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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 experiences affect 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 through simulations that learning enables a firm to make more customized allocations and that acting on long-term customer responses prompts the firm to make proactive decisions that prevent customers from leaving. As a result, the firm can improve customer retention and 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 allocation, customer retention, customer lifetime value, stochastic dynamic optimization, firm decision support system

## Learning and Acting on Customer Information: A Simulation-Based Demonstration on Service Allocations with Offshore Centers

Initially, organizations built call centers 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 three million agents are employed overseas, and this number is likely to increase by 10% per year (Gilson and

Khandelwal 2005). Most outsourced operations are concentrated in the Philippines and India. Early adopters have achieved savings of 40% or more, usually by operating at significant cost scales. However, Purdue University's (2004) recent survey indicates that despite these significant cost savings, both consumers and business customers report lower satisfaction ratings with outsourced call centers. Thus, outsourcing firms 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 (Purdue University 2004).

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 based on their experience with call centers (Purdue University 2004). The call center industry was among the

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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 customized and interactive marketing decisions. For example, the widespread adoption of the sophisticated automatic call distributor (ACD), an automated switch designed to route calls, enables managers to monitor the progress and flow of agents' work, 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, Richardson, and Webster 2000). Most firms also have a 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 need 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.

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 duration. However, these sensitivities become less pertinent when the offshore centers handle technical questions. In addition, some customers tend to incur longer service duration, but they also care less about being serviced by offshore centers, especially when they have technical questions.

Next, we conduct empirically based simulations and investigate a potential way to use offshore centers more effectively, 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 on it. In other words, we study how firms can use recent information to learn about customers and allocate them 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. We formulate the service allocation problem 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 manner.

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 performance implications with four nested alternative optimization frameworks. We show that accounting for customer preferences reduces the attrition rate by 21.4%. We also find additional attrition rate reductions of 4.4%, 14.9%, and 6.9% by adding customer retention, adding customer lifetime value, and allowing the firm to adaptively learn customers' type, respectively. These improvements in customer retention can be translated into a 7.0%, .3%, 1.6%, and .8% increase, respectively, in total profit.

This study contributes to the understanding of service allocations with offshore centers in several ways. First, our findings 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. Second, we propose a stochastic dynamic framework with long-term marketing consequences, adaptive learning, forward looking, and optimization to model a firm's service allocation decisions with offshore centers. Through simulations, we demonstrate that the proposed framework may significantly improve the firm's service allocation decisions and achieve higher profits and retention rates. Finally, although the study pertains to service channel allocations, the proposed dynamic framework can be generalized to other marketing-mix decisions, such as promotion, cross-selling, and targeted Web advertising.

#### PRIOR LITERATURE

The marketing field 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, Kalra, and Staelin 1999; Boulding et al. 1993; Kamakura et al. 2005; Li, Sun, and Wilcox 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, Semester, and Wernerfelt 1994), the relationship between 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, Fornell, and Rust 1997), and customer lifetime value (Gupta, Lehmann, and Stuart 2004; Reinartz and Kumar 2000, 2003; Rust, Lemon, and Zeithaml 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; Gönül and Shi 1998; Kamakura et al. 2002; Lewis 2005; Netzer, Lattin, and Srinivasan 2008; Rust and Verhoef 2005; Venkatesan and Kumar 2004). However, despite the increasing importance of call centers in shaping customer service experience, no marketing research has specifically investigated how customers react to a firm's service channel assignment or studied how the resulting service treatment might affect customer attrition and long-term customer value.

Our proposed framework has the following characteristics: First, with the exception of Gönül 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, using demographic variables and pooled historical data, which result in a score ranking of customers. In contrast, we propose adaptive learning through continuous interactions, during which the firm adopts and integrates customer feedback from the most recent decision execution into its periodic decisions. 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.

#### *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 the continental United States 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 inquiries about billing, e-mail accounts, product news, product services, and registration. When a customer calls, the automated system asks him or her to punch in the type of questions before routing. The customer may experience some waiting time before an agent addresses the call, without knowing for which center he or she is waiting. After an agent picks up a call, 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 manner, 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 refer more cases to supervisors in their center. In addition, offshore centers are often less well equipped to solve technical problems.

Because of significant labor costs, the firm calculates service costs primarily on the basis of the labor costs related to the total time agents remain occupied with a case.<sup>1</sup>

<sup>1</sup>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 telephone costs, waiting time does not incur labor costs

Accordingly, the company measures the service duration as the total time of the service encounter—from the time the agent picks up the telephone 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 rare exceptions when agents must perform some task after the call. This measurement is consistent with operation management literature (Gans, Koole, and Mandelbaum 2003).

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 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 9643 calls (we did not include calls to disconnect service) initiated by 2106 randomly selected customers during 52 weeks between January 2003 and December 2003. Our holdout sample contains 1053 customers, who made a total of 4661 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 before our observation period. Furthermore, we have customer demographic information, including tenure with the firm, 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.

Table 1 lists the definitions and sample statistics of the customer variables. For example, customers paid \$99 to terminate their contract prematurely in 1.58% of all observation occasions. Mostly (62%) residential rather than business, these customers initiated an average of 6.01 service calls per person, and 90% were technical questions. The

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 account for its effect on customer attrition. Accordingly, when we run simulations, we consider the different waiting times caused by the proposed service allocation decisions (see Equation 16). 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.

Table 1  
VARIABLE DEFINITIONS AND SAMPLE STATISTICS

Variable	Definition	M (SD)
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	.17 (.37)
PENALTY	Penalty fee for terminating a contract prematurely	\$99.00 (\$.00)
NCOMPUTER	Number of computers owned by the caller	1.63 (.77)
EXP	Caller expertise self-rating: 1 = "extremely inexperienced/novice," and 5 = "extremely experienced/expert"	3.11 (1.02)
RESIDENTIAL	Whether the caller is a residential customer	.62 (.49)
NCALLS	Total cumulative number of calls	6.01 (18.15)
TECHNICAL	Whether the call is about a technical question	.90 (.30)
FREQ_OFF	The recency-weighted frequency of being serviced by offshore centers	.30 (.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	.84 (.36)

average waiting times, divided by four periods during a day (8–12, 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. During the observation period, 16% of customers left. We chose weeks as our unit of analysis and rated variables, such as prices, accordingly.

Table 2 lists and compares the allocation, service duration, and retention rates between centers and question types.<sup>2</sup> 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 (versus 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

<sup>2</sup>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.

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,  $t = 11.3$ ), the difference in retention rates is much smaller for technical questions (.87 versus .84,  $t = 4.6$ ).

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. If we take into account the significantly lower marginal service costs, the offshore centers in our data set have more cost advantages than the onshore centers for handling technical questions. Moreover, although customers prefer to be serviced by onshore centers, according to their retention rates, they are less sensitive to offshore centers handling their technical questions.

### 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.<sup>3</sup> We also assume that there are  $m = 1, \dots, M$  segments of customers.<sup>4</sup>

We use three dummy variables,  $D_{ikt}$  for  $k = 0, 1, 2$ , to denote whether customer  $i$  calls with question type  $k$  at time  $t$ , with  $k = 0$  representing the case in which customer  $i$  does not call. Thus,  $D_{i0t} + D_{i1t} + D_{i2t} = 1$ . 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

<sup>3</sup>For simplicity, we consider two service centers and two types of questions; we ignore differences in service duration among agents in the same center. The proposed approach can be generalized to incorporate multiple service centers, multiple questions, and multiple agents.

<sup>4</sup>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.

Table 2  
COMPARATIVE ADVANTAGES

	Onshore			Offshore		
	Overall	Transactional	Technical	Overall	Transactional	Technical
ALLOCATION	.84 (.37)	.11 (.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)

Notes: Standard deviations are in parentheses.

define a vector  $D_{it} = (D_{i0t}, D_{i1t}, D_{i2t})'$  and the vector  $A_{it} = (A_{i1t}, A_{i2t})'$ .<sup>5</sup>

### Service Duration

Intuitively, service duration could be determined by the traits of service centers, question types, and customers. Following Mandelbaum and Schwartz (2002), who show that call duration can be captured best by a log-normal distribution, we assume that the log of call duration  $\log[\text{DUR}_{ijkc}(m)]$  for customer  $i$  of segment  $m$  for all call occasions is given by

$$(1) \log[\text{DUR}_{ijkc}(m)] = \alpha_0(m) + \alpha_1(m)D_{i2c} + \alpha_2(m)A_{i2c} \\ + \alpha_3(m)A_{i2c}D_{i2c} + \alpha_4(m)\log[\text{DUR}_{ijkc-1}(m)] \\ + \alpha_5(m)\text{NCOMPUTER}_i + \xi_{ijkc}(m), \text{ and}$$

$$(2) \xi_{ijkc}(m) \sim N[0, \sigma_{\xi}^2(m)],$$

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.<sup>6</sup> 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 duration of offshore centers. If  $\alpha_2(m) > 0$  and  $\alpha_3(m) < 0$ , offshore centers are slower in general than onshore centers. However, the difference is smaller when offshore centers handle technical questions. The variable  $\log[\text{DUR}_{ijkc-1}(m)]$  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  $\text{NCOMPUTER}_i$ , or the number of computers the caller owns, to note the possibility that 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.

Thus, Equation 1 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 as follows:

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

### Customer Retention

We 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  $W_{it}(m)$ :

$$(4) \quad W_{it}(m) = \beta_0(m) + \beta_1(m)\text{SAT}_i + \beta_2(m)\text{FEE}_{it} + \beta_3(m)\text{PROM}_{it} \\ + \beta_4(m)\text{COMP}_{it} + \beta_5(m)\log(\text{TENURE}_{it}) \\ + \beta_6(m)\text{PENALTY}_{it} + \beta_7(m)A_{i2t} + \beta_8(m)A_{i2t}D_{i2t} \\ + \beta_9(m) \sum_{j,k} \{D_{ikt}A_{ijt} \log[\text{DUR}_{ijkc}(m)]\} \\ + \beta_{10}(m) \left( \sum_{j,k} \{D_{ikt}A_{ijt} \log[\text{DUR}_{ijkc}(m)]\} \right)^2 \\ + \beta_{11}(m)\text{WAIT}_{jt} + \beta_{12}(m) \sum_{\tau=1}^t \sum_{k=1}^K D_{ikt\tau} \\ + \beta_{13}(m)\text{FREQ\_OFF}_{it} + \beta_{14}(m)\text{ACCUM\_DUR}_{it} \\ + \zeta_{it}(m).$$

In this equation,  $\text{SAT}_i$  is the customer's overall satisfaction with the firm, measured at the beginning of the observation period. We expect its coefficient to be positive (Bolton 1998). The variables  $\text{FEE}_{it}$  and  $\text{PROM}_{it}$  are fees and promotions specific to customer  $i$  at time  $t$ . In addition,  $\text{COMP}_{it}$  is a dummy variable indicating the presence of competitors, such as cable service, in the geographic area in which customer  $i$  resides. Switching costs also play an important role in determining customer retention. We include  $\log(\text{TENURE}_{it})$  to control for the effect of the length a customer stays with the firm on customer attrition; the log of this variable allows for its possible nonlinear relationship to customer retention, which may be caused by the one-year contract signed by some customers. To account for 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. 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

<sup>5</sup>As we mentioned previously, the data were generated by cost-based routing. By ignoring customer preferences, cost-based routing does not take into account customer-specific call 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.

<sup>6</sup>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 noncall occasions as well.

$\beta_7(m) < 0$  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.

However, as the information in Table 2 demonstrates, service duration varies significantly and might define differential customer service experiences with onshore and offshore centers. We expect the coefficient of  $\sum_{j,k} \{D_{ijt} A_{ij} \log[DUR_{ijkt}(m)]\}$  to be positive because, controlling for everything else (e.g., expertise, number of computers), customers who need help may appreciate an agent who spends a reasonable amount of time listening to their explanation of the problem and then provides solutions in a timely manner.<sup>7</sup> However, customers can quickly become impatient and unhappy when a service call lasts too long, they are put on hold, or their cases are referred 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 must wait before his or her call is answered, or  $WAIT_{jt}$ . 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 has a 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 before 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; Gönül 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.

We use the vector  $\beta(m)$  to represent all coefficients in customer retention in 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

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

Let  $\overline{W}_{it}(m)$  be the right-hand side of Equation 4 without the error term  $[\zeta_{it}(m)]$ . Assuming that  $\zeta_{it}(m)$  follows an independent, identical extreme value distribution, the probability of customer  $i$  staying with the firm at time  $t$  can be represented as follows:

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

### Heterogeneity and Estimation

We use maximum likelihood to estimate  $\alpha(m)$  and  $\beta(m)$ , which parameterize the effects of service allocation decisions on duration and customer retention. To account for 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. Therefore, we 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 the best of its knowledge so that it can maximize long-term expected profits.

#### 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 using demographic variables and know the average probabilities of a customer belonging to a segment, we define the prior belief of customer type  $Pr_{i0}(m)$  as the probability of segment membership, resulting from the latent class approach in the estimation.

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 telephone and likely incur longer service durations. Customer retention observations reveal the customers' reactions to service allocations. For example, if a customer leaves because he or she is serviced by an offshore center, this implies that the customer is sensitive to offshore centers.

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

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

<sup>7</sup>As Gans, Koole, and Mandelbaum (2003) discuss, short calls sometimes occur because agents take small "rest breaks" by hanging up on customers.

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  $\{[\Pr(DUR_{ijkt-1}|m=n)/\Pr(DUR_{ijkt-1}|m=1)][\Pr(RET_{it-1}|m=n)/\Pr(RET_{it-1}|m=1)]\} > 1$ , the likelihood that customer  $i$  belongs to  $m = n$  group increases. When customers do not call,  $\{[\Pr(DUR_{ijkt-1}|m=n)]/[\Pr(DUR_{ijkt-1}|m=1)]\} = 1$ , and the belief is 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

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

*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:

$$(9) \quad \text{PROFIT}_{it} = \sum_{m=1}^M \Pr_{it}(m)RET_{it} \left( \text{FEE}_{it} - \sum_k D_{ikt} \{A_{i1t}[C_1DUR_{i1kt}(m)] + A_{i2t}[C_2DUR_{i2kt}(m)]\} \right)$$

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 before time  $t$  for all  $j = 1, 2$  and  $k = 1, 2$ . For simplicity, we use  $I_{it} = \{DUR_{it-1}^H, RET_{it}^H, \text{and } FREQ\_OFF_{it-1}^H\}$  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 as follows:

$$(10) \quad E[\text{PROFIT}_{it} | I_{it}, A_{it}] = \sum_{m=1}^M \Pr_{it}(m) \Pr_{it}(RET)(m) FEE_{it} - \sum_{k=1}^K D_{ikt} \{A_{i1t} C_1 E[DUR_{i1kt}(m) | I_{it}, A_{it}] + A_{i2t} C_2 E[DUR_{i2kt}(m) | I_{it}, A_{it}]\}$$

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 the 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  $U_{it}$ :

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

Scalar  $\lambda_{01}$  captures the firm’s intrinsic preference to allocate a service call to onshore centers because of factors that are unobserved to the researchers (utilization of capacity is approximated by waiting time as we explain subsequently), and  $\lambda_1$  measures the importance of expected profit in determining the firm’s allocation decisions (relative to the error term). Equation 11 describes a more realistic situation that nests the special case when the firm’s allocation decision is driven solely by financial considerations. The term  $\tau_{ijkt}$  denotes all the unobserved random 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  $\tau_{ijkt}$  when customer  $i$  calls in with question of type  $k$  and is allocated to center  $j$ . Assuming that  $\tau_{ijkt}$  has an i.i.d. 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

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

We estimate the values of  $\lambda_{0j}$  and  $\lambda_1$  from the binary logit model independent from the customer response models.

To account for 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  $i$ :

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

where  $0 < \delta < 1$  is the discount factor that reflects that current utility is preferred to future utility (Erdem, Imai, and Keane 2003; Erdem and Keane 1996; Krishna 1994a, b; Sun 2005; Sun, Li, and Zhou 2006). Thus, the optimal allocation decision is the solution to the Bellman equation:

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

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

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  $k = 0, 1$ , and  $2$ , with the probability  $\rho_1(D_{ikt-1})$ , the customer will call with question type  $k = 1$ ; with the probability  $\rho_2(D_{ikt-1})$ , he or she will call with question type  $k = 2$ ; and with the probability  $1 - \rho_1(D_{ikt-1}) - \rho_2(D_{ikt-1})$ , the customer will not call. The Bellman equation becomes the following:

$$(15) \quad V_{it}(I_{it}, D_{it}) = \max_{A_{ijt}} U_{it} + \delta E[\rho_1(D_{ikt-1})V_{it+1}(I_{it+1}, D_{i1t+1} = 1) + \rho_2(D_{ikt-1})V_{it+1}(I_{it+1}, D_{i2t+1} = 1) + [1 - \rho_1(D_{ikt-1}) - \rho_2(D_{ikt-1})]V_{it+1}(I_{it+1}, D_{i0t+1} = 1)],$$

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 (2006) 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. Table 3 reports the sample statistics.

Similarly, when making allocation decisions, the firm must predict waiting times and their possible effect on customer retention. However, because of data unavailability, we do not explicitly model the firm's capacity constraint in the proposed framework. Instead, we approximate the waiting time as a proportional function of allocation probability. That is, we assume that the effective arrival rate is proportional to the allocation probability and that the expected waiting time is proportional to the effective arrival rate around the realized effective arrival rate. Because we observe the average waiting times of the cost-based routing for four periods during the day for both onshore and offshore centers, we approximate the waiting time as follows:

$$(16) \quad WAIT'_{jt} = \frac{\sum_{i=1}^I \Pr(A'_{ijt})}{\sum_{i=1}^I A_{ijt}} WAIT_{jt},$$

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. The term  $\Pr(A'_{ijt})$  is the percentage of calls allocated

Table 3  
PROBABILITY OF INCOMING CALLS

	Sample Probability		
	Not Call in (%)	Call in with Technical Problem (%)	Call in with Transactional Problem (%)
Starting probability	94.75	4.97	.28
<i>Last Period</i>			
Call in with technical problem	71.91	26.50	1.59
Call in with transactional problem	80.19	13.49	6.32
Not call in	89.40	9.45	1.15

Notes: At  $t = 1$ , we give  $\rho_1(D_{ikt-1})$  and  $\rho_2(D_{ikt-1})$  and by the starting probabilities .28% and 4.97%, respectively. From  $t = 2$  forward, we report the conditional probabilities calculated from the sample in the table.

to center  $j$ , suggested by the proposed allocation  $A'_{ijt}$ . Assuming that the number of callers in the queue is proportional to the allocation probability, Equation 16 adjusts the waiting time upward (downward) when more (fewer) customers are allocated to center  $j$ , as suggested by the proposed allocation decisions.

Given the first-order Markov model of customer call-in, the log-normal model of the service duration, and the assumption that the number of agents stays the same at both onshore and offshore centers without call abandonment, retrials, and returns, we approximate the expected waiting time (or the capacity utilization rate). Though not a comprehensive model for waiting time, our proposed approach is consistent with the M/M/N model (Gans, Koole, and Mandelbaum 2003), a common modeling approach that both operation management academics and practitioners use to approximate the stationary call center system performance of short time intervals (e.g., a half hour) when the arrival rate is sufficiently smaller than the departure rate—a reasonable assumption given the long average service duration in our data. We acknowledge that our modeling of waiting time is a simplification (for comprehensive waiting time models, see Gans, Koole, and Mandelbaum 2003; Mandelbaum 2002).

To solve the dynamic program problem, we undertake two iterative steps: First, 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 second, 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."<sup>8</sup> Adaptive learning enables the firm to follow customers and improve the accuracy of its knowledge about each individual customer. Because the state variables are continuous, we face the problem of a large state space and therefore adopt the interpolation method that Keane and Wolpin (1994) develop to calculate the value functions for a few state space

<sup>8</sup>Conjoint analysis research adopts similar ideas to reveal consumer preferences (Toubia et al. 2003).

points. (The Web Appendix at <http://www.marketingpower.com/jmrfeb11> provides more details.)

The solution results in a sequence of intertemporally related, optimal allocation decisions for all calls initiated by each customer. The proposed allocation decisions should be 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. The allocation decisions should also be proactive because, by taking into account the long-term consequences of alienating customers, the firm can sacrifice short-term costs by allocating a customer to his or her desired center to prevent defection and improve long-term profits.

### EMPIRICAL RESULTS

In this section, we first discuss the parameter estimates  $\Theta$  based on the calibration sample that characterize the relationship of the firm's allocation decision, service duration, and customer retention, and then we compare various customer response models using both the calibration and the holdout samples. On the basis of these estimated parameters, we conduct simulations using our proposed framework to derive the sequence of optimal allocation decisions  $A_{ijt}$  based on the calibration sample. We investigate whether and how the proposed approach offers improvements over four nested alternative frameworks.

#### Estimation

*Model comparison.* To determine whether our proposed model describes customer responses better than 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, which 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. 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 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, in general, it 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, a lack of competition, and a long history with the firm. Not surprisingly, a price penalty prevents customers from leaving. When serviced by offshore centers, both customer segments are more likely to leave, consistent with the Purdue University (2004) study findings. 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 offshore centers' servicing technical questions. 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 manner. As we expected, both segments react negatively to longer waiting times. The greater the total number of questions, the less likely are customers 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

Table 4  
MODEL COMPARISON

Models	Calibration Sample			Holdout Sample		
	LL	BIC	AIC	LL	BIC	AIC
<i>Benchmark Response Models</i>						
1	-27,175.4	54,466.3	54,408.8	-13,455.2	27,016.7	26,968.3
2	-23,896.8	47,949.0	47,871.7	-11,845.2	23,833.5	23,768.4
3	-14,473.3	29,125.8	29,036.5	-7182.3	14,529.6	14,454.5
<i>Proposed Response Model</i>						
1 segment	-16,177.7	32,462.9	32,409.4	-8056.4	16,211.8	16,166.7
2 segments	-13,061.7	26,318.7	26,221.4	-6422.7	13,025.1	12,943.3
3 segments	-23,393.8	47,082.5	46,935.7	-11,418.7	23,108.9	22,985.5

Notes: LL = log-likelihood, BIC = Bayesian information criterion, and AIC = Akaike information criterion. Benchmark Model 1 is the proposed model without duration and waiting time, offshore dummy, and the interaction between offshore and technical question dummy; Model 2 is the proposed model without offshore dummy and the interaction term; and Model 3 is the proposed model without the interaction term. The AIC and BIC show that the four customer response models with two latent segments fit the data best. (Because of space constraints, we present only the results of the two-segment version for the benchmark models.)

**Table 5**  
COMPARISON WITH SAMPLE STATISTICS

Statistics	Actual	Calibration Model (SD)
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 (SD)	
	Segment 1	Segment 2
Segment membership	.663 (.005)*	.337 (.005)*
Intercept	1.065 (.018)*	.000 (.000)
EXP	.079 (.011)*	.000 (.000)
RESIDENTIAL	-1.019 (.028)*	.000 (.000)
<i>Log(Duration) (Regression)</i>		
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)*
<i>Retention (Binary Logit)</i>		
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) <sup>2</sup>	-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)*
ACCUM_DUR	-3.795 (.161)*	-1.462 (.200)*

\*The estimates are significant at the 95% probability level.

Notes: 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 and RESIDENTIAL) in the segment membership equation. For identification purposes, we normalize the coefficients for Segment 2 to 0.

stay; the recency-weighted total service duration has negative effects on retention, such that customers 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 are in the first segment and 33.7% are 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 price than 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,

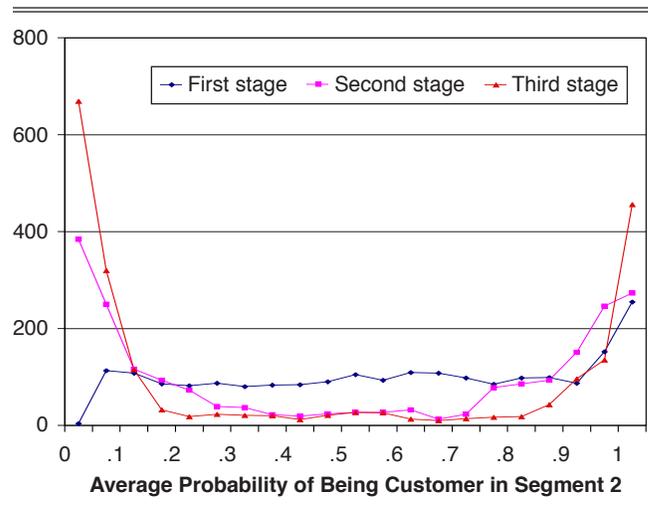
in the duration equation, the intercept and, in the retention equation, the intercept, the coefficients of being serviced by offshore centers, the coefficients of the log of the squared duration, and the interaction between offshore and technical questions. All else being equal, customers in the first 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 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, when we examine the latent class segmentation, it is not intuitively clear which segment should be allocated to offshore centers. For example, although 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. We simulate customer service duration and retention using a calibration sample; these could change with alternative service allocation decisions. We demonstrate the effectiveness of adaptive learning (Figure 1), show how our proposed allocations are tailored to

**Figure 1**  
PERCENTAGE OF CUSTOMERS IN SEGMENT 2 BY PERIOD



the firm's updated information about customer preferences (Figure 2, Panels A and B), establish how service allocation decisions may be driven by long-term marketing consequences (Figure 2, Panel C), and compare the improvement for the proposed model with four nested optimization frameworks (Table 7).

Using the estimated parameters ( $\Theta$ ), the observed call history ( $D_{ikt}$ ), covariates in the customer response model that are exogenously given, customer demographic variables, importance of firm's financial consideration ( $\lambda$ ), and probability of future arrival rate ( $\rho$ ), we simulate optimal allocation decisions ( $A_{ijt}^*$ ).<sup>9</sup> To account for customer aspects, 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  $\delta$  to .995 (Erdem and Keane 1996) and then obtain the optimization by solving the Bellman equation.

*Learning about customer type.* In Figure 1, 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 begin 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 a Segment 2 customer. Approximately 34% are classified to Segment 2 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 summary statistics of the proposed allocations in Table 8 and compare them with observed cost-based allocation decisions. Our proposed approach increases the case assignments to offshore centers from 16% to 19%. Although this increase is marginally noticeable, the composition of question types and customer types change significantly. Among the technical questions, 20% are assigned to offshore cen-

<sup>9</sup>We estimate the values of  $\lambda_{0j}$  and  $\lambda_1$  using the observed data by applying a binary logit model defined by Equation 12, with expected profit being replaced by  $-\{\sum_k D_{ikt}[A_{11t}(C_1 \text{DUR}_{1kt}) + A_{12t}(C_2 \text{DUR}_{2kt})]\}$ . We estimate the intercept of the firm's objective function at 8.94 with standard deviation of 1.91 (we normalize  $\lambda_{02}$  to 0 for identification purpose), indicating that the firm has a greater tendency to route questions to onshore centers (factors that are different from capacity constraint and are unobservable to researchers). The coefficient of the financial consideration is 14.07 with standard deviation of .002, implying that financial consideration (i.e., cost) plays an important role in determining allocation decisions. Because we do not explicitly model capacity constraint and the approximation of waiting time is subject to assumptions in the proposed framework, the values of  $\lambda_{0j}$  and  $\lambda_1$  should be interpreted with caution.

Figure 2  
ALLOCATION FUNCTION

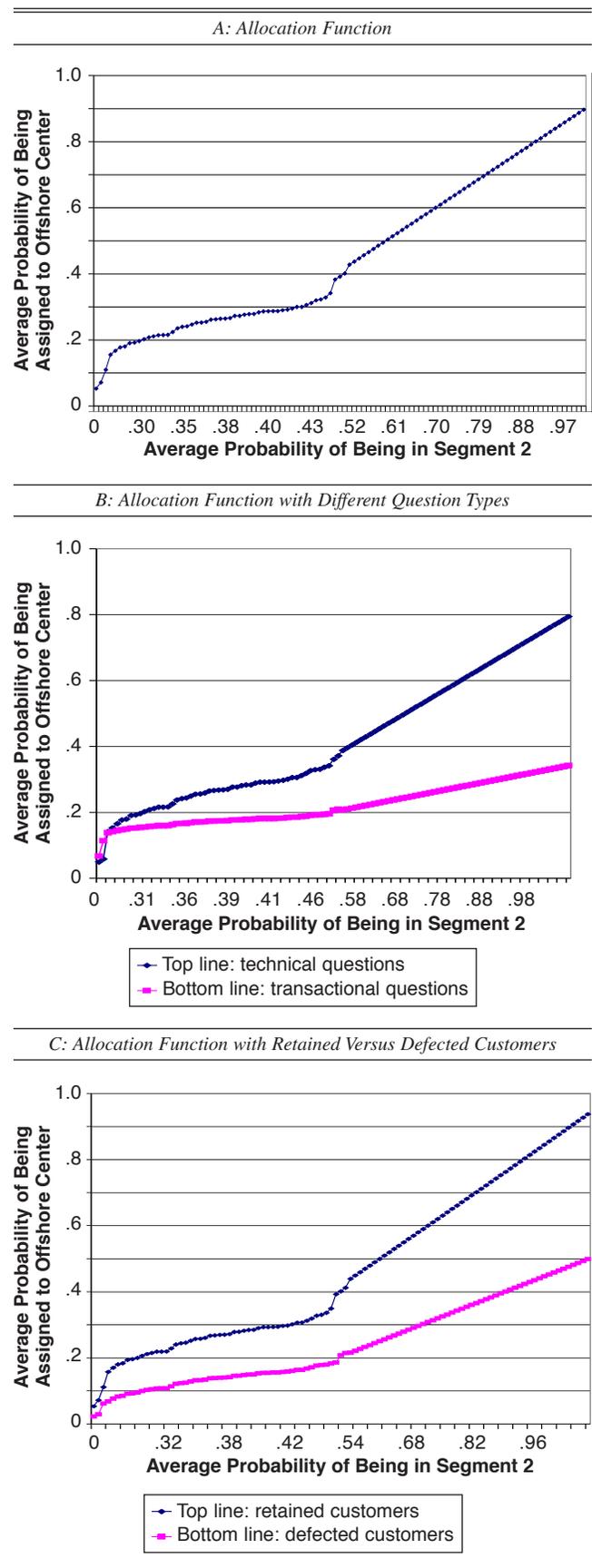


Table 7  
PERFORMANCE COMPARISON ACROSS OPTIMIZATION  
FRAMEWORKS

Optimization Framework	Accumulated Total Profits (\$)	Accumulated Total Costs (\$)	Retention Rate at Last Period (%)
Observed routine	108,984.0	717,204.5	84.00
Alternative nested framework 1	153,214.0	668,619.0	85.26
Alternative nested framework 2	163,879.6	661,692.9	88.42
Alternative nested framework 3	164,346.8	680,782.3	89.07
Alternative nested framework 4	166,797.2	679,539.3	91.26
Proposed framework	167,988.7	669,039.1	92.27

ters, 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 are 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 2, Panel A, we depict the average probabilities of assigning a customer to an offshore center  $\{\Pr(A_{i2t}) = \exp[\bar{U}_{it}(A_{i2t})]/\sum_j \exp[\bar{U}_{it}(A_{ijt})]\}$  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 the individual customer.

However, the relationship will likely be modified by exogenous variables such as question type. Therefore, in Figure 2, Panel B, we compare the allocation functions between transactional and technical questions. For the same perceived likelihood of belonging to Segment 2, the firm is more likely 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 2, 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 noticeably lower 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.

*Alternative optimization frameworks.* Our proposed framework enhances cost-minimization routing in at least four important components: the human aspects represented by customer-specific service duration, customer retention, adaptive learning, and long-term customer value. We are interested in comparing the performance of our proposed framework with four nested optimization frameworks and investigating how adding each of these components helps the firm improve retention rate and profit. To make the simulation results comparable, we assume that the firm maximizes profit (or  $\lambda_0 = 0$  and  $\lambda_1 = 1$ ) in all the five competing frameworks. The first alternative framework (Alternative 1, cost-minimization framework without considering customers) is similar to cost-based routing, which generated our data: When determining the allocation of incoming calls, the firm allocates calls to the center with lower average historical service durations, which is calculated as  $\sum_k D_{ikt}[A_{i1t}(C_1 \bar{DUR}_{1kt}) + A_{i2t}(C_2 \bar{DUR}_{2kt})]$ , the product of the marginal cost ( $C_j$ ) and the average service duration of center  $j$  before time  $t$  for handling question type  $k$  ( $\bar{DUR}_{jkt}$ ). It only recognizes the average differential traits of onshore and offshore centers. Customer aspects are completely ignored. In the second alternative framework (Alternative 2, cost-minimization framework with customer-specific duration), the cost is given by  $\sum_m = 1 \sum_k = 1 \Pr_{it}(m) D_{ikt} \{A_{i1t}[C_1 \bar{DUR}_{ijkt}(m)] + A_{i2t}[C_2 \bar{DUR}_{ijkt}(m)]\}$ . Unlike Alternative 1, which calculates service costs according to  $\bar{DUR}_{jkt}$ , this framework recognizes customers by predicting service costs according to the service duration predicted by customer response Equation 1. Alternative 3 adds customer retention to the second framework, such that the firm accounts for customer retention but remains myopic. In Alternative 4, we add the forward-looking customer lifetime value but not continuous learning to the third framework. Finally, the fifth framework also includes adaptive learning; it represents our proposed framework.

Table 8  
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%

We compare performance improvements across the five alternative frameworks in Table 7; every component contributes to improve retention rates and profit. Specifically, compared with cost-minimization routing, which completely ignores customer preferences (Alternative 1), cost-minimization considering customer-specific duration (Alternative 2) reduces the attrition rate by 21.4%. Moreover, there will be an additional customer attrition reduction of 4.4% by accounting for customer retention (Alternative 3), an additional 14.9% by adding customer lifetime value (Alternative 4), and an additional 6.9% by further allowing the firm to adaptively learn the customer's type (proposed framework). These numbers correspond to a 3.7%, .8%, 2.6%, and 1.2% improvement in retention rate, which can be translated into a 7.0%, .3%, 1.6%, and .8% increase in profit over the cost minimization without considering customers.<sup>10</sup> Thus, more customized and proactive decisions that result from our proposed framework help firms increase customer retention and improve long-term customer value or profit.

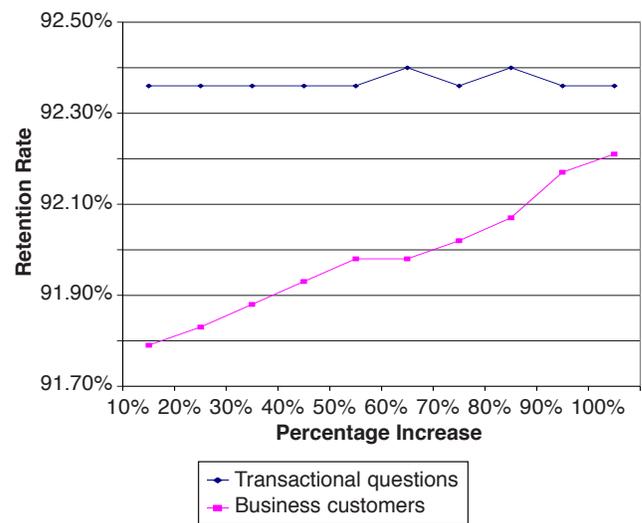
*Improvement over cost-minimization routing.* As Table 8 indicates, attrition rates are approximately 8% with the proposed allocations, a 50% reduction in the attrition rate compared with Alternative 1. To investigate how sensitive the improvement is to the mix of customer types, we increase the percentages of business customers from 0% to 100% and report the customer retention rate at the end of the observation period (Figure 3, Panel A) and the total profit accumulated over the observation period (Figure 3, Panel B) resulting from our proposed framework. When the percentage of business customers is relatively low, the higher the percentage of business customers, the more effective is the proposed approach 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 begins to decrease at the peak of approximately 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 affect retention significantly (Table 2). However, because 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 remains almost constant. These results demonstrate that the improved cus-

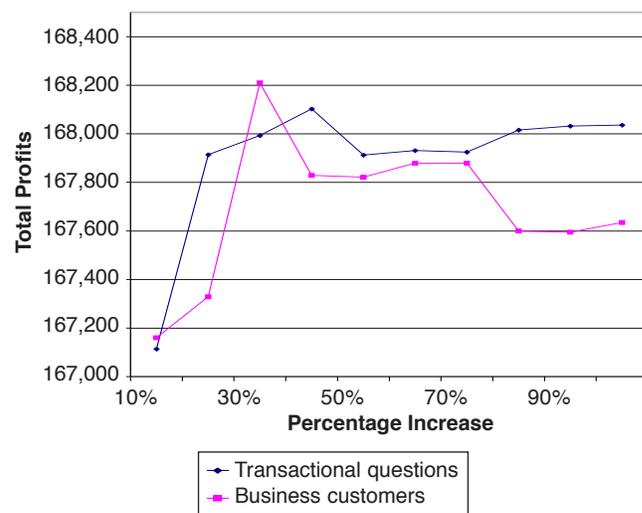
<sup>10</sup>We thank the associate editor for this suggestion. We cannot directly compare the performance of our proposed framework with that of the observed cost-based routing. We need to have the same  $\lambda$ s in the firm's objective function to make the simulation results comparable. Thus, we assume that  $\lambda_0 = 0$  and  $\lambda_1 = 1$  in Equation 11 when preparing Table 7 and Figure 3. This will not significantly affect the comparison results because the comparison is based on the proposed model of the world. We also repeat the same exercise assuming  $\lambda_0 = 8.94$  and  $\lambda_1 = 14.07$ , the values estimated using the observed data. The percentages of attrition rate reduction are 20.5%, 4.3%, 14.0%, and 6.5%, which shows similar improvement when we consider additional components.

Figure 3  
IMPACT ON RETENTION RATE

A: Impact of Percentage Change of Transactional Questions or Business Customers on Retention Rate



B: Impact of Percentage Change of Transactional Questions or Business Customers on Total Profits



tom 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.

### 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 cus-

customer attrition. 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 provide empirical evidence about how the firm's service allocation decisions affect service duration and customer retention. Because of their significantly lower service costs per minute, the offshore centers we study have comparative advantages over onshore centers when it comes to technical questions. Customers 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. Using the estimated parameters, we conduct simulations, apply our proposed framework to derive the optimal call allocation decisions, and demonstrate that adaptive learning enables the firm to improve its allocation decisions by matching customers with their preferred service centers. Forward looking and optimization enable the firm to make proactive decisions to act on its knowledge about customers and long-term marketing consequences. The simulation results show that by recognizing customer aspects and accounting for customer retention and customer lifetime value, our proposed model significantly reduces attrition rate and also improves profit. In other words, firms may be better off by continuously managing and acting on customer information.

Our results provide the first empirical evidence about understanding customer reactions to a firm's service channel allocation decisions. Through a simulation-based demonstration on 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. Learning about customers in a continuous manner and on the basis of their feedback to the firm's most recent decisions, 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. Moreover, it 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, because of data constraints, we make some simplified assumptions about the operations management of service allocation decisions, such as queuing, waiting time, abandonment, and retries. We also cannot separate active talking time from holding time. Further research could examine how these variables affect customer retention. Second, this study is

mainly based on simulations. Research could use field experiments to test and generalize the results further. Third, we assume the customer preferences are static. Research could develop more sophisticated learning routines to allow for dynamic changes in customer preference. Researchers could also integrate different approaches, such as hierarchical Bayes, into the proposed framework to learn more about customer heterogeneity (Allenby, Arora, and Ginter 1998; Allenby and Rossi 1999; Rossi, McCulloch, and Allenby 1996). Fourth, possible price and capacity endogeneity issues could be investigated, and capacity constraint could be explicitly modeled. For example, firms usually increase prices when service quality improves. Firms also may adjust their capacity as a result of improvements in efficiency. Last, because agents at call centers can learn and become more efficient over time, there may be call center heterogeneity on capacity and equipment (e.g., offshore centers may be less well equipped to solve technical problems). Additional research could account for these factors.

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