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High Frequency Gentrification Prediction Using Airbnb Data

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High Frequency Gentrification Prediction with Airbnb Data

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We propose a methodology for estimating neighborhood gentrification using high frequency, publicly available Airbnb data. Leveraging 3.8 million text reviews from Jan 2014 to Dec 2019 across 17 US cities, we find guest reviews and rental characteristics to be predictive of gentrification during the same period. Both structured features (e.g. number of listings) and unstructured features (e.g. word frequency in reviews) are found to be important predictors across multiple specifications. Using our trained model, we predict and map current gentrification rates ahead of official statistics. These models are provided freely to enable rapid policy response and further research. [†]

Gentrification is generally understood as a process of change whereby neighborhoods which have been historically under-capitalized experience an influx of new residents with high social capital. This demographic change corresponds with an increase in investment in the neighborhood, generally transforming the housing stock and character of the neighborhood. In theory, residents of gentrifying neighborhoods stand to benefit from increased retail and housing investment and the affiliated job opportunities and tax revenues. In practice, a gentrifying neighborhood's original residents often find themselves forced out by a

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[†] Models, replication data, and code can be accessed at https://github.com/LeoKitchell/SeniorThesis/

combination of passive market factors, namely increased rents, and active displacement mechanisms such as planned dilapidation, eviction, and reinvestment cycles. This displacement of vulnerable populations is the principal concern of housing activists and is central to gentrification's contentiousness. Unfortunately, the demographic and cultural aspects of gentrification have characteristics which make quantifying their change difficult, and which consequently limits scholarship and effective policy intervention.

One of the principal data challenges is that detailed demographic data is infrequently collected, so researchers and policymakers are fettered by data from the decennial Census or the 5-year American Community Survey (ACS). As a result, research must be conducted on sparse time series, limiting the empirical power of results. On the policy side, the lag makes early identification of gentrification difficult, and dynamic monitoring impossible. Traditional data sources also struggle to capture the cultural elements of gentrification. While the arrival of craft coffee shops, Whole Foods, and street art may be easily visible signs of cultural change for residents of a gentrifying neighborhood, this local knowledge does not get translated into standard data sets. However, new data sources may solve some of these challenges.

Crowdsourced data from online platforms like Yelp, Zillow, and Airbnb are enabling researchers to investigate economic trends at a far more granular level and in real time (Glaeser, Kim, and Luca 2018; Jain 2021). These data supplement traditional metrics with novel features, such as user reviews and textual descriptions. These features represent an exciting frontier in gentrification research and may enable a better understanding of neighborhoods and their residents.

This paper utilizes 3.8 million text reviews from Airbnb listings in 17 U.S. cities to learn neighborhood characteristics and estimate historical gentrification. Our analysis is organized into five parts. Section I summarizes key empirical studies on gentrification with a focus on their specifications of gentrification and the

geographies which are suitable for analysis. A recent study using Airbnb data to predict measures of gentrification, is also discussed. Section II discusses our data sources and outlines our gentrification operationalization. Section III proposes three estimation models to investigate the explanatory power of our Airbnb data, summarizes our model tuning process, and presents their final specifications. Finally, section IV compares the results of our models, discusses the importance of these new data sources, and proposes a method to predict current gentrification rates using our trained model weights.

I. Context and Previous Research

The data challenges introduced in the previous section have hindered gentrification research, but a robust literature still exists, particularly when it comes to identifying areas susceptible to gentrification. The term gentrification originates from the migration of London "gentry" into lower-income neighborhoods in the 1950s and 1960s (Glass 1964). Since the term's coining, researchers have developed progressively more complicated methods of identifying gentrification, and considerable variation still exists in its operationalization. Upon this backdrop of variation, resident income and education level are commonly used measures of quantifying the demographic pillar of gentrification (Freeman 2005; Bates 2013; Ding, Hwang, and Divringi 2016; Lewis et al. 2020). Although some scholars include racial displacement in their gentrification definitions (McKinnish, Walsh, and White 2008; Bates 2013), other research suggests gentrification does not necessarily follow these patterns (Kennedy 2001; Freeman 2005; McKinnish, Walsh, and White 2008; Ellen and Regan 2011; Ding et al. 2016,). Following academic consensus, our specification of gentrification does not explicitly include measures of race. However, through the inclusion of highly correlated variables, namely income and educational attainment, some racial trends are implicitly

included in our modeling. These neighborhood demographic changes are necessary to establish gentrification, they are not sufficient on their own.

A central tenant of gentrification is its disproportionate impact on vulnerable communities and its contrast with historical neighborhood characteristics. Following World War II, mortgage guarantee policies passed in the GI bill helped subsidize Americans to move from metropolitan areas to suburbs (Lewis et al. 2020). However, actions taken by the Federal Housing Administration rendered these suburbs largely unavailable to black Americans (Richardson, Mitchell, and Franco 2019). The resulting migration flows, known as "white flight," spurred a trend of disinvestment in inner city communities which continued into the early 1990s (Hyra 2012). Although the 1990s and 2000s saw a wave of urban investment projects, these have not eliminated the long history of inner-city neglect. It is only in previously disinvested neighborhoods where neighborhood change is considered to be gentrification. To identify these disinvested communities, we turn to 3 recent studies.

Ding et al. (2016) define neighborhoods as *gentrifiable* if their median household income was below the citywide median at the beginning of the analysis time period. Among these eligible neighborhoods, only those which saw an increase in housing costs —as operationalized by median gross rent or median home value— above the citywide rate and which also experienced an above citywide increase in the percent residents with a college degree were considered gentrifying. A similar specification by Meltzer (2017) includes only average household incomes to identify such neighborhoods.

Using similar gentrification specifications to Ding et al. and Meltzer, recent studies have aimed to nowcast gentrification using high frequency data. Most applicable to our investigation is Jain et al. (2021) which uses Airbnb data from Los Angeles, New York, and London to predict neighborhood change at the zip code level. In their modeling, Jain et al. focus on methods to map review sentiment

and word frequency into low dimensional space. In doing so, the variation in reviews is reduced and the interpretations of variable significance is obfuscated. They find that Airbnb data can help predict gentrification, but due to this dimensionality reduction and small sample of cities, do not find strong results for the impact of user review content. Rather, the most significant features in their analysis were two measures of Airbnb density: the number of listings and number of reviews in a neighborhood.

Building upon this, we aim to strengthen the understanding between information captured in user reviews and neighborhood gentrification through machine learning models which are more readily interpretable. By sampling a larger number of cities and using Census tracts as our level of analysis, we model gentrification across significantly more observations ($n_{Jain} = 323$, $n_{Kitchell} = 3,129$), particularly when restricting Jain to US observations.[1] In doing so, we contribute a broader understanding of US gentrification trends with robust results. Using these results, we extend the literature by mapping our predicted gentrification changes from the January 2020 to October 2021.

II. Data and Gentrification Specification

A. ACS Gentrification Data

Following in the footsteps of many others (Meltzer 2017, Lester and Hartley 2014; Ellen and O'Regan 2008; McKinnish, Walsh, and White 2008; Freeman 2008; Hwang 2014) our level of analysis will be the census tract. Census tracts contain approximately 4,000 residents and are frequently used to model neighborhood evolution. Demographic data is sourced from the American

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[1] US only observations in Jain et al. total 137.

Community Survey (ACS) 5-year estimates via the Census API for the periods January 2009 to December 2014 and January 2015 to December 2019.

As with the authors in sections I and II, our analysis of gentrification begins with identifying gentrifiable tracts. These will be defined as tracts with median household incomes below the Metropolitan Statistical Area's (MSA) median. Only tracts contained within a census designated MSA are included. While MSAs contain some tracts which are outside of the urban core, where gentrification is most apparent and pressing, they provide a definition of urban tracts which is consistent across states and immune to subjectivity.

(1) $G_{i,MSA,y} = \frac{1}{3}(Income_{\%ile,i,MSA,y} + Rent_{\%ile,i,MSA,y} + Education_{\%ile,i,MSA,y})$

To measure gentrification, each gentrifiable tract will be given two scores composed of three variables for the 5-year ACS periods ending in 2014 and 2019, respectively. These variables are median household income, median gross rent, and percent of residents with a bachelor's degree or higher. To normalize across MSAs, each component of a tract's gentrification index is constructed using the percentile score relative to other tracts in an MSA. For example, a tract which was in the 25th%ile for income, 30th%ile for rent, and 35th%ile for education in 2014 would have a 2014 gentrification index of 0.30.

(2) $Gentrification\ Change_i = G_{i,2019} - G_{i,2014}$

Our variable of interest is the change in this gentrification index between 2014 and 2019. Figure 1 shows the distribution of our indices and dependent variable in gentrifiable neighborhoods. By construction, these indices are skewed below 0.5 in 2014, and the same is largely true in 2019. The index changes appear symmetrically distributed around a modest increase of 0.02, but the distribution offers

considerable exploitable variation exists, with a range of 0.87. Additional summary statistics are available in Table 1.
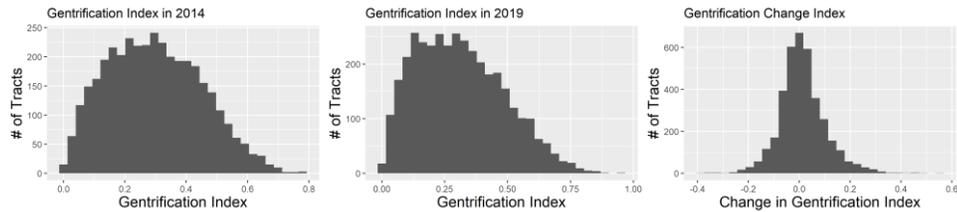

FIGURE 1. DISTRIBUTION OF GENTRIFICATION INDEX IN GENTRIFIABLE NEIGHBORHOODS

B. Population Control Variables

A key motivation of this study is providing a framework for gentrification prediction that does not require a significant number of control variables which are collected with a delay or are otherwise arduous to obtain. As such, our control variables are limited to initial tract population, and tract population growth between 2014 and 2019. While annual ACS population estimates are not provided at the tract level, population characteristics may be known to policymakers and researchers through proxies such as tax returns or mobile device mobility data (Smolak et al. 2020).
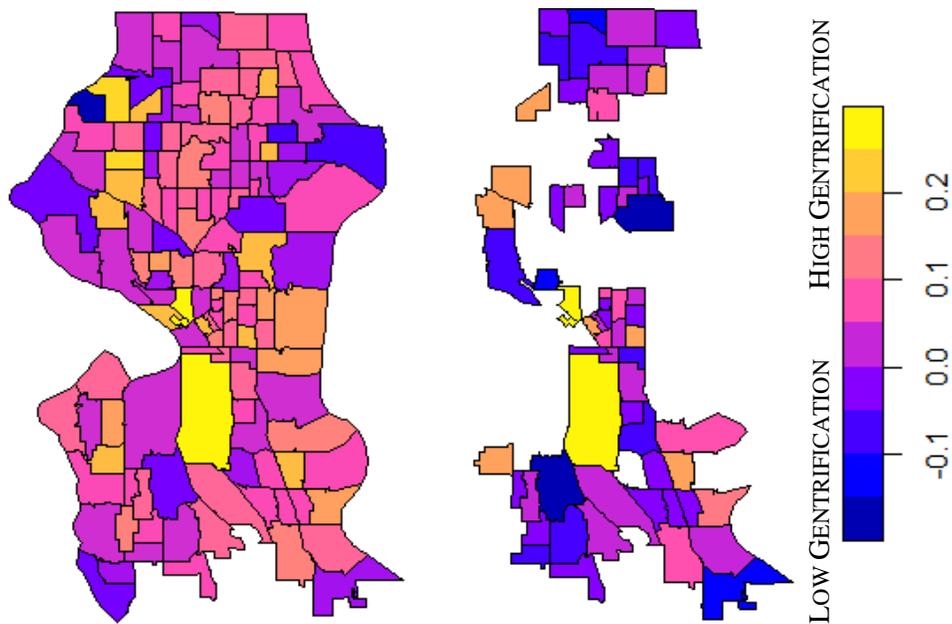
FIGURE 2. GENTRIFICATION CHANGE IN SEATTLE
ALL TRACTS (LEFT) AND GENTRIFIABLE TRACTS (RIGHT)

Notes: Gentrification is prevalent in South Central Seattle and in pockets of North Seattle including Ballard and Wallingford. Color differences between maps at left and right is due to graphing parameters; gentrification change values are not recalculated or adjusted after removing neighborhoods with high initial household incomes.

C. Airbnb Data

Airbnb was founded in 2007 as a peer to peer home rental platform and has since expanded to include 4 million hosts, 5.6 million listings worldwide, and over 1.0 billion all-time guest visits. To facilitate bookings, prospective guests are able to view photos and characteristics of each listing, as well as see ratings and reviews from past guests. This represents a trove of geolocated data on neighborhood composition which has only recently started appearing in academic research. This is primarily due to Airbnb's infancy, as the majority of listings and have been on the platform for fewer than 5 years.
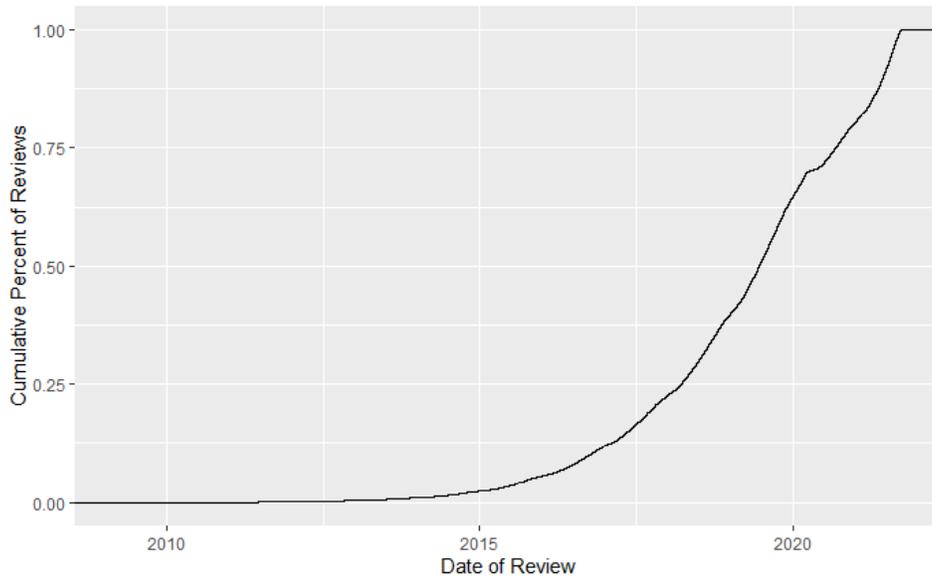
FIGURE 3. AIRBNB REVIEWS IN GENTRIFIABLE TRACTS BY YEAR

Notes: Over half of Airbnb reviews in gentrifiable tracts were made after 2019. The limited number of reviews present before 2014 prevents research on a larger time window.

To conduct our analysis, we collect data for the complete set of Airbnb listings and reviews for 17 US cities[2]. These data include 5.95 million reviews spread across 141,000 listings. Using the latitudes and longitudes of listings, we geocode each listing inside of census tracts which are contained within MSAs. [3] [4] We then separate our Airbnb into structured and unstructured features for processing.

Structured Features.—

For each listing we collect four primary variables: number of bedrooms, average daily listing price in USD, average user rating of listing, average user rating of

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[2] Airbnb data downloaded from InsideAirbnb.com, which scrapes features the Airbnb website monthly

[3] Airbnb reports the location of each listing with a small amount of noise to protect the privacy of listing owners. This noise is symmetrically distributed in latitude and longitude and limited to an area approximately three city blocks in diameter. As such, in aggregate, our mapping to census tracts should be unbiased.

[4] Listings are geocoded to their full FIPS code using the FCC Block Geocoding API. The tract FIPS codes are then extracted. Blocks are completely enclosed in tracts, so there is no loss in accuracy during this conversion.

listing location, and number of reviews. These listing features are aggregated[5] at the tract level in our final specification, and tracts which do not contain an Airbnb listing or are not classified as gentrifiable are dropped. For each tract we also calculate the total number of listings and the total number of reviews, which serve as proxies for Airbnb popularity. After these filtering steps, our final sample includes data from 34,387 listings. The summary statistics of these aggregated tract variables can be found in Table 1.

Unstructured Features.—

Unstructured data features are created from user reviews using Natural Language Processing (NLP) techniques. First, we restrict our sample of reviews to only include those in gentrifiable tracts during our period of analysis, January 2015 to December 2019. The resulting 1,642,408 reviews are then preprocessed to remove punctuation, commonly used words in both English and Spanish, and the names of cities and states. Neighborhood names contain important gentrification information and are therefore retained. In the final step of preprocessing, each remaining word is then stemmed to its root form.[6] This leaves us with 409,700 unique stems.

To reduce this to a reasonable number of covariates for training random forest models and to eliminate the occasional stemming error, we remove words from our sample which are infrequently used. To find the optimal sparsity parameter we test 8 different levels of sparsity ranging from 0.40 to 0.99. This word sparsity is calculated at the tract level. If a word only appeared in reviews in 2% of tracts it would not be included in our analysis using the 0.40 threshold but would be using the 0.99 threshold. The number of unique words included in our testing after this restriction ranged from 347 to 14,102 and is described in Figure 4.

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[5] For each tract we report the average number of listing bedrooms, the average of average listing price, the average of average location and average listing rating, and the total number of listings and reviews.

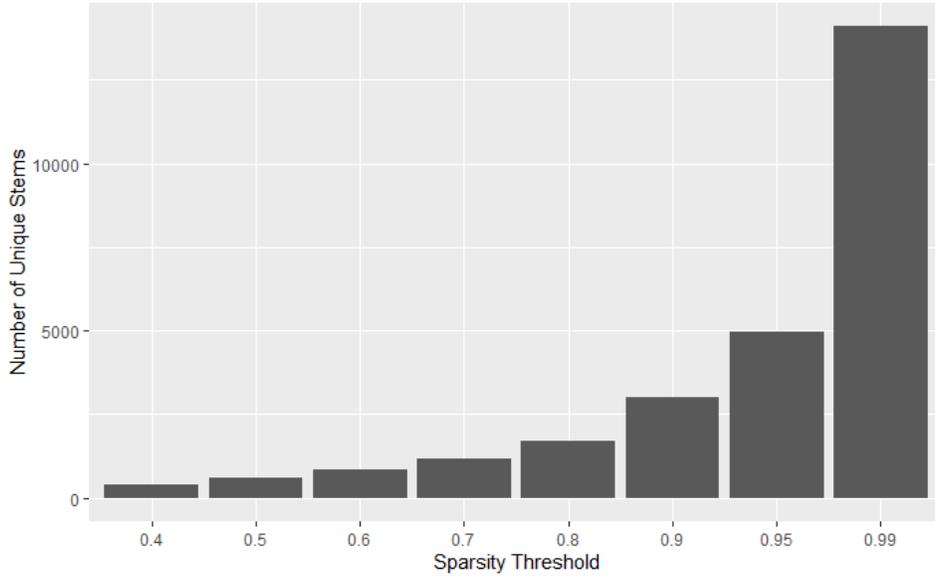[6] e.g. "walking" and "walked" are converted to "walk."

FIGURE 4. DISTRIBUTION OF FEATURE DENSITY FOR VARYING SPARSITIES

TABLE 1—SUMMARY STATISTICS OF CENSUS AND AIRBNB VARIABLES

	Minimum	Median	Mean	Maximum	Std. Dev.
Gentrification Change	-0.37	0.01	0.02	0.50	0.09
Initial Population	173.00	3,931.00	4,142.00	28,827.00	1,796.71
Population Change	-0.61	0.02	0.04	1.17	0.15
# of Listings	1.00	5.00	10.73	783.00	21.25
# of Reviews	1.00	182	512.3	2,8041	1,092.00
Avg. Listing Price	19.00	107.00	133.23	9,900	222.79
Avg. Listing Rating	1.00	4.76	4.63	5.00	0.51
Avg. # of Bedrooms	1.00	1.37	1.56	6.00	0.67
Avg. Location Rating	1.00	4.74	4.67	5.00	0.31

Notes: n = 3,129 for all variables. 34,387 listings are aggregated to create the Airbnb features. Summary statistics of tract demographic data not provided due to normalization technique; all demographic variables range from 0th percentile to 100th percentile before excluding gentrifiable tracts.

III. Model Selection

In selecting random forest models, we considered two properties. First, the fundamental coherence of language dictates that our text data be collinear predictor variables. Second, our data is feature rich relative to our tract sample size. When our sparsity threshold is 0.99, for example, there are more than four times as many

features as tracts to estimate. Traditional linear regressions are ill-equipped for such an estimation task. Standardized linear models such as ridge regression and LASSO regression were briefly considered, but they proved to be far inferior to random forest predictions.

To test the efficacy of Airbnb data in gentrification prediction we consider three sets of random forest models using two representations of text importance. The first set of models includes all data sources, including population control variables, structured Airbnb features, and the unstructured review data. To discern the additional predictive power of the text data, we create a second model using only the population controls and structured features. Finally, we test a baseline model using only population data.

$$(3) \qquad\qquad tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{i,j}} \;\; ; \;\; df(w) = \log(\frac{N}{df_t})$$

$$(4) \qquad\qquad w_{i,j} = tf_{i,j} \times df(w)$$

For the first model we consider two mappings of text features to importance levels. The first, Bag of Words, counts the number of times each stem word is used in a tract's reviews and feeds that raw number of occurrences into the random forest. The second, Term Frequency Inverse Document Frequency (TF IDF), is a two-step process which first counts the number of times a word appears in a tract as a fraction of total words in that tract, shown in equation 3. This term frequency is then multiplied by a weighting of how rare words are across all tracts, calculated in equation 4 as the log of the number of tracts divided by the number of tracts which contain reviews with the given word.

To determine the superior text mapping strategy and ideal sparsity thresholds a total of 192 random forests were trained. Each mapping strategy was tested using a small model of 200 trees and a large model of 500 trees. At each sparsity, six models

were trained using a low, medium, and high value for the mtry parameter, which represents the number of variables available for splitting at each tree node.[7] For each combination of mapping, sparsity, and number of trees, the model with the lowest prediction error is plotted in figure 5. We find that the 500 tree model outperformed the 200 tree model across all sparsities, with lower sparsities having consistently lower error rates. No mapping strategy was consistently superior, but the lowest error was achieved with the 90% sparsity, 500 tree Bag of Words model.
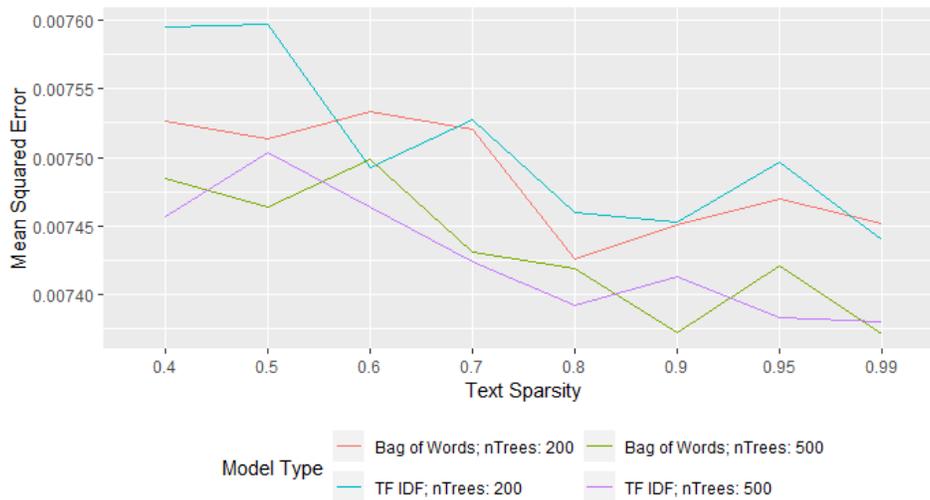
FIGURE 5. OUT OF BAG PREDICTION ERRORS BY MODEL SPECIFICATION

Notes: Mtry of plotted models varies from 403 to 14,111. Each data point represents the best model trained from 6 candidate models with varying levels of mtry.

These results were then used to learn the best value of the mtry parameter. Tuning algorithms were initialized with varying levels of mtry, which were iteratively changed to minimize error rates. Through this process, an optimal mtry of 913 was discovered for the 90% sparsity models. This optimal value was then used to train another set of 500 tree, Bag of Words models across sparsities to confirm our ideal sparsity specification.

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[7] The low, medium, and high values for mtry were 2, $\sqrt{n}$, and $n-1$, where n represents the number of predictor variables. Each specification was run twice to minimize random variation
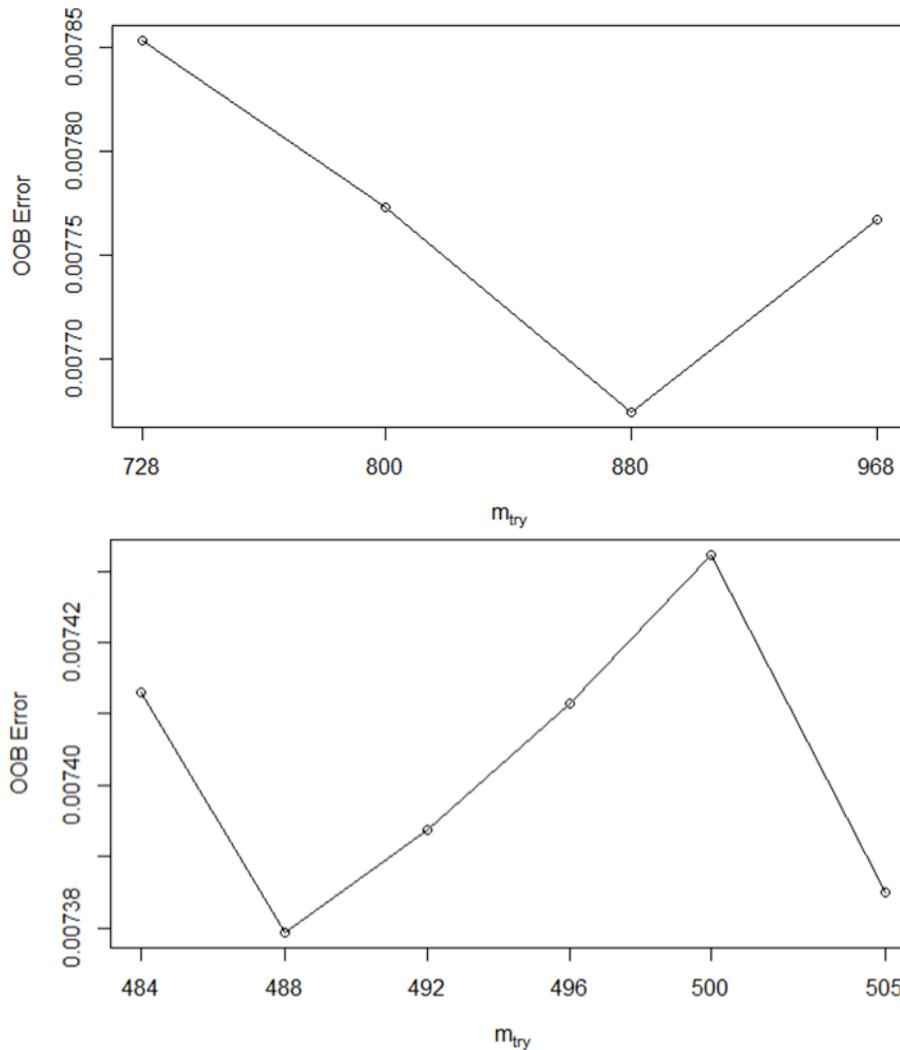
FIGURE 6: EXAMPLE TUNING RUN FOR MTRY PARAMETER

Notes: Tuning runs were first run using 100 trees and initialized at 10 values of mtry between 2 and 3029 using a scaling factor of 2 Once local optima were discovered, they were set as the new initialized values, the number of trees were increased to 500, and the scaling factors were reduced until a single optimal mtry was discovered. The figure at top reports errors from the 90% sparsity models, while the second reports errors from the 80% sparsity models.

However, running these models again with an mtry of 913 rather than the previous defaults, we found that models using the 80% sparsity threshold consistently outperformed our heretofore considered optimum. To find the true optimum, we again iterated over mtry values with a new sparsity of 80% and found an optimal value of 488. Using this optimal we re-trained our models across our

sparsity spectrum and found the parameter set to be stable and minimize error. The
final specification of this estimation model is summarized in Table 2.
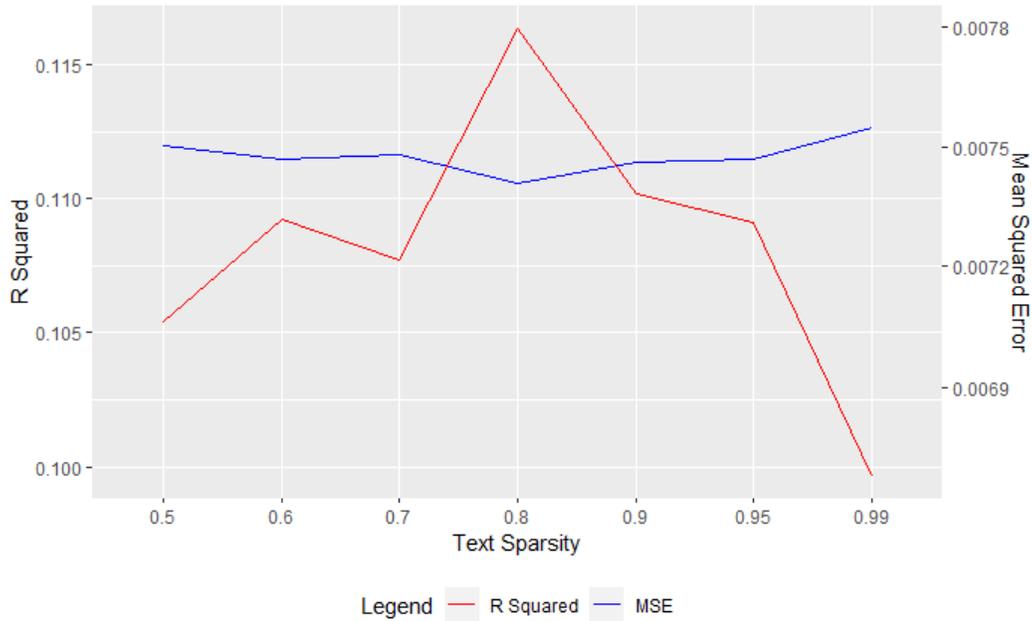
FIGURE 7: ERROR AND EXPLAINED VARIATION FOR 500 TREE BAG OF WORDS MODEL WITH MTRY = 488

Notes: Error is minimized and explained variation is maximized using a sparsity of 0.8. Presented R squared is pseudo R squared, calculated as $1 - Mean\ Squared\ Error\ \div Variance$

TABLE 2 —FINAL MODEL PARAMETERIZATIONS

Model Name	Text Mapping	Num. Trees	Mtry	Sparsity	Min. Nodes Per Leaf	Split Rule
Full Model	Bag of Words	500	488	0.80	5	Variance
Structured	N/A	500	8	N/A	5	Variance
Baseline	N/A	500	1	N/A	5	Variance

IV. Results and Discussion

A. Estimation
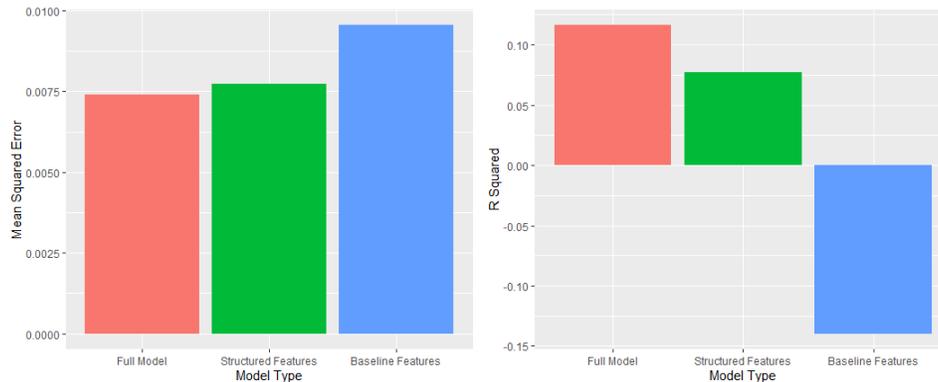
FIGURE 8: EFFICACY OF BASELINE, STRUCTURED, AND FULL MODELS IN GENTRIFICATION PREDICTION

Notes: Each model was trained using 500 trees, a minimum of 5 nodes per leaf, and variance as the split rule. The full model is trained using mtry = 488. For the structured features and baseline features models, mtry is set to $n-1$.

TABLE 3 —MODEL ACCURACY AND EXPLAINED VARIATION

	Baseline	Structured Features	Full Model
Mean Squared Error	0.009556	0.007765	0.007408
Pseudo R Squared	-13.98%	7.38%	11.64%

Notes: R Squared is calculated using $1 - Mean\ Squared\ Error \div Variance$

In this section, we begin by comparing our three models for accuracy and explanatory power before investigating the importance of their features. We find that the inclusion of structured Airbnb data greatly increases the accuracy of our model, and that text reviews provide additional predictive power. Accuracy, as measured by mean squared error, increased by 23.06% between the baseline and structured models. Using just six Airbnb variables and our two population metrics, we recorded a pseudo R^2 of 7.38%. Among Airbnb variables, we found the average listing price and number of reviews in a tract to be the most important, although less so than our population variables. Notably, these population variables were only informative when combined with the Airbnb data; the pseudo R^2 of the population variables on their own was -11.39%, indicating that predictions using just population variables would estimate worse than simply using the mean

gentrification increase. Moving to the full model, we find that adding user reviews further increases the accuracy of predictions, and the explained variation. With the text data, our accuracy increases 4.7%; more notably, our pseudo R^2 increases by 57.8%. To explain this jump, we turn to variable importance.
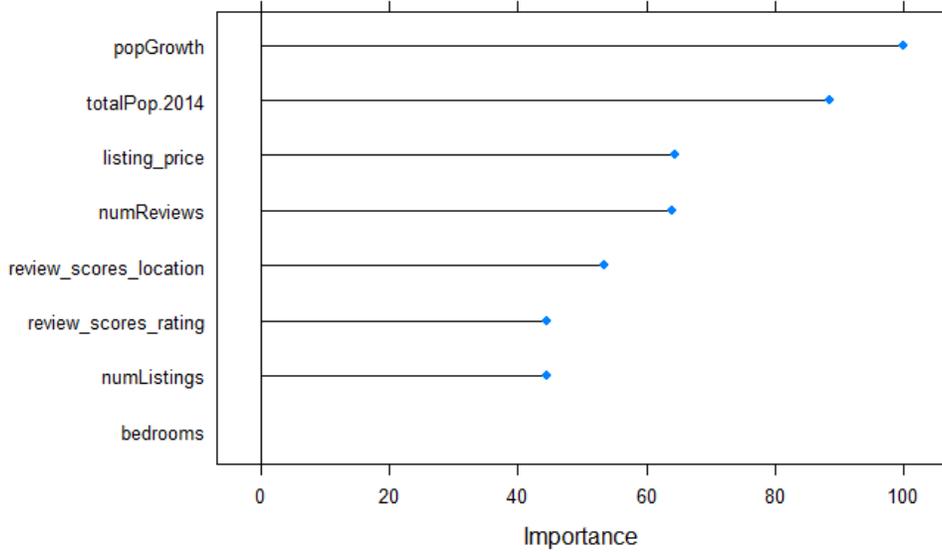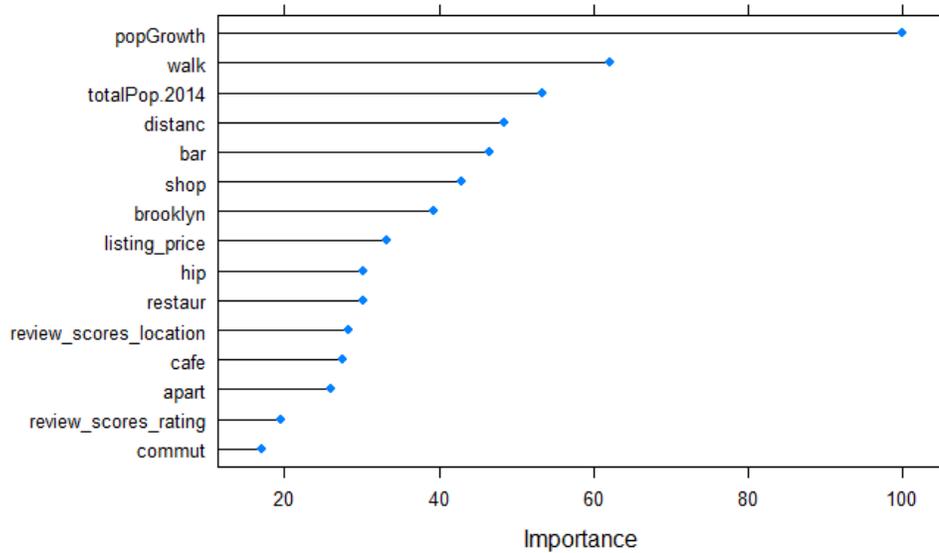

FIGURE 9: FEATURE IMPORTANCE IN STRUCTURED MODEL

Notes: Importance is calculated as the decrease in node impurity weighted by the probability of reaching that node, as calculated by the percentage of total samples which reach that node. Mtry of 8.

FIGURE 10: FEATURE IMPORTANCE IN FULL MODEL

We find considerable heterogeneity in the predictive power of word stems. Across specifications, unstructured variables are interspersed with the structured in importance rank. Mentions of stems associated with location, such as "walk," "distanc," "commut," and "train" provide significant information about the gentrification status of neighborhoods. A second set of stems associated with neighborhood businesses, such as "bar," "shop," "café," "restaur," and "grocerie," are also found to be significant across specifications. These stems are consistently more informative than our structured location feature, which ranks approximately 10th most important across specifications.

We identify two other stem sets of interest. The first, named neighborhoods, includes "brooklyn" and "flush," the stem of the New York City neighborhood "Flushing." A large portion of our listings and reviews come from New York City, and as such, large neighborhood names show up in many tracts. Because many tracts in Brooklyn are gentrifying, and these tracts make up a significant portion of our sample, Brooklyn shows up as a key stem. Gentrification in Brooklyn is a well-known phenomenon, but this demonstrates a strength of our methodology. Especially when trained on review data from individual MSAs, we can identify the importance of a reviewer's perceptions of neighborhoods on gentrification. If two neighborhoods with differing levels of gentrification have with identical population and Airbnb data profiles save for their name in reviews, it may signal the popularity of a neighborhood among new gentrifiers, or potentially intangible changes associated with gentrification.
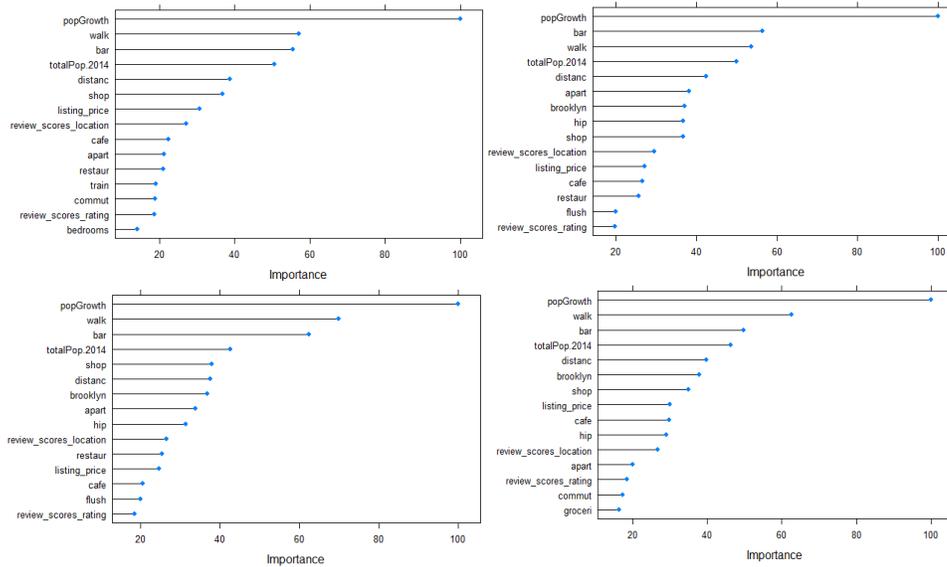
FIGURE 11: FEATURE IMPORTANCE IN FULL MODEL – ALTERNATE SPECIFICATIONS

Notes: Clockwise from top left: sparsity 0.7, mtry 488; sparsity 0.9, mtry 488; sparsity 0.8, mtry 844; sparsity 0.9, mtry 844

This leads us to the final stems of interest, neighborhood character. As mentioned previously, changes in the cultural character of neighborhoods is a core pillar of gentrification, but it's identification and quantification has been elusive in empirical studies. Across specifications we find certain adjectives such as "hip," "clean," "modern," "cute," and "local," to be predictive of gentrification. While we cannot discern whether these features refer to neighborhood or listing characteristics, they provide an interesting path for future research.

B. Prediction

In investigating the explanatory power of Airbnb data, we aimed to create a supplement to traditional measures of gentrification that may be able to serve as a proxy during the gaps between semi-decennial releases of official statistics. To this end, we now apply our trained variable weightings from the full model to a new set of Airbnb reviews written after the December 2019 ACS cutoff. These data span

the 22 months from January 2020 to October 2021 and include over 2 million new reviews.[8] The resulting predictions are mapped and provided in Appendix I.
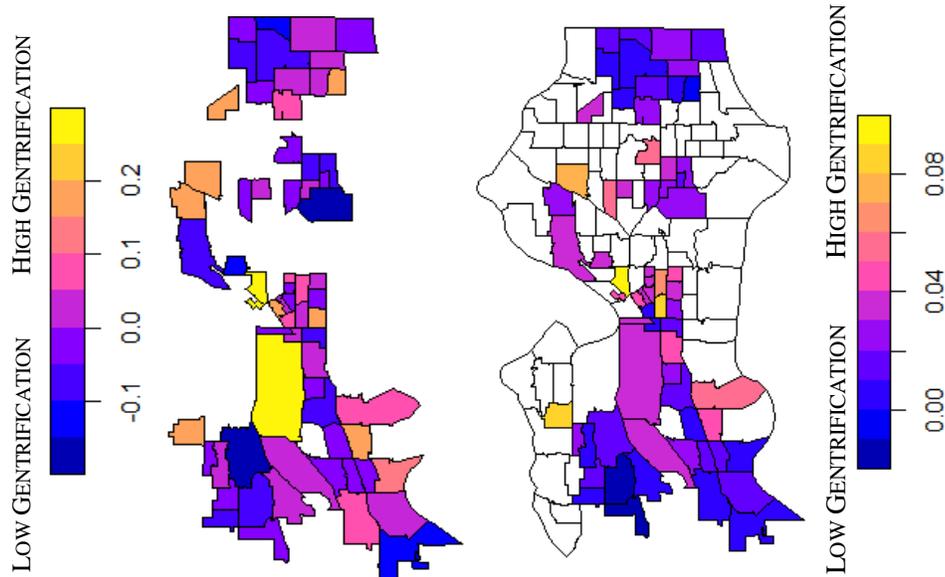
FIGURE 12. HISTORICAL (LEFT) AND PREDICTED (RIGHT) GENTRIFICATION CHANGE IN SEATTLE

Notes: Data at right represent changes between Jan 2020 – Oct 2020 and Mar 2018 – Dec 2019.

Examining the map for Seattle, we see gentrification is predicted to be higher in central Seattle, and taper on the northern and southern most fringes of the city. This trend may be partially driven by the density of Airbnb's, which also are clustered in the center of the city. We also see that predicted gentrification is lower on average than in the historical data. This highlights one shortcoming of aggregating Airbnb data from multiple cities in our model. In doing so, the gentrification rate of cities is also aggregated, leading to estimations of neighborhood gentrification which may over-index towards the national average.

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[8] Exact number of reviews is 2,001,869

To amend this issue, we propose future research which trains a set of supplemental, city specific models using the Airbnb data. The predictions of these models could then be merged with a nationwide model, such as the one we have trained, to provide an estimate which both reflects local and national features of gentrification. Such an approach is consistent with our original discussion of gentrification as a local phenomenon, and may also help to elucidate cultural changes in neighborhoods that are not present at a national scale.

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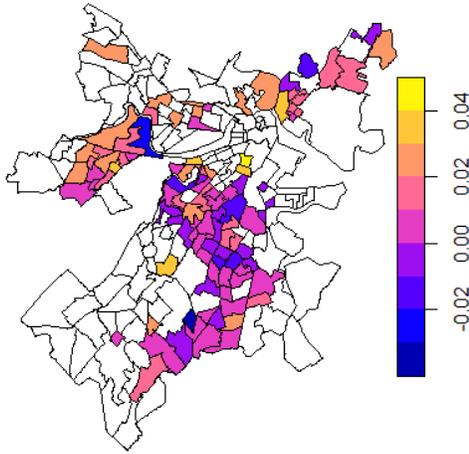
Richardson, Jason, Bruce Mitchell, and Juan Franco. "Shifting neighborhoods: Gentrification and cultural displacement in American cities." (2019).

Appendix I. – Predicted Gentrification Maps

Notes: All figures in Appendix II. display predicted gentrification using the optimal full model specification, described in table 2. Predictions are constructed using review data collected between January 1, 2020 and October 14, 2021.

Asheville, NC

Austin-Round Rock-Georgetown, TX

Columbus, OH

Denver-Aurora-Lakewood, CO
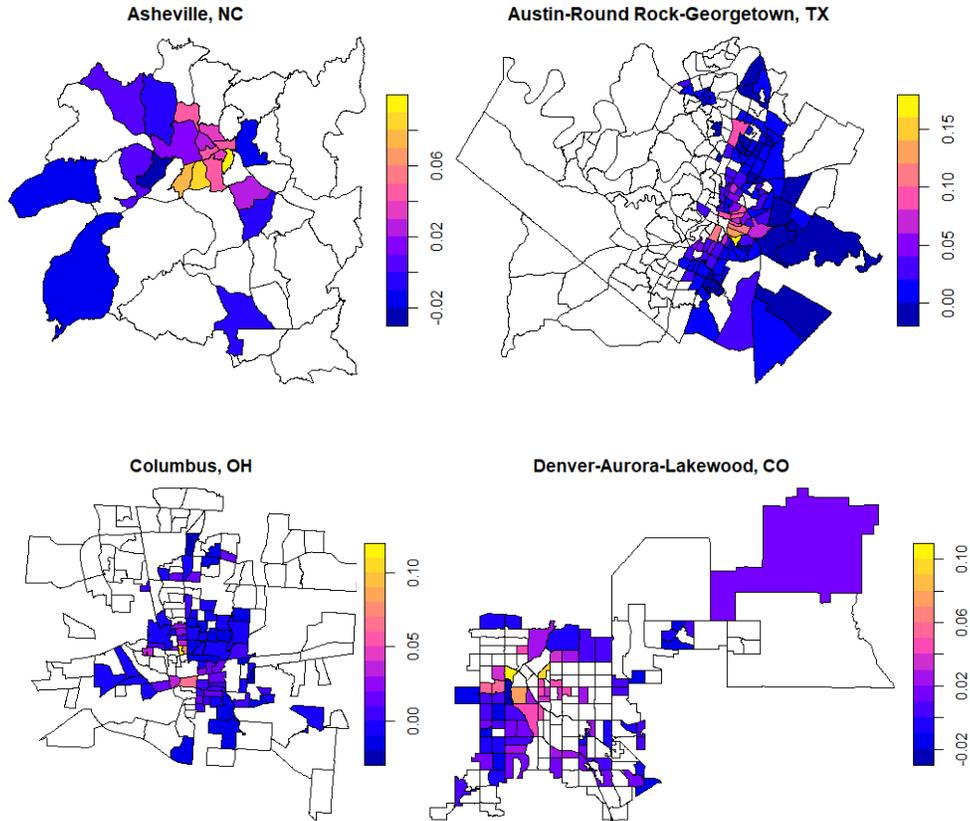
Boston-Cambridge-Newton, MA-NH

Chicago-Naperville-Elgin, IL-IN-WI
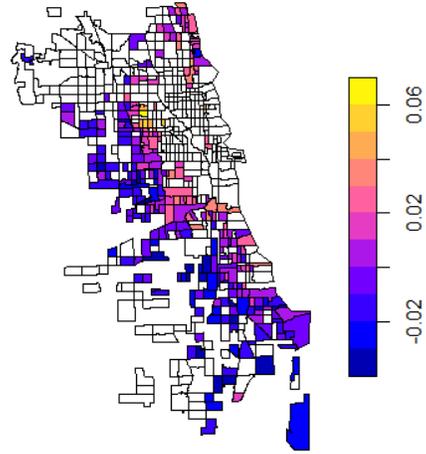
Minneapolis-St. Paul-Bloomington, MN-WI
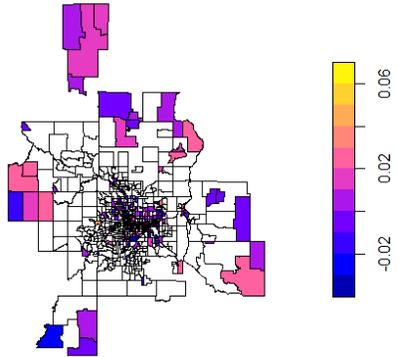
Nashville-Davidson--Murfreesboro--Franklin, TN
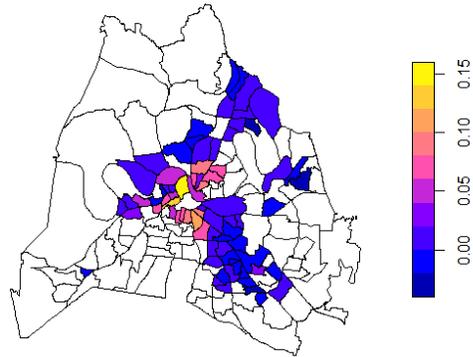
New Orleans-Metairie, LA
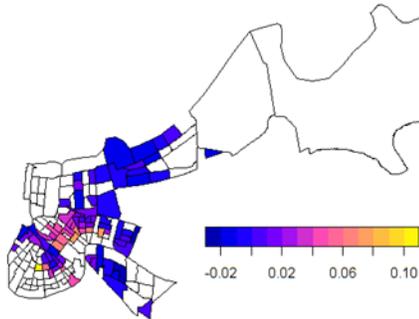
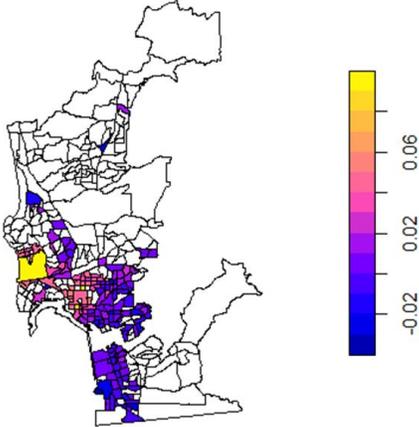**Portland-Vancouver-Hillsboro, OR-WA**
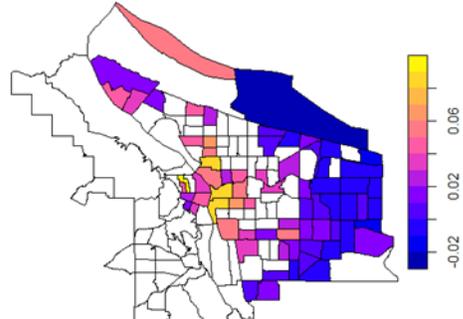
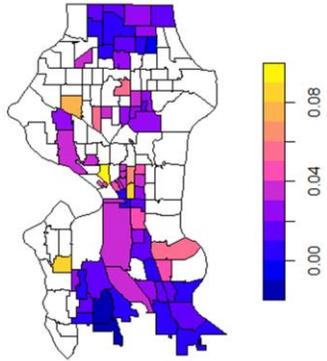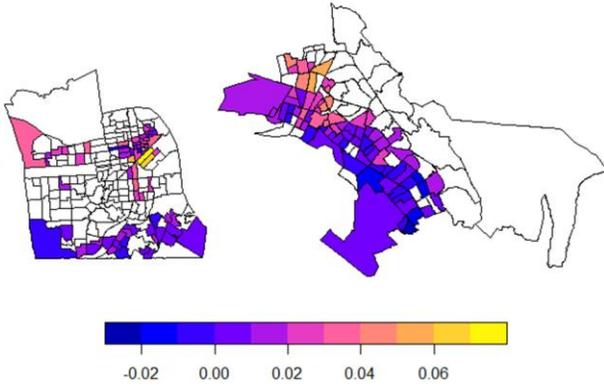# New York-Newark-Jersey City, NY-NJ-PA
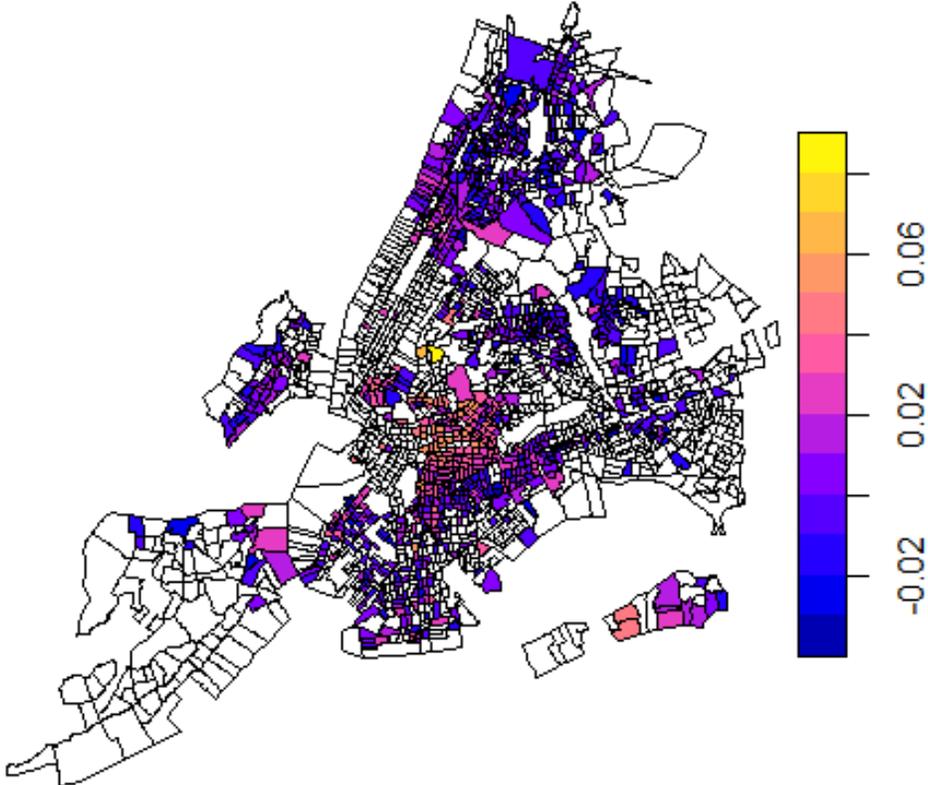
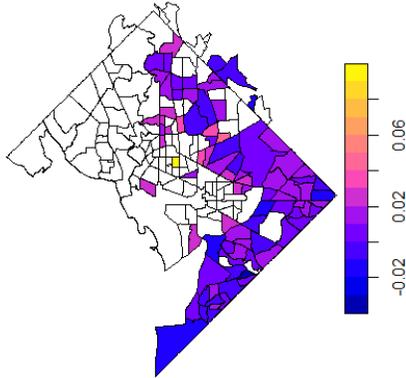## Salem, OR
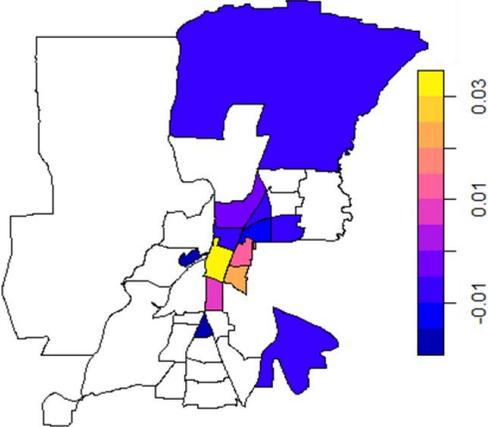
San Diego-Chula Vista-Carlsbad, CA

Seattle-Tacoma-Bellevue, WA

San Francisco-Oakland-Berkeley, CA

Washington-Arlington-Alexandria, DC-VA-MD-WV

Los Angeles-Long Beach-Anaheim, CA