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# Investigating consumer response to promotions with multichannel behavioral data

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# Investigating consumer response to promotions with multichannel behavioral data

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**Abstract**

Recent advancements in modeling consumer purchase behaviors enable researchers to examine how promotions influence consumer purchase decisions across three stages: inter-purchase time, purchase quantity, and brand choice. To model those purchase decisions, the authors apply a conditional normal model and a multinomial logit model to multichannel purchase data. The data help address the limitation in studies focusing on a single channel: the existence of unobservable consumer purchases made in other channels. The results based on subsets of channels used by consumers suggest that the effects of promotions on inter-purchase time and purchase quantity may be biased. The study highlights the importance of using multichannel data to understand consumer responses to promotions and plan marketing policies.

- Keywords

  inter-purchase time, purchase quantity, brand choice, advertising, price, multiple channels

# 1 Introduction

Manufacturers and retailers invest in promotions to induce consumer purchases; however, these investments do not necessarily yield substantial results. Marketers develop more efficient promotion strategies and implement

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practices that enhance consumer profitability for their companies by understanding the effects of promotion on each purchase decision: whether to buy, how much to buy, and what brand to choose.

Researchers in academia are also interested in consumer purchase decision-making process and elaborately model it by dividing it into stages and analyze the effects of marketing policies on those stages (Lamei *et al.*, 2025; Paetz and Schultz, 2025). Consumers' purchase decision-making is divided into the stages of inter-purchase time, purchase quantity, and brand choice, and modeling this flow enables researchers to quantify the effects of marketing policies on consumer purchase decisions (Mehta and Ma, 2012; Gupta, 1988). Moreover, modeling of consumer behavior is progressing; for example, Kim *et al.* (2018) models the correlation between purchase decisions such as inter-purchase time and purchase quantity.

Considering the necessity from managerial and academic perspectives, our research has two main objectives. First, we explore the effects of promotion on consumer purchase decision-making. Although a conditional normal model quantifies the direct effects of inter-purchase time on purchase quantity and is more suitable for consumer purchase data (Jen *et al.*, 2009), few studies have considered this approach in investigating the effects of promotion (Neslin *et al.*, 1985). Second, we show the importance of analyzing consumer purchase data through multiple channels to clarify the effects of marketing variables such as advertising and price on commodity product purchases. Numerous previous studies investigate consumer purchases using singular channel data, such as those collected in only supermarkets. Such single-channel data are insufficient in determining the cause of increased consumer inter-purchase time; we cannot differentiate between no purchase made by the customer and the customer's purchases replaced with those in other channels. As consumers access multiple channels to make purchases (Narang *et al.*, 2025; Blömker and Albrecht, 2024), multichannel data are important for investigating consumer inter-purchase time for frequently purchased commodity products (Rains and Longley, 2021). Using data from more than four purchase channels, this study addresses unobserved consumer purchases in a single channel replaced with purchases in other channels and investigates the effects of promotions on consumer purchase behavior. By studying consumer purchases in two product categories, we ensure the robustness of our results.

Our research contributes to several research areas. First, we contribute to the study on modeling consumer purchase behavior with detailed modeling of the consumer purchase process (inter-purchase time, purchase quantity, and brand choice) in grocery categories. Second, our research contributes to studies on response to promotion. Our results show that consumer purchase data should be collected from various channels to estimate unbiased effects of marketing policies. Third, we contribute to and expand the research on multichannel purchases to investigate the effects of various marketing variables, such as price and advertising. In addition, this research simultaneously investigates inter-purchase time and purchase quantity and uses multichannel data collected in more than four channels.

The remainder of the paper is organized as follows. In Section 2, we review the relevant studies; in Sections 3 and 4, we describe consumer purchase behavior models and their estimation methods. In Section 5, we explain our data. Sections 6 and 7 present the results. Section 8 highlights the importance of analyzing multichannel purchase data. Finally, in Section 9, we discuss our findings and conclude.

# 2 Literature review

Promotions change consumer behavior, increasing sales and profits for manufacturers and retailers. Previous research has investigated the impact of promotions on consumer purchase behavior by disentangling each consumer's complicated purchase decision-making (purchase decision). Gupta (1988) categorizes a consumer's purchase decision into three decision-making stages: inter-purchase time (purchase incident), purchase quantity, and brand choice. Following Gupta (1988)'s work, numerous studies have explored the effects of marketing variables on each purchase decision-making stage. For example, purchase decisions are examined along with cross-category effects (Song and Chintagunta, 2007; Mehta and Ma, 2012).

Studies on consumer purchase decisions usually posit that the inter-purchase time (purchase incident) decision-making is followed by the purchase quantity choice (Jen *et al.*, 2009; Niraj *et al.*, 2008; Neslin *et al.*, 1985); then, the purchase quantity choice is followed by brand choice (Mehta and Ma, 2012).

Analyzing consumer purchase decisions helps sales managers decide their marketing strategies by forecasting consumer behavior or quantifying the effect of marketing policies. Previous studies employed a condensed lognormal negative binomial model (Trinh and Wright, 2022) and Poisson lognormal distribution (Martin *et al.*, 2020) to approximate consumer purchase behaviors. Although consumer brand choice behavior is analyzed in many studies (Guadagni and Little, 1983; Martinovici *et al.*, 2023), prior stages of brand choice are modeled in some research (Ursu *et al.*, 2023; Kim *et al.*, 2022; Haviv, 2022). Accounting for various decision-making stages helps sales managers to plan effective marketing policies. For both brand choice and inter-purchase time modeling, previous studies investigate the effects of upand down-selling promotions (Park and Yoon, 2022) or the long-term effects of a retailers' loyalty programs on inter-purchase time and purchase quantity (Nishio and Hoshino, 2024).

A more precise consumer behavior model could help understand consumer purchase decisions. Some research suggests that modeling the purchase process stages dependently is consistent with consumer behavior rather than modeling each stage independently. For example, explicitly modeling the effects of inter-purchase time on purchase quantity helps quantify the effects of marketing variables when modeling inter-purchase time and purchase quantity decisions (Neslin *et al.*, 1985; Jen *et al.*, 2009).

However, few studies simultaneously investigate the effects of marketing variables such as price and advertising on inter-purchase time, purchase quantity, and brand choice (Table 1). Although some researchers investigate those decision-making stages simultaneously (Chintagunta, 1993), some of them independently estimate each stage (Gupta, 1988) or simply consider the correlation between the stages (Kim *et al.*, 2018). Simultaneously modeling multiple purchase stages and investigating direct effects of inter-purchase time on purchase quantity contribute to a better understanding of the effects of marketing policies (Jen *et al.*, 2009).

Additionally, it is important to consider consumer purchases through various channels when investigating the effects of marketing policies on inter-purchase time; not all consumer purchases are observed in a single channel (Narang *et al.*, 2025; Blömker and Albrecht, 2024). Currently, although previous research investigates the effects of marketing variables on inter-purchase time and purchase quantity, few researchers consider multichannel purchases (Mark *et al.*, 2024). Even for low-involved product categories, frequently purchased products are obtained through various channels (Nakano and Kondo, 2018).[1] Researchers cannot observe the purchases replaced by those through other channels when investigating consumers' inter-purchase time with purchase data in a single channel. Therefore, investigating consumer purchase decisions made through multiple channels is important.

Although some studies on consumer purchases across multiple channels investigate the effects of marketing policies on purchase quantity (Liu *et al.*, 2024; Zantedeschi *et al.*, 2017), an important variable has not always been considered. Especially, it is suggested that price affects brand choice (Blattberg and Wisniewski, 1989; Kwon *et al.*, 2023), purchase quantity (Mehta and Ma, 2012), or inter-purchase time (Han *et al.*, 2022). Additionally, traditional advertising media such as TV are recognized as having important

[1]When consumers purchase high-involved products, they use the multichannel to gather product information beforehand (Dholakia *et al.*, 2010).

effects on consumer behavior (Thomas, 2020; Deng and Mela, 2018; He and Klein, 2023). Hence, price and advertising are important variables to include in consumer purchase decision-making models.

When investigating consumer purchase behaviors, we need to model heterogeneous consumer responses to marketing policies (Bell *et al.*, 1999). Previous research models consumer heterogeneity in inter-purchase time (Narang *et al.*, 2025; Abe, 2009) or purchase quantity (Narang *et al.*, 2025; Zantedeschi *et al.*, 2017).

This research expands previous research on purchase decision-making stages in two main ways. First, we show the importance of analyzing multichannel purchase data. It is difficult to collect almost all consumer purchase data in the grocery categories in which consumers purchase through various channels (Blömker and Albrecht, 2024). With the data collected in one channel (supermarket), researchers cannot determine fully the cause of increased consumer inter-purchase time; inter-purchase time may increase due to both no purchase made by the customer and the customer's purchases replaced with those in other channels. This research conducts a more precise investigation compared to previous research, using data including whole consumer purchases. Although previous research finds cross-channel effects of promotions on purchase decision-making (Filippou *et al.*, 2024), the importance of multichannel data for studying consumer responses to promotions has remained unclear.

Second, we apply a relatively new model to consumer grocery purchase data. By modeling the direct effects of inter-purchase time on purchase quantity with a conditional normal model (Jen *et al.*, 2009), we avoid assuming independence between inter-purchase time and purchase quantity. This conditional normal model is in line with the current research effort to develop a more accurate prediction model of consumer purchase behaviors (Turlo *et al.*, 2025; Reutterer *et al.*, 2021) without assuming a Poisson process, which is far from real consumer purchase behavior. Although previous research applies a conditional normal model to health and beauty goods sales data (Jen *et al.*, 2009), this model has not been applied to grocery purchase histories, which are investigated by previous studies. In the grocery category, direct effects of inter-purchase time on purchase quantity have also been investigated while independently modeling inter-purchase time and purchase quantity (Neslin *et al.*, 1985). Simultaneously modeling them allows correlations among their error terms and jointly deriving parameter estimates (Valenti *et al.*, 2024).

Table 1: Selected previous studies on purchase decision-making

| | Ip time | Quantity | Brand choice | Marketing variables | Effects of ip time on quantity | Consumer heterogeneity | Multi |
|---|---|---|---|---|---|---|---|
| Neslin *et al.* (1985) | ✓ | ✓ | | ✓ | ✓ | | |
| Gupta (1988) | ✓ | ✓ | ✓ | ✓ | | | |
| Chintagunta (1993) | ✓ | ✓ | ✓ | ✓ | | ✓ | |
| Boatwright *et al.* (2003) | ✓ | ✓ | | | ✓ | ✓ | |
| Chib *et al.* (2004) | ✓ | | ✓ | ✓ | | ✓ | |
| Song and Chintagunta (2007) | ✓ | ✓ | ✓ | ✓ | | ✓ | |
| Niraj *et al.* (2008) | ✓ | ✓ | | ✓ | | ✓ | |
| Jen *et al.* (2009) | ✓ | ✓ | | | ✓ | ✓ | |
| Mehta and Ma (2012) | ✓ | ✓ | ✓ | ✓ | | ✓ | |
| Schweidel and Knox (2013) | ✓ | ✓ | | ✓ | | ✓ | |
| Glady *et al.* (2015) | ✓ | ✓ | | | | ✓ | |
| Kim *et al.* (2018) | ✓ | ✓ | | ✓ | | ✓ | |
| Danaher *et al.* (2020) | | ✓ | | ✓ | | ✓ | ✓ |
| Han *et al.* (2022) | ✓ | | ✓ | ✓ | | ✓ | |
| Park and Yoon (2022) | ✓ | ✓ | | ✓ | | ✓ | |
| Trinh and Wright (2022) | ✓ | | | | | | |
| Mark *et al.* (2024) | ✓ | ✓ | | ✓ | | | ✓ |
| Nishio and Hoshino (2024) | ✓ | ✓ | | ✓ | | | ✓ |
| Our study | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Note 1: “Ip time” implies inter-purchase time.
Note 2: “Quantity” implies purchase quantity.
Note 3: “Multi” implies multichannel purchases.

# 3 Model

We estimate conditional normal and multinomial logit models to model consumer purchase decisions: inter-purchase time decision, purchase quantity decision, and brand choice. The conditional normal model quantifies the effects of marketing policies on inter-purchase time and purchase quantity and models the direct effects of inter-purchase time on purchase quantity (Jen *et al.*, 2009). A multinomial logit model is suitable to analyze consumer brand choice behavior (Kim and Kim, 2024; Guadagni and Little, 1983).

## 3.1 Conditional normal model

Let $y_{1it}$ and $y_{2it}$ be the logarithm of inter-purchase time and purchase quantity for consumer $i$ at purchase occasion $t$. The inter-purchase time of the $t$th purchase occasion is defined as the number of weeks from the $t-1$th purchase occasion to the $t$th purchase occasion. $\mathbf{x}_{it}$ denotes explanatory variables. The distribution of inter-purchase time and the conditional distribution of purchase quantity are Equation (1) and (2) (Jen *et al.*, 2009).

$$f(y_{1it}) \sim N(\boldsymbol{\nu}_i'\mathbf{x}_{it}, \sigma^2), \tag{1}$$

$$f(y_{2it}|y_{1it}) \sim N(\boldsymbol{\mu}_i'\mathbf{x}_{it} + \eta_i y_{1it}, \tau^2). \tag{2}$$

To investigate the effects of marketing policies on inter-purchase time and purchase quantity, $\mathbf{x}_{it}$ includes two major marketing variables: price and advertising stock variables.[2]

$$\mathbf{x}_{it} = (intercept, price_{it}, Adstock_{i,t}, Inv_{i,t-1}, channel\_dummy\_variables_{it})'.$$

The definitions of variables are presented in Table 2.

The advertising stock variable ($Adstock$) is defined as an accumulation of consumer $i$'s advertising exposure ($Ad\_ex$) at the $w$th calendar week (Zenetti and Klapper, 2016).

$$Adstock_{i,w} = \log(1 + Ad\_ex_{i,w}) + \lambda Adstock_{i,w-1}. \tag{3}$$

An initial value of advertising stock ($Adstock_{i,0}$) is calculated with $\log(1 + \overline{Ad\_ex_{i,w}})$; $\overline{Ad\_ex_{i,w}}$ is mean $Ad\_ex_{i,w}$. We set decay parameter $\lambda$ as $\lambda =$

[2] $\mathbf{x}_{it}$ includes *price* and *Adstock* of the purchased brand. In our data explained in detail in Subsection 5.1, no consumer who purchases multiple brands at the same time is observed. We confirmed that *Adstock* which is calculated with consumers' exposures to all brands' advertising did not change our main results in Subsection 7.1.

Table 2: Description of variables

| | |
|---|---|
| Price | Price per milliliter (ml) |
| Adstock | Accumulation of advertising exposures |
| Inv | Inventory which a consumer has |
| Super | It takes 1 when the purchase is made through a supermarket, and 0, otherwise. |
| Conveni | It takes 1 when the purchase is made through a convenience store, and 0, otherwise. |
| Drug | It takes 1 when the purchase is made through a drugstore, and 0, otherwise. |
| Vend | It takes 1 when the purchase is made through a vending machine, and 0, otherwise. |
| Other | It takes 1 when the purchase is made through a home center and online, and 0, otherwise. |

0.5.[3] To account for the diminishing marginal returns of advertising, we use the logarithmic transformation in Equation (3) (Zenetti and Klapper, 2016).

The $\mathbf{x}_{it}$ also includes consumer $i$'s previous inventory $Inv_{i,t-1}$. We denote consumer $i$'s purchase quantity, inter-purchase time, and total number of observations as $Q_{i,t}$, $IPT_{j,t}$, and $n_i$ respectively. $R_i$ is the average usage rate (Bucklin and Gupta, 1992). $Inv_{i,t-1}$ is defined as follows (Neslin *et al.*, 1985; Bucklin and Gupta, 1992).[4]

$$\begin{aligned} Inv_{i,t-1} &= Inv_{i,0} + \Sigma_{c=1}^{t-1} Q_{i,c} - R_i \Sigma_{c=1}^{t-1} IPT_{i,c}, \\ \text{where } Inv_{i,0} &= \Sigma_{c=1}^{n_i} Q_{i,c}/n_i, \\ R_i &= \Sigma_{c=1}^{n_i} Q_{i,c}/\Sigma_{c=1}^{n_i} IPT_{i,c}. \end{aligned} \tag{4}$$

$Inv_{i,0}$ is the initial value of inventory (Neslin *et al.*, 1985).

In addition, $\mathbf{x}_{it}$ includes four channel dummy variables: convenience store dummy ($Conveni$), drugstore dummy ($Drug$), vending machine dummy ($Vend$), and other channel dummies ($Other$).[5] For identification, the supermarket dummy is the base dummy variable.

[3] $\lambda = 0.5$ is close to the average decay parameter set in previous studies (Zenetti and Klapper, 2016). We determine the decay parameter that shows the best model fit by grid search (Danaher *et al.*, 2020; Jedidi *et al.*, 1999) using $\lambda = 0.3, 0.35, 0.4, 0.45$ and $0.5$. The value of $\lambda$ does not change our results.

[4] We assume that the inventory is a minimum of zero (Haviv, 2022; Ailawadi and Neslin, 1998), hence consumer $i$'s consumption at time $t$ is $\min\{Inv_{i,t-1}, R_i \times IPT_{i,t-1}\}$.

[5] Other channel dummies consist of two minor channels: home center and online.

## 3.2 Multinomial logit model

We model consumer $i$'s brand choice at purchase occasion $t$ using the multinomial logit model. Its matrix of explanatory variables, $\mathbf{x}^*_{it}$, is

$$\mathbf{x}^*_{it} = \begin{pmatrix} \mathbf{x}^*_{i1t} \\ \vdots \\ \mathbf{x}^*_{iJt} \end{pmatrix},$$

$$\text{where } \mathbf{x}^*_{ijt} = (brand\_dummy\_variables_j, Adstock^*_{ijt}, price_{ijt}). \quad (5)$$

Let $w$ and $j$ ($j = 1, \cdots, J$) denote the calendar week and brand, respectively. $Adstock^*$ consists of one order lag and advertising exposure. We use the logarithmic transformation in Equation (6) to account for diminishing marginal returns of advertising (Zenetti and Klapper, 2016).

$$Adstock^*_{ij,w} = \rho_i Adstock^*_{ij,w-1} + \log(1 + Ad\_ex_{ij,w}), \quad (6)$$

$$\text{where } \gamma_i = \log\left(\frac{\rho_i}{1-\rho_i}\right), \ \gamma_i \sim N\left(\theta_\gamma, \sigma_\gamma\right).$$

An initial value of advertising stock ($Adstock^*_{ij,0}$) is calculated with $\log(1 + \overline{Ad\_ex_{ij,w}})$; $\overline{Ad\_ex_{ij,w}}$ is mean $Ad\_ex_{ij,w}$ for each $i$ and $j$.

Consumer $i$'s utility of choosing brand $j$ on purchase occasion $t$ is[6]

$$u_{ijt} = \alpha_{0i} + \alpha_{ji} brand\_dummy_j + \alpha_{6i} Adstock^*_{ij,t} + \alpha_7 price_{ij,t} + \varepsilon_{ijt}. \quad (7)$$

$\varepsilon_{ijt}$ follows independent and identically distributed extreme value distribution. For identification, we impose $J$th brand's intercept $\alpha_{Ji} = 0$.

# 4 Estimation

## 4.1 MCMC estimation

Our models are estimated by using the Markov chain Monte Carlo (MCMC) procedure. We implement 11,000 MCMC loops and discard the initial 1,000 samples as the burn-in period. Prior and posterior distributions are reported in Appendix A. To check the parameters' convergence, the Gelman and Rubin diagnostic is implemented.

[6]In Equation (7), the price coefficients are homogeneous across consumers to make parameters converge.

## 4.2 Endogeneity

Since consumer $i$'s previous inventory ($Inv_{i,t-1}$) is calculated based on the lagged value of purchase quantity ($Q_{i,t}$) and inter-purchase time ($IPT_{i,t}$), this may include the lagged component of endogenous variables of $y_{1it}$ and $y_{2it}$. To address concerns about the endogeneity of $Inv_{i,t-1}$, we use one lagged inventory variable, $Inv_{i,t-2}$, as an instrument for $Inv_{i,t-1}$ (Neslin *et al.*, 1985).

# 5 Data

## 5.1 Data explanation

This research uses two sources provided by the National Institute of Informatics: consumer panel data and single-source data (INTAGE Inc., 2019). The dataset was originally collected by INTAGE Inc., which is a major marketing research company in Japan with reliable accuracy. The data are collected from the Keihin region[7] of Japan to be representative data of Japanese consumers. The data includes weekly records of 700 consumers' purchases and advertising exposure across seven beverage categories.[8] Each consumer has a unique ID, which enables us to match each consumer's data of consumer panel data to the single-source data.

Details of our dataset are as follows. The consumer panel data records what soft drink category products consumers purchase, when they do so, what quantity they purchase, and how much they spend to purchase. Those data are aggregated at a weekly level. The single-source data automatically records consumer exposure to TV advertising; hence, this advertising exposure data does not suffer from biases of consumer memory. Matching the consumer ID of consumer panel data to the single-source data, we study the relationship between TV advertising and purchase behavior. These data were collected from December 26, 2016, to December 25, 2017.

We analyze purchase data for bottled tea and coffee categories included in the soft drink category's purchase data. Each bottled tea and coffee category includes multiple brands' purchases: five brands in the bottled tea and three brands in the coffee categories, respectively (INTAGE Inc., 2019); hence, they are suitable for investigating brand choice behavior. The coffee category is investigated in many previous studies (Draganska and Klapper, 2011; Gupta,

[7]The Keihin region is the Greater Tokyo Metropolitan area, which consists of Tokyo, Chiba, Saitama, and Kanagawa (INTAGE Inc., 2019).

[8]The names of manufacturers and brands have been anonymized to maintain confidentiality.

1988; Neslin *et al.*, 1985), and the bottled tea category represents one of the most frequently purchased consumer packaged goods, similar to coffee.

Our dataset is sampled as follows. We exclude purchase data through "the rest" channel because we cannot detect where such purchases were made. Such data account for only three percent[9] of the observed consumer purchases; hence, excluding such data little affects the results of our study. In addition, we analyze the data of consumers who purchased more than two times during the data observation period to estimate consumer heterogeneous parameters in our model; three hundred thirty-five consumers in the bottled tea category and two hundred eighty consumers in the coffee category meet this standard. Such consumers account for ninety-five percent of consumers who purchase bottled tea or coffee.[10] Leaving each consumer's last purchase data as hold-out samples (Jacobs *et al.*, 2021), we use the remaining data for estimating our models.

Price is defined as unit price: monetary value (Japanese yen) over purchase quantity (ml). However, the price of brands not chosen by consumer $i$ on purchase occasion $t$ is unobserved. To interpolate the missing price, we use the average price on the same week in the same channels across consumers for each brand. If no consumer purchased a brand on the week in the channel, then we estimate these data with mean price in the channel during the observation periods (Tellis, 1988; Kamakura and Russell, 1989). Only one brand of bottled tea has no data in online channels; hence, we interpolate the price data by inserting the average price of the brand over other channels.

Summary statistics of our data are presented in Table 3. For both bottled tea and coffee categories, inter-purchase time and purchase quantity differ across consumers. Moreover, consumers mainly purchase those two categories at supermarkets and convenience stores.

## 5.2 Consumers using multiple channels

Figure 1 shows the number of channels the consumers use; the left histogram is the distribution of the numbers in the bottled tea category, and the right one is that in the coffee category. In both categories, more than eighty-three percent of consumers use multiple channels.[11]

Frequently purchased daily necessities such as bottled tea and coffee are obtained through various channels. Hence, using only the data collected in

[9]2.9% for the bottled tea while 2.4% for the coffee category.

[10]No consumer purchases multiple brands at the same purchase occasion.

[11]Most of the consumers purchase bottled tea (83.4%) and coffee (87.6%) through various channels in our dataset.

Table 3: Summary statistics

| | Bottled tea | | Coffee | |
|---|---|---|---|---|
| | Mean | SD | Mean | SD |
| Inter-purchase time | 3.73 | 6.11 | 4.24 | 7.46 |
| Purchase quantity | 0.21 | 0.10 | 0.38 | 0.13 |
| Price | | | | |
| Brand1 | 0.26 | 0.04 | 0.42 | 0.11 |
| Brand2 | 0.20 | 0.52 | 0.39 | 0.11 |
| Brand3 | 0.19 | 0.52 | 0.39 | 0.11 |
| Brand4 | 0.18 | 0.02 | | |
| Brand5 | 0.21 | 0.02 | | |
| Ad exposure | | | | |
| Brand1 | 0.90 | 0.82 | 0.80 | 0.96 |
| Brand2 | 0.44 | 0.71 | 0.42 | 0.46 |
| Brand3 | 0.58 | 0.88 | 1.36 | 1.16 |
| Brand4 | 0.60 | 0.85 | | |
| Brand5 | 0.92 | 0.76 | | |
| Super | 0.29 | 0.45 | 0.20 | 0.40 |
| Conveni | 0.38 | 0.49 | 0.33 | 0.47 |
| Drug | 0.07 | 0.25 | 0.06 | 0.23 |
| Vend | 0.06 | 0.24 | 0.05 | 0.22 |
| Other | 0.20 | 0.40 | 0.36 | 0.48 |
| Num observation | | 4,542 | | 3,871 |

one channel, such as supermarkets, does not allow us to identify the reason why inter-purchase time increases—whether consumers postpone their purchases or purchase through another channel. When researchers investigate how TV advertising that affects consumer purchase behavior in various channels impacts inter-purchase time, using whole consumer purchase data is preferable. Because our data includes consumers' purchase histories in various channels, it is useful for us to investigate the effects of marketing variables on each purchase decision.

# 6 Model comparison

As suggested by previous research (Jen *et al.*, 2009), we regard the model that allows the direct effect of inter-purchase time on purchase quantity as the better model to correspond to consumer purchase behaviors. To confirm our expectation, we compare the conditional normal distribution model with the

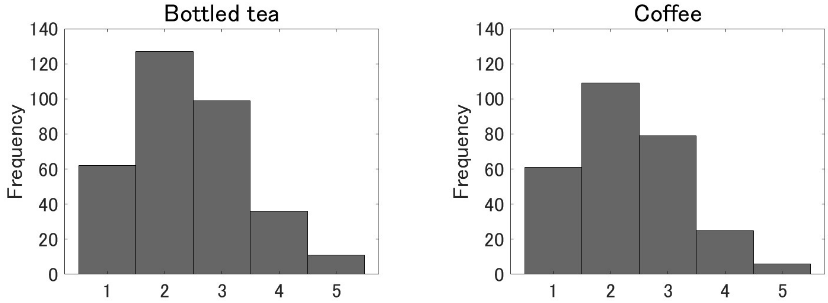


Figure 1: Number of channels used
*Note*: The left panel shows the histogram of the number of channels consumers use in the bottled tea category. The right panel shows that for the coffee category.

Table 4: Model comparison (bottled tea)

| | In-sample | | | Hold-out sample | | |
|---|---|---|---|---|---|---|
| | Ip time | Quantity | CV | Ip time | Quantity | CV |
| | | | MSE | | | |
| CN model | 0.22 | 0.42 | 0.46 | 0.42 | 1.17 | 1.23 |
| MVN model | 0.77 | 5.89 | 5.49 | 14.20 | 52.97 | 55.13 |
| | | | MAD | | | |
| CN model | 0.14 | 0.28 | 0.34 | 0.28 | 0.87 | 0.93 |
| MVN model | 0.45 | 5.60 | 5.19 | 7.34 | 28.70 | 30.71 |

Note 1: "Ip time" implies inter-purchase time.
Note 2: "CN" implies conditional normal.

multivariate normal (MVN) model,[12] which does not explicitly consider the direct effect of inter-purchase time on purchase quantity. As the comparison criteria, we use the mean squared error (MSE) and mean absolute deviation (MAD)[13] for the in-sample and holdout-sample. A model with a small MSE and MAD fits consumer purchase data better, and such a model can estimate the effects of price and advertising on consumer purchase decisions well.

The conditional normal model outperforms the MVN model in both MSE and MAD (Table 4·5). This result is consistent with previous research (Jen *et al.*, 2009). The better fit of the conditional normal model implies the

[12]The model formulation of the MVN model is available in Appendix B.

[13]We calculate the MAD and MSE of inter-purchase time, purchase quantity, and customer value (CV) following Jen *et al.* (2009). CV is calculated as $CV = purchase\ quantity/inter-purchase\ time$ (Jen *et al.*, 2009).

Table 5: Model comparison (coffee)

| | In-sample | | | Hold-out sample | | |
|---|---|---|---|---|---|---|
| | Ip time | Quantity | CV | Ip time | Quantity | CV |
| | | | MSE | | | |
| CN model | 0.18 | 0.41 | 0.44 | 0.38 | 1.34 | 1.42 |
| MVN model | 0.69 | 6.31 | 5.89 | 1.33 | 6.19 | 5.77 |
| | | | MAD | | | |
| CN model | 0.11 | 0.27 | 0.32 | 0.24 | 0.99 | 0.96 |
| MVN model | 0.49 | 6.26 | 5.82 | 0.95 | 6.14 | 5.59 |

Note1: "Ip time" implies inter-purchase time.

Note2: "CN" implies conditional normal.

relationship between inter-purchase time and purchase quantity. Therefore, researchers should try to observe consumers' actual inter-purchase time with multichannel data to accurately estimate the effects of marketing policies on purchase quantity.

Regarding inter-purchase time and purchase quantity, we discuss the results of the conditional normal model in the next section.

# 7 Result

## 7.1 Inter-purchase time and purchase quantity

Neither price nor advertising significantly affects inter-purchase time for the bottled tea category, and only price positively affects inter-purchase time for the coffee category (Table 6). Weak effects of marketing policies are consistent with prior studies (Gupta, 1988), which do not explicitly model the direct effects of inter-purchase time on purchase quantity. Inventory does not significantly affect inter-purchase time.

In addition, collecting consumer purchase data through various channels is important to model the inter-purchase time of frequently purchased products. Purchase data obtained through only one channel provides longer inter-purchase time than the actual one because of unobservable purchases made in other channels (Figure 1). No significant difference across channels in inter-purchase time (Table 6) supports that consumers obtain bottled tea and coffee through various channels.

For purchase quantity, some significant effects are found. Price negatively affects purchase quantity in two categories (Table 6), which implies that the more price increases, the fewer quantities consumers purchase. Some signifi-

Table 6: Estimates for the conditional normal model.

| | Bottled tea | | | Coffee | | |
|---|---|---|---|---|---|---|
| | Pos mean | | Pos SD | Pos mean | | Pos SD |
| Inter-purchase time | | | | | | |
| Intercept | 1.10 | * | 0.08 | 0.97 | * | 0.09 |
| Price | 0.09 | | 0.21 | 0.31 | * | 0.13 |
| Adstock | -0.02 | | 0.04 | -0.06 | | 0.04 |
| Inv | 0.00 | | 0.01 | 0.00 | | 0.01 |
| Conveni | 0.02 | | 0.07 | -0.15 | | 0.07 |
| Drug | -0.02 | | 0.11 | -0.11 | | 0.14 |
| Vend | -0.06 | | 0.08 | -0.19 | * | 0.09 |
| Other | -0.19 | | 0.14 | 0.14 | | 0.16 |
| Purchase quantity | | | | | | |
| Intercept | 7.80 | * | 0.06 | 7.17 | * | 0.06 |
| Price | -7.58 | * | 0.32 | -3.78 | * | 0.11 |
| Adstock | -0.01 | | 0.03 | 0.02 | | 0.03 |
| Inv | -0.00 | | 0.01 | 0.00 | | 0.01 |
| Conveni | 0.22 | * | 0.05 | 0.04 | | 0.06 |
| Drug | 0.03 | | 0.09 | 0.03 | | 0.11 |
| Vend | 0.38 | * | 0.08 | -0.01 | | 0.07 |
| Other | 0.64 | * | 0.01 | 0.18 | | 0.14 |
| Inter-purchase time | 0.01 | | 0.01 | -0.01 | | 0.01 |
| Num observation | | | 4,542 | | | 3,871 |

Note 1: "Pos" implies posterior.

Note 2:* indicates that the 95% credible interval does not include 0.

cant differences across channels exist in purchase quantity for the bottled tea category but not the coffee category. Hence, strong differences across channels are not suggested in purchase quantity. Additionally, purchase quantity is not affected by inter-purchase time and inventory.

Although the negative and significant price coefficient suggests that price cuts increase purchase quantity, consumer stockpiling behaviors may be induced by promotions. In our case, consumers are less likely to stockpile bottled tea and coffee because the coefficients of inventory ($Inv$) and the direct effects of inter-purchase time on purchase quantity are insignificant. Our result may be explained by consumers' strong size loyalties (Neslin *et al.*, 1985) and fixed inter-purchase time (Kim and Park, 1997).

Some additional investigation is necessary to determine which type of consumers increase purchase quantity under a price cut. Hence, we study the relationship between the consumer-specific direct effect of inter-purchase

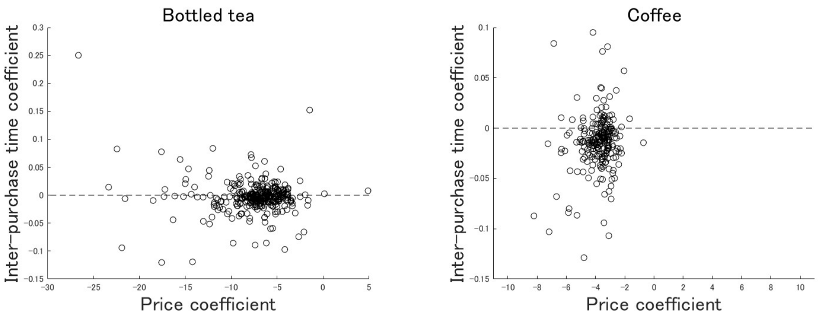


Figure 2: Plots of price coefficient $\beta_{price}$ and inter-purchase coefficient $\eta$

time on purchase quantity ($\eta$) and the price ($\beta_{price}$) coefficients.

The plot of these two coefficients (Figure 2) suggests that there are two types of consumers whose purchase quantity increases under price cuts. The left panel of Figure 2 shows the relationship between price ($\beta_{price}$) and inter-purchase time ($\eta$) coefficients in the bottled tea category. In the figure, the plots above the dashed horizontal line imply that the inter-purchase time coefficients ($\eta$) are positive, which implies that the longer the inter-purchase time, the more the purchase quantity; those consumers frequently purchase bottled tea. However, plots under the dashed line imply that the inter-purchase coefficients are negative, which suggests that the longer the inter-purchase, the lesser the purchase quantity and consumers who purchase bottled tea less frequently. While most coefficients of inter-purchase time ($\eta$) are nonsignificant, those of price ($\beta_{price}$) are significant and negative signs. Hence, consumers who increase purchase quantity with price cuts are those who frequently and less frequently purchase bottled tea. Similarly, these two kinds of consumers also increase purchase quantity with price cuts in the coffee category.

## 7.2 Brand choice

No strong effect of marketing variables is found. If there are significant effects of advertising on consumer choices, advertising weakly induces consumers to choose promoted brands (Table 7). Moreover, whether price negatively affects brand choices depends on product categories. Luxury items such as coffee are less likely to be subject to negative effects from price (Li *et al.*, 2022).

Consumers relatively memorize past advertising exposures because each consumer's advertising carry-over parameter concentrates on $\rho_i = 0.5$. The

Table 7: Estimates for the multinomial logit model.

| | Bottled tea | | | Coffee | | |
|---|---|---|---|---|---|---|
| | Pos mean | | Pos SD | Pos mean | | Pos SD |
| Brand dummy 1 | 1.49 | * | 0.21 | -0.98 | * | 0.11 |
| Brand dummy 2 | -2.22 | * | 0.41 | 0.26 | * | 0.11 |
| Brand dummy 3 | 0.88 | * | 0.18 | | | |
| Brand dummy 4 | -1.06 | * | 0.25 | | | |
| Adstock | 0.15 | * | 0.07 | 0.00 | | 0.01 |
| Price | -6.28 | * | 0.81 | 0.37 | | 0.30 |
| Num observation | | | 4,542 | | | 3,871 |

Note 1: "Pos" implies posterior.
Note 2:* indicates that the 95% credible interval does not include 0.

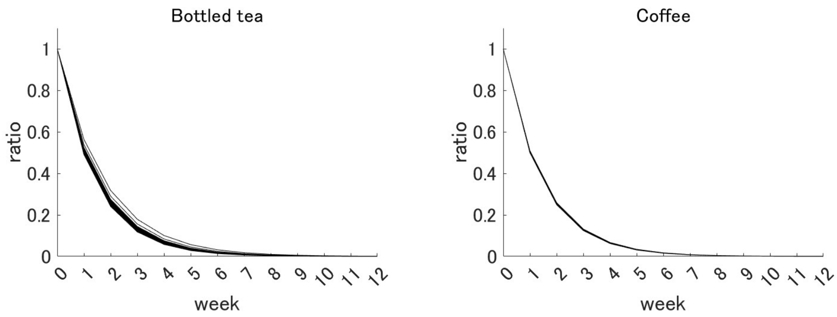


Figure 3: Consumer's advertising carry-over parameter
*Note*: Each line is the consumer's forgetting curve. The thick line indicates that each forgetting curve differs among consumers.

$\rho_i$ denotes the decreasing ratio of consumer $i$'s exposures to advertising per week. The power of $\rho_i$ presents a consumer forgetting curve of one exposure to advertising (Figure 3). Their memories do not plunge; half of the effects of advertising exposure remain one week later. The variation in the consumer forgetting curves is small, especially for the coffee category.

# 8 Importance of analyzing multichannel data

In this section, we implement additional verification for the importance of analyzing multichannel data, as suggested in Subsection 7.1. By re-estimating the same model in Subsection 7.1 using the purchase data collected from a single channel, we investigate whether the existence of unobservable purchases replaced by those in other channels affects the estimates of marketing policies. If this is the case, it would highlight the importance of observing actual consumer inter-purchase time.

## 8.1 Sampling a subset of purchase data

To create a dataset collected in a single channel, we select the consumer purchase data recorded in supermarkets, which are one of the major channels in Japan (Nakano and Kondo, 2018), from the estimation sample in Subsection 7.1. In this section, it is assumed that consumer purchases made in other channels are unobservable. Therefore, the inter-purchase time is defined depending solely on purchase data collected from the supermarket channel.

In addition to the supermarket channel, consumer purchases in other channels exist in reality. With data collected only in the supermarket channel, we cannot observe purchases replaced with those from other channels. To determine whether unobserved replacement purchases affect the estimates of marketing policies based on single-channel data, we calculate the number of purchases that consumer $i$ made in other channels during the observation period, $UR_i$. We standardize the value of $UR_i$ and add it to the model in Section 7.1 as a consumer demographic variable (Appendix C).

## 8.2 Result

The results in the bottled tea category suggest the necessity of analyzing consumer purchase data from multiple channels to investigate the effects of marketing policies on consumer purchase decision-making. The estimates in the UR column are nonsignificant (Table 8), suggesting that multichannel users show neither stronger nor weaker reactions to price and advertising than those who use a small number of channels. This implies that supermarket data records purchases made by consumers, who have homogeneous sensitivities and heterogeneous channel-usage tendencies.[14] Therefore, if researchers cannot observe purchases across other channels, then the inter-purchase time based on purchase data is longer than the actual one for multichannel users. The same pattern is found in the coffee category; the estimates in the column of UR are nonsignificant.

Our results from two product categories suggest that single-channel analysis may lead to misleading marketing policies in two ways. First, estimates for price and advertising may be biased. Although we found nonsignificant

[14] In our dataset, consumers use multiple channels (Figure 1).

Table 8: Estimates for the conditional normal model (supermarket only).

| | Bottled tea | | | Coffee | | |
|---|---|---|---|---|---|---|
| | Constant | | UR | Constant | | UR |
| Inter-purchase time | | | | | | |
| Intercept | 0.83 | * | -0.06 | 1.74 | * | 0.04 |
| | (0.10) | | (0.09) | (0.19) | | (0.20) |
| Price | -0.23 | | 0.21 | 0.02 | | -0.49 |
| | (0.36) | | (0.29) | (0.53) | | (0.61) |
| Adstock | -0.03 | | 0.04 | 0.12 | | -0.07 |
| | (0.07) | | (0.06) | (0.15) | | (0.11) |
| Inv | -0.00 | | -0.00 | 0.00 | | 0.00 |
| | (0.01) | | (0.01) | (0.02) | | (0.02) |
| Purchase quantity | | | | | | |
| Intercept | 8.20 | * | 0.04 | 7.35 | * | 0.03 |
| | (0.10) | | (0.10) | (0.09) | | (0.10) |
| Price | -11.05 | * | -0.89 | -4.49 | * | -0.32 |
| | (0.69) | | (0.68) | (0.32) | | (0.33) |
| Adstock | -0.05 | | 0.02 | 0.09 | | -0.01 |
| | (0.05) | | (0.05) | (0.08) | | (0.07) |
| Inv | 0.00 | | -0.00 | 0.00 | | -0.00 |
| | (0.01) | | (0.01) | (0.02) | | (0.02) |
| Inter-purchase time | -0.01 | | 0.00 | -0.02 | | 0.03 |
| | (0.02) | | (0.02) | (0.02) | | (0.02) |
| Num observation | | | 1,361 | | | 704 |

Note 1: Values in parentheses are posterior standard deviation.
Note 2:* indicates that the 95% credible interval does not include 0.

effects of inter-purchase time on purchase quantity, previous research found a significant effect of inter-purchase time in some product categories (Neslin *et al.*, 1985). In such cases, inaccurate inter-purchase time may indirectly affect the estimates for price and advertising in the purchase quantity model. The analysis of a subset of consumer channels depends on inaccurate inter-purchase time, so the exact effects of marketing policies cannot be estimated. Second, analyzing consumer purchase data collected in a subset of channels may underestimate the effects of marketing policies on purchase behaviors, especially on inter-purchase time. Price does not significantly affect inter-purchase time (Table 8), although it has significant negative effects on inter-purchase time derived from multichannel purchase data in the coffee category (Table 6).

# 9 Discussion and conclusion

To implement an effective promotion, there is a need to model complicated consumer purchase decisions and investigate promotional effects on the decisions (Turlo *et al.*, 2025; Haviv, 2022). By estimating a conditional normal model that has a direct effect of inter-purchase time on purchase quantity (Jen *et al.*, 2009) and multinomial logit models, this research quantifies the effects of marketing policies, such as price and advertising, on each purchase decision. Our results support explicitly modeling the effects of inter-purchase time on purchase quantity (Table 4·5). In addition, multichannel data to observe consumer's actual inter-purchase time is important to estimate unbiased effects of marketing policies and to understand consumer reactions to the policies.

Our findings suggest that marketing variables differently affect inter-purchase time, purchase quantity, and brand choice in magnitudes. Advertising relatively weakly affects inter-purchase time, purchase quantity, and brand choice; even if there are positive effects on brand choice, the effects are subtle. This result is consistent with the fact that advertising affects consumer attitudes toward brands or mental processes rather than directly affecting purchase behaviors (Berger and Mitchell, 1989; Jiang *et al.*, 2024). Price significantly decreases purchase quantity, but it does not affect inter-purchase time. Price has negative or nonsignificant effects on brand choice depending on product categories.

## 9.1 Theoretical implications

This research contributes to several research areas. First, we contribute to the research area of modeling consumer purchase decisions. Although previous studies argue for the importance of modeling inter-purchase time and purchase quantity simultaneously (Kim *et al.*, 2018; Jen *et al.*, 2009), such models are relatively new. Hence, the models have not yet been frequently applied to investigate the effects of marketing variables on inter-purchase time and purchase quantity. Compared with the MVN model in terms of MSE and MAD, the conditional normal model aligns with consumer decision-making in terms of inter-purchase time and purchase quantity. Although nonsignificant direct effects of inter-purchase time on purchase quantity are found for frequently purchased commodity goods categories, the same results are found in other kinds of B2C data (Jen *et al.*, 2009; Neslin *et al.*, 1985). Our research is valuable because it investigates the direct effect of inter-purchase time on purchase quantity in grocery products for the first time with accurately measured inter-purchase time.

Second, this research contributes to research on consumer response to promotion. Our analysis includes major promotion variables—advertising and price—and investigates the effects of promotions on inter-purchase time (Mark *et al.*, 2024), purchase quantity (Valenti *et al.*, 2024), and brand choice (Paetz and Schultz, 2025). Consequently, we find that manufacturer's advertising has no significant effects on inter-purchase time and purchase quantity, but price has negative significant effects on purchase quantity. To the best of our knowledge, this research investigates, for the first time, the effects of major promotion variables on consumer purchase decision-making with a conditional normal model (Jen *et al.*, 2009). This model captures the direct effects of inter-purchase time on purchase quantity and shows a better fit for consumer purchase data (Section 6). In addition, the necessity of collecting consumer purchase data through multiple channels is suggested for investigating the effects of marketing policies on inter-purchase time in frequently purchased goods because of no significant differences in inter-purchase time across channels (Table 6), consumer multiple channel usage (Figure 1), or the possible effect of inaccurate inter-purchase time on the estimates for marketing policies (Section 8).

Third, this research contributes to studies on consumer purchases made through multiple channels. Recent studies suggest that marketing policies, such as price and advertising, have varying effectiveness in each consumer purchase decision stage (Mark *et al.*, 2024). However, the models in only a few previous studies simultaneously investigating inter-purchase time and purchase quantity with multichannel data include the price variable (Mark *et al.*, 2024; Liu *et al.*, 2021) and conventional media advertising such as TV advertising. Excluding a major marketing variable such as price from a model may yield biased estimators of the marketing variables. Because our study and previous research found that price and advertising affect multichannel purchase behaviors (Zantedeschi *et al.*, 2017), models on multichannel purchases should include price and advertising variables. In addition, previous studies investigate a single firm's multichannel data, which may lead to misleading marketing policies, as we showed in this research, due to a lack of information on consumer purchases replaced with those in other channels (Section 8). However, our data are not limited to a particular firm's product information and include consumer purchase records across more than four channels. In summary, our results show the importance of analyzing multichannel data for a better understanding of consumer responses to marketing policies, using models with various marketing variables in multichannel consumer purchases.

## 9.2 Managerial implications

We have three managerial implications. First, manufacturers may get a poor return on their investments when they advertise their products to shorten consumer inter-purchase time or increase purchase quantity. This does not imply that advertising has no meaning. Because consumers' advertising stock does not plunge (Figure 3), sales managers should advertise their products regularly to induce consumers to choose them.

Second, retailers should collect multichannel data to delineate consumer purchase behaviors. Although collecting multichannel purchase data is difficult, doing so may provide sales managers insights into effective marketing policies (Neslin *et al.*, 2006). With multichannel purchase data, retailers can identify frequent shoppers who use multiple channels and issue discount coupons available for their next purchase occasion. Such coupons may attract multiple channel users who would purchase in other channels without the coupons in the case where the number of their shopping trips may be stable (Subsection 7.1).

Third, retailers can increase consumer purchase quantity by implementing price promotions, which leads to the market expansion effect for the bottled tea and coffee category (Maier and Dost, 2024). Price cuts attract consumers who are both frequent and infrequent shoppers (Figure 2). Sales managers would not need to worry that increasing purchase quantity prolongs inter-purchase time because bottled tea and coffee are less likely to be purchased for stockpiling (Subsection 7.1). One possible reason behind this is that the numbers of consumers' shopping trips tend to be stable (Kim and Park, 1997) and consumers have strong size loyalties (Neslin *et al.*, 1985) for bottled tea and coffee categories. For product categories that have similar characteristics to those of bottled tea or coffee, sales managers can use price promotions to increase their earnings.

## 9.3 Limitations and future studies

This research investigates the effects of marketing variables on consumer purchase decision-making, but it has some limitations. We do not investigate commodity goods but the bottled tea and coffee categories due to the limited data correction. Future research can investigate other commodity goods sold onsite and in online stores, such as apparel (Valenti *et al.*, 2024; Ansari *et al.*, 2008). As another limitation, the interaction between categories is not modeled (Song and Chintagunta, 2006; Mehta, 2007). Researchers can investigate the interaction effects of promotions on various product categories, using multichannel purchases of multiple product categories. Although this research has several limitations, it provides many implications from a model that indicates the direct effect of inter-purchase time on purchase quantity and consumer heterogeneity. Our findings are expected to motivate future research on promotions and consumer purchase decision-making stages.

# A MCMC algorithm

## A.1 Conditional normal model

To estimate the conditional normal model in Subsection 3.1, we can use Gibbs sampling (Jen *et al.*, 2009). We list the prior distribution and posterior distribution below. Each prior distribution is set to be noninformative or follow prior studies (Terui *et al.*, 2011).

### A.1.1 Conditional posterior distribution of $\boldsymbol{\nu}_i$

The prior distribution is

$$\boldsymbol{\nu}_i \sim N(\boldsymbol{\psi}, \boldsymbol{\xi}).$$

Let $\mathbf{X}_i = (\mathbf{x}_{i1}, \cdots, \mathbf{x}_{iT_i})'$ and $\mathbf{Y}_{1i} = (y_{1i1}, \cdots, y_{1iT_i})'$. $T_i$ denotes consumer $i$'s final purchase. The posterior distribution is

$$\boldsymbol{\nu}_i | \mathbf{Y}_{1i}, \mathbf{X}_i, \boldsymbol{\beta}, \eta_i, \boldsymbol{\xi}, \boldsymbol{\psi}, \sigma^2 \sim N\Bigg(\Big(\boldsymbol{\xi}^{-1} + \sigma^{-2}\mathbf{X}_i'\mathbf{X}_i\Big)^{-1}\Big(\boldsymbol{\xi}^{-1}\boldsymbol{\psi} + \sigma^{-2}\mathbf{X}_i'\mathbf{Y}_{1i}\Big), \Big(\boldsymbol{\xi}^{-1} + \sigma^{-2}\mathbf{X}_i'\mathbf{X}_i\Big)^{-1}\Bigg).$$

### A.1.2 Conditional posterior distribution of $\boldsymbol{\psi}$

The prior distribution is

$$\boldsymbol{\psi} \sim N(\boldsymbol{\psi}_0, \boldsymbol{\xi} \otimes V_{\psi}^{-1}), \text{ where } \boldsymbol{\psi}_0 = \mathbf{0}, V_{\psi} = 0.01.$$

Let $\iota = (1, \cdots, 1)'$ denote $H \times 1$ vector, where $H$ is the number of consumers. The posterior distribution is

$$\boldsymbol{\psi} | \{\boldsymbol{\nu}_i\}, \boldsymbol{\xi} \sim N\Bigg(\mathrm{vec}\bigg(\Big(V_{\psi} + \iota'\iota\Big)^{-1}\Big(V_{\psi}\boldsymbol{\psi}_0' + \iota'\mathbf{V}\Big)\bigg), \boldsymbol{\xi} \otimes \Big(V_{\psi} + \iota'\iota\Big)^{-1}\Bigg),$$

$$\text{where } \mathbf{V} = \begin{pmatrix} \boldsymbol{\nu}_1' \\ \vdots \\ \boldsymbol{\nu}_H' \end{pmatrix}.$$

### A.1.3 Conditional posterior distribution of $\boldsymbol{\xi}$

The prior distribution is

$$\boldsymbol{\xi} \sim IW(s_{\boldsymbol{\xi}}, \boldsymbol{\xi}_0), \text{ where } s_{\boldsymbol{\xi}} = 12, \boldsymbol{\xi}_0 = s_{\boldsymbol{\xi}} \times \mathbf{I}.$$

$\mathbf{I}$ denotes an identity matrix with a size equal to the corresponding parameter.

The posterior distribution is

$$\boldsymbol{\xi}|\boldsymbol{\psi}, \{\boldsymbol{\nu}_i\} \sim IW(s_{\boldsymbol{\xi}} + H, \boldsymbol{\xi}_0 + \mathbf{S}_{\boldsymbol{\xi}}), \text{ where } \mathbf{S}_{\boldsymbol{\xi}} = \Sigma_{i=1}^{H}(\boldsymbol{\nu}_i - \boldsymbol{\psi})(\boldsymbol{\nu}_i - \boldsymbol{\psi})'.$$

### A.1.4 Conditional posterior distribution of $\sigma^2$

The prior distribution is

$$\sigma^2 \sim IG(\sigma_0^2/2, q_{\sigma^2}/2), \text{ where } \sigma_0^2/2 = 6, q_{\sigma^2}/2 = 1.$$

The posterior distribution is

$$\sigma^2|\{\boldsymbol{\nu}_i\}, \{\mathbf{Y}_{1i}\}, \{\mathbf{X}_i\} \sim IG\left(\frac{\sigma_0^2 + H}{2}, \frac{q_{\sigma^2} + \Sigma_{i=1}^{H}\Sigma_{t=1}^{T_i}(y_{1it} - \boldsymbol{\nu}_i'\mathbf{x}_{it})^2}{2}\right).$$

### A.1.5 Conditional posterior distribution of $\boldsymbol{\mu}_i$

The prior distribution is

$$\boldsymbol{\mu}_i \sim N(\boldsymbol{\beta}, \boldsymbol{\zeta}).$$

Let $\mathbf{Y}_{2i} = (y_{2i1}, \cdots, y_{2iT_i})'$. The posterior distribution is

$$\begin{aligned}&\boldsymbol{\mu}_i|\mathbf{Y}_{1i}, \mathbf{Y}_{2i}, \mathbf{X}_i, \boldsymbol{\beta}, \eta_i, \tau^2, \boldsymbol{\zeta} \\ &\quad \sim N\left(\left(\boldsymbol{\zeta}^{-1} + \tau^{-2}\mathbf{X}_i'\mathbf{X}_i\right)^{-1}\left(\boldsymbol{\zeta}^{-1}\boldsymbol{\beta} + \tau^{-2}\mathbf{X}_i'(\mathbf{Y}_{2i} - \mathbf{Y}_{1i}\eta_i)\right), \left(\boldsymbol{\zeta}^{-1} + \tau^{-2}\mathbf{X}_i'\mathbf{X}_i\right)^{-1}\right).\end{aligned}$$

### A.1.6 Conditional posterior distribution of $\boldsymbol{\beta}$

The prior distribution is

$$\boldsymbol{\beta} \sim N(\boldsymbol{\beta}_0, \boldsymbol{\zeta} \otimes V_\beta^{-1}), \text{ where } \boldsymbol{\beta}_0 = \mathbf{0}, V_\beta = 0.01.$$

The posterior distribution is

$$\boldsymbol{\beta}|\{\boldsymbol{\mu}_i\}, \boldsymbol{\zeta} \sim N\left(\text{vec}\left(\left(V_\beta + \iota'\iota\right)^{-1}\left(V_\beta\boldsymbol{\beta}_0' + \iota'\mathbf{B}\right)\right), \boldsymbol{\zeta} \otimes \left(V_\beta + \iota'\iota\right)^{-1}\right),$$

$$\text{where } \mathbf{B} = \begin{pmatrix} \boldsymbol{\mu}_1' \\ \vdots \\ \boldsymbol{\mu}_H' \end{pmatrix}.$$

### A.1.7 Conditional posterior distribution of $\zeta$

The prior distribution is

$$\boldsymbol{\zeta} \sim IW(s_{\zeta}, \boldsymbol{\zeta}_0), \text{ where } s_{\zeta} = 12, \boldsymbol{\zeta}_0 = s_{\zeta} \times \mathbf{I}.$$

The posterior distribution is

$$\boldsymbol{\zeta}|\boldsymbol{\beta}, \{\boldsymbol{\mu}_i\} \sim IW(s_{\zeta} + H, \boldsymbol{\zeta}_0 + \mathbf{S}_{\zeta}), \text{ where } \mathbf{S}_{\zeta} = \Sigma_{i=1}^{H}(\boldsymbol{\mu}_i - \boldsymbol{\beta})(\boldsymbol{\mu}_i - \boldsymbol{\beta})'.$$

### A.1.8 Conditional posterior distribution of $\tau^2$

The prior distribution is

$$\tau^2 \sim IG(\tau_0^2/2, q_{\tau^2}/2), \text{ where } \tau_0^2/2 = 6 \text{ and } q_{\tau^2}/2 = 1.$$

The posterior distribution is

$$\tau^2|\{\boldsymbol{\mu}_i\}, \{\eta_i\}, \{\mathbf{Y}_{1i}\}, \{\mathbf{Y}_{2i}\}, \{\mathbf{X}_i\} \sim IG\left(\frac{\tau_0^2 + H}{2}, \frac{q_{\tau^2} + \Sigma_{i=1}^{H}\Sigma_{t=1}^{T_i}(y_{2it} - (\boldsymbol{\mu}_i'\mathbf{x}_{it} + y_{1it}\eta_i))^2}{2}\right).$$

### A.1.9 Conditional posterior distribution of $\eta_i$

The prior distribution is

$$\eta_i \sim N(\phi, \omega).$$

The posterior distribution is

$$\eta_i|\sigma^2, \omega, \phi, \boldsymbol{\mu}_i, \mathbf{Y}_{1i}, \mathbf{Y}_{2i}, \mathbf{X}_i \\ \sim N\left(\left(\frac{\Sigma_{t=1}^{T_i}y_{1it}^2}{\sigma^2} + \frac{1}{\omega}\right)^{-1}\left(\frac{\Sigma_{t=1}^{T_i}y_{1it}(y_{2it} - \boldsymbol{\mu}_i'\mathbf{x}_{it})}{\sigma^2} + \frac{\phi}{\omega}\right), \left(\frac{\Sigma_{t=1}^{T_i}y_{1it}^2}{\sigma^2} + \frac{1}{\omega}\right)^{-1}\right).$$

### A.1.10 Conditional posterior distribution of $\phi$

The prior distribution is

$$\phi \sim N(\phi_0, V_{\phi}), \text{ where } \phi_0 = 0, V_{\phi} = 100.$$

The posterior distribution is

$$\phi|\{\eta_i\}, \omega \sim N\left(\left(\frac{H}{\omega} + \frac{1}{V_{\phi}}\right)^{-1}\left(\frac{\Sigma_{i=1}^{H}\eta_i}{\omega} + \frac{\phi_0}{V_{\phi}}\right), \left(\frac{H}{\omega} + \frac{1}{V_{\phi}}\right)^{-1}\right).$$

### A.1.11 Conditional posterior distribution of $\omega$

The prior distribution is

$$\omega \sim IG(\omega_0/2, q_\omega/2), \text{ where } \omega_0^2/2 = 6, q_\omega/2 = 1.$$

The posterior distribution is

$$\omega|\{\eta_i\}, \phi, \sim IG\left(\frac{\omega_0 + H}{2}, \frac{q_\omega + \Sigma_{i=1}^{H}(\eta_i - \phi)^2}{2}\right).$$

## A.2 Multinomial logit model

Our model in Subsection 3.2 is a hierarchical multinomial logit model. We generate draws of parameters $\mathbf{A}_i = (\alpha_{i0}, \cdots, \alpha_{i6})', \alpha_7$ and $\gamma_i$ from the posterior conditional distributions by running the random-walk Metropolis-Hastings (M-H) algorithm (Rossi *et al.*, 2005). We generate draws for parameters $\mathbf{\Theta}, \theta_\gamma, \mathbf{V}_\Theta$, and $\sigma_\gamma$ from the posterior by running Gibbs sampling (Rossi *et al.*, 2005).

Let $p(r_{it} = j)$ and $V_{ijt}$ denote the choice probability, where consumer $i$ chooses brand $j$ in week $t$ and the determinant part of the utility in Equation (7), respectively.

$$p(r_{it} = j) = \frac{\exp(V_{ijt})}{\Sigma_{m=1}^{J}\exp(V_{imt})}.$$

Let $y_{it}$ represent consumer $i$'s choice in week $t$. The likelihood function of consumer $i$ ($L_i$) is:

$$L_i = \Pi_{t=1}^{T_i} p(r_{it} = y_{it}).$$

Using this likelihood function and prior distributions, we ran the M-H algorithm and Gibbs sampling.

### A.2.1 Posterior conditional for $\mathbf{A}_i$

The prior distribution is expressed as

$$p(\mathbf{A}_i) \sim N\left(\mathbf{\Theta}, \mathbf{V}_\Theta\right).$$

Let $\mathbf{X}_i^* = (\mathbf{x}_{i1}^*; \cdots; \mathbf{x}_{iT_i}^*)$. The posterior distribution is expressed as follows:

$$p(\mathbf{A}_i|\mathbf{X}_i^*, \alpha_7, \mathbf{\Theta}, \mathbf{V}_\Theta, \rho_i) \propto p(\mathbf{A}_i|\mathbf{\Theta}, \mathbf{V}_\Theta) L_i(\mathbf{A}_i; \mathbf{X}_i^*|\alpha_7, \rho_i).$$

### A.2.2 Conditional posterior of $\mathbf{\Theta}$

The prior distribution is expressed as

$$\mathrm{vec}(\mathbf{\Theta})|\mathbf{V}_\Theta \sim N\left(\mathrm{vec}(\mathbf{\Theta}_0), \mathbf{V}_\Theta \otimes A_\Theta^{-1}\right), \text{ where } \mathrm{vec}(\mathbf{\Theta}_0) = \mathbf{0}, A_\Theta = 0.01$$

$H$ denotes the number of consumers and $\iota$ is $H \times 1$ vector. The posterior distribution is expressed as follows:

$$\mathrm{vec}(\mathbf{\Theta})|\{\mathbf{A}_i\}, \mathbf{V}_\Theta \sim N\left(\mathrm{vec}\left(\left(A_\Theta + \iota'\iota\right)^{-1}\left(A_\Theta \mathbf{\Theta}_0 + \iota'\mathbf{A}_i\right)\right), \mathbf{V}_\Theta \otimes \left(A_\Theta + \iota'\iota\right)^{-1}\right).$$

### A.2.3 Conditional posterior distribution of $\mathbf{V}_\Theta$

The prior distribution is

$$\mathbf{V}_\Theta \sim IW(s_{\mathbf{V}_\mathbf{\Theta}}, \mathbf{V}_{\Theta_0}), \text{ where } s_{\mathbf{V}_\mathbf{\Theta}} = 9, \mathbf{V}_{\Theta_0} = s_{\mathbf{V}_\mathbf{\Theta}} \times \mathbf{I}.$$

$\mathbf{I}$ denotes an identity matrix with a size equal to the corresponding parameter.

The posterior distribution is

$$\mathbf{V}_\Theta|\{\mathbf{A}_i\}, \mathbf{\Theta} \sim IW(s_{\mathbf{V}_\mathbf{\Theta}} + H, \mathbf{V}_{\Theta_0} + \mathbf{S}_{\mathbf{V}_\Theta}), \text{ where } \mathbf{S}_{\mathbf{V}_\Theta} = \Sigma_{i=1}^H (\mathbf{A}_i - \mathbf{\Theta})(\mathbf{A}_i - \mathbf{\Theta})'.$$

### A.2.4 Posterior conditional for $\alpha_7$

The prior distribution is expressed as

$$p(\alpha_7) \sim N\left(\alpha_{7,0}, V_{\alpha_7}\right), \text{ where } \alpha_{7,0} = 0, V_{\alpha_7} = 100.$$

The posterior distribution is expressed as follows:

$$p(\alpha_7|\{\mathbf{X}_i^*\}, \{\mathbf{A}_i\}, \{\rho_i\}) \propto p(\alpha_7)\Pi_{i=1}^H L_i(\alpha_7; \{\mathbf{X}_i^*\}|\{\mathbf{A}_i\}, \{\rho_i\}).$$

### A.2.5 Conditional posterior of $\theta_\gamma$

The prior distribution is expressed as

$$\theta_\gamma|\sigma_\gamma \sim N\left(\theta_0, \sigma_\gamma A_{\theta_\gamma}^{-1}\right), \text{ where } \theta_0 = 0, A_{\theta_\gamma} = 0.01.$$

The posterior distribution is expressed as follows:

$$\theta_\gamma|\{\gamma_i\}, \sigma_\gamma \sim N\left(\left(A_{\theta_\gamma} + \iota'\iota\right)^{-1}\left(A_{\theta_\gamma}\theta_0 + \iota'\mathbf{\Gamma}\right), \sigma_\gamma\left(A_{\theta_\gamma} + \iota'\iota\right)^{-1}\right),$$

$$\text{where } \mathbf{\Gamma} = \begin{pmatrix} \gamma_1 \\ \vdots \\ \gamma_H \end{pmatrix}.$$

### A.2.6 Conditional posterior distribution of $\sigma_\gamma$

The prior distribution is

$$\sigma_\gamma \sim IG(\sigma_{\gamma 0}/2, q_{\sigma_\gamma}/2), \text{ where } \sigma_{\gamma 0}/2 = 6, q_{\sigma_\gamma}/2 = 1.$$

The posterior distribution is

$$\sigma_\gamma | \{\gamma_i\}, \theta_\gamma \sim IG((\sigma_{\gamma 0} + H)/2, (q_{\sigma_\gamma} + S_{\sigma_\gamma})/2), \text{ where } S_{\sigma_\gamma} = \Sigma_{i=1}^{H}(\gamma_i - \theta_\gamma)(\gamma_i - \theta_\gamma)'.$$

### A.2.7 M-H algorithm for $\rho_i$

Now, we explain the M-H algorithm for $\rho_i$. Let $\gamma_i^{(l-1)}$ denote the $l$th MCMC loop sample of $\gamma$.

In the *lth* MCMC loop, $\gamma_i^*$ is the draw sampled, as in Equation (A.1) (Terui *et al.*, 2011);

$$\gamma_i^* = \gamma_i^{(l-1)} + w_i, \; w_i \sim N(0, 0.01). \tag{A.1}$$

Let $J_{\rho_i^{(l)} \to \gamma_i^{(l)}}$ be the Jacobian of transformation. The acceptance probability, *a.p.*, is

$$a.p. = \min\left[\frac{\pi(\gamma_i^*|\theta_\gamma, \sigma_\gamma, \mathbf{X}_i^*, \mathbf{A}_i, \alpha_7)}{\pi(\gamma_i^{(l-1)}|\theta_\gamma, \sigma_\gamma, \mathbf{X}_i^*, \mathbf{A}_i, \alpha_7)}, 1\right],$$
$$\text{where } \pi(\gamma_i^{(l)}|\theta_\gamma, \sigma_\gamma, \mathbf{X}_i^*, \mathbf{A}_i, \alpha_7) \propto p(\gamma_i^{(l)}|\theta_\gamma, \sigma_\gamma) L_i(\gamma_i^{(l)}; \mathbf{X}_i^*|\mathbf{A}_i, \alpha_7) \left| J_{\rho_i^{(l)} \to \gamma_i^{(l)}} \right|.$$

We derive $l$th $\rho_i$ as

$$\rho_i^{(l)} = \frac{\exp(\gamma_i^{(l)})}{1 + \exp(\gamma_i^{(l)})}.$$

# B Benchmark model

The MVN model is a benchmark model in Section 6. Its formulation is presented below.

$$\begin{pmatrix} y_{1it} \\ y_{2it} \end{pmatrix} = \begin{pmatrix} \boldsymbol{\nu}_i' \mathbf{x}_{it} \\ \boldsymbol{\mu}_i' \mathbf{x}_{it} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,it} \\ \epsilon_{2,it} \end{pmatrix}, \text{ where } \begin{pmatrix} \epsilon_{1,it} \\ \epsilon_{2,it} \end{pmatrix} \sim N(\mathbf{0}, \boldsymbol{\Sigma}).$$

# C Model in Section 8

In Section 8, $UR_i$ is inserted in our model as a consumer demographic variable. Let $\mathbf{z}_i = (1, UR_i)'$, then

$$\begin{aligned}
\boldsymbol{\nu}_i &\sim N\Big( \begin{bmatrix} \boldsymbol{\psi}_1 & \boldsymbol{\psi}_2 \end{bmatrix} \mathbf{z}_i, \boldsymbol{\xi} \Big), \\
\boldsymbol{\mu}_i &\sim N\Big( \begin{bmatrix} \boldsymbol{\beta}_1 & \boldsymbol{\beta}_2 \end{bmatrix} \mathbf{z}_i, \boldsymbol{\zeta} \Big), \\
\eta_i &\sim N\Big( \begin{bmatrix} \phi_1 & \phi_2 \end{bmatrix} \mathbf{z}_i, \omega \Big).
\end{aligned}$$

The estimation algorithm is the same as we describe in Appendix A.1.

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