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Toss a Coin to your Host - How Guests End up Paying for the Cost of Regulatory Policies

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Completed Research Paper

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Abstract

Given their rapid growth in recent years, peer-to-peer rental markets like Airbnb have gained increasing attention from scholars and legislators. Scholars have uncovered the adverse effects these platforms have on the traditional lodging industry and housing affordability, fueling the public demand for regulation. While legislators around the world have implemented various regulatory policies to address these issues, little is known about their economic consequences. Therefore, we analyze a policy implemented in New Orleans, where short term rentals were legitimized by introducing a licensing system while simultaneously banning Airbnb from the touristically popular French Quarter. Our estimates reveal that hosts increase their prices by up to 3.17% in response to the policy shift. We find that this price hike is not driven by an increase in demand but rather by a pass-through of higher bring-to-market costs. This cost pass-through implies that the policy falls short of reducing pressure on housing affordability.

Keywords: Peer-to-Peer Rental Markets, Short-Term Rental Regulation, Motivational Types, Difference-in-Differences, Price Setting

Introduction

Peer-to-peer rental markets have grown immensely over a short space of only a few years. Enabled by information technology and online marketplaces, peer-to-peer rental platforms facilitate the process of renting out unused space to potential guests. Their success has famously disrupted traditional industries. In its wake, a budding stream of literature has documented the consequences of the peer-to-peer rental economy on the housing (Barron et al. 2018) and hotel industry (Li and Srinivasan 2019; Zervas et al. 2017). These studies find that peer-to-peer rental market entries have been blamed for raising housing prices and

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rents, while reducing hotel revenues. Additionally, both scholarly (Ikkala and Lampinen 2015) and anecdotal evidence (Wong 2017) points to a range of motivational types amongst suppliers, according to whether they are more or less financially driven. While some hosts still follow the initial idea of peer-to-peer rental platforms (e.g., AirBnb) and strive for social interaction with guests to enable them genuine local experiences, others merely participate on the platform to endeavor additional income without even talking to their guests. Anecdotical evidence emphasizes the increasing share of hosts with hundreds of listings and those who rent out properties without being physically present during guest stays (Wong 2017). In that sense, especially those financially motivated suppliers have heated up the public debates on commercialization of peer-to-peer rental platforms (Nieuwland and van Melik 2018).

Naturally, these trends have attracted the attention of municipal governments, many of which having brought in regulatory policies with measures aimed at regulating the economic activity of peer-to-peer rentals in local markets (Nieuwland and van Melik 2018). Examples of such measures include restricting the areas in which they can operate or by levying additional fixed costs onto hosts in the form of licenses. But how do peer-to-peer rental suppliers, e.g., Airbnb hosts, respond to regulatory policies? For example, do they increase prices in cities which place restrictions on renting out private accommodation to temporary guests? Do financially motivated suppliers – as key drivers for the demand of regulatory action– react differently to those policies compared to socially motivated suppliers, such that commercializing debates cool down afterwards? Even though the aforementioned literature has informed us about the impact of peer rental markets on various traditional industries, there is little empirical research to date on how peer rental suppliers have responded to regulatory policies.

This lack of knowledge presents a handicap to scholars, legislators, and consumers. For legislators, apart from the income generated from levies, their main aim is to mitigate the negative externalities, e.g., to avoid increases in housing prices and rents. Prior theoretical work (Filippas et al. 2020) suggests that if bring-to-market costs (e.g., cleaning, managing the check-in, taxes) are borne by peer-rental suppliers, acquiring a property merely for the sake of peer-renting becomes relatively unappealing. This, in turn, can keep the increase in housing prices and rental rates at bay, which is in the interest of the legislator. However, if bring-to-market costs are to a large extent passed through to guests, peer-renting would still remain attractive.

Our study examines a regulatory policy in New Orleans that was introduced in April 2017 and that banned Airbnb rentals from a certain area and legitimizes it in others, requiring eligible hosts in these locations to purchase a license. In order to tease out the effect that this policy has had on listing prices set by hosts, we leverage the policy's exogenous shock on listing supply, demand, and bring to market costs levied onto hosts. A key novelty of our study is that we develop a natural language-based machine learning algorithm that maps the motivational type of hosts on a spectrum comprising, at one end, financial motivation, and social motivation at the other end. The aim of our study is to analyze the heterogeneous impact of policy regulations on the prices charged by peer rental suppliers. Thus, we formulate the following research question:

How do socially- and financially motivated peer rental suppliers set prices in response to a policy shift which affects demand, supply, and bring-to-market costs?

Intuitively, there are three conceivable pricing behaviors in response to a policy shift. In the first two, hosts may increase their prices either in order to pass license costs through to consumers, or due to increased demand stemming from the restrictions imposed on rental supply in certain areas. Alternatively, hosts may decrease their prices due to an increased supply resulting from regulatory policies. Applying a difference-in-difference estimation strategy, we find that hosts on average respond to the policy shift by increasing prices by up to 3.17%. Financially motivated hosts, however, increase their prices much more drastically than socially motivated hosts. We find that prices are already being increased directly after the announcement of the policy, suggesting that hosts are forward-looking in their price setting. Interestingly, our estimations suggest that the main driver of this price increase is the cost pass-through of the licenses to consumers and not the changes in supply and demand subsequent to the policy announcement and implementation. We lend robustness to our estimates by using matching strategies, alternative operationalizations of focal constructs, and with additional sensitivity tests.

This paper makes several contributions to the literature. To the best of our knowledge, we are the first to present empirical evidence in support of the claim that consumers are bearing the cost of municipal regulatory policies. First, we present evidence that this effect is not caused by the change in supply and demand prompted by the policy, but by the additional bring-to-market cost imposed on the host which is transferred to the consumer. Second, we show that hosts are increasing prices immediately after the announcement of the policy and before its effective implementation. Third, by differentiating between financially and socially motivated hosts, we show that the price increase is primarily driven by the former group of Airbnb hosts. Thus, we present evidence that contributes to the literature on the difference between socially and financially motivated suppliers in the sharing economy (Ikkala and Lampinen 2015). To the best of our knowledge, this degree of differentiation between host heterogeneity has hitherto not been possible and presents a valuable tool to any scholar, legislator, and practitioner investigating the supply side of peer rental platforms.

Related Literature

This research is related to price setting behavior on Airbnb. In contrast to other platforms like Uber, Airbnb occupies a special place in the domain of peer-to-peer sharing in the sense that suppliers (i.e., hosts) can freely decide on their pricing. Given that a substantial number of suppliers expect financial returns from their participation, they also face a profit maximization problem when setting their prices on the platform. There is evidence that hosts on Airbnb exhibit difficulties when it comes to adjusting their prices in response to changing demand (Gibbs et al. 2018). Notably, few hosts adjust their prices to weekly or seasonal demand patterns (Gibbs et al. 2018). Still, there is some evidence of strategic price setting on Airbnb. Several studies have shown that hosts try to monetize on the quality signals that are presented on their listings' pages. For instance, an improvement of the listing's reputation in form of online reviews and ratings can cause hosts to increase their prices (Gutt and Herrmann 2015; Neumann and Gutt 2017). Similarly, some hosts ask for a price premium after having received virtual badges, such as Airbnb's superhost badge (Neumann and Gutt 2017; Teubner et al. 2017). Furthermore, prior literature suggests that hosts are heterogenous in their motivation to participate on Airbnb. It has been found that economic benefits are the key motivator for suppliers to join the platform (Ikkala and Lampinen 2015). However, there are also suppliers that consider profits rather as supplementary income and have come to enjoy the social aspects such as getting to know new people (Ikkala and Lampinen 2015) and the enjoyment in sharing (Hawlitschek et al. 2016). Our study contributes to the field of price setting on Airbnb by (1) providing insights on pricing responses to significant geographical changes in the market situation caused by regulatory policies, (2) establishing a method to reliably distinguish financially from socially motivated hosts, and (3) studying heterogeneous price reactions of these hosts.

We also contribute to research on policy regulations for peer-to-peer short term rentals. Research generally recognizes three approaches towards regulating Airbnb, namely, prohibition, laissez-faire, and allowing (Miller 2016). While there are studies that conceptually and empirically derive policy recommendations (e.g., Quattrone et al. 2017), only a few investigate the direct effect of policy regulation on the Airbnb market. Alyakoob and Rahman (2018) investigate a policy shift in New Orleans that legalized Airbnb and introduced licensing costs as well as taxes. Simultaneously, the city banned Airbnb activity from the French Quarter, a tourist hotspot. They find that supply (i.e., the number of listings on Airbnb) in this area decreased after the policy shift had been implemented, while demand for short term rentals had increased in adjacent districts (Alyakoob and Rahman 2018). Considering policy shifts in multiple US cities, Chen et al. (2018) analyze changes in supply on Airbnb. The regulation implemented by some cities requiring that hosts need to be present in the city when renting out their property has not been found to significantly affect supply (Chen et al. 2018). On the contrary, license costs levied on suppliers negatively affects supply in the short term but increases it in the long term (Chen et al. 2018). Furthermore, regulating the market by requiring hosts to adhere to standards for health and safety (e.g., installing fire alarms) effectively reduces the number of listings in non-affluent neighborhoods (Chen et al. 2018). Policy shifts in general are associated with an overall decrease in the demand for short-term rentals in a city (Furukawa and Onuki 2019). While these studies focus on supply and demand, there is also evidence that rental suppliers increase their prices when a policy raising taxes has been introduced. In particular, Airbnb hosts react to an increase in taxes for short-term rentals by increasing their prices and essentially passing their additional costs onto consumers (Bibler et al. 2020).

As outlined above, many policy interventions entail changes to demand and supply which in turn can affect price setting behavior. However, pricing responses towards these kinds of policies have not yet been investigated. We aim to address this gap by studying pricing behaviors in response to policies that not only increase bring-to-market costs for Airbnb hosts but also affect supply and demand in the market via the regulation of Airbnb by City authorities in certain geographic locations. Further, neither of the existing studies, be they on the disruptive effects of Airbnb or on the host responses to regulation, consider heterogeneity stemming from different host motivations. Therefore, this study is, to the best of our knowledge, the first to investigate how socially and financially motivated Airbnb hosts differ in their price reactions towards a policy shift.

Theoretical Background

Market Equilibrium Theory

As presented in the previous section, potential financial benefits are a main driver for Airbnb hosts to participate on the platform. Therefore, one would expect that market participants behave according to microeconomic models. Market equilibrium theory predicts how an equilibrium price on markets is found based on the relationship between supply and demand (Varian 1999). The demand curve describes the relationship between the market price and the quantity of goods demanded. Consumers are heterogeneous in their willingness to pay for a good. For a high price, only a small number of consumers is willing to buy the good. For instance, in the case of Airbnb, relatively few consumers are willing to pay a high price for staying in a large apartment with a pool. Similarly, the supply curve describes the relationship between the market price and the quantity of goods suppliers offer for this price. For exposition purposes, we assume that goods are homogeneous.[2] Suppliers differ in their willingness to provide goods. If they can demand a high price, they will offer more goods. Naturally, offering one's apartment on Airbnb becomes more attractive to hosts if they can ask for a high price. Supply can increase by either a single host offering additional listings or new hosts entering the market. The intersection of the demand- and supply curve determines the market's equilibrium price p^*. External shocks like policy changes may shift the demand and/or the supply curve. These shifts also affect the equilibrium price and the equilibrium amount of goods. For instance, a policy change might increase the market demand so that after the change, there are more consumers demanding the good for the initial price. This policy change essentially shifts the demand curve to the right which implies a new equilibrium price.

Cost Pass-through Effect

In classic competition theory, where marginal costs and demand elasticity are held constant, an increase in input prices is directly passed through to the consumers (e.g., Besley and Rosen 1998; Poterba 1996). That is because the equilibrium price is equal to marginal costs and any increase in input price therefore translates into an increase in equilibrium price. A common example of a policy-related increase in input price is the introduction of minimum wages. Previous research consistently documents how firms react with price increases after an increase in minimum wages (Aaronson 2001; Card and Krueger 1993). In the context of the sharing economy, Filippas et al. (2020) theorize that owners of goods (in our case Airbnb hosts) partially pass increased bring-to-market costs through to their consumers by increasing their prices. These costs include, for instance, cleaning costs as well as taxes. As documented by Bibler et al. (2020) empirically, the cost pass-through effect is indeed present on the Airbnb market as hosts increase their prices following a tax increase.

Social Reward Theory

Market equilibrium theory and cost pass-through theory are widely accepted for analyzing traditional markets. In these traditional settings it is assumed that all market participants maximize their utility according to their preferences (Varian 1999). In general, suppliers maximize their utility by maximizing their profit. However, the sharing economy deviates from this setting. As formulated in the initial idea of Airbnb and as outlined by previous literature (Hawlitschek et al. 2016), Airbnb hosts also participate in the market to experience social benefits such as the enjoyment of sharing or the social interaction with their guests. Therefore, they might not be interested in setting profit maximizing prices because their focus is on

[2] Notwithstanding the horizontal and vertical differentiation of Airbnb listings in the real world, we control for a wide range differentiation of listings in our empirical analyses.

social benefits. To account for the social benefits that hosts expect from engaging in sharing their accommodation, we build on social reward theory (Fareri and Delgado 2014; Sanfey 2007). This theory postulates that social activities trigger a feeling of reward in individuals. They incorporate these rewards into their decision-making (Fareri and Delgado 2014). Relevant social activities that trigger these rewards include social interactions with others (Fareri and Delgado 2014), such as getting to know new people and cultures (Ikkala and Lampinen 2015) or even the mere act of establishing social contact (Buss 1983).

Research Environment and Hypotheses

Research Environment

We collect monthly panel data from insideairbnb.com for all Airbnb listings available in New Orleans during the time between August 2016 and August 2017 (Cox 2020). These data contain the entirety of information usually observable by a visitor of the airbnb.com website. For each listing, we obtain accommodation-level information (e.g., price, number of bedrooms, room type), host-level information (e.g., self-description, Airbnb membership duration, response rate, verified identity), and review-level information (the overall rating and the six-dimensional ratings). The regulatory policy shift in New Orleans came into effect in April 2017 and was announced in December 2016. Our panel data thus provides the opportunity to analyze price setting behavior in the time before the announcement, during the four months between the announcement and the policy's coming-into-effect, and in the first five months following its implementation. Figure 1 displays the timeline of events.

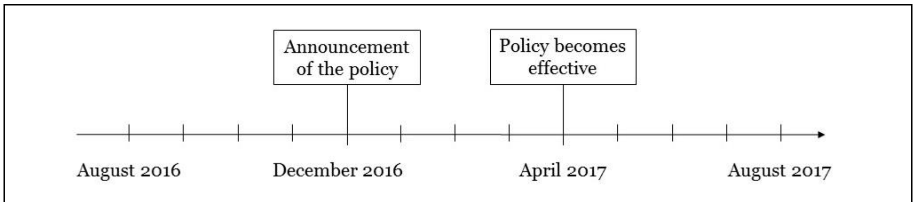

Figure 1. Time Line of Events

The regulatory policy by the city council of New Orleans essentially consisted of three parts. First, it banned Airbnb activity in the French Quarter, a neighborhood that is particularly popular among tourists.[3] Second, it legalized Airbnb activity in the rest of the city, requiring hosts to be licensed. However, after the announcement of the policy and it coming into effect, there was a notable increase Airbnb activity. Third, every Airbnb host now needs to obtain a short-term rental (STR) license, of which there are three different types, which vary in annual costs: Accessory Short Term Rentals ($200) Temporary Short Term Rentals ($50-$150), and Commercial Short Term Rentals ($500) (New Orleans Government 2017).[4] To build a control group, we collect Airbnb listing data from Portland, New York, and San Francisco from insideairbnb.com for the same period. These cities were, at the time of the research, not subject to a municipal Airbnb regulatory policy shift and therefore the listings from these cities can serve as a control group. We take a more granular approach to the exact construction of our control group listings in our robustness checks. In total, our panel data set comprises 105,661 listings operated by 79,502 hosts.

Development of Hypotheses

The policy shift that we consider in our research context affects the market in two major ways. First, on the supply side, hosts whose listings are located in the French Quarter are banned from the market, whereby all other hosts face new tax regulation and license costs for short term rentals. Second, the legitimization of Airbnb provides assurance to guests on the demand side. Anecdotal evidence reports substantial

[3] At the time of writing, some listings were exempt from this regulation, such as listings by hotels that merely use Airbnb as an additional sales channel.

[4] As a visitor of the airbnb.com website, it is not possible to see which license type a New Orleans host has acquired. More information on the licenses can be otained from New Orleans Government (2017).

inconvenience to guests who booked illegitimate listings (e.g., they had to move to hotels and where denied entry by apartment managers (Reddit 2017)). As a consequence of the new policy, these concerns should decrease while the potential willingness of guests to book Airbnb listings in New Orleans should increase. This would imply an increase in demand for listings located outside the French Quarter.

On the one hand, hosts on Airbnb (i.e., the supply side) can respond to this new market setting by reducing supply. Although hosts might expect additional bookings due to increased demand, the upcoming constraints and cost may scare off both new and already participating suppliers. However, remaining hosts that are willing to pay for taxes and the required license will face both increased demand and lower competition. Following market equilibrium theory, the supply curve would shift to the left in this case, while the demand curve moves to the right. To reconstitute market equilibrium, the equilibrium price will move upward, suggesting a price increase. We term this the *equilibrium effect*. Since extant hosts face new tax regulations and license costs for short term rentals, they might also consider passing the additional costs to their visitors as pointed out in previous studies (Bibler et al. 2020; Filippas et al. 2020). In line with the literature (Aaronson 2001), we refer to this effect as the *cost-pass through effect*. Considering both the equilibrium and the cost pass-through effect, we hypothesize an overall price increase if supply decreases:

Hypothesis 1a: Airbnb hosts in New Orleans increase their prices after the policy shift.

In our empirical analysis, we will disentangle the role of the two distinct effects for the price increase postulated by Hypothesis 1a.

On the other hand, suppliers could also anticipate a massive increase in demand and increase supply instead. Given that offering listings on Airbnb became regulated after the policy shift and allowable in parts of the city, a higher number of homeowners might have decided to participate in the market. In this case, hosts might bear the additional tax and license costs to skim the market's increased demand side. This increase in supply would shift the supply curve to the right. Following the *equilibrium effect*, an increased market competition results in a decrease in prices. If many new hosts were to enter the market, hosts would be limited in their market power and thus in their ability to pass additional bring-to-market costs to their guests. For that reason, the *cost pass through effect* is not likely to appear in case of increased competition. Instead, market equilibrium theory predicts that an over-proportional increase in supply evoked by the policy results in an overall price decrease:

Hypothesis 1b: Airbnb hosts in New Orleans decrease their prices after the policy shift.

Finally, we consider the role of social rewards in hosts' responses to the policy shift. As outlined in the previous sections, hosts who participate in the market may also be motivated by social benefits, to a greater or lesser extent (Hawlitschek et al. 2016; Ikkala and Lampinen 2015). These benefits are socially rewarding experiences (Fareri and Delgado 2014) and thus form part of a host's utility maximization decision. Naturally, there are some hosts who value financial benefits more than social benefits and vice versa (Ikkala and Lampinen 2015). For instance, some hosts may place a greater emphasis on the social aspect and might have dinner with their guests. Others have very little interaction and manage their Airbnb listing rather like a hotel. We refer to hosts as either socially or financially motivated. From a rational perspective, all hosts benefit from optimally setting their prices. However, socially motivated hosts should behave differently compared to financially motivated hosts as their utility for social interaction is higher. In response to an increase in demand after the policy, socially motivated hosts will set relatively low prices, so that they will have a better chance of being booked and obtaining those social experiences (Cui, 2019). Contrarily, social utility will be substantially lower for financially motivated hosts and thus, their main goal is to maximize profits by maximizing prices after the policy. Therefore, financial motivation should affect the relationship between prices and the policy shift:

Hypothesis 2: Financially motivated hosts respond to the policy shift in New Orleans by raising their prices more than socially motivated hosts.

Empirical Analysis

Distinguishing between Financially motivated and Socially motivated Hosts

A key aspect of our study is to investigate the differential impact of the introduction of regulatory policies in New Orleans on the prices of Airbnb listings for both financially and socially motivated hosts. This approach challenges the implicit assumption of homogeneously motivated Airbnb hosts made in prior literature (Hawlitschek et al. 2016; Ikkala and Lampinen 2015). We assume that the motivation of a host to list their accommodation on Airbnb can be located on a spectrum where one end represents hosts that are purely financially motivated and the other those that are purely socially motivated. It is well-established in prior literature, that hosts on Airbnb are typically motivated by a mix of financial and social aspects (Hawlitschek et al. 2016; Ikkala and Lampinen 2015). In line with these studies, we define hosts as socially motivated when they *enjoy meeting people, when they find pleasure in communicating with guests, and when they express willingness to conduct social interaction* (derived and adapted from Buss (1983); Cui et al. (2019); Ikkala and Lampinen (2015)). In contrast, we define hosts as financially motivated when *there is no personal interaction possible due to absence of the hosts, when the host does not offer the guest opportunities for personal interactions, when hosts are out of town during rental periods or when company names are used in the host description instead of personal names* (derived and adapted from (Li et al. 2015; Sherblom 2010)).

Naturally, identifying unambiguously whether an Airbnb host is rather financially or socially motivated is a challenge. Earlier studies have mainly relied on two simple strategies. First, hosts can be divided into single- and multi-listing hosts (Li et al. 2015), assuming that single-listing hosts are socially motivated and multi-listing hosts are financially motivated. This strategy may suffer from imprecision since single-unit hosts who only temporarily inhabit an apartment (e.g., commuters) may be financially motivated although having only one listing. These hosts might rent out their apartment only during their absence which rules out any physical social interaction with guests and therefore rather indicates financial motivation. A second strategy classifies socially motivated hosts as those who offer shared rooms and private rooms on Airbnb and financially motivated hosts as those who offer whole units, be it apartments or houses (Cui et al. 2019). Moreover, hosts of shared rooms may also be financially motivated as inhabiting shared apartments may be merely looking for an additional income to finance their apartment. Also, hostels that use Airbnb as an additional channel to receive bookings might enlist shared bedrooms as shared apartments, which undermines the strategy of classifying hosts that provide shared rooms per default as socially motivated. Thus, an appropriate policy evaluation for heterogeneous host types requires a way more precise classification procedure for distinguishing socially and financially motivated hosts.

Our approach

To overcome these limitations, we develop a unique machine learning and natural language processing-based approach that incorporates textual information on the Airbnb hosts in our sample. To distinguish between financially and socially motivated hosts, we rely on the following pieces of information contained on Airbnb listing pages: 1) self-descriptions of hosts, 2) information on guest interaction, 3) information provided in the host's reviews. In the self-descriptions, hosts usually provide information about themselves, about their hobbies or the reason why they joined Airbnb. In the information on guest interaction, hosts lay out their preferred nature of interaction with guests, e.g., if they want to be left alone or if they are happy to take the guests round the neighborhood. The reviews provided by the guests usually also contain information about the host's behavior during guest stays. The texts provided in these pieces of information, as well as the tone in which the texts are written, enable unique insights into the motivation of hosts. Our classification method uses this textual information and proceeds in the following three steps.

Step 1: Labelling the Training Data

In step 1 of our approach, we randomly draw 1000 listings from our data sample and extract the host's self-description and the information on guest interaction. We then hired workers on Amazon Mechanical Turk (referred to as Mturkers) to read and label this information. On a scale from 1 to 5, each Mturker had to rate if the hosts appear to be rather financially or socially motivated, where a score of 1 represents financial, and a score of 5 social motivation. Scores of 2 and 4 can be used if the motivation is not clear-cut but tendencies are visible, and scores of 3 can be used for unclear or ambiguous motivations. The listing of each host's self-description and information on guest interaction was processed by two Mturkers. Before starting the task, we explained the task to the Mturkers (recruited from the US, Canada, and the UK), introduced them to our definition of financial and social motivation (explained earlier), and provided them with pre-selected examples of financially and socially motivated hosts. Moreover, we restricted the pool of eligible Mturkers to those who have an acceptance rate of 85% for annotation tasks and we remunerate them with $0.10 per labelled host. Mturkers could determine themselves how many hosts they were going to label. On average, Mturkers labelled 10.78 hosts and took a median of 48 seconds per host. Thus, the pure labelling time of each Mturker was approximately 8.62 minutes ($10.78 * 48/60 = 8.62$) during which they earned $1.08 ($10.78 * \$0.1 = \$1.078$) on average. This equals an hourly salary of $7.45 and hence surpasses the median hourly Mturks salary of $2.11 reported by prior literature (Hara et al. 2018) by an enormous margin. Before the actual task, they were required to complete a paraphrasing task, shown to be effective for verifying and eliciting linguistic attentiveness (Munro et al. 2010). After the task, Mturkers had to fill out a short survey in which they had to indicate their age, gender, and native language. Upon completion of the labeling, we manually checked all the labels as a quality insurance. To this end, we excluded those by Mturkers who did not pass the linguistic attentiveness task, who indicated an unrealistically high age (e.g., 120 years), and dropped hosts for which Mturkers completely disagreed in ratings. For each host, we computed the average rating of the two Mturker ratings and assessed them, whereby the 25% percent (the first quartile) of hosts with the lowest scores were classified as financially motivated and those with the 25% highest scores (the fourth quartile) as socially motivated. Hence, we eliminate all ambiguously classified hosts from the training data.

Step 2: Training and Classification

For the hosts' self-descriptions and the information on guest interaction of the labelled training data, we conducted standard text pre-processing via the spaCy library, comprising stemming, lemmatizing, tokenization, removal of stop words, and of non-alphabetical words. We transform the resulting pre-processed texts into a vector using *scikit-learn*'s *TFIDF Vectorizer* so that each host is characterized by a vector of words. We enrich this factor with a variable indicating the length of the texts (Ma et al. 2017). We also integrated a percentage score of how often guests utilize the host's name in their reviews relative to the total number of reviews for a specific listing. On top of this, we use the Language Inquiry and Word Count (LIWC) (Tausczik and Pennebaker 2010) tool to obtain a variable called "social" and add it to the vector. We compute "social" for each host based on their textual information as well as for the corresponding reviews of a given host. The variable "social" is a continuous variable from 1 to 100 where a score of 1 indicates that nothing social is written at all and 100 indicates that the text is written in a social manner. To train our classifier, we used 90% of our labelled sample to train and 10% to validate the algorithm. As algorithms we deployed k-nearest neighbors, support vector machines (SVM), and random forests. Adapting approaches from prior work (Larpin et al. 2019; Li et al. 2015), we imposed the boundary conditions that hosts with more than 5 listings are automatically classified as financially motivated and that only hosts with no more than one listing can be classified as socially motivated. We evaluate the performance of the algorithms using accuracy and F1 scores, as depicted in Table 1. We conclude that the SVM and random forest have yielded the best training data performance, with an accuracy of 0.85 and high F1 scores for both types of motivation. Because the SVM and random forest dominate the k-nearest-neighbors in performance, in the following analyses we proceed with these two classifiers and apply them to our whole sample data set of listings. Our classification procedure results in two binary outcome variables for each listing – named "social motivation" and "financial motivation" – which depict whether the corresponding host is classified as either socially or financially motivated. In this context, "social motivation" ("financial motivation") is set to 1, if the classification algorithm predicts a probability 60% or more of belonging into the "social" ("financial") class, based on the host's textual description and the corresponding reviews. In case of a so called "50:50" classification decision, both "social motivation" and "financial motivation" equal zero. Descriptive statistics of our classification reveal that more than 45% of hosts with one listing are classified as financially motivated and more than 59% of socially motivated hosts offer an entire home, which indicates potential measurement error of previously used strategies.

Table 1. Evaluation of Classification Algorithms on the Training Set

Algorithm	Accuracy	F1 Score (social motivation)	F1 Score (financial motivation)
K-Nearest-Neighbors	0.82	0.82	0.82
SVM	0.85	0.85	0.85
Random Forest	0.85	0.86	0.84

Step 3: Validation

Even though we have trained a carefully designed supervised machine learning classifier, most of the feature vector used to train the classifier is based on written text. As written text understanding can be associated with many difficulties (humor, irony, double negations etc.) that might deteriorate the precision of our classifiers, we would like to validate their performance using human coders. This is to ensure that hosts who exhibit financial motivation in their written texts have not been classified as socially motivated and vice versa. For our human coding validation, we recruited two independent research assistants (hereafter referred to as C1 and C2) and asked them to read a random sample (N=300) of host information and classify them as either socially- or financially motivated. Naturally, the human coders could not see how our classifiers classified the host. We instructed the human coders during an in-person coaching based on the same information that the Mturkers received. In Table 2, we report the interrater agreement separately for our two classifiers and the two motivational types.

Table 2. Interrater Agreement Between Human Coders and Algorithms

	Motivational Type	% Agreement	N	Krippendorff's Alpha	Cohen's Kappa
C1 & C2	Social	96 %	300	0.917	0.917
SVM & C1 & C2	Social	80.33 %	300	0.729	0.729
RF & C1 & C2	Social	82.33 %	300	0.759	0.759
C1 & C2	Financial	95 %	300	0.898	0.898
SVM & C1 & C2	Financial	75.33 %	300	0.671	0.670
RF & C1 & C2	Financial	72.66 %	300	0.636	0.636

As indicated by Krippendorff's Alpha and Cohen's Kappa, the interrater agreement between the human coders and the algorithms is substantial for both motivational types and both algorithms. In most cases, both metrics are higher than 0.7 which is above the value 0.6 which is commonly used as the threshold value for substantial agreement (Stemler 2004). We also computed the interrater agreement between human coders and previously used strategies to identify social and financial hosts (e.g., unihost for social motivation and multihost for financial motivation), which resulted in values of only 0.17 for both metrics. In summary, we conclude that classification algorithms are superior to prior used strategies, since they compare very well to human judgement and have thus reliably identified the motivational types of hosts, conditional on their information provided on Airbnb. We report all following results based on the Support Vector Machine's classification.

Data

Table 3 presents the summary statistics of our panel dataset which we obtained from insideairbnb.com for the cities of New Orleans (our treated city) as well as for Portland, New York, and San Francisco (our control group cities). The statistics represent monthly averages and our observation period spans 12 months. We present the statistics separately for all hosts (N=623,303), socially motivated hosts (N=175,934), and financially motivated hosts (N=280,537). To rule out that hosts enter Airbnb due to the French Quarter ban, we only include listings in our dataset that were set up before December 2016. Moreover, we excluded the listings located in the French Quarter from our sample. Our dataset comprises several variables capturing listing attributes, host attributes, and online rating information. The listing attributes include the number of baths (NUM_BATHS), the number of bedrooms ($NUM\_BEDROOMS$), the number of guests a listing can accommodate (NUM_GUESTS), the number of amenities offered by a listing (e.g., hair dryers, wifi, smoke detectors etc.) ($NUM\_AMENITIES$), and the room type (shared, private, or whole house/apartment as dummy variables) ($ROOMTYPE\_SHARED$, $ROOMTYPE\_PRIVATE$, $ROOMTYPE\_WHOLE$). We also calculated a listing's geographic distance to the city center as the haversine distance between the listing's geolocation on Airbnb and the city's town hall ($DISTANCE\_TO\_CENTER$). The host provides information on how many months they have been registered as a host on Airbnb ($MEMBERSHIP\_DURATION$), whether they have acquired a superhost badge at the time of observation ($SUPERHOST$), and whether their account has been verified with an official ID ($VERIFIED\_ID$). Moreover, we also have variables on the online ratings of a listing for the overall rating as well as the six-dimensional ratings for accuracy, cleanliness, check-in, communication, location, and value. Due to space limitations, Table 3 presents an excerpt of variables. Nevertheless, in our analyses we use all the control variables mentioned above.

Table 3. Excerpt of Summary Statistics[5]

Variable	*All hosts (N=623,303)*		*Social hosts (N=175,934)*		*Financial hosts (N=280,537)*	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	St. Dev.
$ROOMTYPE\_SHARED$	0.027	0.162	0.014	0.119	0.036	0.187
$ROOMTYPE\_PRIVATE$	0.428	0.495	0.383	0.486	0.430	0.495
$ROOMTYPE\_WHOLE$	0.545	0.498	0.602	0.490	0.534	0.499
$DISTANCE\_TO\_CENTER$	3.806	2.503	3.773	2.351	3.783	2.601
$SUPERHOST$	0.139	0.346	0.207	0.406	0.068	0.251
$NUM\_REVIEWS$	22.147	37.862	28.784	41.408	13.322	27.227
$PRICE$ (in $US)	165.981	261.372	162.562	246.273	175.440	297.255
$DEMAND$	1.209	2.116	1.508	2.287	0.830	1.749
$COMPETITION$	1838.611	1333.189	1800.511	1341.712	1903.828	1327.906

As the dependent variable, we use the listing price in $US for one night ($PRICE$). As the main independent variable we use BAN, which equals 1 if the listing is located in New Orleans, where Airbnb activity was banned from the French Quarter, and 0 if it was located elsewhere. Moreover, we have two main control variables pertaining to the mechanisms laid out in our hypotheses, namely $DEMAND$ and $SUPPLY$. To proxy the demand a particular listing enjoys, we follow prior literature (Alyakoob and Rahman 2018) and use the number of new reviews a listing obtains in a month. The variable is computed by taking the monthly first differences of the total number of reviews (NUM_REVIEW) a host has obtained. As the insideairbnb.com data are crawled from Airbnb at the beginning of each month, this variable reflects the demand from the preceding month which rules out reverse causality between $PRICE$ and $DEMAND$. As Airbnb only allows reviews of guests who have spent at least one night at a listing, this measure is a lower bound metric for the demand of a listing. Prior research corroborates this stance. Fradkin et al. (2015) use proprietary Airbnb data and find that around 67% of Airbnb guests write reviews. To proxy the supply of listings available on Airbnb, we count the number of other Airbnb listings within a 1-mile radius around the focal listing in each month. This measure also enables us to capture the competitive landscape around a focal listing in a fine-grained manner and to control for the supply-side mechanism laid out in our hypotheses. As supply increases (decreases), competition among listings increases (decreases) which should exert a downward (upward) pressure on listing prices, ceteris paribus. To rule out reverse causality between $PRICE$ and $SUPPLY$, we incorporate the supply from the precedent month of each listing in our specification.

Empirical Model

To empirically test our hypotheses, we estimate a classical difference-in-difference design with multiple interactions between the treatment and the monthly time dummies, as depicted in equation (1).

$$ln(Y_{it}) = \beta_0 + \sum_{j=1}^{T} \alpha_j \cdot MONTH_{itj} * BAN_i + \beta_1 \cdot BAN_i + \sum_{j=1}^{T} \theta_j \cdot MONTH_{itj} + \beta_3 \gamma_{it} + \delta_i + \varepsilon_{it} \qquad (1)$$

5 We additionally computed t-test statistics between social and financial hosts for all our variables, which are all statistically significant at a 5% level.

Y_{it} represents the natural logarithm of the price of listing i in month t. The key variables of interest are the interactions $MONTH_{itj} * BAN_i$ which represent the difference-in-difference estimator and capture the average treatment effect on the treated (ATT) listings. Naturally, we also incorporate the variables of the interaction separately in our specification, where $MONTH_{itj}$ represents a single month dummy that is equal to 1 if t represents its respective month. Finally, γ_{it} is a vector of control variables, δ_i represents listing fixed effects, and ε_{it} is a random error term.

Identification

Our research design mimics a natural experiment where New Orleans listings are subject to a treatment (the ban) and listings in our remaining cities serve as the control group. Technically, $MONTH_{ij} * BAN_i$ identifies the ATT, i.e., the effect of the French Quarter ban coupled with the introduction of STR licenses, on the prices of all the listings in New Orleans. The identification of the causal effect hinges upon the conditional independence assumption of the treatment and the common trends assumption (Angrist and Pischke 2008). Given the exogenous nature of the ban, we have reason to believe that the conditional independence assumption is not violated. We probe endogeneity concerns pertaining to self-selection sample composition in our robustness checks. We also scanned the literature and internet resources for possible policy changes in our control cities but have found none during the time of our observation. The common trends assumption will be assessed when we present the empirical results. We also examined whether any automatic Airbnb pricing tools were launched during the time of our treatment. Reassuringly, we find there is no such incidence, therefore this should not bias our results.

Before ban anouncement (October 2016)	After ban implementation (July 2017)

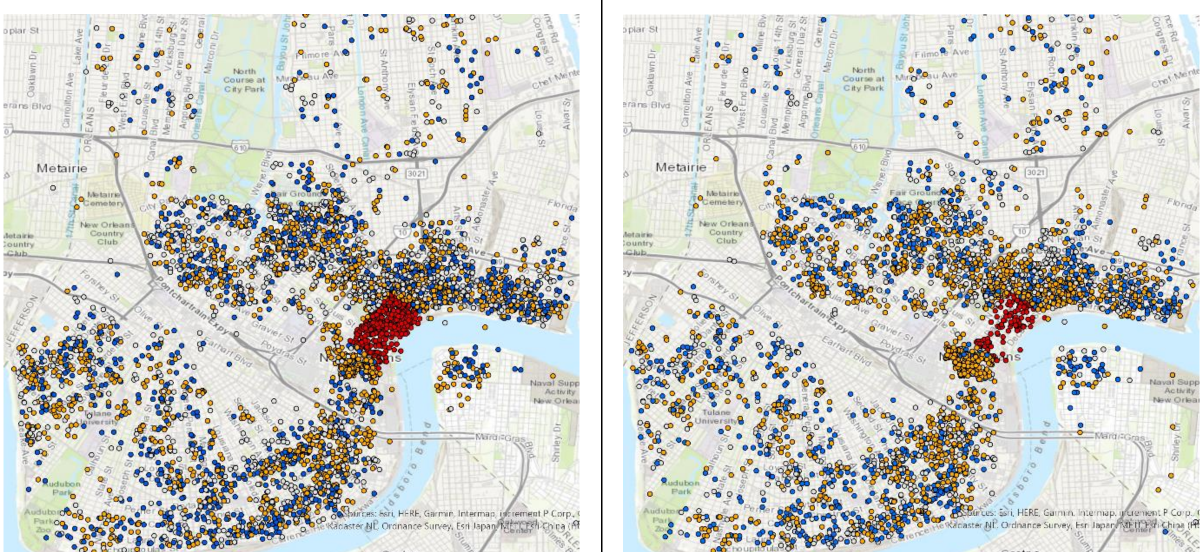

Figure 2. Airbnb Listings in New Orleans in October 2016 and July 2017

Figure 2 displays the consequences of the French Quarter Airbnb ban on the listings located in that particular location. The red bubbles indicate French Quarter listings and the blue (yellow) bubbles correspond to hosts that our algorithm classified as socially (financially) motivated. The grey bubbles indicate hosts that have not been classified into either category. It is easy to see that after the implementation of the French Quarter ban, almost all the listings have disappeared from the French Quarter. The policy implementation had at least two potential consequences. First, it reduced Airbnb listing supply from the French Quarter, as depicted in Figure 2, and stimulated new listings in other parts of the city in response. Note that the higher bring-to-market costs might also prevent new listings from entering the market and thus result in a density decrease of listings in some areas outside the French Quarter (see

Figure 2). If more listings disappear than newly open up while the regulation of Airbnb drives up demand in general, the remaining hosts enjoy, ceteris paribus, excess pricing power due to lower competition and higher demand per listing in equilibrium. Second, the ban also introduced bring-to-market costs via STR licenses. Hosts might pass on the costs of the licenses to the guests which would translate into higher prices (i.e., *cost pass-through effect*). In our empirical design, we are able to disentangle the *equilibrium effect* from the *cost pass-through effect* by controlling for monthly demand and supply for each listing, keeping these factors constant. Listing fixed effects complement our identification strategy in controlling for time-constant heterogeneity around the listings, e.g., spatial proximity to tourist attractions.

Results

Table 4 presents our empirical results when estimating equation (1). The results in column (1) display the results for the model assessing the *cost pass-through effect*, where we control for $DEMAND$ and $SUPPLY$. In column (1), we find a significant price increase of 1.3% immediately after the announcement of the ban in January 2017. This price increase grows to 3.17% in March 2017 and diminishes gradually in magnitude to 0.9% by August 2017 but remains positive and statistically significant. This means due to facing additional costs because of STR licenses, keeping demand and competition constant, Airbnb hosts increase their prices over a period of at least 8 months. We thus find support for Hypothesis 1a but have to reject Hypothesis 1b. From the mostly insignificant coefficients of the interaction terms before December 2016, we can also see insignificant pre-treatment trends which supports the common trends assumption (Autor, 2003). While the coefficient for $DEMAND$ is insignificant at a 5% level, an increased level of competition is associated with a price decrease of approximately 2%. But when we drop $DEMAND$ and $SUPPLY$ as control variables in column (2), we see that not much of the price change is explained by the *equilibrium effect*. Although we obtain a significant coefficient of $SUPPLY$ in column (1), the coefficients in the months after the ban announcement remain unchanged in sign and virtually the same in magnitude. This suggests that the changes in supply due to the ban and the reallocation of demand to the remaining listings outside of the French Quarter have almost no effect on the increased prices that hosts set. Thus, our results indicate that the price increase is driven by the *cost pass-through effect*. Moreover, the relatively sharp increase in prices directly after the policy announcement compared with later months might be the result of hosts wanting to have the additional costs immediately reimbursed by their guests.

In column (3) and (4) we investigate how the *cost pass-through effect* differs between financially and socially motivated hosts. If our classification approach has correctly identified the different host types, we would rationally expect financially motivated hosts to increase their prices more than socially motivated hosts. Indeed, the results in column (3) and (4) confirm these expectations. Financially motivated hosts increase their prices substantially by between 2.14% and 4.17%. Remarkably, the price increase remains substantial up until August 2017 (3.03%). Financially motivated hosts increase their prices by between 130% (in February 2017) and 290% (in June 2017) more than socially motivated hosts. Therefore, we also find support for Hypothesis 2. One can even infer that financially motivated hosts already started to increase their prices in November 2017 before the regulation was officially announced, possibly because the information about the ban leaked to them through informal channels.

Table 4. Baseline Results				
	(1) All hosts	(2) All hosts	(3) Financial	(4) Social
Variables	$ln(PRICE)$	$ln(PRICE)$	$ln(PRICE)$	$ln(PRICE)$
$SEPTEMBER\_16 * BAN$	0.063 (0.00408)	-0.0006 (0.00385)	0.004 (0.00870)	-0.007 (0.00587)
$OCTOBER\_16 * BAN$	-0.004 (0.00377)	-0.004 (0.00369)	0.00053 (0.00828)	-0.010** (0.00506)
$NOVEMBER\_16 * BAN$	0.005 (0.00360)	0.007** (0.00362)	0.0168** (0.00777)	0.000 (0.00458)
$DECEMBER\_16 * BAN$ (ban announcement)	Omitted			
$JANUARY\_17 * BAN$	0.0128*** (0.00337)	0.0133*** (0.00341)	0.0214*** (0.00725)	0.00927* (0.00458)
$FEBRUARY\_17 * BAN$	0.0271*** (0.00309)	0.0279*** (0.00318)	0.0336*** (0.00651)	0.0260*** (0.00457)
$MARCH\_17 * BAN$	0.0317*** (0.00320)	0.0313*** (0.00333)	0.0394*** (0.00682)	0.0268*** (0.00455)
$APRIL\_17 * BAN$ (ban comes into effect)	0.0296*** (0.00336)	0.0289*** (0.00348)	0.0417*** (0.00677)	0.0241*** (0.00528)
$MAY\_17 * BAN$	0.0228*** (0.00333)	0.0223*** (0.00346)	0.0334*** (0.00700)	0.0176*** (0.00503)
$JUNE\_17 * BAN$	0.0161*** (0.00359)	0.0156*** (0.00372)	0.0261*** (0.00742)	0.009* (0.00551)
$JULY\_17 * BAN$	0.0164*** (0.00423)	0.0165*** (0.00435)	0.0342*** (0.00943)	-0.001 (0.00602)
$AUGUST\_17 * BAN$	0.009** (0.00436)	0.00112** (0.00445)	0.0303*** (0.00977)	-0.006 (0.00580)
$DEMAND_{t-1}$	-0.000* (0.0001)		-0.000* (0.0002)	0.053 (0.00002)
$SUPPLY_{t-1}$	-0.020*** 0.00610		-0.008*** 0.00801	-0.023** 0.01143
Other control variables	✓	✓	✓	✓
Monthly Fixed Effects	✓	✓	✓	✓
Listing Fixed Effects	✓	✓	✓	✓
N	548,859	619,151	244,277	156,723
R^2	0.983	0.981	0.986	0.980

*August 2016 is dropped because of missing observations for DEMAND and SUPPLY due to the first differences computation. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Robustness Checks

One might be concerned that our results could be confounded because the listings in New Orleans are systematically different from the listings in our control group. For example, if listings between the cities differed systematically in observable attributes, they might have different price setting potentials which might confound our results. To alleviate this concern, we identify listings in the control group cities that are statistical twins of the New Orleans listings using propensity score matching (PSM) (Rosenbaum and Rubin 1983). The rationale is that the listings thus identified do not statistically differ from each other based on observable covariates, but only with respect to treatment status. We apply a kernel matching algorithm with an epanechnikov kernel and a 0.0001 bandwidth to arrive at our PSM sample of statistical twins. We use the aforementioned control variables as matching variables. Assessing the relative bias before and after matching each covariate, we see that our PSM has substantially reduced the bias between the treated and the control listings. In fact, after matching, nearly all our control variables exhibit insignificant mean differences ($p>0.05$) and the reduced bias per covariate ranges between 3 and 91.4%. We conclude that our PSM approach has effectively balanced treatment and control listings in our sample. We re-run all the regression models from our baseline results and find qualitatively unchanged results. Therefore, it is unlikely that systematic differences between treatment and control listings are biasing our estimation results. We also replicate our PSM approach for different matching algorithms (1:1 nearest neighbor matching and radius matching) and find qualitatively unchanged results.

To complement our PSM approach that uses observable covariates to balance our sample, we make use of the Rosenbaum Bounds approach (Rosenbaum 2005). This strategy allows us to test the sensitivity of our results by quantifying the amount of bias Γ represented by an unobserved covariate that causes selection into the treatment. The underlying concern is that hosts establish listings because they predict that due to the French Quarter ban, they can ask for disproportionately high prices. While our sampling strategy is designed to rule this out, by only including listings registered before December 2016, we nevertheless want to rule out any distortions created by hosts who could have entered their Airbnb listings even before December 2016, based on the public discussion prior to the passing of the policy. Using the Rosenbaum Bounds approach, we are able to check how strong this bias would have to be to make us having to revise our findings. We find that our results remain statistically significant up to Γ values between 1.2 and 1.3. Even though the literature lacks consensus over what constitutes substantial insensitivity, values between 1.2 and 1.5 are generally considered to be reasonably insensitive (Sen 2014).

One might also be concerned about the possibility of a measuring error in our variable $DEMAND$ which is only a lower-bound estimate for the demand a listing enjoys. If there was a measurement error, this could bias our estimate. Therefore, we replace $DEMAND$ measured by the number of monthly reviews with a variable indicating how many days a listing was unavailable over a month, either because the listing was fully booked or that the host was not offering any listing on a given day. This effectively represents an upper-bound variable. We find qualitatively unchanged results using this alternative operationalization and thus conclude that our results are not biased by a measurement error in $DEMAND$. Moreover, we conduct robustness checks regarding our measurement of $SUPPLY$. We re-run our regression utilizing a 1.5-mile and 2-mile radius threshold instead of a 1-mile radius and again, find qualitatively unchanged results.

Since one host can have multiple listings (our dataset comprises 105,661 listings operated by 79,502 hosts) our effects might be overestimated if we were to neglect this feature of our data structure. To rule out this overestimation bias, we also run our baseline models with robust standard errors clustered at the host level and, again, find qualitatively unchanged results. To alleviate concerns that the differential results for financially and socially motivated hosts are partly driven by the fact that we used the SVM classification in our baseline results, we re-run these analyses using the Random Forest classification. Again, we find qualitatively unchanged result, suggesting that our analyses are agnostic to the two machine learning approaches. Besides, we relaxed our boundary condition that only hosts with no more than one listing can be classified as socially motivated such that hosts with two or three listings can also be classified as social. Once more, our results remain qualitatively unchanged.

Additionally, other events which take place simultaneously to our treatment (e.g., the yearly Mardi Garden Festival in February) might be an alternative explanation for raised prices in the post-treatment periods. To alleviate this concern, we re-run our regression with data one year after the policy was implemented. Although significant price increases are discernible from January 2018 till August 2018, the estimation coefficients are much lower than a year before. Thus, we conclude that events like Mardi Garden do not primary drive the price increases we observe immediately after the policy announcement.

Quantifying the Policy Effect in Additional Dollars Spent

Given that we dispose of a lower bound (number of reviews multiplied by the minimum number of rental nights) and an upper bound (number of booked out days) of listing demand per month, we can conduct a back-of-the-envelope calculation to quantify the amount of $US that were transferred from guests to hosts as a result of the policy shift. For each month, we multiply the base month price (December 2016) by our estimate of the price increase in month t and by the lower, respectively upper bound, demand in month t. During the time span from January 2017 to August 2017, this results in between $465,722 (lower bound) and $2,371,043 (upper bound) that accrue to Airbnb guests solely due to the policy shift and collected by the hosts. We repeat the same calculation separately for financially and socially motivated hosts and discover that financially motivated hosts account for between 62% (lower bound) and 76% (upper bound) of these additional payments. Given the positive spillover effects of Airbnb visitors to local ancillary industry such as restaurants (Alyakoob and Rahman 2018), these are dollars that could have gone to local restaurants but instead went to Airbnb hosts.

To break down the additional amount of dollars per host, we calculate the midpoint as $\frac{lower\ bound + upper\ bound}{2}$ separately for financially and socially motivated hosts and then divide this by the number of hosts. This calculation yields that financially motivated hosts each obtain approximately $565.46 of additional income on average over a period of eight months. Taking into consideration that hosts, especially financially motivated ones, may have multiple listings, it suggests that hosts have taken advantage of the policy by collecting more money than they would have paid for their STR license. Recall that upon policy implementation, Airbnb hosts were required to obtain an official license ranges from $50 to $200 annually for private hosts and $500 for commercial hosts.[6] Note that these values are almost certainly understating the per-year value as our calculations are only based on the time span between January and August. Socially motivated hosts, on the other hand, received an additional $227.36 on average and thus considerably less than financially motivated hosts, but nevertheless more than the STR license costs. While financially motivated hosts passed through the additional costs of licenses to Airbnb guests far more than socially motivated hosts, all hosts surpass the actual additional bring-to-market costs, thus representing a net transfer of costs to guests.

Conclusion

Peer-to-peer rental platforms have experienced tremendous growth over the past 10 years as they gained in popularity all over the globe. At the same time, they have been met with increasingly rigorous regulatory intervention from municipal governments aiming to minimize the negative externalities of the peer-to-peer rental market to local communities, as documented in prior literature (Barron et al. 2018; Zervas et al. 2017). Our paper represents a first attempt to evaluate such a regulatory policy, which entailed the ban of Airbnb in certain parts of a city, its legalization in others, and the introduction of mandatory licenses. Our results demonstrate that hosts have increased their prices in response to – and even ahead of – the policy announcement and implementation, yet financially motivated hosts have responded with greater increases than socially motivated hosts. Our analysis further suggests that the mechanism at play is the cost pass-through effect to consumers rather than the shock to supply and demand. We calculate that these additional costs vary between $465,722 and $2,371,043 in the period January to August 2017.

Practically, our results imply that policy makers can establish a licensing system for short term rentals to effectively diminish price differences between hotels and peer-to-peer offerings and thus enabling a more equitable market competition. To strengthen this effect for financially motivated hosts, the establishment of different license types depending on host activity seems to be a fruitful approach. However, since bring-to-market costs are to a large extent passed through to guests, peer-renting still remains attractive (Filippas et al. 2020). This implies that the policy falls short of reducing pressure on housing affordability. Our work also adds useful information to the literature on the economic behavior of Airbnb. Prior work has studied the influence of temporal demand patterns (Gibbs et al. 2018; Li and Srinivasan 2019). We find that the price-setting behavior by hosts is responsive to bring-to-market costs imposed on them but relatively unresponsive to supply and demand shocks. Finally, a nascent stream of literature has started to investigate short term rental policy regulations, with studies mainly focusing on policy effects on the supply of and demand for short term rentals (Alyakoob and Rahman 2018; Chen et al. 2018; Furukawa and Onuki 2019). Only one study so far has investigated the impact of Airbnb policy regulation on the pricing behaviors of hosts (Bibler et al. 2020). We extend this stream of literature by studying price behaviors in response to a policy shift that not merely increases the costs to Airbnb hosts but also affects local Airbnb market supply and demand. To the best of our knowledge, we are also the first to showcase how financially and socially motivated hosts differ in their responses to policy regulation.

As any research, this study also comes with limitations. We only investigate the price effects for regulations implemented in New Orleans, which arguably limits the transferability of these results to other regions.

[6] Based on our data, we cannot observe which host had to acquire which STR license type.

Moreover, our approach to determining the underlying motivation of each host also comes with drawbacks, since we do not consider that hosts are typically motivated by a mix of financial and social aspects. Furthermore, we cannot completely rule out that the heterogeneous price changes we obtain for socially and financially motivated hosts are driven by the fact that those hosts face different types of license costs. Finally, future research could extend our analysis by enriching our datasets with hotel sales data, and thus allowing to take a more differentiated view on the competitive environment faced by Airbnb hosts.

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