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Long-term effects of advertising on consumers' choices made for other people: The case of choosing consumer packaged goods

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Long-term effects of advertising on consumers' choices made for other people: The case of choosing consumer packaged goods

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Abstract

This study investigates the effects of advertising on consumers' choices made for others, such as family members. The authors employ a multinomial logit model to account for the long-term promotional effects on consumers' choices made for others. Using consumer purchase data, which includes purchase object information and TV advertising exposure log data, this study quantifies the long-term effects of TV advertising on choices made for others in the consumer packaged goods sector. The authors find that TV advertising continues to affect choices made for others. Sales managers should invest in advertising to support consumer decision-making and increase sales.

- Keywords

self-other choices, advertising, promotion, decision making

1 Introduction

In their daily lives, consumers purchase goods for themselves and others (Lu *et al.*, 2016). What they choose for themselves may differ from that which they choose for others (Wight *et al.*, 2024; Cavagnaro *et al.*, 2024; Choe *et al.*, 2023; Yang and Urminsky, 2024; Eggert *et al.*, 2019; Liu *et al.*,

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2018) because consumers have to consider recipient preferences as well as the relationship between the consumers and their recipients (Liu *et al.*, 2019). Consumer choices for others largely occur in four situations: joint consumption, caregiving, gift-giving, and everyday favors/pick-ups (Liu *et al.*, 2019). An example of joint consumption is going to a movie with friends. Caregiving includes a parent's food choices for their children. In a gift-giving situation, consumers purchase presents for others. Finally, in an everyday favors/pick-ups situation, people purchase consumer packaged goods, such as bottled tea, for family members or friends.

These choice situations impose a heavier decision-making burden on consumers because it is difficult to accurately identify recipients' preferences (Kim *et al.*, 2023). Consumers must infer these preferences through their own preferences, a process that consumes considerable energy (Epley *et al.*, 2004); however, consumer decision-making burdens differ across situation types.

One common choice people make for others involves everyday favors/pick-ups situations. For example, consumers may purchase bottled tea or beer for their family members. In such situations, consumers must reduce their decision burdens because they also have to make decisions for themselves throughout the day. That is, they must reduce the complexity of purchase decisions for others and save energy.

Fortunately, consumers reduce their decision-making complexity through heuristic decision-making processes (Giráldez-Cru *et al.*, 2023) and responding to promotions in everyday favors/pick-ups situations (Chandon *et al.*, 2000). Advertising aids with consumers' brand awareness and encourages them to purchase advertised goods (Terui *et al.*, 2011; Honka *et al.*, 2017; Tsai and Honka, 2021).

In this study, we investigate everyday favors/pick-ups situations using consumer purchase and advertising data. Recently, researchers have investigated choices made for others using various approaches such as by conducting laboratory experiments (Schumacher *et al.*, 2021; Choe *et al.*, 2023; Yang and Urminsky, 2024) or utilizing real-world consumer purchase data (Delre *et al.*, 2016).

Real-world data have an advantage in the study of market development, consumer purchase behaviors, and the long-term marketing policy effects of choice behaviors for others (Delre *et al.*, 2016).

We use consumer purchase data, which has unique properties such as records on "for whom" consumers purchase beverages, that is, the choice-target. This information enables us to distinguish purchases for others from those for themselves, which in turn enables us to more accurately investigate the long-term effects of marketing policy on consumer behaviors.

Although the long-term effects of advertising have been thoroughly investigated (Danaher *et al.*, 2020; Jedidi *et al.*, 1999), the impact on making a choice for others remains unclear because of difficulties in data collection. However, our datasets contain records of choices for others over the course of one year and are sufficient to evaluate the long-term effects of advertising on choices made for others.

We apply these datasets to consumer choice models to quantify the long-term effects of marketing policies on consumer purchase behavior, especially in everyday favors/pick-ups situations. Our consumer choice models also provide insights into other marketing activities such as price cuts.

Previous studies have evaluated the long-term effects of advertising on joint consumption (Delre *et al.*, 2016). However, to the best of our knowledge, this study is the first to evaluate the long-term effects of advertising on consumer purchase behaviors in everyday favors/pick-ups situations.

This study contributes to the research on advertising and making choices for others. We model the difference between consumer response to advertising on choices for oneself and others. Moreover, using real-world data, our results support previous findings that closeness between consumers and their recipients moderates the difference between making choices for others and making choices for oneself (Cavagnaro *et al.*, 2024; Polman, 2012).

The remainder of the paper is organized as follows. In Section 2, we review the relevant studies; in Section 3, we describe consumer choice models; and in Section 4, we explain our data. Sections 5 and 6 present the results and check their robustness, respectively. Finally, in Section 7, we discuss our findings and present the conclusion.

2 Literature Review

In the following subsections, we introduce a common feature of choices made for others and describe the decision-making process of choosing for others in which heuristic decision making is used. Finally, we discuss the contribution of advertising to the promotion of choices for others.

2.1 Choice for Others

In our daily lives, we often purchase consumer packaged goods, such as snacks and bottled drinks, and gifts for family members, friends, or colleagues (Liu *et al.*, 2019). Although these choices are commonly made (Polman, 2012; Givi and Mu, 2023; Delre *et al.*, 2016), the decision-making process thereof is often complicated because givers must consider or infer recipients' preferences while simultaneously considering the message of the chosen items. In previous studies aiming to clarify this decision-making complexity, factors affecting choices for others have been investigated compared with those for oneself (Yang and Urminsky, 2024; Kim *et al.*, 2023; Choe *et al.*, 2023; Schumacher *et al.*, 2021; Polman, 2012; Polman and Vohs, 2016; Yang and Paladino, 2015).

There are many distinct features in choices for others. For example, the prices of selected items for others in some cases are higher (Choe *et al.*, 2023) or lower (Yang and Urminsky, 2024) as compared to cases for oneself. In addition, when consumers choose for others, they seek to choose items with positive outcomes (Polman, 2012; Liu *et al.*, 2018), more indulgent items such as fatty food (Laran, 2010), or a variety of items in a set (e.g., snacks) (Choi *et al.*, 2006). The reasons behind such choices include that consumers recognize their choice as a rare opportunity (Choe *et al.*, 2023), they are psychologically rewarded for their choices in their recipients' feedback (Yang and Urminsky, 2024), and they overestimate their recipients' variety-seeking tendencies (Choi *et al.*, 2006).

Despite these distinct features in choices for others, in some cases, choices for others and oneself lead to the same results (Astle and Schmeichel, 2024; Baumann and Hamin, 2014); for example, when choosers have no reference point for their expenditures, such as a budget (Choe *et al.*, 2023) or when choosing foods (Lu *et al.*, 2016). When such situations were investigated by previous studies,[1] consumers do not expect to receive their recipients' feedback on their choices every time, which is similar to their daily purchase behaviors. The results of previous research suggest that the choices of consumer packaged goods for others—the most frequent choice made for others (Chang *et al.*, 2012)—do not differ significantly from those made for oneself (Wilken *et al.*, 2022; Baumann and Hamin, 2014). When making frequent choices for others, consumers think less about what they choose than when making infrequent choices for others.

Based on the extent to which consumers emphasize the preferences of receivers and the items' message, choices made for others can be classified into four main categories: joint consumption, caregiving, gift-giving, and everyday favors/pick-ups (Liu *et al.*, 2019). In joint consumption situations, consumers consider both others' (the recipients) and their own preferences and try to convey relational messages to their recipients based on what they choose (Liu *et al.*, 2019). In caregiving situations, consumers consider both their recipients' and their own preferences but do not try to communicate

[1] Lu *et al.* (2016) has investigated consumer choices from a set of products with different attributes but in the same category. Some product categories are commodity goods.

relational messages (Liu *et al.*, 2019). In gift-giving situations, consumers consider recipients' preferences and focus on their relationships with their recipients (Liu *et al.*, 2019). In an everyday favors/pick-ups situation, which corresponds to frequent purchases of consumer packaged goods, consumers consider their recipients' preferences but do not try to convey their relational messages to their recipients (Liu *et al.*, 2019).

Consumers must reduce the decision-making costs of making frequent choices for others because any choice for others is more complicated than that for themselves (Kim *et al.*, 2023; Schumacher *et al.*, 2021) as they must infer others' preferences and expend additional energy (Epley *et al.*, 2004; Polman and Vohs, 2016). Consumers have a limit when making complicated decisions (Polman and Vohs, 2016); therefore, they must reduce the burden of each choice in less important decision making. Two methods have been proposed to reduce this decision load: a heuristic decision-making process and the promotion-aiding effects of decision making.

2.2 Heuristic Decision Making in Everyday Favors/Pick-Ups Situations

Consumers use heuristic decision-making processes to reduce their decision-making costs (Giráldez-Cru *et al.*, 2023; Gilbride and Allenby, 2004; Fader and McAlister, 1990). In these processes, consumers screen options that match their criteria, such as their preferences,[2] and reduce the number of options to consider and the decision-making complexity (Gilbride and Allenby, 2004; Fader and McAlister, 1990). These heuristic processes become particularly critical in the context of making frequent, low-involvement choices for others.

Heuristic decision-making processes are also useful in making daily choices for others (everyday favors/pick-ups situations). These processes help consumers reduce their decision-making costs to choose what they believe their recipients will accept.[3] Consumers can infer the psychological states (Mobbs *et al.*, 2009) and uncertain preferences of others to a certain degree by adjusting their own preferences (Epley *et al.*, 2004). Hence, they can choose what their recipients will not refuse from the set of options they screen.

This screening process often leads to similar choices for others and oneself. Because consumers follow rules based on their own preferences (Giráldez-Cru

[2]Consumers' preferences for particular product attributes affect their purchase decision making (Giráldez-Cru *et al.*, 2023).

[3]In everyday favors/pick-ups situations, consumers aim to choose what their recipients will not refuse (Liu *et al.*, 2019).

et al., 2023; Hoyer, 1984), their choices are reflected in the screened options.[4] When consumers use a heuristic decision-making process in their choosing for others, their choices for others are likely to be the same as those for themselves. To sum up the above discussion, we developed the following hypothesis:

H1: Consumer choices made for others are not greatly different from those for oneself in everyday favors/pick-ups situations.

2.3 Effects of Advertising on Choices for Others

Promotion by manufacturers and retailers helps consumers reduce their decision-making costs regarding their choices for others. Promotions such as advertisements assist consumers in recognizing and considering the promoted products (Andrews and Srinivasan, 1995; Mehta *et al.*, 2003; Terui *et al.*, 2011; Barroso and Llobet, 2012; Honka *et al.*, 2017; Tsai and Honka, 2021) and reduces the emotional burden of acquiring information about alternative products (Van Nierop *et al.*, 2010). These effects of advertising help consumers reduce their purchase decision burden by screening alternatives (Fader and McAlister, 1990). Although the consumer screening process has generally been investigated under the assumption that consumers choose for themselves, the process is also used when consumers purchase for others (Chang *et al.*, 2012).

Advertising also influences consumer purchases made for others in the long run. Companies' past advertisements have positive effects on consumers' purchases, which is supported in both macro- and micro-level research (He and Klein, 2023; Miller *et al.*, 2021; Draganska and Klapper, 2011). The long-term effects of advertising on consumers' choices have been reported to be nonnegligible (Danaher *et al.*, 2020; Jedidi *et al.*, 1999). Likewise, in the long run, advertisements influence the purchases of consumer packaged goods for others; purchase choices made for others are tougher than those made for oneself. Therefore, advertisements' help in consumers' decision-making screening processes can be particularly beneficial.

However, few studies have investigated the long-term effects of advertising on choices for others. Joint consumption has been investigated; for example, Delre *et al.* (2016) report a long-term sales increase accompanying large expenditures on advertising. Research in this area is limited due to data collection issues. Investigations of the long-term effects of advertising require

[4] Choices from screened options reflect consumers' preferences, even if they are choosing for others, because their preferences for particular brands are formed by their past purchase behaviors (Guadagni and Little, 1983) and consumer preference of particular product attributes affect consumer screening rule (Giráldez-Cru *et al.*, 2023).

consumer data such as scanner data with long-term purchase records and identifications "for whom" each consumer purchased.[5] This research utilizes purchase data of consumer packaged goods, including consumer's purchase records of "for whom," to investigate the effects of advertising on everyday favors/pick-ups situations. Thus, we developed the following hypotheses.

H2: Advertising positively influences consumer choices made for others in everyday favors/pick-ups situations in the short run.

H3: Advertising positively influences consumer choices made for others in everyday favors/pick-ups situations in the long run.

3 Model and Framework

A hierarchical multinomial logit model is used to investigate consumer choice behaviors. The model consists of intrapersonal and interpersonal sections.

3.1 Intrapersonal Part

First, we define consumer i's utility in week t for brand $j (j = 1, \cdots, J)$ as in Equation (1). $AdStock_{ij,t}$ denotes advertising stock variables. $Others_{it}$ denotes a dummy variable, which is equal to 1 when consumer i purchases alternative j in week t for others. $Brand_j$ is a brand dummy. We set $Brand_J = 0$ for identification.

$$\begin{aligned} U_{ijt} =& \alpha_{ij} + \beta_{i1} AdStock_{ij,t} + \beta_{i2} Others_{it} + \xi_p Price_{ij,t} \\ &+ \xi_{Ad\times o} AdStock_{ij,t} \times Others_{it} + \xi_j Brand_j \times Others_{it} + \varepsilon_{ijt} \end{aligned} \tag{1}$$

We assume ε_{ijt} follows a type-1 extreme value distribution. Consumer i selects j which maximizes Equation (1). We set $\alpha_{iJ} = 0$ for identification.

$AdStock$ variable in Equation (1) comprises a first-order lag and $Ad_{ij,w}$. $Ad_{ij,w}$ denotes the number of times consumer i is exposed to j's advertisement in week t.

$$AdStock_{ij,w} = \rho_{i,j} AdStock_{ij,w-1} + \log(1 + Ad_{ij,w}) \tag{2}$$

Note that w $(w = 1, \cdots, 53)$ denotes the calendar week. The initial frequency of advertising exposure $(Ad_{ij,0})$ is the value of $(Ad_{ij,w})$ averaged separately for i and j. To account for diminishing marginal returns of advertising, we

[5]Consumer purchases of gift products enable us to distinguish their choices for others (gift-giving) from those for themselves (Eggert *et al.*, 2019). However, this does not apply to purchasing consumer packaged goods; that is, we cannot specify "for whom" the consumer purchases the goods.

use the logarithmic transformation in Equation (2) (Zenetti and Klapper, 2016).

To allow for the carry-over parameter $\rho_{i,j}(0 \leq \rho_{i,j} < 1)$ for consumer heterogeneity, we reparametrize $\rho_{i,j}$ as $\gamma_{i,j}$ (Terui *et al.*, 2011).

$$\gamma_{i,j} = \log\left(\frac{\rho_{i,j}}{1-\rho_{i,j}}\right) \tag{3}$$

3.2 Interpersonal Part

We allow parameters α, β, and γ to vary across consumers. The parameters α and β follow Equation (4).

$$\begin{pmatrix} \alpha_{i1} \\ \vdots \\ \beta_{i1} \end{pmatrix} \sim N\left(\Theta, V_\Theta\right) \tag{4}$$

$$where \quad \Theta = \begin{pmatrix} \theta_{\alpha_1} \\ \vdots \\ \theta_{\beta_1} \end{pmatrix}, \quad V_\Theta = \begin{pmatrix} \sigma_{\alpha_1\alpha_1} & \cdots & \sigma_{\alpha_1\beta_1} \\ \vdots & \ddots & \vdots \\ \sigma_{\beta_1\alpha_1} & \cdots & \sigma_{\beta_1\beta_1} \end{pmatrix}$$

Similarly, parameter $\gamma_{i,j}$ follows Equation (5):

$$\gamma_{i,j} \sim N\left(\theta_{\gamma_j}, \sigma_{\gamma_j}\right) \tag{5}$$

3.3 Model Estimation

We estimate the model described above using the Markov chain Monte Carlo (MCMC) estimation procedure. Its estimation algorithm is described in Web appendix A. We ran 61,000 MCMC loops and sampled the parameters in every fortieth loop, discarding the first 250 samples, which were regarded as the burn-in period.

4 Data

In this section, our dataset is described and tested for advertising endogeneity concerns.

4.1 Datasets

The dataset consists of three sources provided by the National Institute of Informatics: consumer panel data and single-source data (INTAGE Inc., 2019).

Those two kinds of data are collected by INTAGE Inc., which is a large marketing firm in Japan. These data were collected in the Keihin region,[6] in the Greater Tokyo Metropolitan area of Japan, by INTAGE Inc., from December 26, 2016, to December 25, 2017.

The first type of data, consumer panel data, includes consumers' purchase data. The dataset records 700 consumers' purchases across seven beverage categories.[7] Consumers' purchase information is collected as home-scan data; the information of those who cooperate with INTAGE Inc., including when and what they purchase through the marketing firm's web page and its application installed on the consumers' cell phones, is recorded. The advantage of this dataset is that it records "for whom consumers purchase products." INTAGE Inc. collects not only common consumer purchase records but also consumers' purchase objects; they purchase products "for themselves," "for others," or "for themselves and others." Each consumer has a unique ID that is used for the single-source data.

The second type of data, the single-source data, includes a log of exposures to advertising that is automatically collected by devices set on consumers' TVs. This dataset records when consumers are exposed to TV advertising of which product and when. By matching this single-source data and consumer panel data with the consumer ID, we can investigate the relationship between consumer exposure to TV advertising and consumer choice behaviors.

Using these two kinds of data, we constructed datasets as follows. We matched each consumer purchase record with the frequency of TV advertising exposures from the consumer panel data and the single-source data. As described in Equation (2), *AdStock* variables are generated using the number of TV advertising exposures. Using consumer panel data, we defined the *Others* variable as described in Subsection 3.1. When this data report says, "this purchase occasion is for others," $Others = 1$; otherwise, $Others = 0$. Price is defined as expenditures (Japanese currency) per volume (ml). Unfortunately, price information of brands not purchased is unobserved. To complement the missing price information, we inferred the values using the mean prices across goods and weeks.

This study examines purchase behaviors among 281 consumers, focusing on data from the bottled tea category, which includes five brands. As a type of everyday favors/pick-ups situation, bottled tea purchasing data provide us with suitable information to analyze everyday favors/pick-ups situations.

[6] The Keihin region consists of Tokyo, Chiba, Saitama, and Kanagawa (INTAGE Inc., 2019).

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

The summary statistics are shown in Table 1.

We observe more than 300 consumer purchases for others. We employ strict criteria of "choices made for others" to estimate the exact effects of advertising and other marketing variables on choices for others. If we relax our criteria of choices for others, we can include more consumer purchases. The consumer panel data also records when "this purchase occasion is for others or themselves." Although the products from this type of consumer purchase can be used by others and the consumer themselves, broadly, the purchase occasion is also regarded as a choice for others. One example is bottled tea purchases for one's household. Households include oneself and family members; hence, a choice for one's household is also a choice for others (everyday favors/pick-ups situations) (Liu *et al.*, 2019). Therefore, a purchase occasion labeled as "for others or themselves" can alternatively be classified as a choice for others: $Others = 1$. This definition is an alternative to the original definition. Under this definition, purchase occasions for others are observed 1,635 times with a mean of 0.25. The results of the alternative definition are shown in Subsection 6.2.

We analyze data of purchases of 500 to 600 ml because some volume ranges are more likely chosen for others or consumers themselves. For example, purchases of 1,000 ml and above are often made for more than one person; therefore, this volume range is less likely to be chosen for only the consumer themself. Likewise, 200 to 250 ml is often purchased in bulk and handed out at parties or events; therefore, this volume range is also more likely to be chosen for others. Considering these points, volume is an important factor that could affect whether items are purchased "for themselves" or "for others." In contrast to a volume of more than 1,000 ml or between 200 and 250 ml, a volume between 500 and 600 ml is often chosen for both consumers and others. Thus, the choice "for themselves" or "for others" in this volume range is considered less affected by the volume factor. In addition to this volume range selection, we exclude certain consumer data to estimate the consumer heterogeneous choice models in Section 5. Specifically, we eliminate the data of consumers whose purchases occurred fewer than five times during the observation period. Through these screening processes, 185 consumer data points with 4,157 observations were selected and submitted for further analysis.

We also check the stationarity of bottled tea sales using store panel data because dynamic factors, such as a new brands entry, may exist. In such cases, we could not attribute consumer responses to advertising to whether the choices are for others or themselves because the dynamic factor also affects advertising effectiveness. New products are often introduced through advertising to inform consumers about the existence of products. Such ad-

Table 1: Summary of Statistics and Brand Shares

	Summary of Statistics				Brand Share	
Variable Name	Mean	SD	Max	Min		
Ad	1.72	2.58	33	0	Brand1	0.29
Others	0.05	0.22	1	0	Brand2	0.09
Price	0.21	0.10	0.61	0.05	Brand3	0.29
					Brand4	0.12
					Brand5	0.20
No. of observations	6,267					

Table 2: Correlation of Brand Share with Ad Exposure Share

	correlation	p-value
Brand1	0.01	0.84
Brand2	0.04	0.40
Brand3	-0.06	0.33
Brand4	0.01	0.83
Brand5	0.02	0.73

vertising affects consumers' awareness of new products and significantly increases product sales. Therefore, the magnitude of the effects of advertising new products is greater than that of advertising existing products. Without considering the effects of advertising, the estimated effects would be larger than usual. In our case, the brand's market share during the observation period remains almost stable. Hence, there is a lower possibility of confusing the effects of advertising of existing products with that of new products.

4.2 Testing Advertising Endogeneity

We tested whether potential endogeneity of advertising exists. If manufacturers target consumers subject to advertising, consumers are exposed to a particular manufacturer's brand and purchase that brand. This results in a correlation between brand share and brand advertising exposure share among consumers (Deng and Mela, 2018). We find no correlation in Table 2; hence, serious endogeneity of advertising does not occur in our dataset.

5 Result

In this section, we investigate consumers' responses to promotions in everyday favors/pick-ups situations using the aforementioned bottled tea data.

We estimated four consumer choice models to quantify the effects of advertising on consumer choice behavior. Model 1 has brand dummies, *Others*, *AdStock*, and *Price* as explanatory variables in Equation (1) and has a consumer heterogeneous carryover parameter, ρ_i, which is brand homogeneous. Model 2 has the same set of explanatory variables and a heterogeneous carryover parameter across consumers and brands: ρ_{ij}. Model 3 is the same as Model 2, except it includes two additional interaction terms: *AdStock* $\times$ *Others* and *Brand* $\times$ *Others*. Model 4 is the same as Model 3, except it has an additional interaction term, *Price* $\times$ *Others*. The estimation results of the interpersonal parameters are shown in Table 3.[8]

Among the four models, the estimates of the common parameters are nearly the same. The coefficients of the brand dummy variables (θ_α) suggest that consumers tend to prefer Brands 1 and 3 to Brand 5. The negative coefficient of *Price* (ξ_p) suggests that the price negatively affects consumer purchases. In addition, heterogeneity across brands and consumers plays an important role in explaining consumer responses to advertising, because Model 2 is superior to Model 1 regarding the deviance information criterion (DIC).

Our main interest is the effect of advertising on the choices made for others (everyday favors/pick-ups situations). The short-term effects of advertising are positive and significant, as captured by parameter θ_{β_1} in all four models. The interaction terms of *AdStock* and *Others* in Models 3 and 4 are nonsignificant. These results suggest that advertised brands are more likely to be chosen both for others and for consumers themselves immediately after or within a week of seeing the product advertisement. Hence, hypothesis 2 (**H2**) is supported.

Next, we compute the long-term effects of advertising on consumers' choices for both themselves and others by inserting estimates of the carry-over parameter ($\rho_{i,j}$) and the short-term effect of advertising (β_{i1}) into Equation (6) (Terui *et al.*, 2011). In this computation, $\rho_{i,j}$ in Model 2 is used because Model 2 shows the best performance regarding DIC (Table 3).

$$\text{Long-Term Effect of Advertising}_{\ i,j} = \frac{\beta_{i1}}{1-\rho_{i,j}} \tag{6}$$

The calculated consumers' long-term effects of advertising are heterogeneous across consumers and brands. Although the value of most consumers' long-term effects of advertising is between 0 and 1, some for Brands 1 and

[8]We evaluated the convergence status of parameters in Table 3 and Web appendix Table B.1by visually checking trace plots of MCMC samples and conducting Geweke's (1992) test.

Table 3: Posterior Mean (Posterior Standard Deviation)

	Model 1		Model 2		Model 3		Model 4	
θ_{α_1}	1.49	*	1.19	*	1.20	*	1.17	*
	(0.25)		(0.17)		(0.17)		(0.17)	
θ_{α_2}	-2.22	*	-2.62	*	-2.65	*	-2.64	*
	(0.41)		(0.37)		(0.37)		(0.39)	
θ_{α_3}	0.88	*	0.54	*	0.55	*	0.56	*
	(0.18)		(0.16)		(0.16)		(0.16)	
θ_{α_4}	-1.06	*	-1.53	*	-1.56	*	-1.53	*
	(0.25)		(0.24)		(0.25)		(0.24)	
θ_{β_1}	0.15	*	0.18	*	0.18	*	0.18	*
	(0.07)		(0.07)		(0.07)		(0.07)	
ξ_p	-6.28	*	-6.44	*	-6.48	*	-5.30	*
	(0.82)		(0.82)		(0.81)		(0.83)	
$\xi_{Ad\times o}$					-0.04		-0.07	
					(0.23)		(0.24)	
ξ_1					-0.24		0.57	
					(0.38)		(0.43)	
ξ_2					0.09		-0.63	
					(0.65)		(0.68)	
ξ_3					-0.04		-0.38	
					(0.39)		(0.51)	
ξ_4					0.23		-0.38	
					(0.48)		(0.51)	
$\xi_{p\times o}$							-23.03	*
							(3.83)	
DIC	8,802		5,383		6,184		6,139	

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

3 are close to 3. The long-term effects are 2.01 times larger than the short-term effects (β_{i1}) averaged separately for consumers and brands. Since the long-term effects of advertising are positive, hypothesis 3 (**H3**) is supported.

Our estimation results provide several insights into consumer purchase behaviors. The negative coefficient of the interaction term of *Others* and *Price* ($\xi_{p\times o}$) in Model 4 implies that consumers are 5.3 times more price-sensitive[9] when they choose for others than for themselves. The consumer high price sensitivity in choices for others suggests that consumers respond to sales promotions such as price cuts to reduce their decision-making costs

[9] $\frac{(-5.30-23.03)}{-5.30} \approx 5.3$

(Hoyer, 1984; Chandon *et al.*, 2000).

In addition, no significant difference exists between consumers' choices for others and themselves as indicated by the nonsignificant interaction terms of $Others$ and the brand dummy (ξ_j) in Model 3·4. Hence, consumers in everyday favors/pick-ups situations make choices for others based on their own preferences as they also do for themselves. This is not surprising, because consumers can infer their recipients' (others') preferences based on their own preferences (Epley *et al.*, 2004). Instead of selecting what they believe the recipient will desire, consumers focus on choosing items they expect the recipient will not reject (Liu *et al.*, 2019). Since purchase decision making for others is demanding,[10] consumers use a heuristic decision-making process in which they screen options based on criteria such as their own preferences (Giráldez-Cru *et al.*, 2023; Hoyer, 1984). Therefore, our results support hypothesis 1 (**H1**).

6 Robustness Checks

6.1 Robustness Check 1: Alternative Advertising Stock

We tested the robustness of the results in Section 5 by comparing them with those of the alternative models. In the alternative models, the *AdStock* variable in Equation (2) is replaced with *AdStock* in Equation (7), which is a geometric series of past exposure to advertising (Jedidi *et al.*, 1999).

$$AdStock_{ij,w} = \Sigma_{l=0}^{4} \lambda^l \log(1 + Ad_{ij,w-l}) \tag{7}$$

In Equation (7), we assume that the effects of advertising disappear within one month and set $\lambda = 0.5$.[11] This value is close to the estimates of $\rho_{i,j}$ in Section 5 and similar to those in previous studies (Miller *et al.*, 2021).

The estimates of the alternative models are nearly identical to those in Section 5. In Table 4, the estimate of θ_{β_1}, which captures the short-term effects of advertising, is significant and positive, suggesting that advertising positively affects consumer choices. Both the interaction terms—*Others* and *AdStock*, and *Others* and brand dummies—are nonsignificant; however, the interaction term of *Others* and *Price* is significant and negative (Table 4). Therefore, consumers who choose for others are not more likely to purchase advertised brands and choose the same brand as they do for themselves;

[10] Consumers feel tired in daily shopping trips due to that decision making (Ursu *et al.*, 2023; Polman and Vohs, 2016).

[11] We use weekly-level consumer panel data. When we set $\lambda = 0.5$, exposure to advertising one month ago is reduced by being multiplied by $\lambda^4 \risingdotseq 0.06$.

rather, they are more price-sensitive. The estimates from the alternative models suggest that the results in Section 5 are robust.

Table 4: Posterior Mean (Posterior Standard Deviation)

	Robustness check 1						Robustness check 2			
	Model 5		Model 6		Model 7		Model 8		Model 9	
θ_{α_1}	1.18	*	1.20	*	1.17	*	1.26	*	1.07	*
	(0.17)		(0.17)		(0.17)		(0.17)		(0.17)	
θ_{α_2}	-2.68	*	-2.68	*	-2.65	*	-2.81	*	-2.65	*
	(0.40)		(0.40)		(0.39)		(0.41)		(0.40)	
θ_{α_3}	0.52	*	0.53	*	0.55	*	0.59	*	0.67	
	(0.15)		(0.15)		(0.16)		(0.16)		(0.16)	
θ_{α_4}	-1.57	*	-1.60	*	-1.53	*	-1.74	*	-1.61	*
	(0.24)		(0.25)		(0.25)		(0.25)		(0.24)	
θ_{β_1}	0.16	*	0.16	*	0.16	*	0.18	*	0.18	*
	(0.07)		(0.07)		(0.07)		(0.08)		(0.07)	
ξ_p	-6.43	*	-6.47	*	-5.29	*	-6.46	*	-1.69	
	(0.80)		(0.83)		(0.84)		(0.83)		(0.92)	
$\xi_{Ad\times o}$			-0.05		-0.08		-4.08×10^{-3}		-3.60×10^{-3}	
			(0.22)		(0.24)		(0.13)		(0.14)	
ξ_1			-0.23		0.56		-0.39		0.43	
			(0.37)		(0.42)		(0.21)		(0.24)	
ξ_2			0.10		-0.60		0.56		0.01	
			(0.63)		(0.67)		(0.42)		(0.44)	
ξ_3			-0.03		-0.60		-0.28		-0.74	*
			(0.38)		(0.41)		(0.22)		(0.23)	
ξ_4			0.24		-0.40		0.88	*	0.33	
			(0.48)		(0.50)		(0.28)		(0.29)	
$\xi_{p\times o}$					-23.07	*			-22.42	*
					(3.69)				(2.11)	
DIC	6,197		6,203		6,160		6,162		6,052	

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

6.2 Robustness Check 2: Alternative Definition of Choice for Others

To further check the robustness of the results in Section 5, we conducted another robustness check. In Section 5, we used a strict definition of purchases for others ("this purchase of bottled tea is for others") that fails to cover a broad sense of choices for others such as household purchases (Liu *et al.*, 2019). In this subsection, we use the alternative definition[12] of choices for others and re-estimate the consumer choice models in Section 5.

By comparing the results in Table 4 and Web appendix Table C.1 with those in Table 3 and Web appendix Table B.1, we confirm that the strict definition does not affect the results in Section 5. The estimation results of the alternative models[13] do not differ from the results in Section 5 except ξ_p, ξ_3 and ξ_4 (see Table 4). Hence, advertising positively affects consumers' choices, not only for themselves but also for others. In addition, consumers who purchase for others tend to choose the same brand and are more price-sensitive than those who choose for themselves. Therefore, the main results in Section 5 are robust.

7 Discussion and Conclusion

Decision making for others, while complex and cognitively demanding due to the need to infer recipients' preferences, is a frequent activity in daily life (Polman, 2012; Liu *et al.*, 2019; Delre *et al.*, 2016). Therefore, understanding the effects of advertising on decision making for others and placing more effective advertisements that reduce the costs involved in decision making for others will make the process easier and encourage purchasing. However, few studies have investigated the long-term effects of advertising on choosing for others using real-world data, especially the long-term effects of advertising (Delre *et al.*, 2016), due to the limited availability of data regarding for whom the items were purchased. Using consumer purchase data that contain information about "for whom" items were purchased and advertising exposure log data, we estimated consumer choice models to confirm the positive short-term and long-term effects of advertising on choices for others in everyday favors/pick-ups situations.

Using various models with different advertising stocks, we confirm that long-term advertising affects everyday favors/pick-ups situations, as does short-term advertising. Consistent with previous reports suggesting the positive long-term effects of advertising on choosing for oneself (Danaher *et al.*, 2020; Jedidi *et al.*, 1999), we show that long-term advertising is twice as effective as short-term advertising on choosing for others. Furthermore, we reveal that consumers are more susceptible to sales promotions (e.g., price cuts) in everyday favors/pick-ups situations than when choosing for them-

[12] In Subsection 4.1, we define "this purchase of bottled tea is for others or themselves" as an alternative definition of choices for others.

[13] To pass Geweke's (1992) test, we ran 81,000 MCMC loops and sample parameters every fifth loop. We discarded the first 200 samples as the burn-in period.

selves. Considering that making choices for others is a complicated and more demanding process than making choices for oneself (Liu and Min, 2020), it is unsurprising that consumers are more strongly affected by sales promotions when making choices for others than for themselves (Hoyer, 1984; Chandon *et al.*, 2000).

7.1 Theoretical Implications

Our research contributes to several research fields. First, we contribute to the literature on advertising. We complement previous research by investigating the effects of advertising on choosing for others. Building on previous research that elaborately models consumer response to advertising and choice behaviors (Zenetti and Klapper, 2016; Terui *et al.*, 2011), we add consumer purchase purpose—"for whom consumers purchase products"—to consumer choice models. To the best of our knowledge, the effectiveness of TV advertising for choices made for others is quantified in our research for the first time.

Second, we contribute to studies on consumers' choices for others, revealing no significant differences between choices for consumers and their close recipients. Some studies find that choices for close people, such as family members or friends, are similar to those for consumers themselves. For example, consumers are likely to choose the same things for close people that they would choose for themselves (Polman, 2012) or their choices for close people are as creative as for themselves (Polman and Emich, 2011). Along with these prior experimental studies, we find similarities of choices for close others and themselves in real-world consumer purchase data that record daily consumer behaviors.

7.2 Managerial Implications

Our findings provide sales managers with two managerial implications. First, our findings on the short- and long-term sales impact of advertising highlight the critical importance of sustained investments in advertising strategies. As shown in prior studies (Terui *et al.*, 2011), advertising induces consumer brand choices. In addition, we found positive effects of advertising on consumer choices not only for oneself but also for others. Hence, sales managers can increase their products' shares in everyday favors/pick-ups, which is one of the major purchase occasions, by advertising their products.

Second, we recommend that retailers leverage in-store promotions, such as strategic product displays or discount announcements, to drive purchases for others. Because promotions such as in-store displays reduce the costs involved in decision making (Hoyer, 1984; Van Nierop *et al.*, 2010; Chandon *et al.*, 2000), customers making choices for others are susceptible to sales promotions. Our research found strong consumer reactions to price cuts while choosing for their recipients. Therefore, in-store promotion is effective in making choices for others easier, which leads to an increase in sales.

7.3 Future Studies and Limitations

Future research could explore consumer purchasing behaviors in varied contexts such as caregiving or gift-giving scenarios. Researchers could use consumer purchase and advertising data on products other than consumer packaged goods. Consumer behaviors in these situations may differ from everyday favors/pick-ups situations regarding consumers' tendencies to infer their recipients' preferences or advertising effectiveness.

Our study has several limitations. First, it lacks detailed data on advertisement content, limiting our ability to assess how specific messaging elements influence consumer decisions. Thus, whether our advertising content caused the additional positive effects of advertisements cannot be investigated (Cao *et al.*, 2025), although some advertising content is expected to strongly encourage purchases made for others. For example, promotional videos with scenes in which characters purchase goods for their family members encourage consumers to purchase goods for others, as suggested by research on product placement (Goli *et al.*, 2022). Second, due to limitations in data collection, we only considered price and advertising as factors that affect consumer choices. Future research could incorporate additional factors, such as in-store displays or product features, to better understand their roles in reducing decision-making costs for consumers choosing for others (Andrews and Srinivasan, 1995; Chandon *et al.*, 2000). Hence, various types of sales-promotion data can enable researchers to investigate how consumers who choose for others respond to sales promotions. In addition, the data make it possible to estimate consumer choice models that explicitly have a screening process (Andrews and Srinivasan, 1995; Fader and McAlister, 1990; Mehta *et al.*, 2003). Despite these limitations, our research is the first to demonstrate the short- and long-term effects of advertising on choices for others and provides new insights into the relationship between advertising and choices for others.

Statements and Declarations

Competing Interests

The authors declare no competing interests.

Web appendix

A MCMC Estimation Algorithm

Our models in Section 5 are hierarchical multinomial logit models. Hence, all parameters except γ were sampled by standard MCMC estimation procedure. We define $\mathbf{A}_i = (\alpha_{i1}, \alpha_{i2}, \alpha_{i3}, \alpha_{i4}, \beta_{i1})'$. The M-H algorithm for parameters $\mathbf{A}_i$ and ξ is available in Rossi *et al.* (2005). The posterior distributions of $\Theta, V_\Theta, \theta_\gamma, \sigma_\gamma$ are available in 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 (1), respectively.

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

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

$$L_i = \Pi_{t=1}^{T_i} p(r_{it} = y_{it}) \tag{A.2}$$

where T_i denotes consumer i's final purchase. Using this likelihood function and prior distributions, we ran the M-H algorithm and Gibbs sampling.

We generate draws of parameters $\beta_{ij}, \xi_j, \gamma_{i,j}$ from the posterior conditional distributions by running the random-walk Metropolis-Hastings (M-H) algorithm. We generate draws for parameters $\Theta, V_\Theta, \theta_\gamma, \sigma_\gamma$ from the posterior by running Gibbs sampling.

A.1 The conditional posterior of $\mathbf{A}_i$

The prior distribution is expressed as

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

The posterior distribution is expressed as follows:

$$p(\mathbf{A}_i|X_i, \xi, \Theta, V_\Theta) \propto p(\mathbf{A}_i)L_i$$

where X_i denotes the explanatory variables for consumer i.

A.2 The conditional posterior of Θ

The prior distribution is expressed as

$$\mathrm{vec}(\Theta)|V_\Theta \sim N_K\left(\mathrm{vec}(\Theta_0), V_\Theta \otimes A_\Theta^{-1}\right) \quad \textit{where}\ \mathrm{vec}(\Theta_0) = \mathbf{0}, A_\Theta = 0.01$$

K denotes the dimension of vec(Θ). H denotes the number of consumers and ι is $H \times 1$ vector. The posterior distribution is expressed as follows:

$$\mathrm{vec}(\Theta)|\{\mathbf{A}_i\}, V_\Theta \sim N_K\left(\mathrm{vec}\left(\left(A_\Theta + \iota\iota'\right)^{-1}\left(A_\Theta\Theta_0 + \iota'\mathbf{A}_i\right)\right), V_\Theta \otimes \left(A_\Theta + \iota\iota'\right)^{-1}\right)$$

A.3 The conditional posterior distribution of V_Θ

The prior distribution is

$$V_\Theta \sim IW(s_0, V_{\Theta_0}) \quad \textit{where}\ s_0 = 11, V_{\Theta_0} = s_0 \times I$$

I denotes an identity matrix with a size equal to the corresponding parameter.

The posterior distribution is

$$V_\Theta|\{\mathbf{A}_i\}, \Theta \sim IW(s_0 + H, V_{\Theta_0} + S), \quad \textit{where}\ S = \Sigma_{i=1}^H(\mathbf{A}_i - \Theta)(\mathbf{A}_i - \Theta)'$$

A.4 The conditional posterior of ξ

The prior distribution is expressed as

$$p(\xi) \sim N_{K^*}\left(\xi_0, V_\xi\right) \quad \textit{where}\ \xi_0 = \mathbf{0}, V_\xi = 100 \times I$$

The posterior distribution is expressed as follows:

$$p(\xi|\{X_i\}, \{\mathbf{A}_i\}) \propto p(\xi)\Pi_{i=1}^H L_i$$

A.5 The conditional posterior of θ_{γ_j}

The prior distribution is expressed as

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

The posterior distribution is expressed as follows:

$$\theta_{\gamma_j}|\{\gamma_{i,j}\}, \sigma_{\gamma_j} \sim N\left(\left(A_{\theta_\gamma} + \iota\iota'\right)^{-1}\left(A_{\theta_\gamma}\theta_0 + \iota'\gamma_{i,j}\right), \sigma_{\gamma_j}\left(A_{\theta_\gamma} + \iota\iota'\right)^{-1}\right)$$

A.6 The conditional posterior distribution of σ_{γ_j}

The prior distribution is

$$\sigma_{\gamma_j} \sim IG(q_0/2, S_\sigma/2) \quad where\ q_0/2 = 6, S_\sigma/2 = 1$$

The posterior distribution is

$$\sigma_{\gamma_j}|\{\gamma_{i,j}\}, \theta_{\gamma_j} \sim IG((q_0 + H)/2, (S_\sigma + S')/2), \quad where\ S' = \Sigma_{i=1}^{H}(\gamma_{i,j} - \theta_\gamma)(\gamma_{i,j} - \theta_\gamma)'$$

A.7 M-H algorithm for $\rho_{i,j}$

Now, we explain the M-H algorithm for $\rho_{i,j}$. Let $\gamma_{i,j}^{(l-1)}$ denote the lth MCMC loop sample of γ.

In the lth MCMC loop, $\gamma_{i,j}^{*}$ is the sampled draw, as in Equation (A.3) (Terui *et al.*, 2011).

$$\gamma_{i,j}^{*} = \gamma_{i,j}^{(l-1)} + w_{i,j},\ w_{i,j} \sim N(0, 0.01) \tag{A.3}$$

Let $J_{\rho_{i,j}^{(l)} \to \gamma_{i,j}^{(l)}}$ be the Jacobian of transformation. The acceptance probability, *a.p.*, is:

$$a.p. = \min\left[\frac{\pi(\gamma_{i,j}^{*}|\theta_\gamma, \sigma_\gamma, A_i, X_i)}{\pi(\gamma_{i,j}^{(l-1)}|\theta_\gamma, \sigma_\gamma, A_i, X_i)}, 1\right] \tag{A.4}$$

$$where\ \pi(\gamma_{i,j}^{(l)}|\theta_\gamma, \sigma_\gamma, X_i) \propto N(\theta_\gamma, \sigma_\gamma) L_i \left| J_{\rho_{i,j}^{(l)} \to \gamma_{i,j}^{(l)}} \right|$$

We derive lth $\rho_{i,j}$ as

$$\rho_{i,j}^{(l)} = \frac{\exp(\gamma_{i,j}^{(l)})}{1 + \exp(\gamma_{i,j}^{(l)})} \tag{A.5}$$

B Results of Section 5

We report the remaining results of the parameter estimated in Section 5.

Table B.1 Posterior Mean (Posterior Standard Deviation)

	Model 1		Model 2		Model 3		Model 4	
$\sigma_{\alpha_1\alpha_1}$	4.76	*	3.35	*	3.36	*	3.39	*
	(0.76)		(0.54)		(0.54)		(0.55)	
$\sigma_{\alpha_1\alpha_2}$	3.69	*	2.00	*	2.00	*	2.10	*
	(1.03)		(0.70)		(0.72)		(0.75)	
$\sigma_{\alpha_1\alpha_3}$	2.32	*	0.67	*	0.68	*	0.68	*
	(0.56)		(0.30)		(0.30)		(0.30)	
$\sigma_{\alpha_1\alpha_4}$	2.60	*	0.62		0.63		0.63	
	(0.70)		(0.37)		(0.37)		(0.38)	
$\sigma_{\alpha_1\beta_1}$	-0.06		-0.01		-0.01		-0.01	
	(0.17)		(0.10)		(0.10)		(0.10)	
$\sigma_{\alpha_2\alpha_2}$	10.00	*	8.35	*	8.39	*	8.50	*
	(2.04)		(1.81)		(1.78)		(1.91)	
$\sigma_{\alpha_2\alpha_3}$	2.79	*	0.67		0.65		0.66	
	(0.86)		(0.47)		(0.47)		(0.48)	
$\sigma_{\alpha_2\alpha_4}$	3.55	*	0.76		0.74		0.75	
	(1.18)		(0.58)		(0.59)		(0.58)	
$\sigma_{\alpha_2\beta_1}$	0.06		0.01		0.01		0.01	
	(0.25)		(0.17)		(0.16)		(0.16)	
$\sigma_{\alpha_3\alpha_3}$	3.43	*	2.58	*	2.58	*	2.60	*
	(0.60)		(0.43)		(0.43)		(0.44)	
$\sigma_{\alpha_3\alpha_4}$	1.86	*	0.87	*	0.90	*	0.88	*
	(0.63)		(0.45)		(0.44)		(0.45)	
$\sigma_{\alpha_3\beta_1}$	0.09		0.14		0.14		0.13	
	(0.14)		(0.13)		(0.13)		(0.13)	
$\sigma_{\alpha_4\alpha_4}$	4.70	*	3.94	*	3.98	*	3.97	*
	(1.01)		(0.87)		(0.88)		(0.88)	
$\sigma_{\alpha_4\beta_1}$	0.01		0.02		0.02		0.01	
	(0.17)		(0.16)		(0.16)		(0.16)	
$\sigma_{\beta_1\beta_1}$	0.29	*	0.31	*	0.31	*	0.31	*
	(0.05)		(0.06)		(0.06)		(0.06)	
θ_γ	0.04							
	(0.11)							

Table B.1 (continued) Posterior Mean (Posterior Standard Deviation)

	Model 1	Model 2	Model 3	Model 4
θ_{γ_1}		0.05	0.04	0.04
		(0.11)	(0.11)	(0.11)
θ_{γ_2}		0.00	-0.00	0.01
		(0.11)	(0.11)	(0.11)
θ_{γ_3}		-0.03	-0.02	-0.02
		(0.11)	(0.11)	(0.10)
θ_{γ_4}		0.01	0.01	0.01
		(0.11)	(0.11)	(0.11)
θ_{γ_5}		0.04	0.04	0.05
		(0.11)	(0.11)	(0.11)
σ_{γ}	0.14 *			
	(0.04)			
σ_{γ_1}		0.15	0.15	0.15 *
		(0.05)	(0.05)	(0.05)
σ_{γ_2}		0.13	0.13	0.13
		(0.04)	(0.04)	(0.03)
σ_{γ_3}		0.13	0.13	0.13 *
		(0.04)	(0.04)	(0.04)
σ_{γ_4}		0.13	0.13	0.13
		(0.04)	(0.04)	(0.04)
σ_{γ_5}		0.15	0.15	0.16 *
		(0.05)	(0.05)	(0.05)

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

C Results of Section 6

We report the remaining results of the parameter estimated in Section 6.

Table C.1 Posterior Mean (Posterior Standard Deviation)

	Robustness check 1						Robustness check 2			
	Model 5		Model 6		Model 7		Model 8		Model 9	
$\sigma_{\alpha_1\alpha_1}$	3.45	*	3.49	*	3.53	*	3.36	*	3.31	*
	(0.54)		(0.54)		(0.55)		(0.54)		(0.54)	
$\sigma_{\alpha_1\alpha_2}$	2.13	*	2.14	*	2.22	*	1.99	*	2.08	*
	(0.75)		(0.72)		(0.77)		(0.73)		(0.74)	
$\sigma_{\alpha_1\alpha_3}$	0.72	*	0.74	*	0.76	*	0.68	*	0.67	*
	(0.30)		(0.30)		(0.31)		(0.30)		(0.30)	
$\sigma_{\alpha_1\alpha_4}$	0.68		0.70		0.72	*	0.59		0.55	
	(0.38)		(0.39)		(0.39)		(0.36)		(0.39)	
$\sigma_{\alpha_1\beta_1}$	-0.01		-0.01		-0.01		-0.01		-0.01	
	(0.10)		(0.10)		(0.10)		(0.10)		(0.10)	
$\sigma_{\alpha_2\alpha_2}$	8.66	*	8.64	*	8.63	*	8.54	*	8.11	*
	(2.01)		(1.98)		(1.89)		(1.87)		(1.86)	
$\sigma_{\alpha_2\alpha_3}$	0.7		0.72		0.74		0.65		0.65	
	(0.48)		(0.47)		(0.48)		(0.47)		(0.48)	
$\sigma_{\alpha_2\alpha_4}$	0.81		0.80		0.84		0.71		0.68	
	(0.60)		(0.61)		(0.62)		(0.57)		(0.55)	
$\sigma_{\alpha_2\beta_1}$	0.00		0.00		0.00		0.01		0.00	
	(0.16)		(0.15)		(0.16)		(0.16)		(0.16)	
$\sigma_{\alpha_3\alpha_3}$	2.61	*	2.62	*	2.65	*	2.59	*	2.64	*
	(0.43)		(0.44)		(0.44)		(0.43)		(0.44)	
$\sigma_{\alpha_3\alpha_4}$	0.94	*	0.96	*	0.97	*	0.84	*	0.78	*
	(0.45)		(0.46)		(0.45)		(0.43)		(0.43)	
$\sigma_{\alpha_3\beta_1}$	0.10		0.10		0.09		0.15		0.14	
	(0.12)		(0.12)		(0.13)		(0.13)		(0.13)	
$\sigma_{\alpha_4\alpha_4}$	4.14	*	4.20	*	4.10	*	3.71	*	3.53	*
	(0.89)		(0.93)		(0.90)		(0.86)		(0.77)	
$\sigma_{\alpha_4\beta_1}$	0.01		0.02		0.00		0.02		0.01	
	(0.15)		(0.16)		(0.15)		(0.16)		(0.15)	
$\sigma_{\beta_1\beta_1}$	0.29	*	0.29	*	0.29	*	0.32	*	0.32	*
	(0.06)		(0.06)		(0.06)		(0.06)		(0.06)	

Table C.1 (continued) Posterior Mean (Posterior Standard Deviation)

	Robustness check 1			Robustness check 2		
	Model 5	Model 6	Model 7	Model 8	Model 9	
θ_{γ_1}				0.05	0.04	
				(0.11)	(0.11)	
θ_{γ_2}				0.00	0.01	
				(0.10)	(0.11)	
θ_{γ_3}				-0.01	-0.01	
				(0.11)	(0.11)	
θ_{γ_4}				0.01	0.01	
				(0.11)	(0.11)	
θ_{γ_5}				0.04	0.04	
				(0.11)	(0.11)	
σ_{γ_1}				0.15	0.15	*
				(0.04)	(0.05)	
σ_{γ_2}				0.13	0.13	
				(0.04)	(0.04)	
σ_{γ_3}				0.13	0.13	*
				(0.04)	(0.04)	
σ_{γ_4}				0.13	0.13	
				(0.04)	(0.04)	
σ_{γ_5}				0.15	0.16	*
				(0.05)	(0.05)	

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

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