure models. The *exp* model had the lowest average effect on the log-odds of using a credit card for all income groups.

Table 5.3: Log-Odds Effect of Expenditure by Income Type for CHI.

The MidWest: Chicago										
Income Group	**2015**		**2016**		**2017**		**2018**		**2019**	
	W/O HH	**WITH HH**	**W/O HH**	**WITH HH**	**W/O HH**	**WITH HH**	**W/O HH**	**WITH HH**	**W/O HH**	**WITH HH**
Low-Income:										
exp	-0.010	0.049	-0.061	0.065	-0.052	0.061	-0.017	0.048	-0.024	0.056
p-value	0.052	0.000	<2E-16	0.000	<2E-16	0.000	0.000	0.000	0.000	0.000
log_exp	-0.066	0.303	-0.278	0.276	-0.172	0.249	-0.035	0.266	-0.103	0.354
p-value	0.006	0.000	<2E-16	0.000	0.000	0.000	0.088	<2E-16	0.000	0.000
rel_exp	0.068	0.322	0.054	0.202	0.048	0.252	0.052	0.265	0.076	0.358
p-value	0.018	0.000	0.059	0.001	0.026	0.000	0.025	0.000	0.001	0.000
Observation	*8910*	*8910*	*9431*	*9431*	*11452*	*11452*	*11170*	*11170*	*12297*	*12297*
Lower-Mid Income:										
exp	0.007	0.028	-0.011	0.014	-0.027	0.032	-0.041	0.007	-0.041	0.018
p-value	0.031	0.000	0.000	0.046	<2E-16	0.000	<2e-16	0.258	<2e-16	0.011
log_exp	0.023	0.114	-0.092	0.053	-0.126	0.149	-0.236	0.228	-0.193	0.169
p-value	0.185	0.002	0.000	0.159	<2E-16	0.000	<2e-16	0.000	<2e-16	0.000
rel_exp	0.064	0.144	0.032	0.087	0.066	0.205	0.024	0.112	0.041	0.114
p-value	0.003	0.000	0.090	0.021	0.000	0.000	0.166	0.002	0.030	0.002
Observation	*15812*	*15812*	*19719*	*19719*	*22092*	*22092*	*22567*	*22567*	*20442*	*20442*
Upper-Mid Income:										
exp	-0.030	0.023	-0.029	0.017	-0.031	0.019	-0.030	0.044	-0.041	0.013
p-value	<2E-16	<2E-16	<2E-16	0.010	<2E-16	0.011	<2e-16	0.000	<2e-16	0.049
log_exp	-0.227	0.160	-0.223	0.078	-0.249	0.129	-0.205	0.302	-0.264	0.176
p-value	<2E-16	0.001	<2E-16	0.034	<2E-16	0.001	<2e-16	0.000	<2e-16	0.000
rel_exp	0.041	0.172	0.034	0.105	0.023	0.045	0.062	0.290	0.037	0.137
p-value	0.084	0.000	0.067	0.004	0.216	0.251	0.001	0.000	0.030	0.000
Observation	*14496*	*14496*	*19814*	*19814*	*20330*	*20330*	*20100*	*20100*	*22661*	*22661*
High Income:										
exp	-0.003	0.034	-0.021	0.002	-0.029	-0.009	-0.032	0.014	-0.020	0.020
p-value	0.274	0.000	0.000	0.697	<2E-16	0.202	<2e-16	0.064	<2e-16	0.000
log_exp	-0.070	0.152	-0.164	0.125	-0.200	0.197	-0.247	0.179	-0.181	0.232
p-value	0.000	<2E-16	<2E-16	0.002	<2E-16	0.000	<2e-16	0.000	<2e-16	0.000
rel_exp	0.074	0.230	0.039	0.110	0.047	0.113	0.043	0.178	0.059	0.189
p-value	0.003	0.000	0.060	0.007	0.016	0.019	0.023	0.000	0.001	0.000
Observation	*16066*	*16066*	*22793*	*22793*	*26485*	*26485*	*27289*	*27289*	*29489*	*29489*

Note: Model type includes (i) without household random effect (W/O HH) and (ii) with household random effect (WITH HH). Model 1 is expenditure in its level form (*exp*), Model 2 is expenditure in its log form (*log_exp*), and Model 3 is the relative expenditure (*rel_exp*).

For the models without a random household effect, the effect of a one-unit increase in *rel*_exp on the log-odds of using a credit card for the low-income households was on average 0.06, being higher than that of the other income groups. The lower-middle- and low-income groups had the smallest negative average effect on the log-odds of credit card use when we looked at the *log_exp* model while the high-income group had the smallest negative effect of the probability of using a credit card for the *exp* model.

5.2. The South Region: Dallas (DFW)

In this section, we examine the results for the predictors income and expenditure for the DMA in the south region. In subsection 5.2.1, we provide some descriptive statistics for the income groups and payment types with a special focus on expenditure. Subsection 5.2.2 discusses the expenditure densities and subsection 5.2.3 presents the expenditure and income results for the logistic regression analysis.

5.2.1. DFW Data Analysis

The Dallas sample data comprised 60,290 observations or unique trip codes and 871 unique households. Households in the south region spent on average US$59.56 per trip (*total_spent*) and paid about US$4.95 per item (*price_paid*). Households in Dallas used debit cards per trip more than credit cards when shopping at retail stores. Figure 5.2 shows that debit use was consistently above credit use for all years, suggesting that it's a more preferred payment choice for transactions. Approximately 52% of the households used debit cards, however, the share of credit card use increased over time to about 50.6%

in 2019 while the use of debit cards decreased. However, Table B1 in Appendix B shows that the number of unique households that used a credit card (735) was higher than the number that used a debit card (692 unique households), suggesting that more households used only credit cards as a means of payment but had fewer annual shopping trips. Though the average price paid per item was higher for credit card payments than debit card payments (US$5.25 versus US$4.67), debit cards were used for transactions with a higher average expenditure than credit cards (US$61.18 versus US$57.82).

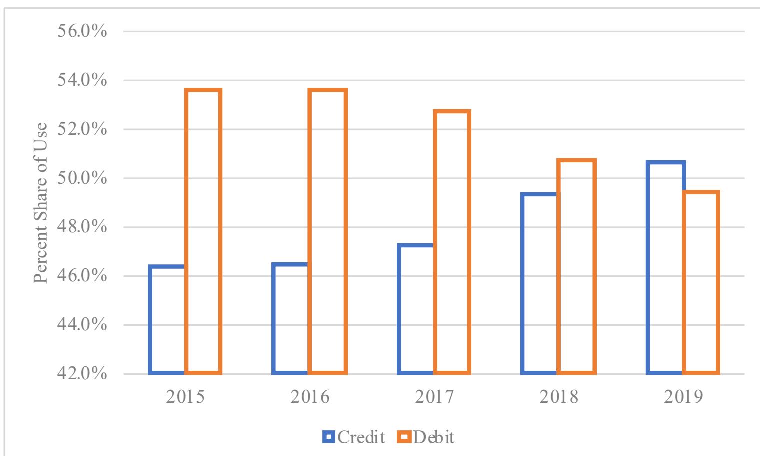

Figure 5. 2: Types of Payment Instruments Used – DFW.
Note: The trend in the share of payment instruments

Like in Chicago, most HHs in the Dallas-Fort Worth area revealed a preference toward a single type of payment instrument. The majority of the HHs (54%) used a specific payment type at least 90% of the times and 82% of the HHs used a specific payment type at least 70% of the times. We found that only 9% of the HHs used a single payment instrument.

For the disaggregated data by income type, the largest share of households in Dallas fell within the high-income bracket (30%) followed by the upper-middle (27%), lower-middle (26.5%), and then low income (16.5%). As such, most of the transactions or observations were for the high- and mid-income groups. High-income households consistently used a credit card to pay for their transactions more times than a debit card and the lower-middle- and low-income categories used a debit card per trip more than a credit card (see Table B1 in Appendix B). Table 5.4 displays that all income groups visit similar amounts of unique retail chains (approximately 33 retail chains). However, low-income households visited significantly fewer individual stores (469) compared to the other income groups while the lower-middle income category shopped at the most stores (624). As expected, higher-income households bought more unique products or quantity of distinctive UPCs (11,311) and had a higher overall spending per shopping trip (US$64.54). The higher-income households also spent more per item on their purchases (US$5.17). The average shopping trip expenditure for the upper-middle- and high-income groups was higher for debit card payments than for credit card payments. The opposite was true for the lower-middle- and low-income groups (Table B1).

Table 5.4: Selected Variables Count and Average Values by Income Type for DFW.

Income Type	Unique retailer code	Unique store code	Unique UPC	total_spent US$	price_paid US$
Low	31	469	6748	48.85	4.61
Lower-mid	35	624	10323	56.26	4.76
Upper-mid	32	604	10455	64.06	5.13
High	32	601	11311	64.54	5.17

5.2.2. DFW Distribution Analysis

In Table B2 (see Appendix B), the KS and AD test statistics indicate differences in the distributions of the expenditure data for credit and debit card usages by income type. The KS and AD tests mostly revealed a rejection of the null hypothesis of no difference between two distributions, except for in 2015 where the AD test statistic for high-income households was statistically insignificant. The statistical values of the AD test for the upper-middle income data are somewhat of an outlier as they are much larger than that of the other income groups.

The differences in the expenditure distributions were visible in the payment type density plots for the income groups. For total expenditure, the density plots of the debit data showed that the densities for low- and lower-middle income groups are similar; while for credit, the density for the low-income group has a higher mode than the other income groups (see Figures B1). When we looked at the densities for log expenditure, the densities for high- and upper-middle income groups were similar and were more right-modal whereas the densities for the low-income group across the years were consistently more left-modal. This is the case for both payment types. Figures B2 showed discrepancies across the income group densities for normalized expenditure. In the case of the debit densities by income group, the lower-middle and high-income groups have the highest modes. However, for the credit densities by income groups, the upper-middle and high-income groups show similarities in their distribution while the lower-middle and low-income categories are similar. The log of normalized expenditure densities showed no definite pattern across the densities over time. However, the credit densities by income type have a higher normalized expenditure mean than the debit densities.

The difference in distribution is also visible in the income-group density plots by payment type. For the total expenditure densities by income type, lower-middle- and low-income groups tend to have higher modes for the debit density while the upper-middle- and high-income groups have higher modes for the credit density (see Figures B3). Also, the debit payment densities for lower-middle- and low-income had a higher mode for normalized expenditure but there was no consistency with the mode for upper-middle- and high-income during the time (see Figures B4). For the upper-middle- and high-income groups, the log expenditure densities show that the debit card distributions for each year are more left-modal than the credit card distributions. Also, the lower-middle- and low-income groups have higher modes for the debit densities. There were close similarities in the credit and debit densities for log normalized expenditure for the high-income group while the low-income group had a more left-skewed density for credit over debit.

Overall, we observe some differences and similarities for the distributions. High- and upper-middle income groups shared some likeness for both payment types whereas the lower income groups were more alike for the debit payment instrument.

5.2.3. DFW Logistic Regression Analysis

DFW Predictor Results for Income and Expenditure

Table 5.5 presents the effect of the income and expenditure covariates on the log odds that households used a credit card, adjusting for the other predictor variables. The estimated log-odds of a low-income household using a credit card was lower than the estimated log-odds for a high-income household with and without factoring for random household effect. Table 5.5 showed that this was also true for lower-middle and upper-middle income groups. Moreover, the estimated log-odds of using a credit card were consistently the lowest for low-income households throughout the years suggesting that they were less likely to use credit cards compared to the other income categories.

Table 5.5: Estimated Log-Odds of Income Categories and Expenditure Types for DFW.

The South: Dallas														
Year	Model Type	Low Income		LowerMid Income		UpperMid Income		exp		log_exp		rel_exp		Observation
		Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	
2015	W/O HH	-1.138	<2E-16	-1.099	<2E-16	-0.531	<2E-16	-0.009	0.000					48079
	WITH HH	-13.096	0.000	-9.148	0.001	-8.502	0.001	0.038	<2E-16					48079
	W/O HH	-1.142	<2E-16	-1.099	<2E-16	-0.532	<2E-16			-0.066	0.000			48079
	WITH HH	-14.028	0.000	-6.806	0.365	-7.683	0.151			0.276	<2E-16			48079
	W/O HH	-1.133	<2E-16	-1.095	<2E-16	-0.531	<2E-16					0.072	0.000	48079
	WITH HH	-25.269	0.000	-21.351	0.000	-19.888	0.000					0.282	<2E-16	48079
2016	W/O HH	-1.013	<2E-16	-0.770	<2E-16	-0.291	<2E-16	-0.008	0.000					57819
	WITH HH	-11.168	0.000	-8.276	0.000	-2.627	0.095	0.029	0.000					57819
	W/O HH	-1.016	<2E-16	-0.770	<2E-16	-0.291	<2E-16			-0.052	0.000			57819
	WITH HH	-9.215	0.000	-7.067	0.000	-1.582	0.251			0.285	<2E-16			57819
	W/O HH	-1.005	<2E-16	-0.762	<2E-16	-0.289	<2E-16					0.062	0.000	57819
	WITH HH	-10.567	0.000	-7.939	0.000	-0.216	0.883					0.234	<2E-16	57819
2017	W/O HH	-1.084	<2E-16	-0.794	<2E-16	-0.590	<2E-16	-0.016	<2E-16					64355
	WITH HH	-7.199	0.000	-5.148	0.000	-2.829	0.019	0.032	<2E-16					64355
	W/O HH	-1.086	<2E-16	-0.794	<2E-16	-0.587	<2E-16			-0.091	<2E-16			64355
	WITH HH	-11.094	0.000	-9.999	0.000	-7.482	0.000			0.248	<2E-16			64355
	W/O HH	-1.067	<2E-16	-0.788	<2E-16	-0.590	<2E-16					0.062	0.000	64355
	WITH HH	-13.021	0.000	-10.572	0.000	-7.867	0.000					0.233	<2E-16	64355
2018	W/O HH	-1.161	<2e-16	-0.868	<2e-16	-0.505	<2e-16	-0.016	<2e-16					65826
	WITH HH	-12.230	0.000	-7.748	0.000	-5.412	0.000	0.033	<2e-16					65826
	W/O HH	-1.163	<2e-16	-0.869	<2e-16	-0.502	<2e-16			-0.109	<2e-16			65826
	WITH HH	-14.720	0.000	-12.782	<2e-16	-6.529	0.000			0.224	<2e-16			65826
	W/O HH	-1.144	<2e-16	-0.863	<2e-16	-0.509	<2e-16					0.055	0.000	65826
	WITH HH	-10.670	0.000	-7.536	0.000	-5.386	0.000					0.173	0.000	65826
2019	W/O HH	-1.415	<2E-16	-1.222	<2E-16	-0.627	<2E-16	-0.004	0.004					65372
	WITH HH	-10.620	<2E-16	-8.202	<2E-16	-3.760	<2E-16	0.032	<2E-16					65372
	W/O HH	-1.414	<2E-16	-1.221	<2E-16	-0.627	<2E-16			-0.020	0.019			65372
	WITH HH	-12.215	0.000	-11.314	0.000	-6.366	0.001			0.201	<2E-16			65372
	W/O HH	-1.411	<2E-16	-1.221	<2E-16	-0.627	<2E-16					0.045	0.000	65372
	WITH HH	-8.277	0.000	-7.811	0.000	-3.687	0.006					0.172	0.000	65372

Note: Model type includes (i) without household random effect (W/O HH) and (ii) with household random effect (WITH HH). Model 1 is expenditure in its level form (*exp*), Model 2 is expenditure in its log form (*log_exp*), and Model 3 is the relative expenditure (*rel_exp*).

The effects of the different expenditure definitions on credit card use were positive for all years for the random effects model, implying that higher outlays per shopping trip increases the log-odds of using a credit card. For the models without a random household effect, expenditure in its level form (*exp*) and expenditure in logarithmic form (*log_exp*) indicated that the estimated probability of using a credit card decreases as transaction costs increase. However, the opposite was true for expenditure in its relative form (*rel_exp*). A one-unit increase in *log_exp* had the smallest average effect on the log-odds of using a credit card (see Table 5.5).[17] For the models with a random household effect, a one-unit increase in *log_exp* and *rel_exp* had a similar effect on the probability of using a credit card as payment for a transaction. With *rel_exp* having a consistently positive effect for each year suggests that there is some element of systematic differences across households when deciding between the payment instrument choices.

When we disaggregated the data by income category, the effects were somewhat similar across the income groups (see Table 5.6). For the random household effect models, the association between all the expenditure types and the probability of using a credit card were positive. For each income group, the log-odds effects of *exp* on credit card use had the smallest positive effect while the coefficient estimate for *log_exp* and *rel_exp* had similar magnitude. The log-odds effects for the high-income group were stronger than those of the other income groups, highlighting a greater probability of a high-income household using a credit card for retail purchases. The *log*_exp model had the highest average estimate for the high-income group (0.375). Thus, the probability of using a credit

[17] The average effect for each income bracket and model were determined by finding the mean of the estimate for each year, i.e., $\sum \frac{\beta_{it}}{n}$.

card is estimated to increase the probability of using a credit card for high-income households by 45% ($e^{0.375}$).

Table 5.6: -Odds Effect of Expenditure by Income Type for DFW.

The South: Dallas										
Income Group	**2015**		**2016**		**2017**		**2018**		**2019**	
	W/O HH	**WITH HH**	**W/O HH**	**WITH HH**	**W/O HH**	**WITH HH**	**W/O HH**	**WITH HH**	**W/O HH**	**WITH HH**
Low-Income:										
exp	-0.009	0.050	-0.004	0.021	-0.016	0.032	-0.014	0.015	-0.005	0.006
p-value	0.019	0.000	0.282	0.020	0.000	0.004	0.001	0.250	0.280	0.631
log_exp	-0.065	0.426	-0.012	0.212	-0.060	0.193	-0.056	0.059	0.020	0.057
p-value	0.004	0.000	0.596	0.001	0.014	0.000	0.013	0.276	0.385	0.334
rel_exp	0.111	0.393	0.068	0.207	0.070	0.198	0.024	0.024	0.019	0.034
p-value	0.000	0.000	0.013	0.001	0.012	0.000	0.342	0.342	0.456	0.507
Observation	*9365*	*9365*	*9755*	*9755*	*9687*	*9687*	*10197*	*10197*	*10850*	*10850*
Lower-Mid Income:										
exp	0.023	0.047	0.013	0.031	0.000	0.025	-0.014	0.010	-0.005	0.024
p-value	0.000	<2E-16	0.000	0.000	0.966	0.000	0.000	0.167	0.104	0.002
log_exp	0.199	0.392	0.076	0.361	0.026	0.221	-0.084	0.128	0.003	0.160
p-value	<2E-16	0.000	0.000	<2E-16	0.103	0.000	0.000	0.002	0.866	0.001
rel_exp	0.096	0.320	0.059	0.157	0.061	0.185	0.038	0.098	0.046	0.135
p-value	0.000	0.000	0.002	0.000	0.002	0.000	0.056	0.012	0.031	0.001
Observation	*13625*	*13625*	*17652*	*17652*	*17374*	*17374*	*16239*	*16239*	*14916*	*14916*
Upper-Mid Income:										
exp	-0.030	0.029	-0.021	0.023	-0.025	0.016	-0.027	0.026	-0.008	0.013
p-value	<2E-16	<2E-16	0.000	0.000	<2E-16	0.006	<2E-16	0.000	0.001	<2E-16
log_exp	-0.248	0.244	-0.174	0.217	-0.200	0.206	-0.164	0.280	-0.100	0.119
p-value	<2E-16	0.000	<2E-16	0.000	<2E-16	0.000	<2E-16	0.000	0.000	0.004
rel_exp	0.033	0.262	0.049	0.151	0.041	0.142	0.068	0.267	0.040	0.133
p-value	0.138	0.000	0.016	0.000	0.034	0.001	0.002	0.000	0.039	0.002
Observation	*12339*	*12339*	*15082*	*15082*	*17530*	*17530*	*18057*	*18057*	*18428*	*18428*
High Income:										
exp	-0.014	0.031	-0.011	0.060	-0.019	0.057	-0.008	0.048	0.001	0.041
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.783	0.000
log_exp	-0.123	0.284	-0.069	0.381	-0.109	0.433	-0.074	0.356	0.033	0.421
p-value	0.000	0.000	0.000	0.000	0.000	<2E-16	0.000	<2e-16	0.035	<2e-16
rel_exp	0.066	0.224	0.082	0.406	0.088	0.358	0.082	0.330	0.071	0.346
p-value	0.004	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observation	*12750*	*12750*	*15330*	*15330*	*19764*	*19764*	*21433*	*21433*	*21178*	*21178*

Note: Model type includes (i) without household random effect (W/O HH) and (ii) with household random effect (WITH HH). Model 1 is expenditure in its level form (*exp*), Model 2 is expenditure in its log form (*log_exp*), and Model 3 is the relative expenditure (*rel_exp*).

In the case of the models without a random household effect, there was a general significant and negative relationship between the expenditure types of *exp* and *log_exp* and the probability of using a credit card. However, this relationship did not hold for the lower-middle income group as we found significant and positive effects for most of the years. There was also a positive association between *log_exp* and credit card use for the high-income in 2019. When we consider the average estimate effect for each expenditure type by income group, we found that the high-income group had the largest log-odds estimate of 0.78 while the lower-middle and low-income groups had a similar average effect of 0.06 and 0.058, respectively. Given the positive estimates on exp and *log*_exp for the lower-middle income group, they had the highest effect on the probability of using a credit card.

5.3. The West Region: Los Angeles (LA)

In this section, we examine the results for the predictors income and expenditure for the west region. In subsection 5.3.1, we provide some descriptive statistics for the income groups and payment types with a special focus on expenditure. Subsection 5.3.2 discusses the expenditure densities and subsection 5.3.3 presents the expenditure and income results for the logistic regression analysis.

5.3.1. LA Data Analysis

The data for LA comprised approximately 78,304 observations or unique trip codes and 1204 unique households. These households spent on average US$51.20 per trip (*total_spent*) and US$5.29 per item (*price_paid*). Average expenditure was higher for debit card payments when compared to credit card payments, however, average price paid per item was higher when a credit card was used. Figure 5.3 shows that households in LA used mostly credit cards to pay for their transactions, with a share of about 51.2% of the total unique households. We observed that this ratio increased significantly over the period. From Table C1 in Appendix C, there were about 144 more unique households that used a credit card as a means of payment than a debit card, suggesting that credit cards were preferred more by the households in LA.

Like in CHI and DFW, most HHs in LA revealed a preference toward a single type of payment instrument. Just over a half of the HHs (52%) used a specific payment type at least 90% of the times and 82% of the HHs used a specific payment type at least 70% of the times. We found that only 8% of the HHs used a single payment instrument.

There were mostly high-income households (33.1%) in the aggregated data for LA. Lower-middle, upper-middle, and low-income households represented about 25.3%, 23.5%, and 18.2%, respectively. High-income and upper-middle income households used a credit card to pay for most of their transactions. The lower-middle- and the low-income categories used debit cards per transaction more than credit cards (see Table C1). Table 5.7 shows that all income groups visited similar amounts of unique retail chains (41). However, low-income households visited significantly fewer individual stores (965) compared to the average of the other income groups (1201). The high-income households shopped at the most stores (1309), purchased the greatest number of distinct products or UPCs (14,382), and spent on average the most on each shopping trip (US$57.79) and per item/product (US$5.59).

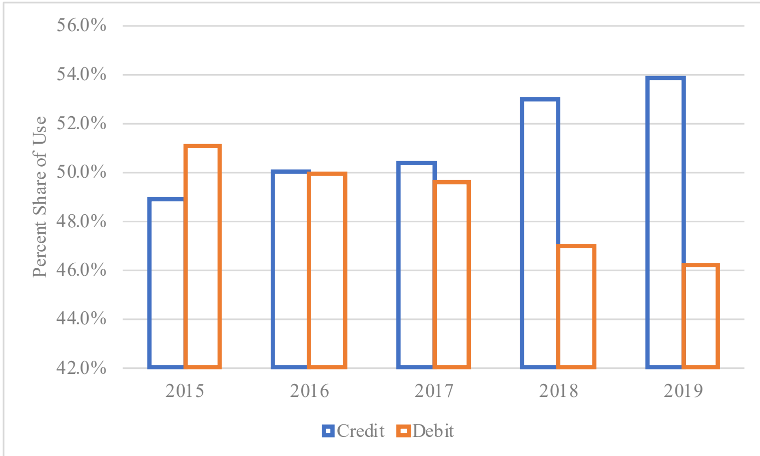

Figure 5.3: Types of Payment Instruments Used – LA.
Note: The trend in the share of payment instruments.

Table 5.7: Selected Variables Count and Average Value by Income Type for LA.

Income Type	Unique retailer code	Unique store code	Unique UPC	total_spent US$	price_paid US$
Low	41	965	8801	43.52	4.87
Lower-mid	42	1174	11731	46.94	5.15
Upper-mid	41	1120	11137	52.54	5.36
High	40	1309	14382	57.79	5.59

5.3.2. LA Distribution Analysis

The KS and AD test statistics indicated differences in the expenditure distributions across income types (see Table C2 in Appendix C). The rejections of the null hypothesis of all the KS and AD tests was not surprising given the large sample size.

The total expenditure density plots for payment type by income group showed similarities between lower-middle-and low-income and upper-middle- and high-income for both credit and debit (see Figures C1 in Appendix C). When we consider the log expenditure density plots, the upper-middle- and high-income are mainly left-skewed for the debit densities while the high-income is more left-skewed for the credit densities.

There was a different distribution association for the normalized expenditure plots (see Figures C2). The mid-income groups showed some similarities for the debit densities, especially in 2015 and 2016. However, the credit densities revealed that the high-income group has the highest mode and has some likenesses to the mid-income groups. There is no clear association across the log normalized distribution plots by income type for the debit densities while the low-income group were mostly left-skewed for the credit densities.

In the case of the densities of the income-group by payment type, Figures C3 displayed that credit appears to have a higher mode for total expenditure regardless of income type. After taking the logarithm of total expenditure, we observe negative skewness for the debit densities for all income groups over time. There are discrepancies across the income type when total expenditure is normalized by household size (see Figures C4). For the high-income group, the mode for credit densities for normalized expenditure was significantly higher than the mode for debit while the mid-income groups had a higher mode for the debit densities in the earlier years (2015 and 2016), but a higher mode for the credit densities in the later years (2017 – 2019). The log normalized expenditure density plots show no clear relationship for the densities of the mid-income groups. The debit densities are positively skewed for the high-income group and have the highest mode for the low-income group.

Overall, we found that the low-income group appeared to be different from the other income groups with an exception for the total expenditure plots where the group was like the lower-middle income bracket. The mid income groups and the high-income were more similar in the density plots.

5.3.3. LA Logistic Regression Analysis

LA Predictor Results for Income and Expenditure

Analysis of the income effect on credit card use showed that for any fixed value of all the other explanatory variables, the estimated log-odds of all the income groups using a credit card is lower than the estimated log-odds for a high-income household (see Table 5.8). In some years, the estimated odds for low-income households using a credit card were higher than the estimated odds for lower-middle income households. However, the results from all the models indicated that the estimated odds for upper-middle income consumers were always higher than that for low-income and lower-middle income groups.

In the case of the random effect models, the effects of the different expenditure definitions on credit card use were positive for all years. The effect of a one-unit increase in *log*_exp on the log-odds of using a credit card was on average 0.24, being significantly higher than that of *exp* (0.034) but slightly above *rel_exp* which was on average 0.202.[18] For the models without a random household effect, *exp* and *log_exp* indicated that the estimated probability of using a credit card decreases as households spend more per transaction. However, the opposite was true for expenditure in its relative form (*rel_exp*). We found that for the *exp* model without random household effects, a one-unit increase in

[18] The average effect for each income bracket and model were determined by finding the mean of the estimate for each year, i.e., $\sum \frac{\beta_{it}}{n}$.

expenditure has a negative effect of about 0.03 on the log-odds of using a credit card. This effect was smaller than that of *log_exp* which was approximately -0.204 (see Table 5.8). *rel_exp* had the only positive average effect on the log-odds of using a credit card under the model without random effect (0.05).

Table 5.8: Estimated Log-Odds of Income Categories and Expenditure Types for LA.

The West: Los Angeles														
Year	Model Type	Low Income		LowerMid Income		UpperMid Income		exp		log_exp		rel_exp		Observation
		Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	
2015	W/O HH	-1.590	<2E-16	-1.300	<2E-16	-0.679	<2E-16	-0.022	<2E-16					65793
	WITH HH	-20.685	<2E-16	-17.288	<2E-16	-16.102	<2E-16	0.028	0.000					65793
	W/O HH	-1.604	<2E-16	-1.313	<2E-16	-0.686	<2E-16			-0.186	<2E-16			65793
	WITH HH	-12.492	0.000	-11.864	0.000	-1.254	0.195			0.183	0.000			65793
	W/O HH	-1.580	<2E-16	-1.278	<2E-16	-0.671	<2E-16					0.040	0.000	65793
	WITH HH	-11.674	0.000	-9.585	0.000	-4.001	0.007					0.177	0.000	65793
2016	W/O HH	-1.064	<2E-16	-0.911	<2E-16	-0.519	<2E-16	-0.027	<2E-16					72388
	WITH HH	-16.773	0.000	-14.120	0.000	-7.262	0.000	0.039	<2E-16					72388
	W/O HH	-1.077	<2E-16	-0.918	<2E-16	-0.521	<2E-16			-0.192	<2E-16			72388
	WITH HH	-9.542	0.000	-9.637	0.000	-5.676	0.000			0.269	<2E-16			72388
	W/O HH	-1.036	<2E-16	-0.882	<2E-16	-0.499	<2E-16					0.059	0.000	72388
	WITH HH	-26.205	<2E-16	-23.514	<2E-16	-19.353	<2E-16					0.152	0.000	72388
2017	W/O HH	-1.177	<2E-16	-0.833	<2E-16	-0.594	<2E-16	-0.037	<2E-16					80033
	WITH HH	-22.540	<2E-16	-19.003	<2E-16	-19.854	<2E-16	0.032	0.000					80033
	W/O HH	-1.195	<2E-16	-0.842	<2E-16	-0.596	<2E-16			-0.243	<2E-16			80033
	WITH HH	-13.016	0.000	-9.765	0.000	-8.808	0.000			0.223	<2E-16			80033
	W/O HH	-1.123	<2E-16	-0.788	<2E-16	-0.575	<2E-16					0.053	0.000	80033
	WITH HH	-14.047	0.000	-8.320	0.000	-9.898	0.000					0.230	<2E-16	80033
2018	W/O HH	-0.846	<2e-16	-0.651	<2e-16	-0.388	<2e-16	-0.031	<2e-16					80805
	WITH HH	-11.462	0.000	-8.192	0.000	-6.661	0.000	0.032	0.000					80805
	W/O HH	-0.853	<2e-16	-0.659	<2e-16	-0.387	<2e-16			-0.198	<2e-16			80805
	WITH HH	-7.568	0.025	-4.363	0.044	-3.708	0.061			0.226	<2E-16			80805
	W/O HH	-0.812	<2e-16	-0.616	<2e-16	-0.374	<2e-16					0.041	0.000	80805
	WITH HH	-7.648	0.000	-5.343	0.001	-3.594	0.013					0.181	0.000	80805
2019	W/O HH	-0.807	<2e-16	-0.745	<2e-16	-0.462	<2e-16	-0.033	<2e-16					92499
	WITH HH	-7.747	<2e-16	-7.373	<2e-16	-5.406	<2e-16	0.041	<2e-16					92499
	W/O HH	-0.820	<2e-16	-0.752	<2e-16	-0.460	<2e-16			-0.199	<2e-16			92499
	WITH HH	-7.124	<2e-16	-8.206	<2e-16	-3.487	<2e-16			0.296	<2e-16			92499
	W/O HH	-0.777	<2e-16	-0.720	<2e-16	-0.452	<2e-16					0.056	0.000	92499
	WITH HH	-9.157	0.000	-8.926	0.000	-4.212	0.001					0.268	<2e-16	92499

Note: Model type includes (i) without household random effect (W/O HH) and (ii) with household random effect (WITH HH). Model 1 is expenditure in its level form (*exp*), Model 2 is expenditure in its log form (*log_exp*), and Model 3 is the relative expenditure (*rel_exp*).

Table 5.9 shows the log-odds effect of the expenditure variables on the use of credit cards for LA by income type. Analysis of the disaggregated data by income category remained relatively consistent across the groups. There was a positive relationship across all expenditure types for the random household effects model as well as the *rel_exp* model without random effects. The *exp* and *log_exp* models without random effects had a negative effect. The log_exp and the rel_exp models without a random household effect had the lowest and highest impact on the probability of using a credit card across all income groups, respectively. Considering the $log_$exp models, the probability of using a credit card was most adversely affected for the high- and upper-middle income groups as the likelihood were expected to be reduced by 26% ($e^{-0.295}$) and 20% ($e^{-0.224}$). For the rel_exp models, a one unit increase in expenditure relative to the household size was more likely to increase the probability of using a credit card for the lower-middle income group.

Table 5.9: Log-Odds Effect of Expenditure by Income Type for LA.

The West: Los Angeles										
Income Group	**2015**		**2016**		**2017**		**2018**		**2019**	
	W/O HH	**WITH HH**	**W/O HH**	**WITH HH**	**W/O HH**	**WITH HH**	**W/O HH**	**WITH HH**	**W/O HH**	**WITH HH**
Low-Income:										
exp	-0.015	0.026	-0.010	0.059	-0.010	0.077	-0.018	0.049	-0.022	0.060
p-value	0.001	0.028	0.010	0.000	0.031	0.000	0.000	0.000	0.000	0.000
log_exp	-0.072	0.285	-0.109	0.271	-0.072	0.310	-0.100	0.250	-0.139	0.418
p-value	0.001	0.000	0.000	0.000	0.000	<2E-16	0.000	0.000	0.000	<2e-16
rel_exp	0.046	0.220	0.052	0.233	0.069	0.320	0.051	0.232	0.069	0.327
p-value	0.067	0.000	0.021	0.000	0.002	0.000	0.029	0.000	0.000	0.000
Observation	*12526*	*12526*	*13598*	*13598*	*14777*	*14777*	*13525*	*13525*	*16727*	*16727*
Lower-Mid Income:										
exp	-0.020	0.019	-0.005	0.051	-0.034	0.042	-0.019	0.075	-0.030	0.035
p-value	0.000	0.029	0.083	0.000	<2E-16	0.000	0.000	<2E-16	<2E-16	0.000
log_exp	-0.191	0.051	-0.083	0.336	-0.221	0.259	-0.161	0.407	-0.163	0.271
p-value	<2E-16	0.319	0.000	0.000	<2E-16	0.000	<2e-16	<2E-16	<2E-16	0.000
rel_exp	0.035	0.093	0.079	0.332	0.072	0.337	0.078	0.307	0.052	0.206
p-value	0.082	0.084	0.000	0.000	0.000	0.000	0.000	0.000	0.002	<2E-16
Observation	*18271*	*18271*	*20503*	*20503*	*19470*	*19470*	*20015*	*20015*	*20750*	*20750*
Upper-Mid Income:										
exp	-0.012	0.035	-0.022	0.057	-0.051	0.009	-0.029	0.023	-0.041	0.029
p-value	0.000	0.000	0.000	0.000	<2E-16	0.212	<2e-16	0.006	<2e-16	0.000
log_exp	-0.147	0.155	-0.181	0.286	-0.326	0.105	-0.213	0.155	-0.254	0.222
p-value	<2E-16	0.003	<2E-16	0.000	<2E-16	0.012	<2e-16	<2e-16	<2e-16	0.000
rel_exp	0.037	0.129	0.062	0.305	0.035	0.093	0.043	0.205	0.054	0.230
p-value	0.080	0.009	0.004	0.000	0.080	0.030	0.030	0.000	0.004	0.000
Observation	*16122*	*16122*	*16225*	*16225*	*18741*	*18741*	*19091*	*19091*	*21702*	*21702*
High Income:										
exp	-0.035	0.042	-0.048	0.005	-0.041	0.025	-0.042	-0.004	-0.036	0.028
p-value	<2E-16	0.000	<2E-16	0.446	<2E-16	0.000	<2e-16	0.559	<2e-16	0.000
log_exp	-0.334	0.227	-0.351	0.194	-0.305	0.264	-0.263	0.071	-0.224	0.273
p-value	<2E-16	0.000	<2E-16	<2E-16	<2E-16	0.000	<2e-16	0.067	<2e-16	0.000
rel_exp	0.046	0.200	0.043	0.110	0.045	0.191	0.012	-0.008	0.056	0.179
p-value	0.019	0.000	0.026	0.015	0.009	0.000	0.450	0.846	0.000	0.000
Observation	*18874*	*18874*	*22062*	*22062*	*27045*	*27045*	*28174*	*28174*	*33320*	*33320*

Note: Model type includes (i) without household random effect (W/O HH) and (ii) with household random effect (WITH HH). Model 1 is expenditure in its level form (*exp*), Model 2 is expenditure in its log form (*log_exp*), and Model 3 is the relative expenditure (*rel_exp*).

In the case of the models with random effect, the magnitude of the log-odds effects of the expenditure types of *log_exp* and *rel_exp* on credit card use were similar for all income categories (0.24 and 0.212, respectively) compared to *exp*, which had an average log-odds effect of 0.037. The *log_exp* average effect was the highest for the low-income group, where a one unit increase in *log_exp* is likely to increase the probability of using a credit card by 36% ($e^{0.307}$). The *exp* models had the lowest effect on the log-odds of using a credit card for all income types.

5.4. The Northeast Region – New York City (NYC)

In this section, we examine the results for the predictors income and expenditure for the northeast region. In subsection 5.4.1, we provide some descriptive statistics for the income groups and payment types with a special focus on expenditure. Subsection 5.4.2 discusses the expenditure densities and subsection 5.4.3 presents the expenditure and income results for the logistic regression analysis.

5.4.1. NYC Data Analysis

The northeast region (NYC) had the largest average observations or unique trip codes and unique households of 89,861 and 1444, respectively, between 2015 and 2019. Households in this region spent on average US$56.70 per trip (*total_spent*) and US$5.27 per item (*price_paid*) The average total expenditure was higher for debit card purchases whereas the average price paid per item was higher for purchases where a credit card was used (see Table D1 in Appendix D). Credit card use was more dominant in the northeastern households than debit card use. There were about 408 more unique households using credit cards as a means of payment than credit cards. About 62.4% of the households used credit cards, with this ratio remaining relatively constant throughout the period (see Figure 5.4 and Table D1).

Like the other regions, most HHs in NYC revealed a preference toward a single type of payment instrument. The majority of the HHs (56%) used a specific payment type at least 90% of the times and 84% of the HHs used a specific payment type at least 70% of the times. We found that only 9% of the HHs always used a single payment instrument.

The largest share of households in NYC was the high-income (39.2%) followed by the upper-middle (23.6%), lower-middle (23.5%), and then low-income (11.9%). All income categories used a credit card to pay for their transactions more times than a debit card (see Table D1). Table 5.10 shows that all income groups visited similar amounts of unique retail chains (54). However, low-income households visited significantly fewer individual stores (2,410) compared to the average of the other income groups (1,312). The high-income households shopped at the most stores (1,546), purchased the greatest number of unique products or UPCs (18,603), spent the most on each shopping trip (US$61.40) but did pay the most per item (US$5.38). In NYC, the upper-middle income group incurred the highest price paid per product. Table D1 also shows that transactions paid for using a debit card had a higher average cost across all income types whilst higher average price paid per item was reported for credit card transactions.

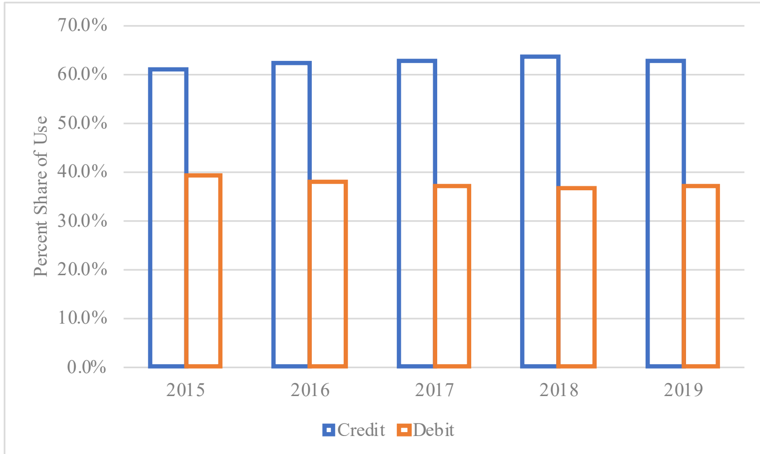

Figure 5.4: Types of Payment Instruments Used – NYC.
Note: The trend in payment instruments used for the sample data

Table 5.10: Selected Variables Count and Average Values by Income for NYC.

Income Type	Unique retailer code	Unique store code	Unique UPC	total_spent US$	price_paid US$
Low	52	833	7737	45.31	4.91
Lower-mid	54	1196	12706	52.40	5.18
Upper-mid	53	1193	12678	59.96	5.41
High	55	1546	18603	61.40	5.38

5.4.2. NYC Distribution Analysis

Based on the KS and AD tests, there are differences in the expenditure distributions of payment types across the income groups (see Table D2 in Appendix D). The density plots for total expenditure by payment type show that the low-income group has the highest mode for both the credit and debit densities. There are also similarities between the upper-middle- and high-income groups for both payment types (see Figures D1 in Appendix D). The log expenditure density plots did not indicate any definite similarities for the lower-middle- and low-income groups in either of the densities, however, the upper-middle- and high-income groups show semblance for both the credit and debit densities. For the normalized expenditure debit and credit density plots, the high-income group had the highest mode except for in 2015. The other three income groups showed some similarities for both densities (see Figures D2). Like the log expenditure densities, there was no clear association across the log normalized distribution plots by income type for the debit and credit densities for the income groups.

As for the total expenditure densities of the payment types by income groups, Figures D3 show that credit had a higher mode for the upper-middle- and high-income groups. However, there was no definite pattern for the lower-middle- and low-income categories. The log expenditure densities for the lower-middle- and low-income groups were also distinct over the years. There was however a left modal distribution for the upper-middle- and high-income groups. There were no density patterns for the income types when we consider the normalized and log normalized densities (see Figures D4). Generally, we see similarities between the upper-middle- and high-income groups and little semblance between the low- and lower-middle income groups.

5.4.3. NYC Logistic Regression Analysis

NYC Predictor Results for Income and Expenditure

Ceteris paribus, the estimated odds of all the income groups using a credit card were lower than the estimated log-odds for a high-income household with and without factoring for household effect (see Table 5.11). However, the estimated log-odds of using a credit card were inconsistent across the other income categories, as there was no one income group that used credit cards more than the other throughout the period. This result was true despite the model type (with or without random effects) and conflicts with the proposition that higher-income consumers use credit cards more than debit cards given that they have fewer credit constraints.

Table 5.11: Estimated Log-Odds of Income Categories and Expenditure Types for NYC.

The Northeast: NYC														
Year	Model Type	Low Income		LowerMid Income		UpperMid Income		exp		log_exp		rel_exp		Observation
		Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	
2015	W/O HH	-0.797	<2E-16	-0.885	<2E-16	-0.667	<2E-16	-0.019	<2E-16					72458
	WITH HH	-7.259	0.000	-8.332	0.000	-5.885	0.000	0.026	0.000					72458
	W/O HH	-0.806	<2E-16	-0.882	<2E-16	-0.666	<2E-16			-0.105	<2E-16			72458
	WITH HH	-4.194	0.007	-5.517	0.000	-2.903	0.007			0.293	<2E-16			72458
	W/O HH	-0.771	<2E-16	-0.876	<2E-16	-0.673	<2E-16					0.065	0.000	72458
	WITH HH	-9.361	0.000	-9.760	0.000	-3.893	0.014					0.266	<2E-16	72458
2016	W/O HH	-0.496	<2E-16	-0.720	<2E-16	-0.553	<2E-16	-0.015	<2E-16					84225
	WITH HH	-5.977	0.000	-3.952	0.000	-4.715	0.000	0.036	<2E-16					84225
	W/O HH	-0.498	<2E-16	-0.718	<2E-16	-0.553	<2E-16			-0.082	<2E-16			84225
	WITH HH	-9.556	0.000	-9.620	0.000	-6.871	0.000			0.339	<2E-16			84225
	W/O HH	-0.478	<2E-16	-0.711	<2E-16	-0.553	<2E-16					0.065	0.000	84225
	WITH HH	-6.513	<2E-16	-4.970	<2E-16	-4.970	<2E-16					0.349	<2E-16	84225
2017	W/O HH	-0.443	<2E-16	-0.506	<2E-16	-0.458	<2E-16	-0.019	<2E-16					92165
	WITH HH	-3.230	0.001	-3.266	0.000	-2.951	0.000	0.031	<2E-16					92165
	W/O HH	-0.452	<2E-16	-0.505	<2E-16	-0.456	<2E-16			-0.121	<2E-16			92165
	WITH HH	-3.990	0.001	-5.082	0.000	-5.034	0.000			0.305	<2E-16			92165
	W/O HH	-0.434	<2E-16	-0.500	<2E-16	-0.456	<2E-16					0.058	0.000	92165
	WITH HH	-4.514	0.000	-3.863	0.000	-3.611	0.000					0.223	<2E-16	92165
2018	W/O HH	-0.526	<2e-16	-0.767	<2e-16	-0.579	<2e-16	-0.020	<2e-16					96936
	WITH HH	-4.045	<2e-16	-4.844	<2e-16	-3.532	<2e-16	0.031	<2e-16					96936
	W/O HH	-0.540	<2e-16	-0.770	<2e-16	-0.581	<2e-16			-0.150	<2e-16			96936
	WITH HH	-4.818	0.002	-6.218	0.000	-3.131	0.006			0.258	<2e-16			96936
	W/O HH	-0.511	<2e-16	-0.755	<2e-16	-0.578	<2e-16					0.051	0.000	96936
	WITH HH	-4.197	0.001	-4.582	0.000	-3.326	0.000					0.190	<2e-16	96936
2019	W/O HH	-0.617	<2e-16	-0.526	<2e-16	-0.409	<2e-16	-0.014	<2e-16					103521
	WITH HH	-1.449	<2e-16	-2.779	<2e-16	-2.742	<2e-16	0.041	<2e-16					103521
	W/O HH	-0.628	<2e-16	-0.529	<2e-16	-0.407	<2e-16			-0.113	<2e-16			103521
	WITH HH	-4.186	0.000	-3.932	0.000	-4.131	0.000			0.341	<2e-16			103521
	W/O HH	-0.608	<2e-16	-0.516	<2e-16	-0.409	<2e-16					0.063	0.000	103521
	WITH HH	-0.197	<2e-16	-2.187	<2e-16	-4.415		<2e-16				0.301	<2e-16	103521

Note: Model type includes (i) without household random effect (W/O HH) and (ii) with household random effect (WITH HH). Model 1 is expenditure in its level form (*exp*), Model 2 is expenditure in its log form (*log_exp*), and Model 3 is the relative expenditure (*rel_exp*).

Table 5.11 shows that the effects of the different expenditure definitions on the probability of credit card use were positive for all years in the case of the random effects model. For the models without a random household effect, expenditure in its level form (*exp*) and expenditure in logarithmic form (*log_exp*) indicated that the estimated probability of use of credit cards decreases as households spend more per transaction; and the opposite is true for expenditure in its relative form (*rel_exp*). For *log_exp* under the random effects model, the effect on the log-odds of using a credit card was on average 0.31, being significantly higher than that of *exp* (0.033) but slightly above *rel_exp* which was on average 0.266. *rel_exp* had the highest multiplicative effect on the log-odds of using a credit card under the model without random effect (on average 0.061) while *log_exp* had the lowest average effect (-0.114).

Table 5.12: Log-Odds Effect of Expenditure by Income Type for NYC.

The Northeast: NYC										
Income Group	**2015**		**2016**		**2017**		**2018**		**2019**	
	W/O HH	**WITH HH**	**W/O HH**	**WITH HH**	**W/O HH**	**WITH HH**	**W/O HH**	**WITH HH**	**W/O HH**	**WITH HH**
Low-Income:										
exp	-0.016	0.017	-0.022	0.019	-0.040	0.006	-0.026	0.038	-0.002	0.031
p-value	0.004	0.150	0.000	0.028	<2E-16	0.476	0.000	0.003	0.490	<2E-16
log_exp	-0.005	0.298	-0.060	0.274	-0.181	0.147	-0.124	0.217	-0.069	0.327
p-value	0.827	0.000	0.003	0.000	<2E-16	0.004	0.000	0.000	0.000	0.000
rel_exp	0.093	0.238	0.068	0.208	0.032	0.076	0.037	0.109	0.045	0.156
p-value	0.003	0.000	0.006	0.000	0.211	0.119	0.163	0.037	0.043	0.002
Observation	*11165*	*11165*	*12343*	*12343*	*12096*	*12096*	*11718*	*11718*	*14074*	*14074*
Lower-Mid Income:										
exp	-0.016	0.036	-0.010	0.046	-0.011	0.051	-0.016	0.040	-0.016	0.038
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
log_exp	-0.098	0.329	-0.033	0.354	-0.033	0.425	-0.100	0.291	-0.082	0.329
p-value	0.000	0.000	0.047	<2E-16	0.036	<2E-16	0.000	0.000	0.000	0.000
rel_exp	0.072	0.314	0.061	0.285	0.075	0.385	0.068	0.312	0.066	0.304
p-value	0.001	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observation	*18161*	*18161*	*19384*	*19384*	*21146*	*21146*	*23954*	*23954*	*23082*	*23082*
Upper-Mid Income:										
exp	-0.019	0.021	-0.019	0.020	-0.024	0.050	-0.014	0.030	-0.027	0.025
p-value	0.000	<2E-16	0.000	0.001	<2E-16	0.000	0.000	0.000	<2e-16	0.000
log_exp	-0.138	0.216	-0.128	0.340	-0.191	0.390	-0.160	0.257	-0.203	0.294
p-value	0.000	0.000	0.000	0.000	<2E-16	<2E-16	<2e-16	0.000	<2e-16	0.000
rel_exp	0.058	0.190	0.070	0.279	0.067	0.394	0.044	0.229	0.042	0.249
p-value	0.013	<2E-16	0.001	0.000	0.000	<2E-16	0.013	0.000	0.020	0.000
Observation	*16198*	*16198*	*20426*	*20426*	*22708*	*22708*	*22730*	*22730*	*24023*	*24023*
High Income:										
exp	-0.016	0.019	-0.014	0.044	-0.016	0.031	-0.024	0.037	-0.013	0.058
p-value	0.000	0.003	0.000	0.000	0.000	0.000	<2e-16	0.000	0.000	<2e-16
log_exp	-0.118	0.365	-0.100	0.294	-0.120	0.324	-0.190	0.271	-0.097	0.355
p-value	0.000	0.000	0.000	0.000	<2E-16	<2E-16	<2e-16	0.000	<2e-16	<2e-16
rel_exp	0.063	0.235	0.069	0.300	0.051	0.200	0.053	0.212	0.088	0.367
p-value	0.001	0.000	0.000	0.000	0.001	0.000	0.001	0.000	0.000	<2e-16
Observation	*26934*	*26934*	*32072*	*32072*	*36215*	*36215*	*38534*	*38534*	*42342*	*42342*

Note: Model type includes (i) without household random effect (W/O HH) and (ii) with household random effect (WITH HH). Model 1 is expenditure in its level form (*exp*), Model 2 is expenditure in its log form (*log_exp*), and Model 3 is the relative expenditure (*rel_exp*).

Analysis of the disaggregated data by income category remained relatively consistent across the groups (see Table 5.12). There was a positive relationship across all expenditure types for the random household effect models as well as the *rel_exp* model without random effects. The *exp* and *log_exp* models without random effects had a negative relationship with the probability of credit card use. The average effect on the log-odds of a one unit increase in the *exp* was similar for the low- and upper-middle income groups at -0.021 but the least negative effect was observed for lower-middle- and high-income of -0.014 and -0.017, respectively.[19] For *log*_exp, the average estimates suggested that the upper-middle- and high-income groups were least likely to use a credit card. However, the estimates for *rel*_exp showed a higher impact on the log-odds of using a credit card for lower-middle- and high-income households. The lower-middle income households had the highest multiplicative effect ($e^{0.068}$), suggesting that a one unit increase in *rel_exp* would increase credit card use by an average of 7.1%.

In the case of the models with a random household effect, the *log_exp* models had the highest impact on the probability of using a credit card. Again, the lower-middle- and the high-income groups had a higher probability of using a credit card as its payment instrument. A one unit increase in *log*_exp would on average increase credit card use for the lower-middle income households by 41% ($e^{0.346}$) and the high-income households by 38% ($e^{0.322}$). The *exp* models had the lowest effect on the log-odds of using a credit card across all income groups when compared to the *log_exp* and *rel_exp* model estimates. The average effect was highest for the lower-middle- and the high-income groups, with a multiplicative effect of 4.3% and 3.9%, respectively.

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[19] The average effect for each income bracket and model were determined by finding the mean of the estimate for each year, i.e., $\sum \frac{\beta_{it}}{n}$.

5.5. Regional Comparison Discussions

In this subsection we highlight the most pertinent results after comparing the DMA findings for the predictors income and expenditure. Subsection 5.5.1 gives a summary of the data analysis results whereas subsection 5.5.2 provides a discussion for the binomial logistic regression results.

5.5.1. Regional Data Analysis

For each DMA, the sample size increased over time, with New York City having the highest average observation and unique households, while Dallas had the lowest. Across all regions, there were on average 1138 unique households. Higher-income households comprised the most transactions in our analysis. High income and upper-middle income households represent about 56% of the transaction data as well as the unique households.

The average shopping trip per household was the highest for Chicago and Dallas at about 72 and 69, respectively. On the other hand, LA and NYC households made on average 65 and 62 shopping trips. This is not surprising since both NYC and LA have a lower vehicles per capita ratio than Dallas and Chicago. According to data from the U.S. Department of Transportation, the states of New York and California had 557 and 753 vehicles per 1000 persons while Texas and Illinois had 758 and 819 vehicles per 1000 persons.[20] Thus, vehicle ownership can have a positive influence on the frequency of trips (Choudhary & Vasudevan, 2017; Clark et al., 2016; Sillaparcharn, 2007).

There was an inverse relationship between income level and the average number of household's in-store visits. Though low-income households shopped at the least unique stores, we found that on average each of these households visited more stores (4.79) than those of the other income groups. The high-income group households' each visited on average 3.5 stores while each household in the middle-income groups visited on average 4.0 stores. Since lower income households have less resources and are more financially constrained, we can attribute the higher average number of household's store visits to families engaging in bargain hunting to get a good value. Moreover, high-income households have been shown to exhibit more brand loyalty, thus shopping at fewer stores. This might be due to the opportunity cost of time spent searching (Murthi and Srinivasan, 1999; Goldman, 1976; Frank et al., 1968; Farley, 1964). Our results show that low-income households are just as informed as other income groups, possibly due to the technological advancement of the Internet and the subsequent improved ability to compare prices across stores. This finding refutes the work done by Thorelli (1971), who found lower-income consumers to be less aware of the existence and nature of specialized consumer information service. It also contradicts the notion that low-income households prefer familiar stores because they know they can get what they need at the "right" price (Hartman Group, 2018).

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[20] See https://www.fhwa.dot.gov/policyinformation/statistics.cfm

The average total expenditure per shopping trip and per item for all regions were US$56.04 and US$5.03, respectively. Households in DFW spent the most per trip at US$59.56 while households in LA spent the most per item at US$5.29. High-income households bought the least products or unique UPCs (49) but had the highest overall spending on each shopping trip (US$55.40). The higher-income households also spent more per item on goods (US$4.66), suggesting that they might be buying more brand-name products over store brands and have fewer financial constraints. On the other hand, lower-income households bought the most unique UPCs (52) and had the lowest overall average spending per shopping trip (US$40.62) and the lowest average spending per item (US$4.25). This reflects the possible financial constraints faced by these households and the purchase of store-branded products. Hartman Group (2018) noted that low-income consumers shopped from fewer food and beverage categories because those items are outside their price point. However, they may purchase more items as they generally have a larger household size. The lower-income households also spent less per item on goods, implying that they might be buying more economical foods and store or generic brands over brand name products (Hartman Group, 2018; Kaufman et al., 1997).

The majority of HHs showed a preference toward a single type of payment instrument. Over 80% of the HHs in all the regions used a specific payment type at least 70% of the times. We found that less than 10% of the HHs used a single payment instrument in the regions. Our results indicate that households rarely use a single payment instrument for 100% of their transactions and engage in switching over the year of investigation as found in Cohen & Rysman (2013). Since this study employed household-level data and not the individual consumer, single-homing behavior is not as prominent as found in Shy (2013) or Stavins (2017). This finding lends support to ***hypothesis 10***.

As for credit and debit use, 56% of the total observations for all regions combined used credit over debit. The households in DFW were found to have used debit cards more than credit cards (51.5% of all transactions) whereas the other DMAs used credit more than debit. The households in NYC used credit cards the most, 62.5% of the unique shopping trips.

Income level influenced households' use of credit or debit cards for retail transactions. Households within the lower income brackets showed greater preference for debit cards. About 48.4% and 48.9% of the transactions for low-income and lower-middle income households were paid for using a credit card. However, for the higher income groups, we observed that most of the transactions were paid for using a credit card. The upper-middle income and high-income groups used a credit card 54.2% and 66.2% of the time, respectively. High-income households in each region consistently used credit as their payment instrument more often than debit whereas low-income households used debit cards more often than credit, except for NYC.

When checking for systematic differences across income groups, the data summary findings showed that upper-middle- and high-income groups were somewhat similar. This was also the case for the expenditure density functions. However, the low-income group appeared to be different from the other income brackets. The lower-middle income group had more similarities with the upper-middle income group than the low-income group as relates to payment choice, the average shopping trips, number of unique products purchased and spending habits.

5.5.2. Regional Logistic Regression Analysis

Though the holding of credit cards was more widespread among households at all income levels, our findings suggest that higher-income families are more likely to utilize credit cards for a point-of-sale transaction compared to the other income groups. As such, all the binomial logistic regression analyses for the regions indicated that the probability of using a credit card for transactions increases as household income rises, thus, confirming ***hypothesis 1***. This result echoes Bagnall et al. (2016), and Shy (2013); both studies found that card usage increases with income. Furthermore, the *rel_exp* and *log_exp* models had similar estimated log-odds effects which were larger than those for the exp model. This could be partly a reflection of the fact that higher credit limits are generally extended to those with higher income levels. Evidence of a positive relationship between income and credit card use was also found in Shy (2013), Simon et al. (2010), Bertaut & Haliassos (2006), and Stavins (2001).

The type of logistic regression model was found to influence the multiplicative effect of increasing expenditure on the probability of using a credit card. We found varying results by expenditure type, however, these results showed consistency across the regions and time periods. The higher average spending while using a debit card is reflected in the logistic regression when the random household effect is not considered. This is observed for both expenditure in its level form (*exp*) and its logarithmic form (*log_exp*). Expenditure in its level form (*exp*) and *log_exp* tend to have a negative and significant relationship with credit card use for the models without a random effect, but a positive effect for *rel_exp*. For the models with random household effect, positive and significant relationships were found for all expenditure types, implying that the estimated probability of use of credit cards increases as households spend more per transaction. This result is consistent with those of Chen et al. (2019), Fujiki and Tanaka (2017), Shy (2013), Klee (2008), and Hayashi and Klee (2003). After disaggregating the data by income category, we also observe a positive relationship between expenditure types and the probability of credit card use after accounting for random household effects and for relative expenditure (*rel_exp*) without a random household effect. This relationship held across districts. Therefore, we found support for ***hypothesis 9*** when we controlled for household effects. Otherwise, there was a negative relationship between transaction value and credit use.

The coefficients for *log_exp* and *rel_exp* were analogous in the random effects models, especially when both models were estimated with high precision (i.e., with low p-values). This similarity between the coefficient values occurs since the log scale transformation makes a variable scale free and the *log_exp* variable is transformed into a "relative" measure of expenditure. However, this is a universal transformation; unlike our construction of *rel_exp*, which is household specific. Therefore, we only see the similarity when we properly control for individual household effects in our regressions. This highlights the importance of controlling for individual effects and the proper construction of the expenditure variable in model development.

5.6. Predictor Results for Other Factors

In this section, we discuss the findings of the effects of the other factors on the probability of using a credit card. The results are presented for our five sample datasets: the aggregated data and the disaggregated income-group data for each DMA. Each of these data included six models for each year (2015-2019). For each year, there were two models with or without a random household effect and for each of these models there were three models for each expenditure definition (*exp*, *log_exp*, *rel_exp*). For each predictor variable, we analyze the direction of the association of the predictor variable on the response variable for the different models and each year. A predictor is said to have a positive (negative) effect if there is a consistently positive (negative) relationship across all years and models. The explanatory variable results are inconclusive if there are both positive and negative relationships across the period and models. We present the findings by variables to determine if the relationship holds not only across the years and models but also across DMA or region. The regression model results are provided in Appendix E and a summary of these model results is discussed below.

5.6.1. Household Size

For the metropolitan areas CHI and LA, the logistic regression results indicate a negative relationship between *HH_Size* and the probability of using a credit card. This relationship also held across all income groups. Any model with a positive coefficient was found to be statistically insignificant. Thus, as household size increases, there is a lower probability of using a credit card. We also found similar results for DFW and NYC for our sample data. These results differ from ***hypothesis 8***, perhaps owing to families engaging in budgeting given the greater level of expenses. However, when we disaggregate the data by income type, we found mixed results for the low-income group in DFW and for both the lower-income groups in NYC. These results imply that some lower income households with increasing members residing in the same home may find themselves using credit cards more while others use debit cards more. The inconsistency with these income groups may reflect some households having lack of access to credit and must resort to using debit cards while others may have financial constraints to meet expenses and borrow from future consumption.

5.6.2. Marital Status

The results for CHI and DFW signal a positive relationship between marital status and the use of a credit card, that is, a HH that is married has a higher probability of using a credit card compared to those homes that may have a head that is single, separated, or widowed. These results lend support to ***hypothesis 4***. This may be due to married households being more likely to qualify for a higher credit limit with a combined income. When we look at the results for different income groups for these two areas, we found that all other income groups in DFW, except for the high-income group, hint to a similar relationship as the aggregated data. The lower-middle income group in CHI indicated a positive relationship between being married and using a credit card. However, we found mixed results for the low-, upper-middle-, and high-income brackets in CHI.

In general, being married was found to have an inconclusive effect on the use of a credit card in LA. This result held across all income types except for the upper-middle income group which showed that married persons are less likely to use a credit card. As for NYC, the findings were mixed across all the models, contradicting the hypothesis.

5.6.3. Age

For CHI, we found mixed results for the effect of age on the probability of using a credit card. This inconclusive finding held for all income groups. There were also no conclusive results for the aggregated data in DFW. However, all years indicated a positive relationship except for in 2019. This positive relationship was observed for the low-income group while all other income groups had mixed findings, suggesting that there is no strong association between age and the utilization of a credit card. The findings differed for the different data samples in LA. The aggregated data, and the low- and lower-middle income groups showed an inconclusive result for the effect of age on the use of a credit card. However, for the upper-middle income group, households with the head above 49 years old were found to use a credit card more while for the high-income group, households with the head less than 49 years old were found to use a credit card more than a debit card. As for NYC, the results had a positive coefficient for all the years, except for in 2019 suggesting an inconclusive finding. Mixed results were also found for the lower-middle- and high-income groups. However, for the low-income and upper-middle income groups older persons were more likely to use a credit card than younger persons.

Generally, the regional findings hint to age having different effects on credit card utilization. However, there was some support for ***hypothesis 3*** in the low-income group in DFW, and NYC. This could be explained by the wealth accumulation in their life cycle. Thus, as the head of household for the low-income group ages, they achieve higher creditworthiness which allows for increased ownership and utilization of a credit card. Also, younger persons are less likely to qualify for a credit card or a high credit limit compared to older persons given their position in the income life cycle.

5.6.4. Gender

In general, we found no definitive relationship between gender and the use of credit cards for CHI. However, when we consider the type of model, i.e., with or without a random effect, we found a positive relationship for the models without a random effect while the models with a household random effect had mixed results. This was also the case for the low-income group while the results differed across model types for the middle-income groups. Males within the high-income bracket were found to use credit cards more than females.

For DFW, we found inconclusive results for the aggregated data models and for the middle-income groups. Like CHI, males were more likely to use credit cards more than females in the high-income group. However, the opposite was true for the low-income group.

Mixed results were also mostly found for NYC. In addition, there were no clear relationships for the effect of gender on the lower income groups. But, for the higher income groups, males had a higher probability of using a credit card. The results for the metropolitan area of LA were positive for the aggregated data, low-, upper-middle-, and high-income groups. However, the lower-middle income group illustrated mixed findings. The positive results across the high-income group in each region lend support to ***hypothesis 6***. This may be related to men taking greater investment risks (Merikull et al., 2021).

5.6.5. Education

For CHI and LA, the education variable was found to have a positive effect on the probability of using a credit card. Therefore, higher educated persons are more likely to use a credit card than the less educated. These results held across all income groups and generally had high statistical significance. We saw similar findings for DFW and NYC. Thus, there is evidence in support of ***hypothesis 2***. However, not all income groups showed that individuals with a college degree were more likely to use a credit card than those with a lower education degree. For DFW, the lower-middle households showed inconclusive findings while for NYC, the upper-middle income group had one model that was negative and significant (in 2018, the *exp* model with household random effect had a negative coefficient).

In general, credit card ownership and utilization are strongly correlated with education and are in line with most of the literature. Of notable mention, this relationship was consistent across DMAs for the low- and high-income groups. Bertaut & Haliassos (2016) noted that awareness and ownership of credit card instruments increases with education. The mixed findings that we see for the middle-income categories in DFW, and NYC may be explained by the pronounced increase in bank-card ownership at lower income and education levels, reflecting in part improvements in industry credit scoring techniques and risk analysis.

5.6.6. Work

The results for CHI support a highly negative and significant association between working more hours and the probability of using a credit card. This finding held across the household income type. Perhaps, individuals that work more are not as credit constrained and have less need to use credit or borrow from future consumption. For DFW, working hours appeared to have a negative relationship with the use of credit cards, suggesting that as households work more hours per week, they are less likely to use a credit card. This was the case within all income groups except for the low-income households. Since low-income HHs are normally financially constrained, working more hours is generally associated with earning more. Thus, a low-income household is more likely to enjoy higher personal credit scores, thus qualifying for a credit card with higher limits which increases credit use. Higher credit use within this income group could also be attributed to the perception of higher prestige to others.

For LA and NYC, we generally found that HHs that work higher hours are more likely to use a credit card. This relationship held for the lower income groups in both DMAs. However, for NYC we found inconclusive findings for the higher income groups whilst for LA the results for the upper-middle income group were mixed and the high-income group were positive. Thus, there is evidence against ***hypothesis 7*** in the metropolitan areas of Chicago and Dallas, with some support for the hypothesis in LA and NYC.

5.6.7. Race

In general, there was a positive association for race and the use of credit cards with white people having a higher probability of using a credit card in CHI. The results were highly significant for the aggregate data models. When we looked at the income type models, a positive relationship held across both model types, however, for the high-income group the models with a random household effect generated positive but insignificant findings. For DFW, households that identified as white were also more likely to use a credit card than another ethnic household. However, this relationship was not found for the low-income group. White HHs were also more likely to use a credit card than non-whites in NYC. This was also the case for the lower income groups. However, for the higher income brackets, we saw that there was no clear relationship between HH ethnicity and the probability of using a credit card. The results were different for LA. White households in LA were generally less likely to use a credit card, but at the disaggregated data level, the results were mixed across all income groups.

Overall, there was a higher positive association of white families using a credit card, providing support to ***hypothesis 5***. This may be linked to white-identified homes having more wealth than black, Hispanic, and other or multiple race families as found in the 2019 SCF survey (Bhutta et al., 2020, September 28). Moreover, there might be supply-side reasons such as the limited targeting of credit cards to non-whites by financial institutions (Bertaut & Haliassos, 2016). The inconclusive findings in LA could be attributed to non-white families experiencing growth in wealth between 2013 and 2019 or the overall increase in credit card debt[21] (Bhutta et al., 2020). Credit card debt revolvers are more likely to use debit than those who do not, as they are unable to capitalize on the grace period for new purchases and are thus subject to high interest rates (Zinman 2004).

5.6.8. Day of Purchase

The day of purchase did not have a conclusive impact on the use of credit cards across all DMAs. The model outcomes were mostly statistically insignificant, hinting that the time of purchase is not an important factor that influences the use of credit cards. For those models in specific years that did indicate a statistically significant result, the effects on the probability of credit card use were small. As for the income groups, the model results were mostly mixed with few exceptions. For the high-income group, the few significant results indicated a negative association for CHI and NYC. A negative relationship was also found for the lower-middle income group for NYC. These results did not provide strong support for ***hypothesis 11***.

[21] Credit card debt was the most widely held type of debt in 2019, Bhutta et al. (2020) noted that more than 45% of families reported a credit card balance after their last payment.

5.6.9. Summary

Households' socio-demographic factors have a significant effect on the use of credit over time. Education level, the number of work hours per week, and household size have a consistent effect on the probability of credit card use across regions and time. However, we found variation in the direction of the effects of these predictors across regions and time when we considered households' income type. We found inconclusive results for the predictor *race* between regions and for the predictors *marital _status*, *age*, *gender*, and *purchase_day* both within and between regions over time. These results suggest that household income types and location have varying effects on credit and debit use, thus, providing support for ***hypothesis 12***.

CHAPTER 6

CONCLUSION

In this chapter, we summarized the research work undertaken to explain the determinants that affect households' payment choice between credit and debit for point-of-sale transactions. Additionally, we include suggestions for policy- and decision-makers within commerce, the banking sector, and government. We also highlight the limitations of the paper and some future areas for research within the scope of our study.

6.1. Summary

Consumers face increasing payment options at point-of-sale (POS). Traditionally, a typical customer had mainly one method of payment – cash or check for POS transactions. However, consumers today can choose between various payment instruments – cash, checks, debit cards, credit cards, or mobile payments given technological evolution in information processing. The percentage of households using electronic modes of payment increased over the years.

Advancement in technology has increased the number of payment methods and reduced the popularity of consumers using cash for in-store POS transactions. Generally, people were found to use cash out of convenience, or when the total payment amount is small, or perhaps if they don't have a checking account or credit card. Though the findings from the cashless society literature in Chapter 2 still have relevance to policy makers and banking professionals in the U.S. and elsewhere, the general decline in cash use signaled a need to analyze more advanced payment types. We saw that the U.S. retail payment system is dominated by the utilization of debit and credit cards. Therefore, our study assessed technological advancement of payment choices, focusing on credit and debit for POS transactions. The results from this study are useful for merchants, policymakers, and banking specialists in areas of marketing to targeted users and monetary policies.

There has been an increasing amount of work done in the payments area over the past couple of decades or so. Four important sets of factors were identified as affecting consumer payment choice (1) consumer characteristics, (2) transaction characteristics, (3) store characteristics, and (4) payment method attributes. The earlier works of Stavins (2001) highlighted the role of socio-demographic factors while the role of elasticities was the core factor in Humphrey et al. (2001). Humphrey and others also noted that the average value of transactions influenced the types of payment instruments used. Hayashi & Klee (2003) underscored technological factors on the propensity to use electronic payment systems and Bolt et al. (2010) showed that the size and location of the store affected payment type decisions.

Though the literature on payment-choice has increased, some interesting issues remain. There is still a dearth of empirical work investigating the factors influencing consumers' choice of in-store payment method. Most studies examined multiple payment instruments and the factors influencing the likelihood of use of each instrument. Few research focused solely on electronic modes of payment (Zinman, 2009; Bertaut & Haliassos, 2006; Zinman, 2004; Stavins, 2001), which are currently dominating the market. With the declining use of cash and check as a means of payment, more research work is required to assess why consumers choose the payment method debit over credit or vice versa.

Little is known about the latent factors of consumer payment behavior for in-store POS transactions. Most of the literature used survey data which was based on consumers' perception on payment instruments. We studied multiple locations and time periods in the United States using observed data on consumer choices rather than a survey on consumer perception or opinions. Our research concentrated on the socio-demographic and transaction factors affecting consumer choice between credit card and debit card, which are the two most used payment instruments in the U.S. in recent years. The use of scanner data allowed us to consider both observed and latent consumer characteristics that affect consumer choice of payment instrument. Moreover, including location in our analysis helped with cross-region comparison and the identification of heterogeneity among the households. As such, these considerations provide better and more targeted results to help with policy making within commerce, the banking sector, and government.

In this study, we utilized a quantitative research methodology to answer our main research questions of whether the monetary value of the basket of items purchased affect the choice of payment method, whether higher-income families use a credit card more often, and whether consumers are funding their purchases out of current income or wealth (debit card) or with borrowed funds (credit card). We also sought to investigate the effect of other factors, which helped in explaining systematic differences amongst household income types. These research questions include: Do consumers generally pay using a single payment instrument? Which payment instrument is used more often for the POS transactions? Does the choice of payment depend on the time of month of the transaction? What demand-side factors influence choice of payment method between credit and debit? Are there any systematic differences that exist across household-income type and regions that affect payment choice?

We estimated the effects of several head of household characteristics and transaction characteristics on the probability of using a credit card by employing kernel distribution functions and binary logistic regression models. These relationships were investigated for four designated market areas – Chicago, Dallas-Fort Worth, Los Angeles, and New York City – over the period 2015 to 2019 using scanner data from the Nielsen company. These areas provided complete coverage of the U.S. through units that are similar in terms of historical development, population characteristics, and the economy, thus allowing us to conduct research that can be generalized for the U.S. population.

Our results provided evidence for statistically significant effects of both socio-demographic and transaction characteristics on the probability of consumers using credit. Credit card use was affiliated with higher-valued transactions. Thus, consumers financed the bulk of their in-store purchases with borrowed funds instead of their own wealth. Household effects were important in influencing the effect of transaction value on credit use. The estimated coefficients for *log_exp* and *rel_exp* were different without controlling for household effects, but quite similar once we controlled for them. This emphasizes the importance of controlling for individual effects and the proper construction of the expenditure variable.

Consumer heterogeneities were also present across income groups and regions. Higher-income families were more likely to utilize credit cards for a point-of-sale transaction than debit cards. Larger size families and those that worked longer hours were more prone to use their own funds for purchases rather than borrowing via credit. There was a general positive relationship for race and education for credit use across regions and income groups. We also found some systematic differences across households when we compared income groups and regions. There were greater similarities between the upper-middle and high-income households when compared to the low- and middle-income households. Generally, the low-income group was regularly quite different from the other income groups. This may point to possible latent-type factors in the lower-income groups, with some being credit constrained while others are budget-conscious.

Assessing the payment choice of credit and debit gave us a better understanding of consumer behavior. Financial institutions can better target customers with its products based on their demographics and thus enhance the utility and convenience of the payment instruments to them. This enhances customer satisfaction and loyalty. Also, with consumer preference toward credit and debit use growing over the recent years, and the onset of the Covid-19 pandemic which has resulted in an increase in online purchases, we can improve the security features of these cards.

Our income group results can help decision makers with social planning. With low-income households and non-whites having the lowest probability of using a credit card, the government in conjunction with the financial sector and other stakeholders can adjust public policy governing financial credit bureaus. Policy measures can focus on providing greater access to different payment instruments to affected demographics and social groups. This could help alleviate food insecurity issues which increasingly challenge many lower-income Americans.

The findings from our results can positively affect commerce. Merchants have greater insights on which payment type is preferred by households and the factors that influence their payment choices. Thus, firms can market adequately and provide the technology to the consumers. All of which can increase sales and profitability.

6.2. Study Limitations

This dissertation provides numerous benefits to various stakeholders in the economy, yet it is not void of limitations. Though the results addressed some dimensions of payment and shopping behaviors of households within different income brackets and regions, consumer behavior is a complex phenomenon and requires additional analysis to derive more conclusive statements. Shopping behavior is also complex, as some households shop for recreational aspects while others may compete directly with wage-earning activity (Bawa & Ghosh, 1999).

Also, our model and findings are useful for describing utilization of patterns across demographic groups and how each characteristic contributes to such utilization, controlling for other characteristics, but not for identifying ownership nor the household's financial position. Our data do not observe whether a card balance for a given household existed nor the household's debt or finance profile. We saw in Bhutta et al. (2020) that credit card debt was the most widely held type of debt in 2019, with more than 45% of households reporting a credit balance after their last payment. The debt constraint of the consumer may influence their choice. We also didn't have information on all the payment instruments held by households at the time of the transaction. One might be able to assume that if a household owns a credit card, it is likely that they have a debit card. However, it is difficult to assume the opposite. Additional data on the portfolio of the cardholder can improve the model to analyze consumer choice as well.

In our model, we did not consider supply-side and other factors. Therefore, the effect of consumer characteristics on their use of electronic payments indicates their probability of using credit in the absence of supply-side constraints. Incorporating information on merchants' acceptance of card types and the size of the store can help improve our model and give more insights for policy making. There may also be some omitted variables bias in our study when assessing the effect of location on the probability of using credit by not considering rural data. However, given that the bulk of consumer activity comes from mostly densely populated areas, the degree of bias is anticipated to be small.

6.3. Future Research

The U.S. population's demographics have changed over time, as found in Kosse & Jansen (2013), there could exist a migration effect on the choice of payment. Lobaugh et al. (2019) noted that the U.S. consumer base is becoming increasing diverse with diverging incomes. Thus, it would be interesting to assess whether there are implications to migration on the U.S. consumers' use of credit cards. Such results can better inform targeted policy decisions.

Though mobile payment was noted to be a relatively new technology with low penetration rate in the U.S. (Jung et al., 2020), the Covid-19 pandemic has brought about numerous changes in consumer behavior. Additionally, we looked at a time frame where the macroeconomic performance was generally positive. Future work could focus on recessionary periods or post-Covid years to see if the behavior observed in this study changes. A comparative analysis of the different periods could also be used for analyzing any changes in consumer behavior and inform availability of payment instruments at the merchant level.

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APPENDIX A

CHICAGO

Table A1: CHI – Selected Variables' Count and Averages by Income Group and Payment Type.

2015

		Low	Lower-Mid	Upper-Mid	High	All
		Household Income Group				
Credit	Average exp	44.78	53.96	52.94	60.08	54.76
	Average price	4.98	5.39	5.31	5.25	5.27
	Unique HHs	122	210	190	230	752
	Observations	3834	8291	8397	11283	31805
Debit	Average exp	46.99	52.77	63.42	64.98	56.86
	Average price	4.21	4.53	4.66	4.71	4.53
	Unique HHs	120	196	180	179	675
	Observations	5316	7914	6491	5214	24935

2016

		Low	Lower-Mid	Upper-Mid	High	All
		Household Income Group				
Credit	Average exp	38.52	48.92	50.66	57.62	51.50
	Average price	4.77	5.21	4.99	5.04	5.04
	Unique HHs	111	239	233	297	880
	Observations	4834	10517	11092	16234	42677
Debit	Average exp	49.36	52.88	59.86	67.53	57.77
	Average price	4.27	4.59	4.74	4.81	4.64
	Unique HHs	103	221	207	212	743
	Observations	4758	9639	9092	6987	30476

2017

		Low	Lower-Mid	Upper-Mid	High	All
		Household Income Group				
Credit	Average exp	38.91	47.22	50.32	55.99	50.40
	Average price	4.98	5.17	4.98	5.09	5.07
	Unique HHs	134	263	265	336	998
	Observations	5982	11703	11260	19125	48070
Debit	Average exp	47.20	52.16	60.43	67.62	57.24
	Average price	4.37	4.56	4.89	4.79	4.68
	Unique HHs	132	230	215	223	800
	Observations	5693	10873	9567	7872	34005

2018

		Low	Lower-Mid	Upper-Mid	High	All
		Household Income Group				
Credit	Average exp	43.20	45.54	50.40	54.45	49.98
	Average price	4.99	4.92	5.01	5.07	5.01
	Unique HHs	132	256	243	339	970
	Observations	5662	12417	11366	19878	49323
Debit	Average exp	46.06	56.56	58.64	65.58	57.47
	Average price	4.40	4.83	4.94	4.77	4.77
	Unique HHs	121	215	209	208	753
	Observations	5696	10518	9141	7856	33211

2019

		Low	Lower-Mid	Upper-Mid	High	All
		Household Income Group				
Credit	Average exp	45.32	45.80	49.11	56.82	51.02
	Average price	5.08	5.18	4.97	5.13	5.10
	Unique HHs	149	246	278	366	1039
	Observations	6600	11817	12792	21401	52610
Debit	Average exp	50.35	55.49	60.86	63.60	58.30
	Average price	4.72	4.99	4.83	5.18	4.94
	Unique HHs	128	204	221	246	799
	Observations	5882	9014	10353	8622	33871

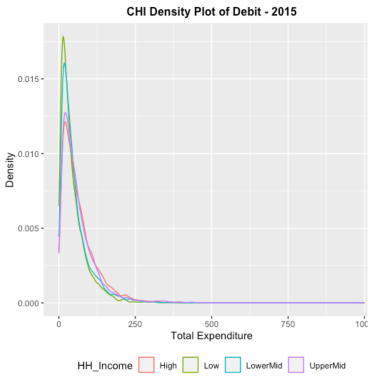
Notes: The tables above show the summary statistics for selected variables for each year. (i) Average exp is the average amount spent by all households by income group in US dollars. (ii) Average price is the average price per item spent by all households by income group in US dollars. (iii) Unique HHs is the unique number of households in each income group. (iv) All is the aggregated data of all household types.

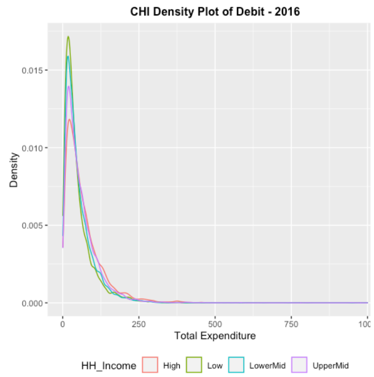
Table A2: CHI – Testing Total Expenditure Distribution for Debit and Credit by Income Group.

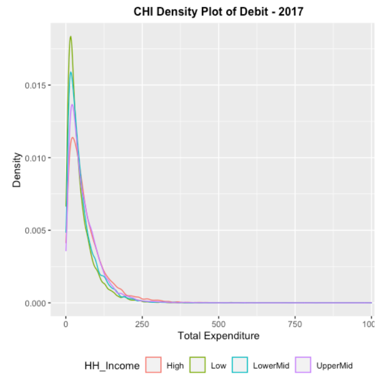
CHI 2015				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.02	0.02	0.11	0.05
p-value	0.19	0.26	< 2.2E-16	0.00
AD test statistic	2.21	1.41	92.50	24.30
p-value	0.07	0.20	0.00	0.00
CHI 2016				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.11	0.05	0.10	0.08
p-value	< 2.2E-16	0.00	< 2.2E-16	< 2.2E-16
AD test statistic	79.50	32.40	125.00	82.80
p-value	0.00	0.00	0.00	0.00
CHI 2017				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.08	0.05	0.11	0.10
p-value	< 2.2E-16	0.00	< 2.2E-16	< 2.2E-16
AD test statistic	46.70	36.10	159.00	135.00
p-value	0.00	0.00	0.00	0.00
CHI 2018				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.04	0.10	0.08	0.10
p-value	0.00	< 2.2E-16	< 2.2E-16	< 2.2E-16
AD test statistic	11.10	160.00	93.30	161.00
p-value	0.00	0.00	0.00	0.00
CHI 2019				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.04	0.08	0.10	0.07
p-value	0.00	< 2.2E-16	< 2.2E-16	< 2.2E-16
AD test statistic	13.60	86.20	168.00	75.00
p-value	0.00	0.00	0.00	0.00

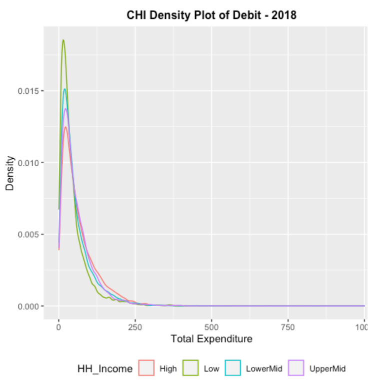
Total Expenditure Density Plots by Income Type – CHI

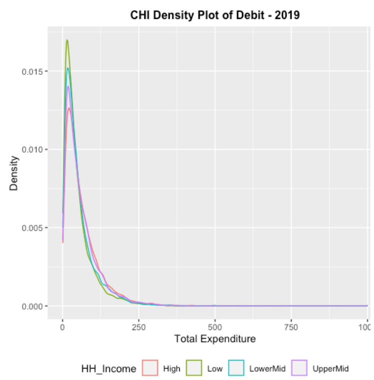
Debit Plots



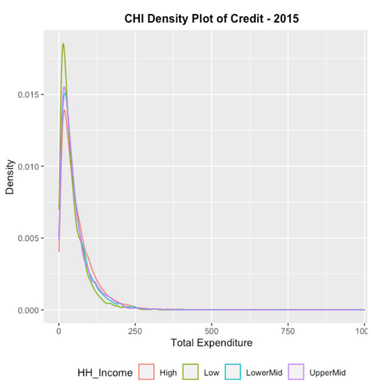


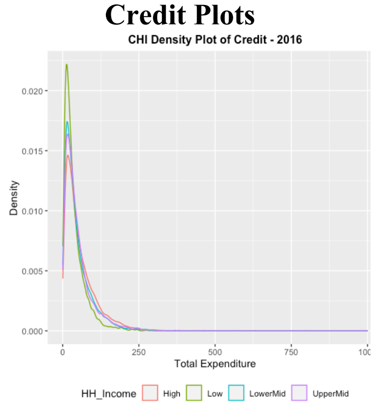


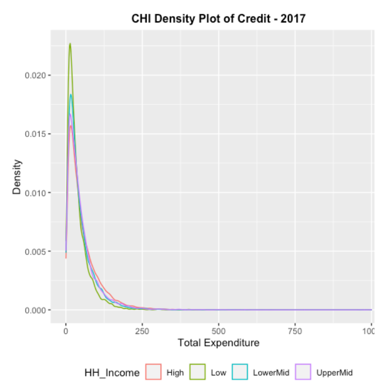




Credit Plots







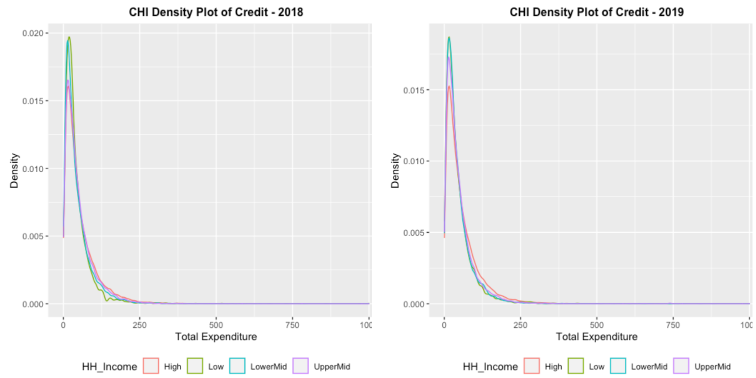
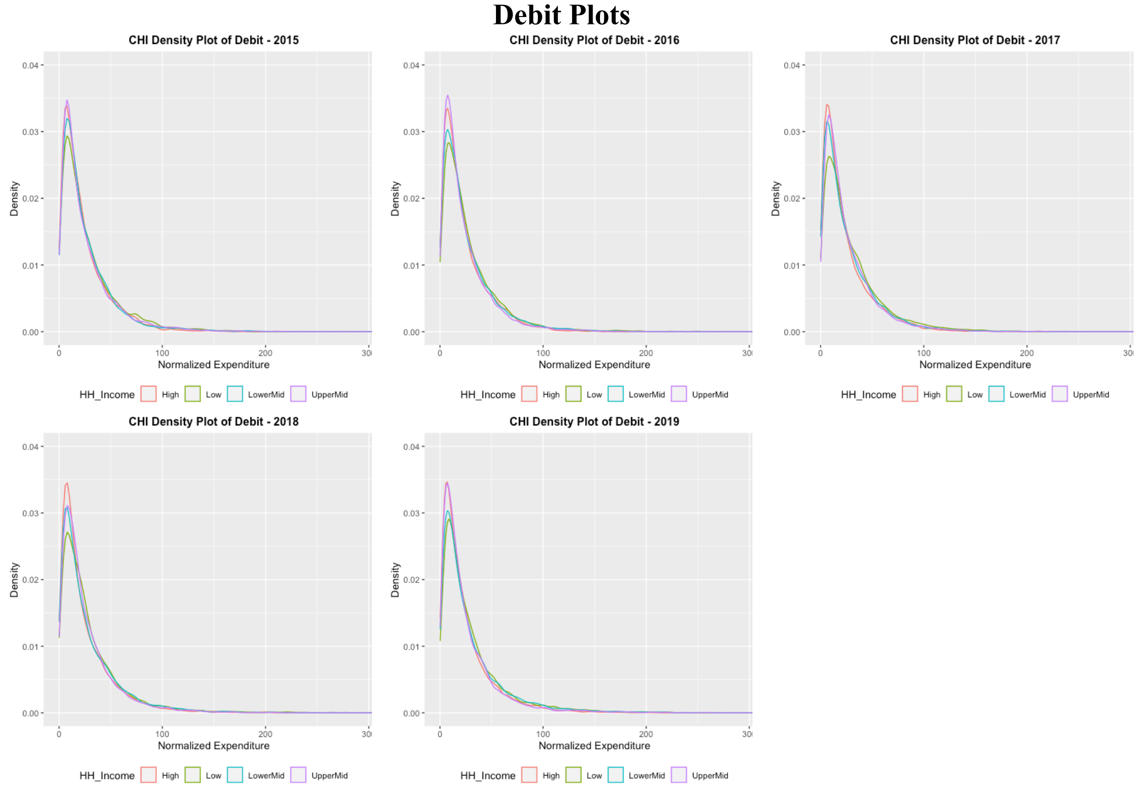


Figure A1: CHI – Total Expenditure Density Plots for Payment Types by Income Group.

Normalized Expenditure Density Plots by Income Type – CHI

Debit Plots



Credit Plots

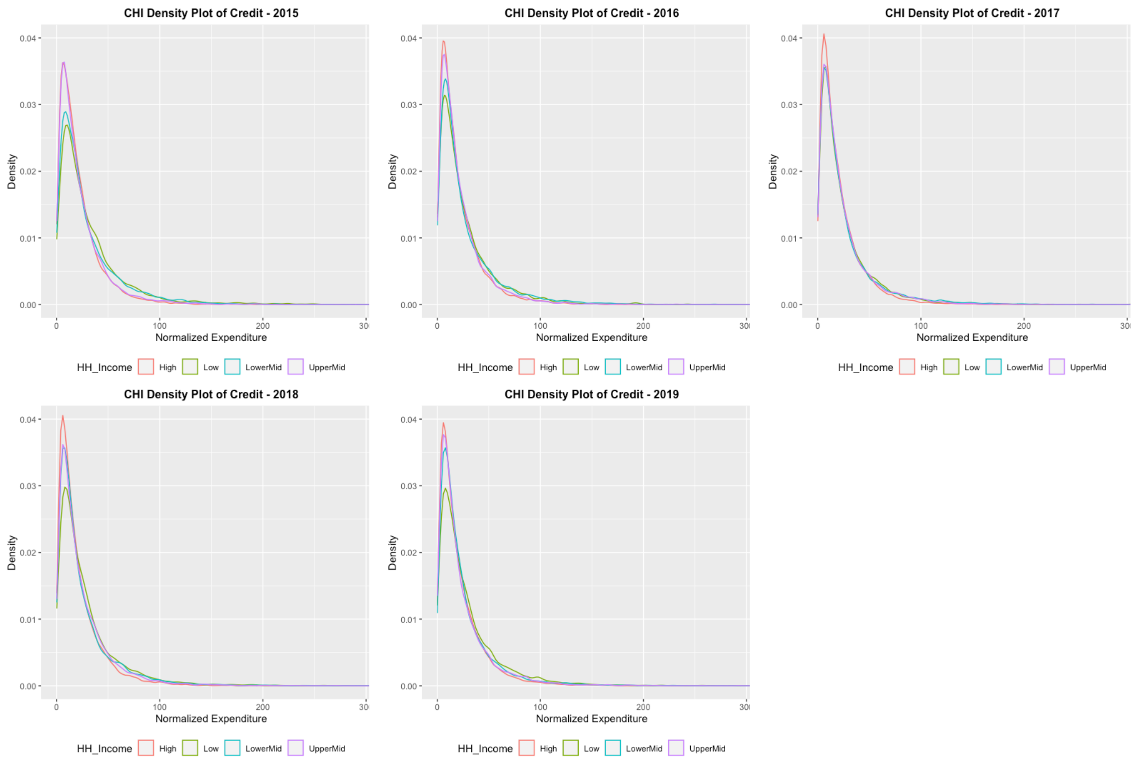


Figure A2: CHI – Normalized Expenditure Density Plots for Payment Types by Income Group.

Total Expenditure Density Plots by Payment Type – CHI

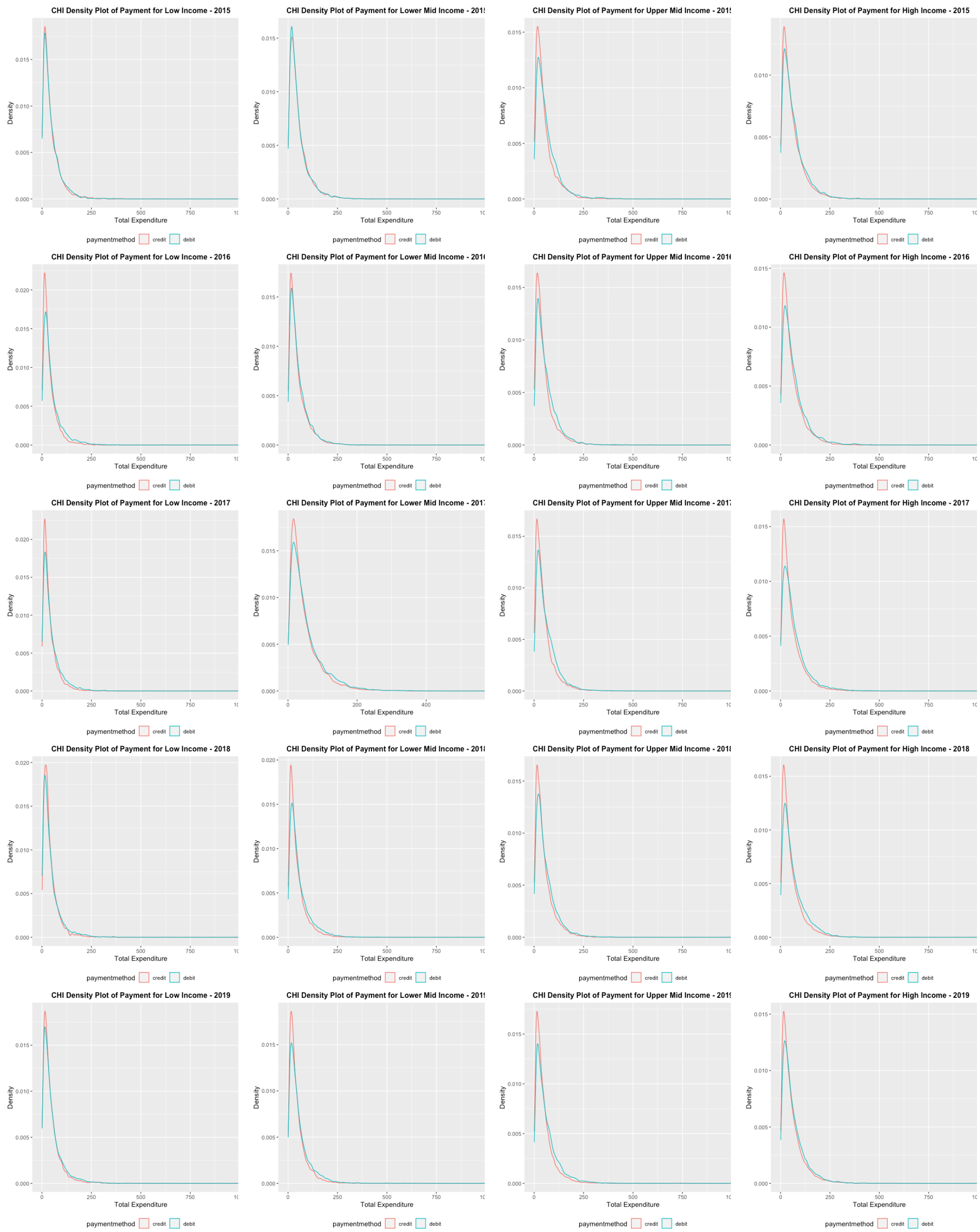


Figure A3: CHI – Total Expenditure Density Plots for Income Group by Payment Type (2015 – 2019).

Normalized Expenditure Density Plots by Payment Type – CHI

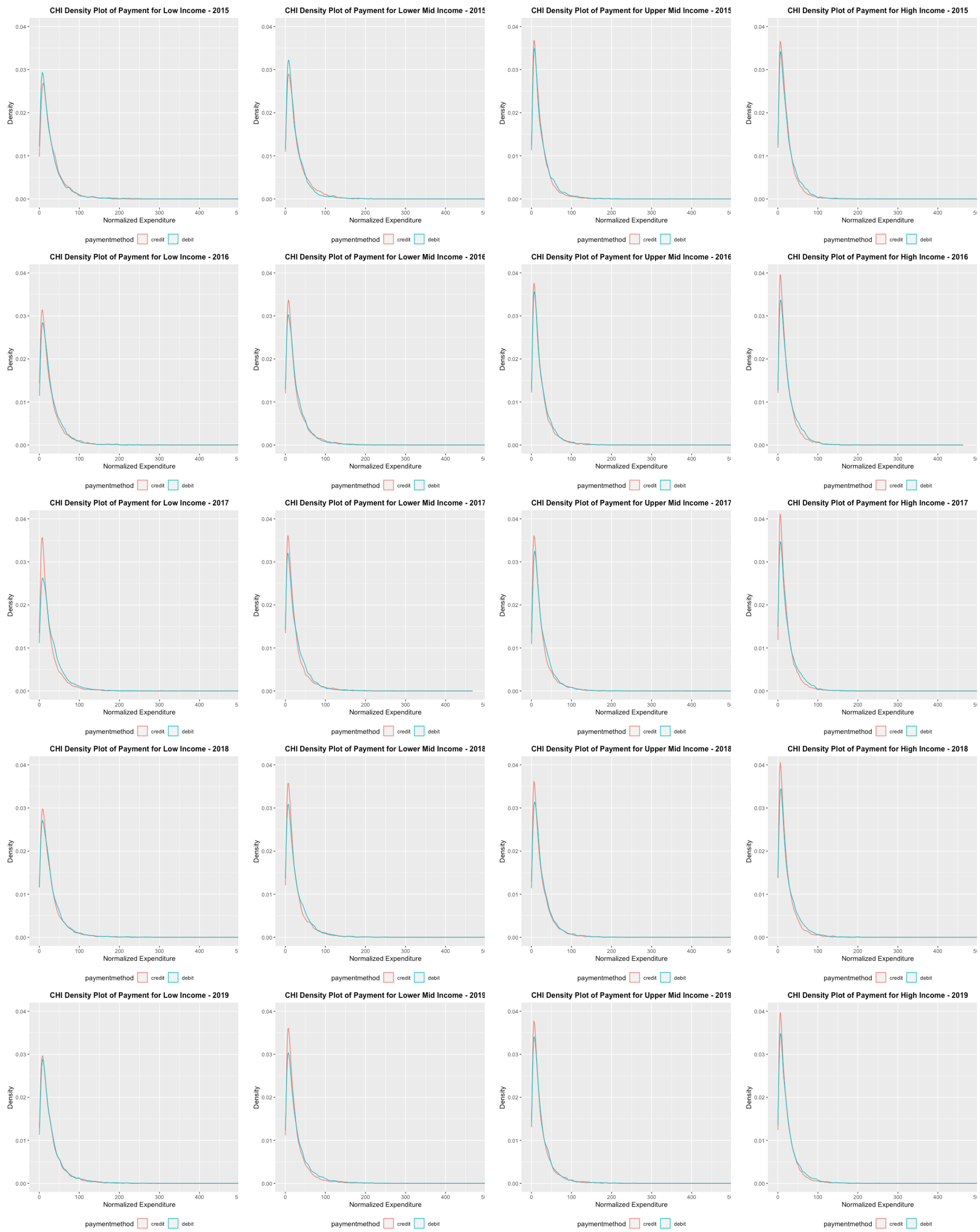


Figure A4: CHI – Normalized Expenditure Density Plots for Income Group by Payment Type (2015 – 2019).

APPENDIX B

DALLAS-FORT WORTH

Table B1: DFW – Selected Variables' Count and Averages by Income Group and Payment Type.

		2015				
		Household Income Group				
		Low	Lower-Mid	Upper-Mid	High	All
Credit	Average exp	53.93	58.45	56.66	61.72	58.31
	Average price	4.94	5.16	5.31	5.34	5.22
	Unique HHs	105	154	156	159	574
	Observations	3817	5226	6214	7724	22981
Debit	Average exp	52.65	53.22	72.47	70.05	61.21
	Average price	4.32	4.47	4.86	4.76	4.59
	Unique HHs	124	168	144	138	574
	Observations	5758	8684	6376	5307	26125

		2016				
		Household Income Group				
		Low	Lower-Mid	Upper-Mid	High	All
Credit	Average exp	52.46	56.02	59.41	63.77	58.97
	Average price	5.09	4.81	5.47	5.45	5.24
	Unique HHs	114	212	189	187	702
	Observations	3862	7162	7750	8925	27699
Debit	Average exp	52.45	53.62	69.62	71.53	61.10
	Average price	4.50	4.31	4.79	4.99	4.61
	Unique HHs	128	217	171	170	686
	Observations	6171	10909	7639	6716	31435

		2017				
		Household Income Group				
		Low	Lower-Mid	Upper-Mid	High	All
Credit	Average exp	47.57	56.76	59.22	59.55	57.33
	Average price	4.73	4.92	5.48	5.23	5.16
	Unique HHs	109	226	214	238	787
	Observations	3861	7337	8332	11761	31291
Debit	Average exp	45.77	59.37	68.63	72.04	62.68
	Average price	4.48	4.45	4.83	5.01	4.70
	Unique HHs	117	221	208	205	751
	Observations	5996	10427	9605	8391	34419

		2018				
		Household Income Group				
		Low	Lower-Mid	Upper-Mid	High	All
Credit	Average exp	45.55	54.37	59.84	60.52	57.04
	Average price	4.91	5.36	5.33	5.16	5.21
	Unique HHs	128	196	213	271	808
	Observations	4468	7001	9047	12823	33339
Debit	Average exp	49.69	59.79	69.38	65.94	62.34
	Average price	4.32	4.44	4.74	4.96	4.64
	Unique HHs	128	191	203	222	744
	Observations	5848	9564	9393	8954	33759

		2019				
		Household Income Group				
		Low	Lower-Mid	Upper-Mid	High	All
Credit	Average exp	42.81	54.53	60.19	61.97	57.45
	Average price	5.10	5.39	5.53	5.50	5.43
	Unique HHs	133	198	214	262	807
	Observations	4757	6070	9539	13533	33899
Debit	Average exp	45.37	56.58	64.25	64.76	58.58
	Average price	4.20	4.91	5.00	4.93	4.80
	Unique HHs	126	182	199	198	705
	Observations	6333	9211	9254	8037	32835

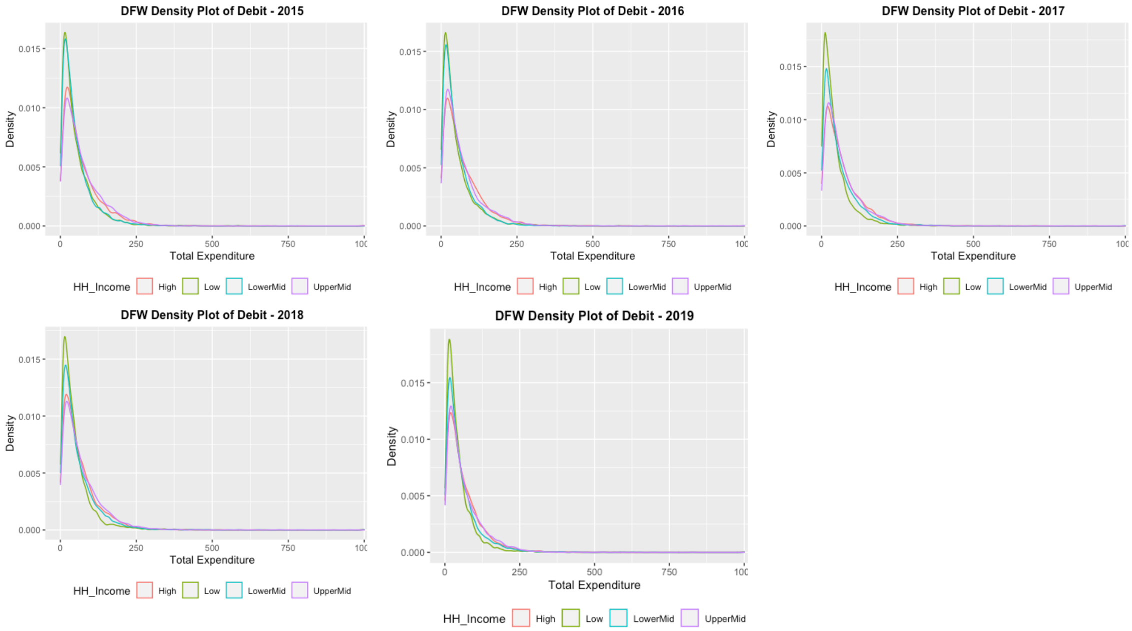
Notes: The tables above show the summary statistics for selected variables for each year. (i) Average exp is the average amount spent by all households by income group in US dollars. (ii) Average price is the average price per item spent by all households by income group in US dollars. (iii) Unique HHs is the unique number of households in each income group. (iv) All is the aggregated data of all household types.

Table B2: DFW – Testing Total Expenditure Distribution for Debit and Credit by Income Group.

DFW 2015				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.029	0.063	0.140	0.060
p-value	0.050	0.000	0.000	0.000
AD test statistic	2.200	30.500	174.000	36.700
p-value	0.072	0.000	0.000	46.940
DFW 2016				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.031	0.030	0.092	0.068
p-value	0.023	0.001	0.000	0.000
AD test statistic	3.660	6.960	89.800	40.500
p-value	0.013	0.000	0.000	0.000
DFW 2017				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.065	0.028	0.101	0.091
p-value	0.000	0.003	< 2.2E-16	< 2.2E-16
AD test statistic	17.300	4.540	114.000	102.000
p-value	0.000	0.005	0.000	0.000
DFW 2018				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.054	0.043	0.075	0.055
p-value	0.000	0.000	< 2.2E-16	0.000
AD test statistic	11.800	20.400	84.200	45.100
p-value	0.000	0.000	0.000	0.000
DFW 2019				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.029	0.024	0.044	0.024
p-value	0.022	0.026	0.000	0.006
AD test statistic	3.140	4.130	27.300	5.280
p-value	0.023	0.008	0.000	0.002

Total Expenditure Density Plots by Income Type – DFW

Debit Plots



Credit Plots

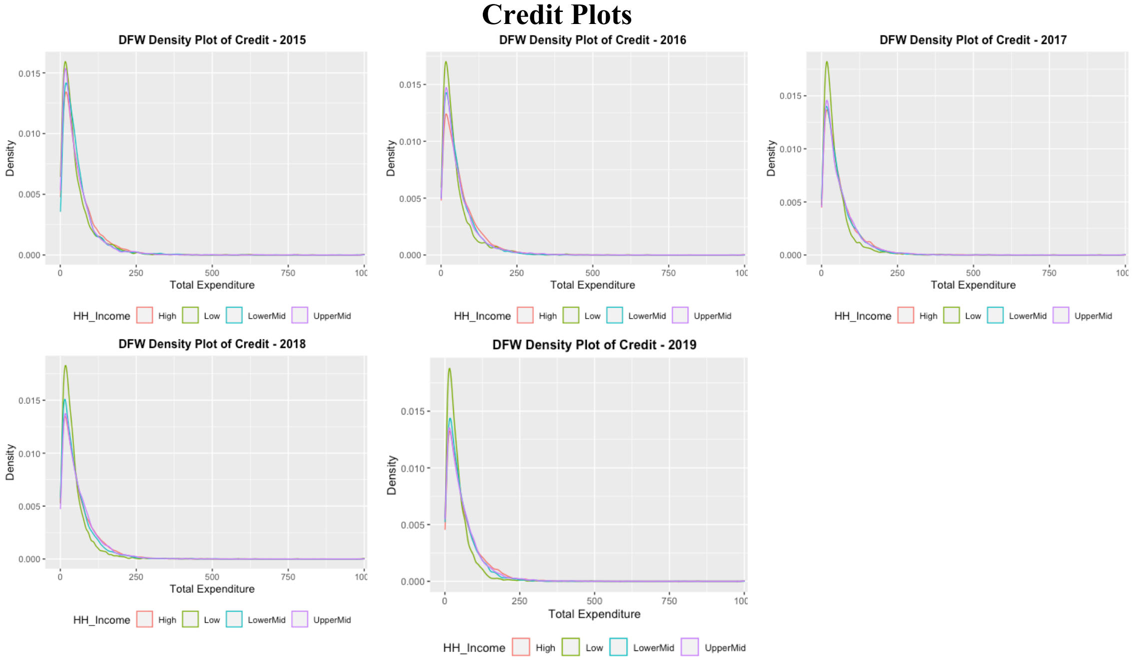
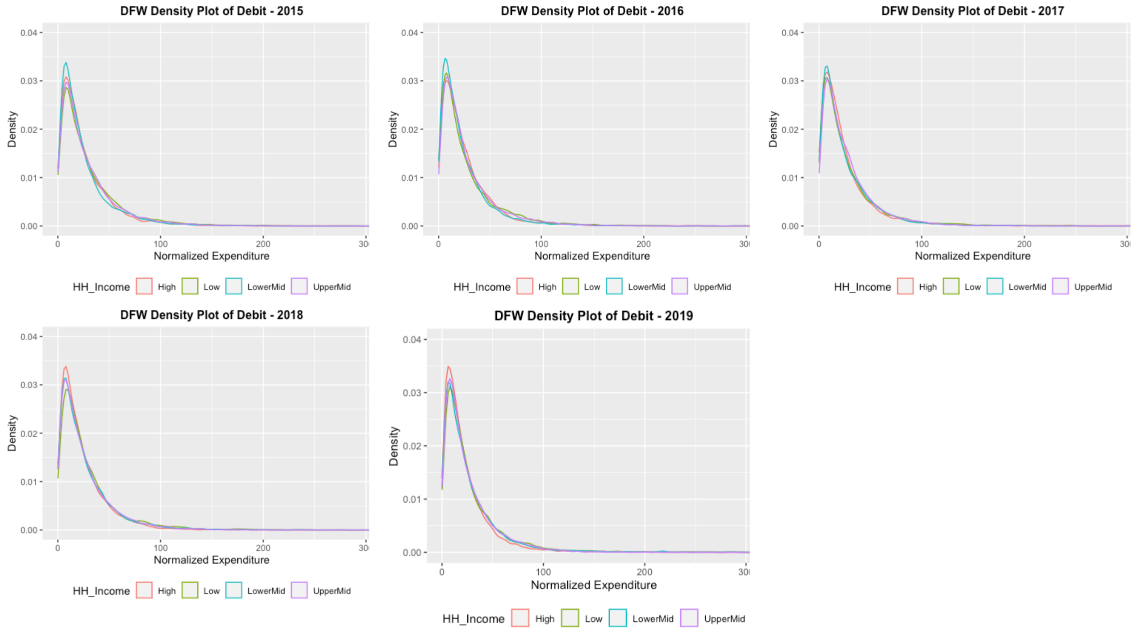


Figure B1: DFW – Total Expenditure Density Plots for Payment Types by Income Group.

Normalized Expenditure Density Plots by Income Type – DFW

Debit Plots



Credit Plots

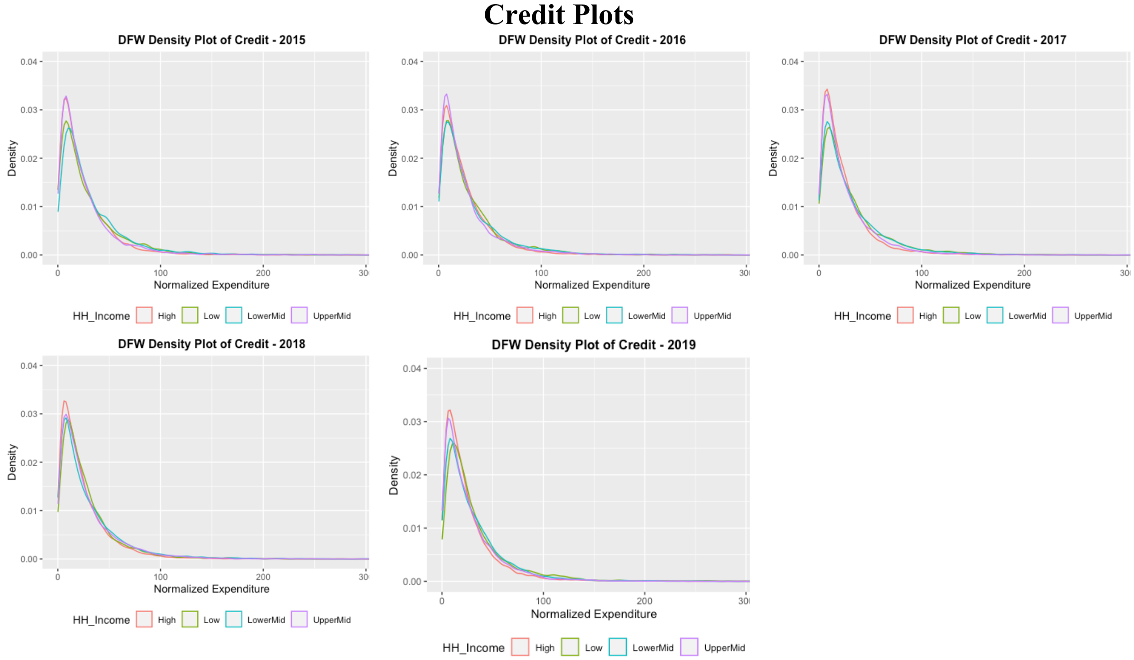


Figure B2: DFW – Normalized Expenditure Density Plots for Payment Types by Income Group (2015 – 2019).

Total Expenditure Density Plots by Payment Type – DFW

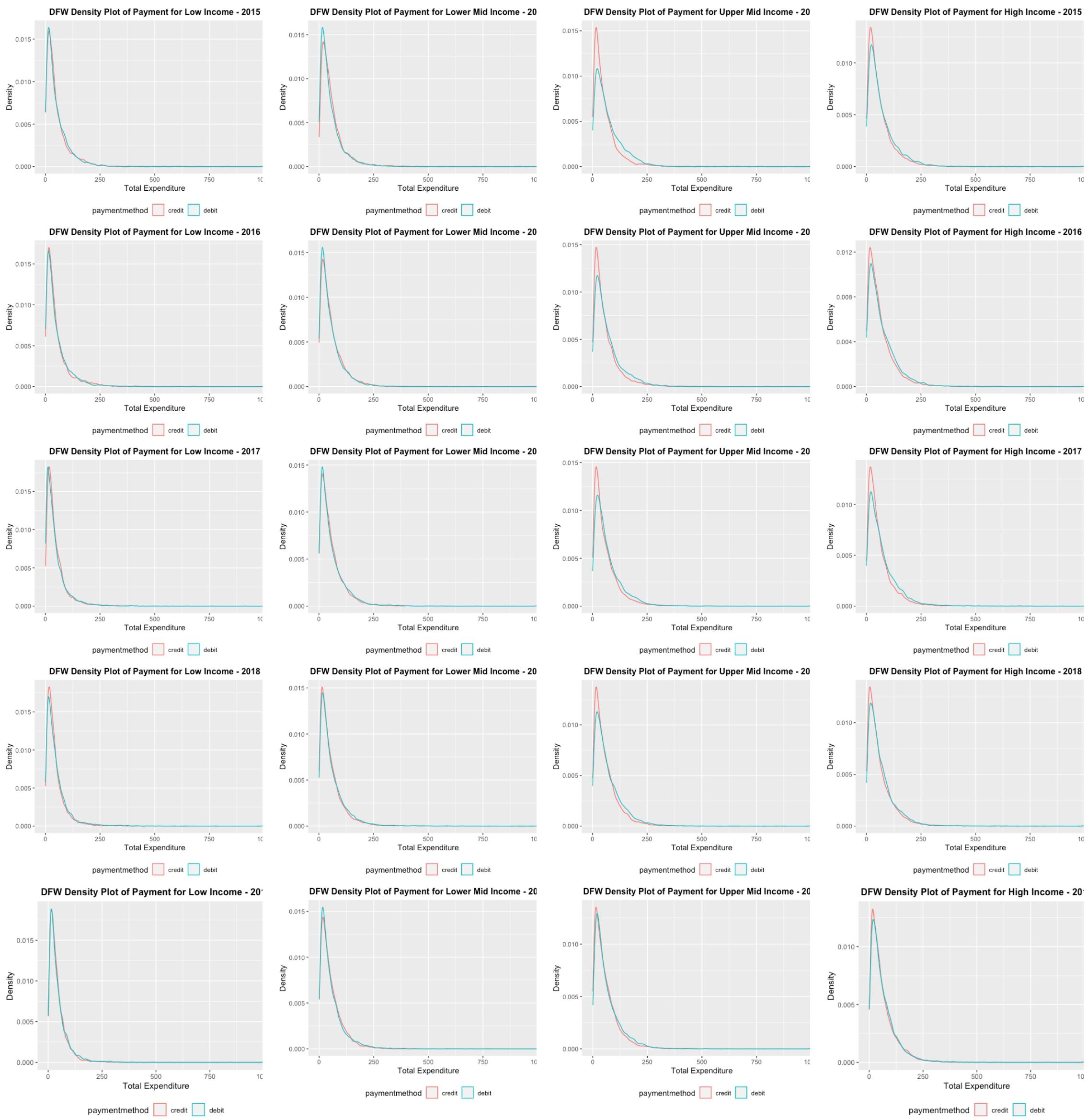


Figure B3: DFW – Total Expenditure Density Plots for Income Group by Payment Type.

Normalized Expenditure Density Plots by Payment Type – DFW

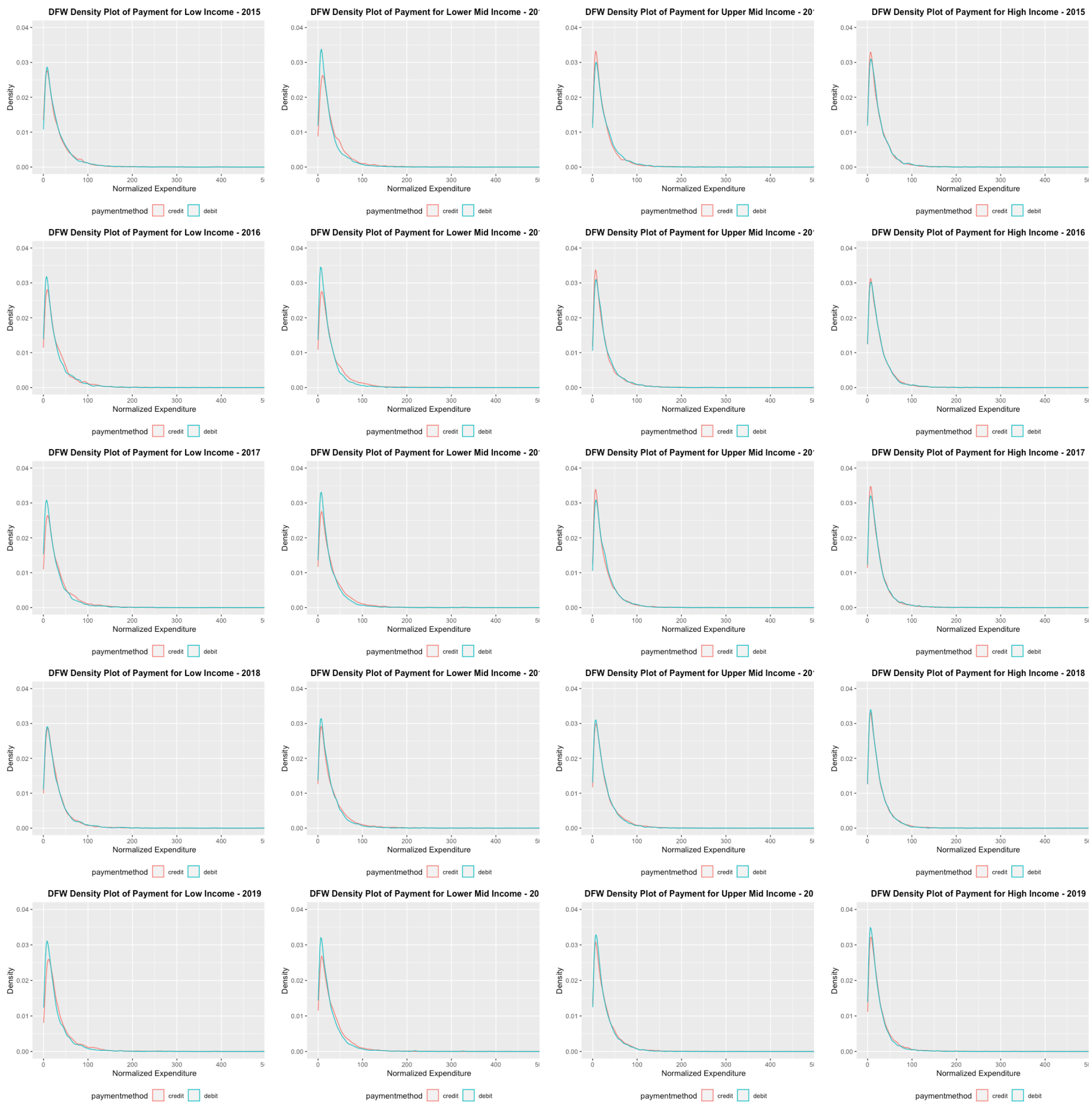


Figure B4: DFW – Normalized Expenditure Density Plots for Income Group by Payment Type (2015 – 2019).

APPENDIX C

LOS ANGELES

Table C1: LA – Selected Variables' Count and Averages by Income Group and Payment Type.

2015

		Household Income Group				
		Low	Lower-Mid	Upper-Mid	High	All
Credit	Average exp	44.26	43.90	50.21	53.31	49.15
	Average price	5.61	5.61	5.68	5.84	5.71
	Unique HHs	169	226	215	266	876
	Observations	4734	7348	8363	12683	33128
Debit	Average exp	50.68	48.48	57.66	65.71	54.52
	Average price	4.45	4.96	5.11	5.39	4.96
	Unique HHs	181	220	188	193	782
	Observations	8077	11344	8104	6620	34145

2016

		Household Income Group				
		Low	Lower-Mid	Upper-Mid	High	All
Credit	Average exp	43.10	48.68	48.94	54.08	49.91
	Average price	5.35	5.36	5.61	5.78	5.58
	Unique HHs	180	262	235	333	1010
	Observations	5891	8764	8566	14172	37393
Debit	Average exp	46.78	51.19	57.41	73.04	56.62
	Average price	4.71	5.13	5.07	5.40	5.09
	Unique HHs	184	259	206	235	884
	Observations	8036	12183	8135	8454	36808

2017

		Household Income Group				
		Low	Lower-Mid	Upper-Mid	High	All
Credit	Average exp	38.98	44.10	45.89	53.92	47.77
	Average price	4.89	5.26	5.48	5.71	5.44
	Unique HHs	186	267	239	390	1082
	Observations	6137	8849	9590	16964	41540
Debit	Average exp	43.74	50.01	61.72	68.62	56.32
	Average price	4.47	4.90	5.04	5.49	5.00
	Unique HHs	187	260	216	290	953
	Observations	8983	11154	9555	10726	40418

2018

		Household Income Group				
		Low	Lower-Mid	Upper-Mid	High	All
Credit	Average exp	38.92	41.37	47.52	50.40	46.16
	Average price	4.99	5.30	5.57	5.58	5.44
	Unique HHs	167	253	254	386	1060
	Observations	6066	9521	10541	17756	43884
Debit	Average exp	44.04	46.82	56.02	65.25	53.64
	Average price	4.61	5.08	5.23	5.41	5.11
	Unique HHs	168	241	208	267	884
	Observations	7771	10925	8992	10983	38671

2019

		Household Income Group				
		Low	Lower-Mid	Upper-Mid	High	All
Credit	Average exp	37.81	42.68	44.47	50.37	45.56
	Average price	5.44	5.11	5.43	5.63	5.46
	Unique HHs	197	270	271	438	1176
	Observations	7851	9898	11989	21328	51066
Debit	Average exp	42.73	49.28	57.60	61.51	53.41
	Average price	4.78	5.00	5.35	5.23	5.10
	Unique HHs	189	245	232	311	977
	Observations	9203	11357	10212	12655	43427

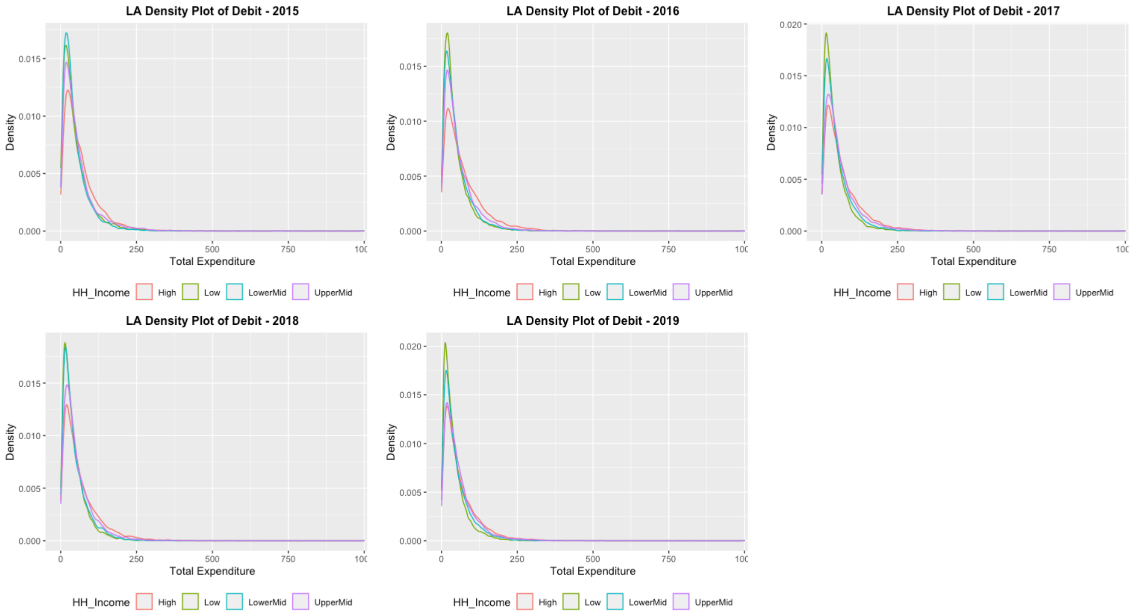
Notes: The tables above show the summary statistics for selected variables for each year. (i) Average exp is the average amount spent by all households by income group in US dollars. (ii) Average price is the average price per item spent by all households by income group in US dollars. (iii) Unique HHs is the unique number of households in each income group. (iv) All is the aggregated data of all household types.

Table C2: LA – Testing Total Expenditure Distribution for Debit and Credit by Income Group.

LA 2015				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.063	0.074	0.086	0.129
p-value	0.000	< 2.2E-16	< 2.2E-16	< 2.2E-16
AD test statistic	31.300	58.400	72.800	194.000
p-value	0.000	0.000	0.000	0.000
LA 2016				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.069	0.046	0.085	0.148
p-value	0.000	0.000	< 2.2E-16	< 2.2E-16
AD test statistic	34.700	20.900	100.000	324.000
p-value	0.000	0.000	0.000	0.000
LA 2017				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.060	0.079	0.152	0.117
p-value	0.000	< 2.2E-16	< 2.2E-16	< 2.2E-16
AD test statistic	39.000	85.300	302.000	267.000
p-value	0.000	0.000	0.000	0.000
LA 2018				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.078	0.078	0.105	0.115
p-value	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16
AD test statistic	41.600	89.500	121.000	271.000
p-value	0.000	0.000	0.000	0.000
LA 2019				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.070	0.067	0.139	0.088
p-value	< 2.2E-16	< 2.2E-16	< 2.2E-16	< 2.2E-16
AD test statistic	46.900	71.600	271.000	188.000
p-value	0.000	0.000	0.000	0.000

Total Expenditure Density Plots by Income Type – LA

Debit Plots



Credit Plots

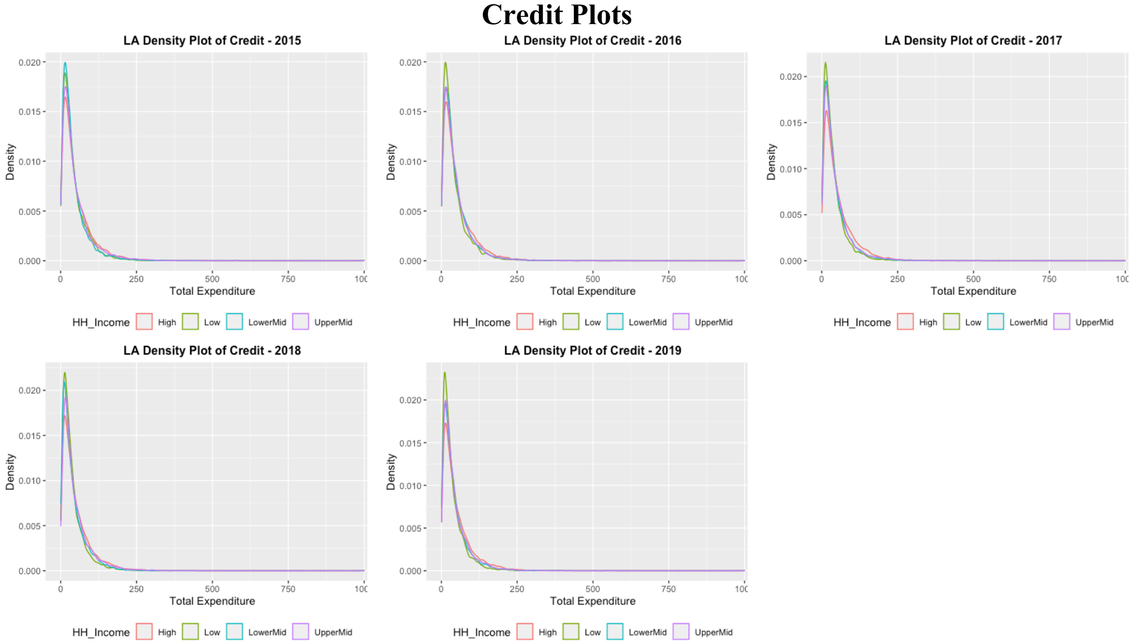
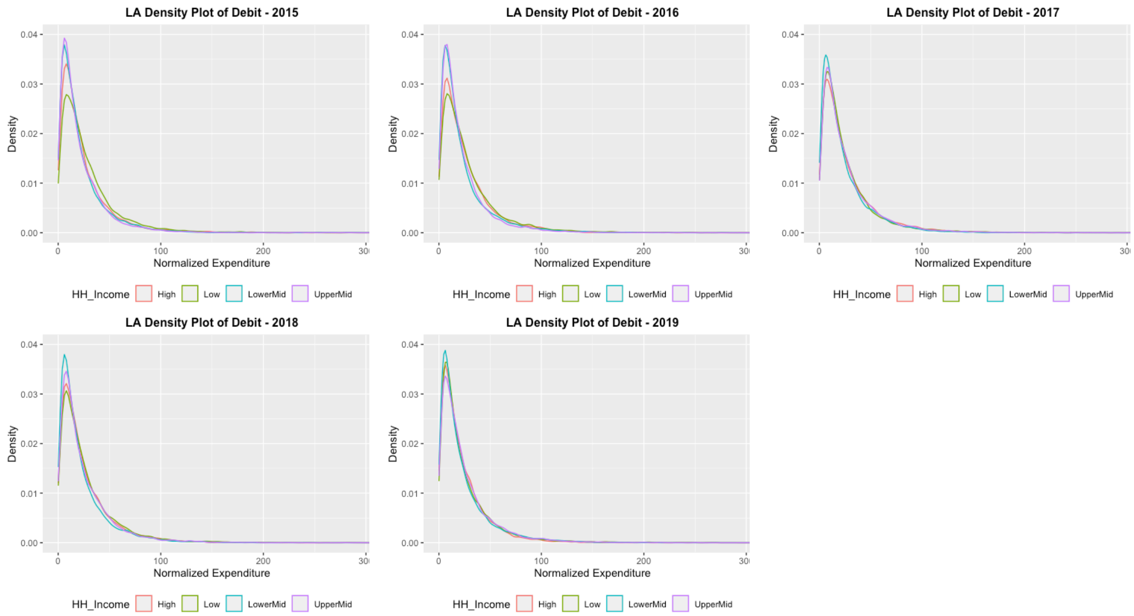


Figure C1: LA – Total Expenditure Density Plots for Payment Types by Income Group (2015 – 2019).

Normalized Expenditure Density Plots by Income Type – LA

Debit Plots



Credit Plots

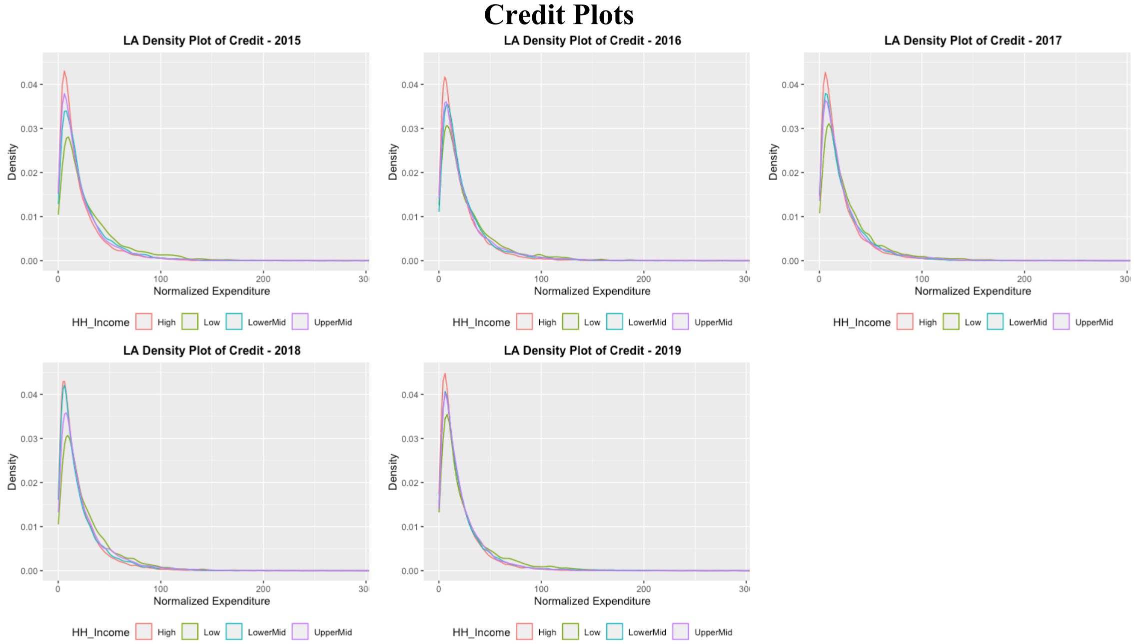


Figure C2: LA – Normalized Expenditure Density Plots for Payment Types by Income Group (2015 – 2019).

Total Expenditure Density Plots by Payment Type – LA

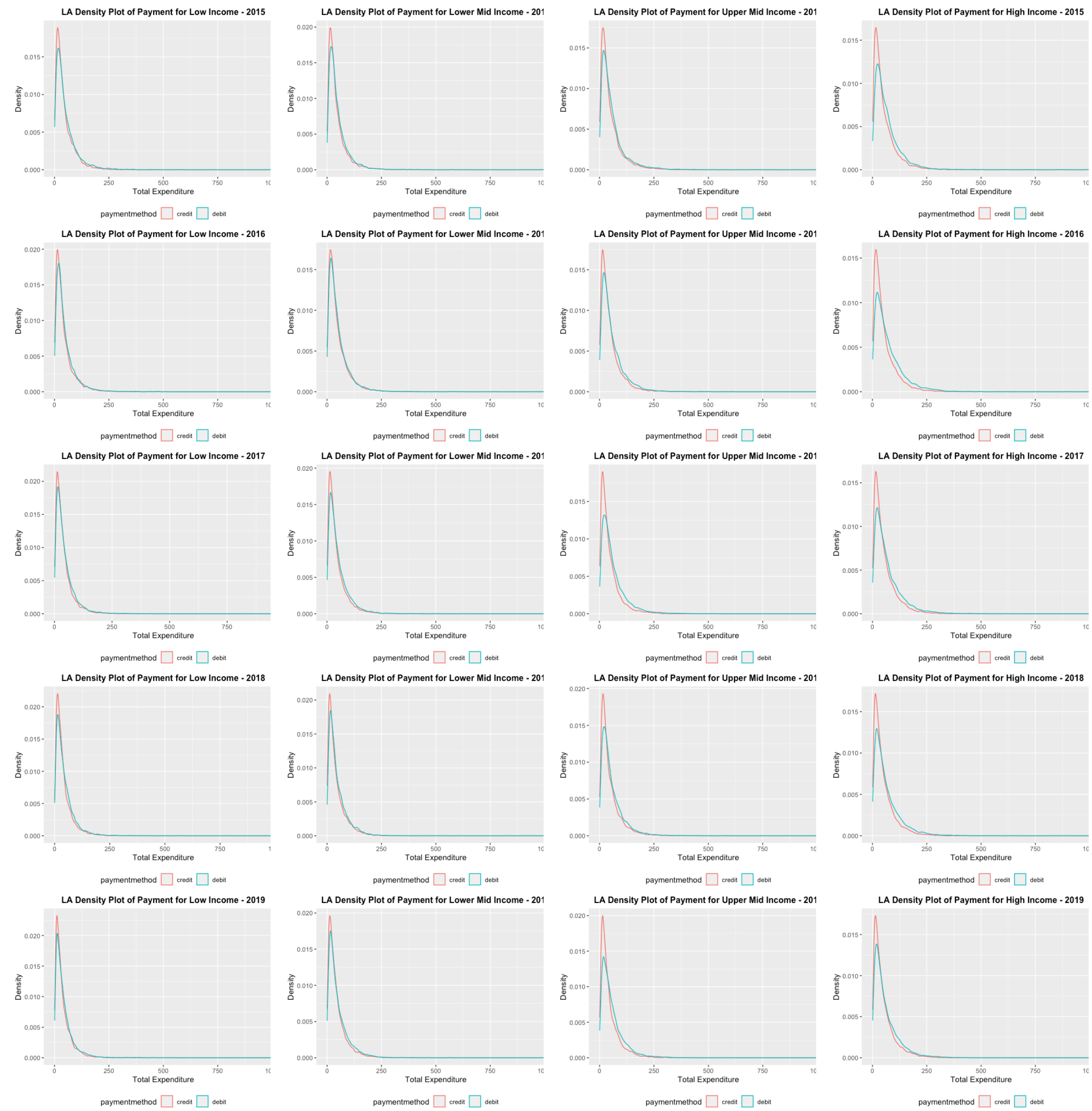


Figure C3: LA – Total Expenditure Density Plots for Income Group by Payment Type.

Normalized Expenditure Density Plots by Payment Type – LA

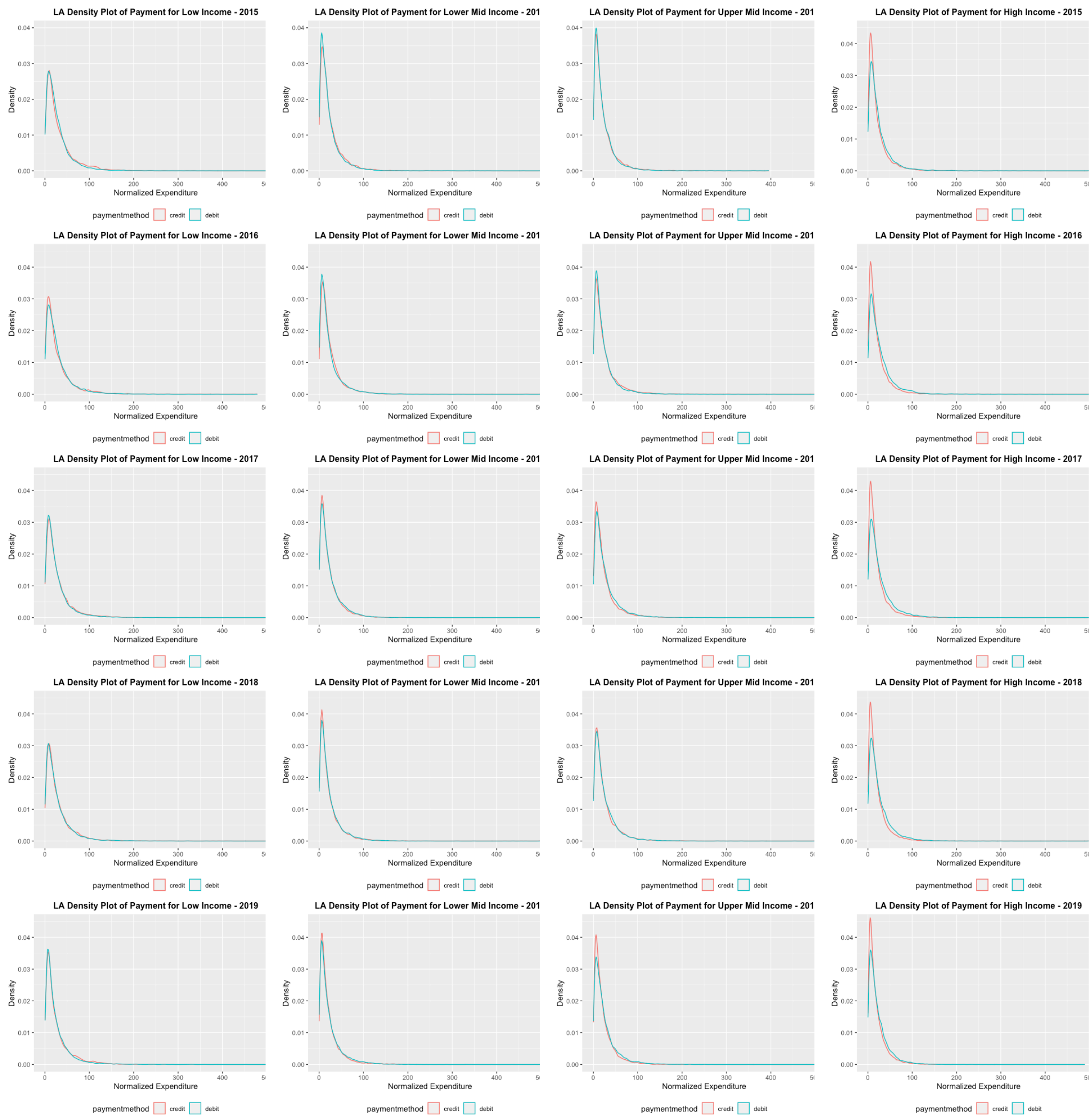


Figure C4: LA – Normalized Expenditure Density Plots for Income Group by Payment Type (2015 – 2019).

APPENDIX D

NEW YORK CITY

Table D1: NYC – Selected Variables' Count and Averages by Income Group and Payment Type.

2015

		Household Income Group				
		Low	Lower-Mid	Upper-Mid	High	All
Credit	Average exp	40.81	52.51	58.42	59.76	55.23
	Average price	4.81	5.31	5.36	5.65	5.40
	Unique HHs	167	251	258	420	1096
	Observations	6447	9549	9591	19494	45081
Debit	Average exp	41.03	58.47	71.49	68.29	61.35
	Average price	4.46	5.05	5.27	4.94	4.97
	Unique HHs	126	213	195	256	790
	Observations	4960	9034	7025	7994	29013

2016

		Household Income Group				
		Low	Lower-Mid	Upper-Mid	High	All
Credit	Average exp	42.91	51.26	55.72	59.71	54.69
	Average price	5.02	5.03	5.43	5.40	5.28
	Unique HHs	180	267	321	500	1268
	Observations	7694	10746	12178	22912	53530
Debit	Average exp	46.75	53.63	67.92	67.72	60.73
	Average price	4.33	5.14	5.44	5.01	5.06
	Unique HHs	139	221	243	306	909
	Observations	4917	9029	8780	9969	32695

2017

		Household Income Group				
		Low	Lower-Mid	Upper-Mid	High	All
Credit	Average exp	44.50	52.07	53.48	59.05	54.39
	Average price	4.86	5.56	5.41	5.48	5.40
	Unique HHs	185	308	356	551	1400
	Observations	7616	12529	13805	25103	59053
Debit	Average exp	52.95	55.82	66.15	67.15	62.02
	Average price	4.84	5.02	5.15	5.02	5.03
	Unique HHs	145	237	259	318	959
	Observations	4775	9082	9537	11785	35179

2018

		Household Income Group				
		Low	Lower-Mid	Upper-Mid	High	All
Credit	Average exp	44.31	48.55	55.35	57.97	53.63
	Average price	5.21	5.25	5.63	5.57	5.47
	Unique HHs	183	329	348	555	1415
	Observations	7784	13715	13848	27356	62703
Debit	Average exp	49.71	54.73	63.48	69.76	61.36
	Average price	5.18	4.97	5.27	5.15	5.13
	Unique HHs	133	256	237	336	962
	Observations	4154	10745	9422	11852	36173

2019

		Household Income Group				
		Low	Lower-Mid	Upper-Mid	High	All
Credit	Average exp	46.86	47.17	53.76	57.27	53.07
	Average price	5.20	5.27	5.63	5.50	5.44
	Unique HHs	202	324	359	610	1495
	Observations	8502	13727	14860	29399	66488
Debit	Average exp	47.87	52.35	63.77	64.10	58.61
	Average price	4.88	5.02	5.32	5.19	5.13
	Unique HHs	157	245	257	357	1016
	Observations	5902	9956	9763	13753	39374

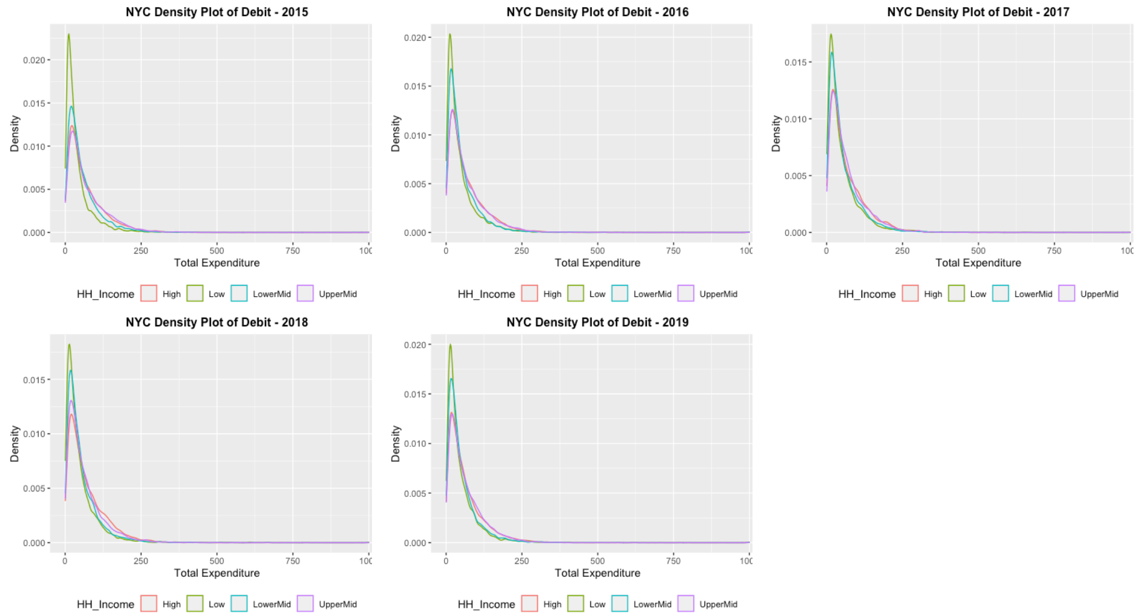
Notes: The tables above show the summary statistics for selected variables for each year. (i) Average exp is the average amount spent by all households by income group in US dollars. (ii) Average price is the average price per item spent by all households by income group in US dollars. (iii) Unique HHs is the unique number of households in each income group. (iv) All is the aggregated data of all household types.

Table D2: NYC – Testing Total Expenditure Distribution for Debit and Credit by Income Group.

NYC 2015				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.055	0.055	0.105	0.067
p-value	0.000	< 2.2E-16	< 2.2E-16	< 2.2E-16
AD test statistic	10.400	30.000	103.000	67.700
p-value	0.000	0.000	0.000	0.000
NYC 2016				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.033	0.020	0.086	0.066
p-value	0.003	0.044	< 2.2E-16	< 2.2E-16
AD test statistic	9.250	2.780	118.000	68.400
p-value	0.000	0.036	0.000	0.000
NYC 2017				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.071	0.042	0.107	0.067
p-value	0.000	0.000	< 2.2E-16	< 2.2E-16
AD test statistic	29.200	13.400	187.000	88.000
p-value	0.000	0.000	0.000	0.000
NYC 2018				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.038	0.049	0.082	0.099
p-value	0.001	0.000	< 2.2E-16	< 2.2E-16
AD test statistic	7.120	47.000	97.900	211.000
p-value	0.000	0.000	0.000	0.000
NYC 2019				
	Low	Lower-Mid	Upper-Mid	High
KS test statistic	0.030	0.041	0.093	0.060
p-value	0.003	0.000	< 2.2E-16	< 2.2E-16
AD test statistic	8.110	25.000	129.000	78.800
p-value	0.000	0.000	0.000	0.000

Total Expenditure Density Plots by Income Type – NYC

Debit Plots



Credit Plots

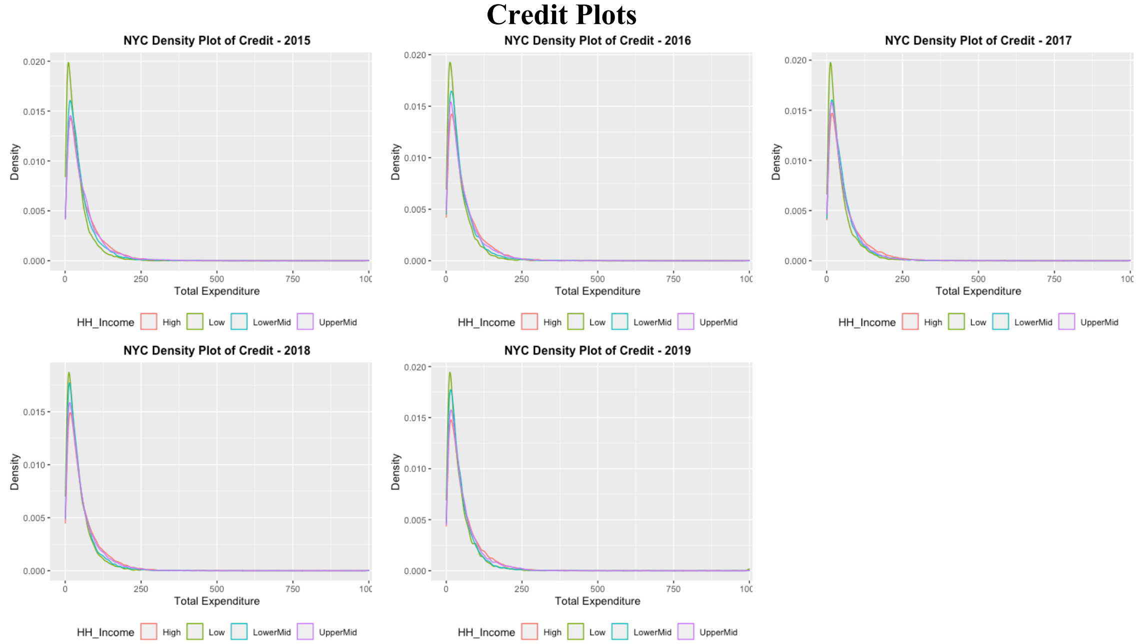
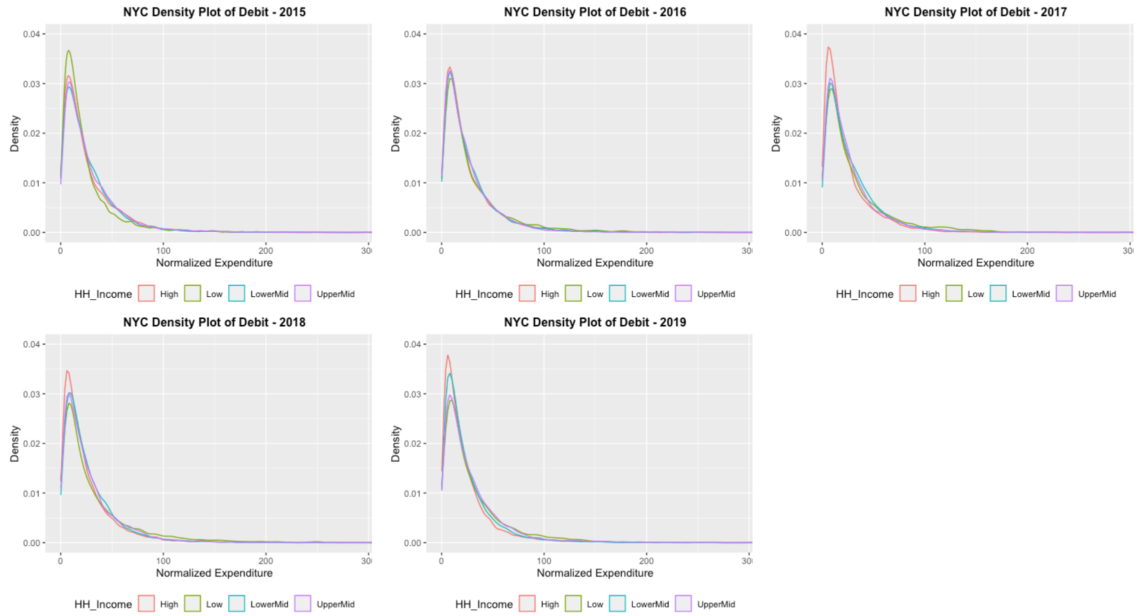


Figure D1: NYC – Total Expenditure Density Plots for Payment Types by Income Group (2015 – 2019).

Normalized Expenditure Density Plots by Income Type – NYC

Debit Plots



Credit Plots

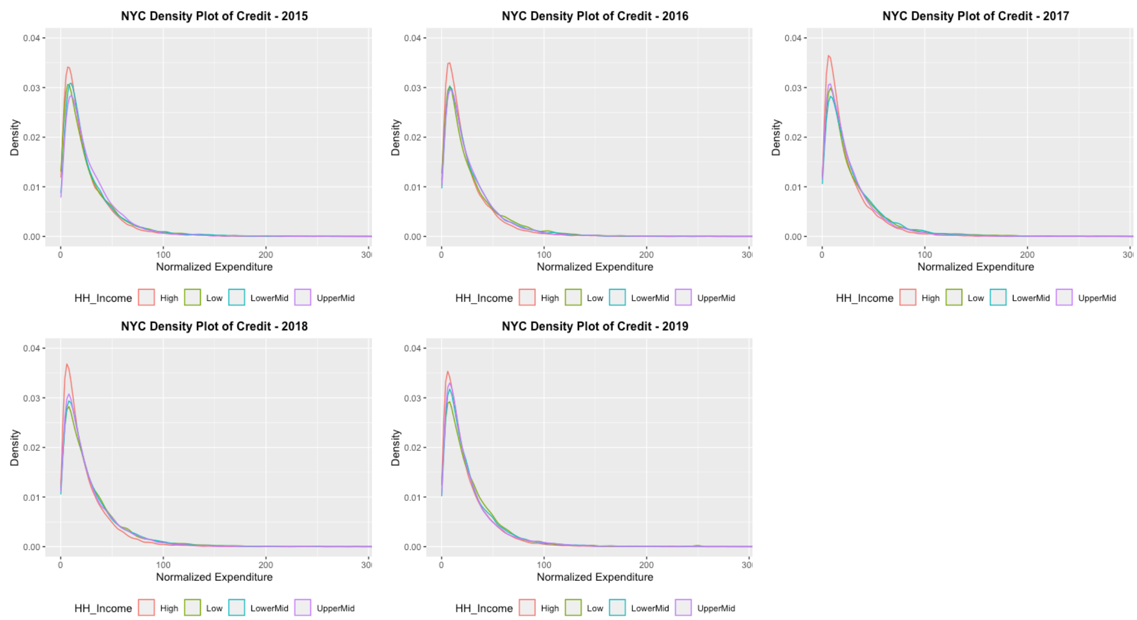


Figure D2: NYC – Normalized Expenditure Density Plots for Payment Types by Income Group (2015 – 2019).

Total Expenditure Density Plots by Payment Type – NYC

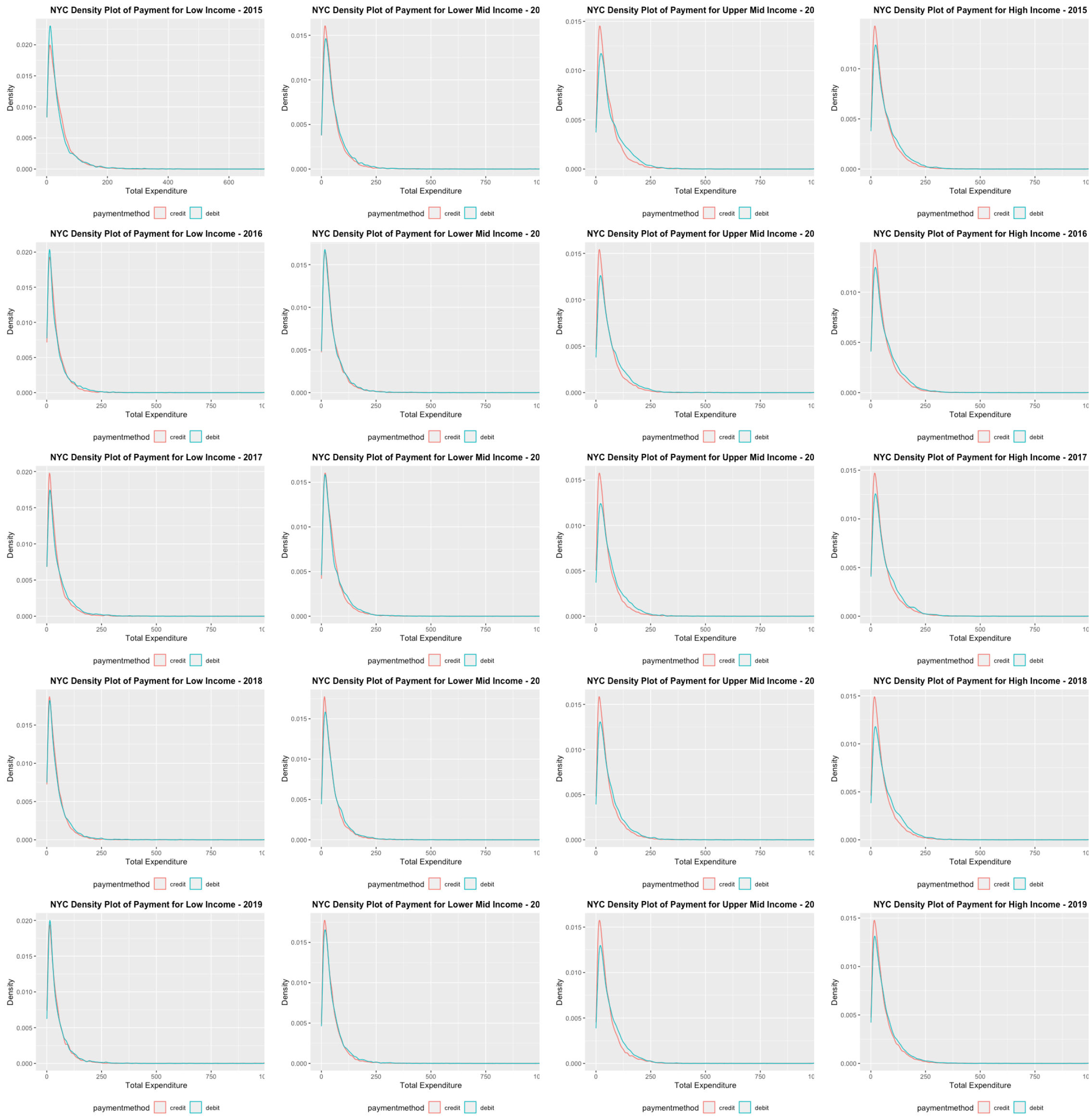


Figure D3: NYC – Total Expenditure Density Plots for Income Group by Payment Type (2015 – 2019).

Normalized Expenditure Density Plots by Income Type – NYC

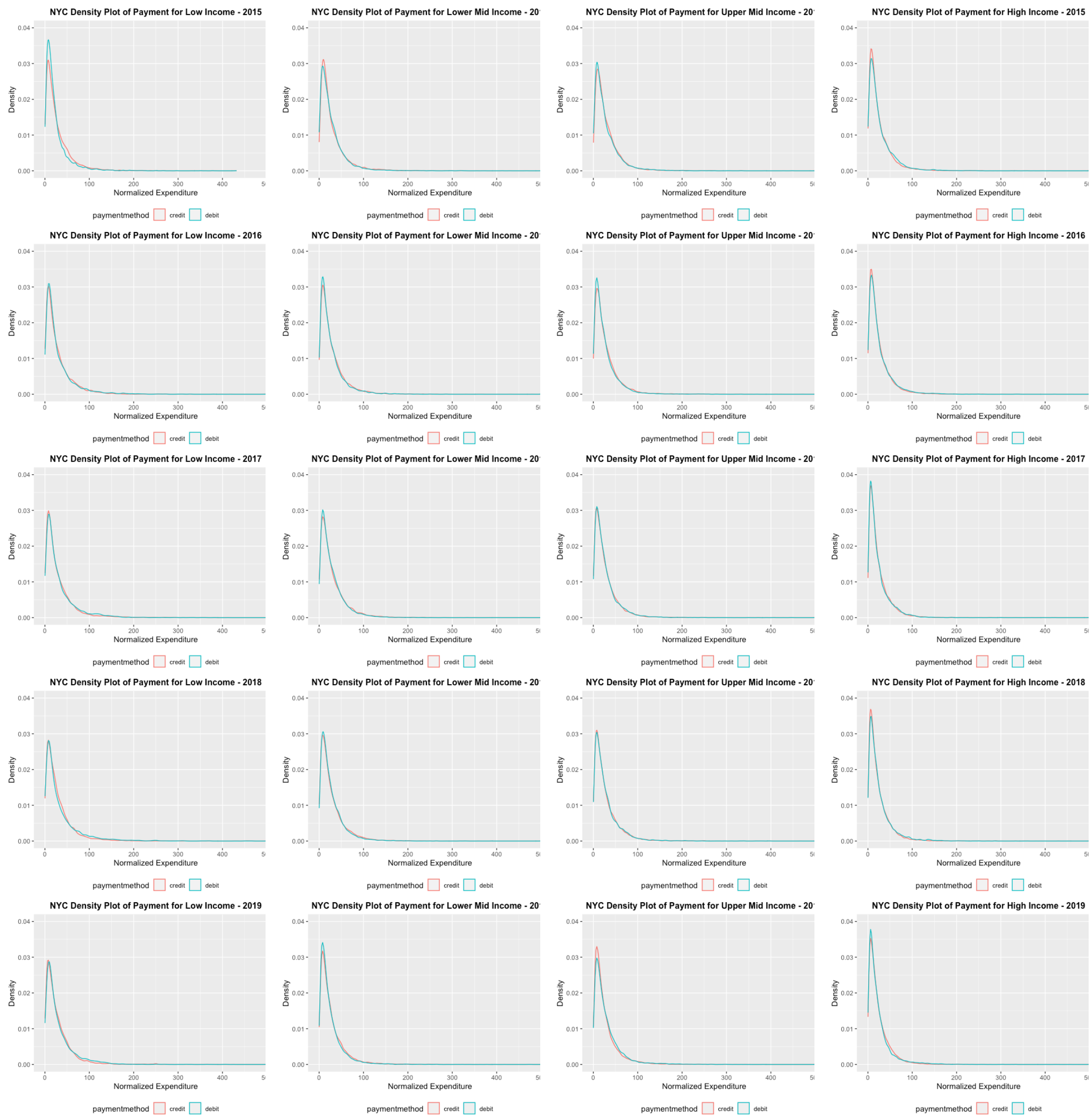


Figure D4: NYC – Normalized Expenditure Density Plots for Income Group by Payment Type (2015 – 2019).

APPENDIX E

CHICAGO – OTHER LOGISTIC REGRESSION RESULTS

Table E1: CHI – Logistic Regression Results for All Income Groups.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.160	< 2e-16	0.105	0.001	0.222	< 2e-16	0.209	0.000	0.552	< 2e-16	-0.335	< 2e-16	0.655	< 2e-16	0.041	0.022	70986
		With HH	-1.017	0.010	0.104	0.944	0.961	0.309	0.996	0.528	7.363	0.000	-2.282	0.049	10.670	0.000	0.031	0.384	
	log_exp	W/O HH	-0.157	< 2e-16	0.107	0.001	0.221	< 2e-16	0.202	0.000	0.547	< 2e-16	-0.333	< 2e-16	0.662	< 2e-16	0.042	0.021	70948
		With HH	-1.082	0.019	-2.934	0.168	0.506	0.625	3.982	0.064	7.364	0.000	-5.552	0.000	8.334	0.000	0.010	0.790	
	rel_exp	W/O HH	-0.166	< 2e-16	0.108	0.001	0.226	< 2e-16	0.214	0.000	0.558	< 2e-16	-0.334	< 2e-16	0.649	< 2e-16	0.041	0.025	70984
		With HH	-1.012	0.014	-0.917	0.545	1.671	0.084	2.556	0.114	6.454	0.000	-2.729	0.017	8.895	0.000	0.008	0.813	
2016	exp	W/O HH	-0.190	< 2e-16	0.179	0.000	0.383	< 2e-16	0.142	0.000	0.545	< 2e-16	-0.357	< 2e-16	0.739	< 2e-16	-0.029	0.071	90668
		With HH	-0.912	0.014	0.492	0.706	0.824	0.316	1.527	0.263	4.276	0.000	-5.228	0.000	9.410	0.000	-0.088	0.006	
	log_exp	W/O HH	-0.186	< 2e-16	0.181	0.000	0.384	< 2e-16	0.128	0.000	0.536	< 2e-16	-0.349	< 2e-16	0.749	< 2e-16	-0.028	0.079	90495
		With HH	-0.999	0.010	1.441	0.302	1.109	0.196	1.981	0.182	4.738	0.000	-5.298	0.000	8.011	0.000	-0.065	0.046	
	rel_exp	W/O HH	-0.202	< 2e-16	0.183	0.000	0.393	< 2e-16	0.151	0.000	0.562	< 2e-16	-0.359	< 2e-16	0.723	< 2e-16	-0.028	0.078	90899
		With HH	-0.781	0.029	0.996	0.452	1.244	0.130	1.696	0.229	4.822	0.000	-4.088	0.000	7.511	0.000	-0.050	0.1188	
2017	exp	W/O HH	-0.087	< 2e-16	0.245	< 2e-16	0.113	0.000	0.069	0.009	0.624	< 2e-16	-0.674	< 2e-16	0.721	< 2e-16	0.026	0.082	101011
		With HH	-0.939	0.008	-4.029	0.014	0.450	0.582	5.255	0.001	5.734	0.000	-6.802	0.000	8.104	0.000	0.009	0.787	
	log_exp	W/O HH	-0.086	< 2e-16	0.244	< 2e-16	0.118	0.000	0.063	0.017	0.621	< 2e-16	-0.664	< 2e-16	0.725	< 2e-16	0.026	0.083	100958
		With HH	-0.526	0.168	-7.227	0.000	2.098	0.020	7.231	0.000	11.415	0.000	-4.431	0.000	11.466	0.000	0.029	0.395	
	rel_exp	W/O HH	-0.098	< 2e-16	0.235	< 2e-16	0.129	0.000	0.079	0.002	0.642	< 2e-16	-0.681	< 2e-16	0.697	< 2e-16	0.026	0.092	101453
		With HH	-0.933	0.010	-0.097	0.947	1.419	0.107	1.915	0.210	7.721	0.000	-4.921	0.000	9.880	0.000	0.015	0.670	
2018	exp	W/O HH	-0.184	< 2e-16	0.542	< 2e-16	-0.056	0.002	0.009	0.746	0.510	<2e-16	-0.635	<2e-16	0.614	<2e-16	0.002	0.877	101513
		With HH	-0.767	0.032	0.700	0.596	-1.208	0.151	1.127	0.380	2.318	0.024	-9.840	< 2e-16	10.464	< 2e-16	0.018	0.604	
	log_exp	W/O HH	-0.182	< 2e-16	0.542	< 2e-16	-0.053	0.003	0.000	0.995	0.501	<2e-16	-0.629	<2e-16	0.625	<2e-16	0.003	0.836	101388
		With HH	-1.289	0.001	3.001	0.023	0.152	0.857	0.311	0.821	4.029	0.003	-5.515	0.000	8.980	0.000	0.071	0.039	
	rel_exp	W/O HH	-0.196	< 2e-16	0.529	< 2e-16	-0.040	0.023	0.028	0.311	0.527	<2e-16	-0.642	<2e-16	0.583	<2e-16	0.002	0.895	101975
		With HH	-2.247	0.000	1.601	0.310	-0.216	0.836	3.686	0.038	1.641	0.156	-5.981	0.000	3.910	0.009	0.042	0.221	
2019	exp	W/O HH	-0.161	< 2e-16	0.477	< 2e-16	-0.177	<2e-16	0.057	0.029	0.577	<2e-16	-0.606	<2e-16	0.660	<2e-16	0.005	0.728	106176
		With HH	-2.069	0.000	4.614	0.004	-3.350	0.002	-0.789	0.601	8.551	0.000	-6.165	0.000	5.363	0.000	-0.021	0.537	
	log_exp	W/O HH	-0.160	< 2e-16	0.478	< 2e-16	-0.174	< 2e-16	0.055	0.035	0.571	<2e-16	-0.601	<2e-16	0.668	<2e-16	0.004	0.762	106054
		With HH	-0.852	< 2e-16	3.100	< 2e-16	-0.922	< 2e-16	-2.508	< 2e-16	6.766	<2e-16	-4.281	<2e-16	5.834	<2e-16	-0.086	<2e-16	
	rel_exp	W/O HH	-0.174	< 2e-16	0.476	< 2e-16	-0.163	< 2e-16	0.057	0.029	0.596	< 2e-16	-0.613	< 2e-16	0.628	< 2e-16	0.004	0.767	106616
		With HH	-1.203	< 2e-16	3.018	< 2e-16	-1.336	< 2e-16	1.250	< 2e-16	8.870	<2e-16	-5.643	<2e-16	7.583	<2e-16	0.067	<2e-16	

Table E2: CHI – Logistic Regression Results for Low-Income Group.

		Model	HH Size	p-value	Marital_Statu	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.279	< 2e-16	0.037	0.644	0.733	< 2e-16	0.102	0.079	0.195	0.000	-0.525	< 2e-16	1.408	< 2e-16	0.079	0.086	10980
		With HH	-0.782	0.425	-2.511	0.543	8.999	0.016	2.215	0.475	-4.838	0.144	-1.053	0.644	11.275	0.000	-0.042	0.670	
	log_exp	W/O HH	-0.275	< 2e-16	0.046	0.561	0.740	< 2e-16	0.094	0.109	0.190	0.000	-0.523	< 2e-16	1.422	< 2e-16	0.079	0.086	10976
		With HH	-0.798	0.567	-0.675	0.855	16.287	0.089	1.156	0.702	-0.324	0.900	-1.288	0.703	17.211	0.018	0.067	0.499	
	rel_exp	W/O HH	-0.288	< 2e-16	0.038	0.636	0.731	< 2e-16	0.112	0.054	0.203	0.000	-0.527	< 2e-16	1.395	< 2e-16	0.079	0.085	10978
		With HH	-1.323	0.260	-1.125	0.771	7.769	0.030	1.313	0.665	-4.611	0.166	-2.361	0.340	9.598	0.002	-0.009	0.927	
2016	exp	W/O HH	-0.508	< 2e-16	0.556	0.000	0.816	< 2e-16	0.442	0.000	0.411	0.000	-0.684	< 2e-16	1.268	< 2e-16	0.004	0.935	11189
		With HH	-2.412	0.013	5.741	0.119	8.393	0.003	-0.474	0.873	-1.661	0.450	-7.729	0.004	9.326	0.003	-0.045	0.678	
	log_exp	W/O HH	-0.507	< 2e-16	0.588	0.000	0.811	< 2e-16	0.374	0.000	0.407	0.000	-0.692	< 2e-16	1.298	< 2e-16	-0.001	0.986	11184
		With HH	-2.416	0.013	5.435	0.135	8.363	0.004	-0.114	0.970	-2.308	0.331	-7.444	0.007	9.318	0.004	-0.040	0.715	
	rel_exp	W/O HH	-0.540	< 2e-16	0.570	0.000	0.843	< 2e-16	0.438	0.000	0.413	0.000	-0.660	< 2e-16	1.236	< 2e-16	-0.011	0.813	11310
		With HH	-2.283	0.017	5.281	0.145	8.670	0.004	-0.088	0.976	-1.731	0.451	-7.055	0.009	9.364	0.005	-0.048	0.658	
2017	exp	W/O HH	0.394	< 2e-16	-1.111	< 2e-16	0.757	< 2e-16	1.014	< 2e-16	0.289	0.000	-0.201	0.000	0.842	< 2e-16	0.049	0.219	14647
		With HH	1.250	0.366	-4.754	0.323	10.267	0.002	10.153	0.002	4.793	0.179	-4.323	0.295	13.563	0.000	0.043	0.668	
	log_exp	W/O HH	0.390	< 2e-16	-1.089	< 2e-16	0.762	< 2e-16	0.991	< 2e-16	0.274	0.000	-0.208	0.000	0.839	< 2e-16	0.049	0.220	14706
		With HH	0.576	0.635	-3.402	0.288	2.643	0.262	11.079	0.000	1.167	0.520	-10.226	0.000	11.805	0.000	0.032	0.744	
	rel_exp	W/O HH	0.385	< 2e-16	-1.139	< 2e-16	0.789	< 2e-16	1.013	< 2e-16	0.280	0.000	-0.244	0.000	0.816	< 2e-16	0.043	0.276	14768
		With HH	0.033	0.976	-2.525	0.450	7.077	0.046	9.553	0.001	2.432	0.291	-5.339	0.174	9.683	0.001	-0.051	0.606	
2018	exp	W/O HH	-0.083	0.000	0.254	0.000	0.331	0.000	0.530	<2e-16	0.145	0.001	-0.101	0.023	0.439	<2e-16	0.062	0.109	15096
		With HH	-2.218	0.010	2.944	0.336	6.145	0.198	1.781	0.571	2.513	0.320	-7.212	0.130	9.775	0.007	0.127	0.162	
	log_exp	W/O HH	-0.088	0.000	0.260	0.000	0.335	0.000	0.523	<2e-16	0.138	0.002	-0.102	0.022	0.430	<2e-16	0.062	0.110	15111
		With HH	-2.639	<2e-16	11.754	<2e-16	5.980	<2e-16	-7.029	<2e-16	1.574	<2e-16	-3.680	<2e-16	8.052	<2e-16	0.155	<2e-16	
	rel_exp	W/O HH	-0.091	0.000	0.259	0.000	0.338	0.000	0.523	<2e-16	0.138	0.002	-0.101	0.023	0.422	<2e-16	0.062	0.114	15109
		With HH	-2.195	0.014	9.160	0.015	6.250	0.022	-4.740	0.139	1.458	0.515	-4.719	0.057	7.782	0.002	0.165	0.069	
2019	exp	W/O HH	0.012	0.518	-0.018	0.776	-0.097	0.046	0.057	0.259	0.361	< 2e-16	-0.040	0.322	0.274	0.000	0.024	0.509	16883
		With HH	-1.115	0.372	0.567	0.898	-4.876	0.123	-3.030	0.429	4.637	0.112	-4.281	0.171	5.711	0.080	0.000	0.999	
	log_exp	W/O HH	0.007	0.710	-0.003	0.961	-0.092	0.058	0.045	0.377	0.352	< 2e-16	-0.043	0.288	0.272	0.000	0.024	0.508	16895
		With HH	-1.064	0.502	-13.531	0.006	-1.925	0.634	-0.202	0.961	6.429	0.052	-1.373	0.675	1.614	0.649	-0.009	0.913	
	rel_exp	W/O HH	-0.004	0.834	-0.007	0.906	-0.087	0.074	0.047	0.354	0.371	< 2e-16	-0.041	0.307	0.252	0.000	0.025	0.495	16912
		With HH	-0.372	0.715	-0.834	0.789	-5.486	0.034	-3.402	0.189	3.715	0.073	-5.952	0.004	4.512	0.042	-0.024	0.755	

Table E3: CHI – Logistic Regression Results for Lower-Middle Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.150	< 2e-16	0.228	0.000	0.280	0.000	-0.056	0.316	0.129	0.000	-0.150	0.000	1.102	< 2e-16	0.062	0.059	21027
		With HH	-1.439	0.094	-0.935	0.729	8.490	0.001	3.330	0.237	9.318	0.000	-0.082	0.959	12.234	0.000	0.077	0.200	
	log_exp	W/O HH	-0.148	< 2e-16	0.229	0.000	0.279	0.000	-0.058	0.306	0.127	0.001	-0.152	0.000	1.102	< 2e-16	0.063	0.058	21030
		With HH	-1.318	0.066	-0.646	0.795	4.396	0.051	3.341	0.202	5.028	0.009	-1.261	0.473	9.767	0.000	0.054	0.368	
	rel_exp	W/O HH	-0.144	< 2e-16	0.228	0.000	0.277	0.000	-0.061	0.276	0.123	0.001	-0.153	0.000	1.105	< 2e-16	0.062	0.058	21022
		With HH	-1.627	0.036	-0.562	0.832	2.605	0.223	3.273	0.224	5.750	0.002	-1.996	0.271	11.114	0.000	0.058	0.328	
2016	exp	W/O HH	-0.139	< 2e-16	0.090	0.082	0.328	< 2e-16	0.033	0.501	0.436	< 2e-16	-0.480	< 2e-16	0.464	< 2e-16	-0.052	0.080	26339
		With HH	-0.715	0.378	0.347	0.890	1.156	0.502	2.616	0.297	7.725	0.000	-6.670	0.000	4.278	0.044	-0.076	0.186	
	log_exp	W/O HH	-0.137	< 2e-16	0.094	0.070	0.334	< 2e-16	0.022	0.6659	0.425	< 2e-16	-0.466	< 2e-16	0.465	< 2e-16	-0.050	0.086	26319
		With HH	-0.608	0.599	-4.536	0.288	1.984	0.396	7.480	0.0229	11.318	0.000	-7.577	0.0082	7.634	0.0146	-0.075	0.194	
	rel_exp	W/O HH	-0.143	< 2e-16	0.087	0.092	0.329	< 2e-16	0.043	0.381	0.446	< 2e-16	-0.484	< 2e-16	0.464	< 2e-16	-0.050	0.089	26350
		With HH	-1.616	0.056	1.185	0.657	-0.138	0.937	2.673	0.325	6.444	0.001	-6.848	0.000	3.904	0.071	-0.079	0.172	
2017	exp	W/O HH	-0.064	0.000	0.680	< 2e-16	0.156	0.000	-0.464	< 2e-16	0.232	0.000	-0.660	< 2e-16	0.444	< 2e-16	0.049	0.077	29374
		With HH	-0.894	0.177	1.790	0.490	-0.580	0.774	-1.110	0.668	2.275	0.257	-7.688	0.000	8.106	0.000	-0.002	0.977	
	log_exp	W/O HH	-0.065	0.000	0.672	< 2e-16	0.162	0.000	-0.460	< 2e-16	0.228	0.000	-0.653	< 2e-16	0.441	< 2e-16	0.048	0.085	29384
		With HH	-0.263	0.690	0.395	0.881	0.086	0.964	-0.669	0.803	1.043	0.560	-9.456	0.000	9.947	0.000	0.066	0.245	
	rel_exp	W/O HH	-0.069	0.000	0.671	< 2e-16	0.159	0.000	-0.457	< 2e-16	0.240	0.000	-0.652	< 2e-16	0.444	< 2e-16	0.046	0.097	29445
		With HH	-0.584	0.323	-0.335	0.881	0.136	0.944	0.912	0.692	1.080	0.561	-7.436	0.000	8.489	0.000	0.033	0.560	
2018	exp	W/O HH	-0.331	<2e-16	0.927	<2e-16	0.021	0.553	-0.196	0.000	0.546	<2e-16	-0.707	<2e-16	0.660	<2e-16	-0.011	0.696	28401
		With HH	-1.876	0.003	1.982	0.377	2.765	0.159	5.308	0.031	6.673	0.000	-2.412	0.156	5.635	0.003	-0.004	0.947	
	log_exp	W/O HH	-0.327	<2e-16	0.917	<2e-16	0.034	0.333	-0.204	0.000	0.535	<2e-16	-0.696	<2e-16	0.671	<2e-16	-0.010	0.736	28357
		With HH	-1.984	0.003	2.800	0.254	2.313	0.259	3.916	0.146	6.416	0.001	-3.042	0.100	6.970	0.001	0.007	0.910	
	rel_exp	W/O HH	-0.343	<2e-16	0.895	<2e-16	0.026	0.466	-0.141	0.002	0.571	<2e-16	-0.709	<2e-16	0.640	<2e-16	-0.014	0.614	28601
		With HH	-2.368	0.005	3.168	0.225	-0.635	0.815	3.183	0.308	4.822	0.058	-4.694	0.069	9.676	0.002	0.023	0.703	
2019	exp	W/O HH	-0.243	< 2e-16	1.195	< 2e-16	-0.176	0.000	-0.269	0.000	1.174	< 2e-16	-0.872	< 2e-16	1.072	< 2e-16	0.011	0.718	24946
		With HH	-2.411	0.001	6.054	0.018	-5.009	0.022	-1.529	0.554	9.408	0.000	-6.793	0.000	9.832	0.000	0.088	0.159	
	log_exp	W/O HH	-0.244	< 2e-16	1.189	< 2e-16	-0.176	0.000	-0.261	0.000	1.175	< 2e-16	-0.863	< 2e-16	1.073	< 2e-16	0.009	0.759	24988
		With HH	-1.912	0.008	5.003	0.061	-2.458	0.231	0.070	0.978	10.882	0.000	-5.950	0.001	9.521	0.000	0.071	0.261	
	rel_exp	W/O HH	-0.267	< 2e-16	1.187	< 2e-16	-0.193	0.000	-0.238	0.000	1.203	< 2e-16	-0.874	< 2e-16	1.053	< 2e-16	0.008	0.782	25122
		With HH	-1.642	0.029	7.881	0.003	-3.065	0.166	-2.009	0.433	12.053	0.000	-6.331	0.002	12.195	0.000	0.037	0.558	

Table E4: CHI – Logistic Regression Results for Upper-Middle Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.276	< 2e-16	0.349	0.000	-0.608	< 2e-16	0.173	0.021	0.759	< 2e-16	-0.538	< 2e-16	0.554	< 2e-16	0.063	0.079	18428
		With HH	-1.530	<2e-16	-0.391	<2e-16	-2.547	<2e-16	6.856	<2e-16	10.500	<2e-16	-3.896	<2e-16	12.120	<2e-16	0.097	<2e-16	
	log_exp	W/O HH	-0.271	< 2e-16	0.350	0.000	-0.611	< 2e-16	0.162	0.031	0.751	< 2e-16	-0.539	< 2e-16	0.555	< 2e-16	0.061	0.085	18376
		With HH	-2.789	0.001	1.502	0.540	-2.714	0.156	4.027	0.210	11.640	0.000	-2.204	0.273	9.889	0.000	0.152	0.034	
	rel_exp	W/O HH	-0.299	< 2e-16	0.419	0.000	-0.580	< 2e-16	0.141	0.059	0.777	< 2e-16	-0.532	< 2e-16	0.544	< 2e-16	0.059	0.094	18511
		With HH	-1.698	0.021	0.971	0.734	-4.035	0.041	2.894	0.379	11.844	0.000	-4.172	0.034	11.216	0.001	0.114	0.112	
2016	exp	W/O HH	-0.190	< 2e-16	-0.153	0.014	0.034	0.311	0.073	0.246	0.268	0.000	-0.124	0.000	0.998	< 2e-16	-0.021	0.469	26107
		With HH	-1.329	0.089	1.240	0.683	-0.521	0.767	-0.256	0.938	4.097	0.042	0.157	0.937	8.869	0.002	-0.020	0.725	
	log_exp	W/O HH	-0.184	< 2e-16	-0.164	0.008	0.027	0.420	0.074	0.238	0.257	0.000	-0.127	0.000	1.001	< 2e-16	-0.021	0.481	25997
		With HH	-1.252	0.126	-0.500	0.869	-0.653	0.725	2.041	0.548	4.551	0.043	0.388	0.852	9.236	0.003	-0.026	0.646	
	rel_exp	W/O HH	-0.208	< 2e-16	-0.126	0.043	0.057	0.083	0.068	0.278	0.287	0.000	-0.118	0.001	0.978	< 2e-16	-0.019	0.511	26188
		With HH	-1.528	0.036	2.092	0.446	-1.152	0.497	-1.401	0.621	3.796	0.047	0.142	0.942	8.220	0.001	-0.025	0.665	
2017	exp	W/O HH	-0.111	0.000	0.043	0.486	-0.317	< 2e-16	-0.199	0.001	0.844	< 2e-16	-0.704	< 2e-16	0.799	< 2e-16	0.049	0.101	26220
		With HH	-0.680	0.438	-8.312	0.002	-1.908	0.388	6.361	0.067	9.534	0.000	-8.888	0.000	11.263	0.000	0.004	0.944	
	log_exp	W/O HH	-0.101	0.000	0.031	0.624	-0.330	< 2e-16	-0.207	0.001	0.832	< 2e-16	-0.699	< 2e-16	0.814	< 2e-16	0.047	0.114	26097
		With HH	-0.948	0.210	-7.291	0.026	-2.597	0.136	3.899	0.221	9.386	0.000	-9.010	0.000	10.600	0.000	0.022	0.727	
	rel_exp	W/O HH	-0.126	< 2e-16	0.058	0.350	-0.289	< 2e-16	-0.203	0.001	0.879	< 2e-16	-0.716	< 2e-16	0.779	< 2e-16	0.048	0.105	26337
		With HH	-1.055	0.158	-5.057	0.062	-3.163	0.090	3.100	0.177	9.699	0.000	-8.431	0.000	8.631	0.001	0.031	0.628	
2018	exp	W/O HH	-0.080	0.000	0.235	0.000	-0.167	0.000	-0.268	0.000	0.434	<2e-16	-0.755	<2e-16	0.838	<2e-16	0.008	0.793	26356
		With HH	-1.158	0.259	-0.394	0.907	-2.647	0.332	1.124	0.714	8.373	0.072	-6.355	0.032	7.036	0.067	0.031	0.630	
	log_exp	W/O HH	-0.076	0.000	0.234	0.000	-0.171	0.000	-0.281	0.000	0.425	<2e-16	-0.750	<2e-16	0.856	<2e-16	0.009	0.760	26297
		With HH	-0.545	0.606	-1.379	0.657	2.944	0.545	0.775	0.778	8.637	0.084	-4.773	0.086	6.519	0.118	0.052	0.429	
	rel_exp	W/O HH	-0.092	0.000	0.243	0.000	-0.154	0.000	-0.275	0.000	0.454	<2e-16	-0.777	<2e-16	0.801	<2e-16	0.009	0.748	26453
		With HH	-1.414	0.284	-0.593	0.864	0.516	0.888	0.969	0.759	6.552	0.066	-5.220	0.064	5.581	0.1408	0.044	0.504	
2019	exp	W/O HH	-0.299	<2e-16	0.537	<2e-16	-0.360	<2e-16	-0.098	0.124	0.058	0.092	-0.650	<2e-16	0.822	<2e-16	0.008	0.766	29160
		With HH	-1.241	0.145	0.533	0.864	-1.543	0.4301	1.945	0.520	-0.965	0.561	-9.598	0.000	9.459	0.000	-0.061	0.345	
	log_exp	W/O HH	-0.297	<2e-16	0.533	<2e-16	-0.362	<2e-16	-0.105	0.101	0.052	0.134	-0.655	<2e-16	0.829	<2e-16	0.008	0.783	29083
		With HH	-2.068	0.039	1.715	0.574	-1.980	0.401	2.348	0.484	-1.654	0.374	-8.613	0.000	8.450	0.001	-0.063	0.331	
	rel_exp	W/O HH	-0.315	< 2e-16	0.537	< 2e-16	-0.345	< 2e-16	-0.096	0.127	0.093	0.007	-0.678	< 2e-16	0.772	< 2e-16	0.005	0.860	29393
		With HH	-1.578	0.104	1.510	0.630	-1.661	0.416	1.574	0.591	-1.116	0.508	-9.294	0.000	8.483	0.000	-0.061	0.342	

Table E5: CHI – Logistic Regression Results for High Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.080	0.000	-0.971	< 2e-16	0.668	< 2e-16	1.927	< 2e-16	1.280	< 2e-16	-0.062	0.263	0.188	0.000	-0.027	0.447	18696
		With HH	0.250	0.619	-2.783	0.216	1.609	0.207	6.150	0.091	6.744	0.133	-2.033	0.202	0.654	0.603	-0.116	0.107	
	log_exp	W/O HH	-0.075	0.000	-0.972	< 2e-16	0.663	< 2e-16	1.918	< 2e-16	1.272	< 2e-16	-0.051	0.365	0.203	0.000	-0.027	0.459	18684
		With HH	0.516	< 2e-16	-2.675	< 2e-16	1.893	< 2e-16	8.790	< 2e-16	13.100	< 2e-16	-3.588	< 2e-16	1.429	< 2e-16	-0.142	< 2e-16	
	rel_exp	W/O HH	-0.082	0.000	-0.971	< 2e-16	0.670	< 2e-16	1.933	< 2e-16	1.283	< 2e-16	-0.065	0.242	0.184	0.000	-0.029	0.425	18688
		With HH	0.125	0.777	-2.458	0.312	1.140	0.283	4.355	0.161	17.972	0.000	-1.250	0.401	0.733	0.506	-0.110	0.127	
2016	exp	W/O HH	-0.219	< 2e-16	0.711	< 2e-16	0.498	< 2e-16	0.399	0.000	1.296	< 2e-16	-0.427	0.000	0.484	< 2e-16	-0.025	0.417	25595
		With HH	-0.476	0.307	-1.909	0.335	1.049	0.307	5.282	0.052	8.234	0.001	-1.597	0.228	2.158	0.232	-0.135	0.027	
	log_exp	W/O HH	-0.216	< 2e-16	0.702	< 2e-16	0.498	< 2e-16	0.402	0.000	1.289	< 2e-16	-0.418	0.000	0.501	< 2e-16	-0.025	0.415	25562
		With HH	-0.430	0.339	-0.152	0.931	0.247	0.802	2.537	0.292	11.716	0.000	-2.478	0.072	1.456	0.353	-0.149	0.015	
	rel_exp	W/O HH	-0.228	< 2e-16	0.706	< 2e-16	0.509	< 2e-16	0.396	0.000	1.322	< 2e-16	-0.437	< 2e-16	0.458	< 2e-16	-0.024	0.439	25658
		With HH	-0.872	0.112	-1.654	0.498	1.434	0.192	8.381	0.042	14.297	0.004	-2.565	0.214	1.024	0.504	-0.120	0.050	
2017	exp	W/O HH	-0.286	< 2e-16	0.384	0.000	0.356	< 2e-16	0.888	< 2e-16	1.537	< 2e-16	-0.940	< 2e-16	0.878	< 2e-16	-0.044	0.133	28021
		With HH	-0.785	0.388	-1.632	0.698	0.645	0.773	6.701	0.133	5.230	0.068	-3.395	0.375	1.329	0.589	-0.153	0.033	
	log_exp	W/O HH	-0.284	< 2e-16	0.381	0.000	0.364	< 2e-16	0.880	< 2e-16	1.542	< 2e-16	-0.920	< 2e-16	0.889	< 2e-16	-0.044	0.140	27997
		With HH	-0.826	0.051	0.035	0.984	-0.974	0.268	2.537	0.215	2.918	0.127	-1.054	0.338	0.920	0.370	-0.135	0.060	
	rel_exp	W/O HH	-0.299	< 2e-16	0.353	0.000	0.375	< 2e-16	0.908	< 2e-16	1.550	< 2e-16	-0.950	< 2e-16	0.835	< 2e-16	-0.043	0.149	28160
		With HH	-0.757	0.068	-0.206	0.904	-0.104	0.901	2.642	0.199	2.583	0.142	-1.063	0.342	1.650	0.13383	-0.132	0.065	
2018	exp	W/O HH	-0.189	< 2e-16	0.784	< 2e-16	-0.208	0.000	0.058	0.397	1.086	< 2e-16	-0.600	<2e-16	0.451	< 2e-16	-0.013	0.643	30558
		With HH	-0.774	0.061	1.669	0.283	-1.370	0.112	-0.296	0.877	1.959	0.182	-1.533	0.134	0.585	0.546	-0.187	0.009	
	log_exp	W/O HH	-0.185	< 2e-16	0.794	< 2e-16	-0.212	0.000	0.043	0.529	1.076	< 2e-16	-0.585	<2e-16	0.470	< 2e-16	-0.013	0.633	30457
		With HH	-0.562	0.130	1.405	0.337	-0.625	0.430	0.027	0.988	2.675	0.110	-1.106	0.261	0.537	0.557	-0.142	0.047	
	rel_exp	W/O HH	-0.203	< 2e-16	0.764	< 2e-16	-0.172	0.000	0.069	0.307	1.129	< 2e-16	-0.609	<2e-16	0.409	< 2e-16	-0.013	0.652	30730
		With HH	-0.724	0.079	1.632	0.282	-1.282	0.129	-0.219	0.907	1.897	0.192	-1.852	0.086	0.060	0.950	-0.233	0.001	
2019	exp	W/O HH	-0.043	0.000	-0.391	0.000	-0.102	0.001	1.232	< 2e-16	0.994	< 2e-16	-0.802	< 2e-16	0.479	< 2e-16	-0.017	0.520	33139
		With HH	-1.065	0.023	1.661	0.323	-1.320	0.175	0.124	0.949	8.515	0.007	-1.930	0.099	-0.047	0.960	-0.192	0.004	
	log_exp	W/O HH	-0.041	0.000	-0.405	0.000	-0.104	0.000	1.261	< 2e-16	0.994	< 2e-16	-0.777	< 2e-16	0.498	< 2e-16	-0.019	0.489	33053
		With HH	-0.025	0.939	-1.577	0.460	0.354	0.665	3.497	0.142	20.767	< 2e-16	-0.640	0.528	0.739	0.384	-0.073	0.279	
	rel_exp	W/O HH	-0.051	0.000	-0.377	0.000	-0.079	0.008	1.208	< 2e-16	1.006	< 2e-16	-0.817	< 2e-16	0.452	< 2e-16	-0.016	0.552	33205
		With HH	-0.859	0.046	1.684	0.317	-1.253	0.175	0.172	0.929	8.587	0.006	-1.800	0.106	0.289	0.7518	-0.142	0.034	

APPENDIX E

DALLAS-FORT WORTH – OTHER LOGISTIC REGRESSION RESULTS

Table E6: DFW – Logistic Regression Results for All Income Groups.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.115	< 2e-16	0.622	< 2e-16	0.319	< 2e-16	-0.628	< 2e-16	0.455	< 2e-16	-0.583	< 2e-16	0.321	< 2e-16	-0.004	0.830	61949
		With HH	-0.757	0.095	2.474	0.180	-0.119	0.905	-3.216	0.120	1.594	0.168	-12.801	0.000	1.137	0.309	-0.096	0.023	
	log_exp	W/O HH	-0.114	< 2e-16	0.624	< 2e-16	0.320	< 2e-16	-0.631	< 2e-16	0.450	< 2e-16	-0.580	< 2e-16	0.326	< 2e-16	-0.005	0.816	61941
		With HH	-1.951	0.048	5.254	0.038	-0.464	0.767	-4.523	0.250	5.397	0.054	-10.187	0.047	0.998	0.473	-0.100	0.017	
	rel_exp	W/O HH	-0.120	< 2e-16	0.609	< 2e-16	0.323	< 2e-16	-0.619	< 2e-16	0.463	< 2e-16	-0.588	< 2e-16	0.308	< 2e-16	-0.001	0.953	61945
		With HH	-1.620	0.068	5.597	0.111	-1.162	0.583	-2.992	0.413	2.422	0.327	-6.446	0.003	-0.184	0.932	-0.109	0.010	
2016	exp	W/O HH	-0.206	< 2e-16	0.241	0.000	0.362	< 2e-16	0.184	0.000	0.244	< 2e-16	-0.522	< 2e-16	0.426	< 2e-16	-0.025	0.154	74556
		With HH	-1.304	0.003	-0.934	0.626	2.869	0.026	1.713	0.377	4.677	0.003	-8.545	0.000	0.253	0.813	-0.039	0.294	
	log_exp	W/O HH	-0.206	< 2e-16	0.242	0.000	0.363	< 2e-16	0.182	0.000	0.242	< 2e-16	-0.521	< 2e-16	0.429	< 2e-16	-0.025	0.157	74553
		With HH	-1.398	0.001	1.466	0.404	1.845	0.135	-0.095	0.957	4.811	0.002	-10.047	0.000	0.037	0.970	-0.025	0.498	
	rel_exp	W/O HH	-0.211	< 2e-16	0.237	0.000	0.364	< 2e-16	0.186	0.000	0.254	< 2e-16	-0.527	< 2e-16	0.416	< 2e-16	-0.026	0.134	74551
		With HH	-1.603	0.002	2.734	0.134	3.314	0.017	-1.670	0.341	4.835	0.002	-7.353	0.000	0.046	0.967	-0.078	0.035	
2017	exp	W/O HH	-0.285	< 2e-16	0.529	< 2e-16	0.211	< 2e-16	-0.151	0.000	0.557	< 2e-16	-0.551	< 2e-16	0.433	< 2e-16	0.025	0.131	82228
		With HH	-1.790	0.000	3.844	0.023	4.203	0.000	-1.356	0.430	6.364	0.000	-6.690	0.000	2.959	0.003	0.029	0.406	
	log_exp	W/O HH	-0.285	< 2e-16	0.534	< 2e-16	0.213	< 2e-16	-0.155	0.000	0.558	< 2e-16	-0.550	< 2e-16	0.435	< 2e-16	0.025	0.130	82246
		With HH	-1.987	0.000	5.059	0.004	4.107	0.001	-4.683	0.014	5.251	0.000	-5.394	0.000	3.208	0.005	0.049	0.168	
	rel_exp	W/O HH	-0.292	< 2e-16	0.519	< 2e-16	0.216	< 2e-16	-0.148	0.000	0.570	< 2e-16	-0.554	< 2e-16	0.417	< 2e-16	0.025	0.135	82320
		With HH	-2.068	0.000	1.292	0.472	3.095	0.009	0.424	0.811	4.436	0.000	-7.042	0.000	2.296	0.042	0.035	0.327	
2018	exp	W/O HH	-0.336	<2e-16	0.376	<2e-16	0.006	0.772	-0.127	0.000	0.226	<2e-16	-0.692	<2e-16	0.588	<2e-16	-0.001	0.972	83886
		With HH	-3.011	0.000	-0.261	0.889	2.207	0.111	-0.471	0.804	4.029	0.001	-6.909	0.000	3.419	0.003	-0.075	0.041	
	log_exp	W/O HH	-0.334	<2e-16	0.383	<2e-16	0.009	0.638	-0.132	0.000	0.223	<2e-16	-0.689	<2e-16	0.593	<2e-16	-0.001	0.972	83857
		With HH	-4.429	< 2e-16	-0.471	0.849	-0.433	0.723	-0.911	0.713	6.648	0.000	-8.523	0.000	7.810	0.000	-0.042	0.253	
	rel_exp	W/O HH	-0.342	<2e-16	0.366	<2e-16	0.016	0.427	-0.128	0.000	0.241	<2e-16	-0.694	<2e-16	0.568	<2e-16	0.001	0.959	83993
		With HH	-2.796	0.000	-0.362	0.851	2.089	0.113	0.867	0.662	4.951	0.000	-6.856	0.000	3.932	0.001	-0.086	0.020	
2019	exp	W/O HH	-0.395	< 2e-16	0.316	< 2e-16	-0.229	< 2e-16	0.024	0.455	0.356	< 2e-16	-0.866	< 2e-16	0.614	< 2e-16	0.009	0.596	81802
		With HH	-2.665	<2e-16	3.181	<2e-16	2.223	<2e-16	-1.932	<2e-16	10.460	<2e-16	-5.287	<2e-16	6.330	<2e-16	0.069	<2e-16	
	log_exp	W/O HH	-0.395	<2e-16	0.316	<2e-16	-0.227	<2e-16	0.023	0.467	0.356	<2e-16	-0.865	<2e-16	0.613	<2e-16	0.009	0.5952	81805
		With HH	-3.578	0.000	1.887	0.340	-0.850	0.556	-0.926	0.657	3.325	0.088	-7.334	0.000	8.726	0.000	-0.006	0.879	
	rel_exp	W/O HH	-0.396	< 2e-16	0.314	< 2e-16	-0.227	< 2e-16	0.023	0.475	0.358	< 2e-16	-0.868	< 2e-16	0.608	< 2e-16	0.009	0.589	81791
		With HH	-2.864	0.000	2.135	0.193	1.724	0.158	0.387	0.831	7.685	0.000	-4.657	0.000	6.441	0.000	0.067	0.081	

Table E7: DFW – Logistic Regression Results for Low-Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	0.067	0.001	1.422	< 2e-16	0.556	< 2e-16	-1.214	< 2e-16	0.210	0.000	-0.018	0.727	-0.120	0.025	-0.034	0.440	11992
		With HH	0.498	0.547	2.146	0.363	2.596	0.187	-4.373	0.073	2.409	0.169	-2.414	0.234	-0.609	0.757	-0.217	0.022	
	log_exp	W/O HH	0.070	0.001	1.416	< 2e-16	0.557	< 2e-16	-1.214	< 2e-16	0.202	0.000	-0.013	0.794	-0.108	0.045	-0.035	0.426	11989
		With HH	0.153	0.865	2.896	0.257	2.455	0.223	-4.840	0.055	3.265	0.077	-2.719	0.187	-1.276	0.550	-0.161	0.090	
	rel_exp	W/O HH	0.063	0.003	1.404	< 2e-16	0.559	< 2e-16	-1.201	< 2e-16	0.217	0.000	-0.019	0.704	-0.136	0.011	-0.028	0.524	11978
		With HH	0.368	0.659	2.299	0.336	2.126	0.271	-4.090	0.103	2.007	0.247	-2.514	0.227	-0.476	0.812	-0.189	0.047	
2016	exp	W/O HH	-0.402	< 2e-16	1.097	< 2e-16	0.703	< 2e-16	-0.056	0.370	0.248	0.000	0.153	0.006	0.092	0.126	0.083	0.059	12097
		With HH	-0.953	0.215	4.024	0.130	2.628	0.341	-3.052	0.212	4.135	0.047	-0.432	0.861	1.881	0.508	0.150	0.128	
	log_exp	W/O HH	-0.403	< 2e-16	1.095	< 2e-16	0.701	< 2e-16	-0.057	0.367	0.250	0.000	0.151	0.007	0.092	0.133	0.083	0.058	12098
		With HH	-0.769	0.309	2.518	0.353	-0.523	0.818	-2.918	0.339	3.038	0.255	-2.599	0.308	0.431	0.863	0.056	0.568	
	rel_exp	W/O HH	-0.405	< 2e-16	1.094	< 2e-16	0.702	< 2e-16	-0.057	0.364	0.254	0.000	0.148	0.008	0.086	0.152	0.084	0.057	12092
		With HH	-0.836	0.256	3.435	0.173	2.113	0.378	-3.476	0.163	3.582	0.074	-1.235	0.564	0.452	0.861	0.089	0.366	
2017	exp	W/O HH	-0.440	< 2e-16	1.721	< 2e-16	0.369	0.000	-1.089	< 2e-16	0.775	< 2e-16	-0.377	0.000	1.109	< 2e-16	0.082	0.072	11287
		With HH	-0.890	0.374	21.316	0.000	17.877	0.006	-20.004	0.000	20.225	0.000	-2.145	0.404	3.400	0.337	0.220	0.012	
	log_exp	W/O HH	-0.442	< 2e-16	1.713	< 2e-16	0.365	0.000	-1.088	< 2e-16	0.779	< 2e-16	-0.383	0.000	1.109	< 2e-16	0.081	0.079	11294
		With HH	-1.266	0.205	9.130	0.020	4.618	0.164	-8.713	0.010	8.022	0.026	-7.440	0.008	3.578	0.205	0.172	0.048	
	rel_exp	W/O HH	-0.440	< 2e-16	1.701	< 2e-16	0.363	0.000	-1.086	< 2e-16	0.781	< 2e-16	-0.384	0.000	1.080	< 2e-16	0.083	0.070	11293
		With HH	-0.824	0.427	9.063	0.006	4.367	0.113	-9.063	0.003	5.780	0.129	-5.856	0.059	3.749	0.139	0.174	0.045	
2018	exp	W/O HH	-0.164	0.000	0.487	0.000	0.000	0.995	-0.584	0.000	0.160	0.000	-0.728	<2e-16	0.534	<2e-16	-0.041	0.330	13193
		With HH	0.175	0.871	0.587	0.864	-0.131	0.966	-9.338	0.026	2.467	0.318	-4.028	0.178	3.001	0.233	-0.141	0.120	
	log_exp	W/O HH	-0.167	0.000	0.484	0.000	-0.001	0.991	-0.582	0.000	0.163	0.000	-0.728	<2e-16	0.533	<2e-16	-0.041	0.328	13198
		With HH	0.083	0.939	0.072	0.983	-0.580	0.847	-8.419	0.033	2.346	0.340	-4.468	0.128	3.439	0.174	-0.141	0.118	
	rel_exp	W/O HH	-0.173	0.000	0.487	0.000	0.001	0.992	-0.586	0.000	0.177	0.000	-0.731	<2e-16	0.517	<2e-16	-0.040	0.335	13203
		With HH	-0.079	0.941	0.025	0.994	-1.157	0.697	-8.127	0.031	2.228	0.369	-4.915	0.092	3.594	0.159	-0.145	0.108	
2019	exp	W/O HH	-0.743	< 2e-16	0.757	< 2e-16	0.151	0.014	-0.266	0.000	0.365	0.000	-0.832	< 2e-16	0.722	< 2e-16	0.081	0.055	13184
		With HH	-1.991	0.045	-0.214	0.944	6.937	0.126	-2.293	0.386	11.641	0.013	-5.091	0.223	5.258	0.117	0.035	0.730	
	log_exp	W/O HH	-0.744	< 2e-16	0.760	< 2e-16	0.158	0.010	-0.268	0.000	0.370	0.000	-0.833	< 2e-16	0.710	< 2e-16	0.082	0.052	13184
		With HH	-1.606	0.209	1.251	0.634	12.565	0.076	-1.382	0.508	16.566	0.000	-2.152	0.333	4.795	0.218	0.060	0.549	
	rel_exp	W/O HH	-0.743	< 2e-16	0.757	< 2e-16	0.155	0.011	-0.267	0.000	0.367	0.000	-0.833	< 2e-16	0.716	< 2e-16	0.082	0.053	13185
		With HH	-1.916	0.214	0.265	0.945	9.283	0.001	-1.476	0.637	14.022	0.000	-3.022	0.225	6.249	0.025	0.024	0.812	

Table E8: DFW – Logistic Regression Results for Lower-Middle Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.079	0.000	0.736	< 2e-16	0.225	0.000	-0.852	< 2e-16	0.393	0.000	-1.041	< 2e-16	0.900	< 2e-16	-0.030	0.436	16110
		With HH	-0.512	<2e-16	2.687	< 2e-16	-1.446	< 2e-16	-2.372	< 2e-16	2.599	< 2e-16	-17.390	< 2e-16	1.220	< 2e-16	0.036	< 2e-16	
	log_exp	W/O HH	-0.091	0.000	0.718	< 2e-16	0.212	0.000	-0.825	< 2e-16	0.398	0.000	-1.057	< 2e-16	0.877	< 2e-16	-0.029	0.458	16064
		With HH	-0.349	0.518	1.881	0.441	-1.317	0.343	-1.946	0.410	2.379	0.170	-16.673	0.000	1.455	0.316	-0.023	0.778	
	rel_exp	W/O HH	-0.063	0.001	0.766	< 2e-16	0.231	0.000	-0.881	< 2e-16	0.372	0.000	-1.023	< 2e-16	0.929	< 2e-16	-0.032	0.406	16137
		With HH	-0.390	0.462	2.176	0.360	-1.408	0.298	-1.959	0.391	2.146	0.231	-17.866	0.000	1.285	0.356	-0.052	0.521	
2016	exp	W/O HH	-0.159	< 2e-16	0.123	0.031	0.214	0.000	-0.094	0.093	-0.391	< 2e-16	-0.707	< 2e-16	0.675	< 2e-16	-0.029	0.378	21908
		With HH	-1.072	0.066	1.422	0.554	2.437	0.215	-0.425	0.848	-4.765	0.063	-3.285	0.222	0.433	0.7754	-0.074	0.245	
	log_exp	W/O HH	-0.161	< 2e-16	0.123	0.031	0.211	0.000	-0.094	0.091	-0.390	< 2e-16	-0.704	< 2e-16	0.673	< 2e-16	-0.029	0.373	21904
		With HH	-0.204	0.633	0.433	0.799	-0.152	0.890	-0.548	0.732	-0.593	0.651	-21.040	< 2e-16	0.250	0.829	-0.126	0.051	
	rel_exp	W/O HH	-0.152	< 2e-16	0.131	0.021	0.212	0.000	-0.103	0.066	-0.395	< 2e-16	-0.700	< 2e-16	0.692	< 2e-16	-0.029	0.370	21914
		With HH	-0.395	0.418	3.361	0.246	-0.612	0.622	-3.387	0.224	-0.706	0.640	-19.684	< 2e-16	1.800	0.1730	-0.119	0.065	
2017	exp	W/O HH	-0.347	< 2e-16	0.257	0.000	0.231	0.000	0.382	0.000	0.283	0.000	-0.249	0.000	0.328	< 2e-16	-0.038	0.234	22297
		With HH	-1.581	0.003	-0.799	0.726	2.697	0.064	3.776	0.066	3.418	0.017	-1.477	0.378	3.435	0.010	-0.095	0.131	
	log_exp	W/O HH	-0.350	< 2e-16	0.252	0.000	0.232	0.000	0.386	0.000	0.284	0.000	-0.249	0.000	0.324	< 2e-16	-0.038	0.234	22294
		With HH	-2.219	0.000	1.256	0.678	2.969	0.080	4.515	0.099	4.986	0.010	-0.605	0.753	4.146	0.012	-0.071	0.258	
	rel_exp	W/O HH	-0.347	< 2e-16	0.258	0.000	0.231	0.000	0.382	0.000	0.283	0.000	-0.249	0.000	0.328	< 2e-16	-0.039	0.229	22287
		With HH	-1.677	0.002	0.201	0.933	2.845	0.053	3.211	0.142	3.511	0.015	-0.899	0.582	3.487	0.009	-0.079	0.204	
2018	exp	W/O HH	-0.265	<2.e-16	-0.044	0.490	0.259	0.000	0.195	0.002	-0.327	0.000	-0.445	<2.e-16	0.451	<2.e-16	0.005	0.891	20781
		With HH	-1.444	0.021	0.147	0.968	4.674	0.027	-1.064	0.771	-2.069	0.292	-3.174	0.148	2.967	0.059	-0.073	0.291	
	log_exp	W/O HH	-0.264	< 2.e-16	-0.032	0.610	0.265	0.000	0.175	0.005	-0.330	0.000	-0.445	<2.e-16	0.451	<2.e-16	0.005	0.876	20780
		With HH	-1.343	0.031	-0.470	0.903	4.047	0.058	-0.642	0.867	-1.637	0.406	-4.432	0.094	2.978	0.060	-0.077	0.268	
	rel_exp	W/O HH	-0.271	<2.e-16	-0.041	0.515	0.272	0.000	0.187	0.003	-0.331	0.000	-0.435	<2.e-16	0.438	<2.e-16	0.005	0.892	20801
		With HH	-1.331	0.031	0.496	0.897	4.540	0.031	-1.611	0.671	-2.406	0.230	-3.988	0.102	3.016	0.054	-0.082	0.236	
2019	exp	W/O HH	-0.367	< 2e-16	0.372	0.000	-0.042	0.362	-0.062	0.315	0.372	< 2e-16	-0.538	< 2e-16	0.453	< 2e-16	-0.023	0.516	18900
		With HH	-3.510	0.008	7.138	0.103	2.227	0.390	-4.074	0.339	6.791	0.022	-4.745	0.237	4.393	0.064	0.012	0.870	
	log_exp	W/O HH	-0.368	< 2e-16	0.371	0.000	-0.037	0.421	-0.066	0.284	0.374	< 2e-16	-0.540	< 2e-16	0.445	< 2e-16	-0.023	0.513	18903
		With HH	-3.941	0.007	3.679	0.324	8.366	0.356	0.178	0.959	12.640	0.095	-3.094	0.434	2.792	0.255	-0.009	0.902	
	rel_exp	W/O HH	-0.368	< 2e-16	0.371	0.000	-0.037	0.417	-0.066	0.282	0.374	< 2e-16	-0.540	< 2e-16	0.446	< 2e-16	-0.023	0.515	18898
		With HH	-3.498	0.012	7.294	0.093	4.770	0.150	-4.062	0.343	8.409	0.028	-2.324	0.403	4.777	0.050	0.010	0.894	

Table E9: DFW – Logistic Regression Results for Upper-Middle Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.317	< 2e-16	0.217	0.042	0.142	0.003	-0.590	0.000	0.829	< 2e-16	-0.784	< 2e-16	0.045	0.377	0.047	0.228	15617
		With HH	-1.735	< 2e-16	2.607	< 2e-16	5.713	< 2e-16	-11.690	< 2e-16	7.213	< 2e-16	-10.760	< 2e-16	2.036	< 2e-16	-0.018	< 2e-16	
	log_exp	W/O HH	-0.308	< 2e-16	0.197	0.064	0.144	0.002	-0.576	0.000	0.812	< 2e-16	-0.780	< 2e-16	0.050	0.328	0.047	0.225	15555
		With HH	-2.180	0.138	-1.378	0.813	5.390	0.149	-7.714	0.267	6.374	0.028	-8.896	0.010	-2.099	0.347	-0.045	0.628	
	rel_exp	W/O HH	-0.325	< 2e-16	0.213	0.046	0.165	0.000	-0.607	0.000	0.865	< 2e-16	-0.791	< 2e-16	0.008	0.874	0.048	0.214	15708
		With HH	-0.410	0.576	-0.751	0.803	1.352	0.381	-18.835	0.000	1.853	0.330	-20.765	< 2e-16	2.913	0.216	-0.084	0.369	
2016	exp	W/O HH	-0.275	< 2e-16	-0.098	0.267	-0.032	0.423	0.237	0.008	0.720	< 2e-16	-0.965	< 2e-16	0.548	< 2e-16	-0.107	0.002	19309
		With HH	-2.302	0.009	-3.060	0.546	-0.435	0.835	0.281	0.958	4.081	0.066	-11.832	0.000	2.155	0.226	-0.057	0.405	
	log_exp	W/O HH	-0.267	< 2e-16	-0.115	0.192	-0.022	0.587	0.237	0.008	0.710	< 2e-16	-0.955	< 2e-16	0.566	< 2e-16	-0.106	0.002	19272
		With HH	-2.547	0.004	-1.709	0.740	-1.121	0.590	-0.817	0.884	4.379	0.051	-11.801	0.000	2.072	0.252	-0.082	0.230	
	rel_exp	W/O HH	-0.286	< 2e-16	-0.099	0.263	-0.025	0.524	0.234	0.009	0.748	< 2e-16	-0.957	< 2e-16	0.533	< 2e-16	-0.106	0.002	19361
		With HH	-2.175	0.012	-3.404	0.508	-0.067	0.975	0.543	0.919	3.851	0.083	-11.888	0.000	2.233	0.205	-0.098	0.154	
2017	exp	W/O HH	-0.326	< 2e-16	1.001	< 2e-16	0.034	0.375	-0.926	< 2e-16	0.608	< 2e-16	-0.412	< 2e-16	0.349	< 2e-16	0.006	0.844	22873
		With HH	-2.613	0.005	7.964	0.015	-0.545	0.783	-11.238	0.006	2.780	0.172	-8.517	0.009	-2.860	0.148	-0.006	0.929	
	log_exp	W/O HH	-0.322	< 2e-16	0.975	< 2e-16	0.048	0.213	-0.909	< 2e-16	0.599	< 2e-16	-0.390	< 2e-16	0.368	< 2e-16	0.007	0.816	22814
		With HH	-2.655	0.006	7.825	0.022	-0.291	0.891	-9.940	0.019	3.757	0.070	-7.461	0.020	-2.642	0.192	0.011	0.868	
	rel_exp	W/O HH	-0.339	< 2e-16	1.016	<2e-16	0.026	0.497	-0.948	<2e-16	0.623	<2e-16	-0.415	<2e-16	0.317	< 2e-16	0.007	0.820	22954
		With HH	-2.581	0.005	7.986	0.017	-0.605	0.768	-10.820	0.009	3.923	0.051	-7.627	0.008	-3.421	0.093	-0.036	0.597	
2018	exp	W/O HH	-0.599	< 2E-16	1.378	< 2E-16	-0.129	0.002	-0.837	< 2e-16	0.463	<2E-16	-0.529	<2E-16	1.068	< 2E-16	-0.021	0.517	21568
		With HH	-1.704	0.084	1.798301	0.4711	-1.561	0.376	-20.211	0.000	1.188	0.422	-22.262	< 2e-16	0.767	0.558	-0.051	0.483	
	log_exp	W/O HH	-0.598	< 2E-16	1.358	< 2E-16	-0.121	0.004	-0.811	< 2e-16	0.473	<2E-16	-0.520	<2E-16	1.079	< 2E-16	-0.021	0.518	21561
		With HH	-4.482	0.000	4.67298	0.213	0.648	0.765	-5.360	0.169	3.975	0.120	-6.420	0.00295	5.513	0.008	-0.024	0.739	
	rel_exp	W/O HH	-0.612	< 2E-16	1.387	< 2E-16	-0.130	0.002	-0.856	< 2e-16	0.502	<2E-16	-0.549	<2E-16	1.024	< 2e-16	-0.016	0.625	21643
		With HH	-4.456	0.000	5.40294	0.138	-0.502	0.814	-6.767	0.07883	4.259	0.105	-7.379	0.00172	5.733	0.004	-0.061	0.403	
2019	exp	W/O HH	-0.436	< 2e-16	1.119	< 2e-16	-0.239	0.000	-0.487	0.000	0.642	< 2e-16	-0.844	< 2e-16	0.722	< 2e-16	0.008	0.799	23177
		With HH	-1.761	< 2e-16	1.607	< 2e-16	-1.945	< 2e-16	1.189	<2e-16	6.638	< 2e-16	-11.420	< 2e-16	6.686	< 2e-16	-0.041	< 2e-16	
	log_exp	W/O HH	-0.431	< 2e-16	1.118	< 2e-16	-0.231	0.000	-0.465	0.000	0.641	< 2e-16	-0.832	< 2e-16	0.737	< 2e-16	0.007	0.830	23149
		With HH	-1.435	0.088	1.965	0.475	-0.948	0.608	0.984	0.745	6.296	0.002	-10.935	0.000	6.079	0.001	-0.086	0.200	
	rel_exp	W/O HH	-0.442	< 2e-16	1.119	< 2e-16	-0.243	0.000	-0.495	0.000	0.646	< 2e-16	-0.847	< 2e-16	0.710	< 2e-16	0.010	0.763	23182
		With HH	-1.589	0.067	1.576	0.573	-1.365	0.473	1.669	0.588	6.534	0.001	-11.345	0.000	5.698	0.005	-0.070	0.294	

Table E10: DFW – Logistic Regression Results for High-Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.047	0.008	-0.194	0.008	0.450	< 2e-16	0.097	0.368	0.624	< 2e-16	-0.344	0.000	0.231	0.000	-0.013	0.728	16705
		With HH	-2.180	0.032	-5.457	0.099	-1.893	0.459	0.364	0.921	4.617	0.189	-8.203	0.001	-1.422	0.587	-0.144	0.052	
	log_exp	W/O HH	-0.049	0.006	-0.175	0.017	0.443	< 2e-16	0.079	0.464	0.615	< 2e-16	-0.339	0.000	0.237	0.000	-0.014	0.708	16690
		With HH	-2.058	0.026	-5.271	0.088	-1.711	0.505	0.532	0.891	3.541	0.328	-8.068	0.000	-1.170	0.639	-0.153	0.039	
	rel_exp	W/O HH	-0.051	0.004	-0.221	0.002	0.459	< 2e-16	0.122	0.260	0.630	< 2e-16	-0.363	0.000	0.216	0.000	-0.006	0.866	16722
		With HH	-2.258	0.0532	-3.488	0.364	-1.288	0.696	-1.107	0.786	4.830	0.168	-6.396	0.027	-0.339	0.900	-0.087	0.241	
2016	exp	W/O HH	-0.014	0.381	-0.231	0.000	0.809	< 2e-16	1.297	< 2e-16	0.690	< 2e-16	-0.607	< 2e-16	0.472	< 2e-16	0.011	0.751	19659
		With HH	-1.220	0.297	-14.722	0.051	7.514	0.055	8.698	0.280	9.084	0.019	-11.609	0.002	-0.602	0.830	-0.002	0.981	
	log_exp	W/O HH	-0.016	0.333	-0.221	0.000	0.804	< 2e-16	1.294	< 2e-16	0.691	< 2e-16	-0.611	< 2e-16	0.469	< 2e-16	0.011	0.759	19659
		With HH	-0.865	0.296	-6.204	0.047	8.783	0.000	6.637	0.140	10.142	0.001	-6.771	0.021	0.200	0.923	0.025	0.748	
	rel_exp	W/O HH	-0.018	0.254	-0.237	0.000	0.816	< 2e-16	1.312	< 2e-16	0.712	< 2e-16	-0.622	< 2e-16	0.455	< 2e-16	0.008	0.824	19661
		With HH	-0.849	0.290	-5.495	0.070	8.732	0.000	6.419	0.13976	9.111	0.001	-6.317	0.026	0.616	0.759	0.006	0.942	
2017	exp	W/O HH	-0.185	< 2e-16	-0.010	0.860	0.263	0.000	0.337	0.000	0.925	< 2e-16	-1.522	< 2e-16	0.370	< 2e-16	0.067	0.031	24444
		With HH	-0.884	0.324	-1.611	0.475	17.856	0.000	1.022	0.688	5.616	0.262	-3.587	0.081	0.412	0.812	0.013	0.856	
	log_exp	W/O HH	-0.185	< 2e-16	0.003	0.957	0.265	0.000	0.341	0.000	0.924	< 2e-16	-1.521	< 2e-16	0.367	< 2e-16	0.068	0.027	24461
		With HH	-2.564	0.147	-3.821	0.672	5.572	0.429	3.856	0.357	7.814	0.158	-8.812	0.264	2.301	0.637	0.045	0.530	
	rel_exp	W/O HH	-0.191	< 2e-16	-0.034	0.547	0.284	< 2e-16	0.343	0.000	0.956	< 2e-16	-1.533	< 2e-16	0.363	< 2e-16	0.065	0.035	24488
		With HH	-3.027	0.001	-1.583	0.672	8.750	0.000	1.567	0.748	4.000	0.217	-8.597	0.051	-1.098	0.647	0.058	0.423	
2018	exp	W/O HH	-0.249	< 2e-16	-0.252	0.000	-0.070	0.029	0.578	0.000	0.678	< 2e-16	-1.119	<2e-16	0.379	< 2e-16	0.037	0.204	27101
		With HH	-3.949	0.000	-1.864	0.502	1.156	0.507	4.407	0.124	9.842	0.000	-4.409	0.025	4.291	0.025	0.125	0.066	
	log_exp	W/O HH	-0.248	< 2e-16	-0.224	0.000	-0.071	0.026	0.575	0.000	0.669	< 2e-16	-1.111	<2e-16	0.386	< 2e-16	0.037	0.210	27088
		With HH	-4.253	0.000	-1.905	0.517	0.906	0.626	4.372	0.141	8.613	0.000	-5.298	0.012	3.686	0.042	0.024	0.725	
	rel_exp	W/O HH	-0.251	< 2e-16	-0.275	0.000	-0.061	0.055	0.582	0.000	0.689	< 2e-16	-1.124	<2e-16	0.370	< 2e-16	0.039	0.182	27093
		With HH	-4.991	0.000	-0.087	0.977	-0.299	0.849	3.819	0.250	9.532	0.000	-6.367	0.006	4.406	0.022	0.123	0.070	
2019	exp	W/O HH	-0.325	< 2e-16	-0.830	< 2e-16	-0.429	< 2e-16	1.409	<2e-16	0.131	0.003	-1.270	< 2e-16	0.679	< 2e-16	-0.001	0.984	25596
		With HH	-2.678	0.283	-0.487	0.875	-1.833	0.252	3.817	0.252	1.225	0.535	-4.473	0.054	4.499	0.103	0.141	0.066	
	log_exp	W/O HH	-0.327	< 2e-16	-0.841	< 2e-16	-0.426	< 2e-16	1.419	< 2e-16	0.137	0.002	-1.275	< 2e-16	0.673	< 2e-16	-0.001	0.964	25591
		With HH	-2.872	0.3617	1.050	0.715	-2.009	0.231	2.387	0.482	1.520	0.444	-4.596	0.0740	3.322	0.168	0.143	0.063	
	rel_exp	W/O HH	-0.325	< 2e-16	-0.832	< 2e-16	-0.430	< 2e-16	1.411	< 2e-16	0.131	0.003	-1.270	< 2e-16	0.680	< 2e-16	-0.001	0.968	25582
		With HH	-0.677	0.270	3.524	0.167	0.106	0.930	-3.857	0.302	1.627	0.290	-2.576	0.233	20.968	< 2e-16	0.122	0.113	

APPENDIX E

LOS ANGELES – OTHER LOGISTIC REGRESSION RESULTS

Table E11: LA – Logistic Regression Results for All Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.215	< 2e-16	-0.351	< 2e-16	0.085	0.000	0.230	< 2e-16	0.648	< 2e-16	-0.226	< 2e-16	-0.086	0.000	0.000	0.985	83700
		With HH	-1.347	0.029	1.060	0.596	3.718	0.013	3.266	0.098	7.141	0.000	-1.268	0.405	2.071	0.146	0.088	0.029	
	log_exp	W/O HH	-0.214	< 2e-16	-0.328	< 2e-16	0.084	0.000	0.212	0.000	0.647	< 2e-16	-0.226	< 2e-16	-0.069	0.000	-0.002	0.914	83446
		With HH	-2.565	0.000	0.672	0.583	0.400	0.635	1.393	0.277	7.615	0.000	-0.535	0.522	-0.331	0.680	-0.020	0.617	
	rel_exp	W/O HH	-0.221	< 2e-16	-0.375	< 2e-16	0.086	0.000	0.245	< 2e-16	0.650	< 2e-16	-0.234	< 2e-16	-0.105	0.000	-0.001	0.965	83868
		With HH	-2.356	0.000	1.707	0.259	0.947	0.381	-1.239	0.449	11.764	0.000	-1.445	0.163	-3.586	0.001	-0.084	0.037	
2016	exp	W/O HH	-0.247	<2e-16	0.042	0.090	-0.003	0.859	0.310	< 2e-16	0.724	< 2e-16	-0.287	< 2e-16	-0.234	< 2e-16	-0.010	0.519	94045
		With HH	-1.865	0.001	-1.150	0.434	-0.135	0.888	2.708	0.101	9.109	0.000	-5.595	0.000	-1.032	0.271	0.039	0.280	
	log_exp	W/O HH	-0.245	<2e-16	0.054	0.028	-0.009	0.629	0.294	< 2e-16	0.719	< 2e-16	-0.289	< 2e-16	-0.219	< 2e-16	-0.009	0.568	93828
		With HH	-1.434	0.001	-0.939	0.439	0.865	0.340	2.416	0.089	11.208	0.000	-3.255	0.001	-2.432	0.009	0.018	0.616	
	rel_exp	W/O HH	-0.255	< 2e-16	0.016	0.509	0.010	0.572	0.326	< 2e-16	0.729	< 2e-16	-0.291	< 2e-16	-0.260	< 2e-16	-0.012	0.451	94329
		With HH	-0.112	0.861	-4.160	0.060	2.314	0.162	1.785	0.417	3.835	0.063	-1.391	0.427	1.481	0.3473	0.017	0.643	
2017	exp	W/O HH	-0.163	< 2e-16	-0.113	0.000	-0.028	0.088	0.348	< 2e-16	0.566	< 2e-16	-0.434	< 2e-16	-0.219	< 2e-16	-0.034	0.022	104750
		With HH	-1.563	0.001	-1.697	0.318	-0.417	0.729	1.673	0.303	2.587	0.092	-3.981	0.002	-2.990	0.009	-0.007	0.838	
	log_exp	W/O HH	-0.161	< 2e-16	-0.099	0.000	-0.028	0.092	0.324	< 2e-16	0.561	< 2e-16	-0.433	< 2e-16	-0.208	< 2e-16	-0.033	0.025	104428
		With HH	-2.651	0.000	-3.291	0.022	-1.221	0.181	8.561	0.000	9.019	0.000	-3.943	0.001	-0.902	0.337	-0.094	0.008	
	rel_exp	W/O HH	-0.175	< 2e-16	-0.151	0.000	-0.021	0.193	0.386	< 2e-16	0.585	< 2e-16	-0.442	< 2e-16	-0.252	< 2e-16	-0.035	0.019	105345
		With HH	-2.662	0.000	-2.617	0.102	5.602	0.000	5.670	0.001	8.557	0.000	-2.771	0.049	-3.634	0.002	-0.082	0.021	
2018	exp	W/O HH	-0.171	< 2e-16	0.085	0.000	0.010	0.564	0.483	< 2e-16	0.683	< 2e-16	-0.419	< 2e-16	-0.225	< 2e-16	-0.023	0.114	105717
		With HH	-0.170	0.704	0.139	0.931	1.357	0.239	-1.897	0.229	14.902	< 2e-16	-4.909	0.000	-2.618	0.017	-0.042	0.241	
	log_exp	W/O HH	-0.170	< 2e-16	0.100	0.000	0.011	0.507	0.460	< 2e-16	0.679	< 2e-16	-0.418	< 2e-16	-0.211	< 2e-16	-0.023	0.126	105503
		With HH	-0.580	0.099	-1.454	0.158	1.887	0.054	9.563	0.000	14.620	0.000	-3.089	0.062	-1.114	0.1580	0.068	0.056	
	rel_exp	W/O HH	-0.181	< 2e-16	0.057	0.015	0.020	0.230	0.507	< 2e-16	0.697	< 2e-16	-0.420	< 2e-16	-0.257	< 2e-16	-0.022	0.133	106122
		With HH	-1.249	0.006	1.354	0.306	0.821	0.374	5.347	0.002	12.654	0.000	-2.907	0.009	-1.953	0.024	0.011	0.751	
2019	exp	W/O HH	-0.228	< 2e-16	0.343	< 2e-16	0.022	0.161	0.164	0.000	0.760	< 2e-16	-0.296	< 2e-16	-0.243	< 2e-16	0.025	0.075	120694
		With HH	-1.478	< 2e-16	0.247	< 2e-16	0.798	< 2e-16	3.467	< 2e-16	13.980	< 2e-16	-4.390	< 2e-16	-2.488	< 2e-16	-0.028	< 2e-16	
	log_exp	W/O HH	-0.227	< 2e-16	0.358	< 2e-16	0.016	0.306	0.152	0.000	0.755	< 2e-16	-0.304	< 2e-16	-0.233	< 2e-16	0.025	0.068	120471
		With HH	-1.497	< 2e-16	-0.485	< 2e-16	-0.296	< 2e-16	2.561	< 2e-16	13.697	< 2e-16	-4.401	< 2e-16	-3.988	< 2e-16	-0.042	< 2e-16	
	rel_exp	W/O HH	-0.240	< 2e-16	0.314	< 2e-16	0.037	0.018	0.189	< 2e-16	0.765	< 2e-16	-0.297	< 2e-16	-0.282	< 2e-16	0.024	0.087	121191
		With HH	-1.165	0.002	1.354	0.275	-0.865	0.284	0.396	0.775	12.923	0.000	-2.863	0.002	-1.790	0.012	-0.044	0.168	

Table E12: LA – Logistic Regression Results for Low-Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.368	< 2e-16	-0.061	0.302	-0.340	0.000	0.230	0.000	0.820	< 2e-16	-0.427	< 2e-16	-0.275	0.000	0.044	0.257	15454
		With HH	-3.795	0.000	2.394	0.331	-4.198	0.081	-0.048	0.984	7.799	0.000	-5.005	0.036	-3.314	0.112	0.015	0.858	
	log_exp	W/O HH	-0.370	< 2e-16	-0.053	0.377	-0.340	0.000	0.224	0.000	0.820	< 2e-16	-0.431	< 2e-16	-0.273	0.000	0.043	0.267	15454
		With HH	-3.952	0.000	2.960	0.213	-3.782	0.091	-0.630	0.792	7.805	0.000	-4.272	0.048	-3.207	0.128	-0.004	0.959	
	rel_exp	W/O HH	-0.384	< 2e-16	-0.057	0.340	-0.339	0.000	0.237	0.000	0.817	< 2e-16	-0.431	< 2e-16	-0.298	0.000	0.045	0.247	15463
		With HH	-4.023	0.000	3.579	0.127	-3.578	0.101	-1.200	0.610	7.756	0.000	-3.889	0.057	-3.072	0.144	-0.008	0.928	
2016	exp	W/O HH	-0.041	0.068	-0.375	0.000	0.166	0.000	0.644	< 2e-16	0.426	< 2e-16	-0.367	< 2e-16	-0.463	< 2e-16	-0.028	0.438	17915
		With HH	-0.617	0.504	1.849	0.528	-6.566	0.008	0.283	0.895	10.198	0.000	-9.825	0.000	-0.619	0.731	0.037	0.631	
	log_exp	W/O HH	-0.034	0.124	-0.372	0.000	0.166	0.001	0.630	< 2e-16	0.426	< 2e-16	-0.370	< 2e-16	-0.447	< 2e-16	-0.027	0.454	17889
		With HH	-1.785	0.053	-0.184	0.952	-1.660	0.525	2.576	0.331	6.880	0.002	-7.399	0.001	-5.366	0.043	0.036	0.641	
	rel_exp	W/O HH	-0.046	0.038	-0.379	0.000	0.170	0.000	0.652	< 2e-16	0.423	< 2e-16	-0.371	< 2e-16	-0.474	< 2e-16	-0.029	0.418	17916
		With HH	-0.242	0.806	-0.808	0.777	-1.905	0.516	3.305	0.178	7.631	0.000	-6.623	0.005	-1.229	0.550	0.022	0.777	
2017	exp	W/O HH	-0.382	< 2e-16	0.076	0.133	0.316	0.000	0.713	< 2e-16	0.313	0.000	-0.396	< 2e-16	-0.287	0.000	-0.049	0.164	18731
		With HH	-1.361	0.189	-6.561	0.218	1.050	0.767	6.373	0.185	7.844	0.035	-7.789	0.149	2.860	0.449	-0.052	0.507	
	log_exp	W/O HH	-0.379	< 2e-16	0.082	0.108	0.320	0.000	0.701	< 2e-16	0.310	0.000	-0.388	< 2e-16	-0.285	0.000	-0.050	0.156	18722
		With HH	-2.197	< 2e-16	-1.927	< 2e-16	0.186	< 2e-16	3.866	< 2e-16	5.357	< 2e-16	-6.754	< 2e-16	1.109	< 2e-16	-0.052	< 2e-16	
	rel_exp	W/O HH	-0.386	< 2e-16	0.070	0.169	0.314	0.000	0.723	< 2e-16	0.314	0.000	-0.406	< 2e-16	-0.292	0.000	-0.049	0.164	18726
		With HH	-3.470	0.001	2.044	0.577	5.477	0.112	2.436	0.371	9.705	0.001	-8.010	0.004	5.032	0.074	-0.099	0.201	
2018	exp	W/O HH	-0.434	<2e-16	0.171	0.002	0.412	< 2e-16	0.514	< 2e-16	-0.066	0.127	-0.039	0.350	-0.094	0.024	-0.093	0.010	17745
		With HH	-0.067	0.976	-13.179	0.010	2.317	0.580	13.919	0.000	9.273	0.041	-8.309	0.032	-0.229	0.952	-0.133	0.113	
	log_exp	W/O HH	-0.435	< 2e-16	0.180	0.001	0.413	< 2e-16	0.499	< 2e-16	-0.068	0.118	-0.037	0.367	-0.091	0.028	-0.093	0.010	17736
		With HH	-1.177	0.374	-4.837	0.277	5.227	0.087	5.762	0.168	4.315	0.169	-2.341	0.433	1.704	0.457	-0.131	0.118	
	rel_exp	W/O HH	-0.438	< 2e-16	0.149	0.007	0.413	< 2e-16	0.538	< 2e-16	-0.069	0.109	-0.040	0.334	-0.102	0.014	-0.093	0.010	17756
		With HH	-1.406	0.309	-1.720	0.699	5.543	0.114	2.773	0.429	4.113	0.151	-2.906	0.398	2.223	0.370	-0.147	0.078	
2019	exp	W/O HH	-0.471	< 2e-16	0.757	< 2e-16	0.064	0.107	0.112	0.004	0.387	< 2e-16	-0.113	0.002	0.102	0.004	-0.023	0.468	21994
		With HH	-3.956	0.015	-2.571	0.570	1.907	0.462	9.023	0.015	9.321	0.005	-1.796	0.522	2.721	0.307	-0.174	0.023	
	log_exp	W/O HH	-0.467	< 2e-16	0.771	< 2e-16	0.063	0.113	0.087	0.027	0.385	< 2e-16	-0.113	0.002	0.104	0.004	-0.024	0.465	21961
		With HH	-3.547	0.000	1.414	0.660	0.719	0.728	3.012	0.286	8.753	0.001	-6.715	0.012	1.308	0.528	-0.157	0.040	
	rel_exp	W/O HH	-0.477	< 2e-16	0.743	< 2e-16	0.066	0.095	0.140	0.000	0.393	< 2e-16	-0.115	0.001	0.099	0.006	-0.026	0.426	22014
		With HH	-4.008	0.000	2.282	0.410	0.052	0.981	0.054	0.979	7.195	0.001	-8.320	0.002	-0.435	0.815	-0.187	0.014	

Table E13: LA – Logistic Regression Results for Lower-Middle Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.228	< 2e-16	-0.408	0.000	0.293	0.000	-0.202	0.000	0.210	0.000	0.000	0.994	0.069	0.062	-0.041	0.202	23055
		With HH	-0.034	0.971	-3.380	0.224	1.673	0.438	1.657	0.530	1.875	0.460	-0.794	0.692	1.003	0.637	-0.050	0.525	
	log_exp	W/O HH	-0.229	< 2e-16	-0.395	0.000	0.300	0.000	-0.221	0.000	0.199	0.000	0.007	0.831	0.080	0.032	-0.040	0.206	22972
		With HH	-0.802	0.200	-0.891	0.637	-0.259	0.831	0.170	0.923	-0.236	0.862	-2.657	0.125	-2.077	0.158	-0.116	0.138	
	rel_exp	W/O HH	-0.233	< 2e-16	-0.420	0.000	0.284	0.000	-0.185	0.000	0.220	0.000	-0.011	0.744	0.058	0.117	-0.042	0.186	23086
		With HH	-0.106	0.835	-6.005	0.378	0.563	0.653	4.264	0.514	1.482	0.318	-1.894	0.288	0.065	0.957	-0.100	0.200	
2016	exp	W/O HH	-0.366	< 2e-16	0.435	< 2e-16	-0.076	0.029	-0.021	0.675	0.602	< 2e-16	-0.362	< 2e-16	-0.011	0.748	-0.036	0.215	26580
		With HH	-1.717	0.014	-1.877	0.565	-0.208	0.906	2.740	0.410	3.679	0.037	-6.654	0.019	0.926	0.584	-0.114	0.074	
	log_exp	W/O HH	-0.363	< 2e-16	0.448	< 2e-16	-0.077	0.028	-0.033	0.502	0.606	< 2e-16	-0.364	< 2e-16	-0.001	0.975	-0.035	0.239	26555
		With HH	-1.311	0.125	-4.238	0.260	-0.464	0.775	4.946	0.237	2.835	0.154	-7.817	0.026	0.916	0.562	-0.121	0.058	
	rel_exp	W/O HH	-0.368	< 2e-16	0.432	< 2e-16	-0.076	0.028	-0.017	0.727	0.601	< 2e-16	-0.362	< 2e-16	-0.013	0.709	-0.039	0.185	26564
		With HH	-1.730	0.011	-2.127	0.515	-0.309	0.859	3.015	0.368	3.999	0.023	-6.550	0.013	0.411	0.809	-0.119	0.063	
2017	exp	W/O HH	-0.128	< 2e-16	0.401	< 2e-16	0.403	< 2e-16	-0.383	< 2e-16	0.589	< 2e-16	-0.363	< 2e-16	-0.087	0.007	-0.006	0.853	25570
		With HH	-0.862	0.179	1.755	0.489	6.701	0.485	0.647	0.807	3.528	0.099	-10.582	0.361	-0.758	0.583	-0.124	0.065	
	log_exp	W/O HH	-0.127	< 2e-16	0.413	< 2e-16	0.404	< 2e-16	-0.395	< 2e-16	0.583	< 2e-16	-0.363	< 2e-16	-0.072	0.028	-0.004	0.902	25482
		With HH	-1.849	0.012	6.552	0.023	3.962	0.165	-2.196	0.422	4.779	0.039	-9.450	0.070	-0.886	0.583	-0.086	0.202	
	rel_exp	W/O HH	-0.136	< 2e-16	0.360	0.000	0.402	< 2e-16	-0.349	0.000	0.597	< 2e-16	-0.351	< 2e-16	-0.117	0.000	-0.009	0.764	25655
		With HH	-2.206	0.007	8.462	0.026	-0.362	0.836	0.173	0.949	6.269	0.024	-11.066	0.007	0.581	0.717	-0.111	0.098	
2018	exp	W/O HH	-0.235	< 2e-16	0.582	<2e-16	-0.041	0.263	0.168	0.001	0.936	<2e-16	-0.566	<2e-16	0.117	0.000	0.010	0.731	25940
		With HH	-2.983	0.002	4.852	0.184	1.558	0.542	9.451	0.006	11.060	0.000	-6.979	0.005	-3.501	0.118	-0.048	0.457	
	log_exp	W/O HH	-0.229	< 2e-16	0.591	< 2e-16	-0.040	0.279	0.152	0.002	0.926	< 2e-16	-0.568	< 2e-16	0.138	0.000	0.012	0.681	25864
		With HH	-1.957	0.021	9.490	0.003	-1.318	0.600	-2.461	0.432	8.047	0.000	-8.640	0.012	-0.838	0.635	-0.049	0.442	
	rel_exp	W/O HH	-0.242	< 2e-16	0.578	< 2e-16	-0.037	0.309	0.179	0.000	0.948	< 2e-16	-0.561	< 2e-16	0.103	0.001	0.006	0.836	25952
		With HH	-2.309	0.001	9.363	0.001	-1.936	0.308	-2.647	0.292	6.826	0.000	-9.977	0.000	-1.590	0.341	-0.056	0.379	
2019	exp	W/O HH	-0.237	< 2e-16	0.383	0.000	-0.213	0.000	-0.022	0.622	0.664	< 2e-16	-0.751	< 2e-16	-0.252	< 2e-16	0.050	0.083	27186
		With HH	-1.571	0.037	3.426	0.138	-2.606	0.115	-1.771	0.392	4.801	0.021	-14.622	0.001	-1.570	0.335	0.055	0.382	
	log_exp	W/O HH	-0.233	< 2e-16	0.383	0.000	-0.218	0.000	-0.019	0.675	0.659	< 2e-16	-0.763	< 2e-16	-0.234	0.000	0.052	0.076	27152
		With HH	-1.512	0.067	4.422	0.106	-3.375	0.082	-2.397	0.261	4.685	0.048	-15.260	0.003	-0.574	0.694	0.071	0.266	
	rel_exp	W/O HH	-0.246	< 2e-16	0.370	0.000	-0.191	0.000	-0.023	0.602	0.665	< 2e-16	-0.744	< 2e-16	-0.278	< 2e-16	0.049	0.088	27261
		With HH	-1.769	< 2e-16	3.038	< 2e-16	-2.742	< 2e-16	-1.730	< 2e-16	4.433	< 2e-16	-15.090	< 2e-16	-1.580	< 2e-16	0.019	< 2e-16	

Table E14: LA – Logistic Regression Results for Upper-Middle Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.127	< 2e-16	-0.575	< 2e-16	0.473	< 2e-16	0.270	0.000	0.788	< 2e-16	-0.250	0.000	-0.140	0.000	0.000	0.994	21090
		With HH	-1.871	0.005	-7.881	0.003	1.375	0.389	0.821	0.702	9.481	0.000	-1.014	0.587	-0.090	0.953	0.007	0.929	
	log_exp	W/O HH	-0.124	< 2e-16	-0.555	< 2e-16	0.479	< 2e-16	0.266	0.000	0.781	< 2e-16	-0.249	0.000	-0.130	0.000	-0.002	0.957	21037
		With HH	-1.888	0.003	-7.470	0.005	1.482	0.356	-0.078	0.972	9.503	0.000	-1.343	0.515	0.122	0.940	0.005	0.948	
	rel_exp	W/O HH	-0.131	< 2e-16	-0.596	< 2e-16	0.471	< 2e-16	0.277	0.000	0.794	< 2e-16	-0.254	0.000	-0.146	0.000	0.002	0.946	21104
		With HH	-1.808	0.001	-8.458	0.001	0.980	0.532	1.014	0.644	8.919	0.000	-1.817	0.349	-0.567	0.714	0.002	0.979	
2016	exp	W/O HH	-0.297	< 2e-16	-0.372	0.000	0.143	0.000	0.216	0.000	0.918	< 2e-16	-0.256	0.000	-0.212	0.000	-0.017	0.604	20937
		With HH	-3.097	0.000	-7.259	0.003	4.771	0.009	4.458	0.058	9.955	0.000	-4.493	0.017	-0.314	0.843	-0.015	0.855	
	log_exp	W/O HH	-0.296	< 2e-16	-0.366	0.000	0.130	0.001	0.213	0.000	0.895	< 2e-16	-0.256	0.000	-0.202	0.000	-0.016	0.638	20881
		With HH	-3.177	0.000	-8.343	0.000	5.290	0.005	6.277	0.002	11.135	0.000	-4.364	0.019	-0.380	0.809	-0.022	0.790	
	rel_exp	W/O HH	-0.302	< 2e-16	-0.392	0.000	0.157	0.000	0.214	0.000	0.932	< 2e-16	-0.254	0.000	-0.233	0.000	-0.015	0.660	20976
		With HH	-2.723	0.000	-7.285	0.001	6.423	0.001	5.431	0.009	11.855	0.000	-3.306	0.056	0.370	0.817	-0.054	0.514	
2017	exp	W/O HH	-0.325	< 2e-16	-0.923	< 2e-16	0.100	0.004	1.057	< 2e-16	0.606	< 2e-16	-0.103	0.004	-0.527	< 2e-16	-0.003	0.917	23893
		With HH	-3.581	0.000	-7.452	0.001	0.424	0.815	6.194	0.013	7.451	0.001	2.065	0.294	-5.593	0.006	-0.053	0.443	
	log_exp	W/O HH	-0.321	< 2e-16	-0.921	< 2e-16	0.092	0.009	1.041	< 2e-16	0.582	< 2e-16	-0.109	0.003	-0.515	< 2e-16	0.000	0.988	23772
		With HH	-3.749	0.000	-8.394	0.000	0.852	0.645	8.257	0.002	7.995	0.001	1.574	0.436	-7.926	0.001	-0.015	0.832	
	rel_exp	W/O HH	-0.345	< 2e-16	-0.934	< 2e-16	0.098	0.005	1.052	< 2e-16	0.638	< 2e-16	-0.116	0.001	-0.563	< 2e-16	-0.004	0.895	24150
		With HH	-3.627	0.000	-7.095	0.003	1.065	0.562	5.552	0.029	7.278	0.002	2.626	0.189	-6.225	0.002	-0.012	0.861	
2018	exp	W/O HH	-0.318	< 2e-16	-0.120	0.023	0.137	0.000	0.839	< 2e-16	0.932	< 2e-16	-0.401	< 2e-16	-0.432	< 2e-16	0.006	0.848	24589
		With HH	-3.279	0.000	-2.718	0.228	0.452	0.824	7.791	0.001	15.281	0.000	-2.546	0.213	-6.198	0.005	0.101	0.186	
	log_exp	W/O HH	-0.319	< 2e-16	-0.112	0.034	0.131	0.000	0.827	< 2e-16	0.931	< 2e-16	-0.399	< 2e-16	-0.412	< 2e-16	0.006	0.849	24514
		With HH	-3.443	< 2e-16	-4.657	< 2e-16	3.670	< 2e-16	9.815	< 2e-16	15.118	< 2e-16	-1.913	< 2e-16	-4.936	< 2e-16	0.110	< 2e-16	
	rel_exp	W/O HH	-0.326	< 2e-16	-0.134	0.011	0.136	0.000	0.837	< 2e-16	0.932	< 2e-16	-0.399	< 2e-16	-0.459	< 2e-16	0.008	0.787	24674
		With HH	-2.812	0.003	-3.768	0.171	1.076	0.672	8.511	0.002	17.062	0.000	-4.217	0.057	-5.764	0.015	0.111	0.149	
2019	exp	W/O HH	-0.306	< 2e-16	-0.280	0.000	0.658	< 2e-16	0.627	< 2e-16	0.915	< 2e-16	0.048	0.145	-0.944	< 2e-16	0.021	0.480	27150
		With HH	-0.987	0.259	-5.911	0.410	4.869	0.073	2.209	0.735	8.177	0.000	-0.075	0.964	11.901	0.000	-0.029	0.661	
	log_exp	W/O HH	-0.305	< 2e-16	-0.287	0.000	0.647	< 2e-16	0.628	< 2e-16	0.895	< 2e-16	0.040	0.225	-0.931	< 2e-16	0.020	0.490	27071
		With HH	-0.736	0.280	-5.538	0.265	5.756	0.008	1.393	0.771	7.707	0.000	0.313	0.849	12.756	0.000	-0.027	0.679	
	rel_exp	W/O HH	-0.323	< 2e-16	-0.306	0.000	0.663	< 2e-16	0.635	< 2e-16	0.904	< 2e-16	0.059	0.073	-0.999	< 2e-16	0.020	0.494	27324
		With HH	-1.241	0.206	-8.468	0.017	3.491	0.180	5.944	0.047	7.854	0.000	-0.567	0.747	-11.915	0.000	-0.046	0.481	

Table E15: LA – Logistic Regression Results for High-Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.228	< 2e-16	-0.294	0.000	-0.186	0.000	1.464	< 2e-16	0.965	< 2e-16	-0.391	< 2e-16	0.025	0.475	0.011	0.731	22936
		With HH	-0.459	0.554	-1.114	0.733	0.316	0.873	13.031	0.000	14.215	0.000	-0.857	0.723	-1.178	0.566	-0.043	0.579	
	log_exp	W/O HH	-0.227	< 2e-16	-0.233	0.000	-0.208	0.000	1.439	< 2e-16	0.975	< 2e-16	-0.394	< 2e-16	0.072	0.041	0.008	0.810	22726
		With HH	-0.759	0.219	-11.164	0.186	-1.407	0.305	34.789	0.000	20.412	0.000	-1.831	0.246	-1.918	0.153	-0.110	0.156	
	rel_exp	W/O HH	-0.228	< 2e-16	-0.359	0.000	-0.169	0.000	1.492	< 2e-16	0.945	< 2e-16	-0.402	< 2e-16	-0.025	0.464	0.006	0.851	23097
		With HH	-0.373	0.364	-0.970	0.537	0.497	0.599	18.479	0.000	10.899	0.070	-0.678	0.545	-0.509	0.578	-0.041	0.593	
2016	exp	W/O HH	-0.183	< 2e-16	0.375	0.000	-0.069	0.026	0.693	< 2e-16	1.147	< 2e-16	-0.210	0.000	-0.367	< 2e-16	0.021	0.480	27455
		With HH	-0.359	0.371	-0.816	0.573	0.161	0.869	10.495	0.020	16.653	0.000	-1.784	0.162	-2.057	0.055	0.008	0.911	
	log_exp	W/O HH	-0.181	< 2e-16	0.415	0.000	-0.081	0.009	0.656	< 2e-16	1.131	< 2e-16	-0.210	0.000	-0.339	< 2e-16	0.021	0.472	27327
		With HH	-0.523	< 2e-16	-1.342	< 2e-16	-0.382	< 2e-16	6.724	< 2e-16	14.310	< 2e-16	-2.943	< 2e-16	-3.101	< 2e-16	0.017	< 2e-16	
	rel_exp	W/O HH	-0.196	< 2e-16	0.272	0.000	-0.026	0.399	0.764	< 2e-16	1.186	< 2e-16	-0.270	0.000	-0.435	< 2e-16	0.017	0.547	27835
		With HH	-0.743	0.250	2.498	0.363	-0.922	0.591	-1.427	0.686	12.559	0.000	-2.710	0.251	-2.905	0.109	0.040	0.578	
2017	exp	W/O HH	-0.042	0.000	-0.091	0.048	-0.474	< 2e-16	0.671	< 2e-16	0.738	< 2e-16	-0.861	< 2e-16	-0.174	0.000	-0.062	0.017	34559
		With HH	-0.340	0.639	-0.914	0.785	-1.394	0.472	10.803	0.005	2.161	0.416	-2.909	0.301	-1.331	0.505	-0.292	0.000	
	log_exp	W/O HH	-0.036	0.001	-0.065	0.159	-0.483	< 2e-16	0.617	< 2e-16	0.745	< 2e-16	-0.871	< 2e-16	-0.155	0.000	-0.061	0.019	34395
		With HH	-0.459	0.517	-0.503	0.877	-1.135	0.555	20.899	0.000	5.130	0.0397	-1.939	0.474	-1.151	0.560	-0.297	0.000	
	rel_exp	W/O HH	-0.054	0.000	-0.157	0.001	-0.447	< 2e-16	0.774	< 2e-16	0.777	< 2e-16	-0.875	< 2e-16	-0.224	0.000	-0.062	0.017	34882
		With HH	-0.287	0.506	-2.363	0.243	-2.897	0.057	21.645	0.000	18.422	0.000	-3.508	0.046	-0.675	0.514	-0.279	0.000	
2018	exp	W/O HH	-0.012	0.287	-0.016	0.731	-0.215	0.000	0.469	< 2e-16	0.868	< 2e-16	-0.449	< 2e-16	-0.358	< 2e-16	-0.041	0.106	36004
		With HH	-0.239	0.477	-0.432	0.728	-0.098	0.905	1.681	0.342	17.158	0.000	-1.169	0.273	-1.242	0.114	-0.048	0.461	
	log_exp	W/O HH	-0.011	0.325	0.005	0.907	-0.207	0.000	0.440	0.000	0.868	< 2e-16	-0.455	< 2e-16	-0.340	< 2e-16	-0.041	0.110	35939
		With HH	-0.311	0.409	-1.426	0.351	-2.169	0.032	2.930	0.152	1.970	0.281	-3.753	0.011	-0.712	0.418	0.038	0.559	
	rel_exp	W/O HH	-0.030	0.007	-0.065	0.149	-0.184	0.000	0.495	< 2e-16	0.917	< 2e-16	-0.472	< 2e-16	-0.420	< 2e-16	-0.035	0.161	36328
		With HH	-0.223	0.461	1.790	0.158	0.167	0.832	-1.145	0.491	22.066	< 2e-16	0.776	0.429	-0.871	0.236	-0.018	0.787	
2019	exp	W/O HH	-0.132	< 2e-16	0.367	< 2e-16	-0.183	0.000	0.352	0.000	1.062	< 2e-16	-0.164	0.000	0.014	0.577	0.037	0.111	42306
		With HH	-0.407	0.180	0.991	0.439	0.836	0.272	1.838	0.279	23.406	< 2e-16	1.156	0.247	0.059	0.934	0.139	0.012	
	log_exp	W/O HH	-0.134	< 2e-16	0.392	< 2e-16	-0.190	0.000	0.354	0.000	1.063	< 2e-16	-0.178	0.000	0.023	0.347	0.039	0.099	42224
		With HH	-0.741	0.037	0.976	0.462	-1.164	0.155	0.546	0.727	18.717	< 2e-16	-1.477	0.134	-0.924	0.204	-0.099	0.073	
	rel_exp	W/O HH	-0.148	< 2e-16	0.327	0.000	-0.158	0.000	0.387	0.000	1.079	< 2e-16	-0.181	0.000	-0.046	0.056	0.036	0.119	42553
		With HH	-0.689	0.419	1.580	0.668	-0.438	0.855	-1.386	0.750	10.816	0.000	3.582	0.203	-1.559	0.499	0.025	0.652	

APPENDIX E

NEW YORK CITY – OTHER LOGISTIC REGRESSION RESULTS

Table E16: NYC – Logistic Regression Results for All Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.285	< 2e-16	0.471	< 2e-16	0.366	< 2e-16	-0.062	0.015	0.591	< 2e-16	-0.322	< 2e-16	0.316	< 2e-16	0.007	0.661	89873
		With HH	-3.391	0.000	1.177	0.358	2.890	0.007	2.497	0.058	4.788	0.005	-3.168	0.001	6.400	0.000	0.060	0.113	
	log_exp	W/O HH	-0.285	< 2e-16	0.477	< 2e-16	0.364	< 2e-16	-0.069	0.007	0.592	< 2e-16	-0.324	< 2e-16	0.319	< 2e-16	0.008	0.630	89893
		With HH	-2.168	0.002	1.695	0.146	-0.732	0.370	1.938	0.063	12.440	0.001	-3.701	0.001	3.387	0.008	0.026	0.492	
	rel_exp	W/O HH	-0.298	< 2e-16	0.460	< 2e-16	0.366	< 2e-16	-0.047	0.066	0.603	< 2e-16	-0.325	< 2e-16	0.292	< 2e-16	0.010	0.532	90005
		With HH	-1.760	0.001	1.406	0.468	0.505	0.697	-0.141	0.939	14.244	< 2e-16	-6.575	0.000	1.261	0.338	-0.035	0.358	
2016	exp	W/O HH	-0.213	< 2e-16	0.240	< 2e-16	0.267	< 2e-16	0.175	0.000	0.566	< 2e-16	-0.267	< 2e-16	0.224	< 2e-16	-0.029	0.048	106409
		With HH	-1.936	0.000	0.697	0.528	2.235	0.008	1.148	0.257	6.700	0.000	-2.207	0.007	3.917	0.001	0.014	0.694	
	log_exp	W/O HH	-0.214	< 2e-16	0.245	< 2e-16	0.268	< 2e-16	0.172	0.000	0.567	< 2e-16	-0.269	< 2e-16	0.225	< 2e-16	-0.029	0.051	106436
		With HH	-3.069	0.000	-2.505	0.099	0.280	0.771	3.65298	0.011	5.223	0.042	-3.394	0.007	3.316	0.004	-0.024	0.496	
	rel_exp	W/O HH	-0.225	< 2e-16	0.233	< 2e-16	0.268	< 2e-16	0.187	0.000	0.583	< 2e-16	-0.267	< 2e-16	0.206	< 2e-16	-0.029	0.053	106500
		With HH	-2.046	< 2e-16	-0.080	< 2e-16	2.230	< 2e-16	1.441	< 2e-16	5.499	< 2e-16	-1.871	< 2e-16	0.439	< 2e-16	-0.153	< 2e-16	
2017	exp	W/O HH	-0.197	< 2e-16	0.031	0.200	0.204	< 2e-16	0.315	< 2e-16	0.609	< 2e-16	-0.307	< 2e-16	0.400	< 2e-16	-0.003	0.807	115895
		With HH	-1.981	0.000	0.534	0.571	0.713	0.256	1.736	0.045	4.682	0.000	-1.512	0.019	2.330	0.002	-0.085	0.014	
	log_exp	W/O HH	-0.196	< 2e-16	0.040	0.097	0.209	< 2e-16	0.305	< 2e-16	0.606	< 2e-16	-0.309	< 2e-16	0.404	< 2e-16	-0.004	0.799	115855
		With HH	-2.736	0.000	4.183	0.000	0.211	0.772	-1.860	0.101	5.064	0.000	-1.996	0.009	3.386	0.000	-0.086	0.013	
	rel_exp	W/O HH	-0.210	< 2e-16	0.013	0.589	0.201	< 2e-16	0.335	< 2e-16	0.627	< 2e-16	-0.313	< 2e-16	0.378	< 2e-16	-0.002	0.910	116076
		With HH	-2.281	0.000	2.001	0.050	0.987	0.138	0.151	0.870	4.333	0.000	-1.765	0.010	3.201	0.000	-0.069	0.047	
2018	exp	W/O HH	-0.166	< 2e-16	-0.205	< 2e-16	0.207	< 2e-16	0.408	< 2e-16	0.607	< 2e-16	-0.436	< 2e-16	0.415	< 2e-16	0.008	0.574	120156
		With HH	-1.748	< 2e-16	0.026	< 2e-16	0.845	< 2e-16	0.847	< 2e-16	6.738	< 2e-16	-2.146	< 2e-16	2.016	< 2e-16	-0.100	< 2e-16	
	log_exp	W/O HH	-0.163	< 2e-16	-0.194	< 2e-16	0.210	< 2e-16	0.397	< 2e-16	0.600	< 2e-16	-0.438	< 2e-16	0.425	< 2e-16	0.007	0.594	120023
		With HH	-0.956	0.011	-3.049	0.034	0.927	0.321	2.942	0.039	11.871	< 2e-16	-3.812	0.001	1.078	0.245	-0.079	0.021	
	rel_exp	W/O HH	-0.179	< 2e-16	-0.223	< 2e-16	0.203	< 2e-16	0.425	< 2e-16	0.627	< 2e-16	-0.440	< 2e-16	0.391	< 2e-16	0.009	0.537	120412
		With HH	-1.344	0.000	-2.026	0.041	0.361	0.564	2.674	0.003	8.096	0.000	-2.334	0.002	2.103	0.005	-0.002	0.943	
2019	exp	W/O HH	-0.219	< 2e-16	-0.030	0.182	-0.004	0.769	0.519	< 2e-16	0.527	< 2e-16	-0.531	< 2e-16	0.318	< 2e-16	-0.016	0.219	129860
		With HH	-1.223	< 2e-16	0.878	< 2e-16	-0.839	< 2e-16	1.037	< 2e-16	3.456	< 2e-16	-2.097	< 2e-16	3.241	< 2e-16	0.018	< 2e-16	
	log_exp	W/O HH	-0.216	< 2e-16	-0.014	0.550	-0.002	0.907	0.503	< 2e-16	0.520	< 2e-16	-0.532	< 2e-16	0.328	< 2e-16	-0.017	0.204	129755
		With HH	-1.925	0.000	0.048	0.958	0.231	0.717	2.501	0.003	5.217	0.000	-2.382	0.001	1.443	0.028	-0.010	0.753	
	rel_exp	W/O HH	-0.226	< 2e-16	-0.044	0.051	-0.006	0.6959	0.531	< 2e-16	0.537	< 2e-16	-0.533	< 2e-16	0.304	< 2e-16	-0.016	0.241	129960
		With HH	-0.735	< 2e-16	0.223	< 2e-16	-0.333	< 2e-16	1.576	< 2e-16	3.266	< 2e-16	-1.849	< 2e-16	1.691	< 2e-16	-0.047	< 2e-16	

Table E17: NYC – Logistic Regression Results for Low-Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.016	0.558	1.362	< 2E-16	2.122	< 2E-16	-0.615	< 2E-16	-0.391	0.000	1.277	< 2E-16	0.093	0.045	11425
		With HH	-0.995	0.206	2.838	0.155	15.639	0.000	-0.153	0.918	-1.859	0.253	3.409	0.040	0.030	0.738	
	log_exp	W/O HH	-0.028	0.305	1.354	< 2E-16	2.125	< 2E-16	-0.600	< 2E-16	-0.378	0.000	1.266	< 2E-16	0.092	0.048	11433
		With HH	-1.230	0.140	3.731	0.071	18.303	< 2E-16	-1.382	0.314	-0.560	0.678	0.942	0.462	-0.086	0.337	
	rel_exp	W/O HH	-0.029	0.271	1.356	< 2E-16	2.126	< 2E-16	-0.600	< 2e-16	-0.377	0.000	1.267	< 2E-16	0.092	0.047	11424
		With HH	-0.921	0.214	2.976	0.135	15.582	0.000	-0.588	0.685	-0.813	0.594	3.455	0.0486	-0.004	0.960	
2016	exp	W/O HH	0.050	0.017	0.996	< 2E-16	0.574	< 2E-16	-0.322	0.000	-0.481	< 2E-16	0.550	< 2E-16	-0.014	0.726	15469
		With HH	0.105	0.877	2.056	0.350	1.917	0.349	-0.063	0.969	-8.013	0.003	8.343	0.001	-0.064	0.428	
	log_exp	W/O HH	0.042	0.041	0.999	< 2E-16	0.577	< 2E-16	-0.316	0.000	-0.479	< 2E-16	0.545	< 2E-16	-0.012	0.747	15489
		With HH	0.181	0.802	1.384	0.510	3.573	0.263	0.051	0.974	-6.537	0.032	8.204	0.001	-0.034	0.671	
	rel_exp	W/O HH	0.034	0.099	0.998	< 2E-16	0.583	< 2E-16	-0.306	0.000	-0.473	< 2E-16	0.534	< 2E-16	-0.010	0.787	15490
		With HH	0.413	0.569	2.187	0.340	3.757	0.186	0.031	0.985	-7.295	0.013	6.609	0.009	0.013	0.877	
2017	exp	W/O HH	0.065	0.002	0.310	0.000	1.296	< 2E-16	-0.191	0.000	-0.324	0.000	0.797	< 2E-16	-0.039	0.339	14224
		With HH	-0.082	0.895	-0.392	0.822	11.565	0.000	0.020	0.988	-0.762	0.582	6.933	0.000	0.010	0.905	
	log_exp	W/O HH	0.059	0.004	0.315	0.000	1.289	< 2E-16	-0.199	0.000	-0.331	0.000	0.797	< 2E-16	-0.040	0.334	14253
		With HH	-0.307	0.726	0.264	0.929	14.865	0.000	-0.330	0.900	-1.324	0.539	4.733	0.026	-0.093	0.255	
	rel_exp	W/O HH	0.029	0.159	0.269	0.000	1.288	< 2E-16	-0.137	0.007	-0.315	0.000	0.753	< 2E-16	-0.035	0.398	14325
		With HH	-0.310	0.659	0.202	0.912	12.727	0.000	-0.163	0.906	-1.024	0.483	5.440	0.037	-0.016	0.847	
2018	exp	W/O HH	0.268	< 2E-16	-0.512	0.000	0.377	0.000	0.231	0.000	-0.826	< 2E-16	0.910	< 2E-16	-0.007	0.874	13853
		With HH	2.019	0.056	-3.861	0.095	9.456	0.053	-0.319	0.855	-4.967	0.090	5.235	0.029	-0.036	0.678	
	log_exp	W/O HH	0.269	< 2E-16	-0.502	0.000	0.383	0.000	0.222	0.000	-0.823	< 2E-16	0.924	< 2E-16	-0.007	0.864	13866
		With HH	1.789	0.089	-4.544	0.070	7.023	0.095	1.338	0.494	-4.024	0.059	11.528	0.004	-0.015	0.861	
	rel_exp	W/O HH	0.251	< 2E-16	-0.543	0.000	0.358	0.000	0.267	0.000	-0.816	< 2E-16	0.910	< 2E-16	-0.005	0.901	13898
		With HH	1.877	0.052	-3.457	0.106	8.466	0.016	-0.118	0.943	-3.629	0.070	8.026	0.002	-0.043	0.623	
2019	exp	W/O HH	0.007	0.709	-0.130	0.024	0.026	0.518	0.442	< 2E-16	-0.616	< 2E-16	0.388	< 2E-16	-0.059	0.094	18427
		With HH	-0.623	< 2E-16	0.449	< 2E-16	0.145	< 2E-16	1.975	< 2E-16	-7.101	0.014	2.079	< 2E-16	-0.079	< 2E-16	
	log_exp	W/O HH	0.010	0.566	-0.097	0.096	0.037	0.367	0.420	< 2E-16	-0.612	< 2E-16	0.400	< 2E-16	-0.060	0.090	18413
		With HH	-2.345	0.475	5.813	0.622	-0.576	0.777	1.284	0.654	-3.225	0.448	3.086	0.309	-0.001	0.991	
	rel_exp	W/O HH	0.005	0.762	-0.134	0.020	0.024	0.544	0.444	< 2E-16	-0.617	< 2E-16	0.387	< 2E-16	-0.059	0.096	18423
		With HH	-0.769	0.440	1.536	0.596	0.645	0.744	1.888	0.333	-7.173	0.074	2.207	0.210	-0.083	0.331	

Table E18: NYC – Logistic Regression Results for Lower-Middle Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.223	< 2e-16	-0.020	0.681	0.025	0.498	0.254	0.000	0.790	< 2e-16	-1.011	< 2e-16	0.190	0.000	-0.040	0.205	23209
		With HH	-2.687	0.004	0.070	0.977	0.833	0.685	0.182	0.946	8.089	0.000	-8.549	0.008	2.522	0.210	-0.062	0.390	
	log_exp	W/O HH	-0.224	< 2e-16	-0.014	0.780	0.022	0.558	0.244	0.000	0.794	< 2e-16	-1.008	< 2e-16	0.199	0.000	-0.039	0.221	23208
		With HH	-3.020	0.005	-0.992	0.746	-1.091	0.665	0.915	0.777	6.413	0.006	-11.658	0.002	1.619	0.430	-0.033	0.644	
	rel_exp	W/O HH	-0.233	< 2e-16	-0.033	0.505	0.028	0.454	0.268	0.000	0.795	< 2e-16	-1.004	< 2e-16	0.181	0.000	-0.039	0.220	23228
		With HH	-2.449	0.002	-0.375	0.875	0.719	0.726	0.605	0.823	8.384	0.000	-9.094	0.003	2.071	0.278	-0.029	0.690	
2016	exp	W/O HH	0.008	0.613	-0.353	0.000	-0.141	0.000	0.186	0.000	0.292	0.000	-1.086	< 2e-16	0.270	0.000	-0.062	0.038	25467
		With HH	-2.513	0.006	-0.596	0.792	1.655	0.575	-0.733	0.757	2.272	0.232	-11.008	0.001	-0.591	0.769	-0.017	0.816	
	log_exp	W/O HH	0.003	0.845	-0.352	0.000	-0.141	0.000	0.186	0.000	0.296	0.000	-1.084	< 2e-16	0.267	0.000	-0.061	0.042	25477
		With HH	-2.317	< 2e-16	-0.459	< 2e-16	2.372	< 2e-16	-0.630	< 2e-16	2.467	< 2e-16	-11.940	< 2e-16	0.419	< 2e-16	-0.042	< 2e-16	
	rel_exp	W/O HH	-0.002	0.889	-0.354	0.000	-0.144	0.000	0.193	0.000	0.303	0.000	-1.082	< 2e-16	0.261	0.000	-0.060	0.045	25471
		With HH	-4.210	0.000	1.190	0.666	1.061	0.612	0.745	0.768	1.372	0.552	-11.322	0.000	-2.967	0.153	-0.052	0.480	
2017	exp	W/O HH	0.037	0.017	0.049	0.275	-0.089	0.005	-0.235	0.000	0.373	< 2e-16	-0.456	< 2e-16	0.451	< 2e-16	-0.007	0.814	28175
		With HH	-0.343	0.707	0.264	0.900	0.907	0.534	-2.932	0.195	4.263	0.052	-2.666	0.133	2.557	0.249	-0.054	0.440	
	log_exp	W/O HH	0.033	0.036	0.048	0.285	-0.091	0.005	-0.233	0.000	0.378	< 2e-16	-0.458	< 2e-16	0.448	< 2e-16	-0.007	0.804	28185
		With HH	-0.475	< 2e-16	-0.545	< 2e-16	-0.297	< 2e-16	-2.403	< 2e-16	4.727	< 2e-16	-4.245	< 2e-16	4.696	< 2e-16	-0.052	< 2e-16	
	rel_exp	W/O HH	0.028	0.067	0.045	0.314	-0.098	0.002	-0.227	0.000	0.388	< 2e-16	-0.461	< 2e-16	0.445	< 2e-16	-0.006	0.835	28174
		With HH	-0.483	0.747	-2.988	0.202	-1.246	0.576	0.385	0.845	2.159	0.297	-4.939	0.134	2.239	0.381	-0.101	0.153	
2018	exp	W/O HH	-0.139	< 2e-16	0.093	0.020	0.060	0.048	0.108	0.004	0.669	< 2e-16	-0.494	< 2e-16	0.659	< 2e-16	0.032	0.242	31250
		With HH	-3.566	0.000	-0.522	0.800	0.981	0.465	-0.280	0.848	10.885	0.000	-4.126	0.010	0.896	0.555	-0.007	0.920	
	log_exp	W/O HH	-0.139	< 2e-16	0.097	0.015	0.063	0.041	0.104	0.006	0.666	< 2e-16	-0.498	< 2e-16	0.660	< 2e-16	0.031	0.247	31239
		With HH	-2.529	0.029	1.063	0.588	0.904	0.536	-0.543	0.701	14.749	0.001	-2.351	0.100	1.818	0.329	-0.003	0.967	
	rel_exp	W/O HH	-0.152	< 2e-16	0.086	0.031	0.062	0.044	0.119	0.002	0.693	< 2e-16	-0.493	< 2e-16	0.648	< 2e-16	0.030	0.273	31273
		With HH	-2.419	0.0567	1.568	0.448	5.334	0.377	-0.268	0.891	11.830	0.033	-0.942	0.473	2.278	0.187	-0.019	0.765	
2019	exp	W/O HH	-0.215	< 2e-16	0.145	0.000	0.321	< 2e-16	0.121	0.002	0.476	< 2e-16	-0.348	< 2e-16	0.731	< 2e-16	0.006	0.845	29458
		With HH	-2.204	0.012	-1.236	0.651	1.053	0.625	-1.703	0.518	9.893	0.000	-4.396	0.055	1.293	0.536	-0.118	0.082	
	log_exp	W/O HH	-0.214	< 2e-16	0.150	0.000	0.324	< 2e-16	0.114	0.003	0.475	< 2e-16	-0.348	< 2e-16	0.735	< 2e-16	0.006	0.818	29460
		With HH	-1.403	0.042	-1.786	0.413	2.931	0.062	0.408	0.827	10.296	0.001	-1.387	0.373	4.923	0.026	-0.051	0.454	
	rel_exp	W/O HH	-0.224	< 2e-16	0.130	0.001	0.318	< 2e-16	0.138	0.000	0.491	< 2e-16	-0.339	< 2e-16	0.729	< 2e-16	0.007	0.797	29475
		With HH	-1.289	0.186	0.364	0.850	2.414	0.243	-0.893	0.608	13.385	0.037	-0.974	0.469	2.547	0.336	-0.014	0.841	

Table E19: NYC – Logistic Regression Results for Upper-Middle Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.572	< 2e-16	0.433	0.000	0.426	< 2e-16	0.200	0.001	0.673	< 2e-16	0.436	< 2e-16	0.420	< 2e-16	0.032	0.350	19979
		With HH	-5.252	< 2e-16	3.996	< 2e-16	1.726	< 2e-16	1.488	< 2e-16	8.355	< 2e-16	0.393	< 2e-16	-0.050	< 2e-16	0.042	< 2e-16	
	log_exp	W/O HH	-0.572	< 2e-16	0.457	0.000	0.424	< 2e-16	0.184	0.002	0.674	< 2e-16	0.436	< 2e-16	0.425	< 2e-16	0.031	0.361	19969
		With HH	-5.374	0.000	2.702	0.280	1.245	0.390	2.301	0.319	9.740	0.000	0.670	0.616	0.157	0.910	0.063	0.388	
	rel_exp	W/O HH	-0.592	< 2e-16	0.420	0.000	0.431	< 2e-16	0.229	0.000	0.688	< 2e-16	0.429	< 2e-16	0.390	< 2e-16	0.036	0.292	20017
		With HH	-5.222	< 2e-16	3.786	< 2e-16	2.365	< 2e-16	1.461	< 2e-16	7.820	< 2e-16	0.274	< 2e-16	0.497	< 2e-16	0.070	<2e-16	
2016	exp	W/O HH	-0.561	< 2e-16	0.163	0.003	0.780	< 2e-16	0.514	< 2e-16	0.646	< 2e-16	0.389	< 2e-16	0.122	0.001	0.006	0.839	24983
		With HH	-4.089	0.000	0.272	0.889	6.100	0.000	4.903	0.008	5.232	0.010	-0.111	0.929	-1.810	0.214	-0.036	0.590	
	log_exp	W/O HH	-0.561	< 2e-16	0.176	0.001	0.776	< 2e-16	0.509	< 2e-16	0.641	< 2e-16	0.387	< 2e-16	0.127	0.001	0.007326	0.811	24971
		With HH	-7.129	< 2e-16	5.999	0.045	7.042	0.001	5.015	0.142	6.250	0.002	2.279	0.297	-0.477	0.783	-0.052	0.440	
	rel_exp	W/O HH	-0.577	< 2e-16	0.154	0.004	0.773	< 2e-16	0.533	< 2e-16	0.672	< 2e-16	0.381	< 2e-16	0.106	0.005	0.006	0.836	25020
		With HH	-5.103	0.000	0.948	0.644	6.684	0.001	5.245	0.010	2.578	0.141	-0.614	0.628	-2.043	0.200	-0.073	0.278	
2017	exp	W/O HH	-0.275	< 2e-16	-0.487	< 2e-16	0.204	0.000	0.915	< 2e-16	0.480	< 2e-16	-0.291	0.000	0.030	0.377	-0.005	0.861	28900
		With HH	-4.241	0.000	-1.537	0.485	2.549	0.144	4.830	0.022	4.261	0.081	-1.832	0.167	0.837	0.578	-0.149	0.042	
	log_exp	W/O HH	-0.271	< 2e-16	-0.465	< 2e-16	0.205	0.000	0.895	< 2e-16	0.477	< 2e-16	-0.294	< 2e-16	0.039	0.254	-0.004	0.895	28832
		With HH	-3.778	< 2e-16	-5.472	< 2e-16	4.045	< 2e-16	6.235	< 2e-16	1.762	< 2e-16	-2.836	< 2e-16	-0.803	< 2e-16	-0.184	< 2e-16	
	rel_exp	W/O HH	-0.291	< 2e-16	-0.511	< 2e-16	0.211	0.000	0.947	< 2e-16	0.504	< 2e-16	-0.295	< 2e-16	0.013	0.698	0.001	0.959	28977
		With HH	-4.049	< 2e-16	-1.481	< 2e-16	3.271	<2e-16	4.214	< 2e-16	6.212	< 2e-16	-1.682	< 2e-16	1.668	< 2e-16	-0.098	< 2e-16	
2018	exp	W/O HH	-0.275	< 2e-16	-0.619	< 2e-16	0.221	0.000	1.035	< 2e-16	-0.047	0.200	-0.138	0.000	0.016	0.637	-0.002	0.951	29422
		With HH	-4.211	0.000	1.563	0.402	0.769	0.611	2.842	0.128	-3.324	0.073	-1.269	0.341	2.627	0.237	0.050	0.510	
	log_exp	W/O HH	-0.270	< 2e-16	-0.641	< 2e-16	0.218	0.000	1.027	< 2e-16	-0.055	0.131	-0.132	0.000	0.038	0.251	-0.002	0.934	29342
		With HH	-4.542	0.000	1.044	0.571	0.410	0.760	3.966	0.050	-1.364	0.372	-0.863	0.484	0.591	0.682	-0.070	0.359	
	rel_exp	W/O HH	-0.284	< 2e-16	-0.636	< 2e-16	0.217	0.000	1.046	< 2e-16	-0.040	0.265	-0.150	0.000	-0.002	0.960	0.000	0.991	29454
		With HH	-4.624	0.000	1.008	0.604	0.805	0.564	4.481	0.041	-0.219	0.880	-0.567	0.654	1.976	0.243	-0.037	0.623	
2019	exp	W/O HH	-0.162	< 2e-16	-0.458	< 2e-16	0.195	0.000	1.140	< 2e-16	0.185	0.000	-0.558	< 2e-16	-0.161	0.000	0.001	0.959	30605
		With HH	-6.509	0.000	2.525	0.484	-0.384	0.818	5.520	0.176	-1.300	0.523	-2.263	0.155	-0.373	0.809	0.087	0.233	
	log_exp	W/O HH	-0.160	< 2e-16	-0.428	< 2e-16	0.189	0.000	1.127	< 2e-16	0.178	0.000	-0.566	< 2e-16	-0.147	0.000	-0.001	0.977	30531
		With HH	-4.173	0.000	2.172	0.442	0.175	0.923	3.441	0.217	-0.648	0.767	-2.172	0.327	0.150	0.935	0.096	0.193	
	rel_exp	W/O HH	-0.175	< 2e-16	-0.474	< 2e-16	0.206	0.000	1.152	< 2e-16	0.208	0.000	-0.559	< 2e-16	-0.182	0.000	0.007	0.806	30721
		With HH	-3.440	0.000	2.329	0.431	-1.533	0.421	2.530	0.385	-2.160	0.355	-1.903	0.410	2.134	0.267	0.005	0.940	

Table E20: NYC – Logistic Regression Results for High Income Group.

		Model	HH Size	p-value	Marital_Status	p-value	Age	p-value	Gender	p-value	Education	p-value	Work	p-value	Race	p-value	Purchase_Day	p-value	AIC
2015	exp	W/O HH	-0.263	< 2e-16	0.345	0.000	-0.073	0.017	0.335	0.000	0.685	< 2e-16	-0.284	0.000	-0.287	< 2e-16	0.005	0.844	31249
		With HH	-0.455	0.176	0.257	0.856	-0.342	0.645	0.896	0.563	1.864	0.122	-1.175	0.195	0.249	0.750	-0.118	0.106	
	log_exp	W/O HH	-0.260	< 2e-16	0.345	0.000	-0.072	0.018	0.334	0.000	0.678	< 2e-16	-0.286	0.000	-0.279	0.000	0.005	0.845	31236
		With HH	-0.623	0.074	0.457	0.753	-0.820	0.281	0.790	0.620	0.820	0.444	-1.552	0.099	-0.329	0.687	-0.036	0.620	
	rel_exp	W/O HH	-0.270	< 2e-16	0.340	0.000	-0.076	0.012	0.333	0.000	0.707	< 2e-16	-0.298	0.000	-0.316	< 2e-16	0.010	0.715	31288
		With HH	-0.652	0.071	0.197	0.897	-0.664	0.396	1.387	0.401	2.518	0.085	-1.449	0.140	0.370	0.646	-0.069	0.344	
2016	exp	W/O HH	-0.229	< 2e-16	0.323	0.000	0.205	0.000	0.230	0.000	0.950	< 2e-16	0.063	0.065	-0.022	0.458	-0.050	0.048	37680
		With HH	-0.616	0.050	0.481	0.6945	-0.102	0.883	-0.353	0.793	1.975	0.125	-0.639	0.448	-0.091	0.899	-0.103	0.113	
	log_exp	W/O HH	-0.227	< 2e-16	0.337	0.000	0.207	0.000	0.220	0.000	0.952	< 2e-16	0.060	0.082	-0.015	0.603	-0.050	0.048	37671
		With HH	-0.315	0.317	-2.045	0.312	1.240	0.088	2.013	0.310	21.011	< 2e-16	0.52012	0.565	0.016	0.983	-0.238	0.000	
	rel_exp	W/O HH	-0.238	< 2e-16	0.307	0.000	0.210	0.000	0.247	0.000	0.965	< 2e-16	0.061	0.077	-0.048	0.104	-0.051	0.044	37710
		With HH	-0.195	0.526	-0.817	0.553	0.906	0.182	0.788	0.577	2.471	0.085	-0.402	0.641	0.186	0.792	-0.150	0.021	
2017	exp	W/O HH	-0.300	< 2e-16	-0.195	0.000	0.167	0.000	0.873	< 2e-16	0.831	< 2e-16	-0.172	0.000	0.415	< 2e-16	-0.005	0.843	42636
		With HH	-1.110	0.002	1.164	0.431	-0.869	0.253	3.021	0.072	2.631	0.016	-0.222	0.805	2.260	0.006	-0.083	0.160	
	log_exp	W/O HH	-0.297	< 2e-16	-0.181	0.001	0.172	0.000	0.864	< 2e-16	0.828	< 2e-16	-0.171	0.000	0.422	< 2e-16	-0.005	0.837	42608
		With HH	-0.994	0.010	-3.103	0.241	0.193	0.805	7.406	0.019	4.417	0.044	-0.887	0.390	1.985	0.022	-0.208	0.000	
	rel_exp	W/O HH	-0.310	< 2e-16	-0.216	0.000	0.168	0.000	0.893	< 2e-16	0.848	< 2e-16	-0.181	0.000	0.386	< 2e-16	-0.005	0.842	42691
		With HH	-1.008	0.004	0.954	0.499	-0.247	0.730	2.214	0.156	3.602	0.024	-0.324	0.717	1.821	0.018	-0.232	0.000	
2018	exp	W/O HH	-0.233	< 2e-16	-0.503	< 2e-16	0.182	0.000	0.813	< 2e-16	1.114	< 2e-16	-0.566	< 2e-16	0.312	< 2e-16	-0.002	0.932	43763
		With HH	-0.930	0.013	-0.325	0.807	-0.745	0.326	0.656	0.659	4.974	0.043	-2.948	0.045	-0.335	0.663	-0.259	0.000	
	log_exp	W/O HH	-0.228	< 2e-16	-0.491	< 2e-16	0.189	0.000	0.800	< 2e-16	1.103	< 2e-16	-0.563	< 2e-16	0.329	< 2e-16	-0.003	0.886	43681
		With HH	-0.550	0.073	-1.178	0.387	0.166	0.805	2.108	0.153	10.901	0.000	-0.666	0.436	0.644	0.337	0.017	0.767	
	rel_exp	W/O HH	-0.246	< 2e-16	-0.526	< 2e-16	0.176	0.000	0.839	< 2e-16	1.140	< 2e-16	-0.574	< 2e-16	0.271	< 2e-16	0.000	0.991	43912
		With HH	-1.053	0.004	-0.797	0.575	-0.314	0.671	1.405	0.364	12.260	0.000	-1.179	0.220	-0.016	0.982	-0.058	0.306	
2019	exp	W/O HH	-0.300	< 2e-16	-0.011	0.810	-0.301	< 2e-16	0.597	< 2e-16	0.889	< 2e-16	-0.532	< 2e-16	0.327	< 2e-16	-0.020	0.353	49859
		With HH	-1.266	< 2e-16	0.249	< 2e-16	-1.767	< 2e-16	1.660	< 2e-16	3.758	< 2e-16	-2.579	< 2e-16	1.306	< 2e-16	-0.082	< 2e-16	
	log_exp	W/O HH	-0.298	< 2e-16	-0.003	0.954	-0.298	< 2e-16	0.585	< 2e-16	0.883	< 2e-16	-0.528	< 2e-16	0.336	< 2e-16	-0.021	0.339	49835
		With HH	-0.714	0.021	0.619	0.572	-0.269	0.682	0.560	0.636	0.712	0.430	-1.428	0.084	-0.189	0.777	0.044	0.392	
	rel_exp	W/O HH	-0.306	< 2e-16	-0.020	0.667	-0.302	< 2e-16	0.610	< 2e-16	0.897	< 2e-16	-0.538	< 2e-16	0.307	< 2e-16	-0.022	0.304	49872
		With HH	-1.286	0.001	1.058	0.382	-1.704	0.032	0.911	0.501	4.220	0.011	-2.463	0.010	0.140	0.846	-0.047	0.362	