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

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Abstract

Since the 1990s, the role of call centers has transformed from a cost to be minimized to a crucial element that performs integrated marketing functions. Call centers have become among the most crucial corporate assets to grow customer relationships and firm profits.

Using customer call history data from a DSL service, we empirically investigate how customers' onshore and offshore service experience affect service duration and customer retention and parameterize the relationship among service allocation, service duration, and customer retention. We then formulate firms' call allocations as a matching problem in which the firm learns about heterogeneous customer preferences, balances the trade-offs between short-term service costs and long-term customer reactions, and makes optimal service allocations that maximize long-term profit.

On the basis of the estimation results, we conduct simulations to derive optimal service allocation decisions. We demonstrate that learning enables a firm to make more "customized" allocations tailored to customer preference. Acting on long-term marketing consequences prompts the firm to make "proactive" decisions that prevent customers from leaving. We show that by integrating learning and acting on customer information, the derived optimal allocation decisions (1) reduce service costs, (2) improve customer retention, and (3) enhance profit.

Our findings provide empirical evidence about how customers evaluate offshore centers and shed new light on the drivers of customer retentions, namely, service allocations in general and offshore centers in particular. With the application to service channel allocations, the proposed framework mirrors the recent trend of companies seeking solutions that entail customized and dynamic marketing mix interventions to grow long-term customer profit.

Keywords: call center; service outsourcing; service allocation; service duration; customer retention; customer profitability; long-term customer value; adaptive learning; matching; customer-centric CRM; stochastic optimization

> Of concern for U.S. companies considering offshore outsourcing is that 65% of American consumers would alter their buying behavior toward a company if they know or had the impression the business was using an offshore service center. As American companies consider opening call centers in other countries to serve and sell to U.S. customers, they would be wise to weigh their expected cost benefits against the possibility of potentially alienating their American customers. With this in mind, companies would be prudent to view their customer support call centers as crucial elements of their customer strategy, akin to marketing and loyalty programs.
>
> —*Call center study led by Purdue University's Center for Customer-Driven Quality, 2004*

1. Introduction

Call centers were born of a basic need: Answer in-bound customers' questions. In 1972, Continental Airlines asked the Rockwell Collins division of Rockwell International (now Rockwell Automation) to develop the first automated call distributor, thus launching the call-center industry. Today, all *Fortune* 500 companies have at least one call center. A total of 2.9 million agents are employed at 55,000 facilities in North America, and more than $300 billion is spent annually on call centers around the world.

Because call centers initially were built to deal with customer inquiries, their management traditionally has been considered little more than a cost to be minimized. This attitude led to the increasing popularity of outsourcing. Currently, more than 3 million agents are employed overseas, and this number is predicted to increase by 10% per year (McKinsey Quarterly 2005). Most of the outsourced operations are concentrated in the Philippines and India. Early adopters of outsourcing have achieved savings of 40% or more, generally operating at significant scales. However, a recent survey by Purdue University (2004) indicates that despite the significant cost savings, both consumer and business customers report significantly lower satisfaction ratings with outsourced call centers. Some of the top problems reported are “less well trained staff” and the agents “were unable to resolve my problem.” The survey further shows that 65% of American consumers would alter their buying behavior toward a firm if they knew or had the impression that the business was using an outsourced service center. Outsourcing firms have realized that the initial effort of driving down costs is paid for by alienating customers, and in some cases, customer defections and hidden costs outweigh the potential savings derived from outsourcing (*Offshore Digest* 2005). Although some companies continue to increase their investments in outsourcing, others, such as Dell Computer and Delta Airlines, recently took back their call-center operations from outsourced vendors.

The outsourcing controversy thus calls for research to evaluate the human reactions to outsourced centers and possibly provide innovative approaches to more effectively utilize less expensive off-shore centers. However, call 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). Customer responses to service allocation such as customer satisfaction, retention, and repeat purchase are simply described as constant or a liner function. Therefore, though mature operations management literature significantly advances understanding of efficiency in managing capacity, this stream of literature cannot evaluate the human reaction or the marketing consequences of service allocation decisions.

Furthermore, call centers and their recent successors, contact centers, have gone through significant transformations in both their corporation functions and technological capabilities. Contemporary call centers handle customer surveys, telemarketing, product inquiries, sales, transactions, promotions, cross-selling, advertising, and postpurchase service via telephone, e-mail, fax, or Web pages. Statistics shows that 80% of a firm's interaction with its customers comes 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). Today's call centers perform an integrated marketing function and are becoming a preferred and prevalent channel for interacting with potential and current customers to acquire and retain business, grow sales, and increase profit. Thus, research is needed to recognize the role of call center management in growing customer relationships and firm profit.

Most importantly, call centers were fueled by the advent of software-based routing and customer relationship management (CRM) applications. The call center industry is among the first industries to become equipped with the most advanced technology, which offers them the capabilities of storing detailed customer history, retrieving real-time customer information, automatically analyzing customer preferences, and instantly responding with a highly customized intervention decisions. For example, the wide adoption of the sophisticated automatic call distributor (ACD), an automated switch designed to route calls, allows managers and supervisors to monitor and measure the progress and flow of work done by agents, routinely collect information on each agent's call length and the time it takes the agent to wrap up the call, analyze a wealth of statistical models about agent and team performance, and automatically route calls (Belt et al. 2000). With the increasing availability of rich customer information and the increasing importance for call centers to build customer relationship, managers are seeking customer information management and Analytical Decision Making tools to transform their existing ACD systems into customer revenue growth systems.

In short, call centers have shifted from a cost to be minimized to one of the most crucial corporate assets because of their ability to grow customer relationships and firm profits. As companies make this shift, from minimizing cost to enhancing customer services, they face the challenge of coping with longer service durations. Research therefore 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. Both effectiveness and efficiency—that is, the capacity to provide the best response to customer contacts at the lowest cost—are important. A solution to this problem requires customer service interventions that successfully balance both service costs and long-term marketing consequences. Most existing customer lifetime value (CLV) analysis does not apply because it calculates the static discounted present value of customer profit and treats it as another segmentation variable, without taking into account the future consequences of marketing interventions. As Rust and Chung (2005) and Rust and Verhoef (2005) point out, this approach is subject to the endogeneity problem that a company's intervention changes customers' future purchase probabilities. Berger et al. (2002) summarize that "the reciprocal relationship between marketing actions and CLV has not been addressed in the marketing literature, and it is a rich area for future research." In the specific application of service allocations, many research issues remain open:

- How do customers evaluate the performance of offshore service centers?
- What is the relationship among service allocation, service costs, and customer retention?
- How can a firm use the most recent information to learn about customers and continuously improve its relationship with customers to maximize long-term customer value?

- Is there a way to use offshore centers better without significantly jeopardizing customer retention?

In this article, using customer call history data provided by a DSL service company that operates offshore centers, we first estimate consumer response models to parameterize the relationship among call allocation, service duration, and customer retention. Empirical evidence shows that offshore centers of the focal outsourcing firm are less efficient (in terms of service duration) and less effective (in terms of customer retention) compared with onshore centers, but the differences are much smaller and sometimes even insignificant when technical questions are handled by offshore centers. In general, customers are more likely to leave when being serviced by off shore centers and experience extra long service duration. However, these sensitivities are reduced when technical questions are handled by offshore centers. In addition, customers have heterogeneous sensitivities to factors such as being serviced by offshore centers and service duration. Some customers tend to incur longer service durations, but these same customers care less about being serviced by offshore centers, especially when they have technical questions.

We then formulate a firm's service allocation decisions as a matching problem whose solutions are given by a stochastic dynamic control problem with long-term marketing consequences, adaptive learning, and forward planning. Specifically, allowing both customer-specific service costs and customer retention to be 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 customer long-term profit contributions. Thus, the service allocation problem, which used to be a traditional operation management problem, is formulated as a marketing problem in which the firm attempts to improve its customer relationships and profits by continuously learning about customers and improving its service.

On the basis of the estimation parameters, we conduct simulations using 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 on each individual customer and make "customized" allocation decisions to match customer preference. Able to act on long-term marketing consequences, the firm also can prevent customer from leaving by sacrificing short-term service costs and allocating customers to their most preferred centers. Compared with the "cost-based" routing currently adopted by the focal company, optimal allocation decisions derived from our framework (1) reduce average service costs, (2) improve customer retention (a 50% reduction of attrition rate), and (3) enhance total profit.

Our findings provide empirical evidence about how customers evaluate offshore centers and shed new light on the drivers of customer retentions, namely, service allocations in general and offshore centers in particular. The proposed framework mirrors the recent trend of companies seeking solutions that entail customer-centric marketing interventions, which in turn requires them to obtain more detailed customer information from their databases and make more personalized offerings to enrich the customer experience and grow their long-term profit. Our research also responds to Berger et al.'s (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." With an application to allocations of service channels, the general framework of the adaptive learning rule and the optimization solutions provide an analytical decision support approach for automating many marketing intervention decisions, such as cross-selling, customized coupons, direct TV, and web advertising.

In Section 2, we briefly review the related literature in operations management and marketing. In Section 3 and 4, we describe the data set and specify customer response functions. We develop a dynamic framework with marketing consequence, adaptive learning, and forward-looking in Section 5 and discuss the estimation and simulation results in Section 6. Finally, in Section 7, we provide some conclusions, limitations, and further research ideas.

2. Literature

Call-center management has represented an important research area for operations management. Mandelbaum (2002) and Gans et al. (2003) provide comprehensive tutorials, reviews, and prospects for call-center–related research. However, most research concentrates on queuing control models for multi-server and multi-class systems, human resource problems associated with personnel scheduling, the hiring and training of call-center agents, and service quality (measured by accessibility of agents and number of calls to solve a question). With the rapid development of sophisticated ACD systems, recent research has focused on networking, "skill-based routing," and multimedia. Thus, the majority of this stream of research focuses on managing capacity costs. Prior work generally ignores service quality and customer reaction, with the exception of Gans (2002) and Hall and Porteus (2000), who allow service quality to affect customer churn. However, even these models are highly stylized and cannot capture the dynamics of customer reaction. Gans et al. (2003, page 80-81) state that "traditional operational models do not capture a number of critical aspects of call-center performance …[including] the role played by human factors, as well as the better use of new technologies." In addition, the dominant research methodology is analytical and simulation based; the limited empirical research contains merely descriptive data analysis, such as histograms, and tests for goodness of fit with certain parametric families of distributions. Finally, other than an exploratory survey conducted by the Purdue University Center for Customer-Driven Quality (2004), no research evaluates customer reaction to outsourced service centers.

Marketing offers an ample amount of research documenting the relationship among service quality, customer satisfaction, retention, and financial impacts (Bearden and Teel 1983, Tse and Wilton 1988, Oliver and Swan 1989, Bolton and Drew 1991a and b, Anderson and Sullivan 1993, Rust and. Zhorik 1993, Rust and Zhorick 1995, Boulding et al. 1993, 1999, Bolton 1998, Kamakura et al. 2005, Li et al. 2005, Rust and Chung 2006). 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 (Danaher and Rust 1996, Bolton and Lemon 1998, 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 (Reinartz and Kumar 2000a and b; Rust et al. 2004).

Recent "Holy Grail" CRM models have been proposed to determine multiple personalized marketing interventions over time to manage long-term customer value (Schmittlein and Peterson 1994, Bult and Wansbeek 1995, Gonul and Shi 1998, Kamakura et al. 2002, Anderson and Salisbury 2003, Venkatesan and Kumar 2004, Rust and Verhoef 2005, Lewis 2005, Netzer et al. 2005). For example, controlling for customer heterogeneous characteristics, Gonul and Shi (1998) study the optimal direct mail policy in a dynamic environment, in which customers maximize utility and the direct mailer maximizes profit. Lewis (2005) adopts a dynamic programming-based approach to derive the optimal pricing policy of a newspaper subscription that allows adjusted discounts as the customer relationship evolves. Kamakura et al. (2002) provide an integrative framework to understand how a firm's investments in service operations relate to customer perceptions and behaviors, as well as how they translate into profit. However, despite the increasing importance of call centers as a service channel, no marketing research specifically treat call allocations as service channel assignment and studies how the resulting service treatment affects customer attrition and long-term customer value.

We define service channel assignment decisions as solutions to a stochastic optimization problem under uncertainty in which the firm learns about the heterogeneity of customer preferences, takes into account the dynamic effect of its marketing interventions, and makes optimal service-matching decision to maximize the long-term profit it earns from each customer. The proposed framework is unlike existing CRM studies in several aspects. First, with the exception of Gonul and Shi (1998), Lewis (2005), Lewis (2006), and Rust and Verhoef (205), most existing CRM literature focuses on developing customer response models and assumes firm's decisions are given, so it discusses implications of the firm's CRM intervention decisions only tangentially. We treat the firm as a decision maker that learns about individual customers and makes explicit allocation decisions to match customers with the most appropriate centers. Second, most current research emphasizes developing better approaches to model customer heterogeneity, which is based on demographic variables and the pooled historical data. We propose the idea of adaptive learning through continuous interactions during which customer feedback from the most recent decision execution is adopted and integrated into the firm's periodical decisions. As a result, the firm continuously improves its belief about customer preferences. Thus, the proposed learning is based on the information from firm's most recent interaction with the customer. 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. This is in contrast to most existing customer lifetime value analyses that calculate the net present value of customers' future profit and treat it as another segmentation variable to guide targeting strategies. Our approach mitigates the endogenization problem that the firm's intervention changes customers' future purchase probability, as noted by Rust et al. (2004) and Rust and Verhoef (2005).

Methodologically, our work relates to dynamic structural models with consumer learning, which were developed to examine consumers' dynamic decisions regarding brand, quantity, and purchase timing (e.g., Erdem and Keane 1996, Mehta, Rajiv and Srinivasan 2004) and stockpiling behavior (e.g., Krishna 1994a, 1994b; Sun et al. 2003; Erdem et al. 2004; Sun 2005). Unlike prior research, which intends to establish that consumers are sophisticated decision makers, we treat firms as decision makers that learn about customers, take into account the effect of current marketing interventions on future customer reactions, and optimally adjust their marketing interventions to maximize customer lifetime value.

3. Industry Background and Data Description

The data for our study is provided by 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. To subscribe to the service, customers need to purchase the necessary equipment, such as a modem and software. 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 of the initial subscription requires 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 into technical and transactional questions. 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, email accounts, product news, product services, and registration. When a customer calls in, he or she may experience some waiting time before an agent addresses the call (the customer does not know for which center he or she is waiting). After a call is picked up by an agent, the customer is given the first 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 offshore centers, where front-line agents have less authority to make decisions and more cases need to be escalated to supervisors within the same center.

Because of the significant labor cost, 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

[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 do include waiting time as part of customer service experience in the retention equation to take into account its effect on customer attrition. Accordingly, when we run the simulations, we consider the different waiting times caused by service allocation decisions. Another thing to note is that because of the way the company collects data, we could not separate talking time from holding time. This is a limitation of our data set and we do not expect our results to be significantly altered.

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 solve customer problems while customers are still on the phone, with very rare exceptions when agents must perform some task after customers hang up. Thus, the total service duration can provide a basis for estimating service costs. This measurement is consistent with OM/OR literature (Gans, Koole, and Mandelbaum 2003, p. 126). 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. Because this service allocation rule is determined primarily by the estimated service cost, 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. In the call history panel data, 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. These survey data contain overall satisfaction scores, as well as subsatisfaction scores to rate their overall previous experiences with the company. Most customers participated in only one satisfaction survey. Because these scores pertain to 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. We also observe whether a customer left the firm during the observation period. Finally, the firm provided estimates of average 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 two times less than that of onshore centers.[3]

[Insert Table 1A About Here]

Table 1A lists the definitions and sample statistics of variables that describe customers. The average tenure with the company is 20.29 months, and the average monthly price is $43.91. The firm occasionally offers price promotions, averaging $4.13. We code the presence of a competitive product as 1 if cable was introduced to the geographical area in which the customer resides and 0 otherwise; 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 time, divided by four time periods during a day (8–12, 12–16, 16–20, and 20–24), for both centers are approximately 2, 1, 2, and 0.5 minutes for the onshore centers and 1, 0.5, 1.5, and 0.5 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. The relatively long service duration and short waiting time justify our focus on service duration in this study.

[Insert Table 1B about Here]

To examine whether frequent callers differ from infrequent callers, in Table 1B, we compare percentages of question types, corresponding service duration, and retention rates across those who made different numbers of calls during the observation period. There is no significant variation in the types of questions and retention rates between frequent and infrequent callers.

[Insert Table 1C About Here]

[3] Due to the sensitivity of the cost information, we cannot release the numbers.

In Table 1C, we list and compare the allocation, service duration, customer satisfaction, and retention between centers and question types. The current cost-based routing results in 84% of calls being assigned to onshore service centers and 16% being handled by offshore centers. Among all the questions handled by onshore centers, 11% are transactional and 89% are technical. The split is 3% and 97% for offshore centers. It appears that onshore centers handle a higher percentage of transactional cases. The average service duration 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). The longer service duration at the offshore centers could be the result of training differences or the lower authority of offshore agents to make decisions, which results in increased hold time and more frequent case escalation. 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, the difference in the mean overall satisfaction scores (onshore 3.46, offshore 3.11) is significant at the t = 2.22 level, so customers are in general less satisfied with offshore service centers. The subsatisfaction scores show that the major factors causing this overall difference are the agents' difficulty in understanding questions, lack of ability to provide clear and concise answers, and lack of ability to provide a personalized and courteous response. In terms of customer retention, frequent service by offshore service centers leads to higher average customer attrition (17% versus 12% for onshore, t = 12.6). Thus, the data suggests that customers prefer onshore centers in terms of both satisfaction and retention. However, the extent of this onshore preference differs across question types. Although customers are significantly less happy when offshore centers handle their transactional questions (3.39 vs. 3.11, t = 18.42), the difference in satisfaction scores is insignificant for technical questions (3.32 vs. 3.33, t = 0.67). Furthermore, customers are much less likely to leave when the offshore centers handle technical questions (0.91 vs. 0.82 with t = 11.27 for the difference of on-shore centers and 0.87 vs. 0.84 with t = 4.57 for the difference of off-shore centers).

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 significant lower marginal service cost, the offshore centers in our data set have some cost advantages compared with onshore centers for handling technical questions. In addition, though customers prefer to be serviced by onshore centers, according to their satisfaction and retention ratings, they are less sensitive with regard to technical questions.

4. 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 weeks $t = 1, \ldots, T$, customer $i = 1, \ldots, I$ may call in with question types k = 1 or 2, with k = 1 representing transactional questions and k = 2 representing technical questions.[4] We assume there are $m = 1, \ldots, M$ segments of customers.

We use the 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 when customer i does not call. Therefore, D_{ikt} = 1 if customer i calls in with question type k and 0 otherwise. Note that D_{ikt} recognizes call and no-call occasions and is not a decision variable. We use the dummy variable A_{ijt} to denote the firm's allocations decisions, such that A_{i1t} = 1 if the question is allocated to an onshore service center and A_{i2t} = 1 if the question is allocated to an offshore service center. These variables equal 0 otherwise.

As Table 1C shows, allocating a particular question to onshore or offshore centers yields differential service duration and customer attrition rates. In this section, we first specify the effect of allocation on service duration. Because service duration represents an important component of the customer service experience, we next model the effects of service allocation and corresponding service duration, among other factors, on customer retention.

4.1 Service Duration

Intuitively speaking, service duration can be determined by the traits of service centers, question types, as well as customers. Following Mandelbaum et al. (2002), who show that call duration is best captured by a log-normal distribution, we assume the log of call duration $\log(DUR_{ijkc}(m))$ for customer i of type m for all call occasions is given by

$$\begin{aligned} Log(DUR_{ijkc}(m)) = {} & \alpha_0(m) + \alpha_1(m) D_{i2c} + \alpha_2(m) A_{i2c} + \alpha_3(m) A_{i2c} D_{i2c} \\ & \alpha_4(m) \log(DUR_{ijkc-1}(m)) + \alpha_5(m) NCOMPUTER_i + \xi_{ijkc}(m) \end{aligned} \tag{1}$$

[4] For simplicity, we consider two service centers and two types of questions. Similarly, 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.

$$\text{(2)} \qquad \xi_{ijkc}(m) - N(0, \sigma_{\xi}^{2}(m))$$

for all j = 1, 2 and k = 1, 2. Duration equation is specified for each question type and each service center. Thus, the differences in service duration for different centers and question types are addressed. Subscript c denotes the counting index of all call occasions. This equation applies when calls are actually placed. [5] 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 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 service duration between 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 off-shore centers handle technical questions. The variable $\log(DUR_{ijkc-1}(m))$ is the log of the total service time it takes center j to solve question type k in prior service occasion. Given the equation is specified for each center and each question type, 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 take into account 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 the coefficients appearing in equation (1). $\xi_{ijkc}(m)$ denotes all other unobserved factors affecting service duration.

Equation (1) defines the service durations for all call occasions. When customers do not call, or D_{ikt} = 1 for k = 0, the duration is zero. Thus, for all observation periods $t = 1, \ldots, T$, the expected duration when question type k is allocated to center j is given by

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

[5] Subscript c represents call occasions. It is different from t, which represents time periods. This notation appears only in this equation.

Being defined as customer specific, duration equation considers customer heterogeneity in generating service cost.

4.2 Customer Retention

Assume at each time $t = 1, \ldots, T$, customer *i* of type *m* decides whether to stay with the firm (RET_{it}). RET_{it} is a dummy variable equal to 1 when the customer decides to stay and 0 otherwise. 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). More specifically, the retention decision results from the following function $W_{it}(m)$:

$$
\begin{aligned}
W_{it}(m) = {} & \beta_0(m) + \beta_1(m)SAT_i + \beta_2(m)PRICE_{it} + \beta_3(m)PROM_{it} + \beta_4(m)COMP_{it} \\
& + \beta_5(m)\log(TENURE_{it}) + \beta_6(m)PANELTY_{it} + \beta_7(m)A_{i2t} + \beta_8(m)A_{i2t}D_{i2t} \\
& + \beta_9(m)\sum_{j,k}(D_{ikt}A_{ijt}\log(DUR_{ijkt}(m))) + \beta_{10}(m)(\sum_{j,k}(D_{ikt}A_{ijt}\log(DUR_{ijkt}(m)))^2 + \beta_{11}(m)WAIT_{ijt} \\
& + \beta_{12}(m)\sum_{\tau=1}^{t}\sum_{k=1}^{K}D_{ik\tau} + \beta_{13}(m)FREQ\_OFF_{it} + \beta_{14}(m)ACCUM\_DUR_{it} + \zeta_{it}(m)
\end{aligned}
\tag{4}
$$

In this equation, SAT_i, or the overall satisfaction score measured at the beginning of the observation period, approximates general evaluations of previous service experiences with the firm.[6] 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 its coefficient to be positive. The variables $PRICE_{it}$ and $PROM_{it}$ are fees and promotions specific to customer *i* at time *t*. We include these two variables to take into account the effects of price and promotion on customer retention. $COMP_{it}$ is a dummy variable indicating the presence of competitors in the geographic area where customer *i* resides. The inclusion of this variables controls for competition between DSL and cable. Switching cost also plays 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

[6] 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.

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 many 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 $\beta_7(m) > 0$, customers in general still 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 one view of service quality is of the effectiveness of service encounters and the important aspect is how quickly the service encounter resolves the customer's problem. Thus customer service experience pertains to the duration of the service encounter, $\sum_{j,k}(D_{ikt}A_{ijt}\log(DUR_{ijkt}(m)))$. As demonstrated by Table 1C, 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.[7] 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 calls is answered, $WAIT_{ijt}$. Even though this variable does not directly differentiate

[7] As discussed in Gans, Koole, and Mandelbaum (2003), very short calls are sometimes due to certain agents who were taking small "rest breaks" by hanging up on customers.

customer onshore and offshore service experience, we include it to control for its possible negative effect on customer retention, as being predicted by the OM literature (Gans et al 2003).

Marketing literature establishes that the frequency of marketing mix variables, such as price and promotion, have immediate effects on customer purchases (Kopalle, Mela, and Marsh 1999; Mela, Gupta, and Lehmann 1997). Bolton (1989) argues that frequent feature activity in a category should make current consumers more aware of the prices and the occurrence of promotional activities in the category (Moriaty 1985). Following similar logic, 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 problems 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 happened long ago may have less impact on customers. This is consistent with the idea of using RFM (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; Verhoef et. al. 2003). Their coefficients, $\beta_{13}(m)$ and $\beta_{14}(m)$, capture the effects of past experience with offshore centers and service duration on customer retention.

The coefficients $\beta_1(m)$ - $\beta_{14}(m)$ thus capture the effects of all these variables on customer retention. We use the vector $\beta(m)$ to represent all coefficients that appear 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*, where

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

Let $\overline{W}_{it}(m)$ be the deterministic part of equation (4). Assuming $\varsigma_{it}(m)$ follows an independent and identically extreme value distribution (IID), the probability of customer *i* staying with the firm at time *t* can be represented by

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

4.3 Estimation

We use maximum likelihood to estimate the duration and customer retention equations. We therefore obtain $\alpha(m)$ and $\beta(m)$, which parameterize how duration and customer retention may be affected by service allocation decisions. To take into account customer heterogeneity, we adopt a latent class approach, such that segment membership is affected by expertise with computers (EXP_i) and type of customer ($RESIDENTIAL_i = 1$ if residential and $RESIDENTIAL_i = 0$ 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. With the observed data, we estimate the service duration and customer retention models.

4.4 Cost-Based Routing

The observed data come from cost-based routing, which implies that when determining the allocation of incoming calls, the firm views minimizing immediate service costs as its primary goal, without considering heterogeneous customer preferences or long-term marketing consequences. Therefore, expected cost is given by $E[COST_{it}] = \sum_k D_{ikt}[A_{i1t}(C_1\overline{DUR}_{1kt}) + A_{i2t}(C_2\overline{DUR}_{2kt})$, 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 ($\overline{DUR}_{jkt}$), as calculated from the sample.

However, for many reasons, the allocation of services may not be driven solely by expected cost $E[COST_{it}]$. For example, political and ethical considerations may motivate the firm to assign more cases to onshore centers. To address this possibility, we assume the firm makes allocation decisions between onshore and offshore centers according to the following function U_{it}:

(7) $$U_{it} = \sum_j A_{ijt}\lambda_{0j} + \lambda_1 E[COST_{it}] + \sum_{j,k}(D_{ikt}A_{ijt}\tau_{ijkt})$$

Scalar λ_{0j} captures the firm's intrinsic preference to allocate a service call to onshore centers, λ_1 measures the importance of financial considerations such as cost in determining the firm's allocation decisions, and τ_{ijkt} are all unobserved factors that affect the allocation decisions. Note that equation (7) describes a more general and realistic situation that nests the special case in which λ_{0j} is close to 0 and the firm's allocation decision is driven solely by cost. Accordingly, we approximate the firm's objective in terms of minimizing the following function for the current period:

$$\text{(8)} \qquad \sum_{A_{ijt}} Min(\sum_{j} A_{ijt}\lambda_{0j} + \lambda_1 E[COST_{it}] + \sum_{j,k}(D_{ikt}A_{ijt}\tau_{ijkt}))$$

Assuming that τ_{ijkt} has an IID extreme value distribution, we obtain a binary logit model that approximates the firm's allocation decisions. We define $\overline{U}_{it}$ as the deterministic part of U_{it}. When a customer calls, the probability of the firm making decision A_{ijt} is given by

$$\text{(9)} \qquad \Pr(A_{ijt} \mid D_{ikt}) = \frac{\exp(\overline{U}_{it})}{\sum_{j}\exp(\overline{U}_{it})}.$$

We then obtain the estimates of λ_{0j} and λ_1 using the observed sample.

Note that by using the average service duration of center *j* up to time *t* for handling question type *k* ($\overline{DUR}_{jkt}$), cost-based routing recognizes the differential traits of onshore and offshore centers. However, it differs from using the duration equation, which also recognizes customer differences when generating service durations.

5. A Framework for Customer-Centric Allocation Decisions

Cost-based routing treats customers as homogeneous and minimizes service duration. To improve customer experiences with the firm and use offshore service centers more effectively, the firm must 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. Compared with cost-based routing, the service allocation approach enables the firm to integrate (1) marketing consequences, as measured by customer retention; (2) more accurate estimates of service cost, as measured by customer-specific service duration; (3) a continuous learning process based on accruing customer information collected from their most recent service interactions and thereby improve the accuracy of knowledge about customers; and (4) the firm's forward looking into the customer's long-term profit contribution.

In this framework, when evaluating the allocation decision A_{ijt}, the firm must know the total service costs and marketing consequences. Because of its significant labor costs, the firm calculates the expected service cost on the basis of the expected service duration, given by equation (3). Marketing consequences entail customer retention, as specified in equation (6). From the firm's perspective, the service duration and retention equations serve as predictions.

5.1 Adaptive Learning of Customer Heterogeneous Preference

Given customer heterogeneity, the firm must learn about individual customers' preferences and match customer channel preference with its allocation decisions. However, when customer *i* calls at time *t*, his or her preference remains unknown or uncertain to the firm. To take into account the fact 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 $\Pr_{i0}(m)$ 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.

However, other than static demographic variables, accruing information that can be obtained by observing the customer feedback to firm's most recent interventions can also reveal customer information. There are at least two accruing information source. The first is the observed prior service durations because the same customer usually shows a consistent pattern over time in terms of the length of service durations. For example, retired customers have more time to talk on the phone and incur longer service durations. The second source is observed customer retention, which reveals customer preference by reflecting customer reactions to service allocations and the resulting service treatments. 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 a long service duration leads a customer to leave, it reveals that this customer reacts negatively to long service durations. Define DUR_{it}^{H} and RET_{it}^{H} as all of the history of duration and retention observed up to time *t*. We have $I_{it} = \{DUR_{it}^{H}, RET_{it}^{H}\}$ to denote the most updated information set available to the firm at the beginning of time *t*.

Assuming 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, …, *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

(10)
$$LR_{it}(m=n) = \frac{\Pr_{it}(m=n)}{\Pr_{it}(m=1)} = LR_{it-1}(m=n)\frac{\Pr(DUR_{ijkt-1} \mid m=n)}{\Pr(DUR_{ijkt-1} \mid m=1)}\frac{\Pr(RET_{it-1} \mid m=n)}{\Pr(RET_{it-1} \mid m=1)}$$

for *m* = 1, …, *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 attrition RET_{it-1}. The firm calculates the probabilities of the observed service duration using equation (1) and that of the observed retention according to equation (6) for all customer types *m* = 1, …, *M*. The ratio of the probabilities of the observed service duration and retention when the customer is assumed to belong to *m* = *n* and *m* = 1 can update previous beliefs about the likelihood that customer *i* belongs to segment *m* = *n*. When the joint probability of observing $DUR_{ijk(t-1)}$ 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 $\frac{\Pr(DUR_{ijkt-1} \mid m=n)}{\Pr(DUR_{ijkt-1} \mid m=1)}\frac{\Pr(RET_{it-1} \mid m=n)}{\Pr(RET_{jt-1} \mid m=1)}$ > 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 when the customer is assigned to segment *m*, the firm increases its belief that this customer belongs to segment *m*. When customers do not call in, $\frac{\Pr(DUR_{ijkt-1} \mid m=n)}{\Pr(DUR_{ijkt-1} \mid m=1)}$ =1, and the belief is updated solely on the basis of observed retention.

Given the updating rule, the perceived probability that customer *i* belongs to type *m* at time *t* is given by

(11)
$$\Pr_{it}(m=n) = \frac{LR_{it}(m=n)}{\sum_{m=1}^{M} LR_{it}(m)}$$

for all m = 1, …, M. Thus, continuous learning enables the firm to follow customers' footsteps and derive individual probabilities of each customer belonging to these segments.

The learning process allows the firm to use accrued information to update its beliefs about the customer's intrinsic type continuously. The updated knowledge is used to adjust allocation decisions, and the resulting customer reactions are fed back into the updating process. We term this "adaptive learning." It has the following properties: (1) accrued information is used to update the firm's knowledge of customer preference; (2) the firm's strategic decision is adapted according to the updated knowledge; and (3) as a result, the firm revises its belief in the next period on the basis of successful and unsuccessful interactions with the customer.[8] Adaptive learning is integrated into firm's decision making and enables the firm to improve the accuracy of its knowledge about each individual customer by trial in a real-time fashion. The increasing accuracy of the firm's knowledge about each individual customer provides the basis for customized service matching.

This discussion centers on continuous learning to improve firm knowledge about customers' differential sensitivities to the variables affecting service duration and retention. Another source of uncertainty comes from the heterogeneous capabilities of each center, especially considering the independent ownership of offshore centers and the challenge of controlling service quality. Although we do not allow the firm to learn explicitly about center heterogeneity in an adaptive fashion, we take into account the difference between onshore and offshore service centers in dealing with different types of questions, as shown by equations (1)–(6). The differences are also factored into the firm's adaptive learning about customer heterogeneity, as shown by center and question type specific equation (10).

5.2 Firm's Objective Function

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,

$$\begin{aligned} PROFIT_{it} &= \sum_{m=1}^{M} \Pr_{it}(m) RET_{it} \{ FEE_{it} \\ &\quad - \sum_{k} D_{ikt} [A_{i1t}(C_1 DUR_{ijkt}(m)) + A_{i2t}(C_2 DUR_{ijkt}(m))] \} \end{aligned} \tag{12}$$

[8] Similar ideas have been adopted in conjoint analysis to reveal consumer preference (Toubia et al. 2003).

In the above expression, marketing consequence is measured by customer retention and service costs are measured by service duration. FEE_{it} is the fee paid by customer *i* at time *t* for the service and therefore 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. RET_{it} is the dummy variable that indicates whether customer *i* stays with the firm at time *t*. In addition, C_1 and C_2 are the unit costs of service for onshore and offshore service centers. The profit is weighted by the firm's perceived probability of customer *i* belonging to type *m* at time *t*, $\Pr_{it}(m)$, as given by equation (11).

Following the same logic, we assume that the firm makes allocation decisions between onshore and offshore centers according to the following function U_{ijt}:

$$U_{it} = \sum_j A_{ijt}\lambda_{0j} + \lambda_1 PROFIT_{it} + \sum_{j,k}(D_{ikt}A_{ijt}\tau_{ijkt}) \tag{13}$$

Under the assumption 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, we can use the same scalar λ_{0j} and λ_1 estimated from the observed data for alternative allocations. Then the expected utility at time *t* is given by

$$\begin{aligned} E[U_{it} \mid I_{it}, A_{ijt}] &= \sum_j A_{ijt}\lambda_{0j} + \lambda_1 E[PROFIT_{it} \mid I_{it}, A_{ijt}] \\ &= \sum_j A_{ijt}\lambda_{0j} + \lambda_1\{\sum_{m=1}^{M} \Pr_{it}(m)\Pr_{it}(RET)(m)[FEE_{it} \\ &\quad - \sum_k D_{ikt}\{A_{i1t}C_1 E[DUR_{ijkt}(m) \mid I_{it}, A_{ijt}] + A_{i2t}C_2 E[DUR_{ijkt}(m) \mid I_{it}, A_{ijt}]\}]\} \end{aligned} \tag{14}$$

$E[PROFIT_{it} \mid I_{it}, A_{ijt}]$ is the expected profit given the information set I_{it} and allocation decision A_{ijt}. $\Pr_{it}(m)$ is firm's perceived probability that customer *i* belongs to segment *m* as defined by equation (11). $\Pr_{it}(RET)(m)$ 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). $E[DUR_{ijkt}(m) \mid I_{it}, A_{ijt}]$ 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). I_{it} denotes the information set available to the firm about customer *i* at time *t*. As we explain before, the expected duration and probabilities of customer retention are determined by firm knowledge about customer *i* at time *t* (I_{it}) and its allocation decision (A_{ijt}).

5.3 Dynamic Optimal Allocation Decisions

To take into account marketing consequences, the firm need to incorporate simultaneity between decisions and outcomes. When the firm allocates customers to off-shore centers for the purpose of lowering service costs, the firm faces the consequences of more dissatisfied customers and higher attrition rates. Therefore, it must trade off the current cost of service (service costs) and future customer retention (marketing consequences) to maximize its long-term profit (long-term customer value). Firm's decision process can be parsimoniously formulated as 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*.

(15)
$$\underset{A_{ijt}}{Max}\, E_{it}\{\sum_{\tau=t}^{\infty} \delta^{\tau-1} U_{i\tau}\}\,,$$

where $0 < \delta < 1$ is the discount factor reflecting that current utility is preferred to future utility (Erdem and Keane 1996).

In this dynamic setup, the control variable is the call allocation decision A_{ijt}. The state variable is the firm's knowledge about customers, $\Pr_{it}(m = n)$ for n = 1, 2, …, M. Thus, this formulation allows the allocation decisions to be driven by firm knowledge about customer type, which affects firm's estimates of service costs and long-term marketing consequences. In other words, the firm must act on its knowledge about customers and long-term marketing consequences with service costs under control when making service allocation decisions.

The solution to the dynamic program is such that in any time period and given any state, the optimal solution is the solution to the dynamic program from that time forward. The optimal allocation decision is thus the solution to the Bellman equation:

(16)
$$V_{it}(I_{it}, D_{ikt}) = \max_{A_{ijt}}\{U_{it} + \delta E[\max V_{it+1}(I_{it+1}, A_{ijt+1}, D_{ikt+1})] + \sum_{j,k}(D_{ikt} A_{ijt} \tau_{ijkt})\}$$

where $V_{it+1}(I_{it+1}, A_{ijt+1}, D_{ikt+1})$ is the expected optimal utility beginning from time t + 1. The value function can be determined using backward induction and the dynamics of the state variables. Because the state variables are continuous, we have the problem of a large state space. We therefore adopt the interpolation method developed by Keane and Wolpin (1994) to calculate the value functions for a few state space points and use them 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 backwards recursion solution process.

[Insert Figure 1 About Here]

As we show in Figure 1, the problem 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 I_{it}, which consists of the duration (DUR_{ijkt}) and retention (RET_{it}) realized between t – 1 and t. On the basis of this accrued information, the firm updates its beliefs about customer preference ($\Pr_{it}(m)$) according to the learning rule specified in equations (10) and (11). With this updated knowledge, the firm then 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, as defined by equation (15). When making an allocation decision at time t, the firm must take into account the future marketing consequences, as represented by the probability of customer retention from time t onward. The firm also considers all information resulting from its current allocation decision.

To solve the dynamic program problem, the firm optimally balances (short-term) service costs and (long-term) marketing consequences. Then, to implement customer-centric marketing, it undertakes two iterative steps: The firm continuously learns about each individual customer by analyzing customer information according to revealed customer reactions to the firm's most recent interactions, and then it adapts its decisions according to its recent knowledge about each customer. The second step pertains to acting on information, in that the firm incorporates its updated knowledge into its marketing decisions. 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 interdependent.

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 their 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 profits 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. The experimental property resulting from dynamics decision making under uncertainty has been discussed by Erdem and Keane (1996) 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.

The proposed framework also improves customer segmentation and scoring approaches. First, current 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 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 decision. Real-time learning gets integrated into decision making. Third, by treating each marketing action as a separate decision over time, current segmentation methods maximize the return of each marketing action independently, which means their usefulness is limited to campaign-centric marketing. Our framework, however, views customer long-term profit contribution as a dynamic measure that intertemporally changes in response to a firm's marketing actions. By following the footsteps of a customer, this approach aligns better with the idea of relationship marketing.

5.4 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. We use a multinomial distribution to approximate call-in probabilities. That is, in each period, there is a probability ρ_1 that the customer will call with question type k = 1, probability ρ_2 that he or she will call with question type k = 2, and probability $1-\rho_1-\rho_2$ that the customer does not call. The Bellman equations are:

$$V_{it}(I_{it}, D_{ikt}) = \max_{A_{ijt}} U_{it} + \delta E[\max(\rho_1 V_{it+1}(I_{it+1}, D_{i1t+1}=1) \tag{17}$$

$$+\rho_2 V_{it+1}(I_{it+1,} D_{i2t+1}=1) + (1-\rho_1-\rho_2) V_{it+1}(I_{it+1}, D_{i0t+1}=1] + \sum_{j,k}(D_{ikt} A_{ijt} \tau_{ijkt})$$

where $V_{it+1}(I_{it+1,} A_{ijt+1,} D_{ikt+1}=1)$ is the 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 ρ_1 and ρ_2 using sample call-in frequencies for k = 1 and k = 2 types of questions.[9]

Similarly, when making allocation decision, the firm must predict the waiting time and take into account 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

$$WAIT_{ijt} = \frac{\Pr(A_{ijt} \mid D_{ikt})}{\Pr(\hat{A}_{ijt} \mid \hat{D}_{ikt})} \hat{W}AIT_{ijt}, \tag{18}$$

where $\hat{A}_{ijt}$ and $\hat{W}AIT_{ijt}$ are the observed percentage of calls allocated to center j and the average waiting time of center j during the same time period when customer i calls, respectively. $\Pr(A_{ijt})$ is the percentage of calls allocated to center j, suggested by the proposed allocation. Assuming the number of callers in the queue is proportional to the allocation probability, equation (18) adjusts the

[9] 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 would modify our model by adding a fourth choice to D_{ikt} and making it equal to 1 if a customer calls for multiple reasons. We also would introduce ρ_3 as the probability that customer i calls with multiple questions.

waiting time upwards (downwards) when more (less) customers are allocated to center k as suggested by the alternative allocation decisions.[10] [11]

6 Empirical Results

In this section, we first run estimations to obtain the parameters Θ that characterize the relationship of the firm's allocation decision, service duration, and customer retention. On the basis of these calibrated parameters, we conduct simulations using our proposed framework to derive the sequence of optimal allocation decisions A_{ijt}. We thus investigate whether and how the proposed approach improves over cost-based routing.

6.1 Estimation

[Insert Tables 2A and 2B About Here]

Table 2A reports the model-fitting statistics of the estimated customer and firm models. The Akaike and Bayesian information criteria of the calibration sample show that the customer response model with two latent segments fits the data best. The same finding holds for a cross sample validation using holdout sample. To further demonstrate the fitting power of the estimated models, we compare the simulated frequency of offshore allocations, average call durations, and probabilities of retention with those from the sample in Table 2B. The fit is good on all dimensions, indicating that the estimated consumer model with two segments and firm's model approximate the data quite well.

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[10] Assuming the effective arrival rate is proportional to the allocation probability, we approximate the waiting time as a proportional function of allocation probability. In other words, 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 when the arrival rate is sufficiently smaller than the departure rate, which is a reasonable assumption given the long average service duration observed in our data. We acknowledge that our modeling of waiting time is a simplification. Interested readers can refer to the extensive queuing theory on comprehensive waiting time models.

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

[Insert Table 3 About Here]

Table 3 reports the estimation results. The intercept of firm's objective function is 8.935, indicating that the firm has a greater tendency to route questions to onshore centers. The coefficient of the financial consideration (cost in this case) is 14.067, implying that financial consideration is positively relates to the utility that determines the allocation decisions.

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, it generally takes longer for off-shore centers to solve a case. These findings may be due to the more frequent chances that problems (especially transactional questions) get escalated at offshore centers. However, when technical questions are handled by offshore centers, the service durations are significantly shorter than those associated with transactional questions being handled by offshore centers. These findings are consistent with our observations from the sample data. 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. The positive coefficient of the number of computers suggests that customers with more computers are more likely to ask more questions during each call. The variances of service durations are estimated to be 0.526 and 0.051 for both segments.

In the retention equation, it is shown that overall customer satisfaction makes customers more likely to stay, as do lower prices, promotions, and lack of competition. A long history with the firm also increases the chance that customers stay. Not surprisingly, a price penalty prevents customers from leaving.

We now consider the variables that describe the customer service experience that differentiate onshore and offshore centers. When being serviced by offshore centers, both segments are more likely to leave, which is consistent with the Purdue finding that many customers choose to leave if they know or have the impression that the business was using an offshore service center. However, this negative impact is mitigated when technical questions are handled by offshore centers for customers in the second segment. That is, these customers are less sensitive to having their technical questions serviced by offshore centers. The log-duration has a positive effect on retention, indicating 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, partly because of consumer impatience toward extra-long service time when they likely are put on hold. In other words, customers are more likely to leave when their questions are not addressed in a timely fashion.[12] As we expected, both segments react negatively to waiting time. The greater the total number of questions, the less likely customers will stay, a finding 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 decrease the chance for both segments to stay. The recency weighted total service duration also has negative effect on retention, indicating that customers react negatively to the high total amount of time they have incurred to ensure the functioning of the service.

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 the intercept in the duration equation and, in the retention equation, the intercept, coefficients of log-duration, squared term of log-duration, and interaction between offshore and technical questions. Everything else being equal, customers in segment 1 experience shorter service durations (as indicated by the constant term in the duration equation) and are more likely to stay (as indicated by the constant term in the retention equation). However, they are more sensitive to service times that last too long and react much more negatively to being serviced by offshore centers. In contrast, those in segment 2 seem to incur much longer service durations, are less likely to stay, are more tolerant of extra-long service encounters, and are less sensitive to being serviced by offshore centers. Most important, customers in segment 2 also show less sensitivity about their technical questions being handled by offshore centers. The coefficients of demographic variables in the segment membership suggest that customers with more expertise with computers as well as business customers are more likely to belong to the first segment. We estimate 66.4% of the customers appear in the first segment and 33.6% in the second segment.

In summary, the estimation results show that customers have differential sensitivities to onshore and offshore centers. To improve customer experiences with the company and better use offshore service centers, the firm must match each service call with the right center according to individual customer preferences. 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

[12] To see whether service duration is a good indicator of service quality, we ran a regression of the customer satisfaction score on service duration and the squared term of service duration. The results support that customer satisfaction increases with initial service duration but decreases when the service duration is lasting extra long.

by offshore centers. Thus, the firm should balance all factors that affect service duration and customer retention when deciding on service allocation. Given the comparative advantage of onshore and offshore service centers and the heterogeneity of customer preference, the allocation problem becomes similar to a matching problem. We next demonstrate how firm learning and acting on that knowledge can yield customized and proactive allocation decisions and improve profit.

6.2 Simulation

We conduct simulations to derive optimal allocation decisions using our proposed framework, which adds marketing consequence, adaptive learning, and forward-looking components to the cost-based routing approach. We want to demonstrate the effectiveness of adaptive learning (Figure 2), show how our proposed allocations are tailored to customer preference (Figures 3A and 3B), establish how service allocation decisions are driven by marketing consequences (Figure 3C), and demonstrate whether firm learning and acting on customer knowledge improve customer retention without incurring significant service costs (Figures 4A–C).

On the basis of the estimated parameters (Θ and), the observed call history, and customer demographic variables, we simulate optimal allocation decisions (A^{*}_{ijt}). To recognize marketing consequence in the long un, we incorporate customer retention. We also allow for heterogeneity in service cost as service duration equation is specified to be customer-specific. 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 (10) and (11), using each individual customers' most recent information. To add the forward-looking component, we follow the convention and set δ to 0.995, then obtain the optimization by solving the Bellman equation. Even though the simulation is based on the same history of call incidence as the sample, the simulated optimal allocation decisions will differ from the observed ones, which will cause the resulting service duration and customer retention to differ as well.

[Insert Figure 2 About Here]

In Figure 2, we demonstrate the progress of adaptive learning. We divide the whole observation period equally into three stages and compare the probabilities of segment 2 customers

($\Pr_{it}(m=2)$), which the firm learns 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 is categorized as either a segment 1 or segment 2 customer. The average perceived probability of customers in the second segment is approximately 34% 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 with much greater accuracy.

[Insert Table 4 About Here]

Although gaining more accurate customer knowledge provides the possibility for individualized allocation decisions, developing and executing these allocation decisions to act on that knowledge is the ultimate step in analytical decision making. Using our proposed framework, we obtain a sequence of optimal allocation decisions for all the calls initiated by each customer. To demonstrate how the sequence of allocation decisions can be customized and intertemporally related, we present some summary statistics of the proposed allocations in Table 4 and compare them with actual 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 all the technical questions, 20% are assigned to offshore centers, a 18% increase from the 17% assigned by the cost-based method. In addition, 44% of customers from segment 2 are allocated to offshore centers, an 33% increase from the 34% observed in the sample. Because they are less sensitive to the issue of 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. Furthermore, because this model considers waiting time and its negative effect on customer retention, the proposed allocations do not incur greater waiting times.

[Insert Figures 3A, 3B, and 3C About Here]

In Figure 3A, we demonstrate how knowledge about individual customers can be used to make customized call allocations. We draw the average probabilities of assigning a customer to an offshore center ($\Pr(A_{i2t}) = \frac{\exp(\overline{V}_{it}(A_{i2t}))}{\sum_j \exp(\overline{V}_{it}(A_{ijt}))}$) against the average probabilities that customers are perceived to be segment 2 customers ($\Pr_{it}(m=2)$). The proposed solution shows that, on average, the higher the perceived probabilities of belonging to the second segment, the higher 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 knowledge about each individual customer lays the foundation for customized service allocations. The allocation decisions are tailored according to the firm's most updated knowledge on each individual customer, which warrants a better matching between service center and individual customer. For convenience, we term this allocation function.

However, the increasing relationship likely will be modified by exogenous variables such as question type. In Figure 3B, we 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 (relative to transactional questions) and that customers are less likely to leave if their technical questions are handled by offshore centers. This figure shows that the firm's allocation decisions, as derived from our framework, recognize the comparative advantages of offshore centers for handling technical questions.

In Figure 3C, we compare the allocation function of those customers who left and those who stayed to the end of our observation period under cost-based routing. 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.

Thus, we empirically show that by introducing marketing consequence, firm learning, and forward-looking, our proposed approach results in optimal allocation decisions that are more customized and proactive.

[Insert Figure 4A, 4B and 4C About Here]

We next examine whether the allocation decisions derived from the proposed framework help the firm improve its service effectiveness and profit while restraining its service costs. In Figure 4A–C, we trace the average costs ($\sum_k D_{ikt}[A_{i1t}(C_1 DUR_{ijkt}(m)) + A_{i2t}(C_2 DUR_{ijkt}(m))]$), average retention probabilities ($\sum_{m=1}^{M} \Pr_{it}(m)\Pr_{it}(RET)(m)$), and total profits ($PROFIT_{it}$) over the entire observation period and compare these measurements with their observed counterparts. All three measurements are calculated on the basis of the derived allocation decisions. In Figure 4A, we find that the proposed allocations result in a decrease of average costs over time, which may be attributed to the firm's increasing ability to employ each type of center. The average costs calculated from the actual data or cost-based routing drops only slightly over time. Without being able to recognize the human component, the average costs resulting from the cost-based approach are higher than those derived from the proposed solutions.

In Figure 4B, we draw the average customer retention probabilities over time; attrition rates are approximately 8% with the proposed allocations, which reflects a 9.5% improvement in the customer retention rate and a 50% reduction of the attrition rate over the cost-based routing. Our proposed framework prevents more customers from leaving because customer retention becomes an important element of the firm's objective function. The firm therefore may adapt its allocation decisions to its knowledge about customer preference and give these customers better service to prevent them from leaving. Given the constraint of service costs, the 50% decrease of attrition rate is a significant improvement in service effectiveness.

In Figure 4C, we report the total profit the firm makes over the observation periods. We use the total profit because we want to take into account that some customers leave and no longer contribute to profits. Our framework results in a steady increase of total profit because of the decrease in average costs and increase of retention rates. In contrast, the total profit of the cost-based approach only increases marginally (due to the slight reduction of cost). Therefore, the negative impact of customer attrition offsets the positive impact of cost savings; that is, savings in service costs come at the expense of customer attrition.

In general, we show that the more customized and proactive decisions resulting from our proposed framework help firms save costs, increase customer retention, and improve long-term customer value or profit. Thus, service effectiveness can be improved without incurring significant service cost.

6.3 Brief Discussions about the Implementation of Proposed Solutions

The proposed customized and proactive allocation decisions involve marketing consequence, adaptive learning, and forward-looking. To implement the solutions, the firm must have immediate access to its customer database, analyze customer information, solve the dynamic programming problem to obtain the optimal allocation decision, and update its beliefs on the basis of successful and unsuccessful interactions. All these steps need to occur within seconds of a customer's call, which is impossible for a human operator. In our case, the firm's call center has both a CRM system ready to record customer call histories and ACD systems in place to allocate service calls automatically. Its CRM can be integrated to the ACD system. Because customers are required to provide their account numbers whenever they call in, agents with immediate access to CRM and ACD systems can obtain an integrated view of every customer's call history and all other related information. According to the point estimates of the pre-specified rules, as described in equation (10), the firm can update its knowledge on customer preference. With future marketing consequences in mind, the firm solves for optimal allocation decisions, which maximizes customer long-term profit. The routing decision can then be implemented automatically by the ACD system.

7 Conclusion, Limitations, and Further Research

Today, the role of call centers has shifted from a cost to be minimized 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. Furthermore, the call center industry is one of the first to face the vast possibilities of transforming its CRM system from a data collection and storage technology into service excellence and revenue growth opportunities. In particular, "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).

Using panel data on service allocations, we first provide empirical evidence on how service duration and customer retention is affected by the firm's onshore and offshore allocation decisions. Our findings shed new light on the understanding of customer reactions to firm's service allocations in general and to offshore centers in particular. We find that customers are less satisfied with offshore centers, and being serviced by them leads to higher customer attrition. Although offshore centers take more time to solve both transactional and technical questions, the difference pertaining to technical questions is smaller. Because of their significantly lower service costs per minute, offshore centers under 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 care less about being serviced by offshore centers, especially when they have technical questions.

We then formulate service allocation decisions as a matching problem in which the firm recognizes the marketing consequence, learns about customer heterogeneous preference, 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 knowledge about customers and better match customers with 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. We show that our proposed allocation decisions help the firm to (1) reduce average service costs, (2) improve customer retention, and (3) enhance total profit. In short, through learning and better matching, effectiveness can improve without incurring significant service costs.

Through application to a DSL firm's service channel allocations, the developed learning rule and optimization solutions (or simplified heuristics) provide a computational algorithm for firms to integrate their CRM and operating systems and automate call allocations. For companies that cannot automate, the derived statistical properties of the optimal allocation decisions provide guidance for adjusting their service allocation decisions to accommodate customer reactions. The proposed framework also aligns with the spirit of customer-centric and dynamic CRM, as discussed recently in both academic and practical literature (e.g., Venkatesan and Kumar 2004, Rust and Chung 2006, Sun et al. 2006). It further meets demands from various industries that seek analytical decision making tools to analyze their databases and support their decision making.

However, we acknowledge that our study is limited and can be expanded in several ways. First, due to the data constraints, we make many simplified assumptions about operation management aspects of service allocation decisions such as queuing, abandon, and retrials. We also cannot separate active talking time from holding time. Further research can 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 and customer retention. Additional research should allow satisfaction to change over time to measure the effect of service allocation on perceived service quality and retention more accurately. Third, for demonstration purposes, we adopt a binary logit model to capture the customer retention decision. Further research might capture customer reactions better by allowing for the formation of customer satisfaction, customer learning of service quality, and formation of duration expectation. The hazard rate model can also be adopted to model customer duration. Fourth, we assume the customer segments are static. Research in the future should develop more sophisticated learning routines to allow for dynamic changes in customer preference. Fifth, agents at call centers can learn and become more efficient over time, so additional research should allow for the improvement of agents' service skills.

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Table 1A. 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 offer.	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 1B. 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)	0.88(0.13)
2	20.89	0.12(0.32)	0.88(0.32)	8.14(21.72)	31.06(34.91)	0.87(0.17)
3	16.27	0.11(0.32)	0.89(0.32)	7.72(21.19)	32.08(35.16)	0.86(0.18)
4	12.12	0.12(0.33)	0.88(0.33)	8.46(23.11)	30.46(35.03)	0.87(0.16)
5	8.99	0.12(0.33)	0.88(0.33)	8.93(23.41)	31.40(35.24)	0.86(0.18)
6	5.48	0.09(0.29)	0.91(0.29)	9.41(22.89)	30.02(34.46)	0.87(0.17)
7	4.18	0.09(0.28)	0.91(0.28)	8.08(20.51)	29.47(33.85)	0.86(0.19)
8	2.34	0.06(0.24)	0.94(0.24)	10.93(26.39)	30.95(35.40)	0.88(0.12)
9	1.84	0.06(0.24)	0.94(0.24)	12.27(26.32)	30.69(34.19)	0.78(0.33)
10+	3.93	0.07(0.26)	0.93(0.26)	11.48(24.96)	37.77(38.07)	0.88(0.13)

Table 1C. Comparative Advantages[1]

	Onshore[1]			Offshore		
	Overall	**Transactional**	**Technical**	**Overall**	**Transactional**	**Technical**
ALLOCATION (A_{ijt})	0.84 (0.37)	0.11[2] (0.32)	0.89 (0.32)	0.16 (0.37)	0.03 (0.18)	0.97 (0.18)
DUR	20.46 (27.80)	6.39 (17.61)	22.32 (28.37)	37.62 (24.69)	44.20 (31.79)	36.28 (24.45)
SAT	3.46 (1.27)	3.39[3] (1.16)	3.32 (1.25)	3.11 (1.39)	3.11 (1.40)	3.33 (1.27)
COURTESY	4.44 (0.93)	4.26 (1.03)	4.46 (0.93)	4.27 (0.98)	4.00 (0.01)	4.27 (0.99)
LANGUAGE	4.22 (0.99)	3.96 (1.10)	4.23 (0.99)	3.77 (1.27)	3.75 (0.96)	3.77 (1.28)
CONCISE	4.01 (1.17)	3.74 (1.26)	4.03 (1.16)	3.25 (1.47)	2.75 (1.71)	3.26 (1.46)
UNDERSTAND	3.94 (1.25)	3.72 (1.30)	3.95 (1.25)	2.83 (1.60)	1.50 (0.71)	2.87 (1.60)
ACCURATE	3.72 (1.41)	3.52 (1.36)	3.73 (1.41)	2.87 (1.54)	3.00 (1.63)	2.87 (1.55)
TECH	3.51 (1.25)	3.54 (1.22)	3.58 (1.25)	3.50 (1.13)	3.33 (1.28)	3.18 (1.13)
PERSONALIZED	3.84 (1.29)	3.80 (0.79)	3.84 (1.36)	3.08 (1.47)	4.00 (1.41)	3.07 (1.47)
ABILITY	3.55 (1.49)	3.50 (1.58)	3.56 (1.49)	2.76 (1.59)	3.00 (1.63)	2.76 (1.58)
HOLDTIME	3.22 (0.77)	3.22 (0.68)	3.22 (0.78)	2.51 (1.16)	3.22 (0.65)	2.49 (1.16)
RET	0.88 (0.31)	0.91 (0.29)	0.87 (0.31)	0.83 (0.36)	0.82 (0.38)	0.84 (0.36)

1 We classify customers as onshore or offshore using the recency weighted percentage of calls handled by both centers. A customer is classified as offshore if his or her calls were mostly routed to offshore centers. Using a similar approach, we classify customers according to the type of questions they ask. If most calls are about transactional questions, that customer is classified as asking more transactional questions.

2 The percentage of questions handled by onshore centers that are transactional questions.

3 Overall customer satisfaction score among all the customers who were serviced mostly by onshore centers and asked mostly transactional questions.

Table 2A. Fit Statistics of the Calibration Model

		Firm's Allocation Decision	Customer Reactions 1 Segment	2 Segments	3 Segments
Calibration[a] sample	Log Likelihood	-7352.30	-16176.21	-13062.34	-23387.43
	BIC	14899.83	32448.04	26319.91	47069.69
	AIC	14802.60	32400.42	26222.68	46922.86
Holdout[b] sample	Log Likelihood	-3886.19	-8053.53	-6421.22	-11410.06
	BIC	7952.14	16195.09	13022.20	23091.59
	AIC	7870.38	16155.05	12940.45	22968.13

a. Number of individuals = 2,106; Number of calls = 9,643.
b. Number of individuals = 1,053; Number of calls = 4,661.

Table 2B. Comparison with Sample Statistics

Statistics	**Sample**	**Calibration Model**
Percentage of allocations to offshore	0.16	0.18 (0.04)
Average service duration in minutes	29.99	27.69 (4.01)
Average retention	0.84	0.86 (0.03)

Table 3. Comparing Customer Demand for Service

Parameters		Coefficients (Std. Dev.)	
		Segment 1	Segment 2
Segment Membership		0.664 (0.005)*	0.336 (0.005)*[a]
	Intercept	1.061 (0.018)*	0.000 (0.000)
	EXP	0.080 (0.011)*	0.000 (0.000)
	RESIDENTIAL	-1.016 (0.028)*	0.000 (0.000)
Log(Duration) (Regression)	Intercept	0.508 (0.030)*	5.126 (1.201)*
	Lagged log(Duration)	0.101 (0.007)*	0.356 (0.023)*
	TECHNICAL	0.981 (0.004)*	0.139 (0.001)*
	OFFSHORE	3.154 (0.023)*	3.127 (0.235)*
	OFFSHORE*TECHNICAL	-1.007 (0.029)*	-1.392 (0.136)*
	NCOMPUTER	0.060 (0.014)*	0.402 (0.117)*
	Variance	0.526 (0.010)*	0.051 (0.024)*
Retention (Binary Logit)	Intercept	7.493 (0.327)*	0.596 (0.001)*
	SAT	6.582 (0.387)*	1.951 (0.077)*
	PRICE	-0.049 (0.006) *	-0.466 (0.001)*
	PROM	0.143 (0.026)*	0.188 (0.661)
	COMP	-1.195 (0.479)*	-0.363 (0.024)*
	Log(TENURE)	-0.892 (0.411)*	1.273 (0.133)*
	PENALTY	0.518 (0.182)*	0.399 (0.035)*
	OFFSHORE	-17.704 (7.192)*	-4.379 (1.261)*
	OFFSHORE*TECHNICAL	-3.135 (6.930)	7.114 (0.112)*
	Log(Duration)	4.007 (1.084)*	0.733 (0.113)*
	Log(Duration)^2	-2.262 (0.223)*	-2.050 (0.060)*
	WAIT	-1.483 (0.397)*	-4.111 (1.832)*
	NCALLS	-1.332 (0.077)*	-3.449 (3.148)
	FREQ_OFF	-46.699 (1.847)*	-1.440 (0.123)*
	ACCUMDUR	-3.793 (0.158)*	-1.462 (0.201)*
Firm's allocation decisions (Binary Logit)	Intercept λ_{01} [c]	8.935 (1.812)*	
	Expected cost λ_1	14.067 (0.002)*	

a. Estimate is significant at 5% level.

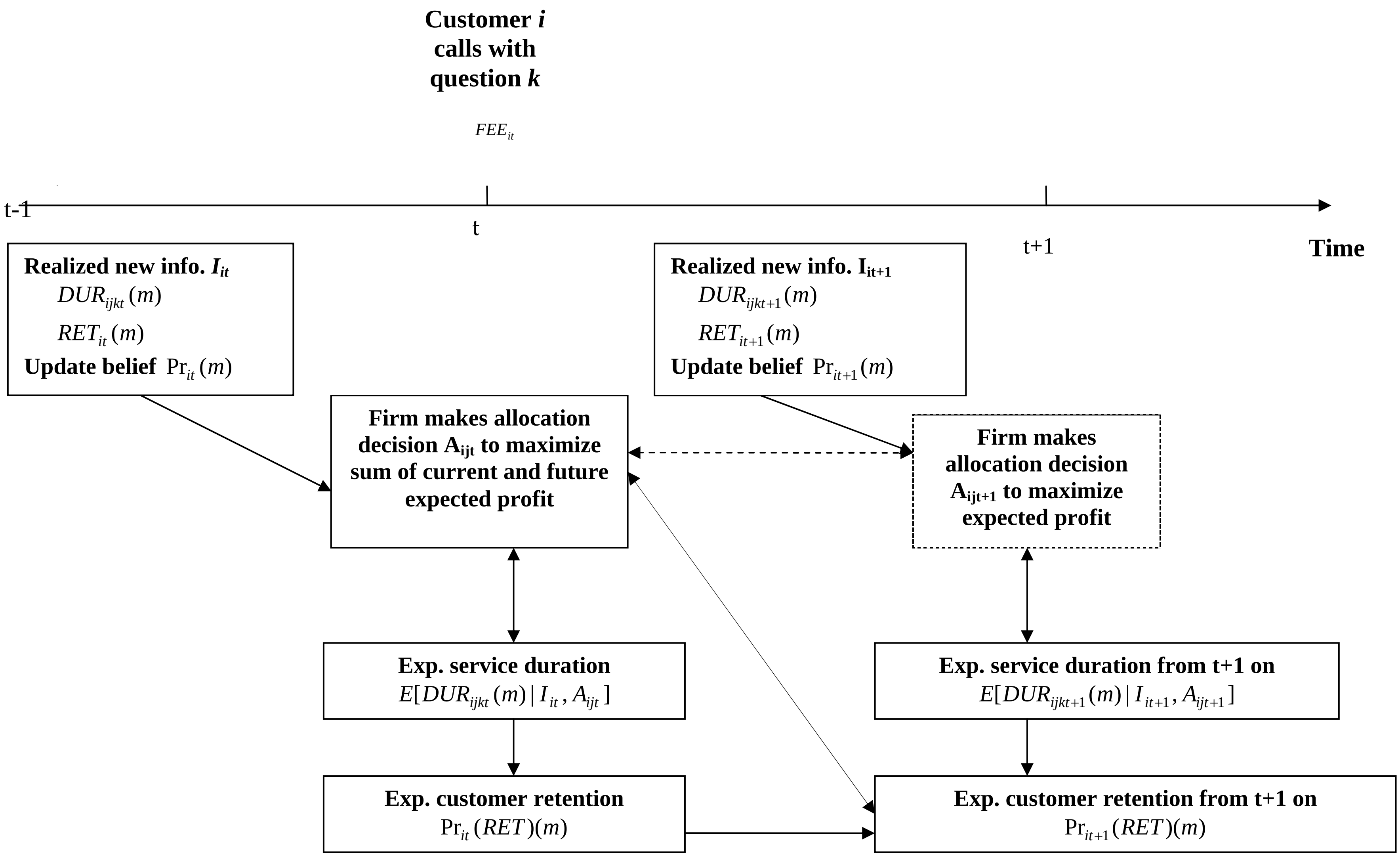
[b] For identification purposes, the coeffic*ients* for segment 2 are normalized to 0 due to the logit-type segment membership setup (i.e., $P(m=2)=\dfrac{1}{1+\exp(\phi_1 x_i)}$, where ϕ_1 and x_i are parameters for segment 1 and the characteristics of consumer *i*, respectively).

c. λ_{02} is normalized to be zero for identification purposes.

Table 4. Comparison of Actual Allocation 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%	56%	44%	100%
Average service duration	20.46	37.62	29.99	14.23	18.69	16.33
Average waiting time	1.07	0.75	0.81	1.04	0.77	0.80
Percentage of customer retention at last period	88%	83%	84%	97%	89%	92%

Figure 1. Timeline of Firm Decision Process



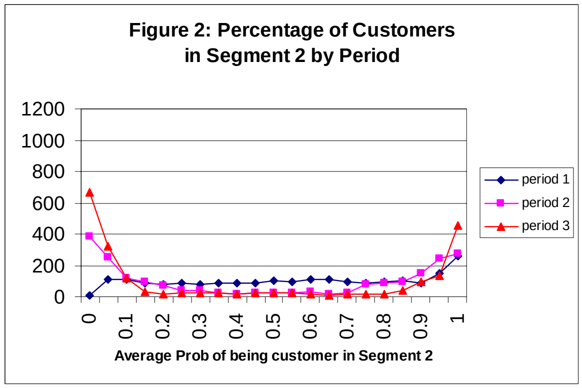


Figure 2: Percentage of Customers in Segment 2 by Period

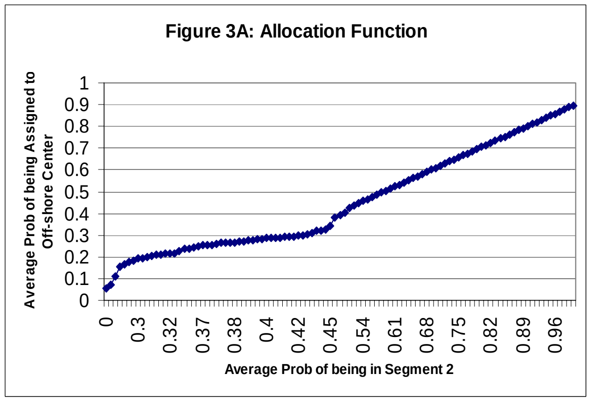


Figure 3A: Allocation Function

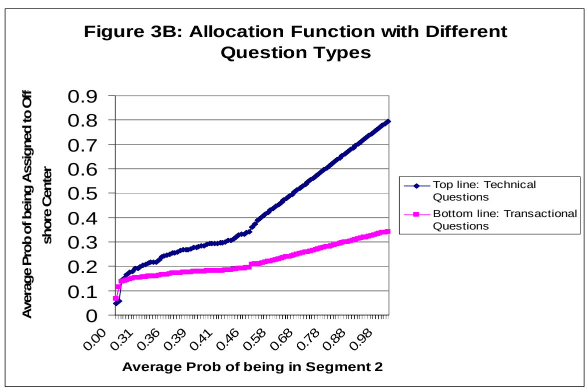


Figure 3B: Allocation Function with Different Question Types

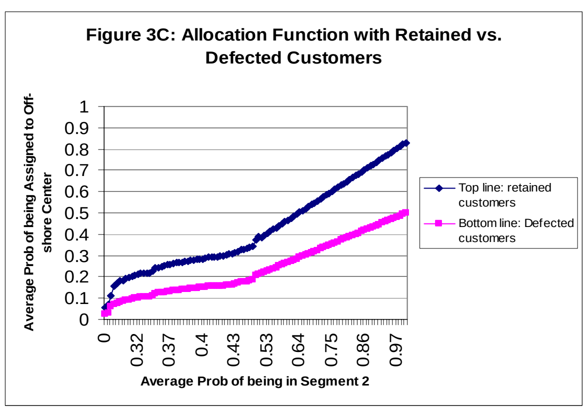


Figure 3C: Allocation Function with Retained vs. Defected Customers

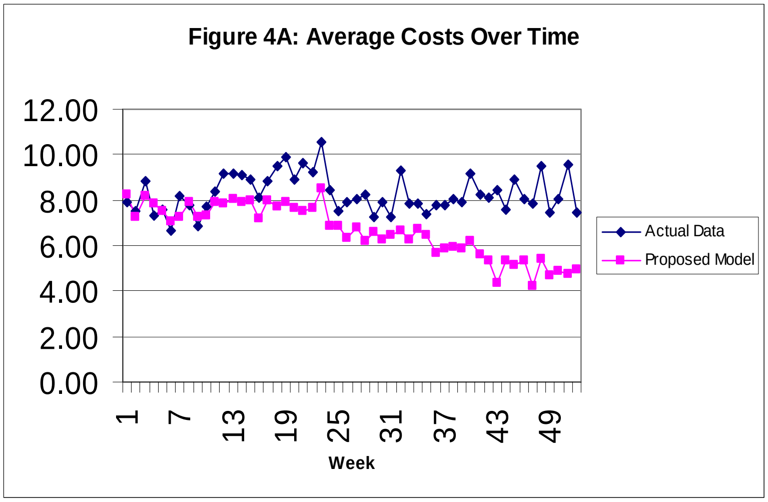


Figure 4A: Average Costs Over Time
12.00
10.00
8.00
6.00
4.00
2.00
0.00
1
7
13
19
25
31
37
43
49
Week
Actual Data
Proposed Model

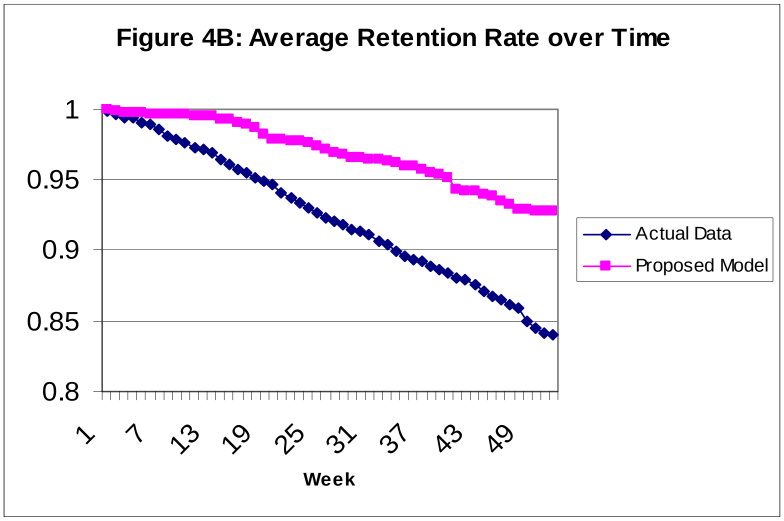


Figure 4B: Average Retention Rate over Time
1
0.95
0.9
0.85
0.8
1
7
13
19
25
31
37
43
49
Week
Actual Data
Proposed Model

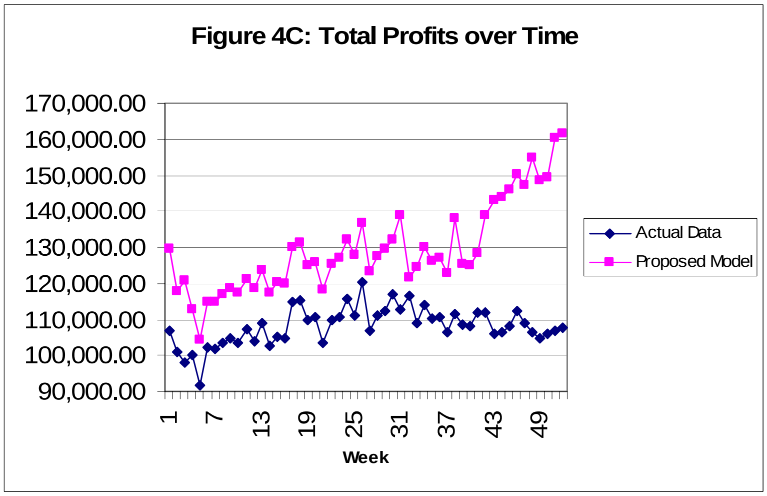


Figure 4C: Total Profits over Time
170,000.00
160,000.00
150,000.00
140,000.00
130,000.00
120,000.00
110,000.00
100,000.00
90,000.00
1
7
13
19
25
31
37
43
49
Week
Actual Data
Proposed Model