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Abstract:
Through a large-scale field experiment with 389,611 customers considering opening a credit card account with a nationwide retail bank, we investigate how providing transparency into an offering's tradeoffs affects subsequent rates of customer acquisition and long-run engagement. Although we find transparency to have an insignificant effect on acquisition rates, customers who were shown each offering's tradeoffs selected different products than those who were not. Moreover, prospective customers who experienced transparency and subsequently chose to open an account went on to exhibit higher quality service relationships over time. Monthly spending was 9.9% higher and cancellation rates were 20.5% lower among those who experienced transparency into each offering's tradeoffs. Increased product usage and retention accrued disproportionately to customers with prior category experience – more experienced customers who were provided transparency spent 19.2% more on a monthly basis and were 33.7% less likely to defect after nine months. Importantly, we find that these gains in engagement and retention do not come at the expense of customers' financial wellbeing – the probability of making late payments was reduced among customers who experienced transparency. We further find that the positive effects of transparency on engagement and retention were attenuated in the presence of a promotion that provided financial incentives to choose particular offerings. Taken together, these results suggest that providing transparency into an offering's tradeoffs may be an effective strategy for informing customer choices, leading to better outcomes for customers and firms alike.

[Keywords: Behavioral operations, operational transparency, customer compatibility, customer behavior]

1. Introduction

It is a common practice that when service firms market to prospective customers, they emphasize the advantages of their offerings and downplay the tradeoffs. This strategy seems quite rational to the extent its objective is to convert browsers into buyers, as accentuating the downsides of an offering might drive some customers away. However, since value arises from the long-term engagement and retention of satisfied customers, marketing messages that provide transparency into a service offering's hidden tradeoffs may help customers make better-informed choices, facilitating the acquisition of more compatible customers, and improving long-run outcomes for customers and firms alike. Although this proposition may have intuitive appeal, the effect of providing prospective customers with such transparency has never been empirically investigated, which is the objective of this paper.

In a manufacturing context, inputs to the process are carefully sourced by the manufacturer to ensure fit with its operation, reducing variability, improving productivity, and boosting performance. Service operations are fundamentally different in that customers, who have heterogeneous needs (Frei 2006), and who provide key inputs to the process (Roels 2014, Sampson and Froehle 2006), have to choose the operation with which they engage. This selection process is fraught with information asymmetry (Buell et al. 2016, Schmidt and Buell 2017), such that services have been classified as "experience goods," in that customers are rarely able to assess them prospectively (Israel 2005). Yet service outcomes, like satisfaction and profitability, have been shown to hinge largely on customer compatibility – the degree of fit between the customer's individual needs, and the capabilities of the operation that serves them (Buell et al. 2018). Hence, investments that reduce information asymmetries between a service business and its prospective customers may help those customers make more well-informed decisions, improving customer compatibility, and leading to better long-term outcomes for all involved.

For this paper, we collaborated with Commonwealth Bank of Australia (CBA), a nationwide retail bank in Australia, which is the largest bank in the southern hemisphere (Buell and John 2018), to conduct a large-scale field experiment with 389,611 customers who were considering applying for bank-issued credit cards. Each customer was randomly assigned to either a control condition, in which they received traditional messaging that emphasized the advantages of each credit card (e.g., our lowest interest rate on purchases, $0 annual fee in the first year, etc.), or a treatment condition, in which they received messaging that emphasized the same advantages, while also providing transparency into each card's tradeoffs (e.g., does not earn awards points, does not include travel insurance, etc.). We subsequently tracked the progression of customers in both conditions through the acquisition funnel and documented the engagement of those who chose to open accounts for nine months after activation, to assess the impact of this transparency on service performance.

Although we find that providing transparency into the tradeoffs of service offerings has no impact on overall rates of acquisition, our results suggest that doing so can influence customers' choices, usage, and retention. Holding constant other factors, customers who experienced transparency selected a different mix of cards, spent 9.9% more on a monthly basis, and after nine months, were 20.5% less likely to cancel their accounts. Importantly, this increased engagement does not come at the expense of customers' financial wellbeing – the probability of making late payments declines 10.8% in the initial six months of the service relationship among those who experienced transparency. We further find evidence that customers' prior experience with the service category moderates the impact of transparency on subsequent engagement. Providing transparency to below median age prospects, who had limited, if any, previous experience with credit cards, had a de minimis effect on usage and retention. In contrast, providing transparency to older, more experienced customers, led to significantly higher levels of engagement – increasing monthly spending by 19.2% and decreasing the probability of cancellation after nine months by 33.7%. Finally, we observe that the effects of transparency on subsequent usage and retention are attenuated among customers who experienced transparency in the midst of a promotion. Midway through the experimental period, the bank introduced a financial incentive for customers who opened specific types of credit cards, and customers who opened accounts during this promotion period exhibited a statistically indistinguishable response to the treatment. The results are consistent with the idea that customers who organically seek out an offering are more likely to consider and benefit from tradeoff transparency than those who are attracted or influenced by a promotion. By examining both the short-term marketing impact and the longer-run operational impact of providing prospective customers with operational transparency into a service offering's tradeoffs, the present study lends support to prior research calling for an integrated approach to marketing and operations (Ho and Zheng 2004). Moreover, it builds on a growing literature that demonstrates how voluntarily revealing facets of an operation that are traditionally kept hidden can improve outcomes for customers and service providers alike (Buell et al. 2017, Mohan et al. 2018).

2. Tradeoff transparency, customer acquisition, and engagement

In an effort to improve customer acquisition, managers may be inclined to present their firms' service offerings in the most favorable light – accentuating the positive attributes and deemphasizing the negative ones. However, doing so may cause customers to make less-informed decisions, reducing the degree of fit between their needs and their chosen firm's operating capabilities, and undermining prospects for satisfaction and profitable long-term engagement (Buell et al. 2016, Guajardo and Cohen 2017). In this section, we explore literature that informs how providing prospective customers with transparency into the tradeoffs inherent in a firm's offerings affects customer acquisition and long-term engagement.

2.1 Tradeoff Transparency and Customer Acquisition

Research has highlighted how the revelation of unflattering information about a company's service offerings, such as poor quality or high prices, can reduce consumer demand. For example, research conducted in online platforms found that the first bad review posted about a firm's offerings can cost a company up to 13% of its revenue (Cabral et al. 2010) and that a one-star increase on Yelp can boost a company's revenue by 9% on average (Luca 2016). Chetty et al. (2009) found that making taxes salient in a retail context – that is, posting sales taxes along with the prices of goods – increases consumers' perceptions of the prices charged by the retailer, and reduces demand by 8%. Similarly, Finkelstein (2009) found that drivers who pay tolls electronically are substantially less aware of, and less sensitive to, toll rate increases, and Blake et al. (2017) illustrated that shrouding service fees on an online ticketing platform can substantially raise revenues. To the extent that disclosing sensitive information can adversely affect demand, these results suggest that firms intent on acquiring new customers may have powerful incentives to hide negative information from prospective buyers.

On the other hand, an extensive array of research in psychology and marketing has demonstrated the benefits of self-disclosure in fostering intimacy. Interpersonally, self-disclosure has been shown to be critical in developing social relationships (Jourard 1971) and in forging a heightened level of trust (Wheeless and Grotz 1977). People disclose in intimate relationships (Derlega 1984), as self-disclosure allows parties to gain knowledge about one another while reducing ambiguity about the other's intentions (Laurenceau et al. 1998, Perlman and Fehr 1987). Similar effects have been documented in non-interpersonal contexts. For example, research has shown how people become more attracted to, and more willing to engage with, computers that self-disclose sensitive information. If a computer shares that its "abilities are really limited…" in that it can "do word processing and spreadsheets, but it cannot do any kind of physical activity, like play sports or walk down the street," people report a higher level of attraction to it, and are more likely to disclose to it things they hate about themselves (Moon 2000). Similarly, when companies self-disclose their costs of producing goods and services – a practice which implicitly reveals their profit margins – consumers report trusting the firm more, are more willing to engage with it, and sales increase (Mohan et al. 2018).

Furthermore, research on operational transparency has demonstrated how disclosing facets of the operation that are typically hidden from view – such as the work being performed behind the scenes – can enhance consumers' appreciation for the firm and their perceptions of the value it creates (Buell et al. 2017, Buell and Norton 2011). Moreover, such transparency can bolster trust in and engagement with the firm, even when it reveals imperfect performance (Buell et al. 2018b, Kalkanci et al. 2015). Common across all of these examples, however, is the notion of voluntary self-disclosure. Indeed, trust and engagement are not engendered when the revelation is involuntary (Hoffman-Graff 1977, Mohan et al. 2018). Taken together, the net effects on acquisition rates of a firm providing transparency into the tradeoffs inherent in its offerings are equivocal. The revelation of unflattering information may suppress demand, but voluntary self-disclosure may engender higher levels of trust and brand attraction. Due to these offsetting effects, we formulate the following hypothesis in null form:

Hypothesis 1 (H1): Providing prospective customers with transparency into the tradeoffs inherent in a firm's offering will have no effect on the firm's rate of customer acquisition.

2.2 Tradeoff Transparency and Customer Engagement

It is well established that customer satisfaction plays a key role in a firm's long-term performance. Research has demonstrated that highly-satisfied customers are more loyal and more profitable over time (Anderson 1994, Anderson et al. 1994, Heskett et al. 1997, LaBarbera and Mazursky 1983). Satisfaction levels, in turn, are largely persistent between firms and individual customers, and are influenced in part by customer compatibility – the degree of fit between the needs of the customer and the capabilities of the operation (Buell et al. 2018a). Customer compatibility can be influenced through a firm's segmentation strategies, wherein offerings are designed around the shared needs of particular operating segments of customers (Guajardo and Cohen 2017). However, the efficacy of such strategies is likely influenced by the degree of transparency firms provide to prospective customers into how those offerings are designed. Customers that are misaligned with a segmented service offering will be less satisfied with their experiences (Buell et al. 2018a, 2016), and will impose more variability on the operation (Frei 2006) which, in turn, will hinder the firm's service performance (Karmarkar and Pitbladdo 1995, Chase and Tansik 1983).

Providing prospective customers with transparency into the tradeoffs inherent in a service offering could improve customer compatibility in two ways: 1) by reducing Type I errors (false positives); and, 2) by reducing Type II errors (false negatives). In the context of customers choosing among service offerings, a Type I error occurs when a customer chooses an offering that is poorly aligned with his or her needs. When firms communicate the positive attributes of their offerings and omit the negative attributes, research in psychology has demonstrated that consumers often fill in the gaps in biased and overly favorable ways, and are more likely to choose the offering (Kivetz and Simonson 2000). Since such customers enter a service relationship with expectations that surpass the capabilities of the operation, the gap between their service expectations and experiences will result in dissatisfaction over time (McDougall and Levesque 2000, Oliver 1993, Parasuraman et al. 1985, Tse and Wilton 1988). In contexts with high switching costs, dissatisfied customers may remain with the firm (E. Anderson 1994, Buell et al. 2010, Yang and Peterson 2004), but are likely to spend less money than more highly-satisfied customers and may be more difficult and costly to serve (Coyles and Gokey 2005, Jones and Sasser 1995, Xue and Harker 2002). To the extent that providing prospective customers with transparency into the tradeoffs inherent in a firm's segmented offering can help reduce Type I errors, it stands to reason that the customers who choose the offering will be more aligned and satisfied with it, and in turn, will be more loyal and profitable to the firm.

On the other hand, in the context of customers choosing among service offerings, a Type II error occurs when a customer fails to select an offering that is well-aligned with his or her needs. Services have been characterized as "experience goods," since empirical research has demonstrated how customers are unable to fully assess them until after they have been delivered. Although providing consumers with incomplete information can trigger a psychological bias causing them to assume the best (Kivetz and Simonson 2000), when the lack of transparency is assumed to be volitional, people may assume the worst, undermining their trust and engagement (John et al. 2016). In this way, transparency into the tradeoffs inherent in a service offering may also result in fewer Type II errors, further promoting service relationships that are value producing and satisfying for customers, and long-lived and highly profitable for firms (Heskett et al. 1997).

To the extent that the information afforded by the provision of transparency may help reduce Type I and Type II errors, we hypothesize that customers exposed to transparency will make different choices when selecting a service offering than those who are not:

Hypothesis 2 (H2): Providing prospective customers with transparency into the tradeoffs inherent in a firm's offerings will result in customers selecting different offerings than they would select in the absence of such transparency.

Furthermore, if the provision of transparency reduces Type I and Type II errors, we would additionally expect engagement to increase among customers who are exposed to transparent messaging when they are choosing among service offerings. In particular, we hypothesize that product usage and retention will increase among customers who receive transparency:

Hypothesis 3 (H3): Providing prospective customers with transparency into the tradeoffs inherent in a firm's offering will increase product usage among those who choose to select the offering, relative to not providing such transparency.

Hypothesis 4 (H4): Providing prospective customers with transparency into the tradeoffs inherent in a firm's offering will increase product retention among those who choose to select the offering, relative to not providing such transparency.

Although we anticipate the main effects on usage and retention described above, prior research in the marketing domain has demonstrated that customers who are more familiar with a product category have the capacity to learn more from technical advertising (R. Anderson and Jolson 1980), and that more experienced consumers, by virtue of their familiarity, are better able to select information about attributes that are more predictive of product performance, in turn leading to better decisions that are more aligned with their needs (Johnson and Russo 1984). Hence, we predict that the long-run benefits of providing prospective customers with transparency into the tradeoffs of a service offering will accrue disproportionately to those with more prior category experience, who can learn from and make better use of the information transparency affords. If transparency can be best leveraged by more experienced customers to make choices that are better aligned with their needs, we would by extension predict that their levels of engagement would be disproportionately impacted. Accordingly, we hypothesize:

Hypothesis 5 (H5): The positive effect of tradeoff transparency on product usage will be most acute for customers who have more prior experience with the service category.

Hypothesis 6 (H6): The positive effect of tradeoff transparency on product retention will be most acute for customers who have more prior experience with the service category.

Lastly, a rich theoretical literature in economics and operations has modelled how customers sort among competing offerings, trading off price and service quality (Cachon and Harker 2002, Cohen and Whang 1997, Gabszewicz and Thisse 1979, Gans 2002, Hall and Porteus 2000, Karmarkar and Pitbladdo 1997, Li and Lee 1994, Shaked and Sutton 1982, Sutton 1986, Tirole 1990, Tsay and Agarwal 2000). Subsequent empirical work has documented that when service offerings are differentiated against the competitive set on the basis of quality, they attract more quality-sensitive customers, who are more likely to defect to higher-quality offerings. When offerings are instead differentiated on the basis of price, firms attract price-sensitive customers, who are less sensitive to quality, and more likely to defect to lower-priced offerings (Buell et al. 2016). Consistently, we predict that the effect of tradeoff transparency on customer engagement and retention will be negatively influenced by the presence of a promotion. Customers attracted to an offering on the basis of a discount or financial incentive may be less sensitive to the quality of the service experience than they are to the incentive itself, and hence, the benefits of increased alignment between their needs and the capabilities of the offering they select afforded by transparency are less likely to accrue to them. Moreover, to the extent that conflicts arise between the offering that's the best fit for a customer, and the promotional incentives provided to select it, we would further expect the presence of a promotion to diminish the impact of transparency on engagement and retention. For both reasons, we hypothesize:

Hypothesis 7 (H7): The positive effect of tradeoff transparency on product usage will be diminished among customers attracted to the offering by a promotion.

Hypothesis 8 (H8): The positive effect of tradeoff transparency on product retention will be diminished among customers attracted to the offering by a promotion.

3. Presentation of field experiment

To conduct this research, we partnered with Commonwealth Bank of Australia (CBA), which at the time of the experiment, had more than 1,000 branches, more than 45,000 employees, and more than 10 million retail banking customers. CBA was the largest issuer of credit cards in its market, with over 3 million credit card holders and annual transaction volume exceeding $50 billion USD. It offered nine types of personal credit cards, spread across three different families – awards cards, low rate cards, and low fee cards (**Figure 1**). We focus our analysis on customers who shopped for personal credit cards.

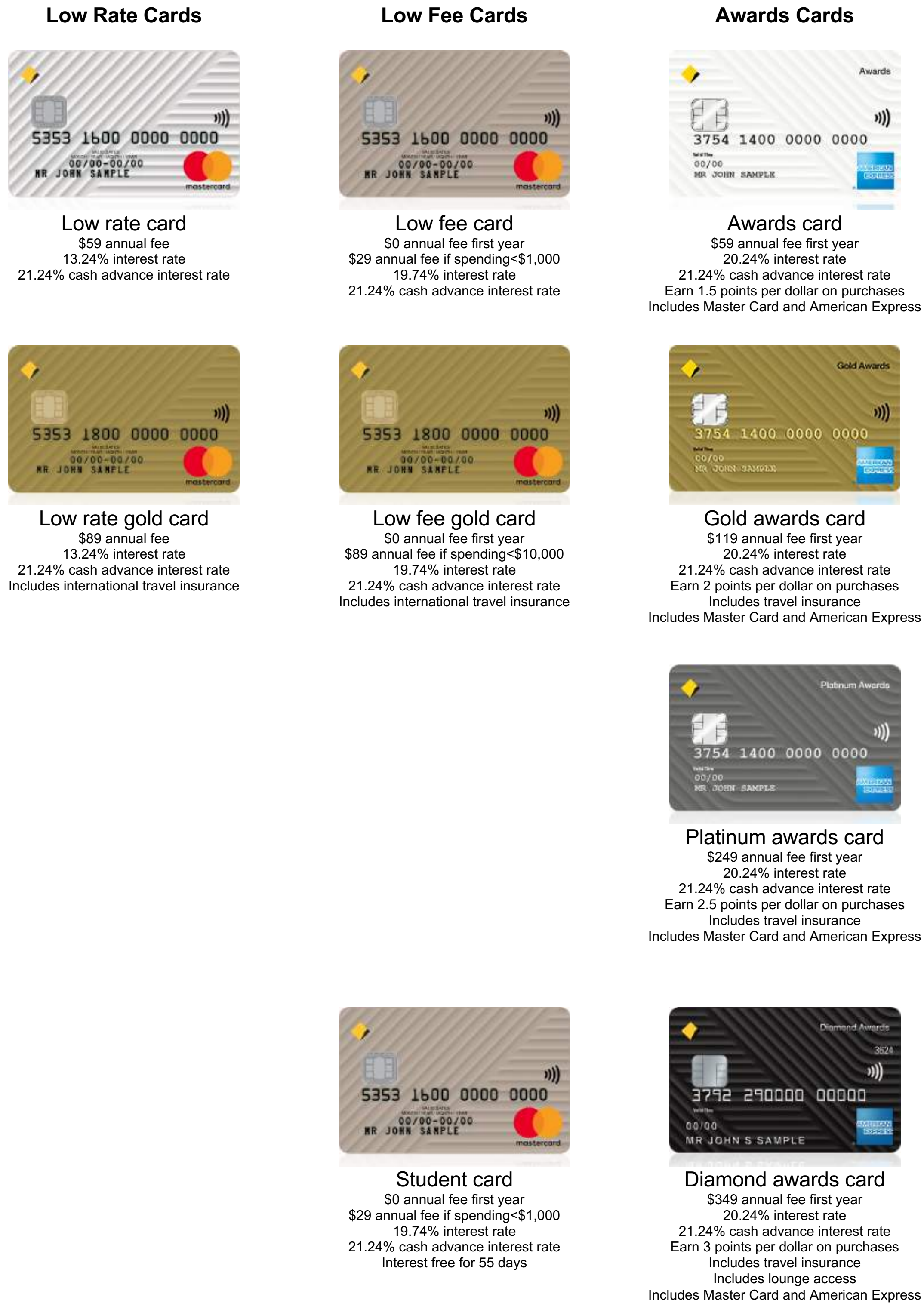

Figure 1. Credit card offerings from CBA during the time of the experiment. The bank offered cards in three families: 1) low rate cards, 2) low fee cards, and 3) awards cards. Because the credit card offerings were designed to serve customers with varying needs and preferences, the value proposition of each credit card included both benefits and tradeoffs, making it more appropriate for some prospective customers and less appropriate for others.

	Benefits (included in treatment and control)	**Tradeoffs** (included in the treatment only)
Low Rate	• Our lowest interest rate on purchases, currently 13.24% p.a. • Minimum credit limit of $500 • Free additional card holder	• The annual fee of $59 is higher than our Low Fee credit card • Does not earn awards points • Does not include travel insurance • International purchases may incur international transaction fees
Low Rate Gold	• Our lowest interest rate on purchases, currently 13.24% p.a. • International travel insurance included • Minimum credit limit of $4,000 • Free additional card holder	• There's an annual fee of $89 • Does not earn awards points • International purchases may incur international transaction fees
Low Fee	• $0 annual fee in the first year* and following years when you spend at least $1,000 in the previous year • Free additional card holder	• Does not earn awards points • Does not include travel insurance • There's an annual fee of $29 in the second and later years if you spend less than $1,000* in the previous year • International purchases may incur international transaction fees
Low Fee Gold	• $0 annual fee in the first year* and following years when you spend at least $10,000 in the previous year • International travel insurance included • Free additional card holder	• The purchase interest rate of 19.74% p.a. is higher than Low Rate credit cards • Does not earn awards points • There's an annual fee of $89 in the second and later years if you spend less than $10,000* in the previous year • International purchases may incur international transaction fees
Student	• $0 annual fee in the first year** • Free additional card holder	• The purchase interest rate of 19.74% p.a. is higher than Low Rate credit cards • Does not earn awards points • Does not include travel insurance • International purchases may incur international transaction fees
Awards	• Earn up to 1.5 Awards points for every dollar you spend • Access to the largest rewards program of any bank in Australia*	• The purchase interest rate of 20.24% p.a. is higher than Low Rate and Low Fee credit cards • There's an annual fee of $59 • Does not include travel insurance • International purchases may incur international transaction fees • There's a $10 p.a. additional cardholder fee
Gold Awards	• Earn up to 2 Awards points for every dollar you spend • Access to the largest rewards program of any bank in Australia* • International travel insurance included when you activate cover within [our online banking platform]	• The purchase interest rate of 20.24% p.a. is higher than Low Rate and Low Fee credit cards • There's an annual fee of $119 • International purchases may incur international transaction fees • There's a $10 p.a. additional cardholder fee
Platinum Awards	• Earn up to 2.5 Awards points for every dollar you spend • Access to the largest rewards program of any bank in Australia* • International travel insurance included when you activate cover within [our online banking platform] • No international transaction fees on overseas purchases made in-store and online using your CommBank Platinum American Express card	• The purchase interest rate of 20.24% p.a. is higher than Low Rate and Low Fee credit cards • There's an annual fee of $249 • There's a $10 p.a. additional cardholder fee
Diamond Awards	• Earn up to 3 Awards points for every dollar you spend • Access to the largest rewards program of any bank in Australia* • International travel insurance included when you activate cover within [our online banking platform] • No international transaction fees on overseas purchases made in-store and online using your CommBank Diamond American Express card	• The purchase interest rate of 20.24% p.a. is higher than Low Rate and Low Fee credit cards • There's an annual fee of $349 • There's a $10 p.a. additional cardholder fee

Figure 2. Website copy used in the treatment and control conditions for each card. Customers randomly assigned to the control condition only experienced the marketing of each credit card's benefits, which is common practice in the industry. Customers randomly assigned to the treatment condition were additionally presented with transparency into the tradeoffs of each offering.

Control Condition

Only the benefits of each credit card are presented

Treatment Condition

The benefits and tradeoffs of each credit card are presented

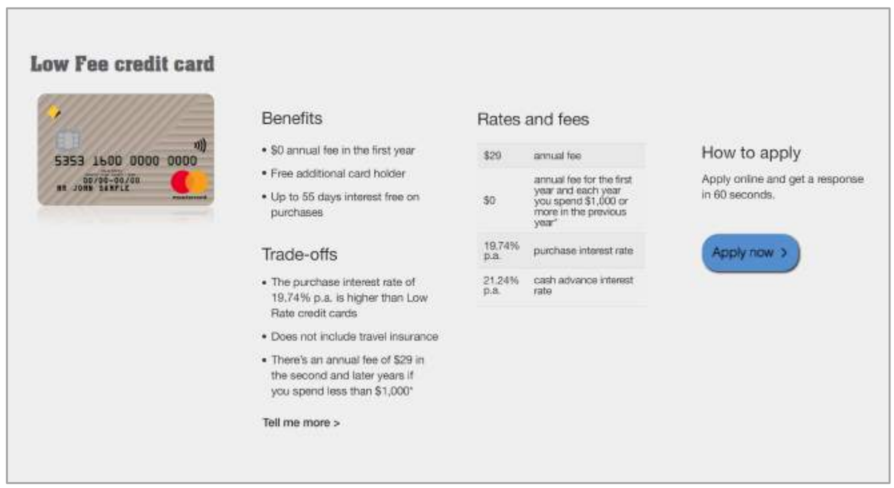

Figure 3. Example credit card product detail pages in the control and treatment conditions. The experimental manipulation involved more than 50 blocks of content on more than 20 pages of CBA's public-facing and secure online banking websites, such that every credit card marketing webpage where the features and benefits of a credit card were described, so too were its tradeoffs for customers randomly assigned to the treatment.

3.1 Data and methods

3.1.1 Participants, design, and procedure. From September 6, 2017 through February 4, 2018, we collaborated with CBA to conduct a field experiment on its website, engaging all customers who were considering opening a new credit card with the bank. 466,322 customers were randomly assigned to one of two experimental conditions.

Customers randomly assigned to the control condition, $TREAT_i = 0$, observed a version of the website that was consistent with the bank's traditional marketing efforts – emphasizing the features and benefits of each credit card in its primary copy. Customers randomly assigned to the treatment condition, $TREAT_i = 1$, observed an augmented version of the website, in which the primary copy additionally revealed the tradeoffs inherent in each offering (**Figure 2**). For example, customers in the control condition who shopped the low fee credit card would be able to view and learn about the card's benefits: $0 annual fee in the first year, free additional card holders, and up to 55 days interest-free on purchases. Furthermore, they would be able to view information about rates and fees, and about the security features of the card. Customers randomly assigned to the treatment condition would additionally be able to view the tradeoffs inherent in the offering: (*i*) the purchase interest rate of 19.74% p.a. is higher than that of the low rate card, (*ii*) the low fee credit card does not include travel insurance, and (*iii*) there is an annual fee of $29 if the cardholder does not spend at least $1,000 on the card. Importantly, information about tradeoffs was disclosed to all customers in the terms and conditions of each offering. However, the experimental treatment promoted its salience by moving its messaging into the website's primary copy. In this way, the experiment was designed to cleanly identify the effects of increasing the transparency of information about an offering's tradeoffs, on the acquisition rates, choices, and subsequent engagement, of prospective customers (**Figure 3**).

During the time of our experiment, the bank offered three channels through which customers could access information about its credit cards: a public-facing website, a secure online banking website, and a mobile banking application. Our experiment manipulated the presentation of information on the two websites, which historically had accounted for roughly 80% of new credit card applications that came in through digital channels. The mobile application, in which it was infeasible to experimentally manipulate content, contained an abbreviated version of the information displayed online to the customers in the control condition. This content was held constant during the period of our experiment.

For each customer, assignment to an experimental condition was randomly determined at the beginning of their first visit to the credit card section of one of the bank's two websites. The consistency of a customer's random assignment to an experimental condition across channels was controlled by a cookie that was passed by the bank's public website to each customer's browser. Once customers logged into the online banking website, their assigned conditions were saved in the bank's databases. Although this design largely ensured consistent presentation of content across multiple sessions, 44,765 customers were identified to have experienced multiple conditions and were dropped from the analysis. We also dropped an additional 20,008 customer observations that were missing relevant data elements – such as the date the customer visited the credit card website, or the types of credit cards for which they browsed – that prevented tracking the customer's progression through the acquisition funnel. We additionally dropped 1,514 customers from the analysis who ultimately applied outside the experimental period. Moreover, midway through the experiment, the bank detected inconsistent benefits information across the treatment and control conditions for one type of low fee card on one page of the bank's website. To distinctly identify the effect of the treatment on the treated customers, for our primary analysis, we withhold observations from the

10,424 customers in both conditions who visited this specific page, though we note in an analysis in the online appendix that the results are substantively similar with these customers included. Our primary analysis, therefore, includes observations from a total of 389,611 customers, 194,175 of whom were randomly assigned to the control condition, and 195,436 of whom were randomly assigned to the treatment condition **(Table 1)**.

	All			Control			Treatment			Diff.
	N	Mean	SD	N	Mean	SD	N	Mean	SD	P-value
Arrived during the promo period	389,611	63.08%	0.48	194,175	62.95%	0.48	195,436	63.20%	0.48	0.11
Customer demographics										
Customer age	389,517	40.12	15.60	194,123	40.12	15.62	195,394	40.11	15.58	0.80
Customer tenure (months)	388,936	198.49	138.63	193,832	198.34	138.74	195,104	198.65	138.52	0.49
Male indicator	389,440	45.08%	0.50	194,088	45.16%	0.50	195,352	45.00%	0.50	0.31
Product indicators										
Transaction product	389,451	89.72%	0.30	194,093	89.71%	0.30	195,358	89.72%	0.30	0.96
Savings product	389,451	67.71%	0.47	194,093	67.70%	0.47	195,358	67.72%	0.47	0.91
Home loan product	389,451	21.99%	0.41	194,093	22.02%	0.41	195,358	21.96%	0.41	0.63
Home insurance policy	389,451	11.47%	0.32	194,093	11.49%	0.32	195,358	11.45%	0.32	0.68
Personal loan product	389,451	10.00%	0.30	194,093	9.96%	0.30	195,358	10.05%	0.30	0.32
Retirement product	389,451	4.74%	0.21	194,093	4.77%	0.21	195,358	4.71%	0.21	0.45
Motor insurance policy	389,451	4.04%	0.20	194,093	4.01%	0.20	195,358	4.07%	0.20	0.38
Term deposit product	389,451	3.89%	0.19	194,093	3.90%	0.19	195,358	3.87%	0.19	0.70

Table 1. Summary statistics for customers in the control and treatment conditions. Customer characteristics were captured as of the time of their first documented arrival on the credit card website, and thus, are unaffected by the experimental treatment. We control for all of these customer-level factors in our empirical models, though we note that customers in both conditions were quite well-balanced on these observable dimensions prior to their random assignment. Differing numbers of observations for different variables reflect missing data.

Furthermore, on November 1, 2017 (midway through our period of experimentation), the bank publicly announced a promotion, offering $300 cash back to customers who opened a credit card in the Low Rate family and spent $1,000 in purchases with the new card within the first 90 days of activation. The announcement was broadly supported by advertising (e.g., television, radio, and print). Random assignment to the experimental conditions proceeded during this promotional period, affording an opportunity to assess whether providing customers with incentives to choose particular offerings moderates the effect of presenting tradeoffs on customer acquisition and engagement. The promotional period ran from November 1 through the end of the experiment. We identified 143,845 customers who initially visited the credit card website prior to the November 1 promotion announcement to not be treated with the promotion, $PROMO_i$ =0, and 245,766 customers who initially visited on November 1 or after to be treated with the promotion, $PROMO_i$ =1.

3.1.2 Acquisition measures. In order to assess the impact of providing transparency into the tradeoffs of a service offering on rates of customer acquisition we tracked: (1) whether the customer progressed through each stage of the acquisition funnel, $\Pr\left(ACQ_{it}\right)$, and (2) which types of credit card accounts customers opened, $\Pr\left(CHOICE_{it}\right)$. At the time of our study, the credit card acquisition funnel for our partner bank had six stages. In order to gain a detailed understanding of how the experimental treatment affected customer acquisition, we used six binary variables to instrument each customer's progress through the acquisition funnel. In particular, we coded each stage of the acquisition funnel to be 1 if the customer passed the stage, and 0 if she did not.

The first stage of the acquisition funnel occurred when the customer *started an application*. During the application process, customers of the partner bank answered a series of 10 to 40 questions, providing their demographic information as well as their financial information (such as assets, liabilities, income, and expenses). For the more than 95% of prospective customers who had existing accounts with the bank, this stage of the process was streamlined considerably; by simply logging into their online banking accounts, these customers would be able to transfer their information from their existing accounts to their credit card applications. Answering these questions typically took customers 5-15 minutes, depending on how much information was required to complete their financial profile.

Submitting the answers to these questions triggered the second stage of the acquisition funnel, which was known as a *soft submission*. In this phase, the bank parsed through the information provided using an automated process to conduct a risk assessment and determine whether the customer's financial profile warranted approval for the credit card for which she had applied, as well as her eligible credit limit. After the results of this process were shared with the customer, the customer could choose to move on to the third stage, providing a *hard submission.* The application submitted at this stage constituted a formal application submission for a credit card; at this stage, customers provided verification documents required by the bank to substantiate their income as well as financial holdings and obligations that resided outside the bank. This stage could last two weeks or longer, depending on the amount of information provided by the customer and the amount of time the customer took to provide all the necessary information.

If the bank's process during the hard submission stage substantiated the information provided in the application, the customer was then moved into the fourth stage, wherein her account was *opened.* Here, the bank created and issued a new credit card for the customer and mailed it to her preferred address. This process typically took about a week. To test whether providing transparency influenced customer choices, we take a snapshot at this stage, comparing which types of card accounts were opened by customers randomly assigned to the treatment and control conditions.

In the fifth stage, the customer *activated* the card either by phone, online, through the mobile application, or by inserting the card into one of the bank's ATM machines. Finally, in the sixth stage, the customer *used* the card to make her first purchase; customers that reached the final stage of the acquisition funnel comprised 4.05% of all customers who shopped for a credit card. For our analyses, we denote a customer to have reached this final stage if a purchase was made with the card within two billing cycles of its activation. Imposing this constraint facilitates comparability among customers acquired early and late in our experimental period, as failure to do so would afford those who opened their accounts early more time to demonstrate usage. We note that 95.42% of all cards that were eventually used to make a purchase in our dataset were used within two billing cycles of their initial activation, and that all results presented in this manuscript are substantively similar if usage is instead defined by whether any transaction behavior is ever observed in our data.

Customer progress through the acquisition funnel could stall during any of these six stages, as each stage was comprised of different dynamics with respect to the customer's experience and the bank's operating costs. Hence, analyzing each stage separately provides important insights about the costs and benefits of providing prospective customers with transparency into the tradeoffs inherent in a service offering.

3.1.3 Engagement measures. For customers who made it all the way through the acquisition funnel, we tracked customer engagement with the card in two ways. First, we tracked product usage by examining logged monthly spending during the first nine months the customer held the card, $\ln\left(SPEND_{it}\right)$. Spend is a relevant engagement metric, both because it is a direct measure of usage that is an important behavioral indicator of a card's utility for the customer, and because it is an important driver of profitability for the bank. Bank-issued credit cards generate revenue through interest spreads (interest paid by customers who don't fully pay off their balances at the end of the month), interchange fees paid by merchants (small percentages of each transaction), and customer fees (usage fees, service fees, and penalty fees). Customer spend directly influences the bank's first two revenue streams.

Second, we tracked customer retention, i.e., whether the customer closed the credit card account during the first nine months it was open, $\Pr\left(RETAIN_{it}\right)$. As with spend, retention is a relevant measure of customer engagement, because loyalty is an important behavioral indicator of the card's utility to the customer, and because it is an important driver of profitability (Levesque and McDougall 1996). Previous research conducted in banking demonstrated that reducing defections by just 5% can increase firm profitability by as much as 100% (Reichheld and Sasser 1990).

We note that these engagement measures were queried on August 28, 2018, which means that six full months of account data are available for any customer who activated their credit cards before February 28, 2018, and nine full months of account data are available for any customer who activated their credit cards before November 30, 2017. Importantly, all customers who were denoted to have used their cards in our analysis had at least six months of available account data. Consistently, we track spend during any observed month for which a credit card account was open and activated, and we track retention six and nine months into the customer relationship.

3.1.4 Control measures. Although customers randomly assigned to the treatment and control conditions appear quite well balanced on observable dimensions (**Table 1**), to get the cleanest possible estimates of the effects of the experimental treatment on treated customers, we control for a vector of customer-level factors which were observable prior to each customer's random assignment. These factors include the non-linear effect of the customer's age, AGE_i and AGE_i^2, and tenure with the bank (in months), $TENURE_i$, and $TENURE_i^2$, their gender $GENDER_i$, and indicators for whether they held a home loan product, $HLOAN_i$, a personal loan product, $PLOAN_i$, a transaction product, $TRANS_i$, a savings product, SAV_i, a home insurance policy, $HINS_i$, a vehicle insurance policy, $VINS_i$, a business transaction, $BTRANS_i$, or savings product, $BSAV_i$, or a retirement product with the bank, RET_i. For the acquisition analyses, we also include a vector of date indicator variables, X_t, signifying the first week the customer visited the credit card pages on the bank's website, to control for time-varying factors that may have affected each customer's initial motivation for seeking a credit card. For the engagement analyses, we include a similar vector of date indicator variables, X_t, signifying the first week the customer activated their credit card, to control for time-varying factors that may influence the way customers interact with the credit card (e.g., a credit card activated before the holidays may be used more intensively than one activated after, etc.)

3.1.5 Category experience and financial incentives. Lastly, to test Hypotheses 5-8, that the effects of providing transparency into the tradeoffs inherent in a service offering will have a greater effect on customers with more experience with the product category (H5-H6), and on customers who were not attracted by a financial incentive (H7-H8), we incorporate data on proxies for both factors into our analysis. First, since we lack complete data on the degree of credit card experience for each prospective customer (e.g., because not every customer provides their financial history, and many customers may have accounts with financial institutions that are not our partner bank), we use the prospective customer's age as the primary proxy in our analysis. In the market where CBA operated during the time of our experiment, the minimum age to apply for a credit card was 18. Data captured by CBA reveals that the probability a prospective customer has at least one credit card increases concavely in age (**Figure 4**). As such, data on the ages of credit card browsers and applicants during our study was right skewed. The average credit card browser was 40.12 years old and the median browser was 37 years old. The average credit card applicant was 31.27 years old, and the median applicant was 28 years old. To test hypotheses 5 and 6, that the effects of providing prospective customers with transparency into the tradeoffs of each offering will have a disproportionate effect on the product usage and retention of customers with more prior category experience, we complement our analyses on the full sample of data with split sample analyses of customers who were 28 and younger (less experienced with credit cards), and customers who were older than 28 (more experienced with credit cards). Using the median applicant age to conduct a split sample analysis yields a comparable number of more-experienced and less-experienced customers. However, as we document in the online appendix, our results are substantively similar with different cutoffs, for example, splitting the bottom quartile of the credit card applicant data (24 and younger) from the top three quartiles.

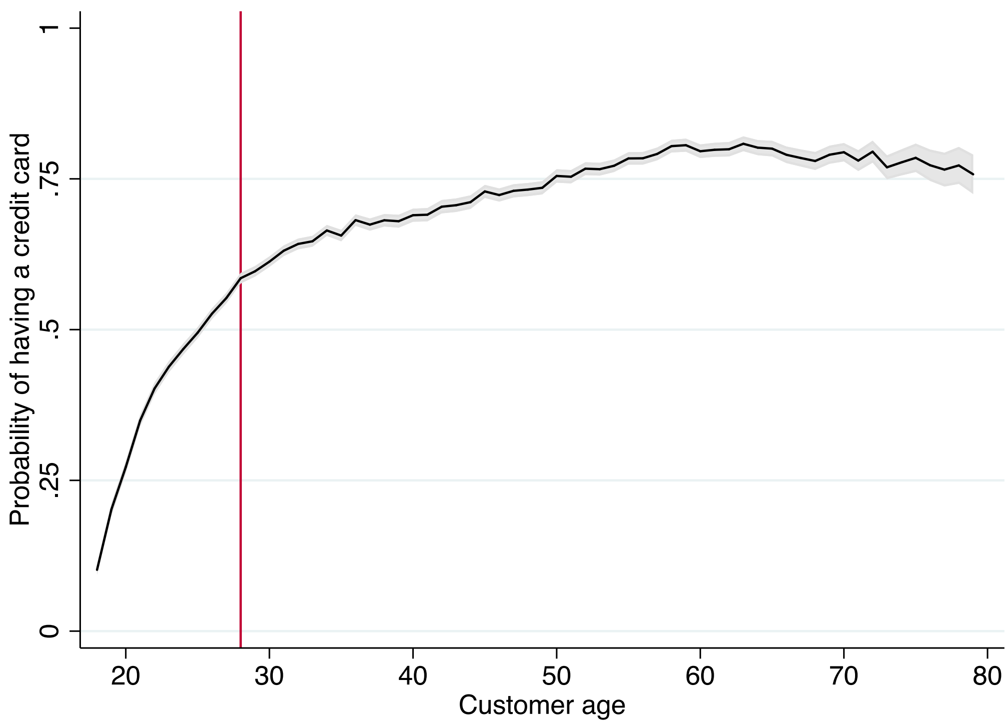

Figure 4: The probability a prospective customer shopping for a credit card already has a credit card, as a function of their age (n=389,085). Predicted plots are based on a logistic regression of the probability of having a credit card as a function of indicator variables for the prospective customer's age, regressed on the full sample of prospective customers aged 18-79 (within support of 99% of the data). A 95% confidence interval band is shown in light grey. For our primary analyses, we denote customers aged 28 and younger (the median age for a credit card applicant) as less experienced, and customers 28 and older to be more experienced with credit cards. This cutoff is shown with a red vertical line, and it demonstrates that the probability a 28-year old prospective customer had a credit card at the time of this study was 58.5%.

Second, to test whether our experimental treatment had differential effects for customers who were motivated to shop for a credit card by a promotion, we include an interaction term in all of our empirical specifications, $PROMO_i$, denoting whether the customer first visited the credit card website or applied for a credit card on or after November 1, 2017, the day the promotion was publicly announced. This empirical approach enables us to directly test the significance of the effect of the treatment on customers who conducted their credit card searches organically (e.g., before November 1, in the absence of a promotion), and also to test whether the treatment had a differential effect among customers who are more likely to have been influenced by the promotion (e.g., on or after November 1, initiating their search or applying for a credit card while the promotion was live). Since we cannot observe whether customers who first began their search on or after November 1, 2017 were directly influenced by the promotion, this empirical approach constitutes an intention to treat design, and hence, should be interpreted as a conservative estimate of the contingent effect of the promotion on the transparency treatment. We note that this empirical design is consistent with prior research in the marketing literature that has analyzed customers who were acquired by means of a promotion differently from those who were acquired organically (Anderson and Simester 2004, Krishnamurthi and Raj 2006, Lewis 2006).

3.2 Empirical approach

We analyze rates of acquisition, card choice, spend, and customer retention as a part of our analysis. This section outlines our empirical approach for each analysis.

3.2.1 Acquisition funnel. To estimate the effects of the experimental treatment on the probability that customer *i* reached each stage of the acquisition funnel (application started, soft submission completed, submission completed, account opened, card activated, card used), ACQ_{it}, we use the following logistic regression model, with standard errors clustered by the date she first visited the credit card marketing site. We note that ACQ_{it} for any particular customer refers to the furthest acquisition funnel stage she reached for any credit card for which she applied during the experimental period.

$$\Pr\left(ACQ_{it}\right) = f\left(\begin{array}{c} \alpha_0 + \alpha_1 TREAT_i + \alpha_2 PROMO_i + \alpha_3 TREAT_i \times PROMO_i + \\ \alpha_4 AGE_i + \alpha_5 AGE_i^2 + \alpha_6 TENURE_i + \alpha_7 TENURE_i^2 + \alpha_8 GENDER_i + \\ \alpha_9 HLOAN_i + \alpha_{10} PLOAN_i + \alpha_{11} TRANS_i + \alpha_{12} SAV_i + \alpha_{13} HINS_i + \\ \alpha_{14} VINS_i + \alpha_{15} BTRANS_i + \alpha_{16} BSAV_i + \alpha_{17} RET_i + X_t + \epsilon_{it} \end{array}\right) \tag{1}$$

3.2.2 Card choice. To estimate the effects of the experimental treatment on the probability that customer *i* opened each type of card (awards, diamond, gold low fee low fee gold, low rate, low rate gold, platinum, or student), $CHOICE_{it}$, we use the following logistic regression specification with standard errors clustered by the date she first visited the credit card marketing site:

$$\Pr\left(CHOICE_{it}\right) = f\left(\begin{array}{c} \beta_0 + \beta_1 TREAT_i + \beta_2 PROMO_i + \beta_3 TREAT_i \times PROMO_i + \\ \beta_4 AGE_i + \beta_5 AGE_i^2 + \beta_6 TENURE_i + \beta_7 TENURE_i^2 + \beta_8 GENDER_i + \\ \beta_9 HLOAN_i + \beta_{10} PLOAN_i + \beta_{11} TRANS_i + \beta_{12} SAV_i + \beta_{13} HINS_i + \\ \beta_{14} VINS_i + \beta_{15} BTRANS_i + \beta_{16} BSAV_i + \beta_{17} RET_i + X_t + \epsilon_{it} \end{array}\right) \quad (2)$$

To account for time-varying differences in the motivation to pursue a credit card, which could affect both persistence in the acquisition process, and one's choice of credit card, we include a vector of indicator variables, X_t, in Models (1) and (2) denoting the week the customer first visited the marketing website.

3.2.3 Spend. To estimate the effects of the experimental treatment on the spend of customer *i*, in month *t,* observed months when the credit card account was open and activated, we use the following fixed effects panel model, with standard errors clustered by the date she activated the card.

$$\ln\left(SPEND_{it}\right) = f\left(\begin{array}{c} \gamma_0 + \gamma_1 TREAT_i + \gamma_2 PROMO_i + \gamma_3 TREAT_i \times PROMO_i + \\ \gamma_4 AGE_i + \gamma_5 AGE_i^2 + \gamma_6 TENURE_i + \gamma_7 TENURE_i^2 + \gamma_8 GENDER_i + \\ \gamma_9 HLOAN_i + \gamma_{10} PLOAN_i + \gamma_{11} TRANS_i + \gamma_{12} SAV_i + \gamma_{13} HINS_i + \\ \gamma_{14} VINS_i + \gamma_{15} BTRANS_i + \gamma_{16} BSAV_i + \gamma_{17} RET_i + X_t + \epsilon_{it} \end{array}\right) \quad (3)$$

3.2.4 Retention. To estimate the effects of the experimental treatment on the retention of customer *i,* six and nine months after the activation of her card, we use the following logistic regression, with standard errors clustered by the date she activated the card.

$$\Pr\left(RETAIN_{it}\right) = f\left(\begin{array}{c} \delta_0 + \delta_1 TREAT_i + \delta_2 PROMO_i + \delta_3 TREAT_i \times PROMO_i + \\ \delta_4 AGE_i + \delta_5 AGE_i^2 + \delta_6 TENURE_i + \delta_7 TENURE_i^2 + \delta_8 GENDER_i + \\ \delta_9 HLOAN_i + \delta_{10} PLOAN_i + \delta_{11} TRANS_i + \delta_{12} SAV_i + \delta_{13} HINS_i + \\ \delta_{14} VINS_i + \delta_{15} BTRANS_i + \delta_{16} BSAV_i + \delta_{17} RET_i + X_t + \epsilon_{it} \end{array}\right) \quad (4)$$

To account for time-varying differences in credit card usage in Models (3) and (4), we include a vector of indicator variables, X_t, denoting the calendar week in which the customer activated the card.

3.3 Analysis and results

3.2.1 Acquisition funnel (H1). **Figure 5** graphically displays the marginal effects of the treatment on the acquisition funnel of the treated customers. The results show three features of consequence. First, rates of conversion were higher during the promotion period, likely owing to the efficacy of the promotion in attracting interested customers to the website and in enhancing the appeal of the promoted products. Second, during the promotion period, when offered transparency into the tradeoffs inherent in each credit card, significantly fewer customers chose to start the application process (17.73% vs 17.38%, p<0.05) or soft submit their application (14.49% vs 14.20%, p<0.05). Interestingly, these differences did not emerge among customers who shopped for credit cards outside the promotion period. Finally, and most significantly, during both periods, there were no significant differences in rates of conversion through the various phases of the acquisition funnel during the submission phase and beyond. As we document in the online appendix, we note that these patterns are substantively similar among customers with high and low experience levels with credit cards. Taken together, these results suggest that, consistent with H1, from an acquisition perspective, voluntarily providing prospective customers with transparency into the tradeoffs of the firm's offerings, had no effect on its overall rate of customer acquisition.

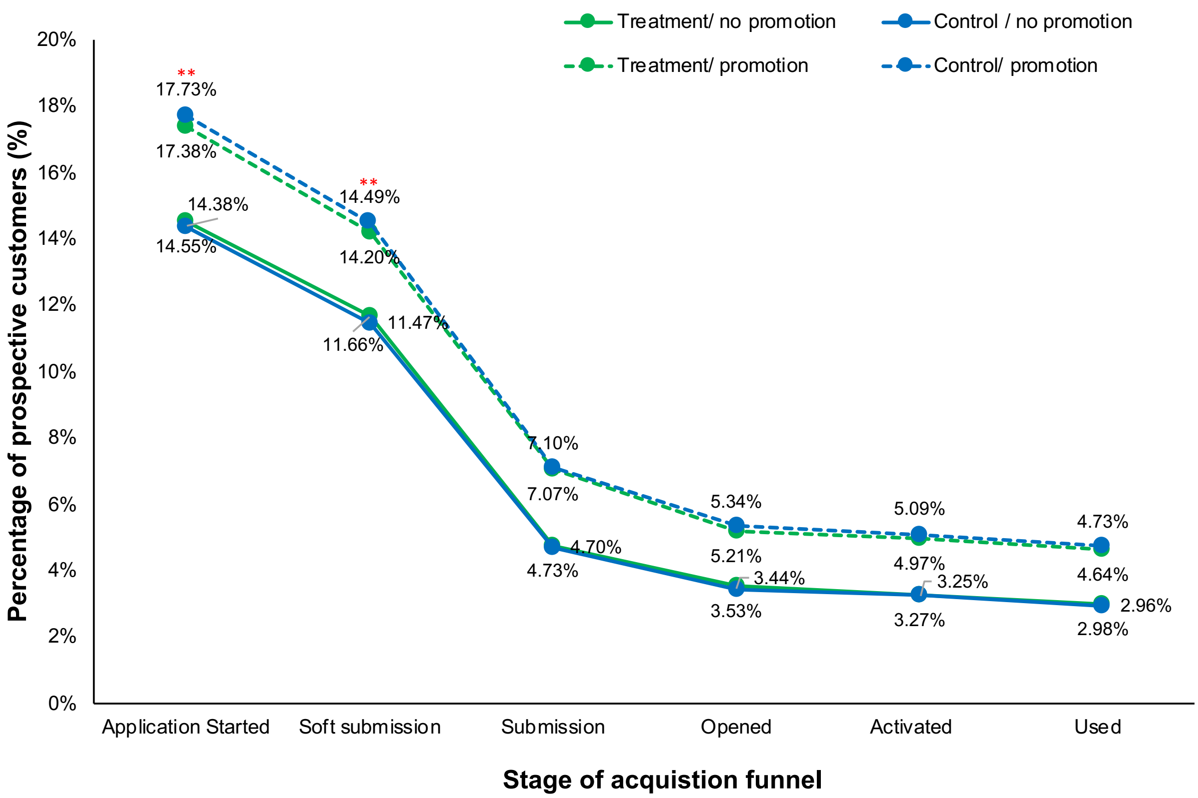

Figure 5: Acquisition funnel conversion percentages during the promotion and non-promotion periods. Marginal effects are from logistic regression models, estimated with robust standard errors clustered at the first website visit date level. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively. The results indicate that conversion rates are significantly higher during the promotion period. Moreover, although fewer customers who are exposed to the treatment during the promotion period start or soft submit an application, the treatment ultimately had no effect on rates of customer acquisition, neither during the promotion nor the non-promotion periods, which is consistent with H1.

3.2.2 Card choice (H2). **Table 2**, Panel A documents the marginal effects of Model (2), regressed first on the full sample of customers who opened credit cards during the entire experimental period, and then on a split sample, median-split by age, with customers at and below the median age presented first and customers above the median age presented second. This analysis is replicated on the subsample of customers who arrived during the non-promotion period and promotion period in Panels B and C, respectively. Each table directly compares the probabilities that applicants in the control and treatment conditions would open different types of cards. The results demonstrate that, consistent with H2, the treatment did affect the credit card choices of customers who opened credit card accounts. Panel A demonstrates that, controlling for other factors, customers of all ages in the treatment condition were less likely to open the low rate card (β = -0.142, $p<0.05$) and more likely to open the low rate gold card (β = 0.220, $p<0.05$) and platinum card (β = 0.262, $p<0.05$) than customers in the control condition.

A.
Entire period
(n=17,944)

	All customers (n=17,944)				**Customer age ≤ 28 (n=8,992)**				**Customer age > 28 (n=8,952)**			
	Control	Treatment		P-value	Control	Treatment		P-value	Control	Treatment		P-value
Awards card	4.77%	5.02%		0.960	4.48%	5.16%		0.992	5.14%	4.76%		0.915
Diamond card	2.14%	2.26%		0.498	1.66%	2.12%		0.883	2.64%	2.46%		0.239
Gold card	2.70%	2.74%		0.228	2.83%	2.99%		0.151	2.71%	2.52%		0.664
Low fee card	14.79%	14.47%		0.466	16.08%	15.11%		0.715	13.43%	14.02%		0.234
Low fee gold card	2.76%	3.09%		0.974	2.85%	3.09%		0.974	2.68%	3.04%		0.936
Low rate card	51.85%	49.82%	**	0.037	51.00%	48.48%		0.093	52.57%	51.11%	*	0.098
Low rate gold card	11.95%	13.03%	**	0.012	10.60%	11.50%		0.111	13.32%	14.42%	*	0.092
Platinum card	5.44%	6.03%	**	0.015	3.98%	4.89%	**	0.045	6.85%	7.14%		0.278
Student card	3.54%	3.60%		0.880	6.73%	6.99%		0.818	0.78%	0.71%		0.418

B.
Non-promotion period
(n=5,006)

	All customers (n=5,006)				**Customer age ≤ 28 (2,599)**				**Customer age > 28 (n=2,407)**			
	Control	Treatment		P-value	Control	Treatment		P-value	Control	Treatment		P-value
Awards card	6.12%	6.12%		0.993	5.71%	5.62%		0.912	6.75%	6.72%		0.979
Diamond card	3.09%	2.81%		0.528	2.55%	2.44%		0.852	3.81%	3.25%		0.341
Gold card	3.83%	3.22%		0.239	4.03%	2.88%		0.148	3.88%	3.54%		0.641
Low fee card	18.53%	19.21%		0.499	18.48%	19.09%		0.652	18.54%	20.22%		0.219
Low fee gold card	4.22%	4.19%		0.965	3.90%	3.88%		0.974	4.51%	4.56%		0.952
Low rate card	43.38%	39.88%	**	0.032	43.88%	40.67%	*	0.094	42.71%	38.51%	*	0.068
Low rate gold card	10.55%	12.89%	**	0.009	9.15%	11.15%	*	0.099	12.17%	14.79%	*	0.062
Platinum card	5.86%	7.52%	**	0.012	4.37%	6.35%	**	0.040	7.52%	8.86%		0.265
Student card	5.34%	5.31%		0.959	9.18%	9.55%		0.745	1.31%	0.87%		0.365

C.
Promotion period
(n=12,938)

	All customers (n=12,938)				**Customer age ≤ 28 (n=6,393)**				**Customer age > 28 (n=6,545)**			
	Control	Treatment		P-value	Control	Treatment		P-value	Control	Treatment		P-value
Awards card	4.24%	4.62%		0.278	4.02%	5.00%	*	0.065	4.57%	4.11%		0.358
Diamond card	1.80%	2.05%		0.311	1.37%	2.04%	**	0.047	2.20%	2.19%		0.957
Gold card	2.28%	2.57%		0.263	2.41%	3.11%	*	0.056	2.36%	2.22%		0.702
Low fee card	13.37%	12.66%		0.276	15.12%	13.55%	*	0.093	11.56%	11.82%		0.738
Low fee gold card	2.23%	2.68%	*	0.078	2.47%	2.77%		0.456	2.04%	2.54%		0.199
Low rate card	55.17%	53.62%	*	0.093	53.91%	51.66%	*	0.094	56.31%	55.65%		0.598
Low rate gold card	12.53%	13.13%		0.319	11.23%	11.69%		0.573	13.83%	14.43%		0.537
Platinum card	5.29%	5.52%		0.596	3.91%	4.48%		0.239	6.65%	6.58%		0.917
Student card	3.44%	3.56%		0.693	5.87%	6.15%		0.639	1.02%	1.10%		0.834

Table 2: Effects of the treatment on card choice. Marginal effects from logistic regression models, estimated with robust standard errors clustered at the first website visit date level are presented. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively. The results indicate that providing transparency into the tradeoffs of the service offering influenced credit card choices, which is consistent with H2.

Examining the split sample analyses provides evidence that transparency into the tradeoffs of each credit card influenced the behavior of customers with varying levels of experience differently. For example, less experienced customers exposed to the treatment were more likely to open the platinum card (β = 0.393, p<0.05). More experienced customers exposed to the treatment were less likely to open the low rate card (β = -0.162, p<0.10), and were more likely to open the low rate gold card (β = 0.208, p<0.10). These differences are interesting, since they suggest that different types of customers with different needs evaluated the tradeoffs differently, which in turn, differentially affected their choices. Moreover, these diverging effects of the treatment among customers with varying experience levels further suggest that the results were not merely driven by tradeoff copy that made some credit cards appear clearly dominant to others.

As additional evidence, it is revealing to consider the differential effects of the treatment on the choices of customers who applied for credit cards in the absence and presence of a promotion, which are presented in Panels B and C, respectively. During the non-promotion period, the patterns of results among all, less experienced, and more experienced customers were consistent with those described above across the entire experimental period, with the addition that less experienced customers were marginally less likely to select the low rate card (β = -0.137, p<0.10), and were marginally more likely to select the low rate gold card (β = 0.225, p<0.10) when provided transparency into each card's tradeoffs. By contrast, during the promotion period, which likely attracted customers with different needs and preferences, the treatment dissuaded less experienced customers from the low rate (β = -0.092, p<0.10) and low fee cards (β = -0.129, p<0.10) , and increased their interest in the awards (β = 0.229, p<0.10), diamond (β = 0.422, p<0.05), and gold cards (β = 0.265, p<0.10). Interestingly, during the promotion period, the treatment exhibited no effect on the credit card choices of more experienced customers. However, marginal effects emerge across the full sample of customers during the promotion period; those exposed to transparency were less likely to select the low rate card (β = -0.063, p<0.10) and were more likely to select the low fee gold card (β = 0.192, p<0.10). In sum, these results suggest that, consistent with H2, transparency influenced customers' credit card choices.

3.2.3 Product usage (H3, H5, H7). In **Table 3**, Columns 1-3, we analyze the average monthly spending of all, less experienced, and more experienced customers. Average monthly spending captures the usage behavior of customers in all months during which they held an active credit card, including months when they had it, but didn't use it (e.g., monthly spend is $0), and excluding months after which they may have cancelled it (e.g., monthly spend is missing, because the customer no longer held the card). As such, monthly spend, as it is estimated in Columns (1-3), is a direct measure of contemporary customer engagement, in that it captures how the card was used while the card was held. Column (1) shows that the treatment led to nominal, though insignificant, increase in average monthly spending (γ=0.080, p=0.122), that the promotion had no effect on spend (γ=-0.104, p=0.314), and that there was an insignificant interaction (γ=-0.097, p=0.111), when the effects were considered across all customers.

	(1) Ln(Spend)	(2) Ln(Spend)	(3) Ln(Spend)	(4) Ln(Spend)	(5) Ln(Spend)	(6) Ln(Spend)
Treatment	0.080	0.035	0.138**	0.095*	0.033	0.176***
	(0.052)	(0.085)	(0.069)	(0.054)	(0.092)	(0.062)
Promotion	-0.104	0.019	-0.230	-0.371***	-0.150	-0.593***
	(0.103)	(0.131)	(0.151)	(0.114)	(0.125)	(0.166)
Treatment x promotion	-0.097	-0.054	-0.162**	-0.109*	-0.045	-0.199**
	(0.061)	(0.103)	(0.082)	(0.064)	(0.110)	(0.080)
Customer age	0.072***	0.077	0.009	0.046***	0.137	0.027
	(0.008)	(0.129)	(0.018)	(0.009)	(0.136)	(0.019)
Customer age²	-0.001***	-0.001	-0.000	-0.001***	-0.002	-0.000
	(0.000)	(0.003)	(0.000)	(0.000)	(0.003)	(0.000)
Customer tenure	0.002***	0.005***	-0.001	0.000	0.004***	-0.002***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Customer tenure²	-0.000	-0.000***	0.000*	0.000	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male indicator	0.050	0.100**	0.001	0.072**	0.106**	0.035
	(0.034)	(0.046)	(0.041)	(0.034)	(0.045)	(0.044)
Retirement product	0.045	0.147	0.027	0.038	0.173	0.015
	(0.105)	(0.160)	(0.123)	(0.108)	(0.164)	(0.122)
Home loan product	-0.038	0.028	-0.045	-0.044	0.142	-0.090
	(0.076)	(0.162)	(0.088)	(0.085)	(0.172)	(0.097)
Personal loan product	0.496***	0.184	0.595***	1.043***	1.120***	0.999***
	(0.105)	(0.231)	(0.121)	(0.101)	(0.228)	(0.123)
Savings product	0.198*	0.406**	0.072	-0.023	0.253	-0.170
	(0.120)	(0.161)	(0.154)	(0.133)	(0.189)	(0.168)
Term deposit product	0.277***	0.403***	0.182***	0.247***	0.369***	0.156***
	(0.040)	(0.062)	(0.050)	(0.040)	(0.062)	(0.050)
Transaction product	-0.324***	-0.437***	-0.230***	-0.209***	-0.376***	-0.071
	(0.039)	(0.063)	(0.054)	(0.043)	(0.065)	(0.057)
Home insurance policy	0.509***	0.736***	0.468***	0.349***	0.500***	0.334***
	(0.049)	(0.126)	(0.059)	(0.062)	(0.141)	(0.070)
Motor insurance policy	0.067	0.019	0.179**	0.105*	0.026	0.270***
	(0.058)	(0.077)	(0.087)	(0.058)	(0.078)	(0.095)
Constant	3.348***	3.060*	4.972***	3.455***	1.802	4.334***
	(0.212)	(1.579)	(0.403)	(0.245)	(1.644)	(0.427)
Observations	121,679	61,231	60,448	126,658	63,237	63,421
Customers	15,942	7,932	8,010	15,942	7,932	8,010
Data treatment for closed accounts	Missing	Missing	Missing	Zero	Zero	Zero
Sample	All	Age≤28	Age>28	All	Age≤28	Age>28
R-squared	0.0321	0.0461	0.0256	0.0271	0.0363	0.0302
Pred(Y): Non-Promotion: Control	$196.64	$158.84	$245.45	$192.67	$151.58	$246.66
Pred(Y): Non-Promotion: Treatment	$212.98	$164.56	$281.63	$211.79	$156.60	$294.06
Pred(Y): Promotion: Control	$177.20	$161.89	$195.12	$132.91	$130.44	$136.26
Pred(Y): Promotion: Treatment	$174.20	$158.90	$190.30	$130.99	$128.84	$133.13

Table 3: Effects of the treatment on monthly spend. Columns (1) – (3) show the results of panel data regression models for all customers as well as younger and older customers, with spend values for months after cancellation set to missing. Columns (4) – (6) show the same specifications with spend values for months after cancellation set to zero. All models include indicator variables for the week the credit card was activated, and are estimated with robust standard errors clustered by activation date. *, **, and *** signify significance at the 10%, 5%, and 1% levels respectively. Marginal effect estimates for monthly spend are provided for each condition. The results indicate that customers exposed to the treatment spent more on their cards, that these effects were stronger for more experienced customers, and that these effects were attenuated by the promotion, which is consistent with H3, H5, and H7.

Similarly, Column (2) shows that the monthly spending of less experienced customers was neither influenced by the treatment (γ=0.035, p=0.675), nor by the promotion (γ=0.019, p=0.885), and that there was no interaction between the two (γ=-0.054, p=0.599). However, Column (3) illustrates that during the non-promotion period, the monthly spending of more experienced customers was 14.74% higher among those who were provided with transparency into the offerings' tradeoffs (γ=0.138, p<0.05). Monthly spending was nominally lower among more experienced customers brought in by the promotion in the control condition (γ=-0.230, p=0.127), and there was a negative interaction, such that in aggregate, the treatment had no effect on monthly spending among more experienced customers during the promotion period (γ=-0.162, p<0.05).

Columns (4-6) present the same specifications, regressed on monthly spend where missing values due to account cancellations were filled with zero. As such, monthly spend, as it is estimated in Columns (4-6), is a direct measure of cumulative customer engagement, in that it captures how the card was used inclusive of the customer's choice of whether to retain it. Column (4) shows that during the non-promotion period, the treatment led to a marginal increase in spend (γ=0.095, p<0.10), increasing average monthly spending by 9.9% across all customers. It further shows that when cancellation dynamics are taken into account, the promotion decreased average monthly spend by 31.0% (γ=-0.371, p<0.01), and that there was a marginally significant interaction wherein the promotion attenuated the effects of the treatment to insignificance (γ=-0.109, p<0.10). Column (5) shows that the monthly spending of less experienced customers was neither influenced by the treatment (γ=0.033, p=0.722), nor by the promotion (γ=-0.150, p=0.229), and that there was no interaction between the two (γ=-0.045, p=0.684). However, Column (6) illustrates that during the non-promotion period, the monthly spending of more experienced customers was 19.2% higher among those who were provided with transparency into the offerings' tradeoffs (γ=0.176, p<0.01). Monthly spending was 44.8% lower among more experienced customers brought in by the promotion in the control condition (γ=-0.593, p<0.01), and there was a negative interaction, such that in aggregate, the treatment had no effect on monthly spending among more experienced customers during the promotion period (γ=-0.199, p<0.05). With respect to monthly spending, taken together, these results suggest that although providing transparency to prospective customers can lead to greater engagement overall, which is consistent with H1, increases in engagement are most acute among more experienced customers, which is consistent with H5. More experienced customers who were provided transparency used their credit cards more intensively, spending 19.2% more on a monthly basis. The results further suggest that promotional efforts that provide incentives to encourage customers to choose one offering over another attenuate the effects of transparency on subsequent product usage, which is consistent with H7.

	(1) Pr(Late Payment)	(2) Pr(Late Payment)	(3) Pr(Late Payment)	(4) Pr(Late Payment)	(5) Pr(Late Payment)	(6) Pr(Late Payment)
Treatment	-0.117	-0.114	-0.135	-0.175**	-0.200*	-0.157
	(0.076)	(0.117)	(0.112)	(0.078)	(0.120)	(0.116)
Promotion	-0.471***	-0.295	-0.626***	-0.447***	-0.356	-0.512**
	(0.139)	(0.206)	(0.186)	(0.168)	(0.230)	(0.228)
Treatment x promotion	0.118	0.127	0.117	0.168	0.214	0.123
	(0.102)	(0.147)	(0.143)	(0.106)	(0.152)	(0.147)
Customer age	-0.074***	-0.170	0.027	-0.071***	-0.112	0.012
	(0.012)	(0.212)	(0.030)	(0.013)	(0.232)	(0.031)
Customer age²	0.001***	0.002	-0.000	0.001***	0.001	-0.000
	(0.000)	(0.005)	(0.000)	(0.000)	(0.005)	(0.000)
Customer tenure	-0.005***	-0.010***	0.000	-0.005***	-0.010***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Customer tenure²	0.000***	0.000***	-0.000	0.000***	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male indicator	-0.111**	-0.222***	0.008	-0.141***	-0.257***	-0.013
	(0.052)	(0.063)	(0.066)	(0.055)	(0.068)	(0.071)
Retirement product	-0.023	-0.077	0.022	-0.049	-0.118	0.004
	(0.095)	(0.116)	(0.150)	(0.101)	(0.123)	(0.161)
Home loan product	-0.752***	-1.430***	-0.603***	-0.752***	-1.383***	-0.617***
	(0.091)	(0.240)	(0.094)	(0.098)	(0.236)	(0.105)
Personal loan product	0.942***	1.062***	0.866***	0.901***	1.066***	0.792***
	(0.064)	(0.095)	(0.085)	(0.069)	(0.100)	(0.095)
Savings product	-0.772***	-0.937***	-0.624***	-0.775***	-0.904***	-0.658***
	(0.054)	(0.089)	(0.077)	(0.057)	(0.091)	(0.084)
Term deposit product	-0.749***	-1.340***	-0.468*	-0.793***	-1.414***	-0.493
	(0.235)	(0.473)	(0.280)	(0.259)	(0.511)	(0.301)
Transaction product	0.415**	1.485***	0.085	0.326*	1.336***	0.031
	(0.169)	(0.407)	(0.182)	(0.175)	(0.417)	(0.187)
Home insurance policy	0.105	0.308	-0.020	0.126	0.290	0.005
	(0.107)	(0.229)	(0.129)	(0.111)	(0.247)	(0.139)
Motor insurance policy	0.184	-0.014	0.213	0.241*	-0.103	0.332**
	(0.138)	(0.251)	(0.160)	(0.139)	(0.264)	(0.162)
Constant	-1.563***	-1.007	-3.792***	-1.483***	-1.573	-3.434***
	(0.295)	(2.459)	(0.648)	(0.325)	(2.711)	(0.695)
Observations	112,641	56,266	56,375	92,988	46,253	46,735
Customers	15,942	7,932	8,010	15,942	7,932	8,010
Account sample	All data	All data	All data	First six months	First six months	First six months
Sample	All	Age≤28	Age>28	All	Age≤28	Age>28
Wald Chi-Square	1177.32	970.85	577.18	1031.43	841.47	461.97
Pred(Y): Non-Promotion: Control	9.24%	9.68%	8.70%	8.82%	9.56%	7.96%
Pred(Y): Non-Promotion: Treatment	8.57%	9.02%	7.96%	7.87%	8.43%	7.15%
Pred(Y): Promotion: Control	6.78%	8.04%	5.66%	6.55%	7.62%	5.58%
Pred(Y): Promotion: Treatment	6.78%	8.11%	5.58%	6.52%	7.69%	5.44%

Table 4: Effects of the treatment on the probability a customer would make a late payment in a given month. Columns (1-3) show the results of panel data regression models for all customers as well as younger and older customers, regressed on the full sample. Columns (4-6) show the same specifications regressed on the first six months of observations for each customer, which balances the sample across customers acquired during the non-promotion and promotion periods. All models are estimated with panel logistic regression, with robust standard errors, clustered by activation date. All models additionally include indicator variables for the week during which the customer activated his or her card, which are withheld from the table for parsimony. *, **, and *** signify significance at the 10%, 5%, and 1% levels respectively. The results indicate that the treatment had an insignificant or negative effect on the probability a customer would make a late payment. In particular, Column (4) demonstrates that the probability that a customer in the treatment condition, who was acquired during the non-promotion period was 10.8% less likely to make a late payment in any given month than customers acquired in the control condition. This result suggests the treatment has the capacity to improve the financial wellbeing of customers.

Importantly, although it may be reflective of firm profitability, we note that increased credit card spending, on its own, may not necessarily be emblematic of a better experience for customers. Indeed, higher spending rates could be detrimental to customers, if they meant customers were spending beyond their means. In a separate analysis, presented in **Table 4**, we analyze the probability that customers in different experimental conditions made late payments from month to month – the state of not having met the minimum required payment amount by the payment due date. Looking across the entire panel of data, in Columns (1-3), we find that the treatment had no effect on the probability a customer made a late payment – among all customers (γ=-0.117, p=0.124), less experienced customers (γ=-0.114, p=0.332), and more experienced customers (γ=-0.135, p=0.227). However, when in Columns (4-6) we consider the first six months of data for each customer – which balances the number of monthly observations among customers who opened accounts during the non-promotion (e.g., before November 1) and promotion (e.g., on or after November 1) periods – we observe that the probability of making a late payment was 10.8% lower among customers who were in the treatment condition (γ=-0.175, p<0.05), which suggests that the increased levels of engagement we observe do not come at the expense of customers' financial wellbeing. In fact, the evidence is supportive of the idea that providing transparency into the tradeoffs of various offerings can improve the financial wellbeing of customers. In the next section, we examine the effects of transparency on customer retention, another important measure of customer engagement, that is both emblematic of customer experiences (e.g., customers who are having more favorable experiences with a service offering are more likely to continue using it), and firm performance (e.g., customers who are retained are generally more profitable than those who defect).

3.2.4 Retention (H4, H6, H8). In **Table 5**, Columns (1-3) and (4-6) show the effects of tradeoff transparency on the retention of all customers, less experienced customers, and more experienced customers, after six and nine months, respectively. Columns (1) and (4) provide evidence that, looking across all customers, the treatment had an insignificant effect on retention after six months (δ=0.259, p=0.198), but that it increased retention after nine months (δ=0.249, p<0.05). After nine months, cancellations among customers in the treatment group were 20.5% lower, which is consistent with H4, and provides evidence that revealing the hidden tradeoffs to prospective customers can have meaningful implications for the long run trajectories of service relationships. Interestingly, Columns (2) and (5) reveal that, consistent with the prior analysis on spend, the positive implications of the treatment for retention were less likely to accrue to customers with less category experience. Less experienced customers in the treatment group were no more nor less likely to be retained after six (δ=0.099, p=0.771) or nine months (δ=0.111, p=0.546). On the other hand, Columns (3) and (6) demonstrate that more experienced customers who received the transparency treatment were more likely to have been retained after six (δ=0.437, p<0.10) and nine months (δ=0.447, p<0.01), which is consistent with H6.

	(1) Pr(Retain6)	(2) Pr(Retain6)	(3) Pr(Retain6)	(4) Pr(Retain9)	(5) Pr(Retain9)	(6) Pr(Retain9)
Treatment	0.259	0.099	0.437*	0.249**	0.111	0.447***
	(0.202)	(0.340)	(0.231)	(0.115)	(0.183)	(0.163)
Promotion	-1.736***	-1.693***	-1.758***	-1.344***	-0.882**	-1.647***
	(0.256)	(0.633)	(0.275)	(0.231)	(0.422)	(0.294)
Treatment x promotion	-0.239	-0.055	-0.410	-0.223	0.114	-0.569**
	(0.220)	(0.365)	(0.258)	(0.165)	(0.258)	(0.226)
Customer age	-0.219***	-0.038	0.060	-0.094**	0.469	0.010
	(0.038)	(0.323)	(0.044)	(0.041)	(0.320)	(0.055)
Customer age²	0.003***	-0.002	-0.000	0.001***	-0.011	0.000
	(0.001)	(0.007)	(0.001)	(0.001)	(0.007)	(0.001)
Customer tenure	-0.009***	-0.011***	-0.009***	-0.005***	-0.007**	-0.006***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
Customer tenure²	0.000***	0.000***	0.000***	0.000***	0.000*	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male indicator	0.046	0.011	0.065	0.078	0.039	0.118
	(0.074)	(0.110)	(0.095)	(0.091)	(0.100)	(0.133)
Retirement product	0.245	0.110	0.414*	-0.107	-0.255	0.036
	(0.154)	(0.221)	(0.229)	(0.155)	(0.176)	(0.235)
Home loan product	-0.595***	-0.775***	-0.539***	-0.564***	-0.545*	-0.538***
	(0.105)	(0.192)	(0.124)	(0.167)	(0.278)	(0.189)
Personal loan product	0.767***	0.408**	1.025***	0.246**	-0.007	0.497***
	(0.110)	(0.159)	(0.164)	(0.106)	(0.171)	(0.164)
Savings product	-0.188**	-0.141	-0.188**	-0.132	-0.070	-0.179
	(0.080)	(0.165)	(0.092)	(0.096)	(0.168)	(0.119)
Term deposit product	-0.617***	-0.574	-0.618***	-0.662***	-0.309	-0.796***
	(0.167)	(0.352)	(0.203)	(0.235)	(0.484)	(0.294)
Transaction product	1.603***	2.235***	1.312***	1.402***	2.034***	1.074***
	(0.125)	(0.269)	(0.159)	(0.222)	(0.413)	(0.282)
Home insurance policy	0.084	0.504	-0.012	-0.068	0.777	-0.233
	(0.154)	(0.383)	(0.162)	(0.170)	(0.668)	(0.199)
Motor insurance policy	0.082	0.585	-0.045	0.027	0.744	-0.109
	(0.198)	(0.492)	(0.224)	(0.202)	(0.561)	(0.235)
Constant	7.509***	5.895	1.963**	3.739***	-2.343	1.345
	(0.711)	(4.006)	(0.914)	(0.773)	(3.835)	(1.219)
Observations	15,942	7,864	8,010	6,314	3,231	3,083
Customers	All	Age≤28	Age>28	All	Age≤28	Age>28
Pseudo R2	0.0845	0.0916	0.0977	0.0551	0.0509	0.0948
Pred(Y): Non-Promotion: Control	98.07%	98.32%	97.76%	93.40%	92.99%	93.38%
Pred(Y): Non-Promotion: Treatment	98.50%	98.47%	98.53%	94.75%	93.66%	95.61%
Pred(Y): Promotion: Control	90.50%	92.14%	88.99%	79.43%	84.98%	75.00%
Pred(Y): Promotion: Treatment	90.67%	92.43%	89.23%	79.83%	87.54%	72.87%

Table 5: Effects of the treatment on customer retention rates. Columns (1) – (3) and columns (4) – (6) show the results of cross-sectional data regression models of all, younger, and older customers for retention six and nine months after card activation, respectively. All models include indicator variables for the week the credit card was activated, and are estimated with robust standard errors clustered by activation date. *, **, and *** signify significance at the 10%, 5%, and 1% levels respectively. The results indicate that transparency can lead to increased customer retention, which is consistent with H4, that the effects are strongest for more experienced customers, which is consistent with H6, and that the effects are dampened during the promotion, which is consistent with H8. Marginal effect estimates for retention after six and nine months are provided for each experimental condition.

The positive effect of tradeoff transparency on product retention was most acute for customers with prior experience with the service category. Among these more experienced customers, nine months into their service relationships, cancellation rates were 33.7% lower for those who had been randomly selected to see the tradeoffs inherent in each service offering before they made their product choice. Finally, Column (6) demonstrates an interaction, wherein the effect of the treatment on retention among more experienced customers was negatively moderated after nine months for customers who were attracted by a promotion (δ=-0.569, $p<0.05$). Similarly, the negative coefficients on the interaction terms reduce the positive and significant effects of the treatment on retention to insignificance during the promotion period ($\chi^2s<0.53$, $ps>0.469$). These results are consistent with H8, in that they demonstrate how the positive effect of tradeoff transparency on product retention can be diminished among customers attracted to an offering by a promotion.

4. General discussion

Through a large-scale field experiment conducted with 389,611 customers of a nationwide retail bank, we have investigated the impact of providing prospective customers with transparency into a service offering's tradeoffs on rates of acquisition, product choice, and subsequent long-term engagement. Our results suggest that although providing prospective customers with this transparency has no net effect on overall rates of acquisition, it can affect customers' choices – causing them to select different offerings than they would in the absence of transparency. Moreover, we find evidence that this transparency can lead to long-term outcomes that are better for customers and firms alike. Customers who were provided transparency into the tradeoffs of each service offering, and who chose to move forward by opening an account, exhibited higher levels of engagement during their first nine months of service, and we find that the effects are strongest among customers who have prior experience with the service category. Monthly spending was 9.9% higher, and after nine months, cancellation rates were 20.5% lower, among all customers who received the transparency treatment. For more experienced customers, monthly spending was 19.2% higher, and rates of cancellation after nine months were 33.7% lower among those who received the transparency treatment. Importantly, we find that increased engagement levels do not come at the expense of customers' financial wellbeing. During the initial six months of their relationships, customers who experienced transparency into each offering's tradeoffs were 10.8% less likely to make late payments on a monthly basis. These results provide evidence that being more transparent with customers – not just about an offering's strengths, but also about its tradeoffs – can lead to better long-run outcomes for customers and firms alike. Finally, we find that the effects of transparency on engagement and retention are attenuated in the presence of a promotion. The results are consistent with the idea that customers who organically seek out an offering are more likely to benefit from tradeoff transparency than those who are attracted or influenced by a promotion.

4.1 Managerial implications and opportunities for future research

Taken together, these results have important implications for managers, while also raising additional questions that will serve as fruitful opportunities for future research.

4.1.1 Being more transparent with prospective customers may not harm acquisition rates. Although research has shown how the revelation of unflattering information can harm demand, and conventional wisdom has long suggested the fallacy of marketing an offering's weaknesses, our results demonstrate that voluntarily providing customers with transparency into an offering's tradeoffs may not harm rates of acquisition. These results are significant, because they suggest that the costs of being fully open with prospective customers that many managers perceive (e.g., that prospective customers who are shown the tradeoffs in an offering may seek service elsewhere) may be misplaced.

These results are consistent with prior research that has shown how the act of being voluntarily transparent with information that customers perceive to be sensitive can engender higher levels of trust in the firm and attraction to its offerings (Mohan et al. 2018). An opportunity for future research would be to delve more deeply into the mechanisms that underlie these effects, exploring the conditions under which transparency is more and less likely to engender trust, and how it affects the relationship with the firm more holistically (e.g., does it affect peoples' willingness to engage with other offerings). Likewise, future research could explore whether the revelation of transparency is generally appealing, or if there are individual differences among appetites for transparency, such that transparent organizations attract different types of customers. Similarly, research on the psychology of choice has demonstrated how providing more information that complicates a choice can lead a customer to opt out of choosing (Gourville and Soman 2005, Iyengar and Lepper 2000). Future research could investigate how tradeoffs could be most effectively communicated to help customers make better-informed decisions as easily as possible.

4.1.2 Being transparent with customers may lead to better long-run outcomes for customers and firms. Although the provision of transparency in our study had no effect on overall rates of customer acquisition, we find that it caused customers to make different product choices than they would make in the absence of transparency. Specifically, we observed that customers in different segments, who were given the same tradeoff information, selected different credit cards. This pattern of results is consistent with the idea that the revelation of information about a product's tradeoffs can help shape their decisions. Furthermore, we find that transparency improves customer engagement – both by increasing product usage and rates of retention over the longer-term. Customers who were randomly-selected to experience transparency into each offering's tradeoffs, and who moved forward in opening an account, used their cards more intensively, spending 9.9% more per month, and were 10.8% less likely to make late payments on a monthly basis. Furthermore, customers who experienced transparency were 20.5% less likely to cancel their credit cards during the first nine months of their relationships. To the extent that heightened engagement and retention are behavioral indicators of a better customer experience, and a more profitable service relationship, these results suggest that providing transparency to prospective customers may be mutually beneficial.

4.1.3 There may be a tradeoff between acquisition and retention-based strategies. Midway through the experiment, our research partner launched a promotion in which they offered a financial incentive to prospective customers who opened a credit card in the Low Rate family, and who spent $1,000 during the first three months of their service relationships. From an acquisition perspective, the efficacy of this promotional strategy is evident. Traffic to the credit card website increased, and the conversion rate of browsers to buyers was enhanced, such that the number of new credit card accounts opened per day went up by 47.3% during the promotion period. Furthermore, the probability a customer would open a promoted credit card went up – during the promotion the probability of opening a low rate or low rate gold credit card increased by 28.1% and 18.0%, respectively – highlighting the promotion's capacity to increase sales and influence customer choices. However, customers acquired during the promotion spent a third less on a monthly basis, due in part to the fact that they were 3.8 times more likely to cancel their cards during the initial months of their relationships than those who were not acquired through a promotion. These results highlight a potential tradeoff for managers between marketing-based promotional strategies that are optimized around increasing rates of customer acquisition, and operations-based transparency strategies that are optimized around increasing customer compatibility and long-term engagement. Future research could delve more deeply into this tradeoff – for example, by examining whether over a longer timeframe, the gains in engagement and retention brought about by transparency might outweigh the improvement in acquisition rates promotions can foster.

4.1.4 Transparency is especially effective for customers who have prior category experience. Consistent with prior research, our results provide evidence that transparency may be particularly effective for improving relationship quality and engagement among more experienced customers. In our experiment, more experienced customers (operationalized as customers older than 28 years of age), who received the transparency treatment, used the credit cards they chose more intensively, exhibiting cumulative spending that was 19.2% higher after nine months, than those who did not experience transparency. They also were 33.7% less likely to cancel their credit cards during the first nine months of their relationship. These results reveal the incredible promise of tradeoff transparency, for customers and companies alike, in helping customers make more well-informed decisions. However, it's interesting that less experienced customers did not exhibit similar gains in subsequent engagement and retention. Less experienced customers (those 28 years of age and younger), who were treated with transparency, spent 3.3% more during a typical month, and were 9.6% less likely to cancel their accounts after nine months – results that are statistically indistinguishable from zero. These patterns highlight an opportunity to explore strategies for helping inform less-experienced customers, who do not appear to benefit from tradeoff transparency as much as their more-experienced counterparts.

4.1.5 Promotions may crowd-out the benefits of providing prospective customers with transparency. Finally, our results suggest that the effects of providing prospective customers with transparency into an offering's tradeoffs may be attenuated by promotions, which themselves are designed to influence customer choices. More experienced customers, in particular, who exhibited the greatest increases in product usage and retention in response to transparency, also exhibited an interaction effect, wherein those gains were mitigated, though not reversed, in the presence of a promotion. Importantly, in our experiment, the promotion in question offered financial incentives for only one family of credit cards, which may have created a conflict for some consumers between the card that offered a bonus and the card that best fit their needs and preferences. Future research could more holistically disentangle whether promotions and transparency are necessarily in conflict by treating every offering with the same promotion. Such a design would afford a better understanding of the mechanisms that drive the crowding-out effect we observe – whether it's driven by the conflict between fit and financial incentives some customers may have experienced, or whether it's driven by promotions attracting customers who are less sensitive to the effects of transparency. Owing to the demonstrated efficacy of promotions to attract new customers, and transparency to foster decision making that boosts long-run engagement, innovations that achieve the best of both worlds could enhance customer experiences while unlocking considerable value for firms.

4.2 Conclusion

Conventional wisdom and common practice dictate that service firms should emphasize the advantages of their offerings and downplay the tradeoffs when marketing to prospective customers. We suggest that taking a different approach – providing transparency into both an offering's advantages and its tradeoffs, in order to help customers make more well-informed decisions – can lead to better outcomes over the long run for everyone involved. We hope that the present work will foster more research in this area, and influence practice, in order to foster better customer experiences, and more engaging service relationships among customers and the organizations that serve them.

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Online appendix for "Improving Customer Compatibility with Operational Transparency"

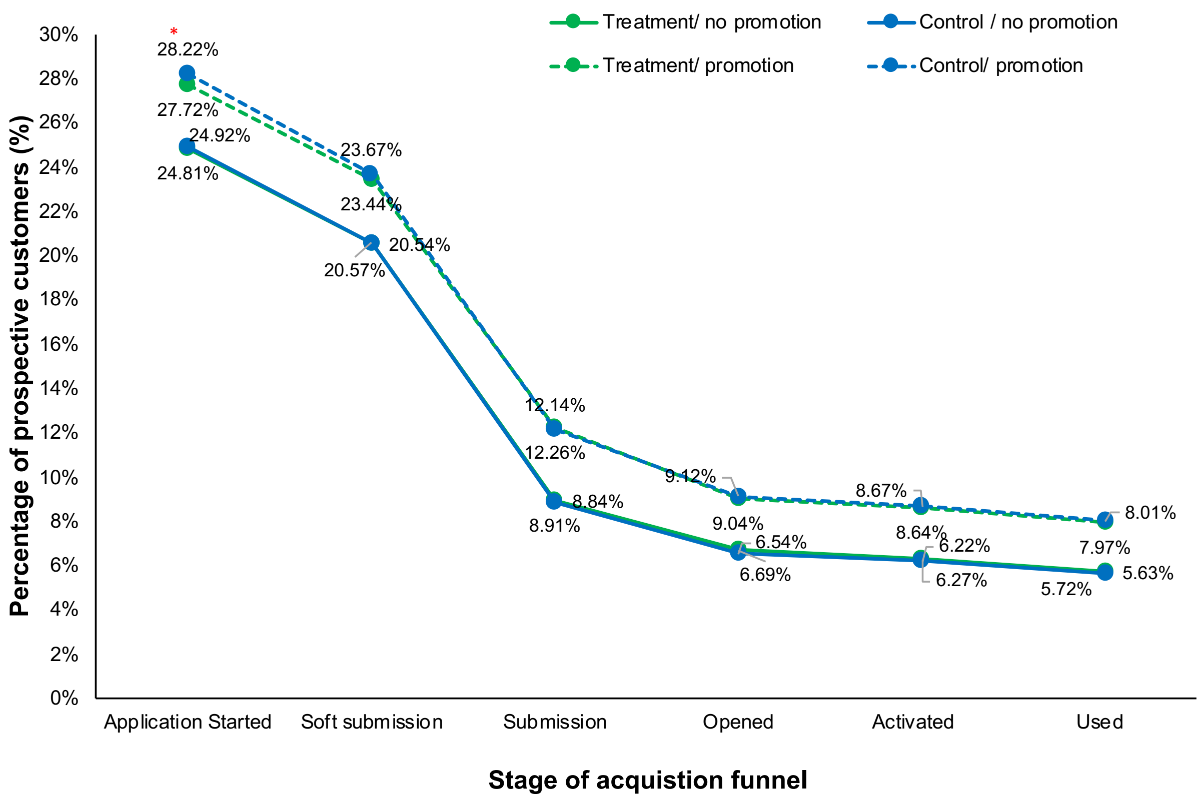

Figure A1: Acquisition funnel conversion percentages during the promotion and non-promotion periods for less experienced customers (28 years of age and younger). Marginal effects are from logistic regression models, estimated with robust standard errors clustered at the first website visit date level. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively. The results indicate that, consistent with Figure 5, conversion rates are significantly higher during the promotion period. Moreover, although fewer customers start the application process in the treatment condition during the promotion period, the treatment ultimately had no effect on rates of customer acquisition, neither during the promotion nor the non-promotion periods, which is consistent with H1.

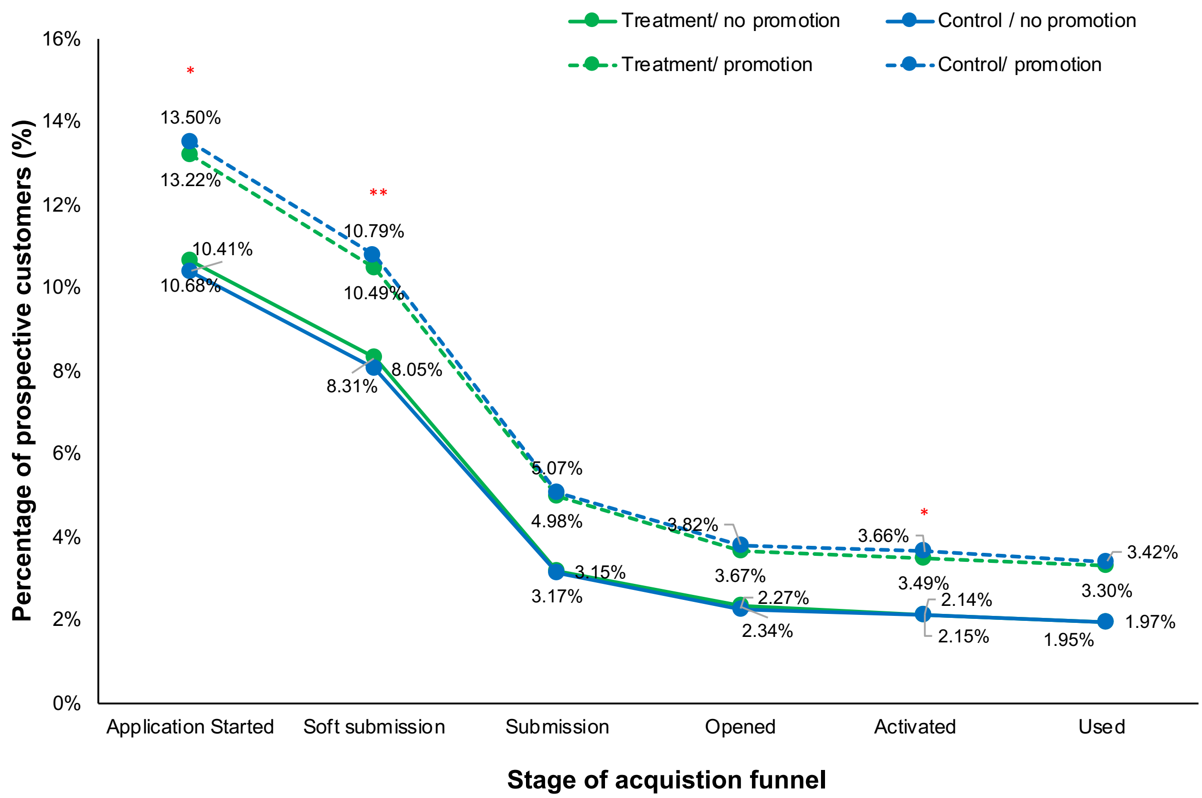

Figure A2: Acquisition funnel conversion percentages during the promotion and non-promotion periods for more experienced customers (over 28 years of age). Marginal effects are from logistic regression models, estimated with robust standard errors clustered at the first website visit date level. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively. The results indicate that, consistent with Figure 5, conversion rates are significantly higher during the promotion period. Moreover, although fewer customers start the application process or soft submit their application in the treatment condition during the promotion period, the treatment ultimately had no effect on rates of customer acquisition, neither during the promotion nor the non-promotion periods, which is consistent with H1.

	(1) Awards	(2) Diamond	(3) Gold	(4) Low Fee	(5) Low Fee Gold	(6) Low Rate	(7) Low Rate Gold	(8) Platinum	(9) Student
Treatment	-0.006	-0.107	-0.183	0.049	0.006	-0.142**	0.220**	0.262**	-0.021
	(0.123)	(0.159)	(0.151)	(0.068)	(0.169)	(0.068)	(0.087)	(0.108)	(0.136)
Promotion	-0.160	-0.775***	-0.546***	-0.516***	-0.615***	0.495***	0.189*	-0.091	-0.295*
	(0.128)	(0.278)	(0.197)	(0.089)	(0.173)	(0.063)	(0.107)	(0.137)	(0.154)
Treatment x promotion	0.092	0.259	0.308	-0.115	0.185	0.080	-0.163	-0.219	0.061
	(0.149)	(0.210)	(0.192)	(0.086)	(0.207)	(0.078)	(0.103)	(0.137)	(0.173)
Customer age	0.025	0.063*	-0.001	-0.037***	-0.005	0.036***	0.037***	0.115***	-0.394***
	(0.023)	(0.037)	(0.027)	(0.011)	(0.021)	(0.009)	(0.012)	(0.021)	(0.027)
Customer age²	-0.000	-0.001**	-0.000	0.000***	0.000	-0.000***	-0.000	-0.001***	0.003***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Customer tenure	0.004***	-0.005***	0.002*	-0.001*	-0.004***	0.001***	-0.000	-0.000	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Customer tenure²	-0.000**	0.000***	-0.000	0.000	0.000	-0.000**	-0.000	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male indicator	0.027	-0.763***	-0.266***	0.101***	-0.358***	0.213***	-0.132***	-0.499***	0.199**
	(0.070)	(0.125)	(0.096)	(0.038)	(0.092)	(0.034)	(0.047)	(0.065)	(0.082)
Retirement product	0.137	-0.226	0.563***	-0.051	0.276	-0.143*	-0.036	0.186	-0.049
	(0.209)	(0.293)	(0.212)	(0.136)	(0.259)	(0.082)	(0.129)	(0.173)	(0.412)
Home loan product	0.133	0.363*	-0.084	-0.136	-0.052	-0.049	0.076	0.059	-1.372**
	(0.147)	(0.203)	(0.203)	(0.090)	(0.250)	(0.068)	(0.108)	(0.139)	(0.700)
Personal loan product	0.167	-0.168	-0.469*	0.156	0.006	-0.433***	0.415***	0.925***	1.007*
	(0.240)	(0.363)	(0.250)	(0.128)	(0.268)	(0.092)	(0.142)	(0.305)	(0.596)
Savings product	0.317	0.541*	0.462	0.435***	-0.275	-0.148	-0.398**	-0.936**	0.213
	(0.225)	(0.299)	(0.285)	(0.149)	(0.371)	(0.101)	(0.173)	(0.365)	(0.343)
Term deposit product	0.287***	-0.046	0.445***	0.037	0.082	-0.110***	0.007	-0.068	0.257*
	(0.084)	(0.109)	(0.131)	(0.051)	(0.097)	(0.038)	(0.060)	(0.075)	(0.132)
Transaction product	-0.272***	-0.438***	-0.486***	-0.584***	-0.425***	0.300***	0.234***	0.514***	-1.470***
	(0.099)	(0.148)	(0.148)	(0.070)	(0.128)	(0.045)	(0.051)	(0.082)	(0.170)
Home insurance policy	-0.110	1.765***	0.284*	-0.111	-0.120	-0.298***	-0.071	0.518***	-2.791***
	(0.120)	(0.130)	(0.151)	(0.081)	(0.179)	(0.052)	(0.087)	(0.110)	(1.004)
Motor insurance policy	0.264**	0.078	-0.232	-0.007	-0.037	-0.091	0.086	0.233**	-0.137
	(0.116)	(0.182)	(0.183)	(0.074)	(0.173)	(0.058)	(0.086)	(0.107)	(0.146)
Constant	-3.762***	-3.363***	-2.694***	-0.767***	-2.548***	-0.760***	-3.314***	-5.889***	3.811***
	(0.506)	(0.873)	(0.593)	(0.284)	(0.492)	(0.204)	(0.276)	(0.576)	(0.668)
Observations	17,939	17,939	17,939	17,939	17,939	17,939	17,939	17,939	17,939
Sample	All Customers	All	All	All	All	All	All	All	All
R-squared	0.197	0.197	0.197	0.197	0.197	0.197	0.197	0.197	0.197

Table A1: Effects of the treatment on the credit card choices of customers. Columns (1)-(9) show the results of the logistic regression models with robust standard errors clustered by customers' first website visit dates. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively. Low rate and low rate gold cards were part of the publicly announced promotion campaign beginning on November 1, 2017. The results indicate that providing transparency into the tradeoffs of the service offering influenced credit card choices, which is consistent with H2.

	(1) Ln(Spend)	(2) Ln(Spend)	(3) Ln(Spend)	(4) Ln(Spend)	(5) Ln(Spend)	(6) Ln(Spend)
Treatment	0.080	-0.008	0.128**	0.095*	0.007	0.149***
	(0.052)	(0.138)	(0.060)	(0.054)	(0.144)	(0.057)
Promotion	-0.104	0.209	-0.251**	-0.371***	0.107	-0.588***
	(0.103)	(0.185)	(0.118)	(0.114)	(0.172)	(0.129)
Treatment x promotion	-0.097	-0.034	-0.138*	-0.109*	-0.039	-0.160**
	(0.061)	(0.153)	(0.071)	(0.064)	(0.158)	(0.070)
Customer age	0.072***	0.556	0.050***	0.046***	0.646	0.042***
	(0.008)	(0.408)	(0.014)	(0.009)	(0.409)	(0.014)
Customer age²	-0.001***	-0.012	-0.001***	-0.001***	-0.014	-0.000***
	(0.000)	(0.010)	(0.000)	(0.000)	(0.010)	(0.000)
Customer tenure	0.002***	0.006***	0.000	0.000	0.005***	-0.001**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Customer tenure²	-0.000	-0.000***	0.000	0.000	-0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male indicator	0.050	0.069	0.031	0.072**	0.081	0.055
	(0.034)	(0.058)	(0.037)	(0.034)	(0.059)	(0.039)
Retirement product	0.067	-0.010	0.123	0.105*	-0.003	0.182**
	(0.058)	(0.095)	(0.076)	(0.058)	(0.096)	(0.077)
Home loan product	0.509***	0.546**	0.516***	0.349***	0.209	0.370***
	(0.049)	(0.219)	(0.053)	(0.062)	(0.229)	(0.063)
Personal loan product	-0.324***	-0.365***	-0.308***	-0.209***	-0.369***	-0.151***
	(0.039)	(0.082)	(0.048)	(0.043)	(0.084)	(0.052)
Savings product	0.277***	0.402***	0.235***	0.247***	0.376***	0.208***
	(0.040)	(0.084)	(0.043)	(0.040)	(0.080)	(0.043)
Term deposit product	0.198*	0.558***	0.100	-0.023	0.503**	-0.150
	(0.120)	(0.196)	(0.136)	(0.133)	(0.218)	(0.151)
Transaction product	0.496***	0.105	0.527***	1.043***	0.990**	1.026***
	(0.105)	(0.445)	(0.111)	(0.101)	(0.455)	(0.108)
Home insurance policy	-0.038	0.158	-0.044	-0.044	0.332	-0.070
	(0.076)	(0.235)	(0.080)	(0.085)	(0.235)	(0.091)
Motor insurance policy	0.045	0.189	0.044	0.038	0.151	0.045
	(0.105)	(0.239)	(0.114)	(0.108)	(0.245)	(0.117)
Constant	3.348***	-2.057	4.010***	3.455***	-3.696	3.843***
	(0.212)	(4.371)	(0.304)	(0.245)	(4.311)	(0.331)
Observations	121,679	36,540	85,139	126,658	37,478	89,180
Customers	15,942	4,686	11,256	15,942	4,686	11,256
Data treatment for closed accounts	Missing	Missing	Missing	Zero	Zero	Zero
Sample	All	Age≤24	Age>24	All	Age≤24	Age>24
R-squared	0.0321	0.0463	0.0277	0.0271	0.0403	0.0292
Pred(Y): Non-Promotion: Control	$196.64	$132.62	$235.76	$192.67	$124.92	$235.17
Pred(Y): Non-Promotion: Treatment	$212.98	$131.62	$268.03	$211.79	$125.79	$272.87
Pred(Y): Promotion: Control	$177.20	$163.51	$183.48	$132.91	$139.02	$130.63
Pred(Y): Promotion: Treatment	$174.20	$156.93	$181.69	$130.99	$134.57	$129.23

Table A2: Effects of the treatment on monthly spend with alternative age cutoff (24 years). Columns (1) – (3) show the results of panel data regression models for all customers as well as younger and older customers, with spend values for months after cancellation set to missing. Columns (4) – (6) show the same specifications with spend values for months after cancellation set to zero. All models include indicator variables for the week the credit card was activated, and are estimated with robust standard errors clustered by activation date. *, **, and *** signify significance at the 10%, 5%, and 1% levels respectively. Marginal effect estimates for monthly spending are provided for each condition. The results indicate that customers exposed to the treatment spent more on their cards, that these effects were stronger for more experienced customers, and that these effects were attenuated by the promotion, which is consistent with H3, H5, and H7.

	(1) Pr(Retain6)	(2) Pr(Retain6)	(3) Pr(Retain6)	(4) Pr(Retain9)	(5) Pr(Retain9)	(6) Pr(Retain9)
Treatment	0.259	0.234	0.314	0.249**	0.247	0.274**
	(0.202)	(0.389)	(0.208)	(0.115)	(0.212)	(0.131)
Promotion	-1.736***	-1.321*	-1.807***	-1.344***	-0.277	-1.658***
	(0.256)	(0.758)	(0.248)	(0.231)	(0.490)	(0.237)
Treatment x promotion	-0.239	-0.115	-0.313	-0.223	-0.033	-0.306
	(0.220)	(0.426)	(0.229)	(0.165)	(0.293)	(0.186)
Customer age	-0.219***	0.634	-0.072*	-0.094**	-0.573	-0.065
	(0.038)	(0.975)	(0.042)	(0.041)	(1.078)	(0.053)
Customer age²	0.003***	-0.018	0.001**	0.001***	0.015	0.001*
	(0.001)	(0.023)	(0.001)	(0.001)	(0.026)	(0.001)
Customer tenure	-0.009***	-0.011***	-0.009***	-0.005***	-0.007	-0.005***
	(0.001)	(0.004)	(0.001)	(0.002)	(0.005)	(0.002)
Customer tenure²	0.000***	0.000*	0.000***	0.000***	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male indicator	0.046	0.042	0.049	0.078	0.288*	0.005
	(0.074)	(0.157)	(0.080)	(0.091)	(0.168)	(0.123)
Retirement product	0.245	0.131	0.284*	-0.107	-0.418	0.036
	(0.154)	(0.322)	(0.162)	(0.155)	(0.258)	(0.194)
Home loan product	-0.595***	-1.322***	-0.556***	-0.564***	-1.118**	-0.534***
	(0.105)	(0.334)	(0.111)	(0.167)	(0.464)	(0.175)
Personal loan product	0.767***	-0.005	0.968***	0.246**	-0.250	0.425***
	(0.110)	(0.205)	(0.142)	(0.106)	(0.236)	(0.145)
Savings product	-0.188**	-0.173	-0.163**	-0.132	0.160	-0.194*
	(0.080)	(0.231)	(0.078)	(0.096)	(0.203)	(0.103)
Term deposit product	-0.617***	-0.122	-0.658***	-0.662***	-0.383	-0.657**
	(0.167)	(0.621)	(0.181)	(0.235)	(0.637)	(0.265)
Transaction product	1.603***	2.696***	1.468***	1.402***	1.976***	1.344***
	(0.125)	(0.494)	(0.133)	(0.222)	(0.641)	(0.254)
Home insurance policy	0.084	1.709*	0.012	-0.068		-0.206
	(0.154)	(1.035)	(0.162)	(0.170)		(0.179)
Motor insurance policy	0.082	0.103	0.087	0.027	0.504	0.058
	(0.198)	(0.630)	(0.209)	(0.202)	(0.932)	(0.222)
Constant	7.509***	-2.371	4.791***	3.739***	7.499	3.145***
	(0.711)	(10.550)	(0.809)	(0.773)	(11.368)	(1.068)
Observations	15,942	4,278	11,256	6,314	1,924	4,357
Customers	All	Age≤24	Age>24	All	Age≤24	Age>24
Pseudo R2	0.0845	0.0666	0.0883	0.0551	0.0462	0.0760
Pred(Y): Non-Promotion: Control	98.07%	98.19%	97.90%	98.07%	98.19%	97.90%
Pred(Y): Non-Promotion: Treatment	98.50%	98.56%	98.45%	98.50%	98.56%	98.45%
Pred(Y): Promotion: Control	90.50%	93.87%	89.07%	90.50%	93.87%	89.07%
Pred(Y): Promotion: Treatment	90.67%	94.49%	89.08%	90.67%	94.49%	89.08%

Table A3: Effects of the treatment on customer retention rates with alternative age cutoff (24 years). Effects of the treatment on customer retention rates. Columns (1) – (3) and columns (4) – (6) show the results of cross-sectional data regression models of all, younger, and older customers for retention six and nine months after card activation, respectively. All models include indicator variables for the week the credit card was activated, and are estimated with robust standard errors clustered by activation date. *, **, and *** signify significance at the 10%, 5%, and 1% levels respectively. The results indicate that transparency can lead to increased customer retention, which is consistent with H4, that the effects are strongest for more experienced customers, which is consistent with H6, and that the effects are dampened during the promotion, which is consistent with H8. Marginal effect estimates for retention after six and nine months are provided for each experimental condition.

	(1) Ln(Spend)	(2) Ln(Spend)	(3) Ln(Spend)	(4) Ln(Spend)	(5) Ln(Spend)	(6) Ln(Spend)
Treatment	0.093*	0.051	0.148**	0.108**	0.047	0.190***
	(0.051)	(0.088)	(0.061)	(0.053)	(0.094)	(0.054)
Promotion	-0.083	0.026	-0.194	-0.348***	-0.139	-0.556***
	(0.099)	(0.131)	(0.146)	(0.111)	(0.125)	(0.162)
Treatment x promotion	-0.107*	-0.076	-0.159**	-0.121*	-0.070	-0.198***
	(0.060)	(0.104)	(0.075)	(0.062)	(0.111)	(0.073)
Customer age	0.070***	0.116	0.008	0.043***	0.164	0.027
	(0.008)	(0.127)	(0.018)	(0.009)	(0.135)	(0.019)
Customer age²	-0.001***	-0.002	-0.000	-0.000***	-0.003	-0.000
	(0.000)	(0.003)	(0.000)	(0.000)	(0.003)	(0.000)
Customer tenure	0.002***	0.005***	-0.001	0.000	0.004***	-0.002***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Customer tenure²	-0.000*	-0.000***	0.000*	0.000	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male indicator	0.040	0.093**	-0.012	0.062*	0.101**	0.020
	(0.033)	(0.045)	(0.042)	(0.033)	(0.044)	(0.044)
Retirement product	0.066	0.027	0.162*	0.094*	0.032	0.229**
	(0.057)	(0.076)	(0.085)	(0.057)	(0.077)	(0.094)
Home loan product	0.504***	0.730***	0.462***	0.344***	0.514***	0.323***
	(0.048)	(0.127)	(0.060)	(0.061)	(0.140)	(0.070)
Personal loan product	-0.337***	-0.459***	-0.232***	-0.223***	-0.401***	-0.073
	(0.039)	(0.060)	(0.053)	(0.042)	(0.062)	(0.056)
Savings product	0.277***	0.408***	0.178***	0.244***	0.376***	0.147***
	(0.039)	(0.060)	(0.050)	(0.040)	(0.061)	(0.051)
Term deposit product	0.180	0.382**	0.059	-0.025	0.240	-0.165
	(0.116)	(0.157)	(0.154)	(0.130)	(0.183)	(0.165)
Transaction product	0.447***	0.155	0.541***	0.987***	1.081***	0.937***
	(0.102)	(0.220)	(0.118)	(0.100)	(0.228)	(0.121)
Home insurance policy	-0.023	0.036	-0.029	-0.023	0.149	-0.066
	(0.076)	(0.160)	(0.088)	(0.085)	(0.169)	(0.098)
Motor insurance policy	0.037	0.121	0.024	0.032	0.142	0.013
	(0.106)	(0.164)	(0.124)	(0.109)	(0.168)	(0.122)
Constant	3.448***	2.704*	5.045***	3.561***	1.561	4.381***
	(0.204)	(1.560)	(0.389)	(0.239)	(1.639)	(0.422)
Observations	125,902	63,661	62,241	131,055	65,737	65,318
Number of Customers	16,487	8,243	8,244	16,487	8,243	8,244
Data treatment for closed accounts	Missing	Missing	Missing	Zero	Zero	Zero
Sample	All	Age≤28	Age>28	All	Age≤28	Age>28
R-squared	0.0316	0.0467	0.0244	0.026	0.037	0.028
Pred(Y): Non-Promotion: Control	$196.15	$161.56	$240.16	$191.83	$154.04	$240.16
Pred(Y): Non-Promotion: Treatment	$215.36	$170.07	$278.58	$213.75	$161.40	$290.41
Pred(Y): Promotion: Control	$180.53	$165.80	$197.75	$135.42	$134.09	$137.66
Pred(Y): Promotion: Treatment	$178.11	$161.69	$195.70	$133.74	$130.96	$136.63

Table A4: Effects of the treatment on monthly spend including customers who viewed inconsistent benefits information for a type of the low fee card. Columns (1) – (3) show the results of panel data regression models for all customers as well as younger and older customers, with spend values for months after cancellation set to missing. Columns (4) – (6) show the same specifications with spend values for months after cancellation set to zero. All models include indicator variables for the week the credit card was activated, and are estimated with robust standard errors clustered by activation date. *, **, and *** signify significance at the 10%, 5%, and 1% levels respectively. Marginal effect estimates for monthly spending are provided for each condition. The results indicate that customers exposed to the treatment spent more on their cards, that these effects were stronger for more experienced customers, and that these effects were attenuated by the promotion, which is consistent with H3, H5, and H7.

	(1) Pr(Retain6)	(2) Pr(Retain6)	(3) Pr(Retain6)	(4) Pr(Retain9)	(5) Pr(Retain9)	(6) Pr(Retain9)
Treatment	0.281	0.084	0.508**	0.234**	0.074	0.462***
	(0.190)	(0.333)	(0.215)	(0.110)	(0.180)	(0.161)
Promotion	-1.777***	-1.718***	-1.791***	-1.313***	-0.902**	-1.566***
	(0.254)	(0.628)	(0.265)	(0.231)	(0.421)	(0.318)
Treatment x promotion	-0.269	-0.067	-0.483**	-0.227	0.102	-0.577**
	(0.208)	(0.356)	(0.242)	(0.158)	(0.245)	(0.226)
Customer age	-0.221***	-0.094	0.065	-0.100**	0.328	0.019
	(0.036)	(0.328)	(0.044)	(0.040)	(0.315)	(0.056)
Customer age²	0.003***	-0.001	-0.000	0.001***	-0.008	0.000
	(0.001)	(0.007)	(0.001)	(0.001)	(0.007)	(0.001)
Customer tenure	-0.008***	-0.010***	-0.009***	-0.005***	-0.007**	-0.006***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
Customer tenure²	0.000***	0.000***	0.000***	0.000***	0.000*	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male indicator	0.048	0.028	0.059	0.075	0.040	0.111
	(0.072)	(0.109)	(0.094)	(0.089)	(0.099)	(0.136)
Retirement product	0.178	0.101	0.270	-0.106	-0.209	-0.027
	(0.141)	(0.215)	(0.208)	(0.151)	(0.178)	(0.223)
Home loan product	-0.617***	-0.754***	-0.575***	-0.550***	-0.439	-0.558***
	(0.106)	(0.189)	(0.125)	(0.170)	(0.281)	(0.193)
Personal loan product	0.758***	0.389**	1.022***	0.249**	0.001	0.493***
	(0.109)	(0.159)	(0.162)	(0.111)	(0.166)	(0.164)
Savings product	-0.201**	-0.114	-0.221**	-0.139	-0.078	-0.182
	(0.081)	(0.167)	(0.091)	(0.095)	(0.166)	(0.117)
Term deposit product	-0.569***	-0.547	-0.565***	-0.619***	-0.221	-0.776***
	(0.166)	(0.358)	(0.201)	(0.236)	(0.488)	(0.288)
Transaction product	1.581***	2.239***	1.284***	1.326***	1.852***	1.034***
	(0.125)	(0.261)	(0.161)	(0.224)	(0.432)	(0.283)
Home insurance policy	0.106	0.527	0.017	-0.046	0.736	-0.186
	(0.151)	(0.380)	(0.159)	(0.173)	(0.662)	(0.204)
Motor insurance policy	0.101	0.597	-0.029	0.031	0.738	-0.120
	(0.194)	(0.494)	(0.221)	(0.196)	(0.559)	(0.231)
Constant	7.519***	6.340	1.907**	3.945***	-0.468	1.241
	(0.683)	(4.068)	(0.893)	(0.775)	(3.809)	(1.229)
Observations	16,487	8,173	8,244	6,565	3,373	3,192
Sample	All	Age≤28	Age>28	All	Age≤28	Age>28
Pseudo R2	0.0823	0.0884	0.0965	0.0528	0.0461	0.0947
Pred(Y): Non-Promotion: Control	98.11%	98.38%	97.75%	93.34%	93.11%	93.17%
Pred(Y): Non-Promotion: Treatment	98.56%	98.50%	98.62%	94.64%	93.56%	95.53%
Pred(Y): Promotion: Control	90.33%	92.22%	88.66%	79.73%	84.93%	75.75%
Pred(Y): Promotion: Treatment	90.43%	92.34%	88.89%	79.84%	86.98%	73.78%

Table A5: Effects of the treatment on customer retention rates including customers who viewed inconsistent benefits information for a type of the low fee card. Effects of the treatment on customer retention rates. Columns (1) – (3) and columns (4) – (6) show the results of cross-sectional data regression models of all, younger, and older customers for retention six and nine months after card activation, respectively. All models include indicator variables for the week the credit card was activated, and are estimated with robust standard errors clustered by activation date. *, **, and *** signify significance at the 10%, 5%, and 1% levels respectively. The results indicate that transparency can lead to increased customer retention, which is consistent with H4, that the effects are strongest for more experienced customers, which is consistent with H6, and that the effects are dampened during the promotion, which is consistent with H8. Marginal effect estimates for retention after six and nine months are provided for each experimental condition.