" Sharing" in Unequal Spaces: Short-term Rentals and the Reproduction of Urban Inequalities

Author: Mehmet Suleyman Cansoy

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“SHARING” IN UNEQUAL SPACES: SHORT-TERM RENTALS AND THE REPRODUCTION OF URBAN INEQUALITIES

Mehmet Süleyman Cansoy

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Mehmet Süleyman Cansoy

Advisor: Juliet B. Schor, Ph.D.

In this dissertation, I argue that questioning the relationship between technological change, specifically the new types of markets and practices enabled by the "sharing economy" and inequality has become an urgent need. While the sector promotes itself as the harbinger of egalitarian access to economic opportunity and consumption, independent studies of its operations and impacts point towards significant discriminatory dynamics favoring the already privileged. As the sector keeps growing, understanding its impact on inequality becomes ever more critical. I focus on one sharing economy platform, Airbnb, which facilitates the practice of "home-sharing," or more accurately short-term rentals. I investigate the relationship between Airbnb and inequality in three papers that focus on how the deeply unequal urban settings where much of the economic activity on Airbnb takes place operate within the context of economic activity enabled by the platform. The analysis for all three papers is based on the data for more than 450,000 Airbnb listings and the demographic and economic characteristics of the neighborhoods they are located in. In the first paper, I look at how race determines the patterns of participation and outcomes for people who rent out their properties. I show that the economic opportunities generated by the platform are unequally distributed across the urban landscape. There are fewer listings in areas with higher concentrations of non-White residents, the listings that are located in these areas charge lower prices, and have lower earnings. The second paper investigates

the relationship between the public reputation system on Airbnb and racial discrimination. I show that characterizing the reputation system as a racially neutral tool, which has the potential to reduce discriminatory outcomes, is highly problematic. Airbnb listings located in neighborhoods with higher percentages of non-White residents have a harder time generating reputation information when they first come on the platform and tend to have systematically lower ratings. The third paper focuses on how short-term rentals generates new dynamics of gentrification in cities, by providing evidence for a new type of "rent gap" between long-term and short-term rentals, and how property owners are exploiting it. I argue that short-term rentals, in the absence of further effective regulation from governments, are likely to drive increasing levels of gentrification as they remain highly profitable and occupy an increasing number of housing units. I believe that studying these aspects of the sharing economy contributes to a fuller understanding of technological change and its understudied interaction with inequality. Moving beyond the mostly theoretical and aggregated understanding of change inherent in the SBTC literature, my research promotes a more concrete and empirical engagement with change in line with some of the research on the "digital divide," and the emergent literature on inequality on online platforms. Ultimately, I think such an engagement can serve as the basis for a broader theoretical reckoning with the increased pace of technological change as more and more of our social life is "disrupted" by technological interventions, with significant consequences.

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INTRODUCTION

How do new markets, operating with novel logics and made possible due to rapid technological and organizational changes, interact with existing inequalities? What new dynamics in inequality are set in motion as a result of changes to how value is generated and extracted? What does the "constant revolutionising of production" (Marx and Engels 2010:16) do to a society with deep fault lines running along the boundaries of race and class? While these questions have motivated academic research for a long time, they have gained even more urgency in the last few decades as income inequality has increased alongside significant technological and organizational innovations (Piketty 2014).

One response within economics and sociology has been to focus on the aggregate impact of innovations and the systemic changes they induce. Research in this vein has generated interesting questions about the nature of innovation, the importance of institutional and political context in mediating change, and the nature of new inequalities in what can broadly be called the skill-biased technological change (hereafter SBTC) literature (Acemoglu and Autor 2012; Autor, Levy, and Murnane 2003; Goldin and Katz 2009; Liu and Grusky 2013). However, its focus on the macro scale means that it has little to say on how existing inequalities will affect any individual innovation, or even as large a set of innovations as those that have enabled the sharing economy. For an analysis at that scale, we have to turn to a broad literature that has focused on digital technologies and inequality, albeit without a firm research agenda or a consistent set of findings.

While some in this body of work have argued that digital technologies have the power to ameliorate inequalities (Fraiberger and Sundararajan 2015; Hall and Krueger 2015; John J. Horton and Zeckhauser 2016; Sperling 2015; Sundararajan 2016), a larger body of work has consistently found that the digital technologies and innovation often result in existing inequalities being reproduced (Ayres, Banaji, and Jolls 2015; DiMaggio and Bonikowski 2008; Doleac and Stein 2013; Hargittai 2010; Nunley, Owens, and Howard 2011; Scholz 2017; Schor 2017; Schor et al. 2016; Slee 2016). They have even reported a retrenchment of these inequalities through the innovations themselves and the economic and cultural practices that are organized around them.

In this dissertation, I argue that questioning the "sharing economy" economy along these lines is a critical endeavor. While the sector promotes itself as the harbinger of egalitarian access to economic opportunity and consumption (Airbnb 2015b; Hall and Krueger 2015; Sperling 2015), independent studies of its operations and impacts point towards significant discriminatory dynamics favoring the already privileged. As the sector keeps growing, there is an urgent need to understand the nature of inequality within the sector.

I limit my research to a single platform, Airbnb, which facilitates the practice of "home-sharing," or more accurately short-term rentals. This focus on a single platform allows me to avoid issues of comparability, because the "sharing economy" incorporates a wide range of business models, practices and technologies. This choice also allows me to study economic dynamics that impact the lives of a large number of people due to Airbnb's scale. Finally, this choice is partially driven by data availability, which I discuss in detail below. I investigate the relationship between Airbnb and inequality in three papers that focus on how the deeply unequal urban settings where much of the economic activity on Airbnb takes place operate within the context of economic activity enabled by the platform. The analysis for all three papers is based on the data for more than 450,000

Airbnb listings purchased from a company which gathers data on the Airbnb platform daily (AirDNA 2017). To understand the demographic and economic characteristics of the neighborhoods the Airbnb listings are located in I use American Community Survey data from 2015 and 2016 (US Census Bureau 2017a). In the first paper, I look at how race determines the patterns of participation and outcomes for people who rent out their properties. I show that the economic opportunities generated by the platform are unequally distributed across the urban landscape. There are fewer listings in areas with higher concentrations of non-White residents, and the listings that are located in these areas charge lower prices, and have lower earnings. The second paper investigates the relationship between the public reputation system on Airbnb and racial discrimination. I show that characterizing the reputation system as a racially neutral tool, which has the potential to reduce discriminatory outcomes, is highly problematic. Airbnb listings located in neighborhoods with higher percentages of non-White residents have a harder time generating reputation information when they first come on the platform and tend to have systematically lower ratings. The third paper focuses on how short-term rentals generates new dynamics of gentrification in cities. I show that a new type of rent gap between long-term and short-term rentals has opened in cities, and property owners have been exploiting it in large numbers. I argue that short-term rentals, in the absence of further effective regulation from governments, are likely to drive increasing levels of gentrification, as they remain highly profitable and occupy an increasing number of housing units.

I believe that studying these aspects of the sharing economy contributes to a fuller understanding of technological change and its understudied interaction with inequality. Moving beyond the mostly theoretical and aggregated understanding of change inherent in the SBTC literature, my research promotes a more concrete and empirical engagement with change in line with some of the research on the "digital divide," and the emergent literature on inequality on online platforms. Ultimately, I think such an engagement can serve as the basis for a broader theoretical reckoning with the increased pace of technological change as more and more of our social life is "disrupted" by technological interventions, with significant consequences.

THE SHARING ECONOMY

The "sharing economy" remains a contested term, in its lexicology as well as its outcomes. Its use can be traced back to Lawrence Lessig's *Remix (2008)* where it referred to strictly non-commercial ways to organize and collaborate, specifically in cultural production. How the term came to be associated with the set of organizations that we today recognize as part of the sharing economy (the giant home-sharing and ride-sharing platforms, the short-term car rental firms, nonprofits and cooperatives) is still somewhat unclear. Belk (2014) suggests that its adoption might be related to the popularity of the word "sharing" in a range of internet applications. A number of authors who opted to classify these emergent practices as instances of sharing have also been influential (Bardhi and Eckhardt 2012; Botsman and Rogers 2010; Gansky 2010). As an alternative term, "collaborative consumption" (Botsman and Rogers 2010), has probably found the widest purchase. However, despite being an accurate description of changes in consumption patterns, this phrasing fails to differentiate between different methods of production, exchange and motivations that are involved in the "sharing economy."

A number of other alternative phrases have been suggested. Belk (2014) has dubbed the sector "pseudo-sharing," to highlight its distinction from genuine, non-monetized sharing practices. There are repeated calls to approach the phenomenon as a developing "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 "digital matching firms" (Telles 2016), which again 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 the exact mix of online marketplaces, reputation systems and algorithmic matching. Others have sought to undercut the dominance of the "sharing economy" have argued in favor of the concept of the "gig economy" (Friedman 2014), 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 the academic or the public debate. While their theoretical implications are critical to understand properly the amalgamation of organizations, technologies, sites and practices that make up the "sharing economy," the concept itself remains a powerful tool for communication. That is why in this proposal I will be employing it.

The most visible, and largest in terms of number of participants or volume of economic activity, segment of the sharing economy has become the tech-based "platforms" which bring together a multiplicity of 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 transaction costs and handles payments electronically and seamlessly (John J. Horton and Zeckhauser 2016). In many of them, crowd-sourced information is used to establish user ratings and reputation as well as quality assessments of the goods and services offered, thereby addressing issues of trust which arise in cases of stranger exchange (Schor and Fitzmaurice 2015).

A small but influential body of work, which Juliet Schor and I dub “disruptionist” in the first paper, have lauded these platforms as an innovation that will disproportionately benefit people and groups that are disadvantaged in the conventional economy. Sundararajan has argued that these platforms represent a “democratization of opportunity” (Sundararajan 2016:125), with low barriers to entry, prospect of higher earnings and more control over one’s own labor. Fraiberger and Sundararajan (2015) have argued that the peer-to-peer nature of the platforms would benefit low-income people disproportionately by allowing them to consume goods and services that would have been beyond their purchasing power in the conventional market and allowing them to either monetize or sell off unproductive capital assets. The platforms themselves have sponsored a number of studies that make similar arguments. Hall and Krueger (2015) make the case that participation on the ride sharing platform Uber allows people to control their labor, can smooth out fluctuations in their income and can even “serve as a bridge” to other employment opportunities. Sperling (2015) suggests that participating on the home-sharing platform Airbnb might allow families to overcome the income stagnation they have faced in the conventional economy over the past 15 years. A competing view of the sector emerges from another school of thought that Juliet Schor and I call “reproductionist.” This body of work highlights how existing inequalities in the conventional economy, especially along lines of class, are reproduced and even strengthened through the sharing platforms (Scholz 2017; Schor 2017; Slee 2016). My analysis throughout the dissertation provides significant support for the reproductionist school of thought as I show how racial inequalities are reproduced in patterns of participation and outcomes on Airbnb, how the reputation system reproduces racial discrimination, and how the increased volume of short-term rentals favors the wealthier property owners over renters and residents who cannot afford rising housing costs.

CASE SELECTION

Airbnb, founded in 2008, is an online marketplace for short-term rentals of residential spaces. It has quickly grown to become one of the highest valued companies within the sharing economy, with a market valuation around $30 billion (O'Brien 2016). The lodgings shared on the platform range from "shared rooms" in which the prospective guest does not have a guarantee of privacy, e.g. 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 on the platform provide details on 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 for them from previous exchanges on the platform. Airbnb itself earns revenue by taking a fee from each transaction on the platform. With low barriers to entry for providers, it has attracted large user base with more than 2 million "listings" worldwide. It has also witnessed skyrocketing demand for its services with 17 million people using the service in the summer of 2015, compared to 47,000 for the same period in 2010 (Airbnb 2015a).

In the conventional economy, large hotels and Bed and Breakfasts are required by law to avoid racial discrimination in whom they accommodate. While this does not apply to smaller providers, who are more like the typical Airbnb host, Airbnb nonetheless competes with the larger and regulated institutions as well and the discriminatory behavior on the platform remains unregulated. To date, studies of inequality on the platforms have focused on this type of unregulated interpersonal discrimination that as a driver of inequality on the platforms. Edelman, Luca and

Svirsky (2017), in an audit study, have found that hosts on Airbnb regularly discriminate against guests that they perceive to be African-American. Guest profiles that had a distinctively African-American name were 16% less likely to be accepted for a reservation than those with distinctively white names. Hosts refused their requests to book even if it meant losing revenue. Another audit study with a slightly different design (Cui, Li, and Dennis J. Zhang 2016) has found a slightly larger discrimination effect against potential guests with distinctively African-American names. Similar discriminatory behavior from providers on other sharing economy platforms have been identified by a number of other studies as well. Ge and co-authors (2016), studied a number of factors including cancellations by drivers and trip length, using research assistants of different races. They found that drivers were more likely to cancel rides for individuals they perceived to be Black than for those they perceived to be White. A survey of TaskRabbit providers in Chicago (Thebault-Spieker, Terveen, and Hecht 2015) has found that they are less willing to travel to areas of the city which have a higher density of non-White residents for work on the platform.

A few studies have also identified interpersonal discrimination against providers on the platform. Another working paper on Airbnb (Edelman and Luca 2014) finds that hosts that can be identified as Black based on their pictures charge less than non-Black hosts for similar listings. While this is not direct evidence of discrimination, the primary factor for the price differential is likely to be lower demand for listings that are managed by Black hosts. These findings are supported by Laouenan and Rathelot (2016), who show that ethnic minority hosts charge prices that are roughly 3.2% lower than ethnic majority hosts.[1] Their study leverages a large-scale digital data collection effort to show that the price differential is statistically significant for hosts without any reviews.

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

Yet, for hosts with at least one review on the platform, the price differential stops being statistically significant, suggesting that the reputation systems can be a powerful tool for mitigating interpersonal discrimination. In fact, many of the studies cited here suggest changes to the way that platforms operate as a way to mitigate discrimination and the resulting inequality. These suggestions include anonymizing users' names and pictures, strengthening the prominence of reputation systems, or taking away the opportunities to discriminate.

Ultimately, this focus on interpersonal discrimination obscures structural inequalities that are highly likely to influence the patterns of participation and exchange on the platforms. Inequalities, such as racial and class-based segregation of urban spaces, confounded by income, employment and education differentials stand to play a big role in who gets to participate in a meaningful way in these platforms, and be successful in them. Especially on Airbnb, which is a market for urban space, the impact of these inequalities that are, often literally, built into these spaces need to be studied further.

While the practice of technologically mediated home-sharing is an interesting phenomenon in itself, the reason I picked Airbnb for my research is its scale, which makes it economically consequential even outside of the debate on the sharing economy. In its largest 10 markets in the USA[2], our data indicates that there is one listing on the platform for every 50 households, with the concentration increasing considerably in the urban centers. Coupled with the volume of economic activity on the platform, this indicates that Airbnb is likely to make a significant impact on the urban economies and the inequalities that run through them.

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

Another reason to focus on Airbnb is more practical. While other sharing economy platforms, specifically Uber and Lyft, also mediate significant amounts of economic activity, large-scale information about the providers on these platforms is not readily available to researchers. However, Airbnb's business model (allowing prospective guests to view all available listings rather than directly "matching" them with a host) allows researchers access to their data by employing web scrapers or obtaining it from a data re-seller. This data can then be matched with other geographical data, primarily from the US Census Bureau for analysis.

On the other hand, it is worth noting that Airbnb is a unique platform among other sharing economy platforms. The service on offer – hosting someone– requires a mix of labor (cleaning the space, greeting and helping the guests, etc.) and capital (having a space to rent) that is heavily biased in favor of the latter. Other large platforms usually offer services (cleaning, delivery, moving, driving, etc.) that depend more heavily on labor rather than capital. This obviously would restrict the generalizability of the result of this research to the broader sharing economy. However, the scale of Airbnb compared to the rest of the sharing economy means that even with limited generalizability, understanding how it interacts with patterns of inequality will still be very valuable.

THEORETICAL FRAMEWORK

How technological and organizational change impact inequality is one of the oldest questions in social sciences. It is one of the primary themes that Marx and Engels explore in *The German Ideology* (Marx and Engels 1970) and lies at the heart of the transformation of mechanical solidarity into organic in *The Division of Labor in Society* (Durkheim 1984). In the unpublished Grundrisse (1973) Marx took his engagement with technological change even further, envisioning how scientific advancement could lead to the increased marginalization of all human labor. The social scientific engagement with "change" at this macro level, as a theoretical abstraction of all individual changes, has continued in their wake. Especially with the marked increase in inequality following the broad and accelerating adoption of computer technologies in the 1980s, theories like Bell's "post-industrial society" (Bell 1976) or the SBTC literature in economics (Acemoglu and Autor 2011; Autor et al. 2003; Goldin and Katz 2009; Liu and Grusky 2013) gained some prominence. However, these approaches have little to say about how any single instance of change is likely to interact with existing inequalities, and they tend to emphasize the agentic capabilities of technology itself, which de-emphasizes social dynamics and the possibility of human agency in challenging inequality. As Piketty (2014:294) reminds us, "if one truly wishes to found a more just and rational social order based on common utility, it is not enough to count on the caprices of technology."

One body of work that has empirically studied smaller scale technological changes and maintained a focus on the social roots of inequality has been a loosely associated literature on digital technologies (Ayres et al. 2015; DiMaggio and Bonikowski 2008; Doleac and Stein 2013; Hargittai 2010; Nunley et al. 2011). This group of scholars has consistently found that existing inequalities tend to reproduce themselves in new fields made possible by the technological changes. While this is a good starting point to investigate the relationship between inequality and the sharing economy, the incentives for participation as well as the institutional qualities of the sharing economy are markedly different from some of activities studied by this literature. Having access to the internet, interpersonal networking or personal entertainment, which have been the focus of the digital divide literature, tend to be less directly market-oriented. Other activities, such as freelancing or selling goods on auction sites, present economic opportunities at a much smaller scale or with higher barriers to entry (having the necessary skills, or a supply of goods to sell) than many sharing economy platforms which require relatively less skilled labor or more widely available goods (such as housing or cars) to rent. Studying inequality dynamics in these new spaces, which has already been the subject of a small but growing body of work (Cui, Li, and Dennis J. Zhang 2016; Edelman and Luca 2014; Edelman et al. 2017; Ge et al. 2016; Hannak et al. 2017; Laouenan and Rathelot 2016), has the potential to inform our understanding of the relationship between technological change and inequality in novel ways.

Schumpeter was among the first theorists to think about change at a more granular level than Marx or Durkheim. He argued that "the new commodity, the new technology, the new source of supply, the new type of organization" (2003:84) were the lifeblood of capitalist societies. In his view, the "gale of creative destruction" (Schumpeter 2003:87) that blows away old technologies, practices and organizations allowed capitalist societies to ensure long-term growth and rein in their inherent monopolistic tendencies. While his preferred agents of change alternated between entrepreneurs (Schumpeter 1934) and corporations (Schumpeter 2003), he maintained that change itself was the only means for social mobility within a capitalist society (Schumpeter 1955:134). It ensured that even though the structures of inequality would remain in place, people – more specifically, families – would move within them over time. They would accumulate resources, create an innovation that could out-compete existing actors, and extract the additional profits that came with such market power to move up the class hierarchy.

Over the following decades, economists came to recognize that the stability of inequality predicted by Schumpeter was not accurate. The economic swings of the 20th century made it clear that the overall patterns of inequality could and did change over time, independent of the intergenerational social mobility. This growing concern with inequality is clearly evident in the Kuznets Curve (Kuznets 1955), which stipulated that income inequality would initially increase as economic development occurred, but then fall as further development in productivity would be translated into higher wages. However, as Kuznets himself pointed out, the underlying data for his findings was relatively weak, and extrapolating from the experience of the developed countries to the developing ones was problematic. While these warnings appear to have been prescient (Fields 2002), Kuznets' contemporaries were also beginning to develop theories on inequality itself as a driver of technological change, studying how the relative price of labor might create incentives for innovations that either increase its productivity in scarcity or capitalize on its abundance (Habakkuk 1962; Kennedy 1964).

It was this second line of research that started to receive attention in the late 1980s and early 90s, as income inequality started to rise in the developed world, and the developing countries followed trajectories which deviated significantly from the Kuznets' curve. A new set of economists turned the original formulation on its head, and started to question whether technological change could be the culprit for the rising inequality. They pointed out how innovations in this period seemed to favor skilled labor over unskilled labor, and this inherently exacerbated income inequality as those who were already advantaged reaped benefits of increased productivity (Acemoglu 2002; Acemoglu and Autor 2012; Autor et al. 2003; Goldin and Katz 2009). Collectively, this approach to rising inequality is known as SBTC. However, it has received significant criticism for failing to adequately explain the evolution of inequality since 1980 (Mishel and Bernstein 1998) and alternately highlighting various aspects of change to explain developments in inequality in different time periods. The critics have instead argued that the impact of the technological change on inequality is mediated by the broader institutional makeup of the labor market, such as unionization, taxation, and the welfare state (Aghion, Caroli, and Garcia-Penalosa 1999:1654; DiPrete et al. 2006). Establishing that the changes are skill-biased is not enough to claim that they will necessarily drive further inequality.

In the same period, sociologists were also engaging with the changing structure of inequality in relationship to the technological changes. One of the more prominent efforts to do so was Daniel Bell's *The Coming of Post-Industrial Society (1976),* which explored how the scientific and technological changes of the 20th century created the conditions for a service-based economy that prioritized technical knowledge and skills. While his themes were picked up and updated over time by others (Esping-Andersen 1993), they have remained outside the debate on inequality for the most part. Other work on inequality, even when it addressed technological change, has focused much more on the structural factors like the occupational structure, labor force composition and labor supply, unionization, minimum wage, occupational hierarchy and the impacts of neoliberalism (Jacobs and Dirlam 2016; Jacobs and Myers 2014; Kristal and Cohen 2016; Mouw and Kalleberg 2010).

However, Liu and Grusky (2013) have broken this mold in mainstream sociology by addressing both the SBTC and post-industrial society accounts centered on Bell's arguments. They first make the case that technological change is not the only driver of payouts to skill. While it could play an important role in influencing the demand for skills in the market, the tastes – in a Bourdieusian sense – of employees also play an important role in determining the skill supply (Liu and Grusky 2013:1336). The supply of skills for the type of work found desirable is likely to increase, while skills that are associated with undesirable jobs are likely to be undersupplied.

They also disaggregate "skill" from a unidimensional construct into more concrete and recognizable sets of abilities and know-how, following the "task framework" (Autor et al. 2003) approach to SBTC. This allows them to show that the set of skills that have really enjoyed a premium in the labor market are "critical thinking, problem solving, and deductive reasoning" (Liu and Grusky 2013:1337) which tend to be hard and costly to replace with technology. Other skills like technical knowledge, or even managerial abilities, highlighted by Bell as the driving force for the post-industrial society, have actually experienced reduced returns to labor in the same period, possibly because they have been substituted by technological and organizational factors.

Their findings, which are in line with some versions of SBTC, still need to be corroborated by further research, and are open to the same set of criticisms that other SBTC approaches have been subjected to. Yet they are nonetheless a good place to start thinking about the impact of the sharing economy on inequality. First of all, their focus on the tastes of workers for certain types of work fits into the trends observed by Schor (Schor 2017), in which highly educated providers appear to be moving into what was formerly blue-collar work through the platforms, with the associated changes in customers' tastes that makes them prefer highly educated providers. However, Schor's argument is that this leads to a crowding-out of less privileged workers from both the sharing economy platforms and potentially even from competing conventional markets as customer demand is diverted away. There is no clear explanation in the technological change and inequality literature for this dynamic. This is partly because this literature treats technological change as a theoretical abstraction. Therefore, the lived reality of change, how it might destigmatize undervalued manual labor, or place highly skilled workers in competition for house cleaning or furniture moving jobs remains outside of its boundaries.

Second, the platforms' reliance on part-time or non-professional providers fits into the SBTC account as well as the case Liu and Grusky make about the "deskilling" impacts of the third industrial revolution. The platforms operate without the large numbers of white-collar skilled workers needed to organize, manage and market similar services in the conventional economy, and therefore eliminate the demand for that type of managerial skill. These collapsing workplace hierarchies, as well as the circumvented barriers to entry (like the taxi medallion systems, certification requirements, permits for commercial hospitality providers, etc.) also reduce the "skill" premium in these sectors for the actual providers, however small that might have been. Yet these institutional changes also open these sectors up to individuals formerly shut out of them, because they face significantly lower barriers to entry.

However, what happens within the platforms once economic opportunity, theoretically, becomes available to a much wider population cannot be addressed within the SBTC literature, or the sociological literature on inequality. One reason for this is the theoretical and empirical dependence of these literatures on occupational categories. Used as proxies for worker skills in much of the literature and partially driven by the availability of data, these categories have become the main unit of analysis for explaining inequality. While the literature has focused on explaining why inequality between occupational groups has been on the rise, within-occupation inequality, which has also been rising since the 1970s (Acemoglu and Autor 2011; Mouw and Kalleberg 2010; Weeden and Kim 2007) is often treated as a residual factor. Since the platforms often provide specific types of labor and services, any inequality within the platform would fall within this residual category. More importantly, the focus on the labor market as a whole within these literatures means that sources of inequality other than skills and occupations are often sidelined in the discussion. However the platforms attract a wide range of people from different class and racial backgrounds, providing services and renting out their properties for a wide range of motivations (Ravenelle 2017; Schor et al. 2018). We need an analysis that can investigate specific sources of inequality within the broader context of technological change being introduced by these platforms. Unlike the types of change addressed by SBTC, the rise of the sharing economy does not influence the skill content of the various types of work people perform. Housecleaning or driving do not require more skill or complex tasks simply because they become mediated by the platform. Providers do need to be able to navigate the platform – but the skill content of that work is, in most cases, very basic.

Fittingly considering the importance of the internet for the platforms, a literature that has undertaken a similar task of studying how a given technological change impacts multiple and overlapping patterns of inequality has been the one on the "digital divide." In its original formulation, the "digital divide" debate was a heavily empirical literature centered on the low rates of adoption of digital technologies (computer use and internet access) in non-white, less educated, lower income households with older residents (NTIA 1995, 1998, 1999, 2000). Early on, the reasons for the divide were often explained with economistic arguments about the diffusion of internet access (Compaine 2001) or the cost of acquiring and maintaining it (Schement 2001).

As the big gaps in access began to close over time, the focus shifted towards questioning the underlying assumption in the literature that "people can convert internet access into other valued goods, services, and life outcomes" (DiMaggio et al. 2001:312). Some research showed a clear benefit to the adopters of technology in the labor market in general (DiMaggio and Bonikowski 2008). However, a growing body of research was beginning to uncover that these benefits were not equally distributed. Early research on computer usage had found that the technology promoted as the great equalizer was disproportionately benefiting the already privileged (Attewell and Battle

1999). Similar findings about the internet were soon rolling in (Bonfadelli 2002; van Dijk 2005, 2006). Today it is a broadly established finding that there are significant and durable differences in internet use between groups defined by race, class, income and education (boyd 2012; van Deursen and van Dijk 2014; Nakamura and Chow-White 2011; Wilson and Costanza-Chock 2012; Zillien and Hargittai 2009). Low-income, non-white populations tend to use digital technologies primarily for entertainment and socialization purposes, while their counterparts in more advantaged groups are much more likely to garner economic benefits out of their use. A good example can be found in Hansen and Reich's (2015) study of massive open online courses (MOOCs). They find that this education innovation, which provides free online college level courses, was utilized disproportionately by the affluent despite the fact that it had significantly low barriers to entry and was touted as a way to boost the educational attainment of students from underprivileged backgrounds. Moreover, recent research by Hargittai (2012, 2015), among others, finds that people from different racial groups tend to self-select into different online services like competing social media platforms, reproducing the segregation of offline spaces.

It is not clear if "digital segregation" dynamics are at play in other online spaces, or to what extent. However, the studies on discrimination on online platforms also highlight the centrality of existing inequality in these spaces. In one of the earliest attempts to use these platforms to conduct research, Shohat and Musch (2003) sold matched pairs of DVDs on eBay's German website, under two accounts which would be identified as German and Turkish. They found that while the account with the Turkish name did not receive fewer bids or fetch lower prices, it was slower in getting the winning bid in its auctions. Nunley, Owens and Howard (2011), used a similar design, but in the US site for eBay and with names associated with White and Black people, selling distinctively White or Black toys. They found that in less competitive auctions, accounts with White names fetched higher prices for distinctively White toys, and accounts with Black names fetched higher prices for distinctively Black toys. Using ethnically distinct names for Moroccan and Spanish applicants for holiday rentals in Spain, Bosch, Carnero and Farre (2010) identified a significant bias against Moroccan sounding names in this market. Similar biases against applicants with Arabic/Muslim names and those with male names was identified by Ahmed and Hammarstedt (2008) in the Swedish housing market, against names associated with Arab and Black people in the Los Angeles rental housing market (Carpusor and Loges 2006), and throughout the US (Ewens, Tomlin, and Wang 2014; Hanson and Hawley 2011).

More recently, the experimental designs of these studies have evolved to include images to signal race, partially due to a concern about how stereotypically Black names in the US might be signaling social class in addition to race (Bertrand and Mullainathan 2004). Doleac and Stein (2013) used matched pairs of pictures, showing a hand belonging to a Black man or White man holding the same product in classified ads on local classified websites. They found that the ad with the Black hand got fewer responses and fetched lower prices. Ayres, Banaji and Jolls (2015) used a similar method in eBay auctions, and found a similarly sized discrepancy in prices. In a deviation from the experimental method, Pope and Sydnor (2011) looked at loan applications on the peer-to-peer lending platform Prosper. They found that an applicant whose pictures identified them as Black had to pay much higher interest rates for their loans, when compared to the applicants whose pictures identified them as White.

Studies of inequality in the sharing economy platforms (discussed above), as well as studies about the demographics of the sharing economy (Pew Research Center 2016b), suggest similar racial dynamics at play. Perhaps more importantly, this literature on inequalities and digital technologies clearly show that technological changes that lower barriers to entry and provide broad economic opportunities are not necessarily harbingers of greater equality. Individuals who already enjoy educational, economic and racial advantages, are better positioned to make use of the new opportunities. Therefore, there is an urgent need to understand how the sharing economy platforms interact with existing inequalities in society.

Equally importantly, the majority of the literature on digital technologies and inequality understand the interaction between the two through the lens of interpersonal discrimination, or individual self-selection. This is partially the result of methodological choices, as the experimental methods used in some studies are designed to detect specifically these facets of inequality. However, the small numbers of studies that have taken a broader view of inequality (Hannak et al. 2017; Laouenan and Rathelot 2016; Pope and Sydnor 2011) by studying large sets of data on platform activities have found systematic differences in outcomes for people of color. These findings highlight a need to understand how existing structural inequalities influence platform dynamics, which motivates my study of how aggregate inequalities in the urban geography influence participation, outcomes, reputation and gentrification on Airbnb.

DATA And Methods

As mentioned above, data on the sharing economy platforms remains scarce, partially due to the reluctance of companies to share it with independent parties. One potential way to overcome this hurdle is to employ automated software to collect information that the companies make publicly available. In my dissertation, I use such a dataset collected by a commercial company specializing in collecting and analyzing the platform's data (AirDNA 2017). This dataset is limited to the 10 biggest urban Airbnb markets in the USA, and includes information on roughly 450,000 listings. I use variants of this dataset across the three papers. Similarly scraped data from the platform has been used before in studies of discrimination on the platform (Edelman and Luca 2014; Edelman et al. 2017; Laouenan and Rathelot 2016), as well as the dynamics of room bookings (Lee et al. 2015), how the ratings system operates (Zervas, Proserpio, and Byers 2015a), the impact of home sharing on the hospitality industry (Zervas, Proserpio, and Byers 2015b), and the gentrification dynamics created by short-term rentals in New York (Wachsmuth and Weisler 2018).

Currently there are legitimate concerns about data validity while conducting online research, especially in the sharing economy (Gelman 2016). This is the case with the dataset I use as well, since there is no way of ascertaining how many of all Airbnb listings were captured in the data collection. However, there is reason to believe that the dataset is relatively exhaustive in its coverage (see the comparison of the AirDNA data to another Airbnb dataset in the first paper), and absent disclosure from Airbnb, this is likely to remain the best available data to study inequality and short-term rentals.

To further enrich the data, I used the location of listings to match[3] them with census tracts using the US Census' Geocoder API (US Census Bureau 2017c). I then merged the listing-level data with the 5-year estimates of the American Community Survey's 2010-2015 data release (US Census Bureau 2017a) for the same census tract. I will be using the census-tract level data from this source in my analysis as a proxy for "neighborhood" data. Census tracts are relatively stable spatial units, drawn for the purposes of the decennial census by the US Census Bureau with local participation (US Census Bureau 2017d). They are designed to have between 1,200 to 8,000

[3] Airbnb does not provide accurate geographical location of listings, but provides a roughly 0.5 mile-wide "circle" within which the property is located. We used the center of these circles as the locations of the listings.

residents, but there are tracts with smaller and larger populations due to the need for proving full geographic coverage. While they might not correspond to actual “neighborhoods” that residents might perceive in these urban areas, data availability as well as mutually exclusive and exhaustive geographic coverage make them adequate units to study spatial patterns. Metropolitan Statistical Areas, on the other hand, are determined by the US Office of Management and Budget as “a core area containing a substantial population nucleus, together with adjacent communities having a high degree of economic and social integration with that core" (US Census Bureau 2017e). This definition allows MSAs to sidestep municipal or county delineations that are often historically determined and do not reflect economic integration of adjacent areas. This makes them ideal units to define separate markets for a service like Airbnb as opposed to the smaller municipalities or counties as travelers are much more likely to base their accommodation decision on economic integration and the accompanying integration of transportation infrastructure.

This approach has some shortcomings, because it assumes that households within a neighborhood are uniform and that neighborhoods are meaningful units of analysis for the phenomena being studied. However, colleting large scale and extensive data on individuals, or households, as well as the relevant spatial units that should be included in the analysis, is prohibitively expensive in time and resources. Using tracts and other census units as a proxy for individual, household and/or “neighborhood” characteristics is a well-established practice because of these reasons (Krivo and Peterson 2000; Lee et al. 2009; Quillian 2012), and has been applied in recent studies (Edelman et al. 2017; Thebault-Spieker et al. 2015; Wachsmuth and Weisler 2018). While some scholars have argued that there are 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, Lichter, and Taquino 2011:835), I believe the use of the slightly larger tracts is justified in this study due to data availability and the uncertainty over the exact listing locations. Other relevant data and methods issues are explained in detail in the individual papers.

LIMITATIONS AND CONTRIBUTIONS

This dissertation has a number of important limitations due to the nature of the data used in the analysis. I do not have access to individual level information on demographic, income or education information that would enable me to study the dynamics of inequality at a more granular level. When studying the number of listings in a tract (paper 1) or the gentrification dynamics at the tract level (paper 3) this does not present an issue, since the dependent variables are also aggreagted. However, when studying the dependent variables measured at the listing level, the census-tract level measurements for these variables could mask significant individual level variance in the data. While using this aggregate level data is an accepted and common practice for studying spatial patterns of racial and other inequalities, it still limits the types of claims I can make about inequality and short-term rentals. The findings of all three papers are thus focused on differences across census tracts (or other geographic units), without being able to further specify how individual level factors complicate them. Future research that can overcome the prohibitive time and resource costs for collecting this granular data would contribute significantly to these findings.

My analysis is also limited because I study a single platform within the broader sharing economy. The set of institutions that make up this new sector are highly varied in their business models, their size and their impact. Therefore, generalizing my findings about Airbnb to the whole sector is an endeavor fraught with significant pitfalls.

Despite these limitations, I believe that this dissertation makes important contributions to our understanding of the emergent sharing economy and its relationship to inequality. Airbnb represents a significant amount of economic activity in the sector, and affects the daily lives of a large number of people who make money, book accommodations and interact with strangers through the platform, as well as those who might face displacement pressures due to gentrification driven by short-term rentals. Its business model might be biased in favor of real estate rent over labor provision, but it uses technologies broadly similar to other sharing economy platforms that match prospective consumers to producers, support community reputation systems, and facilitate electronic transactions. Therefore, one can reasonably expect other sharing economy platforms to reproduce existing inequalities in a similar manner.

I also think that this research will be an important contribution for a broader theoretical engagement with the lived reality of technological change. The existing literature on change, in the SBTC vein or within sociology often conceptualizes change as an abstract and aggregate concept. It is often measured simply by comparing various measures of income and inequality over different time periods. In its most specific incarnation, the conceptualization of change informs the types of tasks (or the occupations associated with them) which should be experiencing stable or decreasing returns on skill.

My approach, in comparison, is focused on a single concrete case of technological change that has created a new market for urban real estate. This is in line with the broad literature that has studied the digital divide and inequality in online platforms for goods and real estate. However, this literature has remained broadly empirical. It lacks an attendant theoretical understanding about what the findings of inequality portend for a social order that is increasingly predicated upon the expectations of constant technological change. I believe that by studying how existing inequalities serve as the basis of their own reproduction in new spaces created by technological change, my research can serve as the beginnings of such a theoretical reckoning.

1.0 WHO GETS TO SHARE IN THE "SHARING ECONOMY": RACIAL INEQUALITIES ON AIRBNB

(co-authored with Juliet B. Schor)

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 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 platforms, how technologically-induced disruptive change affects existing social inequalities is relatively underexplored. Piketty identifies technology as a key determinant of inequality in *Capital in the 21st Century* (Piketty 2014). However, he argues that technological changes do not always favor greater equality. "[I]f one truly wishes to found a more just and rational social order based on common utility, it is not enough to count on the caprices of technology" (Piketty 2014:294).

Scholars have begun to look at the technological change-inequality relation in the context of the sharing economy. A group of authors we call "disruptionists" (Fraiberger and Sundararajan 2015; John J Horton and Zeckhauser 2016; Sundararajan 2016) have argued that the online platforms are agents of creative destruction, breaking down entrenched inefficiencies and generating new economic opportunities for a broader range of people. Others, whom we call "reproductionists," have been skeptical of such claims (Scholz 2017; Schor 2017; Slee 2016). This group contends that the disruptionist accounts often fail to account for longstanding social inequalities and their impact on access to new technologies and platform outcomes.

Airbnb has become a major actor in the lodging sector, used by millions of people. Therefore it is important to understand its impact on social inequalities, and specifically racial inequality. Recent studies have identified racialized outcomes on sharing economy platforms. 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 (Edelman and Luca 2014; Edelman et al. 2017; Ge et al. 2016; Hannak et al. 2017; Thebault-Spieker et al. 2015). These findings have resonated with the public. In 2016, African-American users of Airbnb shared their personal experiences of discrimination on social media and news outlets. 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, small samples, or limited geographical range. Sociological research suggests that we should understand racialized inequality not simply as an outcome of discriminatory attitudes and behavior, but in terms of systemic factors that contribute to the establishment and reproduction of these inequalities (Bonilla-Silva 1997, 2001; Golash-Boza 2016). To date, structural aspects of racial inequality have been absent from the literature on sharing platforms. Particularly with Airbnb, which is heavily dependent on urban real estate, inequalities in housing, economic opportunity and education are likely to play an important role in access to and outcomes on the platform.

Using a unique data set, this paper provides the first large scale study of how structural inequalities, especially racial segregation, operate within the sharing economy. We find that participation and economic outcomes are shaped by systemic racial inequalities. Our sample, which covers roughly 335,000 listings in the 10 largest Airbnb markets in the US, allows us to go beyond the small scales of previous studies and provide a comprehensive estimate of how race operates on the platform. We show that areas with high proportions of residents of color, on average, have fewer listings on Airbnb. These listings charge lower prices and earn less. These inequality-generating dynamics are mediated by income, homeownership, housing values and educational attainment of the residents, which are themselves significant axes of racial inequality. Ultimately, we conclude that Airbnb is likely to reproduce and reinforce existing lines of privilege in American cities.

1.1 LITERATURE REVIEW

1.1.1 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 (Schor and Attwood-Charles 2017; Schor and Cansoy 2018). 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 person-to-person exchange. 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" 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. Hosts provide photos and details about the space they are willing to rent and select the dates on which their “listing” is available. Guests search the platform for the location, dates, prices, and the types of spaces they want to rent. 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 takes a fee from each transaction.

Propelled by low barriers to entry for providers, Airbnb has attracted more than 3 million listings worldwide (Airbnb 2017a). It has also witnessed skyrocketing demand, advertising that more than 200 million “guests” have used its services since it launched (Airbnb 2017a). These are large numbers, and 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).

We focus on Airbnb primarily because of the economic impact it has on participants and the areas in which it operates. In 2016 listings in the 10 markets for which we have data generated $2.6 billion, or more than $8400 per listing, revealing that “home-sharing” has become a significant urban economic activity. Furthermore, data from applications for personal loans and student loan refinancing from one lender, shows that within the “sharing economy” Airbnb offers its participants the largest economic benefits (Bhattarai 2017). Thus, Airbnb is likely to have larger effects on inequality than many other platforms in this sector. It is also the only major platform whose data is accessible to independent researchers. Sharing economy platforms, including Airbnb, have limited access to their data. Even municipal authorities, with court orders, have had difficulties obtaining usable data (Streitfeld 2014a). However, unlike with other platforms, data on pricing, availability and ratings on Airbnb is publicly available online.

1.1.2 Inequality and the Sharing Economy: Disruptionists vs. Reproductionists

The debate on the impact of the sharing economy on inequality has largely fallen into two camps. *Disruptionists* argue that the platforms do away with rent-seeking and inefficiencies in the structures they are replacing and offer economic opportunity to a wider range of participants. These studies are mainly conducted by economists and business analysts, and often address inequality in the abstract. *Reproductionists*, on the other hand, argue that the sharing economy will not ameliorate existing inequalities, but will reflect and reinforce them. This literature, generally based on legal or sociological research, highlights how both structural inequalities outside of the sharing economy, and the processes built into the platforms themselves, generate inequality.

A key feature of the sharing economy is low barriers to entry. Becoming a "provider" is not contingent on time-consuming or expensive formal credentialing, nor does it require access to unequal informal networks, which hamper access to economic opportunity in the conventional economy (Granovetter 1985). Some platforms accept individuals with criminal records (Schor et al. 2018). The flexibility of platforms allows individuals to decide when and whether to participate. This is important for people with family or other obligations that preclude conventional employment. In addition, the absence of managerial mediation on platforms is appealing to many young workers, and results in more equitable and satisfying outcomes (Fitzmaurice et al. 2018). These factors all support disruptionist claims of improved accessibility and equity.

More complex disruptionist arguments are harder to assess. Sundararajan (2016:123) has argued that the sector represents a broader "democratization of opportunity." By renting out a car, or residential real estate, or lending small amounts of money through the sharing economy platforms, individuals who are "traditionally not on the high end of the wealth spectrum" (Sundararajan

2016:124) can earn money at greater rates than via wage labor. Others have argued that being able to monetize (Fraiberger and Sundararajan 2015), or rent (John J Horton and Zeckhauser 2016) high-capital assets like housing or cars can either make ownership of these assets more accessible to low-income households, or less of a necessity to purchase, respectively. The sharing economy is also thought to reduce inequality by providing an additional revenue stream which stabilizes income fluctuations (Sperling 2015), or enables longer job search time in the conventional economy (Hall and Krueger 2015). Our qualitative research with approximately 100 providers on six platforms suggests that 70% use the income they generate on platforms to supplement other earnings (Schor et al. 2018). Some disruptionists have argued that the dynamics of inequality are tangentially related to sharing platforms, and are symptomatic of broader economic changes (Hall and Krueger 2015:25). 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" (Sundararajan 2016:201).

In contrast, the reproductionist critique argues that the sharing economy not only fails to combat inequalities in the conventional economy but reproduces them in novel ways. Scholz's critique (2017) focuses on the failure of regulatory frameworks to police corporations, highlighting how lower-class people's labor becomes more precarious and invisible behind "crowd fleecing" practices. Similarly, Slee (Slee 2016) argues that the sector is 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." Dynamics of inequality are also at the center of the argument that the sharing economy has created new earning opportunities for the better-off segment of the middle class and displaced less educated workers at the low end of the labor market (Schor 2017). The dynamic of unequal access and outcomes is partly explained by differences in economic situations. Participants with access to alternative sources of income who are not dependent on their earnings report high levels of satisfaction with the platforms and higher wages. However, those who rely on their sharing economy earnings for their living expenses earn lower wages and experience increased precarity, supporting the argument that the sector is generating unequal outcomes (Schor et al. 2018).

1.1.3 Racial Inequality in the Sharing Economy

The current debate between disruptionists and reproductionists has mainly addressed issues of income inequality and social class in the sharing economy. However, a growing body of research has identified persistent racial discrimination in individual platform exchanges. A full accounting of the impact of the sharing economy on racial inequality must move beyond person-to-person discrimination and analyze platforms in the context of structural racism, which shapes the life chances of people of color by reducing access to assets and resources that are affect their ability to participate in and succeed on platforms.

Despite the growing popularity and importance of platforms, basic questions, such as the race and class composition of users are not settled, partly because of a lack of national random sample studies. One national survey has found racial disproportionality among users. According to the Pew Research Center (Pew Research Center 2016b), Whites were much more likely to have used sharing economy platforms as customers than Blacks or Latinos. The same survey also found that users had higher incomes, more educational attainment and tended to be younger than the general population. On the earning side, Pew found that Blacks and Latinos had participation rates that were three and two times higher than Whites respectively (Pew Research Center 2016a). A report on the platform economy using bank account data (JPMorgan Chase and Company Institute 2016) also found that earners are younger than the general population, and have lower incomes and more income volatility than those in the conventional labor market. This is especially true for platforms offering labor-intensive services. Further study of the participant population, and specifically the racial composition of producers, is needed, however findings to date suggest that social groups are not accessing the sharing economy equally.

A number of studies have found discrimination against racial minorities on platforms such as Uber, Lyft and TaskRabbit, in their roles as consumers and providers (Ge et al. 2016; Hannak et al. 2017; Thebault-Spieker et al. 2015). For Airbnb, a range of methods have found discriminatory behavior on both sides of the market. Using an audit study, Edelman, Luca and Svirsky (2017), show that hosts on the platform regularly discriminate against guests who they perceive to be African-American, refusing requests for bookings 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), using digitally collected data on a large number of listings, has produced results that are directionally similar, although smaller. These authors found that "ethnic minority" hosts charge prices that are roughly 3.2% lower than ethnic majority hosts, possibly to compensate for lower demand for their services.[4]

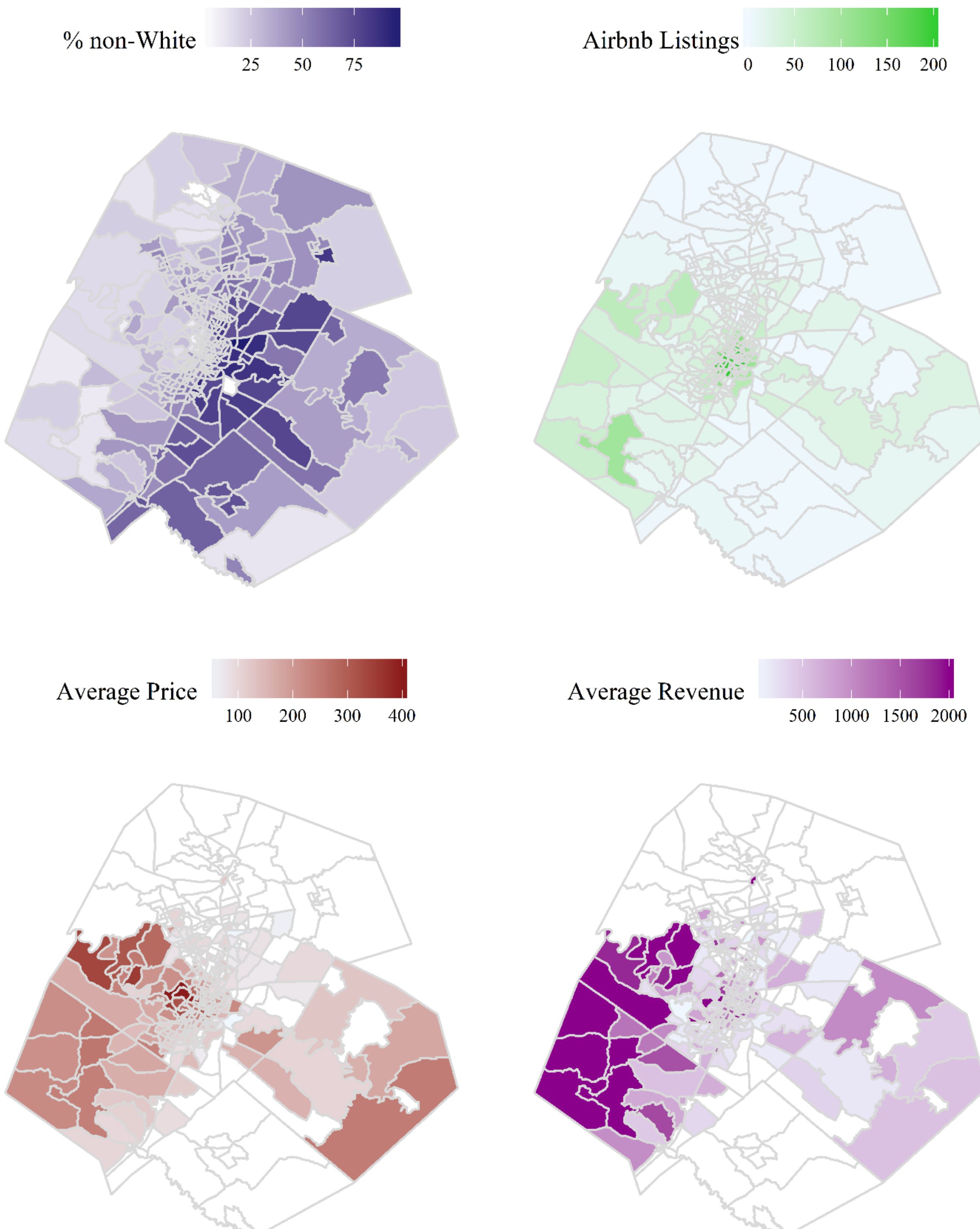
The aforementioned studies focus on indivduals makes racialized decisions in their transactions on platforms. We argue that understanding the role played by race in the sharing economy also requires incorporating durable, structural inequalities into the analysis. Race theorists have argued that racial inequality is not simply an outcome of discriminatory ideologies or personal practice

[4] 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.

but is rooted in racially differentiated benefits individuals can command in our society (Bonilla-Silva 2001:22). Attention to the structural aspects of racial inequality have been part of sociological approaches over the last half century (Knowles and Prewitt 1970; Omi and Winant 1994). Recently, re-assessment of the structural and ideological components of racial inequality has been central to work by Golash-Boza (2016) and Feagin and Elias (2013).

The value of extending research on inequality in the sharing economy beyond person-to-person discrimination is revealed by our Airbnb data. In Figure 1 we illustrate the racial divide in participation in and outcomes on Airbnb in the Austin-Round Rock, TX metropolitan statistical area and Figure 2 does the same for the city of Austin but zooms in to show greater detail. In both figures, the top left map shows the racial segregation of census tracts between people who identify

Figure 1. Geographic Distribution of Racial Segregation and Airbnb Participation and Outcomes in Austin-Round Rock, TX MSA[*]



[*]Average prices and revenue for census tracts with less than 10 listings not shown

Figure 2. Figure 2: Geographic Distribution of Racial Segregation and Airbnb Participation and Outcomes in Austin, TX*

*The maps are same as those in Figure 1, zoomed in on Austin. Average prices and revenue for census tracts with less than 10 listings not shown.

as White, non-Hispanic and everyone else. The other three figures show the number of listings on Airbnb in every census tract, nightly prices for those listings and their annual revenue. These maps show a clear divide between the areas where people of color live, and areas in which Airbnb participation is high and highly remunerated. This pattern suggests that the platform reproduces racial inequalities by reproducing patterns of unequal economic opportunity and resources across the urban landscape. The same pattern is repeated across all 10 metropolitan areas we study.

1.1.4 Housing Inequalities and Airbnb

The patterns we have found in Austin and other cities are best understood by considering inequalities in access to housing. 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 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).

Despite decades of integration efforts, people of color still live in neighborhoods that are highly dissimilar to those of whites in terms of their racial composition (Logan and Stults 2011). Moreover, in recent years segregation at scales larger than the neighborhood has increased significantly, with larger areas within cities, and cities themselves becoming more racially homogeneous (Lichter, Parisi, and Taquino 2015; Parisi et al. 2011). This entrenched segregation has negative impacts on communities of color, in terms of reduced public services and amenities, exclusion from social, professional, and financial networks, and reduced 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 operates on Airbnb. We expect that neighborhoods with higher proportions of non-White residents will have lower levels of participation and that listings in these areas will be less successful due to the discriminatory practices in the user base noted above, as well as the social stigma that is associated with racial segregation.

Racial inequality in American cities is not manifest only in the physical sorting of people into separate neighborhoods. It is also compounded by a host of other inequalities that are less visible, but nonetheless disadvantage people of color in their daily lives. One such inequality is housing values, which have been negatively influenced by practices of residential segregation, and redlining policies that restricted access to credit in areas with residents of color. While some studies have found a decline in the housing value gap between Black and White homeowners since formal redlining ended in the late 1960s (Horton and Thomas 1998), others have maintained that the difference in home values attributed to race actually got worse in the same period (Collins and Margo 2003). More recently, studies of housing markets following the Great Recession have found that Black neighborhoods failed to recover most of the value they lost in the crisis seven years after the start of the housing crisis (Raymond, Wang, and Immergluck 2016). We expect differences in housing values to mediate the impact of racial composition on Airbnb participation and outcomes, as areas with higher proportions of residents of color are also likely to have lower housing values. Thus, areas with lower housing values are likely to have less participation, lower prices, and revenue on Airbnb.

People of color are much less likely to be homeowners than Whites. 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 2017f). 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. Recently the practice of "illegal" rentals (Cox and Slee 2016; Streitfeld 2014a) where a landlord makes housing units exclusively available for short-term rentals and lists multiple units on the platform at the same time, has been the focus of some public and regulatory attention (Schor and Cansoy 2018). To the extent that this practice displaces renters (but not homeowners), we would also expect it to contribute to a participation bias against areas with low homeownership.

1.1.5 Economic Inequality and Airbnb

If platform opportunities are more accessible than those in the conventional labor market, individuals may turn to them as a substitute for traditional employment. This is especially important when we try to understand racial dynamics, because there are large and enduring racial differentials in labor markets. 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 2004; Pager 2003; Pager, Western, and Bonikowski 2009). If, as disruptionists claim, Airbnb has lower barriers to entry and more equitable outcomes, this might result in higher rates of participation in areas with residents of color, as more individuals attempt to take advantage of it. However, in light of the findings of discrimination on Airbnb, as well as the housing inequalities faced by people of color, we are agnostic about whether the increased access to economic opportunity will be sufficient to impact participation, prices and revenue .

Racial disparities in job search are only one dimension of racialized labor market outcomes. Race is also a factor in managerial decisions to channel non-Whites into lower-paying jobs, or into positions without opportunities for advancement (Braddock et al. 1986; Royster 2003). These processes contribute to a durable wage gap across 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). The Economic Policy Institute finds (Wilson and Rodgers 2016) that the gap between White and Black wage earners is growing. Trends in self-employment and entrepreneurship, which are often seen as refuges from the more discriminatory labor market (Boyd 2005), also reveal racial inequalities. Fairlie and Robb (2008) have shown that Black entrepreneurs have access to less capital, education and entrepreneurial experience. These persistent inequalities in income are likely to contribute to unequal outcomes on Airbnb. While people making lower incomes in the conventional economy may have greater incentives to participate on the platform, in the neighborhoods where low incomes are concentrated Airbnb guests are less likely to find housing and amenities that meet their needs and preferences. Thus, we expect that differential income levels might mediate lower levels of participation on Airbnb due to the racial composition of neighborhoods, but they are likely to magnify unequal outcomes in prices and annual revenue. Additionally, the distribution of incomes within a neighborhood, as measured by the Gini coefficient, is likely to play a critical role, as mixed-income neighborhoods are likely to have better housing and amenities at the lower end of the income distribution and more affordable housing in the upper end.

1.1.6 Education Inequalities and Airbnb

Despite decades of local activism and policy reforms, there are still significant gaps in educational attainment between racial groups. In 2016, 42.9% of White adults between 25 and 29 and 65.6% of Asians in the same age group held bachelor's degrees, while only 22.7% of Black and 18.7% of Hispanic people in the same group did (Snyder, de Brey, and Dillow 2018:17). While these gaps have been gradually closing over the last century (Gamoran 2001), differences remain. Many researchers attribute these gaps to the structural inequalities faced by people of color, such as the concentration of poverty or the experience of economic hardship during adolescence (Cameron and Heckman 2007; Orfield and Lee 2005), while others see educational gaps themselves as a cause of persistent economic inequality (Greenwood et al. 2016). In either case, the deep connections between race, education and inequality are undeniable. They suggest the need for a broad approach to studying how these inequalities shape outcomes on Airbnb.

Current research suggests that on Airbnb, and in many other sharing economy platforms, users are very highly-educated (Pew Research Center 2016b). Thus, educational disparities between neighborhoods can partially explain differences in rates of host participation on the platform. Furthermore, Ikkala and Lampinen (Ikkala and Lampinen 2015) have found that Airbnb hosts display homophilic preferences, wanting to stay with people like themselves. Even when hosts talk about interacting with people different than themselves, they want an experience that Ladegaard terms "comfortably exotic" (Ladegaard 2018), indicating a preference to interact with others who possess high cultural capital markers like education. We suspect that the guest population may to have similar tendencies, also preferring to stay with high-educated hosts. For these reasons, we expect more negative platform outcomes in areas with lower education attainment.

Ultimately, the implications of structural racial inequalities for Airbnb participation and outcomes are complex. Persistent inequalities in the conventional economy lead us to expect that the economic opportunities presented on Airbnb and other sharing economy platforms will be attractive to people of color. However, they are more poorly situated than Whites to take advantage of these opportunities, on account of extensive structural inequalities in segregation, homeownership, housing values, labor markets, commerce, and education. We turn now to ssessing the relative strengths of these competing dynamics.

1.2 METHODOLOGY

The methodological strategy in this paper is to use individual listing data generated on Airbnb in conjunction with information about the areas in which these listings are located to measure racial inequality on the platform. We do not measure race, income, or other variables of interest at the individual level. 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. 2017; 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 alternative geographical units such as census blocks (Hansen and Reich 2015; Parisi et al.

2011:835), our use of the slightly larger tracts is justified due to data availability and uncertainty about exact listing locations.[5]

Our dataset contains all listings on the Airbnb platform in the 10 biggest urban Airbnb markets in the US, which were available for rental at least one day in 2016. The data 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 (Edelman and Luca 2014; Edelman et al. 2017), the dynamics of room bookings (Lee et al. 2015), how the ratings system operates (Zervas et al. 2015a) and the impact of home sharing on the hospitality industry (Zervas et al. 2015b). Moreover, scraped data is also available for select urban markets from a public awareness campaign about the impacts of Airbnb (Inside Airbnb 2016). Our dataset contains 334,995 Airbnb listings in 10 urban markets, which are defined using the metropolitan statistical areas designated by the Office of Management and Budget (US Census Bureau 2017e).[6] A comparison of our dataset to other publicly available datasets on Airbnb listings suggests that we have relatively comprehensive coverage of properties available on the site.[7]

We used the scraped location of listings to match[8] them with census tracts using the US Census' Geocoder API (US Census Bureau 2017c). We then merged the listing-level data with the 2011-

[5] Airbnb often uses zip-codes in its own reports of community impact (Airbnb 2016). For a discussion of the limitations of using census tracts, see below.

[6] 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.

[7] 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. Of these listings, 81863 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.

[8] Airbnb does not provide exact geographical location of listings, but provides a roughly 0.3 mile-wide "circle" within which the property is located (see Wachsmuth and Weisler (n.d.) for a detailed description and a unique way to handle locating listings). We used the center of these circles as the locations of the listings. While it is possible that this might

2015 5-year estimates of the American Community Survey (US Census Bureau 2017b) for the same census tract. In our analysis of this data, we use hierarchical fixed-effects models 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 1 miles divided by the distance between the two listings (or tracts) is intended to control for any spatial autocorrelation in our model.[9]

In the models that follow we analyze three variables of interest—participation rates (measured as numbers of listings), nightly prices, and annual revenue. These variables capture both intentions of hosts and outcomes in the market.

1.3 DEPENDENT VARIABLES

Table 1. **Dependent Variables**

Variables	Models	Measurement Level	Clustering Levels	Notes
Number of Listings	Negative Binomial[1]	Census Tract	MSA	
Nightly Price	Linear	Listing	Census Tract, MSA, Host	Log-transformed
Annual Revenue	Linear	Listing	Census Tract, MSA, Host	Log-transformed

[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).

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. Larger clustering units such as zip code areas provided substantively similar results.

[9] We have used larger distances (up to 5 miles) to create spatial lag terms, as well as specifying a set number of closest neighbors. Models using these terms produced substantively similar results.

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 nationwide 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.

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

1.3.1 Independent Variables

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.

Median Housing Value: The median price of a home in a census tract, for homes that have a mortgage.

Percent Renter: The percentage of households that do not own, but rent the unit they are occupying.

Per Capita Income: This is the per capita income for all residents within a census tract.

Gini Coefficient: The Gini coefficient for income inequality within a census tract. An interaction term between per capita income and the Gini coefficient is also included in the full models presented below.

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.

Table 2. **Independent Variables**

	Description	Measurement Level	Notes
Indep. Var. of Interest			
Percent non-White	Perc. of population identifying 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
Median Housing Value	Median value of housing units in the census tract	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	Listings that can be booked 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 City	Distance, in meters, to the closest principal city in MSA	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

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. The fraction of cases for which there was any missing data is at most around 5%, and listwise deletion does not impact our results in any substantive manner.[10] Descriptive statistics for all variables are reported in Table 3.

1.4 FINDINGS

Our analysis, which we present in detail below, identifies two key facets 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, without controlling for factors that we expect to mediate the impact of racial composition, tend to have lower levels of participation on the platform. This effect is reversed once we control for racially unequal distributions of income, housing values, homeownership and education. Outcomes on Airbnb, in terms of prices and revenue are worse in areas with high proportions of residents of color even when all these factors are controlled for, despite the racially unequal distribution of these factors themselves.

[10] This is primarily because of the missingness of the housing value variable. However, analysis with this variable omitted from the models, which reduces the missingness in the data to around 1% of all Airbnb listings, produces substantively similar results.

Table 3. **Descriptive Statistics**

	N	Missing	Mean	Std. Dev.	Median	Min	Max
Dependent Variables							
# of Listings in Tract	16108	0	20.49	50.40	5.00	0	1179
Nightly Price	334995	0	202.4	199.0	140.00	10	1500
Annual Revenue	334995	0	8304	1690.74	2598.0	0	483660
Independent Variables							
Host Level							
# of Listings per Host	220831	0	1.52	3.15	1.00	1	756
Listing Level							
Max. Guests	334995	0	3.42	2.36	2.00	1	16
Number of Reviews	334995	0	12.42	26.83	2	0	919
Dist. to Closest City	334995	0	10191.42	14468.8	7083.73	14.98	155434.18
Room Type							
Entire Home or Apt.	191922	-	-	-	-	-	-
Private Room	129632	-	-	-	-	-	-
Shared Room	13441	-	-	-	-	-	-
Instant Booking							
Yes	273396	-	-	-	-	-	-
No	61599	-	-	-	-	-	-
Tract-Level							
Population	16108	0	4496.45	2020.23	4315.00	0	39454
Median Housing Value	15506	602	414460.2	261554.2	356950	9999	2000001
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, Nightly Price and Annual Revenue**

	Number of Listings[1]		Nightly Price[2]		Annual Revenue[2]	
	Model 1	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*
% non-White	0.894 ***	1.148 ***	-0.045 ***	-0.008 ***	-0.035 ***	-0.027 ***
	(0.010)	(0.016)	(0.001)	(0.001)	(0.004)	(0.006)
Median Housing Value		1.279 ***		0.028 ***		0.007
		(0.019)		(0.002)		(0.006)
% Renter		1.445 ***		0.004 *		0.025 ***
		(0.019)		(0.001)		(0.005)
Median Age		1.136 ***		0.003 **		0.022 ***

		(0.014)		(0.001)		(0.005)
% with BA or Higher		2.100 ***		0.007 ***		0.008
		(0.040)		(0.002)		(0.009)
Per Capita Income		0.677 ***		0.042 ***		0.001
		(0.018)		(0.002)		(0.010)
Gini Coefficient		1.225 ***		0.010 ***		0.020 ***
		(0.013)		(0.001)		(0.004)
Income*Gini		0.980 *		-0.010 ***		-0.008
		(0.009)		(0.001)		(0.004)
N_{Host}			208975	208975	208975	208975
N_{tract}			13158	13158	13158	13158
N_{MSA}	10	10	10	10	10	10
ICC_{Host}			0.468	0.501	0.315	0.315
ICC_{Tract}			0.113	0.074	0.008	0.008
ICC_{MSA}	0.010	0.012	0.045	0.022	0.005	0.004
Observations	15506	15506	316435	316435	316435	316435
AIC	103342.38	99436.49	.912 / .906	.911 / .906	.640 / .573	.640 / .573
Deviance	17555.9	17476.5	-140914.7	-143421.4	1107396.7	1107314.7
Notes	** p<.05 ** p<.01 *** p<.001 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). [1]Reported coefficients are logged odds (incidence rate ratios). [2]Reported coefficients are linear regression coefficients.*					

1.4.1 Number of Listings

In Table 4, Model 1, which excludes a number of controls, shows that tracts with a higher proportion of residents of color are likely to have fewer listings. With other covariates at their means, a tract without any residents of color is expected to have around 12 listings, while a tract that only has residents of color will have around 8 listings. However, once additional control variables are introduced, as they are in Model 2, this relationship is reversed. This model, with the same assumptions, 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. This reversal suggests that racial inequalities, in education, income, homeownership, and home values mediate the relationship between racial segregation of people of color and participation on Airbnb. Once they are accounted for, non-White racial status is an inducement to for people to participate on the platform.

Perhaps the most important additional finding is that the education variable is the strongest predictor of the number of Airbnb listings in a census tract. A standard deviation increase in the education variable is associated with a 110% increase in the number of listings. We also find that per capita income has a significant but negative relationship with the number of listings in a census tract. A one standard deviation increase in income is associated with a 33% decrease in the number of listings. We also find that income inequality is positively associated with participation on the platform. In addition, an interaction effect between income and income equality has a small negative effect on overall participation. Finally, tracts with a higher percentage of renters, higher median age and higher home values tend to have more listings.

1.4.2 Nightly Price

In census tracts with higher concentrations of non-White residents, listings have 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, is about $70 less per night (using Model 1 in Table 4). In the second model, controlling for income, education and other variables of interest, this difference is reduced to $13 less per night. This change supports the idea that the effects of race are considerable and are being mediated through inequalities in these additional factors.

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, however the significant coefficient for the interaction term suggests that in tracts with high incomes, the impact of income inequality on nightly prices is likely to be small or even negative. By contrast, in tracts with low per capita incomes and high income inequality, listings are able to command higher prices. The remaining predictors of interest—housing values, rentership, age, and education—are all positively related to higher nightly prices as well.

1.4.3 Annual Revenue

In census tracts with higher concentrations of non-White residents, our analysis finds 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 \$324 per year in the first model. In the second model, this difference is reduced to \$249 per year. Once again, the difference suggests mediation of the impact of racial segregation on earnings on the platform.

There is also a significant relationship between income inequality and annual revenue, with listings in more unequal census tracts predicted to earn more. Per capita income, and the interaction between these two measures do not have a significant effect on earnings. Annual revenue and the age and rentership variables are also positively related, however, education and housing value variables are not significant predictors of annual revenue on Airbnb.

1.5 DISCUSSION

Our findings demonstrate that participation and outcomes on Airbnb show clear evidence of racial disparities operating in areas with high concentrations of residents of color. For nightly prices and annual revenue of listings, the inequality is straightforward to explain. Listings in areas with a higher proportion of non-White residents charge significantly lower prices and earn less. This can be the result of lower demand for lodgings in these areas because of discriminatory racial preferences of consumers, or lower desirability of 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. We also show strong evidence that these unequal outcomes are mediated by differences in income, education, housing values and homeownership, which are themselves racially unequal. The price and revenue differentials attributed to the racial composition of an area shrink when these factors are accounted for.

Our analysis of the number of listings on the platform, however, provides a more complex picture of the relationship between the racial composition of an area and Airbnb participation. We find that in areas with higher concentrations of residents of color, Airbnb participation is lower without the other controls of interest in the model, but the effect of racial composition becomes positive when controlling for racially unequal distributions of income, education, housing values and homeownership. It is likely that higher participation rates are driven by hosts, for whom the Airbnb platform is more accessible than traditional markets. 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 we do not know if the same dynamics are found in other cities, this study does raise the possibility that in neighborhoods that have a high proportion of residents of color, hosting is disproportionately occurring among Whites. That in turn undermines the argument that the platform is disrupting existing patterns of racial inequality.

An alternative explanation for this phenomenon could be that higher listings in non-White areas are a response to high demand from guests to stay in these areas. Such demand could be explained 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). This demand could also be driven by the relatively lower prices for listings in these areas or because gentrifying areas appeal to Airbnb customers. Yet, in light of our findings regarding nightly prices and revenue, 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 residents of colors appears doubtful. Our findings from the annual revenue analysis suggest that the cheaper listings in these areas are not booked frequently enough to earn at competitive rates support this conjecture.

Taking into consideration the remaining predictors of interest, our findings point to two broad conclusions. The first is that on average, areas that are already privileged, with higher incomes, higher home values, 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 and revenue) 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 the cultural know-how to participate successfully in the short-term rental market. Nonetheless, it undermines arguments that the sharing economy is disrupting existing patterns of inequality.

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 residents of color, are more likely to take advantage of the opportunities provided by Airbnb. The low barriers to entry on platforms (Schor et al. 2018; 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 a 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 (Inside Airbnb 2017; Schor 2017).

These dynamics point to the need for further studies of inequality in the sharing economy. In this pursuit, 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 the development of a theoretical framework to explain how the sharing economy operates as an instance of disruptive change in the organization of economic opportunity and benefits. Our findings show that promises of public benefit through economic disruption need to be critically evaluated (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.

1.5.1 Limitations

The nature of the data we are using places a number of limitations on our analysis. First, even though we have comparable results to other Airbnb scraping efforts, we cannot definitively establish our coverage rate of Airbnb listings in the geographies we are studying. However, we believe that careful data scraping efforts are the best approach in the absence of large-scale company-provided data. The second limitation of our data is that we cannot control for some listing-specific factors, such as amenities like parking spaces or the décor. If these are distributed unequally by race, differences in price and revenue can partly be attributed to differential amenities, which can be considered yet another aspect of structural inequality. We have investigated this question empirically. Using a less comprehensive database, which we scraped ourselves (but which only included price, not revenue) we were able to include listed amenities. We found that the impact of race was greater. However, there may be differences in unlisted amenities which this analysis did not capture. On the other hand, 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, including the churn of users and hosts. Perhaps more importantly, we are unable to measure how the platform itself 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, results in demographic changes. In fact, the debate about Airbnb and gentrification is built on this assumption (BJH Advisors LLC 2016; Inside Airbnb 2017; Wachsmuth and Weisler 2018).

The most important limitation of our data is that we do not measure race, 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. Some data collection methods, such as collecting data on users from social networking sites might be considered a violation of privacy. An alternative 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). However, 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 and 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) used host names as proxies for race. This approach is harder to justify since not all names are unambiguously racialized and hosts do not always use their given names. Given that there is no perfect approach, we believe that Census tract measures of racial composition is a conservative choice that is preferable to the existing alternatives.

1.6 CONCLUSION

The rapid growth of sharing economy platforms has led to considerable controversy (Schor and Attwood-Charles 2017). One area of contention is impacts on inequality. We have identified two main camps of opinion — "disruptionists," who believe that 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, in line with studies that have identified significant racial discrimination in the sector. 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.

Our analytical model finds that areas with a higher proportion of non-White residents participate on Airbnb at higher rates. This finding nominally supports the disruptionist view, however, factors such as homeownership, housing values, 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. Additionally, in these areas hosts charge lower prices and earn less revenue. Ultimately, the sharing economy reproduces these inequalities, albeit in new and varied ways.

2.0 THE FAULT IN THE STARS: PUBLIC REPUTATION AND THE REPRODUCTION OF RACIAL INEQUALITY ON AIRBNB

Public reputation systems, incorporated into most consumer oriented online platforms over the last few decades, have become a ubiquitous feature of our digital lives. From e-commerce to online dating, the ratings and reviews on these systems provide information about products, services, or individuals that is supposed to be accessible and accurate. This is achieved through crowd-sourcing the generation of this information, where either previous users or the general public are invited to provide personal reviews and numeric ratings.

Public reputation systems are central to the operation of the "sharing economy." The platforms that have come to dominate this sector depend on the reputation systems as key features to facilitate exchange among strangers, by providing a measure of trustworthiness (Edelman 2017). Furthermore, the reputation systems have the power to determine who gets to participate in in a platform and have access to the economic opportunities. On some platforms, especially for people providing services or goods on the platform, their power in this regard is near-absolute. For example, ride-hailing platforms often "deactivate" (ban) drivers whose ratings fall below a certain level. On other platforms, or for people participating on the platforms as consumers, this power can be relatively weaker.

The reputation systems were frequently cited (Sundararajan 2016:170) as a key factor in ensuring greater efficiency and ultimately greater equality in the sharing economy. However, the platforms have been far from egalitarian spaces. I have recently argued that people of color lack equitable access to Airbnb, and face outcomes that reproduce inequalities in the conventional economy (Cansoy and Schor 2018). A growing body of work has pointed out the inequality-enhancing aspects of sharing economy platforms in general (Scholz 2017; Schor 2017; Slee 2016). Concerns about the prevalence of racial discrimination on online platforms, where participants of color are frequently passed over for exchanges and face significantly worse outcomes have been at the center of a number of recent studies (Ayres et al. 2015; Doleac and Stein 2013; Edelman et al. 2017; Ewens et al. 2014; Ge et al. 2016; Hanson and Hawley 2011; Nunley et al. 2011). Much like in the research on discrimination outside of the platforms, this literature primarily explains discriminatory behavior as the outcome of taste-based and statistical processes.

A large portion of this literature sees public reputation systems as a key innovation in reducing statistical discrimination. While there have been some efforts to reduce taste-based discrimination on the platforms (Murphy 2016), they are shadowed by the academic, and non-academic, effort which has gone into understanding how reputation systems can reduce statistical discrimination (Ayres et al. 2015; Cui, Li, and Dennis J. Zhang 2016; Edelman and Luca 2014; Laouenan and Rathelot 2016; Nunley et al. 2011). While this effort has provided critical insights into reducing discriminatory outcomes, it has often treated the reputation systems themselves as unproblematic. Studies using experimental methods use reviews and ratings as part of the experimental treatment, manipulating the ratings of participants and implicitly assuming their independence from race (Cui, Li, and Dennis J Zhang 2016). Statistical analysis of platform data use different metrics from the reputation system as controls in their models, making a similar assumption about the lack of a meaningful relationship between race and the metrics generated by the systems (Edelman and Luca 2014; Laouenan and Rathelot 2016). However, these assumptions need to be questioned, and the reputation systems should be studied not simply as mechanisms producing information but as sites of potential discrimination (Hannak et al. 2017; Rosenblat et al. 2017).

Using data on the Airbnb platform from 2015 and 2016, covering the 10 largest urban Airbnb markets in the USA, I find that there are two critical dynamics in the reputation system that place participants of color at a significant disadvantage. First, it is harder for them to enter into exchanges due to racial discrimination, whether statistical or taste-based and thus generate the reputation information, which might be able to ameliorate the effects of that discrimination. I show that among Airbnb listings that came on the platform during this two-year period, those located in areas with a higher percentage of residents of color were both less likely to receive a booking and were available to be booked for longer before receiving their first booking. Equally important, even when participants of color are able to generate reputation information on the platforms, this information itself suffers from racial bias. I find that among the listings that were able to obtain ratings on Airbnb during this period, being located in neighborhoods with higher concentrations of residents of color significantly increased the odds of a listing having a lower rating. These findings suggests public reputation systems are not merely bulwarks against discrimination, as the existing scholarship assumes, but are themselves potential sites of discrimination.

2.1 LITERATURE REVIEW

2.1.1 Reputation Systems and Platforms

In the offline economy, exchanges are facilitated by trust and the buyers need to have confidence in the product or service in order to purchase it. This is often produced by repeated exchanges between buyers and sellers, shared membership in interpersonal networks, institutional checks on bad behavior, or reputation tools such as brands or endorsements (Kollock 1994; Molm, Nobuyuki, and Peterson 2000; Resnick and Zeckhauser 2002). However, for exchanges mediated through multi-sided online platforms, these trust-generating mechanisms are often much weaker, if they exist at all. In many cases, the buyer and seller are strangers, they do not share membership in networks, and in some platforms like eBay, they might even be anonymous. This places a large range of conventional reputation assessment methods out of reach for both parties. Additionally, institutional control over the product and signaling mechanisms like brands or professions are weak, or even non-existent where the peer-to-peer ideals of the platforms are truly embodied. Exchanges are, on many platforms, one-time affairs, which again restricts the generation of trust. Additionally, sellers enjoy significant structural advantages over buyers due to systems that mandate upfront payment and make returns and complaints costly for consumers.

Under such conditions, generating and maintaining trust – thus facilitating exchange – has been possible through the development of public reputation systems. These systems often operate on relatively simple principles. They collect information from all parties to an exchange, in the form of qualitative reviews of the product or service, and a quantifiable rating of satisfaction with it. This information is then made available to audiences of interest. The systems are designed to provide a track record of previous behavior and, in some cases, raise the prospect of sanctions in the form of a drop in public reputation. These functions are absolutely critical for the platforms, many of which would have had a harder time generating and sustaining exchanges in their absence (Dellarocas 2003). This is especially true for the "sharing economy" platforms where reputation systems go beyond simply facilitating exchanges and provide, through the quantified ratings, labor-control functions. However, these systems face some well-documented challenges.

Economists studying these systems are concerned that they depend on information generated for public use, by private actors who do not get compensated for the time and effort they put into the reviews (Bolton, Katok, and Ockenfels 2004). Thus, there is always the possibility that the information necessary for the systems will not be generated at adequate rates. This is a problem that every multi-sided platform faces at its inception, or as it expands, and many participants do not have reviews. For more established platforms and users, freeriding on the reputation system is still a cause for concern, as it might reduce the overall availability or timeliness of information. For example, Resnick and Zeckhauser (2002) found that on the e-commerce platform eBay, buyers provided feedback about sellers about half the time in their dataset from 1999. Dellarocas and Wood (2008) report that by 2002 this rate had increased to about 68% on eBay. However, they show that exchanges without reviews are much more likely to have negative outcomes and argue that the lack of consistent and up-to-date feedback on exchanges can create significant biases in the reputation system. This is in line with Edelman's (2017) observation that platforms employ a range of tools to generate reviews, from repeated reminders to using pricing tools to incentivize exchanges (which are then expected to generate reputation information), to paying or otherwise rewarding users to produce reviews and making reviews mandatory. The newer platforms, especially within the broadly defined sharing economy, do not appear to suffer from freeriding to the extent identified above. Studying the Airbnb platform, Fradkin et. al. (2015) report that less than 1% of all exchanges fail to generate reviews, even though they also note that negative experiences lead to omitted exchanges more often than positive ones. Ultimately, it is not the volume of reviews that should concern researchers, but the quality of the data produced through the reputation systems.

Some data quality issues in the reputation systems are well established. Perhaps the most prominent one is the bi-polar distribution of ratings. Hu et. al. (2009) show that an overwhelming number of reviewers give the highest possible score, followed by a second cluster around extremely low scores, without anything in between. Similar distributions of ratings, which do not reflect the underlying quality of the products or services, are noted by many others studying reputation systems. Nosko and Tedlis (2015) report that the median seller on eBay has a 100% positive rating. Zervas (2015a) have reported a similar distribution of review scores on Airbnb, and the rating data I use in this paper, see below, is definitely overwhelmingly positive. These bipolar reviews, biased towards extremely high scores, are partially the result of intentional design choices. Across many systems, the numerical values reviewers generate are restricted, either to a positive-negative dichotomy, or to a limited 5-point range. Thus, given a limited range of options, users might interact with these systems in limited ways to produce undifferentiated information. For exchanges where products or goods are fairly standardized and the exchange itself is temporally and spatially restricted (one-time, at-a-distance) the simplicity of such a system might be more valuable than alternatives which might generate more differentiation but at greater costs. A large body of work focuses on the fear of retaliation reviewers experience within such a system to explain the positive bias. For bi-directional reputation systems, where both providers and customers get reviewed, there is the fear that people who receive negative reviews could retaliate with negative reviewers of their own. Researchers have found that on eBay, customers are more likely to leave a review after the provider leaves them theirs, suggesting the importance of such a dynamic (Bolton, Greiner, and Ockenfels 2013; Resnick and Zeckhauser 2002). Concerns with retaliation are often highlighted as a potential explanations for extremely high ratings (Dellarocas and Wood 2008; Fradkin et al. 2015). Such concerns are likely to become more or less prominent based on the platform design and the nature of exchanges. On platforms where reviews of customers are less salient (Uber or eBay), fear of retaliation should be a smaller concern for them, compared to those platforms where their reputation plays an important role in whether providers accept exchange offers (Airbnb). In 2016, Airbnb made changes to its review systems to prevent retaliatory reviewing (by not displaying reviews of hosts and guests until both parties have submitted their reviews). On the other hand, if platforms mostly enable exchanges at a distance, retaliatory behavior is likely more limited. However, when platforms enable exchanges where personal information like home addresses change hands, or parties are in physical proximity to one another, the fear of retaliation is likely to be more significant.

The desire to reciprocate positive reviews, or even to leave a positive review because of in-person socialization on some platforms independent of the quality of the exchange itself (Fradkin et al. 2015) is also likely to produce a bias towards extremely positive reputations. The bias in favor of previous reviews, which are in many cases already very high, might also be playing a role, at least for some groups of users (Ma et al. 2013). Many researchers also highlight the importance of fake reviews – purchased or otherwise incentivized by sellers- as an explanation of the extremely high ratings (Luca and Zervas 2016; Mayzlin, Dover, and Chevalier 2014).

The bi-polarity of ratings, independent of its causes, results in important shortcomings for the public reputation systems. While users might generate undifferentiated information, the aggregation of this information creates complexity, so that an eBay user can have 99% positive reviews, or an Airbnb property can have 4.8 stars. More importantly, users ascribe meaning to these differences, even though the underlying data might not justify it (Resnick et al. 2006). In some cases, platforms themselves do this as well. For example, the ridesourcing platform Uber uses reviews as a labor control mechanism, and an overall rating of 4.6 out of 5 puts drivers at risk of being forced off the platform (Cook 2015; Rosenblat and Stark 2016).

The problem of extremely high ratings has been the subject of many attempts at technocratic solutions. Some have advocated for relatively straightforward changes to how reputation information is collected, for example Bolton et. al. (2013) advocate in favor of eBay's expanded reviewing system which asks specific questions about products in addition to the overall exchange experience. Fradkin et. al. (2015), on the other hand, have argued for reducing the chances of retaliatory reviews by removing the users' abilities to see one another's reviews until they have posted theirs. Others have offered novel ways to calculate aggregate reputation scores that they argue are able to handle reporting bias inherent in the reputation systems (Dellarocas and Wood 2008; Nosko and Tadelis 2015). However, these fixes are not able to directly address what is perhaps the most fundamental flaw of public reputation systems, the existence of discriminatory behaviors and attitudes outside of the system itself. To date, there has been little discussion of how these systems operate within a society marked by inequality, especially along lines of race.

2.1.2 Racial Discrimination

Over the last few years, a number of studies have documented racially disparate outcomes in online markets, following in the footsteps of studies focused on racial discrimination in offline markets (Bertrand and Mullainathan 2004; Pager 2003). In one of the earliest attempts to use the platforms to conduct research, Shohat and Musch (Shohat and Musch 2003) sold matched pairs of DVDs on eBay's German website, under two accounts which would be identified as German and Turkish. They found that while the account with the Turkish name did not receive fewer bids or fetch lower prices, it was slower in getting the winning bid in its auctions. Nunley, Owens and Howard (Nunley et al. 2011), used a similar design, but in the US site for eBay and with names associated with White and Black people, selling distinctively White or Black toys. They found that in less competitive auctions, accounts with White names fetched higher prices for distinctively White toys, and accounts with Black names fetched higher prices for distinctively Black toys. Using ethnically distinct names for Moroccan and Spanish applicants for holiday rentals in Spain, Bosch, Carnero and Farre (Bosch et al. 2010) identify a significant bias against Moroccan sounding names in this market. Similar biases against applicants with Arabic/Muslim names, and those with male names was identified by Ahmed and Hammarstedt in the Swedish housing market (2008), and against names associated with Arab and Black people in the Los Angeles rental housing market (Carpusor and Loges 2006), and throughout the US (Ewens et al. 2014; Hanson and Hawley 2011). Studies specifically on Airbnb have found that applicants with distinctly Black names (Cui, Li, and Dennis J Zhang 2016; Edelman et al. 2017) face rejection for their booking requests at greater rates than applicants with stereotypically White names.

More recently, the experimental designs of these studies have evolved to include images to signal race, partially due to a concern about how stereotypically Black names in the US might be signaling social class in addition to race (Bertrand and Mullainathan 2004). Doleac and Stein (2013) used matched pairs of pictures, showing a hand belonging to a Black man or White man holding the same product in classified ads on local classified websites. They found that the ad with the Black hand got fewer responses and fetched lower prices. Ayres, Banaji and Jolls (2015) used a similar method in eBay auctions, and found a similarly sized discrepancy in prices. In a deviation from the experimental method, Pope and Sydnor (2011) looked at loan applications on the peer-to-peer lending platform Prosper. They found that an applicant whose pictures identified them as Black had to pay much higher interest rates for their loans, when compared to the applicants whose pictures identified them as White. Using a similar methodology Edelman and Luca (2014) found that White hosts in New York City could charge higher prices on Airbnb, when compared to Black hosts who had listed similar accommodations. Laouenan and Rathelot (2016) replicated the Edelman and Luca findings in a study that included 19 cities across Europe and North America, for Muslim and Black hosts, respectively. Ge et. al. (2016) found that Black users of ridehailing services faced longer wait times, in a study that looked at both ride requests and physical rides. Within this growing literature, racial discrimination is broadly theorized to be the result of two related processes. On the one hand, taste-based discrimination occurs when individuals have strong preferences about who they engage in interactions with (Becker 1971; Dymski 2005). They either favor people who are the same race as them, or engage in actions discriminatory towards people of other races, even when those actions incur costs on themselves – such as not being able to rent out a house, or buy a cheaper good. On the other hand, statistical discrimination takes place when individuals lack adequate and relevant information about specific individuals, and use biased information of others' race as a proxy for individual qualities (Arrow 1973; Phelps 1972). They are not specifically motivated to engage in racial discrimination, but do so to maximize the utility to themselves. Thus, a landlord might refuse to rent an apartment to a Black applicant, not because they dislike Black people, but because they expect Black tenants, on average, to be less reliable in rent payments. Detailed studies of racial inequality in offline markets are often unable to definitively distinguish between the two dynamics (Guryan and Charles 2013), both of which have received some empirical support (Autor and Scarborough 2008; Charles and Guryan 2008; Fernandez and Greenberg 2013).

While the two dynamics have the same outcome of racial discrimination, they have significantly different remedies. For taste-based discrimination, the suggested remedies range from increased exposure to members of other racial groups (Beaman et al. 2009; Forscher et al. 2017) to allowing market mechanisms to push out discriminating actors, as their behaviors are suboptimal (Arrow 1973; Becker 1971), even though this latter point is contested (Charles and Guryan 2011). Statistical discrimination mandates remedies, focused primarily on expanding the information available to the discriminating party. The primary idea is that when cheap and relevant information on the individual is available, race becomes a much weaker, less salient signal of trustworthiness. Thus, Fernandez and Greenberg (2013) find that when both White and Black job applicants both have a referral from someone working in the firm, their hiring outcomes show no evidence of discrimination. Hanson and Hawley (2011) note that landlords do not discriminate against Black renters when they signal high social class in their email inquiries, while Ewens et. al. (2014) find that the landlord's prior experience with Black renters plays an important role in reducing discriminatory behavior.

For online platforms with persistent user profiles, the reputation systems have become central to understanding how statistical discrimination can be remedied. Many of the eBay studies cited above find that racial discrimination in the auctions they study is mediated by the public reputation system, such that those with high ratings suffer less discrimination (Ayres et al. 2015; Nunley et al. 2011). The same is true for Airbnb studies, which find the overall number of reviews (Laouenan and Rathelot 2016), or the rating of a listing (Edelman and Luca 2014) reduces the price differential attributed to racial discrimination, and that among prospective guests with at least one review the acceptance rates for reservations show no racial bias (Cui, Li, and Dennis J Zhang 2016). These findings are in line with the Abrahao et. al. (2017) finding that reputation systems can create trust between dissimilar people in online contexts.

This line of inquiry into the positive effects of reputation systems on racial discrimination, while critical for designing more equitable platforms, has an important shortcoming. Largely, it treats reputation as independent from racial discrimination. For studies that use experimental methods, reputation is a deliberately manipulated part of the experimental treatment (Ayres et al. 2015; Cui, Li, and Dennis J Zhang 2016; Nunley et al. 2011). For studies that use actual platform data, it is treated as an independent variable (Edelman and Luca 2014; Laouenan and Rathelot 2016). However, there is reason to believe that on the platforms, reputation information is itself likely to exhibit racial bias. While high ratings and positive reviews might be important tools for reducing racial discrimination, they are not equally accessible to all. Existing biases outside the platform are likely to influence these metrics to make them harder to attain for people of color. Thus, even though high ratings might have the potential to reduce racial discrimination, individuals who suffer from discrimination are not able to get them due to the discrimination itself.

In this paper, I present evidence of how the reputation systems are biased against people of color and should be understood as yet another facet of racial inequality and another factor in its reproduction. I study two distinct but related hypotheses about how this bias operates. The first is that the well-documented bias against people of color on the platforms should result in lower volumes of reputation information generated about their listings. Hannak et. al. (2017) observed this problem on TaskRabbit and Fiverr, where people of color received significantly fewer reviews. On Airbnb, Cansoy and Schor (2018) found a clear bias against listings that are located in areas with high concentrations of non-White residents. To understand how this bias operates in the context of the public reputation system on Airbnb, I study how the racial composition of neighborhoods affects the booking dynamics for new listings which do not have any reputation information on the platform. Previous studies have used price to measure the extent of this discrimination; however on Airbnb, unlike on eBay, prices are not set with an auction mechanism. Instead, the prospective hosts set prices ahead of time. This suggests that prices will only be reduced for hosts of color only after experiences of sustained discrimination, either against the individual listings, which would result in a host reducing prices to attract guests, or of all competing listings, which would depress prices across the whole geography facing discrimination.

Studying the actual dynamics of bookings provides a more direct measurement of whether every participant has an equal opportunity to enter into exchanges and thus generate public reputation information about themselves.

The second hypothesis I investigate is that discrimination on the platforms should result in more negative reviews and ratings for people of color. Rosenblat et. al. (2017) have recently argued that this dynamic influences drivers' ratings on Uber and is likely to result in discrimination against drivers of color, as low ratings result in drivers being pushed off the platform. Hannak et. al. (2017) report that TaskRabbit and Fiverr providers of color on average have lower ratings compared to their White counterparts. Ratings on Airbnb are likely to display a similar bias, which would place participants of color at a significant disadvantage, as the vast majority of listings have very high ratings on the platform.

2.2 METHODS

In this paper, I use data about listings on Airbnb in conjunction with information about the areas in which these listings are located to measure whether and how the public reputation system is biased against people of color. While I do not measure race or other variables of interest at the individual level, 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), including in studies of online platforms (Ayres et al. 2015; Edelman 2017; Ewens et al. 2014). While there are some advantages to abandoning the pre-defined units of the census (Lee et al. 2008) or using alternative geographical units such as census blocks (Hansen and

Reich 2015; Parisi et al. 2011:835), using the slightly larger tracts is justified due to data availability and uncertainty about exact listing locations.[2]

The dataset contains 269,688 listings on the Airbnb platform in the 10 biggest urban Airbnb markets in the US[11], which came on the platform on or after January 1, 2015 and were available for rental at least one day in 2015 or 2016. These markets are restricted to the metropolitan statistical areas designated by the Office of Management and Budget (US Census Bureau 2017e). The data was collected by a private company which uses web scraping to collect daily information about the Airbnb market (AirDNA 2017). Scraped data from the platform has been used before in studies of discrimination (Edelman and Luca 2014; Edelman et al. 2017), the dynamics of room bookings (Lee et al. 2015), how the ratings system operates (Zervas et al. 2015a), the gentrification pressures generated by short-term rentals (Wachsmuth and Weisler 2018), and the impact of home sharing on the hospitality industry (Zervas et al. 2015b). Juliet Schor and I (2018) have used a slightly different dataset of all listings active on the platform in 2016 and found substantial racial differences in Airbnb participation and outcomes.

I used the scraped location of listings to match them with census tracts and the relevant data from 2011-2015 5-year estimates of the American Community Survey (ACS) (US Census Bureau 2017b). In the regression models presented below, I use spatial lag terms to control for possible spatial autocorrelation in the model. The lags are calculated as the mean value of the dependent variable in any neighboring listings (including those that came on Airbnb before 2015) within 1 mile divided by the distance between the two listings.

[11] 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.

In the dataset, there are some observations with incomplete data. For about 4.8% of listings (12,884), the median housing unit value in the census tract is missing. Other ACS variables about census tract demographics were also missing for some of the listings, albeit at a much lower rate (i.e. only about 0.2% for median age). For the purposes of keeping the analysis simpler, I handled missingness with listwise deletion, resulting in 256,804 listings used in the following analysis. Models without the median housing value variable, and thus a much lower rate of missingness, produced substantively similar results. Table 1 contains a brief explanation of the variables in the model and their descriptive statistics. All continuous independent variables are standardized and grand mean centered for ease of interpretation.

For the study of booking dynamics in the absence of reputation information, I focused on two variables. The first one, Booked, is a binary variable indicating whether a listing received at least one booking in 2015 or 2016. It was modeled with a logistic regression. The second variable, Days Before First Booking, measures how many days a listing was available to be booked on Airbnb before it received its first booking. This count variable was modeled with a Poisson model.

For ratings, due to overwhelmingly high scores, I opted to transform the data into a series of binary variables indicating whether the rating is above a given threshold. I present logistic regression results for three such variables. Rating (perfect) measures whether a listing has the perfect 5.0 rating, Rating (4.8) measures whether the listing's rating is at or above 4.8, and Rating (4.3) does the same for 4.3. As can be seen in Table 5, these values are at the 29^{th}, 79^{th} and 93^{rd} percentile of all listings with a rating, respectively.

Table 5. **Descriptive Statistics**

Statistic	Description	N	Mean	St. Dev.	Min	Max
Booked	Whether the listing received at least one booking in 2015 or 2016.	269,688	0.77	0.42	0	1
Days Before First Booking	Number of days a listing was available on Airbnb before its first booking.	208,270	41.12	38.41	0.00	564.00
Rating (Perfect)	Whether the listing had a perfect rating of 5.0	92,905	0.29	0.45	0.00	1.00
Rating (Above 4.8)	Whether the listing had a rating of 4.8 or above	269,688	0.79	0.40	0	1
Rating (Above 4.3)	Whether the listing had a rating of 4.3 or above	269,688	0.93	0.26	0	1
Bookable days	Number of days the listing was either available or booked in 2015-2016	269,688	169.38	113.19	1	731
% Booked days	% of bookable days the listing was booked	269,688	0.24	0.26	0	1
Avg. Nightly Price	Average nightly price the listing had in 2015-2016	269,688	165.97	175.43	10	1,500
Max. Guests	Maximum number of guests the listing can accommodate, top-coded to 16.	269,688	3.35	2.36	1	16
Type – Private Room	Guests have access to a private room in the listing. (106,186 listings)	269,688				
Type – Shared Room	Guests only have access to areas shared with others. (12, 803 listings)	269,688				
Instantly Bookable	The listing can be booked instantly. (52, 789 listings)	269,688				
Number of Reviews	Number of reviews a listing had on Airbnb in January 2017.	269,688	4.91	10.68	0	217
Rating	Rating of a listing in January 2017, ranging from 1.0 to 5.0, 0.1 increments.	92,905	4.66	0.40	1.00	5.00
Distance to City	Distance, in meters, between listing and the closest central city in the MSA	269,688	9,804.38	13,209.20	11.73	155,434.50
# Listings by Host	Number of listings on Airbnb managed by the same host.	269,688	8.53	45.20	1	779
# Listings in Tract	Number of listings in the same census tract.	269,688	208.78	242.01	1	1,402
Population - Tract	Population of the census tract	269,688	4,832.77	2,346.36	0	39,454
% non-White	Percentage of the tract pop. that does not identify as White, non-Hispanic.	269,252	0.49	0.25	0.00	1.00
Median Age	Median Age of the tract population.	269,109	37.26	6.86	12.40	82.00
Median Housing Value	Median value of housing in the tract, for housing units with a mortgage.	256,804	596,291.10	340,459.60	9,999.00	2,000,001.00
% Renter	Percentage of the tract population that do not own, but rent their residence.	269,252	0.59	0.24	0.00	1.00
% with BA or more	Percentage of the tract pop. that has at least the equivalent of a BA degree.	269,252	0.40	0.19	0.00	1.00
Per capita Income	The per capita annual income of the census tract.	268,983	49,157.77	27,674.22	1,343.00	254,204.00
Gini Coefficient	The Gini coefficient of income inequality within the census tract.	268,670	0.47	0.07	0.01	0.72

2.3 FINDINGS

2.3.1 Booked

Models 1 and 2 in Table 6 show partial regression results for the Booked variable. In both models, higher concentrations of non-White residents in a census tract are negatively associated with the odds of a listing receiving at least one booking. One standard deviation increase in this concentration is associated with a 2% reduction in the odds of ever receiving a booking in Model 1. Interestingly, this impact is only slightly mediated by the income, age, housing and education variables that are included in Model 2, as the coefficient is unchanged when these variables are added to the model. This suggests that the racial composition of an area affects the odds of an initial booking independent of the variables entered into the regression in Model 2.

In Model 2, we also find that a listing's odds of receiving at least one booking increased where there is higher income inequality, percentage of renters, median housing value and educational attainment in a census tract. However, listings in higher per capita income areas had increased chances of not getting booked, while median age of the population was not a significant predictor. These findings support the idea that not everyone has the same access to exchanges on Airbnb and thus the ability to generate reputation information on the platform that might counteract racially discriminatory attitudes.

Table 6. **Partial Regression Results for Whether a Listing was Ever Booked and the Days It was Bookable Until the First Booking**

	Booked		Days Bookable until First Booking	
	logistic		*Poisson*	
	(1)	(2)	(3)	(4)
(Intercept)	1.38***	1.37***	3.60***	3.61***
	(0.01)	(0.01)	(0.001)	(0.001)
% non-White	-0.02***	-0.02**	0.01***	0.01***
	(0.01)	(0.01)	(0.0004)	(0.001)
Per capita Income		-0.07***		0.03***
		(0.01)		(0.001)
Gini Coefficient		0.05***		-0.02***
		(0.01)		(0.0004)
Median Age		0.01		0.02***
		(0.01)		(0.0005)
% Renter		0.05***		-0.03***
		(0.01)		(0.001)
Median Housing Value		0.05***		-0.03***
		(0.01)		(0.001)
% with BA or more		0.05***		-0.04***
		(0.01)		(0.001)
Observations	256,804	256,804	198,452	198,452
Akaike Inf. Crit.	259,512.60	259,307.10	6,529,355.00	6,512,392.00

Note: *p**p***p<0.001
Regression coefficients are not exponentiated.
See appendix for full results.

2.3.2 Days Before First Booking

Partial regression results for models predicting how many days a listing was available on Airbnb before it received its first booking can be found in the third and fourth columns of Table 6. For both of the models presented there, the percentage of non-White residents in a census tract are positively associated with the days it was available but not booked on Airbnb before receiving its first booking. In Model 3, an entire unit listing in an all-White neighborhood, which cannot be booked instantly and is located in the metropolitan statistical area centered on New York City, with all other covariates at their population mean, is predicted to spend about 35.5 days available on Airbnb before it gets booked. However, an identical listing located in an all non-White neighborhood, with all other covariates held constant, is predicted to spend 37.5 days available before it receives its first booking. In Model 4, this difference shrinks to about 1.3 days, with the effect of racial segregation being mediated through the income, age, housing and education variables. As with the models predicting whether a listing received at least one booking, higher income inequality, higher percentage of renters, higher housing values, and higher educational attainment are associated with better outcomes on Airbnb. Listings in such neighborhoods were available fewer days before they received their first booking. On the other hand, listings in neighborhoods with higher incomes and higher median ages on average were available for longer before they received a booking, possibly due to hosts being more selective with guests.

2.3.3 Ratings

Table 7 presents partial logistic regression results for the three rating variables. The percentage of residents of color in a census tract is a strong predictor of lower ratings in all of the models. Model 1 predicts that the probability of a listing having a perfect rating decreases by about 13.1% for every standard deviation increase in the percentage of residents of color. In Model 2, this decrease is reduced to about 9.5%. The same increase in the percentage of residents of color in Model 3 decreases the probability of a listing having a rating of 4.8 or above by about 15.6%, and in Model 4 by about 12.2%. The corresponding decreases for Models 5 and 6, predicting the probability of a listing having a rating of 4.3 or above are 18.1% and 13.1%, respectively. For all these ratings variables, we can see that the impact of racial segregation on ratings is mediated through the income, age, housing and education variables. Models 2, 4 and 6 predict that listings in areas with higher income inequality and a higher percentage of renters are more likely to have lower ratings, and the same is true for listings in areas with higher per capita incomes in Models 4 and 6, and areas with higher median housing values in Models 2 and 4. On the other hand, all three models predict higher ratings for listings located in census tracts with higher educational attainment.

Table 7. **Partial Regression Results for Listing Ratings**

	Rating (perfect)		Rating (4.8+)		Rating (4.3+)	
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	-0.67***	-0.64***	0.17***	0.20***	2.34***	2.37***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
% non-White	-0.14***	-0.09***	-0.17***	-0.13***	-0.20***	-0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Per capita Income		-0.02		-0.05**		-0.13***
		(0.02)		(0.02)		(0.03)
Gini Coefficient		-0.07***		-0.08***		-0.10***
		(0.01)		(0.01)		(0.01)
Median Age		0.002		0.03*		0.003
		(0.01)		(0.01)		(0.02)
% Renter		-0.09***		-0.10***		-0.07***
		(0.01)		(0.01)		(0.02)
Median Housing Value		-0.03*		-0.05***		0.02
		(0.01)		(0.01)		(0.02)
% with BA or more		0.07***		0.07***		0.17***
		(0.02)		(0.02)		(0.03)
Observations	88,714	88,714	88,714	88,714	88,714	88,714
Akaike Inf. Crit.	99,448.84	99,295.45	116,188.60	115,920.50	49,944.20	49,828.35
Note:	*p<0.05, **p<0.01, ***p<0.001					
	Regression coefficients are not exponentiated.					
	See appendix for full regression results.					

2.4 DISCUSSION

These findings highlight two key ways in which racial discrimination is reproduced through public reputation systems. The results for whether a listing was ever booked, and the days it was available on Airbnb before receiving its first booking both show that Airbnb listings in areas with higher percentages of residents of color are at a significant disadvantage at entering into exchanges. They are less likely to receive a booking, and on average have to wait longer to get their first booking. Consequently, these listings have a harder time generating reputational information about themselves. In the absence of such information, these listings are not able to counteract potential guests who engage in statistical discrimination against them. Even for guests who might not engage in racial discrimination, the lack of reputational information is likely to put these listings at a disadvantage on a platform where the public reputation system plays a critical role in generating trust among strangers (Abrahao et al. 2017). The absence of such information is likely to reduce demand for listings.

Looking at the analysis of the rating variables, we see a similar pattern in which racial inequalities are reproduced through the ratings. Listings located in areas with higher concentrations of residents of color are much more likely to have lower ratings, across all three threshold levels. This is an important finding because it shows that contrary to the unspoken assumptions of the literature on reputation systems, these reputation information produces systematically lower scores for listings located in areas with residents of color. Racial discrimination operates through these systems, not simply alongside them. This bias in ratings against areas with residents of color is likely to have negative impacts on the ability of hosts of color to take part in exchanges on Airbnb as well, especially given the extremely positive ratings prevalent on the platform. Perhaps as importantly, these effects are likely to last over time, since in reputation systems, biases in existing reviews tend to be reproduced in subsequent ones (Ma et al. 2013).

Broadly speaking, other dimensions of inequality included in the model are also likely to be reproduced through the public reputation system through these dynamics. Listings located in areas with fewer homeowners, lower housing values, lower educational attainment and higher income inequality are both less likely to generate bookings, and more likely to be available for longer before they receive their first booking. The same set of variables also predict lower ratings for listings. However, this pattern is broken when we look at inequalities in income, where listings in areas with lower per capita income both have a higher likelihood of getting booked, and shorter wait times for their first reservation and higher ratings. This trend is somewhat counterintuitive, but it could be the explained by the fact that listings in lower income areas are available for bookings more frequently. This greater availability could be explained by hosts who have a greater incentive to make money on the platform, but it could also be due to the concentration of full-time rentals, units converted into exclusive short-term rental properties by owners, in these areas because of the rent gap created by Airbnb (Wachsmuth and Weisler 2018).

These results highlight the need for research that problematizes the public reputation systems of online platforms, rather than assuming that they are equally accessible to all, and produce relevant and unbiased information. Such research should pursue two broad goals—understanding what it is that is actually communicated through these systems, and measuring the extent of racial discrimination in reputation systems across more platforms and in greater detail. Some of the existing research, which focuses on how reputation systems can generate bias due to social dynamics involved in the exchange have already started to formulate questions about the first goal (Bolton et al. 2013; Dellarocas 2000; Fradkin et al. 2015; Zervas et al. 2015a). Further study in this area should focus specifically on how individuals taking part in the reputation system understand their interactions with it. Understanding the rationale behind the decision to leave a review, the selection of topics to mention in the written portion, as well as the meanings reviewers ascribe to the quantitative values they use can play an important role in understanding how these systems actually operate in the context of racial discrimination. Equally important, we need to know a lot more about how other users understand the information provided by the public reputation systems, the meanings they ascribe to the quantitative ratings and the qualitative reviews they see. New experimental studies focused on the reputation systems are needed to pursue the second goal of measuring the extent and scale of racial discrimination. These studies will need to be calibrated to the intricacies of the review systems on different platforms, but many of the experimental methods developed to measure price discrimination or discrimination in the propensity of users to enter into an exchange with people of color can be easily adopted to these purposes.

2.4.1 Limitations

The analysis presented above has a number of limitations imposed by the data. First, it is not possible to assess whether the scraped data has systematically failed to capture some subset of listings, or whether the scraping effort has been consistent across the two-year period I am studying. However, compared to other publicly available datasets on Airbnb, the data I use appears to have more comprehensive coverage (Cansoy and Schor 2018).

Without access to data held by the platforms themselves, large-scale web scraped data provides the best alternative to study these key sites of economic activity. The data is also limited because it does not allow me to control for amenities offered by listings like parking spaces or the décor. Thus, there is the possibility that some of the effects identified above could actually be the effects of unobserved listing qualities, which could be distributed unequally across lines of race. However, even if that were the case, the unequal distribution of such qualities would still mean that the reputation system reproduces bias, albeit more due to economic inequality than due to racial discrimination. The analysis is also limited by the fact that the rating variable was only collected at the end of the two-year period in January 2017. Thus, it does not allow me to study how the ratings evolve over time, and whether there are discriminatory dynamics in how ratings change as listings receive bookings and get reviews. On the other hand, this snapshot of ratings at the end of the period is still useful as it approximates what a given guest sees on the platform when they are searching for accommodations. Thus, analyzing the ratings in this way is more informative about how they might direct guest behavior.

The lack of individual-level measurements of race, income, education or housing variables is the most important limitation of this dataset. The existing literature highlights the importance of these factors at the individual level, and this data does not allow the same dynamics to be measured. However, collecting racial data on platform participants is fraught with difficulties. Airbnb does not collect data on the race of its hosts (Cansoy and Schor 2018). Using pictures to assign racial categories to participants, with automated software and human coders, has been used in one report (Inside Airbnb 2017), one working paper (Edelman and Luca 2014) and one published work (Hannak et al. 2017). However, not all participants use pictures that are ideal for this type of analysis and the decision to avoid racial identifiers in pictures may not be random, given that users are aware of discrimination and might want to avoid it. In the absence of more detailed data, I believe that using census tract level measures of race and other factors is an acceptable choice for the purposes of analyzing racial discrimination in the public reputation systems. Future research using experimental methods can overcome these challenges of individual-level measurement.

2.5 CONCLUSION

While public reputation systems have become increasingly central to online platforms that enable and direct large amounts of economic activity, current research does not problematize them as potential sites of racial discrimination. In fact, a growing number of studies have pointed to the potential of these systems to reduce statistical discrimination by providing relevant information about goods and services on offer. However, in this paper I have argued that this approach to the reputation systems is highly problematic. Using evidence from a study of listings that came on the Airbnb platform in 2015 or 2016, I showed that in areas with higher concentrations of residents of color, listings had a lower probability of receiving a booking and had to wait longer for their first booking, resulting in the unequal production of reputation information across racial lines. Moreover, I showed that ratings for listings in these areas at the end of 2016 were systematically lower, indicating a significant bias in the reputation information that does get produced about them. These results suggest an urgent need to focus on the public reputation systems to better understand the dynamics that generate the reputation information and facilitate its interpretation by users. At the same time, there is a need for studies to measure the extent of racial discrimination in these systems in greater detail, across a broader range of platforms.

3.0 GENTRIFICATION AND SHORT-TERM RENTALS: RE-ASSESSING THE RENT GAP IN URBAN CENTERS

Over the last few years, the regulation of short-term rentals has become a central policy issue for municipal governments around the world. While outright bans against this new type of rentals have been hard to maintain (O'Sullivan 2018), strict regulations that seek to prevent the loss of housing to this practice have increasingly become the norm across major metropolitan areas (Dent 2018; Greenberg 2018; Logan 2018; Loudenback 2018). The regulatory action is a belated response to the rapid expansion of this market, which has altered the economics of urban housing in novel ways. Facilitated by online platforms, short-term rentals now annually channel billions of dollars into cities. Thousands of housing units, which would otherwise be available for long-term tenants, serve this market exclusively. Even before the latest wave of regulatory action, activism against short-term rentals had focused strongly on the issue of housing loss and inexorably linked Airbnb, and the smaller platforms facilitating short-term rentals, to the debate on gentrification.

A long history of academic studies on gentrification trace it to a new wave of private re-investment in urban spaces that began in the 1960s, after decades of suburbanization (Baldassare 1982; Lipton 1977; Sumka 1979; Zukin 1987). Even today, the working definitions of gentrification often highlight re-investment and permanent in-migration of middle- and upper middle-class residents to an area (Hwang and Sampson 2014; Smith 1998). However, the rapid expansion of short-term home rentals, facilitated by online platforms, threatens to upend this understanding in critical ways. These platforms allow urban real estate to be monetized with minimal re-investment or long-term in-migration of higher-class residents. By connecting urban locales to the global flow of people and capital, rental platforms generate significant incentives for rapid and widespread gentrification and threaten to increase inequality within cities and displace disadvantaged populations. Lee (2016) documents the extent of housing lost to Airbnb in Los Angeles's central neighborhoods, and argues that the introduction of short-term rentals into an already tight housing market makes housing even less affordable. Wachsmuth and Weisler (2018) argue that Airbnb has created a significant "rent gap" in some areas of New York City, with short terms rentals bringing in significantly greater revenue than long-term ones. However, these two studies focus on the two largest metropolitan areas in the US, visited by large numbers of travelers, and thus could be unique short-term rental markets.

In this paper, I present the first large-scale analysis of the gentrification dynamics generated by short-term rentals in the ten largest urban markets for Airbnb in the US. Using data on Airbnb activity from 2015 and 2016, in conjunction with American Community Survey 5-year estimates from the same years, I show that the rent gap generated by short-term rentals is a concern across all 10 geographies, with housing units converted into exclusively short-term properties earning up to three times the median rent in some neighborhoods. These units have also come to represent a significant portion of the total rental revenue across these markets, and they occupy a large share of rental properties without long-term tenants. I then propose a new way to measure the gentrification impacts of short-term rentals, which highlights the constant, and increasing pressures for gentrification generated by this practice.

3.1 LITERATURE REVIEW:

3.1.1 Gentrification, Globalization and Short-term Rentals:

Short-term rentals represent a new vector of gentrification that does not easily fit into established theoretical approaches. Perhaps the most widely accepted definition of gentrification is "the process by which central urban neighborhoods that have undergone disinvestments and economic decline experience a reversal, reinvestment, and the in-migration of a relatively well-off middle- and upper middle-class population" (Smith 1998). Smith (1979) proposed that this process was driven by a "rent gap" – a disparity between the potential rent property owners could extract from real estate with re-investment and the actual rent they currently get. After an initial capital investment, relative to the potential rent the actual rent decreases over time, as the property depreciates. When the gap between the two is large enough to justify re-investment, the property owners would make another round of capital investment, and increase the actual rent relative to potential rent. Some of the initial work in this field ascribed gentrification to individual "gentrifiers" who would buy and update urban housing stock, however soon afterwards corporate developers as well as local and federal government projects were identified as key players in this process (Smith 2006). These approaches collectively highlighted the primacy of local dynamics in driving gentrification: new residents, local developers, building and infrastructure projects. This focus on the local is not adequate when we try to understand how short-term rentals operate.

Airbnb and other short-term rental platforms are not "local" actors. To understand them we have to broaden our theoretical scope. This is in line with Smith's (2006, 2002) argument that the local processes are only meaningful in the context of broader processes of globalization.

> [T]he process of gentrification, which initially emerged as a sporadic, quaint, and local anomaly in the housing markets of some command-center cities, is now thoroughly generalized as an urban strategy that takes over from liberal urban policy. No longer isolated or restricted to Europe, North America, or Oceania, the impulse behind gentrification is now generalized; its incidence is global, and it is densely connected into the circuits of global capital and cultural circulation. (Smith 2002)

This globalization of gentrification –both the geographical expansion of the phenomenon and the increased role played by global dynamics in it– has had significant implications for how it is studied. Instead of looking only at central districts of a few "global" cities, research today focuses on the processes going on in "ordinary cities" (Robinson 2006) and the increasing alignment of national and local powers with the global capital (Hackworth and Smith 2001). Davidson and Lees (2005) have argued that these factors have led to the development of a familiar "gentrification blueprint" across the globe, which displaces lower class urban residents and remakes urban spaces for the consumption of middle- and higher class residents. Along these lines, Sigler and Wachsmuth (2016:719) have argued that "gentrification is not merely a local outcome of globalisation." Instead, they show that local actors, both governmental and non-governmental, play a key role in rooting the global flows of people and capital into specific locales. Once rooted, those flows reshape urban geographies by creating a rent gap that drives gentrification to enable the globalized consumption of urban spaces.

These connections between globalization and gentrification provide a good starting point to understand the impacts of short-term rental platforms and their operations on urban geographies. Short-term rentals are intricately connected to global flows of people; they depend on a set of transient "consumers" whose ability to travel is predicated on the global transportation and communication technologies. These rentals are also intricately tied into the global flows of capital, as the platforms are able to leverage both their own economic power, and their ability to accept and make payments across borders, to great effect. The grounding of both these flows in urban centers, where they introduce large amounts of money, new demands for consumption, and ultimately a significant disruption to the local dynamics, is at the heart of a new type of gentrification. This is also aided by the hands-off approach from the federal government towards the platforms over the past decade. In the case of Airbnb, the company has hired multiple former presidential administration officials to lobby the federal government and engage in public relations campaigns (Fiegerman 2016). Local governments have often been ineffective as well. In many locales, the company has either flagrantly violated local laws regulating rentals, building occupancy or taxation with very limited repercussions (Schor and Cansoy 2018). Even when ordered by a court to release information on the illegal use of the platform in NYC, the company engaged in questionable practices and refused to allow city authorities to identify violators individually (Cox and Slee 2016; Streitfeld 2014b). The support of some local residents, who have been enthusiastic participants in the short-term rental practices, have played a key role (Romney, Lien, and Hamilton 2015). The recent wave of regulation at the local level appears to be reversing this trend (Dent 2018; Greenberg 2018; Logan 2018; Loudenback 2018); however, its impacts have yet to be seen.

Wachsmuth and Weisler (2018) suggest that short-term rentals generate a new type of rent gap, partially because they have not been regulated. Unlike traditional model of the rent gap, short-term rentals create a rent gap by driving up the potential rent itself, not through the gradual erosion of actual rent relative to the potential rent. More importantly, this rent gap can be exploited much more cheaply, since converting existing residential real estate to short-term rentals requires very little capital investment. Thus, property owners can rapidly exploit even relatively small differentials in rent, which would drive up rents by both restricting the housing supply and incentivizing rent hikes in the long-term market. A nationwide study of Airbnb rentals has produced empirical evidence for both these dynamics (Barron, Kung, and Proserpio 2017), which are likely to generate significant momentum for gentrification (BJH Advisors LLC 2016).

Wachsmuth and Weisler's (2018) analysis shows that across New York City, between June 2016 and May 2017, entire-unit listings generated 2% of all rental revenue. In some neighborhoods, listings that were likely to be off the long-term rental market (see Methods section for how these were identified) represented more than 60% of all housing that would have been available for long-term rental without Airbnb. These numbers suggests a non-trivial impact on housing within the city. In some neighborhoods, these units earned more than three times the median annual rent, which points to the existence of a significant rent gap, and the consequent pressures for gentrification. They also show that in a different set of neighborhoods, with Airbnb units generating upwards of 8% of all annual residential rents, the gentrification initiated by this gap has already taken place. Their findings contradict earlier claims that Airbnb's presence was too small to have an appreciable effect on the housing stock or prices in cities (Stulberg 2016). However, the results of the two studies are directly not comparable, as they use different definitions of how to identify housing units that have been converted to exclusive short-term use. Wachsmuth and Weisler (2018:15) additionally calculate an "Airbnb gentrification vulnerability index" which identifies areas in which Airbnb has a large current impact (based on the percentage of total rental revenue generated by Airbnb) and the potential for a large future impact (based on the proportion of the annual long-term median rent in a neighborhood to the average annual revenue generated by exclusively short-term rental properties). They then make the observation that while neighborhoods which have already received a large current impact tend to have a higher percentage of White households than the NYC average, those neighborhoods at risk of high future impact have significantly higher percentages of residents of color. Lee's (2016) study of Los Angeles, which is focused on formulating regulatory action against short-term rentals, makes a similar observation about the conversion of long-term housing to exclusively short-term properties, and the subsequent impacts this has on housing affordability and the displacement of residents.

While both of these studies are valuable, they are focused on the two largest metropolitan areas in the US, which attract large numbers of tourists and business travelers every year. It is not clear if short-term rentals will have similar impacts in smaller cities with fewer visitors. In this paper, I provide the first large scale analysis of the gentrification dynamics generated by short-term rentals. I show that the impact of Airbnb on New York or Los Angeles is not an outlier. In the ten metropolitan areas where Airbnb had the largest presence in terms of the number of listings in 2016[12], short-term rentals consistently restrict

[12] 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,

the supply of rental housing, and generate significant pressures to gentrify. I particularly focus on Chicago and Seattle, cities that occupy both extremes of the full time short-term rental density (see Table 2), to show how gentrification impacts of Airbnb are unequally distributed within cities. Finally, I propose an operationalization of the rent gap that is simpler and more informative than Wachsmuth and Weisler's (2018) index of vulnerability.

3.2 METHODS

I use data about listings on Airbnb, aggregated to the appropriate geographic level, to study how Airbnb generates pressures on the housing market. These units are, alternately, metropolitan statistical areas, hereafter MSAs, designated by the Office of Management and Budget (US Census Bureau 2017e), central cities within the MSAs, or the nominal city of each MSA and the census tracts within it, in order to maintain comparability with Wachsmuth and Weisler's study of New York city.

The original dataset on the ten MSAs contains 469,458 listings on the Airbnb platform at the end of December 2016. However, only 133,319 of these listings were entire-unit listings and received at least one booking during 2016 and only 117,553 had done so in 2015. These together make up 210,825 listings that are used in the following analysis. The data was collected by a private company which uses web scraping to collect daily information about the Airbnb market (AirDNA 2017). Scraped data from the platform has

Seattle-Tacoma-Bellevue, WA Metro Area, San Diego-Carlsbad, CA Metro Area, and Austin-Round Rock, TX Metro Area.

been used before in studies of discrimination (Edelman and Luca 2014; Edelman et al. 2017), the dynamics of room bookings (Lee et al. 2015), how the ratings system operates (Zervas et al. 2015a) and the impact of home sharing on the hospitality industry (Zervas et al. 2015b). Juliet Schor and I (2018) have used a slightly different dataset to show the significant racial differences in Airbnb participation and outcomes and I have used another variant of this data (Cansoy 2018) to study the dynamics of racial discrimination on the public reputation system on Airbnb. Wachsmuth and Weisler (2018) study uses data from the same source.

My sample only contains listings in which short-term renters are not expected to occupy the unit along with a long-term tenant, in other words entire-unit listings, since gentrification pressures are more likely to be generated by units that have been converted into exclusively short-term rental properties.[13] Following Wachsmuth and Weisler (2018), I further restricted the sample into*frequently rented listings* which were available to be booked on the platform for at least 120 days during the year, and were booked for at least 60, and *very frequently rented* listings, which were available for 240 days, and booked for 120. The data contains 56,800 *frequently rented listings*, hereafter FR, and 23,321 *very frequently rented listings*, hereafter VFR, which received at least one booking in 2016.

[13] Other types of Airbnb listings, private rooms and shared rooms, can also contribute to an increase in the potential rent. However, because these listings are located in units already occupied by long-term tenants, and it is possible for renters to generate revenue from these types of listings, their impact on potential rent is likely to be delayed since property owners cannot as easily assess the amount of extra earnings generated on Airbnb or increase long-term rents to extract more of it for themselves. Additionally, housing units which are sub-listed (a three-bedroom apartment listed as three "private room" listings) would generate similar gentrification pressures as entire-unit listings. However, they are excluded from the sample, because identifying them present significant challenges. Focusing only on entire-unit listings thus presents a more conservative estimate of the rent gap and other gentrification pressures driven by Airbnb.

Table 8. **Census Tracts and "Entire Unit" Airbnb Listings – All Entire Unit Listings, Frequently Rented and Very Frequently Rented**

Area	**Tracts**	**All 2015**	**All 2016**	**FR 2015**	**FR 2016**	**VFR 2015**	**VFR 2016**
All MSA Tracts	16,108	117,553	164,315	29,803	56,800	13,342	23,231
Central Cities	7,564	100,042	133,319	25,828	46,700	11,779	19,746
New York MSA	4,700	37,835	45,518	8,924	14,544	4,142	5,830
Central Cities	2,354	33,880	38,307	8,231	12,580	3,853	5,255
New York	2,167	33,049	36,973	8,001	12,196	3,735	5,095
Los Angeles MSA	2,929	21,437	31,251	6,575	11,655	3,092	5,176
Central Cities	1,669	18,054	26,182	5,709	9,817	2,734	4,437
Los Angeles	1,011	13,613	19,155	4,485	7,476	2,232	3,505
Chicago MSA	2,215	6,190	8,842	1,339	3,006	547	1,084
Central Cities	1,053	5,915	8,284	1,281	2,820	523	1,030
Chicago	809	5,767	8,036	1,257	2,741	514	1,007
Washington, DC MSA	1,359	5,777	8,779	1,482	3,112	636	1,232
Central Cities	401	4,952	6,998	1,273	2,536	554	1,071
Washington	179	3,982	5,378	1,064	2,057	472	910
Miami MSA	1,219	13,225	22,097	3,321	7,020	1,392	2,714
Central Cities	362	9,718	15,542	2,520	5,093	1,102	2,059
Miami	108	2,613	4,560	594	1,306	225	465
Boston MSA	1,007	4,865	7,432	1,073	2,641	459	972
Central Cities	258	3,470	4,856	792	1,746	344	703
Boston	181	2,455	3,537	551	1,282	230	517
San Francisco MSA	980	11,755	14,801	3,174	5,398	1,474	2,414
Central Cities	513	9,535	11,473	2,559	4,124	1,216	1,866
San Francisco	197	6,965	8,004	1,789	2,831	818	1,271
Seattle MSA	721	4,661	7,205	1,514	3,276	654	1,446
Central Cities	368	3,985	6,031	1,351	2,839	595	1,308
Seattle	136	3,545	5,261	1,206	2,534	520	1,171
San Diego MSA	628	5,672	9,952	1,320	3,666	516	1,373
Central Cities	338	4,714	7,934	1,096	2,936	440	1,129
San Diego	314	4,408	7,355	1,032	2,748	414	1,075
Austin MSA	350	6,136	8,438	1,081	2,482	430	990
Central Cities	248	5,819	7,712	1,016	2,209	418	888
Austin	220	5,786	7,646	1,015	2,192	418	879

I use three different metrics[14] to measure the impact of Airbnb on the housing market across the ten geographies:

% Median Long-term Rent: The average annual revenue of Airbnb listings in an area divided by the annual median long-term rent in the area. This provides a relatively straightforward estimate of a rent gap in an area. Wachsmuth and Weisler (2018) argue that in areas where this percentage is two standard deviations above the regional mean, there is a significant rent gap between short-term and long-term properties, which creates incentives for owners to gentrify by converting their units to exclusive short-term rentals. The variable is calculated for a geography (MSA, Central Cities in a MSA, Nominal City in a MSA) as:

$$\%\, Median\ Long\text{-}\,term\ Rent = \frac{Revenue_{Airbnb}/Units_{Airbnb}}{Median\ Rent_{Long-term}}$$

% Total Revenue: Percentage of total rental revenue in an area, including long-term and Airbnb rents, earned by all Airbnb listings in that area. Wachsmuth and Weisler (2018) argue that in areas where this percentage is two standard deviations above the regional mean, the rent gap created by Airbnb has already been closed as property owners are already exploiting it adequately.

$$\%\, Total\ Revenue = \frac{Revenue_{Airbnb}}{Revenue_{Long-term} + Revenue_{Airbnb}}$$

% Rental Housing: Percentage of all rental units in an area which are exclusively short-term Airbnb listings. This measure is used to assess the amount of housing, which would be otherwise available to long-term tenants, that has been lost to Airbnb.

[14] Wachsmuth and Weisler use four different metrics – the first two are the "% Median Long-term Rent" and "% Total Revenue" measures introduced in the methods section. They also measure the percentage of all housing taken up by exclusively short-term properties, and the percentage of all vacant rental housing taken up by these listings.

$$\% \; Rental \; Housing = \frac{Units_{Airbnb}}{Units_{Long-term} + Units_{Long-term \; (Vacant)} + Units_{Airbnb}}$$

Airbnb Performance: This is the percentage of annual rental revenue earned by Airbnb listings in an area, minus the percentage of all rental properties occupied by Airbnb listings (% Rental Housing, subtracted from % Total Revenue). It is intended to measure whether the exclusive short-term properties are outperforming long-term rentals in the area, and thus whether there is an open rent gap that property owners can exploit by converting their properties. The use of % Median Rent and % Rental Revenue for this purpose by Wachsmuth and Weisler (2018) is not ideal, since it is hard to establish that the rent gap between Airbnb units and long-term rentals is actually closed when the percentage of rental revenue earned through Airbnb is significantly higher in a neighborhood than it is in surrounding areas. The potential process whereby higher Airbnb profitability induces more participation and greater earnings, but also brings down the average rent is reasonable, yet remains unobserved in the cross-sectional use of the data. The Airbnb performance measure I am using has a significant advantage over these measures because it does not depend on such an unobserved process and better fits the cross-sectional nature of the analysis. Additionally, this measure combines the existence of a rent gap into a single value, rather than having to compare both the profitability of listings and the percentage of revenues they generate in two separate steps. It can also be used to rank different geographies, rather than simply classifying whether the rent gap is open or closed.

$$Airbnb \; Performance = \% \; Total \; Revenue - \% \; Rental \; Housing$$

All data used here that is not directly derived from Airbnb activity, about census tracts (used in figures) and cities (used in tables) is based on ACS 5-year estimates for 2015 and 2016. While Wachsmuth and Weisler (2018) focus primarily on FR listings in their analysis, in the Tables below I present the results for the four variables using all entire-unit listings as well as FR and VFR listings. However, the figures are restricted to FR listings to conserve space. In the tables, I present results at three levels of geographic aggregation, the MSA, census tracts within all of the central cities in an MSA, and census tracts within the nominal city of an MSA. In the figures, I present the results for the downtown areas of two cities, Chicago and Seattle, which had the lowest and highest percentage of housing occupied by FR listings in 2016, respectively (see Table 4). The other eight cities display very similar patterns.

3.3 FINDINGS

3.3.1 % Median Long-term Rent

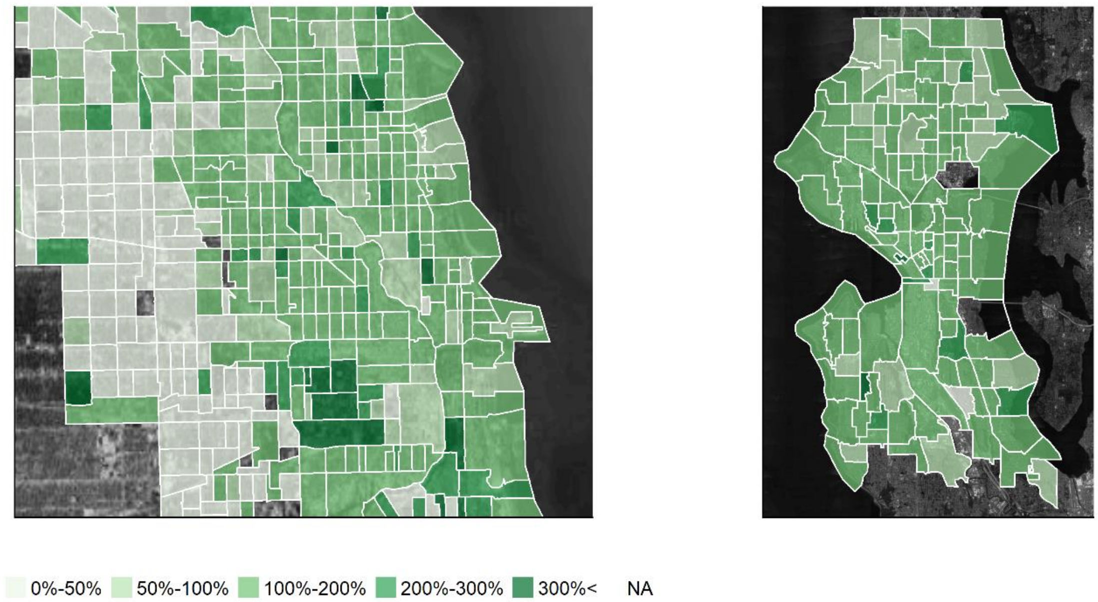
The first finding to note in Table 9 is that the average revenue earned by entire-unit Airbnb listings in 2016 was comparable to the median rent in almost all of the geographies, while in 2015, the ratio between the two was considerably lower. This is an interesting finding, since it indicates that entire-unit rentals, without necessarily displacing long-term tenants, could be contributing to a rent gap simply by driving up potential rents. Within central and nominal cities, these figures are higher than in the MSAs, which is to be expected, as these areas are likely to have greater travel demand. Moving onto FR and VFR listings, we see that they both bring in significantly more revenue, on average, than the median rent in the relevant geographic areas.

Table 9. **Average Revenue Generated by "Entire Unit" Airbnb Listings as a Percentage of Annual Median Long-term Rent – All Entire Unit Listings, Frequently Rented and Very Frequently Rented**

Area	All 2015 % M. Rent	All 2016 % M. Rent	FR 2015 % M. Rent	FR 2016 % M. Rent	VFR 2015 % M. Rent	VFR 2016 % M. Rent
All MSA Tracts						
Central Cities						
New York MSA	68.76%	85.96%	194.05%	195.80%	271.43%	276.61%
Central Cities						
New York	70.22%	85.33%	201.52%	199.28%	284.30%	286.68%
Los Angeles MSA	68.53%	85.92%	158.79%	175.79%	212.30%	241.23%
Central Cities						
Los Angeles	75.82%	91.58%	172.37%	185.74%	227.74%	257.30%
Chicago MSA	61.75%	82.18%	176.81%	174.85%	242.81%	243.46%
Central Cities						
Chicago	63.41%	84.76%	182.05%	181.06%	249.46%	252.26%
Washington, DC MSA	42.67%	55.37%	112.48%	118.56%	156.45%	171.55%
Central Cities						
Washington	51.90%	69.26%	135.26%	143.40%	187.78%	201.97%
Miami MSA	62.74%	75.69%	150.29%	158.15%	195.04%	212.89%
Central Cities						
Miami	70.66%	80.51%	184.11%	181.75%	240.29%	249.39%
Boston MSA	63.75%	91.47%	176.88%	188.69%	249.89%	271.11%
Central Cities						
Boston	62.62%	90.07%	171.89%	189.01%	242.41%	266.15%
San Francisco MSA	67.64%	86.68%	173.75%	180.80%	227.82%	237.54%
Central Cities						
San Francisco	71.53%	94.17%	193.51%	202.83%	258.39%	268.88%
Seattle MSA	63.98%	86.69%	138.78%	152.61%	183.01%	201.58%
Central Cities						
Seattle	66.01%	88.84%	141.38%	152.55%	187.50%	198.88%
San Diego MSA	54.23%	92.81%	135.91%	183.62%	179.69%	233.45%
Central Cities						
San Diego	53.93%	90.22%	136.96%	177.31%	181.82%	235.76%
Austin MSA	69.39%	97.80%	184.86%	213.49%	243.24%	269.71%
Central Cities						
Austin	70.60%	97.25%	189.42%	217.18%	244.91%	276.74%

This ranges from a high of 218% of the median rent in Austin to a relative low of 135% in Washington, DC, indicating significant geographical variation in the relative profitability of converting housing to exclusive short-term rentals. A similar variation can be seen within cities in Figure 3, which shows the percentage of median rent earned by the average FR listing in a census tract in Chicago and Seattle.

Figure 3. Average Revenue of FR listings in a Census Tract as a % of Median Rent, Chicago (left) and Seattle (right)*



*Data for census tracts with less than 400 households not displayed.

In Chicago, which has the lowest concentration of FR listings in the sample, there is significant variations in the relative profitability of the listings. Predictably, in neighborhoods far from the urban core, FR listings earn a much lower percentage of the median rent. However, there are significant clusters of census tracts where FR listings earned more than three times the median rent scattered around the downtown core. In Seattle, partially due to the smaller city boundaries, the profitability of FR listings are relatively uniform and high. In only 24 of the 133 census tracts displayed, the average FR revenue was below the median rent, and in the vast majority of census tracts the average revenue was between a 100% to 200% of the median rent. These findings suggest that while there is a rent gap created by FR listings in Chicago, it is more restricted to the downtown areas. However, in Seattle, the whole city is subjected to the gentrification pressures generated by Airbnb.

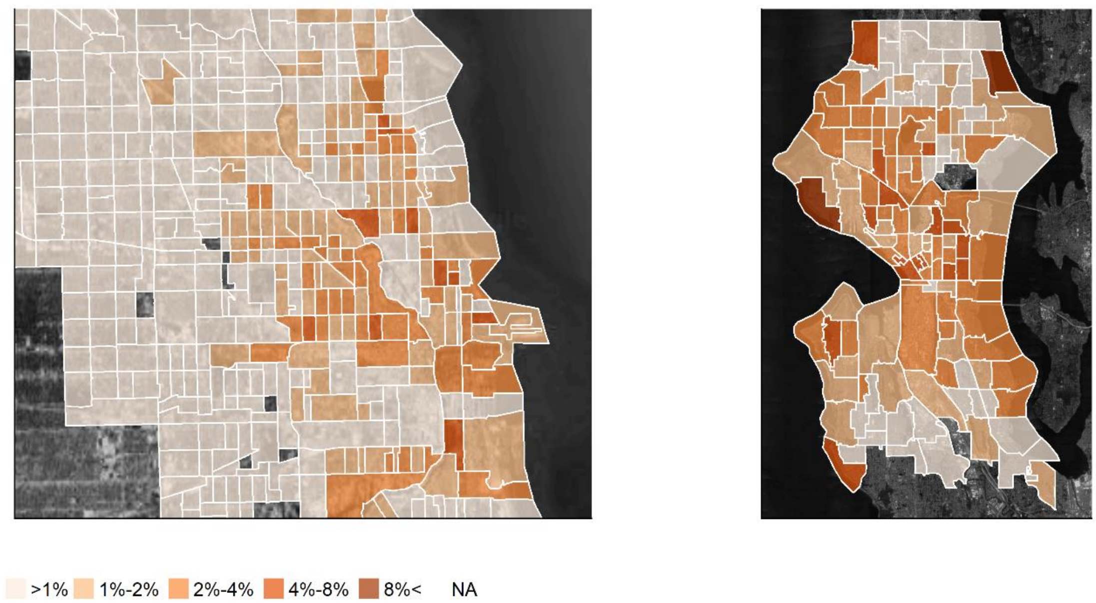
3.3.2 % Total Revenue

Table 10. **Percentage of Rental Revenue Generated by "Entire Unit" Airbnb Listings – All Entire Unit Listings, Frequently Rented and Very Frequently Rented**

Area	All 2015 % Revenue	All 2016 % Revenue	FR 2015 % Revenue	FR 2016 % Revenue	VFR 2015 % Revenue	VFR 2016 % Revenue
All MSA Tracts	0.65%	1.16%	0.43%	0.85%	0.26%	0.48%
Central Cities	0.94%	1.56%	0.64%	1.17%	0.40%	0.69%
New York MSA	0.72%	1.07%	0.48%	0.78%	0.31%	0.44%
Central Cities	0.97%	1.31%	0.68%	1.01%	0.45%	0.61%
New York	1.02%	1.38%	0.71%	1.07%	0.47%	0.64%
Los Angeles MSA	0.63%	1.14%	0.45%	0.87%	0.28%	0.53%
Central Cities	0.80%	1.38%	0.59%	1.07%	0.38%	0.67%
Los Angeles	1.11%	1.84%	0.83%	1.46%	0.55%	0.95%
Chicago MSA	0.29%	0.55%	0.18%	0.40%	0.10%	0.20%
Central Cities	0.48%	0.87%	0.30%	0.64%	0.17%	0.32%
Chicago	0.58%	1.05%	0.36%	0.77%	0.20%	0.39%
Washington, DC MSA	0.31%	0.60%	0.21%	0.46%	0.12%	0.26%
Central Cities	0.61%	1.10%	0.42%	0.85%	0.25%	0.51%
Washington	1.19%	2.09%	0.83%	1.66%	0.51%	1.04%
Miami MSA	1.00%	1.93%	0.60%	1.29%	0.33%	0.67%
Central Cities	2.12%	3.98%	1.31%	2.71%	0.74%	1.45%
Miami	1.44%	2.72%	0.86%	1.77%	0.43%	0.87%
Boston MSA	0.44%	0.97%	0.27%	0.71%	0.16%	0.38%
Central Cities	0.91%	1.77%	0.58%	1.36%	0.35%	0.78%
Boston	0.90%	1.84%	0.56%	1.40%	0.33%	0.80%
San Francisco MSA	0.99%	1.58%	0.69%	1.20%	0.42%	0.71%
Central Cities	1.38%	2.09%	0.97%	1.60%	0.61%	0.96%
San Francisco	2.10%	3.13%	1.47%	2.40%	0.90%	1.44%
Seattle MSA	0.51%	1.04%	0.36%	0.84%	0.20%	0.49%
Central Cities	0.70%	1.40%	0.51%	1.15%	0.29%	0.69%
Seattle	1.35%	2.62%	0.99%	2.17%	0.57%	1.32%
San Diego MSA	0.57%	1.66%	0.33%	1.22%	0.17%	0.58%
Central Cities	0.80%	2.19%	0.47%	1.61%	0.25%	0.83%
San Diego	0.82%	2.21%	0.49%	1.63%	0.26%	0.86%
Austin MSA	1.38%	2.60%	0.65%	1.69%	0.34%	0.86%
Central Cities	1.57%	2.81%	0.74%	1.82%	0.40%	0.94%
Austin	1.72%	3.08%	0.82%	1.99%	0.44%	1.03%

In Table 10, we can see that FR listings, despite earning above the median rent, still only account for a small percentage of all rental revenue at the three aggregation levels. In 2016, they generated 2.4% of all rental revenue in San Francisco, but only 0.77% of all rental revenues in Chicago. With such a small sample, it is hard to establish whether this variation could indicate a closed rent gap (as measured by Wachsmuth and Weisler (2018)) in San Francisco and an open one in Chicago. However, we can see that the rates vary much more significantly within cities in Figure 4.

Figure 4. Total Revenue of FR listings in a Census Tract as a % of all Rental Revenue, including Long-term Rents and Airbnb Revenue, Chicago (left) and Seattle (right)*



*Data for census tracts with less than 400 households not displayed.

The maps of Chicago and Seattle show that census tracts where FR listings earn higher percentages of revenue are more tightly clustered around the downtown areas. Importantly, the census tracts where FR listings earn significantly more than the median rent identified in Figure 1 are not among the tracts with the highest percentage of revenues earned through Airbnb in Figure 2. This could potentially be explained by increased Airbnb participation, which would increase aggregate revenues but ultimately also reduce the average revenues for listings due to price competition. Therefore, Wachsmuth and Weisler's decision to measure the closing of the rent gap through the percentage of total rental revenue earned through Airbnb is justified, to a degree. However, in the following analysis I present a more nuanced way to measure the existence of a rent gap, and whether it has been closed.

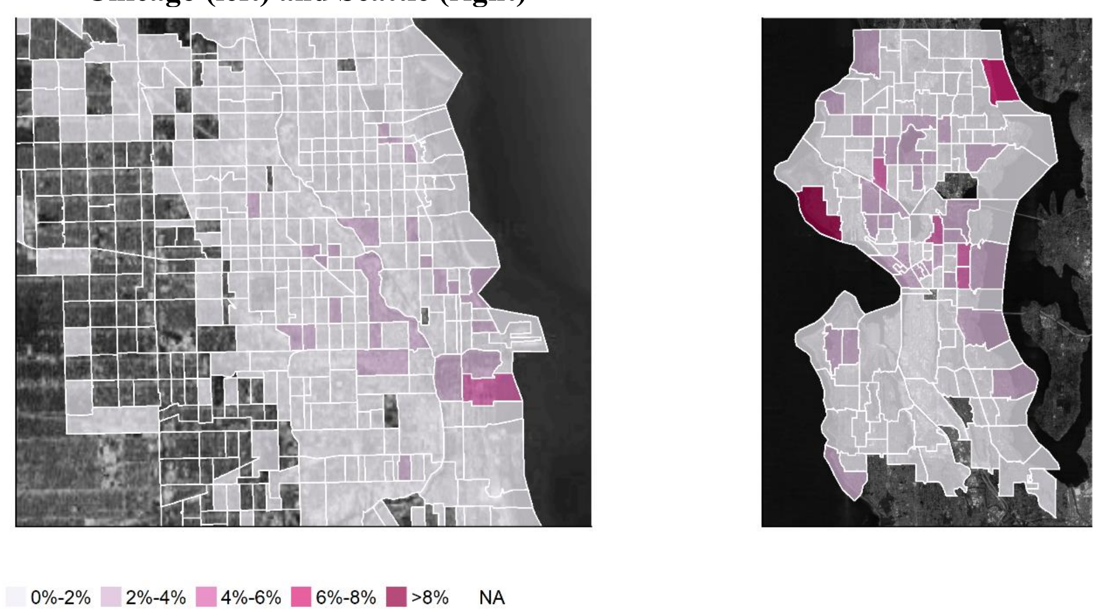
Table 11. **Percentage of Rental Housing Occupied by "Entire Unit" Airbnb Listings – All Entire Unit Listings, Frequently Rented and Very Frequently Rented**

Area	All 2015 % Housing	All 2016 % Housing	FR 2015 % Housing	FR 2016 % Housing	VFR 2015 % Housing	VFR 2016 % Housing
All MSA Tracts	0.99%	1.36%	0.25%	0.47%	0.11%	0.19%
Central Cities	1.41%	1.86%	0.37%	0.66%	0.17%	0.28%
New York MSA	1.04%	1.24%	0.25%	0.40%	0.11%	0.16%
Central Cities	1.40%	1.57%	0.34%	0.52%	0.16%	0.22%
New York	1.48%	1.65%	0.36%	0.55%	0.17%	0.23%
Los Angeles MSA	0.93%	1.34%	0.29%	0.51%	0.14%	0.23%
Central Cities	1.19%	1.69%	0.38%	0.64%	0.18%	0.29%
Los Angeles	1.51%	2.09%	0.50%	0.83%	0.25%	0.39%
Chicago MSA	0.47%	0.67%	0.10%	0.23%	0.04%	0.08%
Central Cities	0.77%	1.07%	0.17%	0.37%	0.07%	0.13%
Chicago	0.91%	1.26%	0.20%	0.43%	0.08%	0.16%
Washington, DC MSA	0.70%	1.03%	0.18%	0.37%	0.08%	0.15%
Central Cities	1.35%	1.86%	0.35%	0.68%	0.15%	0.29%
Washington	2.29%	3.00%	0.62%	1.17%	0.28%	0.52%
Miami MSA	1.51%	2.43%	0.38%	0.79%	0.16%	0.31%
Central Cities	2.94%	4.58%	0.78%	1.55%	0.34%	0.63%
Miami	2.05%	3.43%	0.47%	1.01%	0.18%	0.36%
Boston MSA	0.68%	1.03%	0.15%	0.37%	0.06%	0.14%
Central Cities	1.44%	2.00%	0.33%	0.73%	0.14%	0.29%
Boston	1.39%	1.98%	0.32%	0.73%	0.13%	0.29%
San Francisco MSA	1.46%	1.82%	0.40%	0.67%	0.19%	0.30%
Central Cities	1.97%	2.35%	0.54%	0.86%	0.26%	0.39%
San Francisco	2.93%	3.34%	0.77%	1.21%	0.35%	0.55%
Seattle MSA	0.79%	1.20%	0.26%	0.55%	0.11%	0.24%
Central Cities	1.03%	1.54%	0.35%	0.73%	0.16%	0.34%
Seattle	2.07%	2.99%	0.72%	1.46%	0.31%	0.68%
San Diego MSA	1.04%	1.80%	0.25%	0.67%	0.10%	0.25%
Central Cities	1.50%	2.47%	0.35%	0.93%	0.14%	0.36%
San Diego	1.52%	2.47%	0.36%	0.94%	0.14%	0.37%
Austin MSA	1.96%	2.62%	0.35%	0.78%	0.14%	0.31%
Central Cities	2.24%	2.89%	0.40%	0.85%	0.16%	0.34%
Austin	2.45%	3.16%	0.44%	0.93%	0.18%	0.37%

3.3.2 % Rental Units

In Table 11 shows that at the end of 2016 entire-unit listings occupied a non-negligible 1.36% of all rental housing (renter-occupied, vacant, and exclusively short-term rental) across the 10 MSAs. The comparable figure was 0.47% for FR listings and 0.19% for VFR listings. Looking at the 10 major cities, FR listings range between 0.43% of all housing in Chicago to 1.46% in Seattle. These findings suggest that at these aggregate levels, exclusive short-term rentals are not likely to play an important role in directly restricting the housing supply. However, the rental market is already very tight in urban centers, without enough rental units to absorb housing demand. Even a modest reduction in housing supply due to short-term rentals is likely to contribute to making urban housing even less affordable. When we look at the same measure within cities, we find even higher localized impact on the rental market.

Figure 5. Number of FR listings in a Census Tract as a % of all Rental units, Chicago (left) and Seattle (right)*



*Data for census tracts with less than 400 households not displayed.

Figure 5 shows that the rental housing occupied by exclusive short-term rental properties on Airbnb is heavily concentrated in a small number of neighborhoods. These areas are likely to come under much greater pressures to gentrify, as their former residents are directly displaced with Airbnb-exclusive units occupying more than 8% of all rental properties.

3.3.3 Airbnb Performance

The first thing to note in Table 12 is that in 2015 and 2016, all entire-unit listings were generating a lower share of rental revenue than their share of rental housing in all of the geographies studied. This is relatively in line with the idealized depictions of Airbnb participation, where property owners (or even renters) rent out their units occasionally, but not as an alternative to long-term rentals. However, from 2015 to 2016, this performance gap closed significantly, suggesting that renting out a unit on Airbnb, even without committing to making it available frequently, and succeeding in getting it rented, became an increasingly viable alternative to long-term rentals. A similar increase can be seen in the performance of FR and VFR listings, which were already outperforming long-term rentals in 2015. The gap between the two increased even further in 2016. These findings suggest a robust and growing rent gap across all of these geographies.

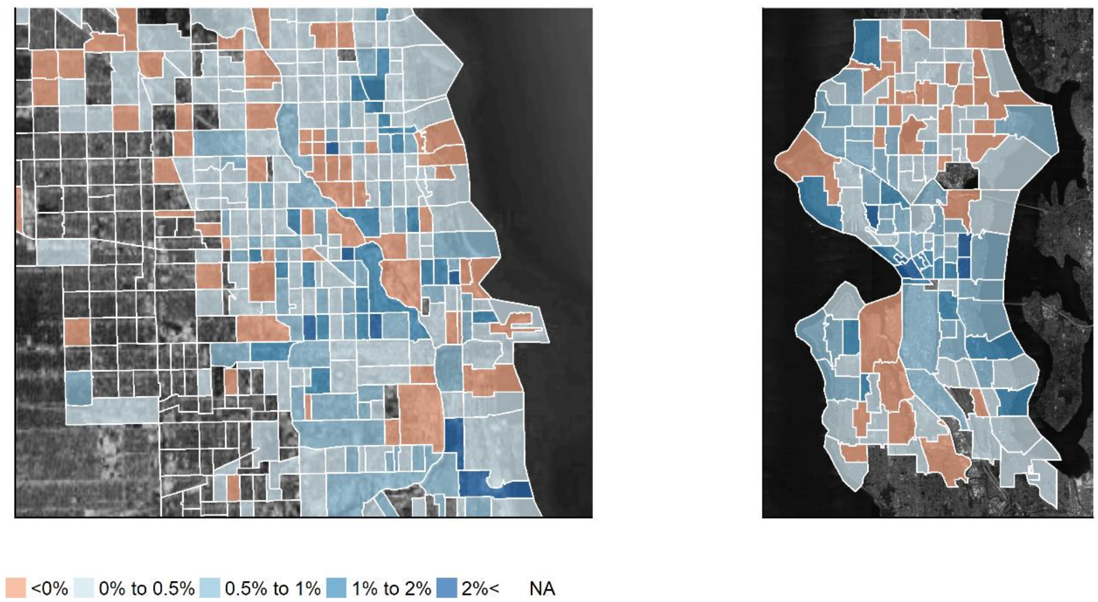
Looking at Airbnb performance within Chicago and Seattle, we can see a more complex dynamic playing out. The share of rental housing occupied by FR listings (Figure 3), does not have a uniform relationship with the performance of those listings (Figure 5). Areas where FR units occupy a large share of rental housing, but do not outperform long term rentals, could indicate a rent gap that has already closed. New exclusive short-term rental properties in these areas are not likely to earn more than long-term rental revenues. The second thing to note is that, when we study these maps in conjunction with the revenue

Table 12. **Performance (% of Rental Revenue, minus the % of Rental Housing) of Entire-Unit Airbnb Listings – All Entire Unit Listings, Frequently Rented and Very Frequently Rented**

Area	All 2015 – Perf.	All 2016 – Perf.	FR 2015 – Perf.	FR 2016 – Perf.	VFR 2015 – Perf.	VFR 2016 – Perf.
All MSA Tracts	-0.34%	-0.21%	0.18%	0.37%	0.15%	0.28%
Central Cities	-0.47%	-0.30%	0.27%	0.52%	0.23%	0.41%
New York MSA	-0.32%	-0.17%	0.23%	0.38%	0.20%	0.28%
Central Cities	-0.43%	-0.26%	0.33%	0.49%	0.28%	0.39%
New York	-0.46%	-0.27%	0.35%	0.52%	0.30%	0.41%
Los Angeles MSA	-0.30%	-0.21%	0.16%	0.37%	0.15%	0.31%
Central Cities	-0.38%	-0.31%	0.21%	0.43%	0.19%	0.38%
Los Angeles	-0.40%	-0.25%	0.33%	0.64%	0.30%	0.56%
Chicago MSA	-0.18%	-0.12%	0.08%	0.17%	0.06%	0.12%
Central Cities	-0.30%	-0.20%	0.13%	0.27%	0.10%	0.19%
Chicago	-0.34%	-0.21%	0.16%	0.33%	0.12%	0.23%
Washington, DC MSA	-0.39%	-0.44%	0.03%	0.09%	0.05%	0.11%
Central Cities	-0.75%	-0.76%	0.06%	0.17%	0.10%	0.22%
Washington	-1.10%	-0.91%	0.21%	0.49%	0.24%	0.52%
Miami MSA	-0.51%	-0.51%	0.22%	0.50%	0.17%	0.37%
Central Cities	-0.82%	-0.60%	0.53%	1.16%	0.39%	0.82%
Miami	-0.61%	-0.72%	0.39%	0.77%	0.25%	0.51%
Boston MSA	-0.23%	-0.06%	0.12%	0.34%	0.10%	0.24%
Central Cities	-0.53%	-0.23%	0.24%	0.63%	0.21%	0.48%
Boston	-0.49%	-0.14%	0.24%	0.68%	0.20%	0.51%
San Francisco MSA	-0.47%	-0.24%	0.29%	0.53%	0.23%	0.41%
Central Cities	-0.59%	-0.26%	0.44%	0.74%	0.35%	0.57%
San Francisco	-0.83%	-0.22%	0.70%	1.19%	0.55%	0.90%
Seattle MSA	-0.28%	-0.16%	0.10%	0.29%	0.09%	0.25%
Central Cities	-0.33%	-0.14%	0.16%	0.42%	0.14%	0.36%
Seattle	-0.73%	-0.37%	0.27%	0.71%	0.26%	0.64%
San Diego MSA	-0.48%	-0.14%	0.09%	0.55%	0.08%	0.33%
Central Cities	-0.71%	-0.29%	0.12%	0.68%	0.11%	0.47%
San Diego	-0.70%	-0.25%	0.13%	0.70%	0.12%	0.49%
Austin MSA	-0.59%	-0.01%	0.30%	0.90%	0.20%	0.54%
Central Cities	-0.67%	-0.08%	0.34%	0.97%	0.23%	0.60%
Austin	-0.73%	-0.08%	0.38%	1.07%	0.26%	0.66%

information from Figure 2, the rent gap generated by Airbnb outside of city centers appears to be relatively small, potentially due to a lack of demand for accommodations in those areas. On the other hand, in a significant majority of neighborhoods, especially in more central areas, FR listings consistently outperform long-term rentals, despite already earning a relatively high percentage of rental revenue. In these areas, the gentrification pressures generated by Airbnb are only likely to increase and thus measuring the continued existence of a rent gap simply by studying the revenue dynamics might not be justifiable.

Figure 6. Airbnb Performance of FR Listings (% of Rental Revenue, minus the % of Rental Housing), Chicago (left) and Seattle (right)*



*Data for census tracts with less than 400 households not displayed. Performance variable not calculated for tracts without FR listings.

3.4 DISCUSSION

The findings presented above point towards three broad dynamics. First, housing units that become exclusive short-term rental properties on Airbnb tend to earn more than long-term rentals on average. Thus, there is a rent gap generated by these listings in urban areas, whereby property owners are incentivized to switch to short-term rentals to capture the higher rents. There is evidence that property owners have responded to this incentive, as an increasing percentage of rental revenue is now generated by exclusive short-term rental properties. The size of the current rent gap varies across the geographies studied; however, across all levels measured, this gap is still likely to induce more property owners to take their units off the long-term rental market or increase long-term rents and induce gentrification pressures.

There are some indications that properties that are exclusively hosting short-term renters are contributing to the housing shortage in these urban areas. FR listings make up a small but significant portion of rental properties in all of these cities. In a number of neighborhoods, Airbnb exclusive properties account for more than 5% of all rental housing. This is likely to place pressure on the rental market and result in higher rents as well as directly displacing renters out of these neighborhoods.

The Airbnb performance measure indicates that across the ten markets studied, the “rent gap” shows no signs of closing. Despite the increasing supply of Airbnb listings, short-term rentals out-perform long-term ones, indicating a lack of price competition. With increasing efforts to regulate Airbnb rentals by cities (Schor and Cansoy 2018), this dynamic might change significantly. Comprehensive and effective regulation has the possibility to curb the conversion of housing to exclusive short-term rental properties. The collection of taxes and fees would also reduce the rent gap generated by short-term rentals. Recently, New York City, Los Angeles, San Francisco and Boston have all passed important regulations aimed at doing precisely these things (Dent 2018; Greenberg 2018; Logan 2018; Loudenback 2018). Future research in this field should study the effects of these regulations and whether they were successful in reducing the gentrification pressures driven by Airbnb.

3.4.1 Impacts of Gentrification

Wachsmuth and Weisler (2018) observe that in New York City, the gentrifying impacts of Airbnb in the future are likely to disproportionately affect neighborhoods where non-White residents are concentrated. The impacts of gentrification on minority and low-income residents – the occupants of gentrified neighborhoods – have been heavily debated even before the introduction of short-term rental platforms. On the one hand, there is some evidence that these groups are displaced as gentrification progresses, either directly due to the loss of their residences or indirectly due to being priced out of their neighborhoods (Atkinson 2004; Zuk et al. 2015). This has been the dominant understanding of gentrification in both academic and lay debates on the phenomenon. It also informs many of the urban social movements which protest and challenge gentrification processes.

On the other hand, Freeman (2005) has called this finding into question, showing that gentrifying neighborhoods do not have higher rates of displaced residents than non-gentrifying neighborhoods. Instead, he suggests that the race- and class-based sorting happens because in-moving residents to gentrifying areas tend to have significantly higher socio-economic status. This is in line with other studies that have shown how neighborhoods undergoing gentrification might actually be attractive for middle-class non-White residents (McKinnish, Walsh, and White 2010) or how they can actually be the initiators of gentrification (Bostic and Martin 2003; Pattillo 2008). However, this body of work does not ignore the fact that whatever the mechanism, gentrification ultimately results in higher income residents taking over areas of the city that used to house lower income residents.

With short-term rentals, there is reason to expect similar trends of displacement, which is part of Wachsmuth and Weisler's (Wachsmuth and Weisler 2018) argument. However, there is some reason to expect that Airbnb-driven gentrification might be weaker in areas with higher concentrations of non-White residents. The economic opportunities generated by the platforms are not distributed equally across urban geographies. A growing body of work documents how users on Airbnb discriminate against people of color (Cui, Li, and Dennis J Zhang 2016; Edelman and Luca 2014; Edelman et al. 2017; Laouenan and Rathelot 2016). Recently, I have argued that structural inequalities along lines of race also play an important role in determining outcomes on the short-term rental platforms (Cansoy and Schor 2017). I found that short-term rentals properties located in areas with higher proportions of residents of color charged lower prices and earned less revenue. In another study (Cansoy 2018), I also showed that it took these properties longer to receive an initial booking and overall they were more likely to have worse ratings, reducing their chances of generating consistent bookings. Consequently, while these unequal outcomes might put property owners located in areas with a higher percentage of non-White residents at a disadvantage, they might also shield these areas from the gentrification pressures generated by Airbnb, or at least reduce them compared to areas with higher concentrations of White residents. Extensive further study is needed to resolve the questions of racial impacts of Airbnb induced gentrification on communities of color.

3.4.2 Limitations:

The analysis presented above has a number of limitations imposed by the data. First, it is not possible to assess whether the scraped data has systematically failed to capture some subset of listings, or whether the scraping effort has been consistent across the two-year period I am studying. This dataset has information on more Airbnb listings, compared to other publicly available dataset on the platform (Cansoy and Schor 2018). It is also the same data used by Wachsmuth and Weisler (2018). Without access to data held by the platforms themselves, large-scale web-scraped data provides the best alternative to study these key sites of economic activity.

Another important limitation of the data is that Airbnb, which only provides a roughly 150 meter-wide circle within which the listing is located, obfuscates the exact location of listings. In this study, I simply used the center of these circles as the location of listings, which might result in some listings being counted in a census tract that they are not actually located in. At the larger geographies, this would only be a concern for listings located in the outside periphery of the area, and thus a smaller concern. Wachsmuth and Weisler (2018) use a proprietary technique to match every listing to the census tract it is most likely located in by utilizing building location data for New York City. Obtaining this type of data and replicating their work across the geographies studied in this paper could increase the accuracy of the findings, but would likely not change the results substantively, since adjacent census tracts tend to be similar in many metrics.

3.5 CONCLUSION

Short-term rentals, enabled by online platforms such as Airbnb, change the economics of housing in urban centers. By increasing potential rents, they generate a significant rent gap, which property owners can exploit with relatively little capital investment. Wachsmuth and Weisler (2018) have argued that this process has already played itself out in some New York City neighborhoods, where property owners have converted significant numbers of units to exclusive short-term rental properties. In other neighborhoods with a significant rent gap, this wave of displacing gentrification has yet to crest.

In this paper, I show that across the ten largest Airbnb markets in the US there are concerning dynamics of short-term rentals inducing gentrification. Short-term rentals generate significant rent gaps across all of the geographies studied, and the rental housing market has already been constricted by the conversion of long-term rentals to exclusive short-term properties. However, unlike Wachsmuth and Weisler (2018), I argue that Airbnb listings' performance, measured as the difference between the percentage of rental revenue generated through Airbnb and the percentage of rental housing occupied by listings, is a better measure of whether the rent gap is open or closed in an area. This measure suggests an expanding rental gap at the both the MSA and city levels. While the picture is more differentiated at the neighborhood level I find that in the central neighborhoods, where exclusively short-term properties already earn a significant amount of total rental revenue, the rent gap remains open. Further research is needed to assess whether the recent municipal regulations can meaningfully curb this rent gap, and whether the effects of gentrification induced by short-term rentals has a disproportionate impact on residents of color.

4.0 CONCLUSION

In this dissertation, I set out to investigate the relationship between technological change and inequality, focusing on the case of short-term rentals facilitated through the online platform Airbnb. This relationship, despite the transformative technological changes we have lived through since the start of the modern era, remains relatively under-theorized. Of the two extant approaches, the SBTC literature conceptualizes technological change at a highly aggregated level, and thus produces little insight into how specific changes, like the set of technologies which enabled the emergence of large sharing economy platforms impact inequality. On the other hand, the loosely associated literature that has studied inequalities in digital technologies remains heavily empirical, without a cohesive theoretical framework or research agenda to produce generalizable insights into the relationship between technological change and inequality.

Throughout three papers, I provide the beginnings of an approach to overcome these shortcomings. I built on the efforts of an emerging "reproductionist" school of thought on the sharing economy, which highlights how existing inequalities are reproduced through these platforms. This insight is supported by my findings in all three papers. Prior inequalities are reproduced through technological change, albeit in novel ways determined by the content of the change itself. The first paper shows that racial segregation hampers the access and success of people of color on Airbnb. Thus people who own or have access to property in urban locales that are already privileged – by virtue of having a greater proportion of White residents, but also with higher incomes and higher educational attainment – are better able to exploit the economic opportunities generated through

Airbnb. The second paper shows that the public reputation system, reproduces racial inequalities rather than ameliorating them. Expectations that the availability of relevant and cheap information on these systems can reduce statistical discrimination are highly problematic, because they ignore how the reputation information itself is produced in a racially biased society. I show that in areas with higher concentrations of residents of color, Airbnb listings face greater hurdles in generating reputation information, and those that succeed receive systematically lower ratings than comparable listings in areas with higher concentrations of White residents. In the last paper, I show how the short-term rentals facilitated by the Airbnb platform create a new vector for gentrification and enhance urban inequalities. These new rentals provide significantly higher profits for property owners and generate dynamics that both directly (through the conversion of long-term rental properties to short-term rental properties) and indirectly (through rising long-term rents) displace urban residents.

These findings indicate that the "reproductionist" insights about the sharing economy should be central to a new understanding of how technological change operates in a context of prior inequality. This understanding needs to focus on how technological change takes places in a society marked by inequality, specifically along lines of race, class, and gender. Technological change, even when it is touted as a solution to inequality, as reputation systems have frequently been characterized, should be met with a robust skepticism that questions its conditions of existence and relevance.

My findings indicate three broad vectors through which technological change facilitates the reproduction of social inequality. The first of these is around access. Technological changes, even when they presumably broaden access, as the sharing economy platforms did for economic opportunity, are not necessarily egalitarian. Existing inequalities, based in economic, cultural, or other factors, play a critical role in determining which groups are better positioned to employ or exploit technological changes to their benefit. In paper one, differential access is evident in evident in how rates of participation change across neighborhoods. In paper two, I provide evidence of differential access in my analysis of how listings in areas with greater concentrations of non-White residents have lower odds of getting an initial booking and have to wait on the platform for longer periods before that booking happens. In paper three, inequalities in access are inherent to the argument that property owners are much better positioned to take advantage of short-term rentals, and renters are much more likely to be displaced due to short-term rental induced gentrification. The second vector by which inequalities are reproduced through technological change is the market mechanisms that are built into these changes. These mechanisms specifically aim to generate differentiated outcomes, often in the pursuit of greater productivity, resource utilization, or disciplinary power. Such mechanisms are prone to generating inequality and not only across these dimensions where the inequality is intended to reward more productive, and disciplined agents utilizing scarce resources in a more efficient way. Even these intended inequalities often result in exploitative relationships between the technology and the individuals, or technology and the environment. However, market mechanisms are also prone to generating systematic inequalities across lines of race, class and gender because they are, often by design, unable to exclude discriminatory behavior, or prevent the accretion of advantage to actors who start at a position of privilege. In paper one, this dynamic is behind the higher prices and higher earnings enjoyed by listings in areas with a greater concentration of White, high-income and highly educated residents. In paper two, this dynamic is evident in the higher odds for low ratings faced by listings in neighborhoods with greater concentration of residents of color. In paper three, market mechanisms reproduce inequality by allowing the unfettered commoditization of urban real estate.

The third vector is embeddedness – technological change and its consequences are not isolated from the society in which they are located. Ultimately, however small the change itself or its consequences, there are spillover effects. Because there are inequalities in access and inequalities enacted through the market outcomes, these spillover effects are more likely than not to reproduce inequality as well. Thus, as the racial inequalities identified in papers one and two accumulate over time, communities of color are likely to face greater economic inequality, as they are not able to take advantage of the economic opportunities presented by the short-term rental platforms. In paper three I argue that these disadvantages might actually shield communities of color from intense gentrification pressures over the medium- to long-term. However, as long-term rents (and ultimately real estate prices) increase in response to short-term rentals, these communities are more likely to be priced out of urban centers.

I do not present these three vectors by which inequality is reproduced through technological change as an exhaustive list, but as foundations for a greater theoretical reckoning with technological change. Such an undertaking must also account for the conditions under which inequalities are identified and understood as solvable by technology. Future research in this area needs to not only develop a new and rigorous approach to data collection and analysis, as I suggest in the papers themselves, but also place a greater premium on fleshing out a political economy of technological change. The claims of egalitarianism and innovation that permeate the popular discourse on technological change, including the sharing economy platforms, needs to be the object of academic skepticism.

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APPENDICES

Appendix A: Full Results For Number Of Listings In Census Tract

	Model 1		Model 2	
	IRR	*std. Error*	*IRR*	*std. Error*
(Intercept)	9.746 ***	0.877	8.441 ***	0.77
Spatial Lag	3.937 ***	0.064	2.183 ***	0.034
Population - Census Tract	1.185 ***	0.011	1.237 ***	0.011
Population - MSA	0.846	0.073	0.737 ***	0.065
Distance to Closest City	1.092 ***	0.009	1.208 ***	0.010
% Non-White	0.894 ***	0.010	1.148 ***	0.016
Median Housing Value			1.279 ***	0.019
% Renter			1.445 ***	0.019
Median Age			1.136 ***	0.014
% with BA or Higher			2.100 ***	0.040
Per Capita Income			0.677 ***	0.018
Gini Coefficient			1.225 ***	0.013
Income*Gini			0.980 *	0.009
N_{MSA}	10		10	
ICC_{MSA}	0.010		0.012	
Observations	15506		15506	
AIC	103342.377		99436.488	
Deviance	17555.894		17476.54	
Notes	** p<.05 ** p<.01 *** p<.001 Reported coefficients are logged odds (incidence rate ratios).*			

Appendix B: Full Results For Nightly Price

	Model 1		Model 2	
	B	*std. Error*	*B*	*std. Error*
Fixed Parts				
(Intercept)	2.253 ***	0.019	2.257 ***	0.013
Spatial Lag	-0.001 **	0.000	-0.001 *	0.000
# of Listings in Tract	0.093 ***	0.002	0.052 ***	0.002
# of Listings per Host	0.008	0.005	0.007	0.005
Instant Booking	-0.015 ***	0.001	-0.015 ***	0.001
Listing Type - Private Room	-0.215 ***	0.001	-0.215 ***	0.001
Listing Type - Shared Room	-0.373 ***	0.002	-0.372 ***	0.002
# of Reviews	-0.010 ***	0.000	-0.010 ***	0.000
Max. Guests	0.131 ***	0.000	0.131 ***	0.000
Distance to Closest City	0.006 ***	0.001	0.022 ***	0.001
Population - Census Tract	-0.011 ***	0.001	-0.007 ***	0.001
Population - MSA	0.004	0.019	-0.010	0.013
% Non-White	-0.045 ***	0.001	-0.008 ***	0.001
Median Housing Value			0.028 ***	0.002
% Renter			0.004 *	0.001
Median Age			0.003 **	0.001
% with BA or Higher			0.007 ***	0.002
Per Capita Income			0.042 ***	0.002
Gini Coefficient			0.010 ***	0.001
Income*Gini			-0.010 ***	0.001
N_{Host}	208975		208975	
N_{tract}	13158		13158	
N_{MSA}	10		10	
ICC_{Host}	0.468		0.501	
ICC_{Tract}	0.113		0.074	
ICC_{MSA}	0.045		0.022	
Observations	316435		316435	
R^2 / Ω_0^2	.912 / .906		.911 / .906	
AIC	-140914.67		-143421.348	
Notes	** p<.05 ** p<.01 *** p<.001 Reported coefficients are linear regression coefficients.*			

Appendix C: Full Results For Annual Revenue

	Model 1		Model 2	
	B	*std. Error*	*B*	*std. Error*
Fixed Parts				
(Intercept)	3.015 ***	0.039	3.017 ***	0.038
Spatial Lag	0.024 ***	0.003	0.025 ***	0.003
# of Listings in Tract	0.079 ***	0.006	0.057 ***	0.007
# of Listings per Host	0.319 ***	0.025	0.318 ***	0.025
Instant Booking	0.049 ***	0.007	0.050 ***	0.007
Listing Type - Private Room	-0.334 ***	0.007	-0.329 ***	0.007
Listing Type - Shared Room	-0.597 ***	0.015	-0.594 ***	0.015
# of Reviews	0.536 ***	0.003	0.536 ***	0.003
Max. Guests	0.147 ***	0.003	0.148 ***	0.003
Distance to Closest City	0.005	0.004	0.011 **	0.004
Population - Census Tract	-0.019 ***	0.004	-0.012 **	0.004
Population - MSA	0.011	0.040	0.000	0.039
% Non-White	-0.035 ***	0.004	-0.027 ***	0.006
Median Housing Value			0.007	0.006
% Renter			0.025 ***	0.005
Median Age			0.022 ***	0.005
% with BA or Higher			0.008	0.009
Per Capita Income			0.001	0.01
Gini Coefficient			0.020 ***	0.004
Income*Gini			-0.008	0.004
N_{Host}	208975		208975	
N_{tract}	13158		13158	
N_{MSA}	10		10	
ICC_{Host}	0.315		0.315	
ICC_{Tract}	0.008		0.008	
ICC_{MSA}	0.005		0.004	
Observations	316435		316435	
R^2 / Ω_0^2	.640 / .573		.640 / .573	
AIC	1107396.671		1107314.692	
Notes	** p<.05 ** p<.01 *** p<.001 Reported coefficients are linear regression coefficients.*			

Appendix D: Full Results For Whether A Listing Was Booked And The Number Of Days Before First Booking

	Booked		Days Bookable until First Booking	
	logistic		*Poisson*	
	(1)	(2)	(3)	(4)
(Intercept)	1.38***	1.37***	3.60***	3.61***
	(0.01)	(0.01)	(0.001)	(0.001)
Spatial Lag	0.12***	0.07***	-0.04***	-0.02***
	(0.01)	(0.01)	(0.001)	(0.001)
MSA - Los Angeles	-0.01	-0.03*	0.01***	0.01***
	(0.02)	(0.02)	(0.001)	(0.001)
MSA - Chicago	0.19***	0.22***	0.06***	0.04***
	(0.02)	(0.03)	(0.002)	(0.002)
MSA - Austin	0.16***	0.20***	-0.01***	-0.04***
	(0.03)	(0.03)	(0.002)	(0.002)
MSA - Washington, DC	-0.17***	-0.12***	0.05***	0.03***
	(0.02)	(0.02)	(0.002)	(0.002)
MSA - Miami	-0.23***	-0.18***	0.17***	0.09***
	(0.02)	(0.02)	(0.001)	(0.001)
MSA - Boston	0.33***	0.33***	-0.04***	-0.04***
	(0.03)	(0.03)	(0.002)	(0.002)
MSA - San Francisco	0.15***	0.14***	-0.13***	-0.13***
	(0.02)	(0.02)	(0.001)	(0.001)
MSA - Seattle	0.39***	0.42***	-0.05***	-0.08***
	(0.03)	(0.03)	(0.002)	(0.002)
MSA - San Diego	0.24***	0.23***	-0.03***	-0.04***
	(0.03)	(0.03)	(0.002)	(0.002)
Distance to City	0.04***	0.06***	0.02***	0.002***
	(0.01)	(0.01)	(0.0003)	(0.0004)
Instantly Bookable	0.27***	0.27***	0.10***	0.09***
	(0.01)	(0.01)	(0.001)	(0.001)
Private Room	-0.31***	-0.30***	0.14***	0.13***
	(0.01)	(0.01)	(0.001)	(0.001)
Shared Room	-0.50***	-0.50***	0.13***	0.13***
	(0.02)	(0.02)	(0.002)	(0.002)
Max. Guests	0.29***	0.30***	0.01***	0.001
	(0.01)	(0.01)	(0.0005)	(0.0005)
Bookable Days	0.48***	0.48***	0.15***	0.15***
	(0.01)	(0.01)	(0.0003)	(0.0003)
Avg. Nightly Price	-0.43***	-0.44***	0.07***	0.08***

	(0.01)	(0.01)	(0.0005)	(0.0005)
# of Listings by Host	-0.07***	-0.07***	0.06***	0.06***
	(0.004)	(0.004)	(0.0003)	(0.0003)
# of Listings in Tract	0.05***	0.04***	-0.03***	-0.01***
	(0.01)	(0.01)	(0.001)	(0.001)
Population - Tract	-0.04***	-0.03***	0.01***	0.01***
	(0.01)	(0.01)	(0.0004)	(0.0004)
% non-White	-0.02***	-0.02**	0.01***	0.01***
	(0.01)	(0.01)	(0.0004)	(0.001)
Per capita Income		-0.07***		0.03***
		(0.01)		(0.001)
Gini Coefficient		0.05***		-0.02***
		(0.01)		(0.0004)
Median Age		0.01		0.02***
		(0.01)		(0.0005)
% Renter		0.05***		-0.03***
		(0.01)		(0.001)
Median Housing Value		0.05***		-0.03***
		(0.01)		(0.001)
% with BA or more		0.05***		-0.04***
		(0.01)		(0.001)
Observations	256,804	256,804	198,452	198,452
Akaike Inf. Crit.	259,512.60	259,307.10	6,529,355.00	6,512,392.00
Note:				*p**p***p<0.001
				Regression coefficients are not exponentiated.

Appendix E: Full Results For Ratings

	Rating (perfect)		Rating (4.8+)		Rating (4.3+)	
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	-0.67***	-0.64***	0.17***	0.20***	2.34***	2.37***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Spatial Lag	-0.13***	-0.09***				
	(0.01)	(0.02)				
Spatial Lag			-0.14***	-0.07***		
			(0.01)	(0.01)		
Spatial Lag					-0.23***	-0.20***
					(0.02)	(0.02)
MSA - Los Angeles	0.22***	0.23***	0.20***	0.22***	-0.05	-0.05
	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)	(0.04)
MSA - Chicago	0.27***	0.23***	0.32***	0.27***	0.21***	0.19**
	(0.04)	(0.04)	(0.03)	(0.04)	(0.06)	(0.07)
MSA - Austin	0.63***	0.58***	0.78***	0.72***	0.73***	0.72***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.09)	(0.09)
MSA - Washington, DC	0.43***	0.31***	0.45***	0.34***	0.28***	0.15*
	(0.04)	(0.04)	(0.03)	(0.04)	(0.06)	(0.07)
MSA - Miami	0.35***	0.29***	0.41***	0.31***	0.27***	0.27***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.05)	(0.05)
MSA - Boston	-0.13***	-0.15***	-0.21***	-0.22***	-0.44***	-0.43***
	(0.04)	(0.04)	(0.03)	(0.04)	(0.06)	(0.06)
MSA - San Francisco	0.18***	0.14***	0.12***	0.09**	-0.08	-0.13**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)
MSA - Seattle	0.27***	0.20***	0.33***	0.27***	0.17*	0.13
	(0.04)	(0.04)	(0.04)	(0.04)	(0.07)	(0.08)
MSA - San Diego	0.34***	0.33***	0.46***	0.45***	0.32***	0.31***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.07)	(0.07)
Distance to City	0.03***	0.02	0.05***	0.03**	0.04*	0.04*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Instantly Bookable	-0.33***	-0.33***	-0.39***	-0.39***	-0.62***	-0.62***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Private Room	0.03	0.01	0.03	0.02	-0.09**	-0.11***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Shared Room	-0.24***	-0.23***	-0.32***	-0.30***	-0.28***	-0.27***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Max. Guests	-0.22***	-0.24***	-0.25***	-0.27***	-0.32***	-0.33***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)

Bookable Days	-0.29***	-0.29***	-0.23***	-0.23***	-0.25***	-0.26***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
% Booked Days	-0.10***	-0.09***	0.04***	0.05***	0.15***	0.15***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Number of Reviews	-0.29***	-0.29***	0.10***	0.10***	0.55***	0.55***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Avg. Nightly Price	0.44***	0.46***	0.51***	0.55***	0.63***	0.66***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
# of Listings by Host	-0.38***	-0.38***	-0.30***	-0.30***	-0.12***	-0.12***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
# of Listings in Tract	-0.08***	-0.06***	-0.12***	-0.11***	-0.08***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Population - Tract	0.04***	0.03***	0.03***	0.02**	0.04**	0.04**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
% non-White	-0.14***	-0.09***	-0.17***	-0.13***	-0.20***	-0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Per capita Income		-0.02		-0.05**		-0.13***
		(0.02)		(0.02)		(0.03)
Gini Coefficient		-0.07***		-0.08***		-0.10***
		(0.01)		(0.01)		(0.01)
Median Age		0.002		0.03*		0.003
		(0.01)		(0.01)		(0.02)
% Renter		-0.09***		-0.10***		-0.07***
		(0.01)		(0.01)		(0.02)
Median Housing Value		-0.03*		-0.05***		0.02
		(0.01)		(0.01)		(0.02)
% with BA or more		0.07***		0.07***		0.17***
		(0.02)		(0.02)		(0.03)
Observations	88,714	88,714	88,714	88,714	88,714	88,714
Akaike Inf. Crit.	99,448.84	99,295.45	116,188.60	115,920.50	49,944.20	49,828.35

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

Regression coefficients are not exponentiated.