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# A. Understanding CL Data

### A-1 Craigslist Market vs Census MSA Definition

For most metros, the corresponding Craigslist site closely matches Census MSA definitions. There are a few discrepancies between Craigslist market and Census MSA definitions. Because we only use Census data at the tract level and follow Craigslist market definitions to determine metro area boundaries, any discrepancies do not impact our results. For example, the 'SFBay' Craigslist site covers both the San Francisco-Oakland-Hayward, CA MSA and the San Jose-Sunnyvale-Santa Clara, CA MSA. We refer to this site as the San Francisco Bay Area. Similarly, while the Census treats Miami, Fort Lauderdale, and West Palm Beach, FL as one MSA, in May of 2017 when we began data collection, each of these areas had its own Craigslist site. During data collection, Craigslist switched to using just one site, with the Fort Lauderdale and West Palm Beach sites now redirecting to the main Miami site. We combine all unique listings from these three sites and refer to them as the Miami metro area. The Los Angeles Craigslist covers Los Angeles County area rather than Los Angeles-Long Beach-Anaheim MSA, which includes Orange County. Craigslist has a separate site for Orange County, which we do not include as part of our Los Angeles metro area. While these examples demonstrate that Craigslist and Census data do not follow identical definitions of metro areas, in our paper we only use Census data at the tract level, and follow Craigslist market definitions to determine metro area boundaries for our MSA fixed effects, so these discrepancies do not impact our results.

# A-2 Data Distribution across MSAs, Tracts, and Neighborhood Types

Table A1: Number of Listings by MSA

	MSA
Atlanta Candy Cominga Daggyall	41974
Atlanta-Sandy Springs-Roswell Austin-Round Rock	
Baltimore-Columbia-Towson	29572 45833
Birmingham-Hoover	21892
Boston-Cambridge-Newton	18746
Buffalo-Cheektowaga-Niagara Falls	22816
Charlotte-Concord-Gastonia	44128
Chicago-Naperville-Elgin	27501
Cincinnati	33301
Cleveland-Elyria	25635
Columbus	36046
Dallas-Fort Worth-Arlington	39943
Denver-Aurora-Lakewood	48877
Detroit-Warren-Dearborn	28637
Hartford-West Hartford-East Hartford	25035
Houston-The Woodlands-Sugar Land	35970
Indianapolis-Carmel-Anderson	34631
Jacksonville	34982
Kansas City	23029
Las Vegas-Henderson-Paradise	25894
Los Angeles-Long Beach-Anaheim	46669
Louisville-Jefferson County	29548
Memphis	25155
Miami-Fort Lauderdale-West Palm Beach	50896
Milwaukee-Waukesha-West Allis	30336
Minneapolis-St. Paul-Bloomington	39494
Nashville-Davidson-Murfreesboro-Franklin	35577
New Orleans-Metairie	29525
New York-Newark-Jersey City	42814
Oklahoma City	26889
Orlando-Kissimmee-Sanford	37223
Philadelphia-Camden-Wilmington	38382
Phoenix-Mesa-Scottsdale	37176
Pittsburgh	32074
Portland-Vancouver-Hillsboro	51815
Providence-Warwick	26694
Raleigh	46891
Richmond	38892
Riverside-San Bernardino-Ontario	42583
Sacramento-Roseville-Arden-Arcade	42214
Salt Lake City	46315
San Antonio-New Braunfels	25808
San Diego-Carlsbad	47671
San Francisco-Oakland-Hayward	54491
Seattle-Tacoma-Bellevue	52170
St. Louis	32525
Tampa-St. Petersburg-Clearwater	36588
Virginia Beach-Norfolk-Newport News	35220
Washington-Arlington-Alexandria	55669
washington-Armington-Alexandra	22009

Table A2: Number of listings in Craigslist and number of census tracts in the entire top 50 MSAs per neighborhood type: Plurality, 30% Poverty

Type	Number of Listings (%)	Number of Tracts in Top 50 MSAs (%)
White Nonpoor	1,196,496	24,643
	(69.73)	(64.10)
White Poor	79,115	976
	(4.61)	(2.54)
Black Nonpoor	137,838	3,081
	(8.03)	(8.01)
Black Poor	77,439	2,148
	(4.51)	(5.59)
Latino Nonpoor	142,051	4,755
	(8.28)	(12.37)
Latino Poor	50,162	1,734
	(2.92)	(4.51)
Asian Nonpoor	28,982	1,011
	(1.69)	(2.63)
Asian Poor	3,730	95
	(0.22)	(0.25)

# **B.** STM Topic Model Robustness Checks

#### **B-1 STM Topic Estimation without Covariates**

STM is very similar to Latent Dirichlet Allocation (LDA), which is one of the most common forms of topic modeling. However, LDA assumes every document in a corpus is generated in the same way and therefore assumes the frequency of each topic and words likely to be used within each topic are the same across each document (Roberts et al. 2014). STM relaxes these assumptions and is better suited for our analyses since topics and word choices within topics will likely vary across advertisements, not all housing units are the same, and landlords may choose to address different themes in their ads. STM also allows us to include covariates when the model is estimating which words appears in each topic and how frequently each topic occurs in each document.

In this section, we demonstrate that STM estimation results and the regression on the topic proportions from the STM are robust to the selection of covariates included in the STM estimation process. We run an STM that does not include any covariates. Table A3 reports the STM topics from the model without covariates. When we compare Table A3 and Table 1, the top 10 words for each topics are identical. The only difference between Table A3 and Table 1 are the average topic proportions. However, the biggest difference in topic proportions is only 0.3 percentage point (for the neighborhood amenity topic).

Table A4 presents respective regression models to Table 2. We use the topic proportions computed by STM that does not include covariates and run regression models predicting these topic proportions. The results in Table A4 have minimal difference with results from Table 2. When we compare the coefficients from our neighborhood type variables, the biggest difference is 0.006.

Table A3: STM Topics from Craigslist Rental Listings: No Covariate STM

Label	Words	%
General	apart, home, communiti, center, pool, call, offer, locat, fit, bedroom	24.4
Logistics	rent, month, applic, will, fee, credit, home, pleas, leas, move	10.6
Unit Amenity	kitchen, floor, center, applianc, room, communiti, loung, fit, stainless, area	12.7
Unit Description	bedroom, room, floor, kitchen, new, includ, larg, bath, bathroom, month	25.1
Pet Policy	pet, polici, apart, restrict, offic, now, home, communiti, hous, hour	8.1
Neighborhood Amenity	park, apart, locat, downtown, walk, shop, restaur, citi, minut, just	10.5
Availability	avail, apart, leas, price, today, unit, manag, chang, properti, subject	8.7

Table A4: Regression on Topic Proportions Estimated from STM without Covariates

		Dependent var	iable:
	Logistics Topic	Unit Amenities Topic	Neighborhood Amenities Topic
	(1)	(2)	(3)
White Poor	0.459**	-0.194**	0.305**
	(0.075)	(0.073)	(0.084)
Black Non-poor	0.104	$-0.097^{*}$	-0.009
-	(0.107)	(0.046)	(0.061)
Black Poor	0.436**	-0.175**	0.173**
	(0.122)	(0.065)	(0.062)
Latino Non-poor	0.289**	-0.115	0.206**
-	(0.082)	(0.073)	(0.058)
Latino Poor	0.562**	-0.227**	0.323**
	(0.148)	(0.073)	(0.078)
Asian Non-poor	0.242*	-0.027	-0.051
-	(0.101)	(0.064)	(0.092)
Asian Poor	0.726**	-0.249	0.384**
	(0.249)	(0.194)	(0.079)
Price (\$1000)	-0.112**	0.341**	0.016
	(0.027)	(0.037)	(0.018)
% College	-0.009**	0.011**	0.011**
· ·	(0.002)	(0.001)	(0.001)
% Foreign Born	-0.015**	0.004*	-0.008**
-	(0.003)	(0.002)	(0.002)
% Units Renter Occ	-0.006**	0.006**	0.006**
	(0.001)	(0.001)	(0.001)
% Unit Built after 2010	-0.013*	0.038**	-0.002
	(0.005)	(0.004)	(0.002)
% Vacancy	2.377**	-0.655**	1.122**
	(0.268)	(0.182)	(0.225)
Observations	1,692,639	1,692,639	1,692,639
$\mathbb{R}^2$	0.154	0.223	0.176
Adjusted R <sup>2</sup>	0.154	0.223	0.176
Residual Std. Error	1.615	1.242	1.047

+p<0.1; \*p<0.05; \*\*p<0.01

## **B-2** STM Topic Estimation with Different Number of Topics

In this section, we demonstrate the topic model results and regression results from STMs that use different numbers of topics. Results from topic models can vary when researchers choose the number of topics. We show that the results from STMs with 5 and 9 topics have similar results to the results from the main text (7 topics). In addition, the results in this section show that STM with 7 topic has more interpretable and cohesive results than 5 or 9 topics.

Table A5 presents the STM results with 5 topics (top 10 frequency words and proportions). The content of the topics is overall similar to the results from STM with 7 topics. However, there are a few topics that are combined together into a single topic. These combined topics are created because the number of topics is not large enough so topics that should be independent are compressed to a single topic. When we compare Table A8 to Table 1 in the main text, the first seven topics are identical to the ones from Table 1. The only differences are the last two topics. These last two topics labelled as apartment 1 and apartment 2 represent generic text from various apartment complexes. These two topics are less coherent than the first seven topics. The STM creates topics that are less interpretable as we increase the number of topics above the ideal number of topic (7).

The regression results reported in Table A7 and Table A8 demonstrate similar results to Table 2. The regression results from STM with 9 topics is more likely to be similar to the models with 7 topics than the results from STM with 5 topics. It is because STM with 9 topics share the same 7 topics as STM with 7 topics and because STM with 5 topics have a few merged topics. The results in Table A7 are similar to Table 2, especially for logistics and unit description topic and unit amenities topic. The regression coefficients for general and neighborhood amenities topic show similar direction as Table 2 but the strength of correlation is weaker than Table 2 because the topic contains a general topic which makes the topic less coherent. The results in Table A8 are very similar to Table 2. In fact, the results for unit amenities topic and neighborhood amenities topic have stronger correlation than Table 2. Altogether, these comparisons support our selection of a model with 7 topics as optimal.

Table A5: STM Topics from Craigslist Rental Listings: STM with 5 Topics

Label	Words	%
Availability and General	apart, home, today, call, avail, leas, price, locat, communiti, manag	16.0
Logistics and Unit Description	bedroom, rent, month, room, floor, includ, park, bath, pet, new	35.2
Unit Amenity	kitchen, park, stainless, applianc, room, steel, center, granit, countertop	24.3
Pet Policy	pet, communiti, apart, home, hour, hous, offic, restrict, now, polici	10.0
General and Neighborhood Amenity	apart, center, home, pool, communiti, call, bedroom, closet, fit, park	14.6

Table A6: STM Topics from Craigslist Rental Listings: STM with 9 Topics

Label	Words	%
General	apart, home, communiti, center, pool, call, offer, fit, locat, bedroom	24.4
Logistics	month, rent, applic, fee, home, will, credit, leas, deposit, move	9.6
Unit Amenity	kitchen, floor, applianc, center, room, stainless, featur, steel, communiti, countertop	11.9
Unit Description	bedroom, room, floor, kitchen, new, larg, includ, bath, bathroom, live	22.0
Pet Policy	pet, polici, restrict, apart, bath, dog, offic, breed, now, per	7.3
Neighborhood Amenity	apart, park, locat, walk, downtown, build, restaur, shop, citi, street	9.7
Availability	avail, apart, price, unit, leas, today, chang, properti, subject, special	6.9
Apartments	communiti, park, center, access, hour, pool, fit, amen, apart, creek	4.3
Apartments 2	beach, bedroom, artnt, pool, unit, view, bay, nth, downtown, rent	3.9

Table A7: Regression on Topic Proportions Estimated from STM with 5 Topics

		Dependent variable:	
	Logistics and Unit Description Topic	Unit Amenities Topic	Neighborhood Amenities Topic
	(1)	(2)	(3)
White Poor	0.670**	-0.672**	0.043
	(0.090)	(0.065)	(0.071)
Black Non-poor	0.042	-0.024	-0.117*
•	(0.102)	(0.064)	(0.052)
Black Poor	0.466**	-0.544**	0.084
	(0.125)	(0.077)	(0.058)
Latino Non-poor	0.368**	-0.421**	0.140*
1	(0.070)	(0.057)	(0.063)
Latino Poor	0.736**	-0.719**	0.101
	(0.138)	(0.082)	(0.068)
Asian Non-poor	$0.216^{+}$	-0.211**	-0.050
1	(0.116)	(0.077)	(0.067)
Asian Poor	0.861**	-0.702**	-0.108
	(0.252)	(0.232)	(0.159)
Price (\$1000)	0.029	$-0.082^{**}$	0.330**
(1 222)	(0.031)	(0.026)	(0.036)
% College	-0.006**	-0.002	0.020**
,, ,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	(0.002)	(0.001)	(0.001)
% Foreign Born	-0.023**	0.023**	$-0.005^*$
, o I orongin Dorin	(0.004)	(0.003)	(0.002)
% Units Renter Occ	-0.009**	0.001	0.008**
76 011105 11011001 000	(0.002)	(0.001)	(0.001)
% Unit Built after 2010	-0.030**	-0.008*	0.039**
,, ,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	(0.005)	(0.004)	(0.003)
% Vacancy	2.676**	-3.242**	0.432**
,,	(0.275)	(0.269)	(0.138)
Observations	1,692,639	1,692,639	1,692,639
$R^2$	0.284	0.310	0.404
Adjusted R <sup>2</sup>	0.284	0.310	0.404
Residual Std. Error	1.456	1.149	1.039

<sup>+</sup>p<0.1; \*p<0.05; \*\*p<0.01

Table A8: Regression on Topic Proportions Estimated from STM with 9 Topics

		Dependent v	ariable:
	Logistics Topic	Unit Amenities Topic	Neighborhood Amenities Topic
	(1)	(2)	(3)
White Poor	0.519**	-0.285**	0.441**
	(0.081)	(0.076)	(0.074)
Black Non-poor	0.159	-0.172**	-0.003
•	(0.107)	(0.052)	(0.065)
Black Poor	0.431**	-0.239**	0.362**
	(0.116)	(0.064)	(0.070)
Latino Non-poor	0.298**	-0.111	0.398**
_	(0.079)	(0.070)	(0.058)
Latino Poor	0.637**	-0.311**	0.633**
	(0.134)	(0.080)	(0.081)
Asian Non-poor	0.166	-0.066	-0.092
•	(0.107)	(0.065)	(0.096)
Asian Poor	0.702**	$-0.447^{+}$	0.608**
	(0.263)	(0.234)	(0.075)
Price (\$1000)	-0.143**	0.326**	-0.035*
	(0.024)	(0.034)	(0.016)
% College	-0.014**	0.016**	0.019**
	(0.002)	(0.001)	(0.001)
% Foreign Born	-0.016**	0.005*	-0.011**
	(0.003)	(0.002)	(0.002)
% Units Renter Occ	-0.008**	0.007**	0.012**
	(0.001)	(0.001)	(0.001)
% Unit Built after 2010	-0.014**	0.046**	-0.011**
	(0.005)	(0.004)	(0.003)
% Vacancy	2.150**	-1.001**	1.910**
<u> </u>	(0.286)	(0.186)	(0.204)
Observations	1,692,639	1,692,639	1,692,639
$R^2$	0.193	0.325	0.447
Adjusted R <sup>2</sup>	0.193	0.325	0.447
Residual Std. Error	1.535	1.251	1.001

<sup>+</sup>p<0.1; \*p<0.05; \*\*p<0.01

## **B-3** Unit Description Topic

Table A9: Regression Model Predicting Unit Description Topic Proportion

	Dependent variable:
	Unit Description Topic
White Poor	0.520**
	(0.084)
Black Non-poor	-0.007
-	(0.089)
Black Poor	0.354**
	(0.110)
Latino Non-poor	0.225**
	(0.071)
Latino Poor	0.564**
	(0.118)
Asian Non-poor	0.162
	(0.118)
Asian Poor	0.666**
	(0.200)
Price (\$1000)	0.067*
	(0.032)
% College	$-0.005^{**}$
	(0.002)
% Foreign Born	$-0.017^{**}$
	(0.003)
% Units Renter Occ	-0.007**
	(0.001)
% Unit Built after 2010	-0.021**
	(0.004)
% Vacancy	2.066**
	(0.270)
Observations	1,692,639
$\mathbb{R}^2$	0.214
Adjusted R <sup>2</sup>	0.214
Residual Std. Error	1.403

 $^{+} p < 0.1; *p < 0.05; **p < 0.01$ 

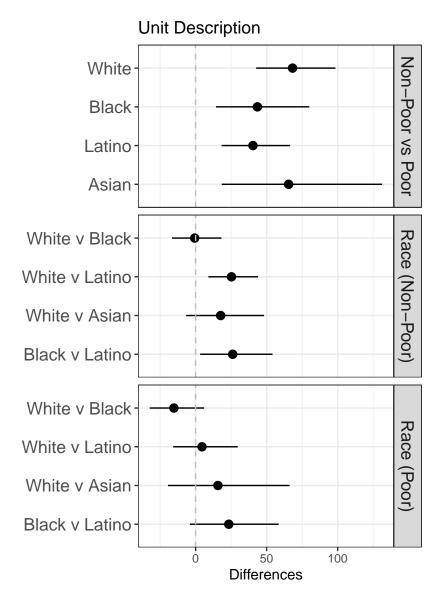


Figure A1: Pairwise Comparison of Unit Description Topic Proportion Across Neighborhood Types. *Note:* The dependent variable is log transformed. The dots and bars indicate the percent change and confidence intervals derived from regression models. For the ease of interpretation, we present percent change instead of regression coefficients. The neighborhood written first (before "vs") is the base category. The first four rows (non-poor vs poor) display the regression coefficients for poor neighborhoods when the non-poor neighborhoods for the respective racial group is the base category. Negative value means poor neighborhoods have less information than non-poor neighborhoods. Positive value means non-poor neighborhoods have less information than poor neighborhoods. The following eight rows compare differences between different racial compositions. The first racial group is the base category. For example, the coefficient for "White v Latino" in the sixth row for the unit amenities topic indicates that Latino non-poor neighborhoods have 25.3 percent more topic proportions in unit description than White non-poor neighborhoods. Neighborhood racial composition and poverty rate are obtained from 2016 ACS 5-year pooled data. The regression models include MSA fixed effects. Standard errors are clustered at MSA level. Plots are based on results presented in Table A9.

# C. Modeling Topic Prevalence Robustness Checks

# C-1 Log-transformation of the Dependent Variables

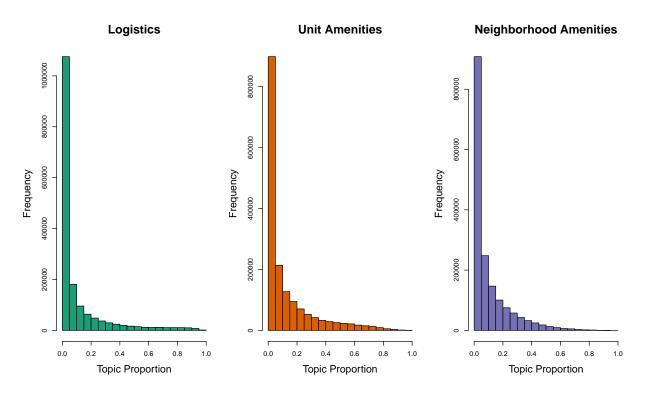


Figure A2: Histogram for Topic Proportions

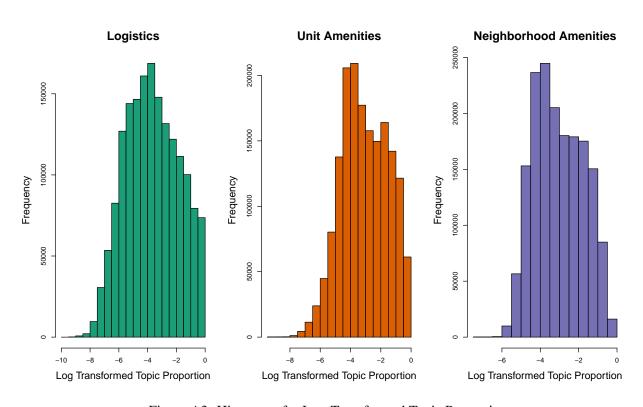


Figure A3: Histogram for Log-Transformed Topic Proportions

Table A10: Topic Proportions without Log Transformation

			Depen	dent variable.	<u>.                                      </u>	
	Logistic	es Topic	Unit Amer	nities Topic	Neighborhoo	d Amenities Topic
	(1)	(2)	(3)	(4)	(5)	(6)
White Poor	0.021**	0.028**	$-0.013^{+}$	$-0.016^*$	0.057**	0.036**
	(0.007)	(0.006)	(0.008)	(0.007)	(0.012)	(0.011)
Black Non-poor	0.038**	$0.014^{+}$	-0.043**	-0.008	-0.024**	0.001
-	(0.008)	(0.008)	(0.006)	(0.006)	(0.005)	(0.005)
Black Poor	0.077**	0.041**	-0.051**	-0.011	0.005	0.016**
	(0.010)	(0.010)	(0.007)	(0.007)	(0.005)	(0.006)
Latino Non-poor	0.037**	0.023*	-0.043**	-0.003	-0.014*	0.029**
•	(0.009)	(0.010)	(0.009)	(0.008)	(0.006)	(0.006)
Latino Poor	0.063**	0.046**	-0.059**	-0.007	-0.004	0.033**
	(0.012)	(0.012)	(0.008)	(0.010)	(0.007)	(0.008)
Asian Non-poor	-0.008	0.009	0.016*	0.006	-0.024**	-0.008
1	(0.006)	(0.006)	(0.007)	(0.009)	(0.008)	(0.009)
Asian Poor	0.022	0.041*	-0.027	-0.027	0.047*	0.043*
	(0.022)	(0.017)	(0.026)	(0.018)	(0.019)	(0.017)
Price (\$1000)	,	-0.015**		0.043**	,	-0.002
(1 2 2 2 )		(0.003)		(0.005)		(0.003)
% College		-0.001**		0.001**		0.002**
		(0.0001)		(0.0002)		(0.0001)
% Foreign Born		$-0.0005^*$		0.0001		-0.001**
,,		(0.0002)		(0.0003)		(0.0002)
% Units Renter Occ		-0.001**		0.0004**		0.001**
		(0.0001)		(0.0001)		(0.0001)
% Unit Built after 2010		-0.0002		0.007**		-0.0002
70 01110 2 4110 41101 2010		(0.0003)		(0.001)		(0.0003)
% Vacancy		0.190**		0.006		0.102**
, a vacancy		(0.024)		(0.025)		(0.023)
Observations	1,692,639	1,692,639	1,692,639	1,692,639	1,692,639	1,692,639
$R^2$	0.119	0.149	0.133	0.233	0.152	0.230
Adjusted R <sup>2</sup>	0.119	0.149	0.133	0.233	0.151	0.230
Residual Std. Error	0.174	0.171	0.165	0.155	0.122	0.116

+p<0.1; \*p<0.05; \*\*p<0.01

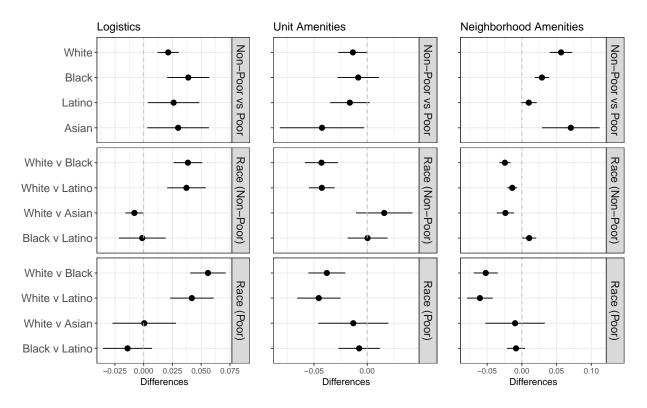


Figure A4: Dependent Variables without Log Transformation: Pairwise Comparison of Topic Proportions Across Neighborhood Types

Note: The dependent variables are topic proportions estimated by STM. The dots and bars indicate the percent change and confidence intervals derived from regression models. For the ease of interpretation, we present percent change instead of regression coefficients. The neighborhood written first (before "vs") is the base category. The first four rows (non-poor vs poor) display the regression coefficients for poor neighborhoods when the non-poor neighborhoods for the respective racial group is the base category. Negative value means poor neighborhoods have less information than non-poor neighborhoods. Positive value means non-poor neighborhoods have less information than poor neighborhoods. The following eight rows compare differences between different racial compositions. The first racial group is the base category. For example, the coefficient for "White v Latino" in the sixth row for the unit amenities topic indicates that Latino non-poor neighborhoods have 0.043 (4.3 percentage point) less topic proportions in unit amenities than White non-poor neighborhoods. Neighborhood racial composition and poverty rate are obtained from 2016 ACS 5-year pooled data. The regression models include MSA fixed effects. Standard errors are clustered at MSA level. Based on Table A10.

## C-2 Defining Neighborhoods

In this section, we test whether our regression results are robust to different neighborhood classifications.

#### C-2-a Majority v. Plurality

We change our classification for neighborhood racial composition. Instead of using plurality to determine the dominant group in each neighborhood, we use majority to classify the dominant group. Census tracts that do not have any majority group are classified as diverse neighborhoods. We use the same poverty rate threshold (16.6%) as Table A14. The overall results reported in Table A11 are similar to Table A14. Black and Latino non-poor neighborhoods show weaker correlations than Table 3. However, poor Black and Latino neighborhoods have stronger correlations than those reported in Table 3 (except for Latino poor neighborhoods for unit amenities topic). Regression coefficients for the neighborhood amenities topic are similar across the three different classification schemes. The new neighborhood types in this regression, diverse neighborhoods, demonstrate a mixed pattern. Diverse poor neighborhoods show the same direction but somewhat smaller magnitudes in terms of regression coefficients compared to Black and Latino poor neighborhoods. They have more logistics and neighborhood amenities topic, but less unit amenities topic than White non-poor neighborhoods. Diverse non-poor neighborhoods have less logistics topic compared White non-poor neighborhoods, although the results for the logistics topic is marginally significant at the 90% confidence level.

Again, overall these comparisons demonstrate robust support for our key conclusion: both neighborhood race and SES structure the types of information available to prospective renters. However, some specific findings are sensitive to our neighborhood racial and poverty composition cut-offs we use.

Table A11: Topic Proportion Regressions – Majority Racial Group and Average Poverty Rate (16.6%)

	Dependent variable:				
	Logistics Topic	Unit Amenities Topic	Neighborhood Amenities Topic		
	(1)	(2)	(3)		
White Poor	0.423**	-0.203**	0.194**		
	(0.046)	(0.044)	(0.047)		
Black Non-poor	0.017	-0.0001	-0.097		
•	(0.214)	(0.177)	(0.079)		
Black Poor	0.654**	-0.355**	0.203**		
	(0.109)	(0.059)	(0.051)		
Latino Non-poor	0.196	-0.102	0.362**		
•	(0.127)	(0.080)	(0.084)		
Latino Poor	0.594**	-0.358**	0.462**		
	(0.134)	(0.082)	(0.082)		
Asian Non-poor	0.230	-0.346**	-0.101		
_	(0.157)	(0.098)	(0.120)		
Asian Poor	0.553*	0.113	0.495**		
	(0.264)	(0.161)	(0.137)		
Diverse Non-poor	$-0.146^{+}$	-0.070	-0.057		
_	(0.083)	(0.064)	(0.062)		
Diverse Poor	0.376**	-0.218**	0.191**		
	(0.083)	(0.053)	(0.060)		
Price (\$1000)	-0.116**	0.334**	-0.006		
	(0.025)	(0.037)	(0.017)		
% College	-0.012**	0.016**	0.018**		
	(0.002)	(0.001)	(0.001)		
% Foreign Born	-0.015**	$0.005^*$	-0.010**		
	(0.004)	(0.002)	(0.002)		
% Units Renter Occ	-0.011**	0.007**	0.010**		
	(0.001)	(0.001)	(0.001)		
% Unit Built after 2010	-0.011*	0.047**	-0.003		
	(0.005)	(0.004)	(0.002)		
% Vacancy	2.459**	$-0.816^{**}$	1.596**		
	(0.239)	(0.181)	(0.205)		
Observations	1,692,639	1,692,639	1,692,639		
$R^2$	0.234	0.351	0.344		
Adjusted R <sup>2</sup>	0.234	0.351	0.344		
Residual Std. Error	1.606	1.233	1.026		

+p<0.1; \*p<0.05; \*\*p<0.01

### C-2-b Diversity

Next, we test an alternative conceptualization of neighborhood diversity developed by Wright, Holloway, and Ellis (2015). We use 2010 data from their site, mixedmetro.us, to test alternative classifications of neighborhood racial/ethnic composition and diversity. First, in Table A12 we categorize neighborhoods based on racial plurality and by diversity (with White and low-diversity neighborhoods as the reference categories), following their definition of diversity. As shown in Table A12, diversity is associated with variation in our key topics. Furthermore, Table A13 demonstrates that when we interact racial plurality with diversity, we can find differences between low and moderately diverse same-race neighborhoods.

However, it is difficult to tell how these results compare to our main models which interact neighborhood race with poverty status. The key question is whether our findings for neighborhood race by poverty status are distinct for diverse neighborhoods. Thus, we next estimate a three-way interaction between neighborhood racial plurality, diversity level, and poverty status. To facilitate interpretation we plot the predicted change between low and moderate diversity neighborhoods by race and poverty status in Figure A5. Our results remain consistent with previous analyses. While neighborhoods with moderate v. low diversity are not identical within racial categories, the results are largely similar; Black and Latino neighborhoods have more language about rental logistics and less about unit amenities in contrast to White neighborhoods; poor non-White neighborhoods remain particularly disadvantaged.

Table A12: Plurality and Diversity of Neighborhoods

		Dependent v	ariable:
	Logistics Topic	Unit Amenities Topic	Neighborhood Amenities Topic
	(1)	(2)	(3)
Black	0.174	-0.176**	-0.036
	(0.113)	(0.053)	(0.042)
Latino	0.290**	-0.128	0.277**
	(0.100)	(0.084)	(0.049)
Asian	0.302*	-0.030	0.021
	(0.145)	(0.079)	(0.071)
Moderate Diversity	-0.111	0.032	-0.100**
•	(0.070)	(0.035)	(0.029)
High Diversity	-0.264*	0.193*	-0.054
	(0.113)	(0.082)	(0.064)
Price (\$1000)	-0.146**	0.336**	-0.015
	(0.024)	(0.039)	(0.012)
% College	-0.013**	0.016**	0.017**
	(0.002)	(0.001)	(0.001)
% Foreign Born	-0.015**	0.004*	-0.009**
	(0.004)	(0.002)	(0.002)
% Units Renter Occ	-0.004**	0.005**	0.013**
	(0.001)	(0.001)	(0.001)
% Unit Built after 2010	-0.014*	0.052**	0.002
	(0.007)	(0.005)	(0.003)
% Vacancy	2.843**	-1.103**	1.770**
	(0.385)	(0.255)	(0.192)
Observations	1,168,994	1,168,994	1,168,994
$\mathbb{R}^2$	0.216	0.359	0.332
Adjusted R <sup>2</sup>	0.216	0.359	0.331
Residual Std. Error	1.581	1.229	1.028

 $^{+}p{<}0.1;$   $^{*}p{<}0.05;$   $^{**}p{<}0.01$ 

*Note:* Dependent variables are log transformed. The base category for neighborhood type is White neighborhoods for racial composition and low diversity neighborhoods for diversity. Listings that are more expensive than \$10,000 are removed. For neighborhood classification, racial composition is based on the plurality racial group. Diversity classification follows Ellis, Holloway, and Wright (2012). Neighborhood covariates are obtained from 2016 ACS 5-year pooled data. Standard errors are clustered at MSA level.

Table A13: Race × Diversity

	Dependent variable:						
	Logistics Topic		Unit Amenities Topic		Neighborhood Amenities Topio		
	(1)	(2)	(3)	(4)	(5)	(6)	
White Moderate Diversity	-0.149*	-0.118	-0.044	-0.0004	-0.001	-0.091*	
	(0.071)	(0.078)	(0.049)	(0.045)	(0.058)	(0.041)	
Black Low Diversity	0.969**	0.198	-1.063**	-0.253**	-0.115	0.038	
-	(0.145)	(0.156)	(0.066)	(0.084)	(0.081)	(0.069)	
Black Moderate Diversity	0.491**	$0.188^{+}$	-0.453**	-0.060	-0.044	-0.0004	
•	(0.109)	(0.109)	(0.086)	(0.079)	(0.072)	(0.053)	
Latino Low Diversity	0.363	0.354	-0.730**	-0.113	$-0.246^{+}$	0.444**	
•	(0.239)	(0.229)	(0.224)	(0.163)	(0.136)	(0.137)	
Latino Moderate Diversity	0.298**	0.171	-0.536**	-0.057	-0.069	0.246**	
•	(0.099)	(0.129)	(0.069)	(0.086)	(0.084)	(0.075)	
Asian Low Diversity	0.201	0.554**	-0.549**	-0.412**	-0.200**	0.321**	
•	(0.125)	(0.176)	(0.080)	(0.087)	(0.062)	(0.107)	
Asian Moderate Diversity	-0.241*	0.139	0.035	-0.065	-0.063	-0.011	
•	(0.099)	(0.169)	(0.075)	(0.093)	(0.099)	(0.109)	
High Diversity	-0.064	-0.122	-0.235**	0.117	-0.070	0.077	
	(0.111)	(0.135)	(0.084)	(0.094)	(0.085)	(0.077)	
Price (\$1000)		-0.149**		0.335**		-0.017	
		(0.025)		(0.040)		(0.018)	
% College		-0.013**		0.017**		0.018**	
C		(0.002)		(0.001)		(0.001)	
% Foreign Born		-0.014**		$0.004^{+}$		-0.009**	
		(0.004)		(0.002)		(0.003)	
% Units Renter Occ		-0.004**		0.005**		0.013**	
		(0.001)		(0.001)		(0.001)	
% Unit Built after 2010		-0.014*		0.052**		0.001	
		(0.006)		(0.005)		(0.003)	
% Vacancy		2.747**		-1.021**		1.687**	
·		(0.361)		(0.264)		(0.251)	
Observations	1,168,994	1,168,994	1,168,994	1,168,994	1,168,994	1,168,994	
$\mathcal{R}^2$	0.179	0.217	0.246	0.358	0.203	0.332	
Adjusted R <sup>2</sup>	0.179	0.217	0.246	0.358	0.203	0.332	
Residual Std. Error	1.618	1.581	1.333	1.229	1.122	1.028	

 $^{+}$ p<0.1;  $^{*}$ p<0.05;  $^{**}$ p<0.01

*Note:* Dependent variables are log transformed. The base category for neighborhood type is White low diversity neighborhoods. Listings that are more expensive than \$10,000 are removed. For neighborhood classification, racial composition is based on the plurality racial group. Diversity classification follows Ellis, Holloway, and Wright (2012). Neighborhood covariates are obtained from 2016 ACS 5-year pooled data. Standard errors are clustered at MSA level.

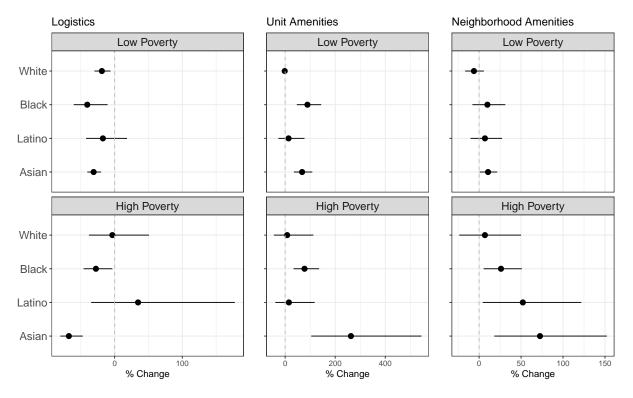


Figure A5: The Change in Topic Proportions When Low Diverse Neighborhoods Become Moderate Diverse Neighborhoods

*Note:* Dependent variables are log transformed. The dots and bars indicate the percent change and confidence intervals derived from regression models. For the ease of interpretation, we present percent change instead of regression coefficients. The first four rows (low poverty) display the percent change in topic proportion for low poverty neighborhoods when low diverse neighborhoods become moderate diverse neighborhoods. Negative value means moderate diversity neighborhoods have less information than low diversity neighborhoods. Positive value means moderate diversity neighborhoods have more information than low diversity neighborhoods. The following four rows compare differences between moderate and low diversity neighborhoods across high poverty neighborhoods. For example, the coefficient for "Black" in the sixth row for the unit amenities topic indicates that Black and high poverty neighborhoods have 77.36 percent more topic proportions in unit amenities when the low diversity neighborhoods become moderate diversity neighborhoods. Neighborhood racial composition and poverty rate are obtained from 2016 ACS 5-year pooled data. The regression models include MSA fixed effects. Standard errors are clustered at MSA level.

## C-2-c Poverty Threshold

We test whether changing the poverty rate threshold (set at 30% in the main text) changes the results from the topic proportion regressions in Table A14. We set the average poverty rate, 16.6% as a threshold for classifying poor and non-poor neighborhoods. The direction and the magnitude of the coefficients are substantively similar to Table 3 except for Black non-poor and Latino non-poor neighborhoods. The differences between Table A14 and Table 3 are only pronounced for the logistic topic and unit amenities topic. The regression results for the neighborhood amenities topic in Table A14 is very similar to those from Table 3. The strength of correlations for Black poor neighborhood is stronger than the results reported in Table 3. This comparison demonstrates that our overall findings are robust to the poverty rate threshold we use to classify neighborhoods but that some results are sensitive to the poverty rate threshold.

Table A14: Topic Proportion Regressions – Poverty Rate Threshold: Average Poverty Rate (16.6%)

		Dependent va	riable:
	Logistics Topic	Unit Amenities Topic	Neighborhood Amenities Topic
	(1)	(2)	(3)
White Poor	0.437**	-0.190**	0.201**
	(0.049)	(0.044)	(0.045)
Black Non-poor	-0.005	-0.072	-0.104
•	(0.200)	(0.086)	(0.107)
Black Poor	0.620**	-0.323**	0.201**
	(0.098)	(0.050)	(0.053)
Latino Non-poor	0.350**	-0.039	0.355**
-	(0.127)	(0.094)	(0.063)
Latino Poor	0.697**	-0.286**	0.468**
	(0.093)	(0.072)	(0.062)
Asian Non-poor	$0.254^{+}$	$-0.161^{+}$	-0.066
•	(0.130)	(0.082)	(0.112)
Asian Poor	0.704**	-0.162	0.264*
	(0.221)	(0.163)	(0.106)
Price (\$1000)	-0.114**	0.336**	-0.005
, ,	(0.025)	(0.037)	(0.017)
% College	-0.012**	0.016**	0.018**
	(0.002)	(0.001)	(0.001)
% Foreign Born	-0.018**	0.005*	-0.011**
C	(0.004)	(0.002)	(0.002)
% Units Renter Occ	-0.011**	0.007**	0.010**
	(0.001)	(0.001)	(0.001)
% Unit Built after 2010	-0.012*	0.047**	-0.003
	(0.005)	(0.004)	(0.002)
% Vacancy	2.536**	-0.837**	1.617**
<u>•</u>	(0.244)	(0.178)	(0.208)
Observations	1,692,639	1,692,639	1,692,639
$R^2$	0.234	0.351	0.345
Adjusted R <sup>2</sup>	0.234	0.350	0.345
Residual Std. Error	1.607	1.234	1.026

 $^{+}p{<}0.1;\,^{*}p{<}0.05;\,^{**}p{<}0.01$ 

#### C-2-d Topic Regressions with Continuous Race and Poverty Variables

In this section, we report the results from regressions that include continuous race and poverty variables instead of our neighborhood type variable. Racial composition measures include % Black, % Latino, and % Asian. We do not include % White because of multicollinearity concerns. We add the poverty rate for each census tract to measure the extent of poverty existing in the neighborhood.

We present two models for each outcome variable. First, we report the results from a model that includes the race variables and other covariates, but does not include the poverty rate variable. We show the results from this model because the % Black and % Latino variables are highly correlated with poverty rate. Next, we include every covariate including the poverty rate. The first models show the proportion of logistics topic increases as % Black and % Latino increase. These correlations become weaker when we include the poverty rate variable. The regression coefficient for the poverty rate show a strong correlation between logistic topic proportion and poverty rate. The second models demonstrate the proportion of unit amenities topic decreases as % Black and % Latino increase. Similar to the logistics topic models, including the poverty rate measure weakens the correlations between unit amenities topic proportion and racial composition variables. Contrary to the first and second models, % Black and % Latino show different results in the third model. Specifically, the neighborhood amenities topic proportion increases as % Latino increases and % Asian decreases. The relationship between the proportion of neighborhood amenities topic and % Black is less consistent. There is no statistically significant relationship in the model without the poverty rate variable but the correlation becomes negative when we include the poverty rate variable.

The overall results from Table A15 are similar to Table 2, demonstrating the robustness of our key conclusions. Neighborhoods with higher % Black or % Latino have more logistics topic and less unit amenities topic. There is more neighborhood amenities topic in neighborhoods with a higher % Latino. Higher poverty rate is positively correlated with logistics topic proportion and neighborhood amenities topic proportion, but negatively correlated with unit amenities topic proportion. These results are largely consistent with the results of Table 2.

Table A15: Topic Regressions with Continuous Race and Poverty Variables

	Dependent variable:						
	Logistics Topic		Unit Amer	Unit Amenities Topic		d Amenities Topic	
	(1)	(2)	(3)	(4)	(5)	(6)	
% Black	0.003*	-0.0005	-0.003**	-0.001	0.0001	$-0.002^{+}$	
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
% Latino	0.006**	0.001	-0.004*	-0.002	0.007**	0.004**	
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
% Asian	-0.008*	-0.012**	-0.002	-0.0005	-0.007*	-0.009**	
	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)	
Poverty Rate		0.028**		-0.010**		0.015**	
•		(0.003)		(0.002)		(0.002)	
Price (\$1000)	-0.114**	-0.122**	0.334**	0.337**	-0.006	-0.010	
	(0.025)	(0.025)	(0.037)	(0.037)	(0.016)	(0.017)	
% College	-0.013**	-0.009**	0.017**	0.015**	0.018**	0.020**	
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	
% Foreign Born	-0.012**	-0.009*	0.006**	0.004*	-0.008**	-0.006*	
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	
% Units Renter Occ	-0.008**	-0.014**	0.006**	0.009**	0.011**	0.008**	
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	
% Unit Built after 2010	-0.012*	$-0.010^{+}$	0.047**	0.047**	-0.003	-0.002	
	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)	
% Vacancy	0.030**	0.022**	-0.010**	-0.007**	0.019**	0.014**	
·	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	
Observations	1,692,643	1,692,643	1,692,643	1,692,643	1,692,643	1,692,643	
$R^2$	0.226	0.240	0.348	0.351	0.342	0.350	
Adjusted R <sup>2</sup>	0.226	0.240	0.348	0.351	0.342	0.350	
Residual Std. Error	1.616	1.601	1.236	1.233	1.028	1.021	

<sup>+</sup>p<0.1; \*p<0.05; \*\*p<0.01

*Note:* Dependent variables are topic proportions estimated by STM. Listings that are more expensive than \$10,000 are removed. Neighborhood covariates are obtained from 2016 ACS 5-year pooled data. Standard errors are clustered at MSA level.

### C-2-e High v Low Rent Units

Next we test whether higher and lower priced (asking rent) units display distinct information patterns, even after accounting for neighborhood characteristics. To do so we categorize listings with an asking rent that is higher than the metro median as high rent, all other listings are classified as low rent. Next, we estimate a model interacting neighborhood race with rental price (see Table A16). Interestingly, we find that classifying listings by neighborhood racial composition and high v. low rent produces similar patterns for the logistics and unit amenities topics compared to our neighborhood race by poverty typology. However, a distinct pattern emerges for neighborhood amenities: while we find that neighborhood amenities language is more prevalent in poorer neighborhoods, we find that it is less prevalent among lower-rent listings.

To further explore this finding, we next created a 3-way interaction across neighborhood racial composition, neighborhood poverty status, and listing asking rent (creating 16 distinct neighborhood categories). These results are reported in Figure A6. We find that neighborhood racial composition, poverty status, and rent all contribute to the prevalence of logistics language in advertisements. Rent appears to be strongly tied to the level of logistics language. However, even after accounting for both neighborhood poverty and rent, racial differences remain: among low-poverty neighborhoods, listings in Black and Latino neighborhoods have more logistics language. This is particularly true for listings with lower rents. Additionally, listings in higher poverty neighborhoods tend to have more logistics language regardless of race or rent. Yet the differences between low and high poverty neighborhoods are greatest for Black and Latino neighborhoods. Altogether these patterns highlight how logistics language remains highly racialized.

Somewhat similarly, unit amenities language is more prevalent in higher-rent listings overall, and appears to have a weaker relationship with neighborhood poverty status compared to logistics language. However, once again racial gaps remain even after accounting for rent, such that listings in both poor and non-poor predominantly Black and Latino neighborhoods have less discussion of unit amenities compared to those in White neighborhoods with similar poverty rates.

Finally, in general, advertisements in higher poverty neighborhoods tend to include more discussion of neighborhood amenities compared to their same-race, lower poverty counterparts. Among high poverty neighborhoods, we see gaps both by race (listings in Black and Latino neighborhoods have less neighborhood amenities language compared to White neighborhoods) and by asking rent, with higher-rent units containing more neighborhood amenities language. Among low-poverty neighborhoods, there are only small (and sometimes non-significant) differences in the prevalence of neighborhood amenities language among higher and lower-rent units; racial differences among low-poverty units are also small, though Black neighborhoods have slightly lower levels than all others. We focus on this last set of findings in the main text of the paper.

Table A16: Race × High and Low Rent Units

	Dependent variable:						
	Logistics Topic		Unit Amer	ities Topic Neighborhood Amer		d Amenities Topic	
	(1)	(2)	(3)	(4)	(5)	(6)	
White Low Rent	0.435**	0.279**	-0.736**	-0.500**	-0.133**	0.022	
	(0.057)	(0.050)	(0.035)	(0.032)	(0.026)	(0.023)	
Black High Rent	0.410**	0.104	-0.377**	-0.041	-0.133	0.030	
	(0.126)	(0.122)	(0.090)	(0.080)	(0.082)	(0.072)	
Black Low Rent	1.039**	0.534**	-1.261**	-0.685**	-0.265**	0.015	
	(0.108)	(0.103)	(0.051)	(0.052)	(0.046)	(0.052)	
Latino High Rent	0.433**	0.428**	-0.402**	-0.082	-0.022	0.417**	
C	(0.071)	(0.091)	(0.079)	(0.071)	(0.071)	(0.063)	
Latino Low Rent	0.732**	0.624**	-1.151**	-0.642**	-0.222**	0.303**	
	(0.100)	(0.104)	(0.067)	(0.074)	(0.070)	(0.054)	
Asian High Rent	-0.136	0.314*	0.021	-0.132	-0.215**	-0.035	
	(0.104)	(0.125)	(0.069)	(0.085)	(0.072)	(0.081)	
Asian Low Rent	0.142	0.523**	-0.595**	-0.608**	-0.238**	0.036	
	(0.167)	(0.148)	(0.147)	(0.120)	(0.086)	(0.099)	
% College		-0.013**		0.017**		0.017**	
•		(0.002)		(0.001)		(0.001)	
% Foreign Born		-0.017**		0.004*		-0.011**	
Č		(0.004)		(0.002)		(0.002)	
% Units Renter Occ		-0.007**		0.006**		0.012**	
		(0.001)		(0.001)		(0.001)	
% Unit Built after 2010		$-0.011^*$		0.045**		$-0.004^{+}$	
		(0.005)		(0.004)		(0.002)	
% Vacancy		2.876**		-0.840**		1.818**	
·		(0.280)		(0.193)		(0.210)	
Observations	1,692,639	1,692,639	1,692,639	1,692,639	1,692,639	1,692,639	
$\mathbb{R}^2$	0.188	0.230	0.287	0.358	0.228	0.341	
Adjusted R <sup>2</sup>	0.188	0.230	0.287	0.358	0.228	0.341	
Residual Std. Error	1.655	1.611	1.292	1.227	1.113	1.029	

+p<0.1; \*p<0.05; \*\*p<0.01

*Note:* Topic proportions for the three topics are computed by STM (Roberts et al. 2014). The base category for neighborhood type is White high rent neighborhoods. Listings that are more expensive than \$10,000 are removed. For neighborhood classification, racial composition is based on the plurality racial group. Rental price higher than metro median is classified as high rent units. Neighborhood covariates are obtained from 2016 ACS 5-year pooled data. Standard errors are clustered at MSA level.

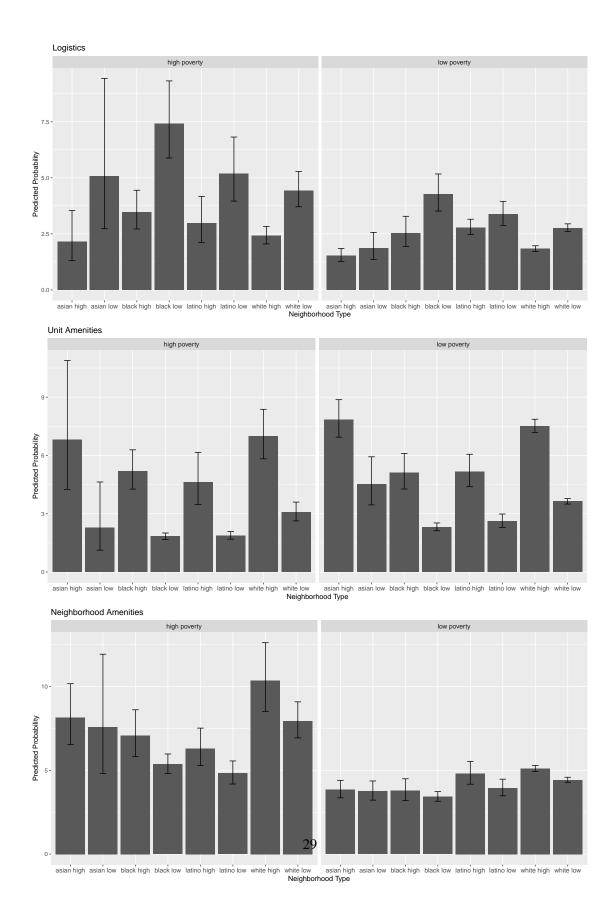


Figure A6: Predicted Probabilities of Topic Proportions across Neighborhood Types (Race  $\times$  Poverty  $\times$  High/Low Rents)

## C-2-f Census Tracts v. Zip Codes

In this section we test if our results hold at the zip code level rather than using tracts. Zip codes are much larger than tracts and are not ideal for representing neighborhoods; however, because of how Craigslist collects geocoded information from posters, zip codes are less likely to be sensitive to any potential user errors. Because the distribution of poverty across zip codes is distinct from that of tracts, we use a poverty threshold of 15% in these models. While there are some differences when we use zip codes, our key results remain: listing information is highly racialized and also corresponds to zip code poverty rates.

Table A17: Zip Code

	Dependent variable:					
	Logistics Topic		Unit Amer	nities Topic	Neighborhood Amenities Topic	
	(1)	(2)	(3)	(4)	(5)	(6)
White Poor	0.501**	0.440**	-0.223**	-0.156**	0.413**	0.219**
	(0.069)	(0.074)	(0.056)	(0.043)	(0.042)	(0.041)
Black Non-poor	0.245	0.005	-0.483**	$-0.144^{+}$	-0.397**	-0.184*
	(0.280)	(0.232)	(0.140)	(0.083)	(0.066)	(0.081)
Black Poor	0.834**	0.363**	-0.667**	-0.170*	0.156*	0.131*
	(0.122)	(0.115)	(0.078)	(0.069)	(0.062)	(0.060)
Latino Non-poor	0.172	0.170	-0.317*	0.013	-0.159	0.295**
-	(0.105)	(0.132)	(0.128)	(0.121)	(0.125)	(0.093)
Latino Poor	0.624**	0.547**	-0.623**	$-0.147^*$	0.143*	0.448**
	(0.067)	(0.091)	(0.077)	(0.067)	(0.066)	(0.075)
Asian Non-poor	$-0.220^{+}$	0.367*	0.091	$-0.169^{+}$	-0.194**	0.114
-	(0.113)	(0.147)	(0.111)	(0.089)	(0.067)	(0.077)
Asian Poor	0.797**	1.081**	$-0.446^{+}$	-0.352	0.109	0.349**
	(0.165)	(0.173)	(0.253)	(0.215)	(0.130)	(0.079)
Price (\$1000)		-0.117**		0.345**		0.015
		(0.025)		(0.036)		(0.018)
% College		-0.027**		0.031**		0.032**
C		(0.004)		(0.003)		(0.002)
% Foreign Born		-0.025**		0.008**		-0.012**
C		(0.005)		(0.002)		(0.003)
% Units Renter Occ		-0.005*		0.007**		0.014**
		(0.002)		(0.001)		(0.001)
% Unit Built after 2010		-0.015**		0.040**		$-0.005^*$
		(0.005)		(0.003)		(0.002)
% Vacancy		0.026**		$-0.009^{**}$		0.017**
·		(0.005)		(0.003)		(0.003)
Observations	1,690,982	1,690,982	1,690,982	1,690,982	1,690,982	1,690,982
$\mathbb{R}^2$	0.184	0.225	0.226	0.342	0.243	0.331
Adjusted R <sup>2</sup>	0.184	0.225	0.226	0.342	0.243	0.331
Residual Std. Error	1.659	1.616	1.347	1.241	1.103	1.036

+p<0.1; \*p<0.05; \*\*p<0.01

# **C-3** Modeling Decisions

# C-3-a Regression Models Including Price Outliers

In this section, we show that our results are robust to the decision to remove listings with a posted price higher than \$10,000. When we include these listings we find minimal differences in the results from the regression models reported in the main text.

Table A18: Including Listings Priced Higher than \$10,000

		Dependent var	iable:
	Logistics Topic	Unit Amenities Topic	Neighborhood Amenities Topic
	(1)	(2)	(3)
White Poor	0.519**	-0.232**	0.382**
	(0.084)	(0.080)	(0.075)
Black Non-poor	$0.193^{+}$	-0.164**	-0.037
-	(0.104)	(0.052)	(0.061)
Black Poor	0.491**	-0.223**	0.281**
	(0.123)	(0.066)	(0.064)
Latino Non-poor	0.360**	-0.093	0.346**
-	(0.085)	(0.076)	(0.055)
Latino Poor	0.664**	-0.304**	0.477**
	(0.150)	(0.081)	(0.076)
Asian Non-poor	$0.250^{*}$	$-0.127^{+}$	-0.055
-	(0.115)	(0.066)	(0.092)
Asian Poor	0.800**	-0.380	0.440**
	(0.276)	(0.234)	(0.078)
Price (\$1000)	0.00000	0.00000**	$0.00000^*$
	(0.00000)	(0.00000)	(0.00000)
% College	-0.015**	0.020**	0.018**
-	(0.002)	(0.001)	(0.001)
% Foreign Born	-0.017**	0.004*	-0.010**
-	(0.004)	(0.002)	(0.002)
% Units Renter Occ	-0.009**	0.006**	0.010**
	(0.001)	(0.001)	(0.001)
% Unit Built after 2010	-0.014**	0.050**	-0.004
	(0.005)	(0.004)	(0.002)
% Vacancy	2.653**	$-0.788^{**}$	1.589**
	(0.273)	(0.209)	(0.212)
Observations	1,695,948	1,695,948	1,695,948
$\mathbb{R}^2$	0.229	0.333	0.346
Adjusted R <sup>2</sup>	0.229	0.333	0.346
Residual Std. Error	1.613	1.250	1.025

+p<0.1; \*p<0.05; \*\*p<0.01

## C-3-b Clustering by Census Tract v MSA

Because our models include MSA fixed effects, we cluster standard errors by MSA. However, because the correlation among advertisements within tracts is greater than the correlation within MSAs, we also estimate models clustering standard errors by tract. The results are substantively unchanged. Some standard errors are slightly larger and some are slightly smaller.

Table A19: Clustering by Census Tract

	Dependent variable: Log Transformed Topic Proportion						
	Logistics Topic		Unit Amer	ities Topic	Neighborhood Amenities		
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	
Neighborhood Type							
White Poor	0.436**	0.520**	-0.215**	-0.234**	0.620**	0.382**	
	(0.075)	(0.076)	(0.075)	(0.069)	(0.058)	(0.052)	
Black Non-poor	0.487**	$0.195^*$	-0.594**	-0.164**	-0.304**	-0.036	
	(0.083)	(0.082)	(0.060)	(0.055)	(0.048)	(0.045)	
Black Poor	0.995**	0.497**	-0.792**	-0.239**	0.193**	0.280**	
	(0.085)	(0.090)	(0.062)	(0.055)	(0.044)	(0.044)	
Latino Non-poor	0.364**	0.362**	$-0.490^{**}$	$-0.095^{+}$	-0.124**	0.347**	
-	(0.061)	(0.077)	(0.048)	(0.052)	(0.038)	(0.042)	
Latino Poor	0.706**	0.664**	-0.822**	-0.305**	0.080	0.478**	
	(0.099)	(0.109)	(0.071)	(0.071)	(0.056)	(0.062)	
Asian Non-poor	-0.270**	0.236*	0.112	-0.081	-0.232**	-0.057	
	(0.089)	(0.099)	(0.083)	(0.077)	(0.056)	(0.072)	
Asian Poor	$0.389^{+}$	0.802**	$-0.303^{+}$	-0.393**	0.494**	0.439**	
	(0.216)	(0.205)	(0.179)	(0.125)	(0.144)	(0.081)	
Unit and Neighborhood Covariates							
Price (\$1000)		-0.114**		0.336**		-0.005	
		(0.014)		(0.011)		(0.009)	
% College		-0.013**		0.017**		0.018**	
		(0.001)		(0.001)		(0.001)	
% Foreign Born		-0.017**		0.004**		-0.010**	
		(0.002)		(0.001)		(0.002)	
% Units Renter Occ		-0.009**		0.007**		$0.010^{**}$	
		(0.001)		(0.001)		(0.001)	
% Unit Built after 2010		-0.013**		0.047**		$-0.004^{+}$	
		(0.003)		(0.002)		(0.002)	
% Vacancy		2.691**		-0.911**		1.592**	
		(0.233)		(0.166)		(0.139)	
MSA Fixed Effects	Y	Y	Y	Y	Y	Y	
Observations	1,692,639	1,692,639	1,692,639	1,692,639	1,692,639	1,692,639	
Number of Census Tracts	37,319	37,319	37,319	37,319	37,319	37,319	
$\mathbb{R}^2$	0.179	0.230	0.231	0.349	0.241	0.346	
Adjusted R <sup>2</sup>	0.179	0.230	0.231	0.349	0.241	0.346	
Residual Std. Error	1.664	1.611	1.342	1.235	1.104	1.025	

 $^{+}$ p<0.1;  $^{*}$ p<0.05;  $^{**}$ p<0.01

# C-3-c Including Month Fixed Effects

Given the potential for seasonality effects in the rental market, we also estimate models with month fixed effects. Results are unchanged.

Table A20: Month Fixed Effects

	Dependent variable:						
	Logistics Topic		Unit Amer	nities Topic	Neighborhood Amenities Topic		
	(1)	(2)	(3)	(4)	(5)	(6)	
White Poor	0.433**	0.517**	-0.213*	-0.231**	0.620**	0.382**	
	(0.088)	(0.084)	(0.093)	(0.078)	(0.084)	(0.075)	
Black Non-poor	0.488**	$0.195^{+}$	-0.595**	-0.165**	-0.304**	-0.036	
	(0.105)	(0.104)	(0.052)	(0.051)	(0.054)	(0.061)	
Black Poor	0.992**	0.493**	-0.789**	-0.235**	0.193**	0.280**	
	(0.112)	(0.122)	(0.063)	(0.066)	(0.064)	(0.063)	
Latino Non-poor	0.364**	0.360**	-0.490**	-0.093	$-0.124^{+}$	0.347**	
•	(0.065)	(0.084)	(0.081)	(0.072)	(0.072)	(0.055)	
Latino Poor	0.704**	0.661**	-0.820**	-0.302**	0.080	0.477**	
	(0.140)	(0.148)	(0.078)	(0.079)	(0.074)	(0.076)	
Asian Non-poor	-0.266*	0.239*	$0.108^{+}$	-0.083	-0.232**	-0.057	
_	(0.109)	(0.114)	(0.058)	(0.065)	(0.065)	(0.092)	
Asian Poor	0.379	0.792**	-0.293	$-0.381^{+}$	0.493**	0.438**	
	(0.286)	(0.267)	(0.315)	(0.215)	(0.159)	(0.077)	
Price (\$1000)		-0.114**		0.337**		-0.005	
		(0.026)		(0.037)		(0.016)	
% College		-0.013**		0.017**		0.018**	
C		(0.002)		(0.001)		(0.001)	
% Foreign Born		-0.017**		0.004*		-0.010**	
C		(0.004)		(0.002)		(0.002)	
% Units Renter Occ		-0.009**		0.007**		0.010**	
		(0.001)		(0.001)		(0.001)	
% Unit Built after 2010		$-0.013^*$		0.047**		-0.004	
		(0.005)		(0.004)		(0.002)	
% Vacancy		2.684**		-0.904**		1.592**	
•		(0.269)		(0.191)		(0.212)	
MSA Fixed Effects	Y	Y	Y	Y	Y	Y	
Month Fixed Effects	Y	Y	Y	Y	Y	Y	
Observations	1,692,635	1,692,635	1,692,635	1,692,635	1,692,635	1,692,635	
$\mathbb{R}^2$	0.180	0.231	0.233	0.351	0.241	0.346	
Adjusted R <sup>2</sup>	0.180	0.231	0.233	0.351	0.241	0.346	
Residual Std. Error	1.662	1.610	1.341	1.233	1.104	1.025	

<sup>+</sup>p<0.1; \*p<0.05; \*\*p<0.01

*Note:* Dependent variables are log transformed. The base category for neighborhood type is White non-poor neighborhoods. For neighborhood classification, racial composition is based on the plurality racial group. We use a threshold of 30% of tract poverty rate as our measure of neighborhood poverty. Neighborhood covariates are obtained from 2016 ACS 5-year pooled data. Models include MSA and month fixed effects. Standard errors are clustered at MSA level.

## D. MNIR Robustness Checks

# **D-1** MNIR Coefficients for Figure 4

Table A21: MNIR Coefficients for Figure 4

	% Black		% P	overty	% Education		
	Words	Coefficients	Words	Coefficients	Words	Coefficients	
1	evictions	0.0196	campus	0.0543	foods	0.0450	
2	section	0.0195	students	0.0432	rooftop	0.0382	
3	polis	0.0151	exposed	0.0369	uptown	0.0326	
4	applicants	0.0147	evictions	0.0358	lobby	0.0317	
5	eat	0.0146	university	0.0351	concierge	0.0316	
6	brick	0.0135	lofts	0.0303	boutique	0.0301	
7	ups	0.0134	museum	0.0286	rise	0.0300	
8	train	0.0133	section	0.0280	bicycle	0.0297	
9	exposed	0.0133	historic	0.0274	midtown	0.0292	
10	hook	0.0132	august	0.0272	union	0.0278	
11	needed	0.0131	studios	0.0270	whole	0.0268	
12	hookup	0.0131	midtown	0.0270	marble	0.0265	
13	clothes	0.0129	proof	0.0259	red	0.0247	
14	discounts	0.0128	duplex	0.0255	nw	0.0246	
15	affordable	0.0127	brick	0.0250	subway	0.0244	
16	wall	0.0127	secured	0.0245	museum	0.0239	
17	perfectly	0.0127	ave	0.0241	nightlife	0.0239	
18	criminal	0.0125	needed	0.0235	elevator	0.0238	
19	proof	0.0122	study	0.0234	backsplashes	0.0237	
20	de	0.0120	original	0.0230	hill	0.0235	
21	money	0.0119	criminal	0.0227	bike	0.0233	
22	military	0.0118	arts	0.0224	streets	0.0233	
23	income	0.0116	applicants	0.0221	broker	0.0231	
24	hospital	0.0115	recently	0.0218	underground	0.0231	
25	porch	0.0115	sky	0.0218	skyline	0.0227	
26	app	0.0115	intercom	0.0218	lined	0.0226	
27	vears	0.0113	income	0.0217	desk	0.0226	
28	rates	0.0114	landlord	0.0217	wine	0.0225	
29	metro	0.0114	block	0.0210	blocks	0.0223	
30	exciting	0.0111	bus	0.0209	classes	0.0219	
31	entrances	0.0111	sewer	0.0207	yoga	0.0216	
32	choice	0.0111	field	0.0207	clubroom	0.0216	
33	br	0.0111	medical	0.0206	urban	0.0214	
34	basement	0.0109	street	0.0206	neighborhoods	0.0214	
35	alarm	0.0109	porch	0.0205	showers	0.0212	
36	must	0.0109	stadium	0.0204	charm	0.0212	
37	townhomes	0.0107	building	0.0204	quartz	0.0209	
38	connections	0.0107	de	0.0202	charging	0.0204	
39	extraordinary	0.0107	painted	0.0199	racks	0.0204	
40	rear	0.0107	skyline	0.0199	lines	0.0204	
41	university	0.0106	roof	0.0196	building	0.0193	
42	background	0.0100	br	0.0196	steps	0.0193	
43	mini	0.0104	affordable	0.0193	sky	0.0191	
44	historic	0.0102	college	0.0193	dry	0.0190	
45	care	0.0101	pay	0.0193	conference	0.0188	
46	anytime	0.0099	pay st	0.0191	shops	0.0187	
47	pointe	0.0099	electricity	0.0189	starbucks	0.0185	
48	largest	0.0099	pays	0.0186	deep	0.0185	
46 49	portal	0.0097	line	0.0186	glass	0.0183	
	DUBLIAN	0.009/	IIIIC	0.0103	giass	0.0162	

### **D-2** MNIR with Different Preprocessing

In this section, we demonstrate that our MNIR results are robust to our preprocessing procedures. We use 1% as a threshold for removing low frequency words in the MNIR model in the main text. Here, we report the MNIR result from a different threshold: 0.7%. We remove words that appear less than 0.7% of the documents. Given we have 1,696,499 documents, the word needs to appear at least in 11,875 documents to not be removed.

Higher % Black	Higher % Poverty	Higher % College
wall-to-wall	campus	floor-to-ceiling
.stubs	student	foods
budget	students	trader
mills	exposed	capitol
priced	university	rooftop
evictions	evictions	triangle
section	lofts	concierge
eat-in	museum	uptown
renoted	section	lobby
scious	historic	facing
applition	august	panoramic
secuty	stubs	bicycle
renovations	midtown	midtown
polis	de	boutique
hook-ups	studios	union
applicants	proof	cafes
order	duplex	whole
suburban	brick	actual
qualify	hospitals	marble
recent	secured	queen
de	hollywood	broker
discounts	ave	tower
exposed	shuttle	subway
bedroo	off-street	nw
posit	sky	joe
hookup	recent	trendy
brick	study	elevator
affordable	original	museum
perfectly	criminal	nightlife
train	renoted	backsplashes
broad	hook	smoke-free
handicap	showings	red
criminal	sewage	hill
proof	arts	streets
ups	intercom	bike
hospital	recently	capital
military	needed	highlands
artnts	applicants	underground
app	block	desk
metro	music	blocks
hook	income	repair
livg	skyline	shuttle
confirm	landlord	wine
years	stadium	skyline
rates	eat	classes
exciting	medical	urban
money	bus	broad
interstates	secuty	walkable
porch	sewer	yoga
choice	roommate	santa
CHOICE	Toominate	Sama

Figure A7: Words with Top 50 Correlation with Neighborhood Covariates

#### **D-3** MNIR Results for Different SES Covariates

In this section, we present MNIR results with different covariates. We run MNIR with census tract median household income and % White. The first column lists the top 50 words that are strongly associated with higher median household income. The top 50 words show that advertisements in neighborhoods with higher median household income tend to have words that emphasize housing and neighborhood amenities. For example, words such as 'whole,' 'foods,' 'metro,' 'yoga,' 'starbucks' describe neighborhood amenities. Words that describe higher-end housing unit amenities 'marble,' 'concierge,' 'whirlpool,' 'high-end,' 'sinks,' 'quartz,' 'showers,' are more likely to appear as the neighborhood median household income increases.

The next column displays the top 50 words that are likely to appear when listings are in neighborhoods with lower median household income. Similar to the results from % Black (presented in the main text), words that emphasize renter qualifications such as 'evictions,' 'section' (8), 'criminal,' 'background,' 'screened,' 'income,' 'application,' 'money,' 'must' are more likely to appear as the neighborhood median household income decreases. There are a few words that describe the unit and the neighborhood. For example, 'historic' and 'hospital' are likely to describe the neighborhood. But the number of words describing neighborhood amenities are more limited compare to the first column. Words such as 'hookup,' 'lofts,' 'porch,' 'painted,' 'intercom' describe housing amenities that are not high-end features.

The results for % White (presented in the third column of Figure A8) show a less obvious pattern than other covariates. They includes word that describe neighborhood amenities ('whole,' 'foods,' 'theatre') and unit amenities ('whirlpool,' 'lawn,' 'carports'). However, these words appear less frequently. They are also more likely to represent high-end neighborhood and unit amenities.

Higher Median HH Income	Lower Median HH Income	Higher % White
ranch	evictions	snow
foods	campus	non-smoking
san	students	removal
wine	polis	salon
backsplashes	section	cherry
cabanas	criminal	woods
marble	hook-ups	commons
classes	hook	salt
hiking	off-street	acre
elementary	proof	underground
conciergé	university	foods
exquisite	posit	country
metro	sewer	biking
union	affordable	nw
acre	duplex	collection
biking	background	pond
charging	hookup	tanning
whirlpool	screened	lawn
whole	hospital	basement
high-end	closed	hill
ge	ups	bike
broker	hookups	august
smoke-free	lofts	streets
pendant	applicants	union
sinks	clud	wine
ball	income	level
level	clothes	river
quartz	artnts	lower
elegant	historic	round
yoga	porch	overlooking
corporate	entrances	smoking
showers	pay	pendant
reflect	studios	charm
starbucks	painted	newer
pre-wired	intercom	whirlpool
gaming	vertical	main
guests	application	saltwater
winning	eat	acres
commitment	арр	finished
hill	original	carports
nw	aable	july
party	money	whole
trails	secured	theatre
seating	speci	golf
attached	refreshing	bonus
cyber	must	utility
conference	patrol	indoor
prestigious	ve	polis
molding	facilities	appointed
soaking	facility	november
5549	,	11010111001

Figure A8: Words with Top 50 Correlation with Neighborhood Covariates

## E. Supplemental Analysis

#### **E-1** Variation in Amount and Types of Information

In supplemental analyses we examine non-text forms of information inequality. We created three simple measures based on our Craigslist data: (1) general information is a count of the number of distinct (optional) information fields that have been filled out in each post, including the number of bedrooms, bathrooms, and square footage, as well as contact information and the exact listing address; (2) number of pictures is a count of the number of pictures posted with the advertisement; and, (3) number of words is a count of the total number of words in the main text body of each advertisement. While these measures do not tell us anything about the content of advertisements, they offer initial, simple indicators of information differences (see Boeing et al. 2020 for similar analyses). Additionally, these measures capture important dimensions of advertisements that can impact the housing search process. For example, Craigslist allows prospective renters to filter which posts are shown to them based on these information categories; e.g., one can select to only be shown postings that contain pictures, or that have two or more bedrooms. We use a similar modeling approach here as with our topic proportions in the main text.

#### **RESULTS**

Table A22 reports descriptive statistics for our numerical (non-text) data. On average, advertisements contain 3.7 distinct fields of information, but range as low as 0 and as high as 5. We see wider ranges in the number of pictures (ranging from 0 to 24, with an average of 9) and overall word count (ranging from 6 – 3,782 words, with an average of about 183 words). Table A22 also reports descriptive statistics for all of our independent variables, which we draw from the ACS.<sup>1</sup>

<sup>&</sup>lt;sup>1</sup>The sample size for information regressions and topic model regressions differ because there are plenty of listings that do not have enough text for topic modeling. There are 1,457 listings that have less than 5 English words in their text; in addition, because our text preprocessing procedures remove very low frequency and very high frequency words, we drop additional listings that do not have enough text after preprocessing.

Table A22: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max	Missing
Dependent Variables <sup>a</sup>								
General Information	1,693,890	3.74	0.99	0	3	4	5	0
Number of Pictures	1,693,890	9.02	5.96	0	5	12	24	4
Number of Words	1,693,890	182.57	115.04	6	99	244	3,782	0
Neighborhood Type <sup>b</sup>								
White Non-Poor	1,179,452	69.2						
White Poor	78,610	4.6						
Black Non-Poor	136,747	8.1						
Black Poor	75,942	4.4						
Latino Non-Poor	141,015	8.3						
Latino Poor	49,535	2.9						
Asian Non-Poor	28,892	1.7						
Asian Poor	3,697	0.2						
Unit Covariate <sup>a</sup>								
Price (\$1,000)	1,693,890	1.42	0.80	0.001	0.91	1.70	10.00	18,604
Tract Covariates <sup>b</sup>								
% College	1,693,890	41.14	21.42	0.00	23.01	58.06	100.00	2,500
% Foreign Born	1,693,890	16.42	12.72	0.00	6.83	22.80	100.00	2,499
% Units Renter Occupied	1,693,890	52.82	23.72	0.00	34.72	71.06	100.00	3,250
% Units Built Post 2010	1,693,890	3.15	5.18	0	0	4.0	88.00	3,250
% Vacancy	1,693,890	10.104	7.62	0.00	5.09	13.03	95.77	3,202
Variables for MNIR <sup>b</sup>								
% Black	1,693,890	17.134	21.263	0.000	3.200	21.500	100.000	2,499
% College	1,693,890	41.136	21.424	0.000	23.010	58.060	100.000	2,500
Poverty Rate	1,693,890	16.161	11.915	0.000	7.370	21.910	100.000	3,224

 <sup>&</sup>lt;sup>a</sup> Source: Craigslist
 <sup>b</sup> Source: 2016 American Community Survey 5-year pooled data

Clearly, there is wide variation in the amount of information included in Craigslist rental housing advertisements. To explore this variation, we estimate an OLS model regressing each outcome on neighborhood type, testing whether there is systematic variation across different types of neighborhoods. We then estimate pairwise difference across neighborhood types by changing the baseline category in our regression models and generating predicted values. Figure A9 reports pairwise comparisons of neighborhood types for each of our information outcomes.

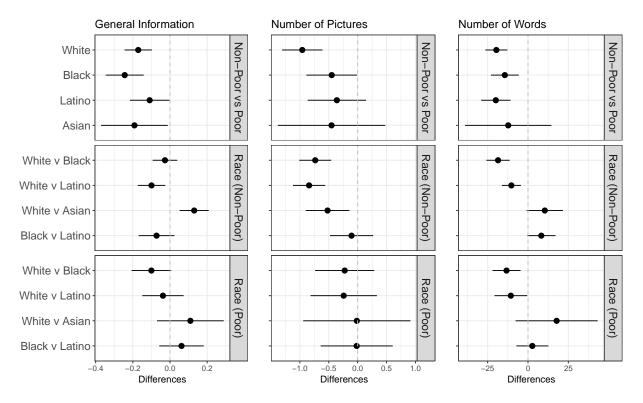


Figure A9: Pairwise Comparison of Information Outcomes Across Neighborhood Types *Note:* The dots and bars indicate the regression coefficients and confidence intervals from regression models. The neighborhood written first (before "vs") is the base category. The first four rows (non-poor vs poor) display the regression coefficients for poor neighborhoods when the non-poor neighborhoods for the respective racial group is the base category. Negative value means poor neighborhoods have less information than non-poor neighborhoods. Positive value means non-poor neighborhoods have less information than poor neighborhoods. The following eight rows compare differences between different racial compositions. The first racial group is the base category. For example, the coefficient for "White v Latino" in the sixth row for the number of pictures indicates that Latino non-poor neighborhoods have 0.84 less pictures than White non-poor neighborhoods. Neighborhood racial composition and poverty rate are obtained from 2016 ACS 5-year pooled data. The regression models include MSA fixed effects. Standard errors are clustered at census tract level.

Figure A9 focuses on theoretically important comparisons across neighborhood types by plotting the differences in each outcome for given pairs of neighborhoods. Starting with the top panel for each outcome measure, we can see a clear pattern across outcomes: listings in poor neighborhoods tend to contain significantly less information than their same-race, non-poor counterparts. The magnitude and significance of

these information gaps varies somewhat across our information measures, but it is clear that holding racial composition constant, advertisements in poorer neighborhoods provide far less information to searchers.

However, poverty status does not account for all the variation in information levels. The middle panel for each outcome compares information differences among non-poor neighborhoods by race. Across measures we consistently find that listings in non-poor Black and Latino neighborhoods contain less information than those in non-poor White neighborhoods. In other words, even when we just compare neighborhoods with similarly low poverty levels, Black and Latino neighborhoods face an information disadvantage compared to White neighborhoods. Advertisements for housing in non-poor Asian neighborhoods contain more overall information and number of words compared to those in non-poor White neighborhoods, but fewer pictures on average, suggesting that listings in Asian neighborhoods do not experience the same racial penalty as Black and Latino neighborhoods. Nevertheless, we find clear evidence of both a socioeconomic and racial hierarchy in terms of basic information: advertisements in neighborhoods with more Black and/or Latino residents and/or more poor households contain significantly less information—measured as the number of distinct information fields, the number of pictures, and the number of overall words provided within advertisements—than do advertisements in neighborhoods with more Asian, White, and/or non-poor residents.

Finally, the bottom panel in Figure A9 measures racial differences in listing information levels among poor neighborhoods. Even among poor neighborhoods we find some evidence of racial inequality: listings in poor Black and Latino neighborhoods have significantly fewer words than those in poor White neighborhoods. While racial differences among poor neighborhoods tend to be smaller in terms of magnitude and are not statistically significant across all outcome measures, they nevertheless underscore the importance of accounting for neighborhood race and poverty status simultaneously to fully understand differences in access to information.

Table A23 repeats our analysis but includes additional neighborhood covariates. We find that higher priced listings tend to contain more information on average, as do listings in neighborhoods with greater proportions of college-educated residents or immigrants. Interestingly, we also find that measures of stronger rental market competition (rental occupancy rate and an indicator of recent construction activity) are also associated with greater information, while higher vacancy rates—an indicator of a weaker rental market—are associated with less information. Searchers who are limited to looking in less desirable neighborhoods have access to far less information about their potential homes.

Overall, our supplementary analyses find clear evidence of neighborhood racial and socioeconomic inequalities in the amount of information presented in rental housing advertisements. These results offer futher support for the conclusions we draw using the text data about racial and socioeconomic inequality in the information provided in housing advertisements.

Table A23: Regression Results Predicting Information Measures with Additional Neighborhood Covariates

	Dependent variable:				
	General Information	Num Pics	Num Words		
Neighborhood Type					
White Poor	-0.194**	-1.008**	-24.444**		
	(0.037)	(0.176)	(3.644)		
Black Non-poor	0.016	-0.179	-10.079**		
	(0.035)	(0.135)	(3.737)		
Black Poor	-0.171**	-0.503*	-20.563**		
	(0.045)	(0.208)	(3.536)		
Latino Non-poor	-0.151**	-0.427**	-8.637*		
_	(0.042)	(0.156)	(3.554)		
Latino Poor	-0.255**	-0.668**	-27.832**		
	(0.047)	(0.237)	(4.648)		
Asian Non-poor	0.006	-0.635**	-1.596		
-	(0.048)	(0.215)	(6.202)		
Asian Poor	$-0.190^*$	-1.283**	-14.516		
	(0.079)	(0.420)	(11.739)		
<b>Unit and Neighborhood Covariates</b>					
Price (\$1000)	0.182**	1.956**	16.301**		
	(0.009)	(0.053)	(0.931)		
% College	0.0002	0.007**	0.269**		
	(0.0005)	(0.002)	(0.052)		
% Foreign Born	0.005**	$0.010^{*}$	0.398**		
	(0.001)	(0.004)	(0.109)		
% Units Renter Occ	0.003**	0.012**	0.357**		
	(0.0004)	(0.002)	(0.044)		
% Unit Built after 2010	0.004**	0.014*	1.218**		
	(0.001)	(0.007)	(0.177)		
% Vacancy	-0.011**	-0.026**	-0.791**		
	(0.001)	(0.005)	(0.117)		
MSA Fixed Effects	Y	Y	Y		
Observations	1,693,890	1,693,890	1,693,890		
Number of Census Tracts	37,392	37,392	37,392		
$R^2$	0.107	0.088	0.110		
Adjusted R <sup>2</sup>	0.107	0.088	0.110		
Residual Std. Error	0.932	5.693	108.556		

<sup>+</sup>p<0.1; \*p<0.05; \*\*p<0.01

*Note:* The base category for neighborhood type is White non-poor neighborhoods. Listings that are more expensive than \$10,000 are removed. For neighborhood classification, racial composition is based on the plurality racial group. We use a threshold of 30% of tract poverty rate as our measure of neighborhood poverty. Neighborhood covariates are obtained from 2016 ACS 5-year pooled data. Standard errors are clustered at census tract level.

## F. Appendix References

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