Information Systems Research
Vol. 25, No. 2, June 2014, pp. 345–363
ISSN 1047-7047 (print) | ISSN 1526-5536 (online)
http://dx.doi.org/10.1287/isre.2014.0521

Consumer Informedness and Firm Information Strategy

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Consumer informedness plays a critical role in determining consumer choice in the presence of information technology deployed by competing firms in the marketplace. This paper develops a new *theory of consumer informedness*. Using data collected through a series of stated choice experiments in two different research contexts, we examine how consumer characteristics and observed behaviors moderate the influence of price and product informedness on consumer choice. The results indicate that different types of consumer informedness amplify different consumer behaviors in specific consumer segments. In particular, we found that price informedness is more influential among consumers in the *commodity segment*. They exhibit greater *trading down* behavior, which represents stronger preferences for choosing the products that provide the best price. In contrast, product informedness is more influential among consumers in the *differentiated segment*. This group exhibits greater *trading out* behavior, involving stronger preferences for choosing products that best suit their specific needs. These results suggest that firm information strategy should take into account consumers' characteristics, their past observed behaviors, and the impact of consumer informedness. We also discuss the theoretical contributions of this research and its broader implications for firm-level information strategy.

Keywords: consumer choice; information strategy; marketing and IS; price and product information; randomized experiment; stated choice experiment; theory of consumer informedness
History: Anitesh Barua, Senior Editor; Kartik Hosanagar, Associate Editor. This paper was received on October 26, 2009, and was with the authors 24 months for 4 revisions. Published online in *Articles in Advance* May 5, 2014.

1. Introduction

The study of strategic pricing and competitive strategy in the presence of increased information availability is an active research area in the information systems (IS) discipline (Clemons et al. 2002, Oh and Lucas 2006, Clemons 2008, Li and Hitt 2008, Granados et al. 2012). Consumers are changing their behavior in the presence of lower consumer search costs for products and services (Bakos 1997); increased market transparency (Granados et al. 2012); and enhanced mass customization and personalization (Dewan et al. 2003, Mendelson and Parlakturk 2008). Consumers are better informed than ever before of the product offerings of firms. This improved *consumer informedness*, the degree to which consumers know what is available in the marketplace, including the precise attributes of different product and service offerings, has changed consumer behavior.[1] Meanwhile, firms are achieving an improved ability to meet the changing needs and requirements of heterogeneous consumers in the highly competitive market environment. Firms are diversifying their strategies because of the increased availability of fine-grained consumer data (Johnson et al. 2004); increased product and service variety through differentiation (Brynjolfsson et al. 2003, Clemons et al. 2006); rising price dispersion (Clemons et al. 2002, Chellappa et al. 2011, Li et al. 2013); and intensified cross-channel competition (Brynjolfsson et al. 2009).

The critical role and value of information are often acknowledged (Dhar and Sundararajan 2007, Kohli and Grover 2008), and there has been much research on measuring the impact of information availability. Previous research has offered theoretical models (Zhu

[1] *Informedness* differs from other terms. *Information endowment* is used by economists to indicate the quantity of information a decision maker has available. *Consumer awareness* suggests only general knowledge on the part of the consumer. Clemons (2008) has suggested that the change in information that consumers have available is so profound that the prior language no longer suffices and also that this is a new design variable for information strategy.

2004) and aggregate empirical analyses (Clemons et al. 2002, 2006; Forman et al. 2008; Granados et al. 2012). There has been little systematic empirical research that examines the decision making of differentially informed consumers at the individual level and the information strategies that firms should follow to sell to them most effectively. The goal of this article is to examine how consumer informedness about prices and products impacts consumer choice and the extent to which their differential effects are contingent on consumer characteristics and observed behaviors that information technology (IT) can help identify. As such, this article develops a new *theory of consumer informedness*. We answer the following research questions: How do price and product informedness impact consumer choice? How do their effects vary by consumer segment? What are the implications for the firm-level information strategy?

We answer these questions and explore the impacts of price informedness and product informedness on individual consumer preferences using stated choice experiments. This research differs from and contributes to the previous literature in two ways. First, we address the issue of consumer informedness by disentangling price informedness and product informedness. We develop theory and empirically test the differential effects of these two types of informedness on heterogeneous consumer preferences. Prior research argued that information availability changes consumer willingness-to-pay (Clemons 2008), and more price and product information leads to changes in price elasticity of demand (Granados et al. 2012). The past work did not distinguish between what types of information are involved though; it ignored how price and product information differentially affect individuals with different price and value sensitivity (Lynch and Ariely 2000). This article provides empirical evidence that the impacts of price and product information vary depending on the match between the type of information offered and the preferences of consumers. Second, to examine heterogeneity in consumer choice for different information strategies, we observed individual-level consumer choices using data from two stated choice experiments based on the random utility framework (McFadden 1974, Louviere et al. 2000). This is different from prior research that employed modeling and empirical analysis of secondary data.

We conducted two choice experiments using two types of products to collect data: transportation ticketing and hotel booking. First, our results provide evidence of two categories of consumer behavior in the presence of improved information, as suggested by Clemons and Gao (2008). *Trading down* behavior occurs with consumers who want to buy something because it is the best discount offering or it offers the best price among adequate alternatives. *Trading out* behavior, in contrast, occurs when consumers make their product choices based on an assessment of what product offers them the best fit, irrespective of price. Second, we found that different types of informedness seem to amplify different consumer behaviors. Higher price informedness has a greater effect on consumers who focus more on price, leading to stronger trading down behavior. These consumers belong to the *commodity segment*. The effect of price informedness is smaller on consumers who focus on product fit rather than price. They are in the *differentiated segment*. In contrast, we found that higher informedness related to non-price attributes has stronger effects on consumers in the differentiated segment, leading to stronger trading out behavior.

Our findings suggest that firms need to tailor their information strategies according to consumer preferences. Firms may have the incentive to facilitate improving consumer informedness in some markets but not others. Managers need to be cautious about estimating market demand in the presence of consumers who possess more price or product information. Winning firms will collect relevant consumer behavior data and use them to develop informedness strategies by considering the impact of information on consumer demand in the design of pricing and revenue management strategies and of service innovations. Further, our evidence opens up the possibility of using consumer experience in making inferences about consumer informedness sensitivity, providing a richer source of information for target marketing.

The rest of the article is organized as follows. Section 2 presents the theoretical background of this research and develops the hypotheses. The research designs of the two studies are described in §3. Then §4 presents our models and empirical results, and §5 discusses the empirical results and the findings. In §6 we conclude with the contributions, limitations, and future research.

2. Theory and Hypotheses

We first present our theoretical observations on firm use of information strategy. Then we discuss consumer behavior in the presence of improved information availability, which equates with greater informedness. Next we develop two sets of hypotheses: one set emphasizes price informedness and its related choice behavior; the other emphasizes product informedness and choice behavior.

2.1. Firm Information Strategy and Informed Consumer Demand

Firm Information Strategy. IT is readily available to all firms in competitive markets and is limited in generating competitive advantage. Information use—with or without technology—can improve and create new capabilities though. Several information strategy trends are apparent at the level of the firm. First, firms are increasingly employing *information transparency strategies* by changing the level of availability and accessibility of information to participants in business-to-business (Zhu 2004) and business-to-consumer settings (Granados et al. 2010). For example, in travel services, the intermediaries, Priceline and Hotwire, conceal a hotel's brand identity until after a booking is made. They intentionally disclose or withhold information to attract customers with different levels of market information.

Second, firms have traditionally sold products to the mass market to generate large purchase volumes among consumers. Today though, firms are engaged in pursuing long-tail sales to capture different consumer preferences. They are customizing their products and services in ways that were never possible before (Dewan et al. 2003, Mendelson and Parlakturk 2008) and also using *hyperdifferentiation strategies*—differentiation without limit—to produce almost anything that any potential customer might want (Clemons et al. 2006). This is because the Internet provides information to make products seem less complex and allows firms to communicate with the market more easily. IT and consumer information also underlie the value propositions that enable customer retention and long-tail selling by increasing product variety.

Third, the critical choice for firms is no longer how many different products to produce but whether and how to serve an increasing number of niches in which consumers are willing to pay premium prices for a near-perfect fit with their preferences. This is called *resonance marketing*: developing products that generate the strongest favorable responses among targeted consumer segments because they are better informed and can find exactly what they want (Clemons 2008, Clemons and Gao 2008). It requires an understanding of the demand of informed consumers and emphasizes what the firm knows about what each segment wants to buy, its willingness-to-pay, and the extent to which consumers are informed. This way, it can identify un-served and under-served consumer segments.

Informed Consumer Demand. With greater information availability, consumers are increasingly informed about relevant product and service offerings and their attributes. The new information comes from various sources: online reviews, community ratings, content-based websites, blogs, and social media help to diminish consumer uncertainty. Recent IS research provides abundant empirical evidence on the effectiveness of online product reviews across different product categories, such as: movies (Dellarocas et al. 2007, Forman et al. 2008); books (Li and Hitt 2008); and beer (Clemons et al. 2006). For example, in the craft beer industry today, consumers can obtain hundreds of reviews about thousands of different kinds of beer by using websites such as Ratebeer (www.ratebeer.com). The reviews enable consumers to be better informed about the taste and quality of a particular product. They will buy more of the ones they like. The reviews also allow brewers to make highly differentiated products because now they have the capability to measure the tastes of the consumers and send clear signals about the quality of their products.

Consumers, as a result, are now in a state of much greater informedness. They often know exactly what is available and at what price, and have a precise understanding of new products and service offerings and their attributes. They will be willing to pay more for what they want: more information reduces their uncertainty (Akerlof 1970, Salop 1979, Demski 1980) about new products and diminishes the compromises the consumer must make (Clemons 2008). As a result, they will experience a sense of delight that encourages them to make purchases. With improved informedness, consumers exhibit behaviors that are different from traditional consumer behavior observed under more conventional mass market strategies.

The first kind of behavior is *trading down* behavior. Trading down behaviors are those involving the purchase of least expensive offering (Clemons and Gao 2008). When they trade down, consumers not only choose products that have the lowest price but also may have a threshold that defines how much of a trade-off they will make for other product attributes. For example, in the case of air travel services, these are the consumers who consider the super-discount or advanced-purchase tickets offered by the airlines. These consumers have a relatively lower willingness-to-pay and can accept restrictions, such as more stopovers, inconvenient departure and arrival times, and advanced travel commitments.

The second kind of behavior is *trading out* behavior. Trading out behaviors are those involving the purchase of offerings that provide the best fit to the consumer's precise preference (Clemons and Gao 2008). When they trade out, consumers look for products that give the best fit rather than the best price. For instance, a person who makes a business trip will pay more than someone who goes on a leisure trip in order to reserve a nonstop flight with a short travel time. Consumer willingness-to-pay is determined by willingness-to-pay for an ideal service and by how closely the service matches or how much it deviates from this ideal.

2.2. Hypotheses

Consumers make purchase decisions while considering many criteria simultaneously. Based on the behavioral theory of decision making, choice behavior is systematically related to the attributes of a product or service (McFadden 1986). For each attribute, a consumer attaches a psychological weight as a means of expressing his perceptions related to his purchase decision. These perceptions are connected systematically with measurable values of the corresponding attributes. The individual aggregates the weights of the individual attributes to create an overall evaluation of a product or service.

Increased information availability enhances consumer awareness of alternatives in the marketplace, including their price and non-price attributes and their associated levels. Research on the differential effects of price and non-price information on consumer choice has concluded that lower search costs for price information increase price sensitivity (Bakos 1997, Degeratu et al. 2000), whereas improved access to quality information decreases price sensitivity (Lynch and Ariely 2000). Similarly, research on advertising found that price advertising leads to higher and non-price advertising leads to lower price sensitivity (Kaul and Wittink 1995, Mitra and Lynch 1995). Ahituv et al. (1998) argued that information value derives from the differences in behavioral outcomes for different information sets available.

We examine consumer heterogeneity in response to increasing price and product informedness and argue that the effects differ between individuals in different consumer segments. Individuals with different price sensitivities have different information needs; this influences the types of information they retrieve and the satisfaction from their search (Oliver 1995). Consumers in different segments seek different kinds of information cues given the type and level of information available. Need fulfillment theory suggests that consumers whose information needs are not met by their information cues will suffer a loss of utility or a potential misfit cost. We distinguish between two consumer segments that differ in their price sensitivity and their preference for a particular product: the commodity and differentiated segments. Consumers who are more price conscious and have higher price sensitivity are in the *commodity segment*. Consumers in the *differentiated segment* seek higher value and have lower price sensitivity.

Price Informedness and Trading Down Behavior. Increased information about prices allows consumers to compare prices of similar product and service offerings and find lower prices. They become more price sensitive, which affects the product or service they choose (Bakos 1997, Degeratu et al. 2000, Lynch and Ariely 2000). With perfect price information, the decision maker has knowledge of the true value of the available products. But with imperfect price information, the decision maker is constrained only to know about the range of prices that are available in the market. The basic difference between the impact of perfect and imperfect information is the richness of the related behavior that is observed. Imperfect information results in noise (Demski 1980). Noisy signals about price information tend to distort decision makers' beliefs about the value of different product offerings and will influence consumer decisions about maximizing the conditional expected utility of the product alternatives. As a result, consumers will have a lower likelihood of choosing a product with imperfect price information.

Though more precise price information seems to increase price sensitivity, the effect should vary depending on the informational cues that consumers focus on. We expect that in the commodity segment, consumers who are more informed about prices will exhibit stronger preferences for choosing products that provide the best price, compared to consumers who are less informed about prices. A consumer's characteristics may be associated with a need for specific information cues. Consumers in the commodity segment are price conscious. They typically seek price-related information cues and attach a stronger psychological weight on price to express their perceptions in their purchase decisions. When these consumers are more informed about prices of alternative products in the market, they are likely to value more highly the information they receive and become more sensitive to prices, leading to stronger trading down behavior. This may explain, for example, why price comparison capabilities matter more for the leisure segment in the air travel market (Granados et al. 2012). Thus, we propose the following:

Hypothesis 1A (H1A) (Commodity Segment, Price Informedness, and Trading Down Behavior). *In the commodity segment, consumers who are more informed about prices exhibit stronger trading down behavior compared to consumers who are less informed about prices.*

Consumers in the differentiated segment, in contrast, will prefer higher value products. They look for products that fit better rather than the best price; they place more weight on non-price attributes in the decision making process. For instance, some people will value having an ocean-view Jacuzzi suite in a hotel more highly than others will. They are likely to be willing to pay more. These consumers seek information cues related to differentiated product attributes that match their needs, so they are more likely to accept information uncertainty about the value of the offer and will have fewer problems with accepting an estimated range of prices rather than specific prices. We expect a weaker effect for imperfect price information in the differentiated segment than in the commodity segment, and suggest the following:

Hypothesis 1B (H1B) (Differentiated Segment, Price Informedness, and Trading Down Behavior). *Greater informedness about prices has a lower impact on the likelihood of trading down behavior for the differentiated segment than for the commodity segment.*

Product Informedness and Trading Out Behavior. The effects of greater product information are twofold. Increased information about product characteristics and quality allows consumers to ascertain the value of a product with higher precision that fits their needs well (Akerlof 1970). But if more product information is available, the consumer will place less weight on price, resulting in less price sensitivity. This is because consumers assign importance weights to the available product attributes. The weights they assign are relative to the available information. Weights cannot be assigned to information that is not available, so to the extent that product information is available, consumers will place less weight on price and vice versa. Thus, more product information is likely to make consumers less price sensitive because they focus on available product characteristics and quality information rather than on price. For example, Lynch and Ariely (2000) showed that allowing consumers to compare store offerings online results in lower price sensitivity because it lowers the search cost for quality information. Obtaining less product information is likely to reduce consumer willingness-to-pay because consumers may have a lower product utility in the absence of information about the salient attributes of a product. This is consistent with past evidence about the impact of missing product information (Johnson and Levin 1985).

The effect of greater product information should vary across individuals with different levels of price sensitivity. In the differentiated segment, consumers who are more informed about products should exhibit stronger trading out behavior compared to those who are less informed about products. Why? First, these consumers have stronger preferences for value and mostly look for product information. They are better able to identify products that fit their needs for differentiated product features. When these consumers are better informed about product attributes, they are more likely to find product options that are close to their true preferences and are more attractive for them to purchase, leading to a higher level of willingness-to-pay and a lower level of price sensitivity. Second, consumers in the differentiated segment will primarily look for product differentiation and fit. They will have a higher chance to detect the incompleteness of the product information presented, and there will be an adverse effect on their evaluation of alternatives for which product information is missing (Johnson and Levin 1985, Simmons and Lynch 1991). Thus, the less product information will reduce these customers' value sensitivity. We assert the following:

Hypothesis 2A (H2A) (Differentiated Segment, Product Informedness, and Trading Out Behavior). *In the differentiated segment, consumers who are more informed about products exhibit stronger trading out behavior compared to consumers who are less informed about products.*

Table 1 Consumer Segment and Firm Information Strategy

	Firm information strategy	
	Price informedness	Product informedness
Consumer segment Commodity	Stronger trading down behavior (−−)	Weaker increase in trading out behavior compared to differentiated segment (+)
Differentiated	Weaker increase in trading down behavior compared to commodity segment (−)	Stronger trading out behavior (++)

By the same token, we expect that the effect of greater product information will be weaker for consumers in the commodity segment than the differentiated segment. Consumers in the commodity segment typically look for the least expensive products, and their information needs for product information are relatively low. Even a small amount of product information may be sufficient for them to reach a purchase decision. This means that as long as they can find the cheapest available alternatives, lower quality or less quality information may not matter much for them. Thus, obtaining more product information is unlikely to strongly influence their searching for the best price for this segment. Thus, we propose the following:

Hypothesis 2B (H2B) (Commodity Segment, Product Informedness, and Trading Out Behavior). *Greater informedness about products has a lower impact on the likelihood of trading out behavior for the commodity segment than for the differentiated segment.*

We summarize our hypotheses related to consumer segment and firm information strategy in Table 1.

3. Research Design

To empirically test our hypotheses, we use a method that allows us to (1) present products or services unavailable at the time of the study, so that consumers could realistically compare new offerings, (2) create different informedness levels for new product offerings in the firms' product attribute space, and (3) assess the relative benefits that consumers attach to various attributes of the new products. To satisfy these criteria, we use a *stated choice experiment* approach, which is rooted in utility theory, to collect data (McFadden 1974, 1986; Louviere et al. 2000, 2010). The approach presents hypothetical choice situations to decision makers and asks them to state their choice preferences among different alternatives. It involves design of multiple experimental *attributes* and the *levels* of each attribute. Multiple alternatives (attributes, levels) are presented to decision makers in a *choice set*.

Decision makers are asked to evaluate the alternatives and choose the most preferred one. This method is based on two things: any product or service can be described by its attributes, and the extent a decision maker expresses utility depends on the nature and levels of these attributes. This method has been used in research and industry domains, including marketing, transportation, and healthcare.

To test our hypotheses, we conducted two experimental studies involving transportation choices (study 1) and hotel choices (study 2). We chose these two contexts because airline, hotel, car rental, and transportation suppliers and intermediaries frequently engage in information transparency strategies, sharing either more or less information. The two studies are complementary for the following reasons. First, we used a real-world setting in study 1 and worked closely with a transportation service provider to define service attributes and levels. The new services were related to the service offerings that the firm considers in view of the present implementation of smart cards and mobile technologies in the industry. In contrast, study 2 was designed and conducted in a controlled environment, involving a sophisticated design and more attributes and levels. Second, to select which attributes to omit when consumers are less informed about a product, we followed the business practices that were observed in study 1 but made our choice based on attribute importance levels in study 2. Third, study 1 involves frequent purchases (trips on commuter trains), whereas study 2 focuses on relatively infrequent purchases (hotel stays).

3.1. Study 1: Transportation Choice

Design and Manipulation. To identify the key attributes and levels in study 1, we interviewed executives of the collaborating service provider and requested they suggest attributes and levels of their new services related to the opportunities that smart cards and mobile ticketing technologies can bring. Next, we engaged two transportation research experts to refine the original list of attributes and levels, to avoid missing important attributes and restrict the number of experimental factors from being too large.

The service attributes are as follows. The first is price (*TransportPrice*), which is what the consumer pays for a trip. It includes three levels: *Low*, *Medium*, and *High*. The second category is basic services: time validity, Internet access, and seat reservation. Time validity (*Validity*) refers to the period that the transportation ticket is valid and includes three levels: *valid all day*, *not valid for morning peak*, and *not valid for morning and evening peaks*. Internet access (*Internet*) is defined as the presence or absence of access to wireless Internet at no additional cost. Seat reservation (*Reservation*) refers to the option of a seat reservation at no additional cost. The last category is related to advanced travel information, which has two attributes. Customized offers (*CustomizedOffer*) based on travel history from

Table 2 Study 1: Transportation Ticket Attributes and Levels

Category	Attribute	Level
Price	Price (*TransportPrice*): service price of a particular trip	• Price low • Price medium • Price high
Basic service	Time validity (*Validity*): time window for transportation, the validity of ticket	• Valid all day • Not valid for AM peak • Not valid for AM/PM peak
	Internet access (*Internet*): optional access to wireless Internet while traveling at no additional cost	• Free Internet access • No Internet access
	Seat reservation (*Reservation*): optional seat reservation at no additional cost	• Reservation possible • Reservation not possible
Advanced travel information	Customized offers based on travel history (*CustomizedOffer*): offers tailored using the traveler's past travel information	• Customized offers available • Customized offers not available
	Availability of real-time update and delay information (*Info*): access to dynamic updates on train status and real-time delay information	• Real-time info available • Real-time info not available

smart cards permit consumers to access new offers, including departure and arrival time, travel frequency, and distance. Availability of real-time update and delay information (*Info*) refers to access to dynamic updates of travel status (departure and arrival) and real-time delay information (travel alternatives in case of delay). Once available, these messages can be pushed directly to customers' mobile devices while they are traveling. Table 2 provides a summary of the choice attributes and levels used in study 1.

We used a 2×2 between-subject design and manipulated *Price Informedness* (*High*, *Low*) and *Product Informedness* (*High*, *Low*). Participants were randomly assigned to one of the four conditions. When *Price Informedness* was set to be *High*, price information was displayed in the form of a value with a narrower range (e.g., €9 up to €11). When *Price Informedness* was *Low*, price information was displayed in a wider range (e.g., €8 up to €12). The range was calculated with the price of a trip at the time of the study. When *Product Informedness* was *High*, we displayed all six product attributes. When *Product Informedness* was *Low*, we displayed four product attributes and cut two advanced travel information attributes.

Within each condition, we used a stated choice experiment design. Once we finalized the attributes and their levels for each condition, we specified the number of choice sets and the number of alternatives in each choice set using a 12-profile fractional factorial design for each condition. Each participant was presented with 12 choice sets, each consisting of two alternative new services. For each choice set, we asked participants to choose based on the new service attributes given their current travel situations, including origin-destination city-pair, travel frequency, and travel purpose. The participants could choose among new service A, new service B, or neither.

Experimental Procedure and Data Collection. We designed a computer-aided survey to collect data. After entering the secure website, the participant was presented with a description of the study and information on the implementation of a smart card ticketing program. The experiment proceeded as follows. First, all participants answered screening questions for participant selection. We selected only those who traveled by train for the typical trips they make and excluded those who traveled by car to ensure meaningful comparisons. We excluded students from the sample because they received free travel passes from the government. Next, the participants completed the questions about their current travel behavior, including their travel purpose; travel class; and detailed departure, arrival time, and location for the specific trip they identified. We then randomly assigned participants to the four conditions. We gave instructions on the tasks and provided extra information on the attributes and levels through pop-up textboxes for each choice set. The between-subject experimental design is realistic and helped to reduce the survey length and minimize boredom. After the experiment, the participants completed some demographic questions.

To collect data, we used a customer panel that was managed by the collaborating service provider. Panel members were the actual customers of the firm. They received a standard reward for participating. The participants were experienced, could handle complicated surveys, and were likely to be motivated by the pay they received for responding. In addition, the panel participants were reliable. Members who filled in suspicious questionnaires were periodically removed. We pre-tested the questionnaire with 100 randomly selected panel participants. Average task completion for participants was 20 minutes, and they did not indicate any difficulties. After we screened participants and cleaned the data, 1,971 valid participants remained. Fifty-four percent of the participants were male and 46% female, and their average age was 45.

3.2. Study 2: Hotel Choice

Design and Manipulation. Study 2 is on hotel bookings. We selected 15 hotel attributes from travel intermediaries and hotel websites, and conducted a pretest with nearly 200 participants to determine their importance. We kept the eight most important attributes for the experiment: hotel price (*HotelPrice*), hotel location (*Location*), hotel facility (*Facility*), customer review score (*Review*), hotel theme (*Theme*), hotel style (*Style*), payment mechanism (*Payment*), and cancellation policy (*Cancellation*). See Table 3.

Table 3 Study 2: Hotel Attributes and Levels

Attribute	Level
Hotel price (*HotelPrice*)	• Price low • Price medium • Price high
Hotel location (*Location*)	• Located in the historic heart of the city • 5 minute walk from the station • Surrounded by beautiful woodland
Hotel facility (*Facility*)	• Free wi-fi access • Free parking • Free swimming pool and spa
Customer review score (*Review*)	• 5 out of 5 • 4 out of 5 • 3 out of 5
Hotel theme (*Theme*)	• Family • City trip • Budget • Romance
Hotel style (*Style*)	• Modern accommodation • Classical décor
Payment mechanism (*Payment*)	• Credit cards only • Transfer only
Cancellation policy (*Cancellation*)	• Allowed until 72 hours before check-in • Allowed until 24 hours before check-in

We used a 2×2 between-subject design and manipulated *Price Informedness* (*High*, *Low*) and *Product Informedness* (*High*, *Low*). Participants were randomly assigned to these four conditions. When *Price Informedness* was *High*, the price was displayed with a narrower range (€50–€60; €70–€80; €90–€100), whereas when *Price Informedness* was *Low*, the price was displayed with a wider range (€30–€80; €50–€100; €70–€120). When *Product Informedness* was *High*, we displayed all eight product attributes; we only displayed the three most important ones when *Product Informedness* was *Low*: *HotelPrice*, *Location*, and *Facility*. For each participant, we presented 12 choice sets, each with two hotel options. We constructed the alternatives and choice sets using a 36-profile efficient design with three blocks for the eight-attribute conditions and a 12-profile efficient design for the three-attribute conditions.

Experimental Procedure and Data Collection. We developed an online survey to collect data. Prior to the experiment, we told the participants to imagine they would be making a holiday trip to Bruges in Belgium and needed to book a hotel.[2] To ensure participants were revealing their willingness-to-pay, we made the study incentive-compatible. We informed them that

[2] We chose a tourist location that is a two to three hours' drive from the participants' home locations. Bruges in Belgium is a popular historical destination for Europeans to spend a short holiday.

by making a choice, they would enter a lottery for a voucher of €150 for one overnight stay in the hotel of their choice. This would be based on the actual choice of their most preferred hotel option. If they won the lottery, they would be allowed to keep the remaining cash based on how much the hotel price was lower than €150. This ensured that there was an incentive for participants to look for higher hotel quality and lower prices; this meant they would get a voucher for a better hotel and would have more remaining money to spend freely.

We presented our participants with 12 choice scenarios and asked them to select one hotel in each scenario based on a hotel's different characteristics. We told them that the prices listed were for a standard room with two queen beds in a three-star hotel. We asked them how often they stayed in a hotel each year on average; the purpose of their stays; and how much on average they spent for the hotels, especially when they paid themselves. We also asked a few questions related to price and product uncertainty to see if our manipulation was successful. We used a professional online panel representing a country-wide sample. We pretested this study with 28 participants. The results were satisfactory. For final data collection, we received valid responses from 614 participants: 46% males and 54% females, with an average age of 35. We summarize the main differences in the research designs across the studies in Table 4.

Table 4 Main Differences in Research Design Between the Two Studies

	Study 1	Study 2
Context	Transportation ticket	Hotel booking
Experimental setup	Close collaboration with a transportation service provider	Controlled experiment
Type of participants	Survey panel of customers of firm	Survey panel with country-wide sample
Purchase frequency	Frequent and infrequent purchases	Relatively infrequent purchase
Attributes and levels	Two 3-level attributes and four 2-level attributes, resulting in $3^2 \times 2^4 = 144$ possible designs	One 4-level attribute, four 3-level attributes, and three 2-level attributes, resulting in $4 \times 3^4 \times 2^3 = 2{,}592$ possible designs
Missing information	Selected based on business practice	Selected based on attribute importance levels
Choice design	A 12-profile fractional orthogonal factorial design for all conditions	A 36-profile efficient design with three blocks for the two high product informedness conditions and a 12-profile efficient design for the two low product informedness conditions
Alternatives	Three alternatives, including a no choice option: New Service A, New Service B, Neither	Two alternatives: Hotel A, Hotel B

4. Empirical Model and Results

We next present the empirical models for the studies and report the results of our hypothesis tests.

4.1. Empirical Model

We apply a random utility theory-based *discrete choice model* to explain individual consumer choice (Ben-Akiva and Lerman 1985, Louviere et al. 2000, Train 2003). A consumer chooses one alternative among the full set of offered alternatives in a choice set to maximize his utility. We model the utility of each alternative j evaluated by consumer i in choice set k as $Utility_{ijk} = \beta X_{ij} + \varepsilon_{ijk}$. X_{ij} is a vector of all observable attributes of alternative j. β is a vector of estimated coefficients expressing individuals' preferences for the different attributes, and ε_{ijk} is an individual and alternative-specific error term that captures unexplained variation in consumers' utility. Consumer i will select alternative j if and only if $Utility_{ijk} > Utility_{imk}, \forall j \neq m$ for all other alternatives m in choice set k. A well-known form of such a model is the *multinomial logit model* (MNL). One drawback of MNL is the restrictive assumption that the error terms are independent and identically distributed. A second drawback is that all individuals' preferences for the observed attributes (β) are assumed to be homogenous.

A *mixed logit model* (ML), also known as the *random parameters logit model*, relaxes the independence of irrelevant alternatives assumption (Hensher and Greene 2003, Train 2003, Hensher et al. 2005). It recognizes that different consumers have different preferences. It accounts for correlation in unobserved factors over different alternatives within and across choice situations by each consumer. The mixed logit utility is $Utility_{ijk} = (\beta + \eta_i)X_{ij} + \varepsilon_{ijk}$. Here, β is the vector of estimated preferences shared by all individuals, and η_i is the vector of individual-specific deviations from the mean. The individual-specific error component is assumed to be independently and normally distributed. This random parameter specification allows us to estimate preference parameters associated with an attribute for each alternative to have both a mean and a standard deviation expressing the distribution of preferences across individuals. This individual-level preference estimation approach is more flexible compared to the multinomial logit model's, which estimates homogeneous tastes for the population (Hensher and Greene 2003).

The dependent variable is the consumer's choice among alternatives. To estimate the relative importance of price versus product fit across the conditions, we first conducted a main effects analysis, which computes each alternative's set of part-worth utilities for each of the attributes. In both studies, we included variables for all non-base-level attributes.[3] We used effects coding for both studies. Instead of coding the base level as 0 like traditional dummy coding, effects coding assigns −1 to the base level. The coefficient of the base attribute level is computed as the negative sum of the coefficients of the other attribute levels. Thus, we omitted the base attribute levels.[4] For a two-level attribute, we included one variable; for a three-level attribute, we included two variables; and for a four-level attribute, we included three variables.

In study 1, the utility of individual i choosing alternative transportation j, represented by $TransportUtility_{ijk}$, is

$$\begin{aligned} &TransportUtility_{ijk}\\ &\quad = (\theta_0+\delta_{0i}) + (\theta_1+\delta_{1i})TransportPrice\_Low_{ij}\\ &\qquad + (\theta_2+\delta_{2i})TransportPrice\_Medium_{ij}\\ &\qquad + (\theta_3+\delta_{3i})Validity\_AllDay_{ij}\\ &\qquad + (\theta_4+\delta_{4i})Validity\_NotValidAMPeak_{ij}\\ &\qquad + (\theta_5+\delta_{5i})Internet_{ij} + (\theta_6+\delta_{6i})Reservation_{ij}\\ &\qquad + (\theta_7+\delta_{7i})CustomizedOffer_{ij} + (\theta_8+\delta_{8i})Info_{ij} + \xi_{ijk} \end{aligned}$$

In study 2, individual i's utility of choosing alternative hotel j, represented by $HotelUtility_{ijk}$, is

$$\begin{aligned} &HotelUtility_{ijk}\\ &= (\lambda_0+\phi_{0i}) + (\lambda_1+\phi_{1i})HotelPrice\_Low_{ij}\\ &\quad + (\lambda_2+\phi_{2i})HotelPrice\_Medium_{ij}\\ &\quad + (\lambda_3+\phi_{3i})Location\_Center_{ij}\\ &\quad + (\lambda_4+\phi_{4i})Location\_Station_{ij} + (\lambda_5+\phi_{5i})Facility\_WiFi_{ij}\\ &\quad + (\lambda_6+\phi_{6i})Facility\_Parking_{ij} + (\lambda_7+\phi_{7i})Review\_High_{ij}\\ &\quad + (\lambda_8+\phi_{8i})Review\_Medium_{ij}\\ &\quad + (\lambda_9+\phi_{9i})Theme\_Family_{ij} + (\lambda_{10}+\phi_{10i})Theme\_City_{ij}\\ &\quad + (\lambda_{11}+\phi_{11i})Theme\_Budget_{ij} + (\lambda_{12}+\phi_{12i})Style_{ij}\\ &\quad + (\lambda_{13}+\phi_{13i})Payment_{ij} + (\lambda_{14}+\phi_{14i})Cancellation_{ij} + \zeta_{ijk} \end{aligned}$$

In these two models, we replaced our earlier β coefficients to be estimated in the general model with θ and λ, the individual-specific deviations η with δ and ϕ, and the error terms ε with ξ and ζ.

We further note that individual-specific constants are included for each model. We estimated the means and the standard deviations for the constants. In study 1, we have three alternatives in the stated choice experiment: new service A, new service B, and neither. We assume the constants for the first two alternatives to be the same because there are no baseline differences between them. Both are completely defined by their attributes. Thus, the utility function has one constant term. The constant captures an individual's average inclination to choose an alternative (either alternative new service A or new service B versus neither) with average attribute levels.[5] In study 2, because there is no neither option in the experiment, the generic constant captures an individual's average inclination to choose an alternative (either hotel A or hotel B) with average attribute levels.

We estimated random parameters for all of the variables for the non-base-level attributes and reported the means and standard deviations. All else equal, a positive coefficient for an attribute level means the probability of selecting the alternative will increase if a given attribute increases from the average level to this level.[6] We estimated the models using simulated maximum likelihood. We chose the Halton sequence draw to secure a stable set of parameter estimates and based the simulated means for individuals on each of the random coefficients from 200 draws.

To investigate trading down behavior, we examined the impact of the price attribute on consumer utility derived from the alternatives. We calculated a *willingness-to-trade-down* (*WTD*) measure by dividing the maximum range of parameters of price by the sum of the maximum range of parameters of all other attributes. This is similar to *marginal rates of substitution*, commonly used in research that implements stated choice experiments (Hensher et al. 2005), but reflects our objective of testing the relative importance of price versus all other attributes.[7] Also, to investigate trading

[3] Each variable takes on a specific attribute level. All attributes are restricted by the experimental design to a mutually exclusive subset. For example, *Price* can take on the levels of either *Low*, *Medium*, or *High*. *Facility* can be either *Wi-Fi*, *Parking*, or *Free swimming pool and Spa*, but not all at the same time.

[4] This coding approach supports the measurement of the effects of different attribute levels. It eliminates the problem of having the base attribute level coded the same way as the average of the means of all of the attribute levels. Thus, it is preferred over dummy coding (Hensher et al. 2005).

[5] When effects coding is used, the constant term is the average of the dependent variable. For data in which the levels of the effects-coded variable are not equally represented (because of the unequal number of times each attribute appears), it is necessary to use a calculated average of all levels of that attribute rather than the overall average. The two typically are close but not identical. An alternative-specific constant involves calculating the average of the means over the utilities for each level of a given alternative. It reflects an individual's inclination to choose an alternative with average attribute levels.

[6] The parameter estimate for each variable is the difference between the average utility for that attribute level and the calculated average of all levels of that attribute.

[7] This approach allows us to place attributes on a common and comparable scale (Lancsar et al. 2007). An additional benefit is that this allows for a comparison of parameters across models with different error scales μ. This is because the scale drops out in the ratio calculation since the scale is multiplicative with each parameter. This permits us to compare across different conditions with different error scales.

Table 5 Study 1: Mixed Logit Estimation Results for the Commodity Segment

		High–High		*High–Low*		*Low–High*		*Low–Low*	
Attribute	Level	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
		Random parameter estimates							
Constant		1.44***	0.32	0.51**	0.24	0.53**	0.27	0.46**	0.23
TransportPrice	Price low	1.39***	0.13	2.04***	0.15	1.14***	0.12	1.54***	0.13
	Price medium	−0.05	0.07	0.05	0.06	0.12**	0.06	0.07	0.06
Validity	Valid all day	1.29***	0.14	1.74***	0.19	1.85***	0.15	1.30***	0.14
	Not valid for AM peak	0.18**	0.09	0.17**	0.08	−0.02	0.08	0.51***	0.08
Internet	Free Internet access	0.03	0.05	−0.04	0.06	0.03	0.05	0.14**	0.06
Reservation	Reservation possible	0.19***	0.06	0.29***	0.06	0.15***	0.06	0.11*	0.06
CustomizedOffer	Customized offers available	0.13**	0.05			0.37***	0.05		
Info	Real-time info available	0.02	0.05			0.07	0.06		
		Standard deviation estimates							
Constant		3.70***	0.36	4.26***	0.26	3.31***	0.26	3.48***	0.23
TransportPrice	Price low	0.93***	0.12	1.80***	0.15	1.19***	0.12	1.18***	0.11
	Price medium	0.02	0.12	0.24	0.15	0.13	0.14	0.12	0.13
Validity	Valid all day	1.42***	0.16	1.90***	0.22	1.66***	0.13	2.04***	0.15
	Not valid for AM peak	0.64***	0.10	0.70***	0.11	0.80***	0.10	0.87***	0.10
Internet	Free Internet access	0.19**	0.09	0.38***	0.08	0.46***	0.07	0.66***	0.09
Reservation	Reservation possible	0.41***	0.07	0.73***	0.07	0.51***	0.06	0.75***	0.06
CustomizedOffer	Customized offers available	0.12	0.09			0.23***	0.09		
Info	Real-time info available	0.17*	0.09			0.09	0.11		
Willingness-to-trade-down (*WTD*)		0.78***	0.09	0.96***	0.11	0.49***	0.05	0.88***	0.09
Willingness-to-trade-out (*WTO*)		1.28***	0.15	1.04***	0.12	2.04***	0.22	1.14***	0.12
N		2,004		3,240		2,928		3,216	
Log-likelihood		−1,436.89		−2,064.28		−2,121.00		−2,205.48	
R^2		0.35		0.42		0.34		0.38	

Notes. Estimation model: mixed logit. *High–High* condition = *Price Informedness High/Product Informedness High* condition. Both random parameter and standard deviation estimates are reported for each attribute level. For each attribute, we omitted the base attribute level estimate from the table. Each participant completed 12 choice sets. Thus, for each condition, we have N = participants × 12 observations.

Significance: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

out behavior, we calculated a *willingness-to-trade-out* (*WTO*) measure by dividing the maximum range of the parameters of the non-price attributes by the sum of the maximum range of the price parameter. Confidence intervals for the *WTD* and *WTO* values were derived using the Wald procedure in NLOGIT 5.0 based on the delta method (Hole 2007). Then we compared the *WTD* and *WTO* values for the informedness conditions.

4.2. Study 1—Transportation Choice: Results

In both studies, we looked for segmentations by firms based on consumers' past behavior that IT can help identify. This provides a relatively easy means for firms to classify consumers in the two segments. In study 1, travel purpose typically has a high impact on consumer price sensitivity. The service provider cannot easily observe a consumer's travel purpose, but we can use travel frequency as a proxy measure. Leisure travelers tend to travel less and are more price sensitive, whereas business travelers and commuters usually travel more often and are less price sensitive. Consistent with what is used by the collaborating service provider, we define consumers that travel less frequently, ranging from once a year to three times per week, as belonging to the commodity segment. High-frequency travelers, who travel more than four times per week, are in the differentiated segment. This resulted in a 50–50 split of our sample.

We estimated mixed logit models across all conditions for both segments and report the mean and standard deviation of each attribute level and the *WTD* and *WTO* values. See Tables 5 and 6. We tested the distribution of the age, gender, education, and income across experimental conditions and did not find significant differences. We further tested the participants' reported travel frequencies and travel purposes across conditions and also did not find significant differences.

Evidence of Trading Down and Trading Out Behavior. The results for the commodity segment are presented in Table 5. Except for the *Low–High* condition, under all other conditions the relative importance of price was the highest among all of the attributes, as indicated by the *WTD* value. This suggests that consumers in the commodity segment show stronger preferences for products that provide them with the best price and permit them to make trade-offs among other product attributes; they exhibit trading down behavior. Under *Low–High* price informedness, participants were not well-informed about price. Thus,

Table 6 Study 1: Mixed Logit Estimation Results for the Differentiated Segment

		High–High		*High–Low*		*Low–High*		*Low–Low*	
Attribute	Level	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
		Random parameter estimates							
Constant		−3.94***	0.25	−3.94***	0.26	−3.71***	0.26	−6.55***	0.55
TransportPrice	Price low	0.58***	0.14	1.48***	0.19	1.03***	0.12	1.24***	0.19
	Price medium	0.21**	0.09	0.11	0.13	−0.44***	0.09	−0.20	0.13
Validity	Valid all day	5.15***	0.28	6.32***	0.39	5.73***	0.33	7.79***	0.58
	Not valid for AM peak	−1.16***	0.19	−1.38***	0.18	−1.27***	0.16	−1.49***	0.36
Internet	Free Internet access	0.12*	0.07	0.03	0.09	0.24***	0.08	0.13	0.12
Reservation	Reservation possible	0.27***	0.07	0.03	0.08	0.42***	0.08	0.04	0.11
CustomizedOffer	Customized offers available	0.32***	0.08			0.38***	0.08		
Info	Real-time info available	0.30***	0.08			0.13*	0.08		
		Standard deviation estimates							
Constant		2.82***	0.24	3.07***	0.25	3.06***	0.24	3.20***	0.29
TransportPrice	Price low	0.83***	0.12	1.37***	0.16	0.43***	0.13	0.85***	0.24
	Price medium	0.22	0.15	0.86***	0.15	0.02	0.16	0.62***	0.21
Validity	Valid all day	2.23***	0.17	2.79***	0.23	3.04***	0.24	3.51***	0.40
	Not valid for AM peak	1.21***	0.17	1.20***	0.20	1.41***	0.18	3.63***	0.46
Internet	Free Internet access	0.40***	0.15	0.76***	0.13	0.60***	0.10	0.82***	0.14
Reservation	Reservation possible	0.55***	0.11	0.46***	0.12	0.46***	0.10	0.83***	0.13
CustomizedOffer	Customized offers available	0.25	0.17			0.43***	0.12		
Info	Real-time info available	0.35**	0.14			0.09	0.14		
Willingness-to-trade-down (*WTD*)		0.12***	0.02	0.27***	0.02	0.13***	0.01	0.16***	0.02
Willingness-to-trade-out (*WTO*)		8.15***	1.21	3.72***	0.32	7.71***	0.84	6.35***	0.80
N		3,240		2,880		3,288		2,688	
Log-likelihood		−1,435.26		−1,169.00		−1,446.48		−985.83	
R^2		0.60		0.63		0.60		0.67	

Notes. Estimation model: mixed logit. *High–High* condition = *Price Informedness High/Product Informedness High* condition. Both random parameter and standard deviation estimates are reported for each attribute level. For each attribute, we omitted the base attribute level estimate from the table. Each participant completed 12 choice sets. Thus, for each condition, we have N = participants × 12 observations.

Significance: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

they had higher price uncertainty and focused on other non-price attributes. This is the only condition that we expected price to become less important: uncertainty diminishes the importance of price. The results for the differentiated segment are in Table 6. As indicated by the *WTO* value, the results show that non-price attributes are more important than price for these consumers across all conditions. This suggests that they place a higher value on product fit, which is evidence for the trading out behavior.

The Effect of Price Informedness. To test Hypotheses 1A and 1B, which address the effect of improved price information, we compared the *WTD* values between the two price informedness conditions. In the commodity segment, the results show increased price sensitivity when consumers are presented with more price information, irrespective of the levels of product information (*High–High* versus *Low–High*: $0.78 > 0.49$, $p < 0.001$; *High–Low* versus *Low–Low*: $0.96 > 0.88$, $p < 0.001$). Consumers in this segment exhibit greater trading down behavior when they are more informed about prices, supporting H1A. In the differentiated segment, the results also show a stronger focus on price in the presence of more price information, but only when the product information is low (*High–Low* versus *Low–Low*: $0.27 > 0.16$, $p < 0.001$). When product information is high, the increase in price sensitivity is slightly lower (*High–High* versus *Low–High*: $0.12 < 0.13$, $p < 0.01$). We also compared the effect of price informedness between the commodity and differentiated segments by aggregating across the two product informedness conditions. The t-test result reveals that on average over the two product informedness conditions, the impact of price informedness on the increases in price sensitivity, in terms of the absolute change in the average *WTD* value, is significantly weaker ($p < 0.001$) for the differentiated segment (*High* versus *Low*: $(0.12 + 0.27)/2 > (0.13 + 0.16)/2 = 0.20 > 0.14$; $p < 0.001$) than for the commodity segment (*High* versus *Low*: $(0.78 + 0.96)/2 > (0.49 + 0.88)/2 = 0.87 > 0.69$; $p < 0.001$). This provides support for H1B: greater informedness about prices has a lower impact on trading down behavior for the differentiated than for the commodity segment.

The Effect of Product Informedness. To examine the effect of product information and test Hypotheses 2A and 2B, we examined the *WTO* values in both segments. In the commodity segment, *WTO* is higher for the high product informedness conditions, irrespective of the levels of price information (*High–High* versus *High–Low*: $1.28 > 1.04$, $p < 0.001$; *Low–High* versus *Low–Low*: $2.04 > 1.14$, $p < 0.001$). In the differentiated segment, we found a similar result (*High–High* versus *High–Low*: $8.15 > 3.72$, $p < 0.001$; *Low–High* versus *Low–Low*: $7.71 > 6.35$, $p < 0.001$), providing support for H2A. This suggests that consumers who are more informed about products exhibit stronger trading out behavior. We also compared the effects of product informedness in the two segments by aggregating across the two price informedness conditions. The t-test result shows that on average over the price informedness conditions, the impact (in terms of the absolute change in the average *WTO* value) is significantly higher ($p < 0.001$) in the differentiated segment (*High* versus *Low*: $(8.15 + 7.71)/2 > (3.72 + 6.35)/2 = 7.93 > 5.04$; $p < 0.001$) than in the commodity segment (*High* versus *Low*: $(1.28 + 2.04)/2 > (1.04 + 1.14)/2 = 1.66 > 1.09$; $p < 0.001$). This supports H2B: product information will be more influential in the differentiated segment.

4.3. Study 2—Hotel Choice: Results

In study 2, to distinguish between the commodity and differentiated segments, we used consumers' average prices paid for a one-night hotel stay in the past. Consumers who paid less than €70 were assigned to the commodity segment, and those who paid higher prices were assigned to the differentiated segment. This gave a 50–50 sample split. Similar to study 1, we estimated our models across all conditions for both segments. We report the means and standard deviations of each attribute level, the *WTD* and *WTO* values, and results in Tables 7 and 8. Our checks showed that the manipulations were successful. We tested the distribution of age, gender, education, and income across experimental conditions and found no significant differences. We then tested the participants' reported average frequencies of staying in a hotel each year and the familiarity of booking online across conditions and also did not find significant differences.

Evidence of Trading Down and Trading Out Behavior. We present the results for the commodity segment in Table 7. The results show that, as expected, the relative importance of price is the highest among all attributes across the four conditions, as indicated by the high *WTD* values. This confirms that consumers in the commodity segment exhibit stronger preferences in choosing the product with the best price. Thus, they are exhibiting trading down behavior. Table 8 presents the results for the differentiated segment. The *WTO* results show that the product fit is the most important for these consumers in all conditions, providing evidence of the trading out behavior.

The Effect of Price Informedness. We compared the *WTD* values between the different price informedness conditions. In the commodity segment, we observed increased price sensitivity when the price information increased, irrespective of the levels of product information (*High–High* versus *Low–High*: $1.02 > 0.55$, $p < 0.001$; *High–Low* versus *Low–Low*: $1.87 > 1.57$, $p < 0.001$). This indicates that consumers exhibited greater trading down behavior when they were more informed about prices, supporting Hypothesis 1A. We found the same result in the differentiated segment (*High–High* versus *Low–High*: $0.135 > 0.131$, $p < 0.001$; *High–Low* versus *Low–Low*: $0.45 > 0.25$, $p < 0.001$). Then we compared the effect of price informedness across the two segments. Hypothesis 1B was supported, and the results showed that on average over the two product informedness conditions, the influence was significantly weaker ($p < 0.001$) in the differentiated segment (*High* versus *Low*: $(0.13 + 0.45)/2 > (0.13 + 0.25)/2 = 0.29 > 0.19$; $p < 0.001$) compared to the commodity segment (*High* versus *Low*: $(1.02 + 1.87)/2 > (0.55 + 1.57)/2 = 1.45 > 1.06$; $p < 0.001$).

The Effect of Product Informedness. To assess the effect of product information, we compared the *WTO* values in both segments. In the differentiated segment, we observed stronger trading out behavior when consumers were more informed about the product, irrespective of the levels of price information they were presented (*High–High* versus *High–Low*: $7.41 > 2.20$, $p < 0.001$; *Low–High* versus *Low–Low*: $7.60 < 4.00$, $p < 0.001$). This provides support for Hypothesis 2A. In the commodity segment, we also found a stronger focus on product fit when consumers received more product information (*High–High* versus *High–Low*: $0.98 < 0.53$, $p < 0.001$; *Low–High* versus *Low–Low*: $1.81 > 0.64$, $p < 0.001$). Comparing the effect of product informedness across the two segments, on average over the two price informedness conditions, the impact is significantly higher ($p < 0.001$) for the differentiated segment (*High* versus *Low*: $(7.41 + 7.60)/2 > (2.20 + 4.00)/2 = 7.51 > 3.10$; $p < 0.001$) than the commodity segment (*High* versus *Low*: $(0.98 + 1.81)/2 > (0.53 + 0.64)/2 = 1.40 > 0.59$; $p < 0.001$). This provides support for Hypothesis 2B.

Our empirical findings support all of our hypotheses. The results of both studies are summarized in Figure 1, which shows the differences in responses between the two segments depending on whether price informedness or product informedness was presented.[8]

[8] The hypotheses are tested based on the average of the two informedness conditions. We conducted *post hoc* analysis to specify the conditions under which the hypotheses hold and will discuss the results in the next section. In addition, to study the impact of price (product) informedness on the increases in price sensitivity across two product (price) informedness conditions, we looked at the absolute changes in the average WTD (WTO) instead of the percentage change, which may lead to slightly different results.

Table 7 Study 2: Mixed Logit Estimation Results for the Commodity Segment

		High–High		*High–Low*		*Low–High*		*Low–Low*	
Attribute	Level	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
	Random parameter estimates								
Constant		−0.05	0.07	−0.16	0.29	0.06	0.06	−0.06	0.21
HotelPrice	Price low	1.14^{***}	0.10	3.79^{***}	1.14	0.62^{***}	0.08	2.68^{***}	0.68
	Price medium	0.20^{***}	0.07	1.11^{***}	0.36	−0.03	0.06	−0.20	0.19
Location	Historic heart of the city	0.56^{***}	0.09	2.07^{***}	0.68	0.52^{***}	0.08	0.88^{***}	0.29
	5 minute walk from the station	-0.23^{***}	0.08	-1.39^{***}	0.46	-0.14^{*}	0.07	-0.82^{***}	0.29
Facility	Free wi-fi access	−0.06	0.08	−0.24	0.29	0.03	0.07	−0.35	0.26
	Free parking	−0.09	0.09	−0.47	0.37	−0.08	0.08	-0.61^{***}	0.21
Review	5 out of 5	0.17^{**}	0.08			0.12^{*}	0.06		
	4 out of 5	0.23^{***}	0.08			−0.03	0.06		
Theme	Family	−0.08	0.09			−0.11	0.08		
	City trip	−0.05	0.09			0.18^{**}	0.07		
	Budget	−0.06	0.09			-0.28^{***}	0.07		
Style	Modern accommodation	−0.07	0.05			0.06	0.05		
Payment	Credit cards only	−0.01	0.06			−0.04	0.05		
Cancellation	Allowed until 72 hours before check-in	-0.11^{**}	0.05			-0.13^{***}	0.05		
	Standard deviation estimates								
Constant		0.00	0.14	0.02	0.39	0.03	0.16	0.16	0.31
HotelPrice	Price low	0.39^{***}	0.09	3.00^{***}	1.09	0.31^{***}	0.08	1.25^{***}	0.43
	Price medium	0.18	0.11	1.28^{***}	0.41	0.01	0.10	0.55^{*}	0.29
Location	Historic heart of the city	0.33^{***}	0.08	2.89^{***}	0.78	0.28^{***}	0.10	0.88^{***}	0.33
	5 minute walk from the station	0.34^{***}	0.09	2.43^{***}	0.81	0.25^{***}	0.08	1.88^{**}	0.73
Facility	Free wi-fi access	0.23^{**}	0.11	1.45^{***}	0.51	0.16	0.10	0.90^{***}	0.35
	Free parking	0.37^{***}	0.08	1.34^{***}	0.42	0.40^{***}	0.09	0.72^{**}	0.31
Review	5 out of 5	0.25^{***}	0.07			0.11	0.07		
	4 out of 5	0.25^{***}	0.07			0.11	0.07		
Theme	Family	0.02	0.11			0.00	0.12		
	City trip	0.16	0.10			0.06	0.10		
	Budget	0.13	0.12			0.03	0.10		
Style	Modern accommodation	0.08	0.09			0.18^{***}	0.05		
Payment	Credit cards only	0.13^{*}	0.07			0.09	0.08		
Cancellation	Allowed until 72 hours before check-in	0.08	0.08			0.12^{*}	0.07		
Willingness-to-trade-down (*WTD*)		1.02^{***}	0.16	1.87^{***}	0.33	0.55^{***}	0.10	1.57^{***}	0.34
Willingness-to-trade-out (*WTO*)		0.98^{***}	0.15	0.53^{***}	0.09	1.81^{***}	0.31	0.64^{***}	0.14
N		1,368		432		1,404		492	
Log-likelihood		−681.89		−177.57		−842.77		−196.13	
R^2		0.28		0.41		0.13		0.42	

Notes. Estimation model: mixed logit. *High–High* condition = *Price Informedness High/Product Informedness High* condition. Both random parameter and standard deviation estimates are reported for each attribute level. For each attribute, we omitted the base attribute level estimate from the table.
Significance: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

5. Discussion

We next will discuss our findings with respect to the recognition of consumer segments that IT makes possible, and the differential effects of price and product informedness that are likely to arise.

5.1. The Choice of Segmentation Variables

In study 1, we used travel frequency instead of travel purpose as the basis for consumer segmentation. We did this because in the transportation market that we studied, consumers do not make reservations when they travel for the most part. Thus, service providers do not know their travel frequency. But the information will become available after the introduction of smart cards and mobile ticketing technologies. Second, a traveler's purpose is difficult to obtain without conducting a consumer survey. Using travel frequency, though, we can efficiently segment consumers into the commodity and differentiated segments.

Consumers who trade down, we found, tend to represent the leisure segment of the transportation market, which consists of people who travel less frequently. They value low prices the most and are most likely to replace their current service with a less expensive one of lower quality (e.g., shorter time validity). Consumers who trade out represent the business segment of the market and they travel more frequently. They exhibit stronger preferences in choosing products that give them the longest time validity rather than the lowest price. This is reasonable because these people have much tighter schedules and lower price sensitivity. They are looking for a product that gives unrestricted

Table 8 Study 2: Mixed Logit Estimation Results for the Differentiated Segment

		High–High		*High–Low*		*Low–High*		*Low–Low*	
Attribute	Level	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
		Random parameter estimates							
Constant		−0.09	0.07	−0.24	0.24	−0.11*	0.07	−0.35*	0.20
HotelPrice	Price low	0.12	0.07	0.72***	0.25	0.18**	0.08	0.56*	0.31
	Price medium	0.15**	0.06	0.28	0.19	0.01	0.07	−0.24	0.19
Location	Historic heart of the city	0.65***	0.08	2.08***	0.48	0.56***	0.08	1.63***	0.34
	5 minute walk from the station	−0.34***	0.08	−1.02***	0.37	−0.31***	0.09	−0.62***	0.24
Facility	Free wi-fi access	−0.13*	0.07	0.32	0.29	−0.17**	0.07	0.42*	0.25
	Free parking	−0.01	0.08	−0.32	0.25	−0.09	0.07	−0.47	0.29
Review	5 out of 5	0.36***	0.07			0.20***	0.07		
	4 out of 5	0.11	0.07			0.07	0.07		
Theme	Family	−0.23***	0.08			−0.20**	0.08		
	City trip	0.12	0.08			0.26***	0.08		
	Budget	−0.14*	0.08			−0.25***	0.08		
Style	Modern accommodation	0.02	0.04			0.06	0.05		
Payment	Credit cards only	0.09**	0.04			0.05	0.05		
Cancellation	Allowed until 72 hours before check-in	−0.12***	0.04			−0.14**	0.05		
		Standard deviation estimates							
Constant		0.01	0.10	0.34	0.37	0.09	0.11	0.06	0.27
HotelPrice	Price low	0.26***	0.08	1.06***	0.37	0.41***	0.07	1.57***	0.55
	Price medium	0.02	0.08	0.64	0.40	0.18**	0.07	0.07	0.17
Location	Historic heart of the city	0.33***	0.09	2.44***	0.62	0.39	0.07	1.97***	0.70
	5 minute walk from the station	0.29***	0.07	1.98***	0.43	0.47***	0.09	2.59***	0.80
Facility	Free wi-fi access	0.16	0.11	1.71***	0.41	0.14	0.11	1.28***	0.35
	Free parking	0.30***	0.08	1.08***	0.36	0.27***	0.08	1.89***	0.59
Review	5 out of 5	0.15**	0.07			0.24***	0.05		
	4 out of 5	0.15**	0.07			0.24***	0.05		
Theme	Family	0.09	0.11			0.04	0.11		
	City trip	0.06	0.10			0.18**	0.08		
	Budget	0.16	0.10			0.18**	0.09		
Style	Modern accommodation	0.05	0.07			0.18***	0.05		
Payment	Credit cards only	0.02	0.06			0.24***	0.06		
Cancellation	Allowed until 72 hours before check-in	0.03	0.07			0.20***	0.05		
Willingness-to-trade-down (*WTD*)		0.13***	0.04	0.45***	0.14	0.13**	0.06	0.25*	0.13
Willingness-to-trade-out (*WTO*)		7.41***	2.25	2.20***	0.70	7.60**	3.30	4.00*	2.15
N		1,260		504		1,404		504	
Log-likelihood		−756.90		−225.58		−872.51		−238.29	
R^2		0.13		0.35		0.10		0.32	

Notes. Estimation model: mixed logit. *High–High* condition = *Price Informedness High/Product Informedness High* condition. Both random parameter and standard deviation estimates are reported for each attribute level. For each attribute, we omitted the base attribute level estimate from the table.

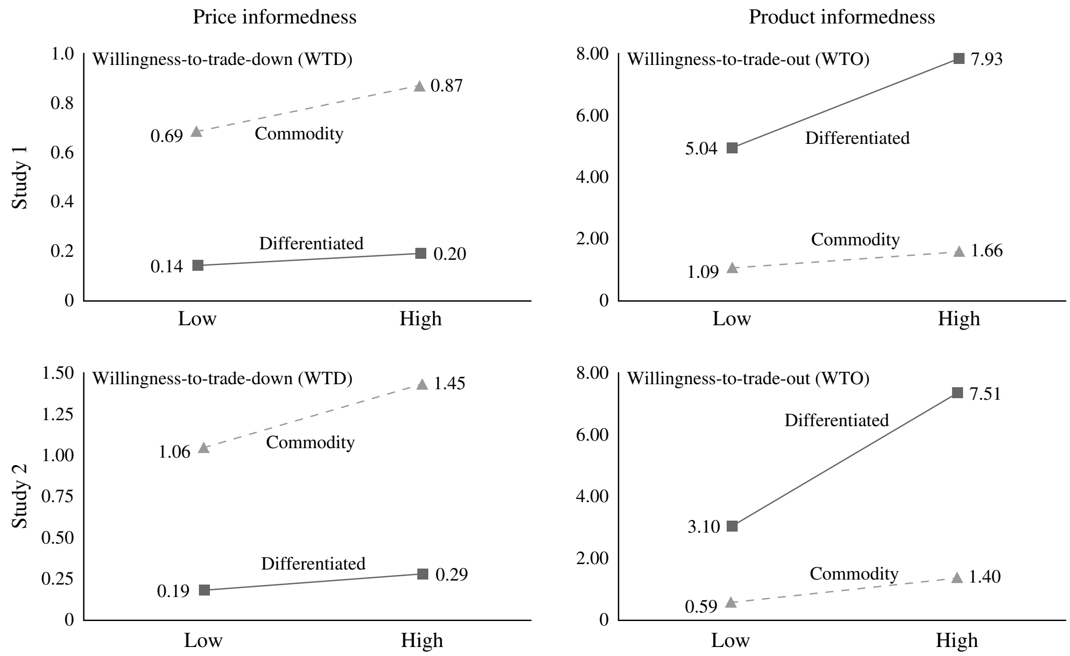
Significance: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

travel throughout the day, irrespective of price, so that they won't worry about peak and off-peak time window travel restrictions.

In study 2, we segmented consumers and demonstrated their heterogeneous preferences related trading down and trading out behaviors in the presence of improved informedness, using the prices consumers paid for past hotel stays.[9] This purchase information is often available through online intermediaries, such as Expedia or Orbitz, or hotel websites. This kind of historical information on consumer behavior has been used to analyze and design new services that are targeted to individual consumer needs. Our results show that it also can be used to distinguish the consumers with different price and value sensitivities. This

[9] The segmentation variable here is context specific, and what works well for one study may not work well for the other. In study 1, since the government regulates prices, historical prices do not vary much for individuals for a particular trip (e.g., between home and work). This explains why we used travel frequency but not the historical prices as the segmentation variable here. In study 2, there is no direct correlation between stay frequency and price sensitivity. For example, some people may stay twice a year in two-star hotels; others may stay twice a year in five-star hotels. Using a survey allows us to ask participants about the prices they paid in a recent stay, so we used consumers' average price paid for a one-night hotel stay in the past instead of stay frequency as the segmentation variable. For robustness, we also checked other customer characteristics as segmentation variables but did not find significant differences across the segments for the trading down and the trading out behaviors in both studies.

Figure 1 The Main Results for Studies 1 and 2



gives useful information on consumers who have a different degree of sensitivity to different informedness levels. Moreover, the findings from both experiments suggest that firms can use customer characteristics and past behavior as predictors of consumer sensitivity to different information strategies.

5.2. Informedness-Based Consumer Heterogeneity

Previous research provided evidence that lower search costs for price information increases price sensitivity, whereas improved access to quality information decreases price sensitivity. In markets in which consumer informedness plays a dominant role, the choice dynamics are often more complex. We examined heterogeneity in consumer choices in the presence of differential information strategies. Our findings on the effects of price informedness confirm our hypothesis that, in the commodity segment, consumers who are more informed about prices exhibit stronger trading down behavior, leading to lower levels of willingness-to-pay and higher price sensitivity. In addition, improved price information may have driven the commodity segment consumers to make informed choices that are more often based on price comparison. Our results also show that more price information does not seem to always increase the price sensitivity of consumers in the differentiated segment (i.e., *High–High* versus *Low–High* condition in study 1). And, even if it does, the effect is weaker compared to the commodity segment. Additional analysis in study 1 shows that this weaker increase in price sensitivity happens when product information is high; otherwise, the effects of price information between the two segments are not different. This may be because when consumers are less informed about products, they will have less information about product quality and less ability to compare products. This leads to a greater emphasis on price comparison. Thus, increased price sensitivity may not differ much between the two segments.

Our findings on the effect of product information also support the hypothesis that more product information has greater effects on consumers in the differentiated segment, leading to stronger trading out behavior. These consumers already focus on product fit, not price, so more product information leads to a stronger preference for fit and lower price sensitivity. In the commodity segment though, the effect is weaker than in the differentiated segment. We summarized our findings in Table 9 regarding the detailed conditions under which the predicted behaviors were observed.

We acknowledge that a consumer who belongs to the commodity segment for one product may also belong to the differentiated segment for another product. This is in contrast to previous research, which argued that price sensitivity is a consumer trait independent of product categories (Ainslie and Rossi 1998). For example, a consumer can look for the cheapest transportation option while seeking a four-star hotel for a holiday trip. Thus, firms may be more effective in garnering sales by offering service bundles and by exploring the differential willingness-to-pay of consumers in different product categories.

There may be cases for which product information leads to trading down: when consumers learn the products are not so different, they will shop for low prices. Or price information will lead to trading out

Table 9 Summary of Detailed Findings

Information strategy	Predicted behavior by segment	Empirical findings: Conditions	Study 1 results	Study 2 results
Price informedness	Commodity segment: stronger trading down	High product informedness	Commodity > Differentiated	Commodity > Differentiated
	Differentiated segment: weaker increase in price sensitivity than commodity segment	Low product informedness	Commodity ≈ Differentiated	Commodity > Differentiated
Product informedness	Commodity segment: weaker increase in value sensitivity than differentiated segment	High price informedness	Differentiated > Commodity	Differentiated > Commodity
	Differentiated segment: stronger trading out	Low price informedness	Differentiated > Commodity	Differentiated > Commodity

when consumers learn that a premium price for a better product is not so high. How information affects consumer behavior is important and complicated. Our approach builds a foundation for understanding the effects of consumer informedness and information availability on consumer behavior.

6. Conclusion

We have examined how price and product informedness affect individuals with different price and value sensitivity and information needs in Internet-enabled business. We conducted experimental studies in a realistic transportation ticket choice setting and a more-controlled hotel booking choice setting. The results confirm that some consumers seek products that give them the cheapest prices while minimizing their chances for being disappointed because of uncertainty—what is referred to as trading down behavior. Others seek products that maximize their utility and provide the best fit between their preferences and what the product can offer—what is called trading out behavior.

We are *not* merely confirming that some consumers focus on price, and others focus on product fit when they make purchase decisions. Instead, the most important finding is that our empirical results suggest different types and levels of informedness will amplify different behaviors—a highly useful finding for firms that can control different aspects of informedness in their marketing of goods and services. Higher informedness about prices will have greater effects on consumers who focus on price, and higher informedness about products and their quality will have more substantial effects on consumers who focus on product fit. These result in different willingness-to-pay levels.

We will point out the theoretical and methodological contributions of our research, discuss managerial implications for firm information strategy, and note some limitations and future directions for research.

6.1. Theoretical and Methodological Contributions

Our research makes theoretical and methodological contributions. First, it adds to the growing body of literature on the strategic use of information and its effects on competitive strategy. The method we used complements typical methods for theoretical modeling and empirical analysis with secondary data. We collected individual-level choice data through stated choice experiments based on a random utility theory model. This research is different from existing studies that use individual data (Smith and Brynjolfsson 2001, Johnson et al. 2004). We directly observed consumer choices among different alternatives and explained the differences in their preferences as a consequence of their willingness-to-pay.

Second, in an effort to develop a new *theory of consumer informedness*, this article addresses consumer informedness by disentangling price informedness and product informedness. Our work is the first to empirically demonstrate the differential impact of price and product information across consumer segments. It develops new theory and teases out the different effects of two types of informedness. We provide evidence that the effects vary depending on the match between the type of information offered and consumer price and value sensitivity. This implies that firm-level online information strategies may not be effective for all consumers, even for the same product offerings.

Third, in most studies, consumer informedness focuses on knowing about product and service attributes, assuming that consumers fully understand the product offerings based on information they acquire. We argued that there are great differences when consumers evaluate the utility of new offerings with different types and levels of information. In addition, the existing theoretical works assume only one dimension of consumer preference (Dewan et al. 2003, Mendelson and Parlakturk 2008). Our research begins with the premise that multiple dimensions matter to consumers.

6.2. Implications for Firm Information Strategy

Our findings reveal that price and product information strategies will have a polarizing effect on consumer behavior when the strategies relate to consumers' price and value sensitivity and information needs. In both studies that we conducted, we classified consumers in segments based on their past behavior. This included travel frequencies for transportation and past purchase prices for hotel bookings. They predicted the behavior split that we expected to see. This further suggests that firms may wish to look at consumers' past behavior—a form of *observation-based behavioral segmentation*—to segment consumers into the commodity and differentiated segments or even smaller micro-segments. Then they can use these segments as predictors of consumer sensitivity to different information strategies. This will permit them to decide on what and how much information to reveal and to whom. This requires firms to develop deeper intelligence from their "big data" for innovative and targeted information strategies. For example, travel intermediary Orbitz uses software to detect whether people browsing its site are using an Apple or Windows machine. It has found that Apple users tend to choose pricier hotels, so it recommends these to them (*The Economist* 2012). This will be the case in many contexts, for example, consumer usage behavior of the mobile Internet, travel behavior of smart card users, viral message browsing behavior of social network participants, and streaming video viewing behavior of computer users.

Firms need to consider developing specific information strategies for each consumer segment. They also must be able to implement these and reflect their awareness that consumers influence each other directly and indirectly via all kinds of social media and social networks. *Differentiated information strategies* will allow consumers with heterogeneous tastes to find products they like. Firms may want to improve consumer informedness selectively in some markets but not others and for different consumer segments—*selective information obfuscation*. As consumer informedness increases, it will not necessarily result in behaviors targeted by the offering firm. Our findings show that the commodity segment reacts more strongly to price information. Firms can engender more purchases from these consumers by providing them with more precise and detailed price information. Though price transparency is appealing to customers for easy price comparisons, it may also erode their willingness-to-pay. Thus, firms may wish to consider withholding price information or make it harder for consumers to compare prices.

Product information is an important dimension to consider in the design of selling mechanisms, either to elicit lower price elasticity of demand or to attract less price-sensitive consumers. Our findings indicate that more product information can overcome the negative impact of more price information. For consumers in the differentiated segment, our findings show that firms can further decrease consumer price sensitivity by offering more detailed product information. Instead of generating profits by introducing more expensive services but more attractive offers, another beneficial approach is to support such consumers by helping them to search for services that offer the best fit by making more relevant product information available to them. In the design of online selling mechanisms, suppliers and intermediaries who rely heavily on using online channels to promote products should provide more product information or product comparison tools to avoid head-on collisions with their competitors. This will effectively lure consumers in the differentiated segment to buy niche products because they can find exactly what they want.

Firms need to recognize the importance of collecting relevant customer information and customizing their product and service offerings based on the range of consumer preferences in the market and the information disclosed to consumers. Firms can now hyperdifferentiate their product offerings much easier than ever before. Nevertheless, this will require senior managers to develop a deeper understanding of the demand side—what each consumer segment wants to buy, its willingness-to-pay, and its responses to different types and levels of informedness. Traditional strategies for products targeted to the mass market can be augmented through the recognition that increasingly informed consumers engage in trading down and trading out behavior to different extents. A winning strategy is not only to develop great products and services but also to tailor information that produces the strongest favorable responses among the targeted consumer segments to improve margins. This supports the predicted move from strategies based on mass-market "fat spots" to strategies involving high-margin "sweet spots" (Clemons 2008).

To understand better what drives individual consumer choice and actual behavior, an emerging stream of research has begun to explore the use of large-scale randomized experiments to examine causality issues related to various consumer behaviors. The stream includes studies examining framing effects and consumer purchases of customized information goods bundles that leverage a natural field experiment (Goh and Bockstedt 2013), using smart card data to understand travel behavior changes in the presence of different pricing strategies (Li and Kauffman 2012), and analyzing interdependencies between Internet and mobile advertising using a randomized field experiment (Ghose et al. 2014). It also includes studies investigating how confirmation biases influence investor decisions, with data from stock message boards (Park et al. 2013); testing the effectiveness of viral product design using randomized social network structures and randomized information sharing treatments in creating peer influences and social contagion with Facebook data (Aral and Walker 2011); and assessing the impact of popularity information on consumer choice (Tucker and Zhang 2011) and on two-sided networks (Tucker and Zhang 2010). This trend has been heavily influenced by the increased availability of online, social, and mobile micro-level data and will continue to grow as both academics and business communities realize the power of big data and business analytics that change the nature of decision making in today's economy (Chang et al. 2013).

6.3. Limitations and Future Research

There are a few limitations of the present study that deserve comment and offer opportunities for future research. First, we acknowledge that the attribute time validity drives the results of trading out behavior in study 1 because it is a dominating non-price attribute. Consumers who are only able to use some types of tickets but not others (e.g., airline tickets for peak-season vacation travel to popular tourist destinations) are willing to trade out to a high extent: to them, a high price is acceptable for tickets that have the required attributes. What we observed in study 1 was an extreme form of trading out behavior. In contrast, in study 2, adding attributes and experimental controls allowed us to strengthen the experimental design.

Second, the choice of missing product information is important in determining the behavioral responses of consumers. In our experimental design, we made the selection based on observed business practices for study 1 and based on prior research and a pre-test of the importance of the attribute levels for study 2. The results are consistent and do not seem to be influenced by the different selection criteria we used. We believe, however, if the core information were missing, it would have had important impacts on consumer choice. The question of how much information is enough, such that an improvement has no significant impact, is a challenging avenue for future research. It is possible for example to design experiments using different levels of product informedness ranging from 3 to 6 to 9 or even 12 of the most important attributes. This will allow us to tease out the nonlinear effects of different levels of product information. One can predict, for example, that the true underlying relationship may be an inverted-*U* shape. The more information revealed, the higher consumer utility will rise while the marginal utility of additional information will diminish. Beyond a certain point though, more information will tend to reduce a consumer's utility because of information overload and limited information processing capability.

Third, we used a stated choice experiment and collected participants' responses for hypothetical rather than actual choice situations. It is useful to study actual purchase behavior with revealed preferences. Approaches involving such preferences increase external validity and provide better results. In future research, we can collect clickstream data to see if consumer purchasing behavior matches their informedness level conditions, demographic background, purchase history, or the service choices they face. Future research also will help to deepen our understanding of the impact of other types of consumer informedness, for example, information regarding the market status and behavior of other market participants.

Fourth, consumers are not fully rational but are boundedly rational instead. They are sensitive to losses, have different perceptions of fairness, and have different attitudes toward risk. Future work should account for the strategic behavior of consumers with different types and levels of informedness. We can explore the application of other normative theories, such as prospect theory and regret theory. We may observe that when making product choices, consumers tend to anticipate and avoid undesirable outcomes. Regret theory suggests that consumers may avoid choices with missing information for which they do not have much information. They may be concerned that a lack of knowledge may lead to costly mistakes.

Acknowledgments

The authors thank the senior editor Anitesh Barua, associate editor Kartik Hosanagar, and three anonymous reviewers for their helpful comments throughout the review process. They also would like to thank the reviewers and participants at the 2007 ICIS Doctoral Consortium, the 2008 Workshop on IS and Economics, the 2009 Hawaii International Conference on Systems Science, and the 2009 INFORMS Conference on IS and Technology. They especially appreciate Eric Clemons' helpful comments on this and related work and John Rose's advice on the empirical modeling. They thank seminar participants at Beijing Jiaotong University, Delft University, Erasmus University, Free University Amsterdam, Netherlands Railways, NS Hispeed, Singapore Management University, and Tsinghua University. Ting Li acknowledges financial support from The Netherlands Organisation for Scientific Research (NWO) (Complexity Grant #645.000.001 and #645.000.008), Erasmus Research Institute of Management (ERIM), Vereniging Trustfonds, and Netherlands Railways. Rob Kauffman is grateful to the W.P. Carey Chair in Information Systems at Arizona State University and the Lee Kuan Yew Faculty Fellowship for Research Excellence for research support. The authors are entirely responsible for the contents of this article, and the usual disclaimers apply.

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