

# SBA\_Analysis

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## Descriptive Analysis

```
library(sf)
```

```
## Warning: package 'sf' was built under R version 4.4.3
## Linking to GEOS 3.13.0, GDAL 3.8.5, PROJ 9.5.1; sf_use_s2() is TRUE
```

```
library(car)
```

```
## Loading required package: carData
```

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
## The following object is masked from 'package:car':
##
##      recode
## The following objects are masked from 'package:stats':
##
##      filter, lag
## The following objects are masked from 'package:base':
##
##      intersect, setdiff, setequal, union
```

```
library(spdep)
```

```
## Loading required package: spData
## To access larger datasets in this package, install the spDataLarge
## package with: `install.packages('spDataLarge',
## repos='https://nowosad.github.io/drat/', type='source')`
```

```
library(lmtest)
```

```
## Loading required package: zoo
##
## Attaching package: 'zoo'
## The following objects are masked from 'package:base':
##
##      as.Date, as.Date.numeric
```

```
library(corrplot)
```

```
## corrplot 0.95 loaded
```

```
library(stargazer)
```

```
##
```

```
## Please cite as:
```

```
## Hlavac, Marek (2022). stargazer: Well-Formatted Regression and Summary Statistics Tables.
```

```
## R package version 5.2.3. https://CRAN.R-project.org/package=stargazer
```

```
SBA <- read.csv("/Users/isabellagermani/Desktop/MS THSS/data/SBA.csv", header = TRUE, stringsAsFactors = FALSE)
```

```
str(SBA)
```

```
## 'data.frame': 55 obs. of 142 variables:
```

```
## $ SBA : int 101 102 103 104 105 106 107 108 109 110 ...
## $ SBA_name : chr "Mott Haven/Hunts Point" "Morrisania/Belmont" "Highbridge/South
## $ med_hous_inc : int 26090 32330 38460 37550 44000 67190 49790 74080 59760 73150 ...
## $ pct_FL_loans : num 30 53.4 10.3 54.8 9.6 0.9 28.6 31.9 27.3 60.6 ...
## $ pct_FL_loans_2_LI : num 100 100 100 100 66.7 14 63.5 11.8 50.3 46 ...
## $ inc_div_ratio : num 5.9 6.2 5.6 5.8 5.7 6.2 6.1 5.8 4.7 5 ...
## $ mort_forc : num 70 115 38 53 25 28 252 135 147 422 ...
## $ pov_pct : num 44.2 35.8 36.4 36.4 32.9 18.5 24.7 10.2 16.4 14.6 ...
## $ pct_asian : num 0.3 1.3 1 1.8 7.1 4.1 8.2 3.6 9.4 2.3 ...
## $ pct_black : num 28.4 32.5 27.7 24.4 11.3 11.8 30.3 28.8 19.8 67.2 ...
## $ prob_race : num 0.47 0.51 0.45 0.43 0.43 0.65 0.59 0.69 0.7 0.49 ...
## $ pct_hispan : num 67.2 61.8 68.8 71.1 74.1 48.8 55.4 39.9 42.3 23 ...
## $ pct_white : num 3.3 3.8 1.3 1 5.1 31.5 3 25.5 26.7 5.4 ...
## $ pop_dens : num 31.9 43 75 98.2 91.5 33.1 42.5 12.2 31.5 22.3 ...
## $ priv_landL_amt : int 2925 3174 3547 3423 3852 3906 3561 4330 4105 3882 ...
## $ med_rti : num 38 34.8 38.9 41.7 41 34 34.1 28.9 37.6 34.7 ...
## $ med_gro_rnt : int 1200 1280 1400 1450 1560 1720 1440 1470 1580 1720 ...
## $ vac_rt : num 0.124 0.1373 0.1265 0.0842 0.0303 ...
## $ pct_condo : num 0.0165 0.0176 0.0122 0 0.0101 ...
## $ pct_coop : num 0.0413 0.0282 0.0857 0.0149 0.0606 ...
## $ sound : num 0.963 0.877 0.971 0.896 0.944 ...
## $ deter : num 0.01653 0.0493 0.00408 0.02475 0.0101 ...
## $ rats : num 0.335 0.324 0.339 0.396 0.303 ...
## $ r_aches : num 0.368 0.313 0.318 0.455 0.449 ...
## $ afford : num 0.616 0.511 0.437 0.436 0.535 ...
## $ unafford : num 0.165 0.148 0.171 0.262 0.247 ...
## $ avg_rti : num 0.392 0.4 0.395 0.422 0.416 ...
## $ avg_age : num 52.8 50.2 51 49.3 47.7 ...
## $ pct_howner : num 0.0579 0.0775 0.0612 0.0396 0.0707 ...
## $ pct_immigrant : num 0.269 0.264 0.31 0.436 0.364 ...
## $ med_year_moved_in : num 2007 2010 2007 2009 2010 ...
## $ med_length_res : num 10 7 10 8 7 9 12 18.5 7 8 ...
## $ pct_recent_moves : num 0.463 0.549 0.461 0.564 0.596 ...
## $ pct_fresh_moves : num 0.273 0.37 0.29 0.356 0.439 ...
## $ pct_displ : num 0.0207 0.0282 0.0245 0.0248 0.0101 ...
## $ pct_gentr : num 0.0331 0.0563 0.0571 0.0495 0.0505 ...
## $ rennov : num 0.0785 0.0775 0.0653 0.0594 0 ...
## $ tot_pop : num 156731 171842 141400 139656 132128 ...
```

```

## $ sq_miles : num 4.86 4.37 1.98 1.51 1.57 ...
## $ t_dollar_stores : int 12 5 7 6 3 1 4 2 5 3 ...
## $ dollars_per_1kpppl : num 0.0766 0.0291 0.0495 0.043 0.0227 ...
## $ dollars_per_sqm : num 2.47 1.14 3.53 3.97 1.91 ...
## $ liqour_per_1kpppl : num 0.2106 0.1397 0.1132 0.1289 0.0908 ...
## $ liqour_per_sqm : num 6.79 5.49 8.06 11.92 7.64 ...
## $ tobacco_per_1kpppl : num 0.00638 0.04074 0.07072 0.0358 0.02271 ...
## $ tobacco_per_sqm : num 0.206 1.601 5.038 3.311 1.909 ...
## $ convenience_per_1kpppl : num 0.1404 0.1397 0.1414 0.0931 0.0984 ...
## $ convenience_per_sqm : num 4.53 5.49 10.08 8.61 8.27 ...
## $ ecig_per_1kpppl : num 0 0.00582 0 0 0 ...
## $ ecig_per_sqm : num 0 0.229 0 0 0 ...
## $ marijuana_per_1kpppl : num 0 0 0 0 0 0 0 0 0 ...
## $ marijuana_per_sqm : num 0 0 0 0 0 0 0 0 0 ...
## $ civsoc_per_1kpppl : num 0.128 0.128 0.141 0.122 0.136 ...
## $ civsoc_per_sqm : num 4.12 5.03 10.08 11.26 11.46 ...
## $ youthorgs_per_1kpppl : num 0.0255 0.0466 0.0354 0.0286 0.0227 ...
## $ youthorgs_per_sqm : num 0.824 1.83 2.519 2.649 1.909 ...
## $ vetorgs_per_1kpppl : num 0 0.00582 0.01414 0 0 ...
## $ vetorgs_per_sqm : num 0 0.229 1.008 0 0 ...
## $ relig_per_1kpppl : num 0.906 1.146 0.785 0.709 0.568 ...
## $ relig_per_sqm : num 29.2 45.1 55.9 65.6 47.7 ...
## $ barber_per_1kpppl : num 0.383 0.396 0.347 0.358 0.242 ...
## $ barber_per_sqm : num 12.4 15.6 24.7 33.1 20.4 ...
## $ beauty_per_1kpppl : num 0.957 0.867 0.969 1.088 0.954 ...
## $ beauty_per_sqm : num 30.9 34.1 69 100.7 80.2 ...
## $ laundry_per_1kpppl : num 0.223 0.169 0.134 0.158 0.204 ...
## $ laundry_per_sqm : num 7.21 6.63 9.57 14.57 17.18 ...
## $ drycl_per_1kpppl : num 0.0638 0.04655 0.03536 0.00716 0.02271 ...
## $ drycl_per_sqm : num 2.059 1.83 2.519 0.662 1.909 ...
## $ I.Fserv_per_1kpppl : num 0.817 0.512 0.332 0.444 0.431 ...
## $ I.Fserv_per_sqm : num 26.4 20.1 23.7 41.1 36.3 ...
## $ E.Dserv_per_1kpppl : num 0.0957 0.0466 0.0212 0.0215 0.0454 ...
## $ E.Dserv_per_sqm : num 3.09 1.83 1.51 1.99 3.82 ...
## $ C.Yserv_per_1kpppl : num 0.0383 0.0407 0.0283 0.0215 0.0454 ...
## $ C.Yserv_per_sqm : num 1.24 1.6 2.02 1.99 3.82 ...
## $ Eserv_per_1kpppl : num 0.0319 0.0233 0.0141 0.0143 0 ...
## $ Eserv_per_sqm : num 1.029 0.915 1.008 1.324 0 ...
## $ MDprog_per_1kpppl : num 0.00638 0 0 0 0 ...
## $ MDprog_per_sqm : num 0.206 0 0 0 0 ...
## $ Gcouns_per_1kpppl : num 0.236 0.163 0.099 0.129 0.136 ...
## $ Gcouns_per_sqm : num 7.62 6.41 7.05 11.92 11.46 ...
## $ SAcouns_per_1kpppl : num 0.01276 0.01746 0 0.00716 0.00757 ...
## $ SAcouns_per_sqm : num 0.412 0.686 0 0.662 0.636 ...
## $ Dayc_per_1kpppl : num 0.555 0.594 0.467 0.652 0.621 ...
## $ Dayc_per_sqm : num 17.9 23.3 33.3 60.3 52.2 ...
## $ C.Sstor_per_1kpppl : num 0.619 0.442 0.502 0.537 0.681 ...
## $ C.Sstor_per_sqm : num 20 17.4 35.8 49.7 57.3 ...
## $ F.Astor_per_1kpppl : num 0.249 0.18 0.163 0.122 0.25 ...
## $ F.Astor_per_sqm : num 8.03 7.09 11.59 11.26 21 ...
## $ Mstor_per_1kpppl : num 0.0957 0.0582 0.0636 0.0501 0.053 ...
## $ Mstor_per_sqm : num 3.09 2.29 4.53 4.64 4.46 ...
## $ H.Gstor_per_1kpppl : num 0.0893 0.0524 0.0566 0.0573 0.0454 ...
## $ H.Gstor_per_sqm : num 2.88 2.06 4.03 5.3 3.82 ...

```

```
## $ D.Vstor_per_1kppl      : num  0.447 0.268 0.339 0.272 0.341 ...
## $ D.Vstor_per_sqm        : num  14.4 10.5 24.2 25.2 28.6 ...
## $ Ustor_per_1kppl        : num  0.0957 0.0989 0.0636 0.0573 0.1211 ...
## $ Ustor_per_sqm          : num  3.09 3.89 4.53 5.3 10.18 ...
## $ pyhs_per_1kppl         : num  0.479 0.39 0.446 0.487 1.082 ...
## $ phys_per_sqm           : num  15.4 15.3 31.7 45 91 ...
## $ pharm_per_1kppl        : num  0.561 0.355 0.332 0.401 0.333 ...
## [list output truncated]
```

```
summary(SBA)
```

```
##      SBA      SBA_name      med_hous_inc      pct_FL_loans
## Min.   :101.0   Length:55      Min.    : 25210   Min.    : 0.00
## 1st Qu.:204.5   Class :character  1st Qu.: 61240   1st Qu.: 0.15
## Median :218.0   Mode  :character  Median : 70680   Median : 2.30
## Mean   :274.4                      Mean   : 78978   Mean   :12.85
## 3rd Qu.:403.5                      3rd Qu.: 90315   3rd Qu.:26.45
## Max.   :503.0                      Max.    :180320   Max.    :60.60
## pct_FL_loans_2_LI inc_div_ratio      mort_forc      pov_pct
## Min.    : 0.00   Min.    :3.400   Min.    : 8.0   Min.    : 6.10
## 1st Qu.: 9.85   1st Qu.:4.900   1st Qu.: 45.0   1st Qu.:10.30
## Median : 35.50   Median :5.700   Median : 104.0   Median :16.20
## Mean    : 37.84   Mean    :5.851   Mean    : 188.1   Mean    :18.34
## 3rd Qu.: 59.15   3rd Qu.:6.400   3rd Qu.: 261.0   3rd Qu.:23.95
## Max.    :100.00   Max.    :9.700   Max.    :1079.0   Max.    :44.20
##      pct_asian      pct_black      prob_race      pct_hispan
## Min.    : 0.30   Min.    : 0.90   Min.    :0.2400   Min.    : 5.70
## 1st Qu.: 4.10   1st Qu.: 4.50   1st Qu.:0.5050   1st Qu.:14.80
## Median : 8.90   Median :12.10   Median :0.6000   Median :20.60
## Mean    :13.95   Mean    :21.89   Mean    :0.5851   Mean    :29.27
## 3rd Qu.:17.70   3rd Qu.:29.60   3rd Qu.:0.6700   3rd Qu.:41.10
## Max.    :54.50   Max.    :87.10   Max.    :0.8000   Max.    :74.10
##      pct_white      pop_dens      priv_landL_amt      med_rti      med_gro_rnt
## Min.    : 1.00   Min.    : 6.20   Min.    :2925   Min.    :22.20   Min.    :1100
## 1st Qu.:12.10   1st Qu.: 27.00   1st Qu.:3730   1st Qu.:29.55   1st Qu.:1515
## Median :26.70   Median : 40.60   Median :4336   Median :32.90   Median :1730
## Mean    :32.01   Mean    : 44.37   Mean    :4543   Mean    :32.69   Mean    :1801
## 3rd Qu.:48.80   3rd Qu.: 55.55   3rd Qu.:5218   3rd Qu.:35.55   3rd Qu.:1910
## Max.    :82.50   Max.    :107.80   Max.    :8507   Max.    :47.70   Max.    :3190
##      vac_rt      pct_condo      pct_coop      sound
## Min.    :0.03030   Min.    :0.00000   Min.    :0.00000   Min.    :0.8512
## 1st Qu.:0.08035   1st Qu.:0.01566   1st Qu.:0.02895   1st Qu.:0.9006
## Median :0.10429   Median :0.03133   Median :0.07865   Median :0.9377
## Mean    :0.11198   Mean    :0.04883   Mean    :0.10684   Mean    :0.9279
## 3rd Qu.:0.12346   3rd Qu.:0.06601   3rd Qu.:0.15952   3rd Qu.:0.9556
## Max.    :0.29778   Max.    :0.18310   Max.    :0.46701   Max.    :0.9937
##      deter      rats      r_aches      afford
## Min.    :0.000000   Min.    :0.02183   Min.    :0.003717   Min.    :0.4356
## 1st Qu.:0.008187   1st Qu.:0.08500   1st Qu.:0.118657   1st Qu.:0.5160
## Median :0.019157   Median :0.14136   Median :0.193717   Median :0.5425
## Mean    :0.026903   Mean    :0.16868   Mean    :0.211167   Mean    :0.5566
## 3rd Qu.:0.036050   3rd Qu.:0.23640   3rd Qu.:0.295429   3rd Qu.:0.5954
## Max.    :0.106061   Max.    :0.39604   Max.    :0.455446   Max.    :0.6782
##      unafford      avg_rti      avg_age      pct_howner
## Min.    :0.03765   Min.    :0.2906   Min.    :43.79   Min.    :0.0396
```

##	1st Qu.:0.08666	1st Qu.:0.3318	1st Qu.:49.29	1st Qu.:0.1354
##	Median :0.11818	Median :0.3551	Median :51.21	Median :0.2604
##	Mean :0.12342	Mean :0.3557	Mean :51.15	Mean :0.2800
##	3rd Qu.:0.14938	3rd Qu.:0.3774	3rd Qu.:52.98	3rd Qu.:0.3862
##	Max. :0.26238	Max. :0.4252	Max. :59.25	Max. :0.6729
##	pct_immigrant	med_year_moved_in	med_length_res	pct_recent_moves
##	Min. :0.1092	Min. :1998	Min. : 5.000	Min. :0.2944
##	1st Qu.:0.1806	1st Qu.:2006	1st Qu.: 7.000	1st Qu.:0.4270
##	Median :0.3102	Median :2008	Median : 9.500	Median :0.4689
##	Mean :0.3088	Mean :2007	Mean : 9.609	Mean :0.4720
##	3rd Qu.:0.3801	3rd Qu.:2010	3rd Qu.:11.500	3rd Qu.:0.5311
##	Max. :0.6718	Max. :2012	Max. :18.500	Max. :0.6130
##	pct_fresh_moves	pct_displ	pct_gentr	rennov
##	Min. :0.1988	Min. :0.000000	Min. :0.008333	Min. :0.00000
##	1st Qu.:0.2809	1st Qu.:0.008772	1st Qu.:0.036700	1st Qu.:0.01553
##	Median :0.3272	Median :0.013043	Median :0.046595	Median :0.02682
##	Mean :0.3253	Mean :0.014456	Mean :0.050032	Mean :0.03685
##	3rd Qu.:0.3757	3rd Qu.:0.020747	3rd Qu.:0.059883	3rd Qu.:0.04348
##	Max. :0.4658	Max. :0.031746	Max. :0.113014	Max. :0.21516
##	tot_pop	sq_miles	t_dollar_stores	dollars_per_1kppl
##	Min. :107532	Min. : 1.447	Min. : 0.000	Min. :0.000000
##	1st Qu.:131604	1st Qu.: 2.689	1st Qu.: 1.000	1st Qu.:0.007131
##	Median :148806	Median : 3.807	Median : 2.000	Median :0.014696
##	Mean :153078	Mean : 5.503	Mean : 3.073	Mean :0.020178
##	3rd Qu.:164332	3rd Qu.: 6.054	3rd Qu.: 4.000	3rd Qu.:0.027246
##	Max. :242631	Max. :24.500	Max. :12.000	Max. :0.077363
##	dollars_per_sqm	liquor_per_1kppl	liquor_per_sqm	tobacco_per_1kppl
##	Min. :0.0000	Min. :0.09082	Min. : 0.8071	Min. :0.006349
##	1st Qu.:0.1735	1st Qu.:0.12907	1st Qu.: 3.8901	1st Qu.:0.023808
##	Median :0.4611	Median :0.15588	Median : 6.8529	Median :0.040533
##	Mean :0.8681	Mean :0.18463	Mean : 8.3457	Mean :0.048502
##	3rd Qu.:1.1573	3rd Qu.:0.21201	3rd Qu.:10.0046	3rd Qu.:0.061812
##	Max. :3.9732	Max. :0.67642	Max. :34.8156	Max. :0.189651
##	tobacco_per_sqm	convenience_per_1kppl	convenience_per_sqm	ecig_per_1kppl
##	Min. :0.0884	Min. :0.02336	Min. : 0.2652	Min. :0.000000
##	1st Qu.:0.7671	1st Qu.:0.09501	1st Qu.: 3.2353	1st Qu.:0.000000
##	Median :1.3655	Median :0.13566	Median : 5.4906	Median :0.007522
##	Mean :2.1207	Mean :0.13218	Mean : 5.5944	Mean :0.013325
##	3rd Qu.:2.5445	3rd Qu.:0.16115	3rd Qu.: 6.9770	3rd Qu.:0.021744
##	Max. :9.7614	Max. :0.26551	Max. :19.4599	Max. :0.051762
##	ecig_per_sqm	marijuana_per_1kppl	marijuana_per_sqm	civsoc_per_1kppl
##	Min. :0.0000	Min. :0.0000000	Min. :0.00000	Min. :0.1217
##	1st Qu.:0.0000	1st Qu.:0.0000000	1st Qu.:0.00000	1st Qu.:0.1810
##	Median :0.2449	Median :0.0000000	Median :0.00000	Median :0.2621
##	Mean :0.5195	Mean :0.0004872	Mean :0.02894	Mean :0.4271
##	3rd Qu.:0.6593	3rd Qu.:0.0000000	3rd Qu.:0.00000	3rd Qu.:0.4479
##	Max. :4.5788	Max. :0.0128457	Max. :0.67450	Max. :2.8701
##	civsoc_per_sqm	youthorgs_per_1kppl	youthorgs_per_sqm	vetorgs_per_1kppl
##	Min. : 1.463	Min. :0.00000	Min. :0.0000	Min. :0.000000
##	1st Qu.: 5.282	1st Qu.:0.01709	1st Qu.:0.4685	1st Qu.:0.008112
##	Median : 9.221	Median :0.03100	Median :0.9617	Median :0.016856
##	Mean : 22.238	Mean :0.03670	Mean :1.7693	Mean :0.019801
##	3rd Qu.: 22.043	3rd Qu.:0.04592	3rd Qu.:2.2845	3rd Qu.:0.028107
##	Max. :147.722	Max. :0.18333	Max. :9.4360	Max. :0.057806

## vetorgs_per_sqm	relig_per_1kpp1	relig_per_sqm	barber_per_1kpp1
## Min. :0.0000	Min. :0.3645	Min. : 2.449	Min. :0.06229
## 1st Qu.:0.3009	1st Qu.:0.6896	1st Qu.: 21.224	1st Qu.:0.14771
## Median :0.5253	Median :0.9106	Median : 29.524	Median :0.18915
## Mean :0.7395	Mean :1.0689	Mean : 47.697	Mean :0.20332
## 3rd Qu.:0.9698	3rd Qu.:1.1861	3rd Qu.: 66.510	3rd Qu.:0.24752
## Max. :3.0462	Max. :4.8063	Max. :236.553	Max. :0.46148
## barber_per_sqm	beauty_per_1kpp1	beauty_per_sqm	laundry_per_1kpp1
## Min. : 0.7072	Min. :0.5762	Min. : 5.551	Min. :0.08565
## 1st Qu.: 4.2185	1st Qu.:0.9480	1st Qu.: 29.418	1st Qu.:0.16011
## Median : 6.9509	Median :1.0831	Median : 47.579	Median :0.20435
## Mean : 9.3637	Mean :1.2453	Mean : 56.157	Mean :0.22541
## 3rd Qu.:12.9680	3rd Qu.:1.3743	3rd Qu.: 66.046	3rd Qu.:0.26916
## Max. :33.1104	Max. :3.7993	Max. :199.830	Max. :0.53672
## laundry_per_sqm	drycl_per_1kpp1	drycl_per_sqm	I.Fserv_per_1kpp1
## Min. : 0.7347	Min. :0.00716	Min. : 0.1424	Min. :0.2257
## 1st Qu.: 6.0361	1st Qu.:0.02754	1st Qu.: 0.6918	1st Qu.:0.4030
## Median : 9.4173	Median :0.04232	Median : 1.8931	Median :0.4644
## Mean : 9.3841	Mean :0.05137	Mean : 2.5018	Mean :0.6049
## 3rd Qu.:12.6005	3rd Qu.:0.07057	3rd Qu.: 2.8963	3rd Qu.:0.6567
## Max. :26.3282	Max. :0.19539	Max. :20.8128	Max. :2.6867
## I.Fserv_per_sqm	E.Dserv_per_1kpp1	E.Dserv_per_sqm	C.Yserv_per_1kpp1
## Min. : 1.592	Min. :0.007522	Min. : 0.1224	Min. :0.00000
## 1st Qu.: 11.147	1st Qu.:0.045079	1st Qu.: 1.3502	1st Qu.:0.01517
## Median : 16.368	Median :0.064196	Median : 2.1588	Median :0.03100
## Mean : 29.834	Mean :0.064022	Mean : 2.7159	Mean :0.03719
## 3rd Qu.: 35.860	3rd Qu.:0.082876	3rd Qu.: 3.2852	3rd Qu.:0.05157
## Max. :138.286	Max. :0.177008	Max. :10.3023	Max. :0.13908
## C.Yserv_per_sqm	Eserv_per_1kpp1	Eserv_per_sqm	MDprog_per_1kpp1
## Min. : 0.000	Min. :0.000000	Min. :0.00000	Min. :0.000000
## 1st Qu.: 0.378	1st Qu.:0.002061	1st Qu.:0.04082	1st Qu.:0.000000
## Median : 1.186	Median :0.013218	Median :0.39527	Median :0.000000
## Mean : 1.915	Mean :0.015425	Mean :0.76168	Mean :0.001824
## 3rd Qu.: 2.537	3rd Qu.:0.023269	3rd Qu.:1.01850	3rd Qu.:0.000000
## Max. :10.367	Max. :0.057806	Max. :4.26467	Max. :0.022227
## MDprog_per_sqm	Gcouns_per_1kpp1	Gcouns_per_sqm	SAcouns_per_1kpp1
## Min. :0.00000	Min. :0.08754	Min. : 0.7347	Min. :0.000000
## 1st Qu.:0.00000	1st Qu.:0.12613	1st Qu.: 3.8707	1st Qu.:0.000000
## Median :0.00000	Median :0.16545	Median : 6.1711	Median :0.005826
## Mean :0.08831	Mean :0.22578	Mean :11.3037	Mean :0.007499
## 3rd Qu.:0.00000	3rd Qu.:0.21604	3rd Qu.:11.6878	3rd Qu.:0.008721
## Max. :0.97420	Max. :1.16319	Max. :59.8699	Max. :0.075861
## SAcouns_per_sqm	Dayc_per_1kpp1	Dayc_per_sqm	C.Sstor_per_1kpp1
## Min. :0.0000	Min. :0.2369	Min. : 1.592	Min. : 0.2617
## 1st Qu.:0.0000	1st Qu.:0.3787	1st Qu.:10.889	1st Qu.: 0.4649
## Median :0.1065	Median :0.4668	Median :17.911	Median : 0.6418
## Mean :0.3746	Mean :0.4840	Mean :20.898	Mean : 0.9937
## 3rd Qu.:0.3990	3rd Qu.:0.5971	3rd Qu.:29.754	3rd Qu.: 0.9239
## Max. :3.9046	Max. :0.8965	Max. :60.261	Max. :10.0642
## C.Sstor_per_sqm	F.Astor_per_1kpp1	F.Astor_per_sqm	Mstor_per_1kpp1
## Min. : 2.00	Min. :0.06682	Min. : 0.449	Min. :0.02169
## 1st Qu.: 14.66	1st Qu.:0.14059	1st Qu.: 4.986	1st Qu.:0.05636
## Median : 28.53	Median :0.19046	Median : 7.469	Median :0.07441
## Mean : 48.81	Mean :0.22297	Mean : 9.830	Mean :0.11965

## 3rd Qu.: 47.78	3rd Qu.:0.26559	3rd Qu.:11.788	3rd Qu.:0.12166
## Max. :518.00	Max. :1.03676	Max. :53.362	Max. :0.80286
## Mstor_per_sqm	H.Gstor_per_1kpp1	H.Gstor_per_sqm	D.Vstor_per_1kpp1
## Min. : 0.1513	Min. :0.02148	Min. : 0.3531	Min. :0.1946
## 1st Qu.: 1.7691	1st Qu.:0.04806	1st Qu.: 1.2071	1st Qu.:0.3232
## Median : 2.9524	Median :0.06028	Median : 2.5541	Median :0.3906
## Mean : 5.9374	Mean :0.07130	Mean : 3.1309	Mean :0.4923
## 3rd Qu.: 7.1341	3rd Qu.:0.08650	3rd Qu.: 4.1562	3rd Qu.:0.4941
## Max. :41.3232	Max. :0.25919	Max. :13.3406	Max. :2.7879
## D.Vstor_per_sqm	Ustor_per_1kpp1	Ustor_per_sqm	pyhs_per_1kpp1
## Min. : 1.469	Min. :0.01470	Min. : 0.1768	Min. :0.248
## 1st Qu.: 9.946	1st Qu.:0.04334	1st Qu.: 1.5008	1st Qu.:0.718
## Median : 16.350	Median :0.06808	Median : 3.0172	Median :1.029
## Mean : 22.637	Mean :0.11090	Mean : 5.7390	Mean :1.464
## 3rd Qu.: 25.456	3rd Qu.:0.11440	3rd Qu.: 4.6444	3rd Qu.:1.593
## Max. :143.492	Max. :0.74596	Max. :48.0677	Max. :7.574
## phys_per_sqm	pharm_per_1kpp1	pharm_per_sqm	post_per_1kpp1
## Min. : 6.531	Min. :0.1875	Min. : 1.265	Min. :0.006349
## 1st Qu.: 17.195	1st Qu.:0.2845	1st Qu.: 7.781	1st Qu.:0.017024
## Median : 36.761	Median :0.3393	Median :16.089	Median :0.024803
## Mean : 74.253	Mean :0.3703	Mean :16.714	Mean :0.026199
## 3rd Qu.: 66.948	3rd Qu.:0.4288	3rd Qu.:22.709	3rd Qu.:0.034749
## Max. :806.745	Max. :0.8281	Max. :42.647	Max. :0.082182
## post_per_sqm	banks_per_1kpp1	banks_per_sqm	R.Pcent_per_1kpp1
## Min. :0.1009	Min. :0.03349	Min. : 1.238	Min. :0.04074
## 1st Qu.:0.5829	1st Qu.:0.09807	1st Qu.: 3.141	1st Qu.:0.09601
## Median :0.7724	Median :0.17832	Median : 5.290	Median :0.15699
## Mean :1.0397	Mean :0.23685	Mean : 10.843	Mean :0.20617
## 3rd Qu.:1.1798	3rd Qu.:0.25352	3rd Qu.: 9.491	3rd Qu.:0.20473
## Max. :4.2299	Max. :1.99134	Max. :102.495	Max. :1.25802
## R.Pcent_per_sqm	G.Drang_per_1kpp1	G.Drang_per_sqm	SK.SW.Tcourt_per_1kpp1
## Min. : 0.884	Min. :0.000000	Min. :0.0000	Min. :0.000000
## 1st Qu.: 2.661	1st Qu.:0.000000	1st Qu.:0.0000	1st Qu.:0.000000
## Median : 5.516	Median :0.000000	Median :0.0000	Median :0.004617
## Mean :10.008	Mean :0.003134	Mean :0.1042	Mean :0.005584
## 3rd Qu.: 9.598	3rd Qu.:0.006608	3rd Qu.:0.1037	3rd Qu.:0.007838
## Max. :64.751	Max. :0.031609	Max. :1.6269	Max. :0.026436
## SK.SW.Tcourt_per_sqm	Members_per_1kpp1	Members_per_sqm	TotRec_per_1kpp1
## Min. :0.00000	Min. :0.07539	Min. : 0.898	Min. :0.1612
## 1st Qu.:0.00000	1st Qu.:0.13685	1st Qu.: 3.401	1st Qu.:0.3069
## Median :0.05044	Median :0.16074	Median : 5.740	Median :0.4002
## Mean :0.25295	Mean :0.19252	Mean : 8.996	Mean :0.5130
## 3rd Qu.:0.39252	3rd Qu.:0.22372	3rd Qu.:12.035	3rd Qu.:0.5678
## Max. :1.48663	Max. :0.82814	Max. :42.625	Max. :2.6994
## TotRec_per_sqm	Share_Priv_Rec	Arts.E_per_1kpp1	Arts.E_per_sqm
## Min. : 2.939	Min. :0.2115	Min. :0.00000	Min. : 0.000
## 1st Qu.: 7.857	1st Qu.:0.3380	1st Qu.:0.07896	1st Qu.: 2.099
## Median : 14.002	Median :0.3898	Median :0.11385	Median : 4.385
## Mean : 23.960	Mean :0.4193	Mean :0.28900	Mean : 15.720
## 3rd Qu.: 24.674	3rd Qu.:0.4871	3rd Qu.:0.26758	3rd Qu.: 12.997
## Max. :138.937	Max. :0.7755	Max. :3.16086	Max. :162.690
## Hotels_per_1kpp1	Hotels_per_sqm	MTAStops_per_sqm	Wavg_download_sp
## Min. :0.01077	Min. : 0.2857	Min. : 0.000	Min. : 28.33
## 1st Qu.:0.05661	1st Qu.: 1.5891	1st Qu.: 5.471	1st Qu.:144.87

```
## Median :0.08596 Median : 2.8321 Median : 37.172 Median :222.40
## Mean :0.20543 Mean : 10.7484 Mean : 36.695 Mean :283.04
## 3rd Qu.:0.14024 3rd Qu.: 7.0604 3rd Qu.: 60.321 3rd Qu.:376.02
## Max. :3.25568 Max. :167.5705 Max. :100.087 Max. :701.90
## Wavg_upload_sp aff_30_pre aff_30_post aff_80_pre
## Min. : 27.66 Min. : 0.000 Min. : 0.900 Min. : 7.70
## 1st Qu.:144.29 1st Qu.: 3.300 1st Qu.: 4.300 1st Qu.:39.45
## Median :221.83 Median : 5.400 Median : 5.400 Median :54.60
## Mean :282.47 Mean : 6.742 Mean : 7.204 Mean :52.45
## 3rd Qu.:375.48 3rd Qu.: 7.350 3rd Qu.: 9.100 3rd Qu.:70.50
## Max. :701.68 Max. :27.300 Max. :29.900 Max. :92.60
## aff_80_post aff_120_pre aff_120_post vac_rnt_pct_pre
## Min. :13.20 Min. : 23.90 Min. : 31.30 Min. :1.400
## 1st Qu.:35.75 1st Qu.: 81.00 1st Qu.: 87.65 1st Qu.:2.300
## Median :54.60 Median : 94.80 Median : 94.80 Median :2.900
## Mean :54.00 Mean : 84.36 Mean : 87.19 Mean :3.373
## 3rd Qu.:70.95 3rd Qu.: 98.65 3rd Qu.: 98.15 3rd Qu.:4.100
## Max. :93.10 Max. :100.00 Max. :100.00 Max. :8.200
## vac_rnt_pct_post housing_quality inv_med_gro_rnt avg_age_grouped
## Min. :0.900 Min. :-1.1371 Min. :0.3135 Length:55
## 1st Qu.:2.300 1st Qu.: -0.7156 1st Qu.:0.5238 Class :character
## Median :3.200 Median :-0.1055 Median :0.5780 Mode :character
## Mean :3.455 Mean : 0.0000 Mean :0.5866
## 3rd Qu.:3.900 3rd Qu.: 0.5368 3rd Qu.:0.6601
## Max. :8.400 Max. : 1.7812 Max. :0.9091
## avg_surrounding_median_income raceth_group resilience_index
## Min. : 31990 Length:55 Min. : 1.818
## 1st Qu.: 64115 Class :character 1st Qu.: 26.364
## Median : 77145 Mode :character Median : 50.909
## Mean : 79917 Mean : 50.909
## 3rd Qu.: 92368 3rd Qu.: 75.455
## Max. :158133 Max. :100.000
## family_index necessary_amenities_index unnecessary_amenities_index
## Min. : 0.00 Min. : 0.000 Min. : 0.000
## 1st Qu.: 17.52 1st Qu.: 6.731 1st Qu.: 2.945
## Median : 25.51 Median : 38.994 Median : 3.904
## Mean : 29.57 Mean : 38.042 Mean : 8.799
## 3rd Qu.: 37.97 3rd Qu.: 61.851 3rd Qu.: 6.848
## Max. :100.00 Max. :100.000 Max. :100.000
## amenity_ratio rent_gap_index displacement_pressure_index
## Min. : 0.00000 Min. : 0.00 Min. : 0.00
## 1st Qu.: 0.06529 1st Qu.: 21.65 1st Qu.: 35.55
## Median : 0.21593 Median : 34.03 Median : 48.50
## Mean : 2.98816 Mean : 37.38 Mean : 49.57
## 3rd Qu.: 0.73905 3rd Qu.: 51.82 3rd Qu.: 69.58
## Max. :100.00000 Max. :100.00 Max. :100.00
```

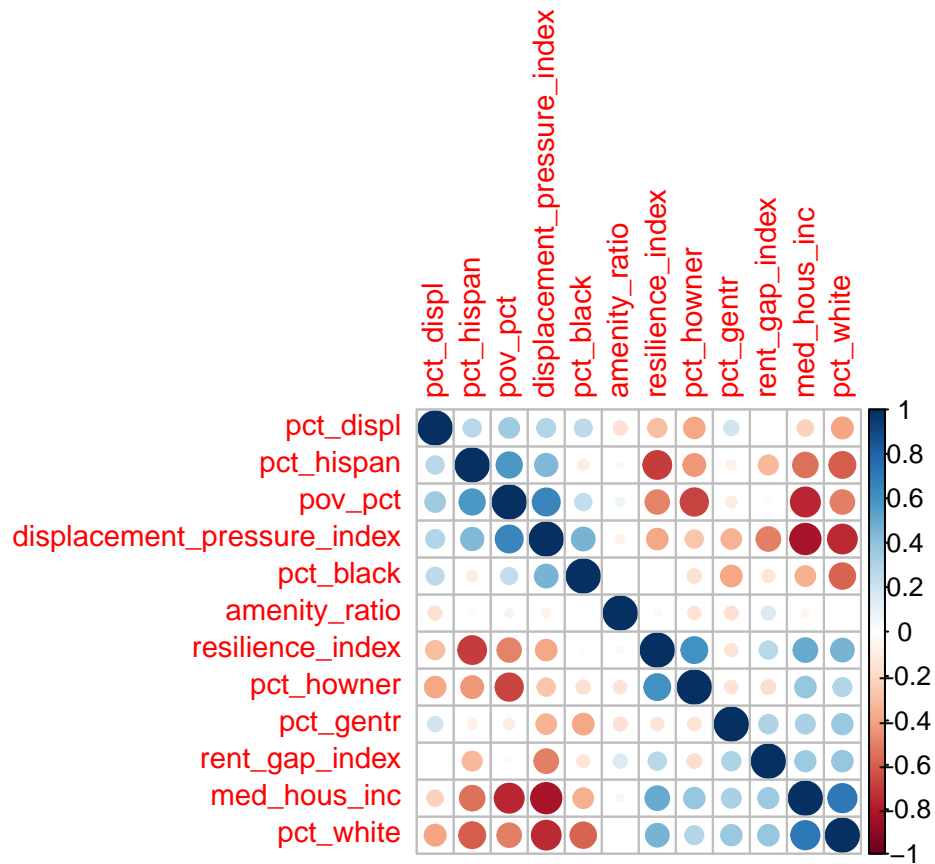
```
# Correlation matrix of some important variables
```

```
vars <- c("pct_gentr", "pct_displ", "med_hous_inc", "pov_pct", "pct_black", "pct_hispan", "pct_white", "
```

```
cor_matrix <- cor(SBA[vars], use = "complete.obs")
```

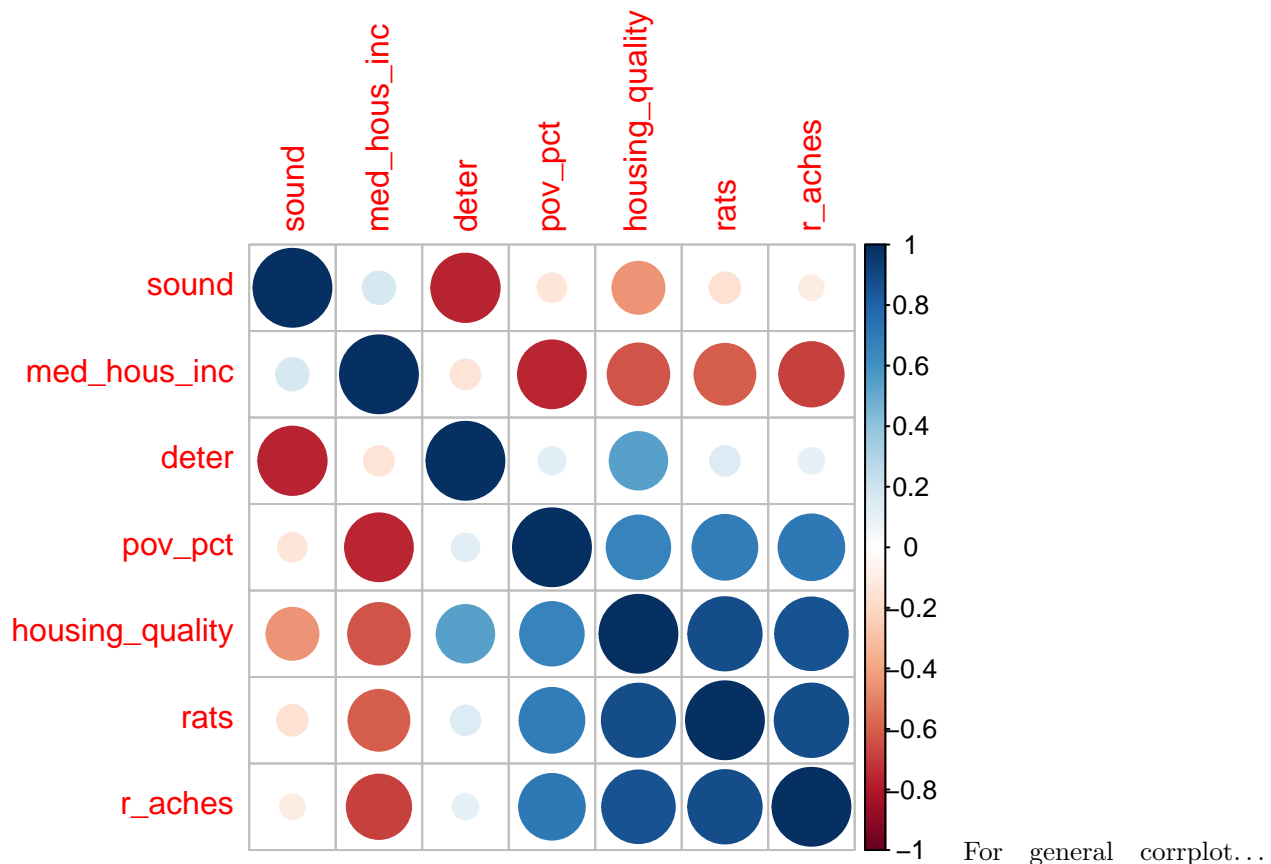
```
corrplot(cor_matrix, method = "circle",
          order = "hclust", tl.cex = 0.9)
```





```
# corr matrix of rats, r_aches, & deter
vars <- c("rats", "r_aches", "deter", "housing_quality", "pov_pct", "sound", "med_hous_inc")

cor_matrix <- cor(SBA[vars], use = "complete.obs")
corrplot(cor_matrix, method = "circle",
          order = "hclust")
```



Poverty rate correlates positively with hispanic & black populations and negatively with homeownership, median household income, & white populations- which all are somewhat expected. Its also positively correlated with displacemt pressures which is reassuring because it reflects that displacement pressures tend to be higher in poorer,non-white neighborhoods.

Similarly, median household income has a very strong negative relationship with displacement pressures indicating again that wealthier neighborhoods tend to be subject to less displacement pressures. Its also negatively correlated with black & hispanic populations, & incoming displacees.

Community resilience being very negatively related to poverty rates goes against my assumptions, unless in 2017 certain neighborhoods were already at a later stage of gentrification that displaces community members and exibits a loss of community networks, or the resilience index doesn't reflect the same local resources that provide effective buffers to gentrification

For rats/r\_aches corrplo... Expected extreme negative relationship between sound & deter, and also with housing\_quality since deter is the main variable in its calculation. Its somewhat interesting that the percent of sound units doesn't really correlate with the presence of rats/r\_aches but "sound" may refer more to a basic structural safety that may not reflect its cleanliness as well. Poverty rate is positively related to both rats & r\_aches, and negatively with med\_hous\_inc which also makes sense if displacees are heavily constrained to move into neighborhoods that have yet to be reinvested in, which might reflect the livability of those neighborhoods.

Rats is highly correlated with r\_aches which is expected but not so much with sound/deter which would support the idea that sound/deter are markers of more basic structural compliances rather than livability/cleanliness so i might remove it from housing quality measure (but r\_aches also doesn't correlate with sound/deter all that much so do i drop both or forget about that index?). Sound/deter & rats/r\_aches measuring two very different things that dont seem to relate with one another.

```
# converting raceth_group to factor where reference category = white
SBA$raceth_group <- factor(SBA$raceth_group,
                           levels = c("White", "Black", "Hispanic", "Asian"))
```

```
# check
levels(SBA$raceth_group)
```

```
## [1] "White"      "Black"      "Hispanic"   "Asian"
```

Regressions:

```
# MODEL1
model1 <- lm(pct_gentr ~ aff_30_pre + rent_gap_index + resilience_index + pov_pct, data = SBA)
# summary(model1)
```

```
# MODEL2
model2 <- lm(pct_gentr ~ aff_30_pre + rent_gap_index + resilience_index + pov_pct + raceth_group, data = SBA)
# summary(model2)
```

```
# MODEL3
model3 <- lm(pct_gentr ~ aff_30_pre + rent_gap_index + pov_pct + resilience_index*raceth_group, data = SBA)
# summary(model3)
```

```
stargazer(model1, model2, model3, type = "text")
```

```
##
## =====
##                                     Dependent variable:
##                                     -----
##                                     pct_gentr
##                                     (1)          (2)          (3)
## -----
## aff_30_pre                -0.001**          -0.001          -0.001
##                           (0.001)          (0.001)          (0.001)
##
## rent_gap_index            0.0004***          0.0003***          0.0003***
##                           (0.0001)          (0.0001)          (0.0001)
##
## resilience_index          -0.0003**          -0.0003***          -0.0003
##                           (0.0001)          (0.0001)          (0.0002)
##
## pov_pct                   0.00002           0.0001           0.00003
##                           (0.0004)          (0.0004)          (0.0005)
##
## raceth_groupBlack                -0.012          -0.017
##                                (0.008)          (0.020)
##
## raceth_groupHispanic             -0.016*          -0.009
##                                (0.008)          (0.015)
##
## raceth_groupAsian                0.001           0.033
##                                (0.009)          (0.028)
##
## resilience_index:raceth_groupBlack                0.0001
##                                                (0.0003)
```

```
##
## resilience_index:raceth_groupHispanic -0.0001
## (0.0003)
##
## resilience_index:raceth_groupAsian -0.0005
## (0.0004)
##
## Constant 0.057*** 0.067*** 0.064***
## (0.010) (0.011) (0.013)
##
## -----
## Observations 55 55 55
## R2 0.278 0.351 0.380
## Adjusted R2 0.220 0.255 0.239
## Residual Std. Error 0.019 (df = 50) 0.018 (df = 47) 0.018 (df = 44)
## F Statistic 4.815*** (df = 4; 50) 3.634*** (df = 7; 47) 2.699** (df = 10; 4)
## =====
## Note: *p<0.1; **p<0.05; ***p<0.001
```

Story...

Multicollinearity checks:

```
vif(model1)
```

```
##      aff_30_pre  rent_gap_index resilience_index      pov_pct
##      2.128219      1.106720      1.495766      2.648185
```

```
vif(model2)
```

```
##              GVIF Df GVIF^(1/(2*Df))
## aff_30_pre      2.538483 1      1.593262
## rent_gap_index  1.185959 1      1.089017
## resilience_index 1.859763 1      1.363731
## pov_pct         2.827371 1      1.681479
## raceth_group    2.207230 3      1.141059
```

```
vif(model3, type = "predictor") # to handle interaction
```

## GVIFs computed for predictors

```
##              GVIF Df GVIF^(1/(2*Df))  Interacts With
## aff_30_pre      2.659353 1      1.630752      --
## rent_gap_index  1.263942 1      1.124252      --
## pov_pct         3.134486 1      1.770448      --
## resilience_index 2.599039 7      1.070606      raceth_group
## raceth_group    2.599039 7      1.070606 resilience_index
##
##              Other Predictors
## aff_30_pre      rent_gap_index, pov_pct, resilience_index, raceth_group
## rent_gap_index  aff_30_pre, pov_pct, resilience_index, raceth_group
## pov_pct         aff_30_pre, rent_gap_index, resilience_index, raceth_group
## resilience_index      aff_30_pre, rent_gap_index, pov_pct
## raceth_group      aff_30_pre, rent_gap_index, pov_pct
```

Blurb here...

F-test:

```
# RESTRICTED model: just the effect of pre-period affordable housing, poverty rate, rent_gap, & commun
restricted_model <- lm(pct_gentr ~ aff_30_pre + rent_gap_index + resilience_index + pov_pct, data = SBA
```

```
# Comparing with FULL model: the additional effect of the dominant race/ethnicity group of each neighbo
f_test <- anova(restricted_model, model3)
```

```
stargazer(restricted_model, model3, type = "text", title = "F-test", column.labels = c("Restricted", "F
```

```
##
## F-test
## =====
##                               Dependent variable:
##                               -----
##                               pct_gentr
##                               Restricted      Full
##                               (1)           (2)
## -----
## aff_30_pre                -0.001**        -0.001
##                               (0.001)        (0.001)
##
## rent_gap_index            0.0004***        0.0003***
##                               (0.0001)        (0.0001)
##
## resilience_index          -0.0003**        -0.0003
##                               (0.0001)        (0.0002)
##
## raceth_groupBlack                -0.017
##                               (0.020)
##
## raceth_groupHispanic            -0.009
##                               (0.015)
##
## raceth_groupAsian                0.033
##                               (0.028)
##
## resilience_index:raceth_groupBlack            0.0001
##                               (0.0003)
##
## resilience_index:raceth_groupHispanic            -0.0001
##                               (0.0003)
##
## resilience_index:raceth_groupAsian            -0.0005
##                               (0.0004)
##
## pov_pct                0.00002            0.00003
##                               (0.0004)        (0.0005)
##
## Constant                0.057***            0.064***
##                               (0.010)        (0.013)
## -----
## Observations                55            55
## R2                0.278            0.380
## Adjusted R2            0.220            0.239
```

```
## Residual Std. Error          0.019 (df = 50)          0.018 (df = 44)
## F Statistic                  4.815*** (df = 4; 50) 2.699** (df = 10; 44)
## =====
## Note:                        *p<0.1; **p<0.05; ***p<0.01
```

blurb here...

Heteroskedasticity test:

```
bptest(model3)
```

```
##
## studentized Breusch-Pagan test
##
## data: model3
## BP = 5.1067, df = 10, p-value = 0.8839
```

Not heteroskedastic (since p value is not less than 0.05, theres not enough evidence to reject the null that errors aren't equally distributed)

Loading Geo dta

```
GEO <- st_read("/Users/isabellagermani/Desktop/MS THSS/data/SBA_GEO.geojson", stringsAsFactors = FALSE,
```

```
## Reading layer `SBA_GEO' from data source
##   `/Users/isabellagermani/Desktop/MS THSS/data/SBA_GEO.geojson'
##   using driver `GeoJSON'
## Simple feature collection with 55 features and 144 fields
## Geometry type: MULTIPOLYGON
## Dimension:      XY
## Bounding box:   xmin: 913175.1 ymin: 120128.4 xmax: 1067383 ymax: 272844.3
## Projected CRS: NAD83 / New York Long Island (ftUS)
```

```
str(GEO)
```

```
## Classes 'sf' and 'data.frame':   55 obs. of  145 variables:
## $ Shape_Leng      : num  90062 68718 35003 37375 51815 ...
## $ Shape_Area      : num  1.38e+08 1.22e+08 5.59e+07 4.23e+07 4.39e+07 ...
## $ SBA              : int  101 102 103 104 105 106 107 108 109 110 ...
## $ SBA_name         : chr  "Mott Haven/Hunts Point" "Morrisania/Belmont" "Highbridge/Sou
## $ med_hous_inc     : int  26090 32330 38460 37550 44000 67190 49790 74080 59760 73150 .
## $ pct_FL_loans     : num  30 53.4 10.3 54.8 9.6 0.9 28.6 31.9 27.3 60.6 ...
## $ pct_FL_loans_2_LI : num  100 100 100 100 66.7 14 63.5 11.8 50.3 46 ...
## $ inc_div_ratio    : num  5.9 6.2 5.6 5.8 5.7 6.2 6.1 5.8 4.7 5 ...
## $ mort_forc       : num  70 115 38 53 25 28 252 135 147 422 ...
## $ pov_pct         : num  44.2 35.8 36.4 36.4 32.9 18.5 24.7 10.2 16.4 14.6 ...
## $ pct_asian       : num  0.3 1.3 1 1.8 7.1 4.1 8.2 3.6 9.4 2.3 ...
## $ pct_black       : num  28.4 32.5 27.7 24.4 11.3 11.8 30.3 28.8 19.8 67.2 ...
## $ prob_race       : num  0.47 0.51 0.45 0.43 0.43 0.65 0.59 0.69 0.7 0.49 ...
## $ pct_hispan      : num  67.2 61.8 68.8 71.1 74.1 48.8 55.4 39.9 42.3 23 ...
## $ pct_white       : num  3.3 3.8 1.3 1 5.1 31.5 3 25.5 26.7 5.4 ...
## $ pop_dens        : num  31.9 43 75 98.2 91.5 33.1 42.5 12.2 31.5 22.3 ...
## $ priv_landL_amt  : int  2925 3174 3547 3423 3852 3906 3561 4330 4105 3882 ...
## $ med_rti         : num  38 34.8 38.9 41.7 41 34 34.1 28.9 37.6 34.7 ...
## $ med_gro_rnt     : int  1200 1280 1400 1450 1560 1720 1440 1470 1580 1720 ...
## $ vac_rt          : num  0.124 0.1373 0.1265 0.0842 0.0303 ...
## $ pct_condo       : num  0.0165 0.0176 0.0122 0 0.0101 ...
## $ pct_coop        : num  0.0413 0.0282 0.0857 0.0149 0.0606 ...
```

```

## $ sound : num 0.963 0.877 0.971 0.896 0.944 ...
## $ deter : num 0.01653 0.0493 0.00408 0.02475 0.0101 ...
## $ rats : num 0.335 0.324 0.339 0.396 0.303 ...
## $ r_aches : num 0.368 0.313 0.318 0.455 0.449 ...
## $ afford : num 0.616 0.511 0.437 0.436 0.535 ...
## $ unafford : num 0.165 0.148 0.171 0.262 0.247 ...
## $ avg_rti : num 0.392 0.4 0.395 0.422 0.416 ...
## $ avg_age : num 52.8 50.2 51 49.3 47.7 ...
## $ pct_howner : num 0.0579 0.0775 0.0612 0.0396 0.0707 ...
## $ pct_immigrant : num 0.269 0.264 0.31 0.436 0.364 ...
## $ med_year_moved_in : num 2007 2010 2007 2009 2010 ...
## $ med_length_res : num 10 7 10 8 7 9 12 18.5 7 8 ...
## $ pct_recent_moves : num 0.463 0.549 0.461 0.564 0.596 ...
## $ pct_fresh_moves : num 0.273 0.37 0.29 0.356 0.439 ...
## $ pct_displ : num 0.0207 0.0282 0.0245 0.0248 0.0101 ...
## $ pct_gentr : num 0.0331 0.0563 0.0571 0.0495 0.0505 ...
## $ rennov : num 0.0785 0.0775 0.0653 0.0594 0 ...
## $ tot_pop : num 156731 171842 141400 139656 132128 ...
## $ sq_miles : num 4.86 4.37 1.98 1.51 1.57 ...
## $ t_dollar_stores : int 12 5 7 6 3 1 4 2 5 3 ...
## $ dollars_per_1kppl : num 0.0766 0.0291 0.0495 0.043 0.0227 ...
## $ dollars_per_sqm : num 2.47 1.14 3.53 3.97 1.91 ...
## $ liqour_per_1kppl : num 0.2106 0.1397 0.1132 0.1289 0.0908 ...
## $ liqour_per_sqm : num 6.79 5.49 8.06 11.92 7.64 ...
## $ tobacco_per_1kppl : num 0.00638 0.04074 0.07072 0.0358 0.02271 ...
## $ tobacco_per_sqm : num 0.206 1.601 5.038 3.311 1.909 ...
## $ convenience_per_1kppl : num 0.1404 0.1397 0.1414 0.0931 0.0984 ...
## $ convenience_per_sqm : num 4.53 5.49 10.08 8.61 8.27 ...
## $ ecig_per_1kppl : num 0 0.00582 0 0 0 ...
## $ ecig_per_sqm : num 0 0.229 0 0 0 ...
## $ marijuana_per_1kppl : num 0 0 0 0 0 0 0 0 0 ...
## $ marijuana_per_sqm : num 0 0 0 0 0 0 0 0 0 ...
## $ civsoc_per_1kppl : num 0.128 0.128 0.141 0.122 0.136 ...
## $ civsoc_per_sqm : num 4.12 5.03 10.08 11.26 11.46 ...
## $ youthorgs_per_1kppl : num 0.0255 0.0466 0.0354 0.0286 0.0227 ...
## $ youthorgs_per_sqm : num 0.824 1.83 2.519 2.649 1.909 ...
## $ vetorgs_per_1kppl : num 0 0.00582 0.01414 0 0 ...
## $ vetorgs_per_sqm : num 0 0.229 1.008 0 0 ...
## $ relig_per_1kppl : num 0.906 1.146 0.785 0.709 0.568 ...
## $ relig_per_sqm : num 29.2 45.1 55.9 65.6 47.7 ...
## $ barber_per_1kppl : num 0.383 0.396 0.347 0.358 0.242 ...
## $ barber_per_sqm : num 12.4 15.6 24.7 33.1 20.4 ...
## $ beauty_per_1kppl : num 0.957 0.867 0.969 1.088 0.954 ...
## $ beauty_per_sqm : num 30.9 34.1 69 100.7 80.2 ...
## $ laundry_per_1kppl : num 0.223 0.169 0.134 0.158 0.204 ...
## $ laundry_per_sqm : num 7.21 6.63 9.57 14.57 17.18 ...
## $ drycl_per_1kppl : num 0.0638 0.04655 0.03536 0.00716 0.02271 ...
## $ drycl_per_sqm : num 2.059 1.83 2.519 0.662 1.909 ...
## $ I.Fserv_per_1kppl : num 0.817 0.512 0.332 0.444 0.431 ...
## $ I.Fserv_per_sqm : num 26.4 20.1 23.7 41.1 36.3 ...
## $ E.Dserv_per_1kppl : num 0.0957 0.0466 0.0212 0.0215 0.0454 ...
## $ E.Dserv_per_sqm : num 3.09 1.83 1.51 1.99 3.82 ...
## $ C.Yserv_per_1kppl : num 0.0383 0.0407 0.0283 0.0215 0.0454 ...
## $ C.Yserv_per_sqm : num 1.24 1.6 2.02 1.99 3.82 ...

```

```
## $ Eserv_per_1kppl : num 0.0319 0.0233 0.0141 0.0143 0 ...
## $ Eserv_per_sqm : num 1.029 0.915 1.008 1.324 0 ...
## $ MDprog_per_1kppl : num 0.00638 0 0 0 0 ...
## $ MDprog_per_sqm : num 0.206 0 0 0 0 ...
## $ Gcouns_per_1kppl : num 0.236 0.163 0.099 0.129 0.136 ...
## $ Gcouns_per_sqm : num 7.62 6.41 7.05 11.92 11.46 ...
## $ SAcouns_per_1kppl : num 0.01276 0.01746 0 0.00716 0.00757 ...
## $ SAcouns_per_sqm : num 0.412 0.686 0 0.662 0.636 ...
## $ Dayc_per_1kppl : num 0.555 0.594 0.467 0.652 0.621 ...
## $ Dayc_per_sqm : num 17.9 23.3 33.3 60.3 52.2 ...
## $ C.Sstor_per_1kppl : num 0.619 0.442 0.502 0.537 0.681 ...
## $ C.Sstor_per_sqm : num 20 17.4 35.8 49.7 57.3 ...
## $ F.Astor_per_1kppl : num 0.249 0.18 0.163 0.122 0.25 ...
## $ F.Astor_per_sqm : num 8.03 7.09 11.59 11.26 21 ...
## $ Mstor_per_1kppl : num 0.0957 0.0582 0.0636 0.0501 0.053 ...
## $ Mstor_per_sqm : num 3.09 2.29 4.53 4.64 4.46 ...
## $ H.Gstor_per_1kppl : num 0.0893 0.0524 0.0566 0.0573 0.0454 ...
## $ H.Gstor_per_sqm : num 2.88 2.06 4.03 5.3 3.82 ...
## $ D.Vstor_per_1kppl : num 0.447 0.268 0.339 0.272 0.341 ...
## $ D.Vstor_per_sqm : num 14.4 10.5 24.2 25.2 28.6 ...
## $ Ustor_per_1kppl : num 0.0957 0.0989 0.0636 0.0573 0.1211 ...
## $ Ustor_per_sqm : num 3.09 3.89 4.53 5.3 10.18 ...
## $ pyhs_per_1kppl : num 0.479 0.39 0.446 0.487 1.082 ...
## [list output truncated]
## - attr(*, "sf_column")= chr "geometry"
## - attr(*, "agr")= Factor w/ 3 levels "constant","aggregate",...: NA NA NA NA NA NA NA NA NA NA ...
## ..- attr(*, "names")= chr [1:144] "Shape_Leng" "Shape_Area" "SBA" "SBA_name" ...
```

Spatial Autocorrelation check:

```
# merging
MERGE <- merge(GEO, SBA,
  by.x = "SBA",
  by.y = "SBA",
  all.x = FALSE) # Keep only matched rows

str(MERGE)
```

```
## Classes 'sf' and 'data.frame': 55 obs. of 286 variables:
## $ SBA : int 101 102 103 104 105 106 107 108 109 110 ...
## $ Shape_Leng : num 90062 68718 35003 37375 51815 ...
## $ Shape_Area : num 1.38e+08 1.22e+08 5.59e+07 4.23e+07 4.39e+07 ...
## $ SBA_name.x : chr "Mott Haven/Hunts Point" "Morrisania/Belmont" "Highbridge/S...
## $ med_hous_inc.x : int 26090 32330 38460 37550 44000 67190 49790 74080 59760 73150
## $ pct_FL_loans.x : num 30 53.4 10.3 54.8 9.6 0.9 28.6 31.9 27.3 60.6 ...
## $ pct_FL_loans_2_LI.x : num 100 100 100 100 66.7 14 63.5 11.8 50.3 46 ...
## $ inc_div_ratio.x : num 5.9 6.2 5.6 5.8 5.7 6.2 6.1 5.8 4.7 5 ...
## $ mort_forc.x : num 70 115 38 53 25 28 252 135 147 422 ...
## $ pov_pct.x : num 44.2 35.8 36.4 36.4 32.9 18.5 24.7 10.2 16.4 14.6 ...
## $ pct_asian.x : num 0.3 1.3 1 1.8 7.1 4.1 8.2 3.6 9.4 2.3 ...
## $ pct_black.x : num 28.4 32.5 27.7 24.4 11.3 11.8 30.3 28.8 19.8 67.2 ...
## $ prob_race.x : num 0.47 0.51 0.45 0.43 0.43 0.65 0.59 0.69 0.7 0.49 ...
## $ pct_hispan.x : num 67.2 61.8 68.8 71.1 74.1 48.8 55.4 39.9 42.3 23 ...
## $ pct_white.x : num 3.3 3.8 1.3 1 5.1 31.5 3 25.5 26.7 5.4 ...
## $ pop_dens.x : num 31.9 43 75 98.2 91.5 33.1 42.5 12.2 31.5 22.3 ...
```



```

## $ priv_landL_amt.x      : int  2925 3174 3547 3423 3852 3906 3561 4330 4105 3882 ...
## $ med_rti.x             : num   38 34.8 38.9 41.7 41 34 34.1 28.9 37.6 34.7 ...
## $ med_gro_rnt.x         : int  1200 1280 1400 1450 1560 1720 1440 1470 1580 1720 ...
## $ vac_rt.x              : num   0.124 0.1373 0.1265 0.0842 0.0303 ...
## $ pct_condo.x           : num   0.0165 0.0176 0.0122 0 0.0101 ...
## $ pct_coop.x            : num   0.0413 0.0282 0.0857 0.0149 0.0606 ...
## $ sound.x               : num   0.963 0.877 0.971 0.896 0.944 ...
## $ deter.x               : num   0.01653 0.0493 0.00408 0.02475 0.0101 ...
## $ rats.x                : num   0.335 0.324 0.339 0.396 0.303 ...
## $ r_aches.x             : num   0.368 0.313 0.318 0.455 0.449 ...
## $ afford.x              : num   0.616 0.511 0.437 0.436 0.535 ...
## $ unafford.x            : num   0.165 0.148 0.171 0.262 0.247 ...
## $ avg_rti.x             : num   0.392 0.4 0.395 0.422 0.416 ...
## $ avg_age.x             : num   52.8 50.2 51 49.3 47.7 ...
## $ pct_howner.x          : num   0.0579 0.0775 0.0612 0.0396 0.0707 ...
## $ pct_immigrant.x        : num   0.269 0.264 0.31 0.436 0.364 ...
## $ med_year_moved_in.x    : num   2007 2010 2007 2009 2010 ...
## $ med_length_res.x       : num   10 7 10 8 7 9 12 18.5 7 8 ...
## $ pct_recent_moves.x     : num   0.463 0.549 0.461 0.564 0.596 ...
## $ pct_fresh_moves.x      : num   0.273 0.37 0.29 0.356 0.439 ...
## $ pct_displ.x           : num   0.0207 0.0282 0.0245 0.0248 0.0101 ...
## $ pct_gentr.x           : num   0.0331 0.0563 0.0571 0.0495 0.0505 ...
## $ rennov.x              : num   0.0785 0.0775 0.0653 0.0594 0 ...
## $ tot_pop.x             : num  156731 171842 141400 139656 132128 ...
## $ sq_miles.x            : num   4.86 4.37 1.98 1.51 1.57 ...
## $ t_dollar_stores.x      : int   12 5 7 6 3 1 4 2 5 3 ...
## $ dollars_per_1kppl.x    : num   0.0766 0.0291 0.0495 0.043 0.0227 ...
## $ dollars_per_sqm.x      : num   2.47 1.14 3.53 3.97 1.91 ...
## $ liquour_per_1kppl.x    : num   0.2106 0.1397 0.1132 0.1289 0.0908 ...
## $ liquour_per_sqm.x      : num   6.79 5.49 8.06 11.92 7.64 ...
## $ tobacco_per_1kppl.x    : num   0.00638 0.04074 0.07072 0.0358 0.02271 ...
## $ tobacco_per_sqm.x      : num   0.206 1.601 5.038 3.311 1.909 ...
## $ convenience_per_1kppl.x : num   0.1404 0.1397 0.1414 0.0931 0.0984 ...
## $ convenience_per_sqm.x  : num   4.53 5.49 10.08 8.61 8.27 ...
## $ ecig_per_1kppl.x       : num   0 0.00582 0 0 0 ...
## $ ecig_per_sqm.x         : num   0 0.229 0 0 0 ...
## $ marijuana_per_1kppl.x   : num   0 0 0 0 0 0 0 0 0 0 ...
## $ marijuana_per_sqm.x     : num   0 0 0 0 0 0 0 0 0 0 ...
## $ civsoc_per_1kppl.x      : num   0.128 0.128 0.141 0.122 0.136 ...
## $ civsoc_per_sqm.x        : num   4.12 5.03 10.08 11.26 11.46 ...
## $ youthorgs_per_1kppl.x   : num   0.0255 0.0466 0.0354 0.0286 0.0227 ...
## $ youthorgs_per_sqm.x     : num   0.824 1.83 2.519 2.649 1.909 ...
## $ vetorgs_per_1kppl.x     : num   0 0.00582 0.01414 0 0 ...
## $ vetorgs_per_sqm.x       : num   0 0.229 1.008 0 0 ...
## $ relig_per_1kppl.x       : num   0.906 1.146 0.785 0.709 0.568 ...
## $ relig_per_sqm.x         : num   29.2 45.1 55.9 65.6 47.7 ...
## $ barber_per_1kppl.x      : num   0.383 0.396 0.347 0.358 0.242 ...
## $ barber_per_sqm.x        : num   12.4 15.6 24.7 33.1 20.4 ...
## $ beauty_per_1kppl.x      : num   0.957 0.867 0.969 1.088 0.954 ...
## $ beauty_per_sqm.x        : num   30.9 34.1 69 100.7 80.2 ...
## $ laundry_per_1kppl.x     : num   0.223 0.169 0.134 0.158 0.204 ...
## $ laundry_per_sqm.x       : num   7.21 6.63 9.57 14.57 17.18 ...
## $ drycl_per_1kppl.x       : num   0.0638 0.04655 0.03536 0.00716 0.02271 ...
## $ drycl_per_sqm.x         : num   2.059 1.83 2.519 0.662 1.909 ...

```

```
## $ I.Fserv_per_1kppl.x : num 0.817 0.512 0.332 0.444 0.431 ...
## $ I.Fserv_per_sqm.x : num 26.4 20.1 23.7 41.1 36.3 ...
## $ E.Dserv_per_1kppl.x : num 0.0957 0.0466 0.0212 0.0215 0.0454 ...
## $ E.Dserv_per_sqm.x : num 3.09 1.83 1.51 1.99 3.82 ...
## $ C.Yserv_per_1kppl.x : num 0.0383 0.0407 0.0283 0.0215 0.0454 ...
## $ C.Yserv_per_sqm.x : num 1.24 1.6 2.02 1.99 3.82 ...
## $ Eserv_per_1kppl.x : num 0.0319 0.0233 0.0141 0.0143 0 ...
## $ Eserv_per_sqm.x : num 1.029 0.915 1.008 1.324 0 ...
## $ MDprog_per_1kppl.x : num 0.00638 0 0 0 0 ...
## $ MDprog_per_sqm.x : num 0.206 0 0 0 0 ...
## $ Gcouns_per_1kppl.x : num 0.236 0.163 0.099 0.129 0.136 ...
## $ Gcouns_per_sqm.x : num 7.62 6.41 7.05 11.92 11.46 ...
## $ SAcouns_per_1kppl.x : num 0.01276 0.01746 0 0.00716 0.00757 ...
## $ SAcouns_per_sqm.x : num 0.412 0.686 0 0.662 0.636 ...
## $ Dayc_per_1kppl.x : num 0.555 0.594 0.467 0.652 0.621 ...
## $ Dayc_per_sqm.x : num 17.9 23.3 33.3 60.3 52.2 ...
## $ C.Sstor_per_1kppl.x : num 0.619 0.442 0.502 0.537 0.681 ...
## $ C.Sstor_per_sqm.x : num 20 17.4 35.8 49.7 57.3 ...
## $ F.Astor_per_1kppl.x : num 0.249 0.18 0.163 0.122 0.25 ...
## $ F.Astor_per_sqm.x : num 8.03 7.09 11.59 11.26 21 ...
## $ Mstor_per_1kppl.x : num 0.0957 0.0582 0.0636 0.0501 0.053 ...
## $ Mstor_per_sqm.x : num 3.09 2.29 4.53 4.64 4.46 ...
## $ H.Gstor_per_1kppl.x : num 0.0893 0.0524 0.0566 0.0573 0.0454 ...
## $ H.Gstor_per_sqm.x : num 2.88 2.06 4.03 5.3 3.82 ...
## $ D.Vstor_per_1kppl.x : num 0.447 0.268 0.339 0.272 0.341 ...
## $ D.Vstor_per_sqm.x : num 14.4 10.5 24.2 25.2 28.6 ...
## $ Ustor_per_1kppl.x : num 0.0957 0.0989 0.0636 0.0573 0.1211 ...
## $ Ustor_per_sqm.x : num 3.09 3.89 4.53 5.3 10.18 ...
## $ pyhs_per_1kppl.x : num 0.479 0.39 0.446 0.487 1.082 ...
## [list output truncated]
## - attr(*, "sf_column")= chr "geometry"
## - attr(*, "agr")= Factor w/ 3 levels "constant","aggregate",...: NA NA NA NA NA NA NA NA NA NA ...
## ..- attr(*, "names")= chr [1:285] "SBA" "Shape_Leng" "Shape_Area" "SBA_name.x" ...

# Specifying how to define neighbors (using queen, where SBAs share either a border or corner)
neighbors <- poly2nb(MERGE, queen = TRUE)

## Warning in poly2nb(MERGE, queen = TRUE): neighbour object has 2 sub-graphs;
## if this sub-graph count seems unexpected, try increasing the snap argument.

# matrix where rows & columns = 55 SBAs & columns (converting neighbors to weights)
nmtx <- nb2listw(neighbors, style = "W") # Cell[i,j] = weight of j's influence on i (0 if not neighbor)

# Test - is gentrification in neighborhood i related to gentrification in its neighbors
result <- moran.test(MERGE$pct_gentr.y, nmtx)
print(result)

##
## Moran I test under randomisation
##
## data: MERGE$pct_gentr.y
## weights: nmtx
##
## Moran I statistic standard deviate = 1.8087, p-value = 0.03525
## alternative hypothesis: greater
```

```
## sample estimates:
## Moran I statistic      Expectation      Variance
##      0.146919789      -0.018518519      0.008366233
```