Data Analysis

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Load packages

```r
library(tidyverse)
```

```
## -- Attaching packages -------------------------------------------------------------------------------------

## v tibble  3.0.0          v purrr   0.3.3
## v tidyr   1.0.2.9000     v dplyr   0.8.5
## v readr   1.1.1          v forcats 0.3.0

## -- Conflicts ------------------------------------------------------------------------------------------ ti
## x lubridate::as.difftime() masks base::as.difftime()
## x lubridate::date()        masks base::date()
## x dplyr::filter()          masks stats::filter()
## x readr::guess_encoding()  masks rvest::guess_encoding()
## x lubridate::intersect()   masks base::intersect()
## x dplyr::lag()             masks stats::lag()
## x purrr::pluck()           masks rvest::pluck()
## x lubridate::setdiff()     masks base::setdiff()
## x lubridate::union()       masks base::union()
```

```r
library(knitr)
library(broom)
library(ggplot2)
library(openintro)
library(nnet)
library(patchwork)
library(pROC)
```

```
## Type 'citation("pROC")' for a citation.

##
## Attaching package: 'pROC'

## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

```r
library(plotROC)
```

```
##
## Attaching package: 'plotROC'

## The following object is masked from 'package:pROC':
##
##     ggroc
```

```r
library(psych)
```

```
##
## Attaching package: 'psych'
```

```
## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha
```

```r
library(RColorBrewer) #custom color palettes
#wrangle and model spatial data
library(sf)
```

```
## Linking to GEOS 3.5.1, GDAL 2.2.2, proj.4 4.9.2
```

```r
library(sp)
library(spatialreg)
```

```
## 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'))`

##
## Attaching package: 'spData'

## The following object is masked from 'package:openintro':
##
##     house

## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack
```

```r
library(spdep)
```

```
##
## Attaching package: 'spdep'

## The following objects are masked from 'package:spatialreg':
##
##     GMargminImage, GMerrorsar, HPDinterval.lagImpact,
##     Hausman.test, Jacobian_W, LR.sarlm, LR1.sarlm, LR1.spautolm,
##     LU_prepermutate_setup, LU_setup, MCMCsamp, ME, Matrix_J_setup,
##     Matrix_setup, SE_classic_setup, SE_interp_setup,
##     SE_whichMin_setup, SpatialFiltering, Wald1.sarlm, anova.sarlm,
##     as.spam.listw, as_dgRMatrix_listw, as_dsCMatrix_I,
##     as_dsCMatrix_IrW, as_dsTMatrix_listw, bptest.sarlm,
##     can.be.simmed, cheb_setup, coef.gmsar, coef.sarlm,
##     coef.spautolm, coef.stsls, create_WX, deviance.gmsar,
##     deviance.sarlm, deviance.spautolm, deviance.stsls, do_ldet,
##     eigen_pre_setup, eigen_setup, eigenw, errorsarlm,
##     fitted.ME_res, fitted.SFResult, fitted.gmsar, fitted.sarlm,
##     fitted.spautolm, get.ClusterOption, get.VerboseOption,
##     get.ZeroPolicyOption, get.coresOption, get.mcOption,
##     griffith_sone, gstsls, impacts, intImpacts, jacobianSetup,
##     l_max, lagmess, lagsarlm, lextrB, lextrS, lextrW, lmSLX,
##     logLik.sarlm, logLik.spautolm, mcdet_setup, mom_calc,
##     mom_calc_int2, moments_setup, powerWeights, predict.SLX,
```

```
##     predict.sarlm, print.ME_res, print.SFResult, print.gmsar,
##     print.sarlm, print.sarlm.pred, print.spautolm, print.stsls,
##     print.summary.gmsar, print.summary.sarlm,
##     print.summary.spautolm, print.summary.stsls, residuals.gmsar,
##     residuals.sarlm, residuals.spautolm, residuals.stsls,
##     sacsarlm, set.ClusterOption, set.VerboseOption,
##     set.ZeroPolicyOption, set.coresOption, set.mcOption,
##     similar.listw, spBreg_lag, spam_setup, spam_update_setup,
##     spautolm, stsls, subgraph_eigenw, summary.gmsar,
##     summary.sarlm, summary.spautolm, summary.stsls, trW,
##     vcov.sarlm
```

```r
library(spData)
library(tibble)
library(dplyr)
```

Loading and Manipulating the Data

```r
gentdata <- read_csv("data/gentdata.csv", col_names = TRUE, col_types = cols())

manual <- read_csv("ImportR.csv", col_names = TRUE, col_types = cols())

manual <- manual %>%
  mutate(black = 100*(black17/total17 - black10/total10)) %>%
  mutate(collegewhite = 100*(collegewhite17/total17 - collegewhite10/total10)) %>%
  mutate(nodiploma = 100*(nodiploma17/total17 - nodiploma10/total10)) %>%
  mutate(highschoolgrad = 100*(highschoolgrad17/total17 - highschoolgrad10/total10)) %>%
  mutate(collegedegree = 100*(collegedegree17/total17 - collegedegree10/total10)) %>%
  mutate(collegedegree = 100*(collegedegree17/total17 - collegedegree10/total10)) %>%
  mutate(early_late = 100*(early_late17/employed17 - early_late10/employed10)) %>%
  mutate(privateschool = 100*(privateschool17/totalpop17 - privateschool10/totalpop10))
```

Mutating new variables to demonstrate change over time:

```r
manual <- manual %>%
  mutate(moved17=as.numeric(moved17)) %>%
  mutate(moved10=as.numeric(moved10)) %>%
  mutate(moved = moved17-moved10) %>%
  mutate(homeprice17=as.numeric(homeprice17)) %>%
  mutate(homeprice10=as.numeric(homeprice10)) %>%
  mutate(homeprice_med = (homeprice17 - homeprice10)) %>%
  mutate(income2017=as.numeric(income2017)) %>%
  mutate(income2010=as.numeric(income2010)) %>%
  mutate(income_med = (income2017 - income2010))
```

```
## Warning: NAs introduced by coercion

## Warning: NAs introduced by coercion

## Warning: NAs introduced by coercion

## Warning: NAs introduced by coercion

## Warning: NAs introduced by coercion
```

```
## Warning: NAs introduced by coercion
```

```r
names(manual)[1] <- "geoid"
```

Recoding variables to be numeric:

```r
manual <- manual %>%
  mutate(income_med=as.numeric(income)) %>%
  mutate(homeprice_med=as.numeric(homeprice)) %>%
  mutate(collegewhite=as.numeric(collegewhite)) %>%
  mutate(whitecollar=as.numeric(whitecollar)) %>%
  mutate(early_late=as.numeric(early_late)) %>%
  mutate(highschoolgrad=as.numeric(highschoolgrad)) %>%
  mutate(collegedegree=as.numeric(collegedegree)) %>%
  mutate(nodiploma=as.numeric(nodiploma)) %>%
  mutate(black=as.numeric(black)) %>%
  mutate(privateschool=as.numeric(privateschool))
```

```
## Warning: NAs introduced by coercion

## Warning: NAs introduced by coercion

## Warning: NAs introduced by coercion
```

Joining data sets:

```r
gent_rural <- gentdata %>%
  group_by(geoid) %>%
  summarise(rural)

manual <- inner_join(manual, gent_rural, copy=T)
```

```
## Joining, by = "geoid"
```

manually imputing the mean value for homeprice

```r
mean_homeprice <- manual %>%
  summarise(mean = mean(homeprice_med, na.rm = T)) %>%
  pull()

manual <- manual %>%
  mutate(homeprice_med = if_else(is.na(homeprice_med), mean_homeprice, homeprice_med))

mean_income <- manual %>%
  summarise(mean = mean(income_med, na.rm = T)) %>%
  pull()

manual <- manual %>%
  mutate(income_med = if_else(is.na(income_med), mean_income, income_med))
```

EXPLORATORY DATA ANALYSIS

#Univariate analysis

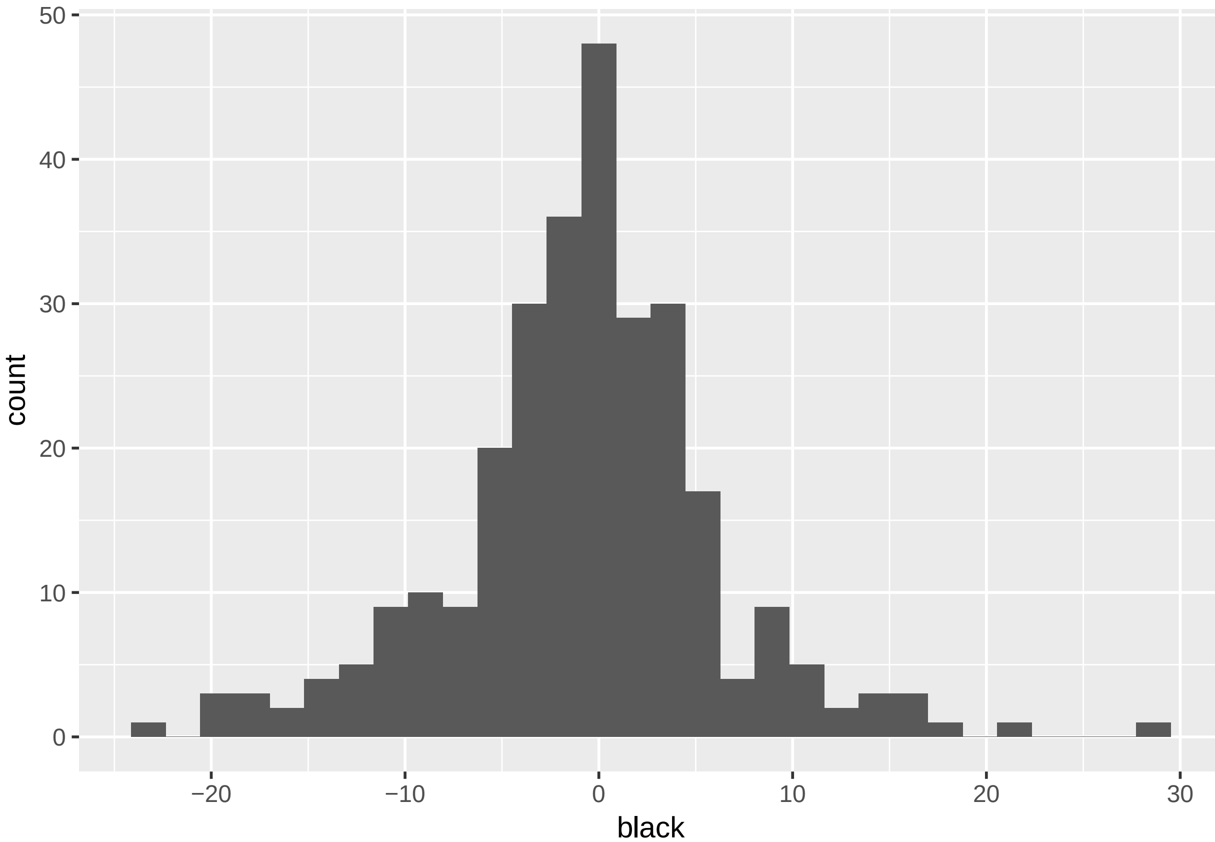
The variable "black" is the change in black population from 2010 to 2017. We will use this variable as our response to predict whether gentrification is occurring in a region in the research triangle.

The distribution of change in Black population:

```r
ggplot(data = manual, mapping = aes(x = black)) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 3 rows containing non-finite values (stat_bin).
```




```r
typeof(manual$black)
```

```
## [1] "double"
```

```r
(sd(manual$black))
```

```
## [1] NA
```

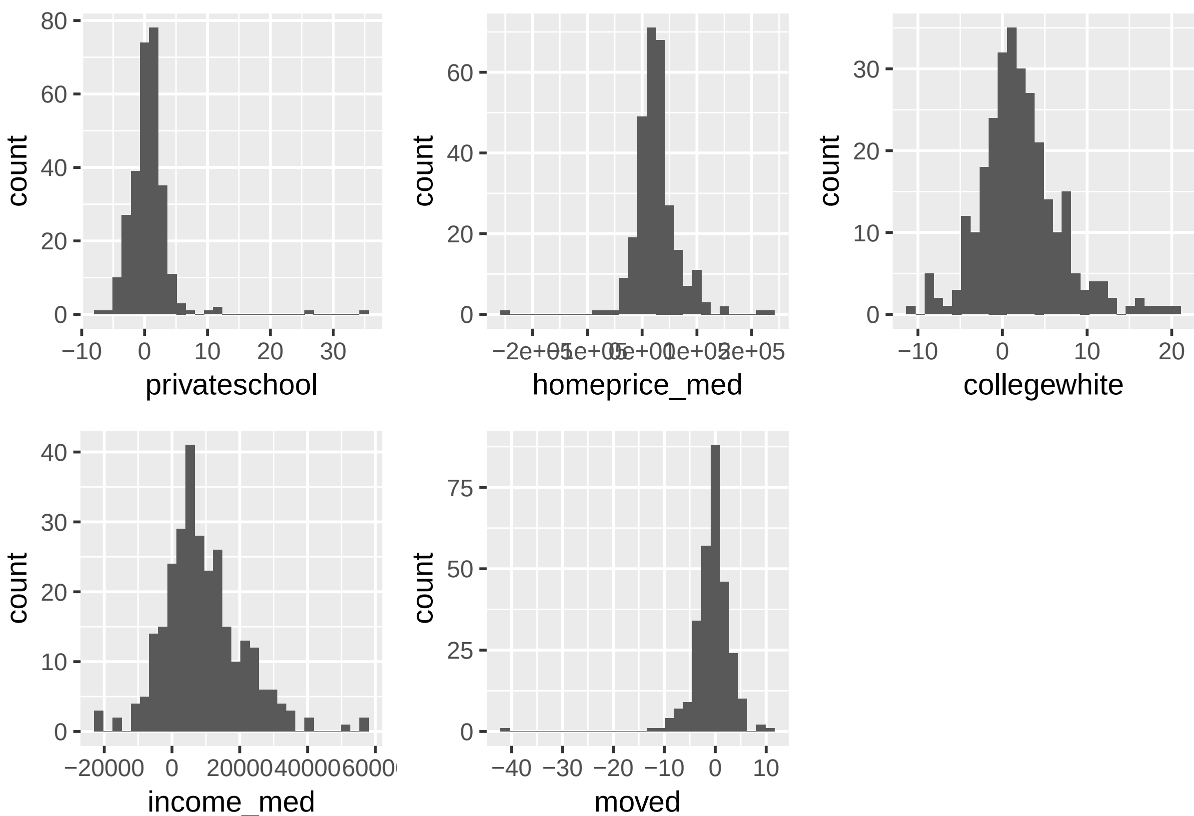
std deviation is = 6.765474

More Univariate EDA:

```r
p1 <- ggplot(data = manual, mapping = aes(x = privateschool)) +
  geom_histogram()

p2 <-ggplot(data = manual, mapping = aes(x = collegewhite)) +
  geom_histogram()

p3 <-ggplot(data = manual, mapping = aes(x = homeprice_med)) +
  geom_histogram()

p4 <-ggplot(data = manual, mapping = aes(x = income_med)) +
```

```r
  geom_histogram()

p5 <-ggplot(data = manual, mapping = aes(x = moved)) +
  geom_histogram()

p1 + p3 + p2 + p4 +p5
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 3 rows containing non-finite values (stat_bin).

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 3 rows containing non-finite values (stat_bin).

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 3 rows containing non-finite values (stat_bin).
```

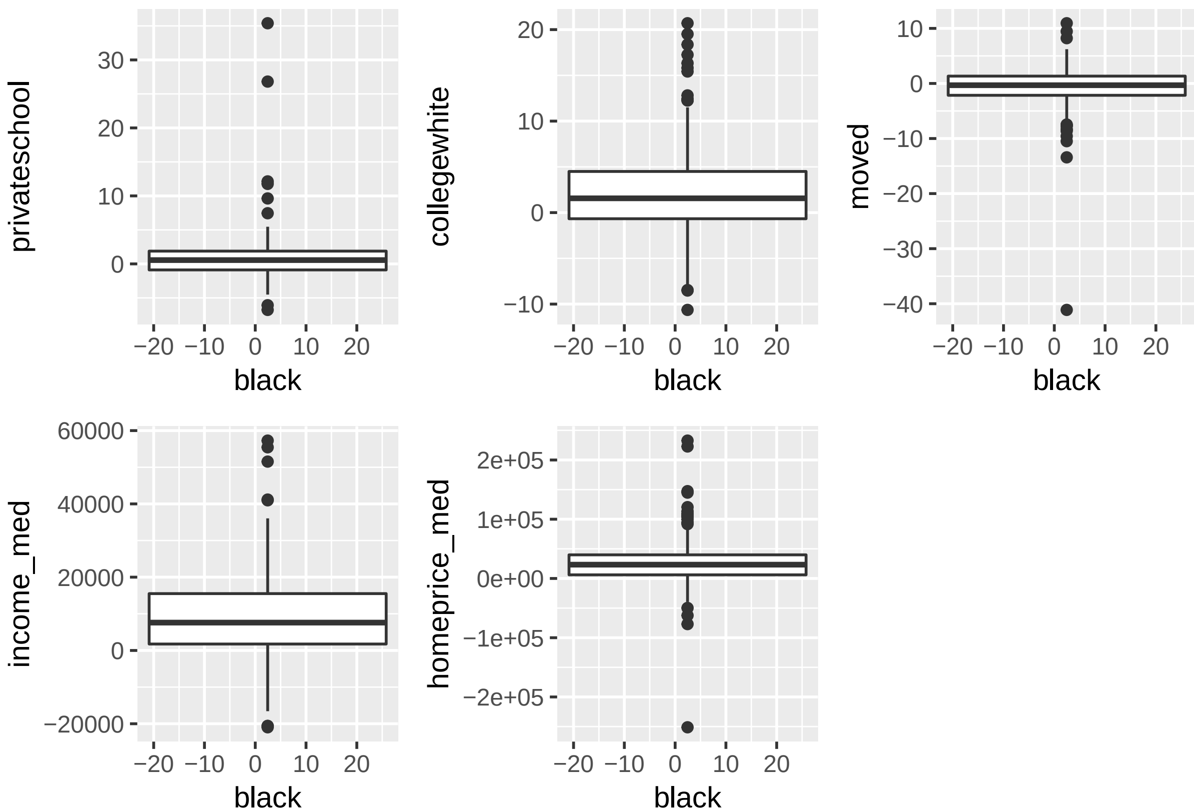


Bivariate EDA:

```r
p6 <- ggplot(data = manual, mapping = aes(x = black, y = privateschool)) +
  geom_boxplot()

p7 <- ggplot(data = manual, mapping = aes(x = black, y = collegewhite)) +
  geom_boxplot()

p8 <- ggplot(data = manual, mapping = aes(x = black, y = moved)) +
  geom_boxplot()
```

```r
p9 <- ggplot(data = manual, mapping = aes(x = black, y = income_med)) +
  geom_boxplot()

p10 <- ggplot(data = manual, mapping = aes(x = black, y = homeprice_med)) +
  geom_boxplot()

p6 + p7 + p8 + p9 + p10
```

```
## Warning: Continuous x aesthetic -- did you forget aes(group=...)?

## Warning: Removed 3 rows containing missing values (stat_boxplot).

## Warning: Continuous x aesthetic -- did you forget aes(group=...)?

## Warning: Removed 3 rows containing missing values (stat_boxplot).

## Warning: Continuous x aesthetic -- did you forget aes(group=...)?

## Warning: Removed 3 rows containing missing values (stat_boxplot).

## Warning: Continuous x aesthetic -- did you forget aes(group=...)?

## Warning: Removed 3 rows containing missing values (stat_boxplot).

## Warning: Continuous x aesthetic -- did you forget aes(group=...)?

## Warning: Removed 3 rows containing missing values (stat_boxplot).
```



###Part I: Location of Gentrification

In part I, the following research question will be examined:

Where in the Research Triangle (counties including Durham, Wake, Orange and Chatham) is gentrification occurring the most?

Recoding our response variable to "1" if change in black population is <= "-6.765" or one standard deviation below the mean and equal to "0" if > "6.765" in order visualize and eventually create a logistic model:

```
manual <- manual %>%
  mutate(gent = case_when(black>(-6.765474) ~ 0, black<=(-6.765474) ~ 1))

manual <- manual %>%
  mutate(gent = if_else(is.na(gent), 0, gent))

manual %>%
  count(gent)
```

```
## # A tibble: 2 x 2
##    gent     n
##   <dbl> <int>
## 1     0   244
## 2     1    44
```

```
typeof(manual$gent)
```

```
## [1] "double"
```

```
manual
```

```
## # A tibble: 288 x 52
##    geoid County total17 total10 black17 black10 `Change in blac~ income2017
##    <chr> <chr>    <int>   <int>   <int>   <int>            <int>      <dbl>
##  1 1400~ Chath~    4557    3784     301     276               25      83750
##  2 1400~ Chath~    4841    4546     123     139              -16      84638
##  3 1400~ Chath~    4334    2342     112     182              -70      87773
##  4 1400~ Chath~    4483    3548     429     514              -85      78897
##  5 1400~ Chath~    7792    7864     803     562              241      64987
##  6 1400~ Chath~    2708    2814     470     509              -39      43594
##  7 1400~ Chath~    5769    5365    1279    1026              253      35952
##  8 1400~ Chath~    5016    5457    1380    1184              196      23848
##  9 1400~ Chath~    3635    4001     254     349              -95      44070
## 10 1400~ Chath~    5720    5811    1105    1135              -30      54914
## # ... with 278 more rows, and 44 more variables: income2010 <dbl>,
## #   income <chr>, collegewhite17 <int>, collegewhite10 <int>,
## #   nodiploma17 <int>, highschoolgrad17 <int>, collegedegree17 <int>,
## #   nodiploma10 <int>, highschoolgrad10 <int>, collegedegree10 <int>,
## #   homeprice17 <dbl>, homeprice10 <dbl>, homeprice <chr>,
## #   employed17 <int>, white1_17 <chr>, white2_17 <chr>, white3_17 <chr>,
## #   whitecollar17 <chr>, employed10 <int>, white1_10 <chr>,
## #   white2_10 <chr>, white3_10 <chr>, whitecollar10 <chr>,
## #   whitecollar <dbl>, early_late17 <int>, early_late10 <int>,
## #   privateschool17 <int>, totalpop17 <int>, privateschool10 <int>,
## #   totalpop10 <int>, moved17 <dbl>, moved10 <dbl>, black <dbl>,
## #   collegewhite <dbl>, nodiploma <dbl>, highschoolgrad <dbl>,
## #   collegedegree <dbl>, early_late <dbl>, privateschool <dbl>,
## #   moved <dbl>, homeprice_med <dbl>, income_med <dbl>, rural <chr>,
## #   gent <dbl>
```

Reading in spatial data

```r
# read the shapefile
shape <- read_sf(dsn = "data", layer = "triangletracts")
```

```
## Error: All columns in a tibble must be vectors.
## x Column `geometry` is a `sfc_POLYGON/sfc` object.
```

```r
# convert RegionID to numeric before we join anddrop some columns that we don't need

shape <- shape %>%
  mutate(geoid = as.character(AFFGEOID))
```

```
## Error in eval(lhs, parent, parent): object 'shape' not found
```

```r
# merge keeping only those in both data sets

merged <- inner_join(shape, manual, by = "geoid")
```

```
## Error in inner_join(shape, manual, by = "geoid"): object 'shape' not found
```

Plotting research triangle area:

```r
ggplot(data = merged) +
  geom_sf()
```

```
## Error in ggplot(data = merged): object 'merged' not found
```

Plotting research triangle area by which regions have experienced gentrification:

```r
ggplot(data = merged, aes(fill = gent)) +
  geom_sf() +
  labs(title = "Research Triangle",
       subtitle = "Gentrification by census tract") +
  theme_void() +
  scale_fill_distiller(palette = 'RdBu', guide = "legend")
```

```
## Error in ggplot(data = merged, aes(fill = gent)): object 'merged' not found
```

###Part 2: Factors Associated with Gentrification

In part 2, the following research question will be examined:

What factors are associated with and the strongest predictors of the gentrification of these areas.

We already determined a model using aic and drop in deviance tests . . . .

##Using Logistic Regression

Creating the logistic model using mutated variable "gent" as our response variable. :

```r
model <- glm(gent ~ collegewhite + whitecollar + privateschool + nodiploma + highschoolgrad + collegede
                  data = manual, family="binomial")

tidy(model, conf.int = TRUE) %>%
  kable(format = "markdown", digits = 5)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	-3.00216	1.76126	-1.70455	0.08828	-6.50546	0.42759
collegewhite	0.14487	0.06063	2.38927	0.01688	0.02889	0.26801
whitecollar	-0.05600	0.03098	-1.80772	0.07065	-0.11837	0.00337
privateschool	0.01855	0.05029	0.36882	0.71226	-0.09732	0.10785
nodiploma	0.12286	0.06408	1.91736	0.05519	0.00077	0.25299

term	estimate	std.error	statistic	p.value	conf.low	conf.high
highschoolgrad	0.05705	0.04424	1.28955	0.19721	-0.02836	0.14590
collegedegree	-0.03647	0.06220	-0.58638	0.55762	-0.16062	0.08438
income_med	-0.00002	0.00002	-0.86680	0.38605	-0.00005	0.00002
homeprice_med	0.00001	0.00000	2.44891	0.01433	0.00000	0.00002
early_late	-0.00940	0.01852	-0.50727	0.61197	-0.04578	0.02715
moved	0.00344	0.04475	0.07697	0.93865	-0.07898	0.10019

Using backward selection to find the optimal model:

```r
model_aic <- step(model, direction = "backward", conf.int=T)
```

```
## Start:  AIC=241.3
## gent ~ collegewhite + whitecollar + privateschool + nodiploma +
##     highschoolgrad + collegedegree + income_med + homeprice_med +
##     early_late + moved
##
##                  Df Deviance    AIC
## - moved           1   219.31 239.31
## - privateschool   1   219.43 239.43
## - early_late      1   219.56 239.56
## - collegedegree   1   219.65 239.65
## - income_med      1   220.07 240.07
## - highschoolgrad  1   221.00 241.00
## <none>                219.30 241.30
## - whitecollar     1   222.71 242.71
## - nodiploma       1   223.19 243.19
## - collegewhite    1   225.34 245.34
## - homeprice_med   1   225.64 245.64
##
## Step:  AIC=239.31
## gent ~ collegewhite + whitecollar + privateschool + nodiploma +
##     highschoolgrad + collegedegree + income_med + homeprice_med +
##     early_late
##
##                  Df Deviance    AIC
## - privateschool   1   219.44 237.44
## - early_late      1   219.56 237.56
## - collegedegree   1   219.66 237.66
## - income_med      1   220.08 238.08
## - highschoolgrad  1   221.00 239.00
## <none>                219.31 239.31
## - whitecollar     1   222.73 240.73
## - nodiploma       1   223.19 241.19
## - collegewhite    1   225.38 243.38
## - homeprice_med   1   225.65 243.65
##
## Step:  AIC=237.44
## gent ~ collegewhite + whitecollar + nodiploma + highschoolgrad +
##     collegedegree + income_med + homeprice_med + early_late
##
##                  Df Deviance    AIC
## - early_late      1   219.66 235.66
```

```
## - collegedegree   1   219.76 235.76
## - income_med      1   220.21 236.21
## - highschoolgrad  1   221.11 237.11
## <none>                219.44 237.44
## - whitecollar     1   222.86 238.86
## - nodiploma       1   223.25 239.25
## - collegewhite    1   225.44 241.44
## - homeprice_med   1   225.82 241.82
##
## Step:  AIC=235.66
## gent ~ collegewhite + whitecollar + nodiploma + highschoolgrad +
##     collegedegree + income_med + homeprice_med
##
##                  Df Deviance    AIC
## - collegedegree   1   219.98 233.98
## - income_med      1   220.52 234.52
## - highschoolgrad  1   221.25 235.25
## <none>                219.66 235.66
## - whitecollar     1   223.04 237.04
## - nodiploma       1   223.43 237.43
## - collegewhite    1   225.57 239.57
## - homeprice_med   1   226.71 240.71
##
## Step:  AIC=233.98
## gent ~ collegewhite + whitecollar + nodiploma + highschoolgrad +
##     income_med + homeprice_med
##
##                  Df Deviance    AIC
## - income_med      1   220.93 232.93
## <none>                219.98 233.98
## - highschoolgrad  1   222.65 234.65
## - whitecollar     1   223.39 235.39
## - nodiploma       1   224.51 236.51
## - homeprice_med   1   226.87 238.87
## - collegewhite    1   228.82 240.82
##
## Step:  AIC=232.93
## gent ~ collegewhite + whitecollar + nodiploma + highschoolgrad +
##     homeprice_med
##
##                  Df Deviance    AIC
## <none>                220.93 232.93
## - highschoolgrad  1   224.01 234.01
## - whitecollar     1   224.36 234.36
## - nodiploma       1   225.70 235.70
## - homeprice_med   1   226.98 236.98
## - collegewhite    1   228.92 238.92
```

```r
tidy(model_aic, conf.int = TRUE) %>%
  kable(format = "markdown", digits = 5)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	-2.23080	0.24515	-9.09985	0.00000	-2.74176	-1.77646
collegewhite	0.10841	0.03943	2.74954	0.00597	0.03290	0.18858

term	estimate	std.error	statistic	p.value	conf.low	conf.high
whitecollar	-0.05692	0.03137	-1.81461	0.06958	-0.11996	0.00321
nodiploma	0.13470	0.06339	2.12476	0.03361	0.01355	0.26289
highschoolgrad	0.06938	0.04021	1.72554	0.08443	-0.00792	0.15022
homeprice_med	0.00001	0.00000	2.37718	0.01745	0.00000	0.00002

Creating a full model to determine if we should add "rural" to the model:

```
model_aic_full <- glm(gent ~ collegewhite + whitecollar + nodiploma + highschoolgrad + homeprice_med + r
tidy(model_aic_full)
```

```
## # A tibble: 7 x 5
##   term             estimate  std.error statistic  p.value
##   <chr>               <dbl>      <dbl>     <dbl>    <dbl>
## 1 (Intercept)    -2.88      0.450          -6.39 1.64e-10
## 2 collegewhite    0.0939    0.0400          2.35 1.88e- 2
## 3 whitecollar    -0.0546    0.0318         -1.72 8.61e- 2
## 4 nodiploma       0.118     0.0631          1.87 6.16e- 2
## 5 highschoolgrad  0.0606    0.0406          1.49 1.35e- 1
## 6 homeprice_med   0.0000108 0.00000468      2.31 2.10e- 2
## 7 ruralUrban      0.891     0.476           1.87 6.12e- 2
```

Drop in deviance test:

```
(dev_m <- glance(model_aic)$deviance)
```

```
## [1] 220.9284
```

```
(dev_full <- glance(model_aic_full)$deviance)
```

```
## [1] 216.9145
```

```
(test_stat <- dev_m - dev_full)
```

```
## [1] 4.013908
```

p-value:

```
1- pchisq(test_stat, 1)
```

```
## [1] 0.04512643
```

Since the chisq p-value for adding "Rural" to the model is less than .05, we reject the null hypothesis that "Rural" is not a significant predictor of whether or not a region has experienced gentrification.

Therefore we will continue with this full model for the remained of our analysis.

###Assumptions

In order to use the full model with the predictor variables collegewhite, whitecollar, nodiploma, highschoolgrad, homeprice_med, and rural, we must first test how well this model satisfies assumptions.

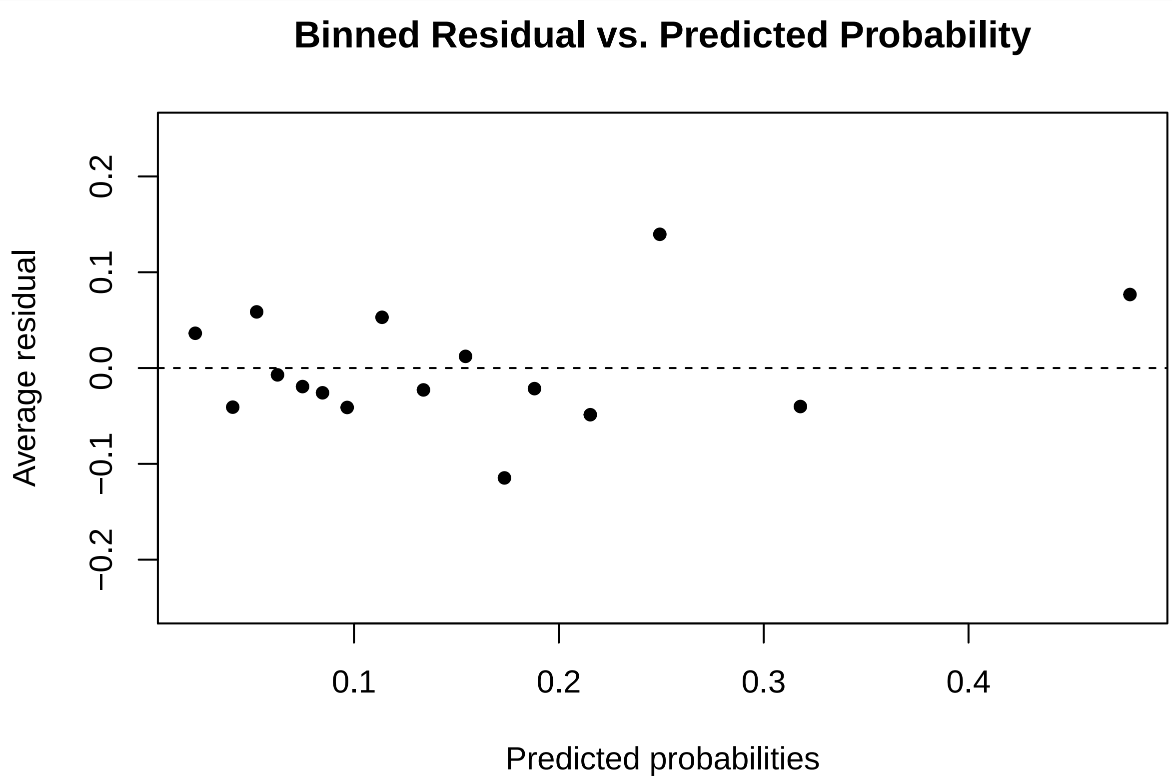
For testing linearity, we will augment the model with predicted probabilities and residuals in order to examine binned residual plots for predicted probability and numeric variables.

```
model_aug <- augment(model_aic_full, type.predict = "response", type.residuals = "response")

model_aug
```

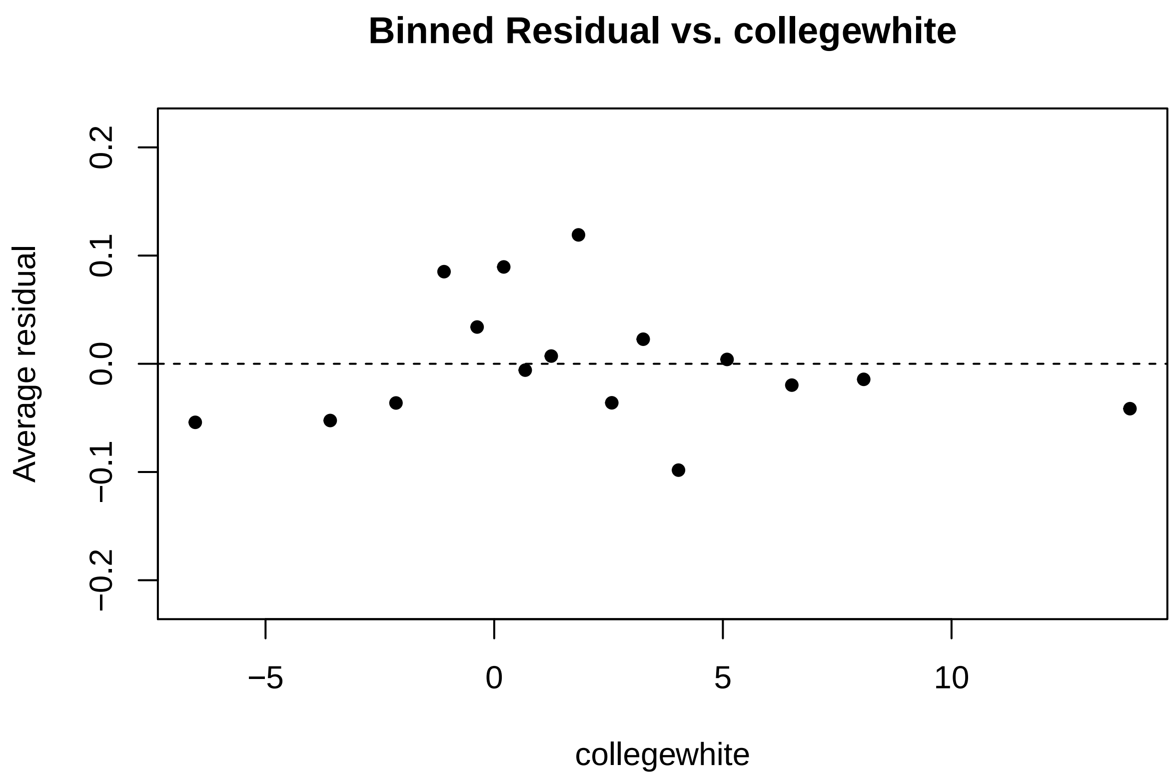
```
## # A tibble: 285 x 15
```

```
##    .rownames  gent collegewhite whitecollar nodiploma highschoolgrad
##    <chr>     <dbl>        <dbl>       <dbl>     <dbl>          <dbl>
##   1 1            0        -8.46       -16.4     7.20           -4.89
##   2 2            0         2.96         3.2    -0.640          -0.658
##   3 3            0        -0.735        4.3     0.807          -1.44
##   4 4            0        -4.08         6.6     0.0800         -1.86
##   5 5            0         2.31        -2.8     1.16           -4.08
##   6 6            0        -1.25         0.5    -0.388          -4.55
##   7 7            0        -0.224        4.3    -7.19            5.87
##   8 8            0         2.17        18.4    -5.19           11.3
##   9 9            0        -1.92        -5.6     2.05            0.321
## 10 10            0         5.44         6.9    -0.837           0.687
## # ... with 275 more rows, and 9 more variables: homeprice_med <dbl>,
## #   rural <chr>, .fitted <dbl>, .se.fit <dbl>, .resid <dbl>, .hat <dbl>,
## #   .sigma <dbl>, .cooksd <dbl>, .std.resid <dbl>
```

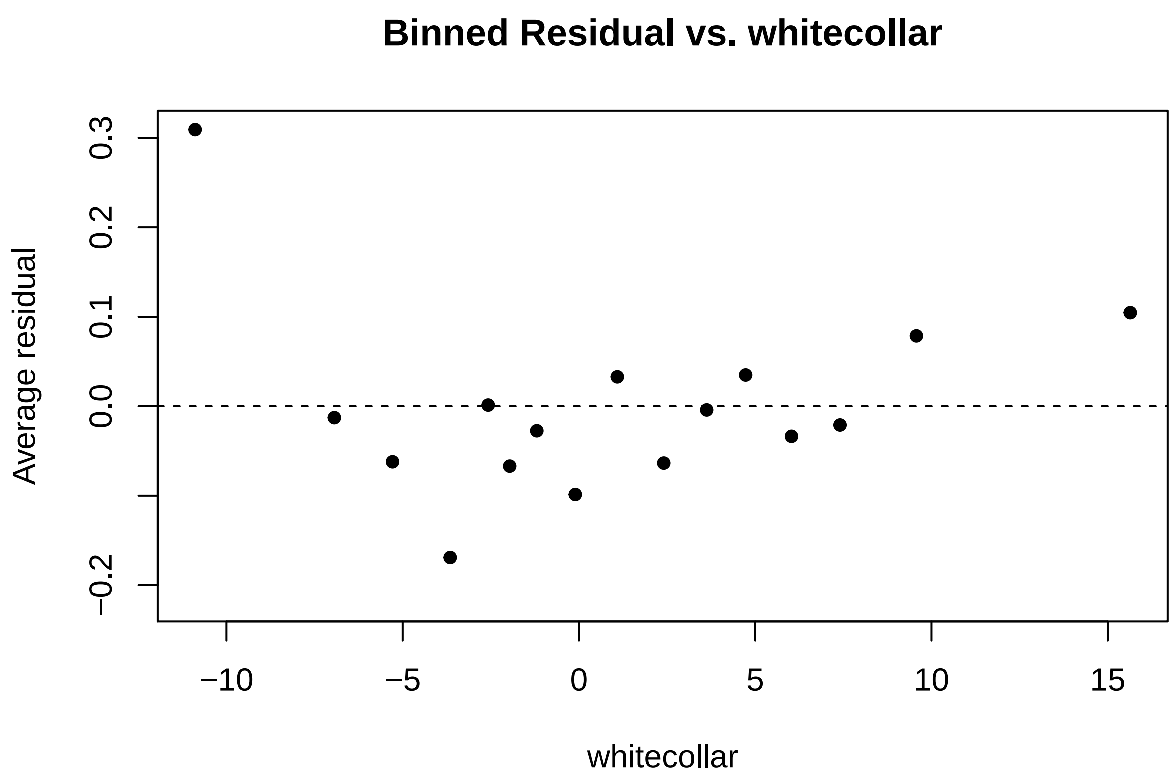
```r
arm::binnedplot(x = model_aug$.fitted,
                y = model_aug$.resid,
                col.int = FALSE,
                xlab = "Predicted probabilities",
                main = "Binned Residual vs. Predicted Probability")
```



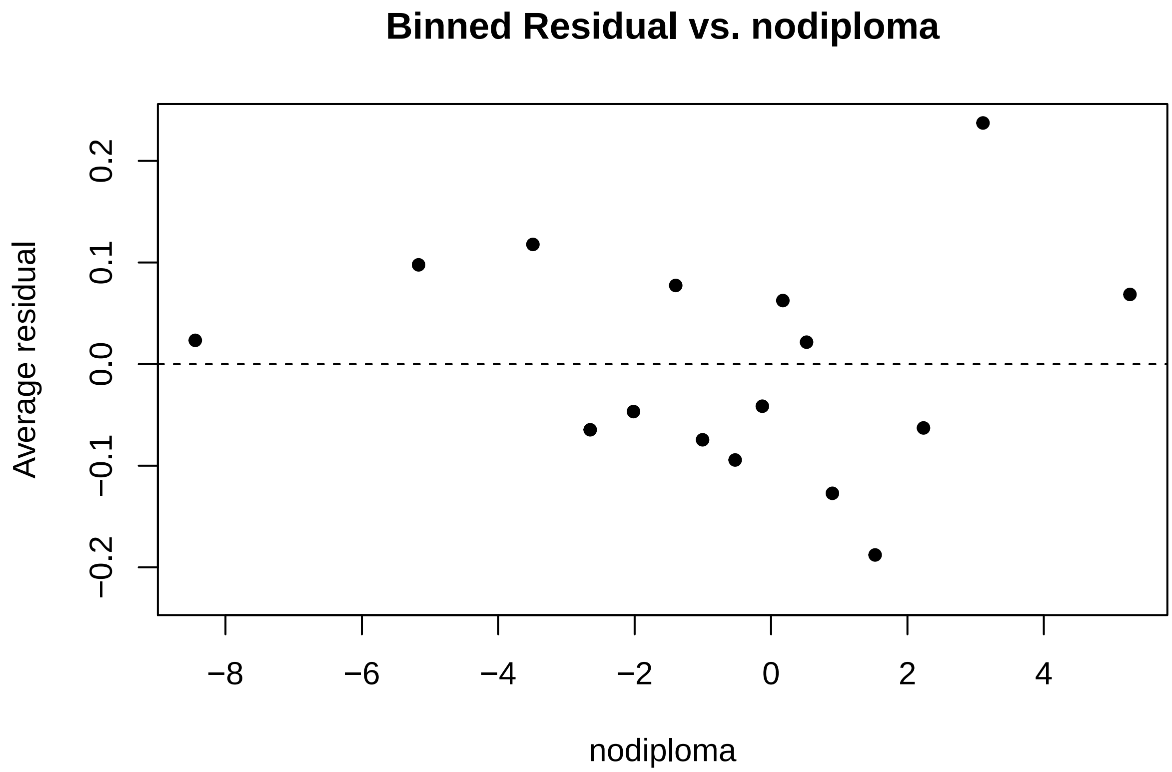

```r
arm::binnedplot(x = model_aug$collegewhite,
                y = model_aug$.resid,
                col.int = FALSE,
                xlab = "collegewhite",
                main = "Binned Residual vs. collegewhite")
```



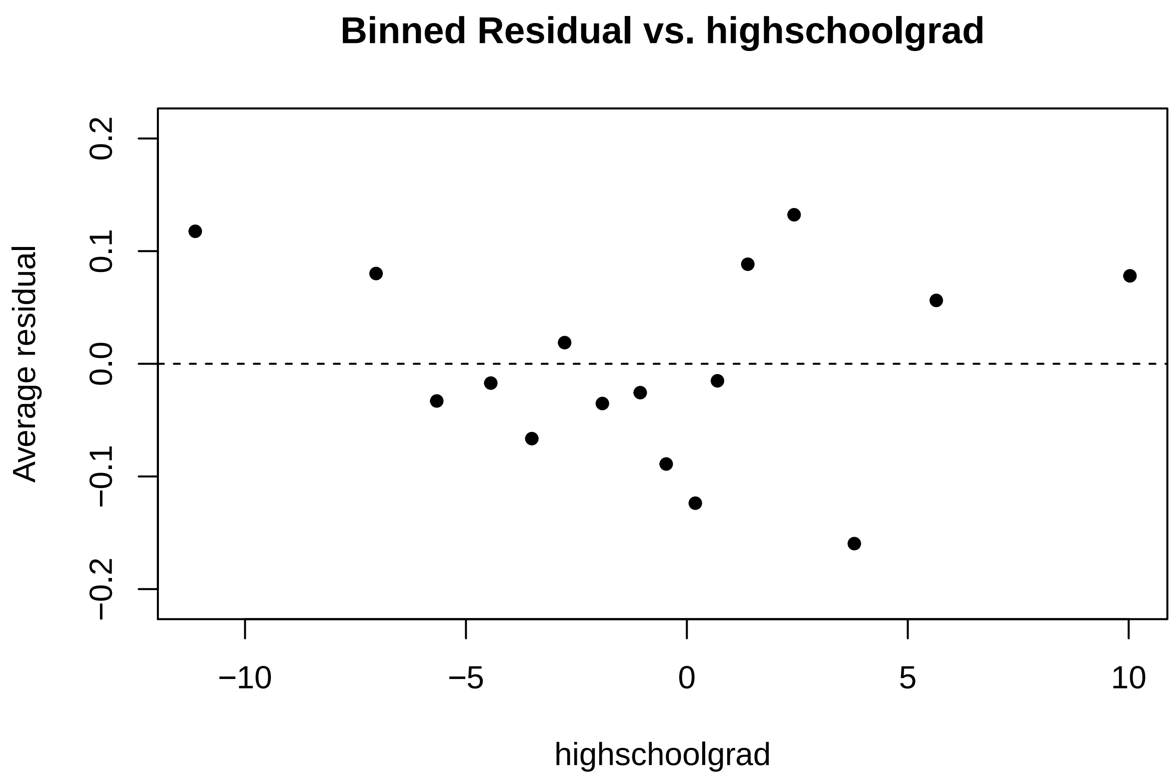

```r
arm::binnedplot(x = model_aug$whitecollar,
                y = model_aug$.resid,
                col.int = FALSE,
                xlab = "whitecollar",
                main = "Binned Residual vs. whitecollar")
```



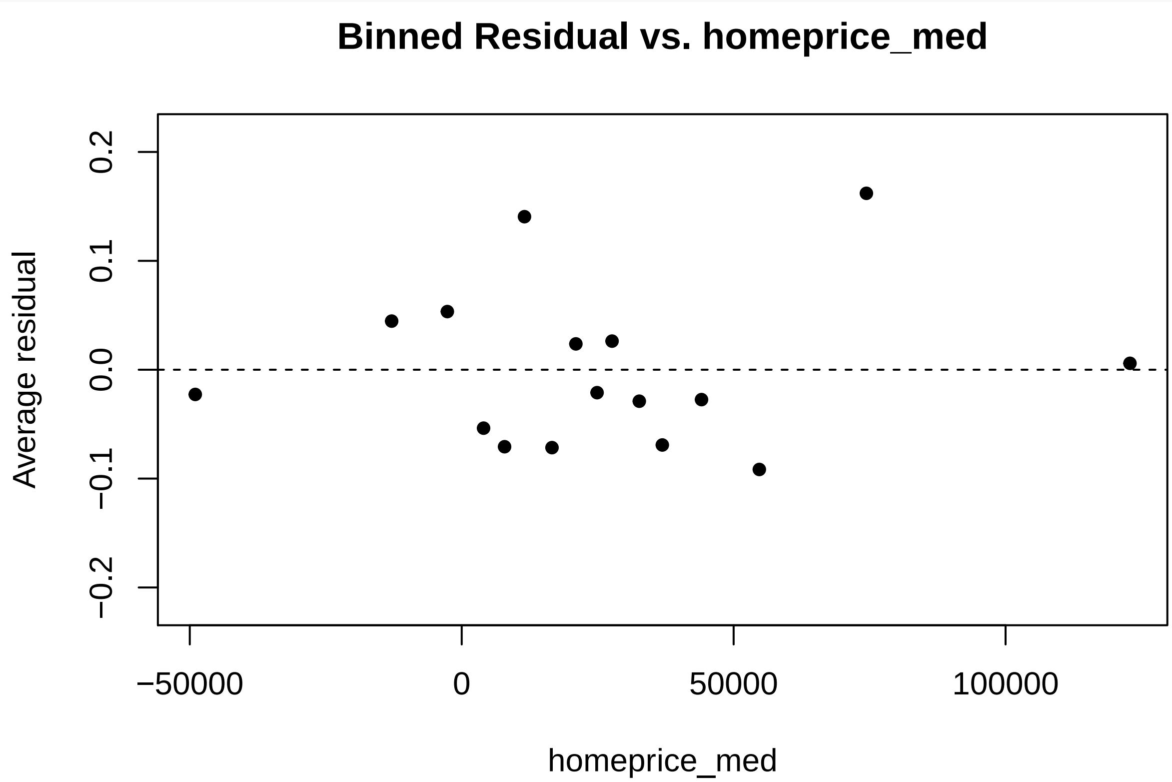
```r
arm::binnedplot(x = model_aug$nodiploma,
                y = model_aug$.resid,
                col.int = FALSE,
                xlab = "nodiploma",
                main = "Binned Residual vs. nodiploma")
```




```r
arm::binnedplot(x = model_aug$highschoolgrad,
                y = model_aug$.resid,
                col.int = FALSE,
                xlab = "highschoolgrad",
                main = "Binned Residual vs. highschoolgrad")
```




```
arm::binnedplot(x = model_aug$homeprice_med,
                y = model_aug$.resid,
                col.int = FALSE,
                xlab = "homeprice_med",
                main = "Binned Residual vs. homeprice_med")
```



```r
model_aug %>%
  group_by(rural) %>%
  summarise(mean_resid = mean(.resid))
```

```
## # A tibble: 2 x 2
##   rural mean_resid
##   <chr>      <dbl>
## 1 Rural  -5.38e-11
## 2 Urban  -4.71e-12
```

The linearity assumption is satisfied. The binned residuals vs. predicted probability plot shows irregularity with a very slight clustering of residual values below 0.0. The binned residuals vs. collegewhite plot shows irregularity. The binned residuals vs. whitecollar plot shows irregularity, with a slight clustering of residual values below 0.0 and a slight increase in residual values as you move right. The binned residuals vs. nodiploma, binned residuals vs. highschoolgrad, and binned residuals vs. homeprice_med show complete irregularity. For the predictor variable rural, which has two categories rural and urban, both mean residuals are very close to zero. There is no strong indication of nonlinearity; therefore, we can assume that there is a linear relationship between log(gent) and the predictor variables.

To discuss randomness and independence, we must go back to the source of our data. All of the data we are using is sourced from the Census Bureau's annual American Community Survey and official North Carolina demographic data. According to the census sampling techniques and methodology, we can reasonably assume that randomness and independence are satisfied. Read more here: https://www.census.gov/programs-surveys/sipp/methodology.html

Interpreting Model Coefficients

Now that we've confirmed that it satisfies assumptions, let's take a look at our chosen logistic model again:

```r
tidy(model_aic_full, conf.int = TRUE, exponentiate = FALSE) %>%
  kable(digits = 3, format = "markdown")
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	-2.877	0.450	-6.392	0.000	-3.867	-2.076
collegewhite	0.094	0.040	2.349	0.019	0.017	0.175
whitecollar	-0.055	0.032	-1.716	0.086	-0.119	0.006
nodiploma	0.118	0.063	1.869	0.062	-0.002	0.246
highschoolgrad	0.061	0.041	1.494	0.135	-0.018	0.142
homeprice_med	0.000	0.000	2.309	0.021	0.000	0.000
ruralUrban	0.891	0.476	1.872	0.061	0.018	1.915

We would like to discuss the variables that have the most impact on the response variable gent. Therefore, we will discuss variables with p-values of <0.05. The variable collegewhite seems to have a reliably strong impact on gent: holding all other variables constant, a unit change in collewhite causes the odds of gentrification are expected to multiply by a factor of $\exp(0.089) = 1.093$. However, this impact is not as strong as that of the rural variable. According to the model coefficient for the term ruralUrban, holding all other variables constant, the odds of gentrification for an urban area is expected to be 2.55 that of a rural locale. We would like to suggest that the change in college-educated whites in a county and urban character likely greatly impact "gentrification" as we have classified it (a significant decrease in black population).