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Who Gets to Share in the "Sharing Economy"?: Racial Inequalities on Airbnb

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In the decade following the Great Recession, consumer markets have undergone rapid change. One catalyst has been the development of online platforms that organize, mediate and regulate delivery of a host of services. The two best known examples, Uber and Airbnb have proudly "disrupted" taxi services and hotels. While a great deal of attention has been paid to these particular platforms, for the most part the question of how this kind of disruptive change affects existing social inequalities has been relatively underexplored. Josef Schumpeter argued that disruptive change, "the competition from the new commodity, the new technology, the new source of supply, the new type of organization" (2003:84) played a key role in ensuring long term equality in capitalist societies, as it undermines monopolistic tendencies, dissipates economic rents and generates intergenerational social mobility. His position is broadly representative of a school of thought that highlights the potential positive impacts of the disruption enacted by the sharing economy. These "disruptionists" (Fraiberger and Sundararajan 2015; Horton, Stern, and Zeckhauser 2016; Sundararajan 2016) argue that the platforms are agents of creative destruction, breaking down entrenched inefficiencies and generating new economic opportunities for a broader range of people. Ultimately, this view sees economic disruption as a net positive, a way to ameliorate inequality.

However, other social scientists have been skeptical of such claims, as they often fail to account for long-standing social inequalities. We can trace this line of thought back to Daniel Bell's *The Coming of Post-Industrial Society* (1976), in which he expressed significant concern with how radical change would further inequality. In his view, this type of change was far more likely to benefit those who were already privileged, the highly educated white-collar workers who had the power and resources to direct and harness the technological changes that were transforming society. A body of work on the disruptive changes wrought by what came to be called "the sharing economy" has largely followed this tradition, highlighting how existing inequalities, especially along lines of race and class, are being reproduced through these platforms.

The size and the growth of the "sharing economy," a term that is often disputed (Belk 2014), suggest its importance for scholars. Consider the case of Airbnb. Propelled by low barriers to entry for providers, it has attracted a large user base, with more than 3 million "listings" worldwide (Airbnb 2017a). It has also witnessed skyrocketing demand for its services, and advertises that more than 200 million individual "guests" (the platform's term for consumers) that have used its services since it launched (Airbnb 2017a). These are not only very large numbers, but they have grown rapidly. According to one company report while only 47,000 guests used the platform in the summer of 2010, more than 17 million people did so for the same period in 2015 (Airbnb 2015a).

With the platform being utilized at this very large scale, understanding its impact on social inequalities, and specifically racial inequality, takes on considerable importance. A number of recent studies have identified racialized outcomes on sharing economy platforms. Their findings suggest that the economic disruption caused by the platforms is also reproducing socio-economic inequality along racial lines. Through field experiments and analysis of company data, researchers have shown that racial minorities, specifically African-Americans, face significant discriminatory behavior both as consumers and earners in the sector (Edelman and Luca 2014; Edelman, Luca, and Dan 2015; Ge et al. 2016; Hannak et al. 2017; Thebault-Spieker, Terveen, and Hecht 2015). These findings have found some resonance in the public debate about Airbnb, particularly as in 2016 African-American users of Airbnb shared their personal experiences of discrimination on social media and in various news outlets. Two Airbnb competitors (NoirBNB and Innclusive) were founded on the premise of being explicitly accommodating to all racial groups. Airbnb has taken highly publicized steps to reduce discrimination on the platform by changing some policies and practices.

However, these studies and the public conversation about discrimination only partially address the relation between racial inequality and disruptive change. They have shown the prevalence of person-to-person discrimination, relying on either anecdotal evidence, relatively small samples, or a limited geographical range. A strong body of sociological research suggests that we should understand racialized inequality not simply as an outcome of discriminatory attitudes and behavior, but recognize how systemic factors contribute to the establishment and reproduction of these inequalities (Bonilla-Silva 1997, 2001; Golash-Boza 2016). Thus far, structural aspects of existing racial inequality, such as residential segregation, or differences in educational attainment, income and homeownership, has been absent from studies of race in the sharing economy. Especially with Airbnb, which is heavily dependent on urban real estate, these inequalities are likely to play an important role in access to and outcomes on the platform.

Using a unique data set, we provide the first large scale study of how structural inequalities, especially racial segregation, operate on Airbnb. Our sample, which covers roughly 335,000 listings in the 10 largest Airbnb markets in the US, allows us to go beyond the smaller scales of previous studies. Analyzing our data on the platform in conjunction with geographical data from the American Community Survey, we find that in areas with higher concentrations of racial minority residents, there are more listings on the platform, and those listings tend to be booked at rates similar to areas that have a higher proportion of white residents. However, hosts in these areas charge lower nightly prices, have lower annual revenues, and receive lower ratings from guests. These patterns show that racial discrimination in the sharing economy goes beyond isolated incidents and that it cannot be explained simply as the outcome of interpersonal discrimination at scale. Instead, they suggest that while these platforms may be having limited success in providing more equitable access to economic opportunity, they ultimately reproduce structural inequalities found in the conventional economy because their outcomes are far from equal.

LITERATURE REVIEW:

Sharing Economy and Airbnb:

The "sharing economy" emerged in the Great Recession era as a mix of novel organizational forms and technical tools that offered consumers powerful new ways to collaborate, produce, and consume. Sharing economy activities ranged from hyper-local tool libraries, to multi-lateral barter exchanges such as time banks, to global marketplaces offering many types of monetized goods and services. Over time, the largest and most visible part of the sharing economy has become the technology-based "platforms" which bring together providers and consumers to facilitate what has been called "peer-to-peer" or person-to-person structured exchange. On the platforms, sophisticated software yields timely information on prices and availability, reduces transactions costs and handles payments electronically and seamlessly. On almost all of them, crowd-sourced information is used to establish user ratings and reputation, thereby addressing issues of trust which arise in cases of stranger exchange (Abrahao et al. 2017; Sundararajan 2016).

This variety of institutions, agents, and practices has generated significant debate on the nomenclature, and even classification of these new economic activities. Belk (2014) has argued in favor of a sharp divide between the commercialized "pseudo-sharing" (as found on the platforms), and what he considers genuine non-commercial sharing activities. There are repeated calls recognize this new sector as a "platform economy" (Kenney and Zysman 2016) to highlight the role of the platforms in creating and managing these spaces, and the power that accrues to them as a result. The US Department of Commerce prefers the term "digital matching firms," (Telles 2016) which highlights the importance of the platforms, and also draws clear boundaries between firms like Airbnb and Uber, and other economic activities that do not employ this mix of online marketplaces, reputation systems and algorithmic matching. Previous work on the subject has focused on dimensions such as the peer-to-peer structure and profit-orientation (Schor and Fitzmaurice 2015), the history of the term (Schor and Attwood-Charles 2017) and the deployment of otherwise "idle assets" (Frenken and Schor 2017). Others have sought to undercut the dominance of the "sharing economy," arguing in favor of the concept of the "gig economy" (Friedman 2014). This term which highlights the unpredictable and unstable employment and income dynamics faced by people making money in these sites. However, these alternate formulations still lack broad purchase in academic and public debate. While these controversies about nomenclature are important for understanding the group of organizations, technologies, sites and practices that make up the "sharing economy," the term itself remains in common use. We therefore adopt it for this paper, although we are keenly aware of its limitations.

One of the largest of the sharing economy platforms is Airbnb. Founded in 2008, it is an online marketplace for short-term rentals of residential spaces. Lodgings offered on the platform range from "shared rooms" in which the prospective guest may lack privacy, such as a couch in a common room, to "private rooms" in which the guest is the only occupant, to "entire residences" in which the host is not present for the duration of the stay. Hosts provide details about the space they are willing to rent, including photos, and select the dates for which they want to make their "listing" available. Guests can then search the platform for the location, dates, prices, and the types of spaces they want to rent. In order to facilitate trust in the exchange, the company verifies the identities of both parties and provides reviews and ratings from previous exchanges on the platform. Airbnb itself earns revenue by taking a fee from each transaction.

We focus on Airbnb in this paper primarily because of the economic impact it has on its participants and the areas in which it operates. Our data shows that in 2016, listings in the 10 markets for which we have data generated $2.8 billion, or more than $8500 per listing. This shows that "home-sharing" has become a significant economic activity within cities. With the exception of ride-sourcing platforms, no other sharing economy company can claim a more extensive impact. In addition, based on data from applications for personal loans and student loan refinancing from one lender, we also know that within the "sharing economy" Airbnb offers its participants by far the largest economic benefits (Bhattarai 2017). Thus, understanding what is happening on this platform with regard to inequality is important since it is likely to have larger effects than many other platforms in this sector. Additionally, we focus on Airbnb because it is the only major platform whose data is accessible to independent researchers. Sharing economy platforms, including Airbnb, have thus far refused to release their data to independent researchers. In fact, even municipal authorities, with court orders, have had a hard time obtaining data that they can utilize (Streitfeld 2014). However, unlike other platforms, a large amount of relevant data on pricing, availability and ratings on Airbnb is publicly available online.

Inequality and the Sharing Economy: Disruptionists vs. Reproductionists

The debate on the impact of the sharing economy on inequality, broadly speaking, has solidified into two camps. *Disruptionists* argue that the platforms do away with inefficiencies in the structures they are replacing and extend greater economic opportunity to a wider range of participants. Studies of the sharing economy in this category, mainly conducted by economists and business analysts, often address inequality in the abstract, without engaging the multi-faceted nature of lived inequalities, such as racial disparities. *Reproductionists*, on the other hand, argue that the sharing economy will not ameliorate inequalities, but rather reproduce them. Studies in this group, generally based on legal or sociological research, highlight how both structural inequalities outside of the sharing economy, and the processes built into the platforms themselves, generate inequality.

The broad contours of the *disruptionist* argument can be traced back to the work of Schumpeter on “creative destruction” (2003:87). Schumpeter argued that radical change, which can successfully replace old institutions, technologies, products or practices, Schumpeter argued, was the only way to ensure long-term growth and competition in a capitalist society. Initiated by entrepreneurs or corporations, this type of change would allow for long-term social mobility and prevent class-structures from ossifying. Ultimately, focusing only on market relationships, he envisioned a relatively stable “churn” of inequality within the population. The fortunes of individuals, or families, would fluctuate in response to their ability to generate innovation and extract profits from the market power those innovations commanded.

Disruptionists’ accounts of the sharing economy share a similar focus on “creative destruction” as a force that yields efficiencies and increased equality. In a number of ways, this focus seems correct. Participation in the sharing economy is not contingent on time-consuming or expensive formal credentialing requirements. It does not require access to unequal informal networks, which hamper access to economic opportunity in the conventional economy (Granovetter 1985). Some platforms do not exclude individuals with criminal records (Dependence and Precarity TK). The flexibility of platforms allows individuals to decide when and whether to participate. This is particularly important for people with family or other obligations who can participate in ways that are precluded by conventional jobs. In addition the absence of managerial mediation on platforms is a benefit to many young workers, which results in more equitable and satisfying outcomes (Fitzmaurice et al. forthcoming).

An early "disruptionist", Arjun Sundararajan (2016:123) has argued that the sector represents a broader "democratization of opportunity." The main thrust of his argument is that platforms enable a larger portion of the population to capture higher rates of return on small initial investments. By renting out a car, or residential real estate, or lending small amounts of money through the sharing economy platforms, individuals who are not "traditionally not on the high end of the wealth spectrum" (Sundararajan 2016:124) can earn money at greater rates than via waged labor. This increased access to higher returns can disrupt processes in the conventional economy that generate income inequality.

In a separate study of a small car-rental platform, Fraiberger and Sundararajan (2015) have argued that the ability to monetize assets such as personal cars or housing can place these assets within reach of low income participants who cannot currently afford them. Similarly, being able to consume these goods through a cheaper rental system can also reduce their living costs (Horton et al. 2016). Giving up on car ownership and not paying the associated taxes, fees and maintenance costs can become a viable option if consumers can either rent cars or get car rides cheaply and easily via sharing platforms.

Another way in which the sharing economy is expected to reduce inequality is by providing an additional revenue stream that can stabilize income fluctuations, to which relatively lower income households are vulnerable (Mills and Amick 2011). In a study of Uber drivers, in association with the company, Hall and Krueger (2015) argue that having the option of driving enables people to extend their job search periods and be more selective. A similar argument about Airbnb hosts is made by Sperling (2015:9) who notes that "for middle-class households that do not have liquid savings sufficient to help during periods of economic transition or lost income, Airbnb provides a source of income that is not tied to their jobs and does not require drawing on retirement savings."

Sperling further suggests that this revenue stream might be one way for middle-class households to stave off income-stagnation in the conventional economy. Other research with providers on six platforms suggests that roughly 70% these opportunities to supplement other earnings (Schor et al. 2017).

Even when disruptionists recognize ways in which the sharing economy could be falling short of its egalitarian potential, these problems are often discussed in terms of how the platform can be "fixed" to prevent these dynamics. For example, Sundararajan recognizes that with the ratings and review systems of the platforms "one's access to opportunities today also shape one's future access to opportunities" (2016:201). However, he does not then connect this observation to how race or class discrimination operates and instead argues in favor of technocratic fixes to the ratings and review system. This system and its potential to combat generalized "social biases," without specific reference to race or class, has been the subject of other studies as well (Abrahao et al. 2017). In other cases, the disruptionists argue that the dynamics of inequality are at best tangentially related to the sharing economy platforms, but are symptomatic of broader economic changes (Hall and Krueger 2015:25).

The reproductionist critique turns this formulation on its head, arguing that the sharing economy not only fails to combat inequalities in the conventional economy, but that those inequalities are reproduced through the sharing economy itself. This approach has its roots in Daniel Bell's work on how evolving technologies for social and organizational control created a post-industrial society. Bell recognized that a range of new technologies for measuring and managing society and complex organizations was resulting in radical changes but, unlike the disruptionists, he recognized that these changes took place in the context of critical power relationships. These relationships, derived from property, political power and increasingly from technocratic skill, allowed some groups to shape the resulting social organization in their favor (Bell 1976:361). Ultimately, Bell argued, the highly skilled white-collar workers who were able to control and take advantage of these new technologies were in a position to benefit from the resulting change. Others, whose power over the outcomes were restricted because they did not have control over property, politics or skills, would be worse off.

Within economics, the skill-biased technological change literature mirrors some parts of Bell's argument about how technological change can generate inequality (Acemoglu 2002; Autor, Levy, and Murnane 2013). This literature assigns a primary role to the technological change itself, arguing that it is the content of such change that generates unequal outcomes by increasing returns to highly skilled occupations. However, the empirical evidence to date on this question has been mixed (Kristal and Cohen 2016).

Reproductionist critiques of the sharing economy, on the other hand, focus on how existing patterns of inequality, which are the basis of power relationships in Bell's account, influence participation in and outcomes on the platforms. Scholtz's critique (2017) focuses on the failure of regulatory frameworks to police corporations, highlights how lower-class people's labor becomes ever more precarious and invisible behind the "crowd fleecing" practices enabled by the platforms, and argues in favor of radical reorganization of the sector towards cooperatives where workers take part in the decision-making processes about their lives and their work. Similarly, Slee (2016:11) argues that the sector has come to be dominated by large corporations who extract value "by removing the protections and assurances won by decades of struggle, by creating riskier and more precarious forms of low-paid work for those who actually work in the Sharing Economy." He argues against vague but positive connotations of sharing, and takes the position that rather than providing an easy panacea for social problems, the sharing economy exacerbates them. For

Slee, the core problem is the combination of an ethics of openness with commercialization, which allows participants to ignore both dynamics of inequality outside of and within sharing initiatives.

Inequality-generating dynamics within the sector are at the center of Schor's argument that "a relatively more privileged middle class has used this technological innovation [the sharing economy] to expand opportunities for itself" (2017:277). In the face of worsening prospects in the conventional economy, Schor argues that high-status individuals, mostly white, upper-class and highly educated, are using the sharing economy to do lower-status work like cleaning and delivery. This type of work has been de-stigmatized by the positive associations of the "sharing economy." This allows them to earn more and generate economic security, while displacing people of lower socio-economic class who have traditionally filled these roles. In more recent research, Schor and co-authors have argued that this dynamic of unequal access and outcomes can be best explained by what they call "platform dependency" (Schor et al. 2017). Individuals who have access to outside economic resources and do not have to depend on earnings in the sharing economy report high levels of satisfaction with the current structure of the sector. However, those who have to rely on their sharing economy earnings experience lower wages and increased precarity, supporting the argument that the sector is generating unequal outcomes.

As is clear from the foregoing, this debate between disruptionists and reproductionists has mainly addressed issues of income inequality and social class. A growing body of research suggests that race is likely to be another salient factor. We turn now to discuss how racial inequality is reproduced within the sharing economy, and particularly Airbnb.

Racial Inequality in the Sharing Economy

The sharing economy is characterized by racialized outcomes. A simple metric is the racial composition of participants. Two national studies (JPMorgan Chase and Company Institute 2016;

Pew Research Center 2016) find that users of sharing economy platforms tend to be whiter, younger, better-educated and have higher income than the general population. A second measure is the racial structure of transactions. A number of studies have identified significant discrimination against racial minorities on platforms such as Uber, Lyft and TaskRabbit, in their roles as both consumers and providers (Ge et al. 2016; Hannak et al. 2017; Thebault-Spieker et al. 2015). Within Airbnb itself, discriminatory behavior on both sides of the market has also been established using a range of methods. Using an audit study, Edelman, Luca and Svirsky (2017), show that hosts on the platform regularly discriminate against guests that they perceive to be African-American, refusing their requests to book even if it means losing revenue. A working paper by Edelman and Luca (2014) shows that hosts identified as Black based on their photos, charge less than non-Black hosts for similar listings, potentially in order to compensate for lower demand for their services. A study by Laouénan and Rathelot (2016), utilizing digitally collected data on a large number of listings, has produced similar results. The authors have found that ethnic minority hosts charge prices that are roughly 3.2% lower than ethnic majority hosts.[1]

The aforementioned studies focus on the ways in which person-to-person transactions are affected by race. We argue that understanding the role played by race in the sharing economy requires incorporating durable, structural inequalities into the analysis. Race theorists have argued that racial inequality is not simply an outcome of discriminatory ideologies but is rooted in the fact that "races in racialized societies receive substantially different rewards" (Bonilla-Silva 2001:22). In other words, racial inequality is reproduced through social structures (Bonilla-Silva 1997). Similar calls for focusing on the structural aspects of racial inequality has been part of other approaches over the last half a century (Knowles and Prewitt 1970; Omi and Winant 1994). More recently, Emirbayer and Desmond (2015) have placed a call for a systematic understanding of race at the center of their theoretical intervention and re-assessments of the structural and ideological components of racial inequality have been central to work by Golash-Boza (2016) and Feagin and Elias (2013).

Our focus on structure is also supported by the literature on the digital divide, which has identified inequalities in access to and utilization of digital resources. This research shows how structural factors are crucial to understanding the reproduction of inequality. Income and education differentials have been identified as key drivers of persistent differences across racial groups, in terms of how they utilize digital resources (boyd 2012; Nakamura and Chow-White 2011; Wilson and Costanza-Chock 2012; Zillien and Hargittai 2009). Low-income, non-white populations, with lower education levels tend to use digital technologies primarily for entertainment and socialization purposes, while their white, higher-income counterparts are more likely to employ them in ways that provide economic benefits, such as online education (Hansen and Reich 2015). There is also some evidence that members of minority groups, excluding Asian-Americans, have less skill and experience with different types of online activities (Hargittai 2010).

These findings highlight the need to extend research on inequality in the sharing economy beyond person-to-person discrimination. Sharing economy platforms, which have more immediate economic benefits than online education and networking, may provide greater incentives for participation by people of color. However whether those incentives can result in better access to or less racialized outcomes for people of color is not clear. For Airbnb, which is our focus in this paper, inequalities in housing and economic opportunities in the conventional economy may play a role in determining whether and how racial inequalities are reproduced on the platform.

Race, Housing and Airbnb:

Understanding inequalities in housing is critical to assessing the role of race in participation and outcomes on Airbnb. The platform enables users to extract rents from urban real estate through short-term leases. However, people of color have historically been excluded from desirable real estate, both within and outside of cities, through a number of discriminatory practices. These include exclusionary zoning and ownership practices, "redlining" of minority neighborhoods, denial of credit and discriminatory tax policies (Frey 1979; Hirsch 2009; Rothstein 2017; Rugh, Albright, and Massey 2015; Rugh and Massey 2010; Squires 1992). Additionally, audit studies going back decades have shown that realtors and landlords often steered racial minorities away from desirable urban real estate (O'Flaherty 2015:274). Even though this particular practice appears to have waned in recent years (Turner et al. 2013), people of color are still much less likely to be homeowners when compared to white people. At the end of the first quarter of 2017, the homeownership rate among non-Hispanic Whites stood at 72.2%, compared to 56.5%, 45.5%, 42.3% for Asians, Hispanics and Blacks, respectively (US Census Bureau 2017d).

This pattern of inequality in homeownership can influence Airbnb participation and outcomes in critical ways. Legal and practical concerns about Airbnb participation tend to favor homeowners rather than renters, especially as increasing numbers of rental contracts and local laws restrict the practice of short-term rentals. Additionally, several reports have documented the practice of "illegal" rentals (Cox and Slee 2016; Streitfeld 2014) where a landlord makes housing units exclusively available for short term rentals and lists multiple units on the platform at the same time. This practice is likely to drive up Airbnb participation in areas with a higher proportion of rentals, simply because there are more rental units available in these areas for landlords to list. Thus, while the exact nature of the impact of homeownership on Airbnb participation and outcomes is not predictable a priori, it seems likely that homeownership is a relevant structural factor in the reproduction of racial inequality on the platform.

Residential segregation, regardless of ownership status, is another structural factor relevant to Airbnb participation and outcomes. Discriminatory and exclusionary housing policies and practices, coupled with factors such as immigration patterns (Iceland and Nelson 2008), have resulted in the racial segregation of residential spaces in the US. Despite decades of integration efforts, members of minority groups still live in neighborhoods that are highly dissimilar to those of whites in terms of their racial composition (Logan and Stults 2011). Moreover, segregation above the neighborhood level has increased significantly, with larger areas within cities, and the cities themselves becoming more racially homogeneous (Lichter, Parisi, and Taquino 2015; Parisi, Lichter, and Taquino 2011). This entrenched segregation has significant negative impacts on minority communities, in terms of reduced public services and amenities, exclusion from social, professional, and financial networks, reduction in health and well-being measures (Jencks and Mayer 1990; Rugh et al. 2015; Rugh and Massey 2010; Sampson 2008; Wilson 2012).

The racial segregation of urban spaces is likely to play an important role in how racial inequality is reproduced on Airbnb. The company regularly makes claims about how it is channeling tourism income into areas not traditionally served by the hotel industry (Airbnb 2016). However, the relative lack of public spaces and amenities, real estate investment, and ultimately the social stigma associated with areas with high concentrations of non-whites are likely to negatively affect hosts and potential hosts in these areas.

<u>Race, Economic Opportunity and Airbnb:</u>

A considerable body of research finds that there are significant and enduring differences between racial groups in terms of their access to economic opportunity, through the labor market and entrepreneurialism. In the labor market, a number of audit studies have shown that hiring practices heavily favor Whites over other racial groups, especially Blacks (Bendick, Jackson, and Reinoso 1994; Bertrand and Mullainathan 2016; Pager 2003; Pager, Western, and Bonikowski 2009). While these studies have been very influential, they are not without their critics. Heckman (Heckman 1998), has argued that the audit method is prone to producing both false negatives and false positives, and Fryer and Levitt (2004) have made the case that the type of discrimination detected by the audit studies does not result in measurable differences in economic outcomes. However, the bulk of the evidence suggests that the studies do reflect an underlying pattern of differential access to the labor market.

Beyond the job search process, there is extensive evidence of racial disparities in labor market outcomes. Race is a factor in managerial decisions to channel non-White people into lower-paying jobs, or into positions without opportunities for advancement (Braddock et al. 1986; Royster 2003). Moreover, there is a significant and consistent wage gap between racial groups. On average White workers enjoy hourly wages higher than workers of color, with White men earning about 30% more than their Black and Hispanic counterparts, and White women earning about 25% more compared to women from these groups (Patten 2016). While Asian men and women have closed a similar wage gap since the late 1990s, and overtaken White workers, there has not been a similar improvement for Black and Hispanic workers. A recent Economic Policy Institute report (Wilson and Rodgers 2016) suggests that the gap between White and Black wage earners is growing worse. Self-employment and entrepreneurship, which are often seen as refuges from the more discriminatory labor market (Boyd 2005), follow similar trends. Fairlie and Robb (2008) have shown that Black entrepreneurs, who have access to less capital, education and entrepreneurial experience because of racial inequalities do not succeed as often as their White or Asian counterparts.

These significant and persistent inequalities in economic opportunity are likely to be determinants of the reproduction of racial inequality on Airbnb. Inequalities in the conventional economy are create incentives for people of color to seek alternative economic opportunities such as those presented by the sharing economy. The association of the sharing economy with entrepreneurialism and the disruptionist rhetoric surrounding the sector may also enhance these incentives. However, the multifaceted nature of racial differences in economic opportunity is likely to produce unequal outcomes for participants on the platform.

METHODOLOGY

Our methodological strategy in this paper is to use data generated on Airbnb about individual listings, in conjunction with information about the areas in which these listings are located to measure racial inequality on the platform. For this purpose, we use a dataset containing all active listings on the Airbnb platform in the 10 biggest urban Airbnb markets in the US for at least one day in 2016. The data on Airbnb was collected by a private company which uses web scraping to collect daily information about the Airbnb market (AirDNA 2017). Similarly scraped data from the platform has been used before in studies of discrimination on the platform (Edelman and Luca 2014; Edelman et al. 2015), the dynamics of room bookings (Lee et al. 2015), how the ratings system operates (Zervas, Proserpio, and Byers 2015a) and the impact of home sharing on the hospitality industry (Zervas, Proserpio, and Byers 2015b). Moreover, scraped data about the platform is also available for select urban markets from a public awareness campaign about the impacts of Airbnb (Inside Airbnb 2016).

Our dataset contains 332,368 Airbnb listings in the 10 urban markets, which are defined using the metropolitan statistical areas designated by the Office of Management and Budget (US Census Bureau 2017c).[2] Currently there are legitimate concerns about data validity while conducting online research, especially in the sharing economy (Gelman 2016). This is case with our data as well, since we have no exact way of ascertaining the fraction of total Airbnb listings that are included in our dataset. However, a comparison of our dataset to other publicly available datasets on Airbnb listings, suggests that we have relatively comprehensive coverage.[3]

We used the scraped location of listings to match[4] them with census tracts using the US Census' Geocoder API (US Census Bureau 2017b). We then merged the listing-level data with the 2011-2015 5-year estimates of the American Community Survey (US Census Bureau 2017a) for the same census tract. In our analysis of this data, we use hierarchical random-effects models[5] with spatial lag terms. The spatial lag term, calculated as the mean value of the dependent variable in any neighboring listings (or, where applicable, tracts) within 3 miles divided by the distance between the two listings (or tracts) is intended to control for any spatial autocorrelation in our model.[6] Studying geographical data in this manner, using tracts and other census units as a proxy for individual, household and/or "neighborhood" characteristics is a well-established practice (Krivo and Peterson 2000; Lee et al. 2009; Quillian 2012), and has been used in studies of online sharing economy platforms (Edelman et al. 2015; Thebault-Spieker et al. 2015). While there are some advantages to abandoning the pre-defined units of the census (Lee et al. 2008) or using other geographical units like census blocks (Hansen and Reich 2015; Parisi et al. 2011:835), we believe our use of the slightly larger tracts is justified due to data availability and the uncertainty over the exact listing locations. Airbnb often uses zip-codes in its own reports of community impact, however we believe those areas are too large to capture the true dynamics of platform participation and outcomes (Airbnb 2016).

Dependent Variables:

(Table 1 about here)

Number of Listings: This variable measures the total number of listings in a census tract. Census tracts with no listings are assigned a value of zero. Exposure was assumed to be uniform across all census tracts and thus was not modeled, because there is no reliable way to trace Airbnb's roll-out in the various MSA's, and the platform has been available nation-wide for a number of years.

Nightly Price: This is the nightly price of a listing advertised on the Airbnb platform at the end of December 2016.

Booked Nights: This is the number of nights that a listing was booked during 2016, with exposure modeled as the total nights the listing was marked as available in the same period.

Annual Revenue: This is the annual revenue of a listing calculated based on the nightly rate and cleaning fees[7] collected by the host, in conjunction with the length of bookings.

Rating: On Airbnb, guests provide a numerical rating for listings they have stayed in, on a scale ranging from 1 to 5 (on the site the average of these ratings is displayed as a 5-star scale). Airbnb often does not make ratings visible for listings that have fewer than 3 reviews (Airbnb 2017b). This means that we have no rating data for about a third of our sample and had to exclude them from our analysis. Additionally, we have about 36,000 listings for which we have ratings data, even though they have less than three reviews. Analysis with these listings excluded from the sample yielded substantively similar results, and we have opted to include them in our models.

While the guests can rate several aspects of a listing such as location and check-in process separately, we only focused on the overall rating in our analysis. Bad ratings on the site are very rare and in our sample more than a third (33.6%) of all listings that have a rating have a perfect one, and a further third (33.8%) have ratings between 4.7 and 4.9.

Independent Variables:

(Table 2 about here)

Percent non-White: This variable is the percentage of the total population in a tract that did not identify as White, non-Hispanic (including those that identified as more than one race, even if one of the races was White). We have investigated other measures of race, including a diversity index as well as the percentages of specific racial and ethnic groups (Black and Hispanic) with broadly similar results. We ultimately selected the percentage of the residents that did not identify as White due to the unequal geographical distribution of racial and ethnic minority groups, so that we could show overarching trends associated with the racial composition of a census tract across all 10 urban markets.

Median Age: The median age of all tract residents. We expect age to play an important role in participation on Airbnb as previous research indicates that younger people participate on the platform at higher rates (Pew Research Center 2016). However, there are also some reports of a critical mass of older (female) hosts (Castrodale 2016). Finally, age might also be a factor on the neighborhood-level with residents of older neighborhoods placing social stigma on the practice of hosting.

Percent Renter: The percentage of households that do not own, but rent the unit they are occupying. We believe this will be an important factor in Airbnb participation and outcomes, with different dynamics that could influence these in negative and positive directions (see above).

Per Capita Income: This is the per capita income for all residents within a census tract. We expect income to play an important but complex role in our models, since having access to real estate assets to monetize on Airbnb is a requirement to participate on the platform, but the amount of additional income to be made as a host is relatively larger in lower income areas.

Gini Coefficient: In order to measure the income distribution within a census tract we use the Gini coefficient. Areas with higher income inequality might be likely to participate on the platform because these tend to be the "gentrifying" neighborhoods, with a mix of high and low income residents, that tend to attract Airbnb activity (BJH Advisors LLC 2016).

Percent with BA or Higher: This is the percentage of the total population 25 and over, that has the equivalent of a BA degree or higher educational credentials. We expect tracts that have a higher percentage of residents with post-secondary education to participate on the platform at higher rates, in line with the survey findings on the platform demographics, while the relationship between education and outcomes is harder to predict. On the one hand, these areas could be more desirable on the platform due to homophily behavior from guests (Ikkala and Lampinen 2015; Ladegaard forthcoming). On the other hand, the highly educated participants of the sharing economy often highlight non-monetary motivations for their participation and therefore might not display profit-maximizing behavior on the platform (Fitzmaurice et al. forthcoming).

Information about the controls included in the models can be found in Table 2. We chose to handle missing data (from the US Census data) with listwise deletion to keep our models simpler. Since the number of cases for which there was any missing data is at most around 1% of all cases, we believe that listwise deletion does not impact our results in any substantive manner. Descriptive statistics for all variables are reported in Table 3.

(Table 3 about here)

FINDINGS:

Our analysis, which we present in detail below, identifies two key facets of the reproduction of racial inequality on Airbnb. In terms of participation on the platform, we find that areas where people of color make up a higher percentage of residents tend to have higher levels of participation on the platform, when controlling for racially unequal distributions of income, income inequality and education. In these areas, Airbnb listings are booked at rates similar to the rest of our sample. However, the outcomes on Airbnb, in terms of prices, revenue or ratings are biased against these areas. Areas that have residents with lower incomes or lower educational attainment are subject to similarly disadvantageous outcomes.

(Table 2 about here)

Number of Listings

The racial composition of the census tract, measured as the percentage of the population that did not identify as White non-Hispanic is a significant determinant of the number of listings on Airbnb within it. The best-fit model, which is reported in Table 1 above, shows that census tracts that have higher fractions of non-White residents tend to have more listings on the platform. This is what we expect, given that Airbnb presents a novel way of earning income for groups that suffer from worse outcomes in conventional market activities. In this model, a standard deviation increase in the percentage of residents identifying as non-White is associated with 11% increase in the number of listings. Ignoring random effects, and with other covariates at their means, this model predicts about 7 listings in a census tract with residents that all identify as White, compared to about 10 listings in a census tract with residents that all identify as non-White.

We also find that per capita income has a significant but negative relationship with the number of listings in a census tract. One standard deviation increase in income is associated with a 25% decrease in the number of listings. We also see that tracts with a higher percentage of renters, higher income inequality and higher median age tend to have more listings in most of the models. Perhaps the most important finding to note here is that the education variable is the strongest predictor. A standard deviation increase in the education variable is associated with a 112% increase in the number of listings.

Nightly Price:

The results of our analysis of the nightly price of listings shows that in census tracts with higher concentrations of non-White residents, listings charge significantly lower nightly prices. This is in line with previous findings about Airbnb prices (Edelman and Luca 2014; Laouenan and Rathelot 2016). The predicted price differential between an all-White and an all non-White neighborhood for a listing that cannot be booked instantly and is not a private or shared room, with all other covariates at their means and random effects ignored is about 15$ less per night. There is also a significant relationship between income and nightly prices, with higher per capita incomes associated with higher nightly prices for listings. The same is true for tracts with higher income inequality and higher percentage of residents with at least a BA degree as well. The rentership and age variables, on the other hand, are not significant predictors of nightly prices.

(Table 3 about here)

Booked Nights:

The concentration of non-White residents in a census tract was not a significant predictor of the number of nights a listing was booked in 2016, controlling for the number of nights it was available on Airbnb. On the other hand, rentership, income, income inequality and education are consistent predictors of booked nights on the platform. Listings in tracts with a higher fraction of renters, higher educational attainment and with higher income inequality tend to have more nights booked, while listings in tracts with higher per capita income tend to have fewer nights booked on Airbnb.

Annual Revenue

In census tracts with higher concentrations of non-White residents, our analysis predicts that Airbnb listings have significantly lower annual revenues. The predicted revenue differential between an all-White and an all non-White census tract, for a listing that can't be booked instantly and is not a private or shared room, with all other covariates at their means and random effects ignored, is around 233$ in Model 6. There is also a significant relationship between income inequality and annual revenue, with listings in more unequal census tracts predicted to earn higher revenues. We see similar relationships between annual revenue and the age, rentership and education variables as well. However, the relationship with education is only significant at the 0.05 level.

Ratings:

In census tracts with a greater proportion of people of color, we find that Airbnb listings have significantly worse ratings. The predicted difference in ratings between an all-White neighborhood and an all non-White neighborhood is roughly 0.1 rating points. Even though this effect size might appear small, given the extremely high ratings on Airbnb, a reduction of this size can have a significant impact on a listing's performance. A reduction of 0.1, about a fifth of the standard deviation of the ratings data, represents a significant drop in a listing's rating. We also find that listings in tracts that have higher income inequality and have more renters tend to have lower ratings. The education variable, on the other hand, is associated with higher ones. Median age and per capita income are not significant predictors of ratings on the platform.

Limitations:

The nature of the data we are using places a number of limitations on our analysis. First, we cannot be sure that our dataset includes all of the listings within the geographies we are studying. Despite comparable results to other Airbnb scraping efforts, we simply have no way of establishing our coverage rate, short of obtaining data from Airbnb. Therefore, our results could be biased in unknown ways due to omitted listings. However, we believe that this is the best independent way to study Airbnb listings and that careful data scraping efforts can potentially be the answer to the absence of large-scale company-provided data.

The second limitation of our data is that we cannot control for some listing-specific factors that might influence participation and outcomes. Specifically, we cannot establish qualitative differences between listings, such as the amenities they offer guests, the condition and maintenance of the premises, or the rules guests are required to follow. However, in many places, amenities, cleanliness, and rules have become fairly standardized.

Our findings are also limited by the cross-sectional nature of our data. This means that we are not able to control for time and time-variant changes in the Airbnb platform in our analysis, including the churn of users and hosts and the success of listings in attracting guests. Perhaps more importantly, we are unable to measure how the platform influences the demographic composition of neighborhoods. It is possible that the financial and other changes wrought by the platform, especially in urban centers where listings are heavily concentrated, could lead to demographic changes. In fact the debate over Airbnb and gentrification is built on this assumption (BJH Advisors LLC 2016; Inside Airbnb 2017).

The fourth and most important limitation of our data is that we do not measure race, or income, education or home-ownership, at the individual level. We know from the existing literature that individual-level factors play a critical role in generating discriminatory interactions and racialized outcomes, however we cannot specifically study these dynamics. However, collecting racial data on individuals is fraught with difficulties. Airbnb has informed our second author that it does not collect data on the race of its hosts. More intrusive data collection methods, such as collecting data on users from social networking sites might be considered a violation of privacy. A third method, which is to assign racial categories on the basis of users' pictures with automated software and human coders, has been used in one report (Inside Airbnb 2017) and one working paper (Edelman and Luca 2014). The Inside Airbnb report found that in areas where Black residents were the largest racial group within New York City, Airbnb hosts were almost 75% White (Inside Airbnb 2017). While New York is different from many other cities, this study does raise the possibility that in neighborhoods that have a high proportion of residents of color, Airbnb hosting is disproportionately occurring among Whites. This highlights the potential for sub-neighborhood level dynamics for racial inequality that we cannot capture using our analytical approach.

While we believe that the visual coding approach is fruitful, the accuracy of automated software for race recognition is only around 90% (Fu, He, and Hou 2014). Furthermore, not all Airbnb hosts use pictures that are ideal for this type of analysis. There are varying levels of lighting and image quality, pictures without any faces, or multiple faces. In addition, the decision to avoid racial identifiers in pictures may not be random, given that media coverage of person-to-person discrimination has been widespread. Laouenan and Rathelot (2016), on the other hand, use host names as proxies for race. However, this approach is harder to justify. Not all names are unambiguously racialized and hosts do not always use their given names, or might use more than one name in their profile. Thus, while there is no perfect approach, for these reasons we believe that using Census tract measures of racial composition is a conservative choice that is currently preferable to the alternatives.

DISCUSSION:

Our findings demonstrate that access and outcomes on Airbnb show clear evidence of racial disparities operating in areas with high concentrations of minority populations. For nightly prices, revenue and ratings of listings, the inequality is straightforward to explain. Controlling for a number of factors that are themselves racially unequal, such as homeownership, income and educational attainment, listings in areas with a higher proportion of non-White residents charge significantly lower prices, earn less and receive lower ratings. This can be the result of lower demand for lodgings in these areas on account of discriminatory preferences of consumers, or lower desirability for these listings due to issues such as access to transportation, distance to points of interest, or lack of public amenities for travelers. The various pricing tools for hosts provided by Airbnb and other companies, which take into account local demand and competitor pricing, are likely to provide strong market feedback mechanisms for making nightly prices highly responsive to consumer demand and could be playing a role in driving down nightly prices.

Our analysis of the number of listings and booked nights on the platform, however, provides a more complex picture of the relationship between race and Airbnb participation. We find that in areas with higher concentrations of residents of color, Airbnb participation is higher, controlling for racially unequal distributions of income, education and homeownership. In these areas, we also find that listings are booked at the same rates as the rest of sample. These findings can be potentially explained by higher demand from guests to stay in these areas, explained perhaps by the desire to consume "the other" (hooks 1992) on the part of the mostly White and well-educated clientele. This would be in line with Airbnb's claims about guests' preference to "live like a local" (Airbnb 2015b), and research that has identified "cosmopolitan aspirations" in the Airbnb user base (Ladegaard forthcoming). This demand could also be driven by the relatively lower prices for listings in these areas, as the hosts price their listings at rates that they think can generate more consistent bookings. Some of these neighborhoods are also trendy, gentrifying areas that still have high non-White populations, which appeal to Airbnb customers.

Yet, in light of our findings regarding nightly prices and ratings, as well as the existing literature on discriminatory practices in the sharing economy, the existence of a high enough demand to be the primary cause of participation in areas with a high proportion of minority residents appears doubtful. It is more likely that higher participation rates are driven by hosts, for whom the Airbnb platform is more accessible than traditional markets. Our findings from the annual revenue analysis support this conjecture. The lower nightly rates in listings in areas with a higher proportion of non-White residents translate into significantly lower revenues in these areas.

On the other hand, a recent (non-peer reviewed) study of New York finds that in areas where Black residents were the largest racial group, Airbnb hosts were almost 75% White (Inside Airbnb 2017). While New York is different from many other cities, this study does raise the possibility that in neighborhoods which have a high proportion of residents of color, Airbnb hosting is disproportionately occurring among Whites. That in turn undermines the argument that the platform is undermining existing patterns of racial inequality.

Taking into consideration the remaining predictors of interest, we believe that our findings point to two broad conclusions. The first is that on average, areas that are already privileged, above all due to a higher concentration of White residents, but also with higher incomes, higher proportions of college graduates or higher proportions of homeowners, are better positioned to take advantage of the opportunities presented by Airbnb. In the models above, we show that in these areas, platform outcomes (prices, booked nights, revenue and ratings) are better than in areas that do not enjoy the same privileges. This is not an unexpected finding, as residents of these areas have the resources and cultural know-how to participate successfully in the sharing economy. Nonetheless, it undermines arguments that the sharing economy is disrupting the existing patterns of inequality. Instead, it suggests that the sharing economy is, to a great extent, reproducing existing inequalities in the conventional economy.

At the same time we find some support for the idea that Airbnb may be increasing opportunity in ways that reduce inequality. Our analysis suggests that areas that are relatively less privileged, in terms of lower income or a higher concentration of minority residents, are more likely to take advantage of the opportunities provided by Airbnb. They have higher rates of participation and are able to attract a comparable rate of bookings than higher income, Whiter areas. The low barriers to entry on platforms (Schor et al. 2017; Sundararajan 2016) likely facilitate high rates of participation in these neighborhoods. This finding is consistent with the idea that individuals who live in these areas, and are at a disadvantage in the conventional market, turn to Airbnb because it offers superior income-earning opportunity. In this regard, the platform appears to be having an ameliorative effect on overall inequality. However, as we noted above, our results may be driven by the phenomenon of relatively privileged individuals in these areas using the sharing economy at higher rates than their less well-off neighbors (Schor 2017). This interpretation is supported by the study of New York racial patterns of hosting noted above (Inside Airbnb 2017).

Our methods do not allow us to definitively answer whether the higher rates of participation and comparable booking rates represent an amelioration of inequality through Airbnb, or its further entrenchment. However, our findings about income inequality might be a useful starting point for this question. We show that tracts with higher income inequality tend to have more listings, with more booked nights, higher prices and higher annual revenue. These findings may point to the conclusion of inequality-enhancement, in which better-off individuals in less-privileged areas using Airbnb to their benefit. In fact, the growing backlash to Airbnb in many communities is based this assumption, as opponents argue that Airbnb is driving a new wave of gentrification by enabling short-term rentals (BJH Advisors LLC 2016).

These dynamics point to the need for further studies of inequality in the sharing economy. In this pursuit, we believe that efforts to improve data quality are critical. Linking listings to individuals and their demographic and socio-economic characteristics is an important next step. This will allow for a deeper understanding of how person-to-person and structural dynamics of inequality operate alongside one another. However, researchers pursuing this goal will need to address privacy concerns and the operationalization of factors like race and class concretely.

Perhaps equally important for the study of inequality in the sharing economy, will be theoretically developing a framework for how the sharing economy operates as an instance of disruptive change in the organization of work and economic opportunity. Our findings show that promises of public good through economic disruption need to be critically evaluated, in line with Schor's call for a critical approach to the sharing economy (Schor 2014). There are aspects of the sharing economy, such as low barriers to entry and exit, anonymity, and flexibility in scheduling which could be beneficial for breaking down structures of privilege. However, our findings make clear that this is by no means automatic, and there are strong dynamics pushing outcomes in the other direction. It is therefore essential that future studies of the sharing economy pay particular attention to dynamics of inequality.

CONCLUSION:

The rapid growth of sharing economy platforms has led to considerable controversy (Schor and Attwood-Charles 2017). One area of contention is its impacts on inequality. We have identified two main camps of opinion—"disruptionists," who believe these new economic opportunities will be more widely dispersed than conventional economic activity, and consequently will reduce inequality, and "reproductionists," who think the platforms will intensify existing privilege and inequity. Although they are not monolithic, our findings largely support the view of the reproductionists. Using a unique dataset of all Airbnb listings in major metropolitan areas of the United States, we show that the platform is not a site of racial equality, nor is it a site where inequalities in the conventional economy can be superseded. We show that existing inequities, specifically those related to race, play a key role in structuring outcomes on the platform. The major exception to this conclusion is that the rate at which people list properties.

Census tracts with a higher proportion of non-White residents participate on Airbnb at higher rates and listings in these areas are booked at a rate similar to other listings. This finding nominally supports the disruptionist view. However, in these areas with a lower proportion of White residents, hosts charge lower prices, earn less revenue and receive worse ratings. Factors such as homeownership, income and education, which are themselves racially unequally distributed, play significant roles in creating the observed patterns of inequality. Neither the low barriers to joining the platform and listing a dwelling nor public statements against discrimination by the company are enough to overcome entrenched structural racial inequalities. Ultimately, the sharing economy reproduces these inequalities, albeit in new and varied ways.

ENDNOTES

[1] Their data includes Airbnb markets in Europe, Canada and US. Ethnic minority hosts are defined as black and/or Muslim identified based on their pictures and names, for the purposes of their study.

[2] These are the New York-Newark-Jersey City, NY-NJ-PA Metro Area, Los Angeles-Long Beach-Anaheim, CA Metro Area, Chicago-Naperville-Elgin, IL-IN-WI Metro Area, Washington-Arlington-Alexandria, DC-VA-MD-WV Metro Area, Miami-Fort Lauderdale-West Palm Beach, FL Metro Area, Boston-Cambridge-Newton, MA-NH Metro Area, San Francisco-Oakland-Hayward, CA Metro Area, Seattle-Tacoma-Bellevue, WA Metro Area, San Diego-Carlsbad, CA Metro Area, and Austin-Round Rock, TX Metro Area.

[3] For example, the dataset we are using in this study includes 99648 listings in the New York-Newark-Jersey City, NY-NJ-PA Metro Area that were available at least one day in 2016. 81863 of these listings were within New York City, which is the only area that is covered by the Inside Airbnb data. Inside Airbnb data for New York City for this period does not include data collected in March 2016 and only covers 62832 listings that were available one day or more for rental. While our data does not contain information on 1630 listings included the Inside Airbnb dataset, the Inside Airbnb dataset is missing 20661 listings that are included in our data.

[4] Airbnb does not provide exact geographical location of listings, but provides a roughly 0.3 mile-wide "circle" within which the property is located. We used the center of these circles as the locations of the listings. While it is possible that this might result in faulty matches to census tracts, we believe that given the limited nature of the data and the size of Census Tracts, the level of aggregation is appropriate and that any mismatches will be randomly distributed across tracts.

[5] The specific distributions assumed by the models as well as details about model specification are provided below in our discussion of individual variables.

[6] We have alternately used both smaller and larger distances (1-5 miles) to create spatial lag terms, as well as specifying a number of closest neighbors rather than restricting them to a pre-set distance. Models using these terms provided substantively similar results.

[7] On Airbnb, hosts can choose to collect a one-time cleaning fee for every booking. Anecdotal evidence suggests that some hosts do the cleaning themselves, while others hire professional cleaners to clean the unit. However, ultimately the fee is a part of their earnings on the platform.

Table 1. Dependent Variables

Variables	Models	Exposure	Measurement Level	Clustering Levels	Notes
Number of Listings	Negative Binomial[1]	Not Modeled	Census Tract	MSA	
Nightly Price	Linear	-	Listing	Census Tract, MSA, Host	Log-transformed
Booked Nights	Negative Binomial[2]	Total Nights Available for Booking	Listing	Census Tract, MSA, Host	
Annual Revenue	Linear	-	Listing	Census Tract, MSA, Host	Log-transformed
Rating	Linear[3]	-	Listing	Census Tract, MSA, Host	

[1] We investigated Poisson models as well as zero-inflation for both negative binomial and Poisson models for this variable, all of which produced substantively similar results. The reported results were produced with the lme4 package in R for all dependent variables (Bates et al. 2014). The analysis for number of listings used Gauss-Hermite Quadrature with 1 integration points, higher number of integration points resulted in no substantive changes to the results. Zero-inflation models (not reported here) were estimated with the glmmADMB package (Fournier et al. 2012; Skaug et al. 2012). [2] Due to the crossed mixed-effects specified, this analysis used Laplace approximation. [3] We have also investigated models that used the reverse coded version of the dependent variable in negative binomial fixed-effects models (with the assumption of uniform exposure) as well as logged reverse coded version of the independent variable in linear fixed-effects models. The results for all three models were substantively similar. We present the results from the linear models with the untransformed dependent variable for ease of interpretation.

Table 2. Independent Variables

	Description	Measurement Level	Notes
Variables of Interest			
Percent non-White	Percentage of total population that self-identify as a race other than White, non-Hispanic	Census Tract	Grand mean centered, standardized
Per Capita Income	Per capita income for all residents in a census tract	Census Tract	Grand mean centered, standardized
Gini Coefficient	Gini coefficient of income inequality within a census tract	Census Tract	Grand mean centered, standardized
Percent with BA or Higher	Percentage of total population that have at least a BA degree	Census Tract	Grand mean centered, standardized
Median Age	Median age of census tract residents	Census Tract	Grand mean centered, standardized
Controls			
Room Type - Shared Room	Airbnb guests to share their room with hosts	Listing	Dummy variable
Room Type - Private Room	Airbnb guests have a private room in a unit	Listing	Dummy variable
Room Type - Entire Home	Airbnb guests do not share the unit with hosts	Listing	Dummy variable, Reference category
Instant Booking	Guests can book the listing without confirmation from hosts	Listing	Dummy variable
Maximum Guests	Maximum number of guests in listing, top coded to 16	Listing	Grand mean centered, standardized
Number of Reviews	The number of guest reviews for a listing in December 2016	Listing	Grand mean centered, standardized
Distance to Closest Principal City	Distance, in meters, to the closest principal city in MSA (US Census Bureau 2017d)	Listing, Census Tract	Grand mean centered, standardized
Number Listings from Host	Number of listings the host has on Airbnb	Host	Grand mean centered, standardized
Population	The number of individuals living in an area	Census Tract, MSA	Grand mean centered, standardized

Table 3. Descriptive Statistics

	N	Missing	Mean	Std. Dev.	Median	Min	Max
Dependent Variables							
# of Listings in Tract	16108	0	20.81	51.24	5.00	0	1192
Nightly Price	335226	0	233.88	414.29	143.00	1	15000
Booked Nights	335226	0	52.86	71.80	22.00	0	364
Annual Revenue	335226	0	8468.18	15320.70	2620.00	0	719900
Ratings	220020	115206	4.65	0.48	4.80	1	5
Independent Variables							
Host Level							
# of Listings per Host	219573	0	1.53	3.26	1.00	1	759
Listing Level							
Max. Guests	335226	0	3.48	2.48	2.00	1	16
Number of Reviews	335226	0	12.39	26.81	2	0	919
Dist. to Closest City	335226	0	10371.47	15077.24	7106.52	14.98	157382
Room Type							
Entire Home or Apt.	193271	-	-	-	-	-	-
Private Room	128483	-	-	-	-	-	-
Shared Room	13472	-	-	-	-	-	-
Instant Booking							
Yes	273537	-	-	-	-	-	-
No	61689	-	-	-	-	-	-
Tract-Level							
Population	16108	0	4496.45	2020.22	4315.00	0	39454
Median Age	15963	145	38.27	7.32	37.90	11.3	83.1
% renter	15976	132	0.42	0.26	0.38	0.00	1.00
Per capita income	15962	146	35210.36	20433.27	31148.50	128	254204
Gini coefficient	15914	194	0.43	0.07	0.42	0.01	0.72
% non-White	15976	132	0.54	0.31	0.50	0.00	1.00
Dist. to Closest City	16108	0	15332.96	15460.95	10746.18	0.03	151774
MSA Level							
Population	10	0	7307768.60	5576135.31	5330990.00	1943299	20092883

Table 4. Partial Results for Number of Listings in a Census Tract and Nights Booked

	Number of Listings [1, 2]	*Booked Nights* [1, 3]
Fixed Effects		
% non-White	1.110 ***	1.002
	(0.016)	(0.005)
Median Age	1.083 ***	0.982 ***
	(0.013)	(0.004)
% Renter	1.350 ***	1.030 ***
	(0.018)	(0.004)
Per Capita Income	0.748 ***	0.934 ***
	(0.014)	(0.006)
Gini Coefficient	1.225 ***	1.011 ***
	(0.012)	(0.004)
% with BA or Higher	2.120 ***	1.067 ***
	(0.039)	(0.007)
N_{host}	-	217563
$N_{Tract:MSA}$	-	13069
N_{MSA}	10	10
ICC_{Host}	-	0.006
$ICC_{Tract:MSA}$	-	0.001
ICC_{MSA}	0.052	0.003
Observations	15378	332368
AIC	98863.009	2939024.633
Deviance	17306.265	3985977.351
Notes	*[1] * p<.05 ** p<.01 *** p<.001* *[2] Intercept, spatial lag, tract population, MSA population, distance to closest principal city are omitted from table. Reported results are exponentiated logged odds (incidence rate ratios).* *[3] Intercept, spatial lag, number of listings in tract, number of listings by host, instant booking, listing type, number of reviews, maximum number of guests, distance to closes principal city, tract population, MSA population omitted from table. Reported results are exponentiated logged odds (incidence rate ratios).*	

Table 5. Partial Results for Nightly Price, Annual Revenue and Rating

	Nightly Price[1]	*Annual Revenue[1]*	*Rating[1]*
Fixed Effects			
% non-White	-0.009 ***	-0.025 ***	-0.026 ***
	(0.001)	(0.005)	(0.002)
Median Age	0.002	0.022 ***	0.000
	(0.001)	(0.005)	(0.002)
% Renter	0.001	0.017 ***	-0.016 ***
	(0.001)	(0.005)	(0.002)
Per Capita Income	0.053 ***	-0.014	-0.001
	(0.002)	(0.008)	(0.003)
Gini Coefficient	0.018 ***	0.022 ***	-0.011 ***
	(0.001)	(0.004)	(0.002)
% with BA or Higher	0.011 ***	0.017 *	0.014 ***
	(0.002)	(0.008)	(0.003)
N_{Host}	217563	217563	147335
$N_{Tract:MSA}$	13069	13069	11475
N_{MSA}	10	10	10
ICC_{Host}	0.473	0.307	0.196
$ICC_{Tract:MSA}$	0.078	0.009	0.015
ICC_{MSA}	0.031	0.005	0.005
Observations	332368	332368	217779
R^2 / Ω_0^2	.903 / .898	.630 / .564	.507 / .384
AIC	-107159.719	1168298.45	276598.877
Notes	*[1] * p<.05 ** p<.01 *** p<.001 Intercept, spatial lag, number of listings in tract, number of listings by host, instant booking, listing type, number of reviews, maximum number of guests, distance to closest principal city, tract population, MSA population omitted from table. Reported results are linear regression coefficients.*		

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Appendix A: Full Results for Number of Listings in Census Tract

	Model 1		Model 2	
	IRR	*std. Error*	*IRR*	*std. Error*
(Intercept)	9.466 ***	0.773	8.477 ***	0.795
Spatial Lag	3.941 ***	0.061	2.407 ***	0.037
Population - Census Tract	1.225 ***	0.011	1.252 ***	0.011
Population - MSA	0.867	0.067	0.807 *	0.072
Distance to Closest City	0.862 ***	0.008	0.990	0.009
% Non-White	0.877 ***	0.009	1.110 ***	0.016
Median Age			1.083 ***	0.013
% Renter			1.350 ***	0.018
Per Capita Income			0.748 ***	0.014
Gini Coefficient			1.225 ***	0.012
% with BA or Higher			2.120 ***	0.039
N_{MSA}	10		10	
ICC_{MSA}	0.032		0.052	
Observations	15378		15378	
AIC	101952.155		98863.009	
Deviance	17378.763		17306.265	
Notes	* $p<.05$ ** $p<.01$ *** $p<.001$			

Appendix B: Full Results For Nightly Price

	Model 1		Model 2	
	B	*std. Error*	*B*	*std. Error*
Fixed Parts				
(Intercept)	2.263 ***	0.019	2.264 ***	0.016
Spatial Lag	-0.001 **	0	-0.001 *	0
# of Listings in Tract	0.093 ***	0.002	0.053 ***	0.002
# of Listings per Host	0.016 ***	0.005	0.015 **	0.005
Instant Booking	0.007 ***	0.001	0.021 ***	0.001
Listing Type - Private Room	-0.014 ***	0.001	-0.014 ***	0.001
Listing Type - Shared Room	-0.212 ***	0.001	-0.212 ***	0.001
# of Reviews	-0.372 ***	0.002	-0.371 ***	0.002
Max. Guests	-0.012 ***	0	-0.012 ***	0
Distance to Closest City	0.145 ***	0	0.145 ***	0
Population - Census Tract	-0.011 ***	0.001	-0.007 ***	0.001
Population - MSA	0.004	0.02	-0.006	0.016
% Non-White	-0.046 ***	0.001	-0.009 ***	0.001
Median Age			0.002	0.001
% Renter			0.001	0.001
Per Capita Income			0.053 ***	0.002
Gini Coefficient			0.018 ***	0.001
% with BA or Higher			0.011 ***	0.002
Random Parts				
N_{Host}	217563		217563	
N_{tract}	13069		13069	
N_{MSA}	10		10	
ICC_{Host}	0.45		0.473	
ICC_{Tract}	0.11		0.078	
ICC_{MSA}	0.042		0.031	
Observations	332368		332368	
R^2 / Ω_0^2	.904 / .899		.903 / .898	
AIC	-104975.856		-107159.719	
Notes	* *p*<.05 ** *p*<.01 *** *p*<.001			

Appendix C: Full Results For Booked Nights

	Model 1		Model 2	
	IRR	*std. Error*	*IRR*	*std. Error*
(Intercept)	0.277 ***	0.014	0.275 ***	0.013
Spatial Lag	1.059 ***	0.003	1.059 ***	0.003
# of Listings in Tract	1.013 **	0.005	0.981 ***	0.005
# of Listings per Host	0.854 ***	0.006	0.854 ***	0.006
Instant Booking	0.903 ***	0.003	0.918 ***	0.003
Listing Type - Private Room	1.193 ***	0.008	1.193 ***	0.008
Listing Type - Shared Room	0.755 ***	0.005	0.761 ***	0.005
# of Reviews	0.598 ***	0.008	0.599 ***	0.008
Max. Guests	1.595 ***	0.004	1.596 ***	0.004
Distance to Closest City	0.941 ***	0.003	0.947 ***	0.003
Population - Census Tract	1.002	0.003	1.009 **	0.003
Population - MSA	1.033	0.055	1.036	0.05
% Non-White	1.020 ***	0.003	1.002	0.005
Median Age			0.982 ***	0.004
% Renter			1.030 ***	0.004
Per Capita Income			0.934 ***	0.006
Gini Coefficient			1.011 **	0.004
% with BA or Higher			1.067 ***	0.007
N_{Host}	217563		217563	
N_{tract}	13069		13069	
N_{MSA}	10		10	
ICC_{Host}	0.004		0.004	
ICC_{Tract}	0.001		0.001	
ICC_{MSA}	0.002		0.002	
Observations	332368		332368	
AIC	2939364.534		2939024.633	
Deviance	385827.809		385977.351	
Notes	* $p<.05$ ** $p<.01$ *** $p<.001$			

Appendix D: Full Results for Annual Revenue

	Model 1		Model 2	
	B	*std. Error*	*B*	*std. Error*
Fixed Parts				
(Intercept)	3.010 ***	0.041	3.010 ***	0.04
Spatial Lag	0.029 ***	0.003	0.029 ***	0.003
# of Listings in Tract	0.072 ***	0.006	0.056 ***	0.007
# of Listings per Host	0.304 ***	0.024	0.304 ***	0.024
Instant Booking	0.005	0.004	0.008	0.004
Listing Type - Private Room	0.054 ***	0.007	0.054 ***	0.007
Listing Type - Shared Room	-0.347 ***	0.006	-0.343 ***	0.006
# of Reviews	-0.611 ***	0.015	-0.609 ***	0.015
Max. Guests	0.543 ***	0.003	0.543 ***	0.003
Distance to Closest City	0.128 ***	0.003	0.129 ***	0.003
Population - Census Tract	-0.014 ***	0.004	-0.008 *	0.004
Population - MSA	0.011	0.042	0.004	0.041
% Non-White	-0.030 ***	0.004	-0.025 ***	0.006
Median Age			0.022 ***	0.005
% Renter			0.017 ***	0.005
Per Capita Income			-0.014	0.008
Gini Coefficient			0.022 ***	0.004
% with BA or Higher			0.017 *	0.008
Random Parts				
N_{Host}	217563		217563	
N_{tract}	13069		13069	
N_{MSA}	10		10	
ICC_{Host}	0.307		0.307	
ICC_{Tract}	0.009		0.009	
ICC_{MSA}	0.005		0.005	
Observations	332368		332368	
R^2 / Ω_0^2	.630 / .564		.630 / .564	
AIC	1168363.711		1168298.445	
Notes	* *p<.05* ** *p<.01* *** *p<.001*			

Appendix E: Full Results For Rating

	Model 1		Model 2	
	B	*std. Error*	*B*	*std. Error*
(Intercept)	4.676 ***	0.013	4.676 ***	0.013
Spatial Lag	-0.002	0.001	-0.001	0.001
# of Listings in Tract	-0.022 ***	0.002	-0.013 ***	0.003
# of Listings per Host	-0.137 ***	0.005	-0.137 ***	0.005
Instant Booking	-0.062 ***	0.003	-0.062 ***	0.003
Listing Type - Private Room	-0.016 ***	0.003	-0.018 ***	0.003
Listing Type - Shared Room	-0.056 ***	0.006	-0.056 ***	0.006
# of Reviews	0.016 ***	0.001	0.016 ***	0.001
Max. Guests	-0.014 ***	0.001	-0.014 ***	0.001
Distance to Closest City	0.013 ***	0.002	0.012 ***	0.002
Population - Census Tract	0.002	0.002	-0.000	0.002
Population - MSA	-0.029 *	0.013	-0.026 *	0.013
% Non-White	-0.041 ***	0.002	-0.026 ***	0.002
Median Age			0.000	0.002
% Renter			-0.016 ***	0.002
Per Capita Income			-0.001	0.003
Gini Coefficient			-0.011 ***	0.002
% with BA or Higher			0.014 ***	0.003
N_{host}	147335		147335	
NT_{ract}	11475		11475	
N_{MSA}	10		10	
ICC_{Host}	0.196		0.196	
ICC_{Tract}	0.017		0.015	
ICC_{MSA}	0.005		0.005	
Observations	217779		217779	
R^2 / Ω_0^2	.508 / .384		.507 / .384	
AIC	276757.717		276598.877	
Notes	** p<.05 ** p<.01 *** p<.001*			