Competitive Positioning of Complementors on Digital Platforms: Evidence from the Sharing Economy

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Completed Research Paper

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Abstract

Various platforms have recently emerged within the sharing economy and the phenomenon has started to affect several industries. While platforms such as Airbnb and BlaBlaCar are providing convenience and economic benefits to end-users, their success also turned them into crowded and competitive markets. With increasing numbers of products and services offered via the platforms, signals such as popularity and reputation have become critical market mechanisms that affect the decision-making processes of end-users. In this paper, we examine the positioning strategies of new hosts on Airbnb, a platform focused on accommodation sharing, to understand how they attempt to cope with the inherent lack of credible quality signals as they join the platform. By analyzing close to 47,000 listings, we find that new hosts follow a cost-leadership strategy rather than trying to differentiate their offerings. We also analyze how this strategy changes depending on prior platform-specific experience of hosts.

Keywords: Competitive positioning, digital platforms, sharing economy, intra-platform competition, differentiation, cost leadership, reputation, popularity

Introduction

Digital platforms bring together distinct groups of market participants (e.g., supply and demand side) in multi-sided markets. Businesses relying on this organizational structure therefore have to manage the value creation that occurs outside of the company instead of creating value through their own output (Parker et al. 2017). This focus on outside value creation through so-called complementors, who develop and deliver the respective content for the platform (e.g., apps, add-ons, plug-ins, modules, or extensions), has enabled
companies such as Apple and Google to scale rapidly, as their growth is not limited by processes of hiring and training employees or by establishing a supply chain (Parker et al. 2016). These processes are now allocated to complementors outside the company itself, who can decide to participate in the platform at their own discretion by utilizing boundary resources (e.g., software development kits and application programming interfaces) offered by the platform in order to facilitate the creation of complementary assets (Ghazawneh and Henfridsson 2010).

For platform businesses, competition does therefore no longer revolve around controlling the value chain but rather around attracting and retaining a sufficient number of qualified complementors (de Reuver et al. 2017). For example, complementors have, to this day, developed a total of 2.2 million mobile applications (apps) for iOS devices (Statista 2017), which are available in Apple’s App Store and collectively represent a significant competitive advantage over rival platforms. While an ever-increasing number of innovative complementary assets can solidify the competitive advantage of the respective platform (i.e., inter-platform competition), the platform will also become a fierce competitive environment for complementors (i.e., intra-platform competition). Most of the prior research has, however, been focused on inter-platform competition (e.g., Boudreau 2010; Eisenmann et al. 2011; Rochet and Tirole 2006; Seamans and Zhu 2017), while only very few empirical studies have recognized the increasing importance of understanding intra-platform competition (e.g., Kapoor and Agarwal 2017; Tiwana 2015).

Intra-platform competition can be expected to be especially fierce, if the platform’s boundary resources restrict the variety of the complementary assets. This is often the case on digital platforms in the sharing economy, as the products and services offered via these platforms (e.g., transportation on Uber or accommodations on Airbnb) are rather standardized, meaning that complementors can only differentiate themselves from rivals to a certain extent. However, as these platforms foster recurring transactions between complementors and end-users, popularity information and reputation have become critical market mechanisms. For these signals to be credible, complementors offering a low quality must have higher costs acquiring them compared to those offering a high quality (Kirmani and Rao 2000; Spence 1973; Spence 2002). Signals such as a high number of previous bookings of a certain Uber driver or a high average rating for an accommodation on Airbnb therefore allow end-users to distinguish between low- and high-quality offerings. Previous research has found these signals to be of critical importance for the decision-making processes of end-users on platforms (e.g., Wells et al. 2011; Zhang and Liu 2012), meaning that a lack of such signals can put complementors at a serious disadvantage.

Newcomers on digital platforms therefore face a cold-start problem. As they have not conducted any transactions via the platform yet, they are unable to send any credible signals of quality to platform end-users. This means that their offerings, despite potentially being of the same quality, are much less likely to attract the attention of platform end-users compared to the offerings of complementors who have already conducted transactions. Though the platform provider could, theoretically, generate additional attention for newcomer offerings, most of them have adopted a neutral position (Filippas and Gramstad 2016). Instead, platform providers focus on establishing and enforcing the fundamental rules on the platform (e.g., what complementors are allowed onto the platform) through platform governance mechanisms and let the market determine winners and losers (e.g., Wareham et al. 2014; Wessel et al. 2017), as the relationship between them and the complementors is at arm’s length rather than a traditional principal-agent relationship (Tiwana et al. 2010).

In this paper, we examine the strategies of new hosts on Airbnb, one of the most successful digital platforms in the sharing economy, to understand how they attempt to cope with the inherent lack of credible quality signals as they join the platform. Officially, Airbnb does not restrict the access to its platform and claims that almost anyone can be a host (Airbnb 2017b). Joining the platform is simple and does not require a financial investment, as the accommodation that is offered via the platform typically belongs to the host anyway. Barriers to entry for new hosts are therefore mainly created by established hosts through their popularity and reputation. In the absence of mechanisms to attract additional attention from platform end-users, new hosts are limited to the boundary resources provided by the platform (i.e., the user interface used to publish accommodations on the platform) to promote their accommodation. However, the question of how complementors position their offerings with respect to their competition in a conscious or unconscious attempt to compensate for their lack of popularity and reputation remains unanswered in prior research. Drawing upon the generic strategies of Porter (1980), they can only achieve an advantage with a strategy that either targets cost leadership, differentiation, or focus. While some hosts on Airbnb follow a
focus strategy, by offering unusual accommodations such as castles or boats, the majority of listings will be chosen due to their location rather than due to their focus on a specific market niche. We therefore focus on examining whether new hosts on Airbnb follow a cost-leadership or a differentiation strategy (or both). Additionally, we examine whether experienced hosts follow a different strategy compared to inexperienced hosts when adding new accommodations to the platform. Our research is guided by the following research questions:

**RQ1:** What competitive strategy do new complementors follow on a digital platform in order to compensate for the lack of quality signals?

**RQ2:** Do experienced complementors position their new offerings differently than inexperienced complementors?

By analyzing close to 47,000 listings from Airbnb at three different points in time, we found that new, inexperienced hosts do not follow a differentiation strategy on the platform. Instead, they target cost leadership by undercutting prices of their competitors in an attempt to compensate for the lack of reputation and popularity. In contrast, experienced hosts offering new accommodations charge above-average prices, while focusing on booking convenience rather than on the quality of their listings.

Our study makes the following contributions to the emerging research on digital platforms. First, while previous studies have mainly been focused on inter-platform competition (e.g., Boudreau 2010; Eisenmann et al. 2011; Rochet and Tirole 2006), little attention has been directed towards intra-platform competition among complementors and possible entry barriers that arise due to competition rather than platform governance mechanisms. Second, we contribute to the literature by demonstrating that different groups of complementors position their offerings differently, depending on their prior platform-specific experience.

The remainder of the paper is structured as follows: First, the theoretical background is laid out, followed by the research context and the hypotheses development. Next, we describe the context the research project has been conducted in as well as the research methodology and data. These sections are follow by a description of the results, including both descriptive as well as econometric evidence. In the concluding section, we discuss the implications for research and practice and point out the paper’s limitations as well as promising areas for future research.

**Theoretical Background**

**Sharing Economy**

The sharing economy can broadly be defined as digital platforms that facilitate peer-to-peer transactions of products and services. Over the last few years, various platforms have emerged within the sharing economy and the phenomenon has started to affect different branches and industries. Today, the products and services available range from housing (e.g., Airbnb) to mobility (e.g., BlaBlaCar) and from labor (e.g., Amazon Mechanical Turk) to finance (e.g., Prosper). Though the label sharing has also been used in B2C and B2B contexts to describe offers such as short-term car rental services (e.g., Car2Go or DriveNow), we focus primarily on the notion of peer-to-peer transactions.

The rise of the sharing economy is driven by a number of societal and technological trends (Puschmann and Alt 2016). First, while ownership of goods such as cars has been the predominant model for centuries, we now see a shift towards temporary usage, often offering consumers more convenience, economic benefits, and ecological sustainability (Bardhi and Eckhardt 2015). Second, the exchange of products and services is only made possible through digital platforms that bring together distinct groups of market participants and facilitate transactions among them, while mitigating risks and ensuring accountability through trust and reputation mechanisms (Puschmann and Alt 2016). These platforms therefore helped to lower the transaction costs of sharing with strangers to such an extent that sharing is no longer restricted geographically or to a person’s own social network (Marton et al. 2017). Furthermore, many of the offerings of the sharing economy have only become feasible with the proliferation of mobile devices, as they rely strongly on the features of mobile applications such as the possibility to share one’s geographic location with others.

Though platforms in the sharing economy often start by targeting niche markets, many have now become a mainstream success. For instance, Airbnb is now offering more rooms than the three world’s biggest hotel
Competitive Positioning of Complementors on Digital Platforms

Over the last few years, major digital platforms such as Apple’s App Store and Google’s Playstore were able to attract hundreds of thousands of complementors (i.e., developers), who are now offering a wide variety of applications on the respective platform. Complementors are thus competing with their offerings against other complementors for the attention of end-users and for a chance to serve a sizable share of the market. Upon joining a platform, complementors therefore have to decide on a competitive strategy, which determines how they will compete with rivals within the respective market segment (Brooksbank 1994). The question of how to identify the most appropriate competitive strategy has been of interest to scholars in strategic management for long. However, with entire markets shifting towards platform-based business models, this question also becomes relevant for digital platforms, as they become increasingly crowded and competitive environments.

The strategy literature distinguishes between two fundamentally different approaches for achieving competitive advantage, namely, the inside-out approach and the outside-in approach (Baden-Fuller 1995). The inside-out approach starts with an analysis of a firm’s internal environment and is guided by the belief that internal resources and capabilities are the keys to achieving competitive advantage in the marketplace (e.g., the resource-based view by Barney (1991)). In contrast, the outside-in approach is concerned with how well a firm’s offerings fit the market and posits that a firm should position its offerings strategically in the market to achieve competitive advantage (positioning school). In this study, we focus on the latter perspective for two reasons. First, since Airbnb’s ecosystem and its boundary resources can be seen as given, complementors have to position themselves within this given market rather than developing resources that might not align with the unchangeable environment. Second, accommodations offered via Airbnb or reputation built up on the platform will seldom represent a rare resource that is difficult to imitate by competitors.

Porter (1980) provides a classification scheme that contains three generic strategies, namely, differentiation, cost leadership, and focus and that, despite limitations (cf., Chrisman et al. 1988), remains popular to this day. A differentiation strategy aims at offering products and services that are perceived as uniquely attractive by the demand side of the market, thus attracting customers that are less price sensitive and have a specific need that is under-served by the other products and services available. A differentiation strategy is therefore focused on creating a product or service that is perceived to be different by the demand side of the market. To achieve this, firms can either focus on innovating differentiation by emphasizing R&D.
and pioneering or on marketing differentiation by offering superior product and service quality, convenience, and promotion (Miller 1986). In contrast, a cost-leadership strategy emphasizes a low-cost position within the market by undercutting prices of competitors (Hill 1988). Cost leaders therefore often supply standard products and services that are interchangeable with those of competitors. Finally, a focus strategy targets a specific market niche (e.g., in terms of customers or geographic location) with either a differentiation or a cost-leadership strategy. As most digital platforms categorize the complementary assets by, for instance, purpose or geographical location, platform providers are essentially forcing complementors to follow a focus strategy, thus leaving them with the choice to aim for differentiation or cost-leadership within the respective segment. Though Porter’s model categorizes firms that attempt to follow a differentiation and a cost-leadership strategy simultaneously as being stuck in the middle with no strategic advantage, this might not necessarily be true in all industries (Chrisman et al. 1988).

Most of the prior work on competition in the context of digital platforms has been focused on the competition among platforms (e.g., Boudreau 2010; Eisenmann et al. 2011; Rochet and Tirole 2006; Seamans and Zhu 2017) rather than within platforms (e.g., Kapoor and Agarwal 2017; Tiwana 2015). As such, there is still a dearth of research studies that examine how complementors position their offerings with respect to their competition in a conscious or unconscious attempt to achieve a favorable market position.

**Platform Experience**

Most digital platforms today are comprised of the same fundamental elements such as boundary resources and distinct groups of market participants that are brought together via the platform. Beyond these fundamental similarities, however, digital platforms can vary significantly with respect to their technological complexity and due to differences in the governance mechanisms applied by the platform provider. For instance, Apple is well known for exercising strong control over the entire platform ecosystem¹, while Google’s strategy is based on the open-source operating system Android, giving complementors much more freedom as to how they develop and market apps for the platform (Ghazawneh and Henfridsson 2013). Therefore, with the existence of major differences among platforms with respect to technological complexity and governance mechanisms, any experience a complementor gathers is likely to be platform-specific. Kapoor and Agarwal (2017) have shown that the platform-specific experience of complementors (e.g., smartphone apps for the iOS platform) has a much greater effect on their ability to sustain a superior performance within a platform ecosystem compared to a more general experience in the industry (e.g., smartphone apps). This means that, without platform-specific experience, it becomes very difficult for complementors to know in advance how their offerings will be perceived by the market and perform compared to other offerings within the same platform ecosystem (Kapoor and Agarwal 2017).

In order to be successful within a specific platform ecosystem, complementors therefore need to acquire direct experience through a process of learning by doing. This direct platform experience is shaped through two major mechanisms, which are responsible for the change in routines and beliefs (Levitt and March 1988). First, trial-and-error experimentation means that routines that are associated with a successful outcome will be used increasingly, while those associated with failure will be avoided (Cyert and March 1963). Second, over time, complementors will develop and accumulate knowledge-based assets such as new capabilities to utilize the platform’s boundary resources more effectively (Kapoor and Agarwal 2017). These capabilities are added to a pool of routines, which are updated whenever improved routines are discovered in an attempt to continuously search and identify higher performing configurations (Kapoor and Agarwal 2017; Levitt and March 1988). How efficient this process is depends on past successes and failures (Radner 1975).

A complementor with more platform experience has therefore accumulated more knowledge-based assets (Nerkar and Roberts 2004). Platform experience thus helps to improve the efficiency of using a platform’s boundary resources but also helps to reduce the costs of experimentation when introducing new offerings to the platform’s ecosystem (Zott 2003).

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¹ A platform and its complementary assets, functioning as a unit, form a platform ecosystem.
Hypotheses Development

Positioning Strategies of New Hosts

As mentioned above, a differentiation strategy is focused on creating a product or service that is perceived to be different by the demand side of the market. On the open market, these differences may be in the design, technology, features, customer service, and so on. However, the sharing economy is different from an open market, as the offered products and services are rather standardized and complementors can often only differentiate themselves from rivals to a certain extent, as the platform’s boundary resources may restrict the variety of the complementary assets.

On Airbnb, this means that hosts may differentiate themselves from their competition primarily from a marketing perspective by putting more effort into detailing the features and advantages of their accommodations, by providing information about them as a host, and by making the booking process as convenient as possible (Miller 1986). This could, for instance, include an exceptionally detailed description of the check-in/-out process and of the amenities of the accommodations and of the surroundings (e.g., distance to public transport or tourist attractions). Collectively, we refer to this as the listing quality. The underlying rationale is that a more detailed description does not only reduce information asymmetries between the parties, but also signals that the host has put more effort into preparing the listing. Additionally, hosts are liable for the information they provide and highlighting the advantages of an accommodations in a longer and more detailed description will be more difficult for a host offering a low-quality.

Similarly, hosts can upload photos of their accommodation that show the facilities, furniture, and also the surroundings. Only these photos allow potential guests to check whether the information that is host provided in the description is accurate, meaning that every additional picture should help to reduce uncertainties (Dimoka et al. 2012). Again, providing a higher number of detailed photos will be more challenging for hosts offering low-quality accommodations, as the picture could reveal possible flaws. Pictures are an especially powerful signal if they have been taken by an unbiased third party. Airbnb offers this option to hosts for free, meaning that a professional photographer visits the host to take photos. These photos will not only present the accommodation more favorably, but will also act as a stronger signal to potential guests, as the host is unable to tamper with them.

Hosts on Airbnb also have the option to present themselves to the community with a picture and a short text about themselves, in order to give prospective guests an idea whom they are dealing with. As joining the platform is very simple, these profiles can very easily be faked (Friedman and Resnick 2000). Hosts can therefore verify the information about themselves in various ways. They can, for instance, connect their profile on Airbnb with their Facebook profile or allow Airbnb to verify their identity based on an official ID.

While all these marketing-related signals can be used by new hosts to differentiate their listing on Airbnb, these signals are only credible because it requires effort to establish them and a certain level of platform-specific experience to identify the most critical ones (Kirmani and Rao 2000). New hosts are likely to refrain from putting much effort into differentiating their listings for three main reasons. First, as they have no market experience, they have high uncertainties as to what marketing-related signals will be the most important ones. Second, even if they invest a lot of effort into preparing a superior listing, their listings are still lacking reputation and popularity. Third, they will still have uncertainties as to the value Airbnb can offer them. It is therefore much more convenient for new hosts to focus on a cost-leadership strategy (or at least the best price-performance ratio), as they might still refrain from using the platform in the future. Offering lower prices will also allow hosts to receive a great number of booking inquiries from potential guests, allowing them to pick the most suitable ones (Ikkala and Lampinen 2015). We therefore hypothesize that:

H1: New inexperienced hosts offer lower quality listings compared to incumbents.
H2: New inexperienced hosts charge lower prices compared to incumbents.
The Role of Platform Experience

Hosts on Airbnb may obtain direct platform experience by actively participating in the platform ecosystem. This means that they rent out their spare rooms, apartments, or any other suitable accommodation to the community via the platform and observe how their offerings perform over time. Through trial-and-error experimentation, they will then learn what strategies with respect to their listings will most likely contribute to additional bookings. More specifically, they will obtain feedback from the community through questions of potential guests, bookings, and reviews from actual guests. When receiving this feedback, hosts will be inclined to use routines that they associate with a successful outcome (i.e., bookings) increasingly and will avoid those associated with failure. When offering more than one accommodation via the platform (multi-hosts), this learning process will be expedited, as these hosts are able to draw inferences from the differences in performance among their separate listings.

This means that over time, hosts will obtain platform experience through the development and accumulation of knowledge-based assets (e.g., better sense of the importance of high-quality photos). As the underlying routines are updated whenever improved routines are discovered, more experienced hosts are expected to possess more and superior assets (Mitchell and Singh 1992; Nerkar and Roberts 2004). This means that when experienced hosts add a new listing to the platform, they can be expected to be more efficient than inexperienced hosts, as they are able to reduce the cost of experimentation (i.e., trying out different strategies). While the numerous options to present an accommodation on Airbnb therefore make it difficult for inexperienced hosts to know in advance how their listing will be perceived by the community, experienced hosts have a clear sense of how to position their offerings in the market. Knowing what the demand side of the market desires thus enables them to compensate for the lack of reviews for the new listing. Their experience with the platform also allows them to differentiate their listings from the other listings available on the platform, something inexperienced hosts are unable to do. Platform experience is therefore required in order to be able to follow a differentiation strategy, meaning that experienced hosts will be less inclined to compete based on price. We therefore hypothesize that:

H3a: Experienced hosts (multi-hosts) offer higher quality listings compared to incumbents when adding new accommodations.

H3b: Experienced hosts (multi-hosts) charge higher prices compared to incumbents when adding new accommodations.

Research Methodology

Research Context

Founded in August of 2008 and based in San Francisco, California, Airbnb refers to itself as a “trusted community marketplace for people to list, discover, and book unique accommodations around the world” (Airbnb 2017a). Airbnb currently has over 3 million listings in over 65,000 cities across 190 countries. While Airbnb does not offer any accommodations directly, it allows anyone to rent their own accommodations to the community.

This platform-driven model enables Airbnb to expand its business with near-zero marginal costs, as new rooms are added, maintained, and handled by the hosts. Therefore, unlike any hotel, there are no additional costs associated with serving new rooms. On the other hand, Airbnb invests heavily in their community management to ensure that best practices are followed and encouraged. It even offers insurance cover to hosts to incentivize usage and create trust among their users (Choudary 2015).

Airbnb’s website resembles a classic booking website for hotels, and offers detailed search options. Furthermore, available locations are mapped with a price tag to conveniently pick a room in a preferred area. Figure 1 illustrates the search window, options and the display of available accommodations in Paris, France. Here, basic information, such as the number of reviews, a star rating, price, the number of beds, and a first picture are given for each listing. Clicking a listing, leads to additional information, including more photos, booking modalities, a textual description, the number of wishlist entries, and guest reviews. Additionally, a profile page of the host can be accessed that includes verified information such as a government ID, an email address, a phone number, or a Facebook account.
Dataset and Variable Descriptions

We collected data from every listing within the boundaries of Paris, France. Among the thousands of cities available on Airbnb, Paris was chosen for two main reasons. First, the city has the most listings on Airbnb worldwide (McCarthy 2016) and a high density of listings per square kilometer, potentially leading to a fierce competition among hosts. Paris therefore perfectly represents the competitive environment that can be expected on sharing economy platforms in major metropolitan areas. Second, as seen in Figure 1, the city of Paris is bounded by the ring road Boulevard Périphérique, with the actual city center being almost at the center of the ring. As a consequence, there is a strong correlation between the distance to the city center and the price for an accommodation per night and person, leading to fewer distortions.

Figure 2. Timeline of Data Acquisition

The data was collected with a self-developed web crawler on three different dates. The initial data collection (T1) took place on April 8, 2016 and yielded 62,496 listings in Paris. In order to identify new listings, we repeated the process 11 days later (T2). Our analysis is then based on data from May 31, 2016 (42 days later), as we can now differentiate the strategies and performance of new listings that were not yet existing in T1, but appeared on Airbnb before or at T2, with older listing that were already present on or before T1. The second data collection yielded 2,235 listings that did not exist before T1 and were therefore marked as new. Figure 2 illustrates the timeline of the data acquisition process.
Before the analysis, some data cleansing had to be performed. First, listings that were not available at T3 or inactive had to be dropped from the dataset. Furthermore, we limited our analysis to the 99% quantile for price per person and night, as extremely expensive or cheap accommodations might distort the results. In total, we used a dataset with 45,566 old listings and 1,351 new listings in Paris.

**Model Specification**

To test our research hypotheses, we employ different modelling techniques. For our set of hypotheses on newcomer strategies, we use ANOVA analysis, allowing us to test the differences between the strategic elements of single-host newcomers (inexperienced), multi-host newcomers (experienced), and incumbents of the marketplace. Here, we compare different strategic elements hosts are able to adjust when offering a room on Airbnb. These elements can be grouped into four categories. First, characteristics of the listing itself, such as the description length, the number of photos LN(#photos), and whether or not professional photos (prof. photos, 0/1) were available. Second, information about the host, such as, whether she has multiple listings on Airbnb (multi-host, 0/1), is also known to use Airbnb as a guest (is user, 0/1), and the number of verifications of her profile. Third, we included indicators of booking convenience, measured with the possibility of instant booking, and the average response time for messages by the host. Fourth, prices can be adjusted by the host and are transparent within the marketplace. Usually, the rate per night and person is shown in the offering, and will be the indicator of the pricing strategy of the host. As a post-hoc analysis, we then demonstrate how these elements influence the success of a listing on Airbnb. We can then infer whether newcomers or incumbents should adjust their strategy to exploit these identified drivers of success. To do so, we use regression modelling with a success variable, which measures the number of additional reviews a listing has received between T2 and T3 as the dependent variable.

As there are several ways to measure success in the hotel industry, such as bookings, market share, sales rank, or profit, we should elaborate on this in detail. Unfortunately, most of these measurements are not publicly available for Airbnb. We therefore follow Floyd et al. (2014) and other studies by using the number of reviews as the main indicator of success. For example, Ögüt et al. (2012) and Ye et al. (2011) used the number of reviews to approximate revenue in the hotel industry. Fradkin et al. (2015) moreover, demonstrated that 67% of trips result in a guest review on Airbnb, making the number of reviews a stable indicator for success and booking rate. Reviews are usually timely submitted within four to five days after the checkout (Fradkin et al. 2015). This keeps a possible distortion due to time lags of reviews to a minimum. Also, being able to submit a review requires a verified transaction. For these reasons, we chose to use the number of additional reviews between T2 and T3 as our indicator of success. It should be noted that success is not an indicator of economic benefit, but rather reflects the number of transactions that take place.

For regression modeling, Poisson models are commonly used when the dependent variable is a count. As the number of reviews is overdispersed, meaning its variance is bigger that its mean, we use negative binomial regression models (NBREG) in our analysis (Cameron and Trivedi 2013). The following model specification therefore results for our regression:

\[
y_i = \alpha + \beta x_i + \gamma z_i
\]

where \(y_i\) is the dependent variable describing the number of additional reviews \(y\) for each listing \((i)\) between T2 and T3. Our set of independent variables is represented by \(\beta x_i\). We consider several characteristics of the accommodation as well as of the host that should influence the success in our model. These characteristics include all aforementioned strategic elements and the price of the listing. Additional control variables that cannot be altered by the directly host, but might influence success, such as the location, room type, number of wishlist entries, and the age of the listing, are also included.

**Results**

We now present the results of our analysis, starting with the descriptive evidence, followed by the results of the contrast and ANOVA-analysis for single-host newcomers, multi-host newcomers, and incumbents. Descriptive statistics and variable descriptions can be found in Table 1. All variables, except success, show the value at T3, with success representing the difference (\(\Delta\)) in the number of reviews between T2 and T3 to ensure comparability of new and old listings.
Table 1. Descriptive Statistics and Variable Descriptions (N= 46,917)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Variable description</th>
<th>Conceptual description</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>LN(Description)</td>
<td>Natural logarithm of the description length in characters.</td>
<td>A detailed and longer description can reduce the information asymmetries.</td>
<td>6.67</td>
<td>1.00</td>
</tr>
<tr>
<td>LN(#Photos)</td>
<td>Number of photos for the accommodation.</td>
<td>More photos can reduce the information asymmetries.</td>
<td>2.48</td>
<td>0.65</td>
</tr>
<tr>
<td>Prof. photos</td>
<td>Dummy turns 1 if professional photos are available.</td>
<td>Professional photos of the accommodation imply higher quality.</td>
<td>0.24</td>
<td>0.43</td>
</tr>
<tr>
<td>Multi-host</td>
<td>Dummy turns 1 if the host manages more than 1 accommodation.</td>
<td>Host that offer multiple listing should imply a more professional method of operation.</td>
<td>0.23</td>
<td>0.42</td>
</tr>
<tr>
<td>Is user</td>
<td>Dummy turns 1 if the host has received reviews as a guest.</td>
<td>Complementors that are at the same time user should have a better understanding of user’s needs.</td>
<td>0.49</td>
<td>0.50</td>
</tr>
<tr>
<td>#Verifications</td>
<td>Number of verified profile characteristics (e.g., Facebook, passport, email, etc.).</td>
<td>A higher number of verifications should increase the trust level between complementor and user.</td>
<td>3.85</td>
<td>1.21</td>
</tr>
<tr>
<td>Instant booking</td>
<td>Dummy turns 1 if instant-booking option is available (No mutual agreement required).</td>
<td>Being able to book without the explicit consent of the host makes the procedure more convenient.</td>
<td>0.13</td>
<td>0.33</td>
</tr>
<tr>
<td>Response time</td>
<td>Average response time in hours (maximum 24+).</td>
<td>Fast response times imply a more professional method of operation.</td>
<td>10.99</td>
<td>10.10</td>
</tr>
<tr>
<td>Price p.p.</td>
<td>Price per person per night.</td>
<td>Hosts can freely set the rate for their listing.</td>
<td>39.74</td>
<td>18.74</td>
</tr>
<tr>
<td>Success</td>
<td>Number of reviews received between T2 and T3.</td>
<td>Main dependent variable and indicator of a successful listing.</td>
<td>1.32</td>
<td>2.46</td>
</tr>
<tr>
<td>Location</td>
<td>Distance to the city center (Théâtre du Châtelet) in kilometers.</td>
<td>The geographic position of a listing cannot be altered.</td>
<td>3.49</td>
<td>1.97</td>
</tr>
<tr>
<td>Room type</td>
<td>Dummy turns 1 if the listing is a single room instead of a whole house or apartment.</td>
<td>Single Rooms are expected to be booked more often, as whole apartments are rarely needed.</td>
<td>0.12</td>
<td>0.33</td>
</tr>
<tr>
<td>#Wishlist</td>
<td>Number of wishlist entries.</td>
<td>Indicator of popularity.</td>
<td>122.86</td>
<td>318.43</td>
</tr>
</tbody>
</table>
Descriptive Statistics

As mentioned before, we gathered data on certain characteristics that can be manipulated by the complementors in order to strategically signal the quality of the offering. Table 1 displays the descriptive statistics for all relevant and quantifiable characteristics of the accommodation as well as the respective host and the price. Furthermore, control variables for the econometric modelling, such as location, room type, and number of wishlist entries are also included. Certain aspects should be highlighted. First, we see that around one fourth of the hosts made use of professional photos to promote their accommodation and another 23% of listings are managed by a host with multiple listings, implying a commercial orientation.

On the other hand, about half of the hosts are using Airbnb as a guest as well, meaning they should have a certain expertise on both market sides. Moreover, the mean price of €39 per night is well below the average price for a hotel room in Paris, which is around €150 and comparable to a bunk bed in a hostel dorm, which costs around €30 (Hotel.com 2014). These market conditions reflect the high demand for accommodations in Paris, creating incentives for private persons to monetize their spare rooms.

Econometric Evidence

We now turn to our econometric modelling to test our developed hypotheses. Results of the contrast analysis are shown in Table 2 with the difference and significance level for the three complementor groups. Column (1) compares single-host Newcomers with Incumbents. Column (2) compares multi-host Newcomers with incumbents and column (3) shows the contrast between single- (inexperienced) and multi-host (experienced) newcomers.

| Table 2. ANOVA for Strategic Elements Compared to Incumbents |
|---------------------------------|-------------|-------------|-------------|
| Variable                        | Single-host newcomers vs. | Multi-host newcomers vs. | Single-host newcomers vs. |
|                                 | incumbent     | incumbent     | multi-host newcomers    |
| LN(Description length)          | -0.46         | -0.21         | -0.25                  |
|                                 | 0.03          | 0.06          | 0.64                   |
|                                 | ***           | ***           | ***                    |
| LN(#Photos)                     | -0.42         | 0.022         | -0.45                  |
|                                 | 0.02          | 0.04          | 0.04                   |
|                                 | ***           | n.s.          | ***                    |
| Prof. photos                    | -0.24         | -0.24         | -0.00                  |
|                                 | 0.13          | 0.024         | 0.03                   |
|                                 | ***           | ***           | n.s.                   |
| Is user                         | -0.16         | -0.10         | -0.07                  |
| #Verifications                  | -0.72         | 0.09          | -0.81                  |
|                                 | 0.04          | 0.07          | 0.08                   |
|                                 | ***           | n.s.          | ***                    |
| Instant booking                 | -0.03         | 0.12          | -0.15                  |
| Response time                   | 6.11          | -4.77         | +10.88                 |
|                                 | 0.31          | 0.57          | 0.64                   |
|                                 | ***           | ***           | ***                    |
|                                 | 0.59          | 1.06          | 1.21                   |
|                                 | ***           | ***           | ***                    |

Note: * p < 0.05, ** p < 0.01, *** p < 0.001

For our first hypothesis, we argued that single-host newcomers will offer lower quality compared to incumbents as they lack the required experience and will avoid the expenses to create a high-quality offering. Results in Column (1) show that listings by single-host newcomers indeed have lower quality indicators in every aspect: The listing itself, information richness about the host, and booking convenience. We can therefore fully confirm H1.

For our second hypothesis, we argued that single-host newcomers will differentiate themselves in the marketplace with a low-price strategy, as competing with incumbents on quality is not a viable option. The analysis clearly shows single-host newcomers strongly focus on a low-price strategy with an average price difference of €-8.44 (-21%) per person per night compared to incumbents, hereby confirming H2.
In our third set of hypotheses, we included the moderating effect of platform experience. We argued that, when multi-hosts add a new accommodation, they will behave differently compared to single-host newcomers. H3a therefore stated that multi-host newcomers will try to differentiate their offerings from those of existing hosts. Surprisingly, this is not entirely the case, as our analysis in column (2) shows that the offerings do not deliver higher quality with regard to the characteristics of the listing. In fact, quite the contrary, as their listings have shorter descriptions, an equal number of photos, and fewer professional photos. Still, multi-host newcomers at least focus on booking convenience, by offering the possibility of instant booking and keeping their response time very low, as they respond to messages almost 5 hours earlier than incumbents. We therefore cannot fully confirm H3a. Interestingly, even though multi-host newcomers offer lower listing quality, they still follow a high price strategy, confirming H3b, with an average price difference of €6.17 (+15%) compared to incumbents.

Turning towards column (3) of Table 2, the differences in newcomer strategies are even more apparent, as single-hosts, compared to multi-hosts, are inferior in almost every aspect of the listing. The only non-significant difference is the number of professional photos, which is not surprising as the creation usually takes time and is therefore hardly comparable.

**Post-Hoc Analysis for Drivers of Success**

In order to supplement our assumptions and arguments about the variable choices and indicators of quality of the listings, we now extend the findings with a post-hoc analysis. Drawing on the results of the ANOVA, we now look into the effectiveness of the strategic elements of newcomers and incumbents in the Airbnb marketplace. The pairwise correlations in Table 3 do not show any obvious multicollinearity problems except a rather high correlation (0.47) in the case of wishlist and success. To further check for any potential problems, we therefore examined the collinearity diagnostics and observed that the variance inflation factor (VIF) is less than 1.24, suggesting that no multicollinearity problems exist.

<table>
<thead>
<tr>
<th>Table 3. Correlation Matrix of Numeric Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Success</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>0.16</td>
</tr>
<tr>
<td>0.04</td>
</tr>
<tr>
<td>0.11</td>
</tr>
<tr>
<td>0.27</td>
</tr>
<tr>
<td>-0.39</td>
</tr>
<tr>
<td>-0.02</td>
</tr>
<tr>
<td>0.015</td>
</tr>
</tbody>
</table>

Table 4 shows our NBREG regression. We can see the expected direction and significance of all characteristics of the listings. The description length, the number of photos, existence of prof. photos positively influence the success of a listing.
Furthermore, guests appear to value when hosts confirm their identity with multiple verifications, such as their Facebook profile and passport. Also, we notice that booking convenience, reflected by the instant booking feature and the response time of hosts increases the success measure. Interestingly, guests appear to discriminate against multi-hosts, indicated by the negative and significant coefficient. Surprisingly, hosts that also act as users of the platform appear to be less successful, even though they should have considerably more knowledge about the demand side of the market.

Additionally, our control variables show that the location within the city matters as seen by the negative and significant coefficient for the location, which measures the distance to the Théâtre du Châtelet, located in the center of Paris. Also, smaller rooms are preferred compared to whole apartments, while popularity evidently also serves as a driver of success.

**Table 4. Negative Binominal Regression for Success**

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Coefficient and significance</th>
<th>T-statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Listing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LN(Description length)</td>
<td>0.0669***</td>
<td>(7.60)</td>
</tr>
<tr>
<td>LN(#Photos)</td>
<td>0.196***</td>
<td>(11.75)</td>
</tr>
<tr>
<td>Prof. photos</td>
<td>0.121***</td>
<td>(6.55)</td>
</tr>
<tr>
<td>Host</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Multi-host</td>
<td>-0.349***</td>
<td>(-19.10)</td>
</tr>
<tr>
<td>Is user</td>
<td>-0.0317*</td>
<td>(-2.01)</td>
</tr>
<tr>
<td>#Verifications</td>
<td>0.0543***</td>
<td>(7.79)</td>
</tr>
<tr>
<td>Booking convenience</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instant booking</td>
<td>0.308***</td>
<td>(16.19)</td>
</tr>
<tr>
<td>Response time</td>
<td>-0.0864***</td>
<td>(-72.52)</td>
</tr>
<tr>
<td>Price</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Price p.p.</td>
<td>-0.0135***</td>
<td>(-28.37)</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Room type</td>
<td>0.328***</td>
<td>(14.05)</td>
</tr>
<tr>
<td>Location</td>
<td>-0.0541***</td>
<td>(-11.96)</td>
</tr>
<tr>
<td>#Wishlist</td>
<td>0.00212***</td>
<td>(31.86)</td>
</tr>
<tr>
<td>Age control</td>
<td>1.36***</td>
<td>(38.66)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.786***</td>
<td>(-9.85)</td>
</tr>
<tr>
<td>Pseudo R2</td>
<td>0.141</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>46,917</td>
<td></td>
</tr>
</tbody>
</table>

**Note:** *p < 0.05, **p < 0.01, ***p < 0.001
Discussion and Implications

The analysis of competitive strategies of new hosts on Airbnb’s platform revealed several noteworthy findings. Our first research question was focused on the competitive strategy new complementors would follow on sharing economy platforms in order to compensate for the lack of quality signals. We were able to demonstrate that the inexperienced market entrants follow a distinct strategic avenue. Our results confirm the expectation that inexperienced newcomers generally do not try to differentiate their offerings and therefore compete based on price rather than quality. A possible explanation for the focus on a cost-leadership strategy might be the lack of popularity and reputation. On platforms, these signals are critical market mechanisms, as they generally allow end-users to distinguish between low- and high-quality offerings (Bikhchandani et al. 1998; Duan et al. 2009; Resnick et al. 2006; Thies et al. 2016; Tucker and Zhang 2011; Ye et al. 2014). As they can only be acquired over time, competing based on a differentiation strategy might appear unattractive for new market entrants, as they cannot effectively signal quality, essentially forcing them to compete based on price. The overall approach therefore seems to be to conduct a number of transactions via the platform in an attempt to receive reviews and therefore be able to gain popularity and reputation. Only when these prerequisites for a successful participation are satisfied, hosts seem to raise their prices and start to focus more on differentiation rather than price. However, this calls for further investigation.

For our second research question, we investigated whether platform experience would motivate complementors to position their offerings differently compared to complementors without experience. Based on the respective hypotheses, we expected that experienced hosts (multi-hosts) would focus on a differentiation rather than a cost-leadership strategy when adding new accommodations. Though the analysis revealed that hosts with platform experience focus more on the quality of their listings compared to inexperienced hosts, the quality of new listings added by multi-hosts is still significantly below that of incumbents’ offers (e.g., shorter descriptions). It is, however, interesting to see that experienced hosts with new offerings strive for booking convenience as a tactic to differentiate their offerings and in order to attract their first guests (i.e., options to book instantly and short response times) but also charge the highest prices per person and night. While inexperienced newcomers therefore appear to neglect all aspects of their offerings and follow a low-cost strategy, experienced newcomers try to offer more convenience in order to justify their price premium.

Theoretical Contributions

Our study makes the following contributions to the emerging research on platform ecosystems. First, while previous studies mainly focused on the competition between platforms (e.g., Boudreau 2010; Eisenmann et al. 2011; Rochet and Tirole 2006), little attention has been paid to the micro-level competition within a platform ecosystem (e.g., Tiwana 2015). Furthermore, early work that considers the competition within platform ecosystems is primarily focused on competition dynamics in the presence of network effects (Markovich and Moenius 2009) or on how the platform providers can shape the competitive intensity within the platform ecosystem through platform governance mechanisms by deciding how open or closed the platform’s ecosystem should be (Benlian et al. 2015; Casadesus-Masanell and Halaburda 2014). Much less attention has been devoted to understanding what the consequences of a highly competitive environment are for platform complementors, even though they are central to the value creation within a platform ecosystem. Therefore, this study is an initial step towards understanding the competitive positioning of complementors in platform ecosystems. We empirically show how different complementors deal with a late market entrance in a highly competitive environment and what diverse strategies they follow.

Second, we are able to show how platform experience influences the strategic decision making in a highly dynamic platform ecosystem. We add to prior research on platform experience (e.g., Kapoor and Agarwal 2017) by showing that, despite their experience, complementors adding new offerings to a platform do not instantly provide a perfect quality and therefore seem to refine their offerings over time.
Practical Contributions

We will now turn to the practical contributions of this work, which are threefold, as all market participants—complementors, platform providers, and users—should be aware of the revealed dynamics.

Regarding the complementors of a platform ecosystem such as Airbnb our contributions are twofold. First, newcomers should be aware of the implicit market entry barriers, and try to overcome these by focusing on their available quality signals. They should focus on easily adjustable signals such as a detailed description, a higher number of photos, and additional verifications. These are one-time efforts that can greatly increase their chances to successfully compete within the marketplace. The initial investment should pay off, as guests appreciate quality signals and adjust their booking behavior accordingly (see Table 4). Increasing booking convenience requires more effort, as keeping the response times low, obviously demands a high level of availability. Allowing guests to instantly book their room on the other hand, does not require more effort, but a high level of trust in the community. Taking these initiatives might decrease the need for a low-price strategy, which apparently makes sense as lower prices do increase the booking rate. But, counterbalancing this with easily adjustable and effective quality signals should be worth considering. As seen from our analysis, multi-hosts adding new accommodations already take some of these steps, but still leave room for improvements. Especially corresponding to their high pricing strategy, sending adequate quality signals such as the number of photos, professional photos, and a detailed description should not be neglected. Competing solely on price can be a valid strategy in the short-run, but should be adjusted later on. Especially, as soon as sufficient reputation and popularity is acquired. Second, incumbent hosts should be aware of their competitive advantage due to reputation and popularity and adjust their pricing accordingly, while paying close attention to the market developments. As seen from our data, over 1,300 new listings were added to the market in merely eleven days, pointing towards ever increasing competition from newcomers that compete with a low-price strategy, requiring incumbents to react quickly. As guests appear to devalue multi-hosts (see Table 4), they might consider to pose as a single-host for each listing with multiple accounts in order to avoid discrimination.

Platform providers should know about the dynamics and possible market entry barriers for newcomers. A strong focus on community-based reputation systems, might deter new complementors from entry, which could lead to a stagnation in growth. Providers should therefore consider to set additional incentives for newcomers and promote their listing in order to overcome entry barriers constituted by the lack of reputation and popularity.

Finally, for guests on Airbnb, our research also provides important results. First, end-users should be aware of the pricing strategies of complementors in order to adjust their decision making. The lower prices of newcomers might offer better deals than incumbents or multi-hosts. Second, reputation and popularity can be a crucial factor in the ecosystem and guests should be aware of the importance.

Conclusion, Future Research, and Limitations

While our study provides new insights and contributions to both research and practice in the context of platform ecosystems and peer-to-peer markets, it is exploratory in many respects, and we therefore acknowledge certain limitations that need to be considered when interpreting the results and implications. First, our dataset only covers a small fraction of the Airbnb ecosystem, as it was limited to a single city and is based on three snapshots in time. We therefore could not account for possible seasonality effects, which are doubtless an important aspect, regarding booking, price decisions, and competition. Also, though Paris is the city with the most listings on Airbnb worldwide, certain cultural or societal norms might affect the results. Furthermore, competition in other cities might be less fierce, leading to different dynamics and strategies. Future studies could address this problem by refining the data, gathering and using repeated measurements to create meaningful panel-datasets across multiple locations. Second, as mentioned before, our dependent variable only constitutes an approximation of the booking behavior as the actual decision-making of guests cannot be monitored effectively. Still, we believe this to be a minor issue, as previous researched showed that reviews can act as an appropriate measurement of success (e.g., Floyd et al. 2014). Third, even though we studied one of the most prominent sharing economy platforms, our results should be used cautiously when extrapolating to other ecosystems. This issue could be addressed in future research by validating our results on other platforms, such as Uber, BlaBlaCar, or TaskRabbit. We hope that this research provides further impetus to explore the inner dynamics of platform ecosystems on the micro-level.
In conclusion, and based on the findings in our research setting, newcomers in a platform ecosystem face strong and implicit difficulties, constituted by their lack of reputation and popularity, which need to be surmounted by a low-price strategy. Still, the fruits may be reaped in the long run, once a superior market position is established.

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**References**


