ESSAYS ON THE EFFECTIVENESS OF CONDITIONAL FREE SHIPPING POLICIES ON CUSTOMERS' PURCHASE BEHAVIORS AND RETAILERS' PROFITABILITY

A Dissertation

By

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ABSTRACT

With the proliferation of e-commerce, designing a free shipping policy that can balance the need to recover shipping costs and retain customers is a big quandary for retailers. This dissertation investigates the effectiveness of several widely adopted free shipping policies to provide significant managerial implications for retailers.

My first essay mainly focuses on Membership Free Shipping (MFS), a trending free shipping policy requiring customers to pay an upfront membership fee in exchange for unlimited free shipping. It takes a comprehensive analysis of the benefits and costs of MFS on how enrollment in MFS affects customers' purchase decisions from multiple dimensions, including how much they buy and what they buy. The results show that MFS enrollment surprisingly does not lift consumers' average spending over the membership period. It might be because the unlimited free shipping benefit encourages order-splitting behavior that members purchase with an increased frequency but a reduced-order size. In addition to the purchasing behaviors, I further analyze whether enrolled customers are profitable by accounting for sales and membership fees and the costs from the free shipping benefits.

My second essay compares the effectiveness of several commonly adopted free shipping policies, including contingent free shipping with different thresholds and MFS. To suggest the optimal shipping option for online retailers, I construct a joint model of customers' online shopping trips, spending, and membership conversion decisions and conduct several policy simulations to quantify the impact of different shipping policies on the retailer's profitability.

DEDICATION

I am dedicating this dissertation to my family, who has meant and continues to mean so much to me. First and foremost, this work is dedicated to my husband, Xing Wang, who has been a constant source of support and encouragement during the challenges of graduate school and life. He inspires me all the way and is always there for me whenever I need help. I am truly thankful for having you in my life.

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CHAPTER I

INTRODUCTION

With the proliferation of online shopping, free shipping has become popular among retailers. Most customers will abandon a purchase due to unsatisfactory shipping options, while free shipping can lead to more sales. However, offering free shipping is not an easy task for retailers, especially when the shipping cost is a heavy burden. Therefore, how to balance the need to retain customers and recover the high shipping costs is a big question. Despite the topic’s importance, only a limited number of studies have examined the free shipping policy.

The current dissertation fills the research gap by investigating the effectiveness of widely adopted free shipping policies and recommending the best policy for the retailers. In the first essay, I mainly examine the effectiveness of membership-based free shipping (MFS) policy. It is a trending shipping policy that has been adopted by many e-commerce giants in recent years, such as Amazon Prime, Walmart Plus, and BestBuy Beta. Despite the popularity of MFS, its effectiveness is still understudied. In this research, I leverage a unique consumer panel dataset provided by a top online retailer in Asia and use a quasi-experimental approach to quantify the enrollment effect of MFS on consumers’ purchase behaviors and retailers’ profits. The results show that MFS enrollment surprisingly does not lift consumers’ average spending over the membership period. It might be because the unlimited free shipping benefit encourages order-splitting behavior that members purchase with an increased frequency but a decreased order size. Yet, it enhances retailers’ profits as membership fees might partially offset the increased shipping costs. Given the long-term orientation of MFS, I find that consumers’ purchase behaviors dynamically change over their membership period, which also reveals the significance of membership fees. Consumers tend to exploit free shipping benefits in the early enrollment stage, leading to increased shipping costs for the online retailer. At this point, the membership fee is mainly used to cover the shipping costs. In the long run, the membership fee is perceived as a sunk cost that locks in consumers' purchases, increasing customer loyalty in terms of higher purchase frequency, broader product categories, and less sensitivity to price promotions. As consumers become more engaged, their spending increases over time and help retailer generate more profits in the long term. However, not all customers are profitable after enrollment. Investigating the individual-level treatment effect, I find that retailers can generate incremental profits from only around 50% of members. Motivated by the enrollment heterogeneity, I examine a possible targeting strategy that promotes MFS to selected customers based on their profit potentials. The proposed method outperforms conventional targeting strategies commonly used in practices: spending- and enrollment probability-based. As upfront membership fees might have the same psychological foundation to predict customer behaviors, my research has broader and significant implications on all fee-based subscription/loyalty programs, such as music and video streaming (e.g., Netflix) and membership programs of retail stores (e.g., Walmart Plus, Costco).

The second essay extends the single shipping policy to multiple shipping policies that retailers might adopt. An important yet unanswered question is: which one is optimal when facing multiple free shipping strategies? To answer this question, I assess and compare the effectiveness of three commonly adopted free shipping strategies, including CFS with low/high free shipping thresholds and with MFS. This essay focuses on three research questions: (1) Do consumers' purchase behaviors change under different shipping policies? (2) what is the optimal CFS free shipping threshold? And (3) should retailers offer CFS and MFS simultaneously? I collaborated with a top online retailer who experimented with these free shipping policies to answer these questions. I construct a joint model of customers' online shopping trips, spending, and membership conversion decisions under these free shipping strategies using a customer transaction-level data set. Finally, to examine the optimal free shipping policy, I conduct several policy simulations which consider the profitability that a retailer will generate with various CFS threshold levels, a combination of CFS and MFS, and variations in price promotion.

CHAPTER II

THE EFFECTIVENESS OF MEMBERSHIP FREE SHIPPING: AN EMPIRICAL INVESTIGATION ON CONSUMERS' PURCHASE BEHAVIORS AND RETAILERS' PROFITS

INTRODUCTION

With the proliferation of e-commerce, one of the challenges for retailers is recovering the constantly increased shipping costs. As Amazon's annual report shows, its shipping costs reached $37.9 billion in 2019, which has risen by about 230% over the past five years (Amazon Annual Report 2019). Despite the high shipping costs, it is hard for retailers to charge consumers as shipping fee is the top reason that drives consumers away. Instead, offering free shipping becomes an expectation rather than an exception. Recently, online retailers have shown a growing interest in membership free shipping (MFS), in which consumers pay an upfront membership fee in exchange for unlimited free shipping. Retailers hope MFS can help them balance the need to offer free shipping while recouping some shipping costs with the membership fee. Nearly 40% of the world's top retailers have adopted MFS or advertised it as a premium service in their membership programs, such as Amazon Prime, Walmart Plus, Sephora Flash Shipping, ASOS Premier Delivery, etc.

Despite the popularity of MFS, industry experts have divergent views on its effectiveness. Some praise the success of MFS by showing higher spending by members than nonmembers (CNET, 2015). Others argue the opposite truth that shipping costs outpace the revenue, making MFS unprofitable (CNET 2016). Given that MFS requires retailers' long-term commitment and carries substantial direct costs, a critical research priority is to assess the effectiveness and profitability of MFS. However, such evidence is missing from the literature as prior studies on shipping policy have mainly focused on other formats of free shipping, such as temporary free shipping as a price promotion (e.g., Shehu, Papies, and Neslin 2020) and contingent fee shipping (CFS), i.e., free shipping applied to orders above a pre-determined threshold (e.g., Leng and Becerril-Arreola 2010; Lewis, Singh, and Fay 2006). The only exceptions are two game-theoretical studies from Tan, Tan, and Ho (2015) and Sun, Cavusoglu, and Raghunathan (2017). While insightful on profit and social welfare, they are of little practical relevance to consumer-level insights. Without real-world data, findings in both studies are not empirically validated.

In the current study, we intend to fill this research gap in the following ways. *First*, we ask whether MFS affects consumers' spending, one of any membership programs' most crucial success indicators (Berger et al. 2002). On the one hand, when consumers pay membership fees, they would be inspired to gain a greater return on their initial investment by purchasing more (Ailawadi, Ma, and Grewal 2018). Thus, MFS enrollment may motivate consumers to consolidate their purchases with the retailer, increasing sales revenue. On the other hand, consumers may take advantage of unlimited free shipping by placing frequent and small orders without spending more. Therefore, an important question remains unanswered: how MFS enrollment changes consumers' purchase behaviors related to *how much to buy*, including spending, purchase frequency, and order sizes.

Next, online shopping is where consumers can easily access millions of products. Regarding product assortment, retailers are very interested in understanding which categories consumers would purchase after MFS enrollment. One interesting fact about top retailers who adopted MFS is that they also offer CFS to consumers who choose not to enroll in MFS (Digital

Commerce 2019). In CFS, consumers may limit their purchase within certain product categories in which price can easily meet the free shipping requirement (Chen and Ngwe 2017). However, in MFS, members may explore more product categories with different price levels when the minimum spending requirement is removed. Moreover, free shipping may stimulate impulsive purchases that consumers add unplanned products to their baskets, further increasing purchase variety (Dawson and Kim 2009). This study also measures how MFS changes consumers' purchase behaviors related to *what to buy*, including purchase variety and purchase types (i.e., impulse vs. nonimpulse products).

Third, we investigate the impact of MFS enrollment on consumers' responsiveness to price promotion. Shipping fee is "an element of price" (Lewis 2004) as it increases consumers' transaction costs. Retailers often adopt free shipping as an effective promotion strategy to stimulate sales. At the same time, they spend millions of dollars on price promotions to stay competitive in the market. As an MFS member, one can enjoy free shipping benefits on top of price discounts. On the one hand, consumers might become more responsive to price promotion as it can significantly reduce transaction costs on top of free shipping (Cortiñas, Elorz, and Múgica 2008). On the other hand, consumers may become less price sensitive if MFS increases customer loyalty towards the retailer (Krishnamurthi and Papatla 2003). By examining the change in consumers' wallet share on discounted vs. regular-priced products after MFS enrollment, we provide further insight into how MFS affects consumers' sensitivity to price promotions.

Fourth, we study the effect of MFS on retailers' profitability. Free shipping benefits in MFS bring enormous shipping costs to retailers, especially when consumers have their orders shipped in a myriad of small packages. Retailers expect that the membership fee could recover some of the increased shipping costs. Indeed, the membership fee is a significant profit contributor to many paid membership programs. For example, Costco's annual membership fees account for 80% of Costco's gross margin (Forbes 2016). However, an estimate for Amazon Prime shows that it lost at least $11 per member after accounting for the membership fee (Tuttle 2013). To investigate whether MFS is truly profitable for retailers, we measure retailers' profit by accounting for the revenue from sales and membership fees and costs from free shipping.

Lastly, we examine the heterogeneous effects of MFS on consumers' profit contribution at an individual level and guide retailers on the member acquisition strategies. In practice, acquisition strategy is generally achieved by targeting consumers who are most likely to join the program or have the strongest relationship with the retailer in terms of spending. For example, when promoting the MFS program, Walmart targeted consumers who previously had multi-channel purchase experience, while JD.com (Top 1 retailer in China, according to Deloitte) sent invitation emails to heavy buyers (Wang 2015). These member acquisition strategies fail to target consumers based on their potential profit contributions and may not be very effective. With the recent advances in machine learning, we can estimate the treatment effect of MFS enrollment at the consumer level. A targeting strategy based on such granular level estimate of consumer's profit contribution may ensure the success of MFS programs.

Taken together, we examine the effect of MFS enrollment on consumers' purchase behaviors, including *how much to buy* and *what to buy*, and retailers' profits with an order-level transaction dataset over 36 months. The dataset is provided by a top online retailer in Asia, which launched MFS during the sample period. Consumers pay an annual membership fee to enroll in MFS and get unlimited free shipping on all orders. We utilize a quasi-experimental design with a difference-in-difference approach to estimate the MFS enrollment effect. To address the endogeneity of MFS enrollment, we use propensity score matching and Heckman correction. We further follow a newly developed machine learning algorithm, causal forest (Athey, Tibshirani, and Wager 2019), to obtain consumers' heterogeneity in profit contribution and propose an efficient targeting strategy for retailers to maximize their profitability with MFS.

We contribute to marketing literature and offer important managerial implications to practitioners in the following ways. *First*, using extensive customer transaction data, we take the first step to quantify the effectiveness of an emerging free shipping policy—MFS on consumer's purchase behaviors and retailers' profits. Our substantive findings show that MFS enrollment is surprisingly ineffective in increasing consumers' overall spending. However, it enhances behavioral loyalty over time through increased switching costs and sunk costs, leading to greater spending and profits in the long run.

Second, we contribute the literature in product assortment planning by studying the effect of MFS on consumers' purchase variety and purchased product types. We find that consumers purchase from broader product categories and enjoy impulsive purchases after enrolling in MFS. To boost sales with MFS, retailers should expand product categories and provide more impulsive products. In addition, members spend less on promoted items over their membership period. Since free shipping and price promotion together will reduce retailers' profit margins, our result suggests that retailers may not get hurt if they reduce their promotional budgets for members.

Third, we expand the membership program literature scope from free to join programs to paid programs (Breugelmans et al. 2015). We provide empirical evidence on the importance of membership fees. Serving more than just a steady revenue source for the retailer, membership fees, perceived as both switching costs and sunk costs in consumers' mental accounts, can effectively prevent consumers from switching to other retailers in the long term. Our findings on the time-varying profitability of MFS also suggest that it is beneficial for retailers to adopt a long-term membership program— annual membership, rather than a short-term monthly membership.

Lastly, our study provides a more efficient approach to help retailers select which customer segments to target when promoting MFS. We find that only around 50% of enrolled consumers would bring incremental profits to retailers. When targeting consumers based on their potential profit contribution, the retailer could generate up to 91% more profit than traditional targeting strategies based on the consumers' pre-enrollment spending level and enrollment likelihood.

INSTITUTIONAL AND CONCEPTUAL BACKGROUND

Institutional Background

Shipping fee is an essential component of the marketing mix (Lewis et al. 2006). It determines online shoppers' purchase decisions and greatly impacts retailers' profitability. Consumers are highly aware of shipping fees, which drive over 60% of them to abandon their shopping cart (Jupiter Communications 2001). Under this situation, free shipping has become a necessary incentive to stimulate consumers' online purchases (Lewis 2004). Among top retailers who offer free shipping, only 17.5% of them offer free shipping on all orders (Digital Commerce 2019). In comparison, over 65.4% of them offer free shipping under certain conditions, such as CFS and MFS (Digital Commerce 2019).

CFS is one of the most popular free shipping policies. It can increase sales revenue since consumers have to buy more to satisfy the free shipping requirement. According to a recent survey, 58% of consumers have added items to their shopping carts to qualify for free shipping (ComScore 2014). However, CFS may reduce store traffic (Lewis et al. 2006) when consumers purchase extra items and use them in the future. To increase competitive advantage, retailers begin to roll out MFS on top of CFS. The prototype of MFS is Amazon Prime. Although it now comes with other services, such as Prime video, the initial design of Prime offers only unlimited free shipping with a membership fee. Over 70% of consumers state that free shipping is the primary reason driving them to enroll in Amazon Prime (Statista 2020). Currently, there are over 100 million Prime members globally (Forbes 2018). Having witnessed Amazon's success in retaining consumers with Prime, retail giants, such as Walmart, CVS, Lululemon, etc., promote similar MFS programs with the expectation to retain consumers while recovering shipping costs with membership fees (Tan et al. 2015). Next, we review shipping policy literature relevant to this study.

Literature Review

Free shipping promotion and CFS. Prior research has shown that shipping costs greatly influence consumers' purchase frequency and order size. Using transaction data from an online grocery and drugstore store, Lewis et al. (2006) examine the impact of different shipping fee schedules on consumers' order incidence and order size. They find that both free shipping promotion and CFS effectively boost sales, but the shipping costs may make such promotions unprofitable to retailers. Moreover, they find heterogeneity in responses across consumers and suggest retailers provide customized shipping offerings.

Similarly, Lewis (2006) finds that free shipping promotion leads to the highest order incidence with the smallest order size, and CFS always outperforms free shipping promotion in acquiring consumers and increasing retailers' profits. Yang, Essegaier, and Bell (2005) also conclude that CFS influences consumers' repeated purchase behavior more effectively than free shipping promotion. Chen and Ngwe (2017) reveal that retailers should modify product prices based on different product categories when changing free shipping thresholds. More recently, Shehu et al. (2020) find that free shipping promotions are unprofitable as they may lead to riskier purchases, which have a high return probability.

Membership free shipping (MFS). A limited number of analytical studies have started to examine the performance of MFS. Tan et al. (2015) compares the profitability between CFS and MFS in a duopolistic setting and conclude that MFS with expedited shipping can generate a higher profit due to price discrimination. Sun et al. (2017) study how MFS affects a single shipping platform (e.g., eBay) and its third-party sellers' profits. They find that MFS can induce high demand and product price, benefiting both sellers and the platform. Although they add profit implications of MFS, their investigations are not in common MFS application settings, where a retailer can adopt CFS and MFS simultaneously. Our study differs from them in at least three aspects. First, we quantify the MFS enrollment effect on consumer actual purchase behaviors from multiple dimensions with real-world data. Second, we evaluate the effectiveness of MFS in conjunction with CFS so that our study could reveal the impact of MFS on top of CFS, which is in line with the real business setting. Third, we further investigate the sources of heterogeneity in the enrollment effect, providing more managerial implications for retailers to maximize MFS profitability.

BEHAVIORAL EFFECTS OF MFS ENROLLMENT

Prior literature on membership programs suggests that program-related factors, such as participation requirements and reward design, can affect consumers' purchase behaviors and loyalty (e.g., Liu and Yang 2009; Yi and Jeon 2003). We thus predict the impact of MFS on consumers' longitudinal purchase behaviors by linking two salient and unique program characteristics—unlimited free shipping and upfront membership fee— to four behavioral effects, including no-minimum free shipping effect, promotion synergy effect, switching cost effect, and sunk cost effect. Figure 1 shows the predictions.

No-minimum free shipping effect. Prior studies suggest that consumers are sensitive to shipping fees and thus responsive to free shipping promotion (Chatterjee 2011; Lewis et al. 2006). Recall that, in our empirical setting, the retailer offers nonmembers CFS (i.e., free shipping above a threshold). Compared with nonmembers, MFS members could enjoy the no-minimum free shipping and thus have no incentive to place large orders (Lewis 2006; Lewis et al. 2006). As a result, consumers may purchase more frequently with smaller order sizes after enrollment. Meanwhile, orders below the CFS free shipping threshold may be abandoned due to shipping fees that will now be completed because of no-minimum free shipping. Thus, consumers' total spending is expected to increase as well.

No-minimum free shipping may also change consumers' purchase variety in terms of purchase breadth and types. Without MFS, consumers often concentrate their purchases within limited product categories to meet CFS free shipping threshold or minimize shipping fees (Chen and Ngwe 2017). After enrolling in MFS, consumers are more likely to explore various product categories with different price levels to fit their true preferences as their orders are no longer subject to any free shipping requirement (Rothschild 1974). We thus expect the no-minimum free shipping effect to positively affect purchase breadth. No-minimum free shipping also reduces consumers' transaction costs. Such monetary benefit can effectively stimulate consumers' impulse purchases as it alleviates their feeling of guilt on buying hedonic items (Khan and Dhar 2010). However, it may not directly affect consumers' purchase of nonimpulse products as these are necessities that consumers will buy regardless of the shipping fee. We thus expect the no-minimum free shipping effect to affect purchasing impulse products positively but have no impacts on nonimpulse products.

Promotion synergy effect. As shipping fees add to the consumers' total expenditure, free shipping has been regarded as a format of price promotions that reduces consumer transaction costs (Lewis 2006). Previous literature has shown that a combination of different promotion vehicles may form synergies or interaction effects on consumers' purchase decisions (e.g., Chen and Rao 2007; Naik, Raman, and Winer 2005). In MFS, members can enjoy free shipping with other price promotions simultaneously. The substantial saving by purchasing promoted products on top of free shipping may entice members' great responsiveness to promoted products. The success of many real-world cases, such as Amazon Prime Day (i.e., price discounts offered exclusively to Prime members), demonstrates the synergy effect of free shipping and price discount on consumers' spending. Therefore, we expect the promotion synergy effect to increase consumers' responsiveness to price promotions after enrollment.

Switching cost effect. Prior literature suggests that membership programs can lock in consumers by increasing switching costs (Henderson, Beck, and Palmatier 2011). In the context of MFS, consumers face both high economic and noneconomic switching costs. The economic switching costs are constituted by the initial investment (i.e., membership fees) and the savings from free shipping benefits (Leenheer et al. 2007). The noneconomic switching costs include learning cost (i.e., learning about another retailer), search cost (i.e., searching for equivalent free shipping promotions and price discounts), and psychological cost (i.e., giving up the satisfaction and trust with the retailer) (Dick and Basu 1994). A well-established finding from previous literature is that switching costs increase consumer repurchase attention and enhance loyalty. Switching costs drive repeat purchases, increasing wallet share (Bolton, Kannan, and Bramlett 2000). When consumers repeatedly patronize a business, they exhibit behavioral loyalty (Liu-

Thompkins and Tam 2013). Moreover, switching costs could moderate the relationship between important determinants, including customer-perceived value (e.g., Yang and Peterson 2004), satisfaction (e.g., Fornell 1992), and consumer loyalty (Leenheer et al. 2007). Therefore, switching costs also have a profound explanatory effect on consumer attitudinal loyalty. We expect switching costs to positively affect consumer spending after MFS enrollment because of the increased behavioral and attitudinal loyalty. As loyal consumers' goodwill and trust increase their intention to expand purchase scope (Aurier and Goala 2010), they may purchase from categories previously bought from other retailers, increasing purchase variety and purchasing impulsive products. Moreover, as consumer loyalty to the retailer develops over time, we expect the effects of switching costs on consumer purchase behavior to become stronger.

Loyalty can also reduce consumers' price sensitivity (Van Heerde and Bijmolt 2005). Because loyal consumers focus more on the relationship with the retailer and thus are willing to pay a premium to continue purchasing with their preferred retailers rather than incur additional search costs, while less loyal consumers focus mainly on the economic aspects and are persuaded to buy only if the price is low enough (Reichheld and Sasser 1990). In the context of MFS, as members develop loyalty to the retailer due to increased switching costs, they are less likely to present opportunistic behaviors and chase promotional benefits than nonmembers. Therefore, we expect the switching costs to weaken consumers' responsiveness to price promotion.

Sunk cost effect. The upfront membership fee is an invertible cost in consumers' mental accounts. It represents a sunk cost, which has shown to be very effective in encouraging consumers to commit to their prior choices (Dick and Lord 1998). Once the membership fee has been paid, consumers have a greater tendency to continue utilizing the membership benefits to maximize their investment (Ailawadi et al. 2018). Moreover, to justify the money spent on the membership fees, consumers will form a positive attitude toward their chosen retailer (Ashley et al. 2016), which affects their commitment and loyalty in the long term (Dick and Lord 1998). Therefore, we expect that the sunk cost of membership fees should have similar effects on consumers' purchase behaviors as the switching cost effect. That is, sunk cost positively influences MFS members' purchase amount and purchase variety while negatively impacting members' responsiveness to price promotion.

Overall, we expect a positive impact of MFS on consumers' total spending, purchase frequency, and purchase variety because of the no-minimum free shipping effect, switching cost effect, and sunk cost effect. However, we expect members' order size to decrease after enrollment because unlimited free shipping is the main reason consumers enroll in MFS. It is unclear how MFS enrollment may influence consumers' responsiveness to price promotion because of the opposite effects of promotion synergy and enhanced consumer loyalty resulting from switching costs and sunk costs.

<Insert Figure 1 about here>

DATA AND VARIABLE OPERATIONALIZATION

Data Overview

We obtain consumer order-level transaction data from a major online retailer in Asia, one of the top 10 online B2C platforms based on market share. It carries a large variety of product assortment, including apparel, electronics, beauty products, home goods, books, etc. The retailer provides us with 36 months of customer transaction data. A vital feature of this dataset is that the retailer launched MFS in the 22nd month of the observation period. To enroll in MFS, consumers pay an annual membership fee for unlimited free standard shipping on all orders. Before the launch of MFS, the retailer offered CFS to all consumers. The CFS is still applicable to consumers who choose not to enroll in MFS. The retailer requires the same minimum purchase amount for CFS during the observation period. The MFS launch was announced via multiple marketing channels such as the retailers' website, opt-in email, and media news. After launching MFS, the retailer did not engage in targeted promotions for members during the observation period, and there was no price discrimination between members and nonmembers. Other than the shipping policy, no significant business changes occurred during our observation period.

Given the data privacy and security reason, the retailer conducted a random selection from its database. To ensure the data is valid for the causal estimation of MFS enrollment, which compares consumers' behavior changes in the pre- and post-enrollment periods between members and nonmembers, we apply the following criteria for consumer inclusion. First, we exclude new consumers who start to shop at the retailer after the MFS launch and consumers who churned anytime between the start of the sample and 12 months after the MFS launch to ensure that pre- and post-enrollment comparison is possible. Second, we only include members who enrolled in MFS at least 12 months before the end of the sample period, which is necessary to analyze MFS enrollment's long-term impact as the membership duration is 12 months after the enrollment. Lastly, we exclude outliers who are possible third-party buyers and have made over 300 orders per year from a single product category and consumers who have exclusively purchased digital items such as e-gift cards and e-books, to which shipping policies are not applicable. After the filtering process, the final sample contains 3,898 consumers, including 1,523 members and 2,375 nonmembers. The order-level transaction data includes a pre-launch period of 22 months and a post-launch period of 14 months. Each transaction records consumer ID, order ID, order type, purchase date and time, delivery method, shipping fee, product category, brand, quantity, transaction amount, and promotion indicator. Moreover, we supplement these data with publicly available city-level data on socioeconomics.

Variable Operationalization

We list the variable operationalization in Table 1 and begin with the outcome variables.

Outcome variables: consumers' purchase behaviors and retailers' profits ($\boldsymbol{Y_{it}}$*)*

As our research objective is to assess the MFS enrollment effect on consumers' purchase behaviors and retailers' profits, we define three sets of outcome measures related to consumers' purchase behaviors, including the purchase amount, purchase variety, responsiveness to price promotions, and one measure related to the retailers' profit.

Consumers' purchase behavior— how much to buy. We first measure a consumers' *spending* (defined as purchase amount in a given month). As total spending is determined by purchase frequency and order size that may change with different shipping policies (Lewis et al. 2006), we thus include *purchase frequency* (defined as the number of orders in a month) and *average order size* (defined as average purchase amount in each order) as another two measures.

Consumers' purchase behavior — what to buy. We investigate the purchase variety and types of products in consumers' shopping baskets. *Purchase variety* is measured by counting the number of distinct product categories a consumer purchases. For the product type, we group products into impulse and nonimpulse purchase types according to the criteria proposed by Bellenger, Robertson, and Hirschman (1978) and Xu et al. (2017). With their classification scheme, we define *impulse purchases* as the percentage of spending on product categories, including clothing, shoes, bags, food, cosmetics, movies, mobile/video games, and music. In addition, we investigate customers' sensitivity to promotion after enrolling in MFS by defining *promoted purchases* as the percentage of spending on promoted products.

Retailers' profits. Free shipping may increase demand but shift high shipping costs to retailers (Sun et al. 2017). Thus, the profitability of MFS is not apparent as it is determined by the balance between the revenue generated from sales and membership fees and the costs of free shipping. To assess the profit implication of MFS, we account for (1) the revenue generated by the consumers' purchases, (2) the revenue from membership fees, and (3) the shipping costs absorbed by the retailer. Specifically,

$$Profit_i = \begin{cases} \sum_j \left(Spend_{ij} \times ProfitMargin - ShipCost\right) + MembershipFee_i & Members \\ \sum_j \left(Spend_{ij} \times ProfitMargin - ShipCost * \mathrm{I}\left(Size_{ij} > C_f\right)\right) & NonMembers \end{cases} \quad (1)$$

where, $Profit_i$ is what the retailer earns from customer i. $Spend_{ij}$ is consumer i's purchase amount in order j. *ShipCost* is the shipping costs absorbed by the retailer. $MembershipFee_i$ is the annual membership fee paid by customer i. $\mathrm{I}(Size_{ij}>C_f)$ is an indicator variable, which equals one when the order size, $Size_{ij}$, is greater than C_f, and 0 otherwise. The above equation reflects that the retailer bears the shipping cost for all orders from members and the large-sized orders ($Size_{ij} \geqslant C_f$) from nonmembers. Nonmembers pay the shipping costs of small-sized orders ($Size_{ij}<C_f$).

*Treatment variable: MFS enrollment (**$Enroll_i$**)*

Treatment starts at different times for different consumers. In our dataset, consumer i decides to either enroll in MFS (i.e., members, as the treatment group, $Enroll_i$=1) or not enroll (i.e., nonmember, as the control group, $Enroll_i$=0).

*Control variables (**X_i**)*

Pre-enrollment purchase characteristics. Since consumers' past purchase behavior may influence their future purchase decisions (Ansari, Mela, and Neslin 2008, Hughes 2000), we construct three groups of pre-enrollment purchase characteristics that are related to *purchase amount* (i.e., Pre-enrollment *total spending*, *purchase frequency*, *average order size*), *purchase* *variety* (i.e., Pre-enrollment *purchase breadth*, *spending on top10 best-selling*, *book purchases*), and *response to price promotion* (i.e., Pre-enrollment *percentage of spending on promoted items*) and *response to shipping fee* (i.e., Pre-enrollment *percentage of orders paying shipping fee*). Consumers who often pay shipping fees and ignore the CFS requirement are less sensitive to shipping fees. Thus, the pre-enrollment percentage of orders paying shipping fees helps us control the possible impact of sensitivity to shipping fees on consumers' purchase behavior.

Pre-enrollment shipping characteristics. Besides shipping fees, shipping methods and the delivery speed may also influence consumers' online shopping motives (Frischmann, Hinz, and Skiera 2012). We construct the following variables related to shipping and delivery. *Home to shipping center distance* is operationalized as the approximate distance from a consumers' shipping address to the closest distribution center. Consumers located closer to a shopping center often experience faster delivery speed. Pre-enrollment *shipping methods* are a vector of variables that capture the percentages of each shipping method a consumer used before enrollment. The shipping methods include *standard delivery*, *express delivery*, *pick-ups*, and *scheduled delivery*.

Please note that both pre-enrollment purchase characteristics and shipping characteristics variables are computed with consumers' historical purchase data at least one year before the MFS launch date (1^{st} month-10^{th} month).

Socioeconomic and demographic variables. We gather additional socioeconomic data from the National Bureau of Statistics before the MFS launch, including the city-level *average income*, *population*, *unemployment rate*, and *internet penetration rate*. These variables may be correlated with consumers' purchase outcomes. For example, consumers living in high-income areas or with a high internet penetration rate may do more online shopping. Besides, we identify whether a consumer has kids based on her transaction histories (Lewis et al. 2006) and include indicator *kid* as a demographic variable.

<Insert Table 1 about here>

RESEARCH DESIGN AND METHODOLOGY

Identification Strategy

Our research goal is to estimate the effect of MFS enrollment on consumers' purchase behaviors and retailers' profits. Consumers may join the program when the perceived value of membership benefits exceeds the cost of enrollment. Thus, their decision to enroll is endogenous. For example, frequent buyers are more likely to enroll in MFS to avoid shipping fees. In contrast, occasional buyers have no incentive to enroll as they often accumulate purchases to meet the free shipping requirement. Since the membership enrollment is not randomly assigned and we cannot observe the counterfactual, i.e., the outcomes when the same MFS members do not enroll in the program, we examine nonexperimental variation by carefully controlling for the selection bias. To this end, we adopt a difference-in-difference (DID) approach with propensity score matching and Heckman correction (Heckman 1979; Gu and Kannan 2021; Rosenbaum and Rubin 1983). The DID method has been extensively used to quantify the treatment effect by comparing the outcomes between the treated and control groups before and after a given treatment period (Meyer 1995). We measure the relationship between MFS enrollment and purchase behaviors for the enrolled consumers in our setting. Therefore, our DID estimates represent a local average treatment effect (LATE) than an average treatment effect (ATE) for the population. The propensity score matching process addresses the endogeneity of enrollment on observables by matching members (i.e., treated group) with similar nonmembers (i.e., control group) based on a rich set of observed characteristics (Rosenbaum and Rubin 1983). The matching process ensures that nonmembers would be close "clones" of members before the treatment (Guo, Sriram, and

Manchanda 2021) and with the exception that nonmembers "randomly" do not enroll in MFS. We next use a formal Heckman correction to control for endogeneity of enrollment due to unobserved factors (Heckman 1979) and identify cases where the instrument variable may be confounded. We also apply a falsification test to show that the instrument meets the exclusion restriction. Lastly, we have done a series of robustness checks to show the stability of our results, including an analysis using late members as an alternative control group for early members.

Difference-in-Difference Regression

We first specify a baseline DID regression. Once consumers enrolled in MFS, their membership privilege lasts for 12 months. The baseline DID is used to estimate the average enrollment effect of MFS on consumers' purchase behaviors and retailers' profits. Specifically, we compare the changes in outcome measures 12-month before and 12-month after the MFS enrollment date for members with those for matched nonmembers. We thus specify the baseline DID regression model as:

$$Y_{it} = \alpha_0 + \alpha_1 Enroll_i \times Post_{it} + \tau_t + \theta_i + \varepsilon_{it} \tag{2}$$

where, Y_{it} (outcome variables for customer i at month t), $Enroll_i$ (treatment variable for customer i). $Post_{it}$ is a dummy variable equals to one for periods after customer i's enrollment date and 0 otherwise. Her matched nonmember will share a similar value for this indicator (Xu et al. 2017). The focal estimate is α_1, the coefficient of $Enroll_i \times Post_{it}$. It captures the average treatment effect of MFS enrollment, i.e., the changes of outcomes for members after enrolled in MFS relative to those for nonmembers. We also include month-fixed effect τ_t and individual-fixed effect θ_i in the DID specifications. ε_{it} is the error term clustered by consumers.

As discussed earlier, consumers' behavior may change longitudinally after enrollment. We thus examine the dynamic effect of MFS enrollment by dividing the 12-month pre- and post-enrollment period into seven quarters. Specifically, we modify Equation 2 as:

$$Y_{it} = \alpha_0 + \alpha_1 Enroll_i + \sum_{t=-3}^{4} \gamma_t Post\_quarter_t + \sum_{t=-3}^{4} \alpha_t Enroll_i \times Post\_quarter_t + \varepsilon_{it} \qquad (3)$$

where, $Post\_quarter_t$ is a dummy variable that denotes three quarters before customer i's enrollment and four quarters after enrollment. Next, we discuss how to address the issue of endogenous enrollment.

Control for Selection on Observables with Propensity Score Matching

Propensity score matching (PSM) is the most used statistical technique when addressing selection bias in observational studies (Rosenbaum and Rubin 1983). The fundamental idea of PSM is to match the treated group to similar subjects in the control group based on the observed covariates and propensity to be treated. Then, the matched control group resembles the treated group in every aspect except for not being treated (Rosenbaum and Rubin 1983). Applied to our setting, we pair each member with a comparable nonmember who has the same probability of MFS enrollment but "randomly" did not do so during the observation period.

We take the following two steps to implement PSM. First, we calculate each consumers' propensity score (i.e., the probability of MFS enrollment) using a binomial logit model. When considering what factors influence consumers' enrollment decisions, we follow prior literature on membership programs, which suggest that the attractiveness of a membership program may depend on factors, such as consumers' usage levels, perceptions of program benefits, and demographic characteristics (e.g., Kim, Shi, and Srinivasan 2001; Leenheer et al. 2007; Liu 2007). Since the control variable ($\boldsymbol{X_i}$) cover all these factors, we regress consumers' enrollment decisions based on them as follow:

$$\Pr(Enroll_i = 1) = \Pr\left(\beta_0 + \boldsymbol{\beta X_i} + \eta_i > 0\right) \qquad (4)$$

where, η_i is type one extreme value distributed error term. Please note that $\boldsymbol{X_i}$ is a set of time invariance control variables computed based on consumers' purchase and socioeconomic data before the MFS launch date (1st month-22nd month). We report the results of the logit propensity score model in Table B1 of the Web Appendix B. The estimates direction has shown face validity: consumers with higher spending, purchase frequency, and purchase variety are more likely to enroll in MFS. Consumers who have kid(s) have higher enrollment probabilities than non-kid consumers. Notably, consumers who regularly use the pick-up service and scheduled delivery or live further from the distribution center are less likely to enroll because standard free shipping offered by MFS is less valuable to them.

We next match nonmembers to similar members based on the estimated propensity scores. The baseline matching algorithm takes the 1:1 matching with a caliper and replacement[1]. This matching algorithm can generate the closest matched pairs without dropping a large proportion of members who do not have ideal nonmembers to match. We also apply other matching algorithms as robustness checks to assess the results' stability and discuss them later.

After the above steps, 89% of members (1,362 out of 1,523) in our sample are matched with similar nonmembers[2]. To test the validity of our propensity score matches, we conduct a set of statistical analyses. We first compare the distributions of propensity scores between members and nonmembers before and after the matching procedure. Figure 2 shows that the distributions are visually indistinguishable after matching relative to before matching. Next, we compared the mean value of observed characteristics ($\boldsymbol{X_i}$) between members and matched nonmembers. The t-tests indicate no difference between members and nonmembers in terms of observed covariates

[1] We use a caliper size 0.01 times the standard deviation of the overall propensity score in the baseline model. we also apply different caliper sizes and/or without replacement, and without matching in the robustness checks section.
[2] Around 11% of members were dropped because their matched nonmembers have churned before the enrollment date or no nonmembers fall into the match range of propensity score of members.

(Table B2 of the Web Appendix B), which is another piece of evidence showing the validity of our matching (Datta, Knox, and Bronnenberg 2018; Rosenbaum and Rubin 1983).

<Insert Figure 2 about here>

Moreover, to test whether the DID approach holds the assumption of parallel pretreatment trends with the matched sample, we conduct a "placebo" test using pre-enrollment data (1-21 months) and define a placebo "enrollment" at the 10^{th} month (the midpoint of consumers' pre-enrollment data) (Datta et al. 2018). We then estimate Equation 2 for all dependent variables with the "placebo enrollment". The results in Table B3 of Web Appendix B suggest no significant treatment effect for placebo treatment, and the pretreatment trends are statistically equivalent across matched groups.

Control for Selection on Unobservables

To control for the endogeneity of MFS enrollment due to unobservables, we utilize the two-stage Heckman correction model (Heckman 1979). As the enrollment decision ($Enroll_i$) is an endogenous variable, we model it with an instrumental variable in the first stage and obtain the inverse Mills ratio (IMR). We then include IMR as an additional covariate in the second stage DID models. Specifically, we use the percentage of members in a consumers' zip code as an instrumental variable. It is correlated with the consumer enrollment decision because people around a customer may form peer effects that influence a consumers' decision to join a membership program (Bapna and Umyarov 2015). The more people around her enroll in MFS, the higher probability she will enroll. We test the strength of the instrumental variable using the incremental F-statistic in the first stage regression. The F-statistic is at 114 that meets the hurdle of 10 (Staiger and Stock 1997), indicating the correlation between the instrumental variable and endogenous enrollment decision.

More importantly, the instrumental variable should satisfy the exclusion restrictions, i.e., it has no direct effect on consumers' purchase outcomes, and the only way it affects the outcomes is via affecting their enrollment decision (Nunn and Wantchekon 2009). It is reasonable to assume that neighbors' enrollments do not directly impact a consumers' purchase outcomes. Undeniably, the percentage of members in an area may be correlated with local socioeconomic features, which also drive consumers' purchase outcomes, such as internet penetration rate, population, unemployment rate, and income. However, as discussed earlier, we have controlled these socioeconomic features with a rich set of covariates in the model.

To further confirm the exclusion restriction is satisfied, we follow previous literature and perform a falsification exercise (e.g., Ailawadi et al. 2018; Nunn and Wantchekon 2009). We examine the reduced form relationship between the percentage of members in a consumers' zip code (the instrument) and her purchase outcomes using a sample of consumers who purchase exclusively digital products (e.g., e-cards, e-books). Because no shipping or delivery is necessary for digital products, these consumers are not subject to any shipping policies, including MFS enrollment. Therefore, it is reasonable to assume that MFS does not apply to this sample. Suppose the instrument variable only affects purchase outcome through MFS enrollment. In that case, we expect to see no relationship between the percentage of members in an area and consumer purchase outcomes for this digital-purchase-only sample after controlling for other observed variables. Indeed, Table B4 of Web Appendix B shows that the coefficient of the percentage of members is not significant for any purchase outcome variables. Therefore, we have theoretical and empirical justification for the exogeneity of our instrument variable. Moreover, we have done a series of robustness checks to demonstrate the stability of our results, including an analysis using late members as an alternative control group for early members. We discuss these analyses in the robustness check section.

EMPIRICAL RESULTS

We report the average treatment effect of MFS enrollment over the 12-month membership period (Equation 2) and the dynamic treatment effects across four quarters of the membership period (Equation 3) on all outcome variables in Panel A and Panel B of Table 2, respectively. We find that the coefficients of IMR are mostly significant for both models and across different outcomes. This result indicates that the estimates of the enrollment effects would be biased without controlling for self-selection using the IMR correction term. We next discuss the main results of the MFS enrollment effects. Please note that we use log-transformed dependent variables, and the elasticities of MFS enrollment should be interpreted with an exponential transformation of the treatment effects.

<insert Table 2 about here>

Consumers' Purchase Outcome

Purchase amount. We first investigate whether MFS enrollment leads to an increased purchase. We surprisingly find no significant average treatment effect on consumers' spending over the 12-month membership period (Panel A first column in Table 2). However, when we look at the changes in their spending over time, we observe an increasing trend in spending in the long term. Specifically, we find that their spending has no significant change in the first two quarters after enrollment (Q1-Q2), but their spending significantly increases from 16.18% to 20.93% in the last two quarters (Q3-Q4). This might be because members' purchases have been locked after enrolling in MFS over time due to the increased switching and sunk costs.

To provide granular level implications of consumers' post-enrollment purchase behavior, we delve into consumers' purchase frequency and average order size (Columns 2 and 3 in Table

2). We find that consumers purchase more frequently (0.19, p<.01) with a smaller order size (-0.16, p<.01) after enrollment. The no-minimum free shipping benefit is the main driver of this change. We find similar upward trends in consumers' purchase frequency and order size by looking at the dynamic patterns. Consumers' purchase frequency continuously increases over time from 20.92% to 32.31% and reaches the highest level in the last two quarters after enrollment. Similarly, although there is a significant decrease in order size in the first quarter of enrollment (-22.89%), the reduction of order size attenuates in the next two quarters (-15.63%- -11.31%), and becomes insignificant in the last quarter of enrollment. These results again support the positive impact of MFS enrollment on consumers' purchases in the long term. Especially in the last quarter of enrollment, consumers keep a high purchase incidence rate without exploiting free shipping benefits (i.e., no change in order size). This behavior change would greatly benefit retailers in the long-term as they gain more revenue but less shipping costs.

Purchase variety. We find that consumers purchase from a broader product category after enrollment (0.13, p<.01), and the enrollment effect on their purchase breadth amplifies over time (Column 4 in Table 2). The result indicates that no-minimum free shipping can diversify consumers' purchases into more categories. As the switching and sunk costs motivate consumers to purchases with the committed retailer, they are more likely to explore other product categories. The finding further explains why consumers' spending increases gradually.

Moreover, average consumers' spending on impulse products slightly increases by around 3.30% over the membership period. This increase reaches the highest in the first quarter and slightly decreases over time (Column 5 in Table 2). The incremental spending on impulse products supports that no-minimum free shipping induces more unplanned and immediate consumption needs.

Interestingly, enrolled consumers become less promotion-driven over the membership period (Column 6 in Table 2). Their spending on the promoted items decreases by around 9.30% on average. The result suggests that sunk cost and switching cost effects overwhelm the synergy effect of multiple promotions. As MFS strengthens consumers' commitment to the retailer, they focus more on the relationship with the retailer and membership benefits. As a result, they become less price sensitive.

Retailers' Profitability

Column 7 in Table 2 presents the retailer's profits from enrolled members after accounting for the membership fee and free shipping costs. Although we do not find an overall increase in consumers' spending, we observe an average increase in profit by 36.34% from each member over the membership period. It suggests that the membership fee could compensate for the increased shipping costs and is an additional revenue source. The result is consistent with real-world cases. For example, the Prime membership fees accounted for 6.8% of Amazon's annual revenue (Digital Commerce 2019). Costco's revenue from membership fees has seen steady growth over the years by 7% (Costco Annual Report 2019).

HETEROGENEITY IN ENROLLMENT EFFECTS AND TARGETING STRATEGY

Consumers' responses to MFS might differ, and not all consumers are profitable (Lewis 2004; Liu 2007). Understanding such individual-level heterogeneous effects of MFS enrollment can help retailers improve their member acquisition strategies and achieve efficient targeting when promoting MFS. Since the ability of DID regression to recover the fine-grained heterogeneous treatment effects is limited (Guo et al. 2021), we leverage Causal Forest (CF) to obtain point estimates and the significance of the treatment effect of MFS enrollment for each member (Athey et al. 2019). Given the knowledge of individual consumers' responses to MFS, we conduct two additional analyses. We first relate consumers' heterogeneity to their pre-enrollment characteristics and provide insights into which customer segment is more valuable to target. In the second analysis, we simulate retailers' profit under different targeting schemes. We demonstrate that targeting consumers based on their response to MFS is more effective than the traditional practice of targeting based on enrollment probability or pre-enrollment spending level.

Causal Forest and Individual Level Treatment Effects of MFS Enrollment

CF is a recently developed approach that combines random forest in machine learning and causal inference in economics (Athey et al. 2019). It estimates individual-level treatment effects with valid asymptotic confidence intervals based on pre-defined covariates (i.e., $\boldsymbol{X_{it}}$) and their nonlinear transformations. The CF method has been increasingly applied in marketing studies, such as churn management (Ascarza 2018), marketing intervention (Chen et al. 2020), and information disclosure (Guo et al. 2021). Next, we provide a brief discussion of this method and refer readers to Web Appendix D and Athey et al. (2019) for details.

CF consists of thousands of individual causal trees. Each causal tree recursively splits a randomly selected training sample into various subsamples based on a subset of covariates. The split is carried out by optimizing a revised Gini criterion until no further improvement can be achieved with at least k observations of each class in a leaf (Athey et al. 2019). The most similar consumers locally in the covariate space will be clustered into the end split known as a leaf (L). The treatment effect of MFS enrollment, $\hat{\tau}(x)$, is estimated by taking the differences between the mean outcomes of members and nonmembers in the same leaf:

$$\hat{\tau}(x) = \frac{1}{|\{i: Enroll_i = 1, X_{it} \in L\}|} \sum_{\{i:Enroll_i=1, X_{it}\in L\}} Y_i - \frac{1}{|\{i: Enroll_i = 0, X_{it} \in L\}|} \sum_{\{i:Enroll_i=0, X_{it}\in L\}} Y_{i.} \quad (5)$$

In the above equation, $Y_i = \log(Y_i^{post}) - \log(Y_i^{pre})$, and Y_i^{pre} (Y_i^{post})is the aggregated outcomes over 12 months before (after) the MFS enrollment. Therefore, Y_i captures the annual change in outcomes due to MFS enrollment. Since our heterogeneity analysis aims to identify the most valuable consumers to the MFS program, we only focus on the following two most relevant outcomes: consumers' total spending and retailers' profits during the membership period. Once the CF generates an ensemble of causal trees ($\boldsymbol{B}$), each with an estimate $\hat{\tau}_b(x)$, the average treatment effect is obtained by averaging the predictions from those trees as $\hat{\tau}(x) = B^{-1}\sum_{b=1}^{B}\hat{\tau}_b(x)$.

Table 3 and Figure 3 show the distribution of the customer-level enrollment effect estimates with a 95% confidence interval. We find substantial heterogeneity in the customer-level enrollment effect. First, not all consumers significantly increase their spending and bring profits to retailers after MFS enrollment. Specifically, MFS enrollment has a significant effect on about 50% of consumers, and the retailer even loses money from a small proportion of consumers who experience a negative effect[3]. Second, there is a great variation in consumer profitability. Profitable consumers' spending increases by 23.20% – 245.56%, and profit contribution increases by 34.37% – 289.62% after enrollment.

<Insert Table 3 and Figure 3 about here>

Heterogeneity in Enrollment Effects across Customer Segments

Following Chen et al. (2020) and Guo et al. (2021), we now examine the sources of treatment effect heterogeneity by regressing the individual-level estimates of enrollment effect on spending and retailers' profit ($\hat{\tau}_i$) on pre-enrollment purchase characteristics ($\boldsymbol{X_i}$) and several exploratory interactions[4]. This analysis helps us understand what consumer types could bring more sales and profits to the retailer.

Table 4 shows similar correlations between the enrolment effect on consumers' spending

[3] There are around 2% of consumers spend even less after enrollment, and 1% of consumers bring negative profits.
[4] Since pre-enrollment shipping characteristics, demographic and socioeconomic has no significant relationship with the individual treatment effects, we excluded them from the regression.

and retailers' profits and customer-related characteristics. There are three major findings to highlight. First, pre-enrollment spending and frequency have a nonlinear relationship with the treatment effect on consumer spending. A possible explanation is that heavy buyers, i.e., consumers with high pre-enrollment spending and high purchase frequency, are subject to the ceiling effect on consumption (Liu 2007). That is, consumers who have reached their consumption limit are less likely to change their subsequent consumption level. On the contrary, moderate buyers are still well under their consumption limits, or "ceilings", and more committed to the retailer than light buyers. As a result, retailers gain more sales from moderate buyers than other customers. Second, pre-enrollment purchase breadth positively correlates with the treatment effects on both spending and retailers' profit, suggesting that consumers who previously purchased from broader product categories tend to spend more after enrollment. The diversity of purchased product categories reflects that consumers have a more favorable attitude toward the retailer, making them more valuable (Dick and Lord 1998). Third, the percentage of pre-enrollment orders paying shipping fees negatively relates to the treatment effects, indicating that consumers who are sensitive to shipping fees (i.e., avoid paying shipping fees) are more responsive to MFS after enrollment. It is straightforward to see that this group of consumers is more likely to enjoy the benefit of unlimited free shipping and increase their spending and profit contribution after enrollment.

In sum, this analysis reveals that consumers who shop with the retailer at a moderate level, seek variety in product categories, and are sensitive to shipping fees, are the most profitable after MFS enrollment.

<Insert Table 4 about here>

Profits on Customer-Level Targeted Strategy When Promoting MFS: A Simulation

"We're targeting each of our audience segments …based on their relationship to Walmart… We've thought about if

you're just an occasional shopper to if you're a full omnichannel shopper who is already using online pick-up and delivery...."

--Walmart CMO William White

The Walmart CMO citation suggests that when Walmart promotes its MFS program, Walmart Plus, it targets customer segments based on their spending and multi-channel purchase experience (Monllos 2020). Similarly, another giant, JD.com, sent MFS membership invitations only to those whose annual spending is above a certain threshold (Wang 2015). The above examples reveal that retailers often target specific consumers to enroll in their MFS programs instead of attracting all populations, because of the possible low return of MFS programs. Moreover, too many members may lead to a backfire to a program by hurting customer experience with less distinctive feelings (Drèze and Nunes 2009). By examining the individual level treatment effect, we have shown that only around half of the enrolled consumers are profitable to the MFS program, and the retailer can even lose money from some consumers. Therefore, finding the optimal targeting strategy is crucial to the success of the MFS program.

The industry standard of MFS program targeting is generally achieved by selecting consumers based on their prior purchase amount (as suggested by the above examples) or their likelihood to enroll (e.g., Haenlein and Libai 2013). However, our heterogeneity analysis shows that heavy buyers are not necessarily the most profitable. Moreover, the treatment effects on consumers with high propensity scores to join are not always statistically significant. One disadvantage of these industry standards of targeting strategies is that consumers' heterogeneous responses to MFS are ignored, leading to a less effective and even futile program. Given the estimates of the individual level heterogeneous treatment effects obtained earlier, we propose a new targeting rule and recommend the retailer identify consumers based on their potential profit contribution after enrollment in this section.

Specifically, we compare the profit improvement of three targeting schemes, including targeting consumers based on (1) prior spending level (*high-spend*); (2) likelihood of enrollment (*high-response*); (3) expected profit contribution (*high-effect*). Correspondingly, we first sort consumers based on the total purchase amount 12 months before MFS enrollment, the propensity scores obtained from Equation 4, and consumer-level enrollment effect on profit from CF, respectively. Next, we select the top deciles of consumers from each scheme and calculate their overall profits increase if they enroll in MFS as follows:

$$\Delta Profit_{kn} = \sum_{i}^{N} Profit_i^{prior} \times \hat{\tau}_{profit,i} \times \Pr(Enroll_i = 1) \quad (6)$$

where $\Delta Profit_{kn}$ is the change in profit contribution for the top n% of consumers selected based on the $k_{(1,2,3)}$ targeting scheme. $Profit_i^{prior}$ is consumer *i*'s profit contribution in the 12-month pre-enrollment period. $\hat{\tau}_{profit,i}$ is the treatment effect on consumer *i*'s profit contribution estimated earlier, capturing the percentage change in consumer *i*'s profit contribution after enrollment. *Pr(Enrolli=1)* is the propensity score estimated using Equation 4.

There are three noteworthy takeaways from this targeting simulation on profits (Table 5). *First*, we find that the *high-effect* targeting scheme (i.e., target with the highest enrollment effect on profit, column 3) generates the highest profit gain compared with the other two targeting schemes. Especially when targeting the top 10% of the customer base, targeting *high-effect* consumers can generate up to 91% (39%) incremental profits than targeting *high-response* (*high-spend*) consumers. *Second*, when reaching 50% of the customer base for the *high-effect* targeting scheme, there is no more profit gain if the retailer targets the rest of the customer base as these consumers don't respond positively to MFS after enrollment. We can even see a slight decrease in profit gains if a retailers' target base increases from 90% to 100%, as the last decile of consumers could even hurt the retailers' profit after enrollment. *Third*, the *high-spend* targeting is more profitable than *high-response* targeting to the MSF program. The *high-spend* consumers have a stronger relationship with the retailer. Although they may not contribute additional spending due to the "ceiling effect", the retailer can still generate incremental profit from the membership fees. However, the high-response consumers are more likely to avail of free shipping benefits, causing higher shipping burdens that exploit profit margins.

In sum, the incremental profit results with different targeting schemes suggest that retailers can maximize the profitability of MFS by targeting high-effect consumers with positive enrollment effects and avoiding those with negative and insignificant enrollment effects.

<Insert Table 5 about here>

ROBUSTNESS CHECKS

Alternative control group. Another method we use to control selection on unobservables is modeling the enrollment effect with only members. Members resemble each other by sharing inherent unobserved characteristics that drive them to enroll simultaneously (Xu et al. 2017). The variation of enrollment dates enables us to use late enrolled consumers as an alternative control group for early enrolled consumers. Specifically, we consider consumers who enrolled in the first four months after the launch of MFS (i.e., 22^{nd} – 25^{th} month) as the treatment group, while consumers who did not enroll until the 26th month (i.e., 26^{th} – 36^{th} month) as the control group. This analysis is in the same spirit as the falsification analysis of Manchanda, Packard, and Pattabhiramaiah (2015) and look-ahead matching of Xu et al. (2017). The results remain consistent and similar to the main results.

Customer-level fixed effects and alternative matching algorithms. We have estimated a model with customer-level fixed effects. Moreover, we also estimate the model with different matching algorithms, including (1) the 1:1 matching without replacement; (2) matching with a bigger caliper size of 0.25 times the standard deviation of propensity scores to test the stability of results under more relaxed matching requirement; (3) the 1:3 nearest neighbors matching to check whether the results are sensitive to more than one matched control consumers (Xu et al. 2017); and (4) no matching and alternative intervention date to estimate a generic treatment effect of MFS on consumers who would potentially enroll in MFS after the launch date. The main coefficients of interest in the modeled static and dynamic enrollment effects are consistent with our baseline model.

CONCLUSIONS AND IMPLICATIONS

This paper is the very first study to quantify the effect of MFS enrollment on both consumers' purchase behaviors and the retailers' profitability using consumer purchase data from a top online retailer. Our findings suggest that MFS has limited ability to generate incremental spending from enrolled consumers. However, as consumers become more engaged with the retailer, customer loyalty grows, driving increased spending in the long run. Moreover, consumers purchase from more product categories, especially impulse products, and become less sensitive to price promotion. Those behavior changes attribute to MFS's unique features, i.e., upfront membership fees and free shipping benefits. These two features form sunk cost and switching cost effects, ensuring that the program remains top-of-mind for consumers. On average, the retailer can generate $17.16 additional monthly profits from each customer, or a $617.76 million increase in total annual profits[5]. The membership fees contribute to retailers' profits by funding the expensive free shipping and being an important revenue source.

This study also provides several managerial insights. First, our research helps inform the

[5] The approximate member base is estimated by its market share multiply the MFS member base of its largest competitor—JD.COM. The revealed of JD can be found from https://tech.qq.com/a/20191111/008002.htm

managerial dilemma of whether MFS pays off. The effectiveness of MFS is reflected from two perspectives. One is its influence on consumers' purchases, while the other is on retailers' financial outcomes after taking out the implementation costs (Bolton et al. 2000). Although unlimited free shipping is the most expected benefit by consumers, it is also the costliest benefit that may dilute retailers' profitability. Such trade-offs delay retailers' way of implementing MFS. Our research suggests that the membership fee is a new revenue source and can fund upfront instant benefits. Additionally, as membership fees build enrollment barriers, MFS will not appeal to all consumers such that the costs of free shipping benefits will not overly extend.

Second, our research suggests that it is profitable for retailers to adopt membership programs with a long-term scheme (annually) than a short-term one (monthly) as consumers' purchase behaviors change over time after enrollment, leading to time-varying profit outcomes. At the beginning of enrollment, consumers are more likely to exploit their unlimited free shipping benefits to get the most out of their investment. Such benefit-prone behavior may hurt retailers' profitability as those benefits always come with high costs. Consumers' purchase behaviors reveal that consumers reduce their order size with the highest degree immediately after enrollment, indicating they take full utilization of free shipping benefits. Even enrolled consumers purchase more frequently than before. In the short run, it is still hard for retailers to generate incremental revenue and lose profits due to the increased shipping costs. However, a long-term-oriented membership program can transform consumers' occasional purchases into repeat patronage behaviors and help consumers build up behavioral loyalty (Liu 2007), which will benefit retailers. Our results suggest that, in the post periods of enrollment, consumers' order size reverts to the pre-enrollment level while their purchase frequency reaches the highest level, indicating that consumers no longer take advantage of the no-minimum free shipping benefits and consolidate their purchases with the focal retailer. Since the profitability might be unchanged in the short term but increased in the long term, retailers should encourage consumers to enroll in an annual membership rather than a monthly recurring option.

Third, our research has important implications on managing customer portfolios and designing effective targeted acquisition strategies—the estimates of the individual-level enrollment effect highlight that consumers respond differently to MFS. Customer characteristics, such as prior spending level, variety-seeking behavior, and sensitivity to price promotion, influence the strength of MFS enrollment effect on consumers' purchase behaviors and profit contribution (e.g., Liu 2007; Meyer-Waarden 2007; Zhang and Krishnamurthi 2004). No more than half percent of enrolled consumers can bring incremental spending and profit, which means MFS seems to be fully profitable only when attracting the right consumers. Identifying consumers with higher profit contributions when promoting MFS is necessary.

Fourth, our research also has implications for retailers' product assortment operation with MFS. As consumers consolidate purchases and expand purchase categories, our research suggests that one way to strengthen behavioral loyalty is to increase the breadth of product categories. Paying the upfront membership fee gives MFS a natural advantage in retaining consumers as they do not want to waste such "investment" by shopping elsewhere. Moreover, as free shipping induces more hedonic and unplanned purchases, retailers may increase demand by recommending more impulse products.

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TABLES AND FIGURES

Table 1. Variable Operationalization

Var.	Operationalization
Outcome Variables (Y_{it})	
(1) How much to buy	
Spending$_{it}$	Total purchase amount for customer *i* at month *t*
Purchase_frequency$_{it}$	The number of orders for customer *i* at month *t*
Average_orde_size$_{it}$	The average order size for customer *i* at month *t*, which is computed by dividing *Spending*$_{it}$ by *Purchase frequency*$_{it}$
(2) What to buy	
Purchase_variety$_{it}$	The number of distinct product categories customer *i* purchased at month *t*
Impulse_purchases$_{it}$	The percentage of spending on impulsive products for customer *i* at month *t*
Promotioned_purchase$_{it}$	The percentage of spending on promoted items for customer *i* at month *t*
(3) Retailers_profits$_i$	The profit generated from customer *i* before or after enrollment after accounting for shipping costs
Focal Independent Variable	
Enroll$_i$	Indicator of whether customer *i* has enrolled in MFS (Member=1, Nonmember=0)
Control Variables (X_i)	
(1) Pre-enrollment Purchase Characteristics	
Pre-enrollment purchase amount	
Spending$_i$	The total purchase amount customer *i* made in pre-enrollment period
Purchase_frequency$_i$	The number of orders customer *i* made in pre-enrollment period
Average_order_size$_i$	The average order size customer *i* made in pre-enrollment period
Pre-enrollment purchase variety	
Purchase_breadth$_i$	The total number of distinct product categories customer *i* purchased
Spending_on_top10_best_selling$_i$	The total spending on the top 10 best-selling products customer *i* purchased
Book_purchases$_i$	The total spending on books customer *i* purchased
Pre-enrollment responsiveness to price promotion	
%_of_spending_on_promoted_items$_i$	The share of spending on promoted items customer *i* purchased
Pre-enrollment responsiveness to shipping fee	
%_of_orders_paying_ship$_i$*pingfee*$_i$	The percentage of orders which size is below CFS free shipping threshold for customer *i*
(2) Pre-enrollment Shipping Characteristics	
Home_to_shipping_center_distance$_i$	The approximate distance from consumer *i*'s shipping address to the closest distribution center
Used shipping options	
% of express shipping$_i$	*The percentage of express shipping consumer i used in the pre-enrollment period*
% of the scheduled shipping$_i$	*The percentage of scheduled delivery consumer i used in the pre-enrollment period*
% of pick-up$_i$	*The percentage of pick-up consumer i used in the pre-enrollment period*
(3) Demographic	
Kid$_i$	Indicator of whether customer *i* has kid(s) or not (has=1, not have=0)
(4) Socioeconomic	
Average income level$_i$	The average income level in consumer *i*'s neighborhood at month *t*
Unemployment rate$_i$	The unemployment rate in consumer *i*'s neighborhood at month *t*
Population$_i$	The population in consumer *i*'s neighborhood at month *t*
Internet penetration rate$_i$	The internet penetration rate of consumer *i*'s neighborhood at month *t*

Not. We used the same city to identify the neighborhoods. The dependent variables are computed at the customer-month level. The control variables (1)-(2) are computed using 1st-10th month data and (3)-(4) using data before the MFS launch date.

Table 2. Estimation Results

	How Much to Buy						What to Buy							
	Spending		Purchase frequency		Average order size		Purchase variety		Impulse purchases		Promoted purchases		Retailers' profits	
Var.	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
Panel A: Average Treatment Effect over 12 months Membership Period														
Enroll× Post	0.03	(0.04)	0.19***	(0.02)	-0.16***	(0.03)	0.13***	(0.01)	0.30***	(0.01)	-0.09***	(0.01)	0.31***	(0.08)
IMR	0.15***	(0.05)	0.09***	(0.03)	0.06	(0.05)	0.04**	(0.02)	-0.12**	(0.02)	-0.11***	(0.02)	-0.16	(0.12)
Panel B: Dynamic Treatment Effects across 4 Quarters of the Membership														
Enroll × PostQ1	-.07	(0.07)	.19***	(0.03)	-.26***	(0.06)	0.11***	(0.02)	0.05***	(0.02)	-0.09***	(0.02)		
Enroll × PostQ2	.07	(0.07)	.24***	(0.03)	-.17***	(0.06)	0.15***	(0.02)	0.02	(0.02)	-0.10***	(0.02)		
Enroll × PostQ3	.15**	(0.08)	.28***	(0.04)	-.12*	(0.06)	0.15***	(0.02)	0.04*	(0.02)	-0.09***	(0.02)		
Enroll × PostQ4	.19**	(0.08)	.27***	(0.04)	-.08	(0.07)	0.13***	(0.02)	0.03	(0.02)	-0.06***	(0.02)		
IMR	0.14***	(0.05)	0.09***	(0.03)	0.06	(0.05)	0.04**	(0.02)	-0.12***	(0.02)	-0.11***	(0.02)		
R^2	0.15		0.17		0.14		0.17		0.12		0.11		0.36	
Obs.	18,448		18,448		18,448		18,448		18,448		18,448		5,448	

Note. Robust standard errors clustered by each customer are in parentheses. IMR is the inverse Mills ratio from the first stage model of Heckman correction. To save space, we report the rest of the estimates in Table C5. of the Web Appendix C. *p<0.1; **p<0.05; ***p<0.01. Retailers' profits are computed by only one-year pre- and one-year post-enrollment periods

Table 3. Summary of Customer-Level Enrollment Effects from CF Estimation

	All					95% Significant					% of Sign.
	N	**Mean**	**S.D.**	**Min**	**Max**	**N**	**Mean**	**S.D.**	**Min**	**Max**	
Spending	2,724	0.18	0.60	-1.78	1.24	1,241	0.57	0.49	-1.78	1.24	46%
Profits	2,724	0.31	0.58	-1.79	1.36	1,375	0.71	0.32	-1.75	1.36	50%

Note. All refer to a summary of estimation from all consumers, while 95% significant are results from consumers whose enrollment effect is significant. We compare the annual change (12 months) of spending and profits in CF. % of Sign. refers to the proportion of significant enrollment effects.

Table 4. Sources of Heterogeneity in Customer-Level Enrollment Effects

	$\tau_{it}^{Spending}$ (1)		$\tau_{it}^{Retailer's\ Profits}$ (2)	
Pre-enrollment Purchase Characteristics				
Spending	0.09^{***}	(0.03)	0.16^{***}	(0.03)
Purchase_frequency	0.18^{***}	(0.03)	-0.06^{**}	(0.03)
Purchase_breadth	0.44^{***}	(0.02)	0.62^{***}	(0.02)
%_of_spending_on_promoted_items	0.02	(0.02)	0.06^{***}	(0.02)
%_of_orders_paying_shipiping_fee	-0.28^{***}	(0.03)	-0.11^{***}	(0.03)
Exploratory Interactions				
$Spending^2$	-0.20^{***}	(0.07)	-0.30^{***}	(0.07)
$Purchase\_frequency^2$	-0.20^{***}	(0.06)	0.08	(0.05)
Intercept	0.20^{***}	(0.01)	0.25^{***}	(0.01)
Obs.	2,724		2,724	
R^2	0.47		0.54	

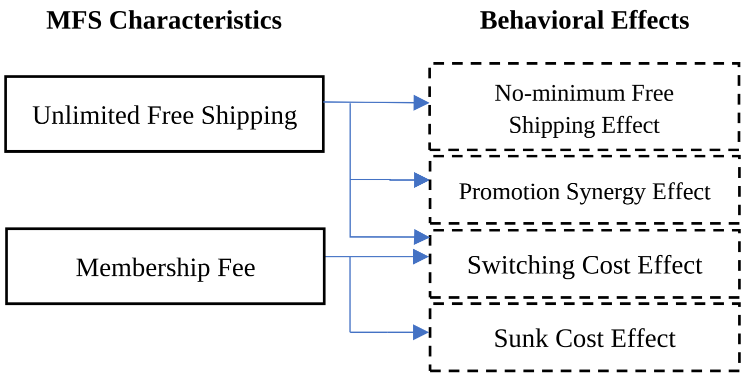
Note. Robust standard errors clustered by each customer are in parentheses. The dependent variables are the individual-level treatment effect estimates. The independent variables are pre-enrollment control variables ($\boldsymbol{X_{it}}$). Here, we only present the variables which have significant effects. *p<0.1; **p<0.05; ***p<0.01.

Table 5. Simulated Post-enrollment Incremental Profits with Different Promoting Targeting Schemes

% of customer base to target	Target scheme 1 *High-spend* (1)	Target scheme 2 *High-response* (2)	Target scheme 3 *High-effect* (3)	Incremental Profits Scheme 3 v.s. 1 (4)	Scheme 3 v.s. 2 (5)
10%	1,872,603.58	1,363,449.42	2,609,829.88	+39%	+91%
20%	2,934,048.81	2,327,387.49	3,617,789.12	+23%	+55%
30%	3,571,012.50	2,958,797.57	4,151,235.70	+16%	+40%
40%	3,983,051.11	3,531,224.11	4,421,367.62	+11%	+25%
50%	4,236,830.82	3,908,235.03	4,506,674.80	+6%	+15%
60%	4,380,561.23	4,106,628.72	4,506,674.80	+3%	+10%
70%	4,455,316.77	4,298,560.91	4,506,674.80	+1%	+5%
80%	4,483,670.05	4,403,344.13	4,506,674.80	+1%	+2%
90%	4,499,551.53	4,454,714.80	4,506,674.80	+0%	+1%
100%	4,501,517.01	4,501,517.01	4,501,517.01	+0%	+0%

Note. The total post-enrollment profit increases are computed based on the matched sample (2,724).

Figure 1. Behavioral Effects of MFS on Consumer's Purchase Behaviors



Behavioral Effects	How Much to Buy			What to Buy		
	Purchase Frequency	**Order Size**	**Total Spending**	**Purchase Breadth**	**Impulse Purchase**	**Promoted Purchase**
No-minimum Free Shipping Effect	+	-	?	+	+	
Promotion Synergy Effect						+
Switching Cost Effect	+	+	+	+	+	-
Sunk Cost Effect	+	+	+	+	+	-
Net Effect	+	-	+	+	+	?

Figure 2.a Distribution of Propensity Scores Before Matching Procedures

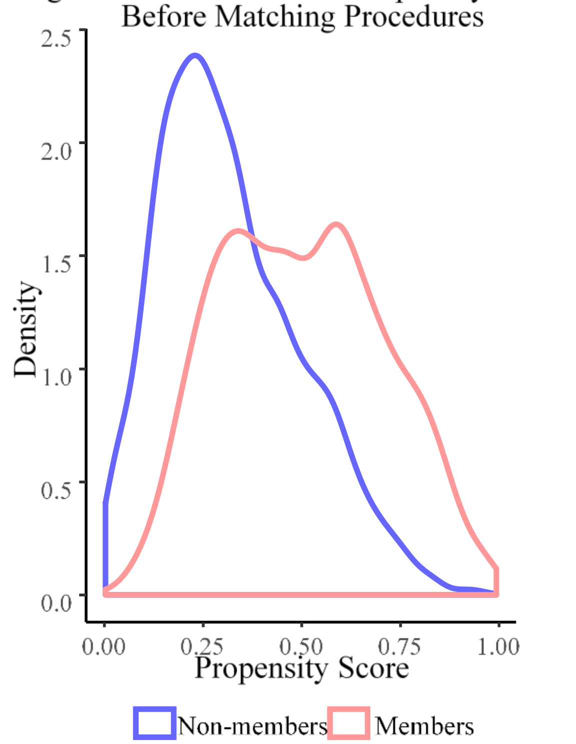


Figure 2.b Distribution of Propensity Scores After Matching Procedures

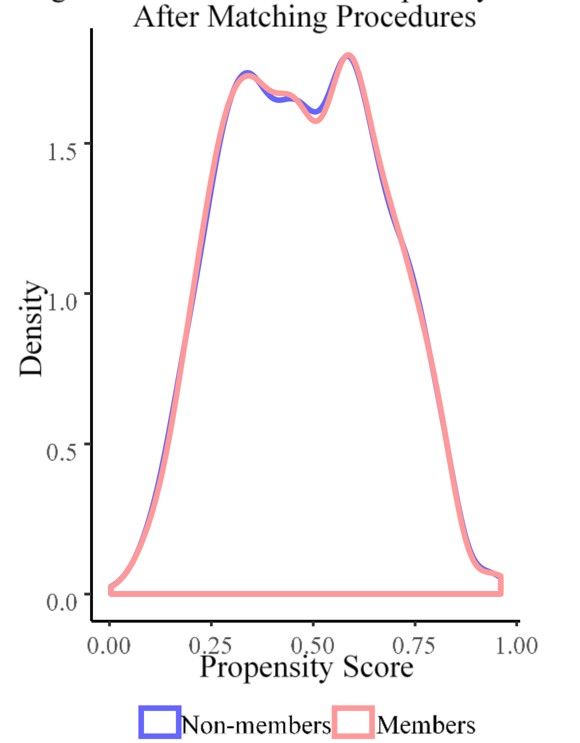


Figure 3.a Distribution of Customer-level Enrollment Effect on Spending

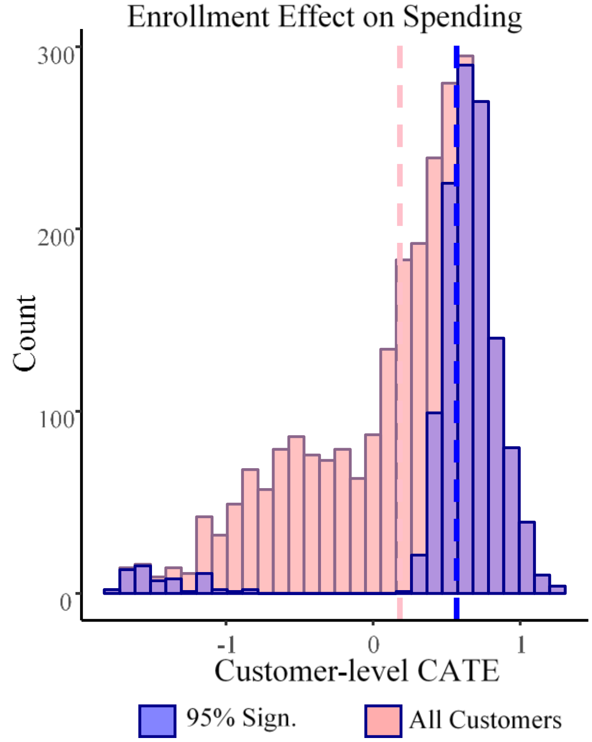
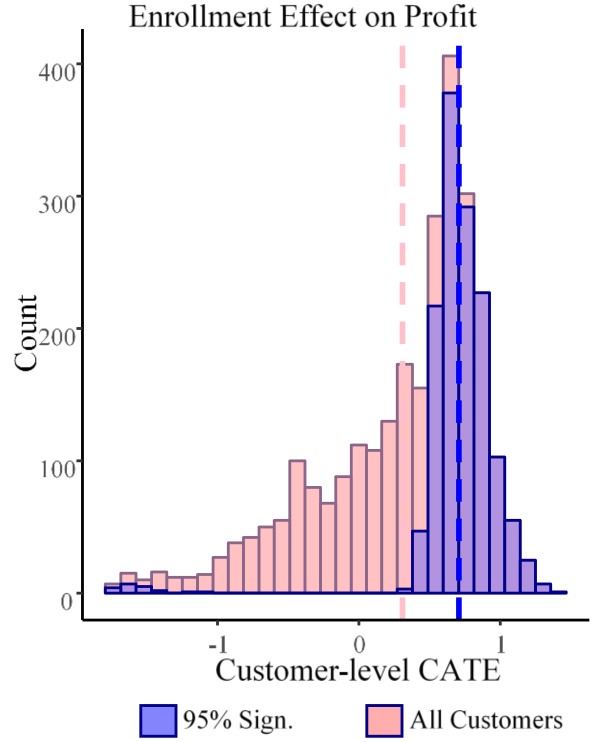


Figure 3.b Distribution of Customer-level Enrollment Effect on Profit



CHAPTER III

SHIPPING POLICIES IN ONLINE RETAILING: AN EMPIRICAL STUDY OF THE IMPACT OF CONDITIONAL SHIPPING POLICIES ON CONSUMERS' PURCHASE

INTRODUCTION

"Any retailer who still is holding on to the past, that shipping isn't free for me, so I can't offer free shipping, will find themselves not being relevant to the retail world."

-- *Satish Jindel, president of ShipMatrix*

Online retailers often face challenges in deciding shipping and delivery charges, which play a crucial role in a successful online business model. According to a recent report, the cost of shipping and transportation services makes up 7.7% of the total operational cost of e-commerce (U.S. Department of Commerce, 2013). Moreover, the shipping charge is an essential step in the online ordering process as it greatly affects the perceived value of the products and ultimately influences purchase decisions. A report shows that more than half of consumers abandon their shopping carts at the very end of the transaction when shipping costs are added (UPS Pulse of the Online Shopper, 2015). In this sense, shipping charges often become the make-or-break factor of e-commerce.

As stated in the citation, an increasing number of retailers adopt free shipping as a necessary strategy to reduce the negative impact of shipping charges and stay competitive (Lewis 2004). However, the cost of free shipping is a huge burden for retailers as it may severely encroach on the firm's profitability (Yang, Essegaier, and Bell 2005). Therefore, many retailers have switched from unlimited free shipping to conditional free shipping. Two formats of conditional free shipping currently dominate online shopping. One is *contingent free shipping* (CFS) that consumers can enjoy free shipping if the total purchase amount reaches a pre-determined cutoff level. For example, Kohl's provides free shipping for orders exceeding $75 in value. The other is membership-based free shipping (MFS) that consumers pay an upfront fee and enjoy unlimited free shipping throughout the membership period. Amazon pioneered the use of MFS by asking consumers to pay an annual membership fee ($119) upfront so that they can enjoy unlimited free shipping on any order throughout the membership period.

Although most retailers have adopted CFS, its effectiveness greatly depends on the choice of the cutoff level (Leng and Becerril-Arreola 2010a; Yang, Essegaier, and Bell 2005). On the one hand, a low cutoff level tends to induce a large number of orders (Yang, Essegaier, and Bell 2005), but at the same time, the transaction values are small in each order. As a result, retailers may incur substantial shipping expenses when choosing a low CFS cutoff level. For example, as Amazon continuously lowered its required minimum total purchase amount qualifying for free shipping, the ratio of shipping cost to net consolidated revenue gradually rose from 0.61% to 2.96% (Amazon Annual Reports 2006). On the other hand, even though high cutoff levels in free shipping policies may encourage consumers to place larger orders and consequently reduce retailers' overall shipping expenses, such policies may drive away potential customers who are not willing to pay for shipping when their total purchase amount is relatively lower than the required purchase amount (Leng and Becerril-Arreola 2010a). Lewis (2006) demonstrates that retailers' site traffic and order incidence rate decrease when the CFS cutoff level increases, leading to the loss of revenue.

To compensate for the disadvantage of adopting a high cutoff level in CFS, retailers recently began to adopt MFS as an alternative. MFS has been regarded as an effective way of retaining consumers who purchase frequently but are unwilling to place large orders for free shipping when the CFS cutoff level is high (Tan, Tan, and Ho 2015). After the appearance of Amazon Prime, the e-tailing industry has shown a growing interest in MFS. For example, Barnes & Noble provides its members express free shipping for $25 per year. To compete with Amazon, Walmart announced Shipping Pass, a two-day free delivery program with an annual membership of $98.

Despite the surging popularity of CFS and MFS, it remains unclear which policy is optimal for retailers (Yang, Essegaier, and Bell 2005). Although free shipping has been studied for years, extant academic research has not yet provided a rigorous investigation into how consumers' purchasing decisions are affected by these two shipping policies and their combinations. It is thus imperative for researchers to evaluate the effectiveness of these shipping policies to serve as important guidelines for retailers to improve their profitability.

This research seeks to develop an empirical approach to examine the relationship between the commonly adopted shipping policies (i.e., CFS with low cutoff level, CFS with high cutoff level, and MFS) and consumer purchase demands. Specifically, we are interested in answering the following research questions:

- How do CFS and MFS affect consumer purchase decisions regarding purchase incidence and purchase amount?
- What behavioral mechanism motivates consumers to join the membership free shipping program?
- What is the optimal shipping policies for retailers to adopt, namely CFS with low cutoff level, CFS with high cutoff level, and MFS combined with CFS of high cutoff level?

The above research questions are addressed through an empirical study, which utilizes a database from one of Asia's biggest online shopping platforms. The data contains transaction records of individual customers in 48 months (Jan. 2014 to Dec. 2017). Over time, the online retailer has offered three different shipping policies, including CFS with a low cutoff level, CFS with a high cutoff level, and MFS complemented with a high CFS cutoff level. We utilize a joint model to analyze the impacts of these shipping policies on consumers' membership decisions, purchase incidence decisions, and purchase amount decisions. Since consumers in different segments may vary in response to shipping policies, a latent class approach (Kamakura and Russell 1989) is adopted to measure the unobserved heterogeneity.

The estimation results suggest that CFS and MFS have significant but different impacts on consumer purchase decisions. In terms of CFS, we find that a high cutoff level greatly increases purchase amount, but at the cost of a decline in purchase incidence. These empirical findings echo the results in related analytical models in the literature (Tan, Tan, and Ho 2015; Yang, Essegaier, and Bell 2005). In terms of MFS, subscribers of MFS tend to purchase more frequently but place smaller orders. In addition, consumers' response to shipping policies varies across customer segments. The estimation results of membership decisions suggest that consumers join MFS based on their ordering pattern. The frequent buyers are more likely to enroll in a membership program for free shipping. However, the consumers who have spent more in the past are less likely to join the membership.

To help identify the most effective free shipping policies, we conduct simulation experiments that evaluate retailers' revenue with different shipping policies. Four shipping policies (i.e., CFS with low cutoff level, CFS with high cutoff level, and CFS with each of the two cutoff levels combined with MFS) are simulated. Comparing the revenue generated by different CFS cutoff levels, we find that the CFS with a low cutoff level always results in lower revenue than that generated by a high cutoff level. In addition, compared to the situation where only CFS is implemented, retailers may generate higher revenue when adopting CFS with a high cutoff level and introducing MFS as a complementary policy. Finally, the optimal shipping policy may differ across customer segments, suggesting that retailers can perform best by providing customized shipping policies to different consumers.

This study contributes to the shipping literature in several ways. First, although research in marketing, operation management, and economics has shown increasing interest in the role of shipping cost, previous studies have mainly focused on issues related to CFS. For example, Leng and Parlar (2005) develop a game-theoretic model to analyze the role of CFS in the B2B context. Lewis, Singh, and Fay (2006) study the relationship between shipping fees and purchase decisions using online grocer data. They find that CFS greatly affects both order incidence and average expenditures. Leng and Becerril-Arreola (2010) obtain similar conclusions through analytical models. Instead of focusing only on CFS, this research is the first empirical study investigating the impact of MFS, a recently developed shipping policy, on consumers' purchase behavior. Moreover, we examine the effect of CFS with different cutoff levels and how such impact changes with the introduction of MFS.

Second, the existing research on MFS (Leng and Becerril-Arreola 2010b; Tan, Tan, and Ho 2015; Wen and Lin 2017) is scarce and typically relies on analytical models due to the limited access to relevant data. The applicability of their models and results in real-world business has not been validated. To the best of our knowledge, our research represents the very first attempt to demonstrate the effectiveness of MFS with real-world data. We provide empirical evidence that MFS positively affects purchase incidence but negatively influences purchase amount and that such effects are nonlinear throughout the membership tenure. Moreover, most existing research on shipping cost assumes that a retailer may adopt only one shipping policy (i.e. either CFS or MFS).

However, in practice, many retailers such as Amazon and Sephora offer free shipping to Prime or Flash members while providing conditional free shipping (CFS) for non-members. We investigate CFS and MFS simultaneously and demonstrate the synergy between the two policies. Our results have significant practical implications as they help managers understand how different shipping policies affect consumer purchase decisions and the shipping policies lead to optimal outcomes.

Third, MFS can be regarded as a loyalty program to retain consumers (Wen and Lin 2017). Our research also contributes to loyalty program literature. Most existing research on loyalty programs focuses on free programs and examines their impact on consumer post-enrollment outcomes (e.g., Bagchi and Li 2011; Drèze and Nunes 2011; Kwong, Soman, and Ho 2011; Wirtz, Mattila, and Lwin 2007; Yi and Jeon 2003). However, some firms have shifted from free to fee-based loyalty programs to cover the program costs. For example, Costco and Sam's Club build a loyal fan base with a paid membership program[6]. The current research focuses on the fee-based membership program and adds to the literature by investigating the behavioral mechanism of joining a membership and comparing the purchase decisions between members and non-members.

DATA AND VARIABLE OPERATIONALIZATION

Data

The data of our empirical study is obtained from a major retailer in Asia[7]. The retailer offers various product categories and conducts online business only. The data set contains consumer transaction records in 48 months. Each transaction record contains the purchase time, prices and quantity of purchased items, product category, promotion availability, shipping method, and membership status. The data is especially suited to our empirical analysis because the retailer

[6] https://www.fool.com/investing/general/2015/05/13/youll-never-guess-just-how-many-people-renew-their.aspx
[7] Due to confidentially agreements, we cannot disclose the retailer's identification.

has changed its shipping policies during the sample period. We discuss the details of the shipping policies in the later subsection.

Household Level Purchase Data. We randomly sampled 8,521 consumers, including both short-term customers (shopped only part of the period) and long-term customers (shopped throughout the period) from the database. Our empirical analysis excludes the consumers who shopped merely for virtual products[8], such as e-gift cards, e-books, and Apps, as the shipping cost is irrelevant for these products. We also exclude orders above $5,000. These records only account for 0.5% of the data set and contain the infrequently purchased products, such as luxury watches. Specifically, we only include consumers who made less than or equal to 300 purchases[9] in the sample period. Applying the above filters yielded a dataset of 1,981 consumers who made 64,580 purchase in total. 65% of consumers shopped throughout the sample period, and 35% shopped only part of the sample period. On average, each consumer makes around 33 purchases, with an average order size of around four items, at the cost of $290.81 approximately. From a modeling perspective, since the consumers' online shopping behaviors have been tracked over a relatively long period of time, it allows us to investigate the effect of different shipping policies.

Data on Shipping Policies. The shipping policies are the focal variables for our empirical analysis. The firm experimented with various shipping schedules, including CFS with different cutoff levels and MFS. Table 1 lists the shipping schedules and reports the various shipping fees at different purchase amounts. Schedule 1 and 2 represent the CFS with LOW and HIGH[10] cutoff levels. For example, the firm adopted CFS with a LOW cutoff level (Schedule 1) during the first

[8] The virtual products does not create shipping cost, because customers purchase those products by downloading.
[9] The consumers who purchase more than 300 times in sample period could be regarded as abnormal shopping behavior, and only account for 1.3% of the whole dataset.
[10] The retailer has requested that we do not disclose the specific threshold levels.

56 weeks in our dataset, in which a consumer pays a fixed shipping fee[11] when the total value of the order falls below the LOW threshold. Otherwise, the consumer is qualified for free shipping. The firm then enhanced the CFS cutoff level from week 57 to week 147. In CFS with a HIGH cutoff level (Schedule 2), consumers are required to increase their purchase amount to the HIGH cutoff level, and then the shipping fee could be waived; otherwise, they must pay a fixed shipping fee. Schedule 3 is of particular interest because the firm introduces MFS after adopting CFS with a high cutoff level for a while. The firm started MFS in week 148. In Schedule 3, the shipping fee is waived in all orders for members who paid an annual membership fee upfront, but non-members have to pay a fixed shipping fee to ship an order less than the HIGH CFS cutoff level. There are 61% members in the sample dataset.

<Insert Table 1 about here>

Variable Operationalization

Dependent Variable. We construct three dependent variables: membership decision, purchase incidence, and purchase amount. The membership decision (M_{it}) variable is inferred from consumer membership status. It takes the value of 1 if the consumer decided to enroll in the membership program and 0 otherwise. The purchase incidence (I_{it}) and the purchase amount (Q_{it}) measure consumer purchase decisions. If a consumer purchases in a given week, the purchase incidence takes 1, otherwise it is 0. The purchase amount is aggregated weekly based on the consumer's purchase quantity[12]. There are 31% of observations in our sample with more than one purchase incidence in a given week.

[11] The retailer charges a fixed shipping fee for the orders which total values are low than the CFS cutoff level, and the fixed shipping fee is the same during the sample period.
[12] For example, if a consumer makes three orders in a week, his/her purchase amount is the sum of the expenditure from all three orders.

Independent Variables. We construct three sets of covariates that are expected to influence consumers' membership decisions and purchase decisions. These covariates include Shipping fee policies, Household transaction history measures, and household demographics and price.

Variables of Shipping Fee Policies. In our model, we define two variables ("CFS_{high_it}" and "MFS_{it}") to represent the firm's shipping schedules. "CFS_{high_it}" is an indicator variable that takes the value of 0 if the firm waived the shipping fee for orders higher than the LOW CFS cutoff level and 1 if it employed free shipping for orders higher than the HIGH CFS cutoff level. "MFS_{it}" is an indicator of consumer membership status. It takes the value of 1 if the customer is a member and 0 otherwise.

Variables of Household Transaction Histories. We use consumer transaction histories to construct measures of their past purchase behavior, which is useful for explaining and predicting consumer decisions. According to Hughes (2002), Recency, Frequency, and Monetary (RFM) measures consumer behavior in direct marketing. We construct five variables based on RFM, including time since last order ($Rencency_{it}$), the number of orders a consumer placed in the past three months ($Freq\_3_{it}$), last purchase amount ($Monetary_{it}$), cumulative purchase amount since the first order ($Cumul\_amount_{it}$), and average purchase amount of previous orders ($Avg\_monetary_{it}$).

Variables of Household Demographics and Price. The household demographic patterns can also be inferred from the household transaction histories as the consumer basket contains the information of products. For example, the purchase of kids' toys indicates the presence of children. In the same way, pet food purchases indicate the presence of pets. According to the content of the consumer basket, we define two demographic variables, child (denote by $Child_i$) and pet (denote by Pet_i). In our sample, we find that 56% of the household have children, and 3% have pets. In addition to consumer-specific variables, we also construct a marketing variable to reflect the pricing environment. Since the online retailer has a wide scope of products, which involves over forty thousand distinct products within hundreds of categories, it challenges measuring the pricing effects. Our dataset contains individual-level transaction prices and an indicator of promotion. Following Lewis, Singh, and Fay (2006) and Jing and Lewis (2011), we construct an index to account for price and promotion effects. The index variable ($Price\_50_t$) is the average price of the 50 best-selling products each week.

Descriptive statistics and correlations for these measures are presented in Table 2 and Table 3. Table 4 presents the definition of key variables.

<Insert Table 2, Table 3, and Table 4 about here>

RESEARCH DESIGN AND METHODOLOGY

This section introduces a model to investigate different shipping policies on consumers' online shopping behaviors. Especially, find the behavioral mechanism that explains consumers' decision to join the membership and their following purchase behaviors.

In the case of MFS, consumers first decide whether to join the membership, and then they decide whether to buy and how much to buy based on their membership status. If customers decide not to join the membership, they may consider how much to buy to avoid shipping fee due to the CFS. Following Zhang and Krishnamurthy (2004), we develop a model to capture the consumers' joint decision of membership and purchase decision. In our model, we also consider the effects of CFS with different cutoff levels.

Model Setup

We assume that the observed behavior is caused by a series of decisions. There are two stages. In the first stage, a consumer decides whether to join the membership; in the second stage, the consumer makes a purchase decision on purchase incidence and purchase amount.

Stage 1—Membership Decision

The model begins with a standard logit model to predict a probability of becoming a member. Consumers' decisions of joining the membership may depend on the transaction histories and consumer characteristics. We assume that a consumer's decision of subscribing to a membership (M_{it}) is based on the utility of the membership. The utility function for customer *i* to join membership at period *t* is given by

$$U_{it}^{M} = V_{it}^{M} + \varepsilon_{it}^{M} = X_{it}\beta_{i} + \varepsilon_{it}^{M} \tag{1}$$

Where, V_{it}^{M} represents the component of transaction histories and demographic patterns. In the membership decision model, we include the following transaction histories measures: purchase frequency in the last three months ($Freq\_3_{it}$) and cumulative purchase amount the consumer has made ($Cumul\_amount_{it}$). For these two variables of transaction history, we expect that the consumers with high purchase frequency are more likely to join the membership to enjoy the free shipping on all orders (Wen and Lin 2017). However, the higher the cumulative purchase amount, the less likely him/her becomes a member. Since most of their orders may be eligible for shipping fee waiver under CFS, they do not have to spend extra money to join the membership for free shipping. We assume that ε_{it}^{M} is a random error, which follows Type I extreme value distribution with location parameter 0 and scale parameter 1. We define M_{it}= 1 if consumer *i* is a member in shopping trip *t* and 0 otherwise. Therefore, the probability of joining the membership is:

$$\Pr(M_{it} = 1) = \frac{\exp\,(V_{it}^{M})}{1 + \exp\,(V_{it}^{M})} \tag{2}$$

Stage 2—Purchase Decision

The consumer's decision of purchase incidence and purchase amount occurs simultaneously, and we follow a joint model developed by Zhang and Krishnamurthi (2004) and Jing and Lewis (2011) to capture the decision of purchase incidence and purchase amount.

Purchase Incidence. Consumer past purchase behavior may be useful for predicting current purchasing activity (Hughes 2000). In addition, consumers may make different purchase decisions in response to the changes in shipping policies. Therefore, the utility function of purchase incidence (I_{it}) of customer *i* at shopping occasion *t* is given by:

$$U_{it}^{I} = W_{it}^{I} + \vartheta_{it}^{I} = Z_{it}\alpha_i + \vartheta_{it}^{I} \tag{3}$$

Where W_{it}^{I} is a function of consumer past transaction, including the time since last order (*Recency$_{it}$*), purchase frequency in last three month (*Freq_3$_{it}$*), and purchase amount in last order (*Monetary$_{it}$*). To measure the effects of marketing activity and shipping policies, we include the price environment in a given week (*Price_50$_{it}$*), shipping policies (CFS and MFS), and demographic variables (*Pet$_i$ and Childe$_i$*). High CFS cutoff may dissuade customers from ordering because they have to purchase more products to qualify for free shipping. Thus, we expect the high threshold of CFS (CFS=1) has a negative effect on purchase incidence. However, the members are assumed to have many orders because they order as needed and obtain free shipping on any orders Tan, Tan, and Ho (2015). Thus, we expect the membership (MFS=1) to positively affect purchase incidence. To account for the dynamic effect of MFS over time, we include the interactions between the membership status (MFS) and membership tenure. The probability of purchase incidence for customer *i* in shopping trip *t* is given by:

$$\Pr(I_{it} = 1) = \frac{\exp{(W_{it}^{I})}}{1 + \exp{(W_{it}^{I})}} \tag{4}$$

Purchase Amount. Once consumers decide to purchase on a shopping trip, they need to consider how much to buy. The purchase amount may depend on both consumers' needs and shipping costs. Let Q_{it}^{*} be a latent variable that determines how much customer *i* plans to purchase in shopping trip *t*, and Q_{it} be the observed purchase amount as follows:

$$Q_{it} = \begin{cases} Q_{it}^{*}, & \text{if } I_{it} = 1 \\ 0, & \text{if } I_{it} = 0 \end{cases}$$

Specify

$$Q_{it}^{*} = N_{it}\phi_i + \xi_{it} \tag{5}$$

N_{it} contains the same set of variables as in the purchase incidence model with one exception: we use the average purchase amount ($Avg\_monetary_{it}$) instead of the last purchase amount ($Monetary_{it}$). Since consumers need to purchase a certain amount to waive the shipping fee under CFS, the higher CFS cutoff level results in a larger order size. Thus, we expect a positive effect of the CFS cutoff level on the purchase amount. Unlike CFS, members of MFS order as needed, so they do not have an incentive to place large orders. Thus, we predict that the MFS leads to a smaller purchase amount.

We can get a closed-form expression of the joint probability of purchase incidence and purchase amount:

$$\begin{aligned} \Pr(I_{it} = 1, Q_{it} = q_{it}) &= \frac{\exp(W_{it}^{I})}{1+\exp(W_{it}^{I})} \times \frac{\delta \exp\big(\delta(N_{it}\phi_i - log q_{it})\big)}{\big[1+\exp\big(\delta(N_{it}\phi_i - log q_{it})\big)\big]^2} \\ &\times \left[1 + \frac{\rho}{1+\exp\,(W_{it}^{I})} \times \frac{-1+\exp\big(\delta(N_{it}\phi_i - log q_{it})\big)}{1+\exp\big(\delta(N\phi_i - log q_{it})\big)}\right] \end{aligned} \tag{6}$$

Since we assume consumer i’s purchase decision is conditional on the membership status, we get the joint probability of purchase decision conditional on membership status:

$$\Pr(I_{it}, Q_{it}|M_{it}) = [\Pr\,(I_{it} = 0|M_{it})]^{1-I_{it}}[\Pr\,(I_{it} = 1, Q_{it}|M_{it})]^{I_{it}} \tag{7}$$

$$\text{Where}, \Pr(I_{it} = 0|M_{it}) = \frac{1}{1+\exp(W_{it})}$$

Therefore, the joint probability of the membership and purchase decision can be computed as:

$$L(H_i) = \Pr(I_{it}, Q_{it}, M_{it}) \tag{8}$$

$$= [\Pr\,(M_{it} = 0) \times \Pr(I_{it}, Q_{it}|M_{it} = 0)]^{1-M_{it}}[\Pr\,(M_{it} = 1) \times \Pr(I_{it}, Q_{it}|M_{it} = 1)]^{M_{it}}$$

$$where, \Pr(M_{it} = 1) = \begin{cases} 1, t^* = 1\ and\ t - t^* \leq 51^{13} \\ \dfrac{\exp(V_{it}^M)}{1 + \exp(V_{it}^M)}, otherwise \end{cases}$$

$$and\ \Pr(M_{it} = 0) = \begin{cases} 0, t^* = 1\ and\ t - t^* \leq 51 \\ \dfrac{1}{1 + \exp(V_{it}^M)}, otherwise \end{cases}$$

Consumer Heterogeneity and the Log-Likelihood Function

Previous research has found that certain consumer segments are more sensitive to shipping fees than others (Lewis, Singh, and Fay 2006). We apply a latent class method to account for the unobserved heterogeneity in the population (Kamakura and Russell 1989). In this model, we assume that there is an unobserved number of homogeneous segments S, and we estimate the parameters as segment-specific instead of subject-specific. π_s is the likelihood of a consumer *i* is assigned to the segment *s*.

$$\pi_s = \frac{\exp\,(\lambda_s)}{\sum_{s'}^{S} \exp\,(\lambda_{s'})} \tag{9}$$

Considering the probability of finding consumer *i* in segment *s*, the Log-likelihood function is given by:

[13] The membership duration is 52 weeks (one year).

$$LL = \sum\nolimits_{i=1}^{N} \log \left[\sum\nolimits_{s=1}^{S} \pi_s \prod\nolimits_{t}^{T} L(H_i|s)\right] \tag{10}$$

$$= \sum_{i=1}^{N} log \left[\sum_{s=1}^{S} \pi_s \prod_{t}^{T} [\mathrm{Pr}_s\ (M_{it} = 0) \times \mathrm{Pr}_s(I_{it}, Q_{it}|M_{it} = 0)]^{1-M_{it}} [\mathrm{Pr}_s\ (M_{it} = 1) \times \mathrm{Pr}_s(I_{it}, Q_{it}|M_{it} = 1)]^{M_{it}}\right]$$

The latent segment S is determined by calculating the Bayesian Information Criterion (BIC) with different S. The optimal S is the one that yields the lowest BIC.

$$BIC = \ln(n)\, k - 2\ln\,(LL)$$

Where LL is the maximum value of the log-likelihood, k is the number of parameters, and n is the number of total data points.

EMPIRICAL RESULTS

The model fit statistics and parameter estimates are presented in Table 5 and Table 6. Table 6 reports the number of parameters, log-likelihoods, and Bayesian information criteria (BIC) fit measures for models that are different in the number of unobserved heterogeneities. Based on the BIC, we find that a two-segment model best fits data and yields intuitive parameter estimates. Table 7 provides parameter estimates and standard errors for homogeneous and two-segment models.

<Insert Table 5 and Table 6 about here>

Estimation Results of Homogeneous Model

We first discuss the parameters in the homogeneous model that are presented in the first column of Table 7. The estimated coefficients for transaction histories in membership decisions are significant and expected. For example, the negative sign associated with the purchase frequency (*Freq_3*$_{it}$) suggests that the probability of subscribing to the membership is higher for frequent online shoppers consumers. Conversely, the significant and positive coefficient of the cumulative purchase amount (*Cum._amount*$_{it}$) suggests that the more consumers spend, the less likely they are to join the membership. A possible interpretation of the results is that consumers who spend a lot can satisfy free shipping under CFS. Thus, free shipping alone cannot incentivize them to become a member. The coefficient of demographic variables indicates that a consumer who has children or pet (s) is more likely to join the membership.

The coefficients associated with RFM are significant but have different signs in purchase incidence and purchase amount. In terms of purchase incidence, the negative sign of monetary (*Monetary*$_{it}$) indicates that the purchase incidence is negatively correlated with purchase quantity since the last purchase, but purchase incidence is positively correlated with high ordering frequency (*Freq_3*$_{it}$) and time interval since last purchase (*Recency*$_{it}$). Regarding purchase amount, the signs of the RFM variables are all positive. Moreover, the coefficient of the marketing-mix variable (*Price_50*$_{it}$) indicates that the price variable only affects the probability of purchase incidence and that higher prices deter ordering.

The main parameters of interest are those associated with the shipping policies. The coefficients of CFS and MFS are significant and have expected signs. The signs of CFS in purchase incidence and purchase amount indicate that as the CFS cutoff level increases, consumer purchase incidence decreases while the purchase amount increases.

Estimation Results of Two-segment Model

We now discuss the estimation results for the two-segment model. As the estimation results suggest two segments of online shoppers, we take a close look to find the segment-specific characteristics. According to Kamakura and Russell (1989), we can assign the consumer to segments by posterior probabilities[14]. Table 7 provides descriptive statistics for the two segments.

[14] The posterior probability of consumer i belongs to segment s is $P\ (i \in s \mid H_i) = L\ (H_i \mid s)\ \pi_s / \Sigma\ [L\ (H_i \mid s)\ \pi_s]$.

We find that segment one customers have higher purchase incidence but lower expenditure. As a result, they may tend to join the membership. Some elements are similar across the two segments. For example, the transaction history variables tend to operate similarly across the two segments. However, we find a significant difference between how the two segments respond to the shipping policies.

<Insert Table 7 about here>

Regarding the previous purchase frequency and total spending in membership decisions, we observe a similar pattern as homogenous results. Consumers are more likely to enroll in the membership program if they frequently purchased in the past, but the more they spend, the less likely they will join the membership for free shipping. The RFM variables have a larger role for the customers of segment 2. The impact of demographics differs between the two segments, especially the effect of pets. The estimates suggest that if consumers in segment 2 have a pet, the probability of joining a membership will decrease.

The estimation results of purchase decisions indicate that the transaction histories and shipping policies affect consumer behavior in several ways. In general, the parameter estimates of RFM have expected signs and have significant effects for both segments. The parameter estimates for the two-segment model may be interpreted similarly as in the homogeneous model. However, there are significant differences between segments in terms of shipping policies. CFS has the same effect on both segments. The estimates suggest that CFS has a significant negative effect on purchase incidence and a positive impact on the purchase amount. However, the impact of MFS differs between the two segments. MFS has a nonlinear effect on purchase incidence, but segment two customers are more sensitive. Regarding purchase amount, it has a nonlinear impact on segment one customers that their purchase amount decreases as soon as they join the membership but slightly increases after that. However, MFS only has a linear impact on segment two customers, decreasing their expenditure over time.

What-If Analysis

In this section, we explore how shipping policies affect firm revenue. We simulate customer decisions regarding purchase incidence and purchase quantity at a weekly level and simulate membership decisions if the firm adopts MFS. We use the joint model results to simulate consumer purchase decisions for 48 months for this analysis. Specially, we investigate the revenue generated by the following shipping policies:

1. Only adopt CFS with a low cutoff level;
2. Only adopt CFS with a high cutoff level;
3. Adopt CFS with a high cutoff level initially and then introduce MFS at week 148;
4. Adopt CFS with a low cutoff level initially and then introduce MFS at week 148;

The baseline shipping policy is the firms' initial shipping policy, in which firms first adopt CFS with a low cutoff level, then enhance the cutoff level, and introduce MFS with a high CFS cutoff level. We report the "revenue" of the population and segments for each simulation. The revenue consists of three parts: (1) revenue from purchases; (2) revenue from membership fee if the firms adopted MFS; (3) shipping cost to the retailer if the orders meet the CFS cutoff level; and the shipping cost for each transaction. Table 8 reports the results of the above simulations.

The results of the revenue generated by different CFS cutoff levels suggest that the CFS with a low cutoff level always results in lower revenue than that generated by a high cutoff level. This result may indicate that the increase in revenue by lowering the CFS cutoff level might not outpace the growth in related shipping costs (Lewis, Singh, and Fay 2006). More specifically, while CFS with a low cutoff level can stimulate demand, it also leads to additional shipping costs, which might offset the benefit of increased merchandise revenue. When comparing the situation where only CFS is implemented to that MFS combined with CFS, a retailer may generate higher revenue if it adopts CFS and introduces MFS as a complementary policy. This result indicates that the revenue generated from the MFS membership fees may compensate for the loss of shipping cost caused by CFS with different cutoff levels and that the combination of MFS with CFS may help firms gain more revenue than only adopting CFS.

In addition, we find that the optimal shipping policy may differ across customer segments. The second column of Table 8 shows that the revenue generated by segment one customers is close to the baseline revenue. However, the revenue generated by segment two customers is three times more than that of segment 1. Combining a high CFS cutoff level and MFS is the best for both segments. It is possible that retailers can achieve the best performance by providing customized shipping policies to different types of consumers.

<Insert Table 8 about here>

CONCLUSIONS AND IMPLICATIONS

The shipping fees have gained increasing attention with the growth of eCommerce, but their effects on shopping behavior are still unclear (Lewis 2006). Although some retailers, such as Amazon, seek the optimal shipping strategy by experimenting with different shipping policies [15], practitioners debated intensely over whether taking these shipping policies is a good decision (Tan, Tan, and Ho 2015). Although CFS and MFS are the most popular shipping policies in the current online market, their impacts on consumer purchase decisions are underexplored. On the one hand,

[15] Amazon initially implemented free shipping for all orders, and then it adopted CFS, in which free shipping was eligible for orders above $99 and lowered to $49 subsequently, and now lowered to $25. In 2005, amazon lunched Amazon Prime, in which consumers prepay $79 a year to join Prime member and get free two-day delivery on an unlimited number of items.

retailers adopt CFS with a high cutoff level to incentivize large orders to reduce the burden of shipping costs. However, the high requirement for free shipping reduces their site traffic, leading to less profitability. On the other hand, MFS may compensate for the loss of CFS, but its impact on consumers' response is not clear. This research develops an accessible method for measuring consumer response to these shipping policies--MFS and CFS.

In the current research, we develop a joint model that enables us to study the role of CFS and MFS in affecting consumers' purchase decisions and the factors that motivate consumers to join the membership. As the CFS cutoff level increases, a consumer's purchase amount increases, whereas the consumer's purchase frequency decreases. This finding suggests that a high cutoff level of CFS exempts the retailers from a large portion of the total shipping cost and entices consumers to consolidate multiple orders into one, reducing the retailer's operational and shipping costs. However, the CFS with a high cutoff level may also deter some consumers with smaller purchase amounts because they cannot afford the shipping fee and are unwilling to increase their purchase amount for free shipping (Leng and Becerril-Arreola 2010a). Our results reveal that MFS influences both purchase incidence and expenditures. Consumers' shopping frequency increases, but they have no incentive to place large orders after subscribing to a membership program, resulting in a smaller purchase amount. The results provide empirical evidence for the analytical models (Wen and Lin 2017; Yang, Essegaier, and Bell 2005). Besides, we find that MFS has a nonlinear effect on consumers' purchase decisions. At the beginning of the membership, consumer purchase incidence slightly decreases but reaches an even higher level than before.

Since the membership fee may take up a portion of consumers' budget, their buying power is negatively affected, leading to less shopping at the beginning of the membership. As the tenure of the membership increases, consumers may take advantage of free shipping by purchasing more frequently. In terms of the purchase amount, when consumers join the membership, they purchase as needed. Initially, they place smaller orders than before because there is no longer a spending requirement for free shipping. Our results also indicate the presence of important, unobserved heterogeneity in responsiveness to shipping policies. We find that consumers who purchase frequently are more sensitive to shipping policies, especially MFS. The simulation experiments show that retailers may customize their shipping policy according to customer traits. The simulation results demonstrate that adopting both CFS and MFS may generate more revenue than only implementing one of them. More importantly, our research provides a guideline and accessible methods retailers can use to implement the optimal shipping policy.

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TABLES

Table 1. Descriptive Statistics—Shipping Policy Schedule

	Schedule 1 CFS_{Low} (week 1-56)	Schedule 2 CFS_{High} (week 57-147)	Schedule3 CFS_{High} and MFS (week 148-209)	
			Member	Non-member
Shipping fees (Chinese Yuan)				
• 0- Low cutoff level	Fixed Fee	Fixed Fee	0	Fixed Fee
• Low cutoff level- High cutoff level	0	Fixed Fee	0	Fixed Fee
• Above High cutoff level	0	0	0	0
Avg. Purchase Incidence	13.44	10.71	3.95	2.18
Avg. Purchase Amount	213.29	307.87	550.93	776.90

Note: We don't disclose the actual free shipping cutoff levels due to confidential agreements.

Table 2. Descriptive Statistics—Variables

Variable Name	Mean	Std.	Variance	Min	Max
Purchase Amount	534.21	747.56	558847.44	2.60	4997.56
Purchase Incidence	1.60	1.29	1.65	1.00	36.00
Recency	7.15	14.43	208.21	0.00	243.00
Monetary	499.99	715.57	512036.10	0.00	4997.56
Freq_3	8.28	9.18	84.19	0.00	94.00
Freq_%	0.80	0.72	0.53	0.01	16.00
Cumul_amount	10,208.22	13,329.59	177,678,002.50	6.25	121,602.17
Avg_monetary	261.39	208.73	43,569.26	6.25	4,956.41
cfs	0.46	0.50	0.25	0.00	1.00
mfs	0.09	0.29	0.08	0.00	1.00
Price_50	26.31	26.71	713.18	10.76	308.11
Pet	0.03	0.18	0.03	0.00	1.00
Child	0.45	0.50	0.25	0.00	1.00

Table 3. Correlation

	Amount	Incidence	Recency	Monetary	Freq_3	Cum. amount	Avg. monetary	CFS	MFS	Price50	Pet
Amount	1										
Incidence	0.34	1									
Recency	0.12	-0.12	1								
Monetary	0.29	0.08	0.02	1							
Freq_3	0.08	0.49	-0.29	0.13	1						
Freq_%	0.08	0.43	-0.25	0.09	0.68						
Cum. amount	0.30	0.14	-0.09	0.33	0.31	1					
Avg. monetary	0.40	-0.05	0.13	0.32	-0.10	0.18	1				
CFS	0.10	-0.04	0.05	0.07	-0.05	0.25	0.05	1			
MFS	0.14	-0.09	0.25	0.14	-0.20	0.19	0.20	-0.29	1		
Price50	0.01	0.01	0.00	0.02	0.02	-0.01	0.00	-0.13	0.02	1	
Pet	0.03	0.04	-0.03	0.03	0.08	0.15	0.01	0.04	0.00	0.00	1
Child	0.03	0.05	-0.05	0.05	0.14	0.26	0.03	0.08	0.10	-0.01	0.05

Table 4. Variable Operationalization

Variable Name	Definitions
Membership Decision	
Freq_3	The number of orders the customer placed in last 3 month
Cumul_amount	The cumulative purchase amount the customer has spent until time t
Child	1 if a customer has children and 0 otherwise, the information is inferred from original data
Pet	1 if a customer has a pet and 0 otherwise, the information is inferred from original data
Purchase Incidence/ quantity	
Recency	The time (in weeks) since the last purchase
Monetary	The purchase amount of the last order
Avg_Monetary	The average of the total purchase amount
Freq_3	The number of orders the customer placed in last three months
Price_50	The average price of the 50 top-selling items in each week
MFS	1 if a customer is a member who can enjoy free shipping for any orders and 0 if otherwise
CFS_{high}	1 if a customer is not a member and CFS with a high threshold is eligible for customers , and 0 if otherwise
Child	1 if a customer has children and 0 otherwise, the information is inferred from original data
MFS_Duration	Time duration since MFS introduced by the retailer

Table 5. Model Fit Statistics

Model	No. of Parameters	LL	BIC
Homogeneous Model			
Without time variation	22	-222,150	444,419.69
With time variation	30	-221,704	443,571.22
Two-segment Model			
Without time variation	45	-217,579	435,402.82
With time variation	61	-217,489	435,309.87

Table 6. Estimation Results

	Homogeneous Model		Segment 1		Segment 2	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Membership Decision Parameters						
INTERCEPT	-4.18***	0.05	-4.18***	0.05	-6.00***	0.19
FREQ_3	8.96***	0.28	8.97***	0.30	0.01	0.17
CUM. AMOUNT	-0.34***	0.03	-0.34**	0.04	-2.90***	0.14
CHILD	6.48***	0.64	0.44	1.91	0.76***	0.01
PET	0.30***	0.01	6.49**	0.62	-0.16**	0.03
Purchase Incidence Parameters						
INTERCEPT	-2.73***	0.02	-2.62***	0.02	-2.97***	0.02
FREQ_3	5.17***	0.03	4.86***	0.04	5.89***	0.06
RECENCY	0.04***	0.00	0.13***	0.01	0.04***	0.01
MONETARY	-0.23***	0.12	-0.51***	0.09	-0.09***	0.07
PRICE_50	-0.02***	0.00	-0.02***	0.00	-0.03***	0.00
CFS	-0.50***	0.01	-0.50***	0.02	-0.51***	0.02
MFS	1.78***	0.04	1.42***	0.06	2.20***	0.06
MFS×TIME	-1.53***	0.04	-1.24***	0.07	-1.78***	0.07
MFS×TIME^2	0.24***	0.01	0.19***	0.01	0.29***	0.01
MFS_Duration	-1.87***	0.09	-1.62***	0.09	-2.63***	0.09
MFS_Duration^2	1.85***	0.08	1.61***	0.07	2.22***	0.07
Purchase Amount Parameters						
INTERCEPT	-0.18***	0.03	-0.59***	0.05	-0.02	0.03
FREQ_3	5.73***	0.24	5.30***	0.43	0.91***	0.07
RECENCY	0.43***	0.04	0.96***	0.08	0.43***	0.05
AVG. MONETARY	0.27***	0.00	0.57***	0.01	0.24***	0.00
PRICE_50	0.00	0.00	-0.00	0.00	0.00	0.00
CFS	2.05***	0.10	1.47***	0.11	1.48***	0.10
MFS	-0.75***	0.12	-0.44***	0.05	-0.09***	0.01
MFS×TIME	-0.18***	0.03	-0.25***	0.04	-0.03	0.04
MFS×TIME^2	0.04***	0.01	0.05***	0.01	-0.00	0.01
MFS_Duration	1.35***	0.08	1.61***	0.07	0.07*	0.04
MFS_Duration^2	-0.76***	0.06	-1.00***	0.06	0.03	0.04
CHILD	0.88***	0.09	0.05	0.05	1.59***	0.04
Scale (δ)	1.76***	0.01	1.90***	0.01	-1.75***	0.01
Correlation (ρ)	0.03***	0.04	-0.04	0.08	0.27***	0.06
Segment size (s)	-	-	0.44		0.56	

*p<.1, **p<.05, ***p<.01

Note: the correlation is computed by $\rho=\sin(\theta)$; the segment size is estimated by $\pi_s = \exp(s)/[1+\exp(s)]$

Table 7. Statistics Descriptions Of Segments

	Avg. purchase amount	Avg. purchase incidence	Member %
Homogeneity	290.81	33.73	61.78%
Segment 1	273.74	51.91	54.54%
Segment 2	325.81	19.63	67.36%

Table 8. Simulation Results

	Revenue ($)		
Scenario	Homogeneity	Segment 1	Segment 2
Baseline	4,926,423.20	3,262,957.51	7,646,825.52
CFS Low Cutoff Level	2,992,563.53	1,384,828.10	3,885,277.62
CFS High Cutoff Level	3,681,353.35	1,591,785.86	4,610,060.55
CFS High Cutoff Level and MFS	5,067,729.14	3,355,912.68	7,798,500.19
CFS Low Cutoff Level and MFS	4,440,054.59	3,133,763.20	7,044,839.66