

Clemson University

TigerPrints

All Theses

Theses

May 2020

The Importance of Platform Producers' Reputation Signals and Product Type on Product Performance in Peer-to-Peer Platforms

Aubrey Johnson

Clemson University, aubrey7@g.clemson.edu

Follow this and additional works at: https://tigerprints.clemson.edu/all_theses

Recommended Citation

Johnson, Aubrey, "The Importance of Platform Producers' Reputation Signals and Product Type on Product Performance in Peer-to-Peer Platforms" (2020). *All Theses*. 3304.

https://tigerprints.clemson.edu/all_theses/3304

This Thesis is brought to you for free and open access by the Theses at TigerPrints. It has been accepted for inclusion in All Theses by an authorized administrator of TigerPrints. For more information, please contact kokeefe@clemson.edu.

**THE IMPORTANCE OF PLATFORM PRODUCERS' REPUTATION SIGNALS
AND PRODUCT TYPE ON PRODUCT PERFORMANCE IN
PEER-TO-PEER PLATFORMS**

**A Thesis
Presented to
the Graduate School of
Clemson University**

**In Partial Fulfillment
of the Requirements for the Degree
Master of Science
Social Science**

**by
Aubrey Johnson
May 2020**

**Accepted by:
Dr. Ye Luo, Committee Chair
Dr. William Haller
Dr. Christina Kyprianou**

ABSTRACT

On two-sided peer-to-peer platforms there exists a supply side (producers) and a demand side (consumers). Platform owners provide the platforms that assist in efficiently matching producers and consumers and an infrastructure that producers can take advantage of to signal quality to consumers. This study examines the effects of producer signals on product performance in the context of Airbnb, a peer-to-peer home sharing platform. Adjusting for producers with multiple listings, the analysis uses 77,445 listings from the platform to produce regression models which tests whether signals are positively related to product performance and if the relationship between producer signals and product performance is moderated by product type. Results show that while producer signals are important to product performance, there is minimal support for the assumption that signals vary by product type. Results also show that certain product attributes may be more important than producer signals in some contexts. Based on these findings, business and theoretical implications are discussed as well as directions for future research.

ACKNOWLEDGEMENTS

I'd first like to thank my committee members. Dr. Ye Luo provided useful guidance and methodological advice, Dr. Christina Kyprianou provided relevant literature and taught me a lot about how two-sided platforms work, and Dr. William Haller provided data visualization advice and made useful suggestions that strengthened the writing in this thesis. Next, I'd like to thank former graduate coordinator Dr. Melissa Vogel for urging my cohort and I to get started on our thesis work early and current graduate coordinator Dr. Bryan Miller for providing both flexibility and stability in our program's time of transition. Finally, I want to thank my mentors at my undergraduate institutions and my family for supporting and encouraging me.

TABLE OF CONTENTS

	Page
TITLE PAGE	i
ABSTRACT	ii
ACKNOWLEDGEMENTS	iii
LIST OF TABLES	v
INTRODUCTION	1
THEORETICAL BACKGROUND	4
Two-Sided Peer-to-Peer Platforms	4
Signaling Theory	6
Signaling in Peer-to-Peer Contexts	7
Product Type	9
DATA AND METHODS	11
Data	11
Measurement	13
Statistical Procedures	18
RESULTS	21
Descriptive Statistics	21
Regression Analysis.....	22
DISCUSSION AND CONCLUSION	28
REFERENCES.....	34

LIST OF TABLES

	Page
Table 1: Descriptive Statistics	21
Table 2: Parameter Estimates for Logged Number of Reviews on Signals	23
Table 3: Parameter Estimates for Rating Score on Signals	26

INTRODUCTION

From transportation to daily errands, many aspects of life have been transformed by the emergence of the sharing economy and the peer-to-peer platforms that inhabit it. The sharing economy is defined as a market for accessing products and services on a temporary basis rather than owning them (Puschmann & Alt, 2016). Peer-to-peer (P2P) platforms play an important role in this market, connecting supply- and demand-side participants (i.e. platform producers and consumers). These platforms often disrupt or change traditional industries like rental/hospitality services, taxi services, car rentals, and even lending (Ryu et al., 2019). This change in consumer behavior is facilitated and amplified by evolving social networks and electronic markets (i.e. P2P platforms).(Puschmann & Alt, 2016).

A key aspect of the value that peer-to-peer platform owners create for customers is the efficiency with which they match supply with demand (Morse, 2015). For example, a 2016 analysis shows that, on average, Uber drivers achieve more capacity utilization than taxi drivers in major United States cities. One reason for Uber drivers' superior performance is the presence of the Uber platform, which provides an efficient matching tool (Cramer & Krueger, 2016). On platforms like eBay, Prosper, and Airbnb where consumers and producers are not automatically matched, the platforms provide a space for producers to communicate quality, competence, and trustworthiness. Thus, signaling theory is used in recent literature to understand the importance of signaling producer quality in order to improve product performance.

Recent P2P platform studies simply use product prominence (number of reviews) as a marker of performance (Benítez-Aurioles, 2018; Zhang et al., 2018). However, a more comprehensive assessment of product performance on P2P platforms based on consumer evaluations of products and producers has received relatively less scholarly attention. By measuring product performance with both review quality and review volume, this study improves the state of P2P platform literature and provides a more robust assessment of performance. Taeuscher (2019) finds that a product's perceived quality and prominence positively impacts sales performance. This is proposed to occur because product quality and product prominence are reputation signals that make it easier for consumers to have confidence in the products they are pursuing (Taeuscher, 2019). Specifically, rating scores and rating volume are markers of perceived product quality and product prominence in online markets, respectively (Taeuscher, 2019). Thus, this study extends prior research by considering the impact of producers' reputation signals on both product quality (rating score) and product prominence (number of reviews).

In addition, there lacks an in-depth understanding of the importance and effectiveness of particular reputation signals by product type. Seminal works on signaling theory do not fully address the importance of considering the type of product (Akerlof, 1970; Lee et al., 2005). Yet, the performance of different types of products, such as entire homes or single rooms on Airbnb's platform, may be influenced by different reputation signals, and thus require different approaches to marketing. In turn, understanding the importance of reputation signals by product type has practical

implications for both platform owners and platform producers. Building on these insights, this study examines the following research questions:

RQ1: How do platform producers' reputation signals contribute to the performance of their products on peer-to-peer platforms?

RQ2: How does product type moderate the relationship between platform producers' reputation signals and product performance?

THEORETICAL BACKGROUND

Two-Sided Peer-to-Peer Platforms

Firms produce goods or services, which they sell to customers to generate revenue and profits. However, firms operating as platforms rely on platform producers to create and deliver goods and services (Van Alstyne et al., 2016). At the same time, they do not directly sell to customers but facilitate the interactions and transactions of platform producers and consumers (Rochet and Tirole, 2006). Such platforms have traditionally existed in the gaming and payment systems. For example, platform owners like Microsoft X-Box, Sony Play Station, and Nintendo Wii, must encourage game developers to create content compatible with their platforms while also encouraging gamers to purchase that content (Rochet & Tirole, 2006). Similarly, payment system operators must encourage merchants and cardholders to interact with each other in order to make a profit (Rochet & Tirole, 2006). In these two-sided markets, platform owners operate as mediators of two interdependent sides of the market, capturing value from the interactions of platform producers and consumers (Rochet & Tirole, 2006; Van Alstyne et al., 2016).

Platform owners' ability to mediate interactions efficiently and at scale, depends to a large extent on the number of both platform producers and consumers (Van Alstyne et al., 2016). This is true in many different types of P2P platforms. In P2P lending, the more lenders there are, the more likely borrowers will get credit. On the other hand, the more borrowers are present, the more likely a lender will have consumers to lend to at their desired risk level (Mariotto, 2016). Similarly, Apple's App Store enables app developers and app users to connect. The app developers represent the supply side of this

two-sided market and the app users represent the demand side. When there are more apps available via the developers, there are more incentives for app users to use the App Store. When there are more app users using the App Store, app developers are incentivized to create appealing apps (Van Alstyne et al., 2016). While speaking of P2P lending, Mariotto (2016) states, “the higher the number on each side, the higher the probability of a successful match between a borrower and a lender and the higher the volume of transactions” (p. 38). This can be generalized to other P2P contexts because in any P2P context, if the balance of enticing enough supply and demand fails, the entire platform could fail due to lack of transactions (Rochet & Tirole, 2003).

With an understanding of how platforms work in two-sided markets, it is important to note there are different types of platforms. The previously mentioned examples of payment system operators and gaming consoles are innovation platforms. These platforms provide “technological building blocks” that a producer can build onto in order to provide for a consumer (Evans & Gawer, 2016:6). Platforms like Airbnb (P2P home sharing), eBay (P2P e-commerce), Uber (P2P ridesharing), and Prosper (P2P lending) are transaction platforms (Evans & Gawer, 2016). Transaction platforms, the focus of this analysis, consist of “a technology, product or service that acts as a conduit (or intermediary) facilitating exchange or transactions between different users, buyers, or suppliers” (Evans & Gawer, 2016:9). While transaction facilitation is the central goal of firms operating transaction platforms, the producers on those platforms are responsible for communicating trustworthiness and quality to consumers. By using signaling theory, many researchers have begun to understand how this process works.

Signaling Theory

When actors in economic transactions have incomplete information about a product, the transaction is considered to contain imperfect information (Lee et al., 2005). Imperfect, or asymmetric, information occurs when one party has more knowledge of a product's quality than the other. In a market setting, the party with more knowledge is usually the producer (Lee et al., 2005), who, if honest, must work to minimize the information asymmetry. Marketers portray their product and themselves in a way that encourages purchase (Lee et al., 2005). This process allows consumers to more easily classify the producer as trustworthy or untrustworthy and evaluate the quality of the product sold (Lee et al., 2005).

In signaling theory, there exists a signaler, signal, and receiver. The signaler is the insider who has information about a product, skill, or service that needs to be conveyed to the receiver (Connelly et al., 2011). These insiders use the information they have to communicate the quality of their products and distinguish themselves from untrustworthy merchants (Lee et al., 2005). This information is often communicated in the form of market signals which transfer information from the producer to the consumer in order to communicate information about a product (Lee et al., 2005). In this framework, consumers are receivers who lack the necessary information to judge the quality of what is being pursued and the receiver uses the aforementioned signals to assist in the decision-making process (Connelly et al., 2011).

In digital markets, signals are important because the absence of a physical space between buyer and seller eliminates observable cues like body language gained from in-

person interactions (Dimoka et al., 2012). Because of the distance between producer and consumer, the risk of adverse outcomes for the consumer is heightened (Lee et al., 2005). Thus, the consumer's burden is that they are in search of quality (Akerlof, 1970). This uncertainty, presence of risk, and search for quality leads to the necessity of producer signals.

Signaling in Peer-to-Peer Contexts

Signals are important in peer-to-peer platforms because they are a useful evaluation tool in many P2P contexts. In P2P crowdfunding, where crowdfunding platforms bring together entrepreneurs and potential funders, signals help potential funders evaluate the quality of the projects being proposed (Kromidha & Robson, 2016). Signals of engagement like updates, comments on the project website, linked friends, and number of shares are correlates of success on P2P crowdfunding platforms (Kromidha & Robson, 2016). Also, in order to reduce uncertainty, producers on eBay's two-sided market signal credibility and quality by using the platform's features (Lu et al., 2009). Some producers engage in the pursuit of eBay promotions for their products in order to signal to consumers that their products are of quality (Melnik et al., 2011). Those who signal successfully the high quality of their products can typically charge higher prices and see better outcomes such as more revenue (Brown, 2015).

In P2P home sharing, homeowners signal trust through reputation signals. Guests must evaluate these homeowners through signals about their competency and credibility in order to proceed with a purchase. Guest satisfaction is in part derived by trust

established through the signals on a homeowner's profile (Moon et al., 2019). Recently, trust signals like host locality, superhost status, response rate, length of tenure, and verification have been used when studying P2P home sharing, particularly on Airbnb (Xie & Mao, 2017). Specifically, Xie and Mao (2017) find that potential guests use the previously mentioned signals to judge the quality of hosts, proving trust facilitation through signals helps foster positive outcomes.

In P2P lending, lenders often have imperfect information about borrowers. This leads to information asymmetries because a borrower knows their own value and risk while the lender does not (Mariotto, 2016). Thus, the burden is on the borrower to convince the lender of their quality in this two-sided P2P market. In P2P lending, platforms like Prosper and LendingClub use social media-like features in order to aid in the resolution of information asymmetry (Mariotto, 2016). In this context, a borrowers' social ties act as a signal of their viability and credit quality (Lin et al., 2013). Specifically, on the Prosper platform, borrowers with friends on their profile had better outcomes, especially when those friends came with signals of quality like being a prolific lender (Lin et al., 2013). Another signal of credibility in this context includes borrower history, which helps lenders navigate a space in which information is scarce and risk is high (Cai et al., 2016).

Whether participating in P2P lending, crowdfunding, or home sharing, those with imperfect information consistently seek signals to aid in decreasing information asymmetry and decision making. When these signals are properly used, research shows that outcomes on the supply side of these two-sided markets are typically more positive.

Signaling theory poses that signals communicated by producers impact consumer behavior by reducing uncertainty and signaling quality (Lee et al., 2005). Those who perform well on platform enabled signals typically have better product performance outcomes (Brown, 2015). Thus, it is hypothesized that:

H1: Producers' reputation signals have a positive relationship with product performance.

Product Type

Through the previously mentioned examples, it is clear there exists a variety of producer signals, some of which are platform specific. Because of this, producer signal importance may depend on the types of products offered on platforms. Studies on market segmentation on P2P platforms show that certain classes of products draw in certain customers. The simplest example comes from an e-commerce context where producers' use of different promotional tools for new and used items suggests their awareness of potential differences in marketing different types of product (Melnik et al., 2011). Examples that include varying levels of physical risk based on product type come from ridesharing and home sharing contexts.

Ridesharing platforms such as Uber and Lyft, allow producers to offer different types of products. Uber Pool and Lyft Shared (formerly Lyft Line) are available as flexible, budget-friendly options that allow users to share rides with others (Pratt et al., 2019; Sarriera et al., 2017; Tell, 2015). For riders who want an elevated experience with increased privacy, Uber X and Lyft Lux may be the preferred option (Pratt et al., 2019).

On home sharing platforms, consumers typically have the option of choosing a shared room or an entire home. Shared rooms typically cater to less formal consumers who are more likely to be men, low income, less concerned with cleanliness, traveling alone or with a large group (as opposed to with a partner), and most importantly, open to social interaction (Lutz & Newlands, 2018). Entire home consumers are typically high income and highly educated individuals more likely to be traveling with a partner or spouse and more likely to be uncomfortable with social interaction (Lutz & Newlands, 2018). Thus, shared rooms have an increased risk due to the presence of other consumers renting the same space, while entire homes contain less risk due to the privacy guaranteed.

If different parts of the demand side of two-sided markets tend to select different products, we can expect producer signals to have different relationships with product performance based on the product. The mentioned examples show how high-risk products may contrast with low-risk products that are meant for consumers looking for a more formal experience or willing to spend more. Logically, the higher the physical risk consumers face while using a product, the more assurances they need that the risks will not materialize, and the more they may depend more on producer signals to relieve their concerns. As a result, the relationship between producer signals and product performance is expected to be stronger for high-risk products. Thus, it is hypothesized that:

H2: Consumers' physical risk positively moderates the relationship between producer signals and performance.

DATA AND METHODS

Data

To examine how producer signals contribute to product performance and how different types of products influence the relationship between producer signals and product performance, this study uses data from Airbnb, a P2P home sharing platform. Airbnb allows homeowners to rent out their spaces to travelers/guests (Moon et al., 2019). Due to its success and large data footprint, Airbnb has been the focal point of those studying P2P platforms and the sharing economy. On Airbnb, typically the producer (also known as the host) is a person, rather than a company, however property management companies are joining the platform as well (Cox, 2019). This P2P model in which guests do not interact with formal hospitality workers or well-known chains has been the subject of many recent works that focus primarily on the relationship between hosts, who share their spaces, and guests, who rent out those spaces.

Specifically, the data come from Inside Airbnb, a non-profit originally put forth to understand the impact of Airbnb on neighborhoods (Cox, 2019). Inside Airbnb accumulates Airbnb's publicly available data, which contain consumer ratings, consumer reviews, host information, and listing information (Cox, 2019). Recently, this dataset has been used for academic studies that focus on topics relevant to P2P platforms and the sharing economy (e.g. Xie & Mao, 2017; Benítez-Aurioles, 2018; Zhang et al., 2018; Zhao & Rahman, 2019).

Because of how Inside Airbnb collects listings, not all cities in the United States are represented. However, based on Teubner (2018)'s methodology, this selection of cities and their surrounding metropolitan areas accounts for at least 25% of the United States population (over 80 million people). This analysis includes seven more cities than Teubner (2018)'s analysis to increase regional diversity and nationwide generalizability. Specifically, this analysis focuses on listings from 23 locations in the United States, which cover a total of 232,347 listings in Asheville, Austin, Boston, Broward County (Ft. Lauderdale, FL), Cambridge, Chicago, Clark County (Las Vegas, NV), Columbus, Denver, Los Angeles, Nashville, New Jersey (statewide), New Orleans, New York City, Oakland, Portland, Rhode Island (statewide), San Diego, San Francisco, Santa Cruz, Seattle, Twin Cities (Minneapolis and St. Paul, MN) and Washington D.C. Following list-wise deletion of missing values and other measurement considerations, a final sample of 77,445 listings is achieved.

The decrease from 232,347 listings to 77,445 listings occurs because of three criteria. Listings that have been on the site for only a few months are more likely to have few or no reviews. Thus, the first criterion for inclusion into the analysis is that listings must be at least one year old. Second, because the Superhost badge was not consistently on Airbnb until 2015, listings in existence before 2015 were dropped. Third, listings with prices below \$10 and above \$10,000 were dropped. Airbnb has these as price limits; therefore, it is not known why a handful of listings have prices below and above this range.

Measurement

Dependent Variables

The dependent variables are measures of product performance. In the context of Airbnb, product performance refers to the performance of a host's listing for an accommodation available for rent. Thus, the term "listing performance" is used. This study measures listing performance in two ways based on the established importance of product quality and prominence for product performance.

Based on prior research, the first measure of listing performance is captured by number of reviews. Benítez-Aurioles (2018) uses number of reviews as a proxy for how many visitors have stayed in a listing. Additionally, Zhang et al. (2018) uses number of reviews as a stand in for number of bookings when predicting trust towards hosts on Airbnb. A 2014 meta-analysis examining how online product reviews impact sales compiled a list of studies measuring retail performance (Floyd et al., 2014). Of the five studies in the hospitality industry, two use reviews per room as a proxy measure of sales (Floyd et al., 2014). Across industries, Floyd et al. (2014) note that many studies resort to using proxy measures of sales. Also, there is a relationship between number of reviews and room sales, further justifying review volume as a measure of listing performance (Lee et al., 2015). This is also seen in other parts of the sharing economy, specifically concerning meal sharing, where number of thank you notes (similar to reviews) is a predictor of sales performance (Huurne et al., 2018).

While number of reviews is a suitable proxy, researchers claim this measure captures the lower bound of number of reviews because not all users leave a review, with review rates ranging from 30% to 70% as of 2017 (Benítez-Aurioles, 2018; Cox, 2019; Teubner, 2018). Because product performance will be measured by number of reviews, listings under one year old at the time of scraping have been dropped. This is because, logically, listings that are new to the site will have fewer reviews than those that have been around longer. Lastly, number of reviews is log transformed to correct for positive skewness.

The second measure of listing performance is a listing's overall rating score. Rating scores are indicators of a listing's quality. In a study of P2P lending, borrowers' past performance helps potential lenders evaluate their reputations (Jie et al., 2019). In the context of Airbnb, past performance is evaluated by consumer reviews, specifically rating scores where users evaluate an accommodation's cleanliness, check-in, and value (Zhang, 2019). A rating score is a signal of product quality (Taeuscher, 2019) and it is related to sales performance. Though the product is an extension of the seller, the seller cannot truly communicate the quality of the product with 100% certainty (Dimoka et al., 2012). Therefore, consumer reviews exist. Consumers judge the quality of their experience which implies producer and product performance. Hotel industry studies find that these consumer ratings positively correlate with online room sales (Ogut & Tas, 2011; Ye et al., 2011). Thus, the rating score is used as the second measure of listing performance.

A listing's overall rating score is provided by Inside Airbnb. This measure goes from 20 to 100 and is based on the average of a listing's cleanliness rating, check-in rating, location rating, accuracy rating, communication rating, and value rating. The variable corresponds to number of stars and as Teubner (2018) explains, "scores between ≥ 75 and 84 yield a star rating of 4.0, scores between ≥ 85 and 94 yield a star rating of 4.5, and so on" (pg. 267). Due to a heavy left skew, this variable is reverse-coded and log transformed. This transformed version of the variable replaces the original variable in all the regression analyses included in this paper.

Independent Variables

The independent variables capture the signals that Airbnb's producers (hosts) send to consumers (travelers) to convince them of their reliability and trustworthiness. These signals include membership length, superhost status, responsiveness, and identity verification. These signals are consistently used in studies of the Airbnb platform (Benítez-Aurioles, 2018; Zhang et al., 2018; Moon et al., 2019; Zhao & Rahman, 2019).

Membership length refers to how long a host has been active on Airbnb; a guest typically sees a phrase like "Joined in 2017" (Airbnb.com). Researchers consistently use learning theory to propose supported hypotheses concerning the length of membership and its impact on performance (Xie & Mao, 2017; Zhao & Rahman, 2019). This suggests length of membership should be an important producer signal to when it comes to listing performance on Airbnb.

Identity verification lets the consumers know whether producers have provided and verified a government ID. Overall, Airbnb guests value credibility and dyadic trust when booking (Moon et al., 2019). There are two studies of Airbnb that address this, one in a western context and one in a non-western context. Though results are mixed on whether ID verification is an important producer signal for listing performance (see Xie & Mao, 2017; Zhao & Rahman, 2019), ID verification is consistently used in studies of Airbnb that examine how producers' attributes impact product performance. The signal is a binary variable, with 1 indicating the host has an ID verification on file, and 0 indicating the opposite. The signal is portrayed on host profiles with a check mark and the word "verified" (Airbnb.com).

A superhost is a host who has maintained a good reputation on Airbnb according to Airbnb's criteria (Airbnb.com). Zhang et al. (2018) finds the superhost badge to be one of the most important parts of reputation building on the Airbnb platform. Superhosts are expected to have at least 10 transactions completed, a review rate of at least 50%, a high response rate, a low cancelation rate, and consistently perform well in reviews (Zhang et al., 2018). Constructed as a binary variable, the Superhost variable is 1 when the host is a Superhost, and 0 when not. This signal was not consistently on the platform until midway through 2014, so listings created before then were dropped.

The responsiveness variable measures how quickly hosts respond to customer inquiries. In a study of P2P interactions on Airbnb, researchers conclude that guests value communicative hosts and put high stakes on encounter satisfaction (Moon, et al., 2019). Thus, host responsiveness is an important communication signal crucial to building trust

and achieving high listing performance (Xie & Mao, 2017; Zhao & Rahman, 2019; Zhang et al., 2018). For ease of interpretation, the measure is a binary variable, with 1 indicating a host “typically responds within an hour”, and 0 meaning the host takes longer than one hour to respond..

Moderator Variable

Product risk is hypothesized to be a moderator in the relationship between producer signals and product performance. In the context of Airbnb, the products are the different types of accommodation available for rent. This recoded binary variable considers whether an accommodation is an entire home (1), or a room rental (0). Entire homes are proxies for low risk products whereas room rentals are proxies for high risk products. Home listings carry the least amount of risk because consumers rent the entire apartment or home during their stay and do not come into regular contact with the host or other tenants. On the other hand, room rentals (private or shared) contain varying levels of physical risk due to the potential presence of the homeowner and other travelers in the space (Airbnb.com).

Control Variables

Product attributes are control variables. In the context of Airbnb, these are listing attributes. When studying Airbnb, Benítez-Aurioles (2018) uses how many guests can be accommodated, number of bathrooms, and number of bedrooms as control variables that imply listing size. Researchers doing similar analyses control for number of beds as well (Xie & Mao, 2017; Zhao & Rahman, 2018). Due to multicollinearity concerns identified

by high variance inflation factor scores, number of beds is included as the main listing size attribute with bedrooms, bathrooms, and accommodates left out to increase parsimoniousness.

Other consistently used controls include price which is log transformed to correct for positive skewness, and to a lesser extent cancellation and instant booking policies (Xie & Mao, 2017; Benítez-Aurioles, 2018; Teubner, 2018; Zhao & Rahman, 2019). To ensure accurate analysis, cases with prices below \$10 and above \$10,000 are dropped. These are the minimum and maximum prices allowable on Airbnb's website. Because some cases had prices at \$0 as well as a few over \$10,000, I dropped those cases to ensure accuracy and consistency.

The cancellation policy variable is recoded following the example of Teubner (2018), who created dummy variables for whether a listing had a flexible, moderate, or strict cancellation policy. One could view this variable as a reflection of the host's overall personality on the platform, but since it is listing specific rather than host specific, it is treated as a listing attribute. The same could be said for instant booking policy. This variable measures whether a listing can be booked instantly, without a host's approval (Airbnb.com). Lastly, dummy variables are created to represent each of the five United States regions and due to the inclusion of number of reviews, the age of a listing in years is controlled for.

Statistical Procedures

Univariate analyses are produced to provide an overview of the data. Descriptive statistics can be found below. General Estimating Equations are also used with adjustments made for clustering to analyze the relationship between producer signals, product attributes, product type, and product performance. The clustering issue is due to the ability of hosts to have multiple listings, meaning not all listings are independent of each other. Three models are estimated for each of the two dependent variables. Logarithmic transformations are used on both dependent variables to address skewing issues. Because of this, when results are discussed, effects are presented in percent change form. To calculate percent change, the following formula is used:

$$(e^{\beta} - 1) * 100$$

The first model estimates the strength of the relationships between producer signals and performance. This provides evidence for the importance of signals to the supply side of P2P platforms and effects and R^2 values will be discussed. The second model incorporates the standard control variables which consist of listing attributes. Finally, a third model introduces interaction terms and tests the moderating effect of accommodation type on the relationship between producer signals and performance. Detailed regression models are found below:

$$M_1: \text{Log}(\text{Number of Reviews}) = \text{Constant} + \beta_1(\text{Superhost}) + \beta_1(\text{Membership}) + \beta_3(\text{Identity Verification}) + \beta_4(\text{Responsiveness}) + \epsilon$$

$$M_2: \text{Log}(\text{Number of Reviews}) = \text{Constant} + \beta_1(\text{Superhost}) + \beta_1(\text{Membership}) + \beta_3(\text{Identity Verification}) + \beta_4(\text{Responsiveness}) + \beta_5(\text{Beds}) + \beta_6(\log(\text{Price})) +$$

$$\begin{aligned} & \beta_7(\text{Flexible}) + \beta_8(\text{Moderate}) + \beta_9(\text{Amenities}) + \beta_{10}(\text{Listing Age}) + \\ & \beta_{11}(\text{Instant Bookable}) + \beta_{12}(\text{East Coast}) + \beta_{13}(\text{South}) + \beta_{14}(\text{Midwest}) + \\ & \beta_{15}(\text{Southwest}) + \beta_{16}(\text{Entire Home}) + \epsilon \end{aligned}$$

$$\begin{aligned} M_3: \text{Log}(\text{Number of Reviews}) = & \text{Constant} + \beta_1(\text{Superhost}) + \beta_1(\text{Membership}) + \\ & \beta_3(\text{Identity Verification}) + \beta_4(\text{Responsiveness}) + \beta_5(\text{Beds}) + \beta_6(\log(\text{Price})) + \\ & \beta_7(\text{Flexible}) + \beta_8(\text{Moderate}) + \beta_9(\text{Amenities}) + \beta_{10}(\text{Listing Age}) + \\ & \beta_{11}(\text{Instant Bookable}) + \beta_{12}(\text{East Coast}) + \beta_{13}(\text{South}) + \beta_{14}(\text{Midwest}) + \\ & \beta_{15}(\text{Southwest}) + \beta_{16}(\text{Entire Home}) + \beta_{17}(\text{Entire Home} * \text{Superhost}) + \\ & \beta_{18}(\text{Entire Home} * \text{Membership}) + \beta_{19}(\text{Entire Home} * \text{Identity Verification}) + \\ & \beta_{20}(\text{Entire Home} * \text{Responsiveness}) + \epsilon \end{aligned}$$

$$\begin{aligned} M_1: \text{Log}(\text{Reverse Rating Score}) = & \text{Constant} + \beta_1(\text{Superhost}) + \beta_1(\text{Membership}) + \\ & \beta_3(\text{Identity Verification}) + \beta_4(\text{Responsiveness}) + \epsilon \end{aligned}$$

$$\begin{aligned} M_2: \text{Log}(\text{Reverse Rating Score}) = & \text{Constant} + \beta_1(\text{Superhost}) + \beta_1(\text{Membership}) + \\ & \beta_3(\text{Identity Verification}) + \beta_4(\text{Responsiveness}) + \beta_5(\text{Beds}) + \beta_6(\log(\text{Price})) + \\ & \beta_7(\text{Flexible}) + \beta_8(\text{Moderate}) + \beta_9(\text{Amenities}) + \beta_{10}(\text{Listing Age}) + \\ & \beta_{11}(\text{Instant Bookable}) + \beta_{12}(\text{East Coast}) + \beta_{13}(\text{South}) + \beta_{14}(\text{Midwest}) + \\ & \beta_{15}(\text{Southwest}) + \beta_{16}(\text{Entire Home}) + \epsilon \end{aligned}$$

$$\begin{aligned} M_3: \text{Log}(\text{Reverse Rating Score}) = & \text{Constant} + \beta_1(\text{Superhost}) + \beta_1(\text{Membership}) + \\ & \beta_3(\text{Identity Verification}) + \beta_4(\text{Responsiveness}) + \beta_5(\text{Beds}) + \beta_6(\log(\text{Price})) + \\ & \beta_7(\text{Flexible}) + \beta_8(\text{Moderate}) + \beta_9(\text{Amenities}) + \beta_{10}(\text{Listing Age}) + \\ & \beta_{11}(\text{Instant Bookable}) + \beta_{12}(\text{East Coast}) + \beta_{13}(\text{South}) + \beta_{14}(\text{Midwest}) + \\ & \beta_{15}(\text{Southwest}) + \beta_{16}(\text{Entire Home}) + \beta_{17}(\text{Entire Home} * \text{Superhost}) + \\ & \beta_{18}(\text{Entire Home} * \text{Membership}) + \beta_{19}(\text{Entire Home} * \text{Identity Verification}) + \\ & \beta_{20}(\text{Entire Home} * \text{Responsiveness}) + \epsilon \end{aligned}$$

RESULTS

Descriptive Statistics

The descriptive statistics in Table 1 show that the number of reviews is positively skewed with a mean of 48.81, a standard deviation of 59.84 and ranging from 0 to 612. About 68% of listings are entire homes and 32% are rooms. For rating score, the average accommodation has a 95.47 score, with a minimum of 20 and maximum of 100 which is negatively skewed. The average host has a membership length of 4.33 years. Also, 49% of hosts are Superhosts, 75% of hosts have the “responds within an hour” message present on their profile, and 54% of hosts are identity verified. An average listing has 2.17 beds, costs \$176.40 per night, and offers 30 amenities. As for the cancellation policies, 14% of listings have a flexible cancellation policy, 35% have a moderate policy, and 51% have a strict policy. Additionally, 46% of listings are available for instant booking. Lastly, the regional split of listings goes as follows: 14% of listings are in the South, 7% are in the Southwest, 7% are in the Midwest, 43% are on the West Coast, and 29% are on the East Coast.

Table 1: Descriptive Statistics

	Minimum	Maximum	Mean*	Std. Dev.
Number of reviews	0	612	48.81	59.84
Rating Score	20	100	95.47	5.46
Superhost	-	-	.49	-
Membership Length	0.27	11.37	4.33	1.87
Identity Verified	-	-	.54	-
Responsiveness	-	-	.75	-
Entire Homes	-	-	.68	-
Beds	0	40	2.17	1.77
Price	10	10000	176.4	259.92
Cancellation Policy				
Flexible	-	-	.14	-
Moderate	-	-	.35	-

Strict	-	-	.51	-
Amenities	1	111	30.45	11.54
Listing Age	1	4.63	2.35	0.97
Instant Booking	-	-	.46	-
Region				
South	-	-	.14	-
Southwest	-	-	.7	-
Midwest	-	-	.7	-
West Coast	-	-	.43	-
East Coast	-	-	.29	-

N=77445

*Mean column contains proportion values for categorical variables (Superhost, Identity Verified, Responsiveness, Entire Homes, Cancellation Policy, Instant Booking, and Region).

Regression Analysis

Regressing Number of Reviews (Product Prominence) on Signals

Due to the large sample size, widespread significance occurs. Therefore, when presenting results, the effect sizes (shown in percent change) are the focal point. Model 1 in Table 2 estimates the relationship between producer signals alone and performance as measured by logged number of reviews. Model 1 has an R-squared value of .180 and all signals are significant at or below the $p < .05$ level. This suggests producer signals alone explain 18% of the variance in number of reviews. When controlling for other producer signals, the presence of the Superhost badge gains hosts 103.40% more reviews than those without the signal. As for membership, for each year of host membership, number of reviews falls by 1.98%. Similar to the Superhost badge, the identity verification badge also has a positive relationship with number of reviews. When host profiles have identity verification, they receive 13.88% more reviews. Finally, the strongest producer signal is responsiveness. When a host's profile indicates that they respond within an hour of inquiries, their listings are expected to receive 131.64% more reviews than those who do not.

Table 2: Parameter Estimates for Logged Number of Reviews on Signals

Parameter	Model 1		Model 2		Model 3	
	β	SE	β	SE	β	SE
Superhost	0.71***	0.03	0.60***	0.02	0.58***	0.03
Membership	-0.02*	0.01	-0.06***	0.01	-0.04***	0.01
Identity Verification	0.13***	0.03	-0.04	0.02	-0.04	0.03
Responsiveness	0.84***	0.03	0.71***	0.03	0.72***	0.03
Beds			0.03***	0.01	0.03***	0.01
Logged Price			-0.49***	0.02	-0.49***	0.02
Flexible Cancellation			0.00	0.02	0.00	0.02
Moderate Cancellation			0.26***	0.02	0.25***	0.02
Amenities			0.02***	0.00	0.02***	0.00
Listing Age			0.44***	0.01	0.44***	0.01
Instant Bookable			0.30***	0.02	0.30***	0.02
East Coast			0.06**	0.02	0.06**	0.02
South			0.07*	0.03	0.06*	0.03
Midwest			-0.01	0.03	-0.01	0.03
Southwest			-0.14***	0.04	-0.14***	0.04
Entire Home (EH)			0.39***	0.02	0.50***	0.06
EH * Superhost					0.02	0.03
EH * Membership					-0.02*	0.01
EH * Identity Verification					0.00	0.04
EH * Responsiveness					-0.02	0.05
(Intercept)	2.48***		3.20***		3.13***	
(Scale)	1.43		1.14		1.14	
R ²	.18		.35		.35	
F	4259.67***		2582.67***		2068.25***	

* p≤.05, ** p≤.01, *** p≤.001

R² values and F-statistics from OLS equivalent.

Model 2 introduces listing attributes into the model and the R-squared value rises to .35. This suggests that producer signals along with listing attributes account for 35% of the variance in number of reviews, an improvement of 16 percentage points. For the Superhost badge, Model 2 still presents a strong positive relationship, but the effect dropped by 23.23 percentage points from 105.44% to 82.21%. As for membership, the effect actually grew from the first to the second model. Instead of a decrease of 1.98% for each year of host membership on Airbnb, listings can expect a decrease of 5.82% for

each year of membership. Originally a positive effect in Model 1, identity verification saw a reversal of its effect to negative. Thus, when controlling for listing attributes and other signals, listings with the identity verification signal receive 3.92% less reviews than those without it. Finally, similar to the Superhost badge, the impact of responsiveness on number of reviews remained positive and decreased in effect by almost 30 percentage points from 131.64% to 103.40%.

The listing attributes in Model 2 are all related to number of reviews in the expected ways. As number of beds, amenities, and listing age increase by one unit, number of reviews increase by 3.05%, 2.02%, and 55.27%, respectively. For each percent increase in price, number of reviews drops by .48%. When a listing has a moderate cancellation policy compared to a strict policy, it is expected to receive 29.70% more reviews. When a listing has instant bookings enabled, they are expected to receive 34.99% more reviews than those that do not allow instant bookings. Some regional variables were also significant. Compared to the West Coast, listings in the South and on the East Coast receive 7.25% and 6.18% more reviews, respectively. Additionally, Southwestern listings receive 13.06% fewer reviews than West Coast listings. The variables for Midwestern region and flexible cancellation policy were not significant. Finally, when a rental is an entire home as opposed to a room, it receives 47.70% more reviews.

Model 3 adds interaction between accommodation type and each of the four major producer signals. This analysis only produces significant interaction between entire homes and membership. This suggests that the effects of the membership signal differ between

entire home bookings and room bookings. For entire home bookings, there is a penalty on the membership signal. This means the negative relationship between membership and number of reviews is stronger for entire homes than for rooms.

Regressing Rating Score (Product Quality) on Signals

Model 1 in Table 3 estimates the relationship between producer signals and performance as measured by rating score. Due to a left skew, the rating score measure was reverse-coded before its logarithmic transformation. Therefore, high rating scores correspond to poor performance and low rating scores correspond to high performance. Thus, a decrease in the reverse-coded rating score is associated with an increase in the pre-transformation rating score.

The model shows that the producer signals alone account for 10% of the variance in rating score. In this base model, all producer signals are significant. Superhost status is associated with a higher rating score as the coefficient indicates that Superhost status is associated with a 60.94% decrease on the reverse-coded rating scale. Membership length is associated with a 1% decrease on the reverse-coded rating scale for each additional year, suggesting higher rating scores for longer membership. Identity verification is also associated with higher rating scores as demonstrated by a 12.19% decrease on the reverse-coded rating scale. Finally, responsiveness is negatively related to rating score, with the signal leading to a 68% increase on the reverse-coded rating scale.

Model 2 adds listing attributes and accounts for 16% of the variance in rating score, a 6-percentage point increase. In the model, all producer signals maintain their statistical significance. For the Superhost badge, when controlling for other signals and

listing attributes, its presence is associated with 56.83% decrease on the reverse-coded rating score, maintaining its association with higher rating scores. For membership, each additional year a host has been on the platform, the reverse-coded rating score falls by 2.96%. For identity verification, when the signal is present, the reverse-coded rating score falls by 16.47% and for responsiveness, the reverse-coded rating score increases by 56.83%.

Table 3: Parameter Estimates for Logged Rating Score on Signals[†]

Parameter	Model 1		Model 2		Model 3	
	β	SE	β	SE	β	SE
Superhost	-0.94***	0.02	-0.84***	0.02	-0.84***	0.02
Membership	-0.01*	0.00	-0.03***	0.00	-0.04***	0.01
Identity Verification	-0.13***	0.02	-0.18***	0.02	-0.16***	0.03
Responsiveness	0.52***	0.02	0.45***	0.02	0.45***	0.03
Beds			0.08***	0.01	0.08***	0.01
Logged Price			-0.47***	0.02	-0.47***	0.02
Flexible Cancellation			-0.34***	0.02	-0.34***	0.02
Moderate Cancellation			-0.18***	0.02	-0.18	0.01
Amenities			-0.01***	0.00	-0.01***	0.00
Listing Age			0.22***	0.01	0.22***	0.01
Instant Bookable			0.33***	0.02	0.33***	0.02
East Coast			0.17***	0.02	0.17***	0.02
South			-0.30***	0.02	-0.30***	0.02
Midwest			-0.13***	0.03	-0.13***	0.03
Southwest			-0.32***	0.03	-0.32***	0.03
Entire Home (EH)			0.29***	0.02	0.25***	0.05
EH * Superhost					0.01	0.03
EH * Membership					0.01	0.01
EH * Identity Verification					-0.03	0.03
EH * Responsiveness					0.00	0.04
(Intercept)	0.90***		2.58***		2.61***	
(Scale)	2.29		2.13		2.13	
R ²	.10		.16		.16	
F	2085.51***		935.50***		748.62***	

* p≤.05, ** p≤.01, *** p≤.001

R² values and F-statistics from OLS equivalent.

†: Original score inverted before log transformation.

The listing attributes in Model 2 are also worth noting. All attributes are significant. For each additional bed and additional year a listing has been active, the reverse-coded rating score increases by 8.32% and 24.61%, respectively, suggesting lower pre-transformation rating scores for these attributes. For each additional percent increase in price and each additional amenity, the reverse-coded rating score falls by .47% and 1%, respectively, suggesting higher pre-transformation rating scores for these attributes. Also, both flexible and moderate cancellation policies have a positive effect on pre-transformation rating scores. Concerning the reverse-coded rating score, flexible policies receive a 28.82% lower score than strict policies and moderate policies receive 16.47% lower score. Additionally, when a listing has instant booking enabled, it receives a 39.10% higher reverse-coded rating score. Regional variables show that the South, Midwest, and Southwest listings receive 25.92%, 12.19%, and 27.39% lower reverse-coded rating scores than West Coast listings, respectively and East Coast listings receive 18.53% higher reverse-coded rating scores than West Coast listings. When an accommodation is an entire home, rather than a room rental, it receives a reverse-coded rating score that is 33.64% higher. Finally, Model 3 adds interaction between accommodation type and producer signals. The model produces no significant interaction terms, suggesting no differences in effect for producer signals based on accommodation type.

DISCUSSION AND CONCLUSION

This study diverges from previous research by considering both product quality and product prominence as measures of product performance on P2P platforms, and thus provides a more inclusive and robust assessment of product performance. The central research questions for this study are: *how do platform producers' reputation signals contribute to the performance of their products on peer-to-peer platforms* and *how does product type moderate the relationship between platform producers' reputation signals and product performance?* These questions are addressed by investigating two hypotheses: *producer signals have a positive relationship with performance* (H1) and *consumers' physical risk positively moderates the relationship between producer signals and performance* (H2). In this analysis, performance is measured in two ways: product quality and product prominence. Product prominence is measured through number of reviews and product quality is measured through rating score. Because of this, separate models are estimated for each of the performance measures.

Hypothesis one, which states producer signals have a positive relationship with performance receives mixed support. In the product prominence analysis, the signals in the base model overall are sufficient correlates of product prominence. However, only three of four producer signals (Superhost, responsiveness, and identity verification) are positively related to prominence, while one (membership) is weakly and negatively related to prominence. One potential explanation for membership length's negative relationship could be that hosts that are newer to the platform are doing more to encourage reviews so that they can build up their reputation. With previously mentioned

research pointing out review rates range from 30-70%, it is easy to imagine newer hosts striving for the high end of this range in review completion. Thus, logically, hosts who have been around longer would be less concerned with number of reviews due to the higher number of reviews that comes with being active on the platform for a longer period.

When considering the product attributes, identity verification, originally a positive correlate, goes negative and loses its significance. This suggests product attributes may play a large role in determining producer signal usefulness. In the product quality analysis, all producer signals are significant. One of the producer signals, membership, has a negative effect. When considering product attributes, the relationships remain the same.

Overall, these mixed results for hypothesis one suggest most producer signals are positively related to performance, while certain producer signals may matter for product performance based on product attributes. The strong influence of product attributes like cancellation policy and instant booking availability suggest that practical features such as policies (cancellation, return, warranties, etc.) may be more important to performance than producer signals like identity verification and membership length. This is consistent with studies that have shown price, location, instant booking, cancellation policy, and renting policies to be important correlates of performance (Benetiz-Airoles, 2018; Guttentag et al., 2018; Jang et al., 2019; Zhu et al., 2019).

Hypothesis two, which states that consumers' privacy risk positively moderates the relationship between producer signals and performance is weakly supported by only one of eight interaction terms. The significant interaction present is between membership length and entire home rentals. The relationship overall is negative, but the penalty is less for high risk products. When one books a room rather than an entire home, they may face a higher level of physical risk because they are often sharing spaces with other customers and even the host (Airbnb). In markets that require trust, the consumer must minimize the risk of adverse outcomes (Lee et al., 2005). Because room rentals are perceived as riskier (Lutz & Newlands, 2018), those booking them may rely on membership length as a risk reduction tool. Thus, this finding supports hypothesis two.

While there is support for hypothesis two, the remaining seven interaction terms are insignificant. This lack of interaction is in line with an early study by Gregg & Walczak (2008) which found no support for interaction between producer signals and product type in a P2P e-commerce context.

While many of this study's results are mixed, they still draw attention to the potential impact producer signals can have on the performance of platform producers and their products on peer-to-peer platforms. This insight is in line with previous studies that find producers' characteristics and firms' e-image influence how consumer evaluate products and services prior to purchasing them (Gregg & Walczak, 2008; Huurne, M. et al., 2018). This is evidenced through producer signals' large impact on performance even after considering the impact of product attributes like price, location, and policies.

As with any research, this study has certain limitations. First, related to the results, causality issues may have caused certain producer signals to be negatively related to performance. For example, in the product quality model, responsiveness was negatively related to performance. A potential explanation for this is that hosts who have low performance are working harder to achieve the responsiveness signal, thus responsiveness is associated with low performing listings.

Another variable related limitation concern is the Superhost signal. While most research considers the producer signal while looking at performance in this context, it is important to note it may have an influence on the model because it is in part achieved through hitting certain performance metrics that are related to the dependent variables. Specifically, the Superhost criteria requiring a high review rate, a high response rate, and high performance in reviews are concerning (Airbnb.com).

Although Airbnb is one of the most popular P2P platforms, these results may have limited generalizability outside of home sharing platforms. Although this study assesses both number of reviews and ratings to provide a more comprehensive assessment than previous studies, measuring performance on P2P platforms with rating scores and reviews may still be inadequate. Researchers find support for a “don’t-want-to-complain-bias” which suggests the accuracy of performance measures like rating scores and reviews may be tainted because of social pressure in P2P markets that lead to fewer negative reviews (Berg et al., 2020).

Despite these limitations, overall, this research helps extend the P2P platform literature by providing useful insights to platform owners, producers, and consumers concerning how both producer- and product-related signals can impact product performance. Producers on two-sided platforms should be mindful of their performance on signal measures as well as how they may vary based on the type of product they are offering. Furthermore, platforms and producers can increase their revenue by embracing flexibility. This is evidenced through the strong impact of transaction related variables like cancellation policy and instant booking on product performance in the analysis.

Platform owners and the demand side of platform markets should also invest in promoting certain types of producer signals. On Airbnb, this study finds that the Superhost badge was a consistently strong correlate of product performance. Airbnb invests a lot in this signal and producers must work hard to achieve it. Because of this, the signal's visibility and cost are high. Costly and highly visible producer signals are better quality than cheap and less visible producer signals (Connelly et al., 2011). Because of this, platform owners should work to create producer signals with high visibility on their platforms with strict criteria in order to better facilitate transactions.

Responsiveness was another strong correlate of performance, specifically considering product prominence. This measure, which considers whether a host responds to accommodation requests within an hour, is important to the booking process. Platform owners should invest in making communication between the two sides of their markets easy, quick, and often. Products whose producer communicates quickly with interested

consumers likely complete more transactions, earning both the platform owner and producer more income.

This work provides an update to the signaling theory framework and conceptual models proposed by Xie and Mao (2017) and Zhao and Rahman (2019). This is achieved by considering the importance of product type as established by research suggesting key differences in consumers based on product offerings. Specifically, this research proposes looking at products through the lens of physical risk for consumers. Though the moderation hypothesis received marginal support, this analysis does lend support to updating, or at least considering product type when discussing the signaling framework. While we cannot say that overall higher risk products are more positively impacted by producer signals than lower risk products, we can conclude that signal performance varies slightly by product type, as evidenced through the interaction between membership length and entire homes. Further research on other platforms, products, and signals should be conducted to lend more support for this assumption. Specifically, studies utilizing P2P lending platforms, ridesharing platforms, and resource sharing platforms may provide sufficient evidence that producer signals should be understood as context- and product-specific rather than universal.

REFERENCES

- Abrate, G. & Viglia, G. (2019). Personal or product reputation? Optimizing revenues in the sharing economy. *Journal of Travel Research*, 58(1), 136-148.
- Akerlof, G. A. (1970). The market for “lemons”: Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3), 488-500.
- Benítez-Aurioles, B. (2018). Why are flexible booking policies priced negatively? *Tourism Management*, 67, 312-325.
- Berg, L., Sletteameas, D. Kjorstad, I., & Rosenberg, T. G. (2020). Trust and the don't-want-to-complain bias in peer-to-peer platform markets. *International Journal of Consumer Studies*, 00, 1-12.
- Brown, R. S. (2015). The role of reputation and signaling in highly fragmented industries. *Entrepreneurial Executive*, 20, 52-60.
- Cai, S., Lin, X., Xu, D., & Xin Fu. (2016). Judging online peer-to-peer lending behavior: A comparison of first-time and repeated borrowing requests. *Information & Management*, 53, 857-867.
- Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of Management*, 37(1), 39-67.
- Cox, M. (2019, March 2). Inside Airbnb: adding data to the debate. Retrieved from <http://insideairbnb.com/>.
- Cramer, J & Krueger, A. B. (2016). Disruptive change in the taxi business: The case of Uber. *The American Economic Review*, 106(5), 177-182.
- Dimoka, A., Hong, Y., & Pavlou, P. A. (2012). On product uncertainty in online markets. *MIS Quarterly*, 36(2), 395-426.
- Evans, P.C. & Gawer, A. (2016). The rise of the platform enterprise: A global survey. *The Emerging Platform Economy Series*, 1, 4-21.
- Floyd, K., Freling, R., Alhoqail, S., Young Cho, H., & Freling, T. (2014). How online product reviews affect retail sales: A meta-analysis. *Journal of Retailing*, 90(2), 217-232.
- Gregg, D. G. & Waiczak, S. (2008). Dressing your online auction business for success: An experiment comparing two eBay businesses. *MIS Quarterly* 32(3), 653-670.
- Guttentag, D., Smith, S., Potwarka, L., & Havitz, M. (2018). Why tourists choose Airbnb: A motivation-based segmentation study. *Journal of Travel Research*, 57(3), 342-359.

- Huurne, M., Ronteltap, A., Guo, C., Corten, R., & Buskens, V. (2018). Reputation effects in socially driven sharing economy transactions. *Sustainability*, 10, 1-19.
- Jang, J., Choi, J., Jeon, H., & Kang, J. (2019). Understanding U.S. travellers' motives to choose Airbnb: a comparison of business and leisure travellers. *International Journal of Tourism Sciences*, 19(3), 192-209.
- Jie, D. Jibo, H., Yong, L., & Meichen, M. (2019). Is there an effective reputation mechanism in peer-to-peer lending? Evidence from China. *Financial Letters*, 30, 208-215.
- Kromidha, E. & Robson, P. (2016). Social identity and signaling success factors in online crowdfunding. *Entrepreneurship & Regional Development*, 28(9-10), 605-629.
- Lee, B., Ang, L., & Dubelaar, C. (2005). Lemons on the Web: A signalling approach to the problem of trust in Internet commerce. *Journal of Economic Psychology*, 26(5), 607-623.
- Lin, M., Prabhala, N. R., & Viswanathan, S. (2013). Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. *Management Science*, 59(1), 17-35.
- Lu, S., Srinivasan, K., & Sun, B. (2009). Internet auction features as quality signals. *Journal of Marketing*, 73(1), 75-92.
- Lutz, C. & Newlands, G. (2018). Consumer segmentation within the sharing economy: The case of Airbnb. *Journal of Business Research*, 88, 187-196.
- Mariotto, C. (2016). Competition for lending in the internet era: The case of peer-to-peer lending marketplaces in the USA. *Digiworld Economic Journal*, 103, 35-58.
- Melnik, M. I., Richardson, P., & Tompkins, D. (2011). How seller and product characteristics impact promotion on eBay. *Journal of Promotion Management*, 17(4), 426-437.
- Moody, J., Middleton, S., & Zhao, J. (2019). Rider-to-rider discriminatory attitudes and ridesharing behavior. *Transportation Research Part F*, 258-273.
- Moon, H., Miao, L., Hanks, L., & Line, N. D. (2019). Peer-to-peer interactions: Perspectives of Airbnb guests and hosts. *International Journal of Hospitality Management*, 77, 405-414.
- Morse, A. (2015). Peer-to-peer crowdfunding: Information and the potential for disruption in consumer lending. *Annual Review of Financial Economics*, 7(1), 463-482.
- Ogut, H. & Tas, B.K.O. (2012). The influence of internet customer reviews on the online sales and prices in hotel industry. *The Service Industries Journal*, 32, 197-214.

- Pratt, A. N., Morris, E. A., Zhou, Y., Khan, S., & Chowdhury, M. (2019). What do riders tweet about the people that they meet? Analyzing online commentary about UberPool and Lyft Shared/Lyft Line. *Transportation Research Part F*, 459-472.
- Puschmann, T. & Alt, R. (2016). Sharing economy. *Business & Information Systems Engineering*, 58(1), 93-99.
- Rochet, J. & Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*, 1(4), 990-1029.
- Rochet, J. & Tirole, J. (2006). Two-sided markets: a progress report. *RAND Journal of Economics*, 37(3), 645-667.
- Ryu, H., Basu, M., & Saito, O. (2019). What and how are we sharing? A systematic review of the sharing paradigm and practices. *Sustainability Science*, 14(2), 515-527.
- Sarriera, J. M., Escovar Álvarez, G., Blynn, K., Alesbury, A., Scully, T., & Zhao, J. (2017). To share or not to share: Investigating the social aspects of dynamic ridesharing. *Transportation Research Record: Journal of the Transportation Research Board*, 2605(1), 109-117.
- Taeuscher, K. (2019). Reputation and new venture performance in online markets: The moderating role of market crowding. *Journal of Business Venturing*, 34(6).
- Tell, C. (2015, December 30). *With Via, Sharing More Than Just a Ride*. The New York Times. <https://www.nytimes.com/2015/12/31/fashion/with-via-sharing-more-than-just-a-ride.html>.
- Teubner, T. (2018). The web of host–guest connections on Airbnb: A network perspective. *Journal of Systems and Information Technology*, 20(3), 262-277.
- Vacation rentals, homes, experiences, & places – Airbnb*. Airbnb. Retrieved Airbnb. November 11, 2019, from <http://airbnb.com/>.
- Van Alstyne, M. W., Parker, G. G., & Choudary, S. P. (2016) Pipelines, platforms, and the new rules of strategy. *Harvard Business Review*.
- Xie, K. & Mao, Z. (2017). The impacts of quality and quantity attributes of Airbnb hosts on listing performance. *International Journal of Contemporary Hospitality Management*, 29(9), 2240-2260.
- Ye, Q., Law, R., Gu, B., & Chen, W. (2011). The influence of user-generated content on traveler behavior: An empirical investigation on the effects of e-word-of-mouth to hotel online bookings. *Computers in Human Behavior*, 27, 634-639.
- Zhang, J. (2019). Listening to the consumer: Exploring review topics on Airbnb and their impact on listing performance. *Journal of Marketing Theory and Practice*, 27(4), 371-389.

- Zhang, L., Yan, Q., & Zhang, L. (2018). A computational framework for understanding antecedents to guests' perceived trust towards hosts on Airbnb. *Decision Support Systems*, 115, 105-116.
- Zhao, D. & Rahman, Md. J. (2019). Effects of Airbnb hosts' quality and quantity attributes on reservation performance: The case of Hong Kong. *Academy of Marketing Studies Journal*, 23(2), 1-13.
- Zhu, Y., Cheng, M., Wang, J., Ma, L., & Jiang, R. (2019). The construction of home feeling by Airbnb guests in the sharing economy: A semantics perspective. *Annals of Tourism Research*, 75, 308-321.