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【要旨】

Customer lifetime value (CLV) is a forward-looking metric that measures each customer's profitability by balancing the costs and benefits from acquisition through retention. Even when promotional programs are directed toward achieving short-term goals (e.g., boosted sales), they can also impact CLV. However, the question remains whether such promotions can deter churn and increase post-promotion CLV in noncontractual settings, where cannibalization and switching behaviors are more prevalent than in contractual contexts. Thus, we conducted a randomized field experiment involving nearly 130,000 customers in Japan to investigate the heterogeneous effects of coupon redemption. Using the interacted two-stage least squares model, we find that coupon redemption decreases the probability of churn by approximately 12 percentage points and increases the promoted product's CLV by more than 30%. While such uplift effects attenuate as pre-intervention CLV (pre-CLV) rises, our marginal treatment effect estimates suggest that even high pre-CLV customers experience positive gains in both outcomes. Additionally, our estimates show that while the manufacturer-level CLV increases, the retailer-level CLV experiences smaller or no gains. These findings indicate that coupon programs, which typically involve collaborations between manufacturers and retailers, may not necessarily benefit both parties equally in terms of CLV.

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Coupon Redemption, Churn, and Customer Lifetime Value for a Newly-Launched Noncontractual Product: Evidence from a Large-Scale Field Experiment in Supermarkets

Manuscript

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Abstract

Customer lifetime value (CLV) is a forward-looking metric that measures each customer's profitability by balancing the costs and benefits from acquisition through retention. Even when promotional programs are directed toward achieving short-term goals (e.g., boosted sales), they can also impact CLV. However, the question remains whether such promotions can deter churn and increase post-promotion CLV in noncontractual settings, where cannibalization and switching behaviors are more prevalent than in contractual contexts. Thus, we conducted a randomized field experiment involving nearly 130,000 customers in Japan to investigate the heterogeneous effects of coupon redemption. Using the interacted two-stage least squares model, we find that coupon redemption decreases the probability of churn by approximately 12 percentage points and increases the promoted product's CLV by more than 30%. While such uplift effects attenuate as pre-intervention CLV (pre-CLV) rises, our marginal treatment effect estimates suggest that even high pre-CLV customers experience positive gains in both outcomes. Additionally, our estimates show that while the manufacturer-level CLV increases, the retailer-level CLV experiences smaller or no gains. These findings indicate that coupon programs, which typically involve collaborations between manufacturers and retailers, may not necessarily benefit both parties equally in terms of CLV.

Keywords: Customer Lifetime Value, Churn, Customer Relationship Management, Price Promotions

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1 Introduction

Customer lifetime value (CLV) represents the net profit/loss that customers create over the duration of their relationship with a company (Gupta et al., 2006). CLV is also a key metric of customer relationship management (CRM), which emphasizes customer acquisition and retention (Bowman & Narayandas, 2004; Dong et al., 2011; Gupta et al., 2004; Musalem & Joshi, 2009; Verhoef, 2003). Within CRM, customers are considered as assets, leading firms to examine the relative value of different customer segments (Jain & Singh, 2002; McCarthy & Fader, 2018). Firms leverage this information to guide their resource allocation strategies, which are typically aimed at high-value customers (Jain & Singh, 2002; Mulhern, 1999).

While CLV is readily associated with contractual products (e.g., insurance services, gym membership, and subscription services) that often involve long-term relationships with customers, the use of promotions can also impact CLV of noncontractual products in the fast-moving consumer goods industry. In fact, although a substantial body of literature has shown that price promotions can effectively boost short-term sales (see, e.g., Anderson and Fox (2019) for a comprehensive review), there are situations in which CLV—as a forward-looking measure of direct customer value (Kumar, 2018)—may decrease. For instance, Lewis (2006) found that customers acquired via deep discounts typically have lower repeat-buying rates than those acquired without such promotions in both the contractual setting (newspaper subscriptions) and noncontractual setting (online grocery retailing). Similarly, Elberg et al. (2019) showed that price promotions make consumers more sensitive to price in the long run. In these cases, even though promotions can boost immediate sales, they may discourage future repeat purchases or foster price-sensitive behaviors, thereby reducing CLV. Consequently, evaluating promotional programs through the lens of CLV can provide a longitudinal view unrestricted by arbitrary time frame (Valentini et al., 2024).

Modeling CLV is particularly useful for assessing a program's impact on future churn, arguably the most critical component of the CLV framework (Ascarza et al., 2018; Lemmens & Gupta, 2020). Estimating the probability of churn is particularly valuable in noncontractual settings, in which churn is not directly observable from sales data. Unlike contractual settings, customers in noncontractual contexts do not provide an explicit signal when they churn, making it difficult to distinguish truly churned customers from temporarily inactive ones (Cambra-Fierro et al., 2021). By using parameter estimates from the Pareto/NBD model (Schmittlein et al., 1987), which estimates the expected number of future transactions for noncontractual products as a key component of CLV, firms can infer churn events that go beyond simple sales observations. This approach provides managers with insights into customer retention and churn dynamics that are otherwise hidden in the transactional record.

In this study, we investigate how a coupon campaign (commonly used to increase short-term sales) impacts each customer's probability of churn and CLV for a noncontractual product. Specifically, we respond to Ascarza et al. (2018)'s call to evaluate the value-lift concept in CLV, which seeks to directly model the incremental impact of a campaign on individual customers, thereby accounting for heterogeneity in their expected CLV when targeted (Ascarza, 2018). This approach allows us to identify which customer segments benefit most from the promotion and to provide practical guidance for targeted marketing strategies. Leveraging a randomized coupon assignment to nearly 130,000 customers of a major Japanese supermarket as an exogenous source of variation, we estimate the causal effects of coupon redemption on churn probability and CLV six months post-redemption.

Our contributions to the literature are fourfold. First, to the best of our knowledge, this is the first study to investigate the effects of price promotions on CLV and its critical component, churn, for noncontractual products. The current research gap regarding the effects of promotions on churn and CLV in noncontractual settings is notable given that the primary goal of marketing efforts is to maximize CLV (Ascarza et al., 2018; Blattberg & Deighton, 1996; Cambra-Fierro et al., 2021). While relevant studies such as Ascarza (2018) and Kim (2019) analyzed the effects of promotions on churn in *contractual* settings, the effects on churn and CLV for noncontractual products remain underexplored. The distinction between contractual and noncontractual products is important because purchase behavior differs markedly across these contexts:

contractual products typically involve routine monthly or annual payments, and switching behavior tends to be relatively stable. In contrast, noncontractual products exist in highly competitive markets, where customers can switch or substitute products impulsively and with less commitment (Dawes, 2012; McColl et al., 2020). Moreover, although many studies have examined the short- and long-term effects of coupons on sales of noncontractual products, their impact on CLV is not necessarily straightforward. Since the expected number of future transactions is a function of the probability of a customer not churning (Bachmann et al., 2021; Schmittlein et al., 1987), insights derived from sales or price sensitivity alone may not generalize to CLV outcomes. Using our rich transaction dataset tracking customer behavior over 20 months from the promoted product's launch, we can estimate the effects of coupon usage from customer acquisition through the end of their engagement with the firm, providing a comprehensive view of how promotions influence long-term customer value.

Second, we explore heterogeneity in the value-lift concept. As a measure of customer heterogeneity, we use pre-CLV, defined as the estimated CLV prior to the coupon intervention. The use of pre-intervention purchase history to capture heterogeneity aligns with previous research (e.g., Zhang et al. (2018); C. Lin and Bowman (2022); Bhatt et al. (2023); Nishio and Hoshino (2024)), which employed customers' RFM values to classify them and to investigate heterogeneous treatment effects. However, pre-CLV offers advantages over such metrics because it avoids arbitrary scoring rules and provides elasticity-based interpretations (e.g., a 1% increase in pre-CLV is associated with a 5% increase in CLV). Investigating the heterogeneous effects of coupon usage also allows us to determine whether targeting high-value customers can yield higher returns. Specifically, analyzing heterogeneity in coupon effects on churn and CLV provides insights for managers regarding (1) which customers are most likely to remain active or experience the largest increase in expected CLV, and (2) whether focusing on high-value customers produces net benefits, given the potential for increased price sensitivity and churn.

Third, we assess how the impact of coupons differs between manufacturers and retailers. In practice, coupon programs typically involve collaborations between the two parties: manufacturers may fund discounts for the coupons, while retailers distribute the coupons to end customers (Wierich & Zielke, 2014). Retailers may also promote manufacturers' products in-store to earn post-purchase discounts. On the surface, these collaborations appear mutually beneficial: retailers can attract customers with deep discounts they could not otherwise offer, and manufacturers can reach end customers directly (Hecht et al., 2020). However, prior research suggests that the "success" of such collaborations may not be evenly distributed due to their differing profit structures. In particular, retailers face more complex effects from cannibalization and product switching, which can obscure the impact of promotions on their category-level sales and profit (Bhatt et al., 2023; Dawes, 2012; McColl et al., 2020; Sunder et al., 2016). Nevertheless, the implications of coupon programs for churn and CLV remain largely unexplored. Therefore, we analyze the coupon effects on these outcomes from the perspectives of both the manufacturer and retailer. Specifically, we define manufacturer-level outcomes as the effects on all within-category products by the promoting manufacturer, and retailer-level outcomes as the effects on all within-category products offered by all manufacturers in the store. In addition, we investigate spillover effects to assess whether coupons generate broader demand expansion for the manufacturer and the retailer, respectively.

Lastly, this study leverages a randomized coupon assignment as an exogenous source of variation to estimate the causal effects of redemption by using an interacted two-stage least squares (2SLS) model. Given the low coupon redemption rate of 3.83% in this study, a simple comparison between the treatment and control groups may risk selection bias, even when the coupon assignment itself is random. Thus, we address this endogeneity from noncompliance by using the randomized coupon assignment as an instrumental variable. In other words, we estimate the effects of *using* a coupon rather than *being offered* one. This allows us to provide robust estimates that both complement and extend previous observational studies.

Based on our randomized field experiment across 267 supermarkets in Japan, we find that coupon redemption reduces the probability of churn and increases CLV. Although the magnitude of these improvements attenuates as pre-CLV rises, our marginal treatment effect estimates indicate that even customers with higher pre-CLV experience improvements in both churn and CLV. Finally, our results indicate that the manufacturer-level outcomes experience the value-lift effect without attenuation, while the retailar's category-level outcomes only experience attenuation effects as pre-CLV increases.

The present study is relevant to Valentini et al. (2024), in which the authors examined the long-term effects of servicescape remodeling on average basket size, purchase frequency, churn, and CLV. Their findings indicated that servicescape remodeling can have a positive impact on CLV in hedonic servicescapes, but fails to produce a notable effect in utilitarian contexts, underscoring the context-dependent nature of such interventions. In contrast, our study offers a different perspective by exploring the persistent and heterogeneous impacts of price promotions. We believe that research investigating the effects of the marketing mix on CLV will continue to attract attention from both academic researchers and industry practitioners.

The remainder of the paper is organized as follows. Section 2 describes previous research on promotional incentives, CLV, and other metrics. Section 3 explains data and methods for CLV estimation and causal inference. Section 4 discusses the results, and Section 5 concludes.

2 Literature Review and Hypotheses Development

2.1 Do Coupons Increase CLV?

CLV is defined as the present value of all future profits generated by a customer over the duration of their relationship with a firm (Gupta et al., 2006). Since CLV is an important component of CRM, understanding how price promotions impact CLV is important for both researchers and practitioners. However, previous research on their impact on CLV or profit in noncontractual settings has been mixed. For example, Anderson and Simester (2004) found that customers who were acquired through deeply discounted catalog items tended to exhibit higher long-term value. In an online platform, Ferreira et al. (2016) demonstrated that price reductions can lead to higher revenue. Conversely, Norvell and Horky (2017) found from their study in a restaurant chain that gift card discounts can stimulate sales growth albeit they may simultaneously reduce profits.

The balance between immediate sales gains and potential long-term losses may explain whether a promotion can enhance or diminish CLV. On the one hand, reducing the perceived cost of product trials can lead to an increase in immediate sales. Promotional incentives can lower the perceived risk of product trials, encouraging new customers to engage with unfamiliar products (Ataman et al., 2008; Lewis, 2006; J. Lin et al., 2024; Mao et al., 2024). This mechanism is especially effective for newly launched or experience-based products for which uncertainty or unfamiliarity is a barrier to purchases (Ailawadi et al., 2007; Mao et al., 2024). By offering low-risk entry points, promotions can help firms acquire customers who may not have considered the product otherwise, initiating a potentially profitable relationship.

Conversely, increased price sensitivity may explain why promotions negatively affect customers' profitability in the long run. Specifically, repeated exposure to discounts can lower the internal reference prices of consumers, making regular prices appear less attractive and reducing the willingness to pay (Ataman et al., 2008; Elberg et al., 2019; Mela et al., 1997). Although long-term sales often remain relatively stable even among more price-sensitive customers (Anderson & Fox, 2019), the implications for CLV may differ. As an ROI-based metric, CLV can decline when profit margins are eroded by promotional discounts. In other words, while price promotions may boost short-term revenue, they can also increase costs borne by firms and reduce profit margins, thereby diminishing CLV, which is a function of profit margin, revenue per transaction, and the expected number of future transactions (Cambra-Fierro et al., 2021).

Given these potential mechanisms that either increase or decrease CLV, the overall impact of a promotion depends on the trade-off between short-term benefits (i.e., reduced trial costs and increased immediate purchases) and long-term risks (i.e., increased price sensitivity). For example, promotions can increase CLV when used to introduce new products or acquire first-time buyers, especially in categories with high trial barriers. In such cases, the value of customer acquisition may outweigh any long-term negative pricing effects. However, for well-established products with existing market familiarity, promotions can cannibalize revenue or diminish long-term value by conditioning customers to wait for certain discounts.

Beyond balancing short-term benefits and long-term risks, CLV is also influenced by whether a customer is expected to remain active at the time of estimation. This is because one of the core components of CLV—the expected number of future transactions—depends on the probability that a customer does not churn (i.e., remains *alive* and continues the relationship with the firm). Although research on customer responses to retention programs is limited, Ascarza (2018) showed that such programs can reduce churn among customers who are highly responsive, in contractual contexts such as wireless services and membership organizations. Therefore, if a program successfully reduces churn among customers with higher responsiveness, CLV, through improved retention probabilities, can correspondingly increase for those customers.

In this study, coupons were issued for a newly launched product in the beer category. Given that customers were likely unfamiliar with the product at the time of the promotion, the coupons reduced the trial cost and encouraged initial purchases. Even if the promotion adjusted customers' reference prices downward, the potential for customer acquisition and trial most likely offset such effects. Furthermore, our causal estimates focus on customers who redeemed the coupon, or 3.83% of those exposed, in order to ensure robust inference (see Section 3.2 for details). As a result, our analysis primarily reflects the responses of program-sensitive customers who are most likely to experience improvements in future churn. Based on this context, we propose the following hypotheses:

H1: Using a coupon decreases the probability of churn for a promoted product.

H2: Using a coupon increases post-CLV for a promoted product.

2.2 The Interplay between Customer Loyalty and Coupon Effectiveness

When customers are considered as heterogeneously valued assets under CRM, the next logical step is to examine the relative value of different customer segments and create differentiated marketing strategies accordingly (Gupta et al., 2004; Lewis, 2006). Previous research has suggested that while coupon campaigns are generally effective at achieving short-term objectives, their effectiveness is not uniform across customer types. In other words, customers with higher levels of observed purchasing behaviors tend to exhibit diminished effectiveness to such interventions. For instance, Zhang et al. (2018) demonstrated that while coupons doubled the sales of targeted products, customers with a history of frequent purchases became more price-sensitive one month after the promotion. Bhatt et al. (2023) showed further evidence that customer loyalty negatively impacted both sales of the discounted products and rest-of-the basket sales. Moreover, similar trends have been observed in the context of loyalty programs (LPs). For example, Nishio and Hoshino (2024) classified customers into 27 groups based on RFM metrics and found that, within clusters with higher RFM scores, the median CLVs of control customers who did not receive a birthday reward were higher than those of treated customers. Thus, although the program had positive effects on customers in lower-RFM clusters, its negative impact on previously engaged customers indicates diminishing returns at higher engagement levels.

Altogether, these studies reveal a consistent pattern: the effectiveness of marketing interventions decreases as customers' existing engagement or value increases. Two mechanisms may help explain this attenuation pattern. First, high-engagement customers are more likely to have a smaller positive retention effect through the program. For instance, Dong et al. (2011) demonstrated that acquisition campaigns can inadvertently trigger churn among existing high-value customers, ultimately reducing the profitability of the customer base. Moreover, as mentioned earlier, Ascarza (2018) found that retention campaigns exhibit clear heterogeneity: the more sensitive a customer is to the intervention, the more likely they are to be retained. This raises the question: who are these highly responsive customers? A hint is provided by Elberg et al.

(2019), who showed that non-loyal customers tend to become more price sensitive in the long term compared with loyal customers. Therefore, it can be inferred that price-sensitive customers, those who with lower engagement with the firm but some prior interest in the product, are both more likely to redeem coupons and more likely to be retained through the program. These results indicate that customers with lower prior engagement are more likely than highly engaged customers to stay active by receiving promotional incentives.

Second, customers with higher engagement have less potential to increase their CLV. Coupon campaigns are intended to encourage incremental purchases, but such gains are more difficult to achieve among already engaged buyers (Nishio & Hoshino, 2024). When high pre-CLV customers redeem a coupon at a discounted price, their per-unit margin declines unless the promotion leads to a substantial increase in future purchases at full price (Norvell & Horky, 2017). In contrast, customers with lower prior engagement are likely to respond more strongly, as coupons can motivate them to initiate or deepen their relationship with the product that can help increase their CLV. Even if they remain discount-driven and only purchase under another promotion, their CLV may still increase from zero to a positive value, provided that the transaction clears the profit threshold. For these previously inactive customers, therefore, even a single trial can result in a larger relative increase than among already-loyal customers.

In sum, previous research has consistently shown that the positive effects of promotional campaigns tend to attenuate as customer engagement increases. This trend holds across various contexts such as online platforms, supermarkets, and loyalty programs. Potential contributing factors include lower retention effect among highly engaged customers and ceiling effects among these customers. Drawing on the literature and the mechanisms discussed, we present the following hypotheses:

H3: The positive effects of coupon redemption on the probability of churn attenuate as pre-CLV increases.

H4: The positive effects of coupon redemption on CLV attenuate as pre-CLV increases.

2.3 Coupon Effects for Manufacturers and Retailers

Coupon programs targeted at end customers frequently involve collaborations between manufacturers and retailers (McColl et al., 2020; Widdecke et al., 2023; Wierich & Zielke, 2014). In this regard, managers from manufacturers regularly negotiate promotional schedules with retailers and employ a wide range of tools, including temporary price reductions, in-store displays, catalogs, coupons, rebates, and free samples (McColl et al., 2020).

Such collaborations allow manufacturers to reach consumers directly at the point of purchase, where the majority of final decisions are made. Indeed, previous studies have shown high rates of unplanned purchases at retail stores. For example, 36.3% of the customers in Suher and Hoyer (2020) and 53.9% of those in Gilbride et al. (2015) made unplanned purchases. Moreover, according to a 2012 report by Point of Purchase Advertising International (POPAI), unplanned purchases accounted for 76% of total purchases (POPAI, 2012). When asked about their impulse purchases, most of the consumers recalled an in-store need or a sale (POPAI, 2012). These findings underscore the importance of in-store advertising and promotions as critical channels for manufacturers.

Hence, manufacturers have become increasingly interested in reaching customers at the point of sale through coupons, price discounts, and in-store visual displays to promote in-store purchasing decisions. To reflect their interest, manufacturers of consumer-packaged goods are steadily increasing their global investment in trade promotions (Tsao & Lu, 2016). Additionally, they are funding coupons for their brand products, referred to as "manufacturer-funded coupons" (Wierich & Zielke, 2014), in order to stimulate various consumer responses, including increased purchase volume, impulse buying, brand switching, and product trials at the point of purchase.

As for retailers, they also have incentives to cooperate with manufacturers in issuing coupons and conducting in-store promotions. Typically operating on slim profit margins of 1 to 3% (Food Marketing Institute, 2025), grocery retailers benefit from manufacturer-funded discounts as an attractive opportunity to draw in customers (Ailawadi & Harlam, 2009; Wierich & Zielke, 2014). Moreover, retailers can benefit from unplanned purchases as well, since the purchase of a discounted item can generate additional sales by fostering a perception of overall low store prices, which in turn encourages consumers to make unplanned purchases of non-discounted items at the store (Bhatt et al., 2023; Johnson, 2017). Some retailers may also combine manufacturer-funded coupons with their own coupons to generate synergy at both the brand and category levels (Widdecke et al., 2023). Furthermore, participation in trade promotions can reduce wholesale costs, especially if the target goal is achieved (Hecht et al., 2020).

At first glance, their partnership appears mutually beneficial. Specifically, manufacturers can gain access to customers at the point of sale, while retailers can attract customers at a lower cost. However, previous research has shown that the net gains are often different for each party. For example, Srinivasan et al. (2004) found that while in-store price promotions can boost manufacturers' short-term sales, they do not necessarily increase retailers' profits, with neither party gaining in the long run. Similarly, Tsao and Lu (2016) showed that rebate design can help shape profit distribution: while unsold discount policies (which provide rebates on unsold inventory) can result in win-win outcomes, target rebate policies (which reward sales beyond a certain threshold) tend to disproportionately favor manufacturers.

These differing outcomes partly stem from the distinct ways in which manufacturers and retailers evaluate promotional success: manufacturers typically focus on outcomes aggregated across all products of a given brand, reflecting combined sales and profits at the brand level. In contrast, retailers must consider broader effects, including cannibalization and brand switching within and across categories, which makes it more difficult to isolate the impact of a single campaign on profits. In fact, McColl et al. (2020) reported that price promotions inherently involve a degree of cannibalization for retailers since such incentives frequently induce product switching within a category or cross-category. Moreover, Bhatt et al. (2023) demonstrated that while multiunit discounts can boost sales of the promoted products, they may reduce revenue from the rest of the basket during the shopping trip, ultimately leading to a decline in retail-level revenue. Thus, the extent of cannibalization should be factored into calculations regarding the profitability of a price promotion (Dawes, 2012; Sunder et al., 2016).

Building on the discussion in Section 2.1, coupons are expected to improve the promoted product's churn and CLV through customer acquisition, which directly affects manufacturer-level outcomes. However, retailers face a more complex profit structure due to within- and cross-category cannibalization and brand switching. In this context, promotions may primarily redistribute demand rather than generate net growth. Based on these considerations, we formulate the following hypotheses:

H5: While coupon redemption decreases manufacturer-level probability of churn, it does not affect retailer-level probability of churn.

H6: While coupon redemption increases manufacturer-level CLV, it does not affect retailer-level CLV.

3 Data and Methodology

3.1 The Field Experiment

To investigate the impact of a coupon program on CLV, we conducted a large-scale field experiment in collaboration with a major everyday low price (EDLP) supermarket chain in Japan. This experiment was implemented across 267 of the chain's stores. During the coupon distribution period, customers in the treatment group who made any purchase at one of the participating stores received a printed paper receipt with a coupon for a newly launched product in the beer category. Specifically, this coupon offered 100 points (equivalent to 100 yen: approximately USD 0.66) redeemable at the store upon purchase of the target product during the designated redemption period. In this case, the 100 points represented a 50% discount from the product's regular shelf price.

This coupon campaign was manufacturer-funded, in which the beverage manufacturer financed the coupons and the retailer distributed them at the point of sale. In this case, the manufacturer is a major player in the Japanese beverage industry, with an estimated 16.6% market share in the beer category. [1] Overall, the coupons were randomly distributed to 129,684 eligible customers based on their shopping behavior in the previous year. The eligibility criteria included patterns of weekly store visits and purchase histories in the beer and ready-to-drink product categories. These customers were then randomly assigned to either the treatment or control group.

Prior to analyses, we performed two data preprocessing operations. First, we sampled the customers for whom age and sex were known. Since purchasing behaviors can differ, depending on the values of these demographic variables (see, e.g., Lambert-Pandraud and Laurent (2010)), we controlled for them in our statistical models. Second, we selected the customers whose age was between 20 and 80 years. Subsequently, 6,986 customers were removed, resulting in a final sample of 125,345 customers with complete demographic information. Figure 1 presents this study's flowchart, ranging from selecting the eligible customers to cleaning the data.

According to Table 2, which provides an overview of this experiment, the promoted product was released in early April 2023, after which the coupons were distributed during a six-week window. Since eligibility was contingent upon making any purchase during this period, majority of the treatment group customers received a coupon. However, only 2,875 customers (3.83% of the treatment group) redeemed the coupon. This low redemption rate is consistent with previous research in which 0.1 to 3% of the recipients redeemed their coupons (Anderson & Simester, 2004; Norvell & Horky, 2017; Sahni et al., 2017; Zhang et al., 2018). It should be noted that due to our experiment design, the control group customers did not receive the coupons and were therefore unable to redeem them.

Finally, to estimate CLV, we merged the individual-level point of sale data with the coupon assignment data. This allowed us to track the purchasing behaviors of each customer over the 20-month observation

[1]This estimate was based on the transaction data of customers who participated in the experiment (April 2022–March 2023), calculated as the manufacturer's total beer-category sales divided by total category sales.

window (April 2022–December 2023).

3.2 CLV Estimation

3.2.1 CLV Model

To estimate CLV for each customer, we adopt the canonical formula proposed by Fader et al. (2005):

$$CLV = margin \cdot revenue\, per\, transaction \cdot DET, \tag{1}$$

where *margin* refers to the profit margin (as a proportion of the selling price), *revenue per transaction* is the expected purchase amount per transaction, and DET, or Discounted Expected Transactions, represents the number of discounted expected transactions that a customer will make over a given time period. Following Nishio and Hoshino (2024), in which CLV of a Japanese retail chain was estimated, we set the margin at 30%. The values for *revenue per transaction* and DET are estimated using the Gamma/Gamma model (Fader et al., 2005) and the Pareto/NBD (Pareto negative binomial distribution) model (Schmittlein et al., 1987), respectively.

The Pareto/NBD model serves as a central framework for estimating the discounted expected transactions in non-contractual settings (Glady et al., 2015)). For customer i whose purchase history is observed in period $(0, T)$, with total purchase count x and the last purchase occurring at time $t_x (0 < t_x \leq T)$, DET is defined as follows:

$$DET = \sum_{t=1}^{n} \frac{E[Y(t)|X = x, t_x, T] - E[Y(t-1)|X = x, t_x, T]}{(1+d)^t}, \tag{2}$$

where the numerator represents the expected number of purchases at time t, and d denotes the discount rate. In line with the previous literature (Fader et al., 2005; Gupta et al., 2006; Nishio & Hoshino, 2024), we set the annual discount rate at 15%.

Through this modeling framework, we estimate several forms of outcomes to capture both treatment effects and customer heterogeneity. Table 3 summarizes the estimated CLV outcomes and their definitions. First, we estimate CLVs that reflect the direct effects of coupon redemption. The direct effects include CLV for the promoted product (*product CLV*), all beer-category products by the manufacturer (*manu CLV*), and all beer-category products sold by the retailer (*ret CLV*). As proposed by Dawes (2012), we use category-level CLV as the retailer's CLV to include within-category cannibalization and brand switching effects in response to the coupon redemption.

Additionally, we construct variables to isolate the spillover effects beyond the promoted product. Since *manu CLV* and *ret CLV* can include an uplift effect from the promoted product's CLV, we construct spillover variables. These variables include the manufacturer's CLV excluding the promoted product (*manufacturer CLV excl. product*), and the retailer's CLV excluding all the products from the manufacturer (*ret CLV excl. manu products*) that measure the extent to which coupon redemption impacts competing brands. Moreover, we include the retailer's CLV for store-brand beer products (*store-brand CLV*), which typically include the highest margins and may be vulnerable to cannibalization. In estimating the CLVs for the direct and spillover effects, we use the purchase logs from April 2022 to July 2023. Since the coupons were distributed and redeemed by June 2023, this period includes information regarding the purchases after the coupon campaign. In this case, we set the prediction period for CLV as December 2023 (i.e., six months post redemption).

Moreover, to determine how the coupon effects vary by customer, we estimate pre-CLVs that capture customers' prior economic value to the manufacturer and retailer, i.e., *pre-manu* and *pre-ret*. These CLV values are constructed by using transaction data from April 2022 to May 2023, indicating that they only include information before the coupons were distributed. Then, we estimate customers' CLVs in July 2023 and employ this information to express customer heterogeneity. In other words, since they estimate customers' economic value prior to the coupon distribution, comparing the redemption effects by pre-CLV allows us to measure the heterogeneity in coupon effects based on previous purchase records.

Additionally, using parameters obtained from estimating DET, we can estimate the probability that a customer with purchase history (x, t_x, T) is "alive" at time T (Schmittlein et al., 1987). Based on this, the probability of churn is given by $1 - P(\text{alive} \mid x, t_x, T)$. In the same way as for CLV, we define the outcomes for the probability of churn six months after redemption. Table 4 summarizes the definitions of each churn outcome measure.

3.2.2 Model Fit

One of the strengths of the Pareto/NBD model is its simplicity, which stems from the three aforementioned assumptions. However, as a trade-off, it may fail to capture certain features of consumers' behaviors such as periodic purchasing patterns or correlations between purchasing and churn (Glady et al., 2015). In order to address these limitations, several studies have extended the seminal Pareto/NBD model to allow more flexibility (Bachmann et al., 2021; Glady et al., 2015).

The present study focuses on beer-related purchases, which tend to exhibit weaker periodicity than other behaviors. Moreover, the correlations among the RFM variables in our data are low. Specifically, for transactions between April 2022 and July 2023, the correlations between recency and monetary are 0.102 for manufacturer-level purchase logs and 0.042 for retailer-level purchase logs, indicating that the independence assumption of the Pareto/NBD model holds. Similarly, the correlations between frequency and monetary are 0.017 for manufacturer-level logs and 0.076 for retailer-level logs during the same period, suggesting that our data also meets the independence assumption of the Gamma/Gamma model. Given that the independence assumptions of both models hold, we use these models for our CLV estimation.

Furthermore, we evaluate the predictive performance of the Pareto/NBD and Gamma/Gamma models by using our category-level transaction data. For the retailer's post-CLV, the learning period is from April 2022 to July 2023, while the estimation period is set as December 2023. Figure 2 shows the observed (solid line) and predicted (dashed line) average number of repeat purchases for the following three groups: customers in the treatment group who redeemed the coupon; customers in the treatment group who *did not* redeem the coupon; and customers in the control group, who had no opportunity to redeem it. Similarly, Figure 3 includes the observed (solid line) and predicted (dashed line) average repeat purchase amounts for these groups. In both cases, the models capture the trends in observed values across purchase frequency levels during the estimation period, demonstrating their predictive accuracy and supporting the validity of applying the Pareto/NBD and Gamma/Gamma models to our data.

3.3 Interacted 2SLS

3.3.1 Assumptions

In our experiment, coupons were randomly assigned to the customers. To confirm that the randomization was successful, we compare the pre-experiment variables between the treatment and control groups. In Table 5, the upper panel reports the *t*-test results, the middle panel shows the results of the analysis of variance (ANOVA), and the lower panel displays the chi-square test results. The reported figures represent group means, with standard deviations in parentheses. As for sex, the figure represents the number of males in each group. All the pre-intervention variables, such as pre-CLV, age, and sex, show no statistically significant differences between the treatment and control groups, indicating that the randomization was successfully performed.

However, there exists noncompliance, since most of the customers who received a coupon did not actually redeem it, rendering coupon usage as an endogenous variable. Thus, to address the endogeneity of such usage, we estimate the causal effect by using an instrumental variable approach. Additionally, the participants in the control group were not provided with coupons and, by design, could not use them. This situation is often referred to as "one-sided noncompliance," since the control group members were required to comply with their assignment of not using the coupon.

Before proceeding to the analysis, we verify the assumptions required for a valid instrumental variable. In this regard, there are four such assumptions. The first is independence, which states that the instrumental variable is unrelated to potential outcomes and potential treatment assignment. Since coupons were randomly allocated in this study, this assumption holds. In practice, we confirm that the covariates were balanced between the customers who received the coupon and those who did not in Table 5.

The second assumption is the exclusion restriction, which states that the instrumental variable only influences the outcome through its effect on the treatment, which assumption cannot be directly tested. However, it is unlikely that the mere assignment of coupons has a direct effect on either the probability of churn nor the post-intervention CLV. Hence, we assume that this condition holds.

The third assumption is referred to as "relevance" (i.e., first-stage), indicating that the instrumental variable must affect the treatment. In this regard, coupon assignment is assumed to influence coupon usage. Indeed, we verify this assumption in the following section and find that it holds in our sample.

The last assumption is monotonicity, which indicates that there are no defiers, i.e., there are no individuals who would use a coupon if it was not distributed, but would refrain from using it if it was distributed. In this context, we assume that distributing a coupon does not reduce the likelihood of coupon usage. As for one-sided noncompliance, the control group members were unable to use the coupons, implying that the monotonicity assumption is satisfied.

Based on these four assumptions, we consider the random allocation of coupons as a valid instrumental variable. Then, we estimate the causal effect of coupon distribution on coupon usage and, in turn, on CLV. In this case, the local average treatment effect (LATE) is used for compliers. However, since it involves one-sided noncompliance, the LATE can be expanded to the average treatment effect on the treated, or ATT (Abadie & Cattaneo, 2018).

3.3.2 Empirical Model

In this study, we use an instrumental variable approach to account for heterogeneity in the treatment effects by employing an interacted two-stage least squares (2SLS) model. This model can be applied when the instrumental variable is randomly assigned without any conditions (Ding et al., 2019; Zhao et al., 2025). The model specification is as follows:

First Stage:

$$D_i = \pi_0 + \pi_1 Z_i + \pi_2 \ln X_i + \pi_3 Z_i \cdot \ln X_i + \gamma \boldsymbol{W} i + \eta_i \tag{3}$$

$$D_i \cdot \ln X_i = \rho_0 + \rho_1 Z_i + \rho_2 \ln X_i + \rho_3 Z_i \cdot \ln X_i + \delta \boldsymbol{W} i + u_i \tag{4}$$

Second Stage:

$$\ln Y_i = \beta_0 + \beta_1 \ln X_i + \beta_2 \hat{D}_i + \beta_3 \hat{D}_i \cdot \ln X_i + \theta \boldsymbol{W}_i + \varepsilon_i \tag{5}$$

In the first stage, D represents coupon usage, Z is the instrumental variable for random coupon allocation, X is the pre-CLV, and $\boldsymbol{W}$ denotes covariates of age and sex. Additionally, Y represents the outcome, which are the probability of churn and the post-CLV. The values for $\hat{D}$ and $\hat{D} \cdot \ln X$ are estimated in the first stage, which are then used in the second stage to estimate the causal effects. Standard errors are obtained via 1,000 bootstrap replications. As for pre-CLV variables, we perform centering by using the estimated mean for compliers. This estimation follows the approach proposed by Abadie (2003). Meanwhile, post-CLV and pre-CLV are expressed in logarithmic form, allowing the results to be interpreted in terms of percentage.

4 Results

4.1 First-Stage Results

Based on the model specifications in the previous section, we employ our interacted 2SLS model. Table 6 presents the results of the first-stage regressions. For each heterogeneity measure, *pre-manu* and *pre-ret*, we estimate two models: one in which the dependent variable is whether the coupon was redeemed D, and another where it is the interaction term $D \cdot \ln X$. Column (1) in Table 6 reports results using *pre-manu* as the heterogeneity variable, while Column (2) presents the results of using *pre-ret*. Additionally, the rows for Z and $Z \cdot \ln X$ show the coefficients for the instrumental variable (i.e., random coupon assignment) and its interaction with log heterogeneity, respectively. The bootstrapped standard errors are reported in parentheses.

For each heterogeneity measure, all four specifications yield strong first-stage results, with f-statistics exceeding 300, suggesting that the instrument satisfies the relevance assumption. Meanwhile, the coefficients for $Z \cdot \ln X$ in the regressions are positive in both cases, indicating that customers with high pre-CLV are more likely to redeem coupons.

4.2 Effects on the Promoted Product

4.2.1 Decreased Probability of Churn from the Promoted Product

Having confirmed that our data satisfies the relevance assumption, we now focus on our main results. Firstly, Table 7 presents the second-stage interacted 2SLS estimates on various churn outcomes. The leftmost column lists the six churn measures of interest, categorized as direct or spillover effects. Columns (1) and (2) report estimates using *pre-manu* as the heterogeneity variable, while columns (3) and (4) present the estimates of using *pre-ret* as this variable. Columns (1) and (3) present coefficients for coupon redemption (D), while Columns (2) and (4) show coefficients for the interaction term ($D \cdot \ln X$). Pre-CLV variables are log-transformed. The interpretation of the interacted 2SLS on the probability of churn is as follows: coefficients for D represent the change in the probability of churn, expressed in percentage points. Additionally, the coefficients for the interaction term show how this effect varies with prior customer value: specifically, a 1% increase in pre-CLV modifies the marginal effect of coupon use on churn by coefficient$\cdot \frac{1}{100}$ percentage points. Thus, the interaction coefficients capture customer heterogeneity in the treatment effect, indicating how the impact of coupon redemption varies with pre-CLV.

A key finding is the contrasting signs of the coefficients for D and $D \cdot \ln X$. Specifically, coupon redemption improves the probability of churn (Columns (1) and (3)), but this effect attenuates with higher pre-CLV (Columns (2) and (4)). For instance, the probability of churn of the promoted product decreases by 11.5 percentage point (12.9 percentage point) after coupon redemption when measured by *pre-manu* (*pre-ret*). However, for every 1% increase in pre-CLV, the improving effect attenuates by 0.059 percentage point (0.004 percentage point) depending on the heterogeneity measure *pre-manu* (*pre-ret*). Therefore, these findings indicate that coupon redemption decreases the probability of churn by approximately 12 percentage points among coupon redeemers, but the improvement attenuates as customers' pre-CLV increases. In other words, the effect on the churn improvement is larger in magnitude among customers with lower pre-CLV values than those with higher pre-CLV values. Based on these findings, we can conclude that H1 and H3 are supported: coupon redemption improves the probability of churn for the promoted product, but the magnitude of this improvement attenuates as pre-CLV rises.

Furthermore, the estimation results for the intention-to-treat (ITT) effect, or a simple comparison of the CLV between the treatment and control groups, are reported in Column (5). In this case, the ITT does not account for selection bias emerging from customers' decisions regarding whether to redeem the coupon. Rather, it identifies the effect of being exposed to the coupon, or seeing the coupon on the receipt. Hence, the ITT loosely captures the coupon's advertisement effect on customers' purchasing behaviors. For example, according to the ITT estimation results, the difference between the treatment and control groups is as little as -0.004 in *product churn*, indicating that a simple comparison between these groups may not effectively capture the coupon's impact on the probability of churn. In other words, being exposed to the coupon itself does not have a practically meaningful impact on the probability of churn.

4.2.2 Increased Post-CLV of the Promoted Product

Next, we investigate the effect of coupon redemption on CLV. With the same first-stage results, we estimate the effects of using coupons on CLV six months later. Table 8 presents the interacted 2SLS estimates for various CLV outcomes, with the table layout mirroring that of Table 7. All CLV variables are log-transformed. In this specification, the coefficient for D represents the semi-elasticity of CLV: coupon redemption increases the outcome CLV by approximately $100 \cdot$ coefficient percent. The interaction term, $D \cdot \ln X$, captures the elasticity of the treatment effect with respect to pre-CLV: a 1% increase in pre-CLV changes the effect of coupon redemption by the magnitude of the coefficient in percentage points.

Consistent with the churn results, the coefficients for D and $D \cdot \ln X$ have opposite signs: coupon redemption increases CLV, but the effect attenuates with higher pre-CLV. For instance, the CLV of the promoted product increases by 31.4% (32.9%) after coupon redemption when measured by *pre-manu* (*pre-ret*). However, for every 1% increase in the manufacturer's pre-CLV, the effect decreases by 0.107% (0.178%), respectively. Yet, the attenuation effect is not statistically significant when measured by *pre-manu*: customers who had higher engagement with the manufacturer did not decrease the positive effect on their CLV. In sum, coupon redemption did increase *product CLV* by roughly 32%, but the positive effect attenuates as customers' pre-CLV increases especially when measured by the retailer's category-level pre-CLV. Based on these results, we can conclude that H2 and H4 are supported: coupon redemption increases product-level CLV, and this increase attenuates as pre-CLV rises. Finally, Column (5) shows a minimal ITT effect (0.013 in *product CLV*), indicating that merely receiving a coupon without redemption has little impact on CLV.

4.2.3 Marginal Effects at ± Standard Deviation of Pre-CLV

To quantify differences across customers with low, mean, and high pre-CLV values, we examine the marginal effects of coupon redemption on both the probability of churn and the CLV of the promoted product. Specifically, we estimate the ATT for each customer with mean pre-CLV, as well as one standard deviation above and below the mean. Table 9 reports these estimates. For each outcome and heterogeneity measure, the table presents the ATT and corresponding standard errors for each level of customer pre-CLV.

The results reveal a clear pattern: customers with higher pre-CLV exhibit substantially smaller improvements in both outcomes compared to customers with mean or lower pre-CLV. For example, coupon redemption reduces the probability of churn by 15.4 (23.0) percentage points among customers one standard deviation below the mean pre-CLV, measured by *pre-manu* (*pre-ret*). In contrast, the effect diminishes or even reverses for customers one standard deviation above the mean, with churn reductions of only 3.9 (-2.3) percentage points. Similarly, the effect on *product CLV* is greater among customers with low pre-CLV, increasing CLV by 46.7% (61.1%), compared with 19.0% (6.3%) among high pre-CLV customers, based on *pre-manu* (*pre-ret*). It is worth noting, however, that customers with high pre-CLV still experience positive gains in CLV. Therefore, we conclude that coupon programs increase the CLV of the promoted product for nearly all customers, with the effect being particularly pronounced among those with lower pre-CLV values.

4.3 Manufacturer vs. Retailer Effects

4.3.1 Churn Probability: Greater Improvements for the Manufacturer

Next, we compare the effects of coupon usage across the manufacturer and the retailer by examining broader impacts beyond the promoted product. We begin with the probability of churn. Considering the direct effects including the promoted product, Table 7 reveals contrasting patterns: manufacturer-level churn decreases by 8.3 percentage points when measured using *pre-manu*, whereas retailer-level churn shows no improvement. In fact, the probability of churn for the retailer, when measured by *pre-ret*, decreases slightly, suggesting that the retailer bears some of the risks associated with coupon redemption without realizing a reduction in churn.

This pattern persists for spillover effects, where the promoted product or the promoting manufacturer's products are excluded to examine indirect effects on other products. Manufacturer-level spillover churn (*manu churn excl. product*) decreases by approximately 8.3 percentage points across both *pre-manu* and *pre-ret* measures, demonstrating a robust positive effect without attenuation. In contrast, retailer-level spillover churn (*ret churn excl. manu products*) shows a small negative attenuation effect (0.091 percentage points) when measured by *pre-ret*, *without* evidence of improvement in churn. Additionally, *store-brand churn* does not improve following coupon redemption under either measure.

4.3.2 CLV Outcomes: Greater Improvements for the Manufacturer

A similar pattern emerges when comparing manufacturer- and retailer-level effects on CLV, but in this case, the heterogeneity by pre-CLV is more pronounced. For the manufacturer, coupon redemption significantly boosts both direct and spillover CLVs. For example, manufacturer's CLV increases by 54.0% (57.4%) when measured by *pre-manu* (*pre-ret*), although the uplift diminishes as pre-CLV increases. Conversely, the spillover effects on the CLV, excluding the promoted product, show no significant attenuation. In this case, the interaction-term coefficients are small and statistically insignificant (0.007 for *pre-manu* and –0.112 for *pre-ret*), while the coefficients for coupon redemption are positive and significant, corresponding to a 40.3% (40.8%) increase in CLV for *pre-manu* (*pre-ret*). These findings suggest that the manufacturer not only benefits from increased CLV of the promoted product, but also from higher CLV across other products. This effect holds across customers with varying pre-CLV levels. However, for the retailer, the story differs. Specifically, coupon redemption does not significantly increase retailer's CLV. Meanwhile, the interaction terms are negative and significant, suggesting that coupon redemption may reduce retailer's CLV among high pre-CLV customers. For example, a 1% increase in pre-CLV is associated with a 0.267% ($p < 0.1$, when measured by *pre-ret*) and 0.402% ($p < 0.05$, when measured by *pre-manu*) decrease in retailer CLV. This pattern persists even when examining spillover CLV (i.e., *ret CLV excl. manu products*), but only when using *pre-manu* as the heterogeneity measure. When using *pre-ret* as the heterogeneity measure, neither coupon redemption nor the interaction terms are statistically significant. In sum, the retailer sees little to no positive CLV effect from coupon redemption and may even suffer declines among high-value customers.

Interestingly, a distinct pattern is observed for store-brand CLV. Here, the interaction terms are positive (0.060 when measured by *pre-manu* and 0.099 by *pre-ret*), indicating a potential CLV uplift from both coupon redemption and high pre-CLV. However, these estimates are statistically insignificant. Thus, although they might hint that store brands may benefit differently from coupons, compared to national-brand products, our 2SLS results do not provide further support for the differentiated trends among store-brand products.

Overall, our interacted 2SLS results from Table 7 and Table 8 highlight a stark contrast between the manufacturer and the retailer. Specifically, the manufacturer enjoys strong, positive effects from coupon redemption, both directly and through spillovers. In contrast, the retailer derives little benefit and may even face negative effects among customers with high pre-CLV. Based on these findings, H5 and H6 are supported: coupon redemption improves the manufacturer's brand-level probability of churn and CLV, but does not significantly affect the retailer's category-level probability of churn or CLV.

5 Discussion

While CLV is often associated with marketing programs of contractual products designed to build long-term customer relationships, short-term promotions can also influence CLV, as the metric incorporates the costs and benefits of customers from acquisition through retention (Ascarza et al., 2018; Lewis, 2006). Within CRM, where customers are treated as assets, firms are encouraged to allocate resources based on the potential probability of churn and increases in CLV in response to the allocation strategy (Ascarza et al., 2018; McCarthy & Fader, 2018). However, despite the long-standing recognition of the importance of understanding how promotional campaigns affect churn and CLV in the context of noncontractual products, whether (1) they have positive effects on such outcomes and (2) targeting high-value customers yields the greatest lift in CLV remains an open question. To address these gaps, this study investigated how coupon redemption affects churn and CLV by using pre-CLV as a heterogeneity measure.

Our interacted 2SLS results showed that coupon redemption significantly reduced the probability of churn and increased CLV at the promoted product level. However, these effects attenuated as customers' pre-CLV increased, suggesting that the coupon effects are larger among customers with lower pre-CLV values. Marginal treatment effect analysis further revealed that even customers with pre-CLV one standard deviation above the mean experience positive effects on churn and CLV. Thus, firms need not worry about degrading CLV for high-value customers, as they still experience a value lift, albeit smaller than that for lower pre-CLV customers.

We also found distinct profit structures across channel partners. The manufacturer benefited strongly from coupon redemption, both directly and through spillover effects, whereas the retailer gained little and may even experience negative effects among high pre-CLV customers. The lack of robust increases in CLV at the retailer category-level aligns with prior literature reporting that category-level sales are largely static in the long run (Anderson & Fox, 2019). Conversely, the significant increases in product-level CLV and manufacturer-level direct and spillover CLV appear to contradict prior findings that price promotions have limited long-term impact on product sales (Anderson & Fox, 2019; Nishio & Hoshino, 2024).

One explanation for the observed product-level CLV growth is that the promoted product was newly launched. New or improved products can stimulate market growth, as higher overall product quality may expand total market size (Ailawadi et al., 2007; Mason, 1990). Therefore, the combination of product launch and coupon promotion likely expanded manufacturer-level demand, though the effects did not extend to the entire category. Furthermore, the ITT effects for CLV were very small, suggesting that coupon receipt alone generates only temporary effects at the product, manufacturer, and category levels.

This study contributed to the literature by providing the first evidence on the heterogeneous effects of coupon redemption on churn and CLV, and by showing how these effects differ between the manufacturer and the retailer. Moreover, we leveraged the randomized coupon assignment as an exogenous source of variation to address the endogeneity of coupon use, a common issue in coupon programs where few customers redeem assigned coupons (Anderson & Simester, 2004; Norvell & Horky, 2017; Sahni et al., 2017; Zhang et al., 2018). In other words, we estimated the effect of *using* a coupon rather than merely *being offered* one to address selection bias.

5.1 Managerial Implications

Our results yield several managerial implications. First, manufacturers are likely to benefit from increases in CLV when distributing coupons, particularly in the context of new product launches. The coefficients for coupon redemption on the manufacturer's spillover effects (*manu CLV excl. product*) were positive and statistically significant across all model specifications. For example, as spillover effects, increases of approximately 40% in *manu CLV excl. product* were found in our data. Thus, manufacturers can not only benefit from coupon programs through increased CLV for the promoted product, but also via the spillover effects on the CLV of other products in the same brand category. This makes coupon campaigns especially attractive for manufacturers, as they can improve not only the CLV of the promoted product, but also the brand's footprint within the category.

Second, retailers should be cautious about targeting higher pre-CLV customers. Across both direct and spillover measures (*ret CLV* and *ret CLV excl. manu products*), we found that these customers did not generate a significant value-lift effect. Meanwhile, losses emerged, since the interaction terms were often negative and statistically significant. Interestingly, these negative effects only emerged when pre-CLV was measured using manufacturer data. In other words, the customers loyal to the promoted product's manufacturer decreased their category-level CLV, indicating that cannibalization occurred within the category. These results suggest that targeting high pre-CLV customers with coupons may not be cost effective for retailers.

Overall, these findings indicate that retailers should focus on lower-CLV segments. Given the imbalance in CLV outcomes in which manufacturers gain and retailers lose, retailers may consider negotiating higher fees from manufacturers to issue coupons in their stores, thus ensuring a more equitable distribution of promotional gains.

5.2 Limitations and Future Research

Although this study followed rigorous analytical measures, there are several limitations that should be noted. First, our focus on a single coupon campaign may not have fully captured the interactive effects with other promotional activities. In practice, manufacturers and retailers frequently employ a series of strategies over time. The interdependencies among numerous promotional programs can influence customers' purchasing behaviors and CLV in complex ways. Second, this study only examined a single level of discount depth (50% off the regular shelf price), even though discount magnitudes can widely vary, ranging from modest reductions (e.g., 3%) to more aggressive offers (e.g., buy-one-get-one-free). These differences may influence the effectiveness of coupons in shaping long-term customer value (Sheinin & Bitta, 2022). Thus, future research should investigate how multiple, sequential promotional campaigns of varying discount depths interact to impact CLV. Finally, while our analysis focused on within-category CLV, coupon usage may also affect cross-category spending patterns (Bhatt et al., 2023; Leeflang et al., 2008). Indeed, purchasing a discounted item can prompt the purchase of a complementary product; for example, buying discounted wine may lead to the purchase of a cheese platter that would not otherwise have occurred. Therefore, expanding the analysis to cross-category CLV can provide a more comprehensive view of coupon effects and enable improved targeting strategies.

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6 Figures and Tables

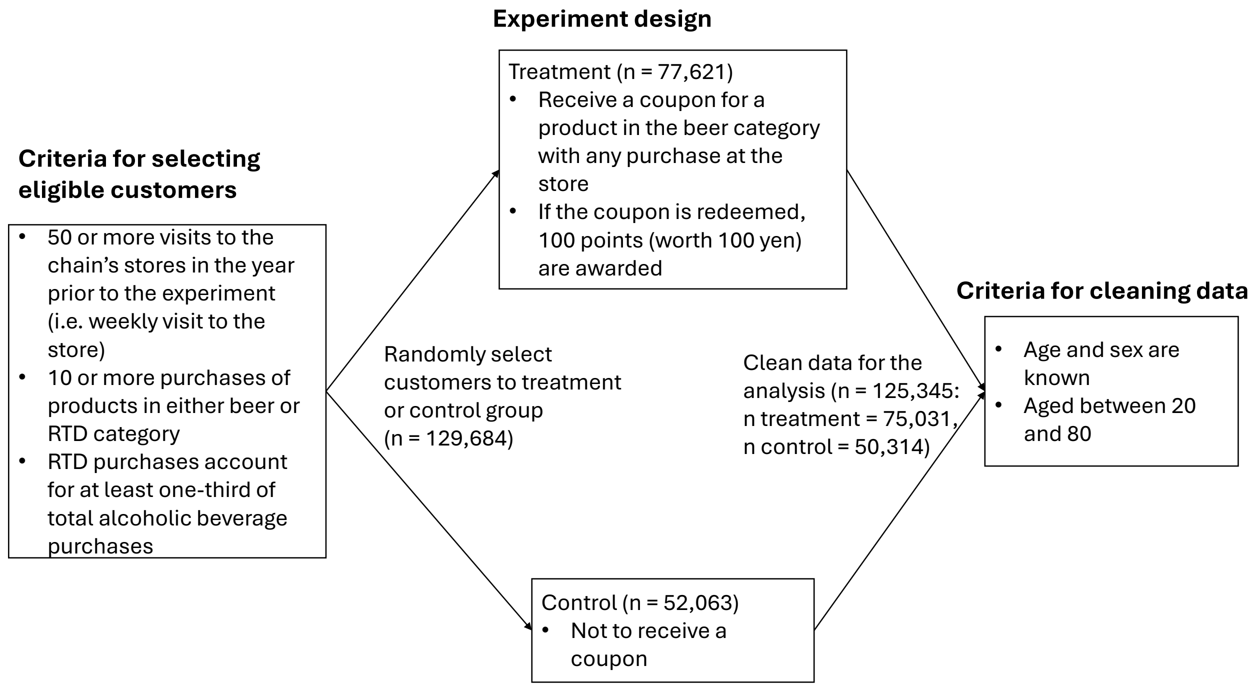

Figure 1: Study Flowchart

This figure provides the flowchart of the experiment, illustrating the criteria for selecting eligible customers, the assignment of treatment within each group, and the data cleaning process.

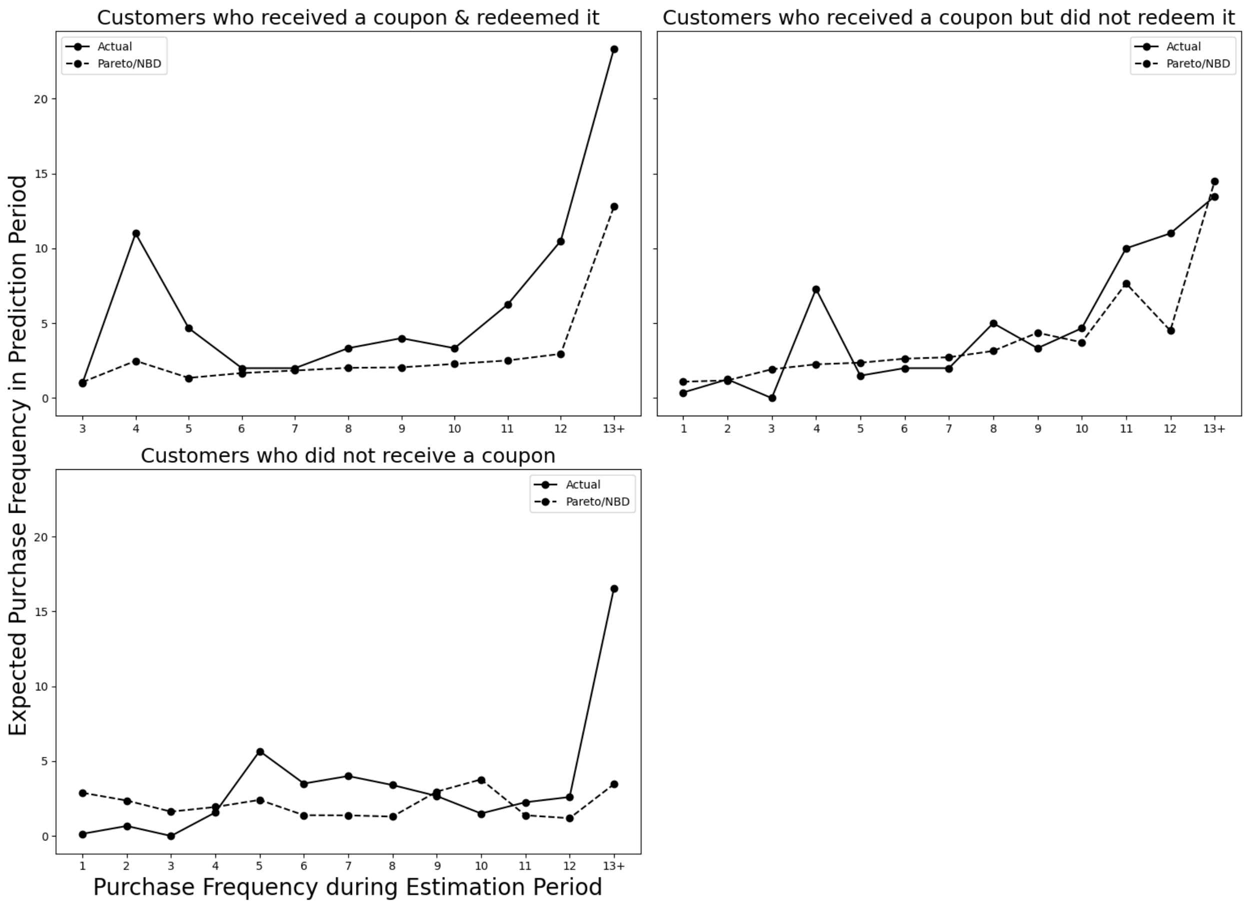

Figure 2: Pareto/NBD Model Fit

The figures show the predictive accuracy of the Pareto/NBD model using category-level transaction data from April 2022 to July 2023. The estimation period is set as December 2023. The observed (solid line) and predicted (dashed line) average number of repeat purchases for the following three groups: customers in the treatment group who redeemed the coupon; customers in the treatment group who did not redeem the coupon; and customers in the control group, who had no opportunity to redeem it.

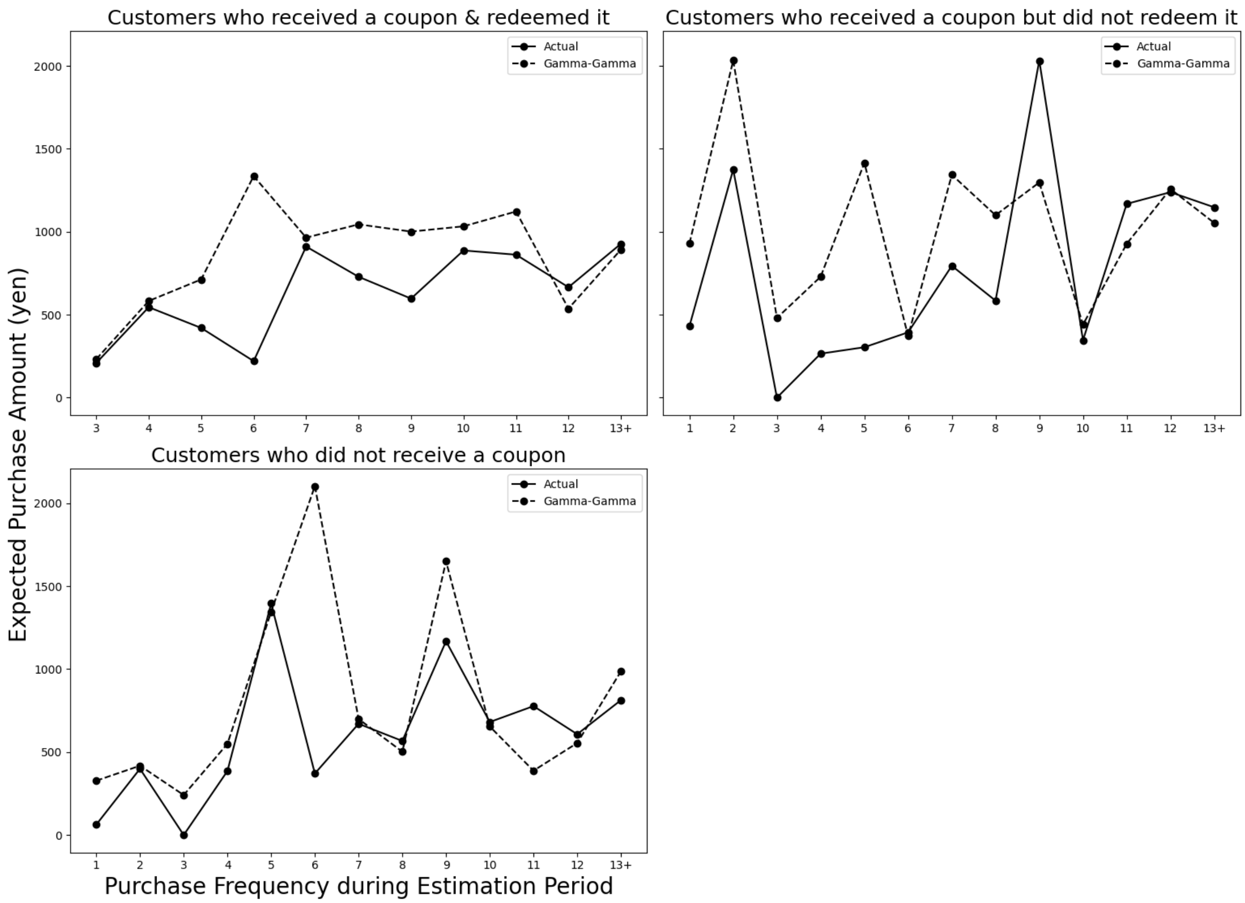

Figure 3: Gamma/Gamma Model Fit

The figures show the predictive accuracy of the Gamma/Gamma model using category-level transaction data from April 2022 to July 2023. The estimation period is set as December 2023. The observed (solid line) and predicted (dashed line) average repeat purchase amounts for the following three groups: customers in the treatment group who redeemed the coupon; customers in the treatment group who did not redeem the coupon; and customers in the control group, who had no opportunity to redeem it.

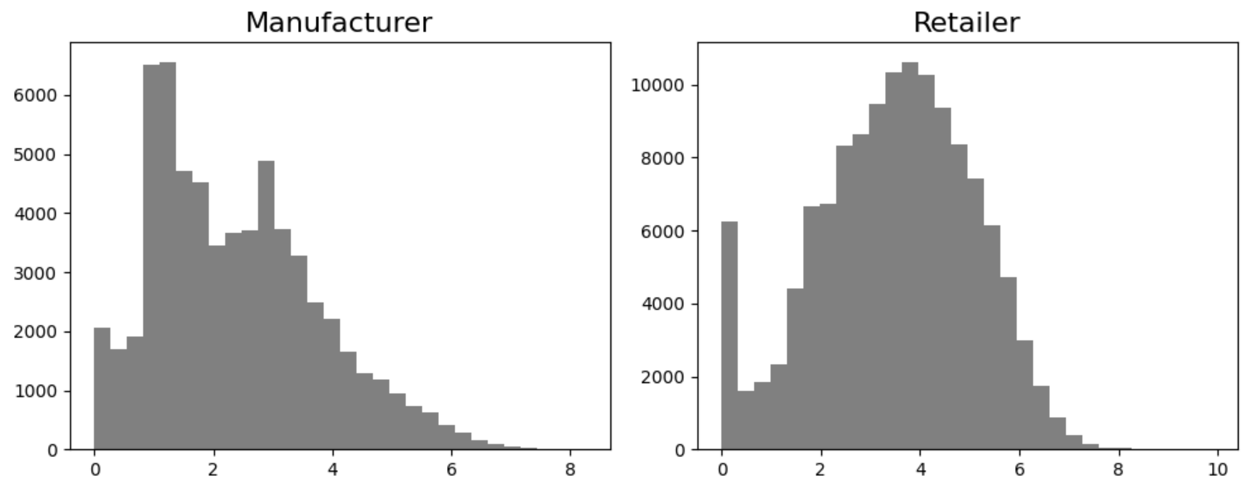

Figure 4: Distribution of Pre-CLV

The histograms show the distribution of pre-CLV for the manufacturer and the retailer, respectively. The former excludes 66,883 observations with a value of zero when plotting the histogram.

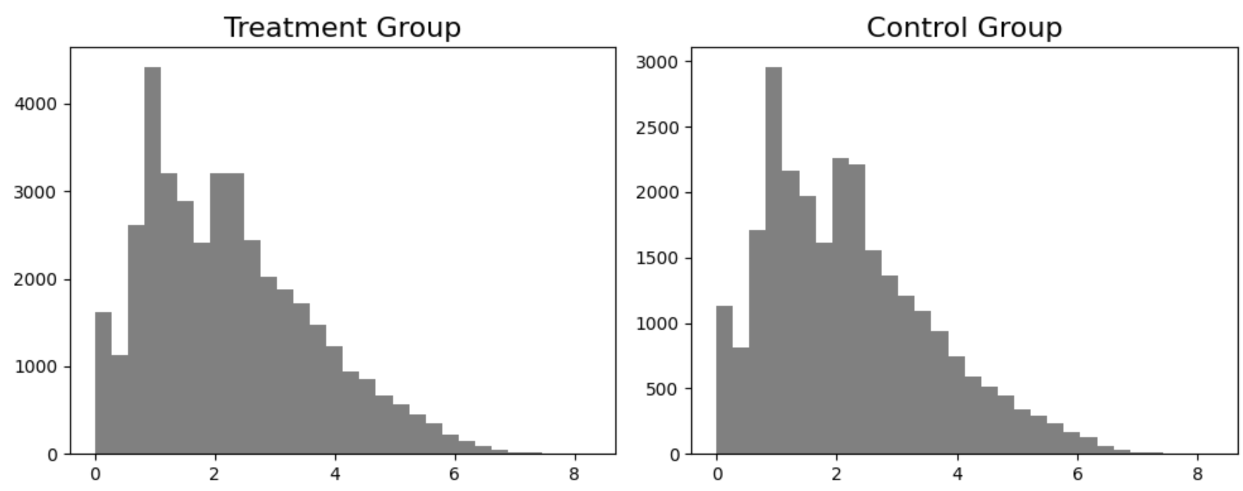

Figure 5: Distribution of Manufacturer CLV

The histograms show the distribution of post-CLV for the manufacturer. They exclude 37,801 observations with a value of zero in the treatment group and 25,511 in the control group when plotting the histogram.

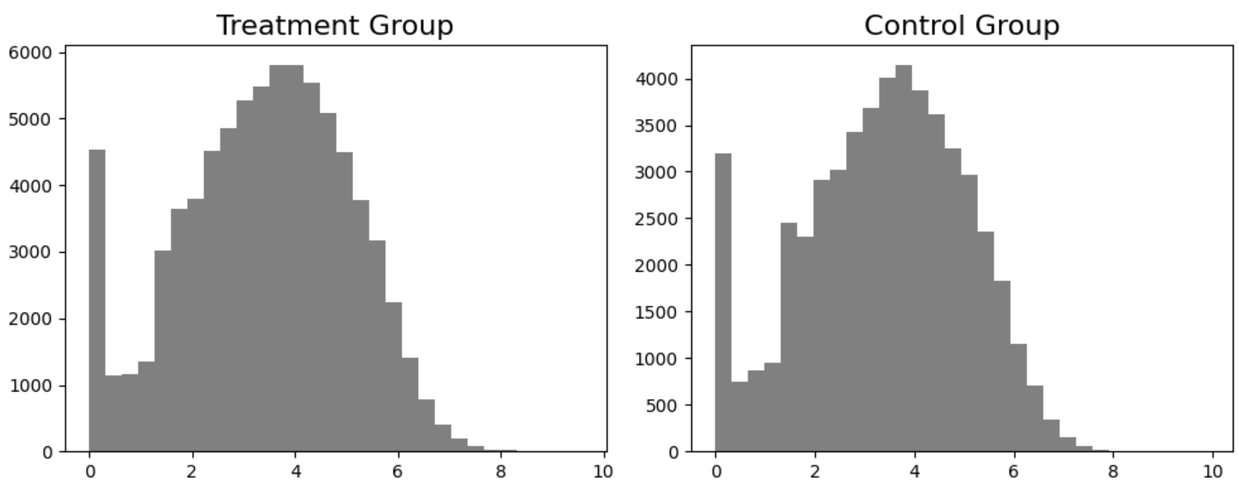

Figure 6: Distribution of Retailer CLV

The histograms show the distribution of post-CLV for the retailer.

Table 1: Summary of Relevant Literature

Author	RCT	Outcome is CLV or Profit	Use IV	Consider Customer Heterogeneity	Promotion Type
Anderson and Simester (2004)	Yes	Yes	No	Yes	Catalogs
Srinivasan et al. (2004)	No	Yes	No	No	Price promotions
Lewis (2006)	No	Yes	No	No	Price promotions
Liu (2007)	No	No (purchase frequency, transaction size)	No	Yes	Loyalty program (discount)
Zhang et al. (2018)	Yes	No (sales)	Yes	Yes	Coupons
Ascarza (2018)	Yes	No (retention rates)	No	Yes	Loyalty programs (bonus offers, renewal gifts)
Norvell and Horky (2017)	No	Yes	No	Yes	Gift card discounts
Bhatt et al. (2023)	No	No (sales)	No	Yes	Multiuint discounts
Nishio and Hoshino (2024)	No	Yes	No	Yes	Loyalty program (birthday rewards)
Valentini et al. (2024)	Yes	Yes	No	No	Servicescape remodeling
This Study	Yes	Yes	Yes	Yes	Coupons

This table summarizes the findings from relevant literature on the relationship between price promotions and CLV. Although a substantial body of research has been conducted in this area, the present study offers novel insights into the heterogeneous effects of coupon campaigns on CLV while accounting for the severe selection bias associated with coupon redeemers.

Table 2: Summary of the Experiment

n total sample (treatment + control)	125,345
n treatment group	75,031
n control group	50,314
n coupon redeemers	2,875
% coupon redemption	3.83
n participating stores	267
coupon distribution period	May 22, 2023 – June 11, 2023
coupon redemption period	May 22, 2023 – June 25, 2023

Note: Coupons were distributed exclusively to customers in the treatment group. The promotion was targeted at a new product launched in April 2023.

Table 3: Definitions of the Outcomes: CLV

	Definition
Direct Effects	
product CLV	CLV of the promoted product
manu CLV	CLV of all the manufacturer's products in the beer category
ret CLV	CLV of all products in the beer category
Spillover Effects	
manu CLV excl. product	CLV of all the manufacturer's products but the promoted product in the beer category
ret CLV excl. manu products	CLV of all products, except for the ones from the promoting manufacturer in the beer category
store-brand CLV	CLV of the retailer's store brand products in the beer category
Heterogeneity Measures	
pre-manu	CLV of all the manufacturer's products in the beer category before coupon distribution
pre-ret	CLV of all products in the beer category before coupon distribution

Note: Learning period for direct and spillover effects is from April 2022 to July 2023; for pre-CLVs, it ends in May 2023 (before coupon distribution). Estimation for direct and spillover effects is conducted in December 2023; for pre-CLVs, in July 2023.

Table 4: Definitions of the Outcomes: the Probability of Churn

	Definition
Direct Effects	
product churn	The probability of churn from the promoted product
manu churn	The probability of churn from all the manufacturer's products in the beer category
ret churn	The probability of churn from all products in the beer category
Spillover Effects	
manu churn excl. product	The probability of churn from all the manufacturer's products but the promoted product in the beer category
ret churn excl. manu products	The probability of churn from all products, except for the ones from the promoting manufacturer in the beer category
store-brand churn	The probability of churn from the retailer's store brand products in the beer category

Note: Learning period for direct and spillover effects is from April 2022 to July 2023. Estimation for direct and spillover effects is conducted in December 2023; for pre-CLVs, in July 2023.

Table 5: Randomization Assessment

	Treatment Group	Control Group	p-statistic
pre-manu	1.18	1.18	0.85
	(1.55)	(1.55)	
pre-ret	3.48	3.47	0.41
	(1.58)	(1.58)	
age	47.65	47.74	0.30
	(14.44)	(14.42)	
sex_{male}	32,155	21,409	0.23

Note: The upper panel reports t-test results, the middle panel shows ANOVA results, and the lower panel displays chi-square test results. Reported figures represent group means, with standard deviations in parentheses. For sex, the number is the count of males in each group. CLV is measured in yen (approximately 1 USD = 150 yen).

Table 6: First-Stage Results

	ln *pre-manu*	ln *pre-ret*
	(1)	(2)
Outcome: D		
Z	0.056*** (0.00)	0.042*** (0.00)
$Z \cdot \ln X$	0.017*** (0.00)	0.009*** (0.00)
f-statistic	463	303
Outcome: $D \cdot \ln X$		
Z	0.044*** (0.00)	0.018*** (0.00)
$Z \cdot \ln X$	0.042*** (0.00)	0.027*** (0.00)
f-statistic	554	369

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Note: This table reports the coefficients for Z (coupon assignment) and $Z \cdot \ln X$ (the interaction between coupon assignment and the heterogeneity measure). The upper panel presents the first-stage estimates for D, while the lower panel presents the estimates for $D \cdot \ln X$. Columns (1) and (2) use *pre-manu* and *pre-ret* as the heterogeneity measure, respectively. Bootstrapped standard errors ($n = 1,000$) are reported in parentheses. $n = 125{,}345$. All CLV values are log-transformed.

Table 7: Interacted 2SLS Results on the Probability of Churn

	ln *pre-manu*		ln *pre-ret*		ITT
	D	$D \cdot \ln X$	D	$D \cdot \ln X$	
	(1)	(2)	(3)	(4)	(5)
Direct Effects					
product churn	-0.115**	0.059*	-0.129*	0.167**	-0.004
	(0.04)	(0.03)	(0.06)	(0.05)	(0.00)
manu churn	-0.083*	0.011	-0.086	0.077	-0.005
	(0.04)	(0.03)	(0.06)	(0.05)	(0.00)
ret churn	-0.040	0.039	-0.033	0.136**	-0.001
	(0.05)	(0.03)	(0.05)	(0.05)	(0.00)
Spillover Effects					
manu churn excl. product	-0.083*	0.011	-0.086	0.077	-0.003
	(0.04)	(0.03)	(0.06)	(0.05)	(0.00)
ret churn excl. manu products	-0.040	0.008	-0.028	0.091^{+}	-0.001
	(0.05)	(0.04)	(0.03)	(0.05)	(0.00)
store-brand churn	-0.032	-0.016	-0.031	-0.002	-0.001
	(0.05)	(0.03)	(0.03)	(0.02)	(0.00)

Note: This table reports the coefficients for D (coupon redemption), $D \cdot \ln X$ (interaction), and ITT. Bootstrapped standard errors are reported in parentheses. $n = 125{,}345$. All CLV values are log-transformed.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 8: Interacted 2SLS Results on CLV

	ln *pre-manu*		ln *pre-ret*		ITT
	D	$D \cdot \ln X$	D	$D \cdot \ln X$	
	(1)	(2)	(3)	(4)	(5)
Direct Effects					
ln *product CLV*	0.314^{**}	-0.107	0.329^{***}	-0.178^{*}	0.013
	(0.10)	(0.08)	(0.10)	(0.08)	(0.00)
ln *manu CLV*	0.540^{***}	-0.180^{*}	0.574^{**}	-0.347^{+}	0.023
	(0.10)	(0.08)	(0.20)	(0.18)	(0.01)
ln *ret CLV*	0.2905	-0.402^{*}	0.120	-0.267^{+}	0.011
	(0.23)	(0.16)	(0.13)	(0.16)	(0.01)
Spillover Effects					
ln *manu CLV excl. product*	0.403^{**}	0.007	0.408^{*}	-0.112	0.018
	(0.12)	(0.09)	(0.20)	(0.19)	(0.01)
ln *ret CLV excl. manu products*	0.170	-0.427^{*}	-0.001	-0.241	0.006
	(0.24)	(0.17)	(0.14)	(0.16)	(0.01)
ln *store-brand CLV*	0.130	0.060	0.107	0.099	0.005
	(0.10)	(0.07)	(0.10)	(0.09)	(0.00)

Note: This table reports the coefficients for D (coupon redemption), $D \cdot \ln X$ (the interaction), and ITT. CLV is measured in yen (approximately 1 USD = 150 yen). Bootstrapped standard errors ($n = 1,000$) are reported in parentheses. $n = 125{,}345$. All CLV values are log-transformed. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 9: Marginal Treatment Effects

Outcome	Pre-CLV	Level	ATT	SE
(1)	(2)	(3)	(4)	(5)
	ln *pre-manu*	- 1SD	-0.154	0.04
product churn		Mean	-0.097	0.03
		+ 1SD	-0.039	0.05
	ln *pre-ret*	- 1SD	-0.230	0.05
		Mean	-0.103	0.03
		+ 1SD	0.023	0.05
	ln *pre-manu*	- 1SD	0.467	0.13
ln *product CLV*		Mean	0.329	0.10
		+ 1SD	0.190	0.18
	ln *pre-ret*	- 1SD	0.611	0.15
		Mean	0.337	0.10
		+ 1SD	0.063	0.19

Note: This table reports the coefficients for D (coupon redemption) by the level of pre-CLVs. CLV is measured in yen (approximately 1 USD = 150 yen). Standard errors (SE) are bootstrapped ($n = 1,000$). n = 125,345. All CLV values are log-transformed.