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The Causal Effect of Service Satisfaction on Customer Loyalty

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Abstract. We propose an instrumental-variable (IV) approach to estimate the causal effect of service satisfaction on customer loyalty by exploiting a common source of randomness in the assignment of service employees to customers in service queues. Our approach can be applied at no incremental cost by using routine repeated cross-sectional customer survey data collected by firms. The IV approach addresses multiple sources of biases that pose challenges in estimating the causal effect using cross-sectional data: (1) the upward bias from common-methods variance resulting from the joint measurement of service satisfaction and loyalty intent in surveys, (2) the attenuation bias caused by measurement errors in service satisfaction, and (3) the omitted variable bias that may be in either direction. In contrast to the common concern about the upward common-methods bias in estimates using cross-sectional survey data, we find that ordinary-least-squares substantially underestimates the causal effect, suggesting that the downward bias resulting from measurement errors and/or omitted variables is dominant. The underestimation is even more significant with a behavioral measure of loyalty, where there is no common-methods bias. This downward bias leads to significant underestimation of the positive profit impact from improving service satisfaction and can lead to underinvestment by firms in service satisfaction. Finally, we find that the causal effect of service satisfaction on loyalty is greater for more difficult types of services.

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Keywords: service satisfaction • customer loyalty • common-methods bias • measurement error • cross-sectional data

1. Introduction

Service encounters are often referred to as *moments of truth*—instances that give customers an opportunity to either form or change their impression about the firm. Service satisfaction is considered a forward-looking metric of the health of a firm's customer base because of its impact on outcomes such as word of mouth, cross-selling, and retention (e.g., Parasuraman et al. 1985, Menezes and Serbin 1991, Cronin and Taylor 1992, Zahorik and Rust 1992, Anderson et al. 2004). For this reason, firms routinely conduct surveys of customers to obtain their evaluations of service encounters (Zeithaml et al. 1996). To be sure, not only do pure service firms/organizations such as banks, hotels, restaurants, and healthcare providers conduct surveys to track their service performance, but firms selling products also use such surveys to track performance on auxiliary services such as delivery, installation, and customer support.

Despite the voluminous literature estimating the relationship between cross-sectional survey–based metrics of service satisfaction and customer loyalty (see extensive reviews in Shankar et al. 2003, Kumar et al. 2013), an enduring debate about whether increasing service satisfaction leads to greater retention and better financial results has continued.[1] One reason for this debate is that the estimated relationships between service satisfaction and loyalty are potentially biased because of multiple sources of potential bias (e.g., the common-methods problem, errors in satisfaction measurement, and omitted variables), whose aggregate impact is unknown a priori.

The goal of this paper is to propose an instrumental-variable (IV) approach for estimating the unbiased causal relationship between customer satisfaction in service encounters and loyalty. The IV approach exploits a common source of randomness, the availability of individual service employees, in the assignment of service employees to customers in service queues. Because the availability of individual service employees (of a certain qualification) at the time of a service request is independent of the waiting customer, we propose using the skill level of the assigned service employee as an instrument for service satisfaction to obtain an unbiased estimate of the causal relationship. The IV approach exploits common cross-sectional surveys of customers and can also be applied to estimate the causal relationship between service satisfaction and other customer outcome metrics and thus is of high practical value at little incremental cost for firms.

Although the relationship between service satisfaction and the various metrics of loyalty is generally expected to be positive, the magnitude of the impact of service satisfaction on loyalty can vary significantly across different settings (Shankar et al. 2003). The variation could be across different types of service activities within a firm (e.g., online/offline, installation/delivery, check-in/room service), across firms within an industry (e.g., as a result of market share, brand strength, and differentiation), and across industries (e.g., extent of competition). Given this variability in the magnitude of the relationship, managers increasingly require firm and context-specific evidence of the financial soundness of investments in service satisfaction through its effects on customer loyalty and profitability (Zeithaml et al. 1996). Thus, our IV approach, which can be applied within a firm, is of significant value to managers seeking to determine the appropriate levels of investment in improving service within their respective firms.

For our empirical application, we consider two commonly used measures of loyalty—one based on surveys and another based on behaviors. The first metric is *willingness to recommend to a friend* (hereafter referred to by its common acronym, *RTF*)—a commonly used survey-based measure of loyalty used by many firms, where RTF is measured on a 1–10 scale, and higher numbers indicate greater likelihood of recommending to a friend.[2] The second metric *(the lack of) attrition* is a behavioral metric of loyalty. In our empirical application using data from the call center of a large credit-card issuer, we define attrition (the opposite of retention) as a customer canceling a card issued by the company. Our IV approach works with both the survey and behavioral measures of loyalty.

We now elaborate on how estimates of the relationship between service satisfaction and loyalty are typically affected by the various sources of bias noted earlier.

1. *Common-methods bias.* It is well known that when multiple constructs are measured through self-reports of perceptions and impressions within the same survey (as is typically the case with measurements of customer satisfaction and RTF), one can have spurious correlations between these constructs because of response styles, social desirability, and priming effects that are independent of the true causal relations among the constructs being measured. This bias, known as *common-methods bias* (Podsakoff et al. 2003, Kamakura 2011), can lead to substantial overestimation of the relationship between satisfaction and self-reported measures of loyalty such as RTF.

2. *Attenuation bias resulting from measurement error.* Satisfaction is a perception measure and can be measured only by surveying the customer who received the service. For the same true satisfaction level, the reported satisfaction levels can vary across respondents as a result of, for example, inattention and differences in customers' response styles (Mittal and Kamakura 2001, Büschken et al. 2013).[3] The literature dealt with the measurement error problem by controlling for the moderating effects of customer characteristics (Mittal and Kamakura 2001). Although it is well known that classical measurement errors lead to attenuation biases (i.e., the magnitudes of the effects being underestimated) in the ordinary-least-squares (OLS) estimates, there has been little acknowledgment in the customer satisfaction literature that the relationship between satisfaction and loyalty can be systematically underestimated because of measurement error in the survey measures of customer satisfaction.

3. *Omitted variables.* More generally, there are likely some omitted variables that are correlated with both satisfaction and customer loyalty. For example, customers' (unobserved) expectations of service quality can affect both their satisfaction and their loyalty, and the unobserved triggers of service calls also can affect both customer satisfaction and loyalty. The sign of the bias caused by an omitted variable is specific to the omitted variable.

These sources of bias also make it challenging to even just determine the direction of the biases in the estimated effects of service satisfaction on loyalty from standard OLS regressions. In estimating the relationship between service satisfaction and stated loyalty (e.g., intent to repurchase, RTF), common-methods bias and attenuation bias will both be present. Whereas common-methods bias leads to upward bias, measurement error leads to downward bias. Furthermore, in estimating the relationship between service satisfaction and the two metrics of loyalty, the existence of possibly multiple omitted variables further adds to the challenge. The omitted variables may cause biases in the estimates in either direction, and the magnitude of the biases is typically unknown. Hence it is not even feasible to "sign" the direction of biases a priori.

We apply our IV approach to estimate the impact of service satisfaction using data from service encounter surveys and internal records from a large credit-card issuer. We focus on answering the following key research questions in our analysis:

1. What are the causal effects of service satisfaction on RTF (stated loyalty) and attrition (behavioral loyalty)?

2. Do the causal effects of service satisfaction on customer loyalty vary with the difficulty and/or the importance of the service requests?

3. Does obtaining unbiased estimates using the IV approach have a significant impact on managerial actions such as investments in service satisfaction and customer targeting with premier service?

Our results show that the IV estimates of the causal impact on customer loyalty are significantly larger than the counterparts obtained through standard OLS regressions. For behavioral loyalty (attrition), the IV estimates are around twice as large as the corresponding OLS estimates. The difference between the IV and OLS estimates are managerially significant. The IV (OLS) estimates suggest that a 0.4-point increase in satisfaction for a single service call can lower the probability of losing the calling customer in the following 18 months by 0.93 (0.47) percentage point (ppt), on average, which implies an increase in the profit per customer by \$15.1 (\$7.7).[4] Thus, basing decisions on the OLS estimates, the company would significantly underinvest in service quality.

Our IV estimates also show that the causal impact of service satisfaction is larger for calls that are more difficult to handle or more important to customers. This differential impact of customer satisfaction suggests that the company may consider creating elite teams of representatives and/or provide stronger incentives to improve the service quality of these more challenging/important types of calls.

To implement our IV approach, practitioners need to fully understand the representative assignment process and conduct tests to confirm that the conditional independence property is satisfied given the included control variables. Because the representative assignment processes are typically known within firms, implementing the tests in practice should be generally feasible.

The rest of the paper is organized as follows. Section 2 describes our data. Section 3 describes our identification strategy and estimation results. Section 4 presents additional results from applying our IV approach to studying the heterogeneity in the causal impact of satisfaction by call types. Section 5 discusses the managerial implications, and Section 6 concludes.

2. Data

We begin with a description of our data. The first part of our data consists of all the responses to the standard service satisfaction surveys conducted by a large credit-card issuer on customers who called and spoke to a service representative (hereafter *rep*) at its customer service center from March 2008 to December 2009. The survey asks customers about their satisfaction with the service of the call center rep with whom they interacted and their likelihood of recommending the company's card products to their friends (the RTF score). The survey data also include the identity of the rep who handled each call and the reason for each call. We use the survey data to construct proxies for the skill levels of reps.

The focus of our empirical analysis is on the roughly 42,000 customers who called in January 2009 and responded to the surveys after their calls. For these customers (but not for those who called and responded to surveys in other months of the approximately two-year period), our data also include the internal descriptive and behavioral data provided by the credit-card issuer. For each rep who appeared in the January 2009 data, we compute two average satisfaction scores, one using the survey data from March–November 2008 and the other using the survey data from April–December 2009. We also compute each rep's average satisfaction score separately for each type/reason using the survey data from March–November 2008 to measure the rep skill level for each type of call. These measures are our proxies for each rep's skill level.

Table 1 reports the summary statistics of our data on customers who called in January 2009. Satisfaction is measured on a scale of one to five. Overall, customers are quite satisfied, with an average of 4.28. RTF is measured on a scale of one to ten, with higher numbers indicating a higher likelihood of recommendation to a friend and ten indicating "will definitely recommend to a friend." The average of RTF across all calls is 8.54. Reflecting the company's position as a premier credit-card issuer, the average size of wallet is large, and the company has a very high average share of wallet at 55%.[5] The FICO score is very high, and the average age of the card holder is also high at about 57 years. Attrition rate—the percentage of the cards in our data being canceled on customers' request or by the company for being inactive—over the 18 months starting from February 2009 is 9%.[6]

We augment the January 2009 data with the skill level (as measured by our proxies) of the corresponding rep for each call. The last three rows of Table 1 report the summary statistics of the call-level rep skill for the January 2009 customer data. The summary statistics show significant variations in the rep skill level across calls. The standard deviation is greater for call-type-specific rep skill level, reflecting additional heterogeneity in rep skill across call types.

There is significant variation in both service satisfaction and the outcome metrics across call types. Table 2 shows the means of satisfaction, RTF, attrition rate (in the following 18 months), and share of each call type. Most saliently, the first four call types (in boldface) are those where reps may have to say no to customer requests; not surprisingly, both the average satisfaction and RTF tend to be much lower for these calls than for other call types where the service is

Table 1. Summary Statistics

Variable	Mean	Standard deviation	Min.	Max.	*N*
Satisfaction	4.28	1.02	1	5	42,337
RTF	8.54	2.34	1	10	42,337
Customer Tenure (years)	10.95	10.47	0	51	42,338
Size of Wallet ($1,000)	32.78	62.34	0	6,285	42,338
Share of Wallet (%)	54.49	34.86	0	100	42,143
FICO Score	757.56	61.64	423	997	41,948
Female	0.24	0.43	0	1	42,338
Male	0.28	0.45	0	1	42,338
Age	56.61	14.79	19	117	37,099
Customer attrition within 18 months	0.09	0.29	0	1	42,338
Rep Avg. Sat. (before)	4.31	0.25	2.42	5	41,965
Rep Avg. Sat. (after)	4.25	0.31	1.83	5	38,093
Rep-Call Type Avg. Sat. (before)	4.32	0.65	1	5	34,357

Notes. The unit of observation is a call with survey result in our January 2009 sample. The variable *Rep Avg. Sat.* (*Rep-Call Type Avg. Sat. (before)*) is the average satisfaction rating (by call type) of the rep handling a call. The means of *Female* and *Male* do not sum up to one because the gender information is missing for some customers.

mostly assessed by the quality of the experience and reps are mostly able to satisfy customer requests.

Figure 1, (a) and (b), shows that the distributions of satisfaction ratings and RTF by call types have similar patterns, as we noted in Table 2. In particular, the figures show that there are significant differences in the distributions across call types. Calls about annual percentage rate (APR) and line of credit tend to have significantly lower ratings for both satisfaction and RTF. It is thus important to control for the fixed effects of call types in estimating the causal effects of service satisfaction on the outcome metrics.

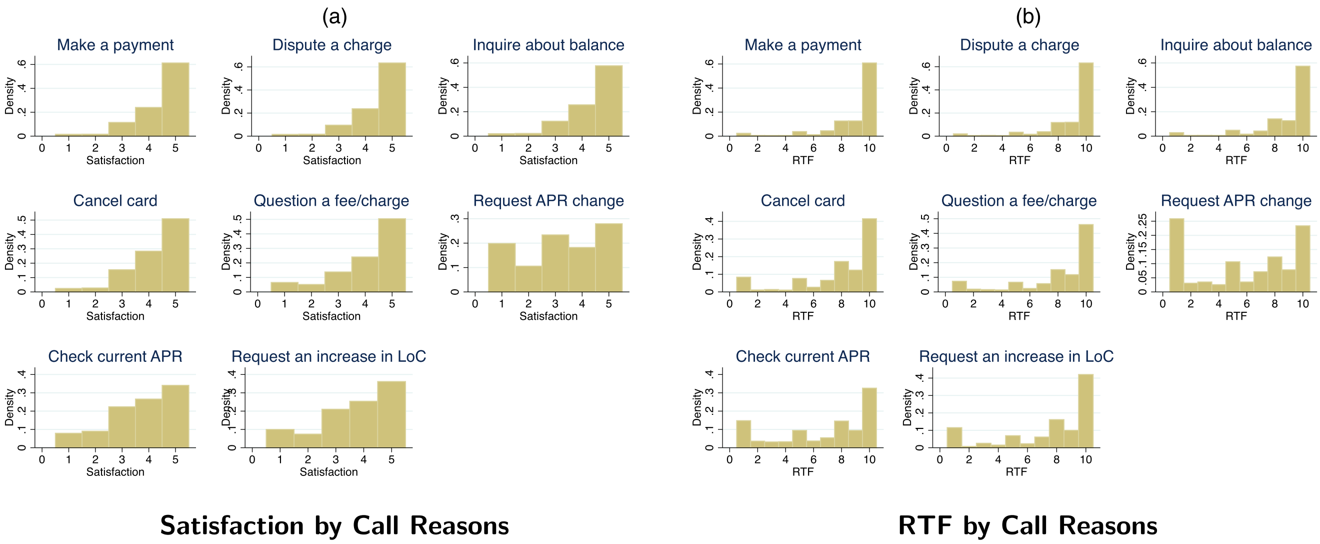
Many other unobserved factors, such as customers' satisfaction with other product features, can also

Table 2. Mean Survey Outcomes and Attrition Rate by Call Types

Call type	Satisfaction	RTF	Attrition	Percent of calls
Request a change in APR	3.239	5.801	0.094	2.75
Check current APR	3.684	6.745	0.089	2.3
Request an increase in line of credit	3.695	7.567	0.067	0.92
Check available line of credit	3.900	7.654	0.072	0.79
Make a payment or make issuer aware of a payment	4.418	8.905	0.061	13.32
Dispute an inappropriate or incorrect charge	4.460	8.983	0.060	12.16
Inquire about balance/account/bill	4.348	8.758	0.075	11.5
Question a fee or charge	4.071	7.984	0.093	6.76
Other reason	4.143	8.401	0.085	4.44
Clarify an unrecognized charge	4.540	9.101	0.055	3.99
Check recent charges/recent credits	4.474	9.023	0.059	3.9
Cancel card	4.227	7.851	0.603	2.9
Card products or benefits	4.222	8.529	0.116	2.44
Request a copy of statement or a specific charge	4.292	8.720	0.061	2.2
Replace a lost, stolen, or damaged card	4.518	9.026	0.069	1.89
Find out why a charge was denied	4.109	8.387	0.040	1.79
Inquire about user ID or password	4.394	8.722	0.056	1.74
Membership rewards	4.139	8.424	0.105	1.68
Other rewards programs such as Delta Sky	4.001	7.885	0.160	1.51
Change or correct address/email/phone	4.454	8.895	0.073	1.43
Check on the status of a renewal/replacement card	4.347	8.671	0.060	1.43
Help locate information on the website	4.306	8.658	0.057	1.4
Charge refused	4.380	8.698	0.078	1.33
Fraud issues (identity theft, stolen identity)	4.365	8.901	0.070	1.25
Traveling out of/back in town/country	4.586	9.015	0.048	1.21
Balance transfer	4.079	8.157	0.111	1.2
Change card products	4.273	8.493	0.163	1.12
Check payment due date	4.451	8.843	0.053	1

Note. Other than the two highlighted call types related to line of credit, only call reasons that are at least 1% of call volume are listed.

Figure 1. (Color online) Distributions of Satisfaction and RTF



Note. The unit of observation is a call with survey result.

affect both service satisfaction and the outcome metrics. For example, Figure 2 shows that the distributions of satisfaction ratings and RTF for calls to request changes in APR also vary by whether reps responded positively or negatively to such requests. Here we define a request to change APR being approved if and only if there was a downward adjustment in the APR for a customer from January to February 2009.[7] As expected, when the customer request was not acceded to, both satisfaction and RTF were more negatively skewed relative to when the APR reduction request was approved.

3. Empirical Analysis

We begin this section with a description of our empirical strategy. Next, we present our empirical results, comparing OLS estimates with those provided by our IV strategy to demonstrate the bias in the OLS estimates and gain insights into the direction and size of the bias. Then we discuss in detail how reps are assigned to calls and the appropriateness of our IV approach. Last, we discuss the robustness of our main findings.

3.1. The IV Approach

We focus the discussion of our IV strategy on the estimation of the following structural equation:

$$RTF_{it} = \alpha Sat_{it} + \mathbf{Z}_{it}\beta + v_{it}, \tag{1}$$

where customer i called customer service at time t, Sat_{it} is customer i's satisfaction with the service call, $\mathbf{Z}_{it}$ is a vector of exogenous control variables, and v_{it} is a scalar random variable. Let customer satisfaction be determined as follows:

$$Sat_{it} = h\big(s_{r(it)}\big) + \mathbf{Z}_{it}\gamma + u_{it}, \tag{2}$$

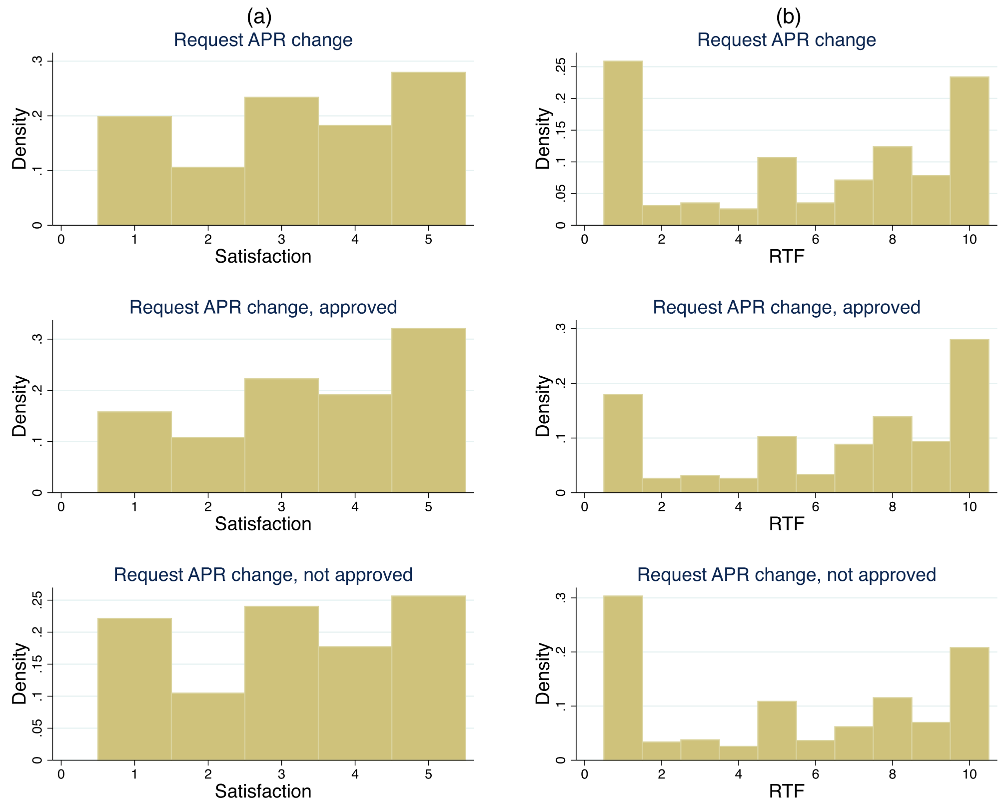
where s_r is the skill level of rep r, $r(it)$ indicates the rep who handled customer i's call at time t, $h()$ is an increasing function, and u_{it} is a scalar random variable.

The objective is to estimate α, the causal impact of customer satisfaction on RTF. As noted earlier, the survey metric of service satisfaction is a noisy measure of the customer's true level of satisfaction with the service encounter and is potentially correlated with the error term (v_{it}) because of unobserved customer-specific expectations, response style, and other omitted factors. A valid instrument here should be correlated with the customer's true satisfaction level but uncorrelated with the error term in the regression.

We propose using the skill level of the assigned rep as an instrument for Sat_{it}: conditional on the profile (which the company uses to clarify a rep's qualification for handling calls regarding certain card products, customers, and special issues) of the assigned rep, the assigned rep (and the rep's skill level in particular) is independent of the calling customer (and, consequently, RTF_{it}). In practice, exogenous external measures of rep skill levels make the ideal instruments. Such exogenous measures may also be available from hiring tests or interview ratings of the rep if sufficient correlation between these skill measures and overall satisfaction can be established.

The conditional independence property of rep skills and RTF is satisfied in our setting because the assignments of reps to calls are automated based on the reps' random availability. The conditional exogenous assignment of reps is confirmed by the company's managers with knowledge about the assignment process. Later, in Section 3.5, we discuss the rep assignment process in greater detail and provide empirical evidence for exogeneity in rep assignments.

Figure 2. (Color online) Distribution of Satisfaction and RTF by Outcome



Satisfaction by Call Reasons **RTF by Call Reasons**

Note. The unit of observation is a call with survey result.

Given that we do not have external measures of rep skill levels, we use rep-level average satisfaction ratings as proxies for reps' skill levels. To avoid the problem of certain contemporaneous factors affecting the service satisfaction with a rep in the same period, we use the average satisfaction rating of each rep in a past/future period as proxies for the skill level of reps. More specifically, let T indicate the period of the data that we use in estimating Equation (1), and let T' and T'' indicate a past period before period T and a future period after T (i.e., $\max T' < \min T$ and $\min T'' > \max T$), respectively. Then our primary proxy for the skill level of rep $r(it)$ is $\overline{Sat}_{r(it)b} = \sum_{j \in C'_{r(it)}} Sat_{jt'}/N'_{r(it)}$, where $C'_{r(it)} = \{j | j \neq i, r(jt') = r(it), t' \in T'\}$ is the set of customers (in the survey data) whose calls were also answered by rep $r(it)$ in period T', and $N'_{r(it)}$ is the number of survey observations available in period T'. Another proxy that we consider for rep skill is $\overline{Sat}_{r(it)a} = \sum_{j \in C''_{r(it)}} Sat_{j}/N''_{r(it)}$, where $C''_{r(it)} = \{j | j \neq i, r(jt'') = r(it), t'' \in T''\}$, and $N''_{r(it)}$ is the number of survey observations available in period T''. We will refer to $\overline{Sat}_{r(it)b}$ and $\overline{Sat}_{r(it)a}$ as *Rep Avg. Sat. (before)* and *Rep Avg. Sat. (after)* later in the discussion of our empirical findings.

We begin with a discussion of issues to be considered in applying our IV approach with the suggested proxies for the rep's skill. We focus our discussion on using $\overline{Sat}_{r(it)b}$ as the IV; the same discussion applies to using $\overline{Sat}_{r(it)a}$ as the IV.

To use $\overline{Sat}_{r(it)b}$ as an IV for Sat_{it}, we require that $\mathrm{Cov}(v_{it}, \overline{Sat}_{r(it)b}) = 0$, where $\mathrm{Cov}(x,y)$ indicates the covariance between random variables x and y.[8] A potential concern is that if group (card product/call type) fixed effects are present but not controlled for, it may lead to violation of the unconditional covariance condition. With group fixed effects, we have $v_{it} = \phi_{g(i)} + \epsilon_{it}$, $u_{it} = \varphi_{g(i)} + \varepsilon_{it}$ for v_{it} and u_{it} in Equations (1) and (2), respectively, where $\phi_{g(i)}$ and $\varphi_{g(i)}$ are the fixed effects of group $g(i)$ (i.e., the group pertaining to customer i) in the two equations, and ϵ_{it} and ε_{it} are idiosyncratic errors. We assume that $\mathrm{Cov}(\epsilon_{it}, \varepsilon_{jt'}) = 0$ and $\mathrm{Cov}(\epsilon_{it}, \mathbf{Z}_{jt'}) = 0$ for $i \neq j$ and $t \neq t'$, which seems reasonable because ϵ_{it} and $\varepsilon_{jt'}$ concern different customers ($i \neq j$) at different points in time and the group fixed effects have been accounted for. By the definition of $\overline{Sat}_{r(it)b}$, we have

$$\overline{Sat}_{r(it)b} = h(s_{r(it)}) + \frac{1}{N'_{r(it)}} \sum_{j \in C'_{r(it)}} \mathbf{Z}_{jt'}\gamma + \frac{1}{N'_{r(it)}} \sum_{j \in C'_{r(it)}} \left(\varphi_{g(j)} + \varepsilon_{jt'}\right).$$

Let $\bar{\varphi}_{r(it)} \equiv \sum_{j \in C'_{r(it)}} \varphi_{g(j)/N'_{r(it)}}$. Then the identification condition $\mathrm{Cov}(v_{it}, \overline{Sat}_{r(it)b}) = 0$ is equivalent to $\mathrm{Cov}(\phi_{g(i)}, h(s_{r(it)}) + \bar{\varphi}_{r(it)}) = 0$, which may be violated if there are group fixed effects that are not controlled for because (1) $\phi_{g(i)}$ and $\varphi_{g(i)}$ can be correlated and $g(j) = g(i)$ (and thus $\varphi_{g(j)} = \varphi_{g(i)}$) for some $j \in C'_{r(it)}$, and (2) the average skill level of the reps responsible for a group of customers may be correlated with certain unobserved characteristics of the group.

However, after controlling for the group fixed effects, we have $\mathrm{Cov}(\phi_{g(i)}, h(s_{r(it)}) + \bar{\varphi}_{r(it)} | g(i)) = 0$. Thus, we have $\mathrm{Cov}(v_{it}, \overline{Sat}_{r(it)b} | g(i)) = 0$, and $\overline{Sat}_{r(it)b}$ is a valid IV for Sat_{it} after controlling for group fixed effects.

In some cases, one might be concerned that $\mathrm{Cov}(\epsilon_{it}, \varepsilon_{jt'}) \neq 0$, for $t - \Delta t < t' < t$ (but $\mathrm{Cov}(\epsilon_{it}, \varepsilon_{jt'}) = 0$, for $t' < t - \Delta t$) for some $\Delta t > 0$. Recall that ϵ_{it} ($\varepsilon_{jt'}$) is the idiosyncratic error term in the RTF (satisfaction) equation after controlling for the group fixed effects. The serial correlation exists if, for example, some common shocks, such as promotion, that affected the RTF of customers in January 2009 also affect the satisfaction with customer service in a prior (later) period. In such cases, we can choose T' such that $\max T' < \min T - \Delta t$ for some Δt when using $\overline{Sat}_{r(it)b}$ as an IV. It is worth noting here that this serial-correlation issue would not be relevant if we had independent external measurements of rep skills.

In our empirical application, the primary IV we focus on is *Rep Avg. Sat. (before)*, the rep average customer satisfaction calculated using the survey data from March–November 2008. We do not use surveys from December 2008 in calculating *Rep Avg. Sat. (before)* to guard against the potential serial correlation in the error terms mentioned earlier. We calculate *Rep Avg. Sat. (after)* using the survey data from April–December 2009. To capture the differences in service quality of the same rep across different types of service requests, we also calculate *Rep-Call Type Avg. Sat. (before)*, the average rep satisfaction for each particular type of call using the surveys from March–November 2008. The first two IVs are overall measures of each rep's skill level, whereas the third IV measures each rep's skill for handling each type of call. The correlation between the first and third rep skill measures is 0.39. We note that even though the *Rep-Call Type Avg. Sat.* may more directly affect customer satisfaction, it is also measured with lower precision because of the smaller sample size given that there are much fewer calls of each type. The additional IVs allow us to conduct overidentification tests to test the exogeneity of the proposed IVs.

We report our empirical results in the next three subsections, starting with first-stage regressions and then the second-stage ones. We use the linear probability models in our analysis for their flexibility to control for a rich set of fixed effects, and we control for the fixed effects of card product by call type in all regressions.

3.2. Factors Determining Service Satisfaction

We report the first-stage regression results on the factors determining service satisfaction in Table 3. These results shed light on the relative importance of the various factors in determining service satisfaction. They also show the power of the IVs that we proposed earlier. The results in columns (1)–(3) of Table 3 show that the rep's skill is an important factor in determining service satisfaction. The estimates in column (1) show that the reported service satisfaction increases by 0.57 on average when *Rep Avg. Sat. (before)* increases by one, and *Rep Avg. Sat. (before)* alone explains 2.1% of the variations in service satisfaction. The results from column (2) are very similar to those from column (1), showing that *Rep Avg. Sat. (before)* and *Rep Avg. Sat. (after)* work similarly well as proxies for rep skill. Meanwhile, in contrast to the other two proxies, *Rep-Call Type Avg. Sat. (before)* explains only about 0.6% of the variations in *Satisfaction*, suggesting that it may work less well as an IV for *Satisfaction*. Across all specifications, the causal impacts of rep skill, as measured by the three proxies, on *Satisfaction* are statistically significant at the 0.1% level.

In contrast, the main customer characteristics, such as customer tenure and share of wallet, explain much less (around 0.16%) of the variations in service satisfaction, as seen in columns (4)–(6). Customers with higher shares of wallet and FICO scores reported higher satisfaction with their service experience. Table A.1 in the *appendix* shows that female customers also rate their satisfaction somewhat higher on average, but age does not have a significant relationship with satisfaction ratings. The relationships between customer characteristics and the reported service satisfaction can be the result, for example, of the heterogeneity in customers' response styles or actual preferences.

3.3. The Causal Effect of Satisfaction on RTF

The regressions in Table 4 show the estimated relationship between *Satisfaction* and *RTF*. The first and fourth columns present the OLS estimates, whereas the third and sixth columns present the corresponding IV (two-stage least squares (2SLS)) estimates with

Table 3. Satisfaction with Service and Rep Skill

	Dependent variable: *Satisfaction*					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Rep Avg. Sat. (before)	0.573***			0.570***		
	(0.0450)			(0.0460)		
Rep Avg. Sat. (after)		0.524***			0.520***	
		(0.0301)			(0.0311)	
Rep-Call Type Avg. Sat. (before)			0.122***			0.121***
			(0.0146)			(0.0146)
Customer Tenure (years)				−0.000296	0.0000467	−0.000149
				(0.000600)	(0.000607)	(0.000688)
Size of Wallet ($1,000)				0.0000974	0.000109	0.0000832
				(0.000101)	(0.000104)	(0.000110)
Share of Wallet (%)				0.000536***	0.000394*	0.000651***
				(0.000147)	(0.000157)	(0.000174)
FICO Score				0.000427***	0.000470***	0.000445***
				(0.000105)	(0.000116)	(0.000110)
No. of observations	40,810	38,093	32,846	40,307	37,624	32,476
R^2	0.0207	0.0264	0.0063	0.0221	0.0277	0.0078
(Incremental) F-statistics	162.2	303.1	70.2	153.6	280.2	69.1

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions.
$^*p < 0.05$; $^{***}p < 0.001$.

Rep Avg. Sat. (before) as the IV for *Satisfaction*. The IV estimates show a significant positive causal effect of *Satisfaction* on *RTF*: a one-point increase in *Satisfaction* leads to a 1.9-point increase in *RTF*. Controlling for the customer characteristics in the sixth column causes little change in the estimated effect of satisfaction. The relatively large R^2, 0.191, in the third column shows that service satisfaction is a major factor in determining RTF.

The second and fifth columns in Table 4 are reduced-form OLS regressions that include *Rep Avg. Sat. (before)* directly in the regressions. The estimates show there is a significant positive causal effect of assigning a more skillful rep on RTF. Estimates in the second column show that the rep skill (and thus customer satisfaction) in a single service encounter can explain at least 1.5% of the variation in *RTF*. This estimate is economically significant in terms of its

Table 4. Customer Satisfaction and RTF

	Dependent variable: *RTF*					
Variable	OLS	OLS	IV	OLS	OLS	IV
Satisfaction	1.204***		1.910***	1.199***		1.902***
	(0.0307)		(0.100)	(0.0313)		(0.105)
Rep Avg. Sat. (before)		1.094***			1.085***	
		(0.112)			(0.117)	
Customer Tenure (years)				0.00439***	0.00421**	0.00477***
				(0.000995)	(0.00129)	(0.000997)
Size of Wallet ($1,000)				−0.000117	−0.0000743	−0.000260
				(0.000157)	(0.000237)	(0.000167)
Share of Wallet (%)				0.00251***	0.00310***	0.00208***
				(0.000369)	(0.000424)	(0.000389)
FICO Score				−0.0000104	0.000530*	−0.000281
				(0.000211)	(0.000257)	(0.000216)
No. of observations	42,337	40,810	40,810	41,814	40,307	40,307
R^2	0.2817	0.0146	0.1907	0.2830	0.0178	0.1928
First-stage partial R^2			0.021			0.020

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

magnitude given the relatively low cost to the firm for a single call.

The comparison of OLS and IV estimates in Table 4 shows that in spite of the significant explanatory power of satisfaction, OLS significantly underestimates the impact of *Satisfaction* on *RTF*. This finding is a bit surprising because researchers typically are more concerned about the upward bias caused by the common-methods problem.

The instruments we propose are not weak instruments. For the first stage of the 2SLS regressions reported in the third and sixth columns in Table 4, the partial R^2 of *Rep Avg. Sat. (before)* is 0.021 and 0.020, respectively, and the corresponding F-statistics (for testing the null hypothesis of the first-stage coefficient of *Rep Avg. Sat. (before)* being zero) are 162 and 154, respectively. The large F-statistics ensure that *Rep Avg. Sat. (before)* is not a weak instrument for *Satisfaction* based on the F-statistic test in Staiger and Stock (1997). Furthermore, *Satisfaction* is indeed endogenous in the RTF equations, as we conjectured earlier. The robust regression-based test of exogeneity suggested by Wooldridge (1995) rejects the null hypothesis of *Satisfaction* being exogenous in the RTF equations at the 0.1% level. The corresponding F-statistics are 40 and 35.7 for the regressions reported in the third and sixth columns of Table 4, respectively.

Table 5 reports the IV estimates of the RTF equation using one of the three proposed IVs for *Satisfaction* in each column. The point estimates of the coefficient of *Satisfaction* are similar for the three IVs, showing the robustness of our IV strategy. Meanwhile, the estimates using *Rep-Call Type Avg. Sat. (before)* as the IV are less accurate than those using the other two IVs, which is not surprising given the significantly smaller partial R^2 of *Rep-Call Type Avg. Sat. (before)* in the first-stage regressions (Table 3). The results suggest that the rep average ratings are actually a less noisy measurement of each rep's relevant skill—there are far fewer survey observations per rep for each specific call type, and each rep's skills for different call types are highly correlated.

Overidentification tests (Wooldridge 1995) cannot reject the exogeneity of the IVs at any standard significance level. In particular, the p-values of the Wooldridge robust score tests are 0.702 and 0.734 for the RTF regressions with and without the controls of customer characteristics, respectively. To show the test results more directly, Table 6 presents the 2SLS estimates that include all three IVs in the first-stage regressions and the additional IVs in the second-stage regressions. None of the IVs included in the second-stage regressions are close to being statistically significant. Wald tests of the null hypothesis of the coefficients of the additional IVs being zero in the second-stage regressions lead to the same results as the corresponding robust score tests. These results provide evidence for the exogeneity of the proposed IVs.

3.4. Causal Effect of Satisfaction on Customer Loyalty

The results in this subsection show that OLS significantly underestimates the impact of customer satisfaction on loyalty, as measured by retention or lack of attrition. Table 7 presents our estimates of the impact of satisfaction on attrition. The robust endogeneity test

Table 5. Customer Satisfaction and RTF, IV Estimates

	Dependent Variable: *RTF*					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Satisfaction	1.910***	1.821***	1.670***	1.902***	1.813***	1.648***
	(0.100)	(0.0865)	(0.168)	(0.105)	(0.0892)	(0.173)
Customer Tenure (years)				0.00477***	0.00415***	0.00506***
				(0.000997)	(0.000977)	(0.00108)
Size of Wallet ($1,000)				−0.000260	−0.000223	−0.000233
				(0.000167)	(0.000162)	(0.000177)
Share of Wallet (%)				0.00208***	0.00222***	0.00227***
				(0.000389)	(0.000394)	(0.000420)
FICO Score				−0.000281	−0.000369	−0.000121
				(0.000216)	(0.000218)	(0.000236)
No. of observations	40,810	38,093	32,846	40,307	37,624	32,476
R^2	0.191	0.210	0.232	0.193	0.211	0.237
IVs	*Rep Avg. Sat. (before)*	*Rep Avg. Sat. (after)*	*Rep-Call Type Avg. Sat. (before)*	*Rep Avg. Sat. (before)*	*Rep Avg. Sat. (after)*	*Rep-Call Type Avg. Sat. (before)*
First-stage partial R^2	0.021	0.026	0.006	0.020	0.026	0.006

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions.

***$p < 0.001$.

Table 6. Testing the Exogeneity of IVs Using Overidentification Tests

	Dependent variable: *RTF*					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Satisfaction	1.731*** (0.182)	1.826*** (0.128)	1.398* (0.669)	1.732*** (0.188)	1.812*** (0.127)	1.303 (0.690)
Rep-Call Type Avg. Sat. (before)	−0.0112 (0.0253)	−0.0144 (0.0232)		−0.0141 (0.0254)	−0.0168 (0.0233)	
Rep Avg. Sat. (after)	0.0339 (0.0871)		0.152 (0.243)	0.0286 (0.0880)		0.181 (0.251)
Rep Avg. Sat. (before)		−0.0378 (0.0978)	0.132 (0.299)		−0.0319 (0.0982)	0.170 (0.307)
Customer Tenure (years)				0.00448*** (0.00105)	0.00448*** (0.00107)	0.00451*** (0.000995)
Size of Wallet ($1,000)				−0.000225 (0.000176)	−0.000224 (0.000175)	−0.000232 (0.000192)
Share of Wallet (%)				0.00222*** (0.000455)	0.00218*** (0.000452)	0.00243*** (0.000498)
FICO Score				−0.000215 (0.000250)	−0.000248 (0.000246)	−0.0000406 (0.000347)
No. of observations	29,810	29,810	29,810	29,469	29,469	29,469
R^2	0.2183	0.1982	0.2718	0.2182	0.2015	0.2777

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions. All three IVs are included in the first-stage regressions for all specifications in this table.
$^*p < 0.05$; $^{***}p < 0.001$.

of Wooldridge (1995) shows that *Satisfaction* is also endogenous in the attrition equation. The estimates show (1) that satisfaction has a significant negative causal impact on attrition and (2) that OLS significantly underestimates the magnitude of the impact. The OLS estimates of satisfaction's impact significantly underestimate the true effect and are only about one-half or less of the corresponding IV estimates. The IV estimates in the sixth column show that a one-point increase in *Satisfaction* leads to a decrease of 2.3 ppts in the attrition rate in the following 18 months. Given that this is the result of a single encounter with customer service, the effect is quite large.

Service satisfaction explains much less of the variation in attrition (as the prior literature anticipated) than for *RTF* (0.2% versus 28% in the first column of Table 7 and Table 4, respectively). Rep skill also explains much less variation in attrition than that in *RTF* (0.02% versus 1.5%). The gap may be driven by both the difference between attrition and RTF and that between behavior and intent.

Table 8 shows estimates of the attrition equation using the three different IVs. The point estimates of the satisfaction coefficient are reasonably similar, and the differences among them are statistically insignificant. The lack of statistical significance of the point estimates in columns (3) and (6) is likely because *Rep-Call Type Avg. Sat.* is a relatively weaker IV (as shown by the smaller first-stage partial R^2 of the IV). The consistent results from using different IVs show again the robustness of the proposed IV approach.

Given these findings, we consider only *Rep Avg. Sat. (before)* and *Rep Avg. Sat. (after)* as the potential IVs for *Satisfaction* in our overidentification tests. The p-values for Wooldridge's robust score tests are 0.872 and 0.761 for the specifications with and without the controls of customer characteristics, respectively. Thus, the tests again cannot reject the exogeneity of the IVs. We also implement the tests by including the extra IVs in the second-stage regressions (Wooldridge 1995). The estimates reported in Table 9 show that none of the coefficients of the additional IVs are close to being statistically significant.[9] The p-values of the coefficients of the additional IVs are the same as the p-values of the corresponding robust score tests. These results provide evidence for the exogeneity of our IVs in the attrition equation.

3.5. The Assignment of Service Reps and the IV Approach

We now explain in more detail the assignment of reps to calls and the extent to which the assignment is independent of the calling customers. For most reps, each belongs to a functional group that specializes in handling calls concerning certain card products. Within some of these major groups, a small set of reps is designated to help high-value customers (HVCMs).

Table 7. Customer Satisfaction and Attrition in the Following 18 Months

	Dependent variable: *Attrition*					
Variable	OLS	OLS	IV	OLS	OLS	IV
Satisfaction	–0.0128*** (0.00152)		–0.0301* (0.0124)	–0.0118*** (0.00150)		–0.0232* (0.0114)
Rep Avg. Sat. (before)		–0.0172* (0.00723)			–0.0132* (0.00673)	
Customer Tenure (years)				–0.00280*** (0.000326)	–0.00282*** (0.000337)	–0.00282*** (0.000335)
Size of Wallet ($1,000)				–0.000135** (0.0000450)	–0.000134** (0.0000456)	–0.000132** (0.0000450)
Share of Wallet (%)				–0.000795*** (0.0000706)	–0.000815*** (0.0000726)	–0.000802*** (0.0000734)
FICO Score				0.000253*** (0.0000426)	0.000255*** (0.0000431)	0.000265*** (0.0000427)
No. of observations	42,337	40,810	40,810	41,814	40,307	40,307
R^2	0.0022	0.0002		0.0227	0.0214	0.0214
First-stage partial R^2			0.021			0.020

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

In addition to the major groups of reps that focus on specific card products, there are several small groups of reps that focus on handling calls concerning some special issues (e.g., fraud) or with special language preferences. The (work) profiles of the reps clarify their qualifications for handling calls regarding certain card products, customers, and special service issues.

The automated call routing process that assigns available reps to calls matches rep profiles with the calling customers' status (regular versus high value) and the card products in question. A service call first in its queue gets assigned a rep from the designated group once one of them becomes available. A rep from another group may be assigned to help a customer if no reps from the designated group become available soon enough. Such less preferred assignments are necessary sometimes because longer time waiting in queues also lowers customer satisfaction. Which particular rep from a designated group (or a nondesignated group, if necessary) first becomes available and handles a call in the queue is random to, that is, independent of,

Table 8. Customer Satisfaction and Attrition in the Following 18 Months, IV Estimates

	Dependent variable: *Attrition*					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Satisfaction	–0.0301* (0.0124)	–0.0295** (0.0110)	–0.0206 (0.0198)	–0.0232* (0.0114)	–0.0263* (0.0107)	–0.0114 (0.0199)
Customer Tenure (years)				–0.00282*** (0.000335)	–0.00286*** (0.000343)	–0.00289*** (0.000362)
Size of Wallet ($1,000)				–0.000132** (0.0000450)	–0.000125** (0.0000437)	–0.000121* (0.0000475)
Share of Wallet (%)				–0.000802*** (0.0000734)	–0.000790*** (0.0000745)	–0.000814*** (0.0000815)
FICO Score				0.000265*** (0.0000427)	0.000269*** (0.0000458)	0.000267*** (0.0000480)
No. of observations	40,810	38,093	32,846	40,307	37,624	32,476
R^2			0.0004	0.0168	0.0200	0.0220
IVs	*Rep Avg. Sat. (before)*	*Rep Avg. Sat. (after)*	*Rep-Call Type Avg. Sat. (before)*	*Rep Avg. Sat. (before)*	*Rep Avg. Sat. (after)*	*Rep-Call Type Avg. Sat. (before)*
First-stage partial R^2	0.0206	0.0263	0.0062	0.0204	0.0261	0.0061

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 9. Testing the Exogeneity of IVs in the Attrition Equation

	Dependent variable: *Attrition*			
Variable	(1)	(2)	(3)	(4)
Satisfaction	–0.0352 (0.0218)	–0.0262 (0.0163)	–0.0220 (0.0214)	–0.0263 (0.0168)
Rep Avg. Sat. (after)	0.00342 (0.0121)		–0.00166 (0.0124)	
Rep Avg. Sat. (before)		–0.00315 (0.0112)		0.00153 (0.0114)
Customer Tenure (years)			–0.00287*** (0.000350)	–0.00287*** (0.000350)
Size of Wallet ($1,000)			–0.000125** (0.0000446)	–0.000125** (0.0000445)
Share of Wallet (%)			–0.000804*** (0.0000774)	–0.000802*** (0.0000755)
FICO Score			0.000272*** (0.0000430)	0.000274*** (0.0000477)
No. of observations	36,849	36,849	36,395	36,395
R^2			0.0222	0.0209

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions. The two IVs that we consider here are included in the first-stage regressions for all specifications in this table.
$^{**}p < 0.01$; $^{***}p < 0.001$.

the calling customers (in terms of, for example, their WTR or attrition in the future).

In our earlier analysis, we included the fixed effects of card product/call type and the metrics that determine customer value to control for the (nonrandom) assignment of reps by card products and customer value. In the following, we provide empirical evidence for the assignments of reps being independent of the calling customers, conditioning on the fixed effects of card products and customer value.

First, Table 10 shows the frequencies of the assignment of reps to calls by the profiles of the assigned reps and the card products in question. We are able to identify the rep profile for only a subset of the reps (928 of a total of 3,675 reps) in our sample because of data limitations.[10] The tabulation shows that, with limited exceptions, the reps are assigned to answer calls concerning the card products covered by their functional groups. For example, reps of the "charge and lending" group handle mainly calls regarding charge cards or lending cards (i.e., credit cards). Within some functional groups, some reps are designated to help high-value customers. For example, reps of "Charge Lending HVCM tier 2" are designated to help high-value customers of charge or lending cards.

Table 11 reports the fixed-effect regressions of the skill (measured by our proxies) of the assigned rep on the calling customer's characteristics, controlling for the fixed effects of card product by call type. The estimates in the first and fourth columns show that the key variables capturing the value of a customer to the firm are positively correlated with the skill (*Rep Avg. Sat. (before)*) of the assigned rep. Nonetheless, the very small R^2 values of 0.003 and 0.0028 suggest that the assignments are almost always determined by reps' random availability. Estimates in the fourth column also show that besides the customer-value-related measures, rep assignments do not depend on any customer demographic variables, suggesting no targeted rep assignments beyond those based on customer value. The regressions of the alternative proxies for rep skill confirm the same qualitative findings.

Table 12 reports the same regressions as in Table 11 using the subsample for which the rep profile information is available. The estimates show similar correlations between measures related to customer value and the skill level of the assigned rep. To show the random assignments of reps with the same profile, we control for the fixed effects of card product by call type by rep profile in the same regressions as in Table 12. Table 13 shows that the correlations between customer-value-related measures and rep skill proxies become insignificant, both statistically and in magnitude, once we further condition on the profile of the reps. In addition, the R^2 drops to close to zero for all regressions. These results suggest that the correlations we observe in Tables 11 and 12 between customer-value measures and rep skill proxies are only the result of the relatively higher skill levels of reps designated to help HVCMs.

One might be concerned that the coefficients of customer-value-related measures become insignificant in Table 13 only because there is less variation

Table 10. Frequencies of Assignment of Reps to Customers by Rep Profiles and Card Products

	Card products									
Rep profile	ChgLen card 1	ChgLen card 2	ChgLen card 3	ChgLen card 4	ChgLen card 5	Cobrand card 1	Cobrand card 2	Premium card	Other cards	Total
Charge lending tier 1	618	1,827	290	1,634	961	100	56	6	697	6,189
Charge lending HVCM tier 2	52	125	21	540	127	18	5	35	71	994
Cobrand tier 1	1	3	0	3	2	637	336	0	157	1,139
Cobrand HVCM tier 2	0	1	0	0	0	356	281	0	173	811
Premium tier 3	1	5	0	142	10	5	2	936	24	1,125
ISU tier 1	26	60	22	52	23	104	43	0	46	376
ISU tier 3	6	22	1	15	3	38	10	20	18	133
Bilingual tier 3	17	57	14	50	54	209	16	7	34	458
Other profiles	33	145	14	229	64	80	127	154	116	962
Total	754	2,245	362	2,665	1,244	1,547	876	1,158	1,336	12,187

Note. ChgLen is "charge or lending"; HVCM is "high-value customer."

available for identification after controlling for the additional fixed effects. To address this concern, we report in Table 14 the fixed-effect regression results that controls for the fixed effects of card product by call type by pseudo–rep profile, where the pseudo–rep profile is generated by a random permutation of the rep profile at the rep level. The estimates in Table 14 show that the correlations between customer-value-related measures and rep skill proxies remain significant if we control for the pseudo–rep profile as opposed to the actual rep profile. In addition, the R^2 values are also similar to the corresponding ones reported in Table 12. These additional results, together with those presented earlier, suggest that the assignment of reps is indeed random once we further condition on rep profile.

Our discussion shows that the skill level of the assigned rep is a legitimate IV for customer satisfaction once we include the necessary fixed effects and control variables, assuming that the availability of the relevant control variables for rep assignment is typically not restrictive for firms or researchers using firms' internal data.

3.6. Robustness of the Main Findings

The IV approach introduced in this paper provides a method to obtain a consistent estimate of the causal impact of service satisfaction specific to individual firms (and service activities within firms) by using routine customer survey data and internal data available within firms. The qualitative finding that the effect of satisfaction has been underestimated is likely not

Table 11. Assignment of Customer Service Reps

Variable	*Rep Avg. Sat. (before)*	*Rep Avg. Sat. (after)*	*Rep-Call Type Avg. Sat. (before)*	*Rep Avg. Sat. (before)*	*Rep Avg. Sat. (after)*	*Rep-Call Type Avg. Sat. (before)*
Size of Wallet ($1,000)	0.000177***	0.000154**	0.000244***	0.000164**	0.000145**	0.000222***
	(0.0000532)	(0.0000480)	(0.0000615)	(0.0000529)	(0.0000484)	(0.0000605)
Share of Wallet (%)	0.000133**	0.000149*	0.0000765	0.000116*	0.000121	0.0000921
	(0.0000479)	(0.0000582)	(0.000115)	(0.0000542)	(0.0000685)	(0.000118)
FICO Score	0.000115***	0.000134***	0.000176**	0.000119***	0.000122***	0.000120
	(0.0000231)	(0.0000266)	(0.0000609)	(0.0000269)	(0.0000325)	(0.0000703)
Customer Tenure (years)				0.0000473	0.0000497	−0.000194
				(0.000185)	(0.000211)	(0.000451)
Female				−0.00299	−0.000195	−0.00704
				(0.00307)	(0.00463)	(0.00837)
Age				0.0000282	−0.00000751	0.000405
				(0.000121)	(0.000151)	(0.000300)
No. of observations	40,307	37,624	32,476	35,409	33,052	28,577
R^2	0.0030	0.0020	0.0008	0.0027	0.0016	0.0006

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects card product by call type are included in all regressions.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 12. Assignment of Customer Service Reps, the Subsample with Rep Profile

Variable	*Rep Avg. Sat. (before)*	*Rep Avg. Sat. (after)*	*Rep-Call Type Avg. Sat. (before)*	*Rep Avg. Sat. (before)*	*Rep Avg. Sat. (after)*	*Rep-Call Type Avg. Sat. (before)*
Size of Wallet ($1,000)	0.0000694	0.0000290	0.000130*	0.0000611	0.0000278	0.000127*
	(0.0000436)	(0.0000540)	(0.0000569)	(0.0000418)	(0.0000569)	(0.0000549)
Share of Wallet (%)	0.000142	0.000161	−0.00000473	0.0000992	0.000176	−0.0000674
	(0.0000728)	(0.0000915)	(0.000203)	(0.0000801)	(0.000107)	(0.000206)
FICO Score	0.000122***	0.000188***	0.000208	0.000151***	0.000193***	0.000239
	(0.0000339)	(0.0000469)	(0.000109)	(0.0000403)	(0.0000526)	(0.000126)
Customer Tenure (years)				−0.000174	−0.000400	0.0000964
				(0.000257)	(0.000411)	(0.000718)
Female				−0.00941	−0.00112	−0.00957
				(0.00585)	(0.00890)	(0.0141)
Age				0.0000439	0.000369	−0.0000824
				(0.000178)	(0.000299)	(0.000526)
No. of observations	11,595	11,809	9,600	10,057	10,249	8,336
R^2	0.0019	0.0015	0.0005	0.0019	0.0014	0.0002

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects card product by call type are included in all regressions.
$^*p < 0.05$; $^{***}p < 0.001$.

limited to our specific data and company because the attenuation bias caused by the measurement error in satisfaction has not been formally addressed in the past. To obtain the quantitative estimates of satisfaction's causal impact for individual firms, our IV approach can be applied to the data from their own customer satisfaction programs.

A potential issue with our IV estimates of the causal impact of customer satisfaction is that they are based on the sample of customers who called in during the data period and responded to the follow-up surveys instead of all those who called in our data period. The survey response rate is typically about 5%, and thus response bias could be a potential issue. Addressing the response bias will not be a problem for firms because the selection effect can be controlled for by jointly estimating the RTF (attrition) equation and the binary-choice model for survey responses (cf. section 24.5 in Greene 2008). Unfortunately, the credit-card issuer with whom we worked did not provide us with the data on customers who called but did not respond to surveys. We therefore use an indirect approach based on survey response timing to test whether the response bias has a significant effect on our estimates.

The company sends the customer satisfaction survey to every customer who received service on the day after the service encounter and allows up to two weeks to receive a response. We are able to identify the survey response timing for around half the observations, but

Table 13. Assignment of Customer Service Reps, the Subsample with Rep Profile

Variable	*Rep Avg. Sat. (before)*	*Rep Avg. Sat. (after)*	*Rep-Call Type Avg. Sat. (before)*	*Rep Avg. Sat. (before)*	*Rep Avg. Sat. (after)*	*Rep-Call Type Avg. Sat. (before)*
Size of Wallet ($1,000)	0.0000147	−0.0000138	0.0000513	0.0000133	−0.00001000	0.0000443
	(0.0000234)	(0.0000162)	(0.0000438)	(0.0000231)	(0.0000155)	(0.0000396)
Share of Wallet (%)	−0.0000612	−0.0000832	−0.000284	−0.0000716	−0.0000490	−0.000395
	(0.0000601)	(0.0000654)	(0.000229)	(0.0000675)	(0.0000700)	(0.000230)
FICO Score	0.0000249	0.0000251	0.000113	0.0000268	−0.00000545	0.000144
	(0.0000276)	(0.0000366)	(0.000113)	(0.0000329)	(0.0000428)	(0.000130)
Customer Tenure (years)				−0.000146	−0.000537	0.000473
				(0.000185)	(0.000275)	(0.000765)
Female				−0.00545	−0.000879	−0.00399
				(0.00443)	(0.00573)	(0.0134)
Age				0.0000138	0.000375	−0.000149
				(0.000122)	(0.000200)	(0.000506)
No. of observations	11,595	11,809	9,600	10,057	10,249	8,336
R^2	−0.0001	−0.0001	0.0001	−0.0001	0.0003	0.0000

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product by call type by rep profile are included in all regressions.

Table 14. Assignment of Customer Service Reps, the Subsample with Rep Profile

Variable	*Rep Avg. Sat. (before)*	*Rep Avg. Sat. (after)*	*Rep-Call Type Avg. Sat. (before)*	*Rep Avg. Sat. (before)*	*Rep Avg. Sat. (after)*	*Rep-Call Type Avg. Sat. (before)*
Size of Wallet ($1,000)	0.0000434	−0.0000122	0.000104*	0.0000344	−0.0000189	0.000121*
	(0.0000423)	(0.0000618)	(0.0000504)	(0.0000417)	(0.0000671)	(0.0000493)
Share of Wallet (%)	0.000126	0.000198	−0.0000922	0.0000733	0.000187	−0.0000394
	(0.0000862)	(0.000112)	(0.000226)	(0.0000994)	(0.000133)	(0.000226)
FICO Score	0.000102*	0.000179**	0.0000793	0.000127**	0.000178**	0.0000698
	(0.0000396)	(0.0000560)	(0.000130)	(0.0000479)	(0.0000576)	(0.000152)
Customer Tenure (years)				−0.000174	−0.000397	−0.000553
				(0.000281)	(0.000444)	(0.000770)
Female				−0.0123	−0.000674	−0.00197
				(0.00703)	(0.0102)	(0.0146)
Age				0.0000147	0.000298	0.000278
				(0.000215)	(0.000379)	(0.000576)
No. of observations	11,595	11,809	9,600	10,057	10,249	8,336
R^2	0.0010	0.0015	0.0000	0.0011	0.0012	−0.0002

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product by call type by pseudo rep profile are included in all regressions, where the pseudo rep profile is generated through a random permutation of the profiles at the rep level.
$^*p < 0.05$; $^{**}p < 0.01$.

not for the rest, in our data because of how the data were shared with us. Table A.2 in the *appendix* shows that the subsample with information on survey response timing is similar to the full sample in all the summary statistics. Table 15 reports the means of *Satisfaction*, *RTF*, *Attrition*, *Age*, and *Customer Tenure* by the response timing (i.e., the number of days between the service encounter and the response to the survey). The frequency by the day of response shows that although some customers respond to the survey quickly, most customers respond to the survey only after some delay.

More important, the patterns in Table 15 suggest that the selection effect is limited to the responses within five days of the service encounter. Those who respond within five days show significantly lower average satisfaction level and RTF, but there is little variation in the average satisfaction and RTF across days for those who responded after five days. The attrition rate for those who respond on the second day is one ppt higher than that for those who respond on most other days; customers who respond earlier are somewhat older than those who respond later; and the tenures of those who respond within three days are somewhat shorter than those who respond later.

To assess the impact of the sample selection on our results, we first compare the estimates of the RTF and attrition equations based on the subsample of customers who respond within five days with the corresponding estimates based on the entire sample (see Tables 16 and 17). The first two columns in Table 16 report the OLS and IV estimates, respectively, of the RTF equation using the subsample of customers who respond within five days, and the third and fourth columns show the corresponding estimates using the entire sample. Even though the subsample of those who responded within five days is most affected by the selection effect, the OLS and IV estimates based on the subsample are not significantly different from those based on the entire sample. Table 17 shows similar findings regarding the estimates of the attrition equation.[11]

We also estimate weighted OLS and IV regressions using 0.01 and 1 as the sampling weights for those who responded within and after five days, respectively. Comparing these weighted regressions with the standard regressions helps assess how accounting for sample selection may impact our findings. The weights used in the weighted regressions follow by assuming a response rate of 5% and assuming that those who did not respond to the surveys are similar to those who responded after five days.[12] We report the results of the weighted regressions in the last two columns of Tables 16 and 17. The results from the weighted regressions are close to those from the standard regressions. The IV point estimates of the impact of customer satisfaction on RTF and attrition are a bit larger in magnitude under the weighted regressions than under the standard regressions.[13] In addition, the difference between the IV and OLS point estimates is also a bit larger under the weighted regressions than under the standard regressions. This suggests that our qualitative finding that the impact of customer satisfaction is underestimated by OLS regressions is likely robust to the sample selection problem.

It seems reasonable to assume that those who wanted to respond but could not by the time they remembered to do so are similar to customers who responded after five days. Our results in Tables 16 and 17 suggest that accounting for those who wanted but could not or forgot to respond should not significantly affect our empirical findings. Meanwhile,

Table 15. Descriptive Statistics by Time to Respond to Surveys

Days until response	Freq.	*Satisfaction*	*RTF*	*Attrition*	*Age*	*Customer Tenure*
2	678	3.57	7.42	0.11	57.21	10.93
3	699	3.75	7.81	0.09	56.63	10.52
4	1,153	3.87	7.88	0.10	56.74	11.74
5	1,430	3.93	7.91	0.10	56.25	11.39
6	3,856	4.24	8.43	0.10	56.98	11.35
7	5,755	4.26	8.43	0.10	56.76	11.24
8	3,010	4.24	8.40	0.10	55.77	11.29
9	1,313	4.24	8.33	0.12	55.45	11.72
10	1,344	4.18	8.28	0.10	55.57	10.77
11	315	4.24	8.57	0.08	54.07	11.72
12	200	4.14	8.20	0.10	53.53	9.74
13	172	4.25	8.59	0.08	54.36	9.77
14	51	4.04	8.73	0.08	55.62	11.28

Note. Based on the subsample for which the survey response timing is available.

we want to add a caveat here that it is possible that customers who responded (later) to the survey may be different from those who never respond to the survey and that our analysis does not allow us to conclude whether such a difference exists.

4. The Differential Impact of Satisfaction Across Call Types

In this section, we apply our IV strategy to assess the heterogeneity in the causal impact of service satisfaction on customer loyalty across call types. We first estimate how the difficulty of the calls moderates the causal impact of service satisfaction. Then we separately estimate the impact of service satisfaction for four specific types of calls. The latter exercise allows us to also assess the differential extent to which service satisfaction affects customer loyalty across the four types of calls.

4.1. The Heterogeneity in Satisfaction's Causal Impact Across Call Types

The effect of service satisfaction on RTF and loyalty can vary across different types of calls because of, for example, the differences in the importance of the requests to customers and the extent to which reps are able to satisfy the requests. For the analysis in this subsection, we classify calls into three categories—*hard*, *average*, and *easy*—based on the average satisfaction ratings for the calls. We also define a fourth category of calls, *cancel card*, as calls involving customers who are likely the most dissatisfied at the time of call and probably the most difficult to retain. The hard calls include calls to check or request a change in APR and to request a credit line increase; the easy calls include those to make a payment, inquire about balance, clarify an unrecognizable charge, check recent charges, replace a lost or stolen card, or inquire

Table 16. Customer Satisfaction and RTF: Robustness to Selection in Response to Surveys

	Dependent variable: *RTF*					
Variable	OLS	IV	OLS	IV	W-OLS	W-IV
Satisfaction	1.239***	1.716***	1.108***	1.941***	1.035***	2.153***
	(0.0446)	(0.187)	(0.0333)	(0.186)	(0.0317)	(0.300)
Customer Tenure (years)	0.00568	0.00811*	0.00420**	0.00474**	0.00408*	0.00352
	(0.00351)	(0.00381)	(0.00149)	(0.00157)	(0.00167)	(0.00198)
Size of Wallet ($1,000)	−0.00102*	−0.00106	−0.0000719	−0.000230	0.000146	−0.000152
	(0.000500)	(0.000593)	(0.000213)	(0.000212)	(0.000154)	(0.000223)
Share of Wallet (%)	0.00264*	0.00236	0.00301***	0.00283***	0.00308***	0.00297***
	(0.00108)	(0.00122)	(0.000537)	(0.000616)	(0.000567)	(0.000658)
FICO Score	−0.000534	−0.000686	−0.000163	−0.000513	−0.0000742	−0.000542
	(0.000688)	(0.000701)	(0.000302)	(0.000338)	(0.000328)	(0.000390)
No. of observations	3,910	3,733	19,715	18,953	19,715	18,953
R^2	0.361	0.313	0.238	0.109	0.187	—
Days until response	≤5	≤5	≤14	≤14	≤14	≤14

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions. The last two columns are weighted regressions, using 0.01 and 1 as the sampling weights for those responded within and after five days, respectively. W-OLS and W-IV indicate the weighted OLS and IV regressions, respectively.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 17. Customer Satisfaction and Attrition: Robustness to Selection in Response to Surveys

	Dependent variable: *RTF*					
Variable	OLS	IV	OLS	IV	W-OLS	W-IV
Satisfaction	−0.0133***	−0.0325	−0.0111***	−0.0432*	−0.00982***	−0.0543
	(0.00387)	(0.0219)	(0.00188)	(0.0180)	(0.00237)	(0.0297)
Customer Tenure (years)	−0.00341***	−0.00363***	−0.00324***	−0.00333***	−0.00321***	−0.00323***
	(0.000706)	(0.000743)	(0.000385)	(0.000391)	(0.000403)	(0.000415)
Size of Wallet ($1,000)	0.0000336	0.0000524	−0.000101	−0.0000950	−0.000129*	−0.000118
	(0.000138)	(0.000136)	(0.0000543)	(0.0000534)	(0.0000631)	(0.0000625)
Share of Wallet (%)	−0.00111***	−0.00112***	−0.000963***	−0.000973***	−0.000927***	−0.000938***
	(0.000187)	(0.000189)	(0.0000988)	(0.000103)	(0.000102)	(0.000106)
FICO Score	0.000222*	0.000254**	0.000325***	0.000355***	0.000350***	0.000384***
	(0.0000862)	(0.0000942)	(0.0000576)	(0.0000568)	(0.0000612)	(0.0000586)
No. of observations	3,910	3,733	19,715	18,953	19,715	18,953
R^2	0.028	0.025	0.025	0.014	0.024	0.007
No. of days until response	≤5	≤5	≤14	≤14	≤14	≤14

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions. The last two columns are weighted regressions, using 0.01 and 1 as the sampling weights for those responded within and after five days, respectively. W-OLS and W-IV indicate the weighted OLS and IV regressions, respectively.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

about user ID or password. The rest are the average calls, which include, for example, those for questioning a fee and for disputing an inappropriate charge. The hard, easy, and cancel card calls account for 6%, 36%, and 3%, respectively, of all calls in our entire survey sample.

The four categories of calls require different levels of effort by the reps. The easy calls require the least amount of effort to satisfy the customers. The average calls require some effort by the reps to, for example, follow the appropriate procedures. The hard calls require the most effort by the reps to satisfy the customers. The reps may need to examine a customer's status and make some potentially discretionary decisions to either explain why the customer's requests cannot be granted, or satisfy certain requests within their authority, or even escalate to get their managers involved.

We empirically analyze how the impact of customer satisfaction on RTF and attrition varies across the four categories of calls. The results of the RTF regressions, augmented with the interactions of *Satisfaction* and call category dummies, are reported in Table 18. The OLS regressions in the first and fourth columns show that, relative to average calls, customer satisfaction of hard (easy) calls has a significantly larger (smaller) positive impact on RTF. In line with the OLS findings, the reduced-form regressions in the second and fifth columns show that, relative to average calls, the impact of rep skill is significantly larger (smaller) for hard (easy) calls. The IV estimates in the third and sixth columns show that customer satisfaction with hard calls indeed has a significantly larger causal impact on RTF, and the impact of customer satisfaction with easy calls is smaller relative to average calls, although the difference for the latter is statistically insignificant. The insignificance of easy calls' moderating effect here is not very surprising given that the easy calls' moderating effect is also statistically less significant in the reduced-form regressions in the second and fifth columns.

The results of the augmented attrition regressions are reported in Table 19. In contrast to the results on RTF, we find that the relative difficulty of the calls do not significantly affect how customer satisfaction impacts attrition. For example, the OLS estimates in the first and fourth columns show that the impact of customer satisfaction on attrition is smaller (larger) in magnitude for easy (cancel card) calls, but the moderating effect is statistically insignificant in both the reduced-form regressions and the IV regressions.

Our findings suggest that increasing the satisfaction for the difficult calls, relative to the average calls, is more effective for improving the calling customers' overall RTF. Thus, the results suggest that the company may want to make additional investment in the quality of service for the hard calls if its objective is to improve attitudinal loyalty (as opposed to behavioral loyalty). We also note the caveat here that not finding significant heterogeneity in the impact on attrition could be the result of the relatively small number of attrition cases in our sample.

4.2. Estimating Satisfaction's Causal Impact by Call Types

The preceding analysis shows that customer satisfaction with the more difficult calls has a larger marginal impact on RTF and customer loyalty. In this

Table 18. Customer Satisfaction and RTF: Heterogeneity in the Causal Effect Across Call Types

	Dependent variable: *RTF*					
Variable	OLS	OLS	IV	OLS	OLS	IV
Satisfaction	1.231***		1.793***	1.226***		1.776***
	(0.0307)		(0.0870)	(0.0308)		(0.0881)
Satisfaction × *Hard Calls*	0.372***		0.530**	0.379***		0.564***
	(0.0555)		(0.164)	(0.0562)		(0.167)
Satisfaction × *EasyCalls*	−0.248***		−0.0997	−0.249***		−0.105
	(0.0389)		(0.248)	(0.0395)		(0.247)
Satisfaction × *Cancel Card Calls*	0.112		0.695	0.129		0.831
	(0.0945)		(0.948)	(0.0927)		(0.958)
Rep Avg. Sat. (before)		1.050***			1.027***	
		(0.0923)			(0.0928)	
Rep Avg. Sat. × *Hard Calls*		1.031***			1.095***	
		(0.250)			(0.253)	
Rep Avg. Sat. × *Easy Calls*		−0.391**			−0.377**	
		(0.135)			(0.137)	
Rep Avg. Sat. × *Cancel Card Calls*		−0.245			−0.223	
		(0.610)			(0.641)	
Customer Tenure (years)				0.00442***	0.00428***	0.00479***
				(0.000950)	(0.00125)	(0.000943)
Size of Wallet ($1,000)				−0.0000826	−0.0000412	−0.000226
				(0.000149)	(0.000232)	(0.000160)
Share of Wallet (%)				0.00258***	0.00319***	0.00217***
				(0.000353)	(0.000403)	(0.000378)
FICO Score				0.0000474	0.000553*	−0.000201
				(0.000200)	(0.000250)	(0.000211)
No. of observations	42,337	40,810	40,810	41,814	40,307	40,307
R^2	0.2881	0.0171	0.1910	0.2895	0.0205	0.1931

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions.
**p* < 0.05; ***p* < 0.01; ****p* < 0.001.

subsection, we report the analysis by a few representative call types, which shows that customer satisfaction with more difficult calls explains more variation in *RTF* and attrition and confirms again that customer satisfaction is a more influential factor for more difficult calls.

Table 20 shows that rep skills have a larger impact and explain more variation in *Satisfaction* for some types of calls than for other calls. For example, the marginal impact of *Rep Avg. Sat. (before)* is more than two times larger for type 4 calls ("Request a change in your APR") than for type 1 calls ("Inquire about your balance/account/bill"), and it explains eight times more variation in *Satisfaction* for type 4 calls than for type 1 calls. In contrast to Table 20, Table 21 shows that customer characteristics explain similarly little variation in *Satisfaction* across different call types.

Table 22 presents the estimates of the RTF equation by call types. The OLS estimates are all smaller than the IV estimates, consistent with our findings using the entire sample. Satisfaction for type 4 calls has the largest impact on RTF. The finding is consistent with the intuition that type 4 (about APR) is the most important type of the four.[14] Adding the controls of customer characteristics has little impact on these results (see Table A.3 in the *appendix*).

Table 23 shows that the IV estimates of the impact of satisfaction on attrition is negative for type 2, 3, and 4 calls and is statistically significant for type 2 and 4 calls. The R^2 value in the regressions for type 4 calls is 0.52% for OLS and 0.22% for the reduced form, both of which are noteworthy for only a single service encounter. In contrast, the impact of satisfaction on attrition for type 1 calls is negative but relatively weaker in both magnitude and statistical significance according to the OLS estimate and is insignificant according to the IV estimate. The results are consistent with the calls to "dispute an inappropriate or incorrect charge" or "request a change in APR" being more important in determining the value of card products to consumers.

5. Managerial Implications

We discuss next, through basic back-of-envelope calculations, the importance of the IV approach for managerial decisions such as investments in customer

Table 19. Customer Satisfaction and Attrition: Heterogeneity in the Causal Effect Across Call Types

	Dependent variable: *Attrition*					
Variable	OLS	OLS	IV	OLS	OLS	IV
Satisfaction	−0.0141***		−0.0387*	−0.0130***		−0.0291
	(0.00185)		(0.0169)	(0.00186)		(0.0161)
Satisfaction × *Hard Calls*	0.00486		0.0343	0.00310		0.0154
	(0.00557)		(0.0252)	(0.00571)		(0.0237)
Satisfaction × *Easy Calls*	0.00620*		0.0211	0.00562		0.0209
	(0.00300)		(0.0312)	(0.00301)		(0.0301)
Satisfaction × *Cancel Card Calls*	−0.0352*		−0.313	−0.0307		−0.178
	(0.0149)		(0.325)	(0.0171)		(0.226)
Rep Avg. Sat. (before)		−0.0226*			−0.0168	
		(0.0105)			(0.00996)	
Rep Avg. Sat. × *Hard Calls*		0.0188			0.00416	
		(0.0197)			(0.0183)	
Rep Avg. Sat. × *Easy Calls*		0.0158			0.0138	
		(0.0148)			(0.0142)	
Rep Avg. Sat. × *Cancel Card Calls*		−0.0910			−0.0479	
		(0.0528)			(0.0461)	
Customer Tenure (years)				−0.00280***	−0.00282***	−0.00281***
				(0.000327)	(0.000337)	(0.000334)
Size of Wallet ($1,000)				−0.000135**	−0.000134**	−0.000129**
				(0.0000450)	(0.0000456)	(0.0000448)
Share of Wallet (%)				−0.000793***	−0.000814***	−0.000791***
				(0.0000704)	(0.0000723)	(0.0000735)
FICO Score				0.000253***	0.000255***	0.000268***
				(0.0000425)	(0.0000430)	(0.0000427)
No. of observations	42,337	40,810	40,810	41,814	40,307	40,307
R^2	0.0028	0.0005		0.0232	0.0215	0.0216

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

service and targeted customer service. Our calculations show that biased OLS estimates can lead to a significant underinvestment in customer service.

Let us first examine the implications for calculating the average profit impact of a one-point increase in a customer's satisfaction with a call to customer service. We limit our calculation to the profit impact generated through the causal impact of a customer's satisfaction with the service call experience in January 2009 on the probability of the customer canceling his or her card in the following 18 months. Recall that a one-point increase in satisfaction lowers the customer attrition rate in the following 18 months by 1.2 ppts based on the OLS estimates (fourth column in Table 7) and by 2.3 ppts based on the IV estimates (sixth column in Table 7). Thus, we need to calculate the expected profit impact of lowering the probability of a customer canceling his or her credit card in the next

Table 20. Customer Satisfaction and Rep Skill, by Call Type

	Dependent variable: *Satisfaction*			
Variable	Type 1 calls	Type 2 calls	Type 3 calls	Type 4 calls
Rep Avg. Sat. (before)	0.434***	0.429***	0.838***	0.933***
	(0.0442)	(0.0750)	(0.109)	(0.0294)
No. of observations	4,704	5,009	2,779	1,132
R^2	0.0111	0.0135	0.0616	0.0809

Notes. Type 1 calls are to "inquire about your balance/account/bill"; type 2 calls are to "dispute an inappropriate or incorrect charge"; type 3 calls are to "question a fee or charge"; and type 4 calls are to "request a change in your APR." Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions.
***$p < 0.001$.

Table 21. Customer Satisfaction and Customer Characteristics, by Call Type

	Dependent variable: *Satisfaction*			
Variable	Type 1 calls	Type 2 calls	Type 3 calls	Type 4 calls
Customer Tenure (years)	0.000530	0.00318*	–0.000281	0.00161
	(0.00101)	(0.00118)	(0.00257)	(0.00676)
Size of Wallet ($1,000)	0.000307*	–0.000334	0.000150	–0.000273
	(0.000144)	(0.000348)	(0.0000778)	(0.00224)
Share of Wallet (%)	0.000618*	0.000310	0.00158***	–0.00120
	(0.000263)	(0.000467)	(0.000386)	(0.000948)
FICO Score	0.000745***	0.000603**	0.000770	–0.00125
	(0.000174)	(0.000203)	(0.000768)	(0.00129)
Constant	3.735***	3.946***	3.395***	4.200***
	(0.126)	(0.164)	(0.572)	(1.006)
No. of observations	4,822	5,130	2,844	1,161
R^2	0.0040	0.0046	0.0041	0.0036

Notes. Type 1 calls are to "inquire about your balance/account/bill"; type 2 calls are to "dispute an inappropriate or incorrect charge"; type 3 calls are to "question a fee or charge"; and type 4 calls are to "request a change in your APR." Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

18 months by 1.2 ppts per OLS estimate versus 2.3 ppts per IV estimate. We calculate the profit impact per customer as 1.2% (2.3%) times the average customer lifetime value (CLV), starting at the nineteenth month from January 2009.

For the customers in our sample of January 2009, the average annual profit is $244, the average annual attrition rate is 7.3%, and the average customer age is 57 years. Meanwhile, the account tenure in our sample is 4.3, 8.8, 15.7, and 30.6 years at the 50th, 75th, 90th, and 99th percentiles, respectively. Given the customer age and account tenures in our sample, we consider three different assumptions on the upper bound on the length (in years) of the remaining customer relationship for all customers in the CLV calculations: 5, 10, and 20 years. On top of these uniform upper bounds, we further assume for every customer that the customer tenure in January 2009 plus the length of the remaining customer relationship does not exceed 31 years, unless this restriction implies that the remaining customer relationship is shorter than one year, in which case we assume it to be just one year. For calculating the CLV, we assume that the company's annual discount rate as $\frac{1}{1+0.05}$. To simplify our calculation, we also assume that customer attrition occurs only at the end of each year.

To calculate the average CLV, we first calculate CLV at the individual customer level using information on the customer-specific annual profit and predicted attrition rate (Fader and Hardie 2010). To provide the estimates under more conservative attrition rate assumptions, we also calculate CLV, and the corresponding profit impact, assuming that each customer's annual attrition rate is 1.25 times the predicted annual attrition rate. We report our results for the various scenarios in Table 24.

The top panel of Table 24 shows results calculated using the predicted annual attrition rate, and the bottom panel shows results calculated using the more conservative annual attrition rate (i.e., 1.25 times the predicted annual attrition rate). Assuming that the upper bound on the remaining customer relationship is 10 years, the average CLV is $1,624.3, and thus, a one-point increase in the satisfaction with a customer service call increases the company's profit, on average, by $19.2 according to the OLS estimates and $37.6 according to the IV estimates. Under the alternative assumption of the upper bound being 5 or 20 years for the remaining customer relationship, the corresponding profit impact calculated using the IV estimates is also about two times larger than the one calculated using the OLS estimates. The bottom panel shows that assuming the more conservative annual attrition rate leads to similar results.

To provide estimates that are directly relevant to managerial decisions, we also need to know how big an increase in service satisfaction is feasible in practice. The 5th and 95th percentiles of *Rep Avg. Sat. (before)* among all the reps in our 2008–2009 survey sample are, respectively, 3.9 and 4.6. According to the estimates in column (4) of Table 3, increasing the call-handling rep's skill level, as measured by our proxy *Rep Avg. Sat. (before)*, by 0.7 leads to a 0.4-point increase in service satisfaction, on average. We report the profit impact of a 0.4-point increase in customer satisfaction in the last two rows of the two

Table 22. Customer Satisfaction and RTF, by Call Type

	Dependent variable: *RTF*			
	Type 1 calls	Type 2 calls	Type 3 calls	Type 4 calls
	Model 1: OLS			
Satisfaction	1.050***	1.152***	1.516***	1.583***
	(0.0504)	(0.0392)	(0.0485)	(0.0398)
Constant	4.184***	3.842***	1.804***	0.682***
	(0.219)	(0.175)	(0.197)	(0.129)
No. of observations	4,868	5,147	2,861	1,163
R^2	0.2174	0.2700	0.4325	0.4386
	Model 2: IV Regression			
Satisfaction	1.829***	1.400***	1.690***	2.199***
	(0.387)	(0.169)	(0.106)	(0.136)
Constant	0.796	2.736***	1.095*	−1.315**
	(1.681)	(0.753)	(0.429)	(0.439)
No. of observations	4,704	5,009	2,779	1,132
R^2	0.105	0.257	0.427	0.375
	Model 3: Reduced form			
Rep Avg. Sat. (before)	0.793***	0.601***	1.416***	2.053***
	(0.190)	(0.118)	(0.215)	(0.124)
No. of observations	4,704	5,009	2,779	1,132
R^2	0.0073	0.0054	0.0331	0.0683

Notes. Type 1 calls are to "inquire about your balance/account/bill"; type 2 calls are to "dispute an inappropriate or incorrect charge"; type 3 calls are to "question a fee or charge"; and type 4 calls are to "request a change in your APR." Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 23. Customer Satisfaction and Attrition in the Following 18 months, by Call Type

	Dependent variable: *Attrition*			
	Type 1 calls	Type 2 calls	Type 3 calls	Type 4 calls
	Model 1: OLS			
Satisfaction	−0.0102*	−0.0158***	−0.0154**	−0.0144**
	(0.00367)	(0.00387)	(0.00531)	(0.00389)
No. of observations	4,868	5,147	2,861	1,163
R^2	0.0012	0.0032	0.0041	0.0052
	Model 2: IV Regression			
Satisfaction	0.0267	−0.0570*	−0.0315	−0.0329***
	(0.0467)	(0.0270)	(0.0353)	(0.00551)
No. of observations	4,704	5,009	2,779	1,132
	Model 3: Reduced form			
Rep Avg. Sat. (before)	0.0116	−0.0245*	−0.0264	−0.0307***
	(0.0199)	(0.0111)	(0.0320)	(0.00532)
No. of observations	4,704	5,009	2,779	1,132
R^2	0.0001	0.0006	0.0011	0.0022

Notes. Type 1 calls are to "inquire about your balance/account/bill"; type 2 calls are to "dispute an inappropriate or incorrect charge"; type 3 calls are to "question a fee or charge"; and type 4 calls are to "request a change in your APR." Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

panels in Table 24. For example, assuming an upper bound of 10 years of remaining customer relationship with the (1.25 times) predicted annual attrition rate, a 0.4-point in the satisfaction with a customer service call causes an increase in the company's profit by \$7.7 (\$7.4) and \$15.1 (\$14.5), on average, according to the OLS and IV estimates, respectively.

We make two observations from these results. First, given the feasibility of an increase of 0.4 in the average customer satisfaction, basing managerial decisions on the OLS estimates can lead to an underinvestment in customer service. Second, the company may find it profitable to increase customer satisfaction by improving the skill level of its customer service workforce. This observation follows given our profit impact estimates and the fact that the cost of increasing customer satisfaction by 0.4 point is unlikely to significantly exceed \$3 per call.[15] Also note that the impact of customer satisfaction on attrition is higher for certain important calls (Table 23) than for the average call (Table 7). Thus, the investment in service quality for such important calls may be considered first. In practice, the company may improve the skill level of its customer service workforce by more effectively recruiting and retaining reps with higher skill levels. Another possible approach is to provide more training and/or incentives for learning/coaching among peers to improve servicing skills.

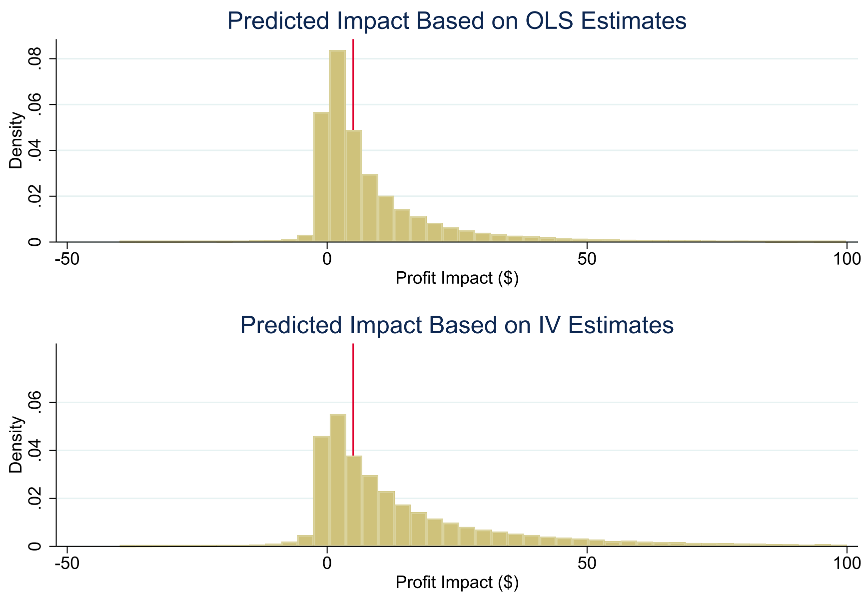
These two observations are likely robust to the sample selection problem. We illustrate this point using a conservative estimate of the profit impact for the nonrespondents. In particular, suppose that the profit impact for nonrespondents is only half that for respondents. Also, suppose that the survey response rate is just 5%. Then the average profit impact of a 0.4-point increase in service satisfaction for all the customers who called in January 2009 would be \$4.04 ($= 7.7 \times 0.05 + 7.7/2 \times 0.95$) and \$7.93 ($= 15.1 \times 0.05 + 15.1/2 \times 0.95$) according to the OLS and IV estimates, respectively. Thus, the profit impact based on the IV estimates still significantly exceeds the estimated cost, and we arrive at essentially the same conclusions as earlier.

The IV and OLS estimates can also lead to very different decisions about the group of customers that the firm may target with premium service. The profit impact of service satisfaction varies across customers

Table 24. Profit Impact of Customer Satisfaction with a Single Service Call ($)

	Upper bounds on the remaining customer relationship		
Modeling choices and assumptions	5 years	10 years	20 years
Predicted attrition rate, average annual profit per customer: $243.7			
Life-time value	1,021.9	1,624.3	2,185.6
The impact of a one-point increase in satisfaction (OLS)	12.1	19.2	25.9
The impact of a one-point increase in satisfaction (IV)	23.7	37.6	50.6
The impact of a 0.4-point increase in satisfaction (OLS)	4.8	7.7	10.4
The impact of a 0.4-point increase in satisfaction (IV)	9.5	15.1	20.3
1.25 × Predicted attrition rate, average annual profit per customer: $243.7			
Life-time value	1,000.4	1,563.3	2,064.6
The impact of a one-point increase in satisfaction (OLS)	11.8	18.5	24.4
The impact of a one-point increase in satisfaction (IV)	23.2	36.2	47.8
The impact of a 0.4-point increase in satisfaction (OLS)	4.7	7.4	9.8
The impact of a 0.4-point increase in satisfaction (IV)	9.3	14.5	20.3

Figure 3. (Color online) Customer-Specific Profit Impact of a 0.4 Increase in Satisfaction Rating



Note. The unit of observation is a customer.

because of variation in the customer-level profit and attrition rate. For example, the median and 75th percentile annual profits per customer in our sample are $142 and $402, respectively; and the attrition rate for customers calling to request a change in the APR is 9.4%, whereas that for those asking why a charge was denied is only 4%.

We report in Figure 3 the distribution of the estimated customer-level profit impact assuming the remaining customer relationship to be at most 10 years. Suppose that we want to target the higher service quality toward customers for whom the profit impact is higher than, for example, $5 per call (indicated by the vertical line in Figure 3). Then the OLS- and IV-based estimates suggest 50% and 63% of the customers in our sample should be targeted with the higher-quality service, respectively. The bias in the OLS estimates would thus lead to significantly fewer customers being targeted with premium customer service.

6. Conclusion

This paper introduces an IV approach to measure the causal relationship between service satisfaction and loyalty (stated and behavioral) using routine cross-sectional data of surveys conducted by firms after service encounters. The approach addresses multiple sources of bias in measuring the relationship—common methods, measurement error, and omitted variables—and allows us to estimate the unbiased magnitude of the relationship. The IV approach exploits the fact that service employees are typically assigned to customers based on the employees' availability, which is independent of the customers, and thus can be used by firms interested in understanding how investing in service quality and satisfaction provides returns in the form of increased loyalty (RTF and customer retention). The method is robust and can be applied even when the rep assignment depends on observable customer characteristics (e.g., when more important customers are assigned to a division of reps with higher skills) as long as we are able to control for such nonrandom elements in the service assignment process. The estimated causal effect of service satisfaction is also robust to observable customer characteristics (e.g., customer tenure) being endogenous as long as the random assignment of service reps is independent of such observable characteristics.[16]

We apply the IV approach to assessing the causal impact of the satisfaction with customer service at the call center of a large credit-card issuer. We find that the OLS approach significantly underestimates the causal effect of satisfaction on loyalty intent, suggesting that the combination of attenuation bias as a result of measurement error in customer satisfaction and (the unsigned) omitted variable bias overwhelms the inflationary bias caused by the common-methods problem. When we measure loyalty by a behavioral metric of retention, we find that the link between satisfaction and behavioral loyalty is underestimated even more by the OLS estimates relative to the IV estimates. Our results show that the return on investment in service satisfaction can potentially be grossly underestimated if we do not take care to address the various sources of bias. Our results also show that the impact of service satisfaction on the stated loyalty is larger for the more difficult/important calls, suggesting additional value in improving the service quality for such calls.

We hope the current research not only offers a practical approach to evaluate and understand the benefits of investments in customer satisfaction but also helps improve the customer experience at many firms. For academics, the approach may be applied to estimate the context-specific impact of service satisfaction on customer loyalty and other interested outcome variables. We did not investigate in this paper whether and how the Likert scale used in measuring satisfaction and RTF may impact the estimated causal relationship between satisfaction and RTF. We leave that issue for future research.

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Appendix

Table A.1. Satisfaction with Service and Rep Skill

	Dependent variable: *Satisfaction*					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Rep Avg. Sat. (before)	0.570***			0.557***		
	(0.0460)			(0.0463)		
Rep Avg. Sat. (after)		0.520***			0.525***	
		(0.0311)			(0.0306)	
Rep-Call Type Avg. Sat. (before)			0.121***			0.122***
			(0.0146)			(0.0142)
Customer Tenure (years)	−0.000471	−0.000112	−0.000340	−0.000917	−0.000638	−0.000582
	(0.000600)	(0.000603)	(0.000689)	(0.000616)	(0.000641)	(0.000712)
Size of Wallet ($1,000)	0.000101	0.000112	0.0000875	0.0000700	0.0000644	0.0000562
	(0.000102)	(0.000105)	(0.000111)	(0.000105)	(0.000107)	(0.000115)
Share of Wallet (%)	0.000550***	0.000406*	0.000665***	0.000465**	0.000335	0.000512**
	(0.000148)	(0.000158)	(0.000175)	(0.000173)	(0.000184)	(0.000198)
FICO Score	0.000423***	0.000466***	0.000441***	0.000433***	0.000450**	0.000452***
	(0.000105)	(0.000116)	(0.000110)	(0.000126)	(0.000143)	(0.000130)
Female	0.0294*	0.0268*	0.0325*	0.0257*	0.0222	0.0287*
	(0.0118)	(0.0120)	(0.0135)	(0.0120)	(0.0125)	(0.0135)
Age				−0.0000425	−0.000131	−0.000213
				(0.000360)	(0.000364)	(0.000405)

Table A.1. (Continued)

	Dependent variable: *Satisfaction*					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
No. of observations	40,307	37,624	32,476	35,409	33,052	28,577
R^2	0.0222	0.0278	0.00797	0.0214	0.0282	0.00768
(Incremental) *F*-statistics	162.2	303.1	70.2	135.1	127.3	135.6

Notes. Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table A.2. Summary Statistics, the Subsample with Survey Response Timing Information

Variable	Mean	Standard deviation	Min.	Max.	*N*
Satisfaction	4.16	1.06	1	5	19,981
Recommend	8.27	2.45	1	10	19,981
Customer Tenure (years)	11.25	10.72	0	51	19,981
Size of Wallet ($1,000)	35.56	76.62	0	6,285.13	19,981
Share of Wallet (%)	54.9	34.81	0	100	19,888
FICO Score	757.08	61.4	439	997	19,778
Customer attrition within 18 months	0.1	0.3	0	1	19,981
Rep Avg. Sat. (before)	4.31	0.26	2	5	19,207
Rep-Call Type Avg. Sat. (before)	4.32	0.65	1	5	15,636
Rep Avg. Sat. (after)	4.25	0.32	1.83	5	19,835

Notes. The unit of observation is a call with survey result in our January 2009 sample. The variable *Rep Avg. Sat.* is the average satisfaction rating of the rep handling a call.

Table A.3. Customer Satisfaction and RTF by Call Types

	Dependent variable: *RTF*			
Variable	Type 1 calls	Type 2 calls	Type 3 calls	Type 4 calls
Satisfaction	0.0374	–0.0357	–0.0271	–0.0377***
	(0.0435)	(0.0274)	(0.0322)	(0.00712)
Customer Tenure (years)	–0.00263*	–0.00126	–0.00300*	–0.00248*
	(0.00108)	(0.000926)	(0.00127)	(0.00104)
Size of Wallet ($1,000)	–0.000362***	0.0000212	–0.0000464	–0.000485
	(0.0000869)	(0.0000715)	(0.0000442)	(0.000289)
Share of Wallet (%)	–0.000760***	–0.000811***	–0.000691***	–0.000307*
	(0.000198)	(0.000215)	(0.000160)	(0.000127)
FICO Score	0.000249	0.000155	0.000188	–0.000167
	(0.000139)	(0.000108)	(0.000145)	(0.000205)
No. of observations	4,659	4,992	2,764	1,130
R^2	—	0.0114	0.0165	0.000771

Notes. Type 1 calls are to "inquire about your balance/account/bill"; type 2 calls are to "dispute an inappropriate or incorrect charge"; type 3 calls are to "question a fee or charge"; and type 4 calls are to "request a change in your APR." Standard errors, clustered at the card product/call type level, are in parentheses. The fixed effects of card product/call type are included in all regressions.
$^*p < 0.05$; $^{***}p < 0.001$.

Endnotes

[1] Service satisfaction (quality) is typically conceptualized as the gap between perceived quality and expected quality. The literature routinely uses service satisfaction and quality interchangeably because service quality can only be measured in terms of customer's satisfaction with the service encounter.

[2] RTF is the loyalty question underlying the net promoter score (NPS) metric that is recommended as a predictor of future growth (Reichheld 2003, Reichheld and Covey 2006), with NPS = percent of customers with RTF ≥ 9″ % of customers with RTF ≤ 6. Heskett and Sasser (2010) note that the RTF question is widely used in industry as a measure of loyalty because of its simplicity and intuitive appeal.

In a Bloomberg report, Kaplan (2016) notes that over two-thirds of Fortune 1000 companies use the RTF question.

[3] Note that the measurement errors in the dependent variables do not cause any biases in the estimates.

[4] A 0.4-point increase in average service satisfaction can result from increasing the call-handling rep's skill level from that of a 5th percentile rep to that of a 95th percentile rep. The numbers are calculated under the assumption that the length of the remaining customer relationship is at most 10 years for all customers.

[5] The *Size of Wallet* is defined as the total spent by a customer on all credit/debit cards over a year. The *Share of Wallet* is defined as the total spent on the company's cards by a customer divided by the customer's size of wallet.

[6] We cannot identify those who cancel because they switched to another card issued by the company. We learned from the company that such cases should be only a small share of the attrition. Furthermore, service satisfaction most likely does not have a significant impact on a customer's decision to continue to use the card in our data or switch to a different card issued by the company. Thus, the impact of the measurement issue on our estimates should be limited.

[7] The APRs for the customers in our January 2009 samples are provided by the same credit-card issuer mentioned earlier.

[8] The covariance condition follows if $\mathrm{Cov}(RTF_{it}, Sat_{jt'}|Sat_{it}, Z_{it}) = 0$ for $j \neq i$, $r(jt') = r(it)$, and $t' \in T'$. By the definition of $\overline{Sat}_{r(it)b}$, we do not require $\mathrm{Cov}(RTF_{it}, Sat_{it'}|Sat_{it}, Z_{it}) = 0$ for $t' < t$. With $t' < t$, $\mathrm{Cov}(RTF_{it}, Sat_{it'}|Sat_{it}, Z_{it}) = 0$ may not hold because $Sat_{it'}$ can directly affect RTF_{it}, and thus $Sat_{it'}$ should not be included in calculating $\overline{Sat}_{r(it)b}$.

[9] Including the two IVs in the tests leads to a smaller sample because the two IVs are missing for two different sets of reps. The estimated coefficients of *Satisfaction* become insignificant in the test regressions, likely because of the smaller sample, the correlation between the two IVs, and the more moderate impact of satisfaction on attrition (relative to on RTF).

[10] The rep identification variables that uniquely identify each rep in our data are missing for many reps in the source data of rep profiles (which is from the same company but maintained by a team different from the one that provided the data we use in our (main) analysis).

[11] The lack of significance of the coefficient of *Satisfaction* in the second column of Table 17 is likely the result of the much smaller size of the subsample.

[12] Of the 19,981 observations with response timing information, 3,960 of them are responses within five days of the service encounter (see Table 15). Thus, the weight for the subsample of responses within five days, relative to that of responses after five days, should be $3{,}960/(19{,}981/5 \times 95 + (19{,}981 - 3{,}960)) \approx 0.01$.

[13] These estimates suggest that those who responded after five days are at least as sensitive to service quality as those who responded within five days, even though the satisfaction ratings reported by the former may be more noisy. This finding helps alleviate a potential concern that those who did not respond to the survey are significantly less sensitive to service quality.

[14] A bit surprisingly, the impact of satisfaction on RTF is also quite significant for type 1 calls (balance inquiries) according to the point estimate. This pattern is in contrast to the much smaller effect of rep skill on RTF for type 1 calls than for type 4 calls. The surprisingly large point estimate in the IV regression for type 1 calls is likely a result of sample variance, noting the significantly larger variance of the corresponding estimate.

[15] Suppose that the difference in the annual total compensation between a 95th percentile rep and a 5th percentile rep is \$36,000 (which is likely an overestimate given the average annual base pay of customer service representatives ranges from \$23,000 to \$39,000 across companies according to glassdoor.com). Each rep in the company answers around 1,000 calls per month. Then the difference in the cost per call between a 5th percentile and a 95th percentile is around \$3.

[16] The IV estimate is not affected when we add additional controls that are independent of the IV estimates.

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