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

Acknowledgments and Credits:

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 (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

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 been called “peer-to-peer” or person-to-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 provi0.2 (he) 9t 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.

The debate on the impact of the sharing economy on inequality, broadly speaking, has solidified into two camps. 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 inequalit 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 fo

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

socio-economic class

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).

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%,

jobs, or into positions without opportunities for advancement (Braddock et al. 1986; Royster 2003). Moreover, there is a si 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). Wf (-) Tj . m BT 50 0 .2 (e)

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.

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 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.

FINDINGS:

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.

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

revenues. We see similar relationships between annual revenue and the age, rentership and 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

of interest, or lack of public amenities for travelers. The various pricing tools for hosts provided 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 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-

[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,

	Nightly Price[1]	*Annual Revenue*[1]	*Rating*[1]
% 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 / ! $_0^2$	.903 / .898	.630 / .564	.507 / .384
AIC	-107159.719	1168298.45	276598.877

[1] * *p<.05*

Notes

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	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	-	