A Salesforce-Driven Model of Consumer Choice

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Abstract

This paper studies how salespeople affect the choices of which product consumers choose, and from that, how a firm should set optimal commissions as a function of the appeal, substitutability and profit margins of different products. We also examine whether firms are better off promoting products through sales incentives or price discounts. To achieve these goals, we develop a salesforce-driven consumer choice model to study how performance-based commissions incentivize a salesperson's service effort toward heterogeneous, substitutable products carried by a firm. The model treats the selling process as a joint decision by the salesperson and the consumer. It allows the salesperson's efforts to vary across different transactions depending on the unique preferences of each consumer, and incorporates the effects of commissions and other marketing mix on the selling outcome in a unified framework. We estimate the model using data from a car dealership. We find that the optimal commissions should be lower for popular items and for items that are closer substitutes with other products. We also find that for the car industry we study, the cost of selling more cars using sales incentives is cheaper than the cost of selling the same number of cars using price discounts.

Keywords: Salesforce management, Incentives, Consumer choice, Differentiated products

1. Introduction

A firm's salesforce is an important marketing tool for both B2C and B2B environments (Kotler and Keller 2008). Data from the Bureau of Labor Statistics show that in 2012 about 14 million people—more than 10% of the workforce—were employed in sales-related occupations. The amount that firms spend on their salesforce is three times as high as spending on advertising (Zoltners et al. 2008). These statistics suggest salespeople's effort can have a significant influence on demand; otherwise, firms would not invest as much in their salesforce.

The traditional consumer-choice literature typically assumes consumers make purchase decisions on their own, with a focus on how a firm's marketing mix (e.g. price promotion) influences their decisions. In reality, consumers may not have complete market information, and the effort from salespeople (e.g., product persuasion, recommendation, and demonstration) can shift consumers' product preferences and thus increase sales. We observe this impact from the sales-management literature, which measures how performance-based commissions help increase sales. The research focus in many of these studies is on designing the optimal compensation structure that solves the classic principal-agent problem. The impact of commissions on consumers' product choices, however, has not been investigated.

This paper studies how, in a market of differentiated products, commissions influence not only the total sales but also *which* products consumers choose. The commissions set for selling various products can incentivize salespeople to allocate different levels of efforts across products and, together with other marketing mix elements that directly influence the consumer preferences, impact the product consumers choose. To understand this deeper, we develop a model that simultaneously incorporates the decisions of salespeople and consumers. The selling process is structurally modeled as a joint decision that involves two sides: although the consumer makes the final product choice, the salesperson's decision of how much service effort to invest in each product influences the consumer's choice. This *salesforce-driven consumer-choice* model enables us to infer the effects of commissions and other marketing mix elements on demand. We empirically estimate this model from a dataset provided by a car dealership in Japan, and use the results to investigate how commissions should be set differently across the dealer's multiple products. We then study the effectiveness of increasing commissions as a "push" strategy, versus discounting prices as a "pull" strategy, to increase the sales of a product. The findings are important for firms that sell diverse substitutable products.

Our study bridges the consumer-choice literature and the sales-management literature by studying decisions on both sides. The majority of the sales-management literature has focused on the salesforce productivity, and the design of the compensation structure based on aggregate sales (see Mantrala et al. 2010 for a thorough overview). From a theoretical analysis, Basu et al. (1986) and Rao (1990) show that a combination of salary plus nonlinear commission with respect to sales is optimal using a common principal-agent framework that links a salesperson's effort to total sales. Empirically, Misra and Nair (2011) estimate a dynamic principal-agent model to estimate the effectiveness of commissions that are combined with quotas and ceilings. They find that the presence of ceilings on commissions demotivates effort. Chung et al. (2014) study a compensation scheme with quotas and bonuses using a dynamic structural model as well, but include latent-class heterogeneity and estimate the discount factors. Daljord et al. (2016) examine the implication of a uniform compensation policy on a firm with a heterogeneous salesforce team, and suggest that while the homogenous plan leads to a much lower profit relative to a fully heterogeneous plan, the ability to choose salespeople mitigates the loss. A key missing component in all of these papers is consumers, as they only look at the link between compensation and aggregate sales. Kim (2014) incorporates consumers, but focuses on the impact of sales representatives on a single product (i.e., car radiator). Our paper extends this literature by noting the fact that there are multiple differentiated products that can receive effort, and estimating how consumers ultimately make the choice of which product to buy in the presence of the effort.

A stream of theoretical research has examined the incentives of salespeople when selling multiple products. Farley (1964) assumes that a salesperson has a fixed amount of time to allocate to selling and decides how much time to devote to each product to maximize their earnings. Sales of each product depends on the time the salesperson allocates to that product. Farley concludes that the salesperson's incentives align with the firm's incentives when commissions are set as an equal percentage of the gross margins across all products. Weinberg (1975) extends this result to the case in which a salesperson also controls prices. Srinivasan (1981) notes that the equal commission policy is generally not optimal when a salesperson chooses the amount of selling time to devote to multiple products based on both the commission they get and the disutility of working, and he recommends setting commission rates higher for products with larger elasticities with respect to the service time. Basu et. al. (1985) note that because these results rely on the assumption of a deterministic relationship between sales and salesforce effort, a firm could instead more efficiently impose requirements on final sales to maximize its profits. Lal and Srinivasan (1993) extend Farley (1964) by modeling a stochastic selling process. They show that commissions should be set higher for products with higher sales-effort responsiveness, lower marginal costs, and lower uncertainty in the selling process. However, this literature still ignores the role of consumers in the transaction outcomes.

In contrast to all of the studies above, we model the selling process as a joint decision by a salesperson and a consumer. While the salesperson decides how much service effort to invest toward each product, the consumer makes the final purchase decisions. The service effort is valuable to consumers and helps match their heterogeneous needs with differentiated products. As such, the likelihood of selling a product is influenced by not only the salesperson's productivity and commissions but also the consumer's product preferences. Our model thus allows the salesperson's efforts to vary across different consumers depending on the unique product preferences of each consumer. In that sense, our model has some similarity to Copeland and Monnet (2003), who allow for a discrete level of high or low effort for each transaction. Furthermore, in a unified framework our model incorporates the effect of commissions that motivate salespeople's effort and other marketing mix variables (e.g. price) that have a direct effect on consumers. It helps us compare the tradeoff between increasing the commission and offering a discounted price for a product. In that sense, our paper also contributes to the consumer choice literature by studying how salesforce effort – in addition to other marketing mix variables – affects purchase decisions. In fact, we show that ignoring the role of salespeople in a choice model can create an omitted-variable problem and bias the estimation of consumers' price sensitivity.

The estimation results show that not only do consumers have heterogeneous product preferences but also salespeople have heterogeneous sensitivity toward commissions. Based on the results, we use counterfactuals to illustrate how product-specific commissions should be set differently based on how attractive the product is for consumers, how substitutable the product is with other products, and the profit margin for the dealer. We also compare the effectiveness of using price promotions and commission incentives to increase sales. We show that when the commission sensitivity among salespeople (relative to the price sensitivity among consumers) is high, increasing commissions is likely to be more profitable for the dealer. When the commission sensitivity is at a moderate level, however, jointly discounting prices and increasing commissions will be more profitable than using either discounted prices or increased commissions alone.

The rest of the paper is organized as follows: we first develop the model in section 2. Model estimation and identification are also discussed in the section. Section 3 presents the results from the empirical application. Finally, we conclude in section 4.

2. A Salesforce-Driven Model of Consumer Choice

To study how the service effort from salespeople influences the consumer purchase decision, we develop a model that incorporates the decisions of both the customer and the salesperson. The model assumes a single firm sells J differentiated products. For a salesperson s, let $C(s)$ be the collection of all consumers who have been served by the salesperson. We assume that the matching of the salesperson and the consumer is random so there is no selection issue.[1]

In period t, a unique consumer $i \in C(s)$ visits the store. The consumer purchases at most one unit of one product, and makes the purchase decision that maximizes her indirect utility. The salesperson chooses which product he will recommend, and also how much service effort to invest in the recommended product, to maximize his indirect utility that is a function of the commission of any product that is sold minus the cost of his selling effort. The consumer has an initial preference for each product, but the salesperson can demonstrate the benefits of the recommended product to increase the consumer's purchase utility. To make the selling efficient, before deciding which product to recommend the salesperson talks to the consumer and obtains perfect knowledge about the consumer's preferences. After the salesperson exerts effort, the consumer makes the final decision of which product she will buy, or walk away without purchase. Because the salesperson's

[1] We discuss this in more detail in Section 3.2.

service effort directly impacts the consumer's decision, we call this model the salesforce-driven consumer-choice model, in contrast to traditional choice models that ignore the influence of salespeople.

2.1 Consumer Utility and Purchase Choice

Assuming the salesperson exerts service effort e_{sijt} on product j. The consumer's indirect utility is specified as

$$U_{isjt} = X_{jt}\beta_i + \gamma_i p_{jt} + e_{sijt} + \varepsilon_{ijt} \qquad (1)^2$$

where X_{jt} is a matrix of product characteristics and other factors that influence the demand, p_{jt} the price of the product at time t. Random coefficients β_i and γ_i represent the individual-specific product preferences and price sensitivity, of which the distributions are F_β and F_γ, respectively. The utility of the no-purchase outside option is normalized as $U_{is0t} = \varepsilon_{i0t}$. The stochastic component ε_{ijt} represents the individual heterogeneous product preference, with a joint distribution $\boldsymbol{\varepsilon_{it}} \equiv (\varepsilon_{i0t}, \dots, \varepsilon_{iJt})' \sim F_{\boldsymbol{\varepsilon}}$. For simplicity, we assume that $\boldsymbol{\varepsilon_{it}}$ are i.i.d. across individuals; however, within-individual product preferences are correlated in $F_{\boldsymbol{\varepsilon}}$. We assume that the service effort e_{sijt} that directly shifts the purchase utility is non-negative.[3] We also assume that it does not influence the utility for other products $U_{isj't}$ for $j' \neq j$.[4] If no service effort is invested in a product, $e_{sijt} = 0$ for that product.

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[2] Each consumer only appears once in our data, so *i* also defines the time period *t*. Time period appears in the subscript since prices and commissions vary over time.

[3] Since e_{sijt} is not observed from data, we normalize the marginal utility of the service effort for the consumer to one. Therefore, one unit of the effort is equivalent to increase the consumer utility by the monetary value of \$1/-γ_i.

[4] One can treat e_{sijt} as services that focus on the product, such as trial use, persuasion, and explaining in detail and demonstrating product functions.

Let y_{sijt} be an indicator function that equals 1 if the consumer chooses to purchase product j, and 0 otherwise. Conditional on the salesperson's service efforts, $e_{si1t}, \dots, e_{siJt}$, for the products sold by the firm, the likelihood that the consumer will purchase product j is

$$Pr(y_{sijt} = 1) = \int_{\boldsymbol{\varepsilon}} \int_{\beta} \int_{\gamma} 1\left\{X_{jt}\beta_i + \gamma_i p_{jt} + e_{sijt} + \varepsilon_{ijt} = max\left\{max\left\{X_{j't}\beta_i + \gamma_i\, p_{j't} + e_{sij't} + \varepsilon_{isj't},\ j' = 1, \dots, J\right\}, \varepsilon_{i0t}\right\}\right\} dF_{\gamma} dF_{\beta} dF_{\epsilon} \tag{2}$$

where $1\{\cdot\}$ is an indicator function that equals 1 if the logical expression inside the bracket is true, and 0 otherwise.

Without service efforts in the utility function, equation (2) is the same as a standard random coefficients discrete choice model, of which consumers are assumed to make own purchase decisions. In our model, however, e_{sijt} is the salesperson's endogenous decision that depends on the commissions of selling various products and the consumer type that is captured by $\left(\beta_i, \gamma_{i,} \boldsymbol{\varepsilon_{it}}\right)$. Furthermore, service efforts are unobserved in data, as such they have to be integrated out when evaluating the likelihood function.

2.2 Salesperson Utility and the Choice of Service Efforts

To evaluate the product choice likelihood in equation (2), we need to model the salesperson's choice of service efforts. We assume that the salesperson's decisions are based on maximizing his transaction utility, which comes from the commission he obtains from the transaction and the effort he exerts. Suppose the salesperson exerts efforts $e_{si1t}, \dots, e_{siJt}$, and the consumer purchases product j. The salesperson's indirect utility is specified as

$$V_{sijt}(e_{si1t}, \dots, e_{siJt}) = \alpha_s \cdot comm_{jt} + \omega_{sijt} - \left(\sum_{k=1}^{J} e_{sikt}\right)^2 \tag{3}$$

where $comm_{jt}$ is the commission that the salesperson obtains from selling product j, and the coefficient α_s represents the salesperson's sensitivity for commissions. We allow α_s to be heterogeneous across salespeople with a distribution F_α. This coefficient captures the salesperson's marginal utility for commissions relative to the marginal cost of exerting one unit of service effort.[5] A less capable salesperson, for example, will be represented by a smaller α_s, implying that given equal commissions he will sell less than his peers who have a larger α_s. Likewise, a salesperson who is less motivated by commissions will also sell less and thus also have a smaller α_s.

In a reduced-form way, the stochastic component ω_{sijt} captures the unobserved factors that may influence the salesperson's choice. As examples, a salesperson in a car dealership may be affected by his manager's nudge for selling certain car models, and the salesperson may not be able to let his customer test-drive a car because other customers are doing it. The change of ω_{sijt} will affect the decision of which product the salesperson will recommend, as we will discuss below.

If the consumer walks away without making a purchase, the salesperson does not receive any commission and his utility will be $V_{si0t}(e_{si1t}, \dots, e_{siJt}) = \omega_{si0t} - \left(\sum_{k=1}^{J} e_{sikt}\right)^2$. We assume that the joint distribution function of $(\omega_{si1t}, \dots, \omega_{siJt}, \omega_{si0t})$ is $F_{\boldsymbol{\omega}}$.

To solve the optimal service efforts that will maximize the salesperson's utility in equation (3), recall that the salesperson is able to correctly identify the customer's utility function from their dialog with the customer. The following two propositions are useful to help reduce the computational burden:

[5] A general utility function is $V_{sijt}(e_{si1t}, \dots, e_{siJt}) = \tilde{\alpha}_s \cdot comm_{jt} + \omega_{sijt} - \tilde{\rho}_s \cdot \left(\sum_{k=1}^{J} e_{sikt}\right)^2$, where $\tilde{\alpha}_s$ represents the salesperson's marginal utility for commissions, and $\tilde{\rho}_s$ the marginal (dis)utility for service efforts. Since service efforts are unobservable, for model identification we normalize the coefficient for service efforts to one, and the coefficient α_s in equation (3) should be treated as the ratio of $\tilde{\alpha}_s / \tilde{\rho}_s$.

Proposition 1: *When dealing with a consumer of type* $(\beta_i, \gamma_{i,} \boldsymbol{\varepsilon_{it}})$, *the vector of the optimal service efforts* $(e^*_{si1t}, \dots, e^*_{siJt})$ *has at most one positive entry, and the rest are all zero. That is, the salesperson will invest his service effort on one product at most.*

The proof is straightforward. Suppose the salesperson puts in positive service efforts for two products. Since the consumer will choose only one product, one of the service efforts is wasted and thus it reduces the salesperson's utility. The salesperson therefore should only focus on the product that the consumer will choose.[6]

Proposition 2: *When dealing with a consumer of type* $(\beta_i, \gamma_{i,} \boldsymbol{\varepsilon_{it}})$, *suppose the salesperson recommends product j. The optimal service effort* e^*_{sijt} *he will invest is*

$$e^*_{sijt} = max\{X_{1t}\beta_i + \gamma_i p_{1t} + \varepsilon_{i1t}, \dots, X_{Jt}\beta_i + \gamma_i p_{Jt} + \varepsilon_{iJt}, \varepsilon_{is0t}\} - (X_{jt}\beta_i + \gamma_i p_{jt} + \varepsilon_{ijt})$$

This proof is also straightforward. Suppose $X_{jt}\beta_i + \gamma_i p_{jt} + \varepsilon_{ijt}$ is equal to $max\{X_{1t}\beta_i + \gamma_i p_{1t} + \varepsilon_{i1t}, \dots, X_{Jt}\beta_i + \gamma_i p_{Jt} + \varepsilon_{iJt}, \varepsilon_{i0t}\}$, i.e., product *j* is the preferred choice without any service. The salesperson does not need to put in any effort for *j* and it will still be purchased. If $X_{jt}\beta_i + \gamma_i p_{jt} + \varepsilon_{ijt}$ is less than $max\{X_{1t}\beta_i + \gamma_i p_{1t} + \varepsilon_{i1t}, \dots, X_{Jt}\beta_i + \gamma_i p_{Jt} + \varepsilon_{iJt}, \varepsilon_{i0t}\}$, the effort $e_{sijt} = max\{X_{1t}\beta_i + \gamma_i p_{1t} + \varepsilon_{i1t}, \dots, X_{Jt}\beta_i + \gamma_i p_{Jt} + \varepsilon_{iJt}, \varepsilon_{i0t}\} - (X_{jt}\beta_i + \gamma_i p_{jt} + \varepsilon_{ijt})$ will increase the utility to the level that the customer will purchase product *j*, but expend no additional effort that would lead to further disutility in the salesperson's utility function.

[6] If the salesperson has uncertainty about consumer preferences, he may put in service efforts for multiple products. The perfect knowledge assumption helps simplify the computation of the optimal service effort in the model. As the identification of the salesperson uncertainty is difficult because we do not observe service efforts in the data, we choose to abstract away from such complication. The recommended product in the Proposition should be treated as the product on which the salesperson will focus his main effort. We note that most of the bargaining and matching models which, like the model in this paper, also involve two-sided decisions in the economics and marketing literature make the same assumption. We view such a model as the first step that approximates the complicated transaction process in a reasonable way.

Note that if the service effort required to sell a product is too high (because the consumer's utility of purchasing any product is too low), the salesperson may decide not to recommend any product and let the consumer walk away without purchase. In this case, the optimal service efforts $\left(e^*_{si1t}, \dots, e^*_{siJt}\right)$ in Proposition 1 are all zero. The salesperson may also put in zero effort if they decide to recommend the customer's most-preferred product (where $X_{jt}\beta_i + \gamma_i p_{jt} + \varepsilon_{ijt}$ is equal to $max\{X_{1t}\beta_i + \gamma_i p_{1t} + \varepsilon_{i1t}, \dots, X_{Jt}\beta_i + \gamma_i p_{Jt} + \varepsilon_{iJt}, \varepsilon_{i0t}\}$), but the product will still be sold (because the consumer's utility of purchasing the product is already high). Proposition 2 treats the latter case as the salesperson recommending product *j*, and distinguishes from the former case of which the salesperson does not recommend any of the products.

Define $\hat{e}_{sijt}$ as the effort that sets $\hat{e}_{sijt}\left(\beta_i, \gamma_{i,}\boldsymbol{\varepsilon_{ist}}\right) = max\{X_{1t}\beta_i + \gamma_i p_{1t} + \varepsilon_{i1t}, \dots, X_{Jt}\beta_i + \gamma_i p_{Jt} + \varepsilon_{iJt}, \varepsilon_{i0t}\} - \left(X_{jt}\beta_i + \gamma_i p_{jt} + \varepsilon_{ijt}\right)$. The two propositions imply that the probability that the salesperson recommends product *j* can be derived from the utility function in equation (3) as

$$Pr_{sijt}(s\ recommends\ product\ j) = \int_\omega \int_\alpha 1\Big\{\alpha_s \cdot comm_{jt} + \omega_{sijt} - \hat{e}^2_{sijt}\left(\beta_i, \gamma_{i,}\boldsymbol{\varepsilon_{it}}\right) = max\{\alpha_s \cdot comm_{1t} + \omega_{si1t} - \hat{e}^2_{si1t}\left(\beta_i, \gamma_{i,}\boldsymbol{\varepsilon_{it}}\right), \dots, \alpha_s \cdot comm_{Jt} + \omega_{siJt} - \hat{e}^2_{siJt}\left(\beta_i, \gamma_{i,}\boldsymbol{\varepsilon_{it}}\right), \omega_{si0t}\}\Big\}\, dF_{\boldsymbol{\alpha}} dF_{\boldsymbol{\omega}} \tag{4}$$

Under the model's assumptions, if the salesperson's optimal decision is to recommend product *j*, the product will be purchased by the consumer (even when the effort level is zero). Therefore, the likelihood that the consumer will purchase product *j* can be represented by

$$Pr\left(y_{sijt} = 1\right) = \int_{\boldsymbol{\varepsilon}} \int_\beta \int_\gamma \int_\omega \int_\alpha 1\Big\{\alpha_s \cdot comm_{jt} + \omega_{sijt} - \hat{e}^2_{sijt}\left(\beta_i, \gamma_{i,}\boldsymbol{\varepsilon_{it}}\right) = max\{\alpha_s \cdot comm_{1t} + \omega_{si1t} - \hat{e}^2_{si1t}\left(\beta_i, \gamma_{i,}\boldsymbol{\varepsilon_{it}}\right), \dots, \alpha_s \cdot comm_{Jt} + \omega_{siJt} - \hat{e}^2_{siJt}\left(\beta_i, \gamma_{i,}\boldsymbol{\varepsilon_{it}}\right), \omega_{si0t}\}\Big\}\, dF_{\boldsymbol{\alpha}}\, dF_{\boldsymbol{\omega}}\, dF_\gamma dF_\beta dF_\epsilon \tag{5}$$

Since $\hat{e}_{sijt}$ is a function of the consumer preferences captured by $(\beta_i, \gamma_{i,} \boldsymbol{\varepsilon_{it}})$, the above equation shows that the probability of selling a product is influenced by (1) the consumer's product preferences, (2) the salesperson's type and, (3) commissions across products. It is important to highlight how our model differs from standard consumer choice models and the recent literature on the salesforce incentives. Compared with the former, which has a similar likelihood function as equation (2), the indicator within the integrals in equation (5) is a function of the salesperson's utility instead of the consumer's utility. This illustrates the centrality of the salesperson's decision that impacts the consumer choice; thus, we call this model the salesforce-driven consumer-choice model. Compared with the literature on the salesforce incentives (e.g. Misra and Nair 2011 and Chung et al. 2014), our model allows the salesperson to allocate different levels of service efforts across differentiated products. Furthermore, it allows the efforts to vary across different consumers in different periods depending on the unique product preferences of each consumer as well as the level of commissions across products.[7] Finally, since there is no non-linearity in the compensation plan we study in this paper, our model is static in nature, without dealing with the dynamic decisions as in Misra and Nair (2011) and Chung et al. (2014).[8]

2.3 Model Estimation

Let Θ be the vector of all model parameters that determine the distribution functions $F_{\boldsymbol{\alpha}}$, $F_{\boldsymbol{\omega}}$, F_{γ}, F_{β} and F_{ϵ}. We estimate Θ by maximizing the likelihood function in equation (5). As the likelihood function involves high-dimensional integrals, we make a parametric distribution assumption

[7] In that sense, our model has some similarities to Copeland and Monnet (2003), who allow for a discrete level of high or low effort for each "transaction", that is, a worker that sorts checks decides whether effort should be exerted for each check.

[8] Other incentives such as the future increase in base salary and career movements (e.g. Yang et al 2017) may influence the salesperson's decisions in a dynamic way. As the focus of this paper is commission, we abstract away from these further complications.

regarding $F_{\boldsymbol{\omega}}$, and assume that $\omega_{sijt} \sim Gumbel(0, \theta_\omega)$ and i.i.d. across s, i, and j. Therefore, equation (5) can be rewritten as

$$Pr\left(y_{sijt} = 1 | \Theta\right) = \int_{\boldsymbol{\varepsilon}} \int_{\beta} \int_{\gamma} \int_{\alpha} \frac{\exp\left(\frac{\alpha_s \cdot comm_{jt} - \hat{e}^2_{sijt}\left(\beta_i, \gamma_i, \boldsymbol{\varepsilon_{it}}\right)}{\theta_\omega}\right)}{1 + \sum_l \exp\left(\frac{\alpha_s \cdot comm_{lt} - \hat{e}^2_{silt}\left(\beta_i, \gamma_i, \boldsymbol{\varepsilon_{it}}\right)}{\theta_\omega}\right)} dF_{\boldsymbol{\alpha}}\, dF_\gamma dF_\beta dF_\varepsilon \qquad (6)$$

Next, we use a simulation method to evaluate equation (6). Conditional on a candidate Θ, the simulation procedure is outlined below:

1. For every observation (*i*,*t*) in the data, make *NS* draws of ($\boldsymbol{\varepsilon_{it}^{sim}}, \beta_i^{sim}, \gamma_i^{sim}$) from F_ε, F_β, F_γ, where *sim = 1, …, NS*. Also make *NS* draws of α_s^{sim} from $F_{\boldsymbol{\alpha}}$ for every salesperson. The same α_s^{sim} will be used for the salesperson for repeated transactions.
2. Conditional on the simulated ($\boldsymbol{\varepsilon_{it}^{sim}}, \beta_i^{sim}, \gamma_i^{sim}$), calculate the effort level $\hat{e}_{sijt}\left(\boldsymbol{\varepsilon_{it}^{sim}}, \beta_i^{sim}, \gamma_i^{sim}\right) = max\left\{X_{1t}\beta_i^{sim} + \gamma_i^{sim} p_{1t} + \varepsilon_{ijt}^{sim}, \ldots, X_{Jt}\beta_i^{sim} + \gamma_i^{sim} p_{Jt} + \varepsilon_{iJt}^{sim}, \varepsilon_{i0t}^{sim}\right\} - X_{jt}\beta_i^{sim} - \gamma_i^{sim} p_{jt} - \varepsilon_{ijt}^{sim}$.
3. Conditional on $\hat{e}_{sijt}\left(\boldsymbol{\varepsilon_{it}^{sim}}, \beta_i^{sim}, \gamma_i^{sim}\right)$ and α_s^{sim}, calculate the likelihood $Pr\left(y_{sijt} = 1 | \boldsymbol{\varepsilon_{it}^{sim}}, \beta_i^{sim}, \gamma_i^{sim}, \alpha_s^{sim}\right)$ in equation (6).
4. Calculate the simulated choice probability $Pr\left(y_{sijt} = 1 | \Theta\right) = \frac{1}{NS} \sum_{sim=1}^{NS} Pr\left(y_{sijt} = 1 | \boldsymbol{\varepsilon_{it}^{sim}}, \beta_i^{sim}, \gamma_i^{sim}, \alpha_s^{sim}\right)$.

We search for the estimate $\widehat{\Theta}$ to maximize the following simulated maximum likelihood function:

$$L = \sum_t \sum_s \sum_i \sum_j \log\left(Pr\left(y_{sijt} = 1 | \Theta\right)\right) \cdot y_{sijt} \qquad (7)$$

2.4 Identification

We only observe consumers' product choice. The main identification of the commission sensitivity (α_s) among salespeople versus the price sensitivity (γ_i) among consumers comes from an exclusion restriction: a change in commissions causes salespeople to reallocate service efforts among products but does not directly impact consumers' utility. Below, we provide more details regarding the identification of different parameters in the model.

The likelihood function in equation (6) indicates what variation in the data is required to identify the model. First, let commissions be fixed. Note that $\hat{e}_{sijt}(\beta_i, \gamma_{i,}\boldsymbol{\varepsilon_{it}}) = max\{X_{1t}\beta_i + \gamma_i p_{1t} + \varepsilon_{i1t}, \ldots, X_{Jt}\beta_i + \gamma_i p_{Jt} + \varepsilon_{iJt}, \varepsilon_{i0t}\} - (X_{jt}\beta_i + \gamma_i p_{jt} + \varepsilon_{ijt})$ is a monotonic function of X_{jt} and p_{jt}, and the probability function $Pr(y_{sijt} = 1)$ is monotonically decreasing in the amount of effort needed to make a sale, $\hat{e}_{sijt}(\beta_i, \gamma_{i,}\boldsymbol{\varepsilon_{it}})$. Thus, parameters β_i and γ_i are identified by how product *j*'s market share changes following changes in X_{jt} and p_{jt}. The identification of $F_{\boldsymbol{\varepsilon}}$ comes from how products are substitutable with each other when their prices and product attributes change, the same argument that has been well-established in the standard consumer choice literature. For example, if a price reduction of product *j* cannibalizes the sales of product *k* more than other products, it implies ε_{ijt} is more positively correlated with ε_{ikt}.

Next, let prices and other product attributes be fixed and assume that $F_{\boldsymbol{\omega}}$ is known. Equation (6) shows directly how α_s is identified from how the probability of salesperson *s* selling product *j* changes with different commissions. The distribution of α_s , $F_{\boldsymbol{\alpha}}$, is identified from the heterogeneity in the responsiveness from commissions across salespeople.[9] Note that we assume so far that p_{jt} and $comm_{jt}$ are not perfectly correlated; otherwise the model cannot separately identify the price coefficient from the commission coefficient. Whether this assumption is valid or

[9] Since the stochastic components ε_{ijt} and ω_{sijt} will also affect the selling outcome, to identify $F_{\boldsymbol{\alpha}}$ it requires that each salesperson serves more than one consumer. This implies the importance of using the panel data of salespeople's performance to estimate the model.

not depends on the commission scheme. If the firm adopts a revenue-based commission, i.e., $comm_{jt} = r \cdot p_{jt}$, where r is a fixed commission rate, then the model cannot be identified.[10]

In addition to changes in commissions and prices, other data variations can also help with the model identification. In particular, product entries and exit change the choice sets for consumers and salespeople over time. Changes in the market share of other products following the entries and exits can identify not only F_ε but also β_i, γ_i as well as α_s. As an example, suppose we observe from data that after an existing product that provides salespeople with a high commission exits, the market share of the products that also provide high commissions increase more than those that provide low commissions. This implies that salespeople are very sensitive to the commission levels.

The above argument about how to identify α_s assumes that $F_{\boldsymbol{\omega}}$ is known. To separately identify α_s from $F_{\boldsymbol{\omega}}$, however, proves to be difficult because service efforts are not observed from the data. For an illustration, assume that $\omega_{sijt} \sim Gumbel(0, \theta_\omega)$. Equation (6) shows that (i) a very positive α_s, or (ii) a very small θ_ω, can both predict that the probability of selling product j increases drastically following an increase in $comm_{jt}$. However, the way that α_s and θ_ω are functionally specified in equation (6) implies that case (i) predicts the magnitude of the change in the selling probability, as commissions vary in data, differently from case (ii) does. Consequently a very positive α_s can be separately identified from a very small θ_ω. However, accurately estimating these parameters separately turns out to be challenging in our data due to the similarity in the effect that both of these parameters have on choices.

[10] As we describe later, the firm in our empirical application adopts a commission that is based on the profit margin. The marginal varies over time and are not fully aligned with the changes in price. Therefore, the price and commission coefficients can be identified in our empirical model.

We use a simulation study to further show that our model can recover the structural parameters. We first draw the prices and commissions of four hypothetical products from a large range over 24 months, and simulate the sales of a set of four product us different sets of parameter values. For simplicity, we assume that each product's utility can be summarized through a unique brand intercept, and normalize the intercept for the fourth product as 0. For this demonstration, we also assume that consumer heterogeneity is present only in the $\boldsymbol{\varepsilon}$ terms, and that the salesforce is homogeneous but draws $\boldsymbol{\omega}$'s for individual transactions. We further assume that the $\boldsymbol{\varepsilon}$'s are normally distributed with mean zero, and that the covariances are all zero except for the covariance of products 1 and 2 (Σ_{12}) and the covariance of products 3 and 4 (Σ_{34}). Finally, ω_{sijt} is assumed to have a Gumbel distribution with θ_{ω} fixed to one. We then use the simulated data to estimate the model parameters using the likelihood function in equation (7). Table 1 presents the results for a variety of parameters. The results show that the model is able to recover the true parameters very well, with the price and the commission coefficients being especially close to the true values.

Table 1. Test of model performance

	β_1	β_2	β_3	γ	α	Σ_{12}	Σ_{34}
True	0.00	0.00	0.00	-0.80	10.00	0.50	0.70
Estimated	0.00	0.01	0.00	-0.80	9.87	0.52	0.71
Standard error	(0.01)	(0.01)	(4.97E-03)	(2.99E-03)	(0.06)	(0.01)	(0.01)
True	3.00	2.00	4.00	-0.70	9.00	0.70	0.50
Estimated	3.07	2.08	4.06	-0.70	8.96	0.73	0.47
Standard error	(0.06)	(0.06)	(0.06)	(3.47E-03)	(0.05)	(0.02)	(0.04)
True	3.00	2.00	4.00	-1.00	5.00	0.50	0.70
Estimated	3.16	2.17	4.16	-1.00	4.98	0.51	0.63
Standard error	(0.09)	(0.09)	(0.09)	(4.34E-03)	(0.04)	(0.02)	(0.05)
True	1.00	2.00	3.00	-0.60	7.00	0.80	0.40
Estimated	0.95	1.96	2.96	-0.59	6.92	0.82	0.46
Standard error	(0.03)	(0.03)	(0.03)	(3.93E-03)	(0.04)	(0.01)	(0.02)
True	3.00	0.00	4.00	-0.90	6.00	0.30	0.50
Estimated	3.13	0.10	4.13	-0.90	5.93	0.15	0.42
Standard error	(0.09)	(0.08)	(0.09)	(4.24E-03)	(0.05)	(0.07)	(0.05)

3. Data and Analysis

3.1. Data Description

We estimate the model using a dataset provided by one of the largest regional chains of automobile dealers in Japan. This dealership sells cars produced by one of the largest car manufacturers in the world. It owns over 70 outlets and sells multiple brands produced by the same manufacturer. All the outlets sell the same set of car models. The dataset spans two years. There are altogether 828 salespeople. The mean and standard deviation of salespeople's tenure is 12.9 and 9.7, respectively. 59.8% of the salespeople have college degree, and all of them are male. The data are well suited for our study because we know not only each salesperson's transactions but also the commissions the salespeople receive from each transaction. Furthermore, for each car we know both the selling price and the cost borne by the dealer, which the dealer calculates based on the price it pays the manufacturer for the car as well as administrative and inventory costs.

In each month, a salesperson receives a guaranteed base salary, which can change over time depending on his tenure and accumulated past work performance, plus commissions from the transactions he completes that month. The commission has a fixed and a profit-based component, with commissions calculated as $q_t + r_{jt} \cdot (p_{jt} - c_{jt})$, where q_t is a commission paid each time a car is sold and is fixed for all car models, r_{jt} the commission rate specific for car model j, p_{jt} the selling price, and c_{jt} the cost for the dealer (thus the commission for selling the model depends on the margin for the dealer). The dealer determines the selling prices and commission rates of each car model. In the data, commission rates differ across car models but remain constant over time except for two car models. However, prices and costs fluctuate across months and do not move in lock-step together, and have an average correlation of 0.52. Commissions make up around half of a salesperson's income, so the salespeople have a strong economic incentive to sell cars.

Table 2. Summary statistics

Class	MPV						Mini-SUV	
Car model	1	2	3	4	5	6	7	8
Price (US$)	12491	15223	18172	15308	16816	14440	11090	20580
	(92)	(234)	(369)	(72)	(455)	(797)	(282)	(256)
Cost (US$)	12344	14233	16850	14844	14950	12853	9868	19405
	(45)	(193)	(218)	(22)	(377)	(439)	(137)	(206)
Commission per car (US$)	191	318	434	262	393	360	353	311
	(10)	(12)	(41)	(13)	(52)	(51)	(36)	(31)
Total unit sales per month	25	29	335	171	34	146	43	65
	(11)	(10)	(154)	(54)	(29)	(53)	(24)	(31)
Total profit per month (US$)	3954	28656	457322	76841	71132	245418	56793	79441
	(2830)	(9808)	(252393)	(16830)	(73887)	(136119)	(37324)	(49729)

Class	Sedan							
Car model	9	10	11	12	13	14	15	16
Price (US$)	11740	12868	16344	12829	14447	14540	10859	9249
	(66)	(162)	(217)	(215)	(164)	(213)	(296)	(211)
Cost (US$)	11195	12125	14802	11253	13442	12868	9297	8035
	(22)	(96)	(254)	(64)	(134)	(101)	(128)	(76)
Commission per car (US$)	306	355	478	484	421	504	497	425
	(19)	(18)	(72)	(44)	(21)	(32)	(66)	(62)
Total unit sales per month	35	111	45	117	43	245	40	77
	(11)	(26)	(23)	(56)	(13)	(99)	(15)	(40)
Total profit per month (US$)	18610	82626	73516	191118	43594	416357	63121	98745
	(4817)	(21502)	(48759)	(113655)	(13774)	(195736)	(27718)	(62940)

*Numbers in parentheses are standard deviations that are calculated from the variation across months.

We focus on the three most popular classes of cars purchased by individual consumers: multi-purpose vehicles (MPV), sedans, and mini sport-utility vehicles (mini SUV), which make up 25,731 transactions over the two years. We focus on the top 16 models with sales greater than 300 units over the 24 months, where each model has a distinct combination of brand, engine and transmission.[11] Table 2 provides summary statistics broken down by car model. We report all monetary values in U.S. dollars using an exchange rate of 118 Japanese Yen per USD. For each

[11] Within each model, sub-models differ by exterior and interior colors and other features. We are told the above three attributes are most important in consumers' decision-making.

car model, we present the mean and standard deviation of its price, cost and commissions on a per unit basis, as well as the average monthly total unit sales and profit.

The standard deviations reported in the table indicate that for each car model. There are significant fluctuations in prices and costs across months. Similarly, the range of prices and costs across cars within each car class is also large. These suggest that the profits of selling a car for the dealer vary across car models and months. Furthermore, the total unit sales averaged over months range from merely 25 (model 1) to 335 (model 3), reflecting large variation in terms of the appeal to consumers across car models. On average, the dealer pays salespeople about 30% of the margin as commission. The commissions also fluctuate across car models and months.

Before estimating the full model, we first estimate a classic consumer choice model where we put the commission into the customer's utility function using the following likelihood function:

$$Pr\left(y_{sijt}=1\right)=\int_{\varepsilon}\int_{\gamma} 1\left\{X_{jt}\beta+\gamma_i p_{jt}+\alpha\cdot comm_{ijt}+\varepsilon_{ijt}=max\left\{max\left\{X_{j\prime t}\beta+\gamma_i p_{j\prime t}+\alpha\cdot comm_{ij\prime t}+\varepsilon_{ij\prime t}, j'=1,\dots,J\right\},\varepsilon_{i0t}\right\}\right\}dF_{\gamma}dF_{\varepsilon} \quad (8)$$

For X_{jt}, we include an indicator of the car model, and year-month indicators (23 indicators for the 24 months) to control for the seasonality. We assume that the price coefficient is distributed such that $\gamma_i \sim N\left(0,\sigma_{\gamma}^2\right)$. For simplicity we assume that there is no heterogeneity in other model parameters, and estimate a multinomial probit model, with $\boldsymbol{\varepsilon_{it}} \sim \mathrm{N}(0,\Sigma)$. The diagonal elements of Σ are normalized to 1 and, to simplify the estimation, we assume the correlation of ε_{ijt} and $\varepsilon_{ij\prime t}$ is τ_c for all car models j and j' belonging to the same class c (MPV, sedan, or mini-SUV), and 0 otherwise. Note that this structure removes any IIA concerns from our model. We restrict the covariances with each class to be non-negative (i.e., $0<\tau_c<1$). Consequently, all MPV car models, for example, are closer substitutes for one another than for sedan or mini-SUV models.

Table 3. Results from "Consumer Choice" Models Estimation

	Without commissior	With commission
Price coefficient: mean	-0.288	-0.405
	(0.03)	(0.038)
Price coefficient: s.d.	0.050	0.051
	(2.12E-06)	(5.40E-06)
Commission coefficient		0.304
		(0.183)
Correlation: MPV	1.000	1.000
	(0.003)	(0.008)
Correlation: Sedan	0.002	0.001
	(0.001)	(0.004)
Correlation: Mini- SUV	0.341	0.411
	(0.001)	(0.002)
Car model indicators	Included	Included
Month indicators	Included	Included
Loglikelihood	-131464.932	-131436.723
BIC	263469.723	263425.573

*Prices and commissions are converted in $1,000 for estimation

For comparison purposes, we also estimate a standard consumer choice model without including commissions in equation (8). The results for both models are reported in Table 3. Price coefficients without commissions (column 1) or with commissions (column 2) are significantly negative. However, the price coefficient in the second model is significantly more negative than the first. To understand the reason, first notice that the coefficient for commissions is significantly positive in the second model, indicating that commissions, like prices, can be an important factor for car sales. Next, since the commission is calculated as $q_t + r_{jt} \cdot (p_{jt} - c_{jt})$, the commission for a car model will decrease when the price drops. From the data, the average correlation between the commission and the price is 0.82 across car models. Suppose there is a price promotion for a car model. Salespeople's incentive of investing service effort on selling the car model may decrease because of the lower commission and, consequently, the effect of the price promotion on sales will be diminished. Ignoring the role of salespeople's incentives in transactions will therefore bias the estimated price sensitivity of consumers towards zero. This result demonstrates the importance of taking account of salespeople's incentives even when the researcher's main objective is to understand the role of prices on sales.

3.2. Details of the Full Estimation Model

We estimate the proposed structural model described in Section 2. The specifications regarding γ_i, X_{jt} and $\boldsymbol{\varepsilon_{it}}$ are the same as the "consumer choice" models in Table 3. For salespeople, we allow them to be heterogeneous in the commission coefficient α_s. We assume that there are two latent types of salespeople. For each type, k, we estimate the coefficient on commissions as

$$\alpha_k = exp(\alpha_{k,1} + \alpha_{k,2} * tenure + \alpha_{k,3} * tenure^2 + \alpha_{k,4} * college) \quad (9)[12]$$

Under this specification, salespeople are differentiated by the latent type and, within each, differentiated by how long they have worked for the dealership (*tenure*, measured by months) and their education level (*college*, which is equal to 1 if the salesperson has a college degree, and 0 otherwise). The heterogeneity in α reflects the differences across salespeople in the marginal utility for commissions and/or the marginal (dis)utility for service efforts.

We also assume that $\omega_{sijt} \sim Gumbel(0, \theta_\omega)$ and is i.i.d. across *s, i,* and *j*. Therefore, the likelihood $Pr(y_{sijt} = 1)$ is specified as in equation (6). Given that it is difficult to identify both θ_ω and the other parameters of the model, as we discussed in Section 2.4, we fix the value of θ_ω to 1 when estimating the model. We then vary θ_ω and re-estimate the model based on each unique value to test how sensitive are other model estimates when the value of θ_ω changes.[13]

[12] The exponential function specification guarantees that the commission coefficient is always positive.

[13] Although the likelihood function value changes (within a magnitude of .02%), parameter estimates are very similar, suggesting that our results are robust to the assumption of θ_ω. Detailed estimation results under different θ_ω are available from the authors upon request.

In the model, consumers may choose the outside no-purchase option. Those consumers are not observed in the data; therefore, we need a proxy for the market potential. That is, the total number of potential consumers who were served by a salesperson in each month. We use an approach based on Albuquerque and Bronnenberg (2012), by assuming that the number of people who consider buying a car in a given year, y, is

$$M_y = \frac{Total\ Number\ of\ Households\ in\ the\ Region_y}{7} \cdot \frac{Observed\ Sales_y}{Regional\ Sales_y}. \tag{10}$$

In this formula, "7" is the average number of years between car purchases we obtain from industry reports, and the first ratio represents the total number of potential consumers who are looking to buy a new car in the region in the year. For the second ratio, "$Observed\ Sales_y$" is the total number of cars sold by the dealership in data, and "$Regional\ Sales_y$" is the total number of cars sold in the region during the year, which we obtain from the Japanese census data. This ratio represents the market share of the dealer in our data. M_y is thus used as a proxy for the number of consumers who visited the dealer in the year.

We further calculate the total number of potential consumers for the dealer as $M_m = M_y \cdot \frac{Observed\ Sales\ in\ m}{Observed\ Annual\ Sales}$, where "$Observed\ Sales\ in\ m$" is the average monthly sales in month m, and "$Observed\ Annual\ Sales$" is the average annual sales, both observed from the data. This way, the number of potential consumers for the dealer is assumed to be proportional to the monthly sales averaged across years.[14] Finally, we calculate the number of potential buyers for each salesperson by dividing M_m by the total number of salespeople employed by the dealer. In other words, we assume that all salespeople have equal selling opportunities. Based on interviews with

[14] Note that, since we include month indicators in the estimation model, our results are less sensitive to the way that we calculate the potential consumers. Suppose we over-estimate the number of potential consumers in a month. The estimated fixed effect of the month will adjust downward to reflect that the over-estimated potential consumers will walk away without purchase from the dealer.

the dealer, we understand that the dealer uses a territorial system: When a consumer walks into a dealer, the salesperson who first sees her will greet her and ask some basic questions including where she lives. The customer will then be assigned to the salesperson who is in charge of the territory where their residence is located. If the salesperson who is in charge of the territory happens to be not in, the person who greets the consumer will take care of her. For fairness, the dealership assigns the territories with the goal of ensuring that each salesperson will serve the same number of customers; therefore, the assumption of equal selling opportunities seems reasonable. Because the territorial system is based on the residence only and not the unique type of each consumer (i.e. $\beta_i, \gamma_{i,}$ and $\boldsymbol{\varepsilon_{it}}$), we further assume that there is no strategic matching between a salesperson and a consumer.

Finally, we are concerned with the issue of price endogeneity in the model estimation. The price of a car may be correlated with the stochastic components ε's and ω's in the model because a consumer may negotiate price with the salesperson in the transaction process. During interviews with the dealer, we were told that, in contrast to US practices, consumer-initiated price negotiations are very rare in Japan. Even when price negotiations occur, salespeople cannot make the decision; instead, they have to let the manager decide the final price. Therefore, price endogeneity is of less concern in this study than in some other studies. However, we further address the issue of endogeneity by adopting a control function approach, proposed in Petrin and Train (2010). We estimate the model in two stages. In the first stage, we regress the price of every car model in each month on product-level indicators and a set of price instruments, which include the total number of car models in the same class and in other classes. We observe new car models enter and old car models exit in various months, and prices of existing car models significantly fluctuate following the entry and exits (as shown from the regression). Assuming the entry and exits are not correlated to the individual ε's and ω's, these variables are valid instruments for prices.

We obtain a residual ξ_{jt} for each car model in each month from the price regression. In the second stage, when estimating the proposed structural model, ξ_{jt} is included as an additional covariate in the consumer utility function in equation (1). Petrin and Train (2010) show that this method helps correct the potential endogeneity problem in discrete choice models.[15]

In addition to the proposed model, we also estimate three alternative models with simpler specifications. The first (Model 1) does not account for the heterogeneity across salespeople in α_s or for the potential price endogeneity. The second model (Model 2) uses the control function approach to correct for price endogeneity, but still does not allow for the heterogeneity across salespeople. The third model (Model 3) assumes that the heterogeneity across salespeople only comes from the tenure and education observed from data (see equation 9) but there are no latent type differences. Comparing the results helps us understand how each of the above components can increase the model fit, as well as how the estimation results are robust to different model specifications.

3.3. Estimation results

Table 4 reports the estimates from the four model specifications. All of the results show that the mean price coefficients are negative and significant; however, after controlling for the potential price endogeneity, the coefficients are more negative in the latter three models. The estimated

[15] It may also be a concern that the cost for the dealer, c_{jt}, which is the wholesale price set by the car manufacturer, may have the endogeneity issue. The wholesale price, however, is the same for every transaction in the same month *t*. In the model, we include the fixed effect of every car model, as well as the fixed effects for years and months. After controlling for these fixed effects, the endogeneity concern should be alleviated.

heterogeneity (standard deviations) of the price coefficients are not statistically significant in all of the model specifications.

Table 4. Estimation Results

	Model 1	Model 2	Model 3	Proposed full model	
Consumers					
Price coefficient: mean	-0.124	-0.244	-0.248	-0.253	
	(0.002)	(0.014)	(0.004)	(0.028)	
Price coefficient: s.d.	0.006	0.006	0.007	0.003	
	(0.005)	(0.013)	(0.4)	(0.203)	
Correlation:MPV	0.929	0.929	0.766	0.316	
	(0.054)	(0.055)	(0.032)	(0.078)	
Correlation:Sedan	0.014	0.011	0.015	0.017	
	(0.285)	(0.414)	(2.587)	(1.061)	
Correlation: Mini-SUV	0.691	0.690	0.665	0.434	
	(0.062)	(0.061)	(0.097)	(0.17)	
Coefficient for the residual		0.120	0.123	0.131	
in the price regression		(0.008)	(0.042)	(0.026)	
Salespeople					
Average	3.060	3.020	3.154	2.578	
				Seg 1	Seg 2
Constant	1.117	1.106	0.843	1.174	-1.203
	(0.114)	(0.111)	(1.089)	(0.04)	(1.599)
Tenure			0.049	0.032	-5.616
			(0.041)	(0.003)	(8.64)
Tenure^2			-0.001	-0.001	-0.010
			(1.17E-03)	(8.92E-05)	(0.185)
College			0.012	-0.026	-0.006
			(0.013)	(0.016)	(2.344)
Segment Size				0.668	0.332
				(0.018)	(0.018)
Car model indicators					
Month indicators	Included	Included	Included	Included	
Loglikelihood	-131426.257	-131425.947	-131272.978	-129971.165	
BIC	263404.641	263416.292	263147.162	260604.883	

*Prices and commissions are converted in $1,000 for estimation

We next turn to how responsive salespeople are to commissions. Because the estimates of the coefficient on commissions follows the form of equation (9), it can be hard to interpret the overall effect of commissions on salesperson utility. For this reason, we report the commission coefficient averaged across all salespeople (in the row labeled "Average"). The coefficients are positive in all four models, suggesting that salespeople are fairly responsive to commission incentives. The level of responsiveness, however, is heterogeneous across salespeople. Results from model (3) suggest that salespeople with a higher tenure are in general more responsive to the commission change (it takes 18 years of tenure before the coefficient reaches its maximum), perhaps indicating that experienced workers have a higher selling ability and therefore the cost of service effort is lower. The coefficient for *College* is positive but statistically insignificant.

Our proposed model allows the responsiveness to commissions to differ among salespeople based on unobserved types. The last column in the table shows that there are two latent segments. The majority segment (67% of salespeople) has a high sensitivity to a change in commissions. Salespeople with a higher tenure in this segment are more responsive to commissions. The smaller segment has a much lower commission sensitivity, which decreases over time. This may imply that salespeople in that segment have a low selling ability and therefore the cost of service effort is high. The decline in commission sensitivity over time perhaps reflects the increases in base salary with tenure.[16] Finally, college education does not have a significant effect for either segment.

The estimated correlation coefficients of the three classes of cars have a direct effect on the own- and cross-price elasticities, which in turn affects the way that the salespeople shift their service efforts in response to changes in commissions. We observe high correlation in preferences for the MPV and mini-SUV segments, but not for the sedan segment. Using the results from the

[16] In Japan, the base salary largely depends on the seniority of workers and less on the work performance.

proposed model, we calculate the average price and commission elasticities and report them in Table 5. Reflecting the estimated correlation coefficients, the own- and cross-price elasticities are the smallest for sedan models. The own-elasticity for commissions, however, is the highest for this class, suggesting that increasing commissions are more effective in increasing sales for this class.

Table 5. Price and commission elasticities

		Price	Commission
MPV	Own	-6.103	0.768
	Cross	0.148	-0.024
Sedan	Own	-5.336	1.011
	Cross	0.026	-0.006
SUV	Own	-6.235	0.824
	Cross	0.311	-0.044

3.4 Counterfactuals

The value of constructing and estimating structural models comes from the capability of conducting counterfactual policy experiments that shed light on important managerial decisions. First, we study the optimal commission schedule for each car and examine how the optimal commissions depend on the appeal of products for consumers, the substitutability of the products, and the profit margins. We then examine whether it is better for the dealer to try to sell more cars through discounted prices or through sales incentives.

3.4.1 Optimal commissions

We use the results from our structural model to understand how the optimal commission levels depend on the characteristics of the products. Specifically, we consider how the attractiveness of products, the substitutability between products, and the profit margins of the products affects the optimal commissions. We take the car models that are available for in the first month in our data, and randomly draw the price, cost, the car model fixed effect (as a measure of the attractiveness of the car model to consumers), and the within-category correlations for all of the car models in our data. For each simulation, we calculate the optimal commission for each car model. We repeat this simulation exercise 100 times,[17] and then run a linear regression with the optimal commission of each car model as the dependent variable, and the fixed effect for the focal car, the average fixed effect of the other cars, the profit margin of the focal car, the average profit margin of the other cars, and the correlation between preferences for the cars as covariates.

The regression results are reported in Table 6. We find that the higher the attractiveness of the car, the lower the optimal commission the dealer should set. This is because it is easier for salespeople to sell the product. Second, the higher the attractiveness of substitute products, the lower the optimal commission because consumers will still purchase other products if effort is not exerted for the focal product. Third, higher profit margins imply higher optimal commissions. Fourth, higher margins for products that are substitutes lead to lower optimal commissions, since the firm has an incentive to reduce cannibalization. Finally, the higher the correlations of the preferences across products, i.e., the more that the focal product has a close substitute, the lower the optimal commission rate because over-incentivizing one product merely means cannibalizing a different close substitute. All of these results, while appearing to be intuitive are useful for the dealer. In particular, deciding the optimal commission for each of the differentiated products is a challenging task because the dealer has to consider the cannibalization effect when changing the commission for a car model. Using the results from Table 6, the dealer will be able to quickly

[17] The ranges we draw from are as follows: price [8.05, 22.39], cost [6.79, 20.73], fixed effect [-2.20, 2.24], correlation [0, 0.91], coefficient on commission [0.17, 2.55]. These numbers are the ranges from realizations, where the draws are made from normal distributions centered at either the mean of the data or the mean parameter estimate. Prices are also constrained to be above the cost of the car. Further details are available upon request.

calculate an approximately optimal commission level for each product, without going through the optimization procedure that we have conducted.[18]

Table 6. Results from optimal commission regression

	Estimate	SE	t	p
Intercept	-0.74	0.27	-2.71	0.01
Baseline attractiveness	-0.08	0.01	-5.87	0.00
Baseline attractiveness_others	-0.12	0.07	-1.77	0.08
Profit margin	0.61	0.01	105.05	0.00
Profit margin_others	-0.10	0.03	-3.80	0.00
Correlation	-0.04	0.02	-2.04	0.04
R^2		0.92		

3.4.2 The profit impact of discounting prices and increasing commissions

In marketing, the use of price promotions is a popular "pull" strategy to stimulate sales. Another strategy that is popular in many industries is to use commissions to incentivize salespeople to invest service efforts thus help increase sales. This can be viewed as a "push" strategy. Our model allows firms to evaluate and compare the effectiveness of the "pull" and "push" strategies within a unified framework.

We use a counterfactual exercise as an illustration. We assume that the dealer's goal is to increase the sales of car model 6 in the MPV class by 50% in the first month of the data because of the need to clear the excess inventory. The dealer can either discount the selling price of the car model or increase the commission for salespeople who successfully sell a car.[19] We calculate the

[18] The high R^2 from the regression indicates the predictions from the linear regression model fit well with the actual optimal commissions.

[19] When the selling price drops, the commission will also decrease based on the way it is calculated. To separate the effects of the "pull" from the "push" strategy, we assume that the commission rate will be adjusted upward to make the commission remain unchanged in the first case. We also assume the selling price remains unchanged when the commission increases in the second case.

level of price discount and the commission increase the dealer has to offer in order to achieve the goal. We then calculate the expected unit sales of other car models that can be affected by the sales strategies (due to product cannibalization), and based on that calculate the total profits of the dealer.

Table 7. Results from the price discounting and commission increase strategies

	Current setting	Price discount	Commission increase
$ Amount		$816	$205
Car model 6 unit sales	144	216	216
Other cars unit sales	647	638	636
Total net profit	$770,683	$722,492	$853,584

Table 7 reports the results. To increase the sales of car model 6 by 50% (a increase in unit sales of 144 to 216), the dealer has to offer consumers an $816 price discount or salespeople a $205 commission increase. In both cases, the unit sales of other car models will only slightly decrease. Table 5 indicates that the magnitude of the own-price elasticity is much larger than the own-elasticity for commissions for all three car classes, which would seem to imply that price discounts are more effective than commission increases. Our counterfactual results show that this is incorrect. In the counterfactual, the commission increase is only a quarter of the size (in terms of dollars) of the price discount required to achieve the sales growth. The reason is that the baseline price and commission are different (see Table 2). As the average selling price of model 6 is $14,440, $816 is merely a 5.7% price discount, while the $205 commission increase represents a 56.7% increase from $360, the original commission level. Because the dealer's margin from selling the car model is small (about $1,600 at the original selling price), the difference between the price discount and the commission makes a significant impact on the dealer's baseline profit. Our results show that the dealer's profit will decrease by 6.25% for the price discount, while increase by 10.75% for the commission increase.

Although the above counterfactual suggests that commission increases are more profitable than price discounts, this result crucially depends on the price and commission coefficients. To illustrate the effect across parameter values, we use further counterfactuals to investigate how a firm's optimal strategy may change under different commission coefficients. Specifically, we keep the other model parameters unchanged and compare whether reducing prices or increasing commissions is the better strategy when the commission coefficient for salespeople drops from the average of 2.58 (see the last column of Table 4) to a lower level at 1, 0.7 or 0.5, respectively. We again assume the dealer's goal is to increase the sales of car model 6 by 50%, and calculate the required price discount and commission increase for the dealer.

The results are reported in Table 8. When the commission coefficient is still high enough ($\alpha = 1$), we find that again it is more profitable for the dealer to only increase commissions ($559) and not to cut the price. When the commission coefficient is much lower ($\alpha = 0.5$), however, it is more profitable for the dealer to only offer price discounts ($770) to consumers and not to change commissions. This demonstrates the importance of quantifying the sensitivity of salespeople in response to commission changes for the optimal promotion strategy. When the commission coefficient is at the medium level ($\alpha = 0.7$), it turns out to be optimal for the dealer to combine both "pull" and "push" strategies. When there is a price discount, salespeople find it easier to sell the car to wider audience of consumers; when the price discount is accompanied by a commission increase, the salespeople have a greater incentive back up the sale with greater sale effort. This result shows that when the salespeople's sensitivity to commissions is neither too high nor too low, the price discount and commission increase can complement the effectiveness of each other to stimulate sales.[20] These results also explain why car companies use both dealer cash and customer cash, even though dealers only pass through a small fraction of the dealer cash (Busse et al. 2006).

Table 8. Optimal promotional strategies under different commission sensitivities

	Price discount	Commission increase
$\alpha = 1$	\$0	\$559
$\alpha = 0.7$	\$456	\$311
$\alpha = 0.5$	\$770	\$0

4. Conclusion

We develop a salesforce-driven model of consumer choice to study how performance-based commissions incentivize a salesperson's service effort toward heterogeneous, substitutable products. This study bridges the gap between the consumer-choice literature and the salesforce-management literature. In particular, the latter literature generally focuses only on how commissions affect the performance of salespeople in terms of aggregate sales. In contrast, we model the selling process as a joint decision by a salesperson and a consumer. The likelihood of selling a product is influenced not only by the salesperson's efforts induced by commissions but also by the consumer's innate product preferences. Our model thus allows the salesperson's efforts to vary across different transactions depending on the unique product preferences of each consumer.

We estimate the model using data from a car dealership in Japan. The results show that not only do consumers have heterogeneous product preferences but also salespeople have heterogeneous sensitivity towards commissions. We then use counterfactuals to compare the

[20] Whether it is optimal to cut prices or increase sales incentives also depends on the baseline prices and commission rates. Our key takeaway is what is optimal in our market, and understanding when one tool is likely to outweigh the other.

effectiveness of using price promotions vs. commission incentives to increase sales. We also illustrate how product-specific commissions should be set differently depending on the popularity and substitutability of products.

Although our model makes significant progress toward accounting for salesforce effort in modeling choices, it also has limitations. First, we assume that salespeople have perfect knowledge regarding consumers' product preferences. Future research may investigate how, when a salesperson is uncertain of the consumer's type, they will allocate different levels of service efforts across differentiated products and how such uncertainty will impact the effectiveness of using commissions as incentives. Second, if salespeople push the wrong products to consumers due to high commissions, this can lead to increased dissatisfaction and reduced trust among consumers; therefore, a short-term increase in profits may lead to a long-run cost for the dealer. In contrast, price promotions directed to consumers will not have this issue. Such long term consequences have not been studied in the paper. For simplicity our model also abstracts from how a price promotion may act as an advertising that can attract more store visits from customers. Finally, we only study consumer and salesforce decisions in a static framework, ignoring any dynamics that may arise if quotas or ratcheting exist. Similarly, current performance might also affect a salesperson's future base salary and career movement. Therefore, the salesperson may face a dynamic optimization problem, which is beyond the scope of the current study. We view this study as the first step in the literature that simultaneously models the two-sided decisions in a market with differentiated products. We hope our study will lead to more research in the future that can address the above issues.

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