

A photograph of four people sitting on a dark stone ledge outdoors. From left to right: a woman with long dark hair wearing a grey blazer and a patterned scarf; a man with a goatee wearing a light beige blazer over a black shirt, gesturing with his hands; and two men in light blue button-down shirts. They are all looking towards the man in the beige blazer. The background shows a city street with green bushes, a 'NO STANDING ANYTIME' sign, and traffic lights.

HUANYU MONTHLY UPDATE

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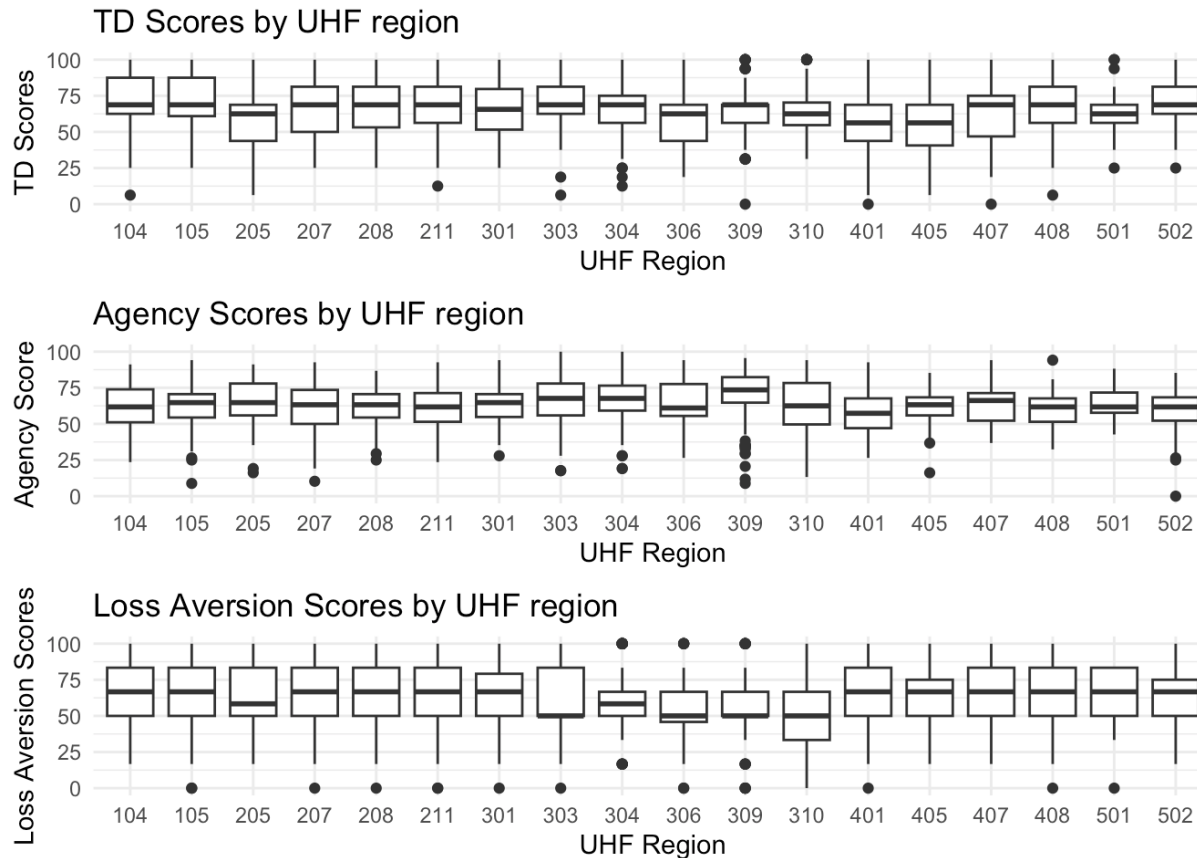
Research Idea Overview

- This study explored **UHF-level population data** to understand the **similarities and differences** across various socio-economic and demographic factors and how these factors influenced **decision-making patterns** and response to health crises during and after the COVID-19 pandemic.

Scores Data: Methods & Results

- Merge 3 Scores:
 - Agency Score
 - Temporal Discounting Score
 - Loss Aversion Score
- Standardization:
 - Scaled all scores to a range of 1-100
- Summarizing Data:
 - Combined scores and participants at the UHF level
 - Calculated the median score for each UHF
- Filtering:
 - Filtered UHF levels where participants > 15 and got 18 regions in total
 - Exported the results into 1_output/dat_merge_2_UHF>=15.csv

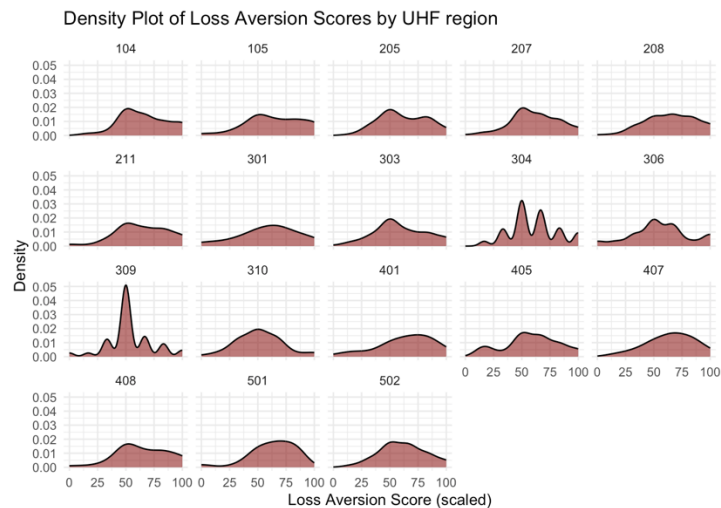
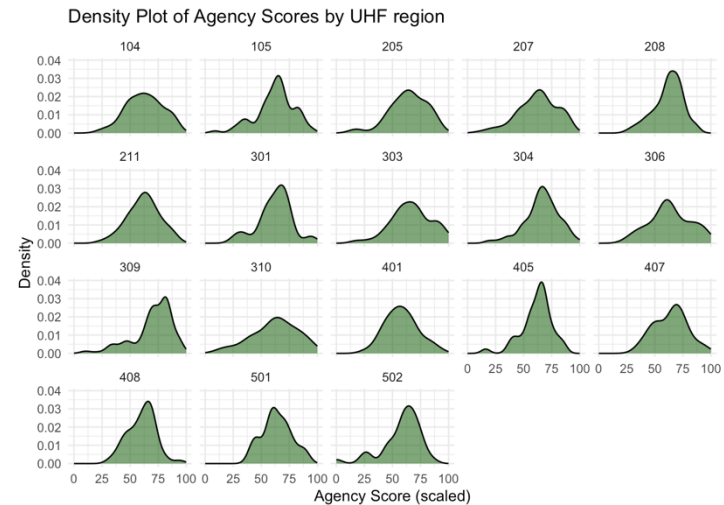
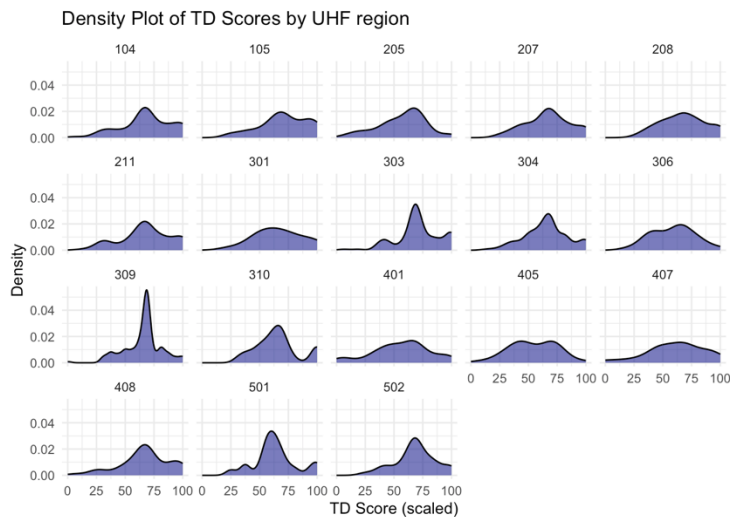
Scores Data: Exploratory Data Analysis



Comment:

UHF 401 (Long Island City - Astoria) has the lowest median scores for both temporal discounting and agency, while UHF 309 (Union Square - Lower East Side) has the highest median score for agency.

Scores Data: Exploratory Data Analysis



Comment:

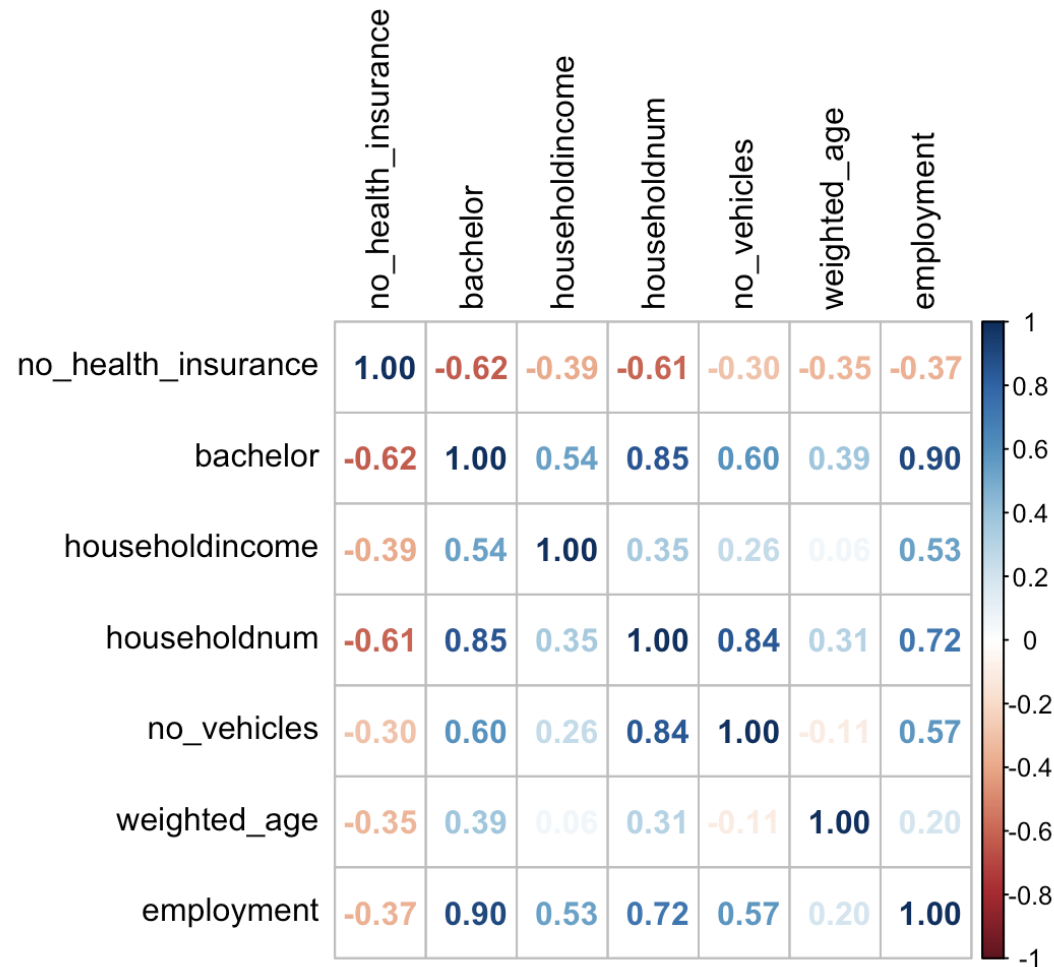
All three scores follow normal distributions on UHF level in general, including those with smaller sample sizes (region 301 - Washington Heights, 407 - Southwest Queens, 501 - Port Richmond).

Census Data: Methods & Results

- Merge ZCTA - ZIP Code - UHF mapping to one dataset
 - Exported the results into 2_output/mapping_guide.csv
- Download census data
 - Include population, individuals without health insurance, education levels, household income, household numbers, households without vehicles, age distribution, and employment status; then calculate the percentage of these variables based on population in UHF-level
 - Converted the census data from ZCTA level to UHF level and got 42 regions in total; 2_output/uhf_summary.csv

Census Data: Methods & Results

- Correlation Plot

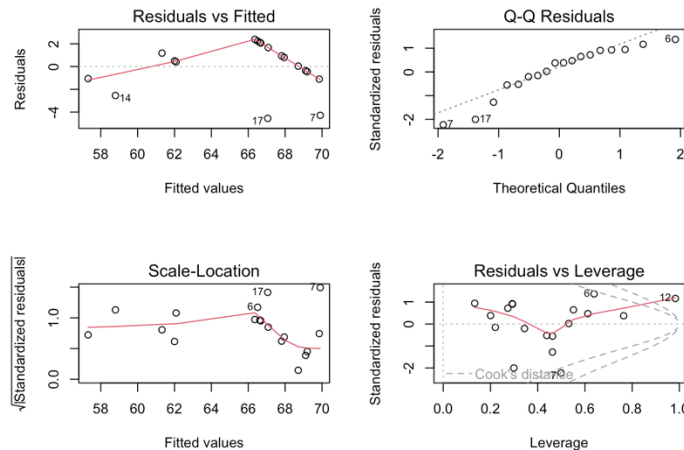


SLR Exploration: Introduction

- Used Ordinary Least Squares (OLS) methods
- Aimed to fit a SLR model about scores based on census data from 18 UHF areas.
- Then used it to predict scores for the remaining 24 UHF regions.

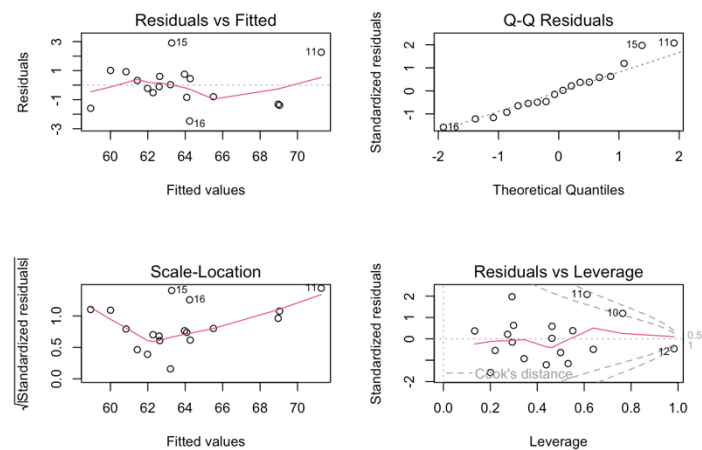
```
##  
## Call:  
## lm(formula = median_td_score ~ no_health_insurance + bachelor +  
##      householdincome + householdnum + no_vehicles + weighted_age +  
##      employment, data = dat)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -4.5563 -0.9092  0.4560  1.5451  2.3923   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept)    118.247278   26.074434   4.535  0.00108 **   
## no_health_insurance -3.343602    0.880388  -3.798  0.00350 **   
## bachelor        -0.641565    0.555444  -1.155  0.27492   .   
## householdincome  -0.005186    0.002767  -1.874  0.09041   .   
## householdnum     -1.494042    0.469305  -3.184  0.00976 **   
## no_vehicles       0.677998    0.179913   3.768  0.00367 **   
## weighted_age     0.145357    0.411473   0.353  0.73123     
## employment       0.407859    0.456678   0.893  0.39279     
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 2.718 on 10 degrees of freedom  
## (24 observations deleted due to missingness)  
## Multiple R-squared:  0.7703, Adjusted R-squared:  0.6095   
## F-statistic: 4.791 on 7 and 10 DF,  p-value: 0.01327
```

SLR Exploration: Model Performance



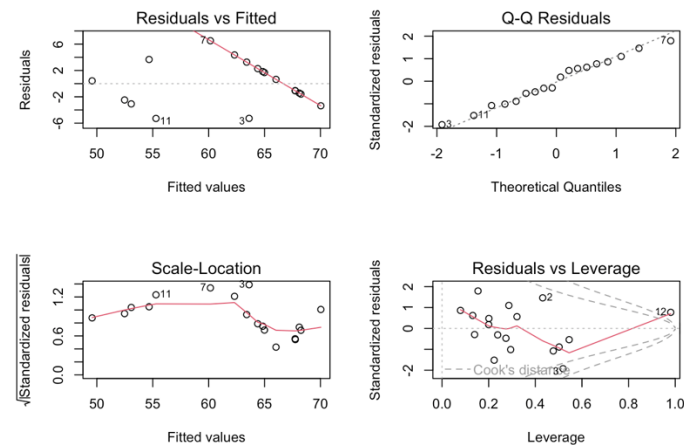
```
mean(model_ld$residuals^2)
```

```
## [1] 4.105642
```



```
mean(model_ag$residuals^2)
```

```
## [1] 1.702577
```



```
mean(model_lds_3$residuals^2)
```

```
## [1] 10.39861
```

Comment:

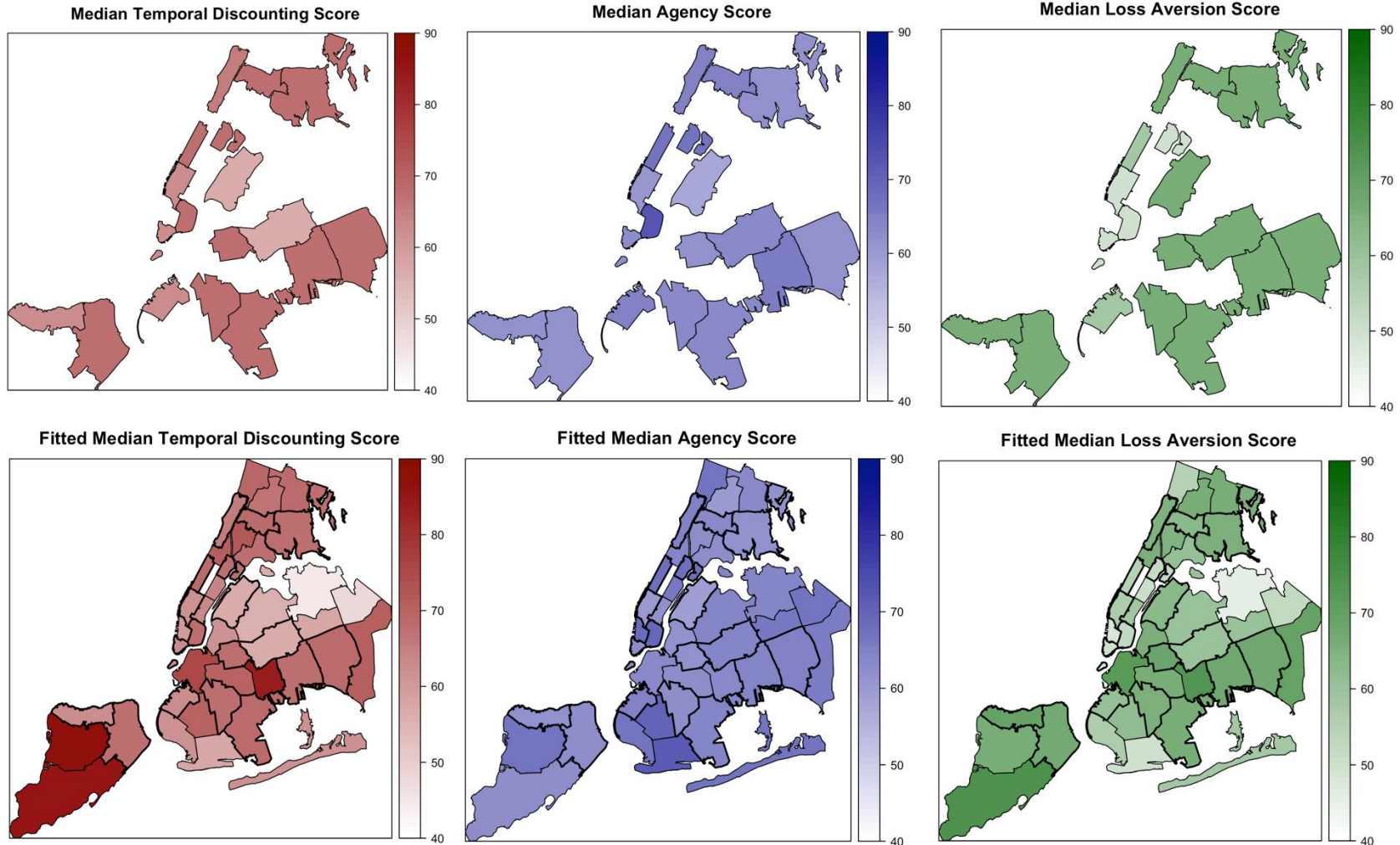
- Detailed code and results:
 - [model.html](#)
- Whole dataset after prediction:
 - [3_output/whole_dataset.csv](#)

GWR Exploration: Introduction

- Aimed to fit a GWR model about scores based on census data from 18 UHF areas.
- Then used it to predict scores for the remaining 24 UHF regions.

```
## Call:
## gwr(formula = median_ag_score ~ no_health_insurance + bachelor +
##      householdincome + householdnum + no_vehicles + weighted_age +
##      employment, data = sp_data_train, bandwidth = bwG_ag, gweight = gwr.Gauss,
##      hatmatrix = TRUE)
## Kernel function: gwr.Gauss
## Fixed bandwidth: 144355.1
## Summary of GWR coefficient estimates at data points:
##               Min.      1st Qu.      Median      3rd Qu.      Max.
## X.Intercept.  98.4617527  99.7803921 100.3350745 100.5905142 100.9987732
## no_health_insurance  0.1599872  0.1660066  0.1697520  0.1783941  0.1908162
## bachelor       1.2324980  1.2460650  1.2551338  1.2572380  1.2803131
## householdincome -0.0014954 -0.0014125 -0.0013940 -0.0013400 -0.0012480
## householdnum    -1.0558823 -1.0394310 -1.0343447 -1.0317301 -1.0221307
## no_vehicles      0.3413946  0.3423886  0.3444250  0.3458659  0.3484888
## weighted_age     0.5415082  0.5487896  0.5554236  0.5650097  0.5807190
## employment     -1.0723346 -1.0644593 -1.0627551 -1.0570106 -1.0481244
##
##               Global
## X.Intercept.    99.8300
## no_health_insurance  0.1829
## bachelor        1.2492
## householdincome  -0.0013
## householdnum    -1.0275
## no_vehicles      0.3426
## weighted_age     0.5566
## employment     -1.0594
## Number of data points: 37
## Effective number of parameters (residual: 2*traceS - traceS'S): 8.42462
## Effective degrees of freedom (residual: 2*traceS - traceS'S): 28.57538
## Sigma (residual: 2*traceS - traceS'S): 1.455421
## Effective number of parameters (model: traceS): 8.219785
## Effective degrees of freedom (model: traceS): 28.78021
## Sigma (model: traceS): 1.450233
## Sigma (ML): 1.279039
## AICc (GWR p. 61, eq 2.33; p. 96, eq. 4.21): 148.69
## AIC (GWR p. 96, eq. 4.22): 131.4333
## Residual sum of squares: 60.52982
## Quasi-global R2: 0.7915936
```

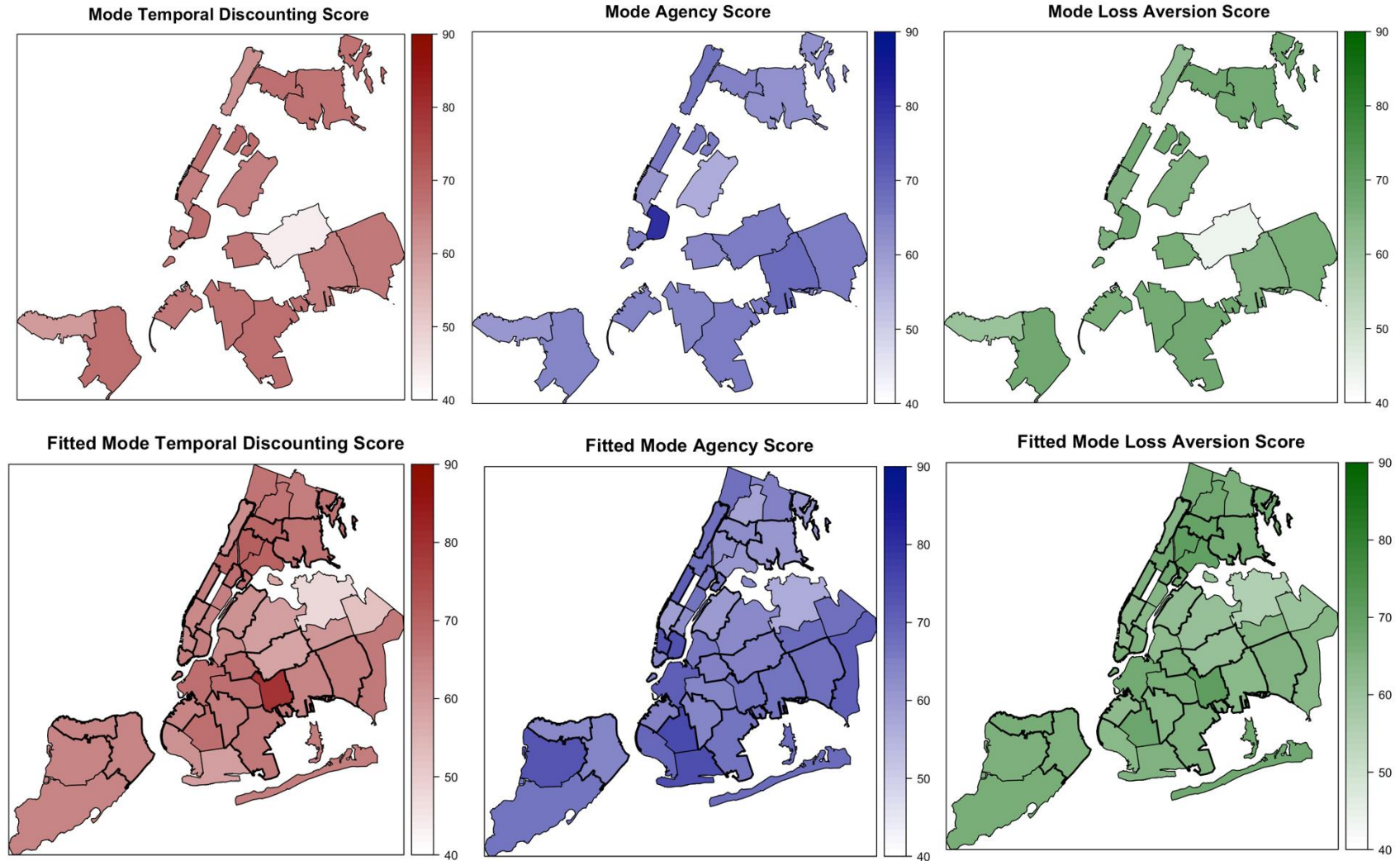
GWR Exploration: Data Visualization (Median)



Comment:

The first row visualized the median scores across 18 UHF areas, with deeper colors indicating higher scores. On the second row, GWR predicted these scores in remaining 24 UHF areas and then presented on the map.

GWR Exploration: Data Visualization (Mode)



Comment:

The first row visualized the mode scores across 18 UHF areas, with deeper colors indicating higher scores. On the second row, GWR predicted these scores in remaining 24 UHF areas and then presented on the map.

GWR Exploration: Model Performance (Median)

```
##
## Brunson, Fotheringham & Charlton (1999) ANOVA
##
## data: gwrG_td
## F = 142.62, df1 = 22.107, df2 = 19.810, p-value < 2.2e-16
## alternative hypothesis: greater
## sample estimates:
## SS GWR improvement    SS GWR residuals
##      124.284685         1.361613
```

```
LMZ.F3GWR.test(gwrG_td)
```

```
##
## Leung et al. (2000) F(3) test
##
##              F statistic Numerator d.f. Denominator d.f.    Pr(>)
## (Intercept)      27.7957          8.0673          19.81 3.650e-09 ***
## no_health_insurance 46.6695         10.8598          19.81 1.048e-11 ***
## bachelor          60.6928         10.6747          19.81 9.340e-13 ***
## householdincome    171.3753         10.1307          19.81 < 2.2e-16 ***
## householdnum       168.3985         14.4766          19.81 < 2.2e-16 ***
## no_vehicles        177.1026          7.8675          19.81 < 2.2e-16 ***
## weighted_age       70.2326          5.6036          19.81 3.700e-12 ***
## employment        91.4077          9.9474          19.81 2.438e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Brunson, Fotheringham & Charlton (1999) ANOVA
##
## data: gwrG_ag
## F = 1.4412, df1 = 15.243, df2 = 28.963, p-value = 0.193
## alternative hypothesis: greater
## sample estimates:
## SS GWR improvement    SS GWR residuals
##      1.296247         60.529822
```

```
LMZ.F3GWR.test(gwrG_ag)
```

```
##
## Leung et al. (2000) F(3) test
##
##              F statistic Numerator d.f. Denominator d.f.    Pr(>)
## (Intercept)      2.42064          4.96514          28.963 0.059999 .
## no_health_insurance 0.63634         18.81581          28.963 0.845530 .
## bachelor          1.60231         14.04152          28.963 0.137868 .
## householdincome    4.44322          7.08409          28.963 0.001798 **
## householdnum       1.89044         13.38983          28.963 0.074013 .
## no_vehicles        0.80142          6.50345          28.963 0.585188 .
## weighted_age       2.27995          3.51705          28.963 0.091817 .
## employment        0.79568         16.36952          28.963 0.680850 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Brunson, Fotheringham & Charlton (1999) ANOVA
##
## data: gwrG_los
## F = 3.7203, df1 = 15.243, df2 = 28.963, p-value = 0.001152
## alternative hypothesis: greater
## sample estimates:
## SS GWR improvement    SS GWR residuals
##      11.79092         213.28765
```

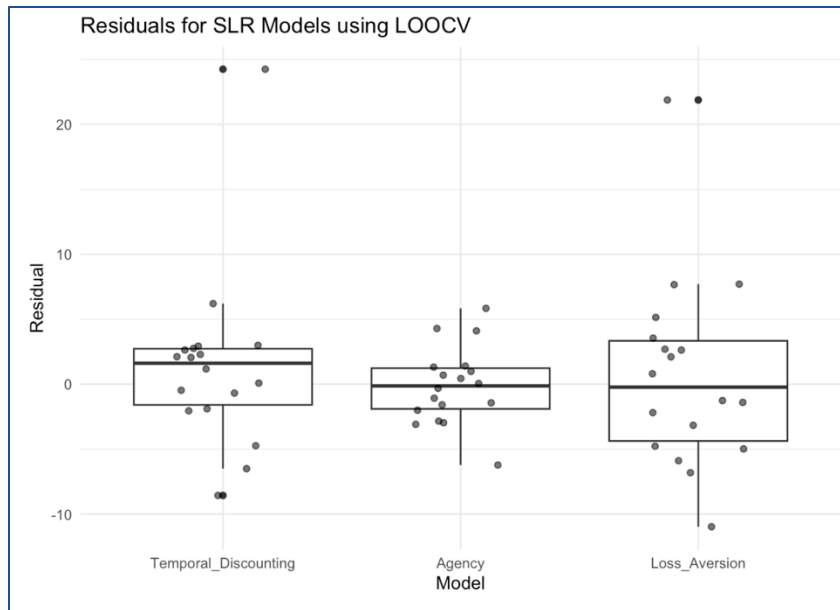
```
LMZ.F3GWR.test(gwrG_los)
```

```
##
## Leung et al. (2000) F(3) test
##
##              F statistic Numerator d.f. Denominator d.f.    Pr(>)
## (Intercept)      1.4488          4.9651          28.963 0.2371267
## no_health_insurance 3.6732         18.8158          28.963 0.0008438 ***
## bachelor          1.0159         14.0415          28.963 0.4651130
## householdincome    3.4878          7.0841          28.963 0.0076523 **
## householdnum       5.1174         13.3898          28.963 0.0001169 ***
## no_vehicles        2.9684          6.5035          28.963 0.0197870 *
## weighted_age       1.9994          3.5170          28.963 0.1279498
## employment        2.0665         16.3695          28.963 0.0426815 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

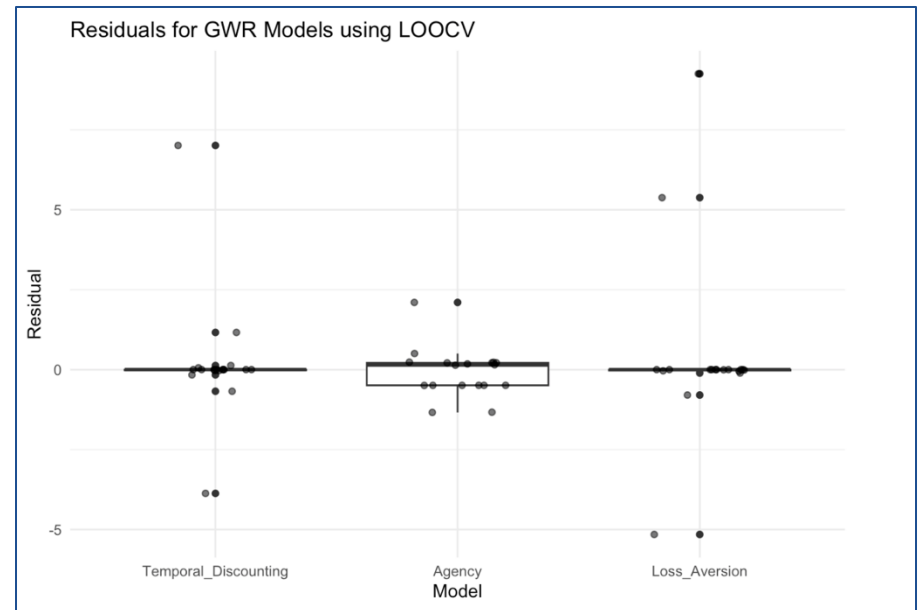
Comment:

- Model fit tests for all three models show an improvement in the explanatory power of GWR over SLR.
- The spatial heterogeneity variables are shown.
- ***AIC** can also be used to test model fit, but it is not possible to infer whether the differences between models are statistically different.

LOOCV (Median)



## Temporal Discounting	Agency	Loss Aversion
## 45.55767	8.31241	51.22241



## Temporal Discounting	Agency	Loss Aversion
## 3.6685299	0.5561021	7.8802843