Essays on the Role of Customer Expectation in Service Markets

by

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To my parents

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ABSTRACT

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Co-Chairs: Puneet Manchanda and Anocha Aribarg

Customer expectations have been considered as customers' pre-purchase beliefs or evaluative beliefs about a product or service. When making a choice, customers first construct their expectations of what is to come whenever they receive new information within a context that is based on the past events. From firms' perspective, a tension exists between raising expectations to increase initial acceptance/trial and lowering expectations to increase satisfaction, and hence future sales. As such, it should come as no surprise that service firms are interested in better understanding how consumers form expectations about quality to manage customer expectations over time. This thesis comprises of two essays where I demonstrate the role of customer expectation in (1) customer satisfaction and repurchase and (2) strategic customer behavior under bounded rationality and its impact on product switching.

In the first essay, I examine the value of measuring customer satisfaction. Many service firms keep track of customer satisfaction ratings, along with objective service performance, after each purchase transaction. This practice results in the large amount of customer satisfaction data and thus raises the question of whether measuring customer satisfaction actually provide additional information relative to what can

be obtained from objective service performance data. I answer this question via the use of unique data consisting of individual-level cross-sectional and time-series measures of objective service performance, customer satisfaction, and purchase behavior. The data come from two different - quick service restaurant and auto rental - service industries. I find that customer satisfaction provides additional information about customer purchase behavior over and above objective service performance. Unlike past research, these results are obtained after controlling for within-customer selection (of service encounters). Overall, the results suggest that measuring customer satisfaction is valuable because it helps firms to better predict their economic outcomes.

The second essay focuses on customers' product switching behavior based on their expectations under bounded rationality. As there is growing interest in customer relationship management, many service firms care about identifying strategic customer behavior that negatively influences economic outcomes for the firms. I answer this question by modeling time-varying customer expectations under imperfect recall and their impact on product switching behavior over time, using the Kalman filter algorithm. The model captures the dynamics of the customer expectations, separating the effects of (recalled) service performance from the impact of the prior expectations accrued through service usage over time. Overall, I find evidence of a decline in carryover of prior expectations and imperfect recall of previous service encounter, which supports my hypothesis on bounded rationality in customer expectations. Furthermore, the results show that customers strategically choose the same alternative that previously results in a free upgrade, anticipating yet another upgrade in a subsequent transaction.

CHAPTER I

The Value of Measuring Customer Satisfaction

1.1 Introduction

Firms use customer satisfaction as a measure of their service performance. When information was stored in analog form, taking a customer-satisfaction survey was expensive and time-consuming, requiring face-to-face, telephone, or mail contact with interviewees. Today, people can respond with a click of a mouse, and their responses are recorded and filtered instantly. These web surveys are sent out after every hotel stay, after every airline flight, after every car repair, to name a few. Perhaps the greatest benefits offered to companies implementing the web survey are decreased cost for data collection and data entry, access to almost every person with access to the Internet, and the ability to present survey information in different formats (*Couper*, 2000). There is no way to determine exactly how many consumer satisfaction surveys are completed each year, but Mindshare Technologies, a small company that conducts and analyzes on-the-spot electronic surveys, says it completes 175,000 surveys every day, or more than 60 million annually. ForeSee, an offshoot of the American Customer Satisfaction Index, a company that measures consumer sentiment about business and government, says it collected 15 million surveys in 2011 (*Grimes*, 2012).

Given that soliciting customer satisfaction after each purchase transaction has become prevalent, service firms face the following question: did these efforts by firms actually provide additional information relative to what can be obtained from objective service performance? It is clear that service firms care about this question, as they currently have capability to monitor (mostly time based) objective service performance. For example, airlines track the percentage of on-time flights (*Grewal, Chandrashekaran, and Citrin*, 2010), UPS uses real-time delivery tracking (*Lund and Marinova*, 2014), and McDonald's monitors its drive-through service time (*Hess, Ganesan, and Klein*, 2003). From the firm's perspective, the evidence that customer satisfaction data provide valuable information over and above objective service performance can help justify and encourage the firm's effort and investment in collecting satisfaction data. Conversely, if such satisfaction data provide no additional value, the firm might want to bypass the collection of customer satisfaction data and rely solely on objective service performance data.

Previous satisfaction literature mostly relies on cross-sectional self-report surveys that measure customers' cumulative evaluations of service performance and subsequent purchase intent, leaving the time period of evaluation open. A limitation in this approach is that it requires the researcher to assume that customers' decisions of whether to rate and what rating to give are independent, opening up the possibility of the results being biased by self-selection. Failing to account for this *within-individual* self-selection will lead to biased inferences with regard to the observable factors that drive satisfaction ratings. It is particularly important for firms to address this within-individual selection, given the fact that customers are repeatedly asked to participate in surveys after each purchase transaction. An additional concern of the cross-sectional approach is that examining variables such as perceived service quality, customer satisfaction, and purchase intent, that are collected from the same survey likely inflates the relationships among the constructs under investigation (i.e., high common-methods variance) (*Fishbein and Ajzen*, 1975).

Unlike most previous customer satisfaction research that uses cross-sectional data, I use the panel nature of the data collected after each purchase transaction, which include objective service performance, customer satisfaction, and actual purchase. The data come from two very different - quick service and auto rental - service industries. These individual-level cross-sectional and time-series data are extremely useful in addressing limitations from which previous satisfaction literature suffers. First, the availability of transactions with and without satisfaction ratings over time allows me to correct for the presence of within-individual selection bias. In addition, observing objective service performance and actual purchase behavior that match to customer satisfaction ratings allows me to address concerns of high common-methods variance and at the same time examine the value of customer satisfaction when it is feasible for firms to measure objective service performance.

I achieve my research goal by modeling rating incidence, satisfaction rating, and purchase behavior, using a two-stage model. In the first stage, I use a system of simultaneous equations with the first equation capturing drivers of customers' propensity to rate and the second equation capturing the drivers of satisfaction rating. In the second stage, I model customers' purchase behavior conditional on interpurchase time as a function of customer satisfaction (along with control variables). To allow for heterogeneous customer responses, I incorporate random effects for the parameters of interest and estimate them using Markov chain Monte Carlo (MCMC) methods. The analysis suggests that objective service performance directly affects both customer satisfaction and purchase behavior. In addition, customer satisfaction has a strong effect on the probability of purchase even in the presence of objective service performance measures. I obtain these results after correcting for *within-individual* self-selection (I find that the decision to rate and the satisfaction rating are correlated). Overall, the results suggest that customer satisfaction provides additional information about customer purchase behavior over and above objective service performance. Moreover, failing to measure customer satisfaction data leads to undesirable prediction in firm's revenue. The results replicate across two different service settings, allowing me to speculate that these results are generalizable. Finally I carry out a set of robustness checks (using difference measures of dependent and independent variables, examining across-individual selection as well as explicitly controlling for product, as opposed to service, quality).

I contribute to the literature in several ways. First, to the best of my knowledge, this research is the first to conduct an individual-level longitudinal analysis in a transaction-based setting to examine the interplay among objective service performance, customer satisfaction, and actual purchase behavior over time in the same framework. Second, I provide insights on this issue by introducing a system of simultaneous equations. This model enables me to address *within-individual* self-selection, something that the previous literature has not been able to do. Finally, I provide empirical evidence on the economic value of measuring customer satisfaction that substantially contributes to firm's revenue prediction.

The remainder of the paper is organized as follows. I first present an overview of the theoretical and methodological issues relating to service performance and customer satisfaction, based on the past literature. Next, I present the model and estimation procedure. I then describe the institutional setting, the data and the operationalization of the variables across the two different industries. I also present the estimation results, a series of robustness checks, and results from policy simulations. Finally, I conclude with a discussion of the key findings, research limitations, and directions for future research.

1.2 Related Research

1.2.1 Cumulative and Transaction-Specific Customer Satisfaction

Previous research defines customer satisfaction as a post-purchase evaluation of a product or service performance resulting from the customer's comparison of the actual performance in relation to pre-purchase expectation (*Churchill and Surprenant*, 1982). Customer satisfaction has been conceptualized either as cumulative satisfaction (e.g., see the description of the American Customer Satisfaction Index - ACSI - in *Fornell et al.* (1996)) or a transaction-specific reaction (*Oliver*, 1980; *Keiningham et al.*, 2014), depending on the research context. These different conceptualizations are more complementary than competing as they serve different purposes (*Johnson, Anderson, and Fornell*, 1995).

Cumulative satisfaction refers to the customer's overall attitude based on all encounters and experiences with the organization. This approach assumes that customers rely on their entire experience when forming intentions and making repurchase decisions (*Olsen and Johnson*, 2003). Notably, this attitude-based satisfaction measure resembles the concept of perceived service quality in the service literature (*Parasuraman, Zeithaml, and Berry*, 1988). To collect cumulative evaluations, previous studies leave the time period of evaluation open. In particular, customers are asked to consider *all of their experiences to date* when evaluating their satisfaction with a product or service (*Fornell et al.*, 1996).

Transaction-specific satisfaction references customer satisfaction with a specific, discrete service encounter and has typically been measured by asking survey participants to consider the most recent experience they had (*Olsen and Johnson*, 2003). This approach allows firms to better track changes in service performance. When a manager makes changes in response to customer feedback, the effectiveness of those changes are more likely to affect customers' perceptions of their most recent episode or experience with the service provider. In contrast, it takes time for quality changes to affect more cumulative evaluations (*Johnson, Anderson, and Fornell*, 1995).

In this research, I focus on transaction-based satisfaction from online survey after each transaction. As such, I am able to investigate the dynamic changes of customer satisfaction and the subsequent purchase behavior over time, in response to the changes in objective service performance.

1.2.2 Antecedents of Customer Satisfaction

The antecedents of customer satisfaction have long been examined and there is general consensus that satisfaction judgments are a function of disconfirmation, the discrepancy between performance and expectation (*Anderson and Sullivan*, 1993; *Oliver*, 1980; *Parasuraman, Zeithaml, and Berry*, 1988; *Weaver and Brickman*, 1974). Previous literature has consistently found that positive disconfirmation of expectation (i.e., performance exceeds expectation) increases customer satisfaction and negative disconfirmation to decrease customer satisfaction (*Oliver*, 1980) and these effects are asymmetric as the negative disconfirmation effect is stronger than the positive counterpart (e.g., *Gijsenberg, van Heerde, and Verhoef*, 2015; *Knox and Van Oest*, 2014). Disconfirmation has been viewed as a distinct and independent construct from its two components: perceived performance and (performance) expectation. Previous research has found mixed or weak effects of these constructs on customer satisfaction (e.g., *Churchill and Surprenant*, 1982; *Voss, Parasuraman, and Grewal*, 1998). For instance, *Churchill and Surprenant* (1982) show that for durable as opposed to non-durable products only perceived performance, neither expectation nor disconfirmation, affects customer satisfaction. The explanation for this is that customers often do not have enough information to form reliable expectation for an infrequently purchase durable product. Based on a post-purchase survey convering a variety of product categories, *Anderson and Sullivan* (1993) also find that disconfirmation together with perceived performance affects customer satisfaction, instead of disconfirmation and expectation.

Scholars have also emphasized the importance of consistent service performance in maintaining customer satisfaction. For example, *McCollough, Berry, and Yadav* (2000) conduct scenario-based experiments to show that customer satisfaction is lower after service failure and recovery (even with high-recovery performance) than in the case of consistent error-free service. *Rust et al.* (1999) demonstrate that it is not necessary to exceed customer expectations to increase preference and receiving an expected level of bad service does not reduce preference. The reason is that despite their desire for better-than-expected service, customers also prefer consistent service performance to time. Other research provides some caveats that some particular situations of performance inconsistency may also lead to positive outcomes. *Bolton, Lemon, and Bramlett* (2006) find a few extremely favorable experiences to be critical for business customers' subsequent re-patronage behavior such as system contract renewal. *Sriram, Chintagunta, and Manchanda* (2015) show that high levels of service variability can increase customer retention when the general service performance is low.

This paper is related to these studies in that it shows how individual-level disconfirmation and performance inconsistency affect transaction-specific satisfaction ratings over time. My operationalizations of disconfirmation and performance inconsistency based on objective service performance, not survey or experimental data, address potential concerns about self-reported measures of service performance. For example, previous studies captures individual's summary judgment of overall disconfirmation using a rating scale anchored at "better than expected" and "worse than expected" (e.g., *Churchill and Surprenant*, 1982). Customer expectations reflected in these self-reported measures of disconfirmation may not match individuals' per-consumption expectations due to cognitive dissonance, assimilation, or contrast *Oliver* (2014).

1.2.3 Consequences of Customer Satisfaction

Satisfaction research has consistently shown the impact of satisfaction on purchase intention (e.g., *Anderson and Sullivan*, 1993; *Oliver*, 1980) and on downstream business outcomes such as service usage (*Bolton*, 1998; *Bolton and Lemon*, 1999), customer retention (*Knox and Van Oest*, 2014; *Mittal and Kamakura*, 2001; *Seiders, Voss, Grewal, and Godfrey*, 2005; *Voss, Godfrey, and Seiders*, 2010), share of customer wallet (*Cooil et al.*, 2007; *Keiningham et al.*, 2014; *Van Doorn and Verhoef*, 2008), and firms' financial performance (*Fornell, Rust, and Dekimpe*, 2010; *Grewal, Chandrashekaran, and Citrin*, 2010; *Luo, Homburg, and Wieseke*, 2010). Nonetheless, some research finds the direct main effect of customer satisfaction on individual-level purchase behavior to be insignificant (*Seiders et al.*, 2005). The absence of the direct effect can be attributed to the subtle relationship between satisfaction an purchase behavior. First, some studies argue that the relationship between satisfaction and repurchase is nonlinear and asymmetric. For instance, *Mittal and Kamakura* (2001) find a convex relationship between satisfaction an repeat purchase, with satisfaction changes at the top end of the scale having the biggest impact. Second, the impact of satisfaction on purchase can be moderated by customer characteristics, the strength/age of customer relationship with the firm, and marketplace characteristics such as competition and satisfaction with competitors (*Seiders et al.*, 2005).

To establish the link between customer satisfaction and these business outcomes over time, the vast majority of these studies relies on customers' cumulative evaluations from multiple cross-sectional surveys, leaving the time period of evaluation open, as they have no access to transaction-specific satisfaction measures after each purchase transaction (See Table 1.1 for the summary). For example, *Van Doorn and Verhoef* (2008) administered three surveys in yearly iterations with one-year time spans between surveys to see the impact of satisfaction on customer share. In contrast, this research matches satisfaction ratings to each purchase transaction in multiple periods and hence better track changes in firms' performance linked to customer satisfaction. I could find only one academic study (*Keiningham et al.*, 2014) that used multiple transaction-specific satisfaction ratings. It is important to note, however, that these studies did not study service performance in the same framework. This study incorporates objective service performance and transaction-based satisfaction and examines the interplay of these constructs with actual purchase behavior at the individual level.

1.2.4 Selection Bias in Satisfaction Ratings

In general, not all customers reply to satisfaction surveys, opening up the possibility of the results being biased by self-selection. Failing to account for this selection bias that arises from systematic survey nonresponse will lead to biased inferences with regard to the observable factors that drive the outcome variable of interest. To address this concern, previous customer satisfaction literature controls for the effect of unmeasured characteristics related to the selection process. *Godfrey, Seiders, and Voss* (2011) take into account *across-individual* selection by first modeling customer's propensity to be included in the satisfaction survey and then using the obtained inverse Mills ratio as a control variable that links customer satisfaction to repurchase. *Mithas, Krishnan, and Fornell* (2005) use a propensity score matching approach to control for the selection bias given rise from the researchers' inability to exogenously assign firms to the CRM treatment.

A limitation in this *across-individual* approach is that it requires the researcher to assume that customers' decisions of whether to rate (i.e., rating incidence) and what rating to give (i.e., rating decision) are independent. However, when customers are repeatedly asked to rate their satisfaction after each purchase transaction and they have an opportunity to opt out from the survey, the unobserved factors driving customers' propensity to rate are likely to be correlated with the observed satisfaction

Table 1.1: Prior Research on the Longitudinal Analysis of Customer Satisfaction and Business Outcomes

Study	Research Context	Dependent Variable(s)	Satisfaction Measure	Study Period	Self-Selection Correction
Bolton (1998)	Telecommunication	Duration of Relationship	Single Cumulative Rating	1 year	X
Bolton and Lemon (1999)	TV/Telecommunication	Minutes of Use per Month	Single Cumulative Rating	6 months	X
Knox and Van Oest (2014)	Internet and Catalog Retailer	Interpurchase Time	Multiple Transaction-Specific Ratings	30 months	X
Mittal and Kamakura (2001)	Automotive Service	Repurchase Behavior	Single Cumulative Rating	Varies	X
Seiders et al. (2005)	Fashion Apparel/Home Furnishing	Repurchase Visits/Spending	Single Cumulative Rating	1 year	Across-Individual
Voss et al. (2010)	Fashion Apparel/Automotive Service	Repurchase Visits/Spending	Single Cumulative Rating	1 year	Across-Individual
Cooil et al. (2007)	Canadian Baking Service	Customer Share of Wallet	Multiple Cumulative Ratings	5 years	X
Keiningham et al. (2014)	Specialty Retailer	Customer Share of Wallet	Multiple Transaction-Specific Ratings	21 months	X
Van Doorn and Verhoef (2008)	Logistics Service	Customer Share of Wallet	Multiple Cumulative Ratings	3 years	X
Fornell et al. (2010)	43 Different Industries	Consumer Spending	Multiple Cumulative Ratings (ACSI)	12 years	X
Luo et al. (2010)	24 Different Industries	Analyst Stock Recommendations	Multiple Cumulative Ratings (ACSI)	12 years	X
Grewal et al. (2010)	Domestic Airline Service	Shareholder Value	Multiple Cumulative Ratings (ACSI)	9 years	X
Current Study	Quick Service Restaurant/Rental Car	Interpurchase Time	Multiple Transaction-Specific Ratings	1/2 year(s)	Within-individual

ratings. This situation gives rise to *within-individual* selection bias and ignoring this bias is likely to result in incorrect inferences regarding the observable factors driving the actual ratings. To the best of my knowledge, this research is the first to address this *within-individual* selection process in satisfaction rating.

1.2.5 Objective and Perceived Service Performance

As objective measures of performance are hard or even infeasible to obtain (e.g., helpfulness of a salesperson, reliability) especially in the service context, most satisfaction research relies on perceived performance measures (e.g., *Churchill and Surprenant*, 1982; *Oliver*, 1980). Objective measures of performance can be based on either observable and concrete metrics (e.g., minutes, number of defects) or expert ratings (*Mitra and Golder*, 2006). In contrast to objective performance, perceived performance is derived from customers' subjective judgment of the observed performance. As a result, perceived performance does not necessarily reflect actual performance as customer perception is likely to be influenced by factors such as marketing communication and experiences of others, as well as prior expectations of performance (*Anderson and Sullivan*, 1993).

Several studies have managed to secure objective performance measures. *Gijsenberg, van Heerde, and Verhoef* (2015) find the proportion of successful connections in the railway service industry to affect aggregate customer satisfaction. *Bolton, Lemon, and Bramlett* (2006) link the objective performance of a supplier's engineering service (e.g., work minutes per a support request), and *Sriram, Chintagunta, and Manchanda* (2015) link signal quality of a video-on-demand service to customer retention. However, these papers do not study satisfaction in the same framework. In non-contractual service settings, *Grewal, Chandrashekaran, and Citrin* (2010) find a significant relationship between objective performance in the airline industry (e.g., percentage of on-time arrival, mishandled baggage and complaint) and overall attitude-based customer satisfaction. *Lund and Marinova* (2014) show that objective service performance in the pizza restaurant industry (i.e., delivery time) negatively moderates the impact of direct marketing effort on retail revenue. In the last two papers, however, objective service performance measures are not obtained at the transaction level.

In this paper, I observe individual-level cross-sectional and time-series measures of objective service performance that match with customer satisfaction and purchase behavior. This unique feature of the data allows me to alleviate high common-methods variance problem (*Fishbein and Ajzen*, 1975). It is widely recognized that self-reported ratings of perceived service performance in the same survey where customer satisfaction, expectation, disconfirmation and purchase intent are also measured, are prone to inflate the relationships among the constructs under investigation.

1.3 Model and Estimation

1.3.1 Model Specification

I model satisfaction rating incidence, satisfaction rating, and purchase behavior as three separable but related processes, by constructing a set of simultaneous equations at the individual level. In the first step, I consider two decisions by the individual at each service encounter: whether to provide satisfaction ratings and if so, what ratings to give. I use a binary probit and a linear regression to model these two decisions, respectively, along with a correlated error structure between the two models. Given customer satisfaction ratings are conditional on her decision on participating in a survey, ignoring rating incidence or treating satisfaction rating as being independent of rating incidence can give rise to a selection bias. To circumvent this *within-individual* selection bias, I need to account for the potential unobserved factors (e.g., competitors' promotional activities) that affect both rating incidence and satisfaction rating (see *Narayanan and Manchanda* (2012) for a similar situation in a different institutional setting). For customer i's purchasing at store j on purchase occasion t, the system of equations is specified as follows:

$$INC^{*}_{ijt} = \alpha'_i X^{INC}_{ijt} + \epsilon^{INC}_{ijt},\ INC_{ijt} = 1 \qquad (1.1)$$

$$\text{where}\ \ INC^{*}_{ijt} > 0,\ INC_{ijt} = 0\ \ \text{otherwise}$$

$$SAT_{ijt} = \beta'_{1i} X^{SAT}_{ijt} + \beta_{2i} IMR_{ijt} + \epsilon^{SAT}_{ijt} \qquad (1.2)$$

where INC^{*}_{ijt}, INC_{ijt}, and SAT_{ijt} represent the underlying latent variables representing customer i's decisions of whether to rate, rating incidence, and overall satisfaction score. IMR_{ijt} illustrates the inverse Mills ratio generated from Equation 1.1. $X^{INC}_{ijt} = \{DIS_{ijt}, VAR_{ijt}, CPN_{ijt}, NTR_{ijt}\}$ and $X^{SAT}_{ijt} = \{DIS_{ijt}, VAR_{ijt}, CPN_{ijt}\}$ are sets of explanatory variables for each equation. Note that the residuals of Equation 1.2, r^{SAT}_{ijt}, are retained and used as a proxy for customer satisfaction based on factors other than objective service performance.

In the second step, I model the probability of purchase conditional on interpurchase time with a semiparametric survival model (*Cox*, 1975), incorporating objective service performance measures and customer satisfaction. Specifically, my approach focuses on the daily purchase decision, that is, customers decide every day whether they plan to purchase as a function of the timing of their last purchase and transaction details at previous service encounter. This model specification treats the no-purchase days for each customer as the survival weeks, whereas it treats the purchase weeks as the failure weeks (for a comparison of alternative specification, see *Manchanda et al.* (2006)). This semiparametric approach is appealing as it does not require the specification of the underlying purchase time distribution (*Gupta*, 1991). Let $h(\tau|X^{INT}_{\tau})$ denote the hazard rate at time τ for an individual having covariate values X_{τ} at time

τ. This hazard rate is assumed to take the form:

$$h(\tau|X_{ij\tau}^{INT}) = h_0(\tau)\exp(\gamma_{1i}r_{ij\tau}^{SAT} + \gamma_{2i}X_{ij\tau}^{INT}), \tag{1.3}$$

In the above expression, $h_0(\tau)$ represents a constant baseline hazard that corresponds to interpurchase time between purchase occasion t and $t-1$, instead of calendar time, τ. $X_{ij\tau}^{INT} = \{DIS_{ij\tau}, VAR_{ij\tau}, CPN_{ij\tau}, INT_{ij\tau}, AMT_{ij\tau}\}$ indicates a set of covariates that enter in the proportional hazard formulation multiplicatively. As such, $\gamma_i = \{\gamma_{1i}, \gamma_{2i}\}$ can be viewed as the individual-specific proportional effect of customer satisfaction and X_τ on the hazard rate. Note that an exponential function renders the estimation of γ_i easier given that no constraints need to be imposed to ensure nonnegativity (*Helsen and Schmittlein*, 1993).

Guided by previous literature (e.g., *Parasuraman, Zeithaml, and Berry*, 1988), I operationalize disconfirmation, DIS_{ijt}, as the difference between current (objective) service performance and prior customer expectations of the performance. Given the availability of multi-period panel data, I specify the evolution of customer expectation to follow an anchoring and adjustment process (*Nerlove*, 1958) and derive it as a function of objective service performance that varies over time. In this setup, the greater the weight on the objective performance, the more significant the effect of immediate past experience on current expectation, or the more adaptive the expectations (*Johnson, Anderson, and Fornell*, 1995). Note that my approach to derive customer expectations helps me circumvent the mere-measurement effect. Previous research argues that prompting customer expectations sensitizes negative feelings. For example, *Ofir and Simonson* (2007) show that customers who had been solicited their expectations by the researchers gave the store lower post-shopping satisfaction ratings than did those who had not. Based on the customer expectation generated, I then specify disconfirmation as the difference between customer expectation and objective service performance, which ultimately affects transaction-based customer satisfaction and the probability of purchase conditional on interpurchase time. This approach is in line with inferred disconfirmation in previous literature. For example, *Parasuraman, Zeithaml, and Berry* (1988) propose a multi-item scale called SERVQUAL to measure perceived service performance where disconfirmation is derived as a difference score between perceived performance and performance expectation ratings on different service aspects.

$$DIS_{ijt} = PERF_{ijt} - EXP_{ijt} \quad \text{where} \quad EXP_{ijt} = \delta\ PERF_{ijt-1} + (1-\delta)\ EXP_{ijt-1} \tag{1.4}$$

In the above expression, $PERF_{ijt}$ and EXP_{ijt} represent objective service performance and customer expectation on the performance, respectively. The parameter δ is an empirically derived factor that determines the relative weights assigned to the prior expectation and the current service performance. To determine the value for exponential smoothing constant, δ, I perform a grid search (e.g., *Fader, Lattin, and Little*, 1992). I let δ vary from 0 to 1 with increments of 0.1. Note that other research has specified disconfirmation, using survey-based measures of expectation. For example, *Boulding et al.* (1993) proposes two different classes of survey-based expectation measures - "will" expectation and "should" expectation. Will expectation is specified as a weighted average of prior expectations and actual service performance (closer to the measure in this study), while should expectation is updated only when the firm's service performance exceeds a customer's prior should expectations. The authors find that will expectation increases perceived (as opposed to objective) quality, while should expectation does the opposite. However, they do not discuss the link between these two types of expectation and customer satisfaction. The use of survey based expectation, objective quality and the lack of the link between expectation and customer satisfaction makes it hard for me to investigate the role of these two forms of expectation in my data in an "apples-to-apples" comparison. For example, preliminary analyses with a measure for should expectation in my setting provides results that are not consistent with those in *Boulding et al.* (1993). I speculate that this is due to the differences in the expectation measures - the measures in this study are objective and transaction specific while the proposed measures are subjective, based broadly on the customers' overall experiences with the firm (and its competitors) in general.

Service performance inconsistency, VAR_{ijt}, is operationalized as an individual-level cumulative standard deviation of delivery time up to the current service encounter, guided by previous literature (e.g. *Sriram, Chintagunta, and Manchanda*, 2015).[1] In addition, I include customer coupon redemption, CPN_{ijt}, and semilog-transformed dollar purchase amount, AMT_{ijt}, as control variables. The error terms in Equation 1.1 and 1.2, ϵ_{ijt}^{INC} and ϵ_{ijt}^{SAT}, are assumed to have a multivariate normal distribution with mean vector of zero and covariance matrix of $(1, 1; \rho_{12})$. This error structure explains the correlation between unobserved components in customer rating behavior and controls for the *within-individual* selection problem. I fix the scale of the latent utilities by imposing the restriction that the variances of ϵ_{ijt}^{INC} and ϵ_{ijt}^{SAT} be unity.

To address the endogenous relationship between rating incidence and satisfaction rating, I use the number of transactions since the last time customer i provided a satisfaction rating, NTR_{ijt}, as an exclusion restriction. This requires the assumption that conditional on being repetitively asked to take the same survey, customers are likely to become satiated (*Bickart and Schmittlein*, 1999). Previous research finds that over-surveying results in lowered response rates because (1) with increasing contacts, respondents' overall attitudes toward the survey may become less favorable, and (2)

[1] In addition to the cumulative standard deviation of service performance, previous service literature has used different measures such as the number of extremely positive or negative performance (*Bolton, Lemon, and Bramlett*, 2006) and the proportion of successful performance (*Gijsenberg, van Heerde, and Verhoef*, 2015).

as people are contacted more often, they feel that the opportunity to provide their opinions in a survey is not a "rare" and, therefore, no longer a valuable experience (*Groves, Cialdini, and Couper*, 1992).[2]

I use random coefficients to control for unobserved heterogeneity at the individual level. Specifically, I cast out model in a hierarchical Bayesian framework to obtain the individual-specific parameters in the rating incidence, satisfaction rating, and purchase equations. Finally, it is also possible that there may be unobserved factors related to store characteristics (e.g., store size, the date when the store opened etc.) that systematically affect the dependent variables of interest. However, I expect that such differences in store characteristics will be captured by the individual-specific random intercepts because the orders from each customer are almost always confined to a certain store based on his or her address.

1.3.2 Estimation

In order to estimate my proposed model, I first fit the satisfaction rating model (Equation 1.2) together with the rating incidence model (Equation 1.1), employing the Heckman selection framework (*Heckman*, 1979). Specifically, I obtain the inverse Mills ratio, $IMR_{ijt} = \phi(\alpha_i' X_{ijt}^{INC})/\Phi(\alpha_i' X_{ijt}^{INC})$ from (Equation 1.1) and use the value as a control variable in Equation 1.2 to address within-individual selection. With the parameter estimates from Equation 1.2 in hand, I obtain the residuals, $r_{ijt}^{SAT} = SAT_{ijt} - (\beta_{1i}' X_{ijt}^{SAT} + \beta_{2i} IMR_{ijt})$, which represents the information contained in the satisfaction rating over and above objective service performance and coupon redemption. I then estimate the proportional hazard function (Equation 1.3) whose

[2]Although the high serial correlations of this exclusion variable and customer satisfaction scores are potential concerns, customer participation decisions are not as serially correlated as those variables with the correlation coefficient of 0.13

overall log-likehood function is as follows:

$$LL_i(\gamma_i) = \sum_{k:C_i=1} \left[\gamma_{1i} r_{ij\tau} + \gamma_{2i} X_{ij\tau} - \log \sum_{i':INT_{i'j\tau} \geq INT_{ij\tau}} \exp(\gamma_{1i'} r_{i'j\tau} + \gamma_{2i'} X_{i'j\tau})\right] \quad (1.5)$$

In the above expression, C_i represents the indicator that the time corresponds to a purchase (i.e., if $C_i = 1$ customer i purchase the product and if $C_i = 0$ the time is a censoring time).

I capture unobserved heterogeneity with the distributions of $\{\alpha_i, \beta_i, \gamma_i\}$ by allowing them to be distributed multivariate normal with mean $\{\alpha_0, \beta_0, \gamma_0\}$ and variance $\{V_\alpha, V_\beta, V_\gamma\}$. The hyperparameters $\{\alpha_0, \beta_0, \gamma_0\}$ and $\{V_\alpha, V_\beta, V_\gamma\}$ are distributed multivariate normal and inverse Wishart, respectively. I derive the full conditional distributions of those unknowns, using the joint density and the specified prior distributions. I then draw sequentially from this series of full conditional distributions, using a MCMC Gibbs sampler combined with data augmentation (e.g., *Kai*, 1998) for satisfaction equations a Metropolis-Hastings sampler for the proportional hazard model. Both the full conditional distributions and the inference process are standard.

1.4 Study 1: Quick Service Restaurant Industry

1.4.1 Institutional Background

I obtained data from a large American company in the quick service restaurant industry. The company has an international presence and operates own stores as well as franchises. The food delivery context is of interest to me because the service aspect, especially delivery time, of the transaction influences both customer satisfaction and purchase behavior (*Verma, Thompson, and Louviere*, 1999). Timely service has been widely accepted as a key to success in the service industry because it is the first interaction in the sequence of experiences that customers have with the firm (*Bitner*, 1992). Firms can also improve service time as a means of differentiation based on convenience (*Lund and Marinova*, 2014). The nature and order of these experiences thus can have an impact on overall service satisfaction (*Chase and Dasu*, 2001). This is true in this study as well with the company's managers confirming that delivery time is the main determinant of service performance for their customers. As a result, the company has made a significant investment in tracking food preparation and delivery time. Specifically, the company requires each store to record four different time stamps for each order: when the order is placed (TS1), when the order comes out of the oven (TS2), when the driver leaves the store (TS3), and when the driver returns to the store (TS4). The delivery time for each order is calculated to be [(TS4 - TS3) / 2 - TS1] + 2 minutes.[3] Based on both the previous literature and the specific setting in this study, I use delivery time as the key objective service performance measure in the analysis. Other measures of service performance (e.g., number of service failures, telephone CSR service quality, frontline employee interactions, product quality) are also potential determinant of customer satisfaction and business outcomes. However, in this industry (and in my setting), none of these are obtained at each transaction level.

In addition to investing in its own tracking, the company has also invested in making the service experience transparent to the customer. Specifically, the company provides its customers with a unique online order experience through its online "order tracker." After an order (online, phone, or walk-in) is placed, the customer can monitor the status of the order directly from the company's website - she can track when the food preparation is complete (at the store) and when the order gets sent out for delivery. On the website the customer is prompted to fill out a five-point scale satisfaction survey with respect to her order. As customers make satisfaction assessments immediately after the delivery, I assume that judgments of the service

[3]The two-minute addition is based on a calibration exercise carried out by the company. I am able to replicate the results if I subtract two minutes from each delivery time.

encounter are affected by only the actual service performance experienced in that transaction (e.g. *Zhang and Kalra*, 2014). Thus, the focus in this study is transaction-based, rather than attitude-based, satisfaction. The survey consists of six questions as below:

- Q1: How likely are you to recommend us to your family and friends?
- Q2: How fast and nice was your phone order?
- Q3: How would you rate your online ordering experience?
- Q4: How would you rate your delivery experience with driver?
- Q5: How would you rate your carryout experience?
- Q6: How would you rate the quality of your order?

1.4.2 Data Description

The data span a total of 743,609 delivery orders from 99,156 unique customers (households)[4] who provided satisfaction ratings at least once during the sample period at 625 stores in Texas and Virginia from January to December 2011.[5] The transaction details include store ID, order date, order ID, delivery time, customer ID, coupon redemption, pick-up method (carryout vs. delivery), purchase amount and satisfaction ratings. Given my interest in delivery time as the objective performance measure, I restrict my attention to delivery orders. I do not observe substantial within-household heterogeneity in ordering methods. Approximately 90% of customers in the data make the same method of order during the sample period (27.5% of carryout-only and 62.1% delivery only). In addition, within-household het-

[4]As the data are at the household level, I cannot separately identify whether repeat purchases by the household represent true repeats by the same person or are new purchases by someone else in the household. I therefore use the term "individual" and "household" interchangeably. This remains a limitation of my approach.

[5]The overall proportion of delivery orders is 57.8%. I also have an additional 6,655,320 delivery orders from 1,136,700 customers who did not provide any ratings during the sample period. I use the data from these "non-raters" to check whether there is a potential *across-individuals* selection bias in the "Robustness Checks" section.

erogeneity in store choices is also minimal. This is because once a customer enters his/her address online, the website automatically locates the stores that are closest to his/her address. This results in only 4.6% of all the transactions where customers order from different stores over time. As I derive performance inconsistency from the observed objective performance (i.e., delivery time), I also need to observe at least three observations per customer, e.g. I need two observations in T_0 and T_1 to compute performance inconsistency and link it to purchase behavior in T_2. I thus limit the sample to 484,440 transactions from 74,080 customers who purchased three or more times. As can be seen from Table 1.2, there is no significant difference in transaction details and behavior between the households in sample with at least three purchases and the entire sample.

From the six questions in the online survey, I use Q3 (How would you rate your online ordering experience?) and Q4 (How would you rate your delivery experience with driver?) to construct a customer satisfaction score. In particular, I take the arithmetic mean of consumer evaluations on the two questions, guided by previous satisfaction literature (e.g., *Morgan and Rego*, 2006). The mean and median of this satisfaction score over the sample period are 4.68 and 5 (on 5-point scale). I do not use Q1 and Q6 because they are in fact measures of the Net Promoter Score and overall perceived quality, respectively. Previous satisfaction literature finds that these measures are conceptually distinct from customer satisfaction (e.g., *Morgan and Rego*, 2006). Additionally, Q2 and Q5 appear to capture responses about phone and carryout order, which are not of my interest.[6] Figure 1.1 shows the distribution of the satisfaction score and its correlation with delivery time. As shown, customer evaluations are skewed towards the highest score and the focal objective service performance in this study - delivery time - is negatively correlated with satisfaction ratings (the correlation coefficient is -0.19 and a regression of satisfaction ratings on delivery

[6] Over 90% of Q2 and Q5 are missing mostly because phone-order/carryout customers do not seem to go to the firm's website to track their order status even if they have access to the tracker.

Table 1.2: Descriptive Statistics (Study 1)

(a) Transactions from raters (n = 632,600)

	Mean	SD	Median	Min.	Max.	Skewness	$\text{Cor}_{t,t-1}$
Delivery Time (minutes)	36.9	13.1	35	3	119	0.78	0.24
Purchase Amount (dollar)	23.24	10.03	21.11	0.01	828.5	4.7	0.45
Coupon Redemption	0.51	0.5	1	0	1	-0.03	0.43
Interpurchase Time (day)	29.81	37.24	15	1	345	2.69	0.15
# of Transactions Since Rating_{t-1}	4.57	4.91	3	1	106	4.48	0.9

(b) Transactions from raters with 3 or more purchases (n = 484,440)

	Mean	SD	Median	Min.	Max.	Skewness	$\text{Cor}_{t,t-1}$
Delivery Time (minutes)	36.84	12.83	35	3	119	0.81	0.24
Purchase Amount (dollar)	23.34	10.09	21.24	0.01	828.5	4.9	0.45
Coupon Redemption	0.5	0.5	1	0	1	-0.02	0.44
Interpurchase Time (day)	28.21	35.27	15	1	345	2.73	0.15
# of Transactions Since Rating_{t-1}	4.98	5.15	4	1	106	4.26	0.9

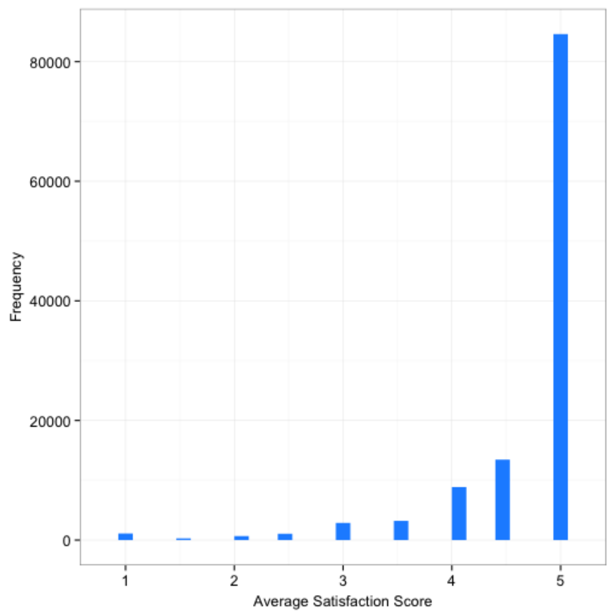
times shows that the latter has a significant and negative coefficient).

Customer satisfaction ratings were provided in 2.2% of all transactions. While this may seem low, this is consistent with industry numbers (based on feedback from the data provider). Conditional on individuals providing a rating during the sample period (i.e., "raters"), participation rates went up quite dramatically with 21.6% of transactions being rated, i.e., 1.8 times per individual on average. Table 1.3 presents the summary statistics (1) from the transactions with satisfaction ratings and (2) from transactions without satisfaction ratings. Overall, there are no statistically significant differences in transaction details across the two different samples. However, interpurchase time is 55.6% longer and the number of transactions since the last rating is 25.4% smaller for transactions with satisfaction ratings relative to those without ratings. In order to exploit the panel nature of the data and to correct for within-individual selection, I use the transactions both with and without satisfaction ratings for these households in the analysis.

As noted earlier, the chosen sample excludes "non-raters" (i.e., households that had not participated in the satisfaction survey even once during the data period). Table 1.4 presents the key variables of the transactions made by (1) "raters" and (2) "non-raters." The descriptive statistics suggest that the differences between "raters" and "non-raters" on the key metrics are not as substantial as those between transactions with and without ratings from customers who rated at least once. As a robustness check, however, I later try to correct for across-individual selection to detect its presence and compare its magnitude to that of the within-individual selection (See the "Robustness Checks" section).

Figure 1.1: Summary of Average Satisfaction Scores (Study 1)

(a) Distribution of Satisfaction Ratings



(b) Relationship with Delivery Time

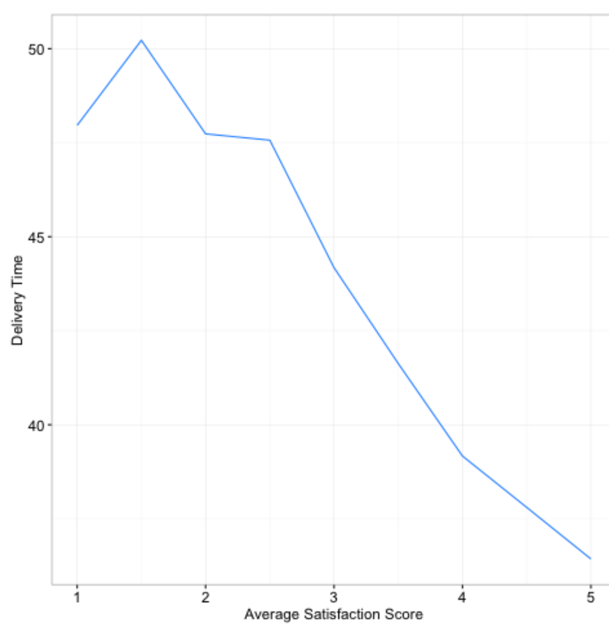


Table 1.3: Descriptive Statistics: Within-Individual Selection (Study 1)

(a) Transactions from raters with 3 or more purchases: with rating (n = 116,096)

	Mean	SD	Median	Min.	Max.	Skewness	$\text{Cor}_{t,t-1}$
Delivery Time (minutes)	37.44	12.17	35	3	119	1.29	0.22
Purchase Amount (dollar)	23.34	9.42	21.39	0.06	361.8	2.83	0.48
Coupon Redemption	0.55	0.5	1	0	1	-0.21	0.42
Interpurchase Time (day)	38.73	46.13	21	1	345	2.24	0.09
# of Transactions Since Rating_{t-1}	3.96	3.8	3	1	106	3.9	0.89

(b) Transactions from raters with 3 or more purchases: without rating (n = 368,344)

	Mean	SD	Median	Min.	Max.	Skewness	$\text{Cor}_{t,t-1}$
Delivery Time (minutes)	36.65	13.03	35	3	119	0.69	0.25
Purchase Amount (dollar)	23.34	10.3	21.19	0.01	828.5	5.39	0.44
Coupon Redemption	0.49	0.5	0	0	1	0.04	0.44
Interpurchase Time (day)	24.89	30.32	14	1	335	2.72	0.15
# of Transactions Since Rating_{t-1}	5.3	5.47	4	1	105	4.18	0.9

Table 1.4: Descriptive Statistics: Across-Individual Selection (Study 1)

(a) Transactions from raters (n = 743,609)

	Mean	SD	Median	Min.	Max.	Skewness	$\mathrm{Cor}_{t,t-1}$
Delivery Time (minutes)	36.9	13.1	35	3	119	0.78	0.24
Purchase Amount (dollar)	23.24	10.03	21.11	0.01	828.5	4.7	0.45
Coupon Redemption	0.51	0.5	1	0	1	-0.03	0.43
Interpurchase Time (day)	29.81	37.24	15	1	345	2.69	0.15
# of Transactions Since Rating_{t-1}	4.57	4.91	3	1	106	4.48	0.9

(b) Transactions from non-raters (n = 6,655,320)

	Mean	SD	Median	Min.	Max.	Skewness	$\mathrm{Cor}_{t,t-1}$
Delivery Time (minutes)	35.38	14.66	35	3	119	0.41	0.33
Purchase Amount (dollar)	22.47	12.5	20.11	0.01	978.9	11.19	0.49
Coupon Redemption	0.36	0.48	0	0	1	0.59	0.39
Interpurchase Time (day)	37.25	45.83	20	1	358	2.36	0.13

1.4.3 Results

1.4.3.1 Customer Rating Behavior

In this section, I show the results from the proposed model of customer rating behavior, which includes both the decision to rate and the actual rating, conditional on the rating decision. Table 1.5 reports the results from two different specifications: (1) a null model where I ignore within-individual selection (i.e., only use a linear regression model for the satisfaction score) and (2) the Heckman selection framework of rating incidence and satisfaction rating to control for within-individual selection. In both specifications, I account for unobserved customer heterogeneity using the random effects specification. Model 2 is the proposed model.

Overall, I find that objective service performance does have a clear impact on customer satisfaction rating. The parameter estimates in Table 1.5 suggest that both disconfirmation and performance inconsistency are key determinants of customer satisfaction rating. First, with higher disconfirmation (delivery time is longer than expected) customers are more likely to participate in surveys and provide lower satisfaction ratings. These results confirm findings from the previous literature that proposes a relationship between disconfirmation and customer satisfaction (e.g., *Oliver*, 1980). Furthermore, inconsistent service performance significantly decreases both survey participation and customer satisfaction, suggesting that customer uncertainty plays an important role in maintaining customer satisfaction.

Model 2 confirms that there is a selection bias in within-household ratings over time as the coefficient of the inverse Mills ratio is significant and negative, and as such, it is important to correct for the within-individual selection. The negative coefficient suggests that customers are less likely to provide rating when they feel satisfied with the service they received.[7] Note that ignoring this correlation results in 1.2% of

[7]Note that the negative coefficient of the inverse Mills ratio is potentially driven by dissatisfied customers participating in the survey. However, the data suggest that most of the participation effect associated with satisfaction rating is attributable to satisfied customers. For example, the

Table 1.5: Parameter Estimates from the Selection Model (Study 1)

	Without Selection			Proposed Model		
	Mean	2.5%CI	97.5%CI	Mean	2.5%CI	97.5%CI
Rating Incidence Model						
Intercept				-0.6708	-0.6863	-0.6557
Disconfirmation				0.2428	0.2222	0.2657
Performance Inconsistency				-0.4079	-0.4630	-0.3518
Coupon Redemption				0.1704	0.1618	0.1788
Number of Transactions Since Rating_{t-1}				0.0036	0.0007	0.0064
Satisfaction Rating Model						
Intercept	4.7457	4.7363	4.7555	4.8018	4.7839	4.8256
Disconfirmation	-0.3780	-0.3993	-0.3598	-0.3826	-0.3986	-0.3633
Performance Inconsistency	-0.4876	-0.5633	-0.4255	-0.4578	-0.5206	-0.3966
Coupon Redemption	0.0174	0.0095	0.0252	0.0121	0.0049	0.0186
Inverse Mills Ratio				-0.0466	-0.0592	-0.0341
Smoothing Factor (δ)		0.3			0.3	
-log(likelihood)		118144			118153	
AIC		236296			236316	
BIC		598386			598433	
Number of Observations		116096			116096	

* The estimates of random coefficients are omitted to save space.

underestimation of disconfirmation elasticity and 6.5% overestimation of performance inconsistency elasticity to customer satisfaction. The number of transactions since the previous rating - the proposed instrument to identify the selection process - significantly increases customers' participation in satisfaction survey. The more recently customers have rated, the less likely they are to provide ratings again.

1.4.3.2 Customer Purchase Behavior

Next I focus on whether customer satisfaction provides additional information over and above the information present in objective service performance. I estimate the proposed model where I link the residuals from Equation 1.2, along with disconfirmation and performance inconsistency, to the probability of purchase conditional on interpurchase time, using only those observations for which I have satisfaction ratings. I then compare the proposed model with a series of alternative models in order to answer my research question. Table 1.6 reports the results.

The results based on the proposed model (Model 1) show that both objective service performance and customer satisfaction have direct effects on the probability of purchase conditional on interpurchase time. First, inconsistent service performance decreases the probability of purchase. Even in the presence of objective service performance measures, customer satisfaction based on other factors than objective service performance (i.e., the residuals from Equation 1.2) significantly increases the probability of purchase, suggesting that satisfaction ratings provide additional information over and above what can be obtained from objective service performance. Note that this direct impact of customer satisfaction on purchase might be attributed to the mere-measurement effect where measurement of customer intentions or customer participation in surveys could positively influence customer retention (*Dong, Janakiraman, and Xie*, 2014). This explanation is unlikely in my context because

negative effect of delivery time on customer satisfaction is not significant when customers provide relatively lower ratings, while delivery time significantly increase survey participation.

Table 1.6: Parameter Estimates from the Probability of Purchase Model (Study 1)

	Proposed Model			Partial Models								
				Actual Satisfaction Rating			Actual Delivery Time			Disconfirmation / Inconsistency		
	(1)			(2)			(3)			(4)		
	Mean	2.5%CI	97.5%CI	Mean	2.5%CI	97.5%CI	Mean	2.5%CI	97.5%CI	Mean	2.5%CI	97.5%CI
Residuals	0.0748	0.0613	0.0880									
Actual Satisfaction				0.0784	0.0710	0.0860						
Actual Delivery Time							-0.0447	-0.0685	-0.0177			
Disconfirmation	0.0070	-0.0144	0.0290							0.0105	-0.0193	0.0316
Performance Inconsistency	-0.0888	-0.1652	-0.0356							-0.0887	-0.1450	-0.0325
Coupon Redemption	-0.0817	-0.0935	-0.0679	-0.0829	-0.0944	-0.0734	-0.0811	-0.0902	-0.0714	-0.0800	-0.0907	-0.0691
Purchase Amount	0.0132	-0.0010	0.0276	0.0118	-0.0062	0.0275	0.0129	-0.0066	0.0283	0.0167	0.0022	0.0297
lag (Interpurchase Time)	-0.1504	-0.1555	-0.1455	-0.1533	-0.1578	-0.1488	-0.1521	-0.1565	-0.1470	-0.1523	-0.1571	-0.1482
-log(likelihood)		1236946			1236758			1236913			1237000	
AIC		2473902			2473524			2473834			2474010	
BIC		2473917			2473536			2473846			2474025	
Number of Observations		116096			116096			116096			116096	

* The estimates of random coefficients are omitted to save space.

the correlation between survey participation and interpurchase time (0.16) is in an opposite direction as suggested by mere-measurement literature.

The proposed model uses constructed and/or transformed measure such as the residuals from the satisfaction equation, disconfirmation, performance inconsistency, etc. However, firms could work directly with the raw subjective and objective measures. Models 2 and 3 use these measures directly. The results from Model 2 suggest that conditional on customers having provided satisfaction ratings, the satisfaction metric (the raw subjective measure of service performance) does have the expected relationship with purchase behavior - satisfied customers are more likely to purchase, compared to the dissatisfied customers. The results from Model 3 present a strong direct relationship between the probability of purchase and delivery time (the raw objective measure of service performance). Model 4 uses only disconfirmation and performance inconsistency (without the residuals) measures and the results are qualitatively similar to those from Model 1. Collectively, the results highlight the value of collecting both objective and subjective measures of performance. The combined set of measures helps link objective service performance to purchase behavior and identify the effect of customer satisfaction over and above that of objective service performance. As such, this research provides implementable suggestion of how firms can improve their service and identify the economic value of customer satisfaction. In the "The Effect of Delay in Service" section, I further explore the impact of managerial actions on firm performance.

1.4.4 Robustness Checks

In this section, I report results from a series of robustness checks. First, I investigate the impact of objective service performance and customer satisfaction on purchase amount instead of the probability of purchase conditional on interpurchase time. Second, I test alternative measures of customer expectation to calculate disconfirmation. Third, I investigate the impact of objective service performance on customer satisfaction and purchase behavior controlling for product performance. Fourth, I explore the asymmetric effect of disconfirmation on customer satisfaction. Finally, I examine the relative importance of across-individuals and within-individual selection biases.

1.4.4.1 Customer Purchase Amount

I first test to see if the results are robust to an alternative measure of business outcome, in my case, the dollar amount of each order. Similar to the approach in Equation 1.3, I treat the residuals from the customer satisfaction equation (Equation 1.2) as an independent variable in a linear regression with the dependent variable being the semilog-transformed dollar purchase amount, which has been used extensively in marketing for modeling sales and expenditure (*Blattberg and Neslin*, 1990). The results are reported in Table 1.7 (Column (1)). Similar to the findings in Table 1.6, both objective service performance and the residuals have significant impacts on the dollar purchase amount of each order. In particular, better-than-expected service performance and higher customers satisfaction increases the purchase amount. These results confirm the role of satisfaction ratings in providing an incremental value to predict customer purchase behavior, providing convergent validity.

1.4.4.2 Alternative Measures of Customer Expectation

Throughout the paper I operationalize customer expectation as an exponentially smoothed average of service performance up to the previous service encounter. As a robustness check, I use two alternative measures of customer expectation: the immediate past service encounter and a simple moving average. For the former, I assume that customers may imperfectly recall their prior service performance because of factors such as high cognitive efforts required for adjusting prior expectation, low involve-

Table 1.7: Parameter Estimates from the Robustness Checks (Study 1)

	Purchase Amount (1)			Expectation: Recent (2)			Control Product Quality (3)		
	Mean	2.5%CI	97.5%CI	Mean	2.5%CI	97.5%CI	Mean	2.5%CI	97.5%CI
Rating Incidence Model									
Disconfirmation	0.2413	0.2224	0.2600	0.1722	0.1550	0.1836	0.2629	0.1319	0.3795
Performance Inconsistency	-0.4035	-0.4585	-0.3511	-0.4013	-0.4491	-0.3511	-0.2265	-0.6961	0.1829
Image Evaluations							-0.0016	-0.1298	0.1604
Number of Transaction Since Rating$_{t-1}$	0.0031	0.0007	0.0048	0.0032	0.0010	0.0053	0.1605	0.1308	0.1902
Satisfaction Rating Model									
Disconfirmation	-0.3822	-0.4040	-0.3639	-0.2563	-0.2715	-0.2409	-0.6298	-0.7817	-0.4989
Performance Inconsistency	-0.4550	-0.5220	-0.4053	-0.4973	-0.5580	-0.4520	-0.4226	-0.7960	-0.1486
Image Evaluations							0.0709	-0.0425	0.1948
Inverse Mills Ratio	-0.0495	-0.0590	-0.0381	-0.0490	-0.0599	-0.0380	-0.0202	-0.0798	0.0269
Probability of Purchase Model									
Residuals	0.0074	0.0052	0.0099	0.0704	0.0592	0.0862	-0.0612	-0.1473	0.0131
Disconfirmation	-0.0088	-0.0160	-0.0021	-0.0256	-0.0461	-0.0066	-0.1339	-0.2882	0.0696
Performance Inconsistency	-0.0164	-0.0365	0.0016	-0.0910	-0.1409	-0.0319	-0.4610	-0.8492	-0.1151
Image Evaluations							0.0731	-0.0930	0.2341
-log(likelihood)		110347			1236960			18016	
AIC		220708			2473932			36047	
BIC		220729			2473950			36057	
Number of Observations		116096			116096			2659	

* The estimates of intercepts, control variables, and random coefficients are omitted to save space.

ment, and low purchase frequencies (e.g., *Mitra and Golder*, 2006). For the latter, I assume that all past service performance contributes equally to customer expectation. Note that the exponential smoothing approach in the proposed model gives higher weights to service performance that occurs more recently. Based on these alternative expectation measures, I calculate disconfirmation as Equation 1.4 illustrates. As shown in Table 1.7 (Column (2)), the results using the immediate past service encounter as customer expectation are robust as higher disconfirmation (i.e., worse-than-expected service performance) increases survey participation, decrease customer satisfaction, and reduce the probability of purchase.[8]

1.4.4.3 Product Image Evaluations

In the analysis so far, I have assumed that the measure of service performance is invariant to the quality of the delivered product. However, I also have a unique opportunity to look at the effect of service performance while explicitly controlling for product performance. This is because, in selected stores, the company has installed a camera to take pictures of food coming out of the oven.[9] Thus, in addition to the satisfaction measure and the tracking of delivery time, the company collects product image evaluations from these stores yielding (novel) measures of product performance.

For each of these stores, each order is photographed each day as it comes out of the oven. Five product images are then randomly picked from each store to be rated by a team of hired raters (up to 139 people) on a binary scale of "good" or "bad." The raters are not aware of which store's products they are scoring. The company has analyzed the scores to provide feedback to franchisees with regard to their food quality and has found that the scores are a valid predictor of store performance. For example, stores with relatively low product performance scores are likely to have sales

[8]The results using a simple moving average as a measure of customer expectation are omitted to save space. The results are qualitatively similar to those present in Column (2).

[9]The proportion of franchise stores in the sample of the stores with the camera - about 62% - is broadly consistent with that in the entire sample.

that were lower than expected, and drops or increases in product performance scores tend to correlate with (delayed) sales shifts. Figure 1.2 shows the distribution of average image scores (i.e., the proportion of "good" ratings) and the distribution of interpurchase time across the different average scores. The product image evaluations during the sample period are reasonably high and they do not appear to be correlated with interpurchase time (the correlation coefficient is -0.03).

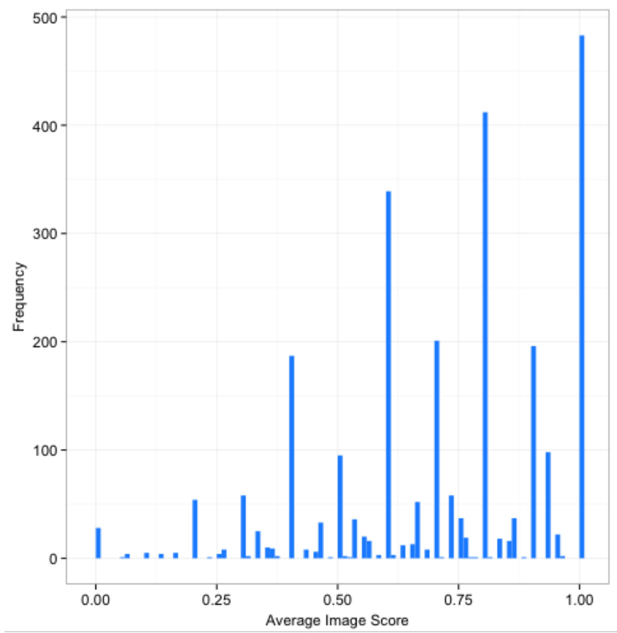
Using only the service transactions where these product image evaluations are available, I re-run the proposed model. In this analysis the store-level daily average of the product image scores (from five randomly selected photos) is used as the measure of product performance for each store for a given day. Notably, the small sample of stores with product image evaluations leads to a much smaller number of observations for this analysis. Despite the small sample, as shown in Table 1.7 (Column (3)), the results demonstrates yet the effects of disconfirmation and performance inconsistency are robust, as worse-than-expected and inconsistent service performance decrease customer satisfaction. However, I do not find the value of satisfaction over and above objective service performance to purchase behavior. The discrepancy between the results in this analysis and those in Table 1.5 and Table 1.6 is likely driven by the difference in sample size. Note that I also do not find product performance to significantly affect either satisfaction or the probability of purchase.

1.4.4.4 Asymmetric Impact of Disconfirmation on Customer Satisfaction

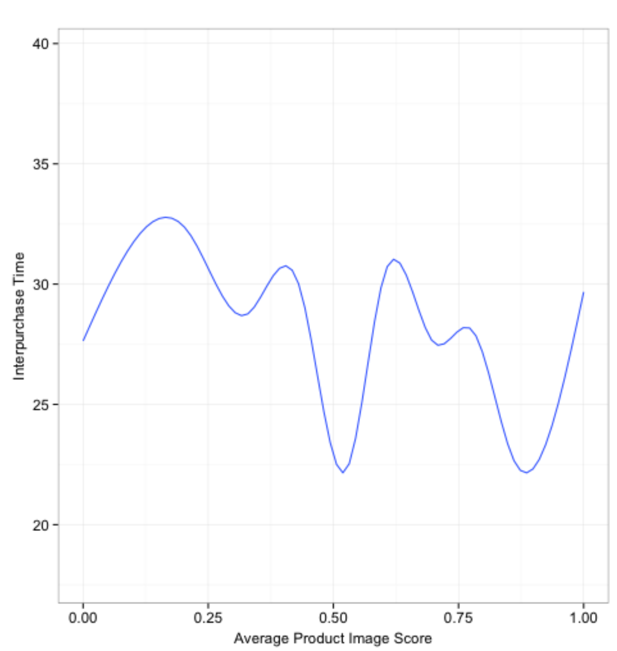
Prospect theory (*Kahneman and Tversky*, 1979) suggests that people are less influenced by actual levels of certain factors than by changes in these factors. Moreover, such changes will have a stronger effect when they are negative compared with positive. In light of this theory, previous service literature (e.g., *Gijsenberg, van Heerde, and Verhoef*, 2015; *Knox and Van Oest*, 2014) has documented that satisfaction is likely to be more sensitive to negative disconfirmation than positive disconfirmation.

Figure 1.2: Summary of Image Evaluation Scores

(a) Distribution of Image Evaluation Scores



(b) Relationship with Interpurchase Time



To test this asymmetric effect of disconfirmation, I decompose the disconfirmation variable, DIS_{ijt}, into positive disconfirmation, PD_{ijt}, and negative disconfirmation, ND_{ijt}(Anderson and Sullivan 1993) and re-run the proposed model with these two disconfirmation constructs:

$$ND_{ijt} = DIS_{ijt} \text{ and } PD_{ijt} = 0, \text{ if } TIME_{ijt} >= EXP_{ijt} \tag{1.6}$$

$$PD_{ijt} = DIS_{ijt} \text{ and } ND_{ijt} = 0, \text{ if } TIME_{ijt} < EXP_{ijt} \tag{1.7}$$

As can be seen in Table 1.8 (Column (1)), I found that customer satisfaction is significantly influenced by both negative and positive disconfirmation. Notably, consistent with previous literature, higher disconfirmation (i.e., worse-than-expected service performance) has a stronger impact on lower disconfirmation (i.e., better-than-expected service performance). In particular, the parameter estimate of negative disconfirmation is 14.7 times larger than that of positive disconfirmation.

1.4.4.5 Selection Problem across Individuals

In the analysis so far, the proposed model accounts for non-rated (for satisfaction) transactions via the selection equation within individuals. There is also the possibility that customers who have never rated are different from those who rated at least once, leading to a different selection problem. Thus, if the firm acts on the satisfaction ratings, they may not be acting optimally with respect to their entire customer base. I estimate an *across-individual* selection model where I include both "raters" and "non-raters" in the sample. To match the same number of observations I use in the models reported in Table 1.5 and 1.6, I draw a sample of 74,080 customers from the population of all customers who made at least three purchases during the data period. As a result, some customers in the sample are "raters" (i.e., rated satisfaction at least once) and the others are "non-raters" (i.e., never rate in this period). I use the last

Table 1.8: Parameter Estimates from the Robustness Checks (Study 1) (Continued)

	Asymmetry of Disconfirmation (1)			Across-Individual Selection (2)		
	Mean	2.5%CI	97.5%CI	Mean	2.5%CI	97.5%CI
Rating Incidence Model						
Disconfirmation				0.1001	0.0151	0.1893
Negative Disconfirmation	-0.1669	-0.1995	-0.1408			
Positive Disconfirmation	0.3443	0.2996	0.3882			
Performance Inconsistency	-0.3134	-0.3811	-0.2517	-0.0654	-0.2429	0.1133
Number of Transaction Since Rating$_{t-1}$	0.0030	0.0007	0.0054	-0.0491	-0.0571	-0.0412
Satisfaction Rating Model						
Disconfirmation				-0.3247	-0.5679	-0.0894
Negative Disconfirmation	-0.7375	-0.6987	-0.7779			
Positive Disconfirmation	0.0500	0.0069	0.0864			
Performance Inconsistency	-0.1645	-0.2117	-0.1097	-0.3349	-0.8957	0.2238
Inverse Mills Ratio	-0.0491	-0.0596	-0.0377	-0.2702	-0.6992	0.1178
-log(likelihood)		119099			1454	
AIC		238209			2918	
BIC		238228			2923	
Number of Observations		484440			74080	

* The estimates of intercepts, control variables, and random coefficients are omitted to save space.

transaction of each customer to create the sample of observations. This sample is very similar to cross-sectional survey data commonly used in industry and the previous literature to obtain satisfaction ratings. Table 1.8 (Column (2)) reports the results of the model estimated on this sample. The results show that across-individual selection is not significant. These results suggest two things - first, the behavior of “raters” and “non-raters” are not significantly different and second, selection remains an important issue vis-á-vis satisfaction ratings within household.

1.4.5 The Effect of Changes in Service Performance

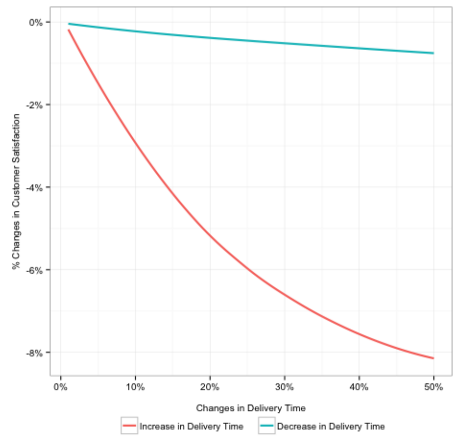
One of the important issues that my research attempts to investigate is the impact of objective service performance on customers' purchase behavior. For instance, I have already seen that disconfirmation and performance inconsistency directly affect (decrease) the probability of purchase conditional on interpurchase time. As such, a delay in service that increases both disconfirmation and performance likely lead to loss in the firm's economic outcomes such as revenue. Another important issue to investigate in this research is the value of measuring customer satisfaction. I have already discussed that customer satisfaction provides an additional value to predict customer behavior over and above what disconfirmation and performance inconsistency do. To more carefully articulate the economic value of customer satisfaction, I use a “what-if” scenario (e.g., *Wu et al.*, 2015), assuming that the firm does not have customer satisfaction data available and make decisions based only on objective service performance. The economic value of customer satisfaction ratings stems from their impact on the firm's sales prediction over and above objective service performance.

I explore this effect of changes in service via a simulation where I manipulate delivery time, the key objective service performance. The delivery time was manipulated as follows: starting from the initial delivery time for each customer, I increased/decreased delivery time by k% each period (with minimum of 2 minutes and maximum of 2 hours) where k ranges from 1 to 50. Next, based on the manipulated delivery time, I calculated the proportional changes in predicted interpurchase time, using the parameters estimated from the proposed model. These proportional changes represent the impact of service delay/improvement over time, as opposed to consistent service performance, on interpurchase time.

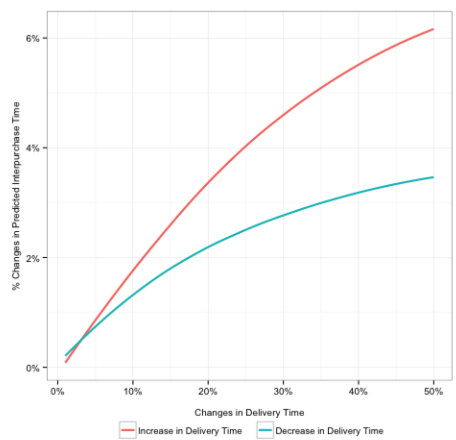
This analysis gives several interesting findings. First, as can be seen in Figure 1.3a, service delay over time, compared to "always consistent" service performance, can substantially decrease customer satisfaction up to 8.1% because of the negative effects of both disconfirmation and performance inconsistency. In contrast, the impact of decreasing delivery time (i.e., service improvement over time) on customer satisfaction is relatively small because of the trade-off between disconfirmation and performance inconsistency. Second, changes in delivery time can slow down customers' interpurchase time because inconsistent service performance reduces the probability of purchase conditional on interpurchase time. Figure 1.3b illustrates the percent changes in predicted interpurchase time as delivery time changes. The results show that delivery time increasing by 50% each period, for example, can lengthen interpurchase time up to 6.2% from "always consistent" service performance. This change can be translated into approximately \$0.34 million of loss in the revenue, considering the average dollar purchase amount of \$23.34 in the data. Finally, as can be seen in Figure 1.3c, ignoring customer satisfaction based on other factors than objective service performance (i.e., the residuals from Equation 1.2) overpredict interpurchase time by approximately 75%, which can be translated into \$0.25 million in the firm's revenue, assuming the same dollar amount spending per each transaction. Addressing such bias in revenue prediction could be a huge incentive to the firm, given the low cost of collecting customers' online survey responses.

Figure 1.3: The Effect of Changes in Service

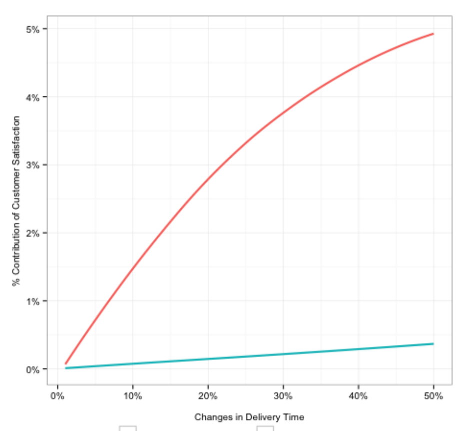
(a) Percent Changes in Predicted Customer Satisfaction Score



(b) Percent Changes in Predicted Interpurchase Time



(c) Percent Changes in the Contribution of the Residuals



1.5 Study 2: Auto Rental Industry

1.5.1 Institutional Background

In the second study I use the data from a major car rental company in the United States. In the auto rental industry, customer demand for different types (i.e., classes) of cars typically does not match the available inventory at rental locations (*Carroll and Grimes*, 1995). This mismatch between demand and supply often results in free car-class upgrades, in which customers receive a higher car-class for no extra charge. In particular, when demand for a lower car-class exceeds the available inventory and the forecasted demand for higher-car class is low, auto rental companies provide free upgrades, using unutilized higher-class cars as a "cheap" way to avert customer complaints and increase customers' positive reactions (*Hoffman, Kelley, and Chung*, 2003; *Jiang, Hoegg, and Dahl*, 2013). Given the prevalence and frequency (54.6% in the data) of overbooking and free upgrades, I assume that customers perceive overbooking as a minor outcome failure[10] and as a result, consider a subsequent free car-class upgrade to be a better-than-expected service performance or a gain. Based on the social exchange and equity theories (*Walster, Berscheid, and Walster*, 1973), a service failure/recovery encounter can be viewed as an exchange in which the organization attempts to provide a gain, in the form of a recovery effort, to make up for the customer's loss and result in customer satisfaction (e.g., *Smith, Bolton, and Wagner*, 1999; *Knox and Van Oest*, 2014). To make a convincing link between free car-class upgrades and service performance, I collected online surveys related to three service scenarios related to overbooking and recovery (car-class upgrade, hotel upgrade and car-class downgrade) among 450 Mechanical Turkers residing in the United States.

[10]Service marketing literature recognizes two types of service encounter failures: outcome and process. The outcome dimension of a service encounter involves what customers actually receive from the service, whereas the process dimension involves how they receive the service, that is, the manner in which it is delivered (*Smith, Bolton, and Wagner*, 1999). This paper focuses on the outcome failure, that is, free upgrades.

The last two scenarios do not occur as often as the car-class upgrade scenario. I find that participants rated (on 7-point scales) car-class upgrade as significantly being less severe service failure (*Maxham III and Netemeyer*, 2002), more satisfied, better than expected (i.e., more positive disconfirmation) and providing more favorable distributive justice (*Smith, Bolton, and Wagner*, 1999) than the remaining two scenarios. It is not surprising for the ratings for car-class downgrade to be lower, but the lower ratings for hotel upgrade suggest that consumers view car-class upgrade as being more of common occurrence. Overall, the service failure severity ratings are low for all the scenarios (car-class upgrade = 2.09; car-class downgrade = 3.82; hotel upgrade = 3.28), suggesting that overbooking is not perceived by consumers as being a serious loss to be recovered, perhaps due to its prevalence. Participants also expect upgrading to be a better way for firms to resolve overbooking (car = 5.33; hotel = 5.09) and perceive it to better fulfill distributive justice (car =6.04; hotel = 5.57) than downgrading (expectation = 3.71; justice = 2.74).

The auto rental firm tracks transaction-specific customer satisfaction from an online survey. In order to complete the survey, customers were provided with a hyperlink in one of the two ways: through email or on their printed receipt. Because the customers make satisfaction assessments after each rental experience, I assume that the customer satisfaction ratings collected reflect transaction-based satisfaction, which is affected by the most recent service performance the customers have encountered. The 10-point scale (except Q3: 5-point scale) satisfaction survey consists of the following eight questions:

- Q1: Please rate your overall experience.
- Q2: How likely is it that you would recommend Hertz to a friend or colleague?
- Q3: How likely are you to rent in the future?
- Please rate your experience with us in the following areas:
  - Q4: Courtesy of staff.

– Q5: Speed of service.
– Q6: Condition of vehicle & equipment.
– Q7: Transaction and/or billing as expected.
– Q8: Value for the money.

1.5.2 Data Description

The data used in this study come from a major car rental company in the United States. The data follow a panel of 454,597 unique loyalty club members from May 2010 through October 2012. The entire sample involves 2,981,503 rental car transactions across 3,422 locations (684 airport and 2,729 off-airport)[11] in the US.[12] Each location offers up to 23 different car groups, while 90.0% of the total transactions consist of 5 most popular car groups: Compact (B), Intermediate (C), Standard (D), Full-Size (F), and Mid-Size SUV (L). Each record in the individual-level data corresponds to one purchase of rental car and provides information on membership ID[13], store ID, the rental's check-out/in date, order number, pickup/return location, car group, rental price, price code (corporate/leisure), customer tier code, and booking channel code. In the data, free upgrades, the key objective service performance measure, are identified based on the following information: the car group customers reserved, the group they actually received, and the group for which they were charged. In case that the reserved and the charged are same with each other but different from the received, I view the transaction a free upgrades as the firm paid for the superior group. These free upgrades consist of 54.6% of the total transactions.

The sample is reduced to 1,982,404 transactions from 126,246 customers after I

[11] 79.2% of the total transactions are from airport locations.

[12] From the original data that contain 6,283,105 observations I drop the transactions with invalid customer ID and missing car-class information. I also delete outliers (> 99the percentile) of rental duration, advance booking, rental price, and purchase frequency.

[13] I identify unique customers by a combination of membership IDs and birth dates on their driver's licenses. By doing this, I rule out the possibility that the purchase history under a single membership consists of multiple customers (i.e., drivers). 17.5% of the club members first appear in the data set on or after May 2010.

focus on customers who purchased 3 or more times and provided satisfaction ratings at least once during the sample period. The reduction is largely due to the fact that one of the primary variables of interest is individual-level performance inconsistency. As can be seen from Table 2.1, I do not observe substantial differences in the behavior between the sample of customers who purchased three or more times and the complete sample.

From the eight questions in the online survey, I use Q4 (courtesy of staff), Q5 (speed of service), Q6 (condition of vehicle/equipment), Q7 (transaction/billing), and Q8 (value for the money) to construct a customer satisfaction score. I do not use the first three questions because they are in fact measures of either customer loyalty or the Net Promoter Score, which are conceptually distinct from customer satisfaction.[14] Consistent with the measure used in Study 1, I take the arithmetic mean of consumer evaluations on these five questions and the mean and median of this satisfaction score over the sample period are 7.53 and 8.2 on 10-point scale. Figure 1.4 shows the distribution of the satisfaction score and its correlation with free upgrades. Notably, more free upgrades are offered to the service encounters with higher customer satisfaction ratings (the correlation coefficient is 0.04 and a regression of satisfaction ratings on free upgrades shows a significant and positive coefficient). Customers provided their satisfaction ratings 1.34 times on average, which are 8.6% of the total transactions.

Table 1.10 reports summary statistics on the key variables, including free upgrade, daily rental price, rental duration, and interpurchase time. I break up the data into the transactions with and without satisfaction ratings, in order to check if there is a systematic difference between the two samples. I observe a very similar data pattern as did with Study 1. For example, average interpurchase times are substantially dif-

[14]I observe a very high proportion of raters (37.5%) gave the company the lowest rating on Q1, something that I find implausible and inconsistent with all the other measures. I suspect that there could be some kind of measurement error. In addition, over 60% of responses to Q3 are missing mostly because the question was phased out in the middle of the data period.

Table 1.9: Descriptive Statistics (Study 2)

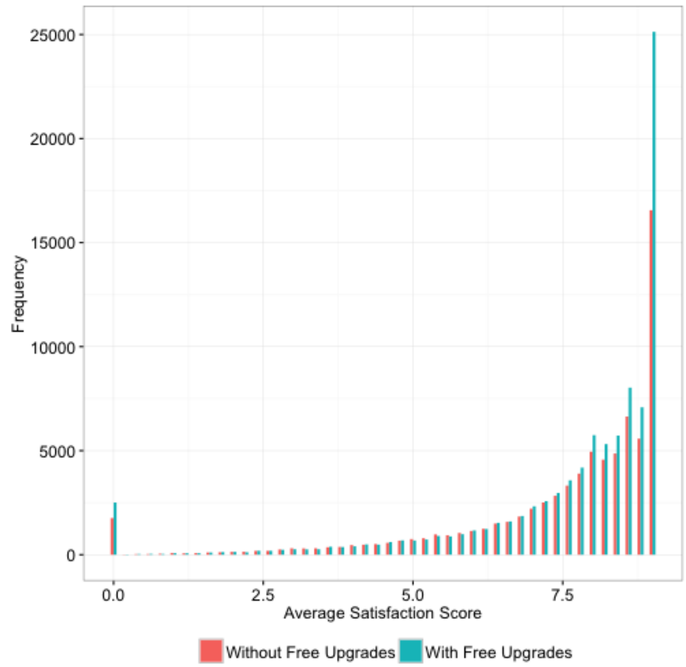
(a) Transactions from all raters (n = 2,981,503)

	Mean	SD	Median	Min.	Max.	Skewness	$\text{Cor}_{t,t-1}$
Upgrade Probability	0.55	0.5	1	0	1	-0.2	0.13
Purchase Amount (dollar)	34.9	18.58	31.5	0	120	1.21	0.34
Rental Duration (day)	4.23	2.94	4	1	29	2.95	0.37
Interpurchase Time (day)	49.65	76.8	21	1	802	3.41	0.26
# of Transactions Since Rating_{t-1}	8.63	10.01	5	1	152	2.9	0.96

(b) Transactions from raters with 3 or more purchases (n = 1,982,404)

	Mean	SD	Median	Min.	Max.	Skewness	$\text{Cor}_{t,t-1}$
Upgrade Probability	0.58	0.49	1	0	1	-0.3	0.13
Purchase Amount (dollar)	34.42	18.16	31.49	0	120	1.15	0.34
Rental Duration (day)	4.06	2.63	4	1	29	2.9	0.36
Interpurchase Time (day)	39.35	58.64	18	1	764	3.6	0.26
# of Transactions Since Rating_{t-1}	8.97	10.01	5	1	152	2.83	0.95

Figure 1.4: Summary of Satisfaction Score (Study 2)



ferent across the two samples, where the transactions with satisfaction rating have the longer interpurchase time and the smaller number of transactions since the last rating, compared to those without ratings. The differences between the two samples open up a possibility of the within-individual selection problem. I thus use the transactions both with and without satisfaction rating to correct for selection. Note that customers in this study are all "raters," who participated in the survey at least once during the 24-month sample period. I therefore cannot examine across-individual selection.

1.5.3 Results

To explore customers' rating behavior in the auto rental industry, I take the same approach as that in Study 1, where I first estimate customer satisfaction rating behavior which includes the decision to rate and conditional on that decision, what ratings to give. Table 1.11 shows the results for (1) a null model where within-individual

Table 1.10: Descriptive Statistics: Within-Individual Selection (Study 2)

(a) Transactions from raters with 3 or more purchases: without rating (n = 192,191)

	Mean	SD	Median	Min.	Max.	Skewness	$\text{Cor}_{t,t-1}$
Upgrade Probability	0.55	0.5	1	0	1	-0.19	0.1
Purchase Amount (dollar)	33.57	18.82	30	0	120	1.27	0.32
Rental Duration (day)	4.47	3.14	4	1	29	2.63	0.35
Interpurchase Time (day)	77.63	92.09	42	1	762	2.19	0.19
# of Transactions Since Rating_{t-1}	6.99	7.45	4	1	136	3.57	0.98

(b) Transactions from raters with 3 or more purchases: without rating (n = 1,790,213)

	Mean	SD	Median	Min.	Max.	Skewness	$\text{Cor}_{t,t-1}$
Upgrade Probability	0.58	0.49	1	0	1	-0.32	0.13
Purchase Amount (dollar)	34.51	18.08	31.58	0	120	1.14	0.34
Rental Duration (day)	4.01	2.57	4	1	29	2.92	0.36
Interpurchase Time (day)	35.26	52.23	16	1	764	3.82	0.25
# of Transactions Since Rating_{t-1}	9.18	10.22	6	1	152	2.76	0.95

selection bias is not corrected and (2) the proposed model where the selection bias is addressed by a simultaneous equation of rating incidence and satisfaction rating. In both specifications, unobserved customer heterogeneity is controlled by the use of random coefficients.

As shown in Table 1.11, the findings are consistent with Study 1. First, I find significant effects of objective service performance on customer satisfaction, as consistent service performance leads customers to participate and better-than-expected service performance increases satisfaction ratings. I also confirm that within-individual selection needs to be addressed, that is, satisfied customers are significantly less likely to rate. Note that ignoring this within-individual selection leads disconfirmation elasticity to customer satisfaction to be overestimated by 3.2%. The instrument to identify the selection process, the number of transactions since the previous rating, significantly increases customers' participation in satisfaction rating, which is also consistent with the results from Study 1.

I then answer my research question of whether customer satisfaction ratings still provide information on the probability of purchase even in the presence of objective service performance data. Consistent with Study 1, I estimate the probability of purchase model, using the residuals from Equation 1.2, along with disconfirmation and performance inconsistency. Table 1.12 (Column (1)) reports the results.

The results show that both customer satisfaction and objective service performance have direct impacts on the purchase of probability conditional on interpurchase time. First, consistent with Study 1, the residuals from Equation 1.2 directly increase the purchase probability, even in the presence of objective service performance measures. This result implies that customer satisfaction provides additional information over and above objective service performance measures. Second, I find the direct effect of objective service performance on purchase. Interestingly, inconsistent service performance increases the probability of purchase conditional on interpurchase time.

Table 1.11: Parameter Estimates from the Selection Model (Study 2)

	Without Selection			Proposed Model		
	Mean	2.5%CI	97.5%CI	Mean	2.5%CI	97.5%CI
Rating Incidence Model						
Intercept				-1.1309	-1.1430	-1.1186
Disconfirmation				-0.0007	-0.0058	0.0050
Performance Inconsistency				-0.1972	-0.2177	-0.1761
Rental Price				-0.0015	-0.0018	-0.0012
Number of Transaction Since Rating$_{t-1}$				0.0091	0.0085	0.0098
Satisfaction Rating Model						
Intercept	7.8187	7.7886	7.8497	7.9495	7.9064	8.0046
Disconfirmation	0.1225	0.1070	0.1361	0.1186	0.1042	0.1337
Performance Inconsistency	-0.0285	-0.0696	0.0269	-0.0228	-0.0703	0.0313
Rental Price	-0.0089	-0.0094	-0.0082	-0.0091	-0.0095	-0.0085
Inverse Mills Ratio				-0.0799	-0.1094	-0.0534
Smoothing Factor (δ)		0.3			0.3	
-log(likelihood)		376320			360455	
AIC		752649			720920	
BIC		752662			720936	
Number of Observations		1729912			1729912	

* The estimates of random coefficients are omitted to save space.

Table 1.12: Parameter Estimates from the Proposed Model and Potential Impact of Competitive Activities (Study 2)

	Proposed Model			Business Customers		
	Mean	2.5%CI	97.5%CI	Mean	2.5%CI	97.5%CI
Rating Incidence Equation						
Disconfirmation	-0.0007	-0.0058	0.0050	0.0003	-0.0158	0.0214
Performance Inconsistency	-0.1972	-0.2177	-0.1761	-0.3888	-0.4618	-0.3225
Rental Price	-0.0015	-0.0018	-0.0012	-0.0007	-0.0019	0.0006
Number of Transactions Since Rating$_{t-1}$	0.0091	0.0085	0.0098	0.0740	0.0687	0.0780
Satisfaction Rating Equation						
Disconfirmation	0.1186	0.1042	0.1337	0.1997	0.1526	0.2456
Performance Inconsistency	-0.0228	-0.0703	0.0313	-0.0532	-0.1983	0.0945
Rental Price	-0.0091	-0.0095	-0.0085	-0.0140	-0.0165	-0.0117
Inverse Mills Ratio	-0.0799	-0.1094	-0.0534	-0.0307	-0.0869	0.0320
Purchase Equation						
Residual	0.0175	0.0138	0.0209	0.0135	0.0002	0.0256
Disconfirmation	0.0250	0.0168	0.0341	0.0413	0.0131	0.0629
Performance Inconsistency	0.0384	0.0084	0.0729	0.1371	0.0481	0.2204
Rental Price	-0.0031	-0.0033	-0.0029	-0.0047	-0.0060	-0.0036
-log(likelihood)		360455			28717	
AIC		720920			57445	
BIC		720936			57456	
Number of Observations		169723			16230	

* The estimates of random coefficients are omitted to save space.

Overall, the results from the proposed model are qualitatively similar to those from Study 1, as shown in Table 1.13.

Notably, customer satisfaction ratings and the subsequent purchase behavior are likely to be influenced by competition. It is safe to say that the auto rental industry has entered the mature stage of its life cycle - the firm of interest in this study has 25.0% market shares as of 2014 and thus competitive activities in the industry might influence customer satisfaction and purchase. In particular, I re-run the proposed model using the data from business customers whose transactions correspond to "corporate" price codes. As shown in Table 1.12 (Column (2)), most of the directional conclusions from business customers are similar as with those from the entire sample. Nonetheless, I do not observe the direct impact of objective service performance on the probability of purchase among these customers. The insignificant effect could be driven by both the smaller sample size and the contractual obligation the business customers have with the firm (i.e., the contract makes these customers to appear more loyal).

1.5.4 The Effect of Free Car-Class Upgrades

As I did in Study 1, I examine (1) the impact of changes in service performance on the probability of purchase conditional on interpurchase time and (2) the economic value of measuring customer satisfaction. To do this, I manipulate the frequency of free car-class upgrades (the objective service performance measure of interest). First, I randomly draw a dummy for free upgrades from a binomial distribution such that the probability of free upgrades varies from 25% to 75%. I then update disconfirmation and performance inconsistency based on the simulated car-class upgrades and predict the percent changes in predicted interpurchase time. The results suggest that frequent but inconsistent free upgrades benefits the firm as they reduces customers'

Table 1.13: Consistent Results across Two Different Service Settings

(a) Quick Service Restaurant Industry

	Rating Incidence	Satisfaction Rating	Purchase probability
Disconfirmation	+	–	
Performance Inconsistency	–	–	–
Customer Satisfaction			+

(b) Auto Rental Industry

	Rating Incidence	Satisfaction Rating	Purchase Probability
Disconfirmation*		+	+
Performance Inconsistency	–		+
Customer Satisfaction			+

* Disconfirmation of free upgrades expectation implies the opposite direction to disconfirmation of delivery time in (a).

interpurchase time.[15] However, these effects of free upgrades are not as substantial as that of delivery time in Study 1. For example, both increasing and decreasing upgrade probability from 50% (i.e., supposedly least consistent service performance) can lengthen customers' interpurchase time by only 0.22%. Interestingly, the effects of changes in upgrade probability appear to be a symmetric convex function. This is because disconfirmation has much lower elasticity to the purchase probability than performance inconsistency (-0.0001 vs. 0.0060). I also examine the value of customer satisfaction in predicting interpurchase time, using a "what-if" scenario where the firm does not have customer satisfaction data available and make decisions based only on objective service performance. As can be seen in Figure 1.5c, ignoring customer satisfaction underestimate the impact of free upgrades on interpurchase time by 0.02%, which can be translated into less than $0.01 million in the firm's US sales, assuming the same dollar amount spending per each transaction.

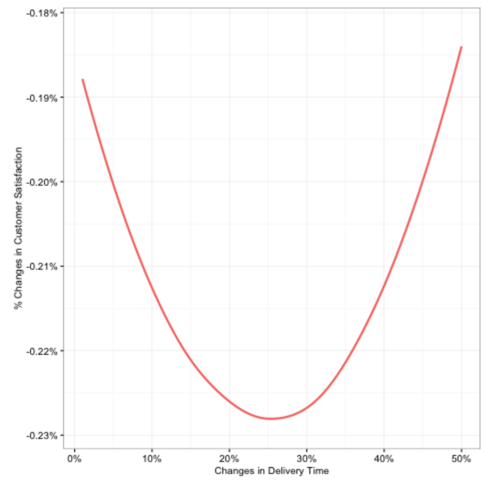
1.6 Conclusion

The aim of this paper is to demonstrate the value of collecting satisfaction ratings in the emerging service environment where firms can track both customer satisfaction and objective service performance after each purchase transaction. The two main issues my research attempts to address via a unique data set obtained from the quick service restaurant and the auto rental industries are (1) the potential *within-individual* selection bias in satisfaction ratings and (2) the difference between customers' perceived and objective service performance. The panel nature of the data, along with ratings (or lack thereof) for all transactions,allows me to deal with the selection issue. In addition, the availability of objective service performance measures helps me measure the economic value of collecting customer satisfaction. I find evidence that cus-

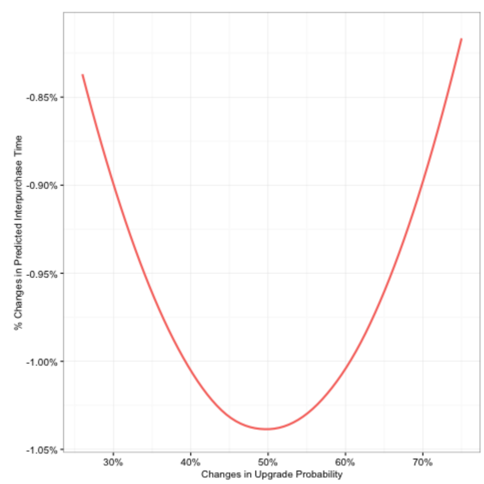
[15]Note that customer satisfaction explained by objective service performance decreases with inconsistent service performance. However, the residual, i.e., additional information over and above objective service performance, increases as free upgrades are frequently and inconsistently offered.

Figure 1.5: The Effect of Free Upgrades

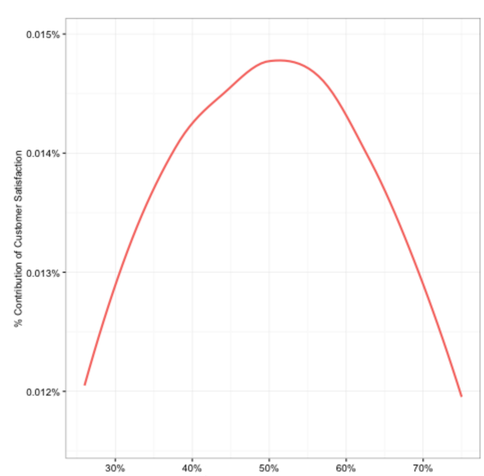
(a) Percent Changes in Predicted Customer Satisfaction



(b) Percent Changes in Predicted Interpurchase Time



(c) Percent Changes in the Contribution of the Residuals



tomer satisfaction provides additional information value to predict firms' sales. The fact that I find a similar pattern of results in the two very different service settings suggests that these results are not idiosyncratic to setting. Overall, the implication is that firms need to continue to collect customer satisfaction data, along with objective measure of service performance, to better predict their economic outcomes. While in some sense these results may not be unexpected, they do open up new questions for further research. First, it is possible that customer satisfaction data provide richer perceptual data than has been previously assumed. In other words, customer satisfaction may capture more than just the difference between expectation and service performance. Second, it could be that firms do not have a very precise understanding of the exact set of objective measures that affect customer satisfaction and subsequent behavior. The analysis suffers from some limitations, primarily driven by the nature of the data. First, the data come from one firm in each of the two industries. Second, in these two industries I have a clear objective metric of service performance, which might not be easily accessible in other industries. Third, I am unable to model competitive effects, especially in Study 1. Finally, given that the data are secondary, I can control for self-selection only via the exclusion restriction. A perfect control for selection can only be implemented via an experimental procedure where customers are somehow assigned randomly to "rater" and "non-rater" conditions.

CHAPTER II

The Past Imperfect: Assessing Strategic Customer Behavior under Bounded Rationality

2.1 Introduction

Customer expectations have been considered as customers' pre-purchase beliefs or evaluative beliefs about a product or service (e.g., *Oliver*, 1980). When making a product choice decision, customers first construct their expectations of what is to come whenever they receive new information (e.g., about the level of a product attribute) within a context that is based on the past events retrieved from memory (*Bettman*, 1979; *Boulding et al.*, 1993; *Johnson et al.*, 1995; *Kopalle and Lehmann*, 1995). From firms' perspective, a tension exists between raising expectations to increase initial acceptance/trial and lowering expectations to increase satisfaction, and hence future sales (*Kopalle and Lehmann*, 2006). As such, it should come as no surprise that service firms are interested in better understanding how consumers form expectations about quality to manage customer expectations over time.

With regard to managing customer expectations, service firms face the following two questions. First, do customer expectations of service performance result in strategic customer behavior? Second, do customer strategies negatively influence economic outcomes for the firms? It is clear that managers care about these questions, as there is growing evidence that firms should identify their most profitable customers and maximize return on service performance (*Lewis*, 2005). From the manager's perspective, if the efforts to raise customer expectations eventually lead customers to strategically choose less profitable alternatives, it might be of firms' interest to allocate their resources towards maintaining service performance to consistently meet customer expectations.

Previous literature on customer expectations mostly considers (completely) rational customers. This approach requires a reasonably strong assumption that customers perfectly recall all past service encounters and use the recollection to form their expectations of current service performance. Few literature has recognized and proposed ways to relax this assumption, documenting that memory affects how customers form expectations and customers are susceptible to forget the past service encounters due to the limited memory (e.g., *Akçura, Gönül, and Petrova*, 2004; *Mehta, Rajiv, and Srinivasan*, 2004; *Mullainathan*, 2002). Despite these findings, little research has explored how customer expectations under imperfect memory affect customers' strategic decision making. My research adds to the literature on customer expectations under bounded rationality. In addition to documenting forgetting in both customer expectation carryover and reflection of previous service encounter, this research provides empirical evidence of its impact on strategic customer behavior and managerial insights on how to take advantage of strategic customer behavior to maximize resource allocation on service performance. To the best of my knowledge, this research is the first to link bounded customer expectations to strategic product switching behavior.

To examine the role of bounded customer expectations in strategic customer behavior, I use data from the auto rental industry. This industry is a particularly interesting test bed for this study in that customer demand for different types (i.e., car-classes) of rental cars typically does not match the available inventory at the rental locations (*Carroll and Grimes*, 1995) and this mismatch often results in free car-class upgrades (i.e., customers receive a higher car-class at no extra charge). The frequent free car-class upgrade offers are likely to encourage customers to form expectations of free upgrades in a subsequent encounter, resulting in strategic car-class choices. That is, customers are likely to request the same car-class that previously resulted in a free upgrade, anticipating yet another upgrade from the class. My individual-level cross-sectional and time-series data are extremely useful in specifying the dynamic evolution of customer expectations under bounded rationality.

I achieve my research goal by modeling time-varying customer expectations under imperfect recall and their impact on product switching behavior over time. I present a framework of customer adaptive expectations influenced by two sources of forgetting: (1) a potential decline in expectation carryover and (2) the amount of time lapsed (in days) since the previous encounter (i.e., interpurchase time). To allow for individual-specific time-varying expectations, I use a state-space model based on the Kalman filter algorithm. The model captures the dynamics of the customer expectations, allowing me to separate the effects of (recalled) free upgrades from the impact of the prior expectations accrued through service usage over time (*Akçura, Gönül, and Petrova*, 2004). Then I model customers' product switching behavior as a function of the predicted customer expectations. Overall, I find evidence of a decline in carryover of prior expectations and imperfect recall of previous service encounter, which supports my hypothesis on bounded rationality in customer expectations. Furthermore, the results show that customers strategically choose the same alternative that previously results in a free upgrade, anticipating yet another upgrade in a subsequent transaction.

The remainder of the paper is organized as follows. In §2.2, I present an overview of the theoretical and methodological issues relating to customer strategic behavior under bounded rationality. In §2.3 I describe the institutional setting, the data, and the model-free evidence. In §2.4 I present the model specification and estimation procedure. In §2.5, I present the estimation results. Finally, I conclude with a discussion of the key findings, research limitations, and directions for future research.

2.2 Related Research

This paper adds to a large literature that has been looking at strategic customers who predict future outcomes based on their experiences about the particular market behavior. In most circumstances, customers are uncertain about future outcomes such as prices and product availability, and thus their beliefs about the outcomes strongly affect their current choices (*Bronnenberg et al.*, 2008). These customers update their expectations of future outcomes to resolve the uncertainty, using the information received from their prior experiences. *Che, Erdem, and Öncü* (2015) examine how brand preferences evolve when customers are uncertain about product quality. They find evidence of customers' strategic sampling behavior where they switch across brands relatively early on and later settle on a small subset of brands once uncertainty is mostly resolved. *Erdem, Zhao, and Valenzuela* (2004) model customer quality expectations over time to investigate its effect on customers' store brand choices, as opposed to national brand choices, and find strong evidence for consumer learning about quality. *Li, Granados, and Netessine* (2014) find empirical evidence for the extent to which this strategic behavior actually take place, by estimating the fraction of strategic customer in the air-travel industry. My research is related to these studies in that it shows how time-varying customer expectations affect their strategic car-class choices over time. It adds to this literature by documenting that customer expectations of free car-class upgrades results in strategic customer behavior where customers request the same car-class that previously resulted in a free upgrade, anticipating yet another upgrade from the class.

Another contribution of this study is to provide empirical evidence of customers' imperfect recall, assessing functional forms of their recollection of relevant information. Theoretically, customer recall of previously encountered information represents either implicit or explicit memory. The former involves non-conscious retrieval of previous encounters (i.e., memory without awareness) where customers might be capable of judging performance in the absence of recall (e.g., *Homburg, Koschate-Fischer, and Wiegner*, 2012; *Monroe and Lee*, 1999; *Vanhuele and Drèze*, 2002). The latter typically refers to conscious recollection of an exposure episode where customers remember the information relevant to their judgments. Studies in behavioral economics and marketing mostly focus on explicit memory, specifying functional forms of customer recall. *Mullainathan* (2002) assesses theoretical models of memory distortions in economic contexts where customers receiving good news about personal income remember other good news and therefore overforecast their future income. *Mehta, Rajiv, and Srinivasan* (2004) propose a structural model to examine the impact of conscious but distorted recall on consumers' rate of learning and their choice of frequently purchased products. *Akçura, Gönül, and Petrova* (2004) model the underlying learning process with regard to firms' price promotions as compounded by time-dependent forgetfulness that is manifested as a potential decline in the valuation carryover. This paper adds to this literature on explicit memory by documenting the role of memory decay in customer expectations and its impact on strategic customer behavior.

This study is also related to a literature that examines the evolution of state parameters to evaluate the dynamic effects of firms' marketing actions. *Sriram, Chintagunta, and Neelamegham* (2006) account for the dynamics of the intrinsic brand preferences in technology product markets influenced by brand-level advertising, using a state-space approach based on the Kalman filter. *Bruce, Foutz, and Kolsarici* (2012) link a movie's revenue to its current and all past advertising and WOM through an aggregate sales response function, accounting for spillover and heterogeneity across theater and video stages. *Van Heerde, Mela, and Manchanda* (2004) construct a dynamic linear model to estimate dynamic market response parameters in the marketplace where a substantial technological innovation increases uncertainty and affects price sensitivity. In this paper, I observe individual-level cross-sectional and time-series measures of free car-class upgrades. It is this feature that enables me to use a state-space approach based on the Kalman filter to account for dynamic customer expectations of free car-class upgrades.

2.3 Data

2.3.1 Institutional Background

In this study I use data from a major car rental company in the United States. In the auto rental industry, firms usually operate up to about 15 car classes where each class contains different cars with comparable quality (e.g., size and equipment). Each class represents a homogenous good with a base rental fee per day (rate). The typical policy of car rental companies is to accept reservations for passenger cars without examination. These reservations are usually not binding on either side. In case that a customer made a reservation for a certain class in advance and no corresponding car is available at the time of checkout, an upgrade to a superior car class can be granted by a rental agent.[1] In practice, single upgrades (i.e., one additional quality level) are granted with no extra charge (*Carroll and Grimes*, 1995; *Fink and Reiners*, 2006).[2]

Given the fact that free upgrades occur frequently, I assume that customers perceive overbooking as a minor outcome failure[3] and as a result, free upgrades are

[1]This practice is analogous to planned overbooking over multiple compartments by airlines, where economy passengers who cannot be accommodated in the coach compartment get free upgrades to business-class. However, the upgrade practice is more prevalent in the auto rental industry because there is the wider range of the classes and the capacities are more evenly balanced across the different car types (*Talluri and Van Ryzin*, 2006).

[2]Note that the station staff may ask customers to get double or triple upgrades with extra charge (i.e., upsell) or downgrades without any discount (i.e., downgrade). These upsells and downgrades rarely occur - 1.1% and 2.1% in our data, respectively. This paper assumes that these events would not affect customer expectation and the corresponding switching behavior.

[3]Service marketing literature recognizes two types of service encounter failures: outcome and

considered to be better-than-expected service performance or a gain. Based on the social exchange and equity theories (e.g., *Walster, Berscheid, and Walster*, 1973), a service failure/recovery encounter can be viewed as an exchange in which the organization attempts to provide a gain, in the form of a recovery effort, to make up for the customer's loss and result in customer satisfaction (e.g., *Smith, Bolton, and Wagner*, 1999; *Knox and Van Oest*, 2014). To make a convincing link between free car-class upgrades and service performance, I collected online surveys related to three service scenarios related to overbooking and recovery (car-class upgrade, hotel upgrade and car-class downgrade) among 450 Mechanical Turkers residing in the United States. The last two scenarios do not occur as often as the car-class upgrade scenario. I find that participants rated (on 7-point scales) car-class upgrade as significantly being less severe service failure (*Maxham III and Netemeyer*, 2002), more satisfied, better than expected (i.e., more positive disconfirmation) and providing more favorable distributive justice (*Smith, Bolton, and Wagner*, 1999) than the remaining two scenarios. It is not surprising for the ratings for car-class downgrade to be lower, but the lower ratings for hotel upgrade suggest that consumers view car-class upgrade as being more of common occurrence. Overall, the service failure severity ratings are low for all the scenarios (car-class upgrade = 2.09; car-class downgrade = 3.82; hotel upgrade = 3.28), suggesting that overbooking is not perceived by consumers as being a serious loss to be recovered, perhaps due to its prevalence. Participants also expect upgrading to be a better way for firms to resolve overbooking (car = 5.33; hotel = 5.09) and perceive it to better fulfill distributive justice (car =6.04; hotel = 5.57) than downgrading (expectation = 3.71; justice = 2.74).

process. The outcome dimension of a service encounter involves what customers actually receive from the service, whereas the process dimension involves how they receive the service, that is, the manner in which it is delivered (*Smith, Bolton, and Wagner*, 1999). This paper focuses on the outcome failure, that is, free upgrades.

2.3.2 Data Description

The data follow a panel of 454,597 unique loyalty club members from May 2010 to October 2012. The entire sample involves 2,981,503 rental car transactions across 3,422 locations (684 airport and 2,729 off-airport)[4] in the US.[5] Each location offers up to 23 different car classes, while 90.0% of the total transactions consist of 5 most popular car classes: Compact (B), Intermediate (C), Standard (D), Full-Size (F), and Mid-Size SUV (L). Each record in the individual-level data corresponds to one purchase of rental car and provides information on membership ID[6], store ID, the rental's check-out/in date, order number, pickup/return location, car class, rental price, price code (corporate/leisure), customer tier code, and booking channel code. In the data, free upgrades are identified based on the following information: the car class customers reserved, the class they actually received, and the class for which they were charged. In case that the reserved and the charged are the same but different from the received, I view the transactions free upgrades as the firm paid for the superior class. As free upgrades occur frequently, I observe substantial differences between the distributions of the reserved and the received car classes (see Figure 2.1).

The sample is reduced to 2,529,876 transactions from 178,884 customers after I focus on customers who purchased 4 or more times and experienced free upgrades at least once during the sample period.[7] In the empirical analysis, I randomly sample 1,000 (out of 178,884) customers with 14,114 transactions. I check if potential bias

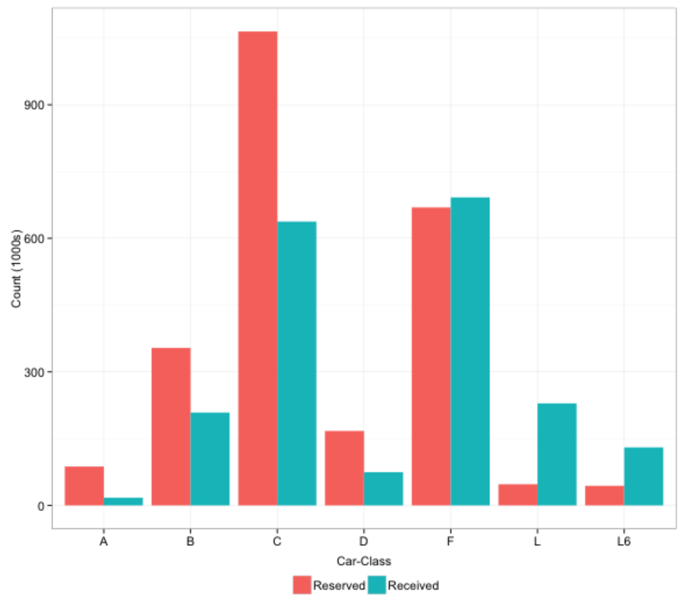
[4] 79.2% of the total transactions are from airport locations.

[5] From the original data that contain 6,283,105 observations I drop the transactions with invalid customer ID and missing car-class information. I also delete outliers (> 99the percentile) of rental duration, advance booking, rental price, and purchase frequency.

[6] I identify unique customers by a combination of membership IDs and birth dates on their driver's licenses. By doing this, I rule out the possibility that the purchase history under a single membership consists of multiple customers (i.e., drivers). Over 80% of these customers had already been loyalty members before the data period of this study.

[7] The reduction is largely due to the fact that our primary variables of interest include the lagged predicted expectation variable. To derive this variable, I need double-lagged car-class switching behavior that requires at least 4 observations for each individual.

Figure 2.1: Distribution of Satisfaction Ratings



due to sample selection could be present by comparing the transactions details of the sample customers with those of the entire customers with 4 or more purchase and free upgrade experiences. I also provide the descriptive statistics of the entire sample. As can be seen Table 2.1, there are no significant differences on key metrics between the three sample classes.

Table 2.2 presents the descriptive statistics of these sample customers across 7 most popular car-classes. Intermediate (C) class was most frequently chosen and repurchased with sales share of 43.7%. On average, free car-class upgrades were offered from 53.6% of the total transactions. Interestingly, over 80% of selected car-classes (e.g., Economy (A) and Standard (D)) were not available and thus upgraded toward higher car-classes with no extra charge. On average, customers pay more for higher car-classes than the lower ones and rebook Intermediate (C) cars within the shortest time interval.

Table 2.1: Descriptive Statistics

(a) Total Transactions (n = 2,981,503)

	Mean	SD	Median	Min.	Max.	Skewness	$\mathrm{Cor}_{t,t-1}$
Free Upgrade	0.52	0.5	1	0	1	-0.06	0.13
Daily Rental Price (dollar)	34.9	18.58	31.5	0	120	1.21	0.34
Rental Duration (day)	4.23	2.94	4	1	29	2.95	0.37
Advance Booking (day)	14.51	22.93	7	-90	834	5.00	0.41
Interpurchase Time (day)	49.65	76.8	21	1	802	3.41	0.26

(b) From customers with upgrade experiences and 4 or more purchases (n = 2,529,876)

	Mean	SD	Median	Min.	Max.	Skewness	$\mathrm{Cor}_{t,t-1}$
Free Upgrade	0.54	0.5	1	0	1	-0.15	0.12
Daily Rental Price (dollar)	34.64	18.23	31.5	0	120	1.17	0.34
Rental Duration (day)	4.08	2.69	4	1	29	2.93	0.37
Advance Booking (day)	14.22	21.95	7	-90	834	5.11	0.4
Interpurchase Time (day)	42.05	61.57	20	1	768	3.4	0.24

(c) From sample customers with upgrade experiences and 4 or more purchases (n = 14,114)

	Mean	SD	Median	Min.	Max.	Skewness	$\mathrm{Cor}_{t,t-1}$
Free Upgrade	0.54	0.5	1	0	1	-0.16	0.12
Daily Rental Price (dollar)	34.97	18.29	32.25	0	120	0.99	0.32
Rental Duration (day)	4.16	2.78	4	1	29	3.1	0.32
Advance Booking (day)	14.64	22.59	7	-3	346	4.96	0.39
Interpurchase Time (day)	42.57	62.67	20	1	681	3.38	0.23

Table 2.2: Descriptive Statistics: Car-Classes

	Car-Class						
	Economy (A)	Compact (B)	Intermediate (C)	Standard (D)	Full-Size (F)	Std. SUV (L)	Lg. SUV (L6)
Sales Share	3.60%	14.50%	43.70%	6.90%	27.50%	1.90%	1.80%
P (Repeat Purchase)	37.40%	64.30%	74.00%	42.50%	65.30%	19.30%	19.30%
P (Upgrade)	86.80%	59.10%	53.40%	82.60%	49.00%	25.70%	17.90%
Rental Price							
Mean	29.28	29.64	34.15	34.41	34.29	51.2	55.27
SD	17.95	15.81	15.65	16.79	18.48	21.85	23.49
Rental Duration							
Mean	4.16	3.95	3.94	4	4.18	4.78	5.13
SD	3.05	2.63	2.55	2.54	2.71	3.28	3.41
Advance Booking							
Mean	12.16	12.45	13.51	12.44	14.64	19.02	21.36
SD	24.11	20.69	18.13	18.02	23.58	29.31	32.95
Interpurchase Time							
Mean	49.36	40.73	38.92	39.83	42.91	59.25	56.52
SD	72.14	60.99	57.4	59.54	62.14	76.03	73.31

2.3.3 Customer Switching Behavior

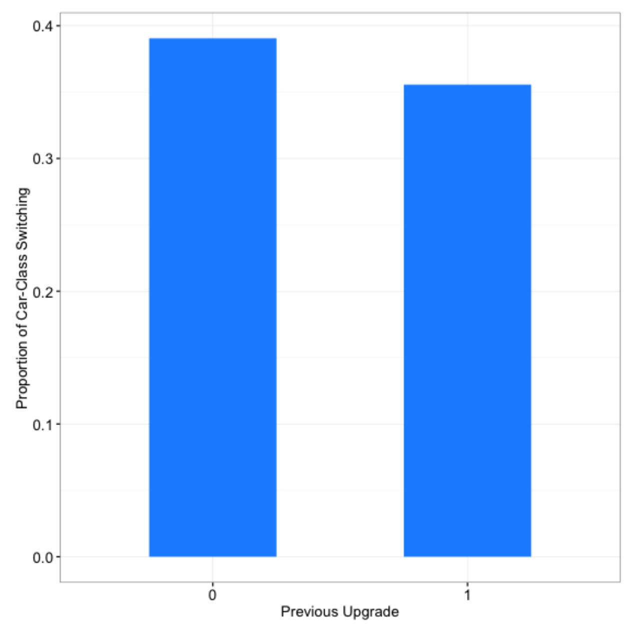
One of the important issues that this research attempts to investigate is how free upgrades affect customers' car-class choices. One possibility is that frequent free upgrades in the previous transactions lead customers to expect another upgrade in a subsequent encounter. As such, these customers are likely to book the same car class as the one that resulted in a free upgrade. To assess this possibility, I first explore car-class switching behavior of customers who were previously offered an upgrade. As can be seen in Figure 2.2a, on average, customers are 9.8% more likely to switch toward different car classes when they were not offered a free upgrade at the previous transaction, compared to when they were (the correlation coefficient is -0.04 and a regression of car-class switching on lagged upgrade shows that the latter has a significant and negative coefficient).[8] This suggests a possibility of strategic customer behavior, as customers might stay with the same car class with one from which they were previously offered the upgrades. To further evaluate how much previous upgrades could affect car-class switching behavior, I exploit the panel nature of the data calculating individual-level cumulative proportion of switching after free upgrades. Figure 2.2b plots this cumulative measure and confirms that customers tend not to switch when they are previously offered free upgrades. Interestingly, this tendency becomes more significant as customers experience more service encounters, suggesting evidence of customers' experiential learning.[9]

[8]Interestingly, previous upgrades appear to be positively related to upward switching, as the correlation coefficient is positive (0.0527). In the data, 24.8% of customers switch toward better car-class after a free upgrade, mostly from A (Economy), B (Compact), and C (Intermediate) car classes. This switching pattern opens up the possibility of firms' strategic behavior where they offer free upgrades towards more profitable car-class and lead customers to choose the car-class in subsequent transactions. Given the data, the intention and effects of this firm strategy are less clear and are certainly worthy of further research.

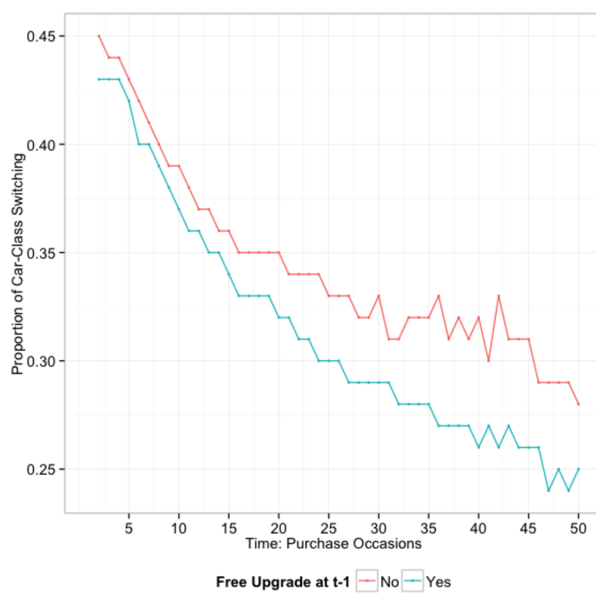
[9]It remains possible that this switching behavior occurs in particular occasions such as holidays and long vacations. To address this concern, I check the correlations of switching with dummies for major holiday (e.g., memorial day, independence day, labor day, thanksgiving, Christmas) weekends and rental duration. The results show that switching behavior appears not to be related with those occasions, as the correlation coefficients are very small (less than 0.03).

Figure 2.2: The Proportion of Switching after Free Upgrades

(a) Most Recent Free Upgrade



(b) Cumulative Free Upgrades



2.3.4 Basic Evidence of Bounded Rationality

Given the assumption that customers make choices based on bounded expectation of free upgrades, it is worth demonstrating whether or not forgetting affects customers' car-class switching behavior. In particular, if customers were offered a free upgrade long time ago, they are likely to forget the event and as such their switching behavior should less correlate with the upgrade. To confirm this intuition, I run a probit regression on whether the car-class customer i chose car-class j in purchase occasion t is different from i's previous choice, controlling for transaction details, X_{ijt} such as rental price, advance booking, and car-class fixed effects. Since this regression includes the lagged car-class switch variable, I exclude first two transactions for each individual from the sample (2,529,876 transactions from 178,884 customers), which leaves 2,172,108 observations in the probit sample. I define the utility of customer i's car-class switching as:

$$U_{ijt}^{Switching} = \beta_{0i} + \beta_{1i}UG_{ijt-1} + \beta_{2i}UG_{ijt-1} \times INT_{ijt,t-1} + \beta_{3i}X_{ijt} + \epsilon_{ijt} \qquad (2.1)$$

Two key independent variables are whether customer i was offered a free upgrade in the last transaction, UG_{ijt-1}, and its interaction with the actual number of days between purchase occasion t and $t-1$ (i.e., interpurchase time), $INT_{ijt-1,t}$. In this analysis, β_{1i} will give the direct effects of an upgrade from the previous service encounter, and β_{2i} will give the incremental effect of interpurchase time on switching, over and above the previous free upgrade.

As shown in Column (1) and (2) of Table 2.3, free upgrades decrease the probability of switching in the following service encounter, even after controlling for customers' intrinsic preference to each car-class. Column (3) adds other sources of information into the switching regression, an interaction between free upgrades and interpurchase time. Interestingly, while results are qualitatively similar, interpurchase time mitigates the effect of free upgrades on car-class switching by 19.1%. This is consistent with my intuition, that is, forgetting leads to a weaker correlation between free upgrades and switching. Note that this regression focuses on the average effect of interpurchase time on customer forgetting, ignoring its role in dynamic customer expectations. This shortcoming will be corrected in the full model.

2.3.5 Endogeneity in Free Upgrades

Firms optimally allocating free upgrades would necessarily direct more upgrade activities to those who provide the most potential profit: those with frequent purchases, or a higher tier level. This practice is analogous to free upgrades by airlines and hotels, where customers who belong to the highest tier level of the loyalty program would often be the first to be upgraded in an overbooking situation.[10] To address this possibility, I compare the average proportion of free upgrades across 3 different customer tiers: Tier 1 (lowest) through Tier 3 (highest). As can be seen in Figure 2.3, customers with higher-tiers are offered free upgrades more frequently, compared those with lower-tiers. [11] In particular, highest-tier customers were provided approximately 25% more free upgrades from Compact (B) and Intermediate (C) car-classes, compared to lowest-tier customers. Given this practice, tier-specific characteristics must be controlled for as much as possible, preferably with a tier fixed effect. Otherwise, the researcher runs the risk of attributing free upgrades to overbooking when a rental location would have offered the upgrades as a promotion to loyal customers.

[10]In this study, I do not take into account customer loyalty to a particular rental location influencing the probability of free upgrades because customers shop around 4.4 different locations for their 6.7 total transactions on average. Only 10.7% of these customers are loyal to a single rental location.

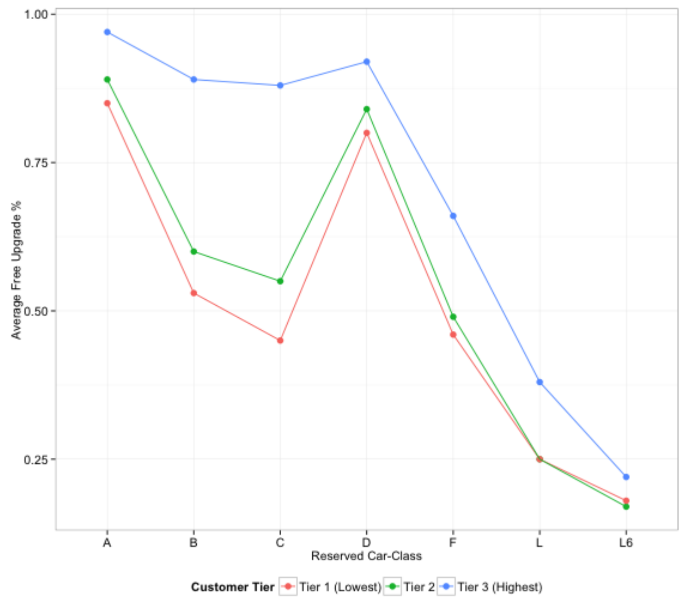
[11]I do not have access to any qualitative description of each of the values or tiers beyond their names. The firm says It is safe to assume that membership on these levels may be based on number of rental transactions, number of rental days, a monthly or annual fee, or some combination of all three. Along with this results, the negative correlation between interpurchase time and free upgrades (-0.0472) supports the idea that frequent customers are likely to obtain higher membership tier.

Table 2.3: Basic Evidence of Bounded Rationality

	(1)	(2)	(3)	(4)
Intercept	-0.8093***	-1.2755***	1.425***	0.9576**
	(0.0073)	(0.0079)	(0.4017)	(0.4044)
lag (Free Upgrade)	-0.1220***	-0.0778***	-0.0909***	-0.2052***
	(0.0031)	(0.0032)	(0.0033)	(0.0099)
ln (Rental Price)	-0.1261***	-0.0790***	-0.1425***	-0.1478***
	(0.002)	(0.0020)	(0.0022)	(0.0022)
lag (Car-Class Switch)	1.7706***	1.7067***	1.7033***	1.6864***
	(0.0031)	(0.0031)	(0.0033)	(0.0033)
Advance Booking	0.0021***	0.0015***	-0.0008***	-0.0015***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ln (Interpurchase Time)				0.1761***
				(0.0022)
lag (Free Upgrade) $\times$ ln (Interpurchase Time)				0.0391***
				(0.0030)
Fixed Effects				
Customer Tier Code		Y	Y	Y
Rental Purpose (Business / Leisure)		Y	Y	Y
Reserved Class			Y	Y
-log(likelihood)	2495440	2450810	2279106	2262611
AIC	4990890	4901638	4558280	4525294
BIC	4990912	4901677	4558427	4525450
Number of Observations	2172108	2172108	2172108	2172108

*** $p < 0.01$, ** $p < 0.05$

Figure 2.3: Free Upgrades across Different Customer Tiers



2.4 Model and Estimation

My overall approach to model car-class switching behavior proceeds in two steps. First, I specify a model of customer expectation, allowing the unobserved customer expectations of free upgrades to change over time. Second, I construct a model of car-class switching behavior, incorporating the predicted customer expectations.

2.4.1 Customer Expectations

Customers may be imperfectly informed and therefore are uncertain about whether they would be offered free upgrades. This uncertainty can persist even after experiences with car rentals because the experiences might provide only noisy information about free upgrades. As such, customers are assumed to form expectations about free upgrades, based on their prior experiences. One of the most widely applied models that relate customers' past experiences to their current expectations is the adaptive expectation framework (*Nerlove*, 1958)[12], that is, a weighted average of

[12] The adaptive expectation framework requires longitudinal data to form customer expectations. In the service literature where such data are not easy to obtain, scholars have most frequently

prior expectation and the most recently observed actual service or product performance.[13] (*Boulding et al.*, 1993), for example, employ a linear updating scheme by which expectation and cumulative service performance perception of a hotel are updated according to the most recent transaction. (*Bruce, Foutz, and Kolsarici*, 2012) construct the goodwill stock toward a movie, which decays in proportion to the lagged goodwill but is maintained by ad spending and online customer rating. Based on this adaptive expectation framework, I first estimate the following:

$$\hat{Q}_{ijt} = \vartheta_{1i}\hat{Q}_{ijt-1} + \vartheta_{2i}Q_{ijt-1} + \epsilon^{Q}_{ijt}, \tag{2.2}$$

In this analysis, θ_{1i} will capture the extent to which customer i's expectations of free upgrades from car-class j at time $t-1$ carry over from period to period and this carry-over can be interpreted as a measure of inertia in customer expectations (e.g., *Akçura, Gönül, and Petrova*, 2004; *Sriram, Chintagunta, and Neelamegham*, 2006). In other words, customers forget (or become less interested in) $(1-\theta_{1i})$ portion of their prior *expectations* over time (e.g., *Bruce, Foutz, and Kolsarici*, 2012). θ_{2i} will give the effect of prior upgrade experiences, Q_{ijt-1}, on customer expectations. As previous literature (*Sweeney et al.*, 2016) has documented, past experience significantly affect in determining service expectations, though the effect decreases over the consumption period. The error term $\epsilon^{Q}_{ijt} \sim N(0, \sigma^2)$ will capture the changes in customer expectations that is not explained by either expectation carryover or previous free upgrade experiences. For example, the error term will account for the effect of competitive activities (*Woodruff, Cadotte, and Jenkins*, 1983), advertising (*Boulding*

conceptualized expectation as a point estimate. The gap model of service quality is one such example, in which service quality is computed as a gap between the point estimates of service perception and expectation (*Sivakumar, Li, and Dong*, 2014). Alternatively, research has conceptualized the reference level as a continuous distribution of an infinite number of reference points, and the expected level is computed as the mean of the distribution (*Rust, Inman, Jia, and Zahorik*, 1999).

[13] The baseline assumption here is that the customers are passive integrator of information. In some cases, however, people actively (strategically) revise their expectations to increase future satisfaction (e.g., *Kopalle and Lehmann*, 2001).

et al., 1993), or 'gut feeling,' which could be used to make strategic decisions for future rental car purchase. One of the implications of Equation 2.2 is that the effect of customer expectations carries over from period to period. Such formulation is consistent with the finding that customer expectations have a long-term effect on customer choice (e.g., *Erdem*, 1998) and the extent of this carry-over will depend on the magnitude of the parameter θ_{1i}, with higher values of θ_{1i}, implying a higher-level of persistence (*Sriram, Chintagunta, and Neelamegham*, 2006).

Note that in this adaptive expectation framework customers are assumed to behave as if they perfectly recall previous *service performances* and its effect will be fully reflected in customer expectations. Although customer expectations under perfect recall provides a reasonable fit to observed choice behavior (*Erdem*, 1998), this is a strong assumption that ignore irrational customers who forget (or are not involved in) the previous service performances. As previous literature (e.g., *Mitra and Golder*, 2006; *Mehta, Rajiv, and Srinivasan*, 2004) has documented, long interpurchase time is likely to increase the extent of forgetting and lead the effect of change in the observed performance not to be entirely reflected in customer expectations. As such, I relax the assumption of perfect recall, allowing the Q_{ijt-1} effects to be mitigated by the time lapsed in days between purchase occasions $t-1$ and t (i.e., interpurchase time), $INT_{t,t-1}$:

$$\hat{Q}_{ijt} = \theta_{1i}\hat{Q}_{ijt-1} + \theta_{2i}Q_{ijt-1} + \theta_{3i}Q_{ijt-1} \times g(INT_{t,t-1}) + \epsilon^{Q}_{ijt}, \tag{2.3}$$

In this analysis, θ_{3i} will capture the incremental effect of interpurchase time on customer expectations, over and above the previous free upgrade. Consistent with the literature, I apply a logarithm transformation of interpurchase time, $g(INT_{t,t-1}) = ln(INT_{t,t-1})$, assuming (nonnegative) interpurchase time to be log-normally distributed (Jen, Chou, and Allenby 2009). Overall, guided by previous literature (*Akçura,* *Gönül, and Petrova*, 2004; *Mehta, Rajiv, and Srinivasan*, 2004), I allow the specification of customer expectations to involve two-types of time-dependent forgetfulness: (1) a potential decline in expectation carryover, θ_{1i}, and (2) the effect of interpurchase time that mitigates the reflection of previous service encounter, θ_{3i}.[14].

2.4.2 Customer Demand

After linking free upgrades to customer expectations, I next examine how these expectations affect customers' car-class switching decision, that is, whether to stay with the same car class with one from which they previously chose. If they were not offered an upgrade from the past, customers may switch toward different car-classes, anticipating an upgrade. The specification of car-class switching behavior is guided by the literature, which reveals customer dynamic expectations influencing switching (or repurchase) behavior. *Iyengar, Ansari, and Gupta* (2007), for example, found the effect of quality and quantity expectations learned by prior experiences on customer retention in the wireless service industry. In the light of these empirical findings, I define the utility of customer i from choosing car-class j at time t as a linear function of the customer's expectation of free upgrades at the point in time, rental characteristics, and a latent utility error:

$$U_{ijt} = \hat{Q}_{ijt} + \beta_{1i} X_{it} + \xi_j + \epsilon_{ijt}^{U}, \tag{2.4}$$

In this analysis, β_{1i} will give the effect of the individual-level rental characteristics, X_{it}, such as daily rental prices (excluding add-ons such as insurance, GPS, prepaid fuel, etc.), advance booking, and lagged switching behavior.[15] The daily rental prices

[14]In this expectation specification, I also incorporate the car-class and the customer-tier specific fixed effects. The former controls for customers' intrinsic expectations of free upgrades across different car-class, while the latter, to some extent, explains the potential impact of customer characteristics based on the average number of previous rentals (See Section 2.3.5)

[15]I assume that there are no changes in demographic factors that may determine the car-class switching behavior, including the number of child and income. This is a reasonable assumption based on the length of the sample period.

vary across different locations and time periods. I acknowledge that this variation in the rental prices can be attributed to the current inventory level of each rental location, which is not available in the data. As such, I consider the rental prices exogenous. The advance booking variable controls the difference in behavior between business and leisure travelers, as leisure travelers start searching for a rental earlier than business travelers do (*Lazarev*, 2013). The lagged switching variable will separate customers' systematic variety-seeking behavior from adherence due to their expectations of free upgrades (e.g., *Dubé, Hitsch, and Rossi*, 2010). ξ_j is the unobserved car-class characteristics. The error term $\epsilon^U_{ijt} \sim N(0, \sigma^2_u)$ will capture the idiosyncratic taste of customer i for car-class j at time t. For example, the error term may include a last-minute deal or interaction with service staff, which I am not able to observe in the data. Given the distributional assumption on the error term, the probability of customer i's car-class switching behavior takes the following form of a standard probit choice probability:

$$Pr_{ijt}(purchase) = \Phi(\hat{Q}_{ijt} + \beta_{1i} X_{it} + \xi_j), \tag{2.5}$$

In the above expression, $Switch_{ijt}$ denotes an indicator variable whether the car-class customer i chose in time t is different from i's last choice. In particular, $Switch_{ijt} = 1$ if customer i switch her car-class from one she previously chose, whereas $Switch_{ijt} = 0$ otherwise.

2.4.3 Estimation

The first objective of the estimation is to recover the state parameter $\hat{Q}_{ijt}$ in the evolution equations (Equation 2.2 and 2.3). A key challenge is that I do not observe customer expectations at each time period t, but need to estimate them. To address this, I use the Kalman filter (*Hamilton*, 1994), which is a recursive algorithm that is capable of tracking the evolution of expectations and obtaining efficient estimates of an unobserved state variable, based on the information observed at that period. The Kalman filter is a two-equation system consisting of (1) an observation equation that relates the time-varying parameters to an observed dependent variable (Equation 2.5) and (2) a system equation that characterizes the dynamics of the time-varying parameter (Equation 2.2 and 2.3). In this study, the system of equations captures the dynamics of the customer expectation, allowing me to separate the effects of (recalled) free upgrades from the impact of the prior expectations accrued through product usage over time.

The full model captures unobserved heterogeneity with the distributions of $\{\theta_i, \beta_i\}$ by allowing them to be distributed multivariate normal with mean $\{\theta_0, \beta_0\}$ and variance $\{V_\theta, V_\beta\}$. The hyperparameters $\{\theta_0, \beta_0\}$ and $\{V_\theta, V_\beta\}$ are distributed multivariate normal and inverse Wishart, respectively. I derive the full conditional distributions of those unknowns, using the joint density and the specified prior distributions. I then draw sequentially from this series of full conditional distributions, nesting the Kalman filter algorithm inside a Markov chain Monte Carlo Gibbs sampler (*Bruce, Foutz, and Kolsarici*, 2012). Specifically, the conditional posterior of the unobserved state parameter, $\hat{Q}_{ijt}$, are obtained via the forward-filtering and backward-smoothing procedure (*Carter and Kohn*, 1994). With this state parameter in hand, I sample the non-state parameters using a Gibbs algorithm (*Rossi and Allenby*, 2003). I place normal conjugate priors on all parameters of the observation equation and inverse Gamma priors on the error variances of both the evolution and observation equations.

2.5 Results

Table 2.4 presents my analyses looking at the effects of previous service performance on customer expectations and car-class switching behavior: (1) a partial model under the assumption of perfect recall, and (2) the proposed model with both distorted expectations and imperfect recall taken into account.

Overall, I find evidence of customers' strategic car-class switching behavior, as the predicted expectations of free upgrades significantly decrease customers' car-class switching (see Column (2)). In other words, customers are strategically request the same car-class that previously resulted in a free upgrade, anticipating yet another upgrade from the class. Interestingly, forgetting significantly affect customer expectations in two ways. First, I observe a considerable decline in expectation carryover. On average, 18.5% of prior expectations are carried over to the next period. The greater the forgetting of prior expectations, the stronger is the effect of previous free upgrade experiences. That is, whenever customers receive new information about free upgrades from the past events, they rely more on the information to make a car-class choice decision, compared to their prior expectations. The parameter estimates show that previous upgrades increase customer expectations on another upgrade in a subsequent transaction. Second, the extent that information from the past events is retrieved from memory is significantly moderated by interpurchase time. Specifically, interpurchase time mitigates the positive contribution of previous service encounter to customer expectations by 20.3%. These results confirm findings from the previous literature that proposes a relationship between interpurchase time and forgetting (e.g., *Mehta, Rajiv, and Srinivasan*, 2004).[16]

2.6 Conclusion

The aim of this paper is to demonstrate the effect of expectations on strategic customer behavior. The two main issues this research attempts to address via a unique

[16]To separate the effect of forgetting from strategic behavior, we can contrast a null model where neither distorted expectations (i.e., expectations are perfectly carried over) nor imperfect recall of previous service encounter is not taken into account, with the full model where both ways of forgetting are incorporated.

Table 2.4: Parameter Estimates from the Proposed Model

	(1)			(2)		
	Mean	2.5%CI	97.5%CI	Mean	2.5%CI	97.5%CI
Expectation Model						
Expectation Carryover	0.1933	0.1751	0.2258	0.1854	0.1656	0.2177
lag (Free Upgrade)	-0.0367	-0.1384	0.0469	-0.5971	-0.8699	-0.3139
lag (Free Upgrade) × Interpurchase Time				0.1728	0.0986	0.2496
Switching Model						
Predicted Expectation	-0.9219	-1.1038	-0.7308	-0.9302	-1.0735	-0.6817
log (Rental Price)	0.1217	0.0776	0.1632	0.1078	0.0361	0.1785
lag (Car-Class Switch)	1.0137	0.8968	1.1476	1.0367	0.9389	1.1732
-log(likelihood)		15846			15849	
AIC		31698			31705	
BIC		31704			31711	
Number of Observations		11114			11114	

* The estimates of random coefficients, fixed effects, and control variables are omitted to save space.

data set obtained from the auto rental industries are (1) how forgetting affects customer expectations over time and (2) whether customer expectations under bounded rationality negatively influence economic outcomes for the firms. The panel nature of my data allows me to deal with the evolution of customer expectations, separating the effect of prior expectations from the reflection of previous service encounters. I find evidence that customer expectations, moderated by forgetting, have a negative impact on customers' car-class switching behavior. This implies that frequent free car-class upgrade offers may result in customer strategy where they request the car-class they were offered an upgrade in the past. In addition, I observe two types of forgetfulness in customer expectations, including expectation carry over and the effect of previous experience mitigated by interpurchase time. Overall, the implication is that free car-class upgrades are not necessarily a "cheap" way to avert customer complaints about and increase customers' positive reactions because they may result in strategic customers who take advantage of those frequent upgrades and choose less profitable alternatives. This study suffers from some limitations, primarily driven by the nature of the data. First, I am unable to model supply availability (i.e., inventory level) that determines the firm's decision of free upgrades and rental prices. Second, given that my data are from loyalty members of the firm, this study requires the assumption that these loyalty members represent the entire customers of the firm.

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