The Effect of Quality Cues on Travelers' Demand for Peer-to-Peer Ridesharing: A Neglected Area of the Sharing Economy

Seongsoo Jang[1], Mehdi Farajallah[2], and Kevin Kam Fung So[3]

[1] Cardiff Business School, College of Arts, Humanities & Social Sciences, Cardiff University, Aberconway Building, Colum Drive, Cardiff CF10 3EU, UK.

[2] Rennes School of Business, 2, Rue Robert d'Arbrissel, 35065 Rennes, France

[3] Center of Economic Excellence in Tourism and Economic Development, School of Hotel, Restaurant and Tourism Management, University of South Carolina, 701 Assembly Street, Columbia, SC 29208, USA

Corresponding Author:

Seongsoo Jang, Cardiff Business School, College of Arts, Humanities & Social Sciences, Cardiff University, Aberconway Building, Colum Drive, Cardiff CF10 3EU, UK.

Email: JangS@cardiff.ac.uk.

The Effect of Quality Cues on Travelers' Demand for Peer-to-Peer Ridesharing: A Neglected Area of the Sharing Economy

Abstract

The emergence of the sharing economy has had a tremendous impact on the tourism industry; however, few quality management mechanisms exist for shared tourism services. Based on unique data of 52,248 transactions collected from BlaBlaCar, the world's leading ridesharing platform, this study examines the independent and combined effects of quality cues on travelers' demand for peer-to-peer ridesharing services. The findings suggest that intrinsic cues (product reputation and seller reputation) and extrinsic cues (relative price and offer duration) are decisive in increasing demand, and their combined effects can be positive or negative. In addition, analyses of the heterogeneous effects of intrinsic and extrinsic cues across seller segments clarify how consumers evaluate product quality using information from multiple cues. These findings contribute to the literature on tourism and marketing by providing new insights into the design of competitive product offers in the sharing economy.

Keywords

sharing economy, peer-to-peer platform, product quality, intrinsic cues, extrinsic cues

Introduction

The sharing economy has become a global socioeconomic trend with influences on resource allocation, supply, operations, and product marketing in many industries, including travel and tourism (Guttentag et al. 2018; So, Oh, and Min 2018). Powered by digital technologies, peer-to-peer platforms have enabled individuals to market unused products and services through the sharing economy (Abrate and Viglia 2019; Ert, Fleischer, and Magen 2016). This modern consumption model effectively allows consumers to become producers, disintermediating many traditional organizations in the value-creation process and providing innovative products and services to satisfy consumers' changing lifestyles and preferences. At least 275 sharing economy platforms have been founded in Europe, and 79% of the country's sharing-economy revenue is derived from the tourism sector (Vaughan and Daverio 2016). Accommodations and cars are the two most widely shared resources; Airbnb and BlaBlaCar operators pose emerging threats to the traditional hospitality and travel industry (Abrate and Viglia 2019).

In the sharing economy, sellers and consumers both benefit from the collaborative consumption business, which emphasizes commercial aspects of sharing (Wirtz et al., 2019). Collaborative consumption can be defined as the acquisition and distribution of an underutilized resource for a fee or other compensation (Belk 2014). Because consumers cannot physically evaluate the quality of shared products and services prior to purchase, they often complete pre-purchase evaluations of product quality and finalize purchase decisions on the basis of non-experiential signals (e.g., seller reputation) (Deephouse and Carter 2005). In the peer-to-peer accommodation sector within the sharing economy, information about hosts and accommodation rentals help travelers make more informed rental decisions (Ert, Fleischer, and Magen 2016). Demographic characteristics also shape the transaction decisions of sellers (how to offer) and consumers (whether to buy). For example, some sellers (e.g., white Airbnb hosts) may set higher prices than other sellers (e.g., African American hosts) (Edelman and Luca 2014), and some consumers (e.g., female guests) demonstrate a lower likelihood than others (e.g., male guests) to purchase certain products or services (e.g., shared rooms offered on Airbnb) (Lutz and Newlands 2018).

Although product quality and demographic factors play pivotal roles in the sharing economy, research remains scarce regarding which quality cues affect travelers' purchase decisions about shared products and services provided by heterogeneous sellers. Studies of collaborative consumption have primarily focused on how the sales of shared products are driven by either (a) intrinsic cues, defined as inherent product attributes that cannot be easily changed (e.g., product reputation; Abrate and Viglia 2019) or (b) extrinsic cues, namely product-related attributes unrelated to the physical product (e.g., price) (So, Oh, and Min 2018). The literature has indicated that a set of multiple cues may exert independent and interactive effects on consumers' product-quality assessment and subsequent purchase decisions (Kirmani and Rao 2000; Langan, Besharat, and Varki 2017; Purohit and Srivastava 2001). However, scholars have not fully examined the impacts of intrinsic and extrinsic cues on the sales of shared products and services within a single conceptual framework.

To address these gaps, this research considers the roles of specific quality cues in the sharing economy. In particular, we focus on (1) the direct effects of intrinsic cues (reputational factors associated with the product and seller) and extrinsic cues (price and temporal features of an offer), and (2) the interactive effects between extrinsic and intrinsic cues on travelers' demand for peer-to-peer ridesharing services. Furthermore, given the critical importance of demographic characteristics in the sharing economy, this study sheds light on product offer strategies for diverse seller segments in terms of gender and race. This study is particularly important because platform operators receive a substantial proportion of revenue, as they benefit from a fee per transaction, whereas individual microentrepreneurs obtain marginal revenue (Stein 2015). Similar to firms, microentrepreneurs must increase their profits by improving the quality of their offers to attract demand and gain a competitive advantage (Dervitsiotis 2010).

Our research makes several theoretical contributions to the tourism and sharing-economy literature. First, this study represents one of the first empirical attempts to investigate cue utilization in the sharing economy, particularly in the context of peer-to-peer ridesharing. Specifically, we demonstrate that multiple cues (i.e., product reputation, seller reputation, price, and offer duration) should be incorporated as major determinants of the sales of shared products and services. Second, we find that the effectiveness of a specific cue (e.g., product reputation) depends on its integration with other cue types (e.g., price and offer duration) presented to consumers, a phenomenon labeled cue diagnosticity theory (Purohit and Srivastava 2001). Finally, we discover that the quality cue mechanism operates differently across sellers in terms of gender (e.g., male or female) and race (e.g., majority or minority). As such, we seek to apply theories of cue utilization and diagnosticity to the sharing economy in the tourism literature.

In addition to the aforementioned theoretical contributions, this study provides practical implications related to marketing shared products and services. Our results suggest that ridesharing consumers are likely to evaluate product quality based on information from multiple cues. Although the reputation information tied to a product and its seller is more useful in purchase decisions than price information, sellers can develop contextual pricing strategies while considering their product's reputation status. Furthermore, given that gender and racial characteristics are fixed and influence consumers' purchase decisions, sellers may tailor quality cues from a short-term (extrinsic) and long-term (intrinsic) perspective to maximize market performance of their shared products and services. Our findings should help microentrepreneurs better understand how consumers process quality cue information, thus enabling sellers to promote competitive products and services on peer-to-peer platforms.

Literature Review and Hypotheses

Quality Cues on Peer-to-Peer Ridesharing Platforms

Consumers often possess less information about products compared to firms and thus assess product quality using different types of information or cues (Kirmani and Rao 2000; Rao and Monroe 1989). According to cue utilization theory, consumers' perceptions of product quality are derived from a set of cues (e.g., price, color, taste, and scent) that serve as surrogate quality indicators (Olson and Jacoby 1972). Scholars have classified these cues, tied to a focal product or service, as either intrinsic or extrinsic (Miyazaki, Grewal, and Goodstein 2005; Purohit and Srivastava 2001; Richardson, Dick, and Jain 1994). Intrinsic cues evolve over time; their valence cannot be changed instantaneously (e.g., brand name and firm reputation). Comparatively, extrinsic cues are transient, as their valence can be altered relatively quickly (e.g., price and warranty) (Purohit and Srivastava 2001; Richardson, Dick, and Jain 1994).

Cue utilization theory also holds that the extent to which a consumer refers to a specific cue when evaluating product quality varies with the cue's diagnosticity (Slovic and Lichtensetin 1971). The cue diagnosticity framework views product quality assessment as a categorization process, suggesting that when consumers are confronted with multiple cues, relatively more diagnostic cues are used to determine product quality (Dick, Chakravarti, and Biehal 1990). In other words, consumers tend to rank cues' relative importance based on a personal ability to differentiate high- and low-quality products (Feldman and Lynch 1988; Skowronski and Carlston 1987). On peer-to-peer ridesharing platforms, the product is defined as a ride offer presented by a driver to travelers (i.e., offering use of a vehicle's empty seats) (Bardhi and Eckhardt 2012). When numerous ridesharing offers are presented in an open market for travelers, various types of cue information could exert significant effects on travelers' determinations of product quality (Langan, Besharat, and Varki 2017). Offer evaluations are likely to be considered in making a final choice as long as overall assessments are consistent (Lynch, Marmorstein, and Weigold 1988). It is therefore important to distinguish among cue types in shared products and services and to incorporate the interactions among them (Purohit and Srivastava 2001; Zou and Liu 2019).

Drawing from the literature on car-sharing characteristics (Bardhi and Eckhardt 2012), we focus on four types of quality cues in the context of peer-to-peer ridesharing services (Table 1). For intrinsic cues, product and seller reputation (Abrate and Viglia 2019; Purohit and Srivastava 2001) represent inherent product attributes, as they cannot be easily changed in the short term. In a ridesharing context, product reputation may include all physical characteristics of a car, such as the car type and level of comfort (Rhee and Haunschild 2006); thus, reputation represents an important intrinsic cue (Noseworthy and Trudel 2011). Travelers tend to regard luxury cars as more reputable than compact cars. In addition, the seller's reputation, which includes their experience (Pera, Viglia, and Furlan 2016), personal photo (Ert, Fleischer, and Magen 2016), and third-party or consumer quality scores (Stuebs and Sun 2010), will be assessed as intrinsic cues given that rideshare sellers are providing travelers a personal service.

[Insert Table 1 here]

Among extrinsic cues, price (e.g., Gibbs et al. 2017; Wang and Nicolau 2017) and offer duration (e.g., Niedrich and Swain 2008) may represent prime attributes affecting the quality of a specific rideshare service. These attributes influence two critical marketing decisions in the open market. In terms of price, a product's relative monetary value is far more relevant to consumers than its absolute value due to customers' willingness to pay for a certain branded product over another (i.e., relative price or price premium) (Cronin, Brady, and Hult 2000). Competitors' price levels represent a major determinant of retailer pricing (Shankar and Bolton 2004), and relative price position can influence retailer performance (Chung 2000; Enz, Canina, and Lomanno 2009). Moreover, the duration of an offer corresponds to the interval between the initial offer time—when a ridesharing offer is first displayed in an open market—and departure time. The latter refers to the period of consumer exposure to product information (Niedrich and Swain 2008) and the temporal distance for potential consumers who may have different product foci. A close distance leads to a concrete construal, and greater distance leads to an abstract construal (Trope and Liberman 2000).

Effects of Intrinsic Quality Cues on Demand for Peer-to-Peer Ridesharing

On peer-to-peer ridesharing platforms, travelers consider the observed comfort level of a shared car when forming perceptions about the ridesharing service's reputation (Rhee and Haunschild 2006). A car used for ridesharing offers passengers utilitarian (e.g., movement) and hedonic (e.g., comfort) value (Babin, Darden, and Griffin 1994). Research has indicated that hedonic products deliver fun, excitement, or pleasure, whereas utilitarian products serve practical and functional purposes (Dhar and Wertenbroch 2000). For example, high-reputation cars (e.g., Audi Q5) are likely to deliver hedonic value (i.e., superior comfort), while low-reputation cars (e.g., Ford Fiesta) tend to deliver utilitarian value (i.e., mobility). Perceptions of high reputation and the pleasure following from those perceptions may prompt consumers to favor affect-based processing over cognition-based, leading them to choose a highly reputable product (Hagtvedt and Patrick 2008).

When travelers are confident about a high-reputation car's functional utility—normally, luxury cars have superior horsepower and safety performance—they may prefer a more aesthetically pleasing design (Noseworthy and Trudel 2011). Furthermore, because a luxury car more often meets or exceeds hedonic criteria compared to a compact car, travelers will likely experience greater excitement during the trip, develop stronger loyalty to the ridesharing offer, and become more inclined to engage in positive word of mouth (Chitturi, Raghunathan, and Mahajan 2008). Compared to material possessions, service experiences are more frequently social and discussed with others, both of which can enhance the enjoyment individuals derive from positive experiences (e.g., Raghunathan and Corfman 2006). Therefore, in the context of peer-to-peer ridesharing, one can assume that travelers will evaluate overall product quality based on product (i.e., car) reputation and choose a highly reputable product over a less reputable one (Cabral and Hortacsu 2010). Therefore, the following hypothesis is suggested:

> *Hypothesis 1*: Product reputation is positively related to travelers' demand for peer-to-peer ridesharing.

The reputation of a seller (i.e., driver), as another intrinsic cue, is an integral component of the ridesharing experience (e.g., Abrate and Viglia 2019; Ert, Fleischer, and Magen 2016). Brand reputation shapes consumers' purchase intentions (Brady, Bourdeau, and Heskel 2005), and consumers tend to emphasize seller reputation (Yoganarasimhan 2013). On peer-to-peer ridesharing platforms, seller reputation can offer a competitive edge in distinguishing a service from competitors (Herbig and Milewicz 1993). Consumers will likely be less confident when purchasing experience-based products (e.g., a rideshare service) than when researching products (e.g., a car) because it is more difficult to evaluate product quality given intangibility (Cui, Lui, and Guo 2012). Research has revealed that the effect of brand reputation is more significant for intangible products than tangible products (Brady, Bourdeau, and Heskel 2005; Herbig and Milewicz 1993). Therefore, travelers may encounter uncertainty over driver quality due to information asymmetry; as such, seller reputation can indicate the true quality of a ridesharing service. We therefore propose the following hypothesis:

> *Hypothesis 2*: Seller reputation is positively related to travelers' demand for peer-to-peer ridesharing.

Effects of Extrinsic Quality Cues on Demand for Peer-to-Peer Ridesharing

As a representative extrinsic cue, consumers consider price an indicator of product quality (Dodds, Monroe, and Grewal 1991) and necessary monetary sacrifice (Teas and Agarwal 2000). Studies on the effectiveness of relative price levels have returned mixed results in the hospitality and tourism industry. Some researchers have found that hotels with an average daily rate above that of competitors obtain higher revenue performance (Enz and Canina 2010), while a price-cutting strategy does not allow hotels to gain greater market share (Chung 2000). Other scholars have argued that when consumers search for advantageous prices, lower prices will positively influence consumers' evaluations and thus promote loyalty toward tour operators (Campo and Yagüe 2008).

In the sharing economy, price value and the functional attributes of accommodations greatly inform overall attitudes toward a shared object (So, Oh, and Min 2018). In addition, the price level of a shared object generally includes competitive market characteristics (Wang and Nicolau 2017). Although Hamari, Sjöklint, and Ukkonen (2016) identified no effect of price on collaborative consumption, most studies have demonstrated that low prices (Tussyadiah 2015) or price value (So, Oh, and Min 2018) can each positively influence consumers' choices of shared objects (e.g., Airbnb accommodations). In the peer-to-peer ridesharing market, if a driver sets a lower (higher) price for his or her ridesharing service rather than a reference price (i.e., the price level of competitors' offers for the same trip), potential riders may perceive the price to be cheaper (more expensive) (Monroe and Lee 1999). As the cost-saving motivation is arguably the main factor influencing participation in collaborative consumption, ridesharing travelers may perceive relatively cheaper (more expensive) ridesharing offers to be fair (unfair) because these customers evaluate fairness by comparing benefits or costs relative to competitors' offers for the same trip (Stefansdotter et al. 2015). Accordingly, the following hypothesis is put forth:

Hypothesis 3: Relative price is negatively related to travelers' demand for peer-to-peer ridesharing.

Although the relative price of a ridesharing service may adversely affect related sales, the extent of the price–sales relationship depends on the degree of product similarity. When two products are perceived similarly, consumers may presume that comparative transactions should also be similar, called the assimilation effect (Major and Testa 1989). Suppose that, for a trip from Paris to Lyon, two drivers with a similar reputation offer ridesharing services using a compact car at 10 euros and 15 euros. Travelers may consider this price difference between similar products to be unfair. However, as the dissimilarity between the products becomes more apparent, consumers will tend to selectively access information that supports the dissimilarity, leading to a contrast effect (Mussweiler 2003). For example, if, for the same intercity trip, one experienced driver (in a comfortable car) offers a service at 15 euros and another unexperienced driver (in a compact car) does so at 10 euros, observable product differences will naturally lead to quality inferences and cost attributions (Bolton, Warlop, and Alba 2003). In such a case, travelers will presumably perceive the price discrepancy as fair.

In an e-commerce context, many researchers have contended that buyers are willing to pay a price premium to high-reputation sellers because a high reputation may imply seller quality (Ba and Pavlou 2002; Li, Srinivasan, and Sun 2009), trustworthiness (Ba and Pavlou 2002; Bruce, Haruvy, and Rao 2004), and greater service quality (Luo and Chung 2010). Therefore, it is commonly believed that high-reputation sellers should charge relatively high prices (Ba and Pavlou 2002; Li, Srinivasan, and Sun 2009). However, some studies have identified a negative price premium effect (i.e., a high-reputation seller who charges a lower price than a low-reputation seller) in light of consumer informativeness and seller competition (Liu, Feng, and Wei 2012). On peer-to-peer ridesharing platforms, prospective travelers can search for and compare offers for a particular trip to choose an offer with the greatest utility (Baylis and Perloff 2002). Consequently, high-reputation and low-price ridesharing offers should be preferable to high-reputation and high-price offers. Therefore, we propose the following hypothesis:

> *Hypothesis 4*: The effect of relative price on travelers' demand for peer-to-peer ridesharing is negative for (a) a higher product reputation or (b) a higher seller reputation.

Potential travelers will encounter multiple ridesharing offers for a specific trip when searching on a given date. As consumers review relevant information, each offer will likely carry either a primacy or recency effect depending on the order of exposure. Specifically, consumers may consider the first offer more novel than subsequent offers; later offers may be seen as redundant and less interesting, resulting in a primacy effect (Castel 2008; Wyer 1970). The first offer will generally be preferred to subsequent offers because consumer evaluations are positively related to the amount of information known about a service

(Anderson 1981; Castel 2008). Conversely, consumers may take the most recent offer as the basis for evaluating subsequent offers, otherwise known as the recency effect (Castel 2008; Houston and Sherman 1995).

In contrast to these mixed findings, research has suggested that consumers tend to prefer first-to-market products to later product entrants (Kerin, Varadarajan, and Peterson 1992) due to exposure to product information (Niedrich and Swain 2008). In the peer-to-peer ridesharing context, attribute recall will be greater for initially encountered ridesharing offers under a long-delay condition (e.g., two weeks before departure) and greater for later offers under a short-delay condition (e.g., one day before departure) (Niedrich and Swain 2008). Ridesharing drivers may post offers with diverse attributes (e.g., different car models and driver demographics) several weeks or days before the planned date of departure. For example, when two trip offers from Paris to Lyon are registered (i) two weeks and (ii) one day before departure, respectively, potential riders will recall (i) the former offer better than (ii) the latter offer due to differential awareness in the marketplace (Boulding and Christen 2003). Therefore, the following hypothesis is suggested:

> *Hypothesis 5*: The offer duration of a peer-to-peer ridesharing service is positively related to travelers' demand for peer-to-peer ridesharing.

Although early ridesharing offers may encourage sales, the degree of this relationship depends on the extent of temporal focus and product similarity. The anticipated timing of a trip affects its construal (Trope and Liberman 2000). In tourism, focusing on planning a trip in the near future leads consumers to a more concrete construal (e.g., a concretely described hotel), whereas focusing on engaging in a trip later in the future leads to a more abstract construal (e.g., an abstractly described hotel) (Kim et al. 2016). These construals then influence how consumers process information regarding sets of tourism products (Förster 2009). Consumers planning a trip in the near future will be more motivated by a set of relatively different offers (i.e., the contrast effect); by comparison, consumers planning a trip in the far future will be more motivated by a set of relatively similar offers (i.e., the assimilation effect) (Förster 2009).

Research has revealed that as the temporal distance from a trip increases, the appeal of the trip depends more on its desirability, namely the value of the trip's end state (a high-level construal feature), and less on its feasibility, referring to the means used to reach the end state (a low-level construal feature) (Liberman and Trope 1998). That is, potential riders will process each offer's time-related information (i.e., the duration between an offer and departure) differently. For instance, when travelers book a ridesharing service three weeks before their departure date, they tend to focus more on being able to travel to a particular city on a date for certain (e.g., the availability of a certain intercity trip and the proximity of the pickup time and place) and less on the attractiveness of the car. Conversely, when potential riders decide on a ridesharing service in the near future (e.g., two days before departure), they focus more on concrete features of each offer, such as the reputation of the product and seller, which are relatively goal-irrelevant characteristics. Hence, the effect of offer duration on demand for peer-to-peer ridesharing services depends on the extent of intrinsic quality cues (i.e., product or seller reputation). Therefore, the following hypothesis is proposed:

Hypothesis 6: The effect of offer duration on travelers' demand for peer-to-peer ridesharing is negative for (a) a higher product reputation or (b) a higher seller reputation.

Figure 1 illustrates the research model of this study, including a summary of the proposed hypotheses.

[Insert Figure 1 here]

Methodology

Data Collection

This study examined how product quality—signaled by intrinsic cues (product reputation and seller reputation) and extrinsic cues (relative price and offer duration)—affects consumer demand for peer-to-peer ridesharing services independently and collectively. To achieve these research objectives, we referred to daily transaction data of ridesharing offers collected via the French BlaBlaCar marketplace. BlaBlaCar is a popular open-market platform for long-distance rideshare offers, which launched in France in 2006. As of October 2018, the site had more than 65 million registered users across 22 countries, with France (15 million users) being one of the most vibrant peer-to-peer ridesharing markets (Smith 2018).

First, after verifying the technical feasibility of data collection from the BlaBlaCar website, one of the authors scraped publicly available data for 40 French intercity (e.g., Paris–Lyon) ridesharing transactions from August 2013 to March 2014. The data collection procedure was automated by scraping the BlaBlaCar website. Our BlaBlaCar Web scraper was built in Java; specifically, we opted for an open-source library (i.e., JSoup) that provides convenient functionality for extracting and manipulating data. The data extraction software regularly gathered all posted offer information about a specific intercity trip (once per day), enabling us to track the evolution of each offer from the offer date to the departure date. To improve data accuracy, we (1) monitored errors by using specific application program interfaces and (2) performed manual checks randomly twice per week throughout the collection period.

Second, out of 5 million observations, we excluded 4 million data points because they did not include sales information (i.e., no seats sold) and used the remaining 1 million data points as the final transaction dataset, which served as the foundation of our investigation. After conducting a preliminary analysis of the collected data, our database and findings were shared and presented to BlaBlaCar in October 2016. The company provided feedback on our findings, confirmed the reliability of our data, and provided permission for the data to be used in academic research. The whole dataset was applied to economic research about pricing behavior in the sharing economy (i.e., our first study).

To test our hypotheses in the current (second) study, we chose the four longest trips (among 40 intercity trips in France) to ensure a tourism-related sample. We considered trips of more than 400 km between two cities where travelers were most likely to stay overnight in the destination city. Trips included Paris–Marseille (774 km), Paris–Brest (591 km), Paris–Lyon (466 km), and Lyon–Paris (466 km). Of these, the non-stop driving time ranges from 4.5 hours (Paris–Lyon) to 7.5 hours (Paris–Marseille), indicating the difficulty of returning to the departure city on the same day. We based our econometric analysis on a sample of 52,248 transactions provided by 24,697 drivers. Data contained product information related to (a) intrinsic and extrinsic cues, indicating travelers' interest and final demand for each offer; and (b) key characteristics of each driver (e.g., name, age, and gender), offer (e.g., round-trip), and time (e.g., departure day and time) to control for the effects of these features on demand.

Variables

To measure *Demand* for peer-to-peer ridesharing (Y_{ijt}), we used the number of seats sold for trip *i* offered by driver *j* on day *t*. As an offer can be observed from the first offer date to the departure date, we calculated the number of seats sold by subtracting the remaining seats on the departure date from the number of seats available on the initial offer date.

For independent variables, we used two measures of intrinsic cues that were publicly observable by potential consumers: *Product Reputation* and *Seller Reputation*. *Product Reputation* was self-assigned by the driver and measured on a 4-point scale (i.e., basic, normal, comfortable, and luxury) (Abrate and Viglia 2019; Rhee and Haunschild 2006), with a higher value indicating a more reputable product. BlaBlaCar classified *Seller Reputation* (Abrate and Viglia 2019; Stuebs and Sun 2010) on a 5-point scale (newcomer, intermediate, experienced, expert, and ambassador) based on four criteria: percentage of profile completed, number of ratings, percentage of positive ratings, and seniority. As shown in prior studies (e.g., Abrate and Viglia 2019), online rating data were collected as an alternative measure of reputational factors of the product and seller. However, BlaBlaCar only allowed for a dichotomous rating, either positive or negative (i.e., dummy variable). The site's seller and product ratings were overwhelmingly positive (97%), which is typical in the sharing economy (Bridges and Vásquez 2018). Therefore, the rating measure was excluded as an intrinsic cue variable.

Regarding independent variables for extrinsic cues, we defined *Relative Price* as the percentage by which the selling price of a specific ridesharing offer exceeded a benchmark price (Farris et al. 2010; Noone, Canina, and Enz 2013). The average price charged by other competing drivers in a given category (i.e., a particular trip between two cities on a certain date) served as the benchmark (Farris et al. 2010). In addition, we defined *Offer Duration* as the number of days between the date when an offer was published on the online marketplace and the date when the trip occurred.

Finally, we included control variables in our model as product characteristics (Z_j) and seller characteristics (W_t). For product characteristics, we controlled for whether the reservation was confirmed automatically or manually (i.e., a driver approved the request) (*Manual Reservation*), whether the trip was one-way or round-trip (*Round Trip*), and whether the trip had a detour time (i.e., when the car arrived at a destination city, the driver took extra time to bring the riders to a specific place) (*Detour Drive*). For seller characteristics, we controlled for one reputational factor (i.e., whether the driver's *Photo* was shown) and three demographic factors: *Age*, *Gender*, and *Race*. Age and gender were revealed by the driver per BlaBlaCar's policy. Because race information was not available on the website, we classified each driver into regions of origin using three name-matching databases: INSEE (www.insee.fr), from the French National Institute of Statistics and Economic Studies, and two well-known French websites (www.prenoms.com and www.signification-prenom.net). Therefore, the race of each driver was classified as either French or (non-French) minority.

To divide sellers into homogeneous groups, we selected two specific demographic variables—gender and race—because the intimacy of many sharing-economy transactions heightens the salience of these variables (Schoenbaum 2016; 2018). In peer-to-peer ridesharing settings, gender preferences manifest from concerns related to privacy, comfort, enjoyment, sexuality, and security (Schoenbaum 2016). Race plays a notable role in positive or negative outcomes associated with collaborative consumption (Edelman and Luca 2014; Edelman, Luca, and Svirsky 2017). Specifically, consumers are likely to be affected by antipathy toward a given ethnic group's services as a symbolic means of discriminating against that group, a pattern called consumer racism (Ouellet 2007). In this study, we created four segmented samples of peer-to-peer ridesharing sellers (French Male, French Female, Minority Male, and Minority Female) by combining these two demographic features and ran regression models to generate meaningful results for each segment.

Empirical Model

We used a fixed-effects panel-data regression with trip-specific fixed effects to model demand for peer-to-peer ridesharing and their determinants. Trip-specific fixed effects enabled us to control for the general characteristics of a given trip and to isolate particular factors affecting consumer demand. The panel-data regression model can be written as follows:

$$Y_{ijt} = Q_{ijt} + X_i + Z_j + W_t + \mu_i + e_{ijt}$$

where *i* (*i* = 1, 2, 3, 4) is the trip, *j* is the driver (*j* = 1, …, 24,697), and *t* is the day. Q_{ijt} refers to a set of independent variables related to intrinsic and extrinsic quality cues for trip *i* offered by driver *j* on day *t*. X_i denotes independent variables related to the characteristics of trip i, Z_j refers to independent variables related to the characteristics of driver *j*, and W_t represents independent variables related to day *t* when a specific trip occurs. Moreover, μ_i captures the time-invariant trip-specific effect of trip *i* that influences the dependent variable but has not been incorporated into any explanatory variables. This proposed two-way panel-data model can resolve potential omitted-variable bias problems (Wooldridge 2010). The error term e_{ijt} is assumed to follow a normal distribution independent from μ_i with a mean of 0 and a standard deviation of σ_ε.

Results

Descriptive Statistics

Table 2 presents the descriptive statistics of variables incorporated into our empirical model. The overall panel dataset consisted of 52,248 transactions from 24,697 drivers across 4 intercity trips from August 2013 to March 2014 in France. The total sample was further divided into four segments: French male (66.6%), French female (20.6%), minority male (11.3%), and minority female (1.5%). The mean value of *Demand* was 2.567 with a standard deviation of 0.006, slightly larger than the *Past Demand* (i.e., control variable) for the same trip (*M*: 1.162; *SD*: 0.001). French drivers demonstrated slightly better sales performance than minority drivers. For variables related to intrinsic cues, *Product Reputation* and *Seller Reputation* had mean values of 2.418 and 2.882, respectively, with female drivers displaying relatively lower product and seller reputations than male drivers. Regarding variables of extrinsic cues, *Relative Price* had a mean value of -0.001; interestingly, female drivers set relatively higher prices than male drivers for the same trip. The mean value of *Offer Duration* was 9.964 (days), and French drivers included longer offer durations than minority drivers. In terms of control variables, 42.6% of trip offers included a *Photo*, 17.9% allowed for a *Manual Reservation*, 22.8% provided a *Round Trip*, and 48% included a *Detour Drive*. The mean age of our sample was 32.365 years; female drivers were generally younger than male drivers. Female drivers and minority drivers accounted for 22.1% and 12.8% of all drivers, respectively.

[Insert Table 2 here]

The correlation matrix of the independent and control variables accompanying the proposed model is presented in Table 3. Most coefficients in Sample 1 were below 0.29, suggesting that no multicollinearity problem existed in this model. Correlation coefficients among independent and control variables in Samples 2–5 were also below 0.34, again indicating an absence of multicollinearity. More detailed information is available upon request.

[Insert Table 3 here]

Research Findings

Table 4 reports the independent and interactive effects of intrinsic and extrinsic quality cues of the chosen peer-to-peer ridesharing service on sales performance for the overall (Model 1) and segmented (Models 2–5) markets. Regarding intrinsic quality cues, the coefficient of *Product Reputation* was estimated to be positive and statistically significant (0.035, $p < 0.01$), providing empirical evidence in support of Hypothesis 1. Interestingly, while this positive relationship persisted for male drivers (French: 0.036, Minority: 0.053, $p < 0.01$), no relationship emerged for female drivers. In addition, the coefficient of *Seller Reputation* was estimated to be positive and statistically significant for the overall market (0.039, $p < 0.01$) and male driver segments (French Male: 0.035, $p < 0.01$; Minority Male: 0.111, $p < 0.01$), lending support to Hypothesis 2. These results imply that, overall, intrinsic quality cues—product reputation and seller reputation—play critical roles in increasing consumer demand for peer-to-peer ridesharing services. Regarding extrinsic quality cues, *Relative Price* showed no correlation with peer-to-peer ridesharing demand, failing to support Hypothesis 3; this lack of relationship persisted across all four segments. The coefficient of *Offer Duration* was estimated to be positive and significant in the overall market (0.005, $p < 0.01$), particularly among male drivers (French Male: 0.006, $p < 0.01$; Minority Male: 0.014, $p < 0.01$), supporting Hypothesis 5.

[Insert Table 4 here]

Although the relative price of a peer-to-peer ridesharing offer had no direct effect on its demand, its association with the higher reputation of a product or seller tended to reduce associated demand (*Relative Price* × *Product Reputation*: -0.139; *Relative Price* × *Seller Reputation*: -0.105, $p < 0.01$), providing support for Hypothesis 4. The negative effect of the relative price–product reputation association was more pronounced within the French female (-0.183, $p < 0.05$) and minority male (-0.332, $p < 0.01$) segments. The negative effect of the relative price–seller reputation association also held for male drivers (French Male: -0.098, $p < 0.01$; Minority Male: -0.217, $p < 0.05$). Moreover, the relationship between offer duration and higher product reputation negatively influenced demand (-0.001, $p < 0.05$), lending support to Hypothesis 6a; this negative effect was mainly applicable to French male drivers (-0.002, $p < 0.01$). Lastly, the association between offer duration and higher seller reputation exerted a marginally significant and positive effect on related demand (0.001, $p < 0.10$), which did not support Hypothesis 6b. However, this positive effect was significant among French male drivers (0.001, $p < 0.01$). These results indicate that the effects of extrinsic cues (i.e., relative price and offer duration) on peer-to-peer ridesharing demand depend on the level of intrinsic cues (i.e., reputational factors) across seller segments.

We verified the robustness of our analysis (Model 1: a 4-trip sample) by testing two alternative models based on (1) a 3-trip sample (Paris–Brest, Paris–Lyon, and Paris–Marseille) consisting of 30,489 observations (Model 6) and (2) a 2-trip sample (Paris–Lyon and Lyon–Paris) consisting of 42,792 observations (Model 7). Table 5 presents the results of parameter estimates, which are consistent with those in Table 4, with one exception: the correlation between offer duration and higher seller reputation demonstrated no relationship with associated demand (Model 6), in contrast to the finding from the main model (i.e., marginally significant). However, the results of Models 1 and 6 did not support Hypothesis 6b; analysis results of these alternative samples thus aligned with our main findings. Table 6 lists hypothesis-testing results based on the main model.

[Insert Table 5 here]

[Insert Table 6 here]

Discussion and Conclusion

Due to the promising growth of online sharing-economy platforms, microentrepreneurs should be provided product-quality management mechanisms to design more competitive offers and maximize their market performance. Microentrepreneurs in the sharing economy, especially in an open market (e.g., BlaBlaCar), generally lack the marketing capabilities to deliver competitive products compared to market-managed platforms (e.g., Uber). Although researchers have investigated the dynamics of quality cue mechanisms (e.g., Langan, Besharat, and Varki 2017), empirical evidence for these mechanisms' dynamic roles in the sharing economy and tourism industry has not been demonstrated. To fill this gap, we explored how different quality cues—intrinsic (i.e., product reputation and seller reputation) and extrinsic (i.e., relative price and offer duration)—affect consumer demand for peer-to-peer ridesharing services relative to microentrepreneurs in general and specifically (e.g., racial minorities and women).

Given assumed independent and combined effects of intrinsic and extrinsic cues on travelers' demand for ridesharing services, rich secondary data were collected from BlaBlaCar, a leading intercity ridesharing platform. Our findings suggest that intrinsic cues, (i.e., reputational factors of the product and seller) are decisive in driving demand, whereas extrinsic cues increase demand in part (i.e., no relationship with relative price but a positive relationship with offer duration). Moreover, an analysis of the combined effects of intrinsic and extrinsic cues facilitates our understanding of how consumers evaluate overall quality based on multi-cue information. These findings imply that the combination of reputational factors (product and seller) and a price premium influences consumers' purchase decisions; essentially, consumers are well-informed about alternative offers and therefore expect a more reputable seller to charge a lower relative price than a less reputable seller. Additional findings indicate that consumers' purchase decisions are shaped by the combination of offer duration (short versus long) and product reputation (low versus high). Specifically, when a ridesharing service is offered at an early (late) stage before a given departure date, consumers tend to regard ridesharing services similarly (dissimilarly). The association of an offer with product reputation thus appears to exert a weak (strong) impact on consumers' overall quality evaluations and further reduces (increases) demand.

Theoretical Implications

Concerning theoretical contributions, this study is one of the first to examine cue utilization theories relative to the sharing economy in general and peer-to-peer ridesharing platforms in particular. Based on research on access-based ridesharing (Bardhi and Eckhardt 2012), this study introduces novel dimensions of peer-to-peer ridesharing quality cues by adding two intrinsic cues (product reputation, as a material [functional] object; seller reputation, as an immaterial [experiential] object) and two extrinsic cues (price and offer duration) that have been overlooked in the literature. Prior tourism and hospitality studies have evaluated the roles of intrinsic cues (e.g., personal reputation and product reputation) (Abrate and Viglia 2019; Ert, Fleischer, and Magen 2016; Mauri et al. 2018) or extrinsic cues (e.g., price) (So, Oh, and Min 2018; Tussyadiah and Pesonen 2016) in the sharing economy; however, such studies have often considered both types of cues separately and focused on accommodation-sharing contexts (e.g., Airbnb). Our study demonstrates the independent and combined effects of intrinsic and extrinsic cues on peer-to-peer ridesharing demand, extending the scope of cue utilization theories (Langan, Besharat, and Varki 2017).

By incorporating intrinsic as well as extrinsic cues, our work also enriches the literature on cue diagnosticity theory, which suggests that quality assessments are performed with regard for multiple cues (Purohit and Srivastava 2001). Research on cue diagnosticity has examined the effectiveness of information from multiple cues of business-to-consumer products (e.g., Langan, Besharat, and Varki 2017; Purohit and Srivastava 2001; Zou and Liu 2019), but no studies have explored multiple cues within the sharing economy. Our research empirically demonstrates that the diagnosticity of some cue types depends on other cue types in the sharing economy, which can be further explained by two theories. First, empirical evidence concerning the combined effect of reputational and price factors has revealed different views related to social comparison theory (Major and Testa 1989), in which consumers tend to perceive a price discrepancy among dissimilar products (due to product or seller reputation) as fair. By contrast, our study presents a negative price premium effect for high-reputation products in an online marketplace where consumers possess extensive information about alternative products (Liu, Feng, and Wei 2012). Second, the combination of reputational and temporal factors extends construal level theory, in which consumers process information about multiple alternative products differently depending on the anticipated timing of an activity (Trope and Liberman 2000). We have found that the late market entry of a ridesharing offer can lead consumers to a more concrete construal, which compels buyers to focus on distinct features (e.g., product reputation) of alternative offers.

Although numerous studies have investigated collaborative consumption and the sharing economy, few have considered the differential effectiveness of quality cues across seller segments. Most research has instead dealt with consumer-oriented segmentation in tourism (e.g., Khoo-Lattimore and Prayag 2015) and in the sharing economy (e.g., Lutz and Newlands 2018). However, segmentation can be applied to consumers and suppliers in the sharing economy because participants may be discriminated against due to race (Edelman and Luca 2014) and gender (Ert, Fleischer, and Magen 2016). This study empirically shows the variable effectiveness of intrinsic and extrinsic cues across seller segments on the basis of race and gender. Specifically, quality cue mechanisms in the ridesharing context appear more critical for male sellers than female sellers, different from findings within the peer-to-peer accommodation market (Ert, Fleischer, and Magen 2016). Our results also indicate that the combined effects of multiple cues are more pronounced for racial minority sellers than majority sellers. This finding supplements research by Doleac and Stein (2013), who found that minority sellers suffered from lower trust and worse market outcomes than majority sellers. Our work also confirms the existence of gender and racial discrimination on sharing-economy platforms (Edelman and Luca 2014; Ert, Fleischer, and Magen 2016).

Practical Implications

These findings have important managerial implications for peer-to-peer ridesharing sellers. First, sellers must understand that ridesharing consumers infer overall product quality from combinations of intrinsic and extrinsic cues. Under the assumption that product reputation is fixed (i.e., switching from a compact car to a luxury car is unrealistic), sellers can improve their personal reputation by revealing all profile information, increasing the number of total and positive ratings, or offering ridesharing services on the open market as early as possible. Although intrinsic and extrinsic quality cues should both be managed for overall quality evaluations, this study suggests that intrinsic cues are more critical in purchase decisions than extrinsic cues.

Second, this study implies that online sellers on sharing-economy platforms should consider contextual pricing strategies to maximize sales. For instance, if a driver has superior intrinsic quality cues through product reputation (e.g., a luxury sedan) or seller reputation (e.g., higher ratings), she should set a relatively lower price compared to competitors' offers. A profile of a 'good' driver (one who charges a lower price and provides superior service) will outperform that of a 'normal' driver (high reputation and high price) or a 'poor' driver (high price and poor services) (Baylis and Perloff 2002). Furthermore, a driver should post her offer early if she has inferior intrinsic quality; early offers can boost sales, such as by enhancing consumers' information exposure and attracting more attention from goal-oriented customers.

Third, our study provides valuable insight into how certain sellers (e.g., racial minorities and women) can manage quality cues of ridesharing services to maximize sales. Our findings suggest that non-minority female sellers with a highly reputable product (e.g., a comfortable car) can benefit from charging relatively lower prices compared to the prices of other (male) competitors. The rationale behind this strategic pricing may be due to gender-based differences in prosocial behavior; scholars have noted that men's sharing behavior is more pronounced in short-term contexts, whereas women's sharing behavior occurs in longer-term contexts within close relationships (Eagly and Crowley 1986). This pattern may imply gender bias in the peer-to-peer ridesharing market. Therefore, female sellers can use a negative price premium strategy (i.e., a high-reputation seller charges a lower price than a low-reputation seller) to maximize sales (Liu, Feng, and Wei 2012). Our results show that this negative price premium strategy is also valid for minority male sellers (Edelman and Luca 2014).

Lastly, the most controversial finding from our segmentation study is that four types of quality cues apparently have no relationship with demand for minority women's ridesharing services. Due to the presence of intimacy (i.e., the revelation of personal information) in peer-to-peer markets, minority female sellers are likely to experience discrimination because of stereotypical images associated with specific ethnic cultures, religions, and practices (Davidson, Fielden, and Omar 2010). Hence, sharing-economy platforms should address racial and gender discrimination by reducing the intimacy of transactions, especially by making transactions more anonymous (Schoenbaum 2018). To achieve equality for sellers and consumers, policymakers should also encourage these platforms to take antidiscrimination measures by reducing the salience of personal traits in the market. In addition, because our proposed model including four types of quality cues did not predict demand for shared products and services offered by minority female sellers, future research can identify alternative quality cues (e.g., consumer reviews and ratings) that determine sales of these sellers' shared products.

Limitations and Future Research Directions

This study has several limitations that can serve as opportunities for future research. First, we did not consider consumer characteristics to assess whether the effects of intrinsic and extrinsic quality cues on demand may vary by consumer segments. Future studies should consider demand-side segmentation based on demographics (e.g., age, gender, and race) and consumption behavior (e.g., ridesharing participation and visiting behavior) (Johns and Gyimóthy 2002). Second, although the dataset adopted in this study consisted of more than 52,000 observations, it only covered an 8-month period in the French market; researchers could examine the dynamics of the peer-to-peer ridesharing market over a longer period and across different countries to further investigate the interplay among intrinsic cues, extrinsic cues, and sales. Finally, future studies may extend the theoretical framework of quality cue typologies by considering additional quality cues. As shown in the tourism and hospitality literature (Banerjee and Chua 2016; Zhang et al. 2013), perceived quality of peer-to-peer ridesharing offers can be evidenced by the number of online reviews (i.e., volume) and average ratings (i.e., valence). The volume of online reviews and the valence of positive reviews may positively influence peer-to-peer ridesharing demand.

Overall, this study contributes to a better understanding of the potential effects of collaborative consumption in the tourism industry and sharing economy by examining how different quality cues shape demand for peer-to-peer ridesharing independently and collectively. Our results indicate that intrinsic and extrinsic quality cues affect demand for peer-to-peer ridesharing services, providing a useful guideline for microentrepreneurs to design competitive product offers in the online marketplace.

References

Abrate, G., and G. Viglia, G. 2019. "Personal or Product Reputation? Optimizing Revenues in the Sharing Economy." *Journal of Travel Research* 58 (1): 136–48.

Anderson. N.H. 1981. *Foundation of Information Integration Theory*. San Diego, CA: Academic.

Ba, S.L., and P.A. Pavlou. 2002. "Evidence of the Effect of Trust Building Technology in Electronic Markets: Price Premiums and Buyer Behavior." *MIS Quarterly* 26 (3): 243–68.

Babin, B.J., W.R. Darden, and M. Griffin. 1994. "Work and/or Fun: Measuring Hedonic and Utilitarian Shopping Value." *Journal of Consumer Research* 20 (4): 644–56.

Banerjee, S., and A.Y.K. Chua. 2016. "In Search of Patterns among Travellers' Hotel Ratings in TripAdvisor." *Tourism Management* 53: 125–31.

Bardhi, F., and G.M. Eckhardt. 2012. "Access-based Consumption: The Case of Car Sharing." *Journal of Consumer Research* 39 (4): 881–98.

Baylis, K. and J.M. Perloff. 2002. "Price Dispersion on the Internet: Good Firms and Bad Firms." *Review of Industrial Organization* 21 (3): 305–24.

Belk, R. 2014. "You Are What You Can Access: Sharing and Collaborative Consumption Online." *Journal of Business Research* 67 (8): 1595–600.

Bolton, L.E., L. Warlop, and J.W. Alba. 2003. "Consumer Perceptions of Price (un)Fairness." *Journal of Consumer Research* 29 (4): 474–91.

Boulding, W., and M. Christen. 2003. "Sustainable Pioneering Advantage? Profit Implications of Market Entry Order." *Marketing Science* 22: 371–92.

Brady, M.K., B.L. Bourdeau, and J. Heskel. 2005. "The Importance of Brand Cues in Intangible Service Industries: An Application to Investment Services." *Journal of Services Marketing* 19: 401–10.

Bridges, J., and C. Vásquez. 2018. "If Nearly All Airbnb Reviews Are Positive, Does That Make Them Meaningless?" *Current Issues in Tourism* 21 (18): 2057–75.

Bruce, N., E. Haruvy, and R. Rao. 2004. "Seller Rating, Price, and Default in Online Auctions." *Journal of Interactive Marketing* 18 (4): 37–50.

Cabral, L., and A. Hortacsu. 2010. "The Dynamics of Seller Reputation: Evidence from eBay." *The Journal of Industrial Economics* 58 (1): 54–78.

Campo, S., and M.J. Yagüe. 2008. "Effects of Price on Tourist Satisfaction." *Tourism Economics* 14 (30): 657–61.

Castel, A.D. 2008. "Metacognition and Learning about Primacy and Recency Effects in Free Recall: The Utilization of Intrinsic and Extrinsic Cues When Making Judgments of Learning." *Memory & Cognition* 36(2): 429–37.

Chitturi, R., R. Raghunathan, and V. Mahajan. 2008. "Delight by Design: The Role of Hedonic versus Utilitarian Benefits." *Journal of Marketing* 72: 48–63.

Chung, K. 2000. "Hotel Room Rate Pricing Strategy for Market Share in Oligopolistic Competition – Eight-year Longitudinal Study of Super Deluxe Hotels in Seoul." *Tourism Management* 21(2): 135–45.

Cronin, J. J., Jr., M.K., Brady, and G.T. Hult. 2000. "Assessing the Effects of Quality, Value, and Customer Satisfaction on Consumer Behavioral Intentions in Service Environments.

Journal of Retailing 76: 193–218.
Cui, G., H.-K. Lui, and X. Guo. 2012. “The Effect of Online Consumer Reviews on New Product Sales.” *International Journal of Electronic Commerce* 17: 39–58.
Davidson, M., S. Fielden, and A. Omar. 2010. “Black, Asian and Minority Ethnic Female Business Owners.” *International Journal of Entrepreneurial Behavior & Research* 16 (1): 58–80.
Deephouse, D.L., and S.M. Carter. 2005. “An Examination of Differences between Organizational Legitimacy and Organizational Reputation.” *Journal of Management Studies* 42 (2): 329–60.
Dervitsiotis, K.N. 2010. “Developing Full-Spectrum Innovation Capability for Survival and Success in the Global Economy.” *Total Quality Management & Business Excellence* 21 (2): 159–70.
Dhar, R., and K. Wertenbroch. 2000. “Consumer Choice Between Hedonic and Utilitarian Goods.” *Journal of Marketing Research* 37 (1): 60–71.
Dick, A., D. Chakravarti, and G. Biehal. 1990. “Memory-based Inferences during Consumer Choice.” *Journal of Consumer Research* 17 (1): 82–93.
Dodds, W.B., K.B. Monroe, and D. Grewal. 1991. “Effects of Price, Brand, and Store Information on Buyers’ Product Evaluations.” *Journal of Marketing Research* 28: 307–19.
Doleac, J.L., and L.C.D. Stein. 2013. “The Visible Hand: Race and Online Market Outcomes.” *The Economic Journal* 123 (November): 469–92.
Eagly, A.H., and M. Crowley. 1986. “Gender and Helping Behavior: A Meta-Analytic Review of the Social Psychological Literature.” *Psychological Bulletin* 100 (3): 283–308.
Edelman, B.G., and M. Luca. 2014. “Digital Discrimination: The Case of airbnb.com.” Harvard Business School, Working Paper 14-054.
Edelman, B.G., M. Luca, and D. Svirsky. 2017. “Racial Discrimination in the Sharing Economy: Evidence from a Field Experiment.” *American Economic Journal: Applied Economics* 9 (2): 1–22.
Ert, E., A. Fleischer, and N. Magen. 2016. “Trust and Reputation in the Sharing Economy” The Role of Personal Photos in Airbnb.” *Tourism Management* 55: 62–73.
Enz, C.A., and L. Canina. 2010. Competitive Pricing in European Hotels. In: J.S. Chen (ed.) *Advances in Hospitality and Leisure* (6), Emerald Group Publishing, pp. 3–25.
Enz, C.A., L. Canina, and M. Lomanno. 2009. “Competitive Pricing Decisions in Uncertain Times.” *Cornell Hospitality Quarterly* 50(3): 325–41.
Farris, P.W., N.T. Bendle, P.E. Pfeifer, and D.J. Reibstein. 2010. *Marketing Metrics: The Definitive Guide to Measuring Marketing Performance*. Upper Saddle River, New Jersey: Pearson Education.
Feldman, J.M., and J.G. Lynch. 1988. “Self-Generated Validity and Other Effects of Measurement on Belief, Attitude, Intention, and Behavior.” *Journal of Applied Psychology* 73 (3): 421–35.
Förster, J. 2009. “Relations between Perceptual and Conceptual Scope: How Global versus Local Processing Fits a Focus on Similarity versus Dissimilarity.” *Journal of Experimental Psychology: General*, 138 (1): 383–99.

Gibbs, C., D. Guttentag, U. Gretzel, J. Morton, and A. Goodwill. 2018. “Pricing in the Sharing Economy: A Hedonic Pricing Model Applied to Airbnb Listings.” *Journal of Travel & Tourism Marketing* 35 (1): 46–56.
Guttentag, D., S. Smith, L. Potwarka, and M. Havitz. 2018. “Why Tourists Choose Airbnb: A Motivation-Based Segmentation Study.” *Journal of Travel Research* 57 (3): 342–59.
Hagtvedt, H., and V.M. Patrick. 2008. “Art and the Brand: The Role of Visual Art in Enhancing Brand Extendibility.” *Journal of Consumer Psychology* 18: 212–22.
Hamari, J., M. Sjöklint, and A. Ukkonen. 2016. “The Sharing Economy: Why People Participate in Collaborative Consumption.” *Journal of the Association for Information Science and Technology* 67(9): 2047–59.
Herbig, P., and J. Milewicz. 1993. “The Relationship of Reputation and Credibility to Brand Success.” *Journal of Consumer Marketing* 10: 18–24.
Houston, D.A., and S.J. Sherman. 1995. “Cancellation and Focus: The Role of Shared and Unique Features in the Choice Process.” *Journal of Experimental Social Psychology* 32: 357–78.
Johns, N., and S. Gyimóthy. 2002. “Market Segmentation and the Prediction of Tourist Behavior: The Case of Bornholm, Denmark.” *Journal of Travel Research* 40: 316–27.
Kerin, R.A., R. Varadarajan, and R.A. Peterson. 1992. “First-Mover Advantage: A Syntheses, Conceptual Framework, and Research Propositions.” *Journal of Marketing* 56: 33–52.
Khoo-Lattimore, C., and G. Prayag. 2015. “The Girlfriend Getaway Market: Segmenting Accommodation and Service Preferences.” *International Journal of Hospitality Management* 45: 99–108.
Kim, J., P.B.C. Kim, J.-E. Kim, and V.P. Magnini. 2016. “Application of Construal-Level Theory to Promotional Strategies in the Hotel Industry” *Journal of Travel Research* 55 (3): 340–52.
Kirmani, A., and A.R. Rao. 2000. “No Pain, No Gain: A Critical Review of the Literature on Signaling Unobservable Product Quality.” *Journal of Marketing* 64: 66–79.
Langan, R., A. Besharat, and S. Varki. 2017. “The Effect of Review Valence and Variance on Product Evaluations: An Examination of Intrinsic and Extrinsic Cues.” *International Journal of Research in Marketing* 34 (2): 414–29.
Li, S.B., K. Srinivasan, and B.H. Sun. 2009. “Internet Auction Features as Quality Signals.” *Journal of Marketing* 73 (1): 75–92.
Liberman, N., and Y. Trope. 1998. The Role of Feasibility and Desirability Considerations in Near and Distant Future Decisions: A Test of Temporal Construal Theory.” *Journal of Personality and Social Psychology* 75 (1): 5–18.
Liu, Y., J. Feng, and K.K. Wei. 2012. “Negative Price Premium Effect in Online Market: The Impact of Competition and Buyer Informativeness on the Pricing Strategies of Sellers with Different Reputation Levels.” *Decision Support Systems* 54: 681–90.
Luo, W.H. and Q.B. Chung. 2010. “Retailer Reputation and Online Pricing Strategy.” *The Journal of Computer Information Systems* 50 (4): 50–56.
Lutz, C., and G. Newlands. 2018. “Consumer Segmentation within the Sharing Economy: The Case of Airbnb.” *Journal of Business Research* 88: 187–96.
Lynch, J. G., Jr., H. Marmorstein, and M.F. Weigold. 1988. “Choices from Sets Including

Remembered Brands: Use of Recalled Attributes and Prior Overall Evaluations.” *Journal of Consumer Research* 15 (2): 169–84.

Major, B., and M. Testa. 1989. “Social Comparison Processes and Judgments of Entitlement and Satisfaction.” *Journal of Experimental Social Psychology* 25: 101–20.

Mauri, A.G., R. Minazzi, M. Nieto-García, and G. Viglia. 2018. “Humanize Your Business. The Role of Personal Reputation in the Sharing Economy.” *International Journal of Hospitality Management* 73: 36–43.

Miyazaki, A.D., D. Grewal, and R.C. Goodstein. 2005. “The Effect of Multiple Extrinsic Cues on Quality Perceptions: A Matter of Consistency.” *Journal of Consumer Research* 32 (1): 146–53.

Monroe, K.B., and A.Y. Lee. 1999. “Remembering versus Knowing: Issues in Buyers’ Processing of Price Information.” *Journal of the Academy of Marketing Science* 27 (2): 207–25.

Mussweiler, T. 2003. “Everything is Relative: Comparison Processes in Social Judgement.” *European Journal of Social Psychology* 33 (6): 719–33.

Niedrich, R.W., and S.D. Swain. 2008. “The Effects of Exposure-Order and Market Entry-Information on Brand Preference: A Dual Process Model.” *Journal of the Academy of Marketing Science* 36: 309–21.

Noone, B.M., L. Canina, and C.A. Enz. 2013. “Strategic Price Positioning for Revenue Management: The Effects of Relative Price Position and Fluctuation on Performance.” *Journal of Revenue and Pricing Management* 12 (3): 207–20.

Noseworthy, T.J., and R. Trudel. 2011. Looks Interesting, but What Does It Do? Evaluation of Incongruent Product Form Depends on Positioning.” *Journal of Marketing Research* 48: 1008–19.

Olson, J.C., and J. Jacoby. 1972. “Cue Utilization in the Quality Perception Process.” *ACR Special Volumes*.

Ouellet, J.-F. 2017. “Consumer Racism and Its Effects on Domestic Cross-Ethnic Product Purchase: An Empirical Test in the United States, Canada, and France.” *Journal of Marketing* 71 (January): 113–28.

Pera, R., G. Viglia, and R. Furlan. 2016. “Who Am I? How Compelling Self-Storytelling Builds Digital Personal Reputation.” *Journal of Interactive Marketing* 35:44–55.

Purohit, D., and J. Srivastava. 2001. “Effect of Manufacturer Reputation, Retailer Reputation, and Product Warranty on Consumer Judgments of Product Quality: A Cue Diagnosticity Framework.” *Journal of Consumer Psychology* 10 (3): 123–34.

Raghunathan, R., and K. Corfman. 2006. “Is Happiness Shared Doubled and Sadness Shared Halved? Social Influences on Enjoyment of Hedonic Experiences.” *Journal of Marketing Research* 43: 386–94.

Rao, A.R., and K.B. Monroe. 1989. “The Effect of Price, Brand Name, and Store Name on Buyer's Perceptions of Product Quality: An Integrative Review.” *Journal of Marketing Research* 26 (35): 1–357.

Rhee, M., and P.R. Haunschild. 2006. “The Liability of Good Reputation: A Study of Product Recalls in the U.S. Automobile Industry.” *Organization Science* 17 (1): 101–17.

Richardson, P.S., A.S. Dick, and A.K. Jain. 1994. “Extrinsic and Intrinsic Cue Effects on

Perceptions of Store Brand Quality." *Journal of Marketing* 58 (4): 28–36.

Schoenbaum, N. 2016. "Gender and the Sharing Economy." *Fordham Urban Law Journal* 43 (4): 1023–70.

Schoenbaum, N. 2018. "Intimacy and Equality in the Sharing Economy." *The Cambridge Handbook of the Law of the Sharing Economy* 459–70.

Shankar, V., and R. Bolton. 2004. "An Empirical Analysis of Determinants of Retailer Pricing." *Marketing Science* 23 (1): 28–49.

Skowronski, J.J., and D.E. Carlston. 1987. "Social Judgment and Social Memory: The Role of Cue Diagnosticity in Negativity, Positivity, and Extremity Biases." *Journal of Personality and Social Psychology* 52 (4): 689–99.

Slovic, P., and S. Lichtenstein. 1971. "Comparison of Bayesian and Regression Approaches to the Study of Information Processing in Judgment." *Organizational Behavior and Human Performance* 6 (6): 649–744.

Smith, C. 2018. "15 Interesting BlaBlaCar Facts and Statistics (October 2018)." https://expandedramblings.com/index.php/blablacar-facts-statistics/ (accessed January 14, 2019).

So, K.K.F., H. Oh, and S. Min. 2018. "Motivations and Constraints of Airbnb Consumers: Findings from a Mixed-Methods Approach." *Tourism Management* 67: 224–36.

Stefansdotter, A., C. von Utfall Danielsson, C.K. Nielsen, and E.R. Sunesen. 2015. "Economic Benefits of Peer-to-Peer Transport Services." Copenhagen Economics.

Stein, J. 2015. "Baby, You Can Drive My Car and Stay in My Guest Room. And Do My Errands. And Rent My Stuff. My Wild Ride Through the New On-demand Economy." *TIME*: 32–40 (February).

Stuebs, M., and L. Sun. 2010. "Business Reputation and Labor Efficiency, Productivity, and Cost." *Journal of Business Ethics* 96 (2): 265–83.

Teas, R.K., and S. Agarwal. 2000. "The Effects of Extrinsic Product Cues on Consumers' Perceptions of Quality, Sacrifice, and Value." *Journal of the Academy of Marketing Science* 28 (2): 278–90.

Trope, Y, and N. Liberman. 2000. "Temporal Construal and Time-Dependent Changes in Preference." *Journal of Personality and Social Psychology* 79: 876–89.

Tussyadiah, I. 2015. "An Exploratory Study on Drivers and Deterrents of Collaborative Consumption in Travel." In *Information & Communication Technologies in Tourism 2015*, edited by I. Tussyadiah, and A. Inversini, 817-30, Switzerland: Springer International Publishing.

Tussyadiah, I. and J. Pesonen. 2016. "Impacts of Peer-to-Peer Accommodation Use on Travel Patterns." *Journal of Travel Research* 55 (8): 1022–40.

Vaughan, R., and R. Daverio. 2016. "Assessing the Size and Presence of the Collaborative Economy in Europe." PwC UK.

Wang, D., and J. L. Nicolau. 2017. "Price Determinants of Sharing Economy-Based Accommodation Rental: A Study of Listings from 33 Cities on Airbnb.com." *International Journal of Hospitality Management* 62: 120–31.

Wirtz, J., So, K.K.F., Mody, M., Liu, S. and Chun, H. (2019), "Platforms in the Peer-to-Peer Sharing Economy", *Journal of Service Management*, 30 (4): 452–83.

Wooldridge, J.M. 2010. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press
Wyer, R.S. 1970. "Information Redundancy, Inconsistency, and Novelty and Their Role in Impression Formation." *Journal of Experiment Social Psychology* 6: 111–27.
Yoganarasimhan, H. 2013. "The Value of Reputation in an Online Freelance Marketplace." *Marketing Science* 32 (6): 860–91.
Zhang, Z., Z. Zhang, F. Wang, R. Law, and D. Li. 2013. "Factors Influencing the Effectiveness of Online Group Buying in the Restaurant Industry." *International Journal of Hospitality Management* 35: 237–45.
Zou, P., & J. Liu. 2019. "How Nutrition Information Influences Online Food Sales." *Journal of the Academy of Marketing Science*. https://doi.org/10.1007/s11747-019-00668-4.

Table 1. Classification of quality cues in peer-to-peer ridesharing services.

Dimension	Definition	Context of peer-to-peer ridesharing	Type of quality cue
Type of accessed object	Nature of service access	Product reputation (functional or material) Seller reputation (experiential or immaterial)	Intrinsic
Anonymity	Relationship with car-sharing providers and other consumers	Seller reputation (experiential or immaterial)	Intrinsic
Market mediation	Level of market mediation	Price	Extrinsic
Temporality	Duration of access to car-sharing service	Offer duration between posting and departure times	Extrinsic

Table 2. Descriptive statistics of variables in total and segmented samples.

	Sample 1 (Total)		Sample 2 (French Male)		Sample 3 (French Female)		Sample 4 (Minority Male)		Sample 5 (Minority Female)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
*Demand**	2.567	0.006	2.700	0.007	2.437	0.011	2.119	0.017	1.827	0.038
Past Demand	1.162	0.001	1.165	0.001	1.166	0.001	1.142	0.002	1.139	0.006
Product Reputation	2.418	0.005	2.489	0.006	2.094	0.010	2.610	0.016	2.248	0.038
Seller Reputation	2.882	0.006	2.961	0.008	2.578	0.013	2.973	0.020	2.865	0.051
Relative Price	-0.001	0.001	-0.003	0.001	0.010	0.001	-0.014	0.002	0.031	0.004
Offer Duration	9.964	0.049	10.003	0.059	11.089	0.116	7.797	0.117	9.152	0.374
Manual Reservation	0.179	0.002	0.167	0.002	0.199	0.004	0.201	0.005	0.289	0.016
Round Trip	0.228	0.002	0.219	0.002	0.243	0.004	0.248	0.006	0.282	0.016
Detour Drive	0.480	0.002	0.492	0.003	0.480	0.005	0.418	0.006	0.427	0.018
Photo	0.426	0.002	0.465	0.003	0.327	0.005	0.389	0.006	0.353	0.017
Age	32.365	0.044	33.004	0.056	30.409	0.094	32.348	0.104	30.940	0.348
Gender	0.221	0.002								
Race	0.128	0.001								
Number of observations		52,248		34,816		10,745		5,902		785
		(100%)		(66.6%)		(20.6%)		(11.3%)		(1.5%)
Number of drivers		24,697		15,358		6,449		2,449		441
		(100%)		(62.2%)		(26.1%)		(9.9%)		(1.8%)

* Demand indicates dependent variable.

Table 3. Correlation matrix of independent variables.

Sample 1: Total (*N* = 52,248)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) *Past Demand*	1.00											
(2) *Product Reputation*	0.02	1.00										
(3) *Seller Reputation*	0.02	0.29	1.00									
(4) *Relative Price*	-0.09	-0.04	-0.10	1.00								
(5) *Offer Duration*	0.05	0.00	-0.02	0.05	1.00							
(6) *Manual Reservation*	-0.05	-0.04	-0.11	0.08	0.00	1.00						
(7) *Round Trip*	0.03	-0.02	0.00	0.02	0.09	-0.01	1.00					
(8) *Detour Drive*	0.00	-0.03	-0.06	0.02	0.04	0.00	0.03	1.00				
(9) *Photo*	0.00	0.17	0.26	-0.06	0.02	-0.07	0.01	0.00	1.00			
(10) *Age*	-0.06	0.07	0.01	0.06	0.00	0.01	-0.05	0.01	-0.03	1.00		
(11) *Gender*	0.01	-0.16	-0.10	0.04	0.05	0.04	0.02	0.00	-0.10	-0.10	1.00	
(12) *Race*	-0.05	0.05	0.02	-0.04	-0.07	0.03	0.02	-0.05	-0.03	-0.01	-0.10	1.00

Sample 2: French Male (*N* = 34,816)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) *Past Demand*	1.00									
(2) *Product Reputation*	0.02	1.00								
(3) *Seller Reputation*	0.02	0.28	1.00							
(4) *Relative Price*	-0.08	-0.01	-0.09	1.00						
(5) *Offer Duration*	0.05	0.02	-0.01	0.05	1.00					
(6) *Manual Reservation*	-0.05	-0.05	-0.12	0.07	-0.02	1.00				
(7) *Round Trip*	0.03	-0.01	0.00	0.02	0.08	-0.01	1.00			
(8) *Detour Drive*	0.00	-0.03	-0.06	0.02	0.04	0.00	0.03	1.00		
(9) *Photo*	0.00	0.15	0.24	-0.05	0.02	-0.08	0.03	0.00	1.00	
(10) *Age*	-0.07	0.06	0.00	0.08	0.00	0.03	-0.05	0.02	-0.04	1.00

Sample 3: French Female (*N* = 10,745)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) *Past Demand*	1.00									
(2) *Product Reputation*	0.02	1.00								
(3) *Seller Reputation*	0.02	0.26	1.00							
(4) *Relative Price*	-0.09	-0.03	-0.08	1.00						
(5) *Offer Duration*	0.07	0.00	-0.05	0.03	1.00					
(6) *Manual Reservation*	-0.06	-0.05	-0.09	0.07	0.03	1.00				
(7) *Round Trip*	0.04	-0.04	-0.01	0.00	0.11	-0.02	1.00			
(8) *Detour Drive*	0.01	0.00	-0.04	-0.03	0.02	-0.02	0.02	1.00		
(9) *Photo*	0.00	0.16	0.25	-0.08	0.02	-0.07	-0.02	0.01	1.00	
(10) *Age*	-0.06	0.06	0.00	0.06	0.00	-0.04	-0.04	0.00	-0.05	1.00

Sample 4: Minority Male (*N* = 5,902)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) *Past Demand*	1.00									
(2) *Product Reputation*	0.04	1.00								
(3) *Seller Reputation*	0.07	0.34	1.00							
(4) *Relative Price*	-0.14	-0.12	-0.12	1.00						
(5) *Offer Duration*	-0.02	-0.01	-0.01	0.09	1.00					
(6) *Manual Reservation*	-0.02	0.01	-0.06	0.09	0.03	1.00				
(7) *Round Trip*	-0.02	-0.08	0.04	0.09	0.10	-0.01	1.00			
(8) *Detour Drive*	0.01	-0.08	-0.11	0.10	0.04	0.02	0.06	1.00		
(9) *Photo*	-0.02	0.22	0.31	-0.03	0.03	0.01	0.02	0.01	1.00	

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(10) *Age*	-0.02	0.05	0.03	0.03	0.00	0.02	-0.02	-0.03	-0.03	1.00
Sample 5: Minority Female (*N* = 785)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) *Past Demand*	1.00									
(2) *Product Reputation*	0.00	1.00								
(3) *Seller Reputation*	-0.04	0.33	1.00							
(4) *Price*	-0.09	-0.13	-0.08	1.00						
(5) *Offer Duration*	-0.03	-0.03	0.03	0.03	1.00					
(6) *Manual Reservation*	0.01	-0.01	-0.09	0.02	0.18	1.00				
(7) *Round Trip*	0.06	-0.02	-0.05	0.05	0.13	-0.10	1.00			
(8) *Detour Drive*	-0.02	-0.01	-0.16	-0.01	0.02	-0.05	0.04	1.00		
(9) *Photo*	-0.05	0.15	0.39	-0.05	-0.02	-0.10	-0.01	-0.19	1.00	
(10) *Age*	-0.03	0.11	0.07	-0.01	0.08	-0.02	-0.11	0.08	-0.06	1.00

Table 4. Estimation results of fixed-effect models with performance measure.

Variable	Model 1 (Total)		Model 2 (French Male)		Model 3 (French Female)		Model 4 (Minority Male)		Model 5 (Minority Female)	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Past Demand	0.346**	0.033	0.395**	0.041	0.377**	0.068	0.045	0.098	0.312*	0.236
Product Reputation	0.035**	0.007	0.036**	0.009	0.014	0.013	0.053**	0.020	0.099	0.049
Seller Reputation	0.039**	0.005	0.035**	0.006	0.001	0.010	0.111**	0.016	-0.040	0.040
Relative Price	0.153	0.116	0.068	0.153	-0.050	0.218	0.388	0.323	0.121	0.999
Offer Duration	0.005**	0.001	0.006**	0.002	-0.001	0.002	0.014**	0.005	0.006	0.010
Relative Price × *Product Reputation*	-0.139**	0.040	-0.063	0.051	-0.183*	0.083	-0.332**	0.104	0.215	0.304
Relative Price × *Seller Reputation*	-0.105**	0.030	-0.098**	0.037	-0.006	0.064	-0.217*	0.091	-0.190	0.242
Offer Duration × *Product Reputation*	-0.001*	0.000	-0.002**	0.001	0.001	0.001	-0.002	0.002	-0.003	0.004
Offer Duration × *Seller Reputation*	0.001†	0.000	0.001**	0.000	0.000	0.001	-0.001	0.001	0.002	0.003
Manual Reservation	-1.069**	0.014	-1.154**	0.018	-1.171**	0.025	-0.523**	0.042	-0.647**	0.082
Round Trip	0.029†	0.013	0.023	0.016	0.034	0.023	0.020	0.040	0.219**	0.083
Detour Drive	-0.006	0.011	-0.025†	0.013	0.050*	0.020	-0.025	0.035	0.173*	0.077
Photo	0.039**	0.011	0.038**	0.014	0.021	0.022	0.035	0.037	0.042	0.084
Age	0.034**	0.003	0.040**	0.004	0.012†	0.007	0.009	0.013	0.050*	0.024
Age^2	-0.001**	0.000	-0.001**	0.000	0.000**	0.000	0.000	0.000	-0.001**	0.000
Gender	-0.224**	0.013								
Race	-0.544**	0.016								
Constant	1.748**	0.083	1.619**	0.104	2.106**	0.164	1.525***	0.280	0.547	0.554
Departure time dummies	Controlled		Controlled		Controlled		Controlled		Controlled	
Departure day dummies	Controlled		Controlled		Controlled		Controlled		Controlled	
Number of observations	52,248		34816		10745		5902		785	
Number of drivers	24,697		15,358		6,449		2,449		441	
σ_μ	0.037		0.046		0.016		0.080		0.037	
σ_ε	1.188		1.221		1.009		1.274		0.992	
Within R_square	0.168		0.153		0.208		0.078		0.154	
Between R_square	0.799		0.743		0.995		0.099		0.828	
Overall R_square	0.169		0.153		0.208		0.077		0.156	

Note: † $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. S.E. denotes standard error.

Table 5. Results of robustness check based on analysis of alternative samples.

Variable	Model 6 (3-trip sample)		Model 7 (2-trip sample)	
	Coefficient	S.E.	Coefficient	S.E.
Past Demand	0.297	0.040	0.448**	0.042
Product Reputation	0.031**	0.009	0.033**	0.008
Seller Reputation	0.043**	0.007	0.044**	0.006
Relative Price	0.156	0.147	0.110	0.132
Offer Duration	0.007**	0.002	0.004**	0.001
Relative Price × *Product Reputation*	-0.123*	0.050	-0.171**	0.046
Relative Price × *Seller Reputation*	-0.113**	0.037	-0.100**	0.033
Offer Duration × *Product Reputation*	-0.001*	0.001	-0.001†	0.000
Offer Duration × *Seller Reputation*	0.000	0.000	0.001*	0.000
Manual Reservation	-1.062**	0.018	-1.052**	0.015
Round Trip	0.008	0.017	0.044**	0.014
Detour Drive	-0.007	0.014	0.000	0.012
Photo	0.039**	0.015	0.039**	0.012
Age	0.032**	0.004	0.036**	0.004
Age^2	-0.001**	0.000	-0.001**	0.000
Gender	-0.227**	0.017	-0.208**	0.014
Race	-0.546**	0.021	-0.546**	0.017
Constant	1.905**	0.109	1.562**	0.095
Departure time dummies	Controlled		Controlled	
Departure day dummies	Controlled		Controlled	
Number of observations	30,489		42,792	
Number of drivers	18,168		20,741	
σ_μ	0.043		0.014	
σ_ε	1.192		1.176	
Within R_square	0.165		0.172	
Between R_square	0.809		1.000	
Overall R_square	0.166		0.172	

Note: † $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. S.E. denotes standard error.

Table 6. Results of hypothesis testing based on main model (Model 1: Total sample).

Hypothesis		Type of effect	Finding	Hypothesis testing
1	Product reputation → Demand	Direct	Positive	Supported
2	Seller reputation → Demand	Direct	Positive	Supported
3	Relative price → Demand	Direct	Not significant	Not supported
4a	Relative price × Product reputation → Demand	Combined	Negative	Supported
4b	Relative price × Seller reputation → Demand	Combined	Negative	Supported
5	Offer duration → Demand	Direct	Positive	Supported
6a	Offer duration × Product reputation → Demand	Combined	Negative	Supported
6b	Offer duration × Seller reputation → Demand	Combined	Positive	Not supported

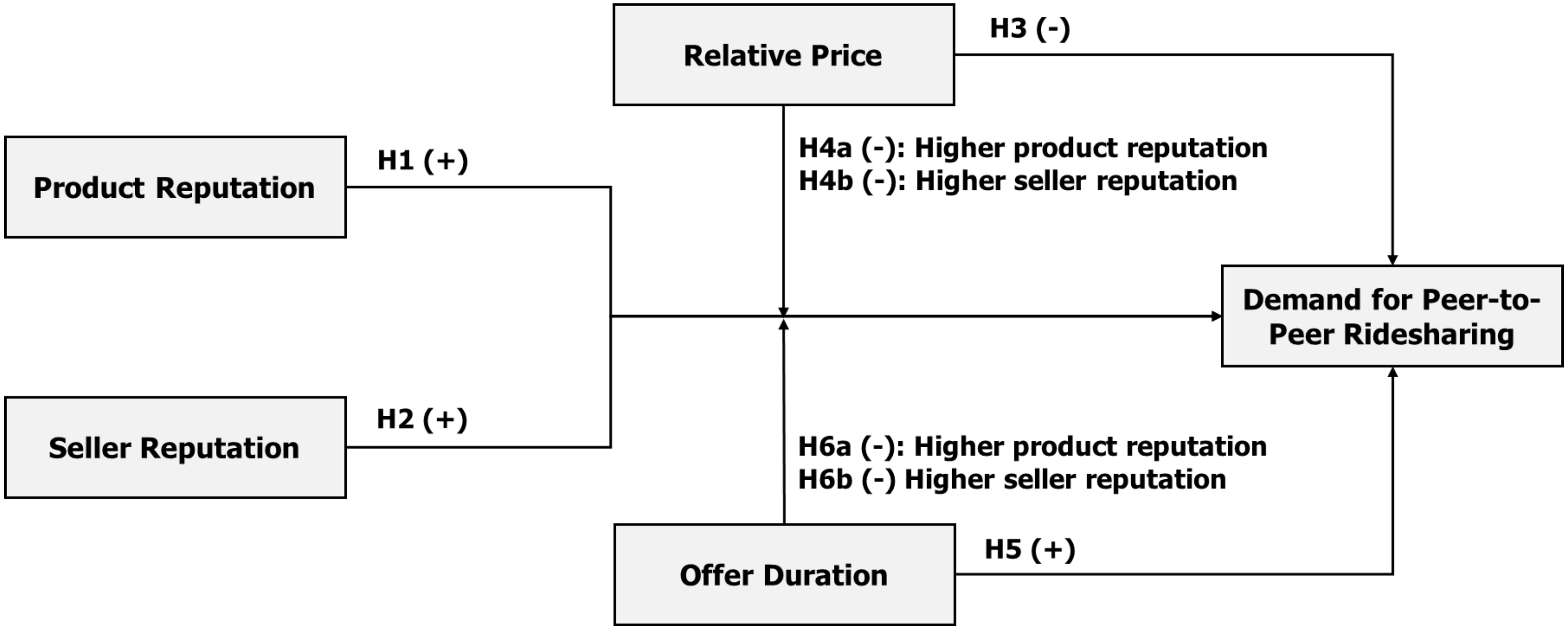

Figure 1. Research model and proposed hypotheses.