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journals.sagepub.com/home/epn **Geoff Boeing**

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Abstract

As the rental housing market moves online, the internet offers divergent possible futures: either the promise of more-equal access to information for previously marginalized homeseekers, or a reproduction of longstanding information inequalities. Biases in online listings' representativeness could impact different communities' access to housing search information, reinforcing traditional information segregation patterns through a digital divide. They could also circumscribe housing practitioners' and researchers' ability to draw broad market insights from listings to understand rental supply and affordability. This study examines millions of Craigslist rental listings across the USA and finds that they spatially concentrate and overrepresent whiter, wealthier, and better-educated communities. Other significant demographic differences exist in age, language, college enrollment, rent, poverty rate, and household size. Most cities' online housing markets are digitally segregated by race and class, and we discuss various implications for residential mobility, community legibility, gentrification, housing voucher utilization, and automated monitoring and analytics in the smart cities paradigm. While Craigslist contains valuable crowdsourced data to better understand affordability and available rental supply in real time, it does not evenly represent all market segments. The internet promises information democratization, and online listings can reduce housing search costs and increase choice sets. However, technology access/preferences and information channel segregation can concentrate such information-broadcasting benefits in already-advantaged communities, reproducing traditional inequalities and reinforcing residential sorting and segregation dynamics. Technology platforms like Craigslist construct new institutions with the power to shape spatial economies, human interactions, and planners' ability to monitor and respond to urban challenges.

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Keywords

Craigslist, digital divide, housing market, housing search, inequality, rental housing, smart cities

Introduction

Large portions of the rental housing market have moved online over the past decade. Today, rental listings are primarily posted on websites like Craigslist, which holds a dominant position in the USA as its 15th overall most-visited website. According to the 2017 American Housing Survey, more renters in urbanized areas found their current homes through a site like Craigslist than through any other information channel. Housing practitioners and researchers, in turn, increasingly collect online listings to assess market supply in the smart cities paradigm of monitoring urban conditions through streams of user-generated data (Hu et al., 2019).

Although online listings have recently become a primary mode of information exchange in US rental housing markets, little is known about how they function or how well they actually represent the full market (Besbris et al., 2018; Boeing and Waddell, 2017; Schachter and Besbris, 2017). If online listings are not representative—that is, if sampling biases exist—what kinds of communities are over- or underrepresented? Biases impact information equity and housing search costs as well as the conclusions that housing researchers and policymakers can draw about the real world from crowdsourced data (Arribas-Bel and Bakens, 2018; Folch et al., 2018; McLaughlin and Young, 2018; Narayanan and MacDonald, 2019). Yet little is currently known about spatial patterns or biases in the rental listings that compose these information landscapes and shape housing search outcomes.

This study assesses online rental market representativeness at the census tract scale, using a dataset of millions of Craigslist listings across the USA. It explores the sociodemographics of over- and underrepresented tracts and estimates spatial regression models to examine these traits' relationships with representation. It finds that listings are spatially concentrated and overrepresent whiter, wealthier, and better-educated tracts. Majority-White tracts are over represented more than twice as often as Hispanic or Black tracts. Although large swaths of this market are affordable to low-to-moderate income and Black families, home-seekers in whiter, wealthier, better-educated, and more-expensive communities have a surplus of information available online to aid their searches, while seekers in other communities face a digital information deficit. The internet helps democratize access to information but it does not necessarily equalize its supply. As the rental housing market moves online, technological self-selection and information supply biases construct new digital inequalities that shape housing search costs, choice sets, residential sorting, and the conclusions planners can draw about rapidly evolving markets.

Inequality in the housing information landscape

Housing technology platforms today forge emerging institutions with the capacity to reshape urban economies, human interactions, and information landscapes (Fields, 2019; Jiao and Bai, 2019; Kim et al., 2019; Shaw, 2018; Wegmann and Jiao, 2017). These information landscapes—and any asymmetries or segregation within them—are central to housing search outcomes and residential sorting (Ben-Shahar and Golan, 2019; Garmaise and Moskowitz, 2004; Kurlat and Stroebel, 2015; Levitt and Syverson, 2008; Metzger et al., 2019).

Prospective renters heterogeneously rely on a constellation of information sources to identify available units, including websites, newspapers, agents/brokers, property-for-rent signs, and word of mouth. Krysan and Crowder (2017) theorize a two-stage search process in which homeseekers decide which neighborhoods to search and then choose which units within them to consider, emphasizing the importance of information supplies. Rae (2015) contends that the internet has emerged as the first port of call for such searches, but online information also impacts the second stage by rendering individual units, and in turn neighborhoods, more legible and accessible to seekers. As the internet constitutes an ever-increasing share of the rental housing information supply, different communities' access to information and capacity to find housing depend both on listings' representativeness and on communities' abilities/interests in engaging with these platforms. This can be considered from the supply side (i.e. the supply of information by landlords, managers, and brokers) and the demand side (i.e. homeseekers' internet usage and search preferences).

On the supply side, information about available housing units for rent traditionally appeared in local newspaper classifieds. Today, however, Craigslist has become the foremost such venue in the USA, even as potential competitors like Facebook, Zillow, and Trulia try to challenge its near-monopoly in online listings (Brown, 2014; Hau, 2006; Kroft and Pope, 2014; Seamans and Zhu, 2014; Yurieff, 2017). Researchers have increasingly turned to Craigslist listings to study individual metropolitan markets (e.g. Besbris et al., 2018; Brown et al., 2017; Halket and Pignatti Morano di Custoza, 2015; Im et al., 2017; Mallach, 2010; Palm, 2018; Schachter and Besbris, 2017; Wegmann and Chapple, 2012). Most studies of demographic representation on Craigslist have focused on discrimination by landlords (e.g. Carlsson and Eriksson, 2014; Evans et al., 2018; Hanson and Santas, 2014; Murchie and Pang, 2018) and the Fair Housing Act (e.g. Larkin, 2010; Oliveri, 2010). Boeing and Waddell (2017) examined Craigslist listings across the USA, concluding that further research was needed to understand sociodemographic submarket representativeness.

On the demand side, who consumes this online supply of information about available rental units? Online housing searches depend on internet access and usage. The rise in internet ubiquity over the past two decades has been accompanied by concerns about a digital divide between information "haves" and "have-nots" (Hersberger, 2003; Riddlesden and Singleton, 2014). This divide may result from cultural differences or social inequalities: age, race, wealth, and education impact exposure and access to technology as well as attitudes, skills, and cultural norms in usage (Jones et al., 2009; Robinson et al., 2015). Younger, whiter, better-educated, and higher-income Americans have higher internet usage rates than other groups (Porter and Donthu, 2006). Internet use and search engine behavior vary among different racial groups and as a function of native language (Slate et al., 2002; Weber and Jaimes, 2011). Older adults are less likely to use the internet, and this effect is more pronounced among those who are low-income, Black, or Hispanic (Choi and DiNitto, 2013). The race gap is closing, however, and as of 2018, 89% of White adults used the internet versus 88% of Hispanic and 87% of Black adults, but usage remains lower today among older, less-educated, and lower-income Americans (Pew Research Center, 2018, 2019).

It is less clear how this translates to housing search: different communities may prefer different information sources as a function of age, education, language, community ties, access to technology, and prior experiences with steering or discrimination. Pre-internet, Newburger (1995) found that Black homebuyers relied on fewer information sources than Whites did, possibly due to housing information being harder to acquire in Black neighborhoods. Farley (1996) found that Blacks relied more on social ties and newspaper ads to find housing than Whites did, due to longstanding practices of real estate agents providing more information to White than Black homeseekers and steering them toward different

neighborhoods. These agents also concentrate in whiter and wealthier neighborhoods, focusing their services and benefits in already-advantaged communities (Besbris and Faber, 2017). Beyond race, DeBoer (1985) argued that elderly homeseekers face higher search costs, more-constrained radii, and fewer information resources than younger seekers: these information asymmetries and inequalities produce housing market disequilibrium, with overpayment rates correlated with seeker characteristics (cf. Desmond and Perkins, 2016; Desmond and Wilmers, 2019).

Do online housing markets attenuate these traditional information supply disparities or do they reproduce historical patterns of information segregation, steering, and sorting? As Stephens (2013: 993) argues, geospatial web platforms and technologies often “reproduce and exacerbate existing representational asymmetries” in the real world (cf. Brannon, 2017; Elwood, 2010; Leszczynski, 2016; Mattern, 2014; Thatcher et al., 2016). Demographics and social networks shape our housing information supplies, producing neighborhood “blind-spots” and gaps in knowledge (Krysan and Bader, 2009). Thus, information democratization and diversity on platforms like Craigslist could help expand and equalize residential searches. Krysan and Crowder (2017) argue that broadening such information sources—including rental search engine results—would expand homeseeker choice sets, in turn lessening the sociostructural factors that guide residential sorting (cf. Sampson and Sharkey, 2008; Steil and Jordan, 2018). While the internet could offer information-disadvantaged homeseekers more information for their searches, it remains unclear if this potential has been realized (Decker, 2010; Palm and Danis, 2001). Besbris et al. (2018) found that the volume and type of information appearing in neighborhoods’ Craigslist listings vary by demographics, with seekers in White- or Asian-majority neighborhoods receiving more information per listing than those in Black or Hispanic neighborhoods. Krysan (2008: 598) found that Blacks were significantly less likely to use the internet to search for housing than Whites, concluding: “Given the rapid growth of the Internet in renting and selling housing, the observed racial digital divide is a point of some concern.”

These studies of representation and participation mainly focus on *demand*. The representativeness of available rental housing *supply* online remains underexplored, yet it could impact equity in multiple ways. First, if internet usage differs between demographic groups—and if certain kinds of communities appear more in online rental listings—neighborhood segregation could be perpetuated through information channel segregation and self-selection: forms of sociostructural steering. Second, it could reproduce longstanding housing information inequalities as new digital inequalities, where privileged communities obtain surpluses of relevant housing information—lessening their search costs—while others face relative deficits. Third, these information supplies could make certain units or neighborhoods more legible and accessible to homeseekers—with implications for gentrification, displacement, and housing voucher utilization.

Methods

Data

Due to its predominance in the information landscape today, Craigslist provides a powerful data source for studying the representativeness of online housing markets. This technology platform and the listings it contains shape human market behaviors while chronicling them for researchers. This study uses it to investigate whether online rental listings over- or underrepresent different communities and how community characteristics explain supply-side representativeness.

The study sites comprise the 12,505 census tracts within the core municipalities of the 50 most populous US metropolitan statistical areas, ignoring tracts that contain no rental units. We adopt the dataset of Craigslist rental housing listings collected in 2014 by Boeing and Waddell (2017), which was filtered to remove duplicates and retain only geolocated listings, resulting in a set of 1.4 million listings (see Boeing and Waddell, 2017, for a detailed explanation of the collection/cleaning process, along with summary statistics of each step).

Next, we spatially join these tracts and rental listings then attach 2014 American Community Survey (ACS) tract-level data (Table 1). Although landlords, not neighborhoods, are the agents of interest, tract-level data offer the finest-scale approximation.

Table 1. List of variables.

Variable	Census source	Description
age2034	DP05_0008PE, DP05_0009PE	Proportion of population 20–34 years old
age65up	DP05_0021PE	Proportion of population 65 years and older
bb1940	DP04_0025PE	Proportion of structures built before 1940
black	DP05_0073PE	Proportion of population that is non-Hispanic Black/ African American
burden	DP04_0139PE, DP04_0140PE	Proportion of occupied rent-paying units paying gross rent > 30% of household income
commute	DP03_0025E	Mean travel time to work (minutes)
dcenter		Straight-line distance (km) from tract centroid to city center
degree	DP02_0067PE	Proportion of population (25 years and older) with bachelor's degree or higher
density	DP05_0001E	Total population (thousands) divided by land area (km ²)
english	DP02_0111PE	Proportion of population (five years and older) with English as the only language spoken at home
foreign	DP02_0092PE	Proportion of population that is foreign-born
hhsiz	DP04_0048E	Average household size of renter-occupied units
hispanic	DP05_0066PE	Proportion of population that is Hispanic/Latino
homeval	DP04_0088E	Median value (US\$, thousands) of owner-occupied housing units
income	DP03_0062E	Median household income (US\$, thousands)
male	DP05_0002PE	Proportion of population that is male
nonrels	DP02_0022PE	Proportion of household members that are non-relatives
poverty	DP03_0128PE	Proportion of families/people with income below the poverty line
rent	DP04_0132E	Median gross rent (US\$, thousands) for occupied units paying rent
rooms	DP04_0036E	Median rooms per housing unit
samesex	DP02_0079PE	Proportion of population (one year and older) who lived in same home a year ago
singldet	DP04_0007PE	Proportion of housing units that are single-unit detached
student	DP02_0057PE	Proportion of population (three years and older) currently enrolled in college or graduate school
units	DP04_0046E, DP04_0005E	Count (thousands) of rental units
vacancy	DP04_0005E	Ratio of vacant units for rent to total rental inventory
white	DP05_0072PE	Proportion of population that is non-Hispanic White

Census sources refer to 2014 ACS tract-level data from which the variable is derived. Percentage estimates are converted to proportions by dividing by 100. Dollar values are 2014 inflation-adjusted US dollars.

The ACS is a sample survey, not an enumeration, and provides average rental vacancy rates rather than snapshots of vacancies at specific times.¹ However, no existing dataset does so at sub-metropolitan scales. US Postal Service vacancy data provide finer spatial granularity, but crucially lack tenure information. Despite imperfections, the ACS offers the best data available to explore these questions by comparing average vacancy rates over time to Craigslist's aggregate listing volumes over time.

Assessing representation

We tally how many listings appear in each tract as count κ . This represents the empirical/observed distribution. The ACS provides the number of vacant units for rent, τ , in each tract. We then calculate a proportional reallocation, ϕ , of these rental listings for each tract in each city as:

$$\phi_t = \frac{\kappa_c \tau_t}{\tau_c} \quad (1)$$

where ϕ_t indicates how many of the observed Craigslist listings in city c would appear in its tract t if these listings were redistributed across c 's tracts according to each's proportion of c 's total vacant units for rent. This represents the theoretical/expected distribution. We then calculate² each tract's over- or underrepresentation on Craigslist, λ , as:

$$\lambda_t = \frac{\kappa_t + 1}{\phi_t + 1} \quad (2)$$

Thus, if $\lambda_t = 1$, tract t has the same number of rental listings on Craigslist that we would expect if the city's listings were redistributed among its tracts in proportion to each's share of the city's total vacant rental units. Higher and lower values indicate over- and underrepresentation respectively. Finally, we calculate Gini coefficients to measure how evenly the listings are distributed across city tracts. A coefficient of 1 indicates that a single tract contains all of the city's listings, while a coefficient of 0 indicates that they are perfectly evenly distributed among all of its tracts.

Between-group differences

Once we have assembled the ACS data and the Craigslist representation indicator λ , we calculate variables' differences-in-means between overrepresented ($\lambda > 1$) and underrepresented ($\lambda < 1$) tracts, as well as statistical significance via t -tests and practical significance (effect size) via Cohen's d :

$$d = \frac{\mu_o - \mu_u}{\sigma_p} \quad (3)$$

where μ_o and μ_u are the means of the over- and underrepresented tracts and σ_p represents their pooled standard deviation. This measures a standardized magnitude of difference between these two groups—namely, by how many standard deviations their means differ. By convention, a d of 0.8 or greater represents a large effect, 0.5–0.8 represents a medium effect, 0.2–0.5 a small effect, and values below 0.2 a negligible effect (Cohen, 1992).

Regression analysis

These differences can be unpacked while controlling for inventory, turnover, and other variables that influence listing volume. To investigate the *ceteris paribus* associations between Craigslist representation and different sociodemographic and built environment characteristics, we estimate a multiple regression model (Model 1) via ordinary least squares (OLS):

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon \quad (4)$$

where the response vector y is tract Craigslist representation (λ), β_0 is the intercept, X_1 is a matrix of observations on tract sociodemographic and neighborhood variables, X_2 is a matrix of city dummy variables, ϵ is random error, and β_1 and β_2 are vectors of parameters to be estimated. To correctly specify a model that is linear-in-parameters, we log-transform the response³ and some of the predictors in X_1 . Thus we can interpret the coefficients on log-transformed predictors as elasticities (the percentage change in the response given a 1% increase in the predictor) and those on untransformed predictors as semi-elasticities (the percentage change in the response given a one-unit increase in the predictor).

We control for intermetropolitan variation with X_2 's spatial fixed effects and for rental inventory and turnover with three variables in X_1 : the count of rental units, the proportion of the population living in the same residence as one year ago, and the rental vacancy rate. Neighborhood character variables include the tract's median rooms per home, proportion of structures built before 1940, distance to the city center, and average commute time. These control for typical building size and age as well as location centrality and job accessibility.

Sociodemographic predictors include the tract's median household income, median gross rent, average renter household size, the proportions of the population 20–34 years old and 65 or older, the proportion currently enrolled in college/graduate school, the proportion with a bachelor's or graduate degree, the proportion that speaks English-only, and the proportions of the population that are White,⁴ Black, or Hispanic. The model includes an interaction term—the White proportion $\times$ median income—to explore how race moderates the effect of income on representation.

Finally, Model 1's diagnostics suggest the presence of spatial diffusion, so we estimate an additional spatial lag model (Model 2) via maximum-likelihood estimation (MLE):

$$y = \rho W y + \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon \quad (5)$$

with variables defined as above, but also including W as a queen-contiguity spatial weights matrix and ρ as the spatial autoregressive coefficient to be estimated.

Findings

Spatial compression

Across these cities, the tract-level observed distribution of Craigslist listings, κ , has a Gini coefficient of 0.80, while the expected distribution, ϕ , has a coefficient of 0.70—that is, rental listings are more spatially concentrated than a proportional distribution would be—but this phenomenon is uneven between cities. In four markets (San Francisco, San Jose, Oklahoma City, and Las Vegas), the ϕ Gini is slightly higher (by 0.4–7.7%) than that of κ , indicating rental listings are slightly more dispersed. However, in St. Louis, Providence, Miami, and

Hartford, the κ Gini is 70–120% higher than that of ϕ , indicating an extreme spatial compression of listings in these rental markets.

As this concentration suggests, most tracts are at least slightly underrepresented on Craigslist (i.e. $\lambda < 1$), but this varies by demographics. Overall, 52% of majority-White tracts are overrepresented, compared to only 19% of majority-Black and 22% of majority-Hispanic tracts. Examining the racial composition of tracts with $\lambda < 0.25$ (i.e. with fewer than 25% of the listings we expect), only 11% of majority-White tracts are as such “very” underrepresented, but 27% of Black and 35% of Hispanic tracts are.

Differences between over- and underrepresented tracts

Figures 1 and 2 illustrate descriptive patterns in how sociodemographic and other neighborhood characteristics differ significantly between over- and underrepresented tracts nationwide. Figure 1 depicts the distributions of key variables, illustrating the differences between these two groups. In particular, the White proportion’s distribution nearly inverts between over- and underrepresented tracts. Six variables’ differences demonstrate medium effect sizes, either positive or negative (Table 2⁵): median income, gross rent, the White population proportion, the proportion with a bachelor’s/graduate degree, the proportion enrolled in college/graduate school, the proportion below poverty, and the proportion experiencing rent burden. Twelve more have small, significant effects. Figure 2 shows how the expected and observed distributions of listings diverge. For instance, we expect only 33% of all listings to appear in tracts with median income exceeding US\$55,000, but instead we observe 56%. Similarly, we expect majority-White tracts to contain 39% of all listings, but instead they contain 59%.

On average, compared to underrepresented tracts, overrepresented tracts have a White population proportion 20 percentage-points (pp) higher,⁶ a Hispanic proportion 8 pp lower, and a Black proportion 14 pp lower (Table 2). The proportion that speaks English-only is 8 pp higher and the foreign-born proportion is 4 pp lower. Average median home values are nearly US\$80,000 higher, median incomes US\$21,000 higher, and median gross rents US \$200 higher. The proportion of the population with a bachelor’s/graduate degree is 17 pp higher and the proportion currently enrolled in college/graduate school is 7 pp higher, on average. In overrepresented tracts the proportion of the population below the poverty line is 9 pp lower and the rent-burdened proportion is 8 pp lower. Overrepresented tracts offer shorter commutes and have slightly lower population densities, smaller household sizes, and higher proportions of single-unit detached housing on average.

These differences are significant, but are they consistent across cities? Although Craigslist represents certain cities more evenly than others, some consistent patterns emerge in the per-city differences between over- and underrepresented tracts (Table 3). Average median income is higher in overrepresented tracts (i.e. $d > 0$) in every city, and more than 1.5 standard deviations higher in Miami and Chicago. Rents are higher in overrepresented tracts in every city with a significant difference, and more than one standard deviation higher in seven cities, again led by Miami and Chicago. The proportion of the population with a bachelor’s/graduate degree is higher in every city with a significant difference, and more than 1.5 standard deviations higher in Miami, Hartford, Chicago, and New Orleans. The proportion enrolled in college/graduate school is higher in every city with a significant difference, and more than one standard deviation higher in Miami, Chicago, and Philadelphia. Similarly, the White proportion is higher in every city with a significant

Figure 1. Variables' estimated probability densities across over-/underrepresented tracts: x-axis is in variable's units (details in Table 1). The probability for any interval equals the corresponding area under the curve.

difference, and more than one standard deviation higher in seven of these, led by Miami and New Orleans. However, the proportion that speaks English-only is more divisive: while some cities have medium-sized negative effects, many more demonstrate medium or large positive effects. Finally, the proportion below poverty is lower in every city with a significant difference, led by Miami, Houston, Washington, and New Orleans, and the average renter household size is lower in all but one city (Las Vegas) with a significant difference, led by Hartford, Miami, and Boston.

Regression results

As the two regression models tell similar stories (Table 4), we focus on Model 1 for interpretability.⁷ A *ceteris paribus* US\$10 increase in tract median rent increases representation on Craigslist by 0.58%, a 1 pp increase in the proportion with a bachelor's/graduate degree increases it 1.03%, and a 1 pp increase in the proportion that speaks English-only increases it 0.69%. A 1 pp increase in the 20–34-year-old population proportion increases it by 0.41%, but a 1 pp increase in the proportion aged 65 and older decreases it 0.50%. A 1% increase in distance from the city center decreases tract representation on Craigslist by 0.12% and a 1 pp increase in the proportion of structures built before 1940 decreases it 0.28%. Although a one-room increase per home increases representation by 4.4%, a 1% increase in renter household size decreases it 0.21%.

A 1 pp increase in the Black population proportion decreases representation by 0.57% and a 1 pp increase in the Hispanic proportion decreases it 0.30%. Thus, even when controlling for income, education, age, and language, greater shares of Black or Hispanic residents predict lower representation in online rental listings, indicating a distinct

Figure 2. Share of total rental listings (expected versus observed distributions) in tracts with various characteristics.

Table 2. Differences-in-means between over-/underrepresented tracts nationwide.

	<i>d</i>	<i>δ</i>
degree	0.79	0.169*
income	0.74	20.734*
white	0.72	0.203*
rent	0.58	0.206*
student	0.39	0.074*
homeval	0.35	79.116*
singldet	0.31	0.096*
english	0.31	0.077*
rooms	0.29	0.324*
nonrels	0.23	0.014*
age2034	0.21	0.021*
male	0.16	0.007*
age65up	0.07	0.004*
dcenter	0.05	0.377*
bb1940	−0.15	−0.038*
density	−0.15	−1.348*
sameres	−0.19	−0.019*
foreign	−0.25	−0.043*
hysize	−0.25	−0.185*
hispanic	−0.33	−0.084*
commute	−0.44	−3.343*
black	−0.47	−0.141*
burden	−0.52	−0.076*
poverty	−0.61	−0.088*

Cohen's *d* represents effect size, *δ* represents difference, *indicates t-test significance at *p* < 0.05.

race/ethnicity effect. Given the interaction term, the marginal effect of income on Craigslist representation depends on the White population proportion. When the population is 10% White, a 1% increase in median income increases representation by 0.33%. But with a 90% White population, a 1% increase in median income increases it by only 0.06%. Thus, higher incomes are associated with greater online representation in less-White communities, but

Table 3. Per-city difference-in-means effect sizes (Cohen's *d*) between over-/underrepresented tracts.

	income	rent	degree	poverty	student	english	white	hhsz
Atlanta, GA	0.45*	0.73*	0.69*	-0.45*	0.42*	-0.32	0.69*	-0.49*
Austin, TX	0.63*	0.40*	0.78*	-0.50*	0.08	0.64*	0.76*	-0.19
Baltimore, MD	0.79*	0.62*	1.21*	-0.53*	0.96*	-0.50*	1.03*	-0.61*
Birmingham, AL	0.84*	0.71*	0.81*	-0.88*	0.24	-0.14	0.61*	0.00
Boston, MA	0.67*	0.60*	0.98*	-0.36*	0.60*	0.57*	1.03*	-0.98*
Buffalo, NY	0.50*	0.61*	0.11	-0.21	0.19	0.26	0.30	0.32
Charlotte, NC	0.63*	0.60*	0.74*	-0.64*	0.34*	0.30*	0.58*	-0.16
Chicago, IL	1.51*	1.33*	1.62*	-0.89*	1.04*	0.32*	1.36*	-0.82*
Cincinnati, OH	0.54*	0.82*	0.62*	-0.45*	0.46*	-0.53*	0.84*	-0.01
Cleveland, OH	0.51*	0.32	0.59*	-0.37*	0.40*	-0.49*	0.63*	-0.17
Columbus, OH	0.92*	0.83*	0.72*	-0.79*	-0.03	0.38*	0.72*	-0.18
Dallas, TX	0.90*	0.91*	1.01*	-0.83*	0.67*	0.61*	0.97*	-0.49*
Denver, CO	0.51*	0.65*	0.42*	-0.47*	0.27	0.40*	0.41*	-0.12
Detroit, MI	0.22	0.42*	0.34*	-0.26	0.30	0.22	0.06	0.08
Hartford, CT	0.57	0.28	1.90*	-0.59	0.79	0.54	0.93	-1.52*
Houston, TX	0.99*	0.95*	0.99*	-0.98*	0.50*	0.73*	1.04*	-0.44*
Indianapolis, IN	0.69*	0.42*	0.60*	-0.69*	0.11	0.30*	0.68*	-0.22
Jacksonville, FL	0.59*	0.39*	0.57*	-0.44*	0.04	-0.13	0.43*	-0.08
Kansas City, MO	0.62*	0.72*	0.57*	-0.51*	0.16	0.28	0.45*	-0.03
Las Vegas, NV	1.01*	1.13*	0.69*	-0.81*	0.18	0.73*	0.65*	0.39*
Los Angeles, CA	0.80*	0.88*	0.78*	-0.67*	0.40*	0.65*	0.79*	-0.35*
Louisville, KY	1.15*	0.79*	0.88*	-0.88*	0.46*	0.14	0.86*	-0.31
Memphis, TN	0.89*	0.89*	0.63*	-0.82*	0.14	-0.08	0.61*	-0.03
Miami, FL	1.68*	1.54*	2.08*	-1.37*	1.26*	0.17	2.00*	-1.18*
Milwaukee, WI	0.77*	0.56*	0.99*	-0.59*	0.98*	0.29	0.90*	-0.47*
Minneapolis, MN	0.35	0.32	0.67*	-0.31	0.34	0.40*	0.59*	-0.35
Nashville, TN	0.70*	0.98*	1.00*	-0.68*	0.35*	0.01	0.79*	-0.25
New Orleans, LA	1.14*	1.11*	1.51*	-0.90*	0.86*	-0.28	1.59*	-0.36*
New York, NY	0.68*	0.67*	0.97*	-0.36*	0.59*	0.37*	0.52*	-0.62*
Oklahoma City, OK	0.74*	0.46*	0.72*	-0.59*	0.26	0.51*	0.63*	-0.07
Orlando, FL	0.62*	0.69*	0.65*	-0.54*	0.27	0.05	0.56*	-0.26
Philadelphia, PA	0.75*	0.76*	1.19*	-0.38*	1.01*	0.31*	0.70*	-0.61*
Phoenix, AZ	0.74*	0.66*	0.60*	-0.81*	0.21*	0.66*	0.73*	-0.01
Pittsburgh, PA	0.75*	0.58*	0.76*	-0.72*	0.27	-0.26	0.83*	-0.11
Portland, OR	0.47*	0.44*	0.48*	-0.45*	-0.06	0.43*	0.46*	-0.28
Providence, RI	0.18	-0.02	0.26	0.09	0.13	0.62	0.38	-0.48
Raleigh, NC	0.67*	0.14	0.89*	-0.46*	0.09	0.34	0.67*	-0.10
Richmond, VA	0.37	1.12*	0.51	-0.05	0.50	-0.64*	0.49	0.13
Riverside, CA	0.44	0.70*	0.38	-0.50*	-0.05	0.20	0.33	-0.27
Sacramento, CA	0.75*	0.57*	0.65*	-0.72*	0.04	0.39*	0.27	-0.35
Salt Lake City, UT	0.46	0.51	0.00	-0.25	-0.26	-0.14	-0.14	0.48
San Antonio, TX	1.01*	0.84*	0.72*	-0.71*	0.04	0.87*	0.80*	0.05
San Diego, CA	1.02*	1.04*	0.72*	-0.81*	-0.12	0.40*	0.43*	0.06
San Francisco, CA	0.41*	0.50*	0.24	-0.41*	-0.03	0.14	0.10	0.12
San Jose, CA	0.59*	0.54*	0.31*	-0.51*	-0.13	0.16	0.13	0.25
Seattle, WA	0.24	0.19	0.27	-0.04	0.24	0.12	0.22	-0.02
St. Louis, MO	0.70*	0.39	0.79*	-0.48*	0.62*	-0.36	0.77*	-0.56*
Tampa, FL	0.77*	0.63*	0.59*	-0.67*	-0.04	0.36	0.45*	-0.14
Virginia Beach, VA	0.40	0.59*	-0.04	-0.23	-0.12	-0.14	0.24	0.39
Washington, DC	1.06*	1.23*	1.34*	-0.91*	0.82*	-0.77*	1.15*	-0.52*

*indicates corresponding difference-in-means t-test significance at $p < 0.05$.

Table 4. Regression model parameter estimates and standard errors.

	Model 1		Model 2	
	Estimate	SE	Estimate	SE
constant	-0.730*	0.316	-0.425	0.313
spatial lag (ρ)	—	—	0.582*	0.032
units	-0.098*	0.020	-0.106*	0.020
vacancy	-11.476*	0.165	-11.326*	0.163
sameres	-0.399*	0.147	-0.385*	0.145
dcenter_log	-0.118*	0.020	-0.134*	0.019
commute_log	-0.069	0.070	-0.028	0.069
bb1940	-0.283*	0.057	-0.246*	0.056
rooms	0.044*	0.019	0.051*	0.019
rent	0.575*	0.052	0.500*	0.052
income_log	0.359*	0.048	0.350*	0.047
age2034	0.406*	0.196	0.294	0.193
age65up	-0.498*	0.223	-0.461*	0.220
student	0.140	0.094	0.161	0.093
english	0.686*	0.121	0.571*	0.120
hhsz_log	-0.212*	0.064	-0.224*	0.064
degree	1.034*	0.112	0.867*	0.110
white	0.734*	0.350	0.787*	0.345
black	-0.572*	0.137	-0.424*	0.136
hispanic	-0.296*	0.106	-0.218*	0.105
white $\times$ income_log	-0.333*	0.081	-0.330*	0.080
R^2	0.46		—	
Pseudo- R^2	—		0.47	
AIC	35,895		35,685	
Log-likelihood	-17,879		-17,773	

Variables/units defined in Table 1. Model 1 (equation 4) is estimated with OLS. Model 2 (equation 5) is estimated with MLE. Spatial fixed effects not reported. Dependent variable is Craigslist representation (λ) and * indicates significance at $p < 0.05$.

homogeneously White communities tend to be represented similarly online nearly irrespective of income. Likewise, in poorer tracts, “whiteness” has a more positive effect: when median income is US\$8000, a 1 pp increase in the White population proportion increases Craigslist representation by 0.04%. But when median income is US\$100,000, a 1 pp increase in the White proportion decreases it by 0.80%. In other words, having a larger proportion of White residents predicts greater online representation in very poor communities, but in high-income communities it predicts lower representation: the model’s interaction/moderation effects suggest that wealthier Whites may be more likely to hire brokers or rely on more-exclusive listing services than the free-and-open Craigslist platform.

Finally, we perform a series of robustness tests,⁸ across which we find the models tell a consistent story, especially regarding key variables of interest. For example, the proportion-Black and proportion-Hispanic parameter estimates remain negative across these tests and remain significant across nearly all of them. The median rent and median income parameter estimates remain positive and significant across all the robustness tests. In other words, these key race/ethnicity and socioeconomic status trends persist throughout various analytical reformulations.

Discussion

Representativeness

These data distill the collective behavior and intentions of millions of people listing rental units online. They do not, however, represent all market segments and activity. It becomes essential to understand these biases as homeseekers and researchers increasingly turn to the internet to explore rental markets. Craigslist listings spatially concentrate more than expected and some markets—such as Miami’s—demonstrate extreme compression. Such cities consistently appear among those with the largest differences between over- and under-represented tracts across multiple sociodemographic variables. Their online housing markets are spatially concentrated and digitally segregated by race and class.

Miami’s disparities starkly illustrate this. Its average population proportion with a college degree and White proportion are both two standard deviations higher in over- versus underrepresented tracts. Its average median income and rent are both 1.5 standard deviations higher. On average in Miami, 51% of the population has a degree in overrepresented tracts versus only 17% in underrepresented tracts; 33% versus 7% of the population is White, household incomes are US\$67,000 versus US\$28,000, and home values are US\$371,000 versus US\$163,000. Nationwide, tracts overrepresented on Craigslist are significantly better-educated, whiter, and wealthier than underrepresented tracts. They have higher rents and larger homes, but smaller household sizes. They contain more college students, more English-only speakers, and fewer immigrants. Majority-White tracts are overrepresented 2.4 and 2.7 times as often as Hispanic and Black tracts. Conversely, only one in nine majority-White tracts is “very” underrepresented, compared to over one-quarter of Black and over one-third of Hispanic tracts. Craigslist’s information-broadcasting benefits concentrate in traditionally advantaged communities.

Controlling for confounds to disentangle relationships, we find that higher rents and larger proportions of the population that are college-educated, aged 20–34, and speak English-only each significantly predict greater representation on Craigslist. Newer housing stock and more rooms per home—but smaller renter household sizes—also predict greater representation. Higher incomes have a universally positive relationship with representation, but a larger one in tracts with higher minority populations. Finally, the key race/ethnicity effects persist in both models and throughout the robustness tests: larger Black and Hispanic shares of the population consistently predict lower representation in online rental listings.

Digital inequality or a redoubt of illegibility?

Beyond identifying sampling biases that render certain communities less legible to big data analytics, these findings also contribute supply-side evidence to theories of the digital divide and disparate housing search. For instance, the literature suggests that Black and elderly Americans are less likely to search for housing online, and we confirm that these communities are less represented in online listings. Our findings on immigrants and non-English speakers may relate to common preferences to use soft ties rather than English-language websites to advertise or seek housing. Craigslist’s information channel dominance varies accordingly within and between cities.

Of course, certain communities may prefer certain information channels for a variety of reasons. But as the housing market moves online, technological self-selection among listers and seekers reinforces the sociostructural sorting mechanisms that perpetuate neighborhood blind-spots, residential segregation, and unequal search costs. This study identifies structural

differences in this information supply between different kinds of communities, but not *why* each submarket behaves differently—many factors could be simultaneously at play. Yet it demonstrates that the spatial patterns of traditional housing information inequality and steering are reproduced online through the segregation and asymmetry of information supplies.

These phenomena have various implications for residential mobility, sorting, and housing policy. As homeseekers tend to search for units in neighborhoods they are already familiar with (Krysan and Crowder, 2017), disadvantaged communities miss out on the reduced search costs and expanded choice sets provided by online platforms—benefits that instead primarily accrue to already-advantaged communities. A two-tiered system emerges in which privileged communities exchange housing information through one channel, while all others resort to separate channels. These forces perpetuate the self-reinforcing cycles of durable inequality: information segregation limits homeseekers' discovery of housing in neighborhoods different from their own—in turn limiting the ability to integrate neighborhoods for more diversity of incomes, education levels, ages, and ethnicities (cf. Ellen, 2018; Krysan and Crowder, 2017; Pendall, 2018; Steil and Jordan, 2018).

Conversely, another important implication is that *not* appearing in online listings could be advantageous for underprivileged neighborhoods if it makes them less accessible to gentrification and displacement. That is, if these communities' members tend to search for housing online less than wealthier seekers do, and if available units in these neighborhoods appear online less, they may be less discoverable to internet-savvy outsiders. Thus, information underrepresentation could shield vulnerable communities in a redoubt of digital illegibility, while reciprocally making overrepresented privileged communities more legible to a broad cross-section of homeseekers who otherwise may not have acquired information about these neighborhoods. The latter has important policy ramifications as it could expand the choice sets of housing voucher holders seeking to move to higher-opportunity neighborhoods, if affordable units can be found (cf. McLaughlin and Young, 2018; Reina et al., 2019; Rosen, 2014; Schwartz et al., 2017). Practitioners, for example, could take advantage of this by broadcasting eligible-unit information online or by helping voucher holders devise online search strategies that focus on unit characteristics in higher-opportunity neighborhoods rather than familiar geographic silos.

Finally, what about market segmentation? Concerns about digital inequality could be assuaged if online listings match high-end housing supply and demand, while other segments simply use a different suitable information channel instead. But, crucially, Craigslist does not merely represent the high end of the market: 49% of these listings are affordable (i.e. asking rent < 30% of income) for households just below the 2014 US median household income, and 23% of them are affordable for households just below the corresponding Black median. Millions of Craigslist rental listings *are* within the reach of low-to-moderate income and Black families—yet listings appear disproportionately infrequently in these communities. Housing brokers historically provided different information to White and Black homeseekers—although the internet promises information democratization, these disparities seem to continue online.

Information landscapes and housing dynamics

A critical project lies ahead in unpacking the cause-and-effect/supply-and-demand question. Do landlords in certain communities advertise online less because they know their market segment uses the internet less to search for housing? Or do certain communities use the internet less to search for housing because of unfamiliarity, its dearth of relevant

information, or past experiences with racialized interactions? If a community member rarely finds suitable units when she does search online, why would she continue doing so? Conversely, a relative affinity for internet use in wealthier, whiter, better-educated neighborhoods could stimulate the local supply of online information. Local landlords in certain neighborhoods may prefer to advertise online as their own internet usage reflects that of the surrounding community. Neighborhoods with more subsidized housing might rely on other information channels, even other online channels such as <https://gosection8.com>. Some landlords even avoid Craigslist to deliberately filter and limit the number of potential applicants (Mendez, 2016). Such patterns reflect path-dependent interactions of supply-and-demand feedback loops, suppressing some communities' usage while buttressing that of others.

Although Craigslist does not constitute the entire online listings marketplace, it holds a dominant market position and has uniquely low barriers to entry. However, these listings were collected during spring and could reflect seasonal biases: future work can confirm these findings with longer-term longitudinal data and larger sample sizes to lessen the lumpiness of real-world volunteered geographic information. This study examined large core cities, not wider metropolitan areas or small towns. Although many core cities contain extensive suburban neighborhoods, the inclusion of further-flung suburbs and exurbs might change estimated model parameters: future research can examine regional markets or estimate individual local models. Finally, due to the discussed limitations of ACS vacant unit counts, follow-up work should confirm these results with additional sources of vacancy data.

Our findings provide a first glimpse into this information landscape. This study modeled tract-level representation, but subsequent research can investigate how demographic, neighborhood, and unit characteristics contribute to asking rents and the difference between asking rents and corresponding ACS rents. This leads to a critical open question: do online listings render units in disadvantaged neighborhoods more accessible to privileged homeseekers, or does underrepresentation shield these communities from "colonization"? Given the substantial demographic disparities identified here, future work can explore how tracts change over time to investigate online listings' role in housing search efficiency and the broader dynamics of gentrification.

Conclusion

If information is power in today's cities and markets, then disparate access to it can influence community futures, opportunities, and equity. As online platforms capture an ever-greater share of the rental housing market's information landscape, data sources like Craigslist offer invaluable opportunities to understand affordability and available rental supply in real time. They do not, however, provide a holistic view of the market, as this information exchange over- and underrepresents certain communities.

This study developed a methodology to identify sampling biases in large harvested urban datasets, providing a glimpse into the supply side of digital inequality and the potential blind-spots of smart city automated analytics. The internet's ability to broaden information sources and democratize access to housing data remains contingent on landlords listing online. Housing seekers in whiter, wealthier, better-educated, and more-expensive communities have a surplus of relevant information online to aid their searches, while seekers in other communities face a deficit, reproducing historical patterns of information inequality. In turn, these biases influence the reinforcing feedback loops of supply and demand in

community usage and residential sorting, as well as the conclusions that housing planners can draw by collecting these data.

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Notes

1. See Cresce (2012), Spielman et al. (2014), and Logan et al. (2019) for comprehensive reviews and discussion of ACS tract-scale representativeness and limitations.
2. We add 1 to the numerator and denominator to avoid occasional division by zero and logarithm of zero.
3. Ratios lack symmetry: when $\kappa < \phi$, λ ranges from 0 to 1, but when $\kappa > \phi$, λ ranges from 1 to infinity. The logarithm corrects this: when $\kappa = \phi$, $\lambda = 1$ and $\log(\lambda) = 0$. It produces symmetry as $\log(a/b) = -\log(b/a)$. That is, $\log(a/b) = \log(a) - \log(b)$, so we evaluate the algebraic difference between logarithmic values.
4. "White" and "Black" are shorthand throughout for non-Hispanic White/Black.
5. As a robustness test, we also recalculate δ in Table 2 after discarding outliers (at ± 2 and ± 3 standard deviations) in each variable and λ . All values remain significant and signed in the same directions, with one exception: distance to city center.
6. We distinguish between percentage-point differences, which are additive, and percent changes, which are not.
7. Due to spatial diffusion, Model 2's coefficients cannot be directly interpreted as marginal effects because the response depends on the predictors' values at all spatially correlated locations (Anselin and Rey, 2014: 164).
8. These tests include re-estimating equations (4) and (5) after: removing response variable outliers (at ± 2 and ± 3 standard deviations); operationalizing a location quotient as an alternative response variable (see Billings and Johnson, 2012); filtering the tracts by various minimum-listings thresholds; adding a spatial-error term to each equation (see Anselin and Rey, 2014); and computing an alternative distance-decay spatial weights matrix.

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