Personal or product reputation? Optimizing revenues in the sharing economy

Graziano Abrate and Giampaolo Viglia

Abstract

The emergence of peer-to-peer platforms, known as the sharing economy, has empowered people to market their own products and services. However, there are information asymmetries that make it difficult to evaluate the reputation of the seller *a priori*. This paper examines how sellers have to enhance their personal reputation in order to optimize revenues. The study proposes a revenue model where, given a frontier that depends on the shared assets, the maximization of revenues depends on reputational factors of the person and of the product. An empirical validation of the framework has been conducted in the context of Airbnb, a popular sharing economy travel platform. The sample comprises 981 establishments across 5 European cities. The findings suggest the crucial importance of personal reputation along with some distinctive reputational attributes of the product itself. These results emphasize the role of trust and personal branding strategies in peer-to-peer platforms.

Keywords: Airbnb; personal reputation; revenue optimization; resource-based view; stochastic frontier; sharing economy

Introduction

Online peer-to-peer (P2P) marketplaces have become widely common due to technological advances and economic and societal considerations (Tussyadiah and Pesonen 2016). Some are specialized in a single business. Others offer a differentiated range of goods and services. These marketplaces involve consumers who transact directly with other individuals (sellers) while the marketplace platform itself is provided by a third party. This realm is commonly labelled as the sharing economy, and it mainly concerns the supply of services. A driving force of its success is the increased consumer need for personal interactions (Guttentag 2015; Guttentag et al 2017). Summarizing the DNA of this market, the co-founder of Airbnb defines the sharing economy as “commerce with a promise of human connection” (Gebbia 2016). Philosophically and conceptually, sharing economy revolves around the idea of gift giving (Belk 2007), with past research investigating the psychological motivations for sharing (Bardhi and Eckhardt 2012; Lamberton and Rose 2012). In recent times, these boundaries have been extended and now sharing is mainly a market mode in the hand of few providers (Kennedy 2016; Heo 2016). The service sector assisted the rapid growth of these providers in the last decade. Operators such as Airbnb, BlaBlaCar, and HomeAway pose new threats to the traditional hospitality and travel industry. In Europe, due to the scarce regulation of this new industry, there have been some legal challenges among governments, traditional operators, and other stakeholders (Dredge 2017).

Ordinary people see the emerging business opportunity and act as hosts by renting out their car spaces, rooms, or entire flats. Through P2P platforms, consumers turn themselves into ‘micro-entrepreneurs’ supplying their existing assets and services to other people (Sundararajan, 2016). Interestingly, very similar assets present substantially different performance data (Wang and Nicolau 2017), but little empirical research has explored the drivers to maximize performance. Sharing platforms display personal reputation indicators, such as sellers' identification data and credentials related to functions they perform. Given that information, we portray that the success of products in sharing economy marketplaces is greatly influenced by the personal reputation of the seller. Personal reputation reduces the level of uncertainty in the transaction and increases the quality of the relationship between all the parties involved (Resnick and Zeckhauser 2002). Specifically, Mathies, Siegfried and Wang (2013) advocate for studies to understand the interplay between customer-centric marketing and revenue management.

To date, there is limited information on the magnitude of personal reputation with respect to product reputation. At the same time, it is important to rule out all the possible alternative explanations for different revenue performance, such as a differentiation in the specific attributes or services.

This work focuses on the question of performance optimization in the sharing economy, a context where, *de facto*, ordinary people and consumers act as micro-entrepreneurs. In particular, the goal of this paper is to unclose the impact of product and personal reputation on revenue optimization in the sharing economy. From a methodological standpoint, the stochastic frontier approach helps to model this setting. More specifically, reputational elements are seen, coherently with resource-based view literature (Dutta et al. 1999; Nath et al. 2010), as the marketing capability that explains whether the seller is close to the level of revenue frontier.

The reminder of the paper is as follows. The next section presents the theoretical framework. The level of achieved revenues, which stems from the value of the shared assets, is shaped by product and personal reputation. An empirical case, assessed through a revenue frontier model, validates the proposed model in the context of Airbnb, a popular sharing economy platform. After presenting the findings, the paper concludes with theoretical and practical implications on personal reputation's ability to reduce revenue inefficiency.

Theoretical framework

Performance benchmarking in the sharing economy

Frontier studies are a popular method to measure tourism performance (Assaf et al. 2017). The underlying idea of these models is that a set of inputs leads to a potential maximum level of output (i.e., the frontier). With respect to other approaches, "the distinctive feature of the frontier methods for performance measurement is that they provide a measure of efficiency that reveals gaps between a firm's actual and optimal performance" (Assaf and Josiassen 2016, p. 613). In their detailed review, Assaf and Josiassen (2016) empirically classify extant tourism frontier literature according to the adopted empirical method (parametric or non-parametric). The majority of these studies focus on the hotel industry, as confirmed also by Sellers-Rubio & Nicolau-Gonzálbez (2009). In general, this methodological framework is widely used to compare different types of firms' performances - productive efficiency, cost efficiency, revenue efficiency or profit efficiency - and to identify the determinants of inefficiencies (Kumbhakar and Lovell 2003).

In a resource-based view of the firm (Wernerfelt 1984; Dutta et al. 1999), marketing capabilities are seen as the ability to deploy the available resources to achieve the desired output (Nath et al. 2010). When focusing on revenue performances, the available firm resources represent the inputs. Deviation from the maximum attainable output (i.e., inefficiency) can be explained by the marketing capability of the firm. In this sense, Trainor (2012) explains that the available resources should be treated separately from capabilities.

Marketing capability is widely operationalized with reputational factors, such as the years of experience in the market (Sellers and Mas 2006; Assaf et al. 2011), brand image (Morgan et al. 2011), the presence and quality of visual shared content (Trainor 2012), and third-party or consumer quality scores (Stuebs and Sun 2010).

Theoretically, Kreps et al. (1982) initially conceptualized reputation as a process where parties continually update their beliefs based on past interactions. It follows that reputation is likely to have an impact on the seller's effectiveness, as it reduces the uncertainty regarding the transaction (Luca 2011).

Given that in the sharing economy individual performance differs quite substantially across sellers even when assets are very similar (Wang and Nicolau 2017), the frontier method is useful to compare the behavior (and performance) of subjects sharing their assets in a peer-to-peer platform. In this context, the assets shared by the individual can be viewed as the input. The characteristics of a rented apartment in Airbnb are an example of this. As presented in Figure 1, starting from the shared assets (the inputs), the frontier model measures the gap between achieved and maximum potential revenues at the individual level. Embracing the marketing capability approach, reputation factors explain this discrepancy. In particular, the proposed model includes two distinct types of reputation, i.e. product and personal reputation, as the mechanisms that explain the individual deviation from the frontier level.

[INSERT FIGURE 1 HERE]

Shared assets

Shared assets in the form of the product's physical and service characteristics represent the basic sharing economy input on commanding a revenue level. In traditional markets, previous literature suggests a clear link between product characteristics and business performance (Phillips et al. 1983; Sashi and Stern 1995; Zhu and Zhang 2010). The same applies to peer-to peer markets although, on average, these markets are characterized by less services and amenities when compared to traditional markets (Zervas and Proserpio 2016).

In the travel industry, the physical attributes comprise all characteristics of the accommodation, such as the location and the type of accommodation being offered (Monty and Skidmore 2003; Zhang et al. 2011; Viglia and Abrate 2017). On the other hand, the service attributes comprise all the different amenities offered at the accommodation, such as conditioning services and technological facilities (Abrate et al. 2011; de Oliveira Santos 2016).

Product reputation

A meta-analysis conducted by Floyd et al. (2014) finds that product reputation exerts a significant effect on revenues. This result holds across a variety of contexts and is consistent across geographical areas, types of products and different methodological approaches.

Previous research agrees that consumers consult online reviews to form their ideas on the reputation of the product (Sparks and Browning 2011; Yacouel and Fleischer 2012; Filieri and McLeay 2014). Generally, literature investigating the impacts of product reviews on choices, intentions, and sales is quite vast (e.g., Chevalier and Mayzlin 2006; Sen and Lerman 2007; Lee and Youn 2009; Tirunillai and Tellis 2012). Online product reviews can be considered in multiple quantitative dimensions, such as review valence, volume and variance, and in multiple qualitative dimensions, such as the presence of product pictures and the correct and complete information on the product being offered (Trainor 2012).

A majority of academic attention is focused on the online reviews' impact on demand and revenues. For the customer review website Yelp.com, Luca (2011) tests the impact of consumer reviews on sales and finds that the impact is stronger if the operator is an individual seller rather than to a franchise. This suggests that the higher the uncertainty regarding the transaction, the higher the weight is attributed to online reviews. In addition, Cabral and Hortacsu (2010) find that a single negative review on eBay has a significant negative impact on the seller's overall growth rate. Nonetheless there are contrasting findings on the relevance of online reviews. For instance, Liu (2006) found that reviews matter *per se* as they increase the awareness of a product while Chintagunta et al. (2010) found that high quality reviews have no direct impact on sales.

Some of these contrasting results depend on the methodological approach used to test for such an impact and the way the relationship between product reputation and revenues is modelled (Sellers-Rubio & Nicolau-Gonzálbez 2009; Cabral and Hortacsu 2010). There is also disagreement on the role of the specific reputational elements. While some researchers (Ho-Dac Carson and Moore 2013; Xiong and Bharadwaj 2014) find evidence that the volume of reviews (i.e., number of reviews) predict product sales, others claim that the main predictor of sales is rather the valence (i.e., review score) (Dellarocas et al. 2007; Chintagunta et al. 2010). A confounding element in this domain lies in the use of a composite valence-volume variable (e.g., the total number of 5-star ratings), which hinders the ability to untangle the specific impact of these review dimensions (Babić et al. 2016).

Online reviews not only influence consumer behaviour but are also the outcome of consumer purchases (Duan et al. 2008), and thus raise endogeneity concerns in empirical analyses. The application of the stochastic frontier model offers the flexibility to consider reputation separately as a marketing capability associated with a reduction of inefficiency (Stuebs and Sun 2010).

Despite some methodological and operational challenges, the above literature converges in considering product reputation as salient in the case of services, where quality is difficult to assess prior to consumption. In sum, we portray that:

H1: *When benchmarking individual revenue performance in the sharing economy, product reputation reduces the gap between potential and achieved revenues*

Personal reputation

Reputation goes beyond product reputation. You, Vadakkepatt and Joshi (2015) extend these boundaries by including several sources of personal reputation, such as the expertise of the seller. This aspect is salient in electronic markets, where consumers cannot always examine the source credibility *a priori* (Huang et al. 2012; Agag and El-Masry 2016). In sharing platforms, reputation systems are similar to the recommendation systems used, for example, by Yelp or TripAdvisor. However, instead of rating just products or services, participants have also the opportunity to analyse and rate the personal characteristics of the seller. Profile characteristics are the main source of personal reputation. Simply reporting basic attributes such as sex, ethnicity, and age is not sufficient, as the globally oriented marketplace attempts to attract customers from diverse and potentially worldwide backgrounds. In traditional businesses, corporate reputation is key (Roberts and Dowling 2002). Parties operating in sharing economy platforms are incentivized to use reputation-signaling mechanisms to maximize the likelihood of a successful transaction. In addition, sharing economy environments are characterized by higher levels of social interactions compared to traditional markets (Tussyadiah 2016a; Tussyadiah and Pesonen 2016). Therefore, it is essential to provide fine-grained knowledge to reduce information asymmetries.

Recently, some factors were shown to play a large role in personal reputation building on sharing economy platforms. These include the full identification of the seller (Edelman and Luca 2014), the seller's personal photo (Ert et al. 2016), and the experience of the seller, measured through the time the seller is present on the platform (Pera et al. 2016).

An active seller with high reputation may see an increase in his or her revenues because of a higher status within the online community. Belk (2014) suggests that personal information disclosure is key in collaborative consumption contexts. Therefore, personal reputation serves as the digital institution that reduces uncertainty and favours the likelihood of the transaction. More formally,

H2: *When benchmarking individual revenue performance in the sharing economy, personal reputation reduces the gap between potential and achieved revenues*

Personal reputation makes transactions between strangers safer and less uncertain (Belk 2014; Masum et al. 2011). This is even more relevant in the sharing economy, where the person who provides the service becomes an integral part of the experience (Ert el al. 2016). Given this, we portray that personal reputation is critical in ensuring the provision of the product and its impact goes beyond the reputational elements of the product itself. In sum,

H3: *Compared to product reputation, personal reputation has a stronger weight in reducing the gap between potential and achieved revenues*

Methodology

Context

Airbnb.com is a popular online marketplace for short-term rentals. It presents more than one million listings spread across 34.000 cities and 190 countries (Sawatzky 2015).

The website resembles traditional accommodation booking websites. To book a room or an entire flat, the guest uses Airbnb request and payment system. Once the guest submits a query, Airbnb presents the guests' request to the host who accepts or rejects. If the host accepts, Airbnb charges the guest and pays the host accordingly. In addition to traditional hospitality services that focus on the characteristics and reviews of the product, Airbnb facilitates an immediate access to the profile characteristics of the sellers.

Airbnb earns its revenue by charging guests a 6-12% fee and hosts a 3% fee and competes in the market at different levels. The platform offers a service that sits generally in the middle compared with the two main groups of competitors. On the one side, there are hotels and upscale listing properties, such as Onefinestay (Guttentag 2015). On the other side, there are accommodation platforms where hosts offer to share a space completely free of charge. One of the largest of these networks that received recently academic attention (Rosen et al. 2011; Pera et al. 2016) is Couchsurfing.

In areas where Airbnb is most popular, hotels have lost about 10% of revenues over the last five to six years (Zervas and Proserpio 2016).

The empirical model

This paper adopts a stochastic frontier approach to model the revenues and their determinants. Coherently with the conceptual model, the assets shared in Airbnb are the characteristics of the flat (or room) that are made available for booking. The underlying hypothesis is that the characteristics of the flat constrain the Airbnb host's maximum achievable revenue. In particular, the potential revenues depend on location factors (e.g. the city where the listing is located), the type of listing (entire flat or shared room in a flat), the number of rooms, beds, bathrooms as well as the services offered to the guests. Given these assets (A), the host aims at maximizing the revenues; however, he or she might be more or less efficient in achieving this goal. Drawing from our theoretical underpinning, we claim that reputational variables (R) are the key factors that can explain revenue efficiency. In other words, the characteristics of the flat define a theoretical maximum level of revenues and represent the "revenue frontier." A good reputation allows the host to perform better than others and be closer to the frontier. On the contrary, a bad reputation will result in a larger distance from the revenue frontier.

The frontier regression model can be written as follows:

$$lnREV_i = f(A_i) + v_i - u_i \qquad [1]$$

The dependent variable is the amount of achieved revenues (REV), taken in log, v_i is the random noise and u_i is the inefficiency term, which is constrained to be nonnegative (no one can perform better than the “frontier” level) and is distributed as a truncated normal $N+(\mu_i, \sigma^2_i)$. The value of μ_i is modeled as a function of the explanatory variables [2]. In the specific case, each reputational variable R_k influences the level of inefficiency through the parameter δ_k. The underlying assumption is a negative relation between inefficiency and (good) reputation.

$$\mu_i = \sum_k R_{ik}\, \delta_k \qquad [2]$$

Data

The dataset includes observations from the Airbnb website concerning the 5 most popular European destinations according to the global destination cities index (GDCI 2014): Barcelona, Istanbul, London, Paris and Rome. The collected rooms and flats listed on Airbnb are the ones within a 2-kilometers maximum distance from the ‘main touristic attraction,’ identified by consulting general tourism websites.[1] The adopted sampling procedure is a multi-stage sampling, with the first stage being the selection of the investigated city and the second stage being the individual collection of Airbnb listings capped at 200 observations per city.

For each Airbnb listing, it was possible to retrieve information on prices, room (or flat) availability, the characteristics of the room (or flat) and reputational attributes. The achieved revenues for a specific room/flat are not directly observable, though they can be obtained by multiplying the price of the listing per its average monthly occupancy. The latter was obtained by repeatedly checking the room (or flat) availability in the Airbnb website in the next 28 days. This method is in line with previous studies (Liu et al. 2014; Viglia et al. 2016) and replicates the average temporal separation between the booking date and the subsequent check-in.[2] This measure of occupancy is a proxy for the true number of nights effectively sold by the host; the listing might also appear as “not available” because the host does not rent it for that specific date. Nonetheless, official bookings, which are not available in the Airbnb platform, would also be a biased measure of the occupancy rate, since hosts might rent the listing outside the official Airbnb website, especially in the case of repeating guests (Forbes 2010). Occupancy rate was checked a first time in the period of October and November 2014 and a second time in the period of February and March 2015. Several controls were at play to spot inconsistencies in room availability, with the primary goal of detecting – and removing from the sample – Airbnb hosts whose listings were never available for booking. Out of the 1014 initial listings, these controls left the sample at 981 units.

Table 1 presents the descriptive statistics for the investigated sample. The average monthly revenue is around 1,500 Euros, with values ranging from 0 to more than 10,000 Euros, thus presenting an intense dispersion. Around 15% of hosts have zero revenues. These performance data are in line with publicly available data from Airbnb (SmartAsset 2016).

[INSERT TABLE 1 HERE]

More than 70% of observations in the sample are entire flats, while the remaining ones are rooms in shared flats. The average listing comprises of 3.4 beds and 1.1 bathrooms. It usually includes breakfast or kitchen facilities (89%) as well as internet connection and TV (77%). The presence of other attributes is less frequent.

A key issue of the study is the measurement of the reputation variables, which are classified according to product and personal reputation, in line with the theoretical framework. Online reviews provide a first source of information for measuring the reputation of the product. In particular, both the number (volume) of reviews and the average review score (valence) are observed. On one hand, the average review score is relatively high (4.68 out of 5) and its variability is low, given that negative reviews are seldom observed. On the other hand, the number of reviews shows a remarkable dispersion, ranging from 0 to 213. The absence of reviews affects around 18% of cases and conveys a problem of missing data concerning the review score. Deleting this observation would raise selection bias concerns. To avoid losing the informative value of these observations, we follow the approach suggested in Howell (2007), attributing the average review score of the other listings. In this regard, traditional criteria to deal with missing data (i.e., deleting observations, imputing median or mean) do not seem to hurt the accuracy of estimates, provided that datasets have up to 20% of missing values (Acuna and Rodriguez 2004). In particular, the authors show that in the 15%-20% missing value range imputing the mean is the most accurate method.

The presence of the flat's professional photos is taken as a qualitative measure of product reputation and it is present in about half of the sample.

As for the personal reputation indicators, three variables describe the profile characteristics. First, the number of days since registration (RH_{REG}) measures the length of the host's experience in the Airbnb platform. Second, a measure of profile completeness is operationalized as a dummy variable that takes value 1 only if the host has completed all the required information for full identification and includes a personal photo (RH_{ID}). Finally, the "Superhost" qualification is an institutional based mechanism certifying the reputation of the host when certain personal reputation requirements are satisfied. In detail, the Superhost qualification is given to those who have hosted at least 10 trips, maintained a 90% response rate or higher, had at least half of his or her guests leave a review, received a 5-star review at least 80% of the time, and completed each of the confirmed reservations without cancelling. The requirements to get this institutional certification are quite demanding as less than 10% of the hosts in the sample achieve such certification. The Superhost measure might raise concerns of multicollinearity with the other reputational variables. However, a Spearman correlation between Superhost and the other previously defined measures of reputation reaches a maximum value of 0.26, well below the 0.5-0.7 threshold that signals potential multicollinearity problems (Dormann et al. 2012). More generally, including all the variables, VIFs were lower than 2.37, suggesting that multicollinearity does not affect the data.

Research findings

Equations [1] and [2] are estimated simultaneously. The empirical strategy was to estimate the stochastic frontier model with respect to (i) the entire sample of 981 observations and (ii) the reduced sample of 824 observations showing positive (non-zero) revenues. When using the entire sample, all revenue values were rescaled by 1 to allow for logarithmic transformation. Working with the reduced sample strengthens the results because it removes those hosts who have zero revenues and thus, by construct, are inefficient.

The stochastic frontier model exhibits a good fit, as shown in Table 2. The significance of both the parameters σ_u and σ_v confirms that the error term successfully splits according to inefficiency and random noise, with most of the variability due to inefficiency. As expected, the part of variability due to inefficiency is much higher when working with the entire sample, while the value of λ (the ratio between σ_u and

σ_v) decreases from 8.24 to 5.78 in the reduced sample, given that the most inefficient units are removed.

The coefficients in the upper part of Table 2 shape the revenue frontier, i.e. the maximum level of potential revenue. Interestingly, when comparing these coefficients for the two samples, they are all very stable, indicating that variables commanding potential revenues do not differ significantly. As expected, all city dummies are significant (A_{ROME} is omitted to avoid multicollinearity). The potential revenues generated by a similar listing in London (Paris) are 72% (58%) higher than in Rome, while, on the contrary, listings in Barcelona and Istanbul generate lower revenues with respect to Rome. Another key characteristic is given by the type of listing, with entire flats that can generate more than 30% additional revenues than rooms. The number of beds and bathrooms are both significant in determining the revenue frontier. The same is true for the presence of the Internet and TV, as well as the presence of washer and drier. The effect of other assets is not significant.

Before moving to the bottom side of Table 2, it is useful to observe a plot of the predicted values of the model, in terms of revenue frontier and efficiency (Figure 2). For the sake of parsimony, the plot considers the reduced sample only. As shown, the achieved revenues are only a fraction of the potential revenues (left-hand side graph). This fraction is the measure of efficiency while, conversely, the distance to the potential revenues represents the inefficiency. The right-hand side graph in Figure 2 shows that, while efficiency varies across observations, it is independent from the level of potential revenues. The efficiency is estimated via the Jondrow et al. (1982) formula, that is exp[-E(u|(v-u))]. On average, its level is around 0.40 in the entire sample and raises to 0.48 in the reduced sample, with a high dispersion among observations. This suggests that only a small portion of hosts exploits the revenue potential of listings on Airbnb.

The variability in host performances is explained by reputational attributes. The coefficients at the bottom of Table 2 inform on the determinants of the inefficiency. The two sets of estimates are consistent, though the magnitude of coefficients shrinks when working with the reduced sample. This is not surprising when recalling that the inefficiency is lower in the reduced sample compared with the entire one. Supporting the theoretical expectations (H1 and H2), both product and personal reputational variables show a significant negative effect on the inefficiency, with the unique exceptions represented by the review score (in both samples) and by the number of days since registration (in the entire sample only).

[INSERT TABLE 2 HERE]

[INSERT FIGURE 2 HERE]

The list of coefficients presented in Table 2 (δ_k) does not directly represent the marginal effects of each reputational variable (*R_k*) on inefficiency. The latter are observation-specific and are computed as follows (Wang, 2002):

$$\frac{\partial E(u_i)}{\partial R_k} = \delta_k * \left[1 - \left[\Lambda \frac{\phi(\Lambda)}{\Phi(\Lambda)}\right] - \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]^2\right] \quad [3]$$

where $\Lambda = \mu_i/\sigma_i$ (the ratio between the mean and the standard deviation of the inefficiency term); ϕ and Φ are the probability and cumulative density functions of a standard normal distribution, respectively.

Table 3 reports the marginal effects and facilitates the comparison of the different reputational variables' impact. For instance, by taking the estimates for the reduced sample, 10 additional reviews (RP_{NUM}) can reduce the inefficiency level by 0.06 (0.006*10). A similar impact would be obtained for the length of registration on the platform (RH_{REG}), if one considers a period of one year (0.0002*365 = 0.07). The comparison is even easier in the case of dummy variables, such as RP_{PHOTO}, RH_{ID}, RH_{SH}, whose marginal effects directly indicate the reduction of inefficiency that can be obtained by achieving that specific status. The Superhost qualification has the highest impact, reducing inefficiency, on average, by 0.44.

A simulation can further shed light on the weight importance of reputational group factors in reducing hosts' inefficiency and, in turn, increase their revenues. By using the marginal effects presented in Table 3, it is possible to measure the overall impact of an improvement in the various reputation indicators, classified according to the product and personal reputation groups of variables. In the simulated case, all the dummies are set to be equal to 1. Moreover, continuous variables are set at their mean values [3]. This implies that when the current value is lower, each listing achieves at least 20 reviews and the number of days from registration is at least 620. Figure 3a and 3b present the findings, splitting the theoretical potential frontier (100% of *efficiency*) in 4 parts: (i) the current level of efficiency, (ii) the amount of efficiency that would be recovered by improving product reputation, (iii) the amount of efficiency that would be recovered by improving personal reputation, and (iv) the amount of residual inefficiency. Overall, the impact of personal reputation (black area) stands out with respect to product reputation (white area), giving support to H3. This result is consistent in the two samples and across the five cities. In particular, both in Figure 3a and 3b, the city of Istanbul presents the lowest average efficiency and the highest impact of reputation, the latter being even more salient than in the rest of the cities.

[INSERT TABLE 3 HERE]

[INSERT FIGURE 3a and 3b HERE]

Finally, Table 4 shows some specification tests that provide support to the model proposed in this paper, a Stochastic Frontier Analysis (SFA) with the reputational variables that explain the gap between potential and achieved revenues (inefficiency). In particular, the AIC and BIC scores, respectively Akaike's Information Criterion and Bayesian Information Criterion, indicate the appropriateness of the model when compared to both a naïve OLS model and an alternative SFA specification where reputation also explains the potential revenues rather than the inefficiency.

[INSERT TABLE 4 HERE]

The information criteria scores' differences indicate a strong preference for the selected model, providing a further empirical support to our conceptual framework.

Discussion and conclusion

Since risk cannot be completely eliminated in online sharing economy platforms, it is important to provide mechanisms to reduce the uncertainty of transactions. This research uncloses the role of these mechanisms and bridges the gap between two salient aspects of the sharing economy, product and personal reputation.

The theoretical framework, based on the resource-based view of the firm (Dutt et al. 1999; Nath et al. 2010), suggests that consumers consider both the product and the personal reputation of the seller during the purchase process. Although expecting an effect of product reputation on revenues is quite obvious, consumer responsiveness to personal reputation, especially when jointly addressed with product reputation, had yet to be assessed.

Under the assumption that reputation is the key marketing capability that explains why subjects sharing similar goods on a platform might achieve a different performance, a stochastic frontier approach methodologically models the revenues for the sharing economy realm. The unique primary data collection through Airbnb captures variations across locations and measures the revenue impact for a reasonable time span. The findings, obtained from the empirical validation of the proposed model to the Airbnb sharing platform, suggest that, while shared assets help revenue generation (i.e., increase the frontier level), both product and personal reputation reduce the inefficiency level, supporting H1 and H2. Interestingly, the level of inefficiency is more than 50% in terms of the maximum possible achievable revenue, and this percentage is independent from the value of the listing in the sharing economy platform. The analysis of the marginal effects facilitates the comparison of the impact of the reputational variables. Among these variables, the role of personal reputation is noteworthy. More specifically, three forms of personal reputation are decisive in reducing revenue inefficiency: the identification of the seller, being a "Superhost", and the date since the seller is present in the platform, with the latter being sensitive to the used sample. Among the product reputation variables, the number of reviews and the presence of professional pictures appear as significant but their relative contribution to efficiency improvement is low. Overall, these results support H3.

In terms of theoretical knowledge, the paper transposes the resource-based view approach to the firm (Dutta et al. 1999; Nath et al. 2010) to the sharing economy environment, by specifically unpacking the role of marketing capabilities. In this sense, the predominant role of personal reputation enforces the importance of personal branding strategies in sharing economy platforms (Tussyadiah 2016b). The picture is more puzzled for what concerns product reputation. Contrarily to previous research (Floyd et al. 2014; Liu 2006), the role of review valance on revenues appears to be negligible. This might be simply due to the presence of extremely high ratings with poor dispersion, making this variable of poor informative value. Paradoxically, while consumers concur that negative reviews are very helpful in evaluating services (Labrecque et al. 2013), people show a tendency to provide exceptionally high review scores to sellers, a phenomenon that is also documented in other P2P market places such as Ebay (Bolton et al. 2013). At the time of our empirical analysis, Airbnb used mutual review mechanisms and was exposed to a potential retaliation bias. However, Airbnb has recently changed its review policy to eliminate the risk of retaliation. It would be interesting to assess in future studies if the right-skewed review scores phenomenon holds after the introduction of this new policy and if it affects the way consumers process this information. The possible persistence of the phenomenon might also be explained by how subjects elaborate their experiences in sharing markets with respect to traditional markets. Specifically, what distinguishes sharing economy markets from more traditional markets is the personal contact experience (Guttentag et al. 2017). Therefore, consumers may show a more understanding attitude towards service failure, e.g., showing non-complaining behavior, if they have created a personal connection with the service provider.

This work is not without limitations. The first relates to the dataset. Despite several controls to retrieve accurate occupancy data, some listings were blocked part of the time and, in this specific case, it was not possible to isolate blocked from booked dates. This issue can now be overcome in future studies through the use of accurate booking data, as offered by the AirDNA platform. On this aspect, it is worth mentioning that hosts can still rent listings outside the official website, especially for returning customers (Forbes 2010). Second, although previous literature has already shown a strong link between reputation and trust (Belk 2014; Agag and El-Masry; 2016; Ert et al. 2016), this research does not investigate directly how product and personal reputation affect consumers' trust. Third, although mean imputation provides generally robust estimates especially for datasets having between 15% and 20% of missing values (Acuna and Rodriguez 2004), replacing the missing average review scores with a single value will deflate the variance and partially impact on the distribution of that variable.

Finally, it remains to be investigated whether these results are fully transferable to P2P platforms offering search and utilitarian goods. In fact, the relative importance weights of product and personal reputation on revenues might change considering the reduced levels of personal risks associated to these other platforms (Schiffman and Kanuk 2000).

To boost their personal reputation, various practical means can be employed by online sellers in sharing economy platforms. Airbnb is already piloting a platform where the seller can present a video with its own storytelling (Airbnb, 2017). Creating a virtual attachment to potential buyers can in fact favor a relationship connection with the host before the actual experience (Pera and Viglia 2016). In this setting, sharing economy platforms have to act as a *tertius iungens*, benefiting from the increased reputation of its sellers.

In conclusion, platform managers can influence the effectiveness of reputation by: i) encouraging hosts to provide more information about themselves to favor full transparency and reduce the uncertainty in the purchase process; ii) facilitating independent institutional mechanisms (Chang et al. 2013) by providing incentives such as a commission reduction; iii) favoring the market penetration with the goal of increasing the number and the accuracy of reviews and iv) enhancing qualitative attributes, such as the presence of professional photos.

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List of Figures and Tables

Figure 1. Theoretical framework of the study

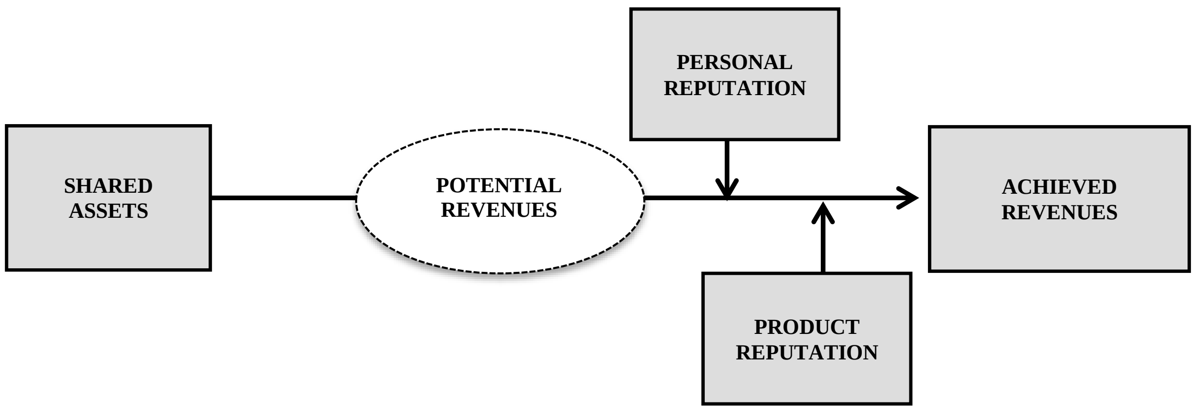

Figure 2. Representation of stochastic frontier estimates.

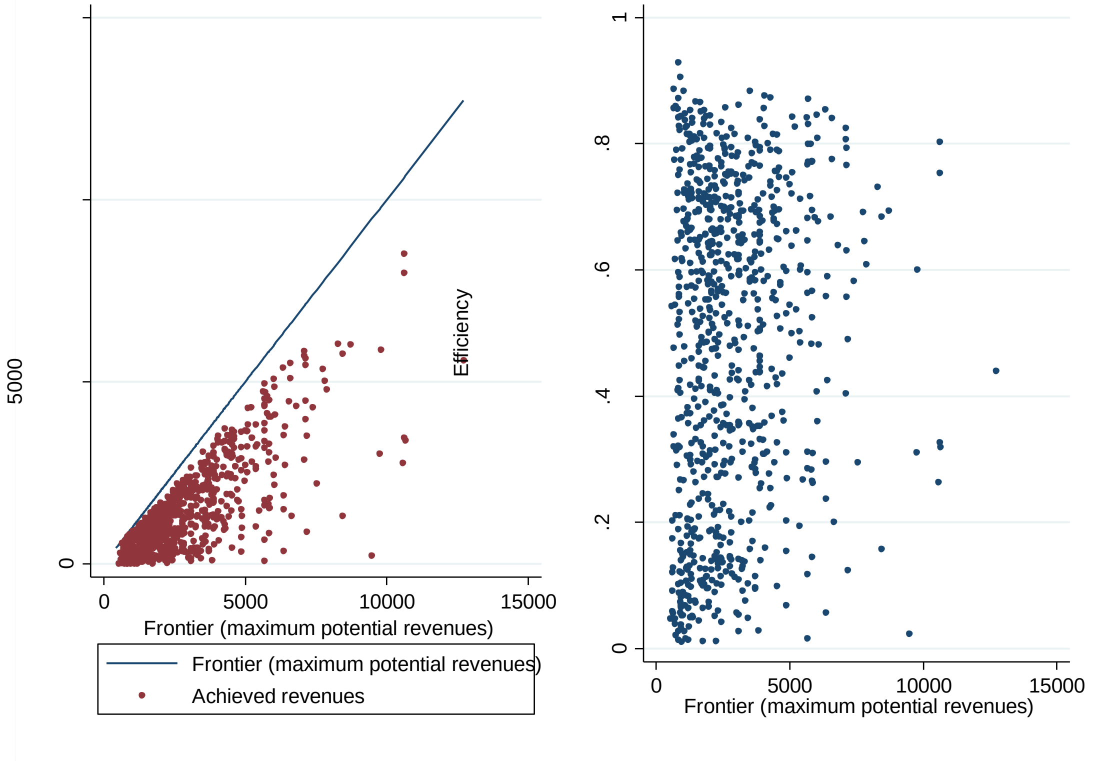

Figure 3a and 3b. Impact of product and personal reputation on efficiency

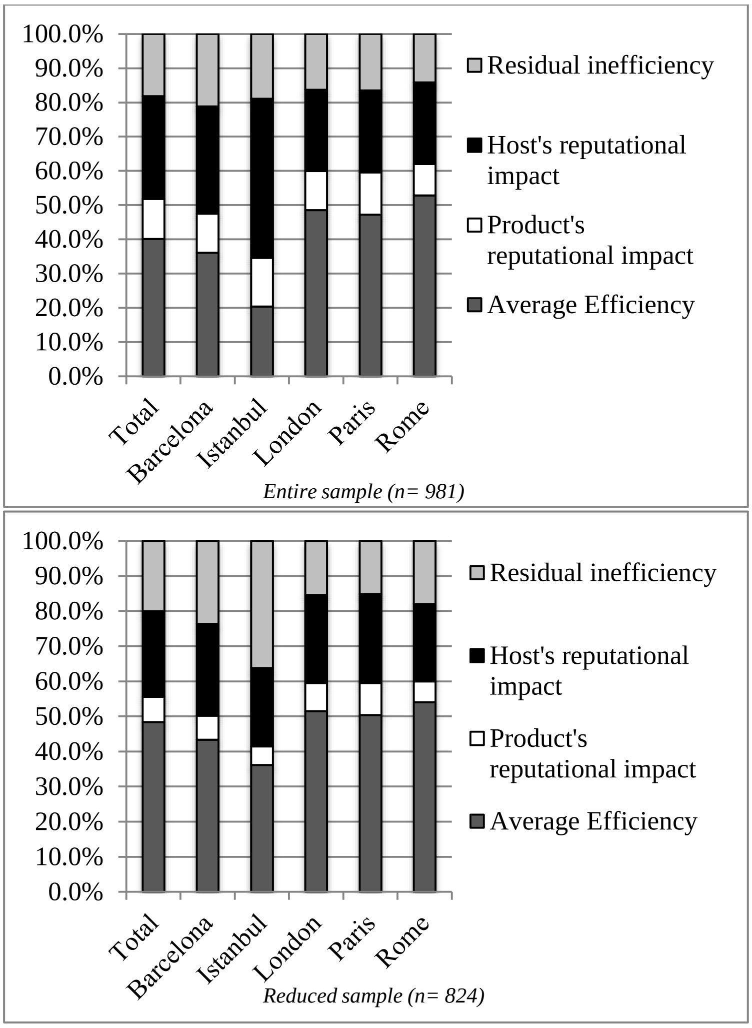

Table 1. Descriptive statistics

Type	Variable	Variable description	Mean	Std. Dev.	Min	Max
Dependent variable	*REV*	Monthly revenues (€)	1287	1525	0	10944
Flat/room characteristics (Shared Assets, A)	A_{BAR}	*Located in Barcelona*	19.57%			
	A_{IST}	*Located in Istanbul*	20.79%			
	A_{LON}	*Located in London*	19.37%			
	A_{PAR}	*Located in Paris*	20.29%			
	A_{ROME}	*Located in Rome*	19.98%			
	A_{TYPE}	Entire flat	71.15%			
	A_{BED}	Number of beds	3.44	1.53	1	10
	A_{BATH}	Number of bathrooms	1.13	0.46	0	5
	A_{COOK}	Kitchen or Breakfast included	89.20%			
	A_{IT}	Internet and Tv	77.06%			
	A_{WASH}	Washer and Drier	27.52%			
	A_{SAFETY}	Safety device	25.89%			
	A_{TOI}	Guest toiletries	32.52%			
	A_{LUX}	Swimming pool or Gym or Jacuzzi	18.86%			
Reputation of the product (*RP*)	RP_{NUM}	Number of reviews	19.80	28.11	0	213
	RP_{SCORE}	Average review score	4.68	0.25	2.75	5
	RP_{PHOTO}	Professional photo	44.24%			
Reputation of the host (*RH*)	RH_{REG}	Registered from (number of days)	620	431	37	4577
	RH_{ID}	Full identification	35.88%			
	RH_{SH}	Super-host	9.48%			

In the case of dummy variables (taking value 1 if the service or characteristic is present and value 0 if it is not), we only present the average value, which corresponds to the percentage of listings in the sample holding that specific characteristic.

Table 2. Results

		Entire sample		**Reduced sample**
Stochastic frontier model	N. observations	981	N. observations	824
	Wald Chi-square	630.45 (p=0.000)	Wald Chi-square	685.71 (p=0.000)
	Log-likelihood	-1478.62	Log-likelihood	-984.79
	AIC	3003.2	AIC	2015.6
	BIC	3115.7	BIC	2124.0

Frontier model Dependent variable is lnREV				
Variables	**Coefficients**	**(std. errors)**	**Coefficients**	**(std. errors)**
A_{BAR}	-0.309	(0.080)***	-0.317	(0.075)***
A_{IST}	-0.861	(0.105)***	-0.661	(0.095)***
A_{LON}	0.723	(0.073)***	0.731	(0.069)***
A_{PAR}	0.577	(0.072)***	0.576	(0.067)***
A_{TYPE}	0.373	(0.069)***	0.316	(0.066)***
A_{BED}	0.112	(0.020)***	0.114	(0.019)***
A_{BATH}	0.200	(0.063)***	0.170	(0.059)***
A_{COOK}	-0.049	(0.089)	-0.053	(0.085)
A_{IT}	0.136	(0.062)**	0.108	(0.059)*
A_{WASH}	0.237	(0.058)***	0.226	(0.054)***
A_{SAFETY}	0.019	(0.057)	0.028	(0.054)
A_{TOI}	-0.072	(0.053)	-0.082	(0.050)
A_{LUX}	-0.052	(0.064)	-0.048	(0.060)
Constant	6.983	(0.133)***	7.002	(0.130)***
Model of inefficiency	$\boldsymbol{\delta_k}$		$\boldsymbol{\delta_k}$	
RP_{NUM}	-0.191	(0.045)***	-0.033	(0.014)**
RP_{SCORE}	-0.117	(0.910)	0.129	(0.230)
RP_{PHOTO}	-2.436	(0.720)***	-0.903	(0.450)**
RH_{REG}	-0.001	(0.001)	-0.001	(0.000)**
RH_{ID}	-3.071	(0.780)***	-1.389	(0.536)***
RH_{SH}	-7.206	(2.441)***	-2.409	(1.085)**
Constant	1.631	(4.251)	-0.477	(1.235)
σ_u	3.075	(0.325)***	1.968	(0.306)***
σ_v	0.373	(0.033)***	0.341	(0.029)***
$\lambda = \sigma_u / \sigma_v$	8.237	(0.328)***	5.778	(0.302)***
Average efficiency	0.408		0.484	

**** p-value <0.01, ** p-value <0.05, * p-value <0.10*

Table 3. Marginal effects of reputation on inefficiency

	Only Active Airbnb				Entire Sample			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
RP_{NUM}	-0.006	0.003	-0.012	-0.001	-0.036	0.026	-0.084	-0.001
RP_{SCORE}	0.024	0.010	0.003	0.047	-0.022	0.015	-0.051	-0.000
RP_{PHOTO}	-0.164	0.070	-0.330	-0.021	-0.461	0.327	-1.081	-0.010
RH_{REG}	-0.0002	0.0001	-0.0004	-0.0000	-0.0002	0.0001	-0.0004	-0.000
RH_{ID}	-0.253	0.107	-0.507	-0.033	-0.581	0.412	-1.364	-0.013
RH_{SH}	-0.439	0.186	-0.880	-0.058	-1.363	0.967	-3.200	-0.030

Marginal effects describe the impact of each variable on the average inefficiency, E(u), through the Wang (2002) method.
Since inefficiency is half-normally distributed and can range from 0 to +∞, the value of marginal effects cannot be interpreted in terms of percentage impact.

Table 4. Specification tests

	Entire sample (N. observations = 981)	**Reduced sample (N. observations = 824)**
SFA, reputation explains inefficiency $lnREV_i = f(A_i) + v_i - u_i$ $u_i \sim N^+(\mu_i, \sigma_i^2)$; $v_i \sim N(0, \sigma_v^2)$; $\mu_i = g(R_i)$	**AIC = 3003,2; BIC = 3115,7**	**AIC = 2015,6; BIC = 2124,0**
Alternative 1: OLS $lnREV_i = f(A_i, R_i) + v_i$ $v_i \sim N(0, \sigma_v^2)$	AIC = 3380,1; BIC = 3447,9	AIC = 2175,0; BIC = 2269,3
Alternative 2: SFA, reputation explains frontier $lnREV_i = f(A_i, R_i) + v_i - u_i$ $u_i \sim N^+(\mu_i, \sigma_i^2)$; $v_i \sim N(0, \sigma_v^2)$	AIC = 3222,3; BIC = 3334,7	AIC = 2043,0; BIC = 2151,5

The lowest values of AIC and BIC indicate the best specification.

Notes

[1] The selected attractions are the following: Sagrada Familia (Barcelona), Hagia Sofia (Istanbul), London Eye (London), Eiffel Tower (Paris) and Colosseum (Rome).

[2] In particular, the availability of a listing in date *t* was collected from the day *t*+1 to the day *t*+28, while all the other information presented in Table 1 refers to date *t*.

[3] A sensitivity analysis available upon request shows that the results do not change significantly using the 25th, 50th (median) or the 75th percentile.