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Unlocking the Predictive Value of Excess and Deficit Customer Patronization Intentions

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Abstract

This study assesses the value of excess and deficit patronization intentions toward a service provider in predicting future customer behavior and its financial consequences for the provider in a continuous service context. The excess and deficit patronization measures employ widely available customer feedback data and can be used by managers to identify at-risk customers and those unlikely to defect. We argue that a customer's satisfaction provides a baseline level of patronization intentions and that excess patronization intentions—intentions greater than those that can be explained by a customer's satisfaction with a firm's offerings (i.e., the residuals in a model that regresses patronization intentions on satisfaction)—are generated in part by the presence of customer-level switching costs. Conversely, any deficit patronization intentions are generated in part by a customer's variety seeking. Using data from the financial services industry, we find that these residuals serve as indicators of the presence and extent of customer-level switching cost and variety seeking. In addition to providing measures of interesting and under-researched phenomena, this suggests that the measures may serve as proxies to test existing theories concerning switching costs and variety seeking in situations where measurement and data availability have previously limited such research.

Keywords

customer defection, patronization intentions, customer satisfaction, switching costs, variety seeking

Introduction

In seeking to improve business performance, managers are constantly looking for ways to make the best use of existing resources by extracting as much customer insight as possible from their existing data to deploy resources to serve customers as efficiently as possible. For managers in service firms, one key to accomplishing this is being able to predict which customers are most likely to switch to another provider. While some managers have access to sophisticated customer behavior databases and complex churn modeling approaches to guide them, many service firm managers have little more than standard customer feedback performance monitoring systems that collect self-reported satisfaction and attitudinal loyalty intentions (e.g., repurchase likelihood) data from samples of their customers. Analogous to the concept of excess behavioral loyalty (e.g., Goodhardt, Ehrenberg, and Chatfield, 1984), there are some suggestions in the literature that, at the firm level, such survey-based customer feedback data can be used to construct residual-based measures of attitudinal loyalty intentions not explained by customer satisfaction that may help predict customer switching (e.g., Rego, Morgan, and Fornell, 2013). We examine whether this approach can be refined and adapted to the individual customer to predict customer-level switching and other downstream customer behaviors and their service provider consequences. We examine whether this approach can be refined and adapted to predict customer-level switching and other downstream customer behaviors and consequences for the service provider(s). If such an approach can be adapted at the customer level, it may not only provide a useful way for managers to predict customer behaviors and efficiently deploy resources across customers but also provide researchers a way to study hard-to-research phenomena. The latter is particularly true since behavioral data on customer-level loyalty is hard for services researchers to obtain—particularly from large samples of firms.

To explore this question, we refine the "unexplained loyalty" measure developed by Rego, Morgan, and Fornell (2013) to identify indicators of excess and deficit intentions to patronize and apply these at the customer level to explore whether and how they may predict downstream customer behavior and its

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consequences for the service provider. Rego, Morgan, and Fornell (2013) developed and used a firm-level measure of unexplained attitudinal loyalty as an indicator of excess behavioral loyalty, which they suggested was a proxy for the presence of firm-level switching costs. Their measure differs from aggregate measures of behavioral loyalty as it is based on customer-level attitudinal data (stated preferences) aggregated at the firm level. Baseline attitudinal loyalty is defined as the satisfaction of the firm's customers with positive residuals being indicative of excess loyalty. The authors did not differentiate what the negative residuals might designate and utilized overall residuals as a proxy for switching costs, where switching costs are defined as inhibitors to customers moving between suppliers (e.g., Klemperer, 1987).

We refine the Rego, Morgan, and Fornell (2013) approach in two ways. First, we more precisely delineate the "attitudinal loyalty" component, capturing brand- or firm-related behavioral intentions as intentions to patronize (hereafter IP), referring to customers' stated intention to choose the same service provider when making repurchase or cross-purchase decisions (e.g., Evans, Christiansen, and Gill, 1996; Vlachos and Vrechopoulos, 2012). Second, we deconstruct customers' "unexplained" intentions to patronize (vis-à-vis their satisfaction with the firm's offerings) and examine the roles of "excess" and "deficit" intentions to patronize (hereafter EIP and DIP, respectively) as additional components of unexplained patronage intentions (hereafter UIP). In a series of studies, we address the following questions: (a) Does the measure of EIP hold any value for managers? (b) What explains EIP? and (c) What is the value and significance of DIP?

To assess the value of EIP and DIP we draw on satisfaction and IP data from a large national financial services provider. In our main Study 1, we use customers' satisfaction and intentions to patronize to obtain excess and deficit values of unexplained (by customer satisfaction) patronization intentions. We then examine the ability of EIP and DIP to predict subsequent switching behavior. Using a penalized logistic model to deal with relatively rare positive (switching) outcomes, we find that the EIP and DIP indicators predict customers' switching behavior significantly better than alternative attitudinal indicators like trust and willingness to recommend. In our main Study 2, we replicate the approach to estimating EIP and DIP from Study 1 and link them to objective growth in downstream customer relationships with the service provider.

In a third set of studies, we seek to offer initial insights into what drives EIP and DIP and explain its predictive value. Based on Rego, Morgan, and Fornell (2013), as well as existing literature on switching costs and variety seeking, we examine whether EIP and DIP may be driven in part by these phenomena. Using a variety of data sources, including primary experimental data as well as customer panels from the American Customer Satisfaction Index (ACSI) and J.D. Power and Associates, we find evidence suggesting that the DIP negative residuals are indicative of a customer's variety seeking, while the positive EIP residuals are indicative of a customer's switching costs.

Our study has important implications for research and practice. Using two different data sets from the financial services industry, we find that unexplained intentions to patronize (UIP) predict both customer switching behavior and other relationship diminishment behaviors even when actual switching does not occur. To further explore the value of EIP, we also use them to create empirical indicators of marketing conceptualizations of "elective" (wishing to stay) versus "non-elective" (unable to switch) customers. Aligned with marketing theorizing, this adaptation of the indicator is predictive of economic benefits to suppliers for providing positive reasons for customers to want to stay as opposed to penalties for leaving.

Second, we provide strong evidence that EIP, at least in part, is generated by higher switching costs and, therefore, may be utilized as an indicator of customer-level switching costs. Similarly, we find some evidence to indicate that deficit patronage intentions (DIP) are generated, at least in part, by greater variety seeking.

Third, we find strong evidence that the indicators of switching costs (EIP) and variety seeking (DIP) have greater predictive value than alternatives commonly used in research and practice. These alternatives include measures like customers' self-reported perceived hassle and risk in switching as well as the likelihood to recommend the service provider—three questions the data sponsor for Studies 1 and 2 uses to identify at-risk customers and customers' frequency of engagement across touchpoints like online and brick-and-mortar channels. For managers who face constraints in reaching and/or getting feedback from a census or even a large sample of their firms' customers, the process requires asking only two questions, which is minimally intrusive and can be administered at multiple points during a customer's relationship with the firm. Even such a short survey allows the construction of measures that predict valuable downstream customer behavior to better segment and/or distribute resources across customers.

Conceptual Background

To set the stage for our empirical demonstration of the role of UIP, we first offer some background highlighting the baseline on which excess and deficit patronage intentions can be determined. A focal point for our discussion is the notion that customer satisfaction can be considered an effective response to customers' experiences with a service provider and its relationship with customers' patronage intentions.

To provide an understanding of how satisfaction-explained patronage intentions provide the baseline patronage intentions on which excesses and deficits are determined, we draw on Oliver's seminal work on satisfaction (2014) and loyalty (1999). From this perspective, a customer's stated satisfaction, as captured in customer feedback surveys, represents their affective response to a cognitive evaluation of the extent to which the product/service they have purchased and consumed meets their expectations (Oliver, 2014). This provides the key "building block" of Oliver's (1999) "cognitive → affective → conative → action" hierarchy of patronage, with a customer's stated satisfaction providing the basis of the cognitive and affective aspects of consumer patronage intentions.[1] Meanwhile, the patronage intentions captured from the same customer survey provide indicators of a customer's conative intent—a brand-specific intention to repurchase or patronize the provider in the future. This patronage intention, aligned with the basis of customer satisfaction, is based on the quality of service experienced in comparison to the customer's expectations of quality.

If a customer's stated conative patronage intent is well above their level of stated satisfaction, that difference can be explained by either the customer's unwillingness to consider/choose alternative service providers because of positive feelings toward the current provider that transcend those captured in their satisfaction (e.g., brand love) or the customer's inability to consider/choose alternative service providers even if their level of satisfaction may motivate them to do so because of binding constraints (e.g., contractual obligations or apprehensions about confrontations with service staff upon switching) that make it too effortful/costly. Thus, such binding constraints/positive feelings toward brands that transcend customers' satisfaction or other factors determining whether a customer intends to stay with (or revisit) the service provider are beyond customers' perceptions of the quality of service delivered.

In the following sections, we describe the data, methods, and results from our two main studies. Study 1 leverages data from a panel of financial services customers, with responses and self-reported behaviors regarding their relationships with a range of providers, enabling us to examine how well unexplained intentions to patronize and their components predict customer switching between providers. In Study 2, we use a financial services firm's customer satisfaction tracking survey data matched to respondents' actual behaviors with the firm, allowing us to assess the predictive value of unexplained intentions to patronize for a variety of downstream customer behaviors related to future product usage and engagement with the firm. We then seek evidence regarding why unexplained intention to patronize may predict customer behaviors and their consequences that we find in a series of follow-up studies. Finally, we discuss the overall findings and consider their implications for theory and practice.

Study 1: Predicting Customer Switching

Study 1 data are drawn from a customer panel representative of the financial services industry, with survey responses from customers of 21 competing retail consumer banks for 1 year, measured in quarterly waves.[2] The same respondents are surveyed in each wave, enabling us to observe attitudinal measures, self-reported product ownership levels and changes within suppliers, and switching behavior across firms for each wave. Such panel surveys are often used to predict buyer behavior and its driving factors (Fader, Hardie, and Sen, 2014). Our sample has 3000 individual-wave customer observations, with some responding to one, two, or three waves during the year.[3] We only include participants in two or more waves so we can observe changes in customers' primary banks. After removing single-wave participants, we have 1279 respondent-wave observations, with 1097 responding in two waves and 182 in three waves. We observe 90 switching instances in those responding twice and six among those answering three waves, for a total of 96 instances (7.5%) of switching. No three-wave respondents switched twice. See Web Appendix B4 for respondent characteristics and survey items across the two studies and data sets.

To estimate UIP and its components, EIP and DIP, we regress patronization intention on satisfaction (equation (1)). The error term (ε_i) is specific to each customer (i subscript) and each wave (t). The regression model for consumer i is summarized in equation (1):

$$Patronization\ Intention_{it} = \beta_0 + \beta_1 \cdot Satisfaction_{it} + \varepsilon_{it} \quad (1)$$

Positive residuals (positive values of ε_{it}) are deemed as excess (EIP), and negative residuals (negative values of ε_{it}) are deemed as deficit (DIP). Web Appendix B2 provides the exact items. Overall satisfaction and intentions to patronize (inverse of likelihood to leave the primary bank within 6 months) are measured on a 10-point Likert scale.[4] The regression estimates are provided in Web Appendix C. Web Appendix D1 and D2 provide descriptive statistics and correlations for Study 1. It should be mentioned here that the measures we use across all studies that we define as patronage intentions also broadly correlate with the survey measure asking customers to rate their loyalty to the provider. Details are provided in Web Appendix D3. Web Appendix L provides a scatter plot of the patronage intention-satisfaction regression.

Predicting Switching Behavior

We measured customers' actual switching behaviors among different providers by observing whether they changed their self-reported primary bank from one survey wave to the next (i.e., reported a different primary bank in the next period). Switching behavior is dummy coded as zero if no switching occurred between survey waves and one if switching occurred. We excluded customers who changed their primary residential ZIP code between waves to prevent capturing buyers who switched involuntarily (e.g., after not finding the same provider near a new home).

While a traditional logit approach could be used to assess the relative predictive value of our customer-level switching costs indicator, since switching is somewhat rare (7.5% incidence) and our 1279 observations sample size is modest, this may introduce inefficient and biased estimates (King and Zeng, 2001). Therefore, it is necessary to use a rare event-adjusted logistic regression. Similar to Kanuri and Andrews (2019) and Salisbury and Zhao (2020), we use a penalized likelihood-based logistic regression: the Firth logit model (Firth, 1993).[5]

Variable Details

The predictive model incorporates known predictors of behavioral switching and customer characteristics, including the estimated individual customer-level switching cost indicator along with attitudinal measures of satisfaction, loyalty, trust (each assessed via a single survey item), engagement with the supplier (sum of self-reported interactions via firm-owned such channels as ATMs, branches, phone, online or mobile banking, and the firm's website), and customer-level demographic indicators (see Web Appendices B1 and B2). Web Appendix B3 provides the respondent characteristics.

Results

As noted earlier, the estimated model includes several predictors of behavioral loyalty, including (a) intentions to patronize, an indicator of positive firm evaluations with previous exchange experiences (Brakus, Schmitt, and Zarantonello, 2009; Liu-Thompkins and Tam 2013); (b) engagement, proxied by customers' interactions with the firm via firm-owned channels, which may indicate a desire to maintain a relationship (Moorman, Zaltman, and Deshpande 1992); (c) trust, signaling confidence in the reliability and integrity of a seller (Morgan and Hunt 1994); (d) willingness to recommend; and (e) satisfaction, which summarizes the valence of customers' service experiences. We develop three models: excess (EIP), deficit (DIP), and satisfaction-explained patronization (SEP). Table 1 shows the estimates. We observe that it is the DIP component of UIP that predicts switching rather than the EIP component, while SEP is also insignificant.

To assess the robustness of our findings, we investigate whether there is a non-linear component to the satisfaction-intended patronization relationship. Past literature (e.g., Aksoy et al., 2013) has shown that delight (very high levels of satisfaction) may create a supranormal impact on both attitudinal and behavioral outcomes. Similarly, the literature on customer reviews (e.g., Schoenmueller, Netzer, and Stahl, 2020) indicates that it is mainly delighted and extremely upset customers who post such reviews. Our analyses (see Web Appendix H1) indicate that non-linearity (with regard to satisfaction) does not seem to be an issue in our data, perhaps because such polarity and its consequences might be less common in financial services. In this context, past research (e.g., Whitlark, Geurts, and Swenson, 1993) has indicated that the relationship between intended and behavioral loyalty may be stronger if intended loyalty is weighted appropriately. Using a coding scheme from their paper, we find support for their results in our data, finding that our substantive findings remain unchanged (see Web Appendices H2 and H3).

Table 1. Study 1: Excess and Deficit Intentions to Patronize and Future Switching Behavior.

Variable	Future Switching	Future Switching	Future Switching	Future Switching	Future Switching
Overall residual (UIP)			−0.295***		
			(0.085)		
DIP				−0.395**	
				(0.146)	
EIP					−0.010
					(0.331)
SEP		−0.143			
		(0.110)			
Trust	−0.049	0.023	0.005	−0.042	−0.067
	(0.044)	(0.048)	(0.047)	(0.061)	(0.062)
Engagement	−0.024*	−0.022	−0.022	−0.017	−0.032*
	(0.012)	(0.012)	(0.012)	(0.018)	(0.015)
Recommend	−0.011	−0.026	0.015	0.084	−0.033
	(0.057)	(0.059)	(0.059)	(0.080)	(0.087)
Age	0.040	0.088	0.076	−0.095	0.174
	(0.079)	(0.081)	(0.081)	(0.128)	(0.107)
Education	−0.049	−0.029	−0.030	−0.113	0.030
	(0.068)	(0.069)	(0.069)	(0.105)	(0.094)
Race (Caucasian)	0.267	0.412	0.398	0.503	0.247
	(0.337)	(0.342)	(0.341)	(0.449)	(0.543)
Race (Hispanic)	−0.222	−0.259	−0.227	0.353	0.220
	(0.779)	(0.777)	(0.775)	(0.835)	(0.815)
Gender	0.069	0.085	0.072	0.073	0.032
	(0.172)	(0.174)	(0.174)	(0.273)	(0.227)
Constant	−1.835*	−1.884*	−2.729***	−1.431	−4.405***
	(0.728)	(0.733)	(0.785)	(1.168)	(1.100)
LL	453.92	444.51	448.32	171.95	270.99
Obs	1,279	1,279	1,279	424	855

Notes: Standard errors reported below estimates in parentheses. ***$p < .001$, **$p < .01$, and *$p < .05$. SEP is satisfaction-explained intentions to patronize. DIP is deficit intentions to patronize, and EIP is excess intentions to patronize.

Study 1 Discussion

Study 1 demonstrates our approach to understanding the value and impact of EIP and DIP and shows the ability of DIP to predict future customer switching behavior. Rego, Morgan, and Fornell (2013) do not distinguish between the positive and negative residuals, a distinction that holds important connotations for understanding why switching behavior may be occurring. Overall, these results indicate that managers can use attitudinal data commonly found in firms' VOC systems to identify customers at risk of defecting.[6]

Study 2: Segmenting Customers

In Study 2, we examine whether unexplained intentions to patronize can also be used to classify customers into segments based on their motivation to stay in a relationship with a service provider in a way that predicts future customer buying behavior and profitability. If so, managers can use the new measure to not only identify "at-risk" customers for differential treatment but also distinguish customers who are likely to remain abnormally loyal. This may offer additional opportunities for resource allocation optimization in firms' CRM programs. Furthermore, the ability to use existing attitudinal data to predict changes in buyer behavior can be extremely valuable since the alternative of observing behavior changes is often only possible when it is either too late or too costly for firms to reverse these changes (Homburg, Steiner, and Totzek, 2009).

Data on Customer-Level Attitudes, Behavior, and Performance

The data for Study 2 are from a survey of a single financial service provider's current customers, matched with internal records of those customers' behaviors, including product ownership, channel usage, revenue, tenure, and profitability. The representative sample was built through randomized surveys (i.e., respondents were selected randomly from the firm's customer population). The behavioral data reflect each customer's entire relationship with the firm (e.g., tenure and first product) and their activity over a 13-month period (e.g., product and channel usage, revenue, fees incurred, and profitability). The survey includes questions regarding customers' satisfaction with various aspects of their relationship with the bank and their intended future behaviors (see Appendices A and B for details). Customer satisfaction is measured across products owned, channels used, and whether respondents have encountered problems with any aspect of their relationship with the firm. The survey is conducted monthly, with sampled customers only surveyed once during the 13-month survey period. Thus, for each respondent, our database includes 13 months of behavioral data summarizing the customer's relationship with the firm and attitudinal data collected once for one of those 13 months. Depending on the survey timing, the data allow us to observe survey responses, followed by up to 12 months (and as little as 1 month) of each customer's behavioral data with the firm. The database includes 59,935 observations, about 5000 per month (see Web Appendices E and B1–B3 for details on behavioral and survey items and Web Appendix F for summary statistics and correlations for key variables).

Disaggregating Unexplained Intentions to Patronize

As in Study 1, we use the attitudinal data to estimate UIP using residuals from equation (1). Web Appendix I provides a scatter plot of the patronage intention-satisfaction regression. Regression estimates are provided in Web Appendix G. However, the main purpose of Study 2 is to use the estimated UIP to classify the firm's customers into three conceptually distinct segments and then examine the utility of this segmentation in terms of the relationship and behavior profiles of each segment. To this end, we first use a plus/minus one standard deviation band around the zero residual to identify those customers whose likelihood to remain in a relationship with the bank is proportional to their satisfaction—i.e., predicted intentions based on their satisfaction are "relatively close" to their observed intentions. Beggs and Klemperer (1992) posit that rational customers engage with a firm while considering the costs and benefits of making a purchase before exhibiting repeat purchase behavior in the future. The plus/minus one standard deviation interval identifies customers who make such satisfaction-informed purchase decisions, with switching costs or variety seeking playing less of a role. We label those whose satisfaction closely predicts their intended patronage as *rational*. Over a finite period, such rational customers may either increase or decrease purchases and investments with their primary supplier, depending on their current satisfaction with its offerings.

Second, we use positive residuals larger than one standard deviation to identify customers who are likely to resist defecting even if their satisfaction is low. Customers with substantial positive residuals exhibit disproportionately high levels of intended patronage for a given level of satisfaction—we label these as *stayers*. Aaker (1996) proposes that attitude strength indicates loyalty, with higher levels of patronage intentions positively impacting subsequent patronization behaviors. Thus, from a behavioral perspective, customers classified as *stayers* should exhibit the highest growth in their future relationship with the supplier relative to other customers.

Third, we use negative residuals larger (in absolute value) than one standard deviation to identify customers who are most likely to buy from other suppliers, even if they may have favorable evaluations of their primary supplier's offering (Sánchez-Garcia et al., 2012)—i.e., their intended patronage is significantly below their predicted patronage based on their reported satisfaction level. We label these customers *variety seekers*, as they are less likely to deepen a relationship with a primary supplier even when satisfied with that supplier's offering (Lee and Neale, 2012). Over time, we expect *variety seekers* to gradually scale down their investments with their primary supplier (relationship diminishment) and even switch to other providers (see Figure 1 for an illustration of these segments).

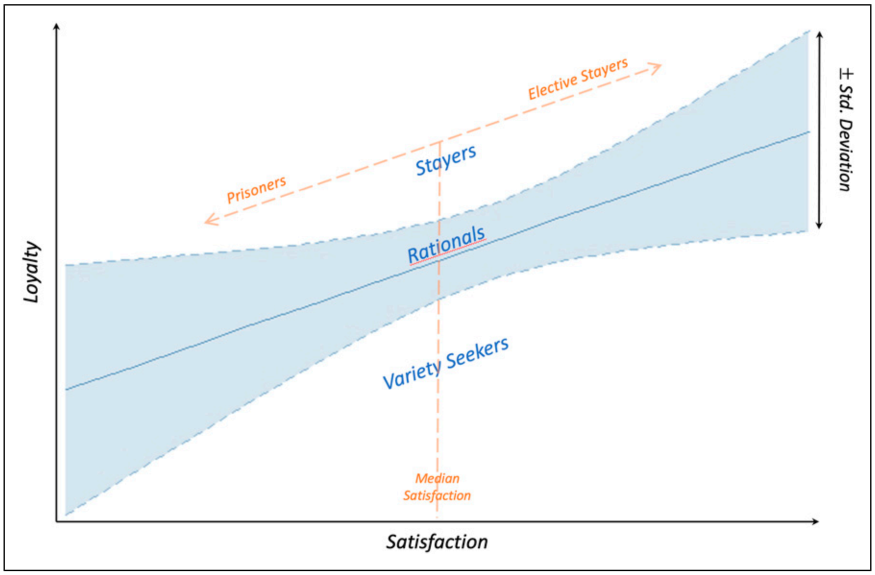

Figure 1. Customer sub-segments.

Overall, we expect stayers to have the highest growth of relational investments with the bank as compared to other customer segments, *rational* customers to maintain their investments around current levels unless their existing satisfaction level changes (which would still be rational), and *variety seekers* to reduce their investments over time as compared to other customer groups. Web Appendices I and J summarize the customer-level development of the *rational*, *stayers*, and *variety seekers* customer segments.

Future customer relationship levels with the supplier for each of these customer segments can be modeled in a variety of ways. We can examine whether a customer continued/discontinued a relationship with the firm during a given time-period. Additionally, we can model relationship levels, either discretely (i.e., a customer diminished, maintained, or increased their relationship with the firm) or continuously (i.e., customer relationship growth or reduction rate). Each of these approaches captures important elements of a supplier's CRM program and can offer valuable insights regarding the downstream consequences of switching costs for the supplier.

In addition to establishing the value of UIP in predicting customer attrition, service providers are interested in predicting the revenues, costs, and profitability associated with expected future customer relationship levels. The databases used in Study 2 allow us to observe the customer-level profitability associated with future relationship levels. In addition to customer profitability, these rich databases allow us to examine changes in customers' portfolio of products with the bank.

Grouping Customers as Rational, Stayers, and Variety Seekers

To assess whether the UIP-based classification of customers into segments has value, we begin by defining and measuring the average relationship growth for each segment using the firm's behavioral customer data. Relationship growth is measured as the number of products from the primary provider added (dropped) during any of the 13 months for which we have data. We adopt a hierarchical Bayesian approach (Rossi and Allenby, 2003) to model product usage growth for the *rational*, *stayers*, and *variety seekers* segments since these methods can effectively address hierarchical (i.e., conditional), discrete, asymmetric, and non-linear data structures.

We follow Rossi and Allenby (2003) and use a Markov Chain Monte Carlo (MCMC) simulation approach to estimate the model parameters. The estimation consists of 40,000 iterations, with the first 20,000 used for burn-in and the remaining 20,000 for parameter inference. We use the calibration data to estimate the probability distribution of the unknown response parameters (growth over time) for customer *i* given the observed customer behavior (relationship growth) and the covariates. We test for convergence via the Gelman-Rubin R-Hat statistic (Gelman and Rubin, 1992). Here, MCMC combines two concepts. The first is obtaining a set of parameter values from the posterior distribution using the Markov Chain, an iterative process that essentially creates a "random search" for the true model parameters, but in a manner that doesn't depend on the starting point (van de Schoot et al., 2021).[7] The second concerns obtaining a distributional estimate of the posterior (unknown response parameters) and associated statistics with the sampled parameters using Monte Carlo integration (van de Schoot et al., 2020). Further details about the MCMC process are beyond the scope of this article, but the interested reader may refer to van de Schoot et al. (2021) for a comprehensive primer.

The MCMC hierarchical Bayesian approach allows us to predict relationship growth profiles while controlling for the inter- and intra-customer dependencies, as well as customers' ties with the bank via the level of customers' monthly deposits (*Monthly Deposits*). Additionally, we control for customer differences in commitment to the provider by including an attitudinal measure of trust (*Trust*) in the bank. Finally, we model temporal differences in customers' future relationship growth patterns by including relationship length (in months) as a linear predictor (*Time*). The proposed MCMC Bayesian multilevel model for customer *i*, time-period *t* is summarized in equations (2) and Equation 3.1 and 3.3 The intercept, temporal trajectory, and customer dependencies predictors can vary by segment—that is, hierarchical. Parameters γ_0, γ_1, and γ_2 represent average segment effects, while u_{0ci}, u_{1ci}, and u_{2ci} are segment-specific (random-effect) coefficients.

$$\begin{aligned} Relationship\ Growth_{cit} = \beta_{0ci} + \beta_{1ci}.Time_{it} \\ + \beta_{2ci}.Monthly\ Deposits_{cit} \\ + \beta_{3c}.Trust_{ci} + \varepsilon_{cit} \end{aligned} \tag{2}$$

$$\beta_{0ci} = \gamma_0 + u_{0ci} \tag{3.1}$$

$$\beta_{1ci} = \gamma_1 + u_{1ci} \tag{3.2}$$

$$\beta_{2ci} = \gamma_2 + u_{2ci} \tag{3.3}$$

Where subscript *c* refers to each segment (i.e., *stayers*, *rationals*, and *variety seekers*), subscript *i* identifies each individual customer, while subscript *t* refers to each period (i.e., month). The *Time* variable captures each segment-specific growth trend in product usage, independent of customer ties with the provider (*Monthly Deposits*) and customer commitment to the provider (*Trust*).

Results

Table 2 summarizes the population-level estimates for the MCMC hierarchical Bayesian model. The Gelman-Rubin R-Hat statistic was around 1.0 for all predictors, confirming model convergence. The positive and significant intercept across all segments reflects that, on average, customers have a non-zero relationship with the firm at the beginning of the period analyzed. Across all three segments, the significance of the *Monthly Deposits* estimates (confidence interval does not include zero) suggests that, as expected, these estimates indicate the level of customers' prior commitment to the firm and positively predict future relationship growth. The significant coefficients for *Trust* also show that this indicator of a customer's relationship explains variance beyond the prior *Monthly Deposits* commitment indicator. The positive and significant *Time* estimate for *stayers* (β_{1c} = 0.010) indicates that, on average, customers from this segment exhibit a small but significant growth in future product usage, as expected. Conversely, *variety seekers* exhibit relationship diminishment (β_{1c} = −0.013), consistent with their depiction as not holding "true" loyalty toward a provider and are likely to scale down their investments over time. On average, customers from the *rationals* segment exhibit a non-significant relationship time trend—that is, they do not exhibit significant changes in their future product usage.

Table 2. Study 2: Relationship Growth (Product Usage) Over Time.

	Estimate	Posterior Standard Deviation	95% Confidence Interval
Stayers segment			
Intercept (β_{0c})	0.760***	0.040	(0.68, 0.83)
Time (β_{1c})	0.010**	0.002	(0.008, 0.011)
Monthly deposits[a] (β_{2c})	0.052**	0.003	(0.05, 0.06)
Trust[a] (β_{3c})	0.076**	0.028	(0.06, 0.14)
Rationals segment			
Intercept (β_{0c})	0.820***	0.042	(0.74, 0.90)
Time (β_{1c})	−0.008	0.003	(−0.02, 0.00)
Monthly deposits[a] (β_{2c})	0.042**	0.004	(0.03, 0.05)
Trust[a] (β_{3c})	0.051***	0.030	(0.04, 0.09)
Variety seekers segment			
Intercept (β_{0c})	.750***	0.042	(0.67, 0.83)
Time (β_{1c})	−0.013**	0.003	(−0.12, −0.15)
Monthly deposits[a] (β_{2c})	0.042**	0.005	(0.03, 0.05)
Trust[a] (β_{3c})	0.050**	0.031	(0.04, 0.09)

*** significant at $p < .001$; ** significant at $p < .01$; * significant at $p < .05$. Significance levels based on Bayes factor.
[a]Monthly deposits and trust are log transformed.

In addition to using the number of products to assess relationship growth, we used product revenue and cost data to estimate each customer segment's profitability, and re-estimated equations (2) and (3) with profitability as the dependent variable (see results in Table 3). Whereas the segments exhibit statistically identical baseline positive profitability (β_{0c} = 40.128, 43.026, and 44.014, for *stayers*, *rationals*, and *variety seekers*, respectively), on average, only customers in the *stayers* segment exhibit a significant increase in future (i.e., *Time*) profitability (β_{1c} = 0.420, $p < .01$). Confirming the previous findings, customer commitments with the firm (*Monthly Deposits*) are positively associated with future profitability, and the level of provider *Trust* significantly predicts future profitability for the *stayers* and *rationals* segments but not for *variety seekers*.

Robustness Checks

While our empirical grouping of customers into these three segments using our unexplained intention to patronize indicator is driven by our theorizing, the classifications based on one standard deviation are still somewhat arbitrary. However, follow-up analyses using ±½ standard deviation bands instead of ±1 SD bands or using data-driven methods like finite mixture

Table 3. Study 2: Customer Profitability Growth Over Time by Segment.

	Estimate	Posterior Standard Deviation	95% Confidence Interval
Stayers segment			
Intercept (β_{0c})	40.128***	3.373	(36.76, 43.08)
Time (β_{1c})	0.420**	0.201	(0.365, 784)
Monthly deposits[a] (β_{2c})	0.108***	0.026	(0.087, 0.129)
Trust[a] (β_{3c})	1.003***	0.244	(0.774, 1.178)
Rationals segment			
Intercept (β_{0c})	43.026***	1.979	(42.51, 46.31)
Time (β_{1c})	−0.003	0.010	(−0.107, 0.089)
Monthly deposits[a] (β_{2c})	0.120***	0.024	(0.087, 0.137)
Trust[a] (β_{3c})	0.307*	0.154	(0.141, 0.431)
Variety seekers segment			
Intercept (β_{0c})	44.014***	4.098	(35.61, 53.78)
Time (β_{1c})	−0.213**	0.409	(−0.263, −0.141)
Monthly deposits[a] (β_{2c})	0.122***	0.042	(0.093, 0.156)
Trust[a] (β_{3c})	0.509	0.315	(0.263, 0.762)

[a]Monthly deposits and trust are log transformed.

models to form the segments produced results that remain substantively identical and consistent with those reported in our study results.

Study 2 Discussion

Study 2 demonstrates how managers can use their existing VOC survey data to estimate unexplained intentions to patronize and use this to classify their firms' customers in ways that not only identify "at-risk" customers but also those who may be unlikely to switch, even when dissatisfied. Results indicate that such UIP data can be used to predict subsequent relationship growth and profitability with a supplier. Importantly, our findings suggest that only customers from the *stayers* segment show increased future relationship growth (product usage) and profitability with their supplier(s).

Stayers as Elective Stayers or Prisoners

Researchers and managers are interested in the downstream consequences of firms creating and maintaining switching barriers in ways that keep customers behaviorally loyal. However, creating switching barriers may result in strong negative customer reactions even while fostering behavioral loyalty (Huefner and Hunt, 2000; Padilla, 1995). Such reactions stem from the degree to which customers perceive they are locked into a relationship with a supplier and not willingly staying (Hirschman, 1970). Customers who willingly stay may regard switching barriers as a binding relational tie to a supplier for which they have a favorable attitude (Dick and Basu, 1994). Alternatively, a customer may be dissatisfied and wish to exit a relationship with a supplier but be unable to do so because of switching barriers. These customers may be "spuriously loyal" in that they would switch suppliers if given an opportunity but cannot for some reason(s) and may even engage in retaliatory behavior against the firm as a result (Dick and Basu, 1994). Thus, consistent with relationship marketing notions of dependence as being either benefit- or cost-based (Scheer, Miso, and Garrett, 2010), switching barriers may be viewed as either elective or non-elective depending on the nature of the underlying customer-supplier relationship (Jones et al., 2007; Vázquez-Carrasco and Foxall, 2006).

Drawing on this logic, we subdivide *stayers* into *elective stayers* and *prisoners* based on each customer's satisfaction level using a median split. Those with upper median satisfaction are more likely to stay in the relationship willingly because of favorable attitudes (*elective stayers*). Customers who exhibit negative attitudes toward a firm (lower median satisfaction) but are unable to leave (e.g., because of situational constraints like the lack of funds or relevant alternatives) are classified as *prisoners* (Lee and Neale, 2012). *Prisoners*, like *elective stayers*, are less likely to switch, but unlike *elective stayers*, they are less likely to increase commitment to or engagement with the firm (Lee and Neale, 2012). Rather, in the long run, they may be more likely to exhibit relationship diminishment as they find ways to overcome constraints binding them to the firm, consistent with the notion that customer value dynamics entail risks in the form of probability that the value of particular customer segments may change over time (Homburg, Steiner, and Totzek, 2009). Conversely, *elective stayers* choose to stay with the supplier firm willingly and are more likely to show relationship growth over time.

Using the data from Study 2, we re-estimated the profitability growth model (summarized in Table 4) on the *elective stayers* and *prisoners* sub-segments. As shown, we find that *elective stayers* exhibit a profit growth trend for the supplier, while *prisoners* do not (β = 0.731, $p < .001$ and β = 0.294, $p > .10$ respectively). Thus, the effects on customer profit growth for the supplier firm for the overall *stayers* segment observed earlier (Table 5) are attributable to *elective stayers*—those customers exhibiting both high levels of EIP and above-median levels of customer satisfaction. This suggests the economic value to suppliers by engaging with customers in ways that make them happy and unwilling to leave and shows that it is much greater than that derived from "locking in" unwilling customers.

What Explains Excess and Deficit Patronage Intentions?

Having empirically shown the predictive value of unexplained patronage intentions, we next turn to explore why UIP and its

EIP and DIP components may be predicting such observed customer behavior outcomes.

An Understanding of the Positive Deviations from the Baseline

Rego, Morgan, and Fornell (2013) attribute the deviations from satisfaction-explained loyalty (residuals) holistically as being indicative of the presence and level of switching costs. Economic conceptualizations of switching costs consider both past customer investments related to existing supplier relationships and future costs associated with switching to new suppliers (Shapiro and Varian, 1999). Economists have typically measured switching costs at the firm level (i.e., switching costs are fixed within a firm for a given year, and the levels of switching costs may vary depending on firm characteristics like market share or brand value) or the market level (e.g., highly concentrated markets may have higher switching costs due to unavailability of alternatives) (Farrell and Klemperer, 2007).

However, from a consumer research perspective, switching costs are not viewed simply in measurable economic terms but rather as an individual-level psychological constructs where customer perceptions of switching costs drive decision making (e.g., Bell, Auh, and Smalley, 2005; Yanamandaram and White, 2006) (see Web Appendix A2 and A3 for further details on these two perspectives). According to such a conceptualization, switching costs may vary across customers for the same firm/brand and for the same level of service. While there may be numerous phenomena that have been separately conceptualized and studied in marketing and consumer research (e.g., brand love, commitment, habit, etc.), these may all be considered antecedents of the broader switching cost phenomenon (see Web Appendix A2 for an overview). In an economic sense, in a market with homogenous goods offered by an infinite number of suppliers, which would, in principle, eliminate search costs for alternative providers (Patterson and Smith, 2003), switching costs are essentially nil. Deviations in quality (heterogeneity of goods) and restrictions in terms of suppliers (availability of alternatives) create switching costs (Dubé, Hitsch, and Rossi, 2009). Since quality and expectations thereof are proxied by customer satisfaction (in the absence of objective quality metrics), customer intentions to remain with the service provider over and above that explained by quality are captured by the market unavailability of equivalent[8] providers. Therefore, it is not unreasonable to consider the excess unexplained intentions to patronize (positive residuals or EIP) as being partly caused by (higher) switching costs. Thus, we argue that EIP can effectively serve as an indicator of switching costs.

Table 4. Study 2: Customer Profitability Growth Over Time of *Stayer* Sub-segments.

	Estimate	Posterior Standard Deviation	95% Confidence Interval
Elective stayers sub-segment			
Intercept (β_{0c})	42.978***	4.517	(38.31, 46.42)
Time (β_{1c})	0.731**	0.247	(0.201, 1.031)
Monthly deposits[a] (β_{2c})	0.081*	0.034	(0.056, 0.105)
Trust[a] (β_{3c})	1.127***	0.340	(0.807, 1.531)
Prisoners sub-segment			
Intercept (β_{0c})	53.628***	3.966	(46.07, 61.17)
Time (β_{1c})	0.294	0.335	(−0.164, 1.106)
Monthly deposits[a] (β_{2c})	0.164***	0.033	(0.126, 0.202)
Trust[a] (β_{3c})	0.361	0.301	(0.272, 0.449)

*** significant at $p < .001$, ** significant at $p < .01$, and * significant at $p < .05$. Bayes factor significance.
[a]Monthly deposits and trust are log transformed.

An Understanding of the Negative Deviations from the Baseline

As opposed to positive deviations, patronage intentions that are lower than would be predicted by a customer's satisfaction with past consumption of the provider's service may be a result of the customer's change or novelty desires driving future purchase intentions despite being satisfied with the incumbent supplier's offerings, consistent with marketing conceptualizations of variety seeking (e.g., Sevilla, Lu, and Kahn, 2019). Such variety seeking may lead to a vacillation over time among an acceptable set of alternatives (McAlister and Pessemier, 1982). The distinction between variety seeking and low switching costs is important. Minimal switching costs may imply that it is easy to switch, while variety seeking implies that the customer will intend to switch even if s/he is satisfied with the quality of service provided.

Table 5. Assessment of UIP as Indicator of Switching Costs and Variety Seeking: ACSI Data.

Known Higher vs. Lower Switching Costs Industry (SIC)	Average UIP	Within-Industry Known Higher vs. Lower Switching Cost Firms (SIC)	Average UIP
Cigarettes (2,111) vs. automobiles (1,311)	1.54 vs. −1.83	Apple vs. Compaq (3,663)	4.56 vs. −1.37
Supermarkets (5,331) vs. processed food (5,142)	0.044 vs. −0.038	Delta vs. Southwest (4,512)	0.81 vs. −0.24

Notes. "High" vs. "Low" switching cost industries and firms similar to those examined in Rego, Morgan, and Fornell (2013). Positive average UIP (Unexplained Patronization Intentions) values indicate that intended patronage is above what would be predicted based on customers' satisfaction with product/service offerings (i.e., switching costs). Negative average UIP values indicate that intended patronage is below what would be predicted based on customers' satisfaction with product/service offerings (i.e., variety seeking).

Empirical Assessment of Proposed Explanations

In terms of conceptual alignment between the EIP indicator and the theoretical construct of switching costs, we note that a generally accepted conceptualization views switching costs as those incurred and/or benefits forgone (i.e., those given up) by a customer in moving from an existing to an alternative supplier (Farrell and Klemperer, 2007). The "costs" components are generally viewed as including financial (e.g., penalties) and procedural (e.g., search and learning) costs, while "benefits foregone" may include valued relationships, loyalty rewards and discounts, and time-saving search and use efficiencies. Thus, the "costs" components can be viewed as "negative" (i.e., things the customer would have to pay to use a new supplier) and "benefits foregone" as "positive" (i.e., valued things a customer would have to give up with their existing provider in order to switch) (Colgate and Lang 2001). This "costs incurred plus benefits foregone" distinction is important in terms of what is and should be captured in a measure of switching costs. For example, a customer's brand attachment, esthetic affect toward a product design, or self-concept overlap with a brand's personality are all sources of "positive" switching costs in that they are benefits that are valued by the customer in a current supplier that would have to be given up to switch to an alternative provider.

Having elaborated on how EIP's predictive value may be explained by providing an indicator of the presence and magnitude of customer-level switching costs, we next empirically examine the extent to which EIP aligns with other indicators of the switching cost construct. We begin by replicating the face validity assessments of the firm-level measure from Rego, Morgan, and Fornell (2013). As Table 5 shows, using the same ACSI database, the face validity assessment results replicate those of Rego, Morgan, and Fornell (2013).

While the Rego, Morgan, and Fornell (2013) unexplained attitudinal loyalty measure is at the firm level and does not differentiate between excess and deficit unexplained loyalty, it is derived by aggregating individual-level consumer responses to ACSI satisfaction and loyalty survey questions. To provide some initial insight into whether our customer-level UIP operationalization and its disaggregation into EIP and DIP may be driven by customer switching costs and variety seeking, respectively, we conducted a consumer survey-based study. Using an online survey, we asked a sample of 314 consumers who use a gym to rate their satisfaction and loyalty to their gym and to provide information regarding the existence and nature of any contracts they may have with their gym memberships. We calculate indicators of EIP and DIP for their gym by regressing customers' stated overall satisfaction on their future patronization intentions with respect to the gym and using the positive residuals as EIP and negative residuals as an indicator of DIP.[9] Overall satisfaction and future patronization intentions (likelihood to remain with the gym) are measured on a seven-point Likert scale.

We then examined how the positive (EIP) and negative (DIP) residuals (calculated according to equation (1)) vary with respect to the existence and level of contractual and financial barriers to switching gyms, which represent clear sources of switching costs (see Table 6). Based on participant responses regarding the contract type, we created four membership categories using the gym contract data (monthly versus yearly and cancelable with penalty versus without penalty). Cancelation penalties and longer contracts are actual switching barriers—consumers should face the greatest switching barriers when they have a yearly contract and also face cancelation charges and the lowest switching barriers when they have a month-to-month contract and no cancelation charges. EIP mean levels vary in the expected way across the four cells in Table 2, and differences in EIP are significant across the four cells,[10] suggesting that the customer-level operationalization of EIP is, to some degree, being driven by customer switching costs. We similarly see that DIP mean levels are significantly lower for customers with a yearly contract than a monthly one, which makes sense as consumers who are interested in looking for alternatives are less likely to sign up for an annual membership.

We also utilize the same gym context in a second evaluation study using an online sample from Prolific (97 usable participants). We asked about respondents' satisfaction and future patronage intentions toward their current gym along with Jones et al.'s (2007) widely used survey measure of customer switching costs. Again, we calculate EIP as the positive residuals from the intended patronage-satisfaction regression. We find that the direct survey-based switching costs measure, the mean of the Jones et al. (2007) survey items, and our EIP indicator are highly correlated (0.732). These two gym-based studies provide evidence that the predictive value of EIP shown earlier in Studies 1 and 2 in the banking context is likely to be

Table 6. Assessment of EIP as an Indicator of Switching Costs and DIP as an Indicator of Variety Seeking: Survey of gym Members.

	With Cancellation Charges	Without Cancellation Charges
Yearly contract	EIP (switching costs): 0.994 DIP (variety seeking): −0.883 Patronage intentions: 3.80 *(n = 35)*	EIP (switching costs): 0.828 DIP (variety seeking): −0.702 Patronage intentions: 3.74 *(n = 64)*
Monthly contract	EIP (switching costs): 0.851 DIP (variety seeking): −0.968 Patronage intentions: 3.66 *(n = 30)*	EIP (switching costs): 0.777 DIP (variety seeking): −0.984 Patronage intentions: 3.55 *(n = 195)*

Note: "Objective" switching costs should be highest when a consumer has a longer contract and faces cancellation charges, and our switching cost measure is significantly different across each cell in ways aligned with this. Levels of patronage intentions do not differ significantly across cells. EIP and DIP are excess and deficit patronage intentions and are indicative of switching costs and variety seeking, respectively.

driven to some degree by EIP capturing the presence and extent of a customer's switching costs.

In the spirit of exploring evidence from a variety of data sources, we examine two additional contexts. First, using customer-level ACSI data on public utilities, we find that in "no-choice" states (i.e., those where customers are not able to switch providers), our average calculated EIP is significantly higher than that in choice states where customers can choose providers (0.83 in no-choice states vs 0.58 in choice states). Unsurprisingly, we also observe that DIP is higher in provider choice (absolute value of 0.62) vs. no provider choice (0.49) states as there is much less point in seeking variety when that is not possible. Next, using proprietary customer-level data on satisfaction and intended loyalty from a large US retail beverage chain, we find that EIP significantly increased after the firm launched a loyalty program (prior to launch: 0.97; two years post-launch: 1.19) while Abs(DIP) decreased (prior to launch: 0.70; two years post-launch: 0.64). Past literature shows that such loyalty programs help foster behavioral loyalty by increasing the levels of switching costs from forgoing program benefits and reducing customer motivations to seek alternatives (e.g., Xie et al., 2015).

The above explorations of why the customer-level UIP-based measures have the predictive value we find in Studies 1 and 2 offer strong indications that EIP is capturing the presence and extent of customer-level switching costs. However, while DIP values generally move in the expected directions, none of these explorations are directly designed to identify or create conditions in which variety seeking is likely to be higher or lower and compare that with the computed DIP values. To address this, we ran an additional study with 200 participants (one participant dropped out, leaving 199.) We asked 100 people to consider a hair salon they had last visited and to rate their intended future patronage ("How likely are you to visit the same salon the next time you need a haircut or other service?") and satisfaction ("How satisfied are you with the salon?"). Depending on the ratings provided, we then asked them why they rated their satisfaction higher than their intention to continue patronizing the salon (or vice versa for those who rated their intended patronage higher than their levels of satisfaction). We then repeated this exercise for a different service category (restaurants) with 100 additional participants. We expect the hair salon condition to be a context with relatively low variety seeking (and higher switching costs) and restaurants to be a context in which there is relatively high variety seeking (and lower switching costs).

Using the same calculation as in Rego, Morgan, and Fornell (2013), we obtain the residuals for a regression of intended patronage on satisfaction. We find that the overall UIP residual for salons is positive (0.153) and significantly higher than that for restaurants (−0.688), which confirms our intuition that there is substantive variety seeking in restaurants and that the switching costs for salons are much higher. We confirmed this by decomposing UIP into its EIP and DIP components, with hair salons having an EIP of 0.81 vs. restaurants at 0.70 and an Abs(DIP) of 0.59 vs. restaurants at 0.97. Simply looking at difference scores, the mode was 0 across categories (>50% of participants provided the same satisfaction and attitudinal loyalty ratings). Responses to being asked why their ratings differed included (for those who rated their satisfaction more than intended patronage), "Because while the service I received was adequate, I do not want to go back if I could get better service elsewhere," "Because they do a good job, but there are multiple options in my area," "a lot of choices now," "There are many other restaurant options nearby," "because I like trying new things," and "I would also like to have variety in the food that I eat," all of which tie in with the concept of variety seeking. For those who rated their intended patronage at levels higher than their satisfaction, responses included, "They do a good job every time, but it is nothing phenomenal. I would rather get good haircuts every time than risk getting a bad one somewhere else," "I don't like to change places if I don't have to," "They try hard, and it's convenient and cost-effective," and "It's just contentment and familiarity with the workers," all of which are consistent with the concept of UIP and its EIP and DIP components being driven by customers' switching costs and variety seeking.

Overall, the consistent evidence from these evaluation studies employing multiple different data sources, measurement approaches, and contexts empirically supports the notion that the measures of customer-level EIP and DIP have predictive value in our financial services Studies 1 and 2 because they indicate customers' switching costs and variety seeking, respectively.

Generalizability and External Validity

Having shown the predictive value of EIP and DIP in two studies in a financial services context, we next seek to establish some evidence of the external validity and generalizability of our findings using longitudinal data from the ACSI database and J.D. Power and Associates. These empirical analyses allow us to verify the managerial relevance and value of firm-level operationalizations of EIP and DIP. They also allow us to examine whether our findings generalize beyond the firm-specific and banking context in our analyses to other service industry contexts.

First, we sought indications of generalizability for our Studies 1 and 2 findings in a larger sample of financial services firms in the ACSI to demonstrate the validity of our measure and findings in the same industry. However, because of significant consolidation in the industry, consecutive annual firm-level ACSI data (i.e., more than three consecutive years) is sparse, yielding a sample of 42 usable firm-year observations. Although this small sample does not allow rigorous empirical analyses, we estimated EIP aggregated at an annual level (based on aggregated individual-level ACSI survey responses) following the approach described in Rego, Morgan, and Fornell (2013). We also calculated indicators of elective and non-elective switching barriers (corresponding to *positive stayers* and *prisoners*) following the customer-level procedure described earlier in Study 2. Consistent with our findings from Study

2 concerning customer-level profit growth, correlations reveal that elective switching costs are significantly and positively associated with these financial service firms' Return on Assets (ROAs)[11] (0.348). Furthermore, non-elective switching costs are significantly and negatively related to these firms' ROA (−0.177), while overall switching costs and ROAs are not significantly related (−0.036).

Second, to assess generalizability beyond financial services, we were able to access J.D. Power and Associates data covering nine major US-based airlines over 5 years (2013–2017). We calculated EIP and DIP as before by using the residual of regressing intended patronage on satisfaction. Using a standard GLS regression with corrections for serial and cross-sectional correlation, firm-level cluster-adjusted standard errors, and one-period lags to mitigate reverse causality, we find that EIP is associated with greater miles traveled and DIP (theorized as an indicator of variety seeking) with higher rates of rewards expiration. We also find that EIP and DIP vary predictably across airline loyalty tiers, where we know that higher tiers have greater switching costs (owing to greater investment in the relationship and greater forgone benefits if a customer switches). In addition, we find that DIP varies predictably by airline type where we know that low-cost airlines exhibit more variety seeking and lower switching costs, likely because customers have no motivation besides low prices to remain behaviorally loyal. Together, these results (Tables 7 and 8) demonstrate the value of UIP data in predicting customer behavior in the airline industry and further suggest that this productive value is likely a function of EIP and DIP being driven by customer-level switching costs and variety seeking.

General Discussion and Implications

Service firms aim to lower the risk of customer defection, costing US firms trillions of dollars annually (Dubé, Hitsch, and Rossi, 2009; Pombriant, 2016). As a result, service firms seek ways to identify customers "at risk" of defection and take proactive actions to reduce this risk (e.g., Burnham, Frels, and Mahajan, 2003; Porter, 1980). While some firms can frequently and directly observe and capture data on their customers' behaviors and build sophisticated predictive customer-level "churn" models, many are unable to do so. For these firms, using alternatives like changes in customer behaviors to predict switching may often be too late since the customer has already embarked on a path that might be difficult to reverse. The studies reported here suggest the predictive value of unexplained patronage intentions through measures of excess and deficit patronage intentions in identifying at-risk customers and those who are likely to remain behaviorally loyal. The approach is practical in needing only two survey questions (customer satisfaction and attitudinal loyalty), making it minimally intrusive and feasible to administer multiple times during a customer's tenure with a supplier. Because these are also two of the most common questions in firms' existing VOC surveys, managers may already have the data to compute the measure for samples of their customers. EIP and DIP are powerful in terms of their ability to predict downstream behaviors. We also find evidence of economic value by using estimated UIP to classify customers into groups that we then show exhibit different behaviors with regard to their future purchases and associated supplier profit outcomes.

This research contributes several new insights. First, we demonstrate the value of customers' unexplained patronage intentions in predicting important downstream behaviors, including switching and relationship growth. We also offer evidence across several different contexts using different data sources that these UIP measures have such predictive value because they indicate the presence and relative magnitude of customer-level switching costs and variety seeking. While both switching costs and variety seeking are important theoretical constructs in economics and marketing, empirical investigations have been hampered by the difficulty of obtaining and measuring data. Economic measurement approaches are focused on the firm or industry level and rely mainly on proxies like market share changes that are noisy and imperfect. Services and marketing researchers seeking to assess customer-level switching costs or variety seeking have typically done so by using direct questions in customer surveys. This approach assumes that customers can accurately gauge their switching costs

Table 7. Impact of Switching Costs and Variety Seeking in Airlines.

Variable	Miles	Miles	Expiry	Expiry
Age	0.008***	0.008***	−0.001***	−0.001**
Income	0.059***	0.059***	−0.003	−0.003
Race (Caucasian)	0.187***	0.184***	0.110***	0.112***
Race (Black)	−0.215*	−0.212*	0.045	0.045
Race (Hispanic)	−0.172*	−0.163*	−0.016	−0.013
Gender	0.204***	0.037***	−0.102***	−0.102***
Tier	0.069***	0.007***	−0.107***	−0.107***
EIP (indicative of switching costs)	0.118***		−0.019	
DIP (indicative of variety seeking)		0.007		0.059***
R^2	4.51	4.38	5.83	6.01
N	9,498	9,498	7,393	7,393

Table 8. Presence of Switching Costs and Variety Seeking in Airline Loyalty Program Tiers. Presence of Switching Costs and Variety Seeking in Airline Types.

Loyalty Tier	EIP (Switching Costs)	DIP (Variety Seeking)
1	0.315	−0.332
2	0.339	−0.322
3	0.369	−0.310
Airline Type	**EIP (Switching Costs)**	**DIP (Variety Seeking)**
Low-cost	0.270	−0.392
Full-service	0.349	−0.325

Note: Correlation between Loyalty Tier and EIP indicator: 0.031.

(or variety seeking) in ways that predict their behavior, an assumption we find to be untrue in our financial services context. Conversely, extant research on excess loyalty has concentrated on behavioral loyalty and mainly sought to explain what causes it rather than what can be gained from it. Combining satisfaction and patronage intention variables, our approach offers an indirect proxy indicator of customer-level switching costs and variety seeking that we find strongly predicts future customer behavior and value.

Second, we enhance our understanding of the switching cost and variety seeking phenomena by looking at their influence on actual behaviors and their consequences for service suppliers (as opposed to stated intentions that almost all prior literature investigating these at the customer level has looked at). We find that lower variety seeking vs. the presence of switching costs reduces behavioral switching in a financial services context. We also empirically confirm the differential effects of elective and non-elective switching barriers on customer behavior and its economic outcomes for supplier firms. Our results support behavioral and economic consequence differences among customers with switching barriers when their attitudes toward the firm are used to infer whether they elect to remain with the supplier for positive reasons (a wish to stay) versus staying involuntarily (an inability to switch). Importantly, our findings indicate that positive stayers have significantly greater engagement with and trust in their primary supplier and that their relationship profitability is both greater and grows significantly over time. The same is not true for prisoners. This offers new support for marketing conceptualizations of “positive” switching costs vs. economic theory perspectives viewing all switching costs as inherently “negative.”

Our study also has practical implications for managers in their efforts to predict switching behavior, reduce defections, and allocate resources across their portfolios of customers. First, because our approach uses existing VOC data, firms that currently ignore switching costs can now incorporate a UIP-based indicator of such costs into their CRM systems. Because only two questions are required for the basic estimate of UIP, firms could feasibly augment their sampling to estimate UIP for a much greater percentage of their customer base than would be possible based on lengthier VOC surveys. The data provider for Studies 1 and 2 relies primarily on its tracking survey’s intended patronage measure to monitor the level of at-risk customers and prioritize initiatives at an aggregate level. It is not the primary source of input for actions at the individual customer level as it is conducted among a random sample of customers. Rather, the firm uses individual-level classifications into tiers based on product ownership and balance levels, along with behavioral indicators of customer inactivity or diminishment (e.g., significant reductions in credit card usage or balances), to trigger offers and communications.[12]

Based on our findings, we would encourage the firm to add a shortened tracking survey, including only the two questions needed to construct UIP and its EIP and DIP components, and target a much larger sample. Further, if EIP is indicative of switching costs, it helps alleviate some of the difficulties measuring or proxying for switching costs in general (see Web Appendix A1). Such an approach may be increasingly practicable given the trend toward shorter surveys among larger samples, facilitated by the use of mobile technology (Bhat, 2018). While the current survey can still be used to gather diagnostic information related to customer satisfaction, the shorter one can identify at-risk customers and those electing to remain with the firm for positive reasons versus staying involuntarily. Furthermore, firms could track how the sizes of the different groups are changing and show other statistics or their associations with metrics like sales and profits in their dashboards. Our approach may be particularly useful after service encounters or other touchpoints, as these are common VOC practices.

We also encourage service providers (including the data sponsor) to test the effectiveness of initiatives tailored to individuals based on their classification into one of these two groups. For example, communications recognizing a customer’s loyalty may not be well received by those who perceive an inability to switch. Understanding the overlap between the data sponsor’s current customer tiers and customers’ classifications as variety seekers or elective stayers could also allow it to refine its investments in and approaches to relationship management, considering both customers’ relationship levels and switching costs/variety seeking indicators. Proactive campaigns may enable firms to take action before issues that might cause churn occur (Ascarza et al., 2018). Given estimates that as much as 70% of CRM data become obsolete annually (Thorp, 2015), appending those systems with EIP and DIP information based on data firms already gather seems valuable.

Limitations and Future Research

Several limitations should be borne in mind when considering our results. First, we assess the value of excess and deficit patronage intentions in predicting switching and other behavioral and economic outcomes in a single service industry with data only for a limited customer sample. Due to the known presence of switching costs and variety seeking in the financial services sector (e.g., Hannan and Adams, 2011), we believe our context presents an appropriate setting. Customers face different types of switching costs in financial services contexts like fees associated with terminating loans or other agreements prior to their maturity or loss of benefits like discounts based on product ownership or usage. Switching providers also entails procedural costs like learning new systems (e.g., online or mobile banking applications) and practices like different fee structures or rewards associated with account usage. There are also likely to be psychological costs associated with moving from a supplier that is personally known and emotional costs if connections with personnel have been established (Patterson and Smith, 2003). Aside from these costs, variety seeking is known to be common in financial services, where consumers often seek out alternate experiences in the hope of finding something better (Baumann, Eliott, and Hamin, 2011). Further, the financial services sector is vast in its own right (employing 7.6 million people in the US, according to IBISWorld) and important to the economy (valued at ~$3.5 trillion in the US, according to the International Trade Administration). Because it is a continuous service industry, the importance of tracking attitudes (and not just behavioral loyalty, which is a discrete event) is amplified. Furthermore, our generalizability assessments using firm-level aggregation of unexplained patronage intentions UIP and its excess (EIP) and deficit (DIP) components in both a larger sample of banks and a sample of airlines provide results that are consistent with the substantive findings in our study. Nonetheless, research applying our customer-level approach to service industries with fewer switching barriers and lower variety seeking to assess its generalizability (e.g., transportation, spas, and nail salons) would be valuable. Further, we did not explicitly test for factors leading to greater excess intentions to patronize. Future research may identify the relative importance of different factors, such as financial constraints and brand strength, in determining EIP and DIP.

Second, due to data limitations, we are only able to test the detailed customer-level predictive ability of EIP and DIP over a 1-year period. While we were able to observe substantial shifts in product ownership and switching of primary providers in our financial services dataset, switching may also take place over longer periods, and customers may vary based on their propensities to switch over shorter versus longer windows. Thus, future studies with longer customer panels are warranted. Furthermore, while we were able to control for certain customer characteristics, additional aspects of customer heterogeneity should be considered in terms of geographies, household sizes, competitive interventions, advertising, etc. The model specification used in our study can easily be extended to include all or a subset of such variables in efforts to further optimize the insights and applicability of the proposed attitudinal data-based customer switching costs metric.

Third, the survey items used in Studies 1 and 2 were gathered at the same time; therefore, we cannot infer a causal direction with regard to satisfaction and attitudinal loyalty. Despite this potential limitation, however, we do not believe that common method bias is an issue with our measure. We are interested in the difference between the cross-sectional estimate of customer satisfaction and intended loyalty since, at the time the customer is surveyed, s/he evaluates both his/her satisfaction and patronage intentions, irrespective of which came first. Thus, none of the self-reported measures in such customer feedback surveys are antecedents to one another.

Fourth, while we provide strong evidence that EIP is indicative of the presence of customer-level switching costs and that DIP is indicative of customer variety seeking, owing to data limitations, we were not able to incorporate an exhaustive list of covariates that may be relevant in this context. Future research may look to include a variety of covariates, such as brand value and attachment and customer traits and personalities, and investigate whether the impact of UIP, EIP, and DIP on relevant downstream outcomes changes.

In addition to future research designed to deal with these limitations, our study raises some interesting new research questions. First, the use of EIP and DIP provides a new way for firms to identify "at-risk" customers and an opportunity to design early interventions to reduce the likelihood of relationship diminishment and defection in customers with high variety seeking motivation and low switching cost barriers. However, little is known about which types of interventions may be effective under different conditions. Future studies should examine different types of interventions that may be used and explore potential boundary conditions that may influence their efficacy in reducing customers' relationship diminishment and switching behaviors and their value (costs vs. benefits) to the firm.

Second, our findings point to the value of elective stayers as a source of revenue growth and profits. Research should explore whether there are boundary conditions to this value. For example, how does the nature and extent of competition impact the level and value of such customers? Furthermore, creating such positive customer bonds is not costless. What approaches are cost-effective for creating such positive reasons to stay among customers? These are theoretically and managerially important questions for service researchers.

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Notes

1. We do not claim that a consumer's stated post-consumption satisfaction with the supplier's service equals their cognitive and affective intent to patronize. Rather, it provides a foundation on which consumers make such assessments and responses.
2. The data for Study 1 were gathered by a market research provider contracted by a large US bank.
3. We observed no customers who responded to all four waves of the survey during the timeframe of our study.
4. Our model accounts for any response style bias by using respondent answers on an unrelated item (overall impression of the banking industry) to scale the measures to remove any positive/negative bias but retain heterogeneity in attitude information.
5. Interested readers may refer to Puhr et al. (2017) for details.
6. We also test two direct survey measures of switching costs and their impact on behavioral switching, one that asked survey participants to rate their anticipated hassle to switch and the other to rate their anticipated risk if they would switch. Neither variable

(nor their combination) significantly predicts future behavioral switching.

7. Definitionally, the Markov Chain is an iterative process where the values of the chain at time t + 1 are only dependent on the values at time t.
8. This perceived equivalency is customer-specific. For instance, a customer bound by a contract will be unwilling to leave even if there are other suppliers present since to reach equivalency, the customer must incur costs to leave the incumbent supplier.
9. Comparable to firm-level switching costs, which can be calibrated using firm, industry, or time fixed effects to control for firm, industry, or time idiosyncrasies, a similar approach can be applied to estimate individual customer-level switching costs.
10. Loyalty intentions are not significantly different across the four conditions. While we do not measure brand-related factors or personal characteristics, there is no reason to believe these are likely to be systematically different across the four cells.
11. Banks have different accounting rules from other types of firms and report deposits (rather than sales) in their 10-Ks, and so, we use ROA as an alternate measure of performance.
12. The firm was not willing to share the details of its modeling approach. There, we are unable to directly compare any of our models with those used by the firm.

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