The Experience of Production: Essays on Customers in Service Operations

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Abstract

Over time, the delivery of services has become increasingly co-productive (customers participate materially in the production of service outcomes) and inseparable from customer view. As a result, a distinctive aspect of service operations is that they feature production processes in which the experience of production influences customer behavior. In particular, operational choices intended to maximize firm profits may backfire if they diminish customer experiences and, in the process, alter whether and how customers choose to perform their role in the firm's operating system. In three studies, my dissertation empirically explores how two specific operational choices - 1) whether and how a firm automates service, and 2) the level of service quality a firm chooses to provide relative to its competitors - affect the experiences and behaviors of its customers, and in turn, the firm's performance.

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Chapter 2 was co-authored with Dennis Campbell and Frances X. Frei.
Chapter 3 was co-authored with Michael I. Norton.
Chapter 4 was co-authored with Dennis Campbell and Frances X. Frei.

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1

The Experience of Production

1.1 Introduction

Over time, the delivery of services has become increasingly co-productive (customers participate materially in the production of service outcomes) and, as a consequence, inseparable from customer view. As a result, a distinctive aspect of service operations is that they feature production processes in which the experience of production influences customer behavior.

In such contexts, operational design choices intended to maximize firm profits may backfire if they perturb customer experiences and, in the process, alter whether and how customers choose to perform their role in the firm's operating system. In my work, which contributes to the growing body of empirical service operations literature, I explore how operational choices, made in the service of customers, affect customer actions, and in turn, firm performance.

1.2 Theoretical and practical significance

A considerable body of the extant operations literature explores how customers affect operating systems. This issue is particularly important in service contexts, where the potential efficiency of the system is a function of the degree of customer contact entailed in the process (Chase 1981). Customers subject service systems to tremendous variability by showing up when they want, asking for different things, varying in their willingness and ability to help themselves, and valuing different service dimensions (Frei 2006). Accordingly, rich streams of research analyze how service systems can perform as designed in the face of this variability.

Much of this work has been a natural extension of previous lines of inquiry initially conducted in manufacturing contexts. Through the application of insights and tools from traditional operations management, such as queuing theory (Afèche and Mendelson 2004, Allon et al. 2011, Anand et al. 2011, de Vèricourt and Zhou 2005, Dewan and Mendelson 1990, Mandelbaum and Shimkin 2000, Stidham 1992, Zohar et al. 2002), demand forecasting (Adrangi et al. 2001, Watson 1987, Willemain et al. 2004), inventory management (Berman et al. 1993, Berman and Kim 1999, Berman and Sapna 2000), and capacity planning(Allon and Federgruen 2009, Hall and Porteus 2000), scholars have been able to make great progress in improving the efficiency of service operating systems. In these cases, traditional approaches were extended to accommodate the important characteristics of services, which include customer participation in the service process, intangibility, simultaneity, heterogeneity of outputs and perishability (Fitzsimmons and Fitzsimmons 2006).

However, while service production processes, by definition, rely on customer inputs (Sampson and Froehle, 2006), far less work has explored how operational choices affect customer behaviors. Broadly speaking, there are two sets of exceptions. The first set includes analytical papers like (Dana and Petruzzi, 2001), in which customers choose where to shop based on a firm's observable prices and expectations about unobserved inventory levels, and (Gans 2002), which models how customers will allocate spending across providers that vary in service quality. These studies consider how anticipated customer responses to operational choices will affect firm performance. However, while most analytical models assume rational consumer behavior, actual customers may depart from rationality (Gino and Pisano, 2008). Where understood, accounting for these departures has been shown to lead to markedly different results (Huang et al., 2011). Moreover, there are a plethora of factors at play in a service interaction, and it's not always clear which operational choices will be most salient to customers in the field. The second set of exceptions, which is much smaller, includes empirical works, like (Olivares et al. 2011), which explores how queues affect the purchase behavior of customers, (Craig et al., 2011), which studies how supplier reliability affects customer demand, and (Dixon and Verma, 2010), which investigates how sequence effects in service bundles affect customer repurchase decisions. These studies differ from the earlier examples, in that they empirically examine the behaviors of actual customers. My work pursues a similar path, by employing both the econometric analysis of large-sample datasets, as well as in-lab and online experimental methodologies. Through my research, I endeavor to improve our discipline's understanding of how customers respond to operational choices, and by extension, improve both the performance of service organizations and the in-process experiences of their customers.

1.3 Overview of dissertation research

In three chapters, my dissertation empirically explores how two specific operational choices - 1) whether and how a firm automates service, and 2) the level of service quality a firm chooses to provide relative to its competitors - affect the experiences and behaviors of its customers, and in turn, the firm's performance.

Chapter 2, titled, *Are Self-Service Customers Satisfied or Stuck?,* explores the implications of service automation for customer outcomes by disentangling the distinct effects of satisfaction and switching costs on self-service customer retention. This is a particularly important issue in the financial services industry where considerable investments have been made in developing, and migrating customers to, self-service distribution channels, which are widely acknowledged to lower the cost of service delivery for individual transactions. Numerous studies in the services literature have demonstrated that self-service customers are retained with greater frequency than their full-service counterparts. There are two competing explanations for this phenomenon. Either self-service channel usage promotes customer satisfaction and in turn, loyalty, or it imposes switching costs on customers that make it more difficult for them to defect. Our empirical analysis of multi-channel banking customers suggests the latter - that self-service customers may be retained through switching costs, not satisfaction effects. In fact, the results of our analysis suggest that self-service customers aren't just stuck, they're actually less satisfied.

Dissatisfied customers held captive by switching costs spend less money and are notoriously difficult and expensive to serve, suggesting that in the near-term, there may be hidden performance costs associated with self-service strategies. Moreover, there may be reason to believe that switching cost-imposed "stickiness" will not be indefinitely sustainable. It has been predicted that over time switching barriers will drop and companies will have to develop new methods for generating customer loyalty. The increasing technological capabilities of consumers combined with the standardization of technology and industry-wide efforts to improve ease-of-use and reduce adoption barriers are all drivers of this change.

Chapter 3, titled, *The Labor Illusion: How Operational Transparency Increases Perceived Value,* extends the previous paper by exploring how operationally transparent interfaces can attenuate the negative satisfaction effects of self-service technologies. Self-service technologies are capable of delivering service outcomes more quickly and conveniently than face-to-face alternatives. However, unlike those who transact in face-to-face settings, self-service customers do not observe physical effort from the service provider and may not observe other visible cues signaling the value created by the service. As such, while an automated solution may objectively deliver superior performance, customers might not perceive it as valuable if it does not appear to be exerting a sufficient level of effort. Conventional wisdom and operations theory suggests that the longer customers wait, the less satisfied they become; we demonstrate that due to what we term the labor illusion, when websites engage in operational transparency by signaling that they are exerting effort, customers can actually prefer websites with longer waits to those that return instantaneous results - even when those results are identical. In particular, we show that perceptions of service provider effort induce feelings of reciprocity, which together mediate the link between operational transparency and increased valuation.

These findings shed light on the hidden costs of strategies employed by an increasingly significant number of firms to infuse technology into service operations. These very strategies, which are designed to enhance the technical efficiency of service, may also counter-intuitively erode consumer perceptions of the value of the services they create. If this is the case, then these strategies may have negative long-term implications for companies that fail to compensate by investing in initiatives that infuse additional meaning into each transaction and into their relationships with their customers.

Chapter 4, titled, *How Do Customers Respond to Service Quality Competition?,* links a firm's choice of service quality relative to local market competitors to the defection decisions of its customers, and in turn, its financial performance. Our customer-level analysis exploits the varying competitive dynamics in geographically isolated markets in which a nationwide retail bank conducted business over a five-year period. We find that customers defect at a higher rate from the incumbent following increased service competition only when the incumbent offers high quality service relative to existing competitors in a local market. We provide evidence that this result is due to a sorting effect whereby the incumbent attracts service (price) sensitive customers in markets where it has supplied relatively high (low) levels of service quality in the past. Furthermore, we show that it is the high quality incumbent's most profitable customers, those with the longest tenure, most products, and highest balances, who are the most attracted by superior service alternatives. Along the way, we also show that firms trade-off price and service quality and that when the incumbent offers relatively low service quality in a local market, its customers are more likely to defect in the wake of entry or expansion by inferior service quality (price) competitors. Our results appear to have long run implications whereby sustaining a high level of service relative to local competitors leads the incumbent to attract and retain higher value customers over time.

These results suggest that firms, which make the strategic decision not to compete on service, may not need to be concerned about the entry or expansion of competitors offering superior service. They also highlight the dangers of complacency for service-positioned firms. The entry of a competitor offering superior service can have sizable short-term implications - increasing defection in our analysis by an average of 9.6% in a single year over baseline defection rates - and significant long-run implications as well. Perhaps most crucially, the positive association we demonstrate between service sensitivity and customer value suggests that models assuming the two are independent will underestimate the importance of service quality, and prescribe suboptimally low service levels. Initiatives to optimize a firm's service level must weigh the long-term costs of losing a firm's most valuable customers against the costs of perpetuating a level of relative service quality that is sufficient to retain them.

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2

Are Self-Service Customers Satisfied or Stuck?

2.1 Introduction

This chapter investigates, how satisfaction and switching costs contribute to retention among self-service technology (SST) customers, and more broadly, the overall impact of self-service usage on customer satisfaction and retention. A number of studies in the services literature have suggested that self-service customers are more loyal than their full-service counterparts (Campbell and Frei, 2006; Hitt and Frei, 2002; Marzocchi and Zammit, 2006; Mols, 1998; Wallace, Giese, and Johnson, 2004; Yen and Gwinner, 2003). There are two competing explanations for why this might be the case. One explanation is that self-service channels offer benefits over full-service offerings that improve customer satisfaction, and by extension, loyalty. The alternative explanation is that self-service usage increases switching costs, which improves retention by making it more difficult for customers to defect to competitors.

It has been well established in the literature that a satisfied customer is more likely to remain loyal to a firm than a dissatisfied one (Anderson, 1994; Bowen and Chen, 2001;

Heskett, Sasser, and Schlesinger, 1997; LaBarbera and Mazursky, 1983; Newman and Werbel, 1973; Oliver, 1980). However, a customer who finds it difficult to switch to a competitor as a result of learning costs, psychological effects, transaction costs, or contractual obligations, may also remain loyal, despite dissatisfaction (Farrell and Klemperer, 2007).

Understanding what motivates self-service customers to remain loyal has significant implications for service organizations. Dissatisfied customers held captive by switching costs spend less money and are notoriously difficult and expensive to serve (Coyles and Gokey, 2005; Jones and Sasser, 1995; Xue and Harker, 2002). Moreover, they will defect from a firm over time if switching costs fall (Evans and Wurster, 1997). Consequently, if switching costs are found to be the driver of increased loyalty among self-service customers, then managers face a crucial expected value calculation: weighing the near-term cost benefits of self-service technologies against the potential reduction in customer lifetime value from those who defect, seeking superior service experiences elsewhere.

As the role of service businesses has grown in prominence, the impact of technological innovation in service delivery has received considerable attention from the operations management community (Apte, Maglaras, and Pinedo, 2008; Roth and Menor, 2003; Spohrer and Maglio, 2008). Our paper broadens this existing literature in two ways. First, the overall impact of self-service usage on satisfaction and retention remains unresolved. While a significant number of prior studies have examined these relationships, their results have conflicted over the direction of the impact. In general, studies that have found that self-service usage increases satisfaction, have also found that it increases retention (Marzocchi and Zammit, 2006; Mols, 1998; Wallace et al., 2004; Yen and Gwinner, 2003). In contrast, those that have found that it decreases satisfaction have also found that it decreases retention (Carmel and Scott, 2007; Meuter, Ostrom, Bitner, and Roundtree, 2003; Price and Arnould, 1999). The multi-channel nature of the personal banking industry affords a unique opportunity to analyze the incremental impact of self-service channel usage on overall customer satisfaction and retention relative to the use of full-service channels. We use actual transaction data to categorize individual customers by channel. This approach provides greater clarity into the relationships between self-service usage, satisfaction and retention. Specifically, it lets us examine the relationship between satisfaction and retention in self-service channels that have varying amounts of switching costs associated with them.

Second, we have disentangled the relative impact of self-service-related satisfaction and switching costs on actual customer retention, rather than on stated intention to stay with a firm. By combining customer surveys to assess satisfaction with longitudinal observations of customers to gauge retention, we provide evidence on the relationship between satisfaction and actual retention in a multi-channel setting. Previous studies examining the impact of self-service channel usage have tended to rely on customer surveys or observational analyses, but not a mix of the two. Studies examining the link between self-service usage and satisfaction have addressed retention by inquiring about customers' future intentions to remain with the firm (Marzocchi and Zammit, 2006; Mols, 1998; Wallace et al., 2004; Yen and Gwinner, 2003). It has been demonstrated that self-reported retention measures overstate switching behavior (Garland, 2002). In contrast, studies focusing specifically on retention that have been observational in nature have not had access to satisfaction data (Chen and Hitt, 2002; Xue and Harker, 2002).

This study does not employ a direct, customer-reported measure of switching costs. Instead, we infer the relative level of switching costs in various channels by examining gains to retention, controlling for satisfaction and other customer-specific characteristics. This approach is consistent with a number of previous studies (Anderson and Sullivan, 1993; Fornell, 1992; Klemperer, 1995). We employ a mediation model to analyze satisfaction survey data and lagged observational data on retention, controlling for proportional channel use. With this approach, we isolate satisfaction effects from switching costs and provide a more detailed picture of how the implementation of self-service technology impacts customer behavior.

The remainder of the paper proceeds as follows. A review of the relevant literature and our hypotheses development are provided in Section 2. Our methodological approach is described in Section 3. Section 4 provides a description of our research site and data collection. Results are discussed in Section 5. Managerial implications of our findings are discussed in Section 6. Section 7 concludes the paper.

2.2 Literature review and hypothesis development

A growing number of firms are augmenting traditional face-to-face service strategies with self-service technology. In part, these firms implement SSTs with the intentions of improving satisfaction and loyalty through increased efficiency, convenience and perceived control for the customer (Hitt, Frei, and Harker, 1999; Meuter, Ostrom, Roundtree, and Bitner, 2000; Yen, 2005). Yet, the interrelationships between self-service channel usage, retention, switching costs and satisfaction remain unresolved in the literature. This section reviews the literature that shapes our understanding of these interrelationships, and motivates a number of relevant hypotheses. Due to conflicting findings among a portion of the relevant studies we cite, we have adopted the convention of stating non-directional hypotheses in null form and directional hypotheses in alternative form.

Our review is divided into three streams. First, we focus on the literature investigating the overall link between self-service channel usage and retention. Numerous studies have explored this relationship in a wide-array of settings, but their findings have often conflicted. Second, we highlight two potential sources of this conflict: switching costs and satisfaction effects. We review a number of theoretical and empirical analyses that have focused on these effects in various self-service settings. Finally, we argue that considering either effect on its own provides an incomplete picture of the link between self-service usage and retention.

2.2.1 The impact of self-service usage on retention

Despite the increasing prevalence of self-service technologies, the link between self-service channel usage and retention remains ambiguous in the literature. Several studies have found a positive relationship, noting that self-service and online customers have higher repurchase ratios than their full-service and offline counterparts (Hitt and Frei, 2002; Mols, 1998; Xue and Harker, 2002). Moreover, to the extent that online channels increase transaction frequency, they have been shown to increase customer retention (Chen and Hitt, 2002). Conversely, going from personal service to self-service has been shown to have a negative effect on bonding and loyalty with low complexity transactions and relationships (Selnes and Hansen, 2001). Furthermore, customer delight in online self-service channels has been shown not to lead to loyalty (Herington and Weaven, 2007). Based on these conflicting findings, we hypothesize that in aggregate, self-service usage has an ambiguous impact on retention. This non-directional hypothesis is stated in null form:

Hypothesis 1 (H1): Relative to full-service channel usage, there is not a significant relationship between self-service channel usage and retention.

2.2.2 The impact of switching costs and satisfaction effects

Switching costs

A portion of the ambiguous relationship between self-service usage and retention can be explained by varying levels of switching costs. Consumers face switching costs when investments specific to their current providers must be duplicated for new providers (Farrell and Klemperer, 2007). Two types of switching costs seem particularly relevant in self-service banking environments: start-up costs and learning costs. Start-up costs exist in channels where customers must setup a product for its initial use (Burnham, Freis, and Mahajan, 2003; Klemperer, 1995). For example, in retail banking, online bill pay imposes start-up costs by requiring up-front manual data entry by its users. Learning costs include the time and effort required to acquire the necessary skills to use a service effectively (Burnham et al., 2003; Farrell and Klemperer, 2007; Guiltinan, 1989; Klemperer, 1995). Online banking systems impose learning costs, as customers must familiarize themselves with the bank's proprietary web interface in order to make efficient use of the service. After start-up and learning costs have been expended, switching to a competitor requires duplicated effort elsewhere, thereby creating a barrier to defection.

While online bill pay and online banking impose switching costs on customers, other channels like ATM and phone banking, which are basically standardized between firms and require no significant start-up investment, are not likely to impose such switching costs. To the extent that high switching cost channels complicate the process of changing banks, ceteris paribus, we would expect customers in low switching cost channels to defect with greater frequency than customers in high switching cost channels. However, switching costs only represent one part of the equation that connects self-service channel usage to customer retention. Understanding the net impact of self-service transactions also requires exploration of the connection between self-service usage and retention driven through satisfaction effects. Consequently, we hypothesize that self-service usage, without accounting for satisfaction effects, will be ambiguously associated with retention in both high and low switching cost channels. The following non-directional hypotheses are stated in null form:

Hypothesis 2 (H2): The usage of high switching cost self-service channels is not associated with customer retention.

Hypothesis 3 (H3): The usage of low switching cost self-service channels is not associated with customer retention.

Satisfaction effects

Self-service technology usage has been found to promote customer satisfaction in a number of settings, including retail banking (Mols, 1998), supermarkets (Marzocchi and Zammit, 2006), online commerce (Szymanski and Hise, 2000; Zviran, Glezer, and Avni, 2006) and travel (Yen, 2005). In one study, 68% of those satisfied with self-service technologies reported that their satisfaction was driven by benefits that go beyond full-service offerings (Meuter et al., 2000). In another, self-service customers were found to be both more efficient and more satisfied than their full-service counterparts (Xue and Harker, 2002). Ease of use, service performance, perceived control and convenience have been shown to be significant drivers of satisfaction in online self-service settings (Yen, 2005). Moreover, multiple channel interaction, including transactions conducted in self-service channels, has been shown to lead to positive disconfirmation, which in turn was found to lead to increased satisfaction and loyalty (Wallace et al., 2004).

On the other hand, with the wrong model, outsourcing work to customers through self-service technology can leave them feeling frustrated and annoyed (Moon and Frei, 2000). Some customers in self-service settings have been found to report technology failures, service design problems, process failures, technology design problems and customer driven failures as sources of dissatisfaction (Meuter et al., 2000). Customers with technology anxiety are less likely to have a positive self-service technology experience, even when things go well (Meuter et al., 2003). Furthermore, while negative feelings towards specific employees diminish a customer's global opinion of the brand, they also have been shown to increase self-service technology usage, which suggests an adverse selection effect may exist among self-service customers (Curran, Meuter, and Surprenant, 2003).

In order to examine the links between self-service usage and retention driven

		Satisfaction Effects	
		Negative	Positive
Switching Costs	Low	Negative retention effect	Retention effect contingent on relative strength of switching costs and satisfaction effects
	High	Retention effect contingent on relative strength of switching costs and satisfaction effects	Positive retention effect

Figure 2.2.1: Drivers of retention in self-service channels.

through satisfaction effects, we test the following non-directional hypothesis, which is stated in null form:

Hypothesis 4 (H4): Relative to full-service channel usage, there is not a significant relationship between self-service channel usage and satisfaction.

2.2.3 Disentangling switching costs from satisfaction effects

If switching costs and satisfaction effects jointly influence the relationship between self-service channel usage and customer retention, then both elements must be considered in order to understand a channel's net impact on retention (Figure 2.2.1). Figure 2.2.1 illustrates the interplay of these factors. In the first quadrant, negative retention is predicted, due to the absence of switching barriers and negative satisfaction effects. In quadrant two, positive satisfaction effects counterbalance the absence of switching barriers, leading to a net impact on retention that is contingent upon the drivers' relative effects. In the third quadrant, the outcome is also contingent on the relative strength of each effect, as high switching barriers endeavor to overcome negative satisfaction effects. Finally, in quadrant four, switching costs and satisfaction effects reinforce one another, leading to a positive net impact on retention.

Figure 2.2.1 elucidates both the importance and the challenge of disentangling the impact of self-service-related satisfaction effects and switching costs on customer retention. As we have described above, to a certain extent, the direction of a self-service channel's impact on switching costs is knowable from an ex-ante perspective due to inherent characteristics of the channel (e.g. start-up costs are present in online bill pay and largely absent in the automated phone channel). However, a specific channel's impact on satisfaction may be more difficult to foresee. By examining the impact of self-service channel usage on retention controlling for satisfaction, we can isolate the portion of retention that is attributable to non-satisfaction effects. In congruence with prior studies, we argue that these non-satisfaction effects are synonymous with switching costs (Anderson and Sullivan, 1993; Fornell, 1992; Klemperer, 1995). As such, we expect that high switching cost channels will exhibit positive retention net of satisfaction, while low switching cost channels will exhibit insignificant or negative retention effects net of satisfaction. The following directional hypotheses are stated in alternative form:

Hypothesis 5: (H5): Controlling for satisfaction, self-service customers who transact in high switching cost channels are more likely to remain loyal to a firm than full-service customers.

Hypothesis 6: (H6): Controlling for satisfaction, self-service customers who transact in low switching cost channels are no more likely to remain loyal to a firm than full-service customers.

By controlling for satisfaction effects, these hypotheses resolve the directional ambiguity in hypotheses 2 and 3. Moreover, using full-service channels as their baseline creates a conservative test of switching costs, as it has been argued in the literature that face-to-face interactions create relational (psychological) switching barriers (Farrell and Klemperer, 2007; Jones, Mothersbaugh, and Beatty, 2000).

2.3 Methodological approach

We conduct our study in the context of the retail banking industry. There are several reasons that retail banking is the ideal setting in which to disentangle the impact of switching costs and satisfaction effects on self-service customer retention. First, retail banks employ multiple channels to serve their customers. These channels range from full-service teller interactions to completely automated self-service channels such as online banking and ATMs. As described above, these channels vary in terms of the level and types of switching costs each imposes. Second, retail banking customers are a diverse group, with varying needs, preferences and experiences. This variability creates a rich environment in which to analyze the impact of operational decisions on consumer behavior. Moreover, the diverse customer base is common to a wide variety of consumer service firms, broadening the relevance of our analysis. Finally, retail banks capture and store a considerable amount of data about their customers, for both strategic and regulatory purposes. We were able to tap into this resource to conduct our empirical analysis.

This study diverges methodologically from past work by analyzing the complete profile of transactions across all channels of service between a bank and a randomly selected sample of its customers. Our observational dataset includes counts of the number of transactions a random sample of customers conducted through each channel over a one-year period. Many of the previous analyses have treated self-service channel usage as a binary variable, but a precedent exists in the literature for characterizing multi-channel customers based on the proportion of overall transactions conducted through specific channels (Montoya-Weiss, Voss, and Grewal, 2003). We follow this precedent by characterizing customers based on their proportional channel mix.

We couple this information with customer-level satisfaction data, gathered through surveys, and customer-level retention information, provided by the bank one year following our period of observation, to analyze the incremental impact of channel mix on customer satisfaction and retention. We examine the impact of channel mix on three levels. First, we compare self-service channel mix to full-service channel mix on an aggregated level. This approach serves as our tests of hypotheses 1 and 4, enabling us to broadly understand if customer involvement in the production of service influences satisfaction and retention. Second, we aggregate transactions conducted in the high and low switching cost self-service channels we identified earlier based on ex-ante characteristics. We compare the effects of the use of each type of channel on retention to test hypotheses 2 and 3, learning if the level of switching costs in a self-service channel differentially drives retention. Third, we analyze the impact of each channel separately, to test hypotheses 5 and 6, and better understand if all channels are created equally with regard to switching costs, satisfaction and retention.

Disentangling the relationships between satisfaction effects, switching costs, and retention in a self-service setting requires analysis of retention controlling for satisfaction. No such study has yet been conducted. Prior studies exploring these relationships have relied on customer surveys or observational analyses, but not both at the same time. Studies examining the link between self-service usage and satisfaction have, by necessity, been survey-based, and when these studies have addressed the question of retention, they've asked customers if they intended to continue patronizing the firm (Marzocchi and Zammit, 2006; Mols, 1998; Wallace et al., 2004; Yen and Gwinner, 2003). Furthermore, a number of observational studies have been conducted focusing on retention, but they did not consider satisfaction in their models (Chen and Hitt, 2002; Xue and Harker, 2002). A general model illustrating these approaches is given by the following equations.

$$\text{satisfaction} = \alpha_1 + \alpha_2(\text{self-service}) + \alpha_3(\text{controls}) \tag{2.1}$$

$$\text{retention} = \beta_1 + \beta_2(\text{self-service}) + \beta_3(\text{controls}) \tag{2.2}$$

$$\text{retention} = \gamma_1 + \gamma_2(\text{self-service}) + \gamma_3(\text{satisfaction}) + \gamma_4(\text{controls}) \tag{2.3}$$

While these studies have provided scholars and practitioners with significant insights about the net effects of self-service channel usage as well as other antecedents on each variable, they are limited by an inability to disentangle the impact of satisfaction effects and switching costs on customer retention. For this study, we employ a mediation model that enables us to tease apart these two effects, as well as understand the ultimate impact of self-service usage use on satisfaction and retention. We use the following model for our analyses:

In contrast to previous studies, which tend to measure self-service participation as a binary variable, we measure self-service usage disaggregated by channel, based on the relative use of those channels. We estimate all equations through OLS regression. This allows for straightforward interpretation of the coefficients in terms of switching costs and satisfaction effects. In particular, this enables us to assess the direct impact of each channel's use on satisfaction, characterized by α_2, and retention, characterized by , our model enables us to understand the relative impact of satisfaction effects and switching costs for each channel. In our model, we define switching costs as gains to retention earned by a channel after controlling for overall satisfaction. This approach is consistent with previous theoretical and empirical treatments of switching costs in several non-service contexts (Anderson and Sullivan, 1993; Fornell, 1992; Klemperer, 1995). Hence, if $\gamma_2 > 0$ for any particular channel, then switching costs exist in that channel. α_2 represents the impact a particular channel's use has on overall satisfaction relative to face-to-face teller transactions, and γ_3 represents overall satisfaction's impact on customer retention. Therefore, the direct effect of satisfaction on retention (satisfaction effect) for a particular channel is given by $\alpha_2\gamma_3$. Comparing α_2 and $\alpha_2\gamma_3$ enables us to understand the relative impact of switching costs and satisfaction effects on retention for each channel. Moreover, the sum of switching costs and satisfaction effects for each channel equals the total effect of each self-service channel's usage on customer retention, $\gamma_2 + (\alpha_2\gamma_3) = \beta_2$.

In circumstances where $\gamma_2 > 0$ and $\alpha_2\gamma_3 > 0$ for a particular channel, use of the channel drives retention both by increasing customer switching costs and improving customer satisfaction. On the other hand, when $\alpha_2\gamma_3 < 0$ for a particular channel, use of the channel dissatisfies customers, increasing the likelihood of their departure from the firm. Similarly, when $\gamma_2 < 0$ for any channel, use of the channel facilitates customer departure from the firm, irrespective of customer satisfaction.
Understanding the direction of satisfaction effects and switching costs for each channel has significant implications for a company's choice of service strategy. For example, channels characterized by $\alpha_2\gamma_3 < 0 < \gamma_2$, where $|\gamma_2| > |\alpha_2\gamma_3|$ are net destroyers of customer satisfaction, but have a positive overall impact on retention because $\beta_2 > 0$. Companies serving customers through such channels may find themselves in a tenuous position if technology advances and switching costs fall, as dissatisfied customers held hostage by switching costs would be liberated to seek service elsewhere.

2.4 Research setting and data

For this study, we observe the behavior of 26,924 randomly selected customers performing a transaction in the branch network of a nationwide U.S. retail bank. (Figures 2.4.1 and 2.4.2) This bank is one of the largest diversified financial services firms in the U.S., and is both highly regarded for its customer service, as well as respected as an industry leader for its initiatives to provide easy-to-use self-service options for its customers. It serves millions of account holders through its network of over 3,000 branches and nearly 7,000 ATM machines located in more than 20 states. Our dataset includes the number of transactions each customer initiated in each of the bank's channels for a one-year period during 2003, as well as demographic and account information, customer satisfaction data, and lagged customer retention data for each customer.

2.4.1 Self-service

During our period of observation, the bank conducted all of its transactions with customers through six channels, including automated teller machines (ATM), online bill payment, online banking, interactive voice response (IVR), phone agent interactions, and face-to-face teller transactions. We consider ATMs, online bill payment, online banking and IVR to be self-service channels. Phone agent and teller transactions are considered full-service channels. For each customer, we sum the transaction counts across self-service channels, and divide by the total number of transactions to create an aggregated self-service mix variable. We also create channel proportion variables for each channel by dividing the annual transaction count in the channel by the customer's total transaction count. When we regress these variables, we control for total transaction count to eliminate frequency-of-use and experience effects.

2.4.2 Customer retention

Retention was measured on the last day of 2004, one year after the initial observation period. Customers who still held accounts with the bank at that time were counted as retained, and those who had closed all of their accounts for any reason were deemed to have defected. By this definition, over the period in question, the bank experienced a customer defection rate of 6.14%, representing the loss of hundreds of thousands of customers across the country. We introduce customer retention into our regressions as a binary, dependent variable.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 Overall satisfaction	1.00																
2 Customer retention	0.07	1.00															
3 Online bill payment percentage	0.00	0.03	1.00														
4 Online session percentage	-0.01	-0.01	0.08	1.00													
5 ATM percentage	-0.01	-0.02	-0.07	-0.11	1.00												
6 IVR percentage	-0.02	-0.04	-0.11	-0.22	-0.10	1.00											
7 Phone agent percentage	-0.06	-0.06	-0.06	-0.09	-0.08	0.11	1.00										
8 Customer tenure	-0.01	0.12	0.00	-0.18	-0.08	-0.07	-0.01	1.00									
9 Customer age	0.05	0.09	-0.02	-0.24	-0.14	-0.05	0.02	0.46	1.00								
10 Direct deposit indicator	0.02	0.09	0.09	0.08	0.07	0.10	0.01	0.17	0.25	1.00							
11 Number of deposit accounts	0.02	0.10	0.07	-0.03	-0.03	-0.08	0.02	0.20	0.15	0.07	1.00						
12 Number of loan accounts	0.03	0.08	0.08	-0.08	-0.05	-0.09	0.00	0.19	0.11	0.04	0.17	1.00					
13 Number of investment accounts	0.02	0.03	0.04	-0.03	-0.04	-0.05	0.00	0.12	0.10	0.05	0.13	0.10	1.00				
14 Deposit account balance	0.02	0.05	0.04	-0.06	-0.07	-0.08	0.02	0.15	0.18	0.03	0.30	0.05	0.11	1.00			
15 Loan account balance	0.00	0.03	0.06	-0.02	-0.02	-0.04	0.03	0.05	0.05	0.01	0.06	0.44	0.06	0.02	1.00		
16 Investment account balance	0.02	0.02	0.02	-0.02	-0.02	-0.02	0.00	0.08	0.07	0.03	0.05	0.05	0.51	0.14	0.04	1.00	
17 Total transaction count	-0.03	-0.03	0.19	0.29	0.12	0.33	0.00	-0.12	-0.15	0.12	0.08	-0.07	-0.05	-0.07	0.00	-0.02	1.00

Percentage variables represent the proportion of total customer transactions conducted in particular channels throughout the period of observation. IVR is the abbreviation for the interactive voice response channel.

Figure 2.4.1: Variable correlations for customer observation period.

	Mean	Median	Standard Deviation	Minimum	Maximum
Customer characteristics:					
Customer tenure (years)	10.41	8	9.74	0	104
Customer age (years)	46.59	46	16.46	0	100
Overall satisfaction	4.15	4	0.96	1	5
Customer retention (end of 2004)	0.94	1	0.24	0	1
Account characteristics:					
Direct deposit indicator	0.55	1	0.50	0	1
Number of deposit accounts	1.80	2	0.99	0	11
Number of loan accounts	0.56	0	0.86	0	9
Number of investment accounts	0.17	0	0.90	0	21
Deposit account balance	$15,902	$2,607	$52,971	-$12,174	$2,778,846
Loan account balance	$4,649	$0	$22,825	-$4,180	$788,390
Investment account balance	$3,266	$0	$45,895	$0	$3,687,567
Transaction counts by channel:					
Total transaction count (all channels)	37.71	27	35.89	0	499
All self-service count	23.78	12	32.23	0	491
High switching cost count	8.57	0	20.61	0	465
Online bill payment count	1.57	0	7.57	0	144
Online session count	7.00	0	17.74	0	465
Low switching cost count	15.22	6	24.25	0	353
ATM count	8.83	3	14.97	0	245
IVR count	6.39	0	17.22	0	340
All full-service count	13.93	11	12.24	0	200
Phone agent count	1.13	0	2.87	0	64
Teller count	12.80	10	11.62	0	200
Transaction percentages by channel:				95th percentile	
All self-service percentage	45.85%	50.56%	34.23%	93.75%	
High switching cost percentage	14.76%	0.00%	24.87%	72.41%	
Online bill payment percentage	2.30%	0.00%	10.25%	16.13%	
Online session percentage	12.46%	0.00%	21.80%	63.64%	
Low switching cost percentage	31.09%	22.86%	30.75%	86.67%	
ATM percentage	20.40%	9.09%	25.43%	75.44%	
IVR percentage	10.69%	0.00%	19.95%	60.00%	
All full-service percentage	54.15%	49.44%	34.23%	100.00%	
Phone agent percentage	3.00%	0.00%	7.25%	15.56%	
Teller percentage	51.14%	44.80%	34.49%	100.00%	

Summary statistics reflect data from 26,924 customers during the period of analysis. IVR is the abbreviation for the interactive voice response channel.

Figure 2.4.2: Summary statistics for customer observation period.

2.4.3 Customer satisfaction

In January of 2004, randomly selected customers were contacted via phone to complete a survey within 24 hours of personally visiting a branch to conduct a transaction. To gauge overall satisfaction, customers were asked, "Taking into account all the products and services you receive from [it], how satisfied are you with [the bank] overall?" Customers rated their overall satisfaction on a Likert scale of 1-5, with a score of 5 representing complete satisfaction. The average satisfaction rating reported was 4.15. In this study, we have chosen to focus on overall satisfaction rather than channel-specific satisfaction because we believe it more directly relates to a customer's decision to remain loyal to the firm.

2.4.4 Control variables

The customer demographic and account information factored into our analysis includes customer age, the length of the customer's relationship with the bank, the numbers of different types of accounts the customer had (deposit, loan and investment), the aggregate balances for each customer by account type (in thousands of dollars), and whether or not the customer had signed-up for direct deposit service. The inclusion of these control variables helps us avoid omitted variable bias, as several of them have explanatory power and are correlated with the variables of interest. (Figure 2.4.1) Customer ages in our sample are roughly normally distributed (skewness = .168, kurtosis = 2.64), with a mean of 46.58, and the average customer had a 10.41-year relationship with the bank. Roughly half of all customers sampled used online banking and direct deposit. Nearly 12% used online bill payment.

2.5 Results

2.5.1 The impact of self-service channel usage on customer retention

We begin by testing the overall impact of self-service usage on customer retention. (Figure 2.5.1) In column 1, our analysis reveals that the aggregate proportion of a customer's total transactions conducted through self-service channels has a marginally insignificant impact on customer retention (.008732, p=.104; two-tailed). This finding is consistent with hypothesis 1.

In column 2, we examine how the proportional usage of high and low switching cost self-service channels impacts customer retention. We find that customers who increase the proportion of their transactions in high switching cost self-service channels are retained with statistical significance (.032670, $p<.01$; two-tailed), while those who increase the proportion of their transactions in low switching cost self-service channels are no more or less likely to be retained (-0.001468, $p=.798$; two-tailed). Consistently, a test on the joint null hypotheses that the coefficients on online bill payment and online session usage in column 3 are both zero yielded a significant F-statistic: $F(2, 26908)=7.10$; $p<.01$, while the same test conducted on ATM and IVR usage yielded an insignificant F statistic: $F(2, 26908)=.6830$; $p=.6830$. These findings do not support hypothesis 2, but are consistent with hypothesis 3.

To summarize, these results suggest that relative to using full-service channels, the usage of self-service channels in aggregate has a statistically insignificant impact on customer retention. However, customers who use high switching cost self-service channels relative to other channels are more likely to be retained, while those who use low switching cost self-service channels relative to other channels are no more likely to be retained.

2.5.2 The impact of self-service channel usage on customer satisfaction

Our next set of tests addresses the impact of self-service usage on customer satisfaction. In column 4, we do not find that aggregated self-service usage impacts satisfaction (-.028028, $p=.196$; two-sided). These findings support hypothesis 4. Moreover, in column 5, we see that there are not systematic differences in the impact of high and low switching cost self-service channels on satisfaction (high switching cost channels: -.012483, $p=.666$; two-sided, and low switching cost channels: -.034652, $p=.135$ two-sided). Column 6 reveals the association between individual channels and customer satisfaction. Customers who utilized the phone agent channel, were less satisfied relative to customers engaging in face-to-face transactions (-.773604, $p<.01$;

Figure 2.5.1 *(following page)*: The associations among aggregated self-service channel usage, high and low switching cost self-service channel usage, individual channel usage, customer retention, overall satisfaction, and switching costs.

	Customer retention			Overall satisfaction			Switching costs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	Customer retention	Customer retention	Customer retention	Overall satisfaction	Overall satisfaction	Overall satisfaction	Customer retention	Customer retention	Customer retention
Self-service percentage	0.0087			-0.0280			0.0092*		
	[0.0054]			[0.0217]			[0.0054]		
High switching cost percentage		0.0327***			-0.0125			0.0329***	
		[0.0071]			[0.0289]			[0.0071]	
Online bill payment percentage			0.0481***			-0.0650			0.0491***
			[0.0148]			[0.0599]			[0.0148]
Online session percentage			0.0178**			-0.0450			0.0185**
			[0.0081]			[0.0327]			[0.0081]
Low switching cost percentage		-0.0015			-0.0347			-0.0009	
		[0.0057]			[0.0232]			[0.0057]	
ATM percentage			-0.0054			-0.0438*			-0.0048
			[0.0062]			[0.0252]			[0.0062]
IVR percentage			-0.0023			-0.0521			-0.0015
			[0.0089]			[0.0359]			[0.0089]
Phone agent percentage			-0.2023***			-0.7736***			-0.1903***
			[0.0201]			[0.0814]			[0.0201]
Overall satisfaction							0.0164***	0.0163***	0.0155***
							[0.0015]	[0.0015]	[0.0015]
Customer age	0.0003***	0.0003***	0.0003***	0.0033***	0.0033***	0.0033***	0.0002**	0.0003***	0.0003**
	[0.0001]	[0.0001]	[0.0001]	[0.0004]	[0.0004]	[0.0004]	[0.0001]	[0.0001]	[0.0001]
Customer tenure	0.0019***	0.0020***	0.0019***	-0.0052***	-0.0052***	-0.0054***	0.0020***	0.0021***	0.0020***
	[0.0002]	[0.0002]	[0.0002]	[0.0007]	[0.0007]	[0.0007]	[0.0002]	[0.0002]	[0.0002]
Direct deposit indicator	0.0307***	0.0299***	0.0311***	0.0243*	0.0239*	0.0286**	0.0303***	0.0295***	0.0306***
	[0.0031]	[0.0031]	[0.0031]	[0.0127]	[0.0127]	[0.0127]	[0.0031]	[0.0031]	[0.0031]
Number of deposit accounts	0.0182***	0.0180***	0.0181***	0.0135**	0.0134**	0.0140**	0.0180***	0.0178***	0.0179***
	[0.0016]	[0.0016]	[0.0016]	[0.0064]	[0.0064]	[0.0064]	[0.0016]	[0.0016]	[0.0016]
Number of loan accounts	0.0135***	0.0133***	0.0127***	0.0338***	0.0337***	0.0323***	0.0129***	0.0127***	0.0122***
	[0.0019]	[0.0019]	[0.0019]	[0.0078]	[0.0078]	[0.0078]	[0.0019]	[0.0019]	[0.0019]
Constant	0.8534***	0.8523***	0.8616***	4.0330***	4.0323***	4.0615***	0.7874***	0.7864***	0.7986***
	[0.0060]	[0.0060]	[0.0060]	[0.0241]	[0.0241]	[0.0244]	[0.0085]	[0.0085]	[0.0086]
Observations	26,924	26,924	26,924	26,924	26,924	26,924	26,924	26,924	26,924
R-squared	0.030	0.031	0.035	0.006	0.006	0.010	0.034	0.035	0.039

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively (two-tailed tests). Brackets contain standard errors. Additional control variables include number of investment accounts, deposit account balance, investment account balance, loan account balance and total transaction count. IVR is the abbreviation for the interactive voice response channel.

two-sided). Phone interviews with executives at the bank suggested that customers may systematically choose to interact with the bank through the phone agent channel to communicate when there is a problem. This factor likely explains the statistically significant relationship between phone agent transactions and dissatisfaction. Customers who used the other channels we analyzed were neither more nor less satisfied than customers who transacted with full-service tellers. These findings suggest that self-service channel transactions do not promote satisfaction relative to face-to-face channel usage.

2.5.3 The impact of self-service-related switching barriers on customer retention

To disentangle the impact of satisfaction effects and switching costs on customer retention, we analyze the impact of channel usage on customer retention, controlling for satisfaction. In this series of regressions, the coefficients on channel mix variables indicate the level of customer retention that is unexplained by differences in customer satisfaction. Channels with positive retention net of satisfaction exhibit characteristics consistent with switching costs. In column 7, we find that on an aggregate basis, self-service channel usage has a marginally insignificant impact on retention net of satisfaction (.009191, p=.086; two-tailed). Column 8 illustrates that customers in high switching cost channels are retained with an intensity greater than that explained by their satisfaction (.032874, p<.01; one-sided), while those transacting in low switching cost channels do not exhibit the same pattern (-.000902, p=.4375; one-sided). These findings offer support for hypotheses 5 and 6. Column 9 shows retention net of satisfaction on a channel-by-channel basis. Usage of online bill payment (.049099, p<.01; one-sided) and online banking (.018541, p<.05; one-sided) corresponds with statistically significant retention net of satisfaction, while usage of other self-service channels has no such effect.

Furthermore, by comparing the coefficients on channel mix variables in columns 1-3 with those in columns 7-9, we can disentangle the relative magnitude of satisfaction effects and switching costs in each context. The negative magnitude of the change of these coefficients represents the strength of satisfaction effects promoted by the corresponding channel. In all cases, the magnitudes of the channel mix coefficients increase after controlling for satisfaction. Hence, we find that while switching costs do serve as a driver of self-service retention, satisfaction effects do not.

2.5.4 Additional factors driving satisfaction and retention

The significant coefficients on a number of the control variables in our regressions are consistent with previous studies examining customer behavior in the financial services sector (Hitt and Frei, 2002). We find that age, direct deposit participation and the number of deposit and loan accounts a customer has are all positively associated with satisfaction and retention. We also observe that customer tenure is negatively associated with overall satisfaction, but positively associated with retention. Consistent with prior studies, these results suggest that tenure imposes switching barriers on experienced customers that can override marginal declines in satisfaction.

2.5.5 Explanatory power of models and heterogeneity of customer behavior

It is worth noting that although we observed statistically significant relationships between the proportional use of specific channels and customer satisfaction and retention, a considerable portion of the variation in a customer's satisfaction and retention remains unexplained by factors accounted for in our model. This is evidenced by the low R-squared values reported in Figure 2.5.1. As with prior research in business-to-consumer service contexts, customer satisfaction and retention remains highly heterogeneous after controlling for characteristics that can be reliably observed and consistently quantified across a large sample of customers. In this context, the explanatory power of our models, while relatively low, is generally consistent with prior studies investigating such metrics (Hitt and Frei, 2002; Ittner and Larcker, 1998; Verhoef, 2003).

Previously published papers using customer-level performance metrics with extremely high explanatory power (e.g. 50%-90%) include lagged values of the performance measures of interest in their empirical models. Not surprisingly, lagged dependent variables account for the majority of the explained variation in these models. Including lagged dependent variables in our retention analysis is not possible since, by definition, all customers remaining in the sample each period would have a lagged retention value equal to 1, and those who are not retained would drop from the sample and not be analyzed in future periods. In our retention regressions, the

R-squared values range from 3-4%. It should be noted that the papers cited above which examine retention typically do so using probit or logit based regression rather than OLS. As a result, these papers report various "pseudo R-squared" measures rather than the traditional R-squared measures from OLS that we report. To make our results more comparable with those of previous studies, we re-estimated our retention models using logit regression and the pseudo R-squared measures range from 9%-10%, which is well in line with these previous studies.

The R-squared values we report for our satisfaction regressions are smaller, which offers a measure of support for our results by highlighting how little of the variation in satisfaction is driven by differences in a customer's proportional use of various channels. To our knowledge, the literature provides no benchmark for appropriate R-squared measures in regressions that model satisfaction primarily as a function of actual customer characteristics and transaction histories. Most of the regressions modeling satisfaction in prior literature that we are aware of rely in part on survey-based measures of customer perceptions of recent experiences with the service provider. Understandably, a customer's perceptions of recent experiences with a company drive a considerable portion of the variation in their overall satisfaction. We were able to obtain a measure of the customer's perception of the ease of their most recent transaction with the bank we studied in our paper. When we include this measure in the satisfaction regressions as a robustness check, the R-squared values climb to approximately 26% (Figure 2.5.2). All of the results we report are robust to the inclusion of this variable.

2.5.6 Channel enthusiasm: a robustness check

Our primary results suggest that self-service channel usage does not necessarily promote satisfaction or retention relative to transactions conducted in full-service channels. We find that self-service usage contributes positively to loyalty only in

Figure 2.5.2 *(following page)*: The associations among aggregated self-service channel usage, high and low switching cost self-service channel usage, individual channel usage, customer retention, overall satisfaction, and switching costs controlling for ease of most recent transaction.

	Customer retention			Overall satisfaction			Switching costs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	Customer retention	Customer retention	Customer retention	Overall satisfaction	Overall satisfaction	Overall satisfaction	Customer retention	Customer retention	Customer retention
Self-service percentage	0.0096*			0.0085			0.0094*		
	[0.0054]			[0.0187]			[0.0054]		
High switching cost percentage		0.0336***			0.0345			0.0331***	
		[0.0072]			[0.0249]			[0.0071]	
Online bill payment percentage			0.0495***			0.0333			0.0490***
			[0.0148]			[0.0518]			[0.0148]
Online session percentage			0.0187**			0.0070			0.0186**
			[0.0081]			[0.0283]			[0.0081]
Low switching cost percentage		-0.0007			-0.0026			-0.0006	
		[0.0057]			[0.0200]			[0.0057]	
ATM percentage			-0.0045			-0.0031			-0.0044
			[0.0062]			[0.0218]			[0.0062]
IVR percentage			-0.0019			-0.0242			-0.0015
			[0.0089]			[0.0310]			[0.0089]
Phone agent percentage			-0.1980***			-0.3989***			-0.1922***
			[0.0202]			[0.0706]			[0.0202]
Overall satisfaction							0.0153***	0.0152***	0.0146***
							[0.0018]	[0.0017]	[0.0017]
Ease of most recent transaction	0.0102***	0.0102***	0.0094***	0.5289***	0.5290***	0.5273***	0.0021	0.0022	0.0017
	[0.0016]	[0.0016]	[0.0016]	[0.0055]	[0.0055]	[0.0055]	[0.0018]	[0.0018]	[0.0018]
Customer age	0.0002**	0.0003***	0.0003**	0.0019***	0.0020***	0.0019***	0.0002**	0.0003**	0.0002**
	[0.0001]	[0.0001]	[0.0001]	[0.0004]	[0.0004]	[0.0004]	[0.0001]	[0.0001]	[0.0001]
Customer tenure	0.0019***	0.0020***	0.0019***	-0.0042***	-0.0042***	-0.0043***	0.0020***	0.0020***	0.0020***
	[0.0002]	[0.0002]	[0.0002]	[0.0006]	[0.0006]	[0.0006]	[0.0002]	[0.0002]	[0.0002]
Direct deposit indicator	0.0308***	0.0301***	0.0312***	0.0258**	0.0250**	0.0277**	0.0304***	0.0297***	0.0308***
	[0.0031]	[0.0031]	[0.0031]	[0.0110]	[0.0110]	[0.0110]	[0.0031]	[0.0031]	[0.0031]
Number of deposit accounts	0.0183***	0.0181***	0.0181***	0.0114**	0.0111**	0.0111**	0.0181***	0.0179***	0.0180***
	[0.0016]	[0.0016]	[0.0016]	[0.0055]	[0.0055]	[0.0056]	[0.0016]	[0.0016]	[0.0016]
Number of loan accounts	0.0132***	0.0130***	0.0124***	0.0203***	0.0201***	0.0190***	0.0129***	0.0127***	0.0121***
	[0.0019]	[0.0019]	[0.0019]	[0.0067]	[0.0067]	[0.0067]	[0.0019]	[0.0019]	[0.0019]
Constant	0.8094***	0.8080***	0.8207***	1.7159***	1.7145***	1.7388***	0.7832***	0.7820***	0.7954***
	[0.0092]	[0.0092]	[0.0092]	[0.0319]	[0.0319]	[0.0322]	[0.0096]	[0.0096]	[0.0097]
Observations	26,839	26,839	26,839	26,839	26,839	26,839	26,839	26,839	26,839
R-squared	0.032	0.032	0.036	0.259	0.259	0.260	0.034	0.035	0.039

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively (two-tailed tests). Brackets contain standard errors. Additional control variables include number of investment accounts, deposit account balance, investment account balance, loan account balance and total transaction count. IVR is the abbreviation for the interactive voice response channel.

channels with high switching costs. We also demonstrate that switching costs may serve as a driver of self-service customer retention, while satisfaction may not. However, it has long been understood that customer tastes differ when choosing between service channels. In an early study, some customers reported preferring self-service channels to full-service channels even when they weren't cheaper or quicker (Bateson, 1985). Subsequent studies found that customers' understanding of their roles in the service, their perceptions of the benefits and features received through the channel, and their beliefs about their own capabilities and technology readiness are significant drivers of individual channel adoption (Curran et al., 2003; Dabholkar and Bagozzi, 2002; Meuter, Bitner, Ostrom, and Brown, 2005; Meuter et al., 2003; Parasuraman, 2000).

Additional studies have highlighted customer efficiency, perception of control, and service confidence as antecedents of satisfaction and loyalty among self-service customers (Xue and Harker, 2002; Yen and Gwinner, 2003). Therefore, it is possible that the intensity of these antecedents is influenced by the customer's level of experience conducting transactions through specific channels. Customers who specialize, concentrating transactions over one or two specific channels, may be more likely to become efficient and feel confident and in control of the service they are receiving, than customers who diversify interactions across a greater number of channels. Moreover, customers who are highly satisfied with the service they receive through a specific channel may decide to conduct as great a proportion of transactions as possible through that channel. Consequently, failure to consider channel enthusiasm might dampen our ability to understand the relationships between self-service channel usage and customer satisfaction and retention for more mainstream customers.

In other words, contrary to the results reported above, channel enthusiasts, who choose to concentrate their transactions through specific self-service channels, might systematically experience higher satisfaction with the bank's service and correspondingly elevated levels of loyalty, relative to more mainstream customers. Hence, as a robustness check, we investigate whether a difference exists between

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Figure 2.5.3 ***(following page)*****:** Comparing the effects of aggregated self-service and individual channel usage on the satisfaction of enthusiasts and non-enthusiasts.

	All customers		Customer enthusiasts by channel											
			Online bill payment		Online sessions		ATM		IVR		Phone agent	
Population	All	All	Enthusiasts	Non-enthusiasts	Enthusiasts	Non-enthusiasts	Enthusiasts	Non-enthusiasts	Enthusiasts	Non-enthusiasts	Enthusiasts	Non-enthusiasts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Customer enthusiasts in any channel	0.0527***											
	[0.0174]											
Customer enthusiasts in any self-service channel		0.0512***										
		[0.0189]										
Online bill payment percentage	-0.1561**	-0.1536**	-0.1558	-0.8619*	0.1840	-0.0527	1.7653	-0.0602	-15.0427	-0.0649	-2.7566	-0.0660
	[0.0671]	[0.0683]	[0.2252]	[0.5238]	[0.7582]	[0.0609]	[3.5775]	[0.0601]	[9.4654]	[0.0602]	[1.6908]	[0.0596]
Online session percentage	-0.0775**	-0.0775**	0.1334	-0.0479	-0.4705	-0.1129***	-0.0994	-0.0393	-1.0169	-0.0449	-0.5738*	-0.0338
	[0.0345]	[0.0349]	[0.2315]	[0.0335]	[0.3455]	[0.0413]	[0.7592]	[0.0332]	[0.9392]	[0.0333]	[0.3002]	[0.0328]
ATM percentage	-0.0650**	-0.0652**	-0.4984**	-0.0395	-1.1690***	-0.0365	-0.1683	-0.0575*	0.0773	-0.0420*	-0.1580	-0.0354
	[0.0262]	[0.0264]	[0.2345]	[0.0255]	[0.3535]	[0.0255]	[0.4092]	[0.0303]	[0.3661]	[0.0254]	[0.1876]	[0.0253]
IVR percentage	-0.0851**	-0.0874**	1.2085**	-0.0590	-0.3738	-0.0578	-0.7296	-0.0456	0.2600	-0.0897*	0.1176	-0.0307
	[0.0375]	[0.0382]	[0.5609]	[0.0364]	[0.9288]	[0.0367]	[0.8267]	[0.0364]	[0.3766]	[0.0465]	[0.2098]	[0.0368]
Phone agent percentage	-0.8809***	-0.7590***	-2.9743***	-0.7592***	-2.7451**	-0.7628***	-2.8685***	-0.7582***	-0.5311	-0.7654***	-0.3417	-1.6000***
	[0.0888]	[0.0816]	[1.0413]	[0.0818]	[1.1955]	[0.0818]	[1.0619]	[0.0817]	[0.6307]	[0.0824]	[0.2316]	[0.1855]
Customer age	0.0032***	0.0032***	0.0036	0.0033***	0.0020	0.0033***	0.0030	0.0033***	0.0043**	0.0032***	0.0020	0.0033***
	[0.0004]	[0.0004]	[0.0024]	[0.0004]	[0.0019]	[0.0004]	[0.0020]	[0.0004]	[0.0020]	[0.0004]	[0.0021]	[0.0004]
Customer tenure	-0.0054***	-0.0054***	-0.0025	-0.0055***	-0.0027	-0.0055***	-0.0049	-0.0054***	0.0000	-0.0056***	-0.0030	-0.0056***
	[0.0007]	[0.0007]	[0.0031]	[0.0007]	[0.0042]	[0.0007]	[0.0034]	[0.0007]	[0.0036]	[0.0007]	[0.0033]	[0.0007]
Direct deposit indicator	0.0287**	0.0286**	0.1324**	0.0254*	-0.0329	0.0336**	0.0122	0.0299**	-0.0007	0.0300**	0.1040	0.0246*
	[0.0127]	[0.0127]	[0.0594]	[0.0130]	[0.0548]	[0.0131]	[0.0575]	[0.0130]	[0.0644]	[0.0130]	[0.0663]	[0.0129]
Number of deposit accounts	0.0144**	0.0145**	0.0425*	0.0129*	-0.0010	0.0146**	0.0198	0.0139**	0.0236	0.0142**	0.0724**	0.0115*
	[0.0064]	[0.0064]	[0.0253]	[0.0066]	[0.0342]	[0.0066]	[0.0348]	[0.0065]	[0.0384]	[0.0065]	[0.0325]	[0.0065]
Number of loan accounts	0.0329***	0.0328***	0.0276	0.0337***	-0.0081	0.0340***	0.0382	0.0321***	-0.0343	0.0345***	-0.0298	0.0366***
	[0.0078]	[0.0078]	[0.0292]	[0.0081]	[0.0475]	[0.0079]	[0.0389]	[0.0079]	[0.0460]	[0.0079]	[0.0403]	[0.0079]
Constant	4.0690***	4.0684***	4.0002***	4.0641***	4.6761***	4.0584***	4.1971***	4.0628***	3.7720***	4.0687***	3.8888***	4.0726***
	[0.0246]	[0.0246]	[0.2040]	[0.0249]	[0.2916]	[0.0250]	[0.3648]	[0.0250]	[0.2962]	[0.0250]	[0.1435]	[0.0249]
Observations	26,924	26,924	1,357	25,567	1,363	25,561	1,354	25,570	1,365	25,559	1,346	25,578
R-squared	0.010	0.010	0.028	0.010	0.022	0.010	0.010	0.010	0.013	0.010	0.017	0.010

Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Additional controls include number of investment accounts, deposit, investment and loan balances and total transaction count.

customers who choose to use specific channels for an uncommonly high proportion of their interactions with the firm and customers who exhibit more diversified channel usage patterns. For the purpose of this analysis, any customer whose proportional use of a specific channel is at or above the 95th percentile in our sample is considered to be a channel enthusiast for that particular channel. We chose to use the 95th percentile threshold for two reasons. First, using a restrictive cutoff poses a conservative test of the theory that a channel's most devoted users are more loyal to the firm due to their heightened satisfaction with the service they are receiving. We would expect that the customers who find particular channels to be the most valuable and satisfying would systematically elect to conduct the greatest proportion of their transactions through those channels. In other words, these channel enthusiasts should be the channel's most satisfied users, and should therefore be the most likely to remain loyal to the firm due to increased service satisfaction. Consequently, if channel enthusiasts exhibit the pattern of results reported in the previous section, then we should feel confident that our findings are robust across customers. Second, we chose a high threshold to minimize the incidence of consumers who qualify as enthusiasts in multiple channels. With the 95th percentile definition, 25.2% of the customers in our sample qualified as enthusiasts in at least one channel, while only .84% qualified as enthusiasts in more than one channel. The 95th percentile for each channel is listed with the summary statistics in Figure 2.4.2.

Customer satisfaction

Figure 2.5.3 summarizes our examination of the association between channel enthusiasm and customer satisfaction. We begin by comparing customers who qualify as an enthusiast in any channel with those who do not. In column 1, the positive and significant coefficient on the dummy variable representing customers who are channel enthusiasts in any channel suggests that customers who qualify as enthusiasts in one or more channels are more satisfied overall than those who do not (.052719, $p<.01$; two-sided). Column 2 shows a similar pattern for the 20.4% of customers who are enthusiasts in at least one self-service channel (.051178, $p<.01$, two-sided). Columns 3 through 12 show the relationship between channel usage and customer satisfaction among channel enthusiasts and non-enthusiasts for specific channels. The results suggest that while the satisfaction of channel enthusiasts is unaffected by proportionally increasing the use of their preferred channels, the satisfaction of non-enthusiasts drops with statistical significance with each interaction through a non-preferred channel.

Customer retention and switching costs

We examine the impact of channel enthusiasm on customer retention and switching costs in Figure 2.5.4. Column 1 shows the statistically insignificant relationship between self-service channel enthusiasm and customer retention (.006122, p=.112, two-sided). However, column 2 shows that customers who are enthusiasts for high switching cost self-service channels are retained with greater frequency (.017523, p<.01; two-sided), while customers who are enthusiasts for low switching cost self-service channels are retained with less frequency (-.013564. p<.01; two-sided). These findings are consistent with our earlier results. Over the period of observation, low switching cost self-service channel enthusiasts had a 91.80% retention rate, while high switching cost self-service channel enthusiasts had a 94.78% retention rate. This difference in retention is statistically significant (t=4.5574; p<.01 two-sided). Column 3 breaks down the impact of channel enthusiasm on retention by channel, comparing the retention of enthusiasts of specific channels to customers transacting through a more diversified portfolio of channels. The results suggest that the only channel enthusiasts who do not defect with increased frequency are those who are enthusiasts in high switching cost self-service channels.

Customers who qualify as enthusiasts in the face-to-face teller channel have a 95.16% retention rate over the period of observation, which is higher than the retention rate of high switching cost channel enthusiasts documented above. However, as can be seen in column 3, face-to-face teller enthusiasts are retained with less frequency than more diversified customers when demographic and account characteristics are held constant. Non-channel enthusiasts had a retention rate of 94.20% during the period of observation. Columns 4 through 6 repeat the analysis above, controlling for satisfaction. By examining retention, net of satisfaction, we can explore the impact of switching costs on channel enthusiasts. The results parallel those

Figure 2.5.4 *(following page)*: Comparing the effects of aggregated self-service and individual channel usage on the satisfaction of enthusiasts and non-enthusiasts.

	Retention, not controlling for satisfaction			Retention, controlling for satisfaction		
	(1)	(2)	(3)	(4)	(5)	(6)
Enthusiast in any self-service channel	0.0061			0.0056		
	[0.0038]			[0.0038]		
Enthusiast in any high switching cost self-service channel		0.0175***			0.0170***	
		[0.0049]			[0.0049]	
Online bill payment enthusiasts			0.0189***			0.0188***
			[0.0064]			[0.0064]
Online session enthusiasts			0.0107*			0.0097
			[0.0064]			[0.0064]
Enthusiast in any low switching cost self-service channel		-0.0136***			-0.0138***	
		[0.0048]			[0.0048]	
ATM enthusiasts			-0.0108*			-0.0110*
			[0.0063]			[0.0063]
IVR enthusiasts			-0.0213***			-0.0215***
			[0.0065]			[0.0065]
Phone agent enthusiasts			-0.0562***			-0.0535***
			[0.0064]			[0.0064]
Face to face teller enthusiasts			0.0000			0.0000
			[0.0000]			[0.0000]
Overall satisfaction				0.0165***	0.0165***	0.0160***
				[0.0015]	[0.0015]	[0.0015]
Customer age	0.0002**	0.0002**	0.0003***	0.0002	0.0002*	0.0002**
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Customer tenure	0.0019***	0.0019***	0.0019***	0.0020***	0.0020***	0.0020***
	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]
Direct deposit indicator	0.0327***	0.0329***	0.0328***	0.0324***	0.0326***	0.0325***
	[0.0031]	[0.0031]	[0.0031]	[0.0031]	[0.0031]	[0.0030]
Number of deposit accounts	0.0188***	0.0184***	0.0184***	0.0185***	0.0181***	0.0181***
	[0.0016]	[0.0016]	[0.0016]	[0.0016]	[0.0016]	[0.0016]
Number of loan accounts	0.0136***	0.0133***	0.0126***	0.0130***	0.0127***	0.0121***
	[0.0019]	[0.0019]	[0.0019]	[0.0019]	[0.0019]	[0.0019]
Constant	0.8552***	0.8557***	0.8589***	0.7890***	0.7895***	0.7946***
	[0.0053]	[0.0053]	[0.0053]	[0.0080]	[0.0080]	[0.0080]
Observations	27,075	27,075	27,075	27,075	27,075	27,075
R-squared	0.030	0.031	0.034	0.035	0.035	0.038

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively (two-tailed tests). Brackets contain standard errors. Additional control variables include number of investment accounts, deposit account balance, investment account balance, loan account balance, and total transaction count. IVR is the abbreviation for the interactive voice response channel.

described in the preceding paragraph. In column 6 as above online bill payment enthusiasts are retained with greater frequency (.018194; p<.01), butcustomers who are enthusiasts in the online session channel are neither more nor less likely to remain loyal to the bank (.009358, p=.144; two-sided). This finding may suggest that learning based switching costs are not as powerful among customers who choose to conduct the majority of their transactions in online channels. By virtue of their own technology readiness and belief in their own technical capabilities, learning-based switching barriers may be less of a factor for these customers.

Furthermore, a comparison of the coefficients on enthusiast variables in columns 4 through 6 with those in columns 1 through 3 reveals that satisfaction effects play a small role as a driver of retention among a channel's most dedicated customers, though this role is dominated by the role of switching costs. For example, the coefficient on the dummy variable representing customers who are enthusiasts in any channel falls from 0.006122 in column 1 to .005642 in column 4 after controlling for satisfaction. Among channel enthusiasts, this pattern holds in every case. However, the magnitudes of the changes in coefficients after controlling for satisfaction are dominated in all cases by the magnitudes of the coefficients on channel enthusiasm controlling for satisfaction. This suggests that satisfaction effects do play a minor role in determining the retention of channel enthusiasts, though this role is secondary to the role of switching costs.

In summary, these findings suggest that even among channel enthusiasts, self-service usage has a positive impact on retention, only in cases where it increases the switching costs for customers. In our analysis, this was the case with online bill payment transactions and online banking. Conversely, among channel enthusiasts, we found that self-service usage has a significant negative impact on retention for channels with low switching costs. Moreover, we find that switching costs serve as the dominant drivers of retention among even a channel's most dedicated users. These findings are consistent with the results reported in the previous section.

2.6 Managerial implications

In this paper, we have illustrated that different service channels engender varying levels of satisfaction effects and switching costs among customers. We have also shown that satisfaction effects and switching costs are important drivers of customer retention. Understanding the relative magnitude of each driver exuded by specific channels enables managers to better understand the nature of their customers' loyalty to the firm. Moreover, it empowers them to tailor service offerings in a manner that reinforces customer loyalty in a more predictable way. This section highlights several managerial implications of our results.

2.6.1 Loyal self-service customers in high switching cost channels may be stuck, not satisfied

From a managerial perspective, customer loyalty is problematic because it is the product of an ongoing, internal dialogue, which remains private to each individual customer. It can only be quantified ex-post by observing attrition, and by the time the firm observes exit behavior, it is too late to react for that particular customer. Moreover, a firm cannot necessarily project retention forward, because the drivers of an individual's retention are opaque to managers. One retained group of customers may be so delighted with the portfolio of services they receive from a firm, that they choose not to seek superior service experiences elsewhere. Another group of equally loyal customers might be dissatisfied with the service they are receiving, but find it difficult to transition to a competitor due to switching costs.

Preceding empirical analyses have identified instances where self-service offerings concurrently increase or decrease satisfaction and retention, but our results suggest that the two do not necessarily move in tandem. In our sample, switching costs dominate satisfaction effects as the primary driver of self-service-related retention. Consequently, retained self-service customers may be stuck, not satisfied as previously suggested. Dissatisfied customers held captive by switching costs spend less money than satisfied customers and are notoriously difficult and expensive to serve (Coyles and Gokey, 2005; Jones and Sasser, 1995; Xue and Harker, 2002).

Moreover, there may be reason to believe that switching cost-imposed "stickiness" will not be indefinitely sustainable. It has been predicted that over time switching barriers will drop and companies will have to develop new methods for generating customer loyalty. Common standards for exchanging and processing information as well as the growing number of people accessing networks have been noted as catalysts for this change (Evans and Wurster, 1997). Additionally, as customers become more technologically adept and companies invest in improving the ease of use of their systems and reducing barriers to self-service technology adoption, it stands to reason that switching costs will fall even further.

If switching costs fall, customer satisfaction will become increasingly important. The link between satisfaction and retention is well established in the literature (Anderson, 1994; Johnson et al., 1995; Meuter et al., 2000; Price et al., 1995). In contexts where switching costs are high, the impact of core-service satisfaction on retention has been shown to diminish, but the positive relationship between customer satisfaction and retention strengthens as switching barriers are eliminated (Jones et al., 2000). Moreover, it has been documented that a 5% reduction in attrition can boost profits by 25-85%, a statistic, which when considered in reverse, foreshadows the devastating repercussions for companies that fail to retain their customers (Reichheld and Sasser, 1990).

2.6.2 Self-service channels should remain available and optional

Despite the potentially negative long-term implications of switching cost driven retention, we do not intend to suggest that firms should abandon self-service offerings. On the contrary, numerous studies including this one support the idea that self-service technologies enhance the satisfaction of certain customers (Bateson, 1985; Marzocchi and Zammit, 2006; Meuter et al., 2003; Yen, 2005). Our examination of channel enthusiasts suggests that those who choose to conduct the lion's share of their transactions in self-service channels are more satisfied than full-service, face-to-face customers. (Table 6, Column 2) In contrast, those who choose to deemphasize these channels (non-enthusiasts) exhibited incremental dissatisfaction from each experience. These findings are consistent with the idea that customers tend to optimize channel selection to maximize their own satisfaction. Hence, self-service offerings should remain available, but customers should not be forced to use them.

Many airlines, technical support operations, banks and investment management firms outwardly encourage customers to transition from personalized channels to lower cost, automated alternatives. They do this by offering rewards such as fee-free checking accounts and interest rate premiums for online account users, and by charging premiums to customers who use higher cost channels. American Airlines for example, charges more to upgrade a reservation over the phone than to upgrade the same reservation through a self-service channel. Hewlett Packard charges $ 25-30 per incident for phone support, but offers free access to its online knowledge base. Bank

One charges $ 1-3 for each customer support phone call, and Charles Schwab charges twice as much for a phone trade as it does for an online trade (Stellin, 2003). Consequently, these firms and others like them may be sacrificing future profitability through customer retention in order to achieve short term cost reduction targets. Such strategies may ultimately backfire if switching costs fall, and customers presently held captive by them are freed to seek superior service experiences elsewhere.

2.6.3 Switching costs and satisfaction effects as levers of managerial influence

We have argued that customer retention is driven by the interaction of switching costs and satisfaction effects. Hence, managers seeking to design retention into their firm's service offerings can incorporate both levers of control into their strategies.

Our analysis reveals that switching costs are one potent driver of customer retention. Switching barriers include learning costs, psychological effects, transaction costs, and contractual obligations (Farrell and Klemperer, 2007). In a banking context, it's easy to think about how switching costs might manifest themselves. Customers intending to transition from one bank to another must undergo a series of time-consuming and often inconvenient steps, which include opening and funding their new account, switching direct deposits and automatic payments, updating checking account information for any linked services, waiting for old checks to clear, emptying safe deposit boxes, and more. Evidence from our study suggests that customers who engage in services that create additional barriers are systematically retained with greater frequency than those who do not.

For example, in our analysis, we found that use of online banking and online bill payment channels impose switching costs that enhance customer retention (Table 4). Similarly, after controlling for satisfaction, we observed that customer characteristics like the presence of direct deposit service, loans and mortgages, multiple deposit accounts, high transaction frequency, and advanced customer age and tenure are positively associated with retention. In this light, one clearly efficacious strategy for retaining customers is to focus on aspects of the relationship that promote and intensify switching barriers. However, it is important to consider that just as banks endeavor to entwine themselves in their customers' financial lives in such a way as to complicate defection, competitors are simultaneously working to reduce barriers to adoption of services. For instance, some banks now employ consultants to help new customers transition from other institutions. Others offer "switch kits," which facilitate the process of moving from one bank to another. Competitors will continue to innovate on opposite ends of the relationship, working to both complicate and simplify the process of defection.

Customer satisfaction is the second retention lever for managers. In the context of our analysis, self-service channels did not promote satisfaction relative to face-to-face transactions, but previous studies have provided counterexamples in different contexts (Mols, 1998; Wallace et al., 2004; Xue and Harker, 2002; Yen and Gwinner, 2003) and have suggested attributes of self-service channels that contribute to satisfaction. Commonly cited attributes include successful completion of the service task, ease of use and convenience of time and place (Meuter et al., 2000). By focusing on these attributes of automated channels, managers may be able to convert customers who are stuck into customers who are satisfied and promote sustainable retention, while benefiting from service cost reductions.

2.7 Conclusions, limitations, and opportunities for future research

Our analysis distinguishes the relative effects of satisfaction and switching costs on customer retention. We interpret our findings to suggest that relative to those who use full-service channels, self-service customers may exhibit retention due to switching costs rather than satisfaction effects. One potential limitation of this study is its focus on customers at a single nationwide bank. While the usage of self-service channels at this firm was not associated with increased satisfaction, it would be careless to generalize that such is the case for all self-service offerings in all domains. Nevertheless, given the dominant design features prevalent among many retail bank offerings, we feel this study offers a relevant perspective for this important class of services. Moreover, it challenges the notion that self-service retention necessarily follows satisfaction.

Another potential limitation of this study is the convenience sample we used to define our dataset. Customers interviewed for the satisfaction survey were selected at random and were called on the phone from a pool of customers who had recently visited a bank branch. This sampling mechanism could conceivably under-represent self-service customers who rarely visit the branch. However, if this were the case, then we might expect to find that enthusiasts in automated channels express diminished satisfaction due to the anomaly that drove them to break from their routine and visit a branch. On the contrary, our results show that enthusiasts in automated service channels report higher levels of satisfaction than non-enthusiasts, who might more regularly frequent the branch. Moreover, previous studies have found that self-service customers tend to be active in full service channels as well (Campbell and Frei 2006). Nevertheless, data limitations in customer satisfaction measurement practices at our research site preclude us from analyzing a random sample of the bank's full population of customers.

Consistent with a number of other studies conducted in this area, we do not employ a direct, quantitative measure of switching costs (Bernheim and Whinston, 1990). Instead, we calculate switching costs by measuring customer retention controlling for satisfaction. While this approach is consistent with prior literature (Anderson and Sullivan, 1993; Fornell, 1992; Klemperer, 1995), we acknowledge that non-satisfaction related channel effects on retention could have alternative explanations to switching costs. However, we note that in this study, non-satisfaction related channel effects seem consistent with switching costs, as they systematically manifest themselves in channels where switching costs are predicted to exist and are absent in those where it is not. Identifying more direct measures of switching costs appears to be a fruitful avenue for future research.

Due to limitations of our data, we were unable to explore the ramifications of self-service customers held captive by switching costs on current firm profitability. Past studies have shown that dissatisfied customers retained by switching costs tend to spend less and consume more resources than satisfied customers (Heskett et al., 1997; Jones and Sasser, 1995). However, it would be enlightening to explore user-level economics in a self-service channel context to understand how a self-service customer retained by switching costs compares to a satisfied full-service customer. Research has shown for example, that online customers tend to spend more than offline ones (Hitt and Frei, 2002) and has documented the cost savings brought about by service automation (Andreu, Benni, Pietraszek, and Sarrazin, 2004; Moon and Frei, 2000). Understanding the relative impact of these factors would be strategically important for practitioners and would deepen our understanding of the overall implications of self-service usage on profitability. As a further extension, it would be worthwhile to compare the customer lifetime value self-service and full-service enthusiasts. Perhaps for self-service enthusiasts, the losses from defection are offset by gains from cost-savings.

Future research can also shed light on the complexity of the retention decision in a multi-channel environment caused by the interactions between channels. In order to simplify our analysis, we focused on proportional channel usage as our primary set of independent variables. However, in some cases this may be an oversimplification. For example, it is possible that a customer who conducts the majority of his transactions through the ATM channel could have his satisfaction with the bank poisoned by one negative experience with a rude telephone representative. Our methodology would disproportionately assign his dissatisfaction to the ATM channel, given his channel usage behavior. However, we have no reason to believe that there would be a systematic relationship between negative experiences in one channel and use of another channel. Therefore, we do not believe the exclusion of interaction terms introduces systematic biases.

Finally, it is difficult to make precise predictions about the sustainability of switching costs as a customer retention strategy. It has been theorized that switching costs will fall over time (Evans and Wurster, 1997), but this phenomenon has not been demonstrated empirically. A longitudinal analysis, exploring the strength of technology-initiated switching costs over time would broaden our view of the strategic landscape in which modern service firms compete.

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3

The Labor Illusion: How Operational Transparency Increases Perceived Value

3.1 Introduction

Rare is the modern consumer who has not found herself staring at a computer screen as a progress bar makes fitful progress toward loading some application, or completing some search, without wondering, *What is taking so long?* and taking that frustration out on her liking for the service. We suggest that taking a different approach - showing consumers what is taking so long - can not only decrease frustration, but actually increase ratings of the service, such that consumers actually value services more highly when they wait. In particular, we suggest that engaging in operational transparency by making the work that a website is purportedly doing more salient leads consumers to value that service more highly. Indeed, we suggest that the mere appearance of effort - what we term the labor illusion - is sufficient to increase perceptions of value. By replacing the progress bar with a running tally of the tasks being performed - the different airlines being searched when the consumer is looking for flights, or the different online dating profiles being searched when the consumer is looking for dates - we show that consumers can actually choose to wait longer for the very same search results. In five experiments, we demonstrate the role of the labor illusion in enhancing service value perceptions among self-service technologies, an ideal setting for testing the impact of operational transparency. Self-service technologies are capable of delivering service more quickly and conveniently than face-to-face alternatives (Meuter et al. 2000). However, unlike customers who receive service in face-to-face settings (such as interacting with a bank teller counting one's money), customers transacting in self-service environments (such as withdrawing money from an ATM) do not observe the effort of the service provider, an important cue that can signal the value of the service being delivered. As such, while an automated solution may objectively deliver faster performance, we suggest that customers may perceive that service as less valuable due to the absence of labor. Adding that labor back in via operational transparency, therefore, has the potential to increase perceptions of value.

3.2 Waiting, Effort and Perceived Value

Because customers treat their time as a precious commodity (Becker 1965), operations researchers have produced numerous models set in service contexts based on the notion that customers are attracted to fast service. These models suggest that a) delivery time competition increases buyer welfare (Li 1992), b) firms with higher processing rates enjoy a price premium and larger market shares (Li and Lee 1994), and c) the choice of an optimal delivery time commitment balances service capacity and customer sensitivities to waiting (Ho and Zheng 2004). Empirical investigations of delivery time have similarly demonstrated that waiting adversely affects customer attitudes and the likelihood of patronage; for example, long delays increase uncertainty and anger, particularly when the delay seems controllable by the service provider (Taylor 1994).

Accordingly, growing streams of the service operations and marketing literatures have sought to identify strategies for both improving the experiences of waiting customers and reducing service duration itself. With regard to the former, research on the psychology of queuing focuses on managing the perceptions of waiting customers by occupying periods of idle time (Carmon et al. 1995), increasing the feeling of progress (Soman and Shi 2003), managing anxiety and uncertainty (Osuna 1985), setting accurate expectations, bolstering perceptions of fairness (Maister 1985), managing sequence and duration effects, providing customers with the feeling of control, shaping attributions (Chase and Dasu 2001), and shaping memories of the experience (Norman 2009). In addition to favorably influencing the perceptions of waiting customers, of course, managers have also sought to reduce actual service duration. In particular, one increasingly common strategy for improving the speed and productivity of service is the introduction of self-service technologies (Napoleon and Gaimon 2004). In 2008, for example, 70% of travel reservations were booked online (J.D. Power and Associates 2008), and over 75% of customers used Internet banking (Higdon 2009). In general, self-service technologies reduce both perceived and actual waiting time for customers, excepting cases when the technology is overly complicated or the customers served lack technical proficiency (Dabholkar 2000). Moreover, perceptions of self-service technology value and quality are driven in part by speed of service delivery (Dabholkar 1996).

While considerable emphasis has been placed on increasing the service speed that customers perceive and experience, offering service that seems to arrive too quickly or too easily can have costs. In particular, customers draw inferences from their in-process experiences about the value being created. If, for example, the outcome of a service is difficult to evaluate, consumers may use service duration as a heuristic to assess its quality (Yeung and Soman 2006). This heuristic is rooted in the notion that service quality increases with time spent with the service provider - as is often the case with customer-intensive services like healthcare, personal services, and financial and legal consulting (Anand et al. 2011). Perceived employee effort, which has a strong positive effect on customer satisfaction in face-to-face contexts (Mohr and Bitner 1995) can serve as a heuristic for product quality as well (Kruger et al. 2004). Similarly, Kahneman, Knetsch and Thaler (1986) suggest that when firms incur higher costs - as when exerting more effort - customers perceive higher prices to be fair. Most relevant to the present investigation, firms that exert more effort on behalf of customers can boost service quality perceptions via the impact of that effort on customer-s psychological feelings of gratitude and reciprocity; even when the quality of the service remains unaffected, consumers can feel that they should reciprocate the efforts of the firm (Morales 2005).

Importantly, however, when the production and delivery of a service are separable, employee effort may be removed from a customer-s service experience. In some cases, such as parcel delivery and automotive repair, the bulk of employee effort occurs out of the customer-s view. In the cases we explore - technology-mediated services - marginal employee effort may be entirely absent. In particular, when service is automated, tasks that would otherwise be performed by employees are instead divided between the consumer and the technology. This omission of employee effort is ironically exacerbated by the efforts of self-service designers to maximize the ease of use, and minimize the complexity, of self-service offerings (Curran and Meuter 2005, Dabholkar and Bagozzi 2002), making such services appear even more effortless. This situation poses a critical tradeoff for companies. While automating service and shielding customers from the complexities of their offerings can promote adoption, these practices may also under-communicate the value of the services being delivered. If perceived value is diminished, then customers engaging with these shielded self-service channels may exhibit diminished willingness to pay, satisfaction and loyalty (McDougall and Levesque 2000).

We suggest a solution to this tradeoff. While self-service technologies necessarily eliminate the opportunity for face-to-face interactions with a service provider in which consumers can witness an employee sweating to get the job done, the interfaces through which consumers engage with self-service can be modified by inserting operational transparency into the process, to demonstrate the *sweat* that the technology is exerting on the consumer's behalf. In particular, we suggest that replacing non-descript, non-informative progress bars with interfaces that provide a running tally of the tasks being undertaken - creating the illusion of labor being performed - can serve to increase consumers' perceptions of effort, and as a result, their perceptions of value. Previous research has demonstrated that perceived effort leads to feelings of reciprocity and increased perceptions of value (Morales, 2005); we suggest that operational transparency provides cues for consumers to better understand how the quantity of work being conducted translates into how hard the company is working for them.

3.3 Presentation of Experiments

In five experiments and across two domains (online travel and online dating websites), we investigate the effect of the labor illusion on perceptions of service value. We define the labor illusion as a representation of the physical and mental work being conducted - signaled via operational transparency - as the customer waits for service delivery. We first demonstrate that the labor illusion increases customer perceptions of value in self-service contexts (Experiment 1). We next demonstrate that customers can even prefer websites that require waiting but demonstrate labor to those that offer the same results instantaneously but without labor (Experiment 2). In Experiment 3, we explore alternative explanations for the labor illusion effect, distinguishing it from the effects of enhanced information, credibility, and uncertainty, while also exploring perceived effort and reciprocity as the mechanisms linking operational transparency to perceived value. In Experiment 4, we compare the impact of operational transparency and actual effort exerted by the firm on perceptions of value, stated satisfaction and repurchase intentions. Finally, in Experiment 5, we explore the role of outcome favorability as a boundary condition on the labor illusion, examining how the quality of the service outcome moderates the relationship between operational transparency and valuation. We conclude the paper with a discussion of managerial implications, limitations and opportunities for future research.

3.3.1 Experiment 1: Demonstration of the Labor Illusion

In this first experiment, we explore how customer waiting time and operational transparency influence customer perceptions of service value. Participants experienced a simulated service transaction using the rebranded interface of a popular online travel website. Online travel websites accounted for $ 84 billion in worldwide sales in 2008, representing over 70% of all travel reservations booked (J.D. Power and Associates 2008). In addition, online travel is an attractive context for studying the impact of the labor illusion, because most service providers have access to the same inventory of available flights. Two online travel websites that search fares and return identical itineraries for the same price have delivered outcomes that are objectively equivalent, a fact that enables us to analyze changes in perceived value while controlling for performance outcome.

Method

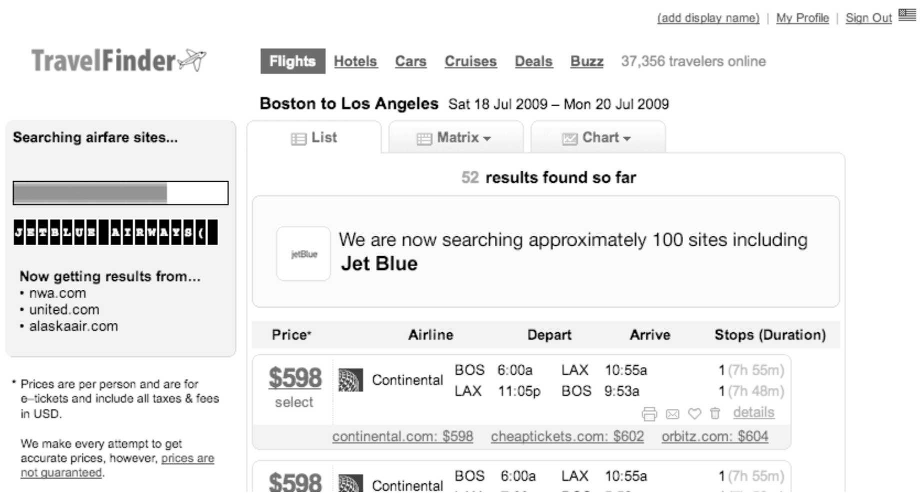
Participants: Participants ($N = 266$, $M_{age} = 35.8$, 26% Male) completed this online experiment over the Internet, in exchange for a $ 5.00 Amazon.com gift certificate.

Design and Procedure: We recreated (and rebranded) the interface of a popular online travel website to provide participants with a simulated technology-mediated service experience. Participants were asked to use the simulated travel website to book travel arrangements for a trip. All participants were instructed to search for the same travel itinerary. Participants entered the point of origin, destination, and departure and return dates into the interface and clicked the search button.

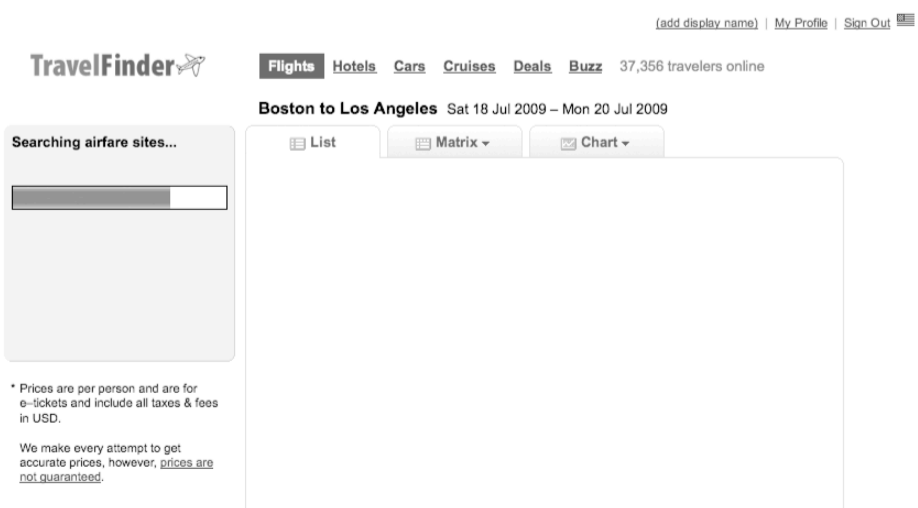
Participants were randomly assigned to one of thirteen experimental conditions. Some participants were assigned to an instantaneous condition, in which there was no delay between clicking the search button and receiving their outcomes. All other participants were assigned to one condition of a 2 (version: transparent versus blind) X 6 (wait time: 10, 20, 30, 40, 50, or 60 seconds) design, in which they experienced a wait with either operational transparency or not, before being presented with an identical list of possible trip itineraries and prices.

In the transparent condition, while the service simulation was *searching* for flights, the waiting screen displayed a continually changing list of which sites were being searched, and showed an animation of the fares being compiled as they were *found.* The animations of compiled results were time-scaled such that each participant in the transparent condition observed the same number of sites searched, and the same number of fares compiled, over their randomly assigned waiting time. When the search was complete, participants were forwarded to a search results page, where they could scroll through the various itineraries retrieved by the service. In the blind condition, in contrast, the waiting screen only displayed a progress bar that gradually filled at a uniform rate; when the progress bar filled completely, participants were forwarded to the same search results page described above (see Figure 3.3.1 for screenshots). This progress bar was designed to reduce the psychological costs of waiting and curb uncertainty by providing individuals with reliable information about the remaining duration of their wait (Osuna 1985). Importantly, we included an identical progress bar in all of our non-zero wait time conditions - including the transparent conditions - in all experiments to control for the effect of uncertainty.

Dependent Measures: At the conclusion of the simulation, participants were surveyed about their perceptions of the service's value. We assessed perceived value using four items adapted from a survey designed to gauge value perceptions of branded durable goods (Sweeney and Soutar 2001): Do you believe this is a high quality



Transparent condition



Blind condition

Figure 3.3.1: Screenshots of transparent and blind conditions (Experiment 1).

service?; Is this a service that you would want to use?; What would you be willing to pay for this service?; Would other people approve of this service? Participants provided responses to the four questions on a 7-point scale, and we averaged these four items to create a composite measure of each participant's perceptions of service value. We use an identical perceived value metric throughout this paper; across our experiments, the four items possess a high level of internal consistency (Cronbach's $\alpha = .82$). Note that this scale captures perceptions of quality as a dimension of perceived value, though the two attributes have also been modeled as distinct, but causally related. Prior literature suggests that perceptions of quality drive perceptions of value (Zeithaml 1988).

Results and Discussion

We conducted a 2 (version: transparent versus blind) X 6 (wait time: 10, 20, 30, 40, 50, or 60 seconds) Analysis of Variance (ANOVA) on the composite measure of participants' value perceptions. We observed a main effect of wait time, $F(5, 212) = 4.47, p < .01$, such that value perceptions showed a general downward trend over time. Most importantly, we observed the predicted main effect of operational transparency, $F(1, 212) = 10.68, p < .01$, such that value perceptions were higher with transparency ($M = 5.36, SD = .79$) than without ($M = 4.96, SD = .91$). As can be seen in Figure 3.3.2, perceptions of value with operational transparency were higher at every time point than perceptions of value without transparency, such that there was no interaction, $F(1, 212) = .55, p = .73$.

Indeed, as evidenced by the line in Figure 3.3.2 indicating value perceptions for the instantaneous service condition, value perceptions for operational transparency compared favorably with perceptions of the service delivering instant results - even though the results returned were identical in the different versions. These results offer initial support for our contention that operational transparency - listing the airlines being searched as participants waited for the outcome of their flight search - has a positive impact on value perceptions, demonstrating the clear value of increasing perceptions of the labor conducted by self-service technologies by creating the labor illusion.

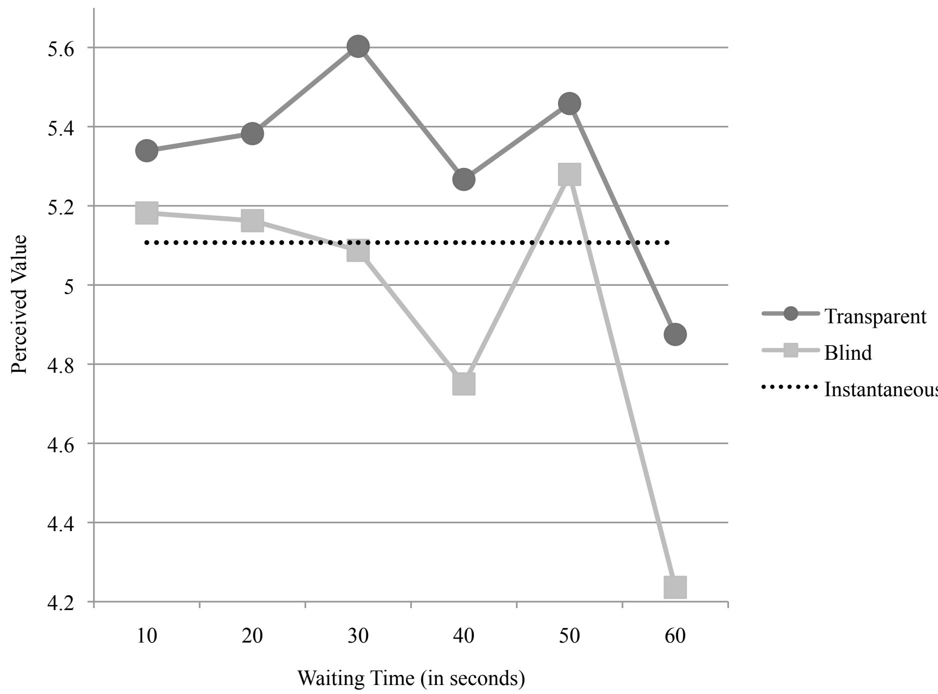


Figure 3.3.2: The effect of operational transparency and wait time on perceived value (Experiment 1).

3.3.2 Experiment 2: Choosing Services

Experiment 1 demonstrated that value perceptions are enhanced when automated service interfaces exhibit cues that indicate that labor is being performed on the consumer's behalf during service delivery. By utilizing a between-participants design, Experiment 1 mimics many of the "one-off" service experiences consumers may encounter. However, in many cases, consumers "comparison shop" between competing providers who employ a variety of delivery strategies; in such cases, consumers may not necessarily prefer the most transparent operation - particularly when providing transparency may lengthen service duration. Given the fact that delivery time is an important component of service satisfaction (Davis and Vollmann 1990, Maister 1985, Taylor 1994), and in turn, firm performance (Cachon and Harker 2002), we wanted to explicitly pit delivery time against the labor illusion: Is the value of operational transparency large enough that participants will choose the service that requires waiting - but induces the labor illusion - over one that gives them objectively similar results instantaneously? In Experiment 2, therefore, we used a within-participants design, asking participants to evaluate and choose between competing services delivering identical outcomes, but different experiences.

Method

Participants: Participants ($N = 118, M_{age} = 37.2, 28\%$ Male) completed this experiment in the laboratory as part of a series of unrelated experiments, in exchange for $ 25.00.

Design and Procedure: We replicated Experiment 1, with two important changes. First, rather than simulate only one travel website, we also simulated a rival, which had different branding from the first site. Second, participants engaged in two service transactions, one with each of the "competing" firms. Participants were instructed to conduct the same travel search on both sites, which returned identical itineraries and prices.

In each case, one firm delivered instantaneous service; the other delivered either blind or transparent service in either 30 or 60 seconds. We randomized which brand was displayed first, which type of service was displayed first, and which brand featured each type of service; these had no impact on the results so we do not discuss them further.

Dependent Measures: The within-participants design allowed us to ask participants to make forced choices between the two services, and we asked participants to express an overall preference for which service they would choose.

Results and Discussion

In all conditions, we gave participants the choice between a service that provided instantaneous results and one that required waiting - and simply varied whether that waiting included operational transparency or not. We observed the predicted effect: Participants for whom the service that required waiting included operational transparency preferred this service over the instantaneous service when waiting for both 30 seconds (62%) and 60 seconds (63%). In contrast, participants who waited without operational transparency selected this service just 42% of the time at 30 seconds, and just 23% of the time at 60 seconds, demonstrating a strong preference for instantaneous results (Figure 3.3.3). We used a logistic regression to analyze the effect of operational transparency on an individual's preference for the service that required waiting. The effect of operational transparency on choice was significant (coefficient$=1.30, p < .01$ two-sided), while the effect of waiting time was not (coefficient $= -.01, p = .37$), and there was no interaction between operational transparency and wait time (coefficient $= .03, p = .26$). These results are particularly interesting because they suggest that, even when customers are given an instantaneous option, they may actively prefer using a service with a longer delivery time, but only when the labor being performed by that service is made tangible through operational transparency.

3.3.3 Experiment 3: Mechanisms Underlying the Labor Illusion

The experiments presented so far suggest that operational transparency increases individuals' perceptions of service value and preferences for services. In Experiment 3, our first goal was to provide evidence for our proposed process underlying the labor illusion: Operational transparency increases perceptions of effort, inducing feelings of reciprocity and therefore boosting perceptions of value. We assess each construct independently in Experiment 3, and then conduct a path analysis that tests our proposed model.

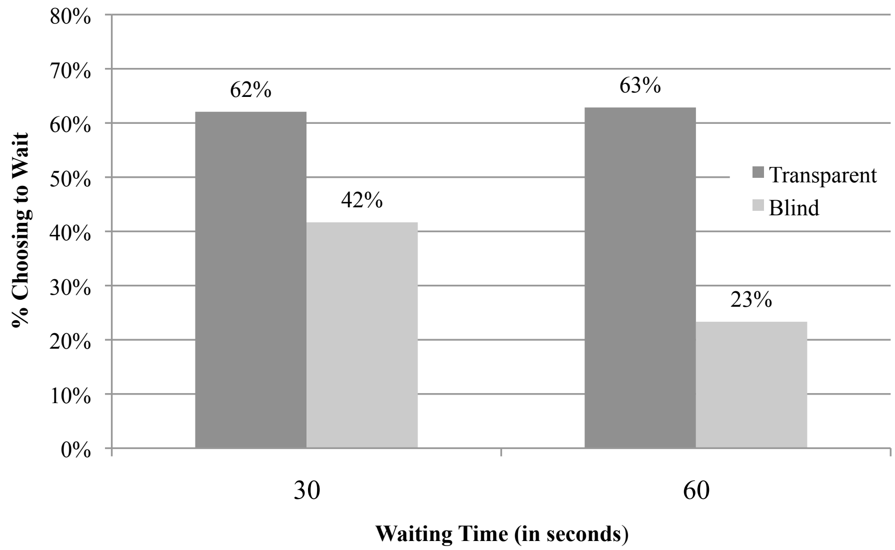


Figure 3.3.3: Percentage of participants preferring the service that required waiting (Experiment 2).

In addition, our second goal in Experiment 3 was to address two alternative explanations for our effects. First, operational transparency may provide customers with information that updates their priors about the amount of work being performed by the service, and this enhanced knowledge may increase their perceptions of service value; indeed, previous research suggests that customers may not always intuit the work that is being done for them behind the scenes (Parasuraman et al. 1985) and therefore often misattribute the source of a wait (Taylor 1994). From this perspective, showing participants a running tally of the work being completed may only enhance value perceptions insofar as it reveals information that updates consumers' priors about the quantity of work undertaken by the website. Furthermore, imposing a 30-second wait may lend additional credibility to the assertion that more work is being undertaken, such that our results could be fully explained by this alternative explanation. If the provision of additional information accounts for the increase in service value perceptions accompanying operational transparency, we would expect that showing participants a list of the work to be performed - even without operational transparency - should also result in elevated perceptions of service value due to the impact of such claims on participants' perceptions of the number of sites the service searches. Furthermore, if credibility explains part of this effect, we would expect that the effect of providing information about upcoming labor is even more positive if the website also imposes a delay while it searches. In contrast, while we predict that providing information about upcoming effort will increase perceptions of credibility, our model suggests that these perceptions will not drive increases in value perception.

Second, it is possible that the impact of operational transparency stems from its effect on the level of uncertainty individuals feel while waiting - an important contributor to the psychological cost of waiting experienced by consumers during service delivery delays (Osuna 1985). While the progress bars utilized in all of our experimental conditions are designed to equate uncertainty (Nah 2004), providing participants with an enhanced level of information in the transparent conditions may further reduce uncertainty and in turn, the psychological costs of waiting. As such, if uncertainty is comparatively high in the blind conditions (and particularly so in blind conditions that require waiting), we would expect that participants in the blind conditions will report being more uncertain than participants in the transparent conditions, and that these differences should be most acute when service duration is increased. In contrast, we suggest that while uncertainty plays an important role in many types of service delivery, the positive effect of operational transparency on value perceptions is due not to decreases in uncertainty, but increases in perceived effort and the reciprocity that such effort perceptions induce.

Method

Participants: Participants ($N = 143$, $M_{age} = 45.5$, 29% Male) completed this experiment online in exchange for \$ 5.00.

Design and Procedure: Participants were randomly assigned to one of five conditions. Some participants were assigned to receive an instantaneous service outcome, before which they were either given information regarding a list of the sites the site was going to search or not. Other participants were assigned to wait 30 seconds; some were given a list of sites before waiting without transparency, some were not given the list of sites and then waited without transparency, while others were not given a list of sites and then waited with transparency. As in Experiment 1, there was no instantaneous condition with transparency, because showing labor requires waiting time. While the transparency manipulation was identical to that used in Experiment 1, participants who received information about the list of sites the site was going to search were briefly shown the message "We are preparing to search 100 sites" accompanied by a list of roughly 100 airline and airfare websites. The list was designed to provide participants with information about the work conducted by the website in the absence of operational transparency. All participants received an identical list of service outcomes.

Dependent Measures: We first assessed participants' perceptions of service value using the same items as in Experiment 1, then included items designed to capture the role of perceived effort and reciprocity in the impact of operational transparency on perceived value. We measured perceived effort using the following three questions: How much effort do you think the website exerted on your behalf? How much expertise do you think the website has? How thorough was the website in searching for your ticket? To measure reciprocity, we followed the procedure outlined by Bartlett and DeSteno (2006), asking participants the following questions: How positive do you feel toward the company? How grateful do you feel toward the company? How appreciative do you feel toward the company? Responses to all items were provided on 7-point scales, and exhibited a sufficient level of internal consistency for both perceived effort (Cronbach's $\alpha = .71$) and reciprocity (Cronbach's $\alpha = .90$).

In order to examine the impact of enhanced information and credibility, we asked participants to report how many websites they believed the service had searched during the service process. To measure uncertainty, we followed the procedure outlined by Taylor (1994), asking participants to rate the extent to which they felt the following emotions while waiting for service using 7-point scales: anxious, uneasy, uncertain and unsettled. These factors possessed a high level of internal consistency (Cronbach's $\alpha = .83$).

Results and Discussion

Perceived value: Perceived value varied significantly across conditions, $F(4, 138) = 7.41, p < .01$ (Figure 3.3.4). First, there was no difference in perceived value between the instantaneous blind ($M = 4.76, SD = 1.04$) and list conditions ($M = 4.97, SD = .77$), $t(59) = .91, p = .37$, suggesting that providing information did not positively impact value perceptions in the absence of a wait. It is possible, however, that the impact of an informational claim about upcoming labor is enhanced by a delay that increases the credibility of that claim. Our results do not offer support

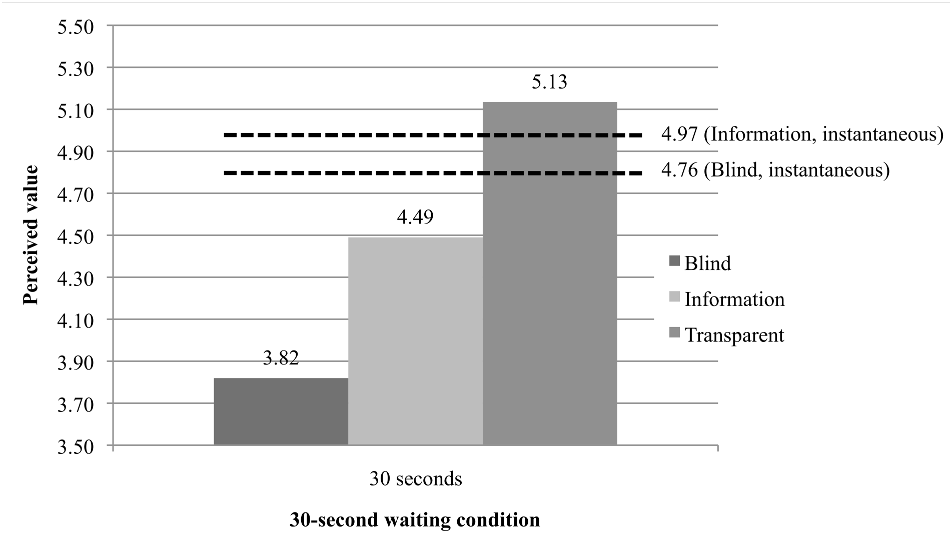


Figure 3.3.4: The effect of enhanced information and credibility on perceived value (Experiment 3).

for this hypothesis. While perceived value varied among the 30-second waiting conditions $F(2, 79) = 12.71, p < .01$, perceived value was highest for the transparent condition ($M = 5.13, SD = .89$), which was significantly higher than perceived value in the list condition ($M = 4.49, SD = .98$), $t(62) = 2.71, p < .01$, which in turn was significantly higher than perceived value in the blind condition ($M = 3.82, SD = .99$), $t(41) = 2.20, p < .05$.

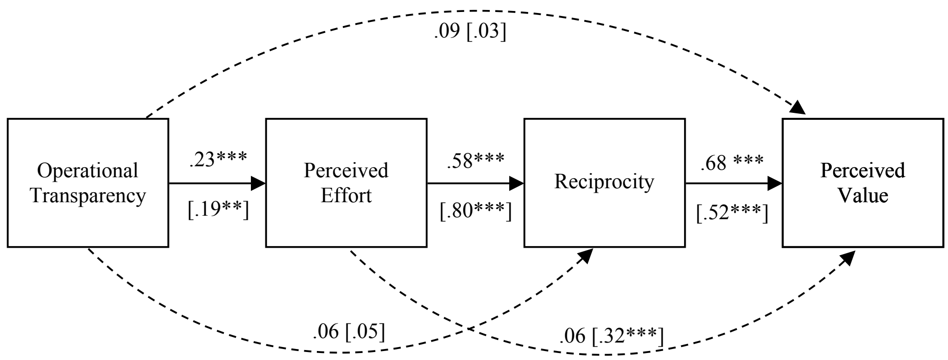
Perceived effort and reciprocity: Closely mirroring these results, perceived effort also varied significantly across conditions, $F(4, 138) = 3.15, p < .05$. There was again no difference in perceived effort between the instantaneous blind ($M = 5.07, SD = 1.05$) and list conditions ($M = 5.13, SD = 1.18$), $t(59) = .20, p = .84$, but differences were significant among the 30-second waiting conditions, $F(2, 79) = 7.01, p < .01$. Perceived effort was highest for the transparent condition ($M = 5.50, SD = 1.01$), which was significantly higher than perceived effort in the list condition ($M = 4.75, SD = 1.01$), $t(62) = 2.94, p < .01$, and blind conditions ($M = 4.59, SD = .23$), $t(55) = 3.12, p < .01$. There was no difference in perceived effort between the 30-second blind and list conditions, $t(41) = .50, p = .62$.

Feelings of reciprocity also varied across waiting conditions in a similar fashion,

$F(4, 138) = 7.56, p < .01$. Participants in the instantaneous blind ($M = 4.90, SD = .24$) and list conditions ($M = 5.09, SD = .20$) reported no difference in reciprocity, $t(59) = .61, p = .55$, but differences were again significant among the 30-second waiting conditions, $F(2, 79) = 12.06, p < .01$. As with perceived value, reciprocity was highest among participants in the transparent condition (M = 5.19, SD = 1.03), which was significantly higher than the list condition (M = 4.43, SD = 1.37), t(62) = 2.54, p < .01, which in turn was higher than the blind condition (M = 3.44, SD = .18), t(41) = 2.21, p < .05.

Path analysis: In order to test our model, which suggests that perceived value and reciprocity underlie the relationship between operational transparency and perceived value, we conducted a path analysis using the perceived effort, reciprocity and perceived value measures. Path analysis facilitates the quantification and interpretation of causal theory by using a series of recursive linear models to disentangle the total and indirect effects of a series of variables on one another (Alwin 1975). In particular, we wished to test the theory that operational transparency increases perceptions of effort exerted by the website, which in turn triggers feelings of reciprocity that lead the consumer to perceive the service as valuable. The path analysis, which is represented graphically in Figure 3.3.5, reports standardized beta coefficients to indicate the relative strength of each link in the theorized causal path. Operational transparency is positively associated with perceptions of effort ($\beta = .23; p < .01$), which in turn is positively associated with reciprocity ($\beta = .58; p < .01$), which has a positive association with perceived value ($\beta = .68; p < .01$). In this analysis, no significant relationships between the variables lie off the hypothesized causal path. Perceived effort fully mediates the relationship between operational transparency and reciprocity; reciprocity fully mediates the relationship between perceived effort and perceived value, and perceived effort and reciprocity fully mediate the relationship between operational transparency and perceived value. These results are highly consistent with our theoretical account of the mechanisms underlying the labor illusion effect.

Information and credibility: In order to test the alternative explanation that increased service duration boosts perceived value by elevating perceptions of the quantity of labor conducted, we compared participants' perceptions of the number of sites searched, which varied significantly by condition, $F(4, 138) = 3.76, p < .01$. While there was no difference between the blind ($M = 18.83, SD = 28.30$) and list



Note. Standardized beta coefficients from Experiments 3 (no brackets) and 4 (in brackets). *, **, and *** signify significance at the 10%, 5% and 1% levels respectively.

Figure 3.3.5: Path analysis (Experiments 3 and 4).

instantaneous conditions ($M = 25.13$, $SD = 36.60$), $t(59) = .71$, $p = .48$, perceptions varied significantly among the 30-second treatments, $F(2, 79) = 5.10$, $p < .01$. Participants who saw the list of sites and waited 30 seconds for the delivery of service ($M = 53.28$, $SD = 43.87$) did perceive that more sites had been searched than participants who saw the operationally transparent condition ($M = 28.13$, $SD = 33.48$), $t(62) = 2.59$, $p < .01$, or the blind condition ($M = 21.28$, $SD = 30.79$), $t(55) = 2.66$, $p < .01$. These results suggest that that information did increase participants' perceptions of the quantity of work being conducted by the website, and that the revelation of information about the amount of work being conducted is more credible when service duration is increased. Importantly, however, additional OLS regression analyses suggest that increases in perceptions of labor do not underlie the impact of operational transparency on perceived value. While transparency is a significant driver of both perceived effort (coefficient $= .58$; $p < .01$ two-sided) and perceived value (coefficient $= .53$; $p < .01$ two-sided), perceptions of the quantity of labor conducted do not predict either (coefficient $= 0.00$; $p = .33$ two-sided; coefficient $= 0.00$; $p = .78$ two-sided, respectively).

Uncertainty: Finally, we find that uncertainty did not vary among conditions, $F(4, 137) = 1.68$, $p = .16$. In particular, participants experiencing the 30-second blind condition reported uncertainty ($M = 1.51$, $SD = .64$) equivalent to participants experiencing the 30-second transparent condition

$(M = 1.69, SD = 1.06)$,$t(55) = .62, p = .54$, suggesting that the positive impact of transparency on perceived value is not due to its impact on uncertainty. In support of this contention, an OLS regression of perceived value on operational transparency and uncertainty reveals a significant effect of operational transparency (coefficient$= .51, p < .01$ two-sided) but an insignificant effect of uncertainty (coefficient $= .12, p = .14$ two-sided), suggesting that differences in uncertainty do not explain the labor illusion effect.

Taken together, results from Experiment 3 offer support for our proposed model - that operational transparency leads to increased perceptions of effort, inducing reciprocity and enhancing value - and address several plausible alternative explanations centered on the roles of credibility, information, and uncertainty. Having provided initial support for the mechanism underlying the labor illusion, we test for boundary conditions in the remaining experiments, exploring whether diminishing the amount (Experiment 4) or quality (Experiment 5) of labor conducted mitigates the relationship between operational transparency and perceived value.

3.3.4 Experiment 4: Quantity of Actual Labor

The results of Experiment 3 indicate that perceived effort matters more for perceived value than perceptions of the quantity of labor conducted - as measured by perceptions of the number of sites searched. As a stronger test of the relative contributions of perceived effort and actual labor, we next manipulated the actual number of sites searched. While our previous analysis suggested that perceptions of labor quantity and perceived effort are unrelated, and that perceived effort leads to perceived value while perceptions of labor quantity do not, it may be the case that if the actual quantity of labor performed by the process is sufficiently low, revealing that labor via operational transparency may not boost perceptions of value. If the actual quantity of labor performed serves as a boundary condition, then we would expect that by sufficiently diminishing the quantity of work performed by the service, the effect of operational transparency on perceived value should cease to hold. Alternatively, if perceptions of labor quantity are independent of perceptions of effort, reducing actual labor may have no effect on the relationship between operational transparency and perceived value. We predicted that operational transparency would promote perceptions of effort independent of actual labor, which, as in Experiment 3, would in turn increase feelings of reciprocity and perceived value.

Finally, while we continue to use our measure of perceived value as our key outcome variable, Experiment 3 includes additional measures of value of relevance to managers: satisfaction and repurchase intentions.

Method

Participants: Participants ($N = 116, M_{age} = 45.4$, 53% Male) completed this experiment online in exchange for $ 5.00.

Design and Procedure: Participants were randomly assigned to one condition of a 2(version: transparent versus blind) X 2 (actual labor: low versus high) design; in Experiment 4, all participants waited 30 seconds for their service outcome.

We made the manipulation of actual labor salient in three ways. First, during the search, participants saw a list of the airfare sites being searched by the service (3 for the low labor condition, 36 for the high labor condition). Second, in order to cycle through more sites in the same amount of time (30 seconds), the list of sites searched in the transparent conditions updated more quickly in the high labor than the low labor condition. Third, when the results were displayed, participants saw differing numbers of sites searched and differing numbers of results (15 results from 3 sites for low labor, 433 results from 36 sites for high labor). Although we manipulated the number of results returned, the best result presented in all conditions was identical, as in the previous experiments.

Dependent Measures: As in Experiment 3, we captured participants' perceptions of service value, perceptions of the number of sites searched, perceived effort and reciprocity. Following the procedure outlined by (Cronin and Taylor 1992), we assessed both participants' satisfaction by asking the following question: My feelings towards these services can best be described as (very unsatisfied to very satisfied, on a 7-point scale) and repurchase intentions, using the following question: If it were made available to me, over the next year, my use of these services would be (very infrequent to very frequent, on a 7-point scale).

Results and Discussion

Perceived value, perceived effort, and reciprocity: We conducted a 2(version: transparent versus blind) X 2 (actual labor: low versus high) ANOVA on perceptions of perceived

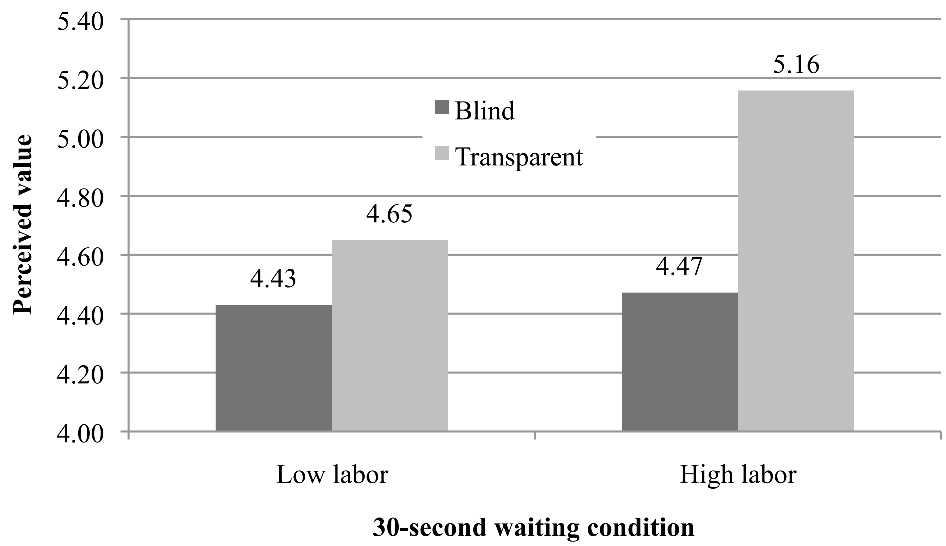


Figure 3.3.6: The effect of actual labor on perceived value (Experiment 4).

value, which revealed a significant main effect of version, such that perceived value was higher in the transparent ($M = 4.89, SD = .98$) than blind conditions ($M = 4.46, SD = 1.22$), $F(1, 112) = 4.69, p < .05$. There was no main effect of actual labor and no interaction, $Fs > 1.70, ps > .19$. As can be seen in Figure 3.3.6, there was no difference in perceived value between the low labor blind ($M = 4.44, SD = 1.16$) and transparent conditions ($M = 4.65, SD = .99$), $t(52) = .73, p = .47$, but the difference was significant between the high labor blind ($M = 4.47, SD = 1.28$) and transparent conditions ($M = 5.16, SD = .92$), $t(60) = 2.35, p < .05$.

Perceived effort demonstrated a similar pattern of results, with a main effect of version, $F(1, 112) = 4.32, p < .05$, but no main effect of actual labor or interaction, $Fs < .28, ps > .59$. Perceived effort did not vary either between the low labor blind ($M = 4.78, SD = .25$) and transparent conditions ($M = 5.27, SD = .24$), $t(52) = 1.39, p = .17$, or the high labor blind ($M = 4.89, SD = .24$) and transparent conditions ($M = 5.42, SD = .24$), $t(60) = 1.56, p = .12$. Results for feelings of reciprocity also followed this pattern, with a main effect of version, $F(1, 112) = 4.67, p < .05$, but no main effect of actual labor or interaction, $Fs < .27, ps > .60$. Feelings of reciprocity did not vary between the low labor blind

($M = 4.31$, $SD = 1.55$) and transparent conditions ($M = 4.78$, $SD = 1.46$), $t(52) = 1.13$, $p = .26$, but did differ marginally between the high labor blind ($M = 4.24$, $SD = .29$) and transparent conditions ($M = 5.00$, $SD = .23$), $t(60) = 1.95$, $p = .06$.

Path analysis: These results demonstrate a clear replication of the primary results from Experiment 3: operational transparency has a significant impact on perceived value, perceived effort, and feelings of reciprocity. We replicated the path analysis conducted in Experiment 3 and observed substantively similar results with significant relationships along the path from operational transparency to perceived value (Figure 3.3.5), standardized beta coefficients from Experiment 4 are displayed in brackets). These results lend further support to our account that operational transparency increases perceptions of effort, which in turn boost reciprocity and perceived value.

Perceptions of actual labor: Given the lack of interaction effects above, our results suggest that the quantity of actual labor does not influence the effect of operational transparency on perceived value. Furthermore, we observe no main effect of quantity of actual labor on perceived value. Importantly, the absence of these relationships was not due to a failure of our manipulation of actual effort: participants in the high labor conditions ($M = 12.95$, $SD = 9.46$) perceived the service as searching more sites than those in the low labor conditions ($M = 7.19$, $SD = 5.93$), $F(1, 112) = 18.01$, $p < .01$. Importantly, however, we also observed a main effect - as with our analyses for the other dependent measures - for operational transparency, $F(1, 112) = 7.02$, $p < .01$; even when we explicitly told participants the amount of labor the site would perform, those in the transparent conditions ($M = 11.88$, $SD = 8.99$) continued to report believing that the service had searched more sites than participants in the blind conditions ($M = 8.71$, $SD = 7.72$). There was again no interaction, $F(1, 112) = .03$, $p = .86$. As in Experiment 3, actual labor (participants' estimates of the number of sites searched) was not a predictor of perceived value (coefficient $= -.00$, $p = .90$two-sided), while perceived effort was (coefficient $= .64$, $p < .01$ two-sided).

Satisfaction and repurchase intentions: Finally, underscoring the importance of the labor illusion for service managers, we also observed main effects of task transparency for both satisfaction, $F(1, 112) = 5.52$, $p < .05$, and repurchase intentions, $F(1, 112) = 8.85$, $p < .01$, such that transparency positively impacted both metrics. For satisfaction and repurchase intentions respectively, there were again no main effects of actual labor, $Fs < 2.65$, $ps > .10$, and no interactions, $Fs < 1.91$, $ps > .17$. Additionally, using OLS regression, we find a strong positive relationship between perceived value and satisfaction (coefficient $= .90$, $p < .01$ two-sided) and perceived value and repurchase intentions (coefficient $= 1.05$, $p < .01$ two-sided), as well as positive and significant relationships between operational transparency and satisfaction (coefficient $= .52$, $p < .05$ two-sided) and operational transparency and repurchase intentions (coefficient $= 1.01$, $p < .01$ two-sided). These results are consistent with previous research suggesting that perceived value is an important antecedent to both of these managerially-relevant service metrics (McDougall, 2000).

Taken together, results from Experiment 4 offer additional support for the model we outlined in Experiment 3, whereby operational transparency increases perceptions of value due to increased perceptions of effort and resultant feelings of reciprocity. Also as in Experiment 3, we find that the actual quantity of labor - whether manipulated or measured - does not appear to play a significant role in producing the labor illusion; at minimum, it appears that operational transparency does not harm value perceptions, even at very low levels of actual labor (3 sites searched). Our goal in Experiment 4 was not to show that actual labor never plays a role in shaping value perceptions during service experiences; clearly, actual labor is an important driver of value in many contexts (Kruger et al. 2004, Morales 2005). Our results suggest, however, that individuals may be relatively insensitive to actual effort in the absence of cues that orient their attention to the amount of labor being conducted. Operational transparency appears to serve as one such cue, helping people understand how the quantity of labor being conducted translates into how hard the company is working on their behalf - and in turn, how valuable the service is. Indeed, we show that operational transparency can increase not only value perceptions, but also satisfaction and repurchase intentions.

3.3.5 Experiment 5: Outcome Favorability as a Boundary Condition

All of the experiments reported thus far have demonstrated that operational transparency promotes service value perceptions with objectively decent outcomes - reasonably-priced flights. However, real world service outcomes vary in favorability, and even those that are technically successful - in that they return a result - sometimes fail to live up to consumer expectations. Experiment 5 was designed to examine the robustness of the labor illusion for creating service value perceptions when technically successful outcomes vary in subjective favorability. While effort in the service of finding decent and excellent options likely adds value (as in the first two experiments), what happens when outcomes are very poor? In the same way that a waiter who is very attentive to your needs yet delivers horrible food will suffer when it comes time to leave a tip, we predicted that when a service searches diligently and carefully and yet still cannot find a decent option, consumers will infer that the service must not actually be of high value.

To test this hypothesis, as well as to examine the generalizability of the labor illusion to other domains, we moved from asking consumers to search for flights to asking them to search for mates. Online dating is a relatively large and rapidly growing technology-mediated service sector; by 2013, Americans are expected to spend $ 1.68 billion per year in the space (Piper Jaffray & Company 2009). From a research perspective, online dating is an attractive context in which to study the labor illusion for several reasons. First of all, online dating sites require the customer to engage in a significant amount of up-front labor, documenting their own personal characteristics as well as their preferences in a mate; this labor should serve to highlight the relevance of the provider's labor as well. Second, while online dating results have an objective component (a compatibility score), the photos presented on the results screen introduce a subjective (and importantly for our purpose, easily manipulated) component to the outcome as well. The dual nature of online dating results enables us to experimentally introduce service outcomes that are technically successful (a good compatibility score), though subjectively dissatisfying (a less than attractive photo). Therefore, we use the context of online dating to unpack how outcome favorability moderates the relationship between the labor illusion and perceptions of service value.

Method

Participants: Participants ($N = 280$, $M_{age} = 29.8$, 42% Male) completed this experiment in the laboratory as part of a series of unrelated experiments, in exchange for $ 25.00.

Pretest: In order to create outcomes that varied in favorability, we asked a different group of participants ($N = 45$) to rate 40 pictures of men and women on a 10-point scale. Images rated above 6 were classified as favorable, those rated between 3 and 6 were deemed average, and those rated below 3 were deemed unfavorable. We used a total of 3 images for each condition, and matched the gender of the image to the participant's stated sexual preference.

Design and Procedure: We created a simulated online dating website called *Perfect Match*. Participants were asked to enter their dating preferences into the website's interface by clicking on those characteristics that were important to them in selecting someone to date (see Figure 3.3.7 for screenshots). Once preferences were submitted, the site "searched" its database of singles to find a compatible match.

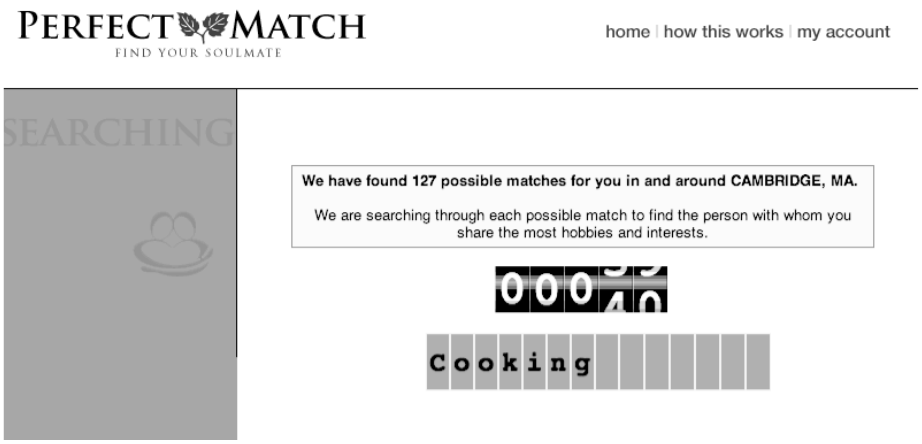
Some participants were assigned to one of three instantaneous service conditions in which they received either a favorable, average, or unfavorable outcome. Other participants were assigned to one condition of a 2 (wait time: 15 or 30 seconds) $\times$ 2 (version: transparent or blind) $\times$ 3 (outcome: favorable, average, unfavorable) design.

The site exhibited operational transparency by stating, "We have found 127 possible matches for you in and around CITY, STATE. We are searching through each possible match to find the person with whom you share the most hobbies and interests." The website then displayed each of the characteristics that the participants had indicated was important in a partner as a signal that it was working to find matches on each characteristic, while displaying an odometer ticking through the 127 people. In the blind condition, participants saw, "We have found 127 possible matches for you in CITY, STATE," along with a progress bar tracking the time until the site was done working.

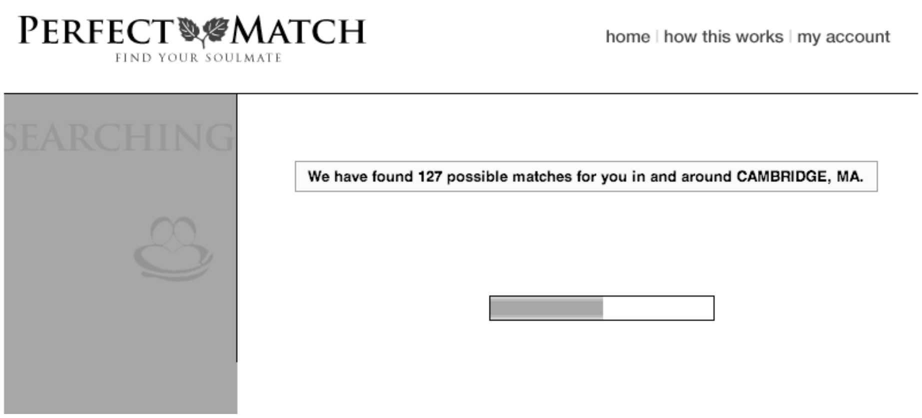
All participants then received the same fictional profile of their "perfect match," such that each profile returned was labeled with an artificially generated "compatibility score" of 96.4%; we varied the photograph associated with that profile to be favorable, average, or unfavorable.

Results and Discussion

As in the previous experiments, we observed a main effect of wait time such that participants rated the service as less valuable when they waited 30 seconds $(M = 2.84, SD = 1.22)$ than 15 seconds $(M = 3.21, SD = 1.16)$, $F(1, 152) = 5.93, p < .05$. Not surprisingly, we observed a main effect of outcome, such that participants were most satisfied when their match was accompanied by an attractive photo $(M = 3.39, SD = 1.30)$, followed by an average photo $(M = 3.08, SD = 1.12)$ and then an unattractive photo $(M = 2.61, SD = 1.06)$,



Transparent condition



Blind condition

Figure 3.3.7: Screenshots of transparent and blind conditions (Experiment 5).

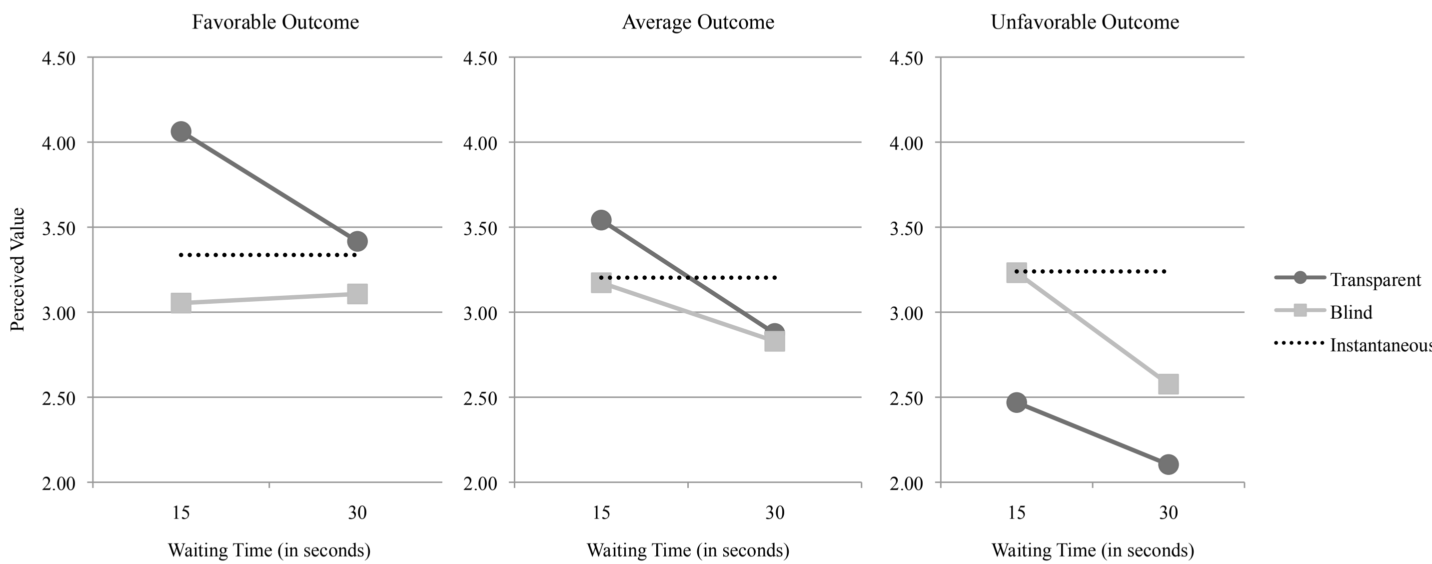
$F(2, 152) = 7.14, p < .01$; participants attributed the favorability of their outcome not to their own personality, but to the ineffectiveness of the service. Most importantly, we observed the predicted interaction of transparency and outcome favorability, $F(2, 152) = 4.42, p < .05$; as can be seen in Figure 3.3.8, the impact of transparency varied as a function of the outcome, with participants valuing transparent service more for both average and favorable outcomes, but actually valuing it less for unfavorable outcomes. There were no other significant main effects or interactions, $Fs < .66, ps > .49$.

We broke these analyses down by outcome favorability to examine how the impact of operational transparency varied by outcome. For favorable outcomes, our results were similar to the previous experiments. At 15 seconds, waiting with transparency $(M = 4.06, SD = 1.28)$ was seen as marginally more valuable than instantaneous service $(M = 3.34, SD = 1.32)$, $t(62) = 1.72, p = .09$; waiting for 15 seconds in the blind condition $(M = 3.05, SD = 1.04)$, on the other hand, was not different than instantaneous, $t(64) = .74, p = .46$. After 30 seconds, neither the blind $(M = 3.11, SD = 1.60)$ nor transparent conditions $(M = 3.42, SD = 1.12)$ were different from instantaneous, $ts < .56, ps > .58$.

This pattern of results stands in striking contrast to those for unfavorable outcomes. Waiting for 15 seconds with operational transparency only to receive an unfavorable outcome led to significantly lower value perceptions $(M = 2.47, SD = .76)$ than instantaneous $(M = 3.24, SD = 1.20)$, $t(62) = 2.40, p < .05$, while the blind condition $(M = 3.23, SD = 1.09)$ was again not different from instantaneous service, $t(60) = .02, p = .98$. At 30 seconds, this pattern intensified, where the blind condition $(M = 2.58, SD = 1.07)$, was marginally worse than instantaneous, $t(59) = 1.80, p = .08$, and the transparent condition was even less valued $(M = 2.10, SD = 1.12)$,$t(58) = 2.97, p < .01$.

Thus while a 15-second wait with transparency for favorable outcomes led to the very highest ratings of value, waiting with transparency for unfavorable outcomes led to the very worst value perceptions. For average outcomes, while the pattern of results is

Figure 3.3.8 ***(following page)*****:** Perceived value of service by waiting time, outcome and waiting condition (Experiment 5).


Favorable Outcome
Average Outcome
Unfavorable Outcome
Perceived Value
4.50
4.00
3.50
3.00
2.50
2.00
15
30
Waiting Time (in seconds)
Transparent
Blind
Instantaneous

similar to that of favorable outcomes, none of the t-tests are significant, $ts < 1.08, ps > .28$.

These results demonstrate an important boundary condition for the benefits of operational transparency. When a service demonstrates that it is trying hard and yet still fails to come up with anything but poor results (in this case, an unattractive dating option), people blame the service for this failure, and rate it accordingly. In contrast, for both positive and average outcomes, the impact of operational transparency is similar to that observed in Experiments 1 and 2: the labor illusion leads people to rate the service more highly if they perceive it as engaging in effort on their behalf than if it does not. In short, no amount of effort can overcome consumers' natural inclination to dislike services that perform poorly; given at least decent outcomes, however, creating the labor illusion leads to greater perceived value.

3.4 General Discussion

We demonstrated that the labor illusion is positively associated with perceptions of value in online self-service settings, even though signaling the effort being exerted by the service through operational transparency increases service duration (Experiment 1). In addition, we have shown that individuals can prefer waiting for service to instantaneous delivery - provided that the delayed experience includes operational transparency (Experiment 2). Moreover, we addressed alternative accounts for the labor illusion effect, including enhanced information, credibility and uncertainty (Experiment 3), established perceived effort and reciprocity as the drivers of the link between transparency and perceived value, and demonstrated that the increases in perceived effort that accompany transparency exert an impact on perceived value independent of labor quantity (Experiments 3 and 4). Operational transparency is a driver not only of perceived value but also of satisfaction and repurchase intentions (Experiment 4). Finally, we demonstrated that outcome favorability serves as a boundary condition on the labor illusion effect (Experiment 5). These insights connect to literature on increasing the tangibility of service. Fitzsimmons and Fitzsimmons (2006), for example, advocate seeking increases in service tangibility to remind customers of their purchases and make the experience memorable. Our results suggest that engaging in operational transparency may be one way a firm can increase the tangibility of service, as it shapes perceptions of service effort, enhances feelings of reciprocity, increases service valuation, and drives satisfaction and repurchase intentions.

While we have demonstrated that perceived effort and reciprocity are significant mediators of the impact of operational transparency on perceived value, prior work has highlighted the importance of quelling uncertainty (Osuna 1985) and directly promoting perceived quality (Zeithaml 1988) in enhancing value perceptions. While we eliminated a role for uncertainty by designing progress bars into both our experimental and control conditions, it is likely that operational transparency may reduce uncertainty through the revelation of information about the service process. As such, service experiences fraught with uncertainty may benefit from the implementation of operational transparency, both in terms of its capacity to promote perceptions of effort and reciprocity, as well as through its potential to reduce feelings of uncertainty. With regard to perceived quality, as noted in Experiment 1, the multi-item scale with which we measured perceived value throughout this paper incorporates a question about perceived quality, and our results are similar if we substitute evaluations of quality for the multi-item scale. As such, our results are consistent with the notion that operational transparency improves perceived quality and perceived value.

It is also likely that the mechanisms that link operational transparency to increases in perceived value vary by the specific nature of the service context. In the contexts we explore in our paper - online search engines - adding additional customers has little or no marginal impact on the speed of service or the quality of results, because searches occur in parallel, and the same results are returned to all customers. In more customer-intensive services such as the delivery of health care and financial and legal consulting, in contrast, increasing the number of customers can both increase wait times and decrease service quality (Anand et al. 2011). A growing stream of the operations literature explores the tradeoff between service quality and duration in such contexts. de Véricourt and Sun (2009), for example, analytically demonstrate and propose a model addressing the tradeoff that firms face in queuing contexts between taking time to accurately serve customers and increasing congestion and delays for those in the queue. When customers are not served with sufficient quality, they may re-enter the system thus further increasing congestion (de Véricourt and Zhou 2005) or choose not to engage with the service at all (Wang et al. 2008). Empirical investigations have also noted this tradeoff: Banking employees facing excess demand compensate by working faster and cutting corners, leading to erosion of service quality (Oliva and Sterman 2001); increased system load in hospitals boosts service rates to unsustainable levels, and the resulting overwork increases patient mortality (Kc and Terwiesch 2009). Take the example of restaurants that offer an open kitchen or offer a "kitchen table," where customers can view the action. While we would expect that the effort chefs appear to be exerting would positively affect customer perceptions of value, it seems likely that the extent to which those chefs are entertaining and engaging may also influence customer experiences and drive value perceptions. To the extent that this specialized service slows down customers' getting their food in a reasonable amount of time, however, we might expect customer perceptions to become more negative. We suggest that perceived effort may be a dominant mechanism when the output of the service process is important, and the perceived link between effort and the quality of the output is high. Such is typically the case when the service output is tailored to suit the needs and preferences of an individual customer, as in most pure and mixed service contexts (Chase 1981).

Exploring the role of operational transparency on service value perceptions in additional contexts is a promising future direction. Opportunities exist in both tangible technology-mediated contexts where customers observe the machinery at work (e.g. automated car washes) and non-technology mediated contexts where customers consume the service, but do not directly observe the service creation process (e.g. print media, quick oil change). In particular, contexts in which waiting is both inevitable and a familiar pain point for consumers may be ideal locations to institute operational transparency. For example, many consumers have been baffled when checking in for a flight or into their hotel room with a customer service agent who seems to type roughly 30,000 words in order to complete the check-in process, while the consumer wonders what information the employee could possibly be entering. The United States Postal Service has experimented with customer-facing terminals that show the steps being completed by postal service employees at each stage of a customer transaction - increasing operational transparency and demonstrating value as it is created.

3.4.1 What is the Optimal Combination of Operational Transparency and Wait Time?

Our results demonstrate that customer perceptions of value may be enhanced by operational transparency in the service delivery process, even when transparency requires waiting. However, our experiments highlight a crucial consideration in determining just how much waiting - whether operational transparency is salient or not - is optimal: In the online travel simulation in Experiment 1, the positive benefits of transparency began to decline after 30 seconds, whereas with the online dating simulation in Experiment 5, the decline began even earlier, at 15 seconds. While there may be a number of reasons for this difference (people may be more impatient to find a mate than a flight, for example), we suggest that one critical factor relates to consumers' expectations. Online dating websites such as Match.com search through their own database of user profiles and return results quickly, while travel websites such as Kayak and Orbitz search through the databases of other airlines - meaning that in the real world, consumers are used to searches for flights taking longer than searches for mates. In short, it is very likely that consumers' experiences with and expectations for the time a service should take to deliver results is related to the point at which operational transparency is most effective. Google, for example, has acclimated its users to returning results in fractions of a second, and thus it is very unlikely that consumers would be happy after a 30 second wait; still, our results suggest that they would be happier if Google told them exactly what it was searching through while they waited for their results. Managers seeking to implement operational transparency would be wise to consider their customers' previous experiences, and then experiment with different waiting times.

While one means by which these expectations are set is likely previous experience, another likely input is the amount of effort that consumers must exert to initiate the search process (Norton et al. 2011). By their very nature, self-service settings require consumers to perform a greater share of the work than face-to-face service settings (Moon and Frei 2000). Problematically, research suggests people tend to claim more credit than they deserve in such collective endeavors (Ross and Sicoly 1979); in addition, customers have been shown to take credit for positive service outcomes in self-service realms, while blaming the company for negative outcomes (Meuter et al. 2000). Operational transparency has the potential to alter customer perceptions of the co-productive proportionality of service transactions conducted in technology-mediated contexts: the labor illusion may help firms regain credit for doing their fair share of the work. From a practical standpoint, we suggest that another key input into determining the optimal level of waiting and transparency lies in considering (and possibly altering) the labor in which customers engage, to more closely match the labor purportedly provided by the service. Finally, the amount of time that customers spend on a given service is likely variable - for example, people may spend either minutes or days preparing their online tax forms - such that a consideration of customer heterogeneity should inform the level of waiting and transparency.

3.4.2 Reduce Delivery Time or Increase Operational Transparency?

Understanding the relationships between service duration, transparency and perceived value enables managers to better understand how to optimize their service processes to promote customer satisfaction and loyalty. These findings shed light on the hidden costs of strategies employed by an increasing number of firms to infuse technology into service operations. In many contexts, the longer customers wait for service, the less satisfied they become (Davis and Vollmann 1990); accordingly, many managers invest considerably to reduce service duration as much as possible. These very strategies, which are designed to enhance the technical efficiency of service - reducing costs while increasing speed and convenience - may counterintuitively erode consumer perceptions of value and satisfaction with the services they create (Buell et al. 2010). While tempting to focus exclusively on objective dimensions like service duration which can be easily modeled and measured, we suggest that managers should also consider how the manipulation of subjective dimensions - like perceived effort exerted by the service provider - influences customer value perceptions, which drive willingness to pay, satisfaction and repurchase intentions (Heskett et al. 1997, McDougall and Levesque 2000). Companies thus need to invest in increasing the technical efficiency of services, and simultaneously invest in initiatives that infuse additional meaning into each transaction - and into their relationships with their customers.

Assuming service outcomes are average to favorable, there are several instances when increasing operational transparency may be preferable to investing in the reduction of service delivery time. First, pruning the inefficiencies from an already streamlined process can be an expensive and difficult task, and in such cases revealing aspects of the process itself to customers instead may result in a considerable cost savings. Second, when service delivery times are already very short, reducing delivery times further may be counterproductive, though increasing transparency may still boost value perceptions. Third, in some cases, the service process may incorporate aspects that customers would appreciate observing. For example, the Spanish bank BBVO has recently redesigned its ATM machines so that customers making withdrawals can see a visual representation of currency being counted and organized, as the machine performs each task. In other cases, however, reducing service delivery times may be preferable to increasing operational transparency. First, our results suggest that the benefits of operational transparency decrease as wait time increases: If wait times are lengthy, reducing them may be more beneficial than implementing operational transparency. Second, reducing wait times may be preferable when service outcomes are subjectively unfavorable: Experiment 5 demonstrated that when outcomes are unfavorable, increasing operational transparency has negative effects on customer value perceptions. Finally, there are many processes that are inherently unappealing or visibly inefficient due to poor design.

3.4.3 Labor Illusion or Operational Transparency

Importantly, we have drawn a distinction in our work between the labor illusion - customers' perceptions of the effort exerted by a service provider - and operational transparency - revelation of the actual operations that underlie a service process. In some cases, of course, the two are one and the same: If it takes an online travel website 15 seconds to search through all airlines, then showing customers which airlines the site is searching and returning results in 15 seconds constitutes true operational transparency. Our results demonstrate, however, that even when the actual operations might take much less time, providing consumers with the illusion of labor can still serve to increase value perceptions, provided participants believe that they are seeing the website hard at work. Thus one view is that increasing actual operational transparency is an effective strategy, but another view is that managing perceptions of operational efforts - the labor illusion - is effective as well. At least two caveats apply to this possibility, however. First, our results raise an ethical dilemma: the fact that firms can induce the labor illusion does not mean that they therefore should induce it. Whereas operational transparency involves firms being clearer in demonstrating the effort they exert on behalf of their customers - an ethically unproblematic strategy - inducing the illusion of labor moves closer to an ethical boundary. Indeed, the fact that consumers are generally skeptical of marketers' efforts to persuade them to buy their products and utilize their services (Friestad and Wright 1994) raises the second caveat to the implementation of the labor illusion. While operational transparency is likely a safe strategy because actual transparency requires honesty, firms who attempt to induce the labor illusion must take care that their customers do not become aware of the attempt - suspicion of manipulation can erode the impact of effort on quality perceptions (Morales, 2005) - or face the consequences of being caught in an unethical practice.

R.W. Buell, Campbell, D., Frei, F.X. 2011. How Do Incumbents Fare in the Face of Increased Service Competition? Working Paper. Harvard Business School. Boston, MA.

4

How Do Customers Respond to Service Quality Competition?

4.1 Introduction

When does increased service quality competition lead to customer defection, and which customers are most likely to defect? While there is a well-established literature linking investments in service quality to customer perceptions and behaviors, and ultimately, firm performance (Sutton 1986, Zeithaml et al. 1996, Heskett et al. 1997), the answers to these questions remain unaddressed. Numerous studies in the domains of operations, industrial organization and marketing model these relationships in stylized cases, or use aggregated data to explore firm-level customer substitution patterns. Broadly speaking, these works emphasize the positive average effects of service quality. However, inter-market and customer-level empirical evidence is generally lacking across these literatures, which limits our understanding of service quality's differential effects between markets and customers. Our paper addresses this gap by presenting the first customer-level empirical investigation of the effects of service quality competition on customer defection in a multi-market setting.

4.1.1 When does increased service quality competition lead to customer defection?

The links between service quality and customer switching behavior are well established tenants of the theoretical literature. Superior quality facilitates customer acquisition (Dana Jr. 2001, Ernst and Powell 1995, Nerlove and Arrow 1962) and retention (Cohen and Whang 1997, Karmarkar and Pitbladdo 1997, Tsay and Agarwal 2000, Cachon and Harker 2002, Li 1992, Li and Lee 1994, Hall and Porteus 2000, Gans 2002). Consistently, empirical work has documented a positive relationship between service quality and market share at the brand level (Allon et al. 2011, Buzzell and Gale 1987, Jacobson and Aaker 1987, Phillips et al. 1983, Guajardo et al. 2012), suggesting that more quality is always desired. However, vertical (quality) differentiation theory notes that customers differ in their marginal willingness to pay for quality (Gabszewicz and Thisse 1979, Shaked and Sutton 1982, Sutton 1986, Tirole 1990). The rational consumer will only defect from the incumbent if the competitor's price/quality bundle will improve her utility. Hence, the aggregate effect of service quality competition on customer retention likely varies by market, depending on the distribution of preferences among the incumbent's customers. This differential effect of service quality between markets has never been empirically studied, but has important implications for how a firm should behave, both operationally and strategically. In particular, while the aggregate results would suggest that higher quality is always preferred, our results highlight circumstances when investments in service quality would be counterproductive.

4.1.2 Which customers defect in response to increased service quality competition?

The theoretical literature on customer switching tends to assume that a customer's sensitivity to service quality and her profitability to the firm are uncorrelated. [1] It is

[1] In models documenting customer switching behavior, customers are assumed to vary in service sensitivity, and either generate homogeneous profitability for the firm or profitability that is uncorrelated with their preferences for quality (Cohen and Whang 1997, Dewan and Mendelson 1990, Karmarkar and Pitbladdo 1997, Mandelbaum and Shimkin 2000, Stidham Jr. 1992, Tsay and Agarwal 2000).

unclear, however, how realistic this assumption is in practice.[2] If the most profitable customers are enmeshed in more complex relationships with the firm, switching costs may reduce their probability of defection when an attractive opportunity presents itself (Klemperer 1995). However, highly profitable customers may have a higher willingness to pay for service quality as posited by the priority pricing literature (Afèche and Mendelson 2004, Lederer and Li 1997, Mendelson and Whang 1990). Furthermore, to the extent that high profitability customers have more at stake in the relationship, and more interactions with the firm than their low profitability counterparts, they may be more acutely aware of its deficiencies (Israel 2005). While the consequences of customer defection for a firm's bottom line depend crucially on the foregone profitability of closed accounts, this differential effect of service quality competition between customers has never been empirically studied either. Indeed, our results suggest that despite increased switching costs, highly profitable customers are disproportionately attracted by the entry or expansion of competitors that offer superior service quality.

Our customer-level analysis leverages the varying competitive dynamics across geographically isolated markets served by a nationwide retail bank over a five year period to test the extant theory on switching behavior due to service quality competition. With this work, we make four primary contributions to the empirical operations literature:

1. *We present the first empirical evidence that reveals the circumstances under which customers defect in response to service quality competition.* Competing firms trade-off price and service quality, and in markets where the incumbent has held a high (low) service quality position relative to local competitors, its customers are more likely to defect following the entry or expansion of a competitor offering superior (inferior) service quality for higher (lower) prices.

2. *We provide evidence that these results are driven primarily by customer sorting within each local market, rather than by a service complacency effect, wherein incumbents offering relatively high service quality strategically diminish their service*

[2]For example, it is well known in the airline industry that service-sensitive customers often fly "business" or "first-class," which is far more profitable for airlines than their coach customers. If a new, higher quality airline enters a particular market, the entrant may be especially attractive to these highly profitable customers.

levels. In markets where the incumbent occupies a high relative service quality position, its customers exhibit heightened sensitivity to service quality: expressing lower levels of satisfaction with comparable transactions, reporting service problems more frequently, and showing a lower level of overall satisfaction with the bank. This pattern persists after controlling for differences in objective service quality between markets, and industry-wide data suggests that the pattern generalizes beyond the focal firm.

3. *We find that more profitable customers are more likely to defect from the incumbent when a provider offering superior service quality enters, or expands in, the market.* Customers with the longest tenure, most products, and highest balances defect disproportionately following these competitive events.

4. *We document a positive relationship between relative level of service quality sustained by a firm in a given market and the profitability of customers it attracts and retains over time.* Controlling for other market-level differences, the incumbent serves customers with significantly higher balances in markets where it sustains a high service quality position relative to its competitors.

4.2 Theory and hypothesis development

4.2.1 A simple model of service quality competition

We consider a vertical differentiation model in which the service offerings of various firms are differentiated by quality, s. The unit mass of consumers differ in their marginal willingness to pay for quality, θ, which is distributed such that $\max(\theta) = \bar{\theta}$ and $\min(\theta) = \underline{\theta}$. Assume that n firms exist in an industry, and each firm j offers a standardized level of service quality denoted by s_j, where $s_{j-1} < s_j < s_{j+1} < \cdots < s_n$, across the multiple markets in which they compete.[3] Further assume that price is a

[3] Interviews with retail banking executives suggested that objective service quality is largely a function of centralized decisions and policies relating to process design, technological infrastructure, incentives, hiring and training, which would be costly and require significant coordination to modify locally. Consistent with this idea, the industrial organization literature in banking reveals that even lending and pricing policies, which would be relatively easy to customize locally, tend also to be standardized, owing in part to the complexities and costs of managing a multi-market organization (Berger et al. 2007, Erel, Hannan and Prager 2004). As further support for this perspective, our own analysis of the 2007-2011 J.D. Power and Associates Retail Banking Satisfaction Studies^{SM} of 81 institutions reveals that firm-level differences account for 74.6% of the variance in customer satisfaction, year-over-year, suggesting that perceived quality is largely a

convexly increasing function of quality that is common across all firms, $p(s)$, such that $p_j = p(s_j)$ and $p_{j-1} < p_j < p_{j+1} < \cdots < p_n$.[4]

4.2.2 Aggregate effects of service competition

When a firm enters or expands in a local market, it attracts new customers from various sources, some of whom defect from incumbent competitors (Caves 1998). However, when entrants and incumbents offer disparate levels of service quality, the effect of entry on incumbent customer defection depends on the relationship between the incumbents' customers' willingness to pay for quality improvements, and the increase in variable costs, and in turn, prices, associated with such improvements (Sutton 1986). On the one hand, entry by a superior service quality competitor may intensify defection from incumbents offering poorer service, as ceteris paribus, incumbent customers would prefer higher quality. However, to the extent that the superior service entrant and inferior service incumbent trade-off price and service quality, customer price sensitivity may mitigate the effect of entry on defection. To illustrate, in the model described above, a consumer's utility from using the service of a particular firm j is given by $\theta s_j - p_j$. If $\theta > \acute{p}(s_j)$ for some set of a firm's customers, those customers would prefer an entrant offering higher quality service at marginally higher prices, but would not be attracted to an entrant offering inferior service quality at marginally lower prices. Alternatively, if $\theta < \acute{p}(s_j)$ for some set of its customers, those customers would be attracted to an entrant offering inferior service quality at marginally lower prices, but would not be attracted to an entrant offering superior quality, since defection to the entrant would diminish their utility. Hence, the effect of service quality competition on customer defection depends crucially on the distributions of θ among a firm's customers in the specific markets where competitive entry occurs. Because the distribution of θ is likely to vary by market, the existence of an average effect of service quality competition on customer defection across all markets is unclear. As such, in the next section, we explore how market-level heterogeneity and customer sorting may affect the relationships between service quality competition and customer defection in

persistent, firm-level characteristic in banking (as was the case in other service industries from 1996-2010 in the American Customer Satisfaction Index: 88.2% for fast food, and 76.7% for airlines). Accordingly, we model service quality as an institution-level characteristic and use an institution-level service quality measure in our empirical analysis. We test the appropriateness of this modeling choice in Section 4.4.

[4] This is consistent with the assumption that marginal costs are increasing in service quality.

particular markets.

4.2.3 Market-level heterogeneity and customer sorting

A rich stream of the theoretical operations management literature models customer switching behavior in response to service deficiencies, either experienced (Gans 2002, Hall and Porteus 2000), or anticipated (Cohen and Whang 1997, Tsay and Agarwal 2000). These models suggest that when customers are underserved, which is most typically modeled as when inventory is unavailable or subject to a lengthy delivery delay (Cachon and Harker 2002, Li 1992, Li and Lee 1994) or when customers encounter an unacceptably long queue (Dewan and Mendelson 1990, Mendelson 1985, Stidham Jr. 1992, Van Mieghem 2000), they are likely to defect in favor of superior service. These service-sensitive customers may trade up to another firm in their market that offers higher service quality, albeit at higher prices.

Assume two firms (firm $j-1$ and firm j) compete in a particular market, in which the distribution of θ is $[\underline{\theta}, \bar{\theta}]$. Customers for whom $\tilde{\theta} = (p_j - p_{j-1})/(s_j - s_{j-1})$ will be indifferent between the two firms, and we assume θ is distributed such that $\underline{\theta} < \tilde{\theta} < \bar{\theta}$.[5] By extension, all customers for whom $\theta > \tilde{\theta}$ will derive higher utility from firm j and will sort themselves over time such that firm j, which has a relatively high quality service position in the market, will attract and retain customers with preferences for higher quality service.

Now, assume that there is an inflow of highly service-sensitive customers with $\theta > \bar{\theta}$, such that the new distribution of *theta* in the market is $[\underline{\theta}, \bar{\theta}']$ where $\bar{\theta}' > \bar{\theta}$.[6] These customers will initially be attracted to firm j, which offers the best available service quality and correspondingly, the highest achievable utility for their given values of θ. However, such a change in the underlying demographic characteristics could make market entry profitable for a competitor offering service quality that is superior to firm j. If a new competitor, firm $j+1$, subsequently enters the market, all customers for whom $\theta > (p_{j+1} - p_j)/(s_{j+1} - s_j)$ would benefit by defecting to the entrant. Due

[5] We further assume that $\max(p_j - p_{j-1})/(s_j - s_{j-1}) \leq \bar{\theta}$ and $\min(p_j - p_{j-1})/(s_j - s_{j-1}) \geq \underline{\theta}\, \forall\, j$.

[6] Changes in a market's underlying demographic conditions and corresponding preferences for service quality are relatively commonplace. For example, an increase in population growth or an improvement in median household income can precipitate an accession of the underlying preferences for service quality in a market. Accordingly, demographic changes are carefully monitored by firms and factored into their market entry and exit decisions. As described in the next section, we control for these market-level characteristics in our empirical analysis.

to the vertical model, customers from firm j will have a positive probability of defecting to the superior service quality entrant, while customers from firm $j-1$ will not. Furthermore, these sorting effects are symmetric and equally relevant to service-insensitive, price-sensitive customers.[7] An entrant offering the market's lowest service quality for correspondingly low prices would draw customers from firm $j-1$, but not from firm j.

While this stylized model suggests that each customer will sort immediately to an optimal provider, it is likely that actual consumers, transacting in the presence of information asymmetries and switching costs, will sort toward such equilibria over time. As such, when a service firm has predominantly held a relatively high (low) service quality position in a local market over time, its customers are likely to be increasingly service (price) sensitive. Consistently, we hypothesize that:

Hypothesis 1A (H1A): The longer a firm has occupied a high service quality position relative to competitors in its local market, the more likely its customers will defect following the entry or expansion of competitors offering superior service quality, and;

Hypothesis 1B (H1B): The longer a firm has occupied a low service quality position relative to competitors in its local market, the more likely its customers will defect following the entry or expansion of competitors offering inferior service quality.

4.2.4 Customer-level heterogeneity

The relationships modeled in the previous section link a firm's relative service position in a local market to the likelihood that its customers will defect in the wake of entry or expansion by incumbents providing superior service. While the multi-period performance impact of the defection of underserved customers has been recognized and extensively modeled in the operations management literature (Caine and Plaut 1976, Hill Jr. 1976, Schwartz 1966), its magnitude depends heavily on the foregone profitability that would have been generated by each individual defector.

While a stream of priority pricing literature models circumstances under which

[7] We note that some customers may exist for whom is sufficiently small such that negative utility would be received for engaging in service with the lowest quality provider in the market. These customers will opt not to purchase service from the existing providers, but may be attracted to new entrants offering lower levels of service quality for correspondingly lower prices.

customers who are disproportionately service sensitive can pay a premium for faster service (Afèche and Mendelson 2004, Lederer and Li 1997, Mendelson and Whang 1990), most of the theoretical literature on customer switching assumes independence between a customer's service sensitivity and her profitability to the firm. Switching models tend to assume that customers have heterogeneous service sensitivity, and presuppose they either generate homogeneous profitability for the firm or that their profitability is uncorrelated with their preferences for service quality (Cohen and Whang 1997, Dewan and Mendelson 1990, Karmarkar and Pitbladdo 1997, Mandelbaum and Shimkin 2000, Stidham Jr. 1992, Tsay and Agarwal 2000). However, if a positive relationship exists between a customer's profitability and her sensitivity to service quality, then models assuming the two are independent would tend to understate the performance implications of service quality.

There are a number of factors that correlate with customer profitability that may affect customer responses to service competition. We discuss three such factors below: switching costs, customer learning and the direct link between service-sensitivity and customer profitability.

Switching costs

Customers face switching costs when investments specific to their current service providers must be duplicated in order to receive service from new providers (Farrell and Klemperer 2007). In general, these investments that engender switching costs tend to be positively associated with a customer's profitability. For example, in banking as in many service contexts, high tenure customers tend to be more profitable than low tenure customers. High tenure customers are typically older and wealthier. Furthermore, high tenure customers typically have invested in more of the provider's offerings, increasing the revenue they generate. Moreover, in many contexts high tenure customers have a deeper understanding of the service provider's offerings, which reduces the cost of serving them. High tenure customers, in particular, tend to possess a high level of switching costs. Over time, as the length of a customer's relationship with a firm increases, psychological switching costs intensify, as customers develop a pattern of repeat purchase through habit or loyalty (Klemperer 1987). Furthermore, as the number of service offerings utilized by the customer increases, setup and learning costs intensify. Setup costs exist when customers must setup a service for its initial use (Burnham et al. 2003, Klemperer 1995). Learning costs include the time and effort required to acquire the necessary skills to use a service effectively (Guiltinan 1989). The relationships between switching costs and customer retention have been shown numerous times in banking and other contexts (Campbell and Frei 2010, Hitt and Frei 2002), and as such, we expect to find that customers who have higher tenure, or who have a broader service relationship with the firm, will be less likely to defect from the firm than customers who have been with the firm for less time or who have a narrower service relationship with it. Consistently, the effects of switching costs should make high profitability customers less likely to defect in response to superior service quality entry.

Customer learning

Customers learn about the service quality offered by a firm by experiencing it through their interactions. The theoretical literature on customer switching behavior models customer learning in two ways: customer defection as an immediate response to a service failure (Hall and Porteus 2000), or updating one's perspective based on a history of service experiences (including failures and successes) (Gans 2002). Assuming service failures are low probability events (and especially low probability events among high quality service firms), customers with higher tenure are more likely to have experienced them than customers with lower tenure. Similarly, customers who have more relationships with the firm, and as a consequence, transact more frequently with it, are more likely to have experienced deficient service. Limited support for this perspective exists in the empirical literature. (Buell et al. 2010) showed that customer defection probabilities increased in the total number of transactions conducted by a customer, controlling for the customer's tenure, balances, and counts of the types of service offerings utilized. The effects of learning would suggest that customers with higher tenure and customers with more relationships with the bank will be more knowledgeable about the level of service offered by the firm and may, as a result, be better positioned to evaluate whether an entrant's value proposition is more attractive. Hence, the effects of customer learning should cause high profitability customers to be more likely to defect following the entry or expansion of competitors offering superior service quality.

Direct link between service sensitivity and customer profitability

Finally, there are several reasons to believe that high profitability customers are inherently more attracted by superior service quality competition. First, customers may "know their worth" to an organization, based on the number of products they have, the balances they hold, and the profits they perceive they generate. Customers who believe they are highly profitable to the firm may wish to be treated accordingly by the firm, and as such, may be particularly sensitive to service deficiencies. Second, high value customers may have more at stake in the service relationship than low profitability customers; in absolute terms, the cost of a service failure is much higher for them. Accordingly, it seems reasonable that they might be more selective about the quality of service offered by their provider, and more willing to pay for it. Consistently, several queuing models feature priority-pricing schemes for the customers whose needs are most time sensitive: such customers are able to pay a higher price for expedited service (Mendelson and Whang 1990, Van Mieghem 2000). Third, to the extent that highly profitable customers are wealthier, they may also be less price sensitive. Correspondingly, they may be more willing to trade-off price for service than low profitability customers. Sutton (1986) underscores this idea, by assuming that richer consumers prefer to purchase higher quality products, and that each income level can be identified with a different preferred quality, . Limited evidence for this perspective also exists in the empirical operations literature, where for example, a deli's most price-sensitive customers are also the least averse to waiting in a queue (Olivares et al. 2011). For these reasons, the service sensitivity effect should make high profitability customers more attracted by superior service competitors.

To the extent that highly profitable customers face higher switching costs, we would predict they would be less likely to defect in the wake of service competition. However, the effects of customer learning and the direct link between service sensitivity and customer profitability may attenuate or overcome the negative effects of switching costs. Accordingly, we state the following non-directional hypothesis in null form.

Hypothesis 2 (H2): On average, there is no relationship between a customer's profitability to the firm and the likelihood he or she will defect following the entry or expansion of superior service competitors.

4.3 Research setting and data

4.3.1 Research setting

We conduct our study in the U.S. domestic retail banking industry. There are several reasons that retail banking is an ideal setting in which to examine customer responses to service competition. First, while the offerings of retail banks tend to be functionally comparable (for example, most banks offer checking accounts, savings accounts, loans, etc.), the industry consists of thousands of local, regional and national players, which invoke a highly variable set of service design strategies, each resulting in a different service quality level. While service design decisions in banking tend to be made centrally, the presence or absence of specific competitors shapes each market's distinctive service quality landscape - a source of variation we exploit in our analysis. Second, retail banking is a useful laboratory for empirical work, due to the quantity of data that are captured by the banks themselves, the government, and third-party institutions. These data quantify customer behavior, firm performance, intra-market competition, and institution-level service quality. Third, retail banking customers are a diverse group, with varying needs, preferences and experiences. This variability creates a rich environment in which to analyze the impact of operational decisions and competitive circumstances on customer behavior. Moreover, the diverse customer base is common to a wide variety of consumer service firms, broadening the relevance of our analysis.

The primary market and customer-level performance data for this study are provided by a bank that is one of the largest diversified financial service firms in the country, serving millions of customers across hundreds of markets in more than 20 states. Importantly for the purposes of our paper, over the time period of our analysis, this bank offered customers a roughly median level of service quality and price, relative to the competitors it faced. In the analyses we describe throughout the remainder of this paper, we refer to this bank as the "incumbent bank".

4.3.2 Data collection

We utilize market-level service competition and demographic data, institution-level service quality data, branch-level pricing data and account-level retention and customer attribute data to conduct our primary analysis. This section outlines the sources of these data.

Market definition and competitive composition

Market definition: The incumbent bank competed without interruption in 644 markets from 2002 to 2006. Its strategy group delineated each market as a block of adjoining zip codes within which customers tend to transact. We note that each market is geographically isolated, as in Olivares and Cachon (2009), which facilitates our empirical approach. These markets are located in more than 20 states, and each contained an average of 12.57 zip codes. We restrict our analyses to the customers and institutions engaging in these markets.

Competitive composition: Within each market, we identified which institutions were competing against the incumbent bank by using the Federal Deposit Insurance Corporation (FDIC) Summary of Deposits (SOD) database. On an annual basis, the FDIC captures branch-level deposit balance data for every active commercial and savings bank; listing these data along with an institution identifier, branch street address and zip code. We augmented these data with specific branch opening dates for de novo entry and closing dates, as well as historical institution ownership data, provided by the incumbent bank's strategy group, to pinpoint the month within which entry, exit and changes of branch ownership occurred. On a monthly basis from 2002-2006, these data enabled us to identify which institutions were competing in each market, how many branches each institution had, and when competitive expansion, entry or exit events occurred.

Market-level demographics: To control for factors that could be correlated with both the propensity for customer defection and the attractiveness of a market to entrants, we incorporate market-level demographic data from ESRI, a geographic information services company, into many of our analyses. Managers at the incumbent bank identified demographic criteria that are used by banking institutions to make market entry decisions. These annual, market-level data, which are summarized in Figure 4.3.1, included population, median household income, median age, population growth, per capita income, median home value, household growth, average household size, gender distribution, and the branch share of non-incumbent competitors in the market preceding the entry event window.

	(1)	(2)	(3)
	All markets	Service markets	Non-service markets
Population (2000)	136,244	148,015	127,075
Current year population	145,792	156,373	137,550
Median household income	$51,116	$51,843	$50,550
Household income percentile	61.66	62.17	61.26
Median age	36.13	36.16	36.10
Population growth percentile	54.20	51.38	56.41
Per capita income	$26,613	$27,894	$25,614
Median home value	$209,249	$235,136	$188,304
Household growth	1.71	1.35	1.99
Average household size	2.69	2.66	2.71
Percentage males	50.1%	50.1%	50.0%
Non-incumbent market share	86.0%	88.5%	84.0%
Average fee change from prior year	-1.3%	-2.1%	-0.7%
Lagged average fee change	4.3%	2.1%	6.0%
Number of markets	644	282	362

Figure 4.3.1: Market summary statistics (2004).

Incumbent performance

Customer-level performance: We created a two-year panel of 100,000 randomly selected customers who were active with the bank as of December 31, 2003. To facilitate linking customers to specific markets, we removed customers from our sample who had home addresses that were outside the 644 markets of interest. In this study, we analyze the behavior of the remaining 82,235 customers. We chose to analyze customer behavior from 2003 to 2004, because it was a relatively stable time period for the industry, predating the financial crisis. For each customer, we tracked end-of-year balances in various types of accounts (checking accounts, loan accounts and investment accounts), depth of cross-sell (counts of various types of products, including checking, loan, and investment accounts, as well as ATM and debit cards), breadth of cross-sell (number of product classes), and customer demographic information (customer tenure and customer age). These data are summarized in Figure 4.3.2.

Notably, 12.06% of customers in the panel who were active at the end of 2003 had

	2003 (pre-entry year)		2004 (entry year)	
	Mean	SD	Mean	SD
Customer demographics				
Customer tenure (years)	10.93	11.11	11.33	11.16
Customer age (years)	44.05	19.01	44.43	19.08
Balance information				
Checking balance	\$9,823	\$58,701	\$12,051	\$138,596
Loan balance	\$3,028	\$16,988	\$3,488	\$18,249
Other balance	\$1,294	\$12,117	\$875	\$11,689
Depth of cross sell				
Total product count	2.92	2.22	3.00	2.17
Count of checking products	1.29	1.08	1.38	2.17
Count of loan products	0.37	0.64	0.42	0.67
Count of investment products	0.08	0.51	0.06	0.42
Count of ATM cards	0.13	0.40	0.09	0.31
Count of debit cards	0.72	0.82	0.66	0.67
Bredth of cross sell				
Number of product classes	2.13	1.28	2.26	1.31
Has checking account	79.5%	40.4%	81.7%	38.7%
Has non-home equity loan	26.3%	44.0%	29.7%	45.7%
Has home equity loan	6.3%	24.2%	6.6%	24.8%
Has other account	4.9%	21.6%	3.6%	18.7%
Has ATM card	11.6%	32.0%	8.5%	27.9%
Has debit card	53.2%	49.9%	56.6%	49.6%
Uses online services	31.6%	46.5%	39.0%	48.8%
Customers retained at end of year	82,235		72,321	

Figure 4.3.2: Summary statistics for customer panel (2003-2004).

defected (closed all of their accounts with the bank) by the end of 2004. Due to this defection trend, average customer age and tenure years don't increment precisely from 2003 to 2004. Moreover, for the panel, average checking account balances grew over the two-year period, as did depth and breadth of cross-sell. With regard to checking account balances, this trend suggests that we have selected a period of moderate growth, isolating the effects of the financial crisis. Furthermore, the cross-sell figures are consistent with the idea that as tenure grows, customers tend to be sold into more products per category (depth) and more product categories (breadth).

Price and service quality metrics

In order to characterize the strategic positioning of competitors facing the incumbent in each market, we integrated branch-level pricing data and institution-level service quality data. Pricing: Pricing data was collected from the FDIC Quarterly Call Reports database, which captures balance sheet entries including RCON6636, interest-bearing deposits in domestic offices, as well as income statement items, such as RIAD4080, service charges on deposit accounts in domestic offices. We calculated a fee income per deposit dollar metric, , by dividing each institution's annual service charges on deposit accounts in domestic offices by their corresponding interest bearing deposits in domestic offices. We use fee income per deposit dollar as our primary measure of price throughout our analysis, owing to the salience of fees in customer evaluations of bank pricing.[8]

Relative service quality: Relative service quality data was captured using the 2006-2009 J.D. Power and Associates Retail Banking Satisfaction Studies[SM]. The studies captured responses from 12,904, 20,898, 19,602 and 28,570 households regarding their experiences with their primary banking providers from 2006 to 2009 respectively. Over the four-year period, the annual study captured user-based perceptions of service quality from customers of 59 banks on five dimensions of

[8]In addition to fees, interest charged on loans is a major source of revenue for retail banks. Accordingly, we also calculate the net interest margin for each institution, a metric capturing the magnitude of the spread between interest paid to depositors and dividends earned on interest-bearing assets, expressed as a percentage of earning assets. Banks with a higher net interest margin can be considered to be more "expensive" for consumers. Importantly, net interest margin and fees are positively correlated with one another ($\rho = 0.346$), suggesting the two tend to be complements, rather than substitutes. While fee income per deposit dollar is the primary measure of price in our analyses, in section 4.1, we confirm that both fees and net interest margin are positively associated with service quality.

	(1)	(2)	(3)	(4)
	Incumbent	Superior Service Entrants	Inferior Service Entrants	Unrated (Local) Entrants
Average number of states	--	4.10	4.07	1.05
Average number of zip codes	--	191.64	238.62	4.05
Average number of branches	--	231.62	301.38	4.75
Average number of branches/zip	1.41	1.21	1.26	1.17
Average number of markets	651.00	69.04	70.54	2.05
Average number of branches/market	4.35	3.35	4.27	2.32
Average deposits/branch (000)	$87,246	$82,112	$63,396	$56,680
Average branch share upon entry	11.21%	6.46%	7.22%	3.42%

To protect the identity of the incumbent bank, we have excluded summary statistics for number of states, number of zip codes and number of branches.

Figure 4.3.3: Comparison of different types of institutions.

service: convenience, account initiation and product offerings, fees, account statements, and transactions.

In creating the service quality metric we used for our analysis, we omitted the rating for fees in order to capture a pure service quality score that did not conflate price and service. The annual mean of the remaining four dimensions for each institution (convenience, account initiation and product offerings, account statements, and transactions) was taken to create an annual service score, and the mean of the annual service scores from each of the four years was taken to produce a relative measure of institution-level service quality, s_j.[9] We use this metric as our measure of service quality throughout our analysis. This aggregated score constitutes a user-based measure of quality, which has been defined in the literature as the capacity to satisfy customer wants (Edwards 1968, Garvin 1984, Gilmore 1974). Similar user-based metrics have been used to measure service quality in numerous empirical studies (Anderson et al. 1997, Fornell et al. 1996, Oliva and Sterman 2001).

Interviews conducted at the incumbent bank confirmed that the relative service ratings assigned to each institution by this aggregated metric were consistent with managerial perceptions of the service quality of competitors. However, it should be noted that the measurement of this particular service quality rating occurs subsequent to our period of competitive and customer analysis (2004-2006). 2006 was the first

[9]While we believe an institution-level service quality metric is most appropriate for the reasons discussed in Footnote 3, in Section 4.4 we explicitly analyze the extent and effect of market-level differences in objective service quality.

year J.D. Power and Associates published its Retail Banking Satisfaction Study. Data for the first study was captured in October of 2005, which occurs after our observation window. While alternative user-based measures of quality exist for our period of observation, we chose this particular measure for several reasons.

First, from a practical perspective, relative to the American Customer Satisfaction Index (ACSI) and Consumer Reports (CR), the J.D. Power and Associates Ratings cover a far broader range of institutions, increasing the power of our analysis. From 2004-2006, ACSI conducted an annual study of the nation's four largest banks. In 2006, Consumer Reports published a similar study that covered nineteen institutions. Over the four years of data included in our metric, J.D. Power and Associates collected data on the service quality of 59 institutions, giving us a far more comprehensive view of the relative service quality offered by firms in the markets we analyze.

Second, the J.D. Power and Associates data are more granular than the ACSI and CR service ratings, which aggregate service evaluations into a single performance score. As discussed above, the granularity provided by J.D. Power and Associates afforded us the opportunity to be selective about the attributes included in our metric, so that we could obtain a purer measure of service quality. Third, to the extent that service ratings are a lagging indicator of actual service performance, using a subsequent service quality metric may be preferable to using one that aligns precisely with a particular period of analysis. It is likely that the transactions customers experienced during 2003 and 2004 influenced their evaluations of service quality in 2005 and beyond.

Fourth, our analysis reveals that perceptions of banking service quality tend to be highly persistent from year to year. Over the period from 1997-2008, the ACSI reported user-based quality perceptions for eight banks in consecutive years. Previous year service rating explained 73.25% of the variation in current year service rating. Adding 2 and 3-year lags sequentially explained 77.67% and 79.68% of the variation respectively. Furthermore, the relative service positioning of the four firms rated by the ACSI did not change between 2003 and 2005. This persistence, which is consistent with literature suggesting that service reputation tends to evolve slowly, gives us confidence that the relative service positioning of firms will not have shifted substantially between the period of our analysis and the period of service quality evaluation.

Moreover, where there is overlap, mean J.D. Power ratings from the 2006-2009 period are highly consistent with those of the American Customer Satisfaction Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Fee income per deposit dollar	Fee income per deposit dollar	Fee income per deposit dollar	Fee income per deposit dollar	Fee income per deposit dollar	Fee income per deposit dollar	Fee income per deposit dollar	Fee income per deposit dollar
Service rating	0.0053**	0.0038**	0.0058**	0.0040**				
	[0.0025]	[0.0018]	[0.0024]	[0.0018]				
Total deposits (in thousands)			0.0000	0.0000			-0.0000***	-0.0000***
			[0.0000]	[0.0000]			[0.0000]	[0.0000]
Branch count			0.0000*	0.0000*			0.0000***	0.0000***
			[0.0000]	[0.0000]			[0.0000]	[0.0000]
Year 2008 indicator		-0.0077*		-0.0074*		-0.0038***		-0.0037***
		[0.0039]		[0.0039]		[0.0004]		[0.0003]
Nationwide retail bank					0.0086***	0.0079***	0.0053***	0.0045***
					[0.0010]	[0.0009]	[0.0013]	[0.0012]
Constant	-0.0042	0.0017	-0.0076	-0.0003	0.0052***	0.0060***	0.0052***	0.0060***
	[0.0074]	[0.0057]	[0.0076]	[0.0059]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Sample selection	Rated institutions (2005-2007)	Rated institutions (2005-2008)	Rated institutions (2005-2007)	Rated institutions (2005-2008)	All institutions (2005-2007)	All institutions (2005-2008)	All institutions (2005-2007)	All institutions (2005-2008)
Observations	79	120	79	120	22,686	29,973	22,686	29,973
Between R-squared	0.114	0.127	0.191	0.181	0.009	0.023	0.015	0.029
Institutions	38	50	38	50	8,068	8,223	8,068	8,223

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively (two-tailed tests). Brackets contain standard errors.

Figure 4.3.4: Firms trade-off price and service quality.

during the 2003-2005 period. There is both a high correlation between the measures (ρ = 0.68) and a high Chronbach's Alpha (α = 0.82). Considering these factors, we believe we have chosen the best available metric for evaluating relative service quality for the purposes of our study.

4.4 Primary analysis and results

4.4.1 Do firms trade-off price and service quality?

We test the assumption that firms trade-off price and service quality by measuring how annual fee income per deposit dollar, p_j, varied with a firm's service ratings, s_j, from 2005-2007. While J.D. Power and Associates collected service data over the 2005-2008 period, we have chosen this particular event window to pre-date the financial crisis.[10] Though J.D. Power and Associates rated the service quality of 42 institutions over this period, three were classified as savings banks by the FDIC, and as such, were not required to submit call report data. Prior to the period of analysis, another bank was acquired by a larger competitor, and its pricing data was aggregated with the larger competitor for reporting purposes. We are left with service quality and pricing data for 38 institutions. We use a between effects linear model of average price on average

[10]We note, however, that all results reported in Figure 4.3.4 are substantively similar if we analyze the entire 2005-2008 period during which J.D. Power and Associates collected service quality data.

service quality over 2005-2007.

$$p_j = \beta_0 + \beta_1 s_j + \varepsilon_j \tag{4.1}$$

The β_1 coefficient reflects the degree to which service quality is associated with price in these markets. If $\beta_1 > 0$, then firms charged customers a higher price in exchange for higher quality service.[11] In order to deepen our understanding of the pricing dynamics in retail banking, we also conduct supplementary analyses, examining relative price positioning as a function of the total number of branches the institution had, the sum of all deposits it held, and whether or not the institution was a nationwide bank.

In Figure 4.3.4, we scale the dependent variable by 1,000 to facilitate coefficient interpretation, such that coefficients represent the marginal effect on a firm's fee income per thousand deposit dollars. Column (1) shows that among service-rated firms, those with higher service ratings charged higher prices (coefficient = 5.61, $p < 0.05$; two-tailed), and column (2) shows that the relationship strengthens after controlling for the institution's total number of branches and total deposits (coefficient = 6.18, $p < 0.05$; two-tailed). Moreover, in column (3), our analysis reveals that nationwide retail banks, those for which a service rating was available, charged higher service fees than regional and local competitors (coefficient = 8.58, $p < 0.01$; two-tailed). In column (4), we find that this difference remains robust after controlling for a firm's total number of branches and deposits (coefficient = 5.16, $p < 0.01$; two-tailed). Taken together, these results suggest that on average, nationwide banks charged higher fees than local and regional competitors and that, among nationwide competitors, those offering high quality service charged the highest fees.[12]

4.4.2 Aggregate effects of service competition

We test the aggregate effects of service quality competition by modeling individual customer defection behavior in 2004 as a function of the number and relative service nature of competitive events that took place within the customer's market in that

[11] Importantly, this test is not intended to show causality, merely correlation between a firm's service quality and the prices it charges to customers for use of its services.

[12] Among nationwide banks, those offering higher service quality also earned a marginally higher net interest margin during the period of analysis (coefficient = 0.02 $p < 0.1$ two-tailed), a relationship that was robust to controls for the institution's number of branches and total deposits. Increasing service ratings by one standard deviation increased net interest margin by 7.4% over baseline rates.

year.[13] We modeled customer defection during 2004 as a binary dependent variable, $DEFECT_i$. In our analysis, a customer has defected if he or she has closed all accounts with the bank by the end of the year. This measure of customer defection has been used in prior empirical studies conducted in retail banking (Buell et al. 2010).[14] Throughout 2004, we counted the number of competitive entry or expansion events (net of exit events) that took place in each market, categorizing events by the competitor's service position relative to the incumbent bank.

Let s_a represent the incumbent's service level and s_c represent the service level of a service-rated competitor. Events pertaining to competitors for which $s_c > s_a$ were defined as *superior* service events, and events pertaining to competitors for which $s_c < s_a$ were defined as *inferior* service events.[15] Events pertaining to institutions for which no service rating is available were defined as local service events.

As detailed in Figure 4.3.3, superior and inferior service institutions tend to be nationwide competitors, operating in a comparable number of states, zip codes and markets, with similar branch share and density. Notably, superior service branches tend to have roughly 30% more deposits on hand than inferior service branches. Local (unrated) institutions, by contrast, typically operate in a single state, with far fewer branches; and lower density, share, and balances than superior and inferior service institutions. This distinction arose from the sampling scheme used by J.D. Power and Associates in conducting the Retail Banking Satisfaction Studies[SM]. Because customers were randomly selected and asked to provide feedback on the service of their primary banking institution, larger institutions, which had more customers, were more likely to be represented in the sample. Institutions for which an insufficient number of responses were collected to draw statistically significant inferences were not reported in the annual study, leading to the systematic exclusion of local and regional competitors.

Within a market, if the number of (superior/ inferior/ local) entry or expansion events exceeded the number of (superior/ inferior/ local) exit events, then using a

[13]While there is a long-standing tradition in the economics and marketing literatures of analyzing substitution patterns using a simulated methods of moments approach with market-level and aggregated consumer-level data (Berry et al. 1995), we directly capture pricing data and conduct our analyses at the level of the individual customer, which facilitates our reduced form approach.

[14]We note, however, that our primary results are substantively similar if defection is instead modeled as a customer who significantly reduces non-home equity balances from one year to the next (95% or more), with or without closing their accounts.

[15]In all cases, the service rating of the focal incumbent was distinct from those of its competitors, such that $s_c \neq s_a$.

binary independent variable, we classified the market as increasing in superior service (SS_m) / inferior service (IS_m) / local (L_m) competition.[16]

To separate the effects of customers departing from the incumbent bank as a result of entrant-driven changes in a market's service quality landscape from those departing in response to intra-market pricing dynamics, we directly control for the annual price changes in each market. We calculate annual market-level changes in mean price, Δp_{mt}, where Δp_{mt} is calculated annually as the mean Δp_{jt} for all institutions competing within a particular market, weighted by the number of branches each institution has in the market. We also institute a lagged price change control, Δp_{mt-1}, intended to capture price changes instituted in anticipation of competitive entry (Goolsbee and Syverson 2008). To simplify notation, we characterize the vector of price change data in the following way: $\Delta p_m = \Delta p_{mt} + \Delta p_{mt-1}$.

As described in the previous section, we also control for a vector of market-level control variables, X_m, as well as a vector of customer-level control variables, X_i. We test the aggregate effects of service quality competition by using a logistic regression to estimate the following cross-sectional model on our random sample of 82,235 customers as of the end of 2004.

$$Pr(DEFECT_i = 1) = f(\gamma_0 + \gamma_1 SS_m + \gamma_2 IS_m + \gamma_3 L_m + \gamma_4 P_m + \gamma_5 X_m + \gamma_6 X_i) \quad (4.2)$$

γ_1 and γ_2 capture the average effect of entry or expansion of superior and inferior service competitors on incumbent customer defection, respectively.[17]

Figure 4.4.1, column (1) demonstrates that on a nationwide basis, entry or expansion by competitors offering superior service quality had an insignificant effect on customer defection (coefficient = 0.0112, $p = 0.751$; two-tailed). Similarly, entry or expansion by competitors offering inferior service quality had an insignificant effect on

[16]We note that all primary results are substantively similar if an alternate set of binary variables are used that indicate whether any entry occurred in each category during the event period.

[17]Technically, standard models of service quality competition such as that presented in section 2.1 would predict that an incumbent would be vulnerable only to the entry of a competitor that is adjacent to it on the dimension of service quality. However, from an empirical standpoint, incumbents may be affected by both adjacent and non-adjacent entry for a variety of reasons including imperfect customer sorting within markets due to the subjective and experiential nature of service quality assessments, the inability of banks to tailor service quality levels within markets and switching costs. In untabulated results, in which defection is modeled as a function of adjacent entry, non-adjacent entry and local entry, we observe that adjacent entry is not significantly associated with customer defection (coefficient = 0.037; $p = 0.26$).

customer defection (coefficient = 0.035, $p = .240$; two-tailed). We next turn to examining whether the absence of an average effect is due to heterogeneity in the effects of service quality competition across markets and customers.

4.4.3 Market-level heterogeneity (H1)

Building on the previous section, we test H1 by modeling customer defection behavior as a function of the incumbent's relative service position in the market. We operationalize the incumbent's service position in the following way. Let $\tilde{s}_m$ represent the median service level for all rated branches competing in a given market during a particular month. We define the incumbent to hold a *high service quality position* in any month where $s_a \geq \tilde{s}_m$. Let C_{mt-1} represent the number of months that the incumbent has held a high service quality position during the preceding two years in a market m as of the last day of year $t-1$. Building on model (2), one of our tests of H1 uses a logistic regression to estimate the following cross-sectional model:

$$\begin{aligned}Pr(DEFECT_i = 1) = f(&\delta_0 + \delta_1 SS_m + \delta_2 IS_m + \delta_3 L_m + \delta_4 P_m + \\ &\delta_5 X_m + \delta_6 X_i + \delta_7 C_{mt-1} + \delta_8 SS_m \times C_{mt-1} + \\ &\delta_9 IS_m \times C_{mt-1} + \delta_{10} L_m \times C_{mt-1})\end{aligned} \tag{4.3}$$

By design, this interaction model explicitly tests whether customer sorting is a continuous process, the effects of which intensify over time. If $\delta_8 > 0$, then as we predict in H1A, the longer an incumbent occupies a high service quality position, the more vulnerable its customers will be to the entry or expansion of competitors offering superior service quality. If $\delta_9 < 0$, then as we predict in H1B, the longer an incumbent occupies a low service quality position in the market, the more vulnerable its customers will be to the entry or expansion of competitors offering inferior service quality.

In Figure 4.4.1, column (2), the negative coefficient on the main effect of superior service entry suggests that when the incumbent has a low service quality position, retention is *marginally higher* for its customers when superior service quality competitors enter or expand (coefficient = -0.127, $p < 0.10$; two-tailed).[18] However,

[18] Since superior service quality competitors tend to have higher prices, their entry may make the incumbent's prices appear relatively more attractive. Moreover, consistent with prior literature (Hannan

	(1)	(2)	(3)	(4)
Dependent variable	Defection	Defection	Defection	Defection
Superior service competitor entry	0.0112	-0.0917*	0.1094**	-0.0598
	[0.0353]	[0.0478]	[0.0486]	[0.0477]
Inferior service competitor entry	0.0353	0.1442***	0.0302	0.0896**
	[0.0301]	[0.0448]	[0.0379]	[0.0417]
Local competitor entry	0.0117	0.1107***	-0.0579	0.0927**
	[0.0291]	[0.0425]	[0.0410]	[0.0380]
Consecutive months with service position		0.0074***		
		[0.0024]		
Superior service entry x consecutive		0.0085***		
		[0.0027]		
Inferior service entry x consecutive		-0.0070***		
		[0.0023]		
Local service entry x consecutive		-0.0077***		
		[0.0024]		
Mean service fee change in the market	-0.1136	-0.1945	0.0757	-0.2504
	[0.2149]	[0.2123]	[0.3034]	[0.2902]
Lagged mean service fee change	0.0296	0.0080	0.2399	-0.1863
	[0.1248]	[0.1270]	[0.1583]	[0.1863]
Incumbent competitor share	-0.0156	-0.2109	-0.0153	-0.2262
	[0.1797]	[0.1970]	[0.3312]	[0.2369]
Constant	-78.3286	-44.7982	75.7879	-84.0835
	[99.9919]	[97.1343]	[150.1256]	[131.7256]
Level of analysis	Customer level	Customer level	Customer level	Customer level
Sample selection	All customers	All customers	Service mkts. (consec. $\geq$ 2 yrs.)	Non-service mkts (consec. < 2 yrs.)
Regression model	Logistic	Logistic	Logistic	Logistic
F test (Sup. entry + 24(Consec. x Sup. entry)>0		F=7.01; p<.01		
P(Defection of Focal Customers | No Entry)			12.02%	11.42%
P(Defection of Focal Customers | Entry)			13.17%	12.31%
Observations	82,235	82,235	34,964	47,271

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively (two-tailed tests). Brackets contain robust standard errors, clustered by market. Additional market-level controls include population, median household income, median age, population growth, per capita income, median home value, household growth, average household size, gender distribution, and incumbent branch growth. Customer-level controls include customer tenure (in years), prior year checking, loan and investment account balances, and counts of checking, loan accounts, investment accounts, credit cards, debit cards and deposit certificates.

Figure 4.4.1: Customer defection following competitive entry.

the coefficient on the interaction of superior service quality entry and the number of months in the preceding two years the incumbent has occupied a high quality service position (coefficient = 0.008, $p < 0.05$; two-tailed) suggests that maintaining a high quality service position attenuates this negative effect. Our next step was to confirm that maintaining a high quality service position for a reasonable number of months overcomes this negative main effect. Given that our competitive composition data for each market began in January 2002 and the event window for competitive entry began in January 2004, in our data, $\max(C_{mt-1}) = 24$. As such, we re-estimated the model using OLS regression and conducted a post-estimation linear test of the hypothesis that when an incumbent has maintained a high quality service position over the past 24 months, its customers will defect in the wake of entry or expansion by a superior service competitor (F = 4.74, $p < 0.05$). This result supports H1A.

Column 2 further shows that the coefficient on the interaction of inferior service quality entry and the number of months in the preceding two years the incumbent has occupied a high quality service position is negative and significant (coefficient=-0.007, $p < 0.01$ two-tailed), suggesting that holding a low service quality position for a longer period of time is associated with increased customer defection probabilities following the entry or expansion of inferior service quality firms. Moreover, after controlling for the incumbent's prior service position, the main effect of inferior service quality entry is positive and significant (coefficient = 0.155, $p < 0.01$; two-tailed), suggesting that when the incumbent has held a low quality service position for the prior two years (equivalently, when $C_{mt-1} = 0$, its customers are more likely to defect following the entry or expansion of competitors offering inferior service quality. These results are consistent with H1B.

A related approach for testing H1 is to use logistic regression to estimate model (4.2) on the subset of our random sample of customers who lived and transacted in markets where C_{mt-1} was sufficiently high to allow for the accumulation of service-sensitive customers by the incumbent. We estimate model (4.2) on the subset of customers for which $C_{mt-1} = 24$. If $\gamma_1 > 0$, then when the incumbent has occupied a high service quality position over the prior two years, its customers are vulnerable to

and Prager 2004, Park and Pennacchi 2009), a separate unreported analysis reveals that average market-prices rise significantly from the pre to post-event periods in markets where superior service entry or expansion occurs. Owing to the local inflexibility of the incumbent's standardized price and service model, such market-level changes make the incumbent relatively more attractive for price-sensitive customers, reducing defection probabilities.

superior service competition, which is consistent with H1A. Using similar logic, we test H1B by estimating model (4.2) on the subset of customers for which $C_{mt-1} < 24$.[19] If $\gamma_2 > 0$, then when the incumbent has not occupied a high service quality position relative to competitors in its market for a sufficient period of time, its customers are vulnerable to the entry or expansion of competitors offering inferior service quality, which is consistent with H1B.[20]

In column (3), the main effect of superior service entry is significant and positive (coefficient = 0.109, $p < 0.05$; two-tailed), suggesting that in markets where the incumbent maintained a high quality service position for the preceding 24 months, its customers were more likely to defect following the entry or expansion of superior service competitors. Defection probabilities increased for the incumbent in these markets from 12.02% when no entry or expansion occurred to 13.17% following entry or expansion by a superior service competitor. In contrast, these same customers were not vulnerable to the entry or expansion of inferior service quality competitors (coefficient = 0.030, $p = 0.43$; two-tailed) or local service quality competitors (coefficient = -0.058, $p = 0.158$; two-tailed). These findings offer further support for H1A.

In column (4), the main effect of the entry or expansion of inferior service quality competitors (coefficient = 0.090, $p < 0.05$; two-tailed) is significant and positive, offering further support for H1B. In these markets, where the incumbent held a low service quality position relative to competitors in its local market, average defection probabilities increased from 11.42% when no entry or expansion occurred to 12.31% following the entry or expansion of competitors offering inferior service. We note that entry and expansion by local and regional competitors increased incumbent customer defection in these markets as well (coefficient = 0.093, $p < 0.05$; two-tailed), a result that is consistent with our earlier findings that such competitors offer lower prices, and our account that the incumbent's customers are price-sensitive in markets where it

[19] We note the results are substantively similar if high (low) service positioned markets are defined on the basis of whether the incumbent held (did not hold) a high service position in the market for an above-median number of months in the pre-entry observation period.

[20] Extending Footnote 17, we note that adjacent competitive entry has an insignificant association with incumbent customer defection in high (coefficient = 0.063; $p = 0.22$) and low (coefficient = 0.067; $p = 0.11$) service quality position markets. Furthermore, adjacent entry had no significant incremental effect on customer defection above and beyond superior service entry in high service positioned markets (coefficient = 0.006; $p = 0.912$) or inferior service entry in low service positioned markets, (coefficient = 0.062; $p = 0.18$).

maintains a low service quality position.[21]

4.4.4 Customer sorting and service complacency

The results presented in the previous section are consistent with the idea that customers sort themselves within a local market, selecting the firm that best fits their service and price sensitivities. Over time, this sorting process leads to intra-market customer-service stratification, in which competitors offering relatively high service quality retain customers who exhibit relatively high service sensitivity, and competitors offering relatively low service quality retain customers who exhibit relatively low service sensitivity.

As further evidence for this phenomenon, in Figure 4.4.2, Column (1) we compare the service quality ratings of 20,890 randomly selected customers surveyed for the J.D. Power and Associates Retail Banking Satisfaction Study[SM] during late 2006. These customers transacted with 78 different banking institutions in 6,098 U.S. cities.[22] Customer ratings were aggregated to produce a mean service quality rating for each institution, which in turn was used to categorize the institution's service position relative to the median in each market.[23] Respondent's ratings were modeled as a function of the firm's relative service position in the respondent's market, as well as institution and market-level fixed effects. The results demonstrate a general tendency for customers to perceive firms to have below average service quality in markets where they have a relatively high service quality position (coefficient = -0.120; $p < 0.05$

[21]Our account is that competitive entry by firms offering varying service quality levels cause the defection effects described in this paper. A potential alternative explanation is that the anticipated propensity of customers to defect caused the entry events we observed. However, we did not find evidence consistent with this alternative when we modeled all entry, superior service quality entry, inferior service quality entry and local entry as a function of the prior year intended loyalty of 27,279 randomly selected customers in these markets, as well as market and customer-level control variables. In all models, we failed to reject the null hypothesis that competitive entry decisions are not a function of intended customer loyalty ($p > 0.26$). Replacing intended loyalty with overall satisfaction yields similar results.

[22]The 2007 study was the first during which J.D. Power and Associates captured respondent-level zip code information, which facilitates this analysis.

[23]For this analysis, markets were defined as a city/state combination.

Figure 4.4.2 ***(following page)***: Customer service sensitivity and objective service quality differences based on incumbent service position.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Service quality rating	Satisfaction with queue time	Labor utilization	Visit satisfaction	Annoyances	Overall satisfaction
High service position market	-0.1196**	-0.0727**	0.0025*	-0.0637**	0.0881***	-0.0611**
	[0.0571]	[0.0310]	[0.0015]	[0.0318]	[0.0282]	[0.0284]
Queuing time (in minutes)		-0.2519***				
		[0.0078]				
Branch-level labor utilization				-4.3321***	1.8004***	-1.7567***
				[0.3532]	[0.3170]	[0.3282]
Constant	7.7045***		-1.4692		-0.6088***	
	[0.2257]		[6.4011]		[0.0718]	
Level of analysis	Customer level	Customer level	Branch level	Customer level	Customer level	Customer level
Sample selection	All rated firms	Focal incumbent	Focal incumbent	Focal incumbent	Focal incumbent	Focal incumbent
Regression model	OLS	Ordered logistic	OLS	Ordered logistic	Logistic	Ordered logistic
Customer-level control variables	No	Yes	No	Yes	Yes	Yes
Market-level control variables	No	No	Yes	No	No	No
Predicted dependent variable in high service mkts.	7.53/10.00	4.01/5.00	16.68%	4.41/5.00	36.84%	4.14/5.00
Predicted dependent variable in low service mkts.	7.65/10.00	4.06/5.00	16.43%	4.44/5.00	34.82%	4.16/5.00
Observations	20,890	23,928	2,816	23,451	23,409	23,451

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively (two-tailed tests). Brackets contain robust standard errors, clustered at the market level, except Column (3) which contains robust standard errors. Column (1) includes institution and city/state fixed effects. Additional controls for transaction type were used for columns (4) and (6). 42 customers did not respond to the question about annoyances and recent service problems. Additional customer-level controls include direct deposit indicator, count of loan, investment and deposit accounts, balances in loan, and investment and deposit accounts. Additional market-level controls include population, median household income, median age, population growth, per capita income, median home value, household growth, average household size, and gender distribution.

two-tailed). On average, customers rated service in these markets to be 1.6% below average for the institution. Indeed, in our prior analysis in Figure 4.4.1, Column (2), the positive and significant coefficient on the number of months the firm held a high service position in the two years preceding the analysis (coefficient = 0.007, $p < 0.01$) suggests that even in the absence of competitive entry or expansion, the incumbent's customers are more prone to defection in markets where it sustains a high relative service quality position for a longer period of time. There are two possible explanations for these patterns: customers may be disproportionately service sensitive due to the sorting effect previously described, or firms may exhibit service complacency, delivering objectively poorer service in markets where they face relatively weak service competition. We proceed by investigating both possibilities.

In Column (2) we model the queue time satisfaction of 23,928 randomly selected customers who engaged in face-to-face service with the focal incumbent during January 2004, as a function of the incumbent's service position in the customer's market. Controlling for the length of time the customer reported waiting in the queue, and customer-level controls, those in high service positioned markets ($C_{mt-1} = 24$) were significantly less satisfied with the length of their wait (coefficient = -0.072; $p < 0.05$ two-tailed). Indeed, the incremental dissatisfaction of customers transacting in markets with a high service quality position was the equivalent of waiting an additional 34 seconds. This result suggests that the incumbent's customers are disproportionately service sensitive in markets where it maintains a relatively high service position, which is consistent with the customer sorting explanation.

As further evidence, in Columns (3-5), we model the perceptions and behaviors of 23,451 randomly selected customers during the same time period as a function of the incumbent's relative service position, and branch-level labor utilization — a proxy for objective service quality differences. After controlling for labor utilization, customers in markets where the firm held a high quality service position still exhibited greater service sensitivity, reporting lower service satisfaction with their visit to the bank (coefficient = -0.064, $p < 0.05$ two-tailed) column (4), an increased likelihood of experiencing a recent problem or annoyance with their service (coefficient = 0.88, $p < 0.01$ two-tailed) column (5), and a lower overall level of satisfaction with the bank (coefficient = -0.061, $p < 0.05$ two-tailed) column (6) than customers transacting in non-service positioned markets, where $C_{mt-1} < 24$. These results offer further support for the customer sorting hypothesis.

A complimentary explanation for this pattern of effects is service complacency; the idea that firms that offer a high level of quality relative to local alternatives may lack incentives to maintain high objective quality levels themselves. For example, Mazzeo (2003) observed that the prevalence and duration of flight delays are increased on routes where only one airline provides direct service. Among airlines, the presence of additional competition is correlated with better on-time performance. Likewise, to the extent that banks with a high relative service quality position in a local market face limited service quality competition, they may, in turn, provide objectively poorer service. While our interviews with banking executives emphasized the standardized nature of service quality in this industry, local managers retain some discretion, particularly with regard to staffing levels. In Column (6) we model branch-level labor utilization (labor hours utilized / labor hours available) as a function of the incumbent's relative service quality position in each market and market-level controls. Labor utilization is marginally higher (1.5%) in markets where the incumbent maintains a high service quality position (coefficient = 0.003; $p < 0.10$ two-tailed), suggesting that tellers are busier, and service quality is in turn, objectively poorer in markets where the incumbent faces limited superior service quality competition. However, in Columns (5-6), we decompose labor utilization, noting that while, controlling for number of transactions demanded, scheduled labor hours are not significantly lower in high service positioned markets (coefficient = -8.178 $p = 0.28$ two-tailed), customers in high service positioned markets consume marginally more time per transaction (coefficient = 1.330, $p < 0.10$ two-tailed). These results suggest that objective service quality deficiencies in markets where the firm holds a high relative service quality position are driven by its failure to account for customer sorting, and the service-sensitive customer's tendency to consume more time per transaction.[24]

[24] This pattern of results suggests that our use of an aggregate measure of service quality in our primary analysis is a conservative choice. In particular, if customer sorting leads service quality to be objectively poorer in markets where the incumbent maintains a relatively high service quality position, and in turn, our aggregated measure over-states the relative service level of the incumbent, then the customers retained prior to entry in those markets should be marginally less service sensitive in equilibrium, and in turn, less attracted by the entry of competitors offering better service quality for higher prices. Similarly, if our aggregated measure of service quality under-states the relative level of service quality the focal incumbent offers in markets where we classify it to hold a low relative service quality position, then the customers attracted in those markets should be marginally more service sensitive in equilibrium, and in turn, less attracted by the entry of inferior service quality competitors, charging lower prices.

4.4.5 Customer-level heterogeneity (H2)

As our test of H2, we further extend the previous models to account for how a customer's reaction to service competition may depend on the profitability he or she generates for the firm. As motivated in the hypothesis development section, we use three customer characteristics that are so closely tied to profitability in retail banking that they're used for customer segmentation purposes: customer tenure, number of product classes, and checking account balances.

Along each dimension, we sort customers into deciles within their markets. We chose this strategy to account for the fact that customers in different markets may have different baseline levels of each dimension, owing to characteristics of the markets themselves. For example, it is likely that on average, markets the incumbent entered in the year 2000 would have customers with lower tenure than markets it entered ten years earlier. Assigning customers to deciles across markets, or analyzing customers in absolute terms without standardizing the profitability they generate relative to others in the markets in which they transact would fail to account for these differences.

For each profitability dimension, we selected a decile cutoff above which customers are considered high profitability. With regard to customer tenure, we define customers in the third decile and above to be high tenure ($T_i = 1$). At a minimum, these customers have transacted with the bank for more than 1 year, a significant retention milestone in retail banking. We characterize customers with an above median number of product classes in their market to have a high number of product classes ($R_i = 1$). With regard to checking account balances, we define customers in the third decile and above as being high balance customers ($B_i = 1$). At a minimum, these customers have positive, non-zero balances, which is of particular relevance to the bank. Our tests of H2, therefore, use logistic regression to estimate the following cross-sectional model on the subset of 34,964 customers who transacted in markets where the firm sustained a high relative service position prior to the event window ($C_{mt-1} = 24$):

$$z = f(\zeta_0 + \zeta_1 SS_m + \zeta_2 IS_m + \zeta_3 L_m + \zeta_4 P_{mt} + \zeta_5 X_m + \zeta_6 X_i + \zeta_7 HP_i + \zeta_8 HP_i \times SS_m) \quad (4.4)$$

Where $z = Pr(DEFECT = 1)$, and HP_i represents a proxy for high profitability on the three dimensions of interest described above. When $HP_i = T_i$ or $HP_i = R_i$, if $\zeta_8 > 0$, then vulnerability to service competition is greater for high tenure or high product class customers, respectively. Since such customers have the opportunity to experience more transactions with the firm (either over a lengthier period of time, or through a more multi-faceted relationship with the firm), such findings would be consistent with the theory that customer learning attenuates the effects of switching costs in the face of increased service competition. Alternatively, if $\zeta_8 < 0$ when $HP_i = T_i$ or $HP_i = R_i$, then high tenure and high product class customers are less vulnerable to service competition. Such a finding would suggest that switching costs dominate customer learning, inhibiting customers from seizing superior service experiences when they become available. Furthermore, if $\zeta_8 > 0$ when $HP_i = B_i$, then high balance customers are more vulnerable to service competition, whereas, if $\zeta_8 < 0$ when $HP_i = B_i$, then high balance customers are less vulnerable.

In Figure 4.4.3, column (1), we demonstrate that while high tenure customers are significantly less likely to defect than low tenure customers (coefficient = -0.523, $p < 0.01$; two-tailed), the coefficient on the interaction term of superior service entry and high tenure suggests that this effect is attenuated when superior quality competitors enter or expand in the market (coefficient = .158, $p < 0.10$; two-tailed). Indeed, for high tenure customers, the annual defection probability increases from 10.18% (with no entry) to 11.62% (following an increase in service competition). Consistently, in column (2), we show that when a customer possesses an above median number of product classes, they are considerably less likely to defect in general (coefficient = -0.463, $p < 0.01$; two-tailed), but they are disproportionately vulnerable to service competition (coefficient = 0.205, $p < 0.05$; two-tailed). The annual defection probability for high product class customers increased from 6.50% (with no entry) to 8.34% (following an increase in service competition).

While high tenure and high product class customers have generally low defection probabilities, they are disproportionately attracted to competitors offering superior service quality. These results are consistent with the account that experiences with the

Figure 4.4.3 *(following page)*: Which customers defect in response to increased service quality competition.

	(1)	(2)	(3)
Dependent variable	Defection	Defection	Defection
High tenure customer (more than 1 year)	-0.5230***		
	[0.0436]		
Superior service entry x high tenure	0.1581*		
	[0.0943]		
High product customer (above median)		-0.4629***	
		[0.0636]	
Superior service entry x high product		0.2051**	
		[0.1016]	
High balance customer (positive balances)			-1.0940***
			[0.0515]
Superior service entry x high balance			0.1779**
			[0.0878]
Superior service competitor entry	-0.0044	0.0599	0.0034
	[0.0901]	[0.0535]	[0.0678]
Inferior service competitor entry	0.0324	0.0380	0.0291
	[0.0386]	[0.0385]	[0.0383]
Local competitor entry	-0.0576	-0.0497	-0.0563
	[0.0417]	[0.0414]	[0.0421]
Mean service fee change in the market	0.0487	0.0159	0.1459
	[0.3071]	[0.3045]	[0.3131]
Lagged mean service fee change	0.2674*	0.2900*	0.2879*
	[0.1598]	[0.1627]	[0.1627]
Incumbent competitor share	-0.0348	-0.0030	-0.0921
	[0.3348]	[0.3293]	[0.3352]
Constant	78.3152	85.0662	35.6284
	[154.4906]	[152.6555]	[150.3961]
Level of analysis	Customer level	Customer level	Customer level
Sample selection	Service mkts. (consec. ≥ 2 yrs.)	Service mkts. (consec. ≥ 2 yrs.)	Service mkts. (consec. ≥ 2 yrs.)
Regression model	Logistic	Logistic	Logistic
P(Defection of Focal Customers | No Entry)	10.18%	6.50%	7.66%
P(Defection of Focal Customers | Entry)	11.62%	8.34%	9.03%
Observations	34,964	34,964	34,964

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively (two-tailed tests). Brackets contain robust standard errors, clustered by market. Additional market-level controls include population, median household income, median age, population growth, per capita income, median home value, household growth, average household size, gender distribution, and incumbent branch growth. Customer-level controls include customer tenure (in years), prior year checking, loan and investment account balances, and counts of checking, loan accounts, investment accounts, credit cards, debit cards and deposit certificates.

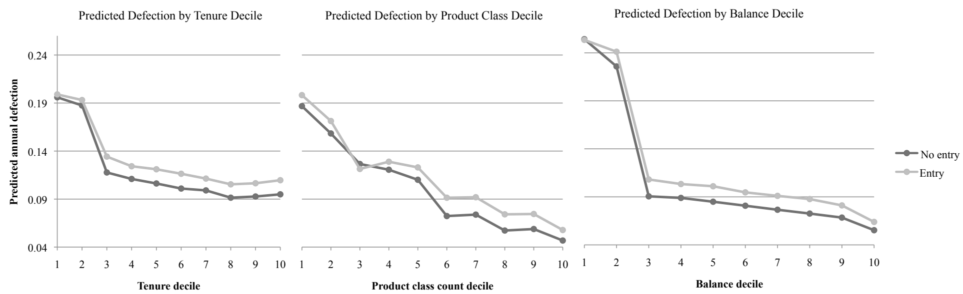


Figure 4.4.4: Predicted defection in service-positioned markets following superior service quality entry by customer type.

firm, increased through relationship duration (tenure) or relationship intensity (product breadth), engender switching costs that, on average, inhibit customer defection. However, having a high number of experiences with the firm makes these same customers more aware of its service deficiencies, facilitating exit when opportunities to experience superior service quality avail themselves.

In column (3), we show that high balance customers exhibit a pattern of relationships that is similar to those of the other high value customers described above. Customers with high balances are less likely to defect from the bank (coefficient = -1.09, $p < 0.01$; two-tailed), but this effect is attenuated in the wake of increased service competition (coefficient = 0.178, $p < 0.05$; two-tailed). Annual defection probabilities of high balance customers rose from 7.66% when no entry occurred to 9.03% following an increase in superior service quality competition.

The predicted annual defection probabilities for each tenure, product class and balance decile are depicted graphically in Figure 4.4.4. Given the direction and significance of these relationships, we reject H2 in favor of the alternative that in service positioned markets, high profitability customers are disproportionately vulnerable to increased service competition.

4.5 Long-run effects of service positioning

Our primary results to this point have been derived by estimating models of customer defection as a function of a single year of competitive entry or expansion. As such, they can be characterized as the short run effects of service competition. Given the direction of these short run effects, it stands to reason that if a firm can sustain a superior service position within a local market, it should be able to attract and retain more profitable customers and achieve superior performance outcomes in the long run.

One market-level measure of retail bank performance is average deposit balance per customer, a metric that ties directly to market-wide revenue potential. The incumbent bank provided us with the aggregated monthly balances for all of its active customer accounts in each of its markets from 2004-2006. In this section, we compare the average deposit balance per customer transacting in markets where the firm has sustained a high service quality position relative to its competitors with the average deposit balance per customer transacting in a matched sample of markets where it has not sustained such a position. In so doing, we test the proposition that sustaining a high service quality position in a market leads to superior performance outcomes.

For each of the 644 markets represented in our sample, we counted the total number of months the incumbent held an above median (high) service quality position relative to its competitors for the five-year period from 2002 through 2006. Markets in which the incumbent maintained a high service quality position for an above median number of months (more than 54) were designated treatment markets. Our set of control markets consisted of the remaining markets, where the incumbent failed to sustain a high service position for an above-median number of months. We pair treatment and control markets using nearest-neighbor propensity score matching (without replacement) on market-level characteristics that co-vary with the balance levels held by customers in each market. Markets are matched on market-level characteristics from 2004 (see Figure 4.5.1 for a complete list).

Our goal in conducting the propensity score matching is to pair treatment and control markets that are similar on as many observable dimensions as possible, excluding the relative service quality position of the incumbent. To improve the balance of our matched treatment and control markets, we trim the 15% of treatment observations for which the available control markets offer the poorest support, leaving us with 544 paired markets. Using this strategy, we significantly improve balance across the covariates (Unmatched R-squared = 0.102, $p < .01$; Matched R-squared = 0.017, $p = 0.998$). Detailed balance statistics are provided in Figure 4.5.1.

Notably, we excluded competitive branch share from the matching procedure described above, because it is highly correlated with the incumbent's service position.

Variable	Sample	Treatment	Control	% Bias	t	$p > \| t \|$
Population (2000)	Unmatched	150,000	120,000	36.7%	4.66	0.00
	Matched	140,000	130,000	13.5%	1.65	**0.10**
Current year population	Unmatched	160,000	130,000	33.8%	4.29	0.00
	Matched	150,000	140,000	12.9%	1.56	**0.12**
Median household income	Unmatched	52,621	49,640	17.3%	2.20	0.03
	Matched	50,958	50,188	4.5%	0.56	**0.58**
Household income percentile	Unmatched	63.24	60.12	12.1%	1.53	0.13
	Matched	62.53	60.87	6.4%	0.77	**0.44**
Median age	Unmatched	36.15	36.10	1.1%	0.14	0.89
	Matched	36.31	36.42	-2.2%	-0.28	**0.78**
Population growth percentile	Unmatched	52.68	55.70	13.0%	-1.65	0.09
	Matched	54.36	54.46	-0.4%	-0.05	**0.96**
Per capita income	Unmatched	28,131	25,122	26.7%	3.39	0.00
	Matched	26,960	25,847	9.9%	1.19	**0.24**
Median home value	Unmatched	240,000	180,000	32.8%	4.17	0.00
	Matched	210,000	190,000	11.1%	1.37	**1.72**
Household growth	Unmatched	1.56	1.86	-19.3%	-2.45	0.02
	Matched	1.66	1.72	-3.8%	-0.45	**0.65**
Average household size	Unmatched	2.66	2.72	-14.7%	-1.86	0.06
	Matched	2.66	2.68	-5.6%	-0.70	**0.48**
Percentage males	Unmatched	50.12	49.99	7.9%	1.00	0.32
	Matched	50.05	50.09	-2.2%	-0.26	**0.79**
Percentge females	Unmatched	49.89	50.02	-7.8%	-0.99	0.32
	Matched	49.96	49.92	2.2%	0.27	**0.79**
Population growth	Unmatched	1.48	1.73	-15.6%	-1.98	0.05
	Matched	1.56	1.59	-2.3%	-0.28	**0.78**
Population growth	Unmatched	1.48	1.73	-15.6%	-1.98	0.05
	Matched	1.56	1.59	-2.3%	-0.28	**0.78**

The psudo R-squared before matching was 0.102; $p < 0.01$. The psudo R-squred post matching was 0.017; $p = 0.998$, suggesting strong balance between the matched treatment and control markets. In addition to the covariates listed above, we also match on the percentage of each population that was within various age buckets during the time of our analysis. For parsimony, we have excluded those balance statistics, though no significant differences were present between the matched markets on these dimensions.

Figure 4.5.1: Balance statistics.

Owing to the fact that the incumbent bank faces a higher number of rated institutions offering inferior service, markets in which the incumbent has a high service position tend to have higher competitor branch share. Including it in the matching procedure would necessitate trimming a significant number of control markets to achieve reasonable balance, thereby diminishing the power of our analysis. Instead, we directly control for competitor branch share post-matching.

We test the proposition that the incumbent exhibits superior performance in markets where it sustains a high quality service position by using random effects GLS panel regression to estimate the following model on the average balances of customers transacting in treatment and control markets from 2004-2006. Standard errors are clustered by market:

$$AB_{mt} = \eta_0 + \eta_1 TR_m + \eta_2 BS_{mt} \tag{4.5}$$

Where AB_{mt} and BS_{mt} represent the average deposit balance per customer and the branch share of competitors respectively, in market m during month t. TR_m is an indicator variable used to distinguish treatment markets. If $\eta_1 > 0$, then maintaining a high quality service position relative to market competitors leads to superior performance outcomes.

In Figure 4.5.2, column (1), we show that over the period of analysis, average balances of customers were 9.71% higher in markets where the firm sustained an above median service position, which is a marginally insignificant difference (coefficient = \$765.88, $p = 0.083$; two-sided). In column (2) we control for competitive branch share as detailed in model (4.5), which reveals a significant difference (coefficient = \$926.58, $p < 0.05$; two-sided). In column (3), we further refine our model by controlling for average service fees in the market (coefficient = \$969.68, $p < 0.05$; two-sided). These results suggest that sustaining a high quality service position relative to competitors in one's local market leads to superior performance outcomes. Monthly deposit balances per customer in treatment and control markets are graphed in Figure 4.5.3.

	(1)	(2)	(3)
Dependent variable	Average active balance	Average active balance	Average active balance
High service postiion market (Treatment)	765.8778*	926.5778**	969.6787**
	[441.4468]	[434.7106]	[433.1254]
Competitive branch share		-4,343.8720***	-4,455.3572***
		[1,524.4688]	[1,536.9329]
Mean service fee in market			-41,797.5357
			[37,209.2080]
Constant	7,890.4283***	11,621.5353***	12,068.6599***
	[208.9859]	[1,353.9428]	[1,468.1158]
Level of analysis	Market level	Market level	Market level
Sample selection	Matched markets (2004-2006)	Matched markets (2004-2006)	Matched markets (2004-2006)
Regression model	GLS	GLS	GLS
Observations	19,584	19,584	19,584

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively (two-tailed tests). Brackets contain robust standard errors.

Figure 4.5.2: Relative service quality position and average customer balances.

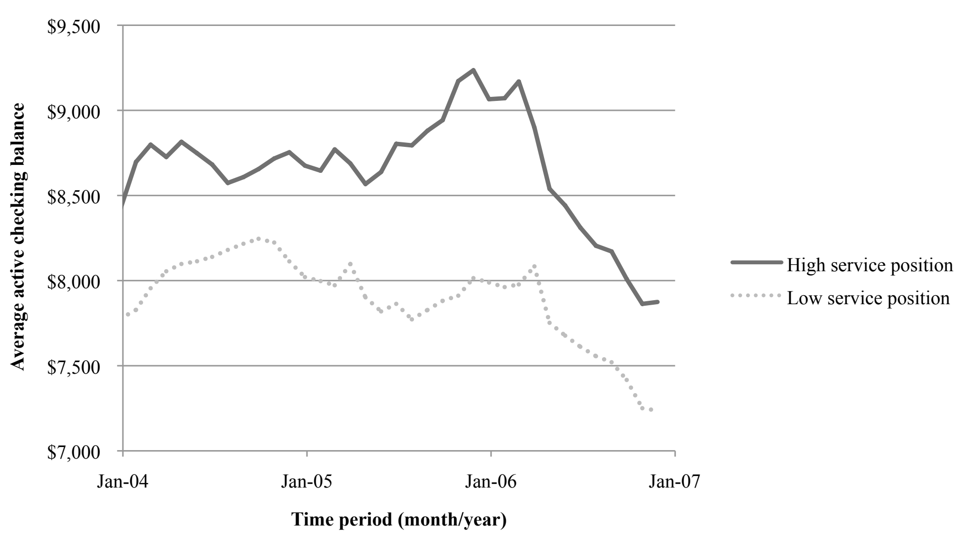


Figure 4.5.3: Matched comparison of market performance by service position.

4.6 Discussion and conclusions

One of the key dimensions upon which a firm competes is the quality of service it chooses to deliver to its customers. In this paper, we explore the links between a firm's service quality and the defection of its customers in the wake of increased service quality competition. Aspects of these relationships have been modeled in the operations management literature, but empirical evidence regarding the conditions under which customers defect from specific competitors is lacking.

While our results suggest that on a nationwide basis, increased service competition in a local market has no effect on customer defection, we show that competing firms trade-off price and service quality, and when the incumbent has sustained a high relative service quality position in the market prior to the entry event, its customers are disproportionately service sensitive and systematically attracted to competitors offering superior service quality. Conversely, when the firm fails to maintain a high service quality position within the market, its customers are more likely to defect in the wake of entry or expansion by inferior service quality (price) competitors. We provide evidence that these results are driven by a sorting effect, whereby customers tend to select the firms within their local markets that best fit their service and price sensitivities. In turn, when a competing firm enters a market offering a service/price bundle that better meets the needs of particular customers, those customers are more likely to defect.

Moreover, while the incumbent's most profitable customers — those with the longest tenure, most products, and highest balances — are less likely to defect in general; we demonstrate that in markets where the incumbent holds a high relative service quality position, its most profitable customers are disproportionately attracted by the entry or expansion of superior service quality competitors. Consistently, controlling for market-level demographic differences, we show that over the long-term, the incumbent retains customers with significantly higher balances in markets where it sustains a high relative service quality position.

These findings have several implications for operations management research and practice. First, firms that make the strategic decision not to compete on service quality may not need to be concerned about the entry or expansion of competitors offering superior service quality. Consistent with prior analytical literature on customer switching behavior, our analyses lend support to the account that customers and firms trade-off service quality and price, such that low quality service firms, attract and retain price sensitive customers who are not vulnerable to high quality service competitors. In fact, depending on the pricing dynamics in the industry and market, increased service competition may make the incumbent relatively *more* attractive to price-sensitive customers.

Second, our results highlight the risks of complacency for service positioned firms. Our analysis suggests that the entry or expansion of competitors offering superior service can have sizable short-term implications — increasing defection in our analysis by an average of 9.6% in a single year over baseline defection rates. We further show that these short-term effects have important long-term performance consequences, resulting in substantial differences in account quality between markets in which the firm maintains a high or low service position. Firms differentiating themselves on the basis of service must remain vigilant about the relative level of service they provide in order to defend against an erosion of the quality of accounts they attract and retain.

Finally, the positive association we demonstrate between service sensitivity and customer value suggests that models assuming the two are independent will underestimate the importance of service quality, and prescribe suboptimally low service levels. Initiatives to optimize a firm's service level must weigh the long-term costs of losing a firm's most valuable customers against the costs of perpetuating a level of relative service quality that is sufficient to retain them.

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Colophon

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