

7-2009

Learning and Acting Upon Customer Information: An Empirical Application to Service Allocations with Offshore Centers

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Published In

Journal of Marketing Research.

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An Empirical Application to Service Allocations with Offshore Centers**

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July 2009

Baohong Sun is Professor of Marketing at Carnegie Mellon University. Shibo Li is Assistant Professor of Marketing at Indiana University. The authors thank participants at a Marketing Seminar at NYU, Wharton, Columbia, Chicago, Dartmouth, INSEAD, University of Texas at Dallas, University of Toronto, University of California at San Diego, the Biennial MSI Young Scholars Program, and the International Workshop on Customer Relationship Management: Data Mining Meets Marketing for helpful comments. The second author also thanks the Center for International Business Education and Research at Indiana University for awarding a faculty research grant to support this research. The authors also thank Laurence Debo for helpful comments.

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Abstract

As service centers become crucial corporate assets for increasing customer relationships and profits, it is imperative to understand customer reactions to service allocations. Using customer call history from a DSL service, the authors empirically investigate how customers' onshore and offshore experience affects service duration and customer retention. They formulate service channel allocation decisions as solutions to a dynamic programming problem in which the firm learns about heterogeneous customer preferences, balances short-term service costs with long-term customer retention, and optimally matches customers with their preferred centers to maximize long-term profit. They demonstrate that learning enables a firm to make more customized allocations, and acting on long-term customer responses prompts the firm to make proactive decisions that prevent customers from leaving. As a result, the derived allocation decisions (1) reduce service costs, (2) improve customer retention, and (3) enhance profit. The proposed framework also mirrors the recent trend of companies seeking solutions that transform customer information into customized and dynamic marketing decisions to improve long-term profit.

Keywords: service outsourcing; channel allocation; customer retention; long-term customer value; customer information management; decision support system; customer-centric marketing; stochastic dynamic optimization

Call centers initially were built to deal with customer inquiries, so their management traditionally has been considered little more than a cost to be saved. This attitude has led to the increasing popularity of outsourcing: More than 3 million agents are employed overseas, likely to increase by 10% per year (McKinsey Quarterly 2005). Most outsourced operations concentrate in the Philippines and India. Early adopters have achieved savings of 40% or more, generally by operating at significant cost scales. However, a recent survey by Purdue University (2004) indicates that despite these significant cost savings, both consumer and business customers report lower satisfaction ratings with outsourced call centers. Outsourcing firms thus have realized that the benefit of driving down costs comes at the cost of alienating customers; in some cases, customer defections even outweigh the potential savings derived from outsourcing (*Offshore Digest* 2005). The outsourcing controversy thus calls for research to evaluate human reactions to outsourced centers and possibly provide innovative approaches to use less expensive off-shore centers more effectively.¹

Modern call centers handle customer surveys, telemarketing, product inquiries, sales, transactions, promotions, cross-selling, advertising, and postpurchase service by telephone, e-mail, fax, or Web pages. In performing integrated marketing functions, these centers are becoming a preferred customer interaction channel. Approximately 80% of a firm's interactions with its customers occur through call centers, and 92% of customers form their opinions about a firm on the basis of their experience with call centers (Purdue University 2004). Thus, research is needed to recognize the marketing function of call centers in improving customer relationships and firm profit.

The call center industry is among the first to become equipped with the most advanced technology, which offers the capacity to store detailed customer history, retrieve real-time customer information, automatically analyze customer preferences, and instantly respond with highly

¹Call allocation historically has remained within the operation management research domain, with its focus on capacity costs and consideration of more efficient ways to engage in call routing, call waiting, queuing, and staffing (Gans, Koole, and Mandelbaum 2003).

customized and interactive marketing decisions. For example, the wide adoption of the sophisticated automatic call distributor (ACD), an automated switch designed to route calls, allows managers to monitor the progress and flow of work done by agents, routinely collect information on each agent's call length, analyze a wealth of statistical models about agents in real-time, and automatically route calls (Belt et al. 2000). Most firms also have customer relationship management (CRM) system in place with rich customer information, though few are integrated with ACD systems, so customer information has been largely ignored in service allocation decisions. With high power technology already in place, managers seek analytical decision-making tools that will enable them to integrate rich customer information into the ACD system and generate one-on-one, interactive, dynamic marketing interventions to transform their service centers into revenue growth systems.

In short, the meaning of call centers has shifted, from a cost to be saved to a crucial corporate asset, because of their ability to enhance customer relationships and firm profits. Research must clarify customer reactions to service allocations, and industry needs business solutions to improve service quality and enrich customer interactions, together with rigorous controls on service costs, to improve profitability. These goals require a firm to learn about customers, take into account the effect of current marketing interventions on future customer retention, and intertemporally adjust marketing interventions to maximize customer lifetime value.

Using customer call history data provided by a DSL service company that operates offshore centers, we develop consumer response models to investigate (1) how customers evaluate the performance of offshore service centers and (2) the relationship among service allocation, service costs, and customer retention. Empirical evidence shows that in general, customers are more likely to leave when they receive service from offshore centers and experience extra-long service durations. However, these sensitivities become less pertinent when the offshore centers handle technical

questions. In addition, some customers tend to incur longer service durations, but they also care less about being serviced by offshore centers, especially when they have technical questions.

We next investigate a potential way to use offshore centers better, without significantly jeopardizing customer retention. Instead of proposing cost-ineffective solutions, such as training service agents, we explore the possibility of improving services by using information about customers and acting upon it. In other words, we study how firms can use recent information to learn about customers and allocate customers to their preferred centers, thus continuously improving relationships with customers to maximize their long-term profit contributions. We formulate a firm's service allocation decisions as a matching problem whose solutions derive from a stochastic dynamic control problem with long-term marketing consequences, adaptive learning, and forward planning. Specifically, by allowing service duration and customer retention to be customer-specific and driven by allocation decisions, we let the firm update its knowledge about customer preferences, trade off between short-term service costs and long-term customer reactions, and make optimal allocation decisions that maximize long-term profit. The service allocation problem is formulated as a channel assignment problem in which the firm attempts to improve customer experience and long-term profit contributions by continuously learning about individual customer preferences and then matching customers with their preferred channel in a customized and dynamic fashion.

On the basis of the estimated parameters that characterize the relationship among service allocation, duration, and retention, we conduct simulations with our proposed framework and compare the simulated profit implications with those observed in the data. The results show that continuous learning enables the firm to improve its knowledge about each individual customer and make customized allocation decisions. With the ability to act on long-term marketing consequences, the firm also can prevent customers from leaving by sacrificing short-term service costs and allocating customers to their most preferred centers. Compared with cost-based routing that is

adopted by the company to generate the data, which completely ignores customer preferences, allocation decisions derived from our framework reduce average service costs, improve customer retention (50% reduction in the attrition rate), and enhance total profits.

Our findings thus provide empirical evidence about how customers evaluate offshore centers and shed new light on the drivers of customer responses to a firm's allocations of service channels. The proposed framework mirrors the recent trend in which companies seek analytical decision support solutions that entail customized and dynamic marketing interventions, for the purpose of enriching customer experience and increasing long-term profit. Our research responds to Berger and colleagues' (2002) call for research into "how to make marketing decisions that recognize customer heterogeneity and customer long-term profit contribution as a measure that dynamically changes in response to a firm's marketing actions." Even though our application pertains to service channel allocations, the proposed dynamic framework, with learning, forward-looking, and optimization, can generalize to other marketing mix decisions, such as promotion, cross-selling, and targeted Web advertising.

PRIOR LITERATURE

Marketing offers ample research documenting the relationships among service quality, customer satisfaction, retention, and financial impacts (Anderson and Sullivan 1993; Bolton 1998; Bolton and Drew 1991a, b; Boulding et al. 1993, 1999; Kamakura et al. 2005; Li et al. 2005; Oliver and Swan 1989; Rust and Chung 2006; Rust, Zahorick, and Keiningham 1995; Tse and Wilton 1988). Various models study the link between satisfaction and salesperson incentive schemes (Hauser et al. 1994), the relationship of measured overall service quality and subsequent usage (Bolton and Lemon 1998; Danaher and Rust 1996; Mittal and Kamakura 2001), the explanatory power of customer satisfaction on duration (Bolton 1998), the relationship between customer satisfaction and the firm's productivity level (Anderson et al. 1997), and customer lifetime value (Gupta et al. 2004; Reinartz

and Kumar 2000a, b; Rust et al. 2004). Recent “Holy Grail” CRM models claim to determine multiple, personalized marketing interventions over time to manage long-term customer value (Anderson and Salisbury 2003; Bult and Wansbeek 1995; Gonul and Shi 1998; Kamakura et al. 2002; Lewis 2005; Netzer et al. 2005; Rust and Verhoef 2005; Schmittlein and Peterson 1994; Venkatesan and Kumar 2004). However, despite the increasing importance of call centers in shaping customer service experience, no marketing research specifically investigates how customers react to a firm’s service channel assignment and studies how the resulting service treatment might affect customer attrition and long-term customer value.

Our proposed framework is unlike existing CRM studies in several aspects. First, with the exception of Gonul and Shi (1998), Lewis (2005), and Rust and Verhoef (2005), most existing work focuses on developing customer response models and discusses implications of the firm’s CRM intervention decisions tangentially. We treat the firm as a decision maker and analytically derive the explicit allocation decisions that match customers with the most appropriate centers. Second, most research emphasizes better approaches to model customer heterogeneity, based on demographic variables and pooled historical data, which result in score ranking of customers. We instead propose adaptive learning through continuous interactions, during which customer feedback from the most recent decision execution gets adopted and integrated into the firm’s periodic decisions. By following the development path of individual customers, the firm continuously improves its knowledge about customer preferences. Third, we treat the firm as a forward-looking decision maker that incorporates the long-term profit implications of customer attrition into its decisions, so future consequences affect the derived optimal decisions. In contrast, most existing customer lifetime value analyses calculate the net present value of customers’ future profit and treat it as another segmentation variable to guide their targeting strategies. Our approach mitigates the endogeneity problem that the firm’s intervention

changes customers' future purchase probability, as noted by Rust and colleagues (2004) and Rust and Verhoef (2005).

Methodologically, our work relates to dynamic structural models, developed to examine consumers' dynamic decisions regarding brand choice, quantity, purchase timing (e.g., Erdem and Keane 1996; Mehta, Rajiv, and Srinivasan 2004), and stockpiling behavior (e.g., Erdem et al. 2004; Krishna 1994a, 1994b; Sun 2005; Sun et al. 2003). Unlike prior research, which intends to establish that consumers are sophisticated decision makers, we treat firms as decision makers that balance both service costs and long-term marketing consequences.

INDUSTRY BACKGROUND AND DATA DESCRIPTION

The data for our study come from a firm that sells DSL services to both residential and business customers. This firm operates service centers in the United States and globally. For simplification, we treat all service centers within the continental United States as onshore service centers and those outside as offshore service centers. Depending on the speed of the modem, customers pay either \$49.95 or \$29.95 as a monthly subscription fee to maintain their access to DSL services. Some initial subscriptions require a one-year contract, but customers can terminate the service at any time, with a penalty if the contract is terminated prematurely.

All customers have access to free, 24/7, live customer support. For simplification, we classify customer questions as technical or transactional. Technical questions include software- or hardware-related issues; questions regarding installation, dial-up, user identifications, or passwords; and downed services or network outages. Transactional questions include inquires about billing, e-mail accounts, product news, product services, and registration. When a customer calls, he or she may experience some waiting time before an agent addresses the call, without knowing for which center he or she is waiting. After a call is picked up by an agent, the customer takes a few minutes to describe his or her problem, and then the agent provides solutions. When a call cannot be solved in a

timely fashion, the customer may be put on hold while the agent processes the case or sends it to higher-level managers. This scenario occurs more frequently at the offshore centers and for transactional questions, whose frontline agents have less authority to make decisions and escalate more cases to supervisors in their center.

Because of significant labor costs, the firm calculates service costs primarily on the basis of the labor costs related to the total time that agents remain occupied with a case.² Accordingly, the company measures the service duration as the total time of the service encounter—from the time the phone is picked up by an agent to the time the problem is solved. This measure includes time speaking with the customer, as well as time during which the customer is on hold and the agent is processing the customer's request. Multiple calls initiated by the same customer for the same problem usually are routed to the same agent, and the firm's policy states that agents should solve customer problems while customers remain on the phone, with very rare exceptions when agents must perform some task after customers hang up. This measurement is consistent with operation management literature (Gans, Koole, and Mandelbaum 2003). When agents begin working, they log on to the center's computer system, which retrieves the agent's profile and case handling history.

When a customer calls in, the ACD system automatically calculates the average service duration of each agent in handling this type of question and routes the incoming call to the available agent with the lowest estimated service costs. It recognizes the average differential traits of service providers and assigns calls to the one with the lowest average service duration in a myopic way; that is, it ignores customer aspects completely when calculating the service cost. Because this service

² Our definition of service duration includes both talking time and (possible) holding time. We do not include waiting time as part of the service duration because from the firm's perspective, only talking time and holding time keep the agent occupied and directly affect service costs. Other than some negligible phone costs, waiting time does not incur labor costs under the ACD system. However, we include waiting time as part of the customer service experience in the retention equation, which we describe subsequently, to take into account its effect on customer attrition. Accordingly, when we run simulations, we consider the different waiting times caused by the proposed service allocation decisions (see Appendix 2). Because of the way the company collects data, we cannot separate talking time from holding time, which represents a limitation of our data set, but we do not expect our results to be significantly altered.

allocation rule is determined primarily by the estimated service costs, not customer heterogeneity, we term this routing rule “cost-based routing.”

Our calibration sample contains the service history of 9,643 calls (calls to disconnect service are not included) initiated by 2,106 randomly selected customers during 52 weeks between January 2003 and December 2003. Our holdout sample contains 1,053 customers who made a total of 4,661 calls. We have access to detailed information about each call, such as the caller’s location, time stamps, call reasons, service allocation, call-center agent, call-center manager, and total service duration. In addition, the company randomly selected customers to participate in a satisfaction survey conducted between January and March 2003. Most customers participated in only one satisfaction survey. Because these scores pertain to overall satisfaction during the first three months of our observation period, we treat them as customer summary evaluations of the company’s service prior to our observation period. Furthermore, we have customer demographic information, including tenure with the firm, region, life stage segment, expertise with computers, and number of computers, as well as whether a customer left the firm during the observation period. Finally, we received estimates of marginal service costs, calculated on the basis of the call center agent’s wage and other variable costs. The average cost per minute of offshore centers is roughly one-third that of onshore centers.³

In Table 1, we list the definitions and sample statistics of the customer variables. Average tenure with the company reaches 20.29 months, and the average monthly price these customers pay is \$43.91. The firm occasionally offers price promotions, averaging \$4.13, such that 17% of the observation occasions occur in the presence of a competitive offer. Customers paid \$99 to terminate their contract prematurely in 1.58% of all observation occasions. Mostly (62%) residential as opposed to business, these customers initiated an average of 6.01 service calls per person, and 90% were technical questions. The average waiting times, divided by four time periods during a day (8–12,

³ Due to the sensitivity of the cost information, these numbers must remain confidential.

12–16, 16–20, and 20–24), for both centers are approximately 2, 1, 2, and .5 minutes for the onshore centers and 1, .5, 1.5, and .5 minutes for offshore centers. The average satisfaction score is 3.40, with a standard deviation of 1.29, and 16% of customers left during the observation period. We choose weeks as our unit of analysis and rate variables, such as prices, accordingly.

In Table 2, we compare the percentages of question types, corresponding service duration, and retention rates across those who made different numbers of calls during the observation period. We find no significant variation in the types of questions or retention rates between frequent and infrequent callers.

In Table 3, we list and compare the allocation, service duration, and retention rates between centers and question types. The current cost-based routing results in 84% of calls being assigned to onshore service centers and 16% handled by offshore centers. Among all questions handled by onshore centers, 11% are transactional and 89% are technical. The split is 3% and 97% for offshore centers. The average service durations are 6.39 minutes for transactional questions and 22.32 minutes for technical questions for onshore centers (cf. 44.20 and 36.28 minutes, respectively, for offshore centers). We note that the difference in technical questions is much lower than that for transactional questions, despite the longer time offshore centers require to solve both types of questions. Between centers, frequent service by offshore service centers leads to higher average customer attrition (17% versus 12% for onshore, $t = 12.6$). Thus, the data suggest that customers prefer onshore centers in terms of retention, though the extent of this onshore preference differs across question types. Although customers are significantly less likely to leave when onshore centers handle their transactional questions (.91 versus .82, $t = 11.27$), the difference in retention rates is much smaller for technical questions (.87 versus .84, $t = 4.57$).

This analysis provides preliminary evidence that though it takes more time for offshore centers to solve both types of questions, the difference for technical questions is much smaller.

Taking into account the significantly lower marginal service costs, the offshore centers in our data set have some cost advantages compared with onshore centers for handling technical questions. In the meanwhile, though customers prefer to be serviced by onshore centers, according to their retention rates, they are less sensitive for technical questions handled by offshore centers.

CUSTOMER RESPONSES

We assume that the firm operates $j = 1, 2$ service centers, with $j = 1$ representing onshore centers and $j = 2$ representing offshore centers. At time $t = 1, \dots, T$, customer $i = 1, \dots, I$ may call in with question types $k = 1$ or 2 , with $k = 1$ representing transactional questions and $k = 2$ representing technical questions.⁴ We also assume there are $m = 1, \dots, M$ segments of customers.⁵

We use three dummy variables, D_{ikt} for $k = 0, 1, 2$, denote whether customer i calls with question type k at time t , with $k = 0$ representing the case when customer i does not call. Thus, $D_{i1t} + D_{i2t} + D_{i0t} = 1$. Note that D_{ikt} recognizes call and no-call occasions and is not a decision variable. We use two dummy variables A_{ijt} to denote the firm's allocations decisions, such that $A_{i1t} = 1$ if the question is allocated to an onshore center and $A_{i2t} = 1$ if the question is allocated to an offshore center, with $A_{i1t} + A_{i2t} = 1$. These variables equal 0 when customer i does not call in at time t , that is, when $D_{i0t} = 1$. To simplify our notations, we define a vector $D_{it} = (D_{i1t}, D_{i2t}, D_{i0t})'$ and the vector $A_{it} = (A_{i1t}, A_{i2t})'$.⁶

⁴ For simplicity, we consider two service centers and two types of questions; we ignore differences in service duration among agents within the same center. The proposed approach can be generalized to incorporate multiple service centers, multiple questions, and multiple agents.

⁵ Because our research goal is to demonstrate the value of firm learning and acting on customer information, we focus on modeling customer interactions with service centers and assume away possible price endogeneity, capacity adjustments, and extra dynamics introduced by agent learning. These simplified assumptions are reasonable for our research context; we leave the relaxation of these assumptions to further research.

⁶ As mentioned earlier, the data were generated by cost-based routing. By ignoring customer preferences, cost-based routing does not take into account customer-specific duration or the center the customer prefers; the allocation depends purely on question type and the average service duration of each center and is a myopic decision. No obvious endogeneity problem exists regarding the estimation of the customer response models. We estimate customer response models for each center and each question type to control for differences between centers and question types.

Service Duration

Intuitively, service duration could be determined by the traits of service centers, question types, and customers. Following Mandelbaum and colleagues (2002), who show that call duration can be captured best by a log-normal distribution, we assume the log of call duration

$\log(DUR_{ijkc}(m))$ for customer i of segment m for all call occasions is given by

$$(1) \quad \log(DUR_{ijkc}(m)) = \alpha_0(m) + \alpha_1(m)D_{i2c} + \alpha_2(m)A_{i2c} + \alpha_3(m)A_{i2c}D_{i2c} \\ + \alpha_4(m)\log(DUR_{ijkc-1}(m)) + \alpha_5(m)NCOMPUTER_i + \xi_{ijkc}(m)$$

$$(2) \quad \text{and } \xi_{ijkc}(m) \sim N(0, \sigma_{\xi}^2(m)),$$

for all $j = 1, 2$ and $k = 1, 2$. We specify the duration equation for each question type and each service center to address the differences in service duration for different centers and question types. The subscript c denotes the counting index of all occasions of calls actually placed.⁷ We include the dummy variables D_{i2c} and A_{i2c} to control for the differential service duration across question types and centers. Their coefficients $\alpha_1(m)$ and $\alpha_2(m)$ indicate whether it takes more or less time for service centers to handle technical questions and whether it takes offshore centers more or less time to solve a case. To determine whether the difference in service duration between the centers varies across question types, we include the interaction term $A_{i2c}D_{i2c}$, whose coefficient $\alpha_3(m)$ indicates how technical questions modify the difference in the service durations of offshore centers. If $\alpha_2(m) > 0$ and $\alpha_3(m) < 0$, offshore centers are generally slower than onshore centers. However, the difference is smaller when offshore centers handle technical questions. The variable $\log(DUR_{ijkc-1}(m))$ is the log of the total service time it took center j to solve question type k in the prior service occasion. Its coefficient $\alpha_4(m)$ captures the persistence of service duration for customer i . We include $NCOMPUTER_i$, or the number of computers owned by the caller, to note the possibility that

⁷ Subscript c represents call occasions. This notation appears only in this equation. As explained subsequently, we define a retention equation for each period t because customers can leave during non-call occasions too.

customers with more computers may incur longer service times. The coefficient $\alpha_5(m)$ measures the effect of this variable on service duration. We use the vector $\alpha(m)$ to represent all coefficients in Equation 1, and $\xi_{ijkc}(m)$ denotes all other unobserved factors that may affect service duration.

Equation 1 thus defines the service durations for all call occasions. When customers do not call, the duration is 0. For all observation periods $t = 1, \dots, T$, the expected duration when question type k is allocated to center j is given by

$$(3) E[DUR_{ijk}(m)] = \begin{cases} \exp\{E[\log(DUR_{ijk}(m))] + \frac{1}{2}Var[\log(DUR_{ijk}(m))]\} & \text{when } D_{i1t} = 1 \text{ or } D_{i2t} = 1, \\ 0 & \text{when } D_{i0t} = 1. \end{cases}$$

Customer Retention

Assume that at each time $t = 1, \dots, T$, customer i of type m decides whether to stay with the firm. We follow extant marketing literature and allow customer satisfaction, price, presence of competition, switching costs, and variables describing the customer service experience with onshore and offshore centers to drive retention (Bolton 1998). Specifically, the retention decision results from the following function $W_{it}(m)$:

$$(4) \begin{aligned} W_{it}(m) = & \beta_0(m) + \beta_1(m)SAT_i + \beta_2(m)FEE_{it} + \beta_3(m)PROM_{it} + \beta_4(m)COMP_{it} \\ & + \beta_5(m)\log(TENURE_{it}) + \beta_6(m)PENALTY_{it} + \beta_7(m)A_{i2t} + \beta_8(m)A_{i2t}D_{i2t} \\ & + \beta_9(m)\sum_{j,k} (D_{ikt}A_{ijt} \log(DUR_{ijk}((m))) + \beta_{10}(m)(\sum_{j,k} (D_{ikt}A_{ijt} \log(DUR_{ijk}((m))))^2 + \beta_{11}(m)WAIT_{jt} \cdot \\ & + \beta_{12}(m)\sum_{\tau=1}^t \sum_{k=1}^K D_{ik\tau} + \beta_{13}(m)FREQ_OFF_{it} + \beta_{14}(m)ACCUM_DUR_{it} + \zeta_{it}(m) \end{aligned}$$

In this equation, SAT_i is the customer's overall satisfaction with the firm, measured at the beginning of the observation period.⁸ Bolton (1998) finds that customer satisfaction ratings obtained prior to the customer attrition decision relate positively to the duration of the relationship; therefore, we expect

⁸ We do not model customer satisfaction because most customers provide only one satisfaction measurement. The static measurements cannot be modeled as consequences of periodical allocation decisions. We include satisfaction scores as explanatory variables in the retention equation to control for customer variations. Further research could examine dynamic changes in customer satisfaction.

its coefficient to be positive. The variables FEE_{it} and $PROM_{it}$ are fees and promotions specific to customer i at time t . In addition, $COMP_{it}$ is a dummy variable indicating the presence of competitors in the geographic area where customer i resides. The inclusion of this variable controls for competition between DSL and cable. Switching costs also play an important role in determining customer retention. We include $\log(TENURE_{it})$ to control for the effect of the length that a customer stays with the firm on customer attrition; the log of this variable allows for its possible nonlinear relationship with customer retention, which may be caused by the one-year contract signed by some customers. To take into account the monetary switching costs, we also include the amount of penalty customers must pay when they terminate the service prematurely.

We are most interested in how variables characterizing customers' experience with onshore and offshore centers affect customer retention. As suggested by the survey conducted by Purdue University, customer retention relates directly to whether they are serviced by onshore or offshore centers. The dummy variable A_{i2t} represents whether the customer is serviced by an offshore center. We include it to capture the effect of being serviced by an offshore center on customer retention. To determine whether having a technical question handled by an offshore center modifies the negative effect on a customer's tendency to leave, we also include the interaction term $A_{i2t}D_{i2t}$. If $\beta_7(m) < 0$ and $\beta_8(m) > 0$, customers in general are likely to leave when being serviced by offshore centers, but they are less likely to do so when their technical questions are answered by offshore centers.

Gans, Koole, and Manddelbaum (2003) argue that customer service experience pertains to the duration of the service encounter, $\sum_{j,k} (D_{ikt} A_{ijt} \log(DUR_{ijkt}(m)))$. As the information in Table 3 demonstrates though, service duration varies significantly and may define differential customer service experiences with onshore and offshore centers. We expect its coefficient to be positive,

because controlling for everything else (e.g., customers are unhappy that they have to ask questions, expertise, number of computers), customers who need help may appreciate an agent who spends a reasonable amount of time to listen to their explanation of the problem and then provides solutions in a timely fashion.⁹ However, customers can quickly become impatient and unhappy when a service call lasts too long, they get put on hold, and/or their cases are escalated to higher-level managers. To account for this effect, we include the squared term of logged service duration and expect its coefficient to be negative. Finally, another component of customer service experience is the time the customer has to wait before his or her call is answered, or $WAIT_{jt}$. This variable does not directly differentiate customer onshore and offshore service experience, but we include it to control for its possible negative effect on customer retention (Gans, Koole, and Mandelbaum 2003).

We suspect that a service encounter with onshore or offshore centers and service duration may have long-lasting impact on customer retention. The variable $\sum_{\tau=1}^t \sum_{k=1}^K D_{ik\tau}$ reflects the cumulative number of calls initiated by customer i up to time t . We include this variable to control for the possibility that customers who face more questions with the service are more likely to leave the company. We also include the recency weighted frequency of being serviced by offshore centers ($FREQ_OFF_{it}$) and the recency weighted cumulative duration of past service calls prior to time t . Recency weights the duration and frequency, to reflect that events that happen long ago may have less impact on customers, consistent with the idea of using recency, frequency, and monetary value to predict customer responses to direct marketing (Colombo and Jiang 1999; Fader, Hardie, and Lee 2005; Gonul and Shi 1998). The coefficients $\beta_{13}(m)$ and $\beta_{14}(m)$ capture the effects of past experience with offshore centers and service duration on customer retention.

⁹ As Gans, Koole, and Mandelbaum (2003) discuss, very short calls sometimes occur because agents take small “rest breaks” by hanging up on customers.

We use the vector $\beta(m)$ to represent all coefficients in customer retention Equation 4 and $\zeta_{it}(m)$ to represent all the unobservable factors that affect the customer retention decision. Let RET_{it} be a dummy variable indicating whether customer i stays with the firm at time t ; then,

$$(5) \quad RET_{it} = \begin{cases} 1, & \text{if } W_{it}(m) \geq 0 \\ 0, & \text{otherwise} \end{cases}.$$

Let $\bar{W}_{it}(m)$ be the deterministic part of Equation 4. Assuming $\zeta_{it}(m)$ follows an independent, identical extreme value distribution, the probability of customer i staying with the firm at time t can be represented by

$$(6) \quad \Pr_{it}(RET)(m) = \frac{e^{\bar{W}_{it}(m)}}{1 + e^{\bar{W}_{it}(m)}}$$

Heterogeneity and Estimation

We use maximum likelihood to estimate $\alpha(m)$ and $\beta(m)$, which parameterize the effect of service allocation decisions on duration and customer retention. To take into account customer heterogeneity, we adopt a latent class approach, such that segment membership depends on expertise with computers (EXP_i) and type of customer ($RESIDENTIAL_i = 1$ if residential and 0 if business) (Kamakura and Russell 1989). Denoting the coefficients of these variables as $\gamma(m)$, we define $\Theta = \{\alpha(m), \beta(m), \gamma(m)\}$ for all m as the vector of parameters to be estimated together with the customer-specific duration and retention models.

FRAMEWORK FOR CUSTOMER-CENTRIC ALLOCATION DECISIONS

To improve customer experience and use offshore service centers more effectively, a firm might match each service call with the right center, according to individual customer preferences. We therefore formulate the service allocation decisions of a firm as solutions to a stochastic dynamic programming problem, in which the firm iteratively learns about customer preferences and adapts its allocation decisions to its best knowledge so that it can maximize long-term expected profits. In this

framework, when evaluating the allocation decision A_{ijt} , the firm must calculate the expected service costs on the basis of the expected service duration, given by Equation 3, and the marketing consequences entailing customer retention, as specified in Equation 6.

Adaptive Learning of Customer Heterogeneous Preference

When customer i calls at time t , his or her preference remains unknown or uncertain to the firm. To acknowledge that companies usually conduct segmentation analysis based on demographic variables and know the average probabilities of a customer belonging to a segment, we define the prior belief of customer type $\text{Pr}_{i_0}(m)$ as the probability of segment membership, resulting from the latent class approach in the estimation. This snapshot segmentation of customers is based on across-customer comparisons and offers average probabilities of segment membership that differ with demographic variables.

In addition to static demographic variables, accrued information obtained by observing customer feedback about the firm's most recent interventions might reveal customer information. There are at least two such information sources: observed prior service duration and observed customer retention. The same customer usually shows a consistent pattern over time in terms of the length of the service duration. For example, retired customers have more time to talk on the phone and likely incur longer service durations. Customer retention observations reveal the customers' reactions to service allocations. For example, if being serviced by an offshore center leads a customer to leave, it implies this customer is very sensitive to offshore centers. Similarly, when long service duration leads a customer to leave, it reveals that this customer reacts negatively to long service durations.

Assuming customers' preferences do not change over time, we let the firm learn about the possibility of a customer belonging to type m , or $\text{Pr}_{it}(m)$ for $m = 1, \dots, M$. Let $LR_{it}(m=n)$ denote the ratio of the probability of customer i belonging to $m = n$ type, relative to that of $m = 1$ type, perceived

by the firm at time t . According to the Bayesian rule of learning, the firm's perceived likelihood ratio of the consumer belonging to type $m = n$ relative to $m = 1$ is given by

$$(7) \quad LR_{it}(m = n) = \frac{\Pr_{it}(m = n)}{\Pr_{it}(m = 1)} = LR_{it-1}(m = n) \frac{\Pr(DUR_{ijkt-1} | m = n) \Pr(RET_{it-1} | m = n)}{\Pr(DUR_{ijkt-1} | m = 1) \Pr(RET_{it-1} | m = 1)}$$

for $m = 1, \dots, M$. The intuition is as follows: At the beginning of time t , the firm observes new information realized between $t - 1$ and t , namely, the duration DUR_{ijkt-1} and customer retention

RET_{it-1} . The firm calculates the probabilities of observed service duration using Equation 1 and

observed retention according to Equation 6 for all customer types $m = 1, \dots, M$. When the joint

probability of observing DUR_{ijkt-1} and RET_{it-1} , under the assumption that customer i belongs to

segment $m = n$, is greater than that under the assumption that he or she belongs to segment $m = 1$ (or

$\frac{\Pr(DUR_{ijkt-1} | m = n) \Pr(RET_{it-1} | m = n)}{\Pr(DUR_{ijkt-1} | m = 1) \Pr(RET_{it-1} | m = 1)} > 1$), the likelihood that customer i belongs to $m = n$ group

increases. In other words, when the observed duration and resulting retention are more likely because

the customer is assigned to segment m , the firm increases its belief that this customer belongs to

segment m . When customers do not call, $\frac{\Pr(DUR_{ijkt-1} | m = n)}{\Pr(DUR_{ijkt-1} | m = 1)} = 1$, and the belief gets updated solely

on the basis of observed retention. Given the updating rule, for all $m = 1, \dots, M$, the perceived

probability that customer i belongs to type m at time t is given by

$$(8) \quad \Pr_{it}(m = n) = \frac{LR_{it}(m = n)}{\sum_{m=1}^M LR_{it}(m)}$$

The learning process allows the firm to use accruing information to update its beliefs about the customer's intrinsic type continuously. As we explain next, the updated knowledge helps adjust allocation decisions, and the resulting customer reactions can be fed back into the updating process in the proposed framework.

Dynamic Optimal Allocation Decisions

Following Berger and Nasr (1998), we define a customer's profit contribution to the firm ($PROFIT_{it}$) as the sum of the discounted net contribution, less the firm's cost of serving him or her:

$$(9) \quad \begin{aligned} PROFIT_{it} = & \sum_{m=1}^M Pr_{it}(m) RET_{it} \{ FEE_{it} \\ & - \sum_k D_{ikt} [A_{i1t} (C_1 DUR_{ijkt}(m)) + A_{i2t} (C_2 DUR_{ijkt}(m))] \} \end{aligned}$$

This expression measures the marketing consequences as customer retention, and service costs are measured by the service duration. The RET_{it} dummy variable indicates whether customer i stays with the firm at time t , and FEE_{it} represents the marginal revenue contributed by customer i at time t . We assume that the fee is paid at the beginning of period t , so the customer remains for the current period and can call to ask questions. In addition, C_1 and C_2 are the unit costs of service for onshore and offshore service centers, respectively.

We define DUR_{it-1}^H , RET_{it}^H , and $FREQ_OFF_{it-1}^H$ as the entire history of duration, retention, and recency-weighted frequency of being serviced by offshore centers, respectively, observed prior to time t for all $j = 1, 2$ and $k = 1, 2$. For simplicity, we use $I_{it} = \{DUR_{it-1}^H, RET_{it}^H, FREQ_OFF_{it-1}^H\}$ to denote the most updated information set available to the firm at the beginning of time t . Thus, the expected profit, given the information set I_{it} and allocation decision A_{ijt} , is

$$(10) \quad \begin{aligned} E[PROFIT_{it} | I_{it}, A_{it}] = & \sum_{m=1}^M Pr_{it}(m) Pr_{it}(RET)(m) [FEE_{it} \\ & - \sum_{k=1}^K D_{ikt} \{ A_{i1t} C_1 E[DUR_{ijkt}(m) | I_{it}, A_{it}] + A_{i2t} C_2 E[DUR_{ijkt}(m) | I_{it}, A_{it}] \}] \end{aligned}$$

where $Pr_{it}(RET)(m)$ is the probability that consumer i of type m will stay with the firm at time t . For periods $t + 1$ and beyond, $Pr_{it}(RET)(m)$ relies on Equation 6. Furthermore, $E[DUR_{ijkt}(m) | I_{it}, A_{it}]$ is the expected service duration when customer i of type m with question k is allocated to center j at time t , as given by Equation 3, and $Pr_{it}(m)$ is firm's perceived probability that customer i belongs to segment m , as defined by Equation 8. The expected profit is weighted by the firm's perceived probability of customer i belonging to type m at time t , or $Pr_{it}(m)$.

In practice, the allocation of services may not be driven solely by expected profit for many reasons. For example, political and ethical considerations may motivate the firm to assign more cases to onshore centers. To address this possibility, we assume that the firm makes allocation decisions between onshore and offshore centers according to a more general function U_{it} :

$$(11) \quad U_{it} = \sum_j A_{ijt} \lambda_{0j} + \lambda_1 E[PROFIT_{it} | I_{it}, A_{it}] + \sum_{j,k} (D_{ikt} A_{ijt} \tau_{ijkt})$$

Scalar λ_{01} captures the firm's intrinsic preference to allocate a service call to onshore centers, λ_1 measures the importance of profit in determining the firm's allocation decisions. Equation 11 describes a more realistic situation that nests the special case when the firm's allocation decision is driven solely by financial considerations (we explain how to obtain the values of λ_{0j} and λ_1 in Appendix 1). τ_{ijkt} denotes all the unobserved factors that affect the firm's allocation decisions, and

$\sum_{j,k} (D_{ikt} A_{ijt} \tau_{ijkt})$ is 0 when customer i does not call at time t (e.g., when $D_{i0t} = 1$ and $A_{ijt} = 0$). It is

τ_{ijkt} when customer i calls in with question of type k and gets allocated to center j . Assuming that τ_{ijkt} has an IID extreme value distribution, we obtain a binary logit model that approximates the

firm's allocation decisions. We also define \bar{U}_{it} as the deterministic part of U_{it} . When a customer calls, the probability of the firm making decision A_{ijt} is given by

$$(12) \quad \Pr(A_{ijt} | D_{ikt}) = \frac{\exp(\bar{U}_{it}(A_{ijt}))}{\sum_j \exp(\bar{U}_{it}(A_{ijt}))}$$

To take into account future marketing consequences, the firm must trade off the current costs of service (service costs) and future customer retention (marketing consequences) to maximize its long-term profit (long-term customer value). The firm's decision process can be parsimoniously formulated as the solutions to a stochastic dynamic programming problem, in which the firm makes allocation decisions to maximize its long-term objective function obtained from each customer i :

$$(13) \quad \text{Max}_{A_{ijt}} E \left\{ \sum_{\tau=t}^{\infty} \delta^{\tau-t} U_{i\tau} \right\},$$

where $0 < \delta < 1$ is the discount factor that reflects that current utility is preferred to future utility (Erdem and Keane 1996). The optimal allocation decision is thus the solution to the Bellman equation (in Appendix 2, we consider the probabilities of incoming calls and waiting time):

$$(14) \quad V_{it}(I_{it}, D_{it}) = \max_{A_{ijt}} \{U_{it} + \delta E[V_{it+1}(I_{it+1}, D_{it+1})]\}$$

where $E[V_{it+1}(I_{it+1}, D_{it+1})]$ is the expected optimal utility beginning from time $t + 1$.

As we show in Figure 1, the decision dynamics may be established as follows: At the beginning of week t , when customer i , who has already paid FEE_{it} , calls in with question k , the firm observes a new information set, which consists of the duration (DUR_{ijkt-1}), retention (RET_{it}), and recency-weighted frequency of being serviced by offshore centers ($FREQ_OFF_{it-1}$) between $t - 1$ and t . On the basis of this accrued information, the firm updates its beliefs about customer preferences ($Pr_{it}(m)$) according to the learning rule specified in Equations 7 and 8. With this updated knowledge, the firm calculates the expected service duration for question type k for each service center ($E[DUR_{ijkt}(m) | I_{it}, A_{ijt}]$), according to Equation 3, as well as the customer's probability of staying, ($Pr_{it}(RET)(m)$), given by Equation 6, for each possible allocation decision. The firm chooses the allocation decision (A_{ijt}) that maximizes its expected long-term utility. In this dynamic setup, the control variable is the call allocation decision A_{ijt} . With the state variables $Pr_{it}(m)$, DUR_{it-1} , $FREQ_OFF_{it-1}$, and $ACCUM_DUR_{it-1}$, this formulation allows the allocation decisions to be driven by firm knowledge about customers. In other words, the firm must act on its knowledge about customers when making service allocation decisions.

Because the state variables are continuous, we face the problem of a large state space and therefore adopt the interpolation method developed by Keane and Wolpin (1994) to calculate the

value functions for a few state space points, which we use to estimate the coefficients of an interpolation regression. The interpolation regression function then provides values for the expected maxima at any other state points for which values are needed in the backward recursion solution process (the Web Appendix provides more details).

To solve the dynamic program problem, we undertake two iterative steps: The firm continuously learns about each individual customer by analyzing customer information according to the customer's revealed reactions to the firm's most recent interactions, and then it adapts its decisions according to its most recent knowledge about each customer. During these integrated and iterative processes, updated knowledge continuously adjusts the firm's decisions, and the resulting customer reactions again inform the learning process. Thus, learning and decision making are integrated, which we refer to as "adaptive learning."¹⁰ Adaptive learning enables the firm to follow customers and improve the accuracy of its knowledge about each individual customer.

The solution results in a sequence of intertemporally related, optimal allocation decisions for all calls initiated by each customer. The proposed allocation decisions should reflect the following properties: First, the allocation decisions are customized, because adaptive learning enables the firm to improve its knowledge about each individual customer and allocate calls according to its best knowledge about that customer's preferences. Second, the allocation decisions are proactive, because the firm takes into account the trade-off between short-term service costs and the long-term consequences of alienating customers, which implies that it can sacrifice short-term costs by allocating a customer to his or her desired center to prevent defection and improve long-term profits. Third, our proposed allocation decisions are experimental, in the sense that the forward-looking firm may suboptimally assign a customer to a center to collect more information and learn about his or her type faster. Erdem and Keane (1996) discuss the experimental property resulting from dynamic

¹⁰ Conjoint analysis research adopts similar ideas to reveal consumer preferences (Toubia et al. 2003).

decision making under uncertainty in the context of consumer purchases of frequently purchased packaged goods; therefore, we leave it to further research to demonstrate the experimental property of the proposed approach explicitly.

EMPIRICAL RESULTS

In this section, we first discuss the parameter estimates Θ that characterize the relationship of the firm's allocation decision, service duration, and customer retention. On the basis of these estimated parameters, we conduct simulations using our proposed framework to derive the sequence of optimal allocation decisions A_{jt} . We thus investigate whether and how the proposed approach offers improvements over the observed cost-based allocations.

Estimation

Model Comparison. To determine whether our proposed model describes customer responses better than do alternative model specifications, we estimate three benchmark customer response models (Models 1–3) with and without the variables that characterize customer experience with onshore and offshore service centers (i.e., service duration and waiting time, service by offshore centers, and interaction term that indicates whether the offshore centers handle technical questions). In Table 4, we report the model-fitting statistics of the three estimated benchmark models and the proposed customer response model. The Akaike and Bayesian information criteria (AIC and BIC) show that the four customer response models with two latent segments fit the data best (due to space constraints, we present only the results of the two-segment version for the benchmark models). For both the calibration and the holdout samples, our proposed customer response model explains customer retention and service duration better than the three benchmark models, which supports the need to incorporate our proposed variables. Furthermore, we compare the simulated frequency of offshore allocations, average call durations, and probabilities of retention with those from the sample

in Table 5. The fit is good on all dimensions, which indicates that the proposed consumer model with two segments approximates the data quite well.

Coefficients. In Table 6, we report the estimation results. In the duration equation, the positive and significant coefficients of D_{i2c} for both segments show that it takes more time to solve technical questions. Similarly, the positive coefficients of A_{i2c} show that it generally takes longer for offshore centers to solve a case. However, when offshore centers handle technical questions, the service durations are significantly shorter than those associated with transactional questions handled by offshore centers. In addition, the positive coefficients of the service duration of the last service call suggest that if the last call initiated by customer i lasts longer, the current call may also last longer. Customers with more computers also are more likely to ask more questions during each call.

The retention equation reveals that overall customer satisfaction makes customers more likely to stay, as do lower prices, promotions, lack of competition, and a long history with the firm. Not surprisingly, a price penalty prevents customers from leaving. For this study, we are more interested in variables that describe the customer service experiences that differentiate onshore and offshore centers. When serviced by offshore centers, both customer segments are more likely to leave, consistent with the finding of the Purdue University study. However, this negative impact is mitigated by technical questions being handled by offshore centers for customers in the second segment, who are less sensitive to the service of technical questions by offshore centers. The log-duration shows a positive effect on retention, such that customers appreciate it when the service agent spends sufficient time to address their questions. However, the negative coefficient of the squared duration indicates that customers react negatively to extra-long service durations. In other words, customers are more likely to leave when their questions are not addressed in a timely fashion. As we expected, both segments react negatively to longer waiting times. The greater the total number of questions, the less likely customers are to stay, which is consistent with the intuition that on average,

customers who face more problems are more likely to leave the company. The recency-weighted frequency of being serviced by offshore centers decreases the chance that both segments stay; the recency-weighted total service duration has negative effects on retention, such that customers appear to react negatively to the high total amount of time they incur to ensure the function of their service.

We estimate that 66.3% of the customers appear in the first segment and 33.7% in the second segment. The coefficients of demographic variables in the segment membership suggest that customers with more expertise with computers and business customers are more likely to belong to the first segment, which may explain why they are more sensitive to service quality but not to price compared with those in the second segment. Customers in the two segments differ in their sensitivities to all the variables in the duration and retention equations. However, the most important differentiators are, in the duration equation, the intercept and, in the retention equation, the intercept, coefficients of being serviced by offshore centers, coefficients of the log of the squared duration, and interaction between offshore and technical questions. All else being equal, customers in the first segment experience shorter service durations (i.e., constant term in the duration equation) and are more likely to stay (i.e., constant term in the retention equation). However, they react much more negatively to being serviced by offshore centers and are more sensitive to service times that last too long. In contrast, those in the second segment seem to incur much longer service durations, are less likely to stay, are less sensitive to being serviced by offshore centers, and are slightly more tolerant of extra-long service encounters. Most important, these customers exhibit less sensitivity to whether their technical questions are handled by offshore centers.

In summary, the estimation results reveal that customers have differential sensitivities to onshore and offshore centers. To improve customer experiences with the company and use offshore service centers more effectively, the firm should match each service call with the right center, according to individual customer preferences and the comparative advantage of the onshore and

offshore service centers. However, examining the latent class segmentation, it is not intuitively clear which segment should be allocated to offshore centers. For example, even though customers in the first segment are more likely to stay, they are also more sensitive to being serviced by offshore centers. Thus, the firm should balance all factors that affect service duration and customer retention when deciding on service allocation. We next demonstrate how firm learning and acting on that knowledge can yield customized and proactive allocation decisions and improve profit.

Simulation

We conduct simulations to derive optimal allocation decisions using our proposed framework. Customer service duration and retention are simulated and may change with alternative service allocation decisions. Specifically, we recalculate the service duration and retention according to Equations 1–6 with the assumption that the coefficients in these equations do not change for the alternative allocations. We hope to demonstrate the effectiveness of adaptive learning (Figure 2), show how our proposed allocations are tailored to the firm’s updated information about customer preferences (Figure 3, Panels A and B), establish how service allocation decisions may be driven by long-term marketing consequences (Figure 3, Panel C), demonstrate whether firm learning and acting on customer knowledge improve customer retention and profit (Figure 4, Panels A–C), and compare the improvement for four nested optimization frameworks, including the proposed model with the cost-based routing adopted by the focal company (Table 5).

On the basis of the estimated parameters (Θ), the observed call history (D_{ikt}), covariates in the customer response model that are exogenously given, customer demographic variables, and importance of firm’s financial consideration (λ), we simulate optimal allocation decisions (A_{ijt}^*). To take customer aspects into account, we incorporate customer-specific predictions of service duration and retention, as specified in Equations 3 and 6. To add adaptive learning, we set the initial

probabilities $\Pr_{i0}(m)$ to be the same as those derived from the latent class estimates and update $\Pr_{it}(m)$ periodically according to Equations 7 and 8, using each customer's most recent information. To add the forward-looking component, we follow the convention and set δ to .995 (Erdem and Keane 1996; Sun 2005), then obtain the optimization by solving the Bellman equation.

Learning about Customer Type. In Figure 2, we demonstrate the progress of adaptive learning by dividing the whole observation period equally into three stages and comparing the probabilities of the segment 2 customers ($\Pr_{it}(m=2)$), which the firm obtains at the end of each stage. The firm perceives customers as relatively the same during the first stage, because the latent class approach results in average segment memberships that are the same across customers with the same demographic variables. As adaptive learning continues, uncertainty falls significantly, and distributions start to show two modes in the second stage. At the end of the observation period, almost every customer can be categorized as either a segment 1 or segment 2 customer. Approximately 34% are classified to the second segment at the end of the observation period, which implies that adaptive learning enables the firm to use the information about each customer's most recent interaction to pinpoint segment membership.

Properties of Proposed Solution. Using our proposed framework, we obtain a sequence of optimal allocation decisions for all calls initiated by each customer. To describe the allocation decisions succinctly, we present some summary statistics of the proposed allocations in Table 7 and compare them with observed cost-based allocation decisions. Our proposed approach increases the case assignments to offshore centers from 16% to 19%. Even though this increase is marginally noticeable, the composition of question types and customer types change significantly. Among the technical questions, 20% get assigned to offshore centers, an 18% increase from the 17% assigned by the cost-based method. In addition, 45% of customers from segment 2 are allocated to offshore centers, a 32% increase from the 34% observed in the sample. Because they are less sensitive to

being serviced by offshore centers, more segment 2 customers get allocated to offshore centers. The average service duration for both centers decreases significantly, and the customer retention rate increases. Because this model considers waiting time and its negative effect on customer retention, the proposed allocations do not incur greater waiting times.

In Figure 3, Panel A, we depict the average probabilities of assigning a customer to an offshore center ($\Pr(A_{i2t}) = \frac{\exp(\bar{U}_{it}(A_{i2t}))}{\sum_j \exp(\bar{U}_{it}(A_{ijt}))}$) and the average probabilities that customers are perceived to be segment 2 customers ($\Pr_{it}(m=2)$). Because this function reflects the relationship between decision variable and state variable, we term it the allocation function. The proposed solution shows that on average, the higher the perceived probabilities of belonging to the second segment, the higher are the probabilities of being routed to offshore centers, because these customers are less sensitive to longer service times and not as sensitive to being serviced by offshore centers. Thus, empowered by adaptive learning, the firm's allocation decisions are tailored to the firm's most updated knowledge about each individual customer. This method warrants a better match between the service center and individual customer.

However, the relationship likely will be modified by exogenous variables such as question type. In Figure 3, Panel B, we therefore compare the allocation functions between transactional and technical questions. For the same perceived likelihood of belonging to the second segment, it is more likely for the firm to allocate technical questions to offshore centers, consistent with our observation that it is less costly for offshore centers to handle technical questions and that customers are less likely to leave if their technical questions are handled by offshore centers. That is, the firm's allocation decisions recognize the comparative advantages of offshore centers for technical questions.

In Figure 3, Panel C, we compare the allocation function of the 16% of customers who left at the end of our observation period and those who stayed under the cost-based routing system. The

proposed solution sacrifices noticeable service costs by allocating customers who are most likely to leave to onshore centers to prevent them from leaving. This trend demonstrates the proactive nature of the allocation decisions enabled by the forward-looking and optimization components of the proposed framework.

Improvement over Cost-Based Routing. We next examine whether the allocation decisions derived from the proposed framework help the firm improve retention and profit while restraining its service costs. In Figure 4, Panels A–C, we trace the average costs

$(\sum_{m=1}^M \sum_{k=1}^K Pr_{it}(m) D_{ikt} [A_{i1t}(C_1 DUR_{ijkt}(m)) + A_{i2t}(C_2 DUR_{ijkt}(m))])$, average retention probabilities

$(\sum_{m=1}^M Pr_{it}(m) Pr_{it}(RET)(m))$, and total profits $(\sum_i PROFIT_{it})$ over the entire observation period and compare

these measurements with their observed counterparts. According to Figure 4, Panel A, the proposed allocations decrease average costs over time, perhaps due to the firm’s increasing ability to recognize the human component and employ each type of center. Figure 4, Panel B, indicates that attrition rates are approximately 8% with the proposed allocations, a 50% reduction of the attrition rate compared with cost-based routing, which reflects the transition of customer retention into an important element of the firm’s objective function. The firm therefore can adapt its allocation decisions to its knowledge about customer preferences and give these customers better service to prevent them from leaving.

Finally, in Figure 4, Panel C, we reveal that our framework results in a steady increase of total profit. In short, the more customized and proactive decisions that result from our proposed framework help firms save costs, increase customer retention, and improve long-term customer value or profit.

To investigate how sensitive the improvement is to the mix of customer types, we increase the percentages of business customers from 0% to 100% and report the customer retention rate at the end of observation period (Figure 5, Panel A) and the total profit accumulated over the observation period (Figure 5, Panel B). When the percentage of business customers is relatively low, the higher the

percentage of business customers, the more effective the proposed approach is in retaining customers. This is because the proposed allocation decisions recognize that business customers are more sensitive to being serviced by offshore centers. Thus, the firm fine-tunes the allocation to retain these customers in the long run. However, improved retention means higher service costs. Profit improvement starts to decrease at the peak of about 30% of business customers.

Similarly, we increase the percentage of transactional questions from 0% to 100%. Customer retention does not change with the mix of question type, because the composition of questions asked does not seem to significantly affect retention (Table 3). However, since technical questions take more time to solve, the saved costs that result from allocating technical questions to offshore centers increase profit. When the percentage of transactional questions increases beyond a threshold (greater than 50% in this context), the profit improvement thereafter remain almost constant. These results demonstrate that the improved customer retention and profit resulting from the proposed approach changes with the nature of the customer base and the composition of questions. However, we suggest caution in generalizing these results, because the direction and magnitude depend on other parameters that are specific to the context.

Alternative Optimization Frameworks. Our proposed framework enhances cost-based routing in at least three important components: the human aspects represented by customer-specific service costs and customer retention, adaptive learning, and long-term customer value. To determine the extent to which adding each component helps the firm, we compare the increases in the retention rate, total costs, and profit that result from our proposed framework and the three nested optimization frameworks with the observed cost-based routing. The first alternative framework (Alternative 1) takes our proposed model without customer retention, adaptive learning, or long-term customer value. Unlike the cost-based routing that generated our data set, this model minimizes service costs according to the service duration predicted by Equation 1 (see Appendix 1

for more detail). The second one (Alternative 2) adds customer retention to the first framework, such that the firm takes customer retention into account but remains myopic. In the third framework (Alternative 3), we add the forward-looking customer lifetime value but not continuous learning to the second framework. Finally, the fourth framework also includes adaptive learning; it represents our proposed framework. We compare performance improvements over cost-based routing in Table 8; every component contributes to improve retention rates and profit. The profit improvement follows similar pattern as the retention rate.¹¹

CONCLUSIONS, LIMITATIONS, AND FURTHER RESEARCH

The role of call centers has shifted from a cost to be saved to a preferred and prevalent channel to handle integrated marketing functions, which makes it an increasingly important corporate strategic asset. When this important corporate asset rests in the hands of a third party, outsourcing firms face the challenge of dissatisfied customers and high customer attrition. Savings are pointless without happy customers. More important, “extraordinary increases in computational speed allow sellers to use more sophisticated tools to quickly analyze traditional databases and to continuously improve targeting strategies,” and “industry might require market research tools to discover genuine value-added applications” (Shugan 2004). The call center industry provides an excellent example of the vast possibilities of transforming customer information into service excellence and revenue growth opportunities.

Using panel data pertaining to service allocations, we first provide empirical evidence about how service duration and customer retention may be affected by the firm’s service allocation decisions. We find that customers are less satisfied with offshore centers, and being serviced by them leads to higher customer attrition. Because of their significantly lower service costs per minute, the

¹¹ It is not surprising that our proposed model incurs a slightly higher accumulative total cost than the cost minimization approach (Alternative 1), because additional costs are incurred when the firm learns about the customer type and compromises to retain the customer.

offshore centers we study have some comparative advantages over onshore centers when it comes to technical questions. Customers also have heterogeneous sensitivities to service duration and allocations. Some customers tend to incur longer service durations, but these same customers also care less about being serviced by offshore centers, especially when they have technical questions.

We formulate service allocation decisions as a matching problem in which the firm recognizes customer-specific service costs and the long-term marketing consequences, learns about customers' heterogeneous preferences, balances the trade-offs between short-term service costs and long-term customer reactions, and makes optimal allocation decisions that best match customer preferences and maximize long-term profit. On the basis of the estimated parameters, we apply our proposed framework to derive the optimal call allocation decisions and demonstrate that adaptive learning allows the firm to improve its allocation decisions by matching customers with their preferred service centers. Forward-looking and optimization allow the firm to make proactive decisions to act on its knowledge about customers and long-term marketing consequences. Our proposed allocation decisions further help the firm (1) reduce average service costs, (2) improve customer retention, and (3) enhance total profit. In short, by better managing and acting on customer information, the firm can improve its effectiveness without incurring significant service costs.

Our results provide the first empirical evidence about understanding customer reactions to a firm's service channel allocation decisions. Through an application to a DSL firm's service channel allocations, our proposed learning and optimization solutions (or simplified heuristics) provide a computational algorithm for firms to integrate with their customer database and operating systems and automate call allocations. The proposed framework also improves customer segmentation approaches and customer lifetime value analysis in several ways. First, current segmentation approaches result in a snapshot segmentation and score rankings of consumers, independent of marketing actions. In contrast, our proposed framework allows for simultaneities, such that forecasts

of customer long-term profit contributions not only influence but also are influenced by the firm's marketing actions. Second, our framework enables firms to learn about customers in a continuous fashion on the basis of their feedback to the firm's most recent decisions. Therefore, the firm can not only follow the footsteps of a customer but also adapt its decisions to customer preferences. This approach aligns better with the recent technology-enabled trends toward one-on-one, interactive, and real-time marketing decision making. Third, by treating each marketing action as a separate decision over time, many current segmentation and customer lifetime value methods maximize the return of each marketing action independently, which means their usefulness is limited to campaign-centric marketing. Our framework instead views customer long-term profit contributions as a dynamic measure that intertemporally changes in response to a firm's marketing actions. It therefore aligns better with the spirit of customer-centricity and dynamic CRM, as discussed in both academic and practical literature (e.g., Rust and Chung 2006; Sun et al. 2006; Venkatesan and Kumar 2004). It further meets the demands of various industries that seek analytical decision-making tools to analyze their customer databases and support their day-to-day marketing decisions.

However, we also acknowledge that our study is limited and could be expanded in several ways. First, due to our data constraints, we make some simplified assumptions about the operations management of service allocation decisions, such as queuing, abandonment, and retries. We also cannot separate active talking time from holding time. Further research should examine how these variables affect customer retention. Second, because we only have one satisfaction measurement, we do not explicitly model the dynamics of customer satisfaction. Additional research should allow satisfaction to change over time. Further customer dynamics also could be captured by allowing for customer learning of service quality and the formation of duration expectations. Third, for demonstration purposes, we adopt a binary logit model to capture the customer retention decision. The hazard rate model can also be adopted to model customer duration. Fourth, we assume the

customer preferences are static. Research should develop more sophisticated learning routines to allow for dynamic changes in customer preference. More advanced approaches, such as hierarchical Bayes, could be integrated into the proposed framework to learn more about customer heterogeneity (Allenby, Arora, and Ginter 1998; Allenby and Rossi 1999; Rossi, McCulloch, and Allenby 1996). Fifth, possible price and capacity endogeneity issues could be investigated. For example, firms usually increase prices when service quality improves. Firms also may adjust their capacity as a result of improvements in efficiency. Lastly, agents at call centers can learn and become more efficient over time, so additional research should account for agents' learning curve.

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Table 1. Variable Definitions and Sample Statistics

Variable	Definition	Mean (Std)
TENURE	Number of months with the service provider since first purchase.	20.29 (12.37)
PRICE	Price of the product plan.	\$43.91 (7.80)
PROM	One-time price promotion for the product.	\$4.13 (15.97)
COMPET	Dummy variable indicating the presence of competitive service such as cable.	0.17 (0.37)
PENALTY	Penalty fee for terminating a contract prematurely.	\$99.00 (0.00)
NCOMPUTER	Number of computers owned by the caller.	1.63 (0.77)
EXP	Caller expertise self-rating: 1=extremely inexperienced/novice; 5=extremely experienced/expert;	3.11 (1.02)
RESIDENTIAL	Whether the caller is a residential customer.	0.62 (0.49)
NCALLS ($\sum_{t=1}^T \sum_{k=1}^K D_{ikt}$)	Total cumulative number of calls.	6.01 (18.15)
TECHNICAL	Whether the call is about a technical question.	0.90 (0.30)
FREQ_OFF	The recency-weighted frequency of being serviced by offshore centers.	0.30 (0.40)
SAT	Overall satisfaction rating of the overall service satisfaction quality of the firm.	3.40 (1.29)
RET	Dummy variable indicating whether the customer disconnects services in each month: 1=retain, 0=leave.	0.84 (0.36)

Table 2. Frequency Distribution of Calls

Frequency Distribution of Calls	Percentage of Customers	Question Type		Duration		Retention Prob.
		Transactional	Technical	Transactional	Technical	
1	23.96	0.09(0.29)	0.91(0.29)	10.35(25.57)	30.05(34.91)	.88(.13)
2	20.89	0.12(0.32)	0.88(0.32)	8.14(21.72)	31.06(34.91)	.87(.17)
3	16.27	0.11(0.32)	0.89(0.32)	7.72(21.19)	32.08(35.16)	.86(.18)
4	12.12	0.12(0.33)	0.88(0.33)	8.46(23.11)	30.46(35.03)	.87(.16)
5	8.99	0.12(0.33)	0.88(0.33)	8.93(23.41)	31.40(35.24)	.86(.18)
6	5.48	0.09(0.29)	0.91(0.29)	9.41(22.89)	30.02(34.46)	.87(.17)
7	4.18	0.09(0.28)	0.91(0.28)	8.08(20.51)	29.47(33.85)	.86(.19)
8	2.34	0.06(0.24)	0.94(0.24)	10.93(26.39)	30.95(35.40)	.88(.12)
9	1.84	0.06(0.24)	0.94(0.24)	12.27(26.32)	30.69(34.19)	.78(.33)
10+	3.93	0.07(0.26)	0.93(0.26)	11.48(24.96)	37.77(38.07)	.88(.13)

Table 3. Comparative Advantages

	Onshore			Offshore		
	Overall	Transactional	Technical	Overall	Transactional	Technical
ALLOCATION (A_{ijt})	.84 (.37)	.11 ^a (.32)	.89 (.32)	.16 (.37)	.03 (.18)	.97 (.18)
DUR	2.46 (27.80)	6.39 (17.61)	22.32 (28.37)	37.62 (24.69)	44.20 (31.79)	36.28 (24.45)
RET	.88 (.31)	.91 (.29)	.87 (.31)	.83 (.36)	.82 (.38)	.84 (.36)

^aThe percentage of questions handled by onshore centers that are transactional questions.

Table 4. Model Comparison

Models		Calibration Sample			Holdout Sample		
		Log	BIC	AIC	Log	BIC	AIC
		Likelihood			Likelihood		
Benchmark	1	-27175.4	54466.3	54408.8	-13455.2	27016.7	26968.3
Response	2	-23896.8	47949.0	47871.7	-11845.2	23833.5	23768.4
Models	3	-14473.3	29125.8	29036.5	-7182.3	14529.6	14454.5
Proposed	1 Segment	-16177.7	32462.9	32409.4	-8056.4	16211.8	16166.7
Response	2 Segments	-13061.7	26318.7	26221.4	-6422.7	13025.1	12943.3
Model	3 Segments	-23393.8	47082.5	46935.7	-11418.7	23108.9	22985.5

Notes: Benchmark model 1 is the proposed model without duration and waiting time, off-shore dummy, the interaction between off-shore and technical question dummy. Model 2 is the proposed model without off-shore dummy and the interaction term. Model 3 is the proposed model without the interaction term.

Table 5. Comparison with Sample Statistics

Statistics	Actual	Calibration Model
Percentage of allocations to offshore	.16	.18 (.03)
Average service duration in minutes	29.99	27.71 (3.67)
Average retention	.84	.86 (.03)

Table 6. Comparing Customer Demand for Service

Parameters		Coefficients (Std. Dev.)	
		Segment 1	Segment 2
Segment Membership		.663 (.005)*	.337 (.005)* ^a
	Intercept	1.065 (.018)*	.000 (.000) ^b
	EXP	.079 (.011)*	.000 (.000)
	RESIDENTIAL	-1.019 (.028)*	.000 (.000)
Log(Duration) (Regression)	Intercept	.508 (.031)*	5.225 (1.631)*
	Lagged log(Duration)	.101 (.007)*	.344 (.019)*
	TECHNICAL	.982 (.008)*	.139 (.001)*
	OFFSHORE	3.154 (.023)*	3.115 (.199)*
	OFFSHORE*TECHNICAL	-1.007 (.029)*	-1.401 (.113)*
	NCOMPUTER	.060 (.014)*	.410 (.094)*
	Variance	.526 (.010)*	.050 (.023)*
Retention (Binary Logit)	Intercept	7.488 (.304)*	.596 (.001)*
	SAT	6.581 (.378)*	1.910 (.030)*
	PRICE	-.049 (.005)*	-.466 (.001)*
	PROM	.142 (.025)*	-.013 (.794)
	COMP	-1.185 (.475)*	-.366 (.024)*
	Log(TENURE)	.889 (.498)*	1.273 (.132)*
	PENALTY	.468 (.136)*	.399 (.035)*
	OFFSHORE	-17.704 (7.553)*	-4.379 (1.223)*
	OFFSHORE*TECHNICAL	-3.135 (7.313)	7.114 (.111)*
	Log(Duration)	4.014 (1.193)*	4.733 (.110)*
	Log(Duration) ²	-2.264 (.248)*	-2.050 (.061)*
	WAIT	-1.486 (.416)*	-4.111 (1.312)*
	NCALLS	-1.333 (.081)*	-3.449 (3.514)
	FREQ_OFF	-46.702 (2.014)*	-1.440 (.124)*
ACCUMDUR	-3.795 (.161)*	-1.462 (.200)*	

^a Following convention, we estimate all coefficients explaining segment membership together with the coefficients in the duration and retention equations and rely on model selection criteria to select the number of segments. We obtain the posterior membership using the logit formula based on the means of covariates (i.e. EXP, RESIDENTIAL) in the segment membership equation.

^b For identification purposes, the coefficients for segment 2 are normalized to 0.

Table 7. Comparison of Actual and Proposed Allocation Strategies over the Entire Observation Period

	Actual			Proposed		
	Onshore	Offshore	Total	Onshore	Offshore	Total
Percentage of cases assigned	84%	16%	100%	81%	19%	100%
Percentage of technical questions	83%	17%	100%	80%	20%	100%
Percentage of customers in segment 2	66%	34%	100%	55%	45%	100%
Average service duration	20.46	37.62	29.99	14.22	18.67	16.32
Average waiting time	1.07	.75	.81	1.04	.76	.80
Percentage of customer retention at last period	88%	83%	84%	97%	89%	92%

Table 8. Performance Comparison across Optimization Frameworks

Optimization Framework	Accumulated Total Profits	Accumulated Total Costs	Retention Rate at Last Period
Cost-Based Routing	108,984.0	717,204.5	84.00%
Alternative Nested Framework 1	163,879.6	661,692.9	88.42%
Alternative Nested Framework 2	164,258.3	679,888.0	89.08%
Alternative Nested Framework 3	166,753.1	678,538.9	91.28%
Proposed Framework	167,981.4	668,012.2	92.26%

Figure 1. Timeline of Firm Decision Process

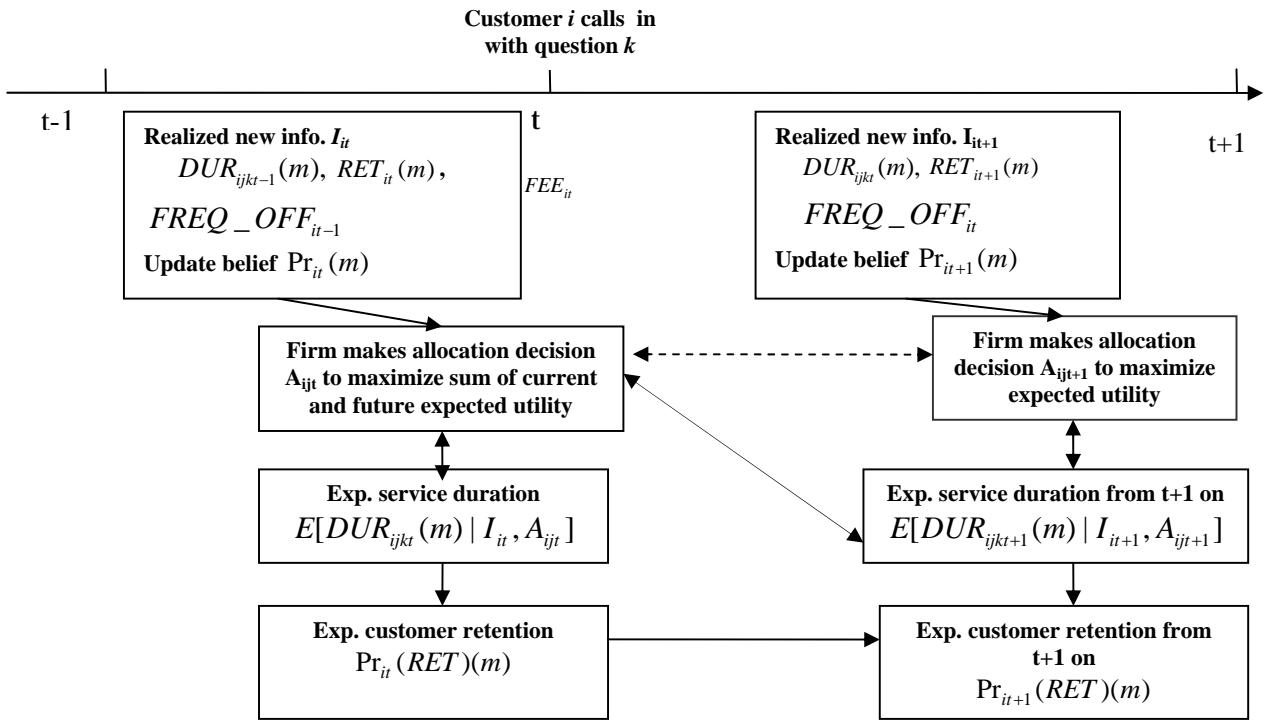


Figure 2: Percentage of Customers in Segment 2 by Period

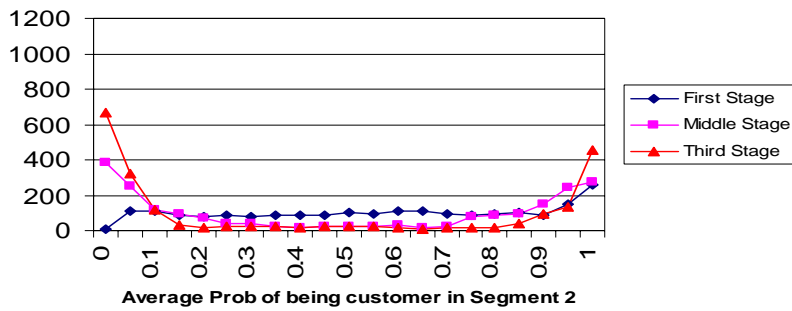


Figure 3A: Allocation Function

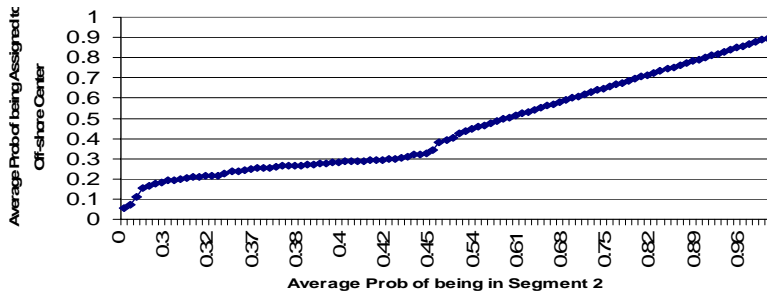


Figure 3B: Allocation Function with Different Question Types

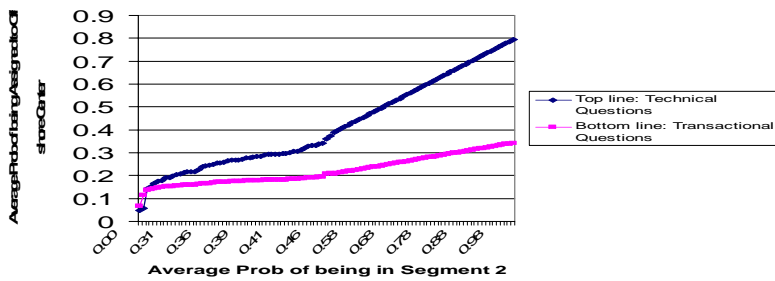
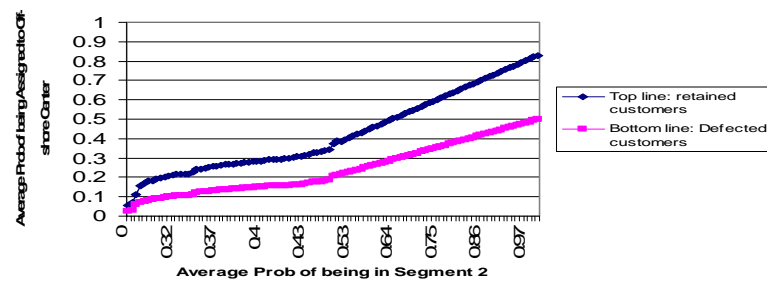
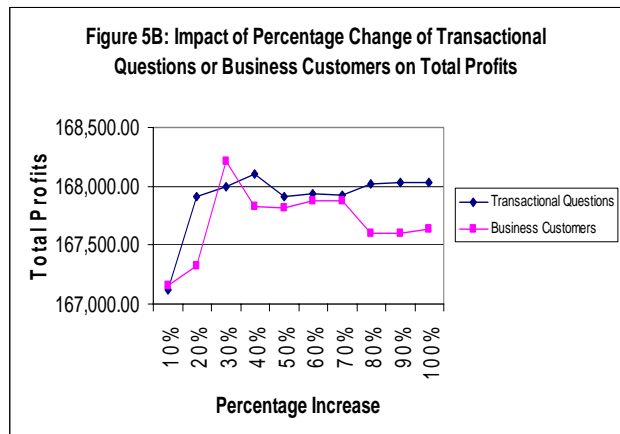
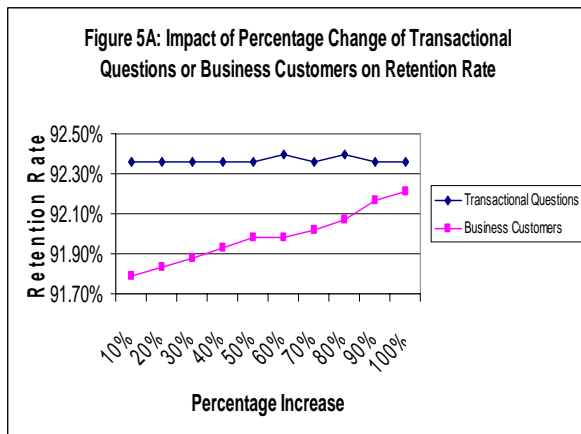
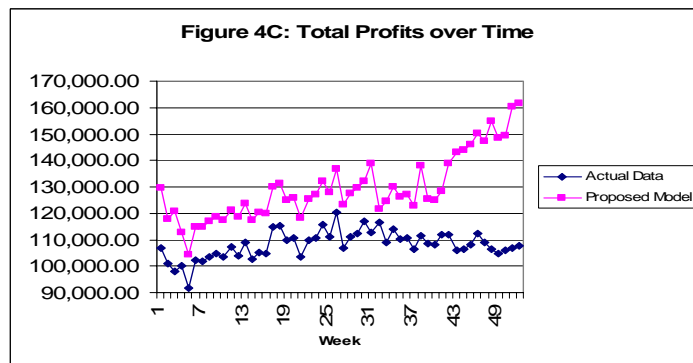
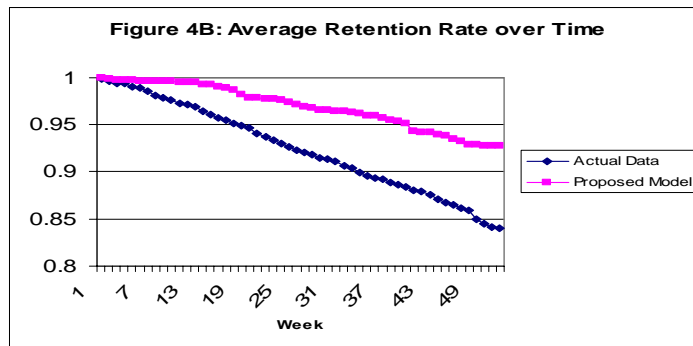
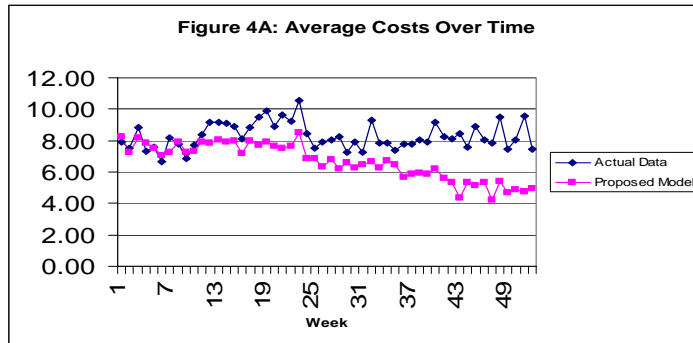


Figure 3C: Allocation Function with Retained vs. Defected Customers





Appendix 1: Cost-Based Routing

The cost-based routing that generates our data implies that when determining the allocation of incoming calls, the firm allocates calls to the center with the lower average historical service durations. The service cost at time t is given by,

$$(A1) \quad \sum_k D_{ikt} [A_{i1t} (C_1 \overline{DUR}_{1kt}) + A_{i2t} (C_2 \overline{DUR}_{2kt})].$$

It is calculated as the product of the marginal cost (C_j) and the average service duration of center j prior to time t for handling question type k (\overline{DUR}_{jkt}). The allocation decision is made based on the average service duration of center j up to time t for handling question type k (\overline{DUR}_{jkt}). It only recognizes the average differential traits of onshore and offshore centers. Customer aspects are completely ignored.

We assume that the same reasons that motivate the firm to assign more cases to onshore centers and the importance of financial consideration still hold under alternative allocation decisions. This allows us to estimate the values of λ_{0j} and λ_1 using the observed data by applying a binary logit model defined by

Equation 12, with expected profit being replaced by $-\{\sum_k D_{ikt} [A_{i1t} (C_1 \overline{DUR}_{1kt}) + A_{i2t} (C_2 \overline{DUR}_{2kt})]\}$, or the product of -1 times service cost, as defined in Equation A1.

The intercept of firm's objective function is estimated at 8.935 (note that λ_{02} is normalized to 0 for identification purpose), indicating that the firm has a greater tendency to route questions to onshore centers. The coefficient of the financial consideration (i.e., cost) is 14.066, implying that financial consideration relates positively to the utility that determines allocation decisions. Assuming the importance of profit does not change under alternative allocation decisions, we use the same scalars as inputs to our proposed allocation framework.

Parameters	Coefficients (Std. Dev.)
Intercept λ_{01}	8.935 (1.910)*
Expected profit λ_1	14.066(0.002)*

Cost-based routing differs from cost-minimization routing (first alternative optimization framework), which nests within our proposed framework. In cost-minimization routing, the cost is given by $-\sum_{m=1}^M \sum_{k=1}^K \text{Pr}_{it}(m) D_{ikt} [A_{i1t} (C_1 DUR_{ijkt}(m)) + A_{i2t} (C_2 DUR_{ijkt}(m))]$, with customer-specific duration predicted by Equation 1. It recognizes customers. In contrast, the cost-based routing calculates service costs based on \overline{DUR}_{jkt} , which only takes into account the average differential traits of onshore and offshore centers and totally ignores customers.

Appendix 2: Probability of Incoming Calls and Waiting Time

To solve the dynamic programming problem at time t , the firm must know whether customer i will call in with question type k from $t + 1$ forward to calculate expected future utilities. Because the type of current calls likely depends on the types of calls in the past, we adopt a first-order Markov chain with three states to approximate the probabilities of incoming question types. Given a call type from the last period D_{ikt-1} , for $k = 0, 1, \text{ and } 2$, with the probability $\rho_1(D_{ikt-1})$, the customer will call with question type $k = 1$, the probability $\rho_2(D_{ikt-1})$ is that he or she will call with question type $k = 2$, and probability $1 - \rho_1(D_{ikt-1}) - \rho_2(D_{ikt-1})$ is the customer does not call. The Bellman equation becomes:

$$(A2) \quad V_{it}(I_{it}, D_{it}) = \max_{A_{ij}} U_{it} + \delta E[\rho_1(D_{ikt-1}) V_{it+1}(I_{it+1}, D_{i1t+1} = 1) + \rho_2(D_{ikt-1}) V_{it+1}(I_{it+1}, D_{i2t+1} = 1) + (1 - \rho_1(D_{ikt-1}) - \rho_2(D_{ikt-1})) V_{it+1}(I_{it+1}, D_{i0t+1} = 1)],$$

where $V_{it+1}(I_{it+1}, D_{ikt+1} = 1)$ is the optimal value function when customer i calls in with question type k at time $t + 1$. Following Hendel and Nevo (2005) and Sun (2005), we approximate the values of $\rho_1(D_{ikt-1})$ and $\rho_2(D_{ikt-1})$ using sample call-in frequencies for $k = 0$, $k = 1$, and $k = 2$ types of questions, as we show in the following table. At $t = 1$, $\rho_1(D_{ikt-1})$ and $\rho_2(D_{ikt-1})$ are given by the starting probabilities .28% and 4.97%, respectively. From $t = 2$ forward, their values are listed as conditional probabilities.

Sample Prob.	Not Call in	Call in with Tech Problem	Call in with Tran Problem
Starting Prob.	94.75%	4.97%	.28%
Not Call-in	89.40%	9.45%	1.15%
Last Call-in with Tech Problem	71.91%	26.50%	1.59%
period Call-in with Tran Problem	80.19%	13.49%	6.32%

When making allocation decisions, the firm must predict waiting times and its possible effect on customer retention. Because we know the average waiting times of the cost-based routing for four time periods during the day for both onshore and offshore centers, we approximate the waiting time as

$$(A3) \quad WAIT_{jt}' = \frac{\sum_{i=1}^I \Pr(A_{ijt}')}{\sum_{i=1}^I A_{ijt}} WAIT_{jt},$$

where $\sum_{i=1}^I A_{ijt}$ and $WAIT_{jt}$ are the observed total number of calls allocated to center j and the average waiting time of center j during the period when customer i calls, respectively. Then $\Pr(A_{ijt}')$ is the percentage of calls allocated to center j , suggested by the proposed allocation A_{ijt}' . Assuming the number of callers in the queue is proportional to the allocation probability, Equation A3 adjusts the waiting time upward (downward) when more (less) customers are allocated to center j , as suggested by the alternative allocation decisions.

Assuming the effective arrival rate is proportional to the allocation probability, we approximate the waiting time as a proportional function of allocation probability. That is, we assume the effective arrival rate is proportional to the allocation probability, and the expected waiting time is proportional to the effective arrival rate around the realized effective arrival rate or probability of allocation. Although we do not provide a comprehensive model for waiting time, our proposed model is consistent with the M/M/1 model (Gans et al 2003) when the arrival rate is sufficiently smaller than the departure rate—a reasonable assumption given the long average service duration in our data. Our modeling of waiting time clearly is a simplification; the extensive queuing theory literature offers more comprehensive waiting time models.

In the simulation, we search for the best allocation rule and resulting waiting time through iteration. Starting from the waiting time ($WAIT_{jt}^0$) that we observe, we calculate a new waiting time $WAIT_{jt}^1$ using the derived allocation. Then $WAIT_{jt}^1$ serves as an input to determine retention, and we derive a new allocation rule. The iteration stops when $WAIT_{jt}^s$ converges such that waiting time is consistent with the proposed allocation rule.

Our data do not feature occasions when customers call with both technical and transactional questions. To take into account this potential situation in more general cases, we could add a fourth choice to D_{ikt} and make it equal 1 if a customer calls for multiple reasons. We also might introduce $\rho_3(D_{ikt-1})$ as the probability that customer i calls with multiple questions and acknowledge customer heterogeneity with respect to their probability of incoming calls. We leave this extension to further research.

Web Appendix: Summary of Computational Algorithm in Simulations

We conduct simulations to derive optimal allocation decisions using our proposed dynamic programming framework in the following main steps.

Step 1: Read in the estimated parameters in the customer response model (Θ), the parameters indicating importance of firm's financial consideration (λ), the observed call history (D_{ikt}), and all the exogenous variables in the customer response models (Equations 1 and 4), and customer demographic variables (i.e., EXP and RESIDENTIAL).

Step 2: Start the customer loop. Within the customer loop, start the time loop for the customer.

Step 3: For each period of time, compute the segment membership probabilities $\Pr_{it}(m)$ (for the first period of time, we use $\Pr_{i0}(m)$ that is derived from the latent class estimates).

Step 4: Start the loop searching for waiting time for each call based on the approach described in Appendix 2.

Step 5: Simulate random draws for the error terms of customer's call duration and retention functions (Equations 1 and 4). Calculate expected service duration ($E[DUR_{ijkt}(m) | I_{it}, A_{it}]$) with Equation 3. Calculate the probability ($\Pr_{it}(RET)(m)$) that consumer i of type m will stay with the firm at time t based on Equation 6. Calculate the firm's the average expected profits according to Equation 10 across all the random draws.

Step 6: Simulate the random draw for the error term of the firm's utility function and compute the average firm's utility across all draws (Equation 11).

Step 7: Derive the simulated optimal call center allocation decisions by solving the Bellman equation (Equation A2) using backward induction.

Step 8: Update the firm's perceived segment membership probability $\Pr_{it}(m)$ periodically according to Equations 7 and 8.

The simulations for other three optimization frameworks in Table 8 are similar for the proposed model. The main difference is that the objective functions in Step 6 and some components in Steps 4–8 differ, according to the different optimization frameworks.