Termpaper

Sindre og Morten

Oppgave 1

A

Hedoniske modeller blir tatt i bruk for å måle marginal «willingness to pay» (MWTP), denne blir tatt i bruk for å måle boligmarkedet sine miljømessige kvaliteter. Den hedoniske modellen ble fremstillt ved å ta i bruk et stort og avansert datasett fra boligmarkeder i store byer som har en avansert økonomi. Jo mer tilgang vi får på data til disse byområdene, desto bedre analyser får vi med bruk av en hedonisk modell.

Rosens første steg handler om å kunne definere et marked som vil tilfredstille «law of one function». «Law of one function» er at hus som er identiske blir solgt for den samme prisen i et gitt marked. Steg to handler om data innsamling. Det forteller oss at det er met oppnålig med å ha et tilfeldig utvalg. Slike datainnsamlinger til en hedonisk modell som omhandler eiendomsverdi har som regel fokus på eneboliger.

C - Why could it be important to define a housing market as a single metropolitan (or travel to work) area and studying a relatively short period of time, when estimating

i. hedonic price function?

Bishop forklarer at i hedonisk modell innebærer det at markedet bør defineres slik at «loven om en prisfunksjon» oppfylles (Bishop mfl. 2020). Med en prisfunksjon menes det at identiske boliger vil selges til samme pris gjennom hele markedet. Likevel, de nøyaktige romlige og tidsmessige grensene som tilfredsstiller denne betingelsen kan variere på tvers av rom og tid ettersom informasjon, institusjoner og flyttekostnader endres (Bishop mfl. 2020). I prakis er det vanlig å definere markedet som et enkelt storbyområde (single metropolian) over noen år. Flyttekostnader vil egentlig bryte med loven om en prisfunksjon, men for husholdninger som flytter innenfor dette storbyområdet er det lite sannsynlig at disse kostnadene vil variere noe særlig.

Årsaken til det er at de fysiske kostnadene som vel som de økonomiske (f.eks lastebil-leie) ikke endrer seg på tvers av destinasjonssteder i hovedstadsområdet. De psykologiske kostnadene er også mer begrenset ved flytting fordi det tillattes i lettere grad å opprettholde relasjonene til familie, venner og nabolag. Dette gjør at loven om én prisfunksjon opprettholdes mellom lokasjoner i et storbyområde gjennom arbitrasje. Altså, hvis to hus som er tilsvarende like i samme storbyområdet selges, så velger kjøperne naturligvis det rimeligste.

ii. Explain intuitively, by using an example, why it is important to avoid omitted variable bias when estimating a hedonic price model.

Gjennom empirien og teorien er det grunn til å tro av miljøfasiliteter er romlig korrelert på grunn av de naturlige trekkene ved geografien som for eksempel fjell og hav, miljøtilbakemeldingseffekter (f.eks urbane varme øyer) og stemming på lokale felles goder. Dette potensialet for romlig korrelasjon har ført til utbredt bekymring for utelatt-variabel skjevhet (Bishop mfl. 2020). Det er først og fremst fordi det virker usannsynlig at forskere vil være i stand til å inkludere alle bekvemmeligheter som betyr noe for kjøpere. I tillegg vil uobserverte fasiliteter sannsynligvis være korrelert med tilbudet av interesse, og dermed forårsake skjevhet. Dette kan forklares ved et eksempel: Hvis velstående og velutdannede boligkjøpere flytter til områder med bedre luftkvalitet og deretter stemmer for å øke offentlig skolefinansiering, vil estimater av MWTP for luftkvalitet være skjev oppover hvis skolekvalitet utelates fra modellen. Potensialet for denne typen oppførsel fra huseiere betyr at for at de resulterende estimatene skal være troverdige, må forskningsdesignet isolere eksogen variasjon i tilbudet av interesse (Bishop mfl. 2020).

Oppgave 2

i.

Så over variablene og definisjonene på dem hos Kaggle.

ii.

Laster inn data

```r
kc_house_data <- read_csv("kc_house_data.csv")
```

```
Rows: 21613 Columns: 21
-- Column specification --------------------------------------------------------
Delimiter: ","
chr   (1): id
```

```
dbl  (19): price, bedrooms, bathrooms, sqft_living, sqft_lot, floors, waterf...
dttm  (1): date

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

iii.

```r
kc_house_data <- arrange(kc_house_data, desc(date))
```

iv.

```r
kc_house_data <- kc_house_data %>%
  distinct(id, .keep_all = TRUE)
```

v & vi.

```r
kc_house_data_sf <- st_as_sf(kc_house_data,
                             coords = c(x = "long",
                                        y = "lat"),
                             crs = 4326) %>%
  st_transform(2926)
```

vii.

koordinatene til Seattle:

Norske (wikepedia): - 47.60621, -122.33207

Engelske (wikepedia): - 47.609722, -122.333056

```r
cbd <- st_sfc(st_point(c(-122.33207, 47.60621)), crs = 4326) %>%
  st_transform(2926)
```

viii.

```r
kc_house_data_sf <-  kc_house_data_sf %>%
  mutate(dist_cbd = st_distance(cbd, .,
                                by_element = TRUE),
    dist_cbd_km = set_units(dist_cbd, km)
  )
```

Oppgave 3

```r
kc_wadoh_map <- here("maps/WADOH_Environmental_Health_Disparities_Index_Calculated_for_Kin
      st_read() %>%
  st_transform(2926)
```

```
Reading layer `WADOH_Environmental_Health_Disparities_Index_Calculated_for_King_County___wad
  using driver `ESRI Shapefile'
Simple feature collection with 398 features and 192 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: -122.528 ymin: 47.08446 xmax: -121.0657 ymax: 47.78058
Geodetic CRS:  WGS 84
```

```r
kc_wadoh_map <- kc_wadoh_map %>%
  select(
  GEO_ID_TRT,
  EHD_percen,#Environmental Health Index, weighted score many vars
  linguist_2,#Pop. age 5+ speaking English less than "very well"
  poverty_pe,#Percentage people living in poverty
  POC_percen,#People of Color in percentage of pop. in tract
  transporta,#% of income spent on transportation median family in tract
  unemploy_2,#percentage unemployed
  housing_pe,#% of households in group "Unaffordable Housing" (>30% inc.)
  traffic_pe,#% of pop. near heavy traffic roadways
  diesel,# nox consentration
  ozone,# ozone consentration
  PM25, # consentration of Particulate Matter in air
  toxic_rele, # Toxic release from factories
  hazardous_, # Hazardous Waste Treatment Storage and disposal Facilities
  lead_perce, # measure of Lead paint in houses
```

```r
  superfund, # Proximity to contaminated sites on national list
  facilities, # Proximity to Risk Management Plan Facilities
  wastewater, # Proximity to wastewater facilities
  sen_pop_pe, # % pop. over 65
  socio_perc # score social economic determants, low best
  )
```

```r
acs_b19101_fam_inc <- read.dbf("../maps/censusSHP/acs_b19101_familyincome.dbf")
attach(acs_b19101_fam_inc)
```

```r
acs_b19101_fam_inc <- acs_b19101_fam_inc %>%
    mutate(low = (E19101138 + E19101139 + E19101140 + E19101141 +
                  E19101142 + E19101143)/E19101137) %>%
    mutate(mid = (E19101144 + E19101145 + E19101146 + E19101147 +
                  E19101148 + E19101149)/E19101137) %>%
    mutate(high = (E19101150 + E19101151 + E19101152 + E19101153)/E19101137)
```

```r
acs_b19101_fam_inc <- acs_b19101_fam_inc %>%
    select(GEOIDTRT, low, mid, high) %>%
    rename(GEO_ID_TRT = GEOIDTRT)
```

```r
kc_wadoh_map_2 <- left_join(
    acs_b19101_fam_inc,
    st_drop_geometry(kc_wadoh_map),
    by = "GEO_ID_TRT")
```

```r
kc_tracts10 <- here("../maps/censusSHP/tracts10.shp") %>%
  st_read() %>%
  st_transform(2926)
```

```
Reading layer `tracts10' from data source
  `/Users/sindreespedal/Documents/HVL /Høst 2022/MSB 204 - Bolig - R/maps/censusSHP/tracts10
  using driver `ESRI Shapefile'
Simple feature collection with 398 features and 22 fields
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: 1217085 ymin: 31406.52 xmax: 1583210 ymax: 287947.2
Projected CRS: NAD83(HARN) / Washington North (ftUS)
```

```r
kc_tracts10_shore <- here("../maps/censusSHP/tracts10_shore.shp") %>%
  st_read() %>%
  st_transform(2926)
```

```
Reading layer `tracts10_shore' from data source
  `/Users/sindreespedal/Documents/HVL /Høst 2022/MSB 204 - Bolig - R/maps/censusSHP/tracts10_
  using driver `ESRI Shapefile'
Simple feature collection with 398 features and 22 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: 1220306 ymin: 31406.52 xmax: 1583210 ymax: 287675.5
Projected CRS: NAD83(HARN) / Washington North (ftUS)
```

```r
kc_tracts10_env_data <- left_join(
  kc_tracts10, kc_wadoh_map_2,
  by = "GEO_ID_TRT"
  )
kc_tracts10_shore_env_data <- left_join(
  kc_tracts10_shore, kc_wadoh_map_2,
  by = "GEO_ID_TRT"
  )
```

```r
kc_houses_env_var <- st_join(kc_house_data_sf, kc_tracts10_env_data)
kc_tracts10_shore_env_var <- st_join(kc_house_data_sf, kc_tracts10_shore_env_data)
```

```r
st_write(kc_house_data, "../maps/kc_house_data.gpkg", append = FALSE)
```

```
Deleting layer `kc_house_data' using driver `GPKG'
Writing layer `kc_house_data' to data source
  `../maps/kc_house_data.gpkg' using driver `GPKG'
Writing 21436 features with 21 fields without geometries.
```

```r
st_write(kc_tracts10, "../maps/kc_tracts10.gpkg", append = FALSE)
```

```
Deleting layer `kc_tracts10' using driver `GPKG'
Writing layer `kc_tracts10' to data source
  `../maps/kc_tracts10.gpkg' using driver `GPKG'
Writing 398 features with 22 fields and geometry type Polygon.
```

```r
st_write(kc_tracts10_shore, "../maps/kc_tracts10_shore.gpkg", append = FALSE)
```

```
Deleting layer `kc_tracts10_shore' using driver `GPKG'
Writing layer `kc_tracts10_shore' to data source
  `../maps/kc_tracts10_shore.gpkg' using driver `GPKG'
Writing 398 features with 22 fields and geometry type Multi Polygon.
```

```r
st_write(kc_houses_env_var, "../maps/kc_houses_env_var.gpkg", append = FALSE)
```

```
Deleting layer `kc_houses_env_var' using driver `GPKG'
Writing layer `kc_houses_env_var' to data source
  `../maps/kc_houses_env_var.gpkg' using driver `GPKG'
Writing 21436 features with 65 fields and geometry type Point.
```

```r
st_write(kc_tracts10_shore_env_var, "../maps/kc_tracts10_shore_env_var.gpkg", append = FAL
```

```
Deleting layer `kc_tracts10_shore_env_var' using driver `GPKG'
Writing layer `kc_tracts10_shore_env_var' to data source
  `../maps/kc_tracts10_shore_env_var.gpkg' using driver `GPKG'
Writing 21436 features with 65 fields and geometry type Point.
```

Oppgave 4

i.

```r
summary(kc_tracts10_env_data)
```

```
  GEO_ID_TRT          FEATURE_ID      TRACT_LBL          TRACT_STR
 Length:398         Min.   :10153   Length:398         Length:398
 Class :character   1st Qu.:25818   Class :character   Class :character
 Mode  :character   Median :44344   Mode  :character   Mode  :character
                    Mean   :36731
                    3rd Qu.:45226
                    Max.   :45837

   TRACT_INT          TRACT_FLT          TRACT_DEL          TRTLABEL_F
```

```
 Min.   :   100   Min.   :   1.00   Length:398         Length:398
 1st Qu.:  9625   1st Qu.:  96.25   Class :character   Class :character
 Median : 24150   Median : 241.50   Mode  :character   Mode  :character
 Mean   : 23022   Mean   : 230.22
 3rd Qu.: 30076   3rd Qu.: 300.76
 Max.   :990100   Max.   :9901.00

  TRTLABEL_C         TRTLABEL_T         COUNTY_STR          COUNTY_INT
 Length:398         Length:398         Length:398         Min.   :33
 Class :character   Class :character   Class :character   1st Qu.:33
 Mode  :character   Mode  :character   Mode  :character   Median :33
                                                          Mean   :33
                                                          3rd Qu.:33
                                                          Max.   :33

  STATE_STR           STATE_INT    LEVEL_1            LEVEL_2
 Length:398         Min.   :53   Length:398         Length:398
 Class :character   1st Qu.:53   Class :character   Class :character
 Mode  :character   Median :53   Mode  :character   Mode  :character
                    Mean   :53
                    3rd Qu.:53
                    Max.   :53

   LEVEL_3            TRACT_AREA           TRACT_PERI       LOGRECNO
 Length:398         Min.   :    2466424   Min.   :  7060   Length:398
 Class :character   1st Qu.:   19330041   1st Qu.: 20586   Class :character
 Mode  :character   Median :   33617571   Median : 29573   Mode  :character
                    Mean   :  161615457   Mean   : 44019
                    3rd Qu.:   56011576   3rd Qu.: 43667
                    Max.   :15258321253   Max.   :738820

   Shape_area            Shape_len           low                 mid
 Min.   :    2466424   Min.   :  7060   Min.   :0.009298   Min.   :0.0000
 1st Qu.:   19330041   1st Qu.: 20586   1st Qu.:0.053302   1st Qu.:0.2391
 Median :   33617571   Median : 29573   Median :0.092424   Median :0.3339
 Mean   :  161615457   Mean   : 44019   Mean   :0.125013   Mean   :0.3327
 3rd Qu.:   56011576   3rd Qu.: 43667   3rd Qu.:0.166534   3rd Qu.:0.4261
 Max.   :15258321253   Max.   :738820   Max.   :1.000000   Max.   :0.6790
                                        NA's   :1          NA's   :1
      high           EHD_percen       linguist_2      poverty_pe
 Min.   :0.0000   Min.   :  1.00   Min.   : 0.45   Min.   : 1.97
 1st Qu.:0.4006   1st Qu.: 25.00   1st Qu.: 3.88   1st Qu.:10.53
 Median :0.5637   Median : 50.00   Median : 8.72   Median :16.75
```

```
 Mean   :0.5423   Mean   : 50.38   Mean   :10.62   Mean   :20.42  
 3rd Qu.:0.6955   3rd Qu.: 75.00   3rd Qu.:15.38   3rd Qu.:27.48  
 Max.   :0.8816   Max.   :100.00   Max.   :46.76   Max.   :75.48  
 NA's   :1        NA's   :1        NA's   :5       NA's   :1      
   POC_percen      transporta      unemploy_2       housing_pe   
 Min.   : 7.54   Min.   :10.00   Min.   : 1.000   Min.   :15.14  
 1st Qu.:23.36   1st Qu.:18.00   1st Qu.: 3.350   1st Qu.:27.34  
 Median :36.29   Median :19.00   Median : 4.480   Median :32.26  
 Mean   :38.64   Mean   :18.97   Mean   : 5.099   Mean   :33.75  
 3rd Qu.:51.01   3rd Qu.:21.00   3rd Qu.: 6.460   3rd Qu.:39.13  
 Max.   :92.70   Max.   :26.00   Max.   :24.400   Max.   :81.89  
 NA's   :1       NA's   :1       NA's   :3        NA's   :1      
   traffic_pe        diesel          ozone            PM25      
 Min.   : 0.00   Min.   : 0.14   Min.   :46.73   Min.   :3.787  
 1st Qu.: 0.00   1st Qu.: 6.65   1st Qu.:48.91   1st Qu.:5.642  
 Median : 3.60   Median :12.65   Median :49.78   Median :6.180  
 Mean   :16.07   Mean   :17.10   Mean   :50.62   Mean   :6.186  
 3rd Qu.:26.17   3rd Qu.:18.99   3rd Qu.:51.28   3rd Qu.:6.872  
 Max.   :97.75   Max.   :92.63   Max.   :62.89   Max.   :7.897  
 NA's   :1       NA's   :1       NA's   :1       NA's   :1      
   toxic_rele         hazardous_         lead_perce      superfund      
 Min.   :   823.9   Min.   :0.02303   Min.   : 0.24   Min.   :0.03454  
 1st Qu.:  5180.9   1st Qu.:0.04168   1st Qu.: 6.46   1st Qu.:0.07358  
 Median : 10186.5   Median :0.05160   Median :13.79   Median :0.13133  
 Mean   : 19398.3   Mean   :0.08190   Mean   :17.08   Mean   :0.24645  
 3rd Qu.: 20058.1   3rd Qu.:0.09280   3rd Qu.:26.20   3rd Qu.:0.28436  
 Max.   :186434.6   Max.   :0.63781   Max.   :54.68   Max.   :1.46778  
 NA's   :1          NA's   :1         NA's   :1       NA's   :1        
   facilities       wastewater          sen_pop_pe       socio_perc    
 Min.   :0.0523   Min.   :0.0000000   Min.   :  1.00   Min.   :  1.00  
 1st Qu.:0.1612   1st Qu.:0.0000055   1st Qu.: 25.00   1st Qu.: 25.00  
 Median :0.3652   Median :0.0005300   Median : 50.00   Median : 50.00  
 Mean   :0.6046   Mean   :0.0262015   Mean   : 50.38   Mean   : 50.38  
 3rd Qu.:0.9119   3rd Qu.:0.0087000   3rd Qu.: 75.00   3rd Qu.: 75.00  
 Max.   :3.3682   Max.   :0.6400000   Max.   :100.00   Max.   :100.00  
 NA's   :1        NA's   :1           NA's   :1        NA's   :1       
          geometry  
 POLYGON      :398  
 epsg:2926    :  0  
 +proj=lcc ...:  0  
```

```r
summary(kc_tracts10_shore_env_var)
```

```
      id                 date                              price        
 Length:21436       Min.   :2014-05-02 00:00:00.00   Min.   :  75000  
 Class :character   1st Qu.:2014-07-22 00:00:00.00   1st Qu.: 324866  
 Mode  :character   Median :2014-10-17 00:00:00.00   Median : 450000  
                    Mean   :2014-10-29 17:30:02.34   Mean   : 541650  
                    3rd Qu.:2015-02-18 00:00:00.00   3rd Qu.: 645000  
                    Max.   :2015-05-27 00:00:00.00   Max.   :7700000  
                                                                      
    bedrooms        bathrooms      sqft_living       sqft_lot      
 Min.   : 0.000   Min.   :0.000   Min.   :  290   Min.   :    520  
 1st Qu.: 3.000   1st Qu.:1.750   1st Qu.: 1430   1st Qu.:   5040  
 Median : 3.000   Median :2.250   Median : 1920   Median :   7614  
 Mean   : 3.372   Mean   :2.117   Mean   : 2083   Mean   :  15136  
 3rd Qu.: 4.000   3rd Qu.:2.500   3rd Qu.: 2550   3rd Qu.:  10696  
 Max.   :33.000   Max.   :8.000   Max.   :13540   Max.   :1651359  
                                                                    
     floors        waterfront            view          condition   
 Min.   :1.000   Min.   :0.000000   Min.   :0.0000   Min.   :1.00  
 1st Qu.:1.000   1st Qu.:0.000000   1st Qu.:0.0000   1st Qu.:3.00  
 Median :1.500   Median :0.000000   Median :0.0000   Median :3.00  
 Mean   :1.496   Mean   :0.007604   Mean   :0.2351   Mean   :3.41  
 3rd Qu.:2.000   3rd Qu.:0.000000   3rd Qu.:0.0000   3rd Qu.:4.00  
 Max.   :3.500   Max.   :1.000000   Max.   :4.0000   Max.   :5.00  
                                                                    
     grade          sqft_above   sqft_basement       yr_built   
 Min.   : 1.000   Min.   : 290   Min.   :   0.0   Min.   :1900  
 1st Qu.: 7.000   1st Qu.:1200   1st Qu.:   0.0   1st Qu.:1952  
 Median : 7.000   Median :1560   Median :   0.0   Median :1975  
 Mean   : 7.662   Mean   :1791   Mean   : 291.7   Mean   :1971  
 3rd Qu.: 8.000   3rd Qu.:2220   3rd Qu.: 560.0   3rd Qu.:1997  
 Max.   :13.000   Max.   :9410   Max.   :4820.0   Max.   :2015  
                                                                 
  yr_renovated        zipcode       sqft_living15    sqft_lot15    
 Min.   :   0.00   Min.   :98001   Min.   : 399   Min.   :   651  
 1st Qu.:   0.00   1st Qu.:98033   1st Qu.:1490   1st Qu.:  5100  
 Median :   0.00   Median :98065   Median :1840   Median :  7620  
 Mean   :  84.73   Mean   :98078   Mean   :1988   Mean   : 12786  
```

```
3rd Qu.:   0.00   3rd Qu.:98117   3rd Qu.:2370   3rd Qu.: 10087
Max.   :2015.00   Max.   :98199   Max.   :6210   Max.   :871200

         geometry        dist_cbd       dist_cbd_km       GEO_ID_TRT
POINT         :21436   Min.   :  3228   Min.   : 0.9838   Length:21436
epsg:2926     :    0   1st Qu.: 32099   1st Qu.: 9.7837   Class :character
+proj=lcc ...:    0   Median : 54280   Median :16.5447   Mode  :character
                       Mean   : 60638   Mean   :18.4824
                       3rd Qu.: 83064   3rd Qu.:25.3178
                       Max.   :253647   Max.   :77.3117

  FEATURE_ID     TRACT_LBL          TRACT_STR          TRACT_INT
Min.   :10153   Length:21436       Length:21436       Min.   :  100
1st Qu.:36346   Class :character   Class :character   1st Qu.:10402
Median :44764   Mode  :character   Mode  :character   Median :24702
Mean   :38270                                         Mean   :21224
3rd Qu.:45279                                         3rd Qu.:31202
Max.   :45838                                         Max.   :32800
NA's   :25                                            NA's   :25
  TRACT_FLT      TRACT_DEL          TRTLABEL_F         TRTLABEL_C
Min.   :  1.0   Length:21436       Length:21436       Length:21436
1st Qu.:104.0   Class :character   Class :character   Class :character
Median :247.0   Mode  :character   Mode  :character   Mode  :character
Mean   :212.2
3rd Qu.:312.0
Max.   :328.0
NA's   :25
 TRTLABEL_T         COUNTY_STR          COUNTY_INT  STATE_STR
Length:21436       Length:21436       Min.   :33   Length:21436
Class :character   Class :character   1st Qu.:33   Class :character
Mode  :character   Mode  :character   Median :33   Mode  :character
                                      Mean   :33
                                      3rd Qu.:33
                                      Max.   :33
                                      NA's   :25
  STATE_INT    LEVEL_1            LEVEL_2            LEVEL_3
Min.   :53   Length:21436       Length:21436       Length:21436
1st Qu.:53   Class :character   Class :character   Class :character
Median :53   Mode  :character   Mode  :character   Mode  :character
Mean   :53
3rd Qu.:53
Max.   :53
NA's   :25
```

```
  TRACT_AREA           TRACT_PERI       LOGRECNO
Min.   :    2791880   Min.   :  8012   Length:21436
1st Qu.:   24853588   1st Qu.: 23500   Class :character
Median :   41226319   Median : 32920   Mode  :character
Mean   :  180883201   Mean   : 48212
3rd Qu.:   73083589   3rd Qu.: 47962
Max.   :15258321253   Max.   :738820
NA's   :25            NA's   :25
  Shape_area           Shape_len          low                 mid
Min.   :    2791880   Min.   :  8012   Min.   :0.009298   Min.   :0.06768
1st Qu.:   22811341   1st Qu.: 23204   1st Qu.:0.047091   1st Qu.:0.21668
Median :   34452366   Median : 31185   Median :0.074766   Median :0.30219
Mean   :  175045321   Mean   : 46861   Mean   :0.100082   Mean   :0.31115
3rd Qu.:   66278818   3rd Qu.: 46624   3rd Qu.:0.133557   3rd Qu.:0.39313
Max.   :15258321253   Max.   :738820   Max.   :0.501433   Max.   :0.67904
NA's   :25            NA's   :25       NA's   :25         NA's   :25
     high           EHD_percen       linguist_2       poverty_pe
Min.   :0.06129   Min.   :  1.00   Min.   : 0.450   Min.   : 1.97
1st Qu.:0.47602   1st Qu.: 19.00   1st Qu.: 3.120   1st Qu.: 8.93
Median :0.61143   Median : 41.00   Median : 7.000   Median :13.60
Mean   :0.58877   Mean   : 43.64   Mean   : 9.003   Mean   :16.65
3rd Qu.:0.72987   3rd Qu.: 67.00   3rd Qu.:12.730   3rd Qu.:22.95
Max.   :0.88162   Max.   :100.00   Max.   :40.350   Max.   :75.48
NA's   :25        NA's   :25       NA's   :220      NA's   :25
  POC_percen      transporta      unemploy_2       housing_pe
Min.   : 7.54   Min.   :12.00   Min.   : 1.000   Min.   :15.14
1st Qu.:21.13   1st Qu.:18.00   1st Qu.: 3.230   1st Qu.:25.64
Median :33.26   Median :20.00   Median : 4.310   Median :30.46
Mean   :35.33   Mean   :19.77   Mean   : 4.775   Mean   :31.37
3rd Qu.:46.34   3rd Qu.:21.00   3rd Qu.: 6.050   3rd Qu.:35.73
Max.   :92.70   Max.   :26.00   Max.   :13.620   Max.   :64.87
NA's   :25      NA's   :25      NA's   :102      NA's   :25
  traffic_pe        diesel          ozone            PM25
Min.   : 0.00   Min.   : 0.14   Min.   :46.73   Min.   :3.787
1st Qu.: 0.00   1st Qu.: 5.60   1st Qu.:49.24   1st Qu.:5.488
Median : 0.10   Median :10.16   Median :49.97   Median :6.044
Mean   :11.52   Mean   :13.68   Mean   :51.17   Mean   :6.002
3rd Qu.:19.14   3rd Qu.:16.88   3rd Qu.:52.32   3rd Qu.:6.579
Max.   :84.98   Max.   :92.63   Max.   :62.89   Max.   :7.897
NA's   :25      NA's   :25      NA's   :25      NA's   :25
  toxic_rele         hazardous_        lead_perce      superfund
Min.   :   823.9   Min.   :0.02303   Min.   : 0.24   Min.   :0.03454
1st Qu.:  4143.8   1st Qu.:0.03985   1st Qu.: 5.34   1st Qu.:0.06595
```

```
 Median :  8827.6   Median :0.05160   Median :11.99   Median :0.11046  
 Mean   : 17251.1   Mean   :0.07409   Mean   :16.60   Mean   :0.21696  
 3rd Qu.: 17237.2   3rd Qu.:0.07891   3rd Qu.:26.48   3rd Qu.:0.23841  
 Max.   :186434.6   Max.   :0.63781   Max.   :54.68   Max.   :1.46778  
 NA's   :25         NA's   :25        NA's   :25      NA's   :25       
   facilities       wastewater          sen_pop_pe      socio_perc    
 Min.   :0.0523   Min.   :0.000000   Min.   :  1.0   Min.   :  1.00  
 1st Qu.:0.1420   1st Qu.:0.000003   1st Qu.: 25.0   1st Qu.: 20.00  
 Median :0.2680   Median :0.000290   Median : 48.0   Median : 43.00  
 Mean   :0.5248   Mean   :0.016168   Mean   : 48.1   Mean   : 44.51  
 3rd Qu.:0.7588   3rd Qu.:0.002900   3rd Qu.: 71.0   3rd Qu.: 67.00  
 Max.   :3.3682   Max.   :0.640000   Max.   :100.0   Max.   :100.00  
 NA's   :25       NA's   :25         NA's   :25      NA's   :25       
```

ii.

Tract10 kartet har ikke havet med seg og får med det en NA observsjon som er utenfor countygrensen. **Tracts10_shore** har med havet på kartet, som gjør at det er flere obserasjoner som "havner" ut i havet og med det blir de til NA verdier (25stk).

I QGIS fant vi følgende observasjoner ved å se på *tracts10*, *tracts10_shore* & *kc_houses_env_var*:

iii.

Dropper Observasjonen 3518000180 ved å:

```r
kc_houses_env_var <- arrange(kc_houses_env_var, desc(id))
kc_houses_env_var_omit <- kc_houses_env_var[-c(11997),]
```

```r
st_write(kc_houses_env_var_omit, "../maps/kc_houses_env_var_omit.gpkg", append = FALSE)
```

```
Deleting layer `kc_houses_env_var_omit' using driver `GPKG'
Writing layer `kc_houses_env_var_omit' to data source 
  `../maps/kc_houses_env_var_omit.gpkg' using driver `GPKG'
Writing 21435 features with 65 fields and geometry type Point.
```

```r
kc_houses_env_var_omit <- kc_houses_env_var_omit %>%
    mutate(
        year_month = substr(date, start = 1, stop = 7))
```

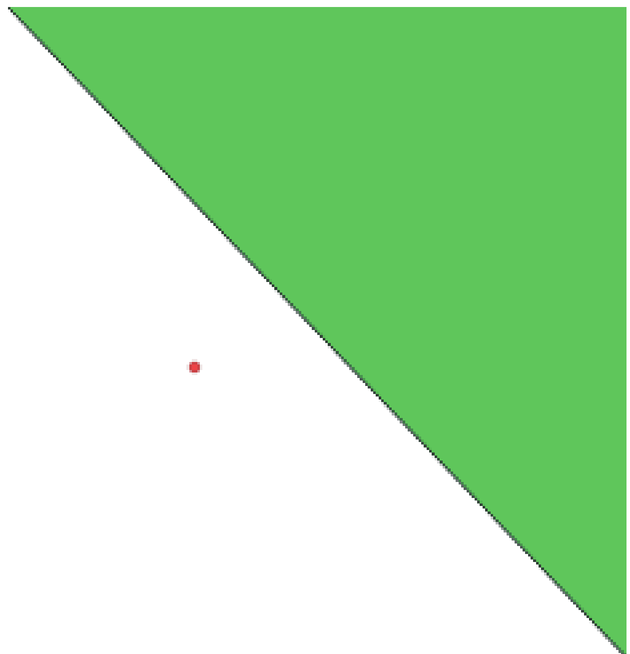


Figure 1: observasjon utenfor WA state

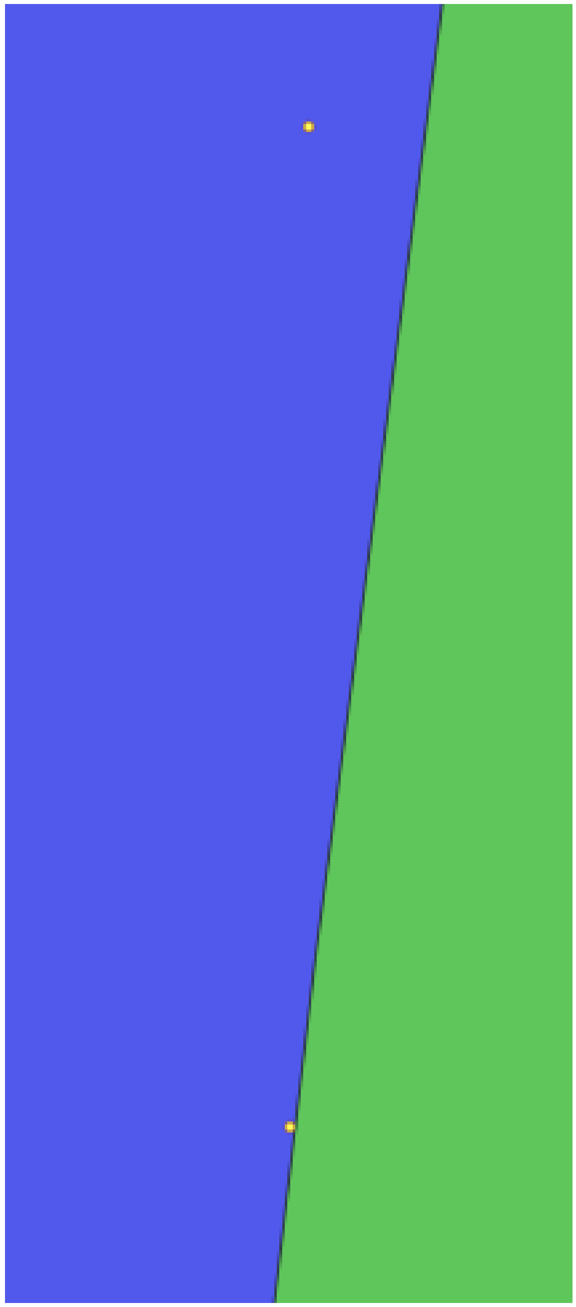


Figure 2: Observasjon utenfor kystlinjen.a

Figure 3: Observasjon utenfor kystlinjen.b

```r
st_write(kc_houses_env_var_omit, "../maps/kc_houses_env_var_omit.gpkg", append = FALSE)
```

```
Deleting layer `kc_houses_env_var_omit' using driver `GPKG'
Writing layer `kc_houses_env_var_omit' to data source
  `../maps/kc_houses_env_var_omit.gpkg' using driver `GPKG'
Writing 21435 features with 66 fields and geometry type Point.
```

Oppgave 5

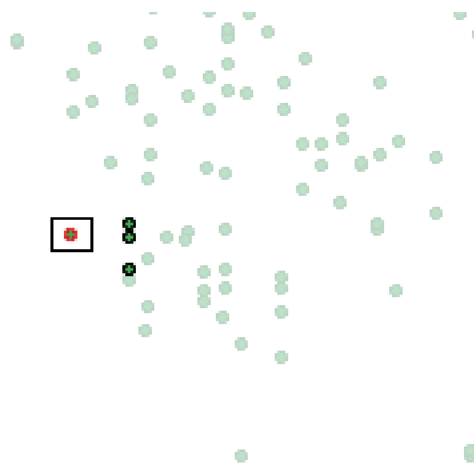


Figure 4: K-nearest 3

Funn fra EDA

Vi ser at de store konsentrasjonene av store boliger til høye priser er i og rett rundt Seattle sentrum, vi kan også se at Mercer Island er veldig dyr plass og at vestsiden av Bellevue har

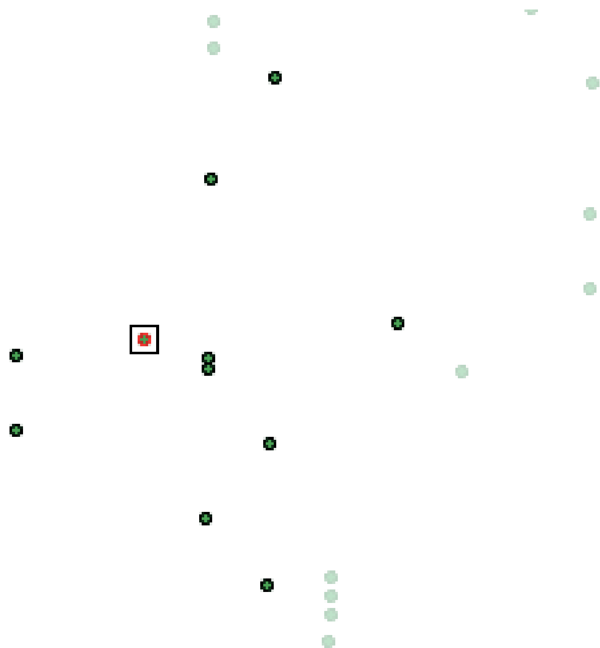


Figure 5: K-nearest 10

store og dyre boliger.

Vi ser at store deler av små boliger til lave priser er i søre del King county.

Vi ser at de små og dyre boligene er rundt bykjernen, noe som gir mening med tanke på at det er mindre områder å bygge store boliger samt et populært område å bo.

Vi kan også se at de store og billige husene plasserer seg sammen med de små og billige boligene, dette sier oss at dette er et fattigere område hvor de lavlønnte bor.

Morans I verdien til K3 er på 0,398 og K10 sin er på 0,350. Når vi skulle regne ut Morgans I valgte vi å bruke price og sqft_living. Vi sammenlignet sqft_living og bedrooms, de så ganske like ut på kartet, men hadde forskjellige verdier på morans I. Verdien er finere med sqft_living fordi det er et tydligere mønster på at når sqft_living øker så lir det dyrere.

Verdier som er positive taler for klynging. Siden verdiene er svakt positive så viser de til litt klynging.

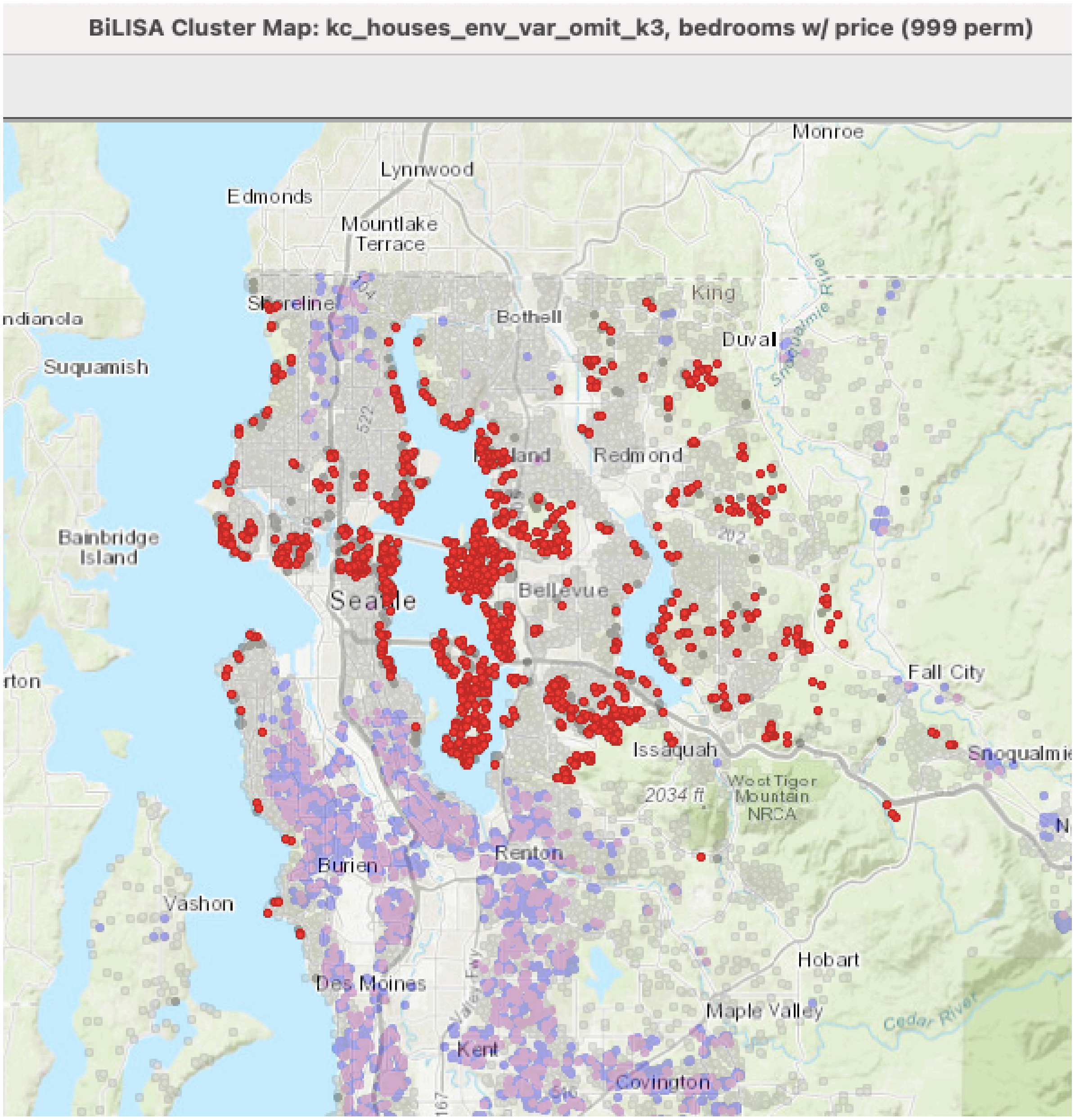


Figure 6: K3 - Store og dyre boliger

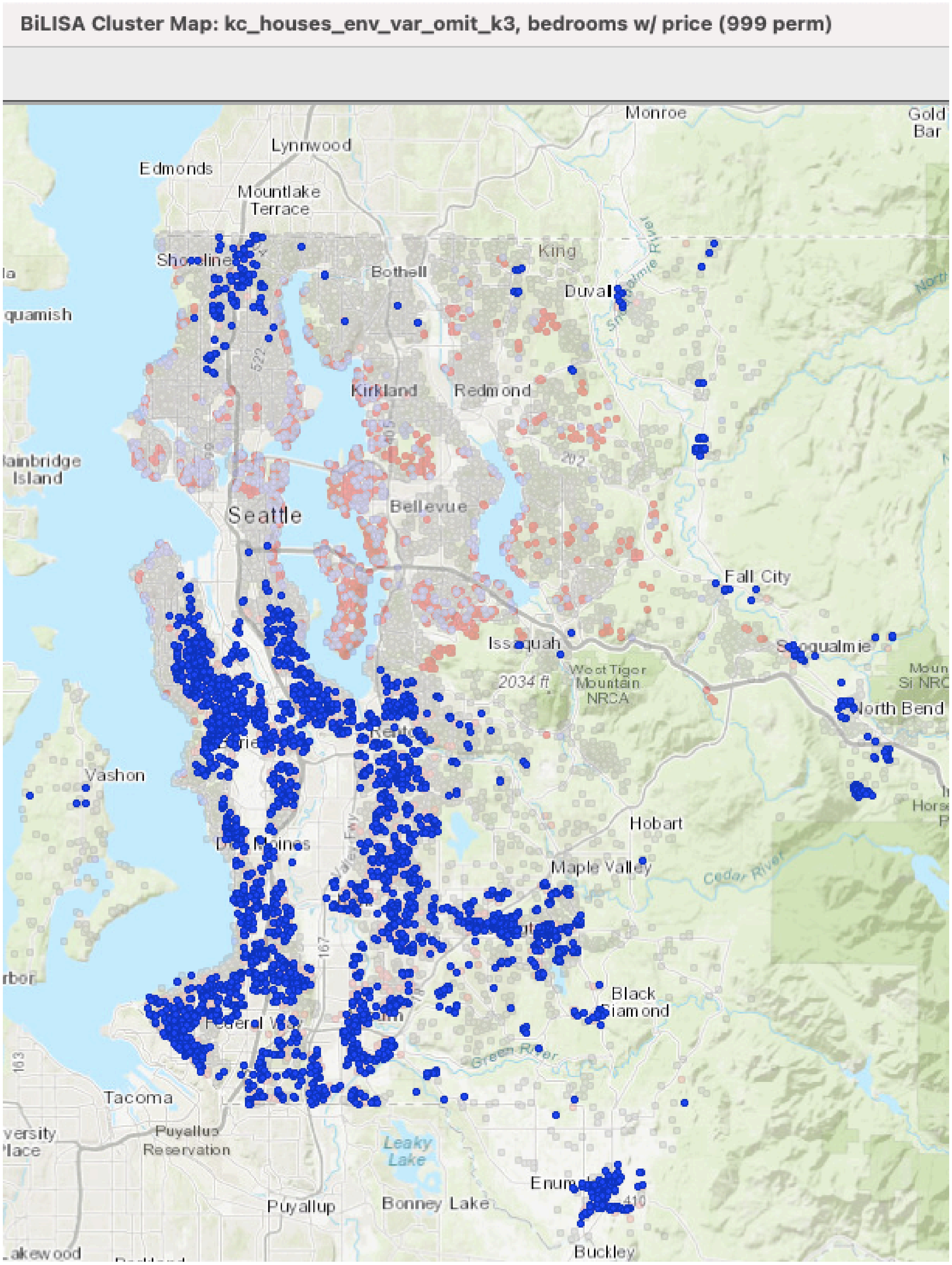


Figure 7: K3 - Små og billige boliger

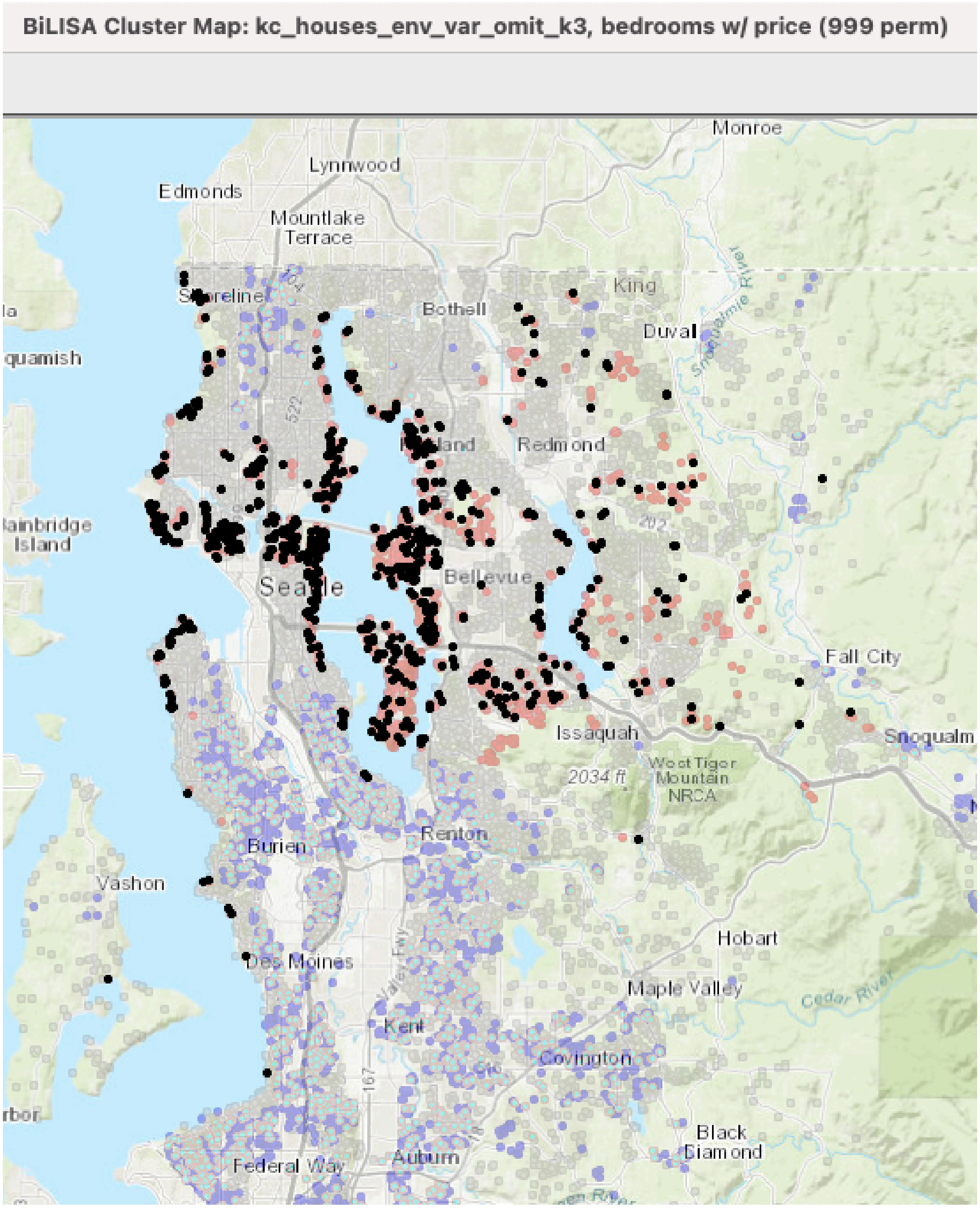


Figure 8: K3 - Små og dyre boliger

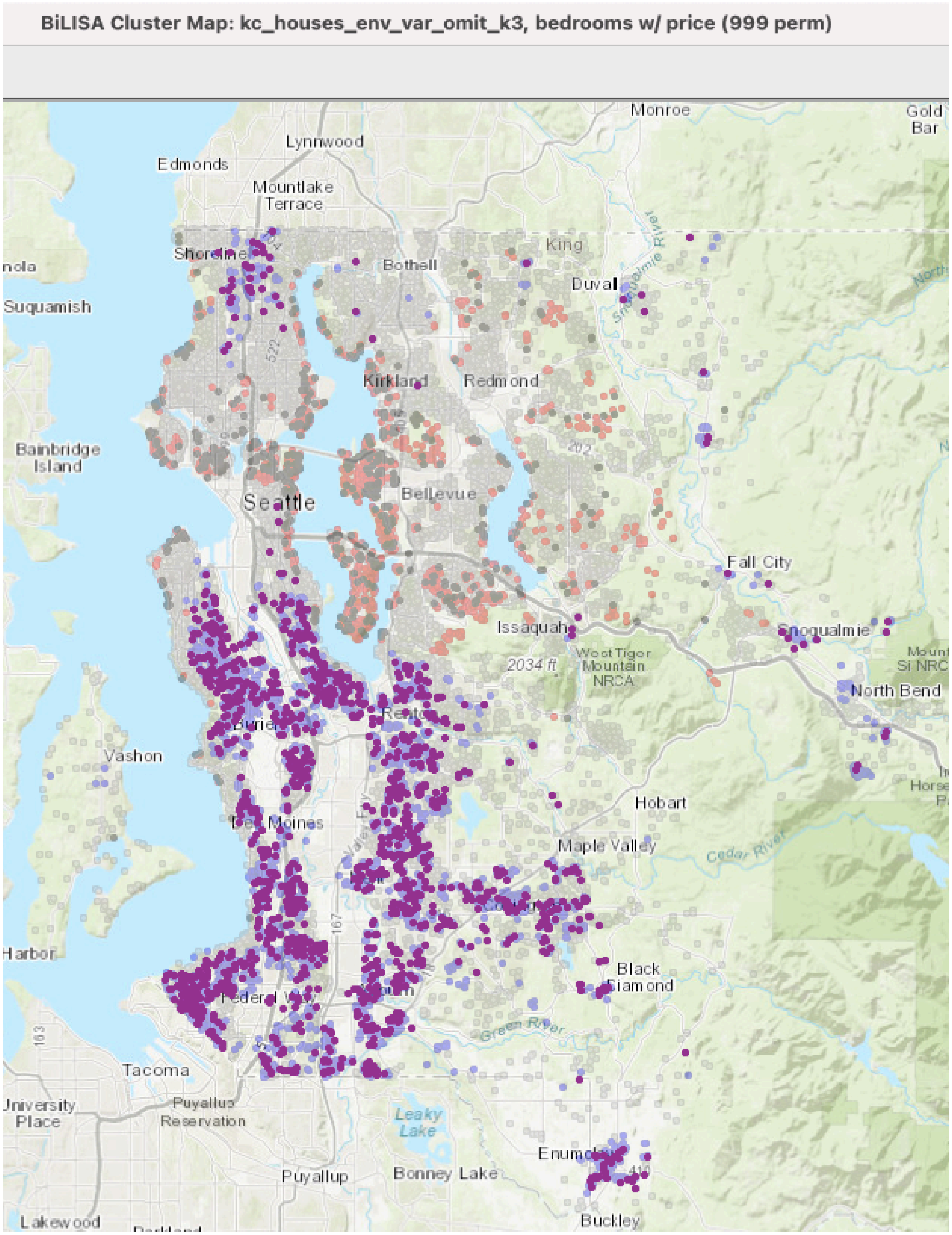


Figure 9: K3 - Store og billige boliger

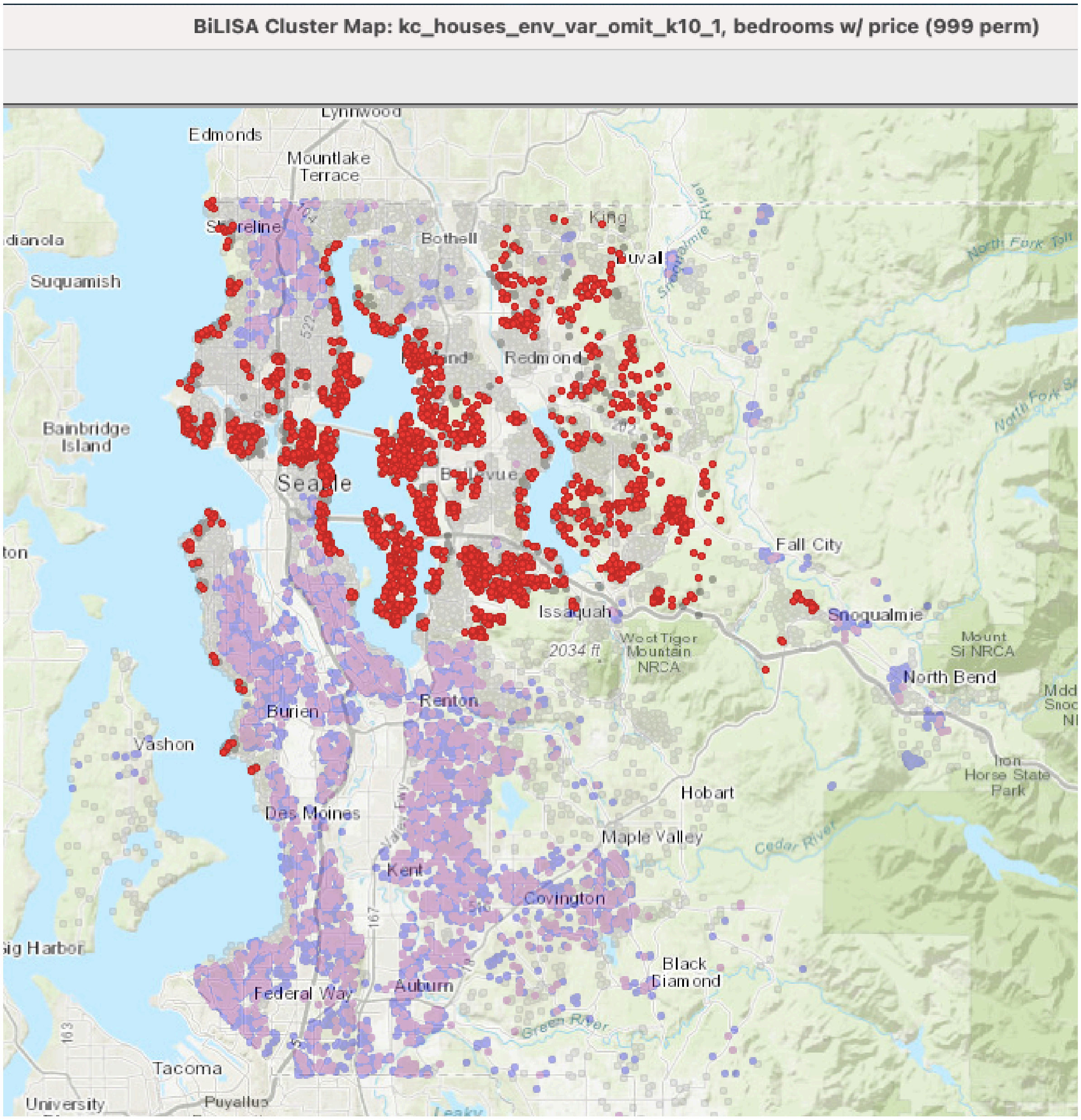


Figure 10: K10 - Store og dyre boliger

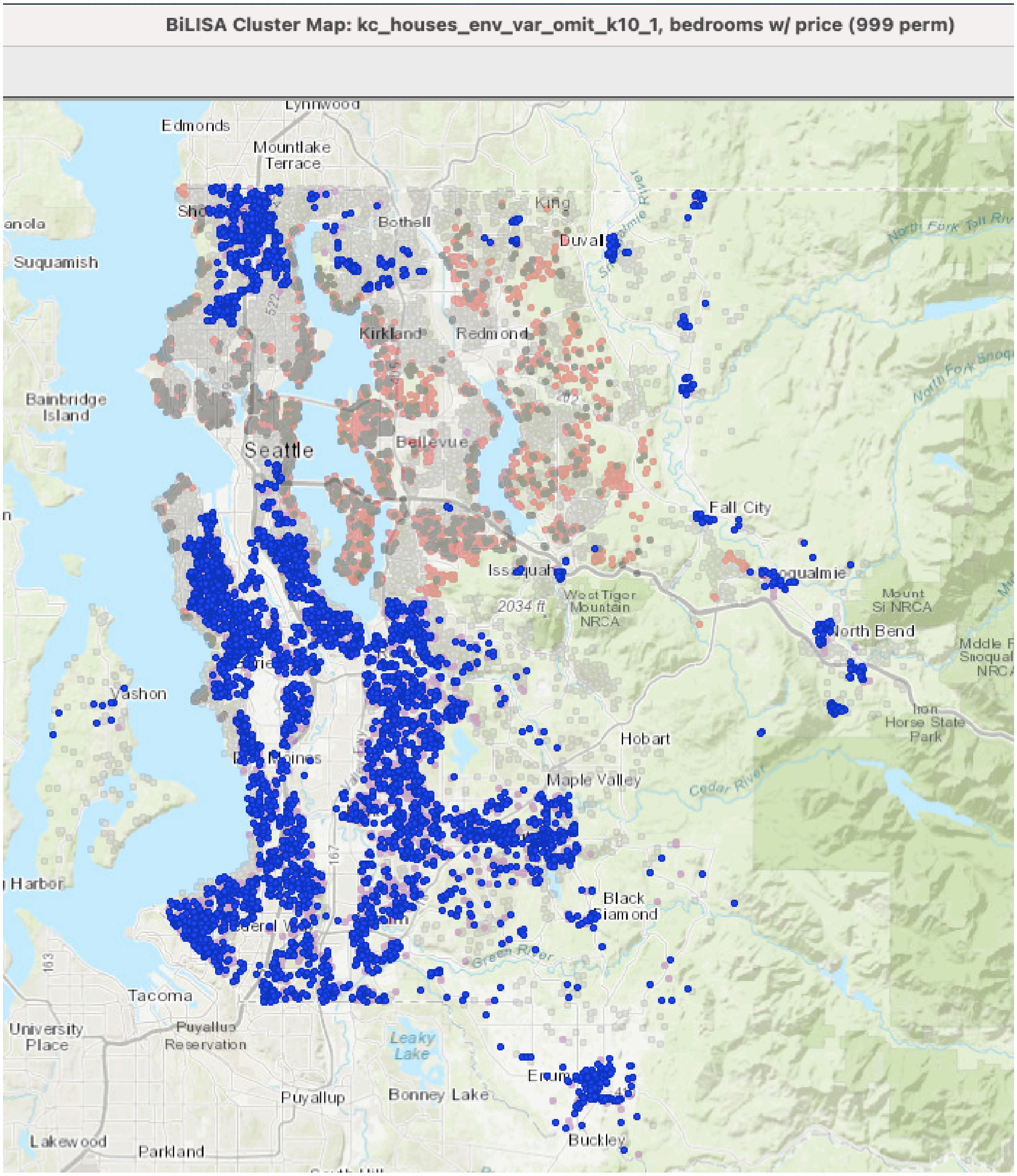


Figure 11: K10 - Små og billige boliger

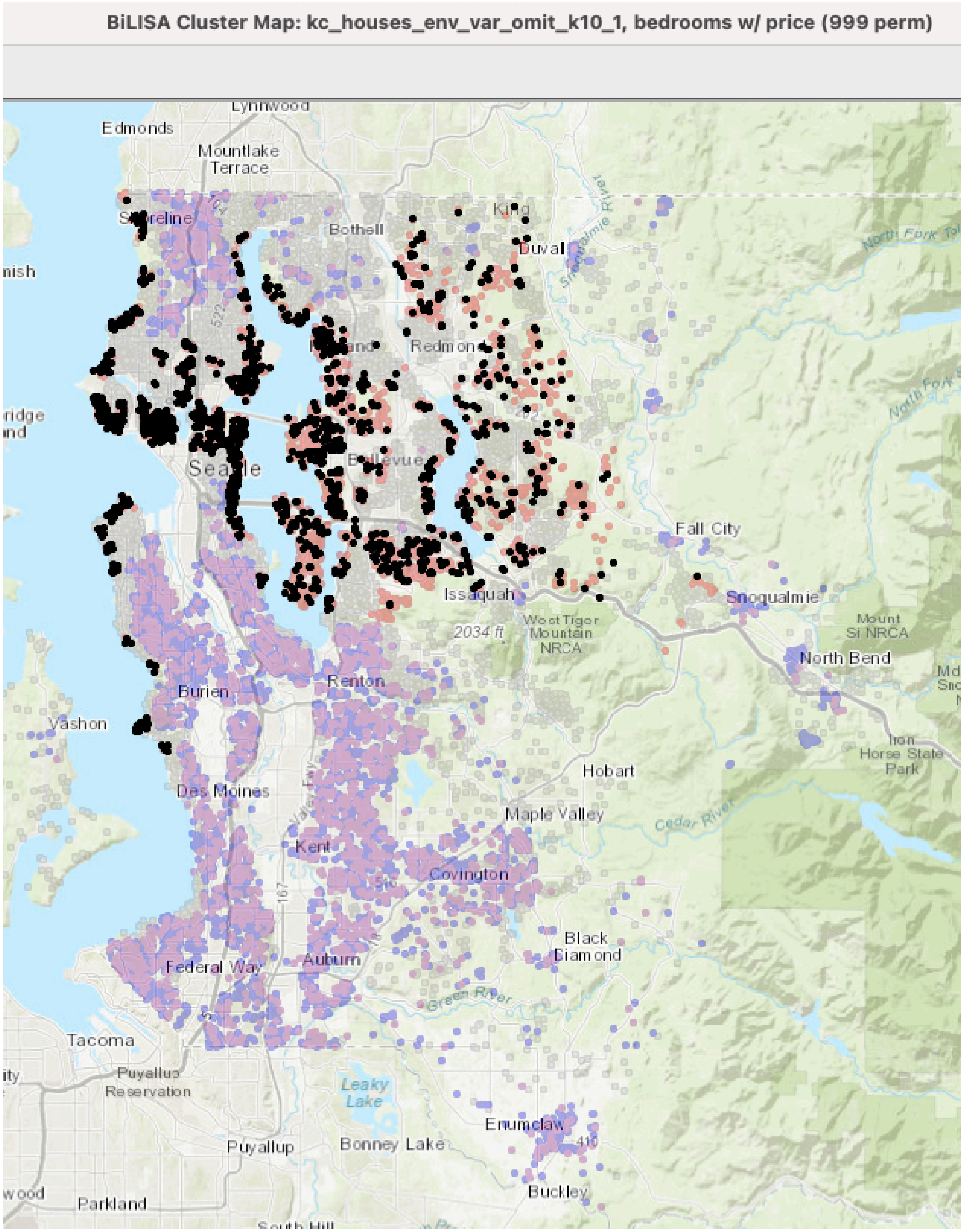


Figure 12: K10 - Små og dyre boliger

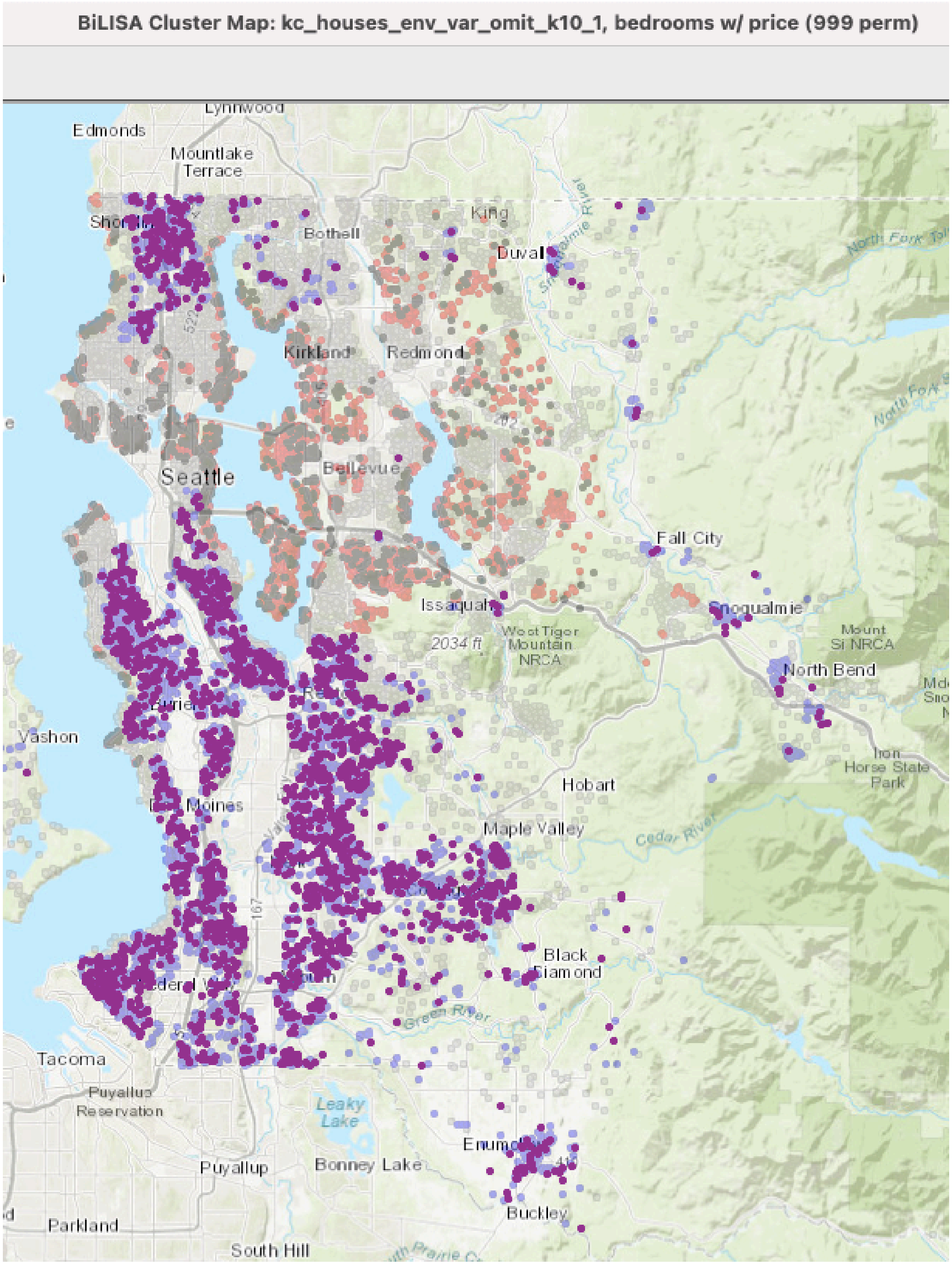


Figure 13: K10 - Store og billige boliger

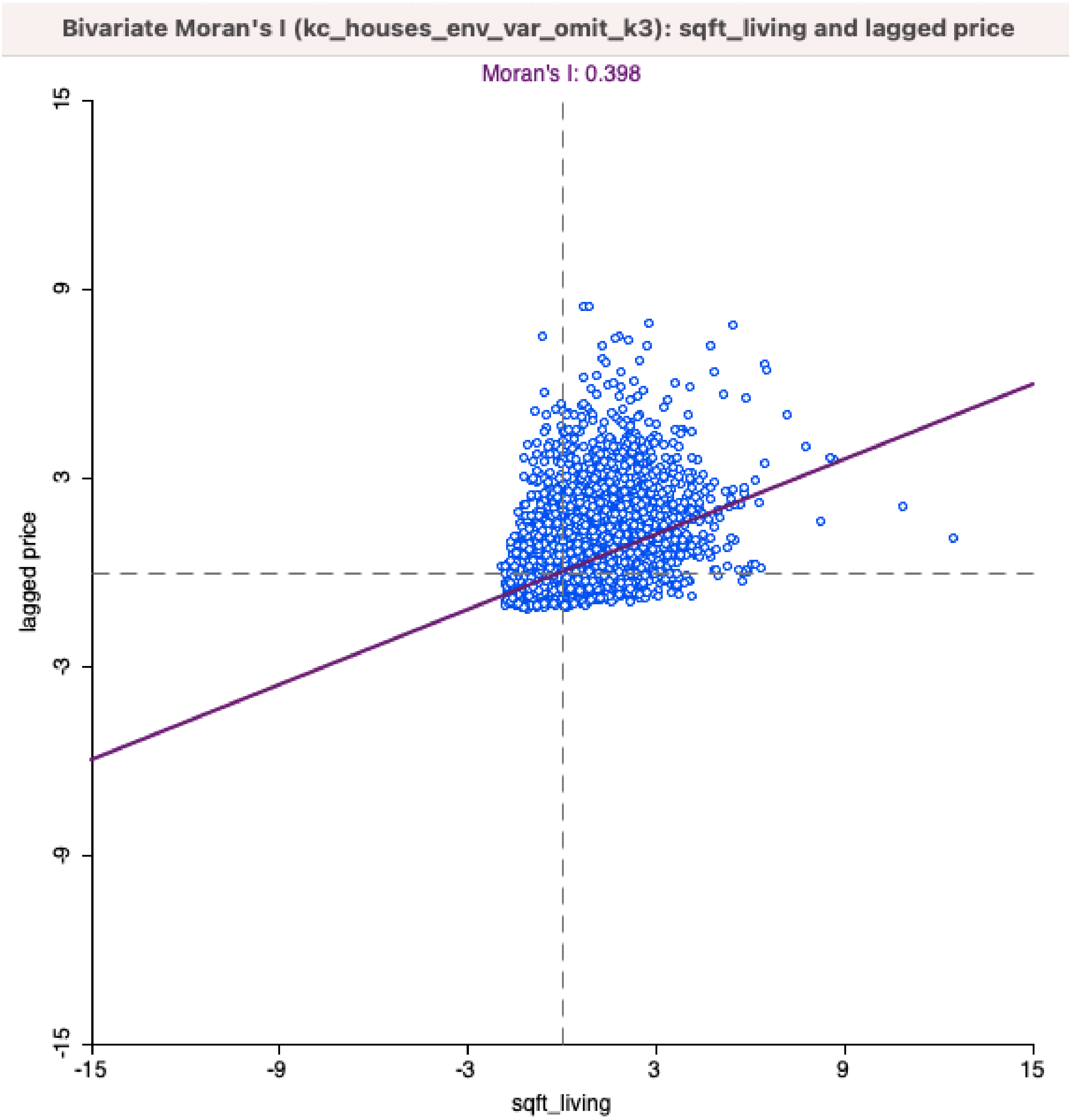


Figure 14: K3 - Bivariate Moran I

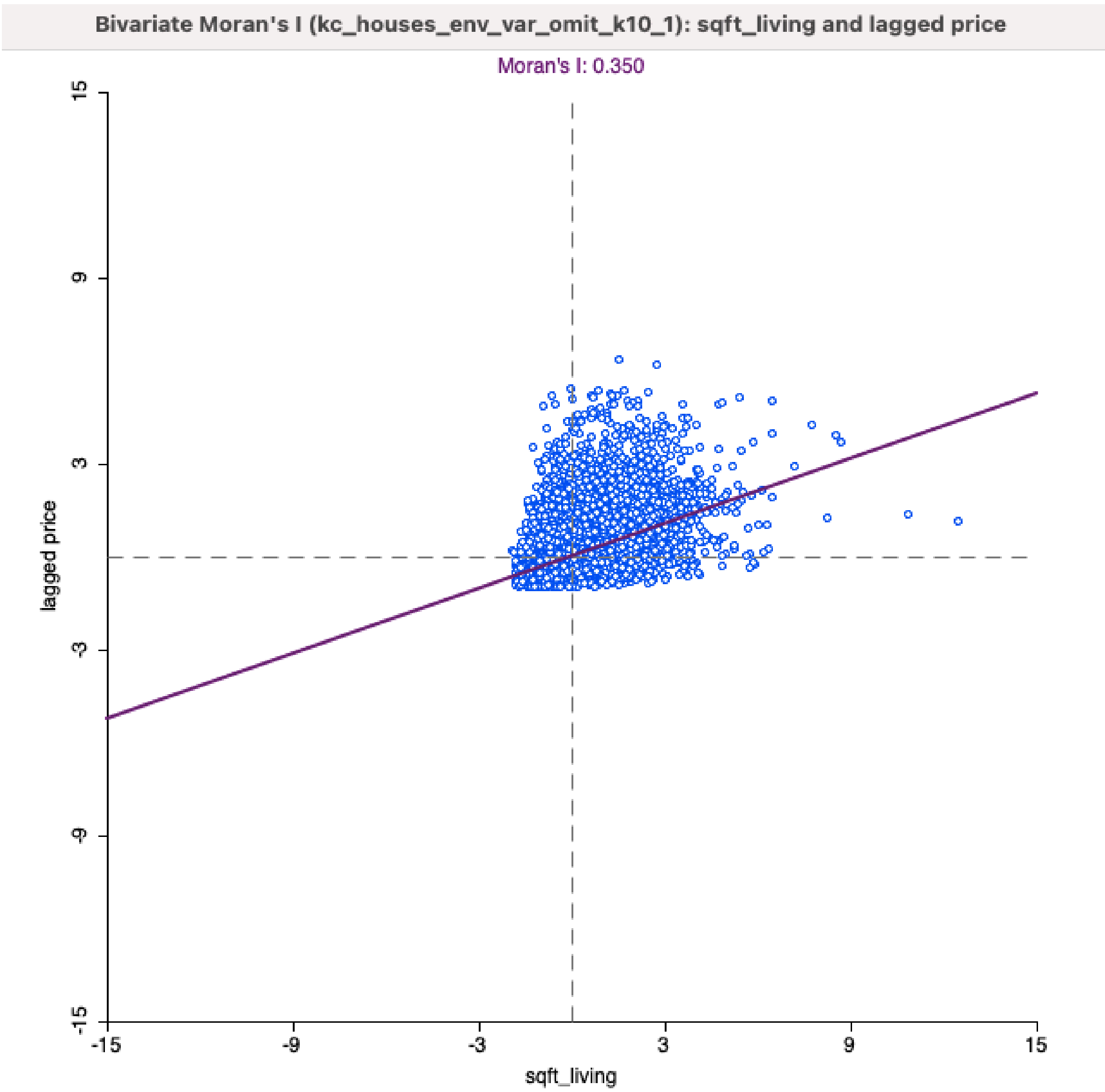


Figure 15: K10 - Bivariate Moran I

Oppgave 6

i)

```
attach(kc_houses_env_var_omit)
```

i. Huskarakteristika

```
mod1 <- "price ~ bedrooms + bathrooms + sqft_living + sqft_lot + sqft_above + floors + gra
```

ii. Huskarakteristika + distanse til cbd + tracts_var

```
mod2 <- "price ~ bedrooms + bathrooms + sqft_living + sqft_lot + sqft_above + floors + gra
```

iii. Huskarakteristika + distanse til cbd + EHD

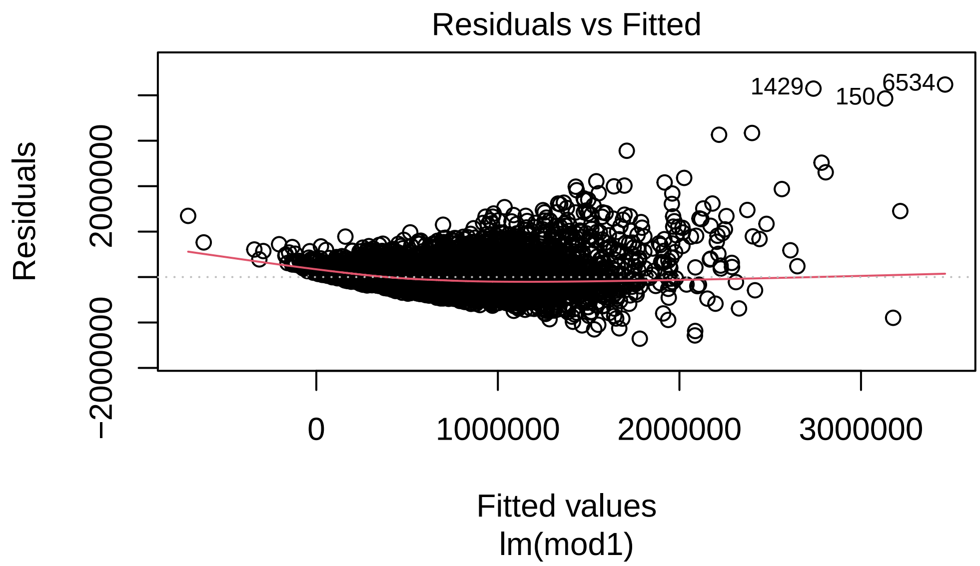
```
mod3 <- "price ~ bedrooms + bathrooms + sqft_living + sqft_lot + sqft_above + floors + gra
```

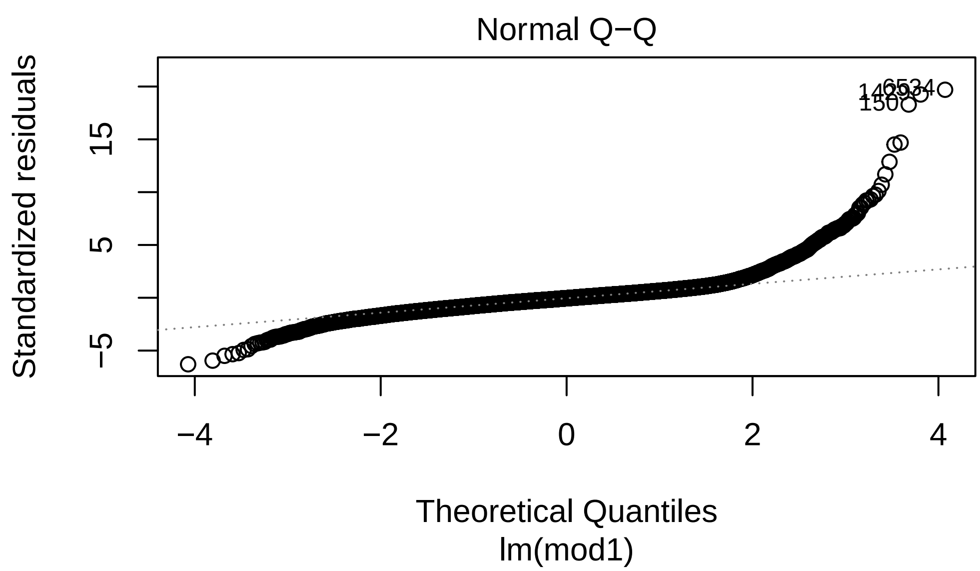
```
hedon1 <- lm(mod1, data = kc_houses_env_var_omit)
hedon2 <- lm(mod2, data = kc_houses_env_var_omit)
hedon3 <- lm(mod3, data = kc_houses_env_var_omit)
```

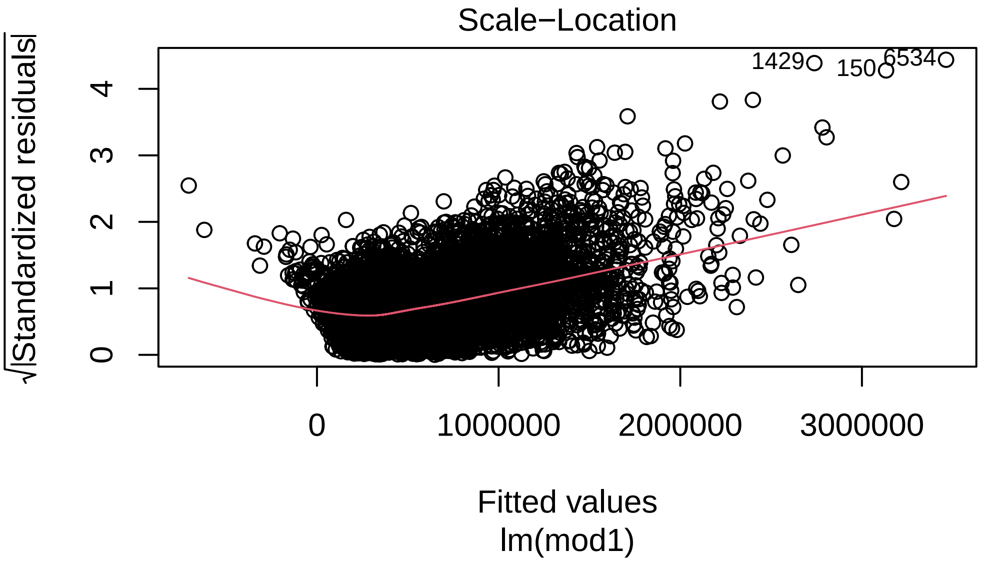
```
huxreg("Hedon1" = hedon1, "Hedon2" = hedon2, "Hedon3" = hedon3,
    error_format = "[{statistic}]",
    note = "{stars}. T statistic in brackets.")
```

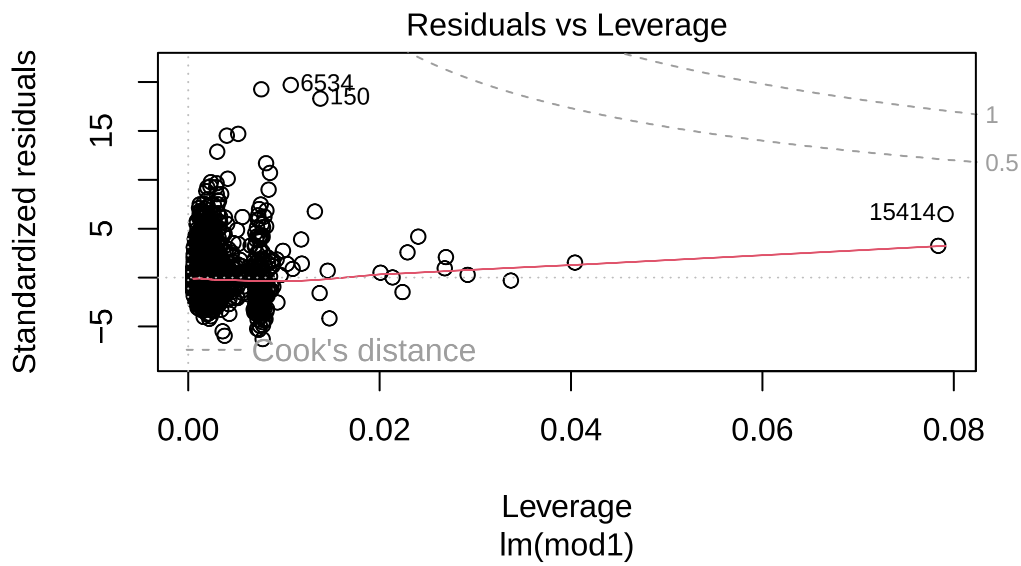
Plots

```
hedon1 %>%
  plot()
```

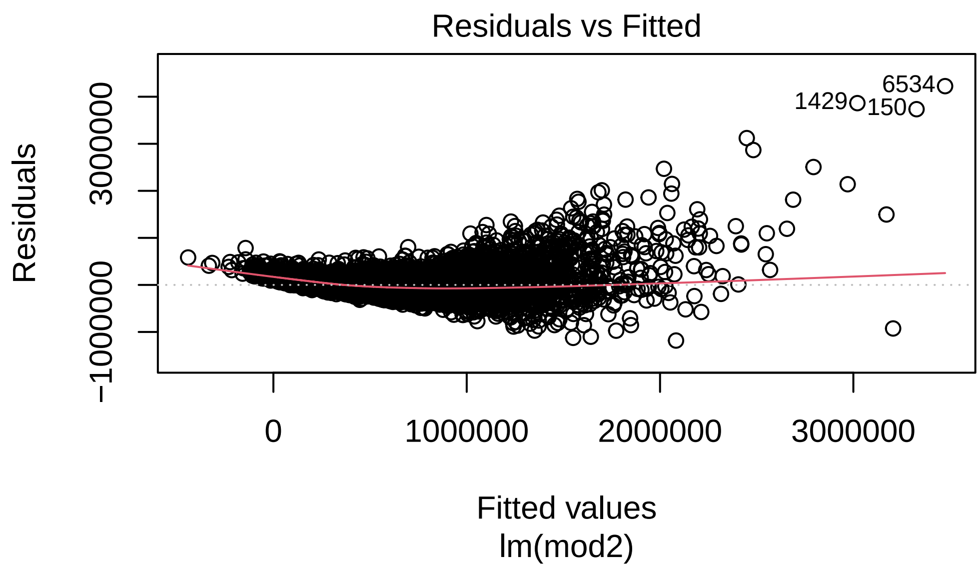

Residuals vs Fitted
Residuals
Fitted values
lm(mod1)
1429
150
6534
−2000000
2000000
0
1000000
2000000
3000000

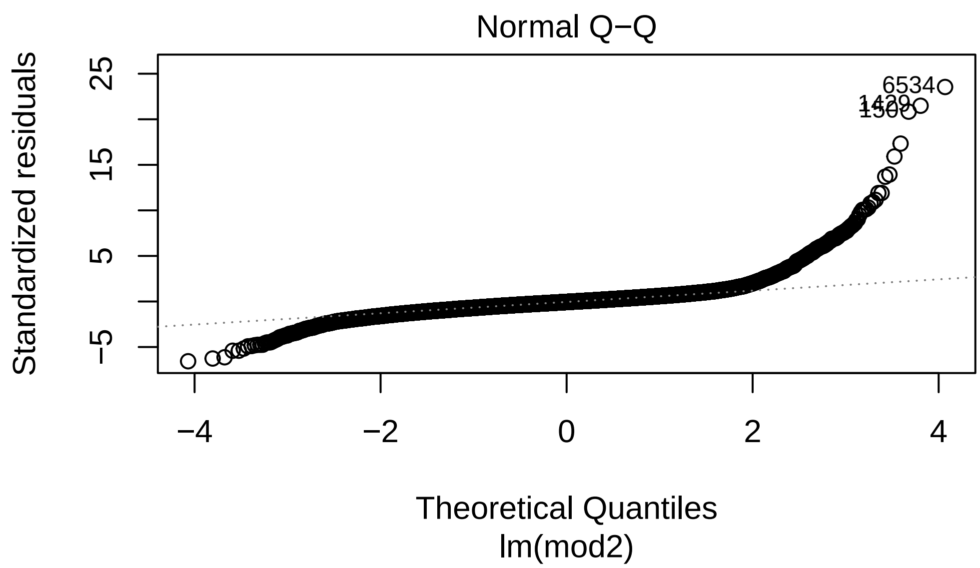

Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(mod1)
1429
150
6534
−5
5
15
−4
−2
0
2
4

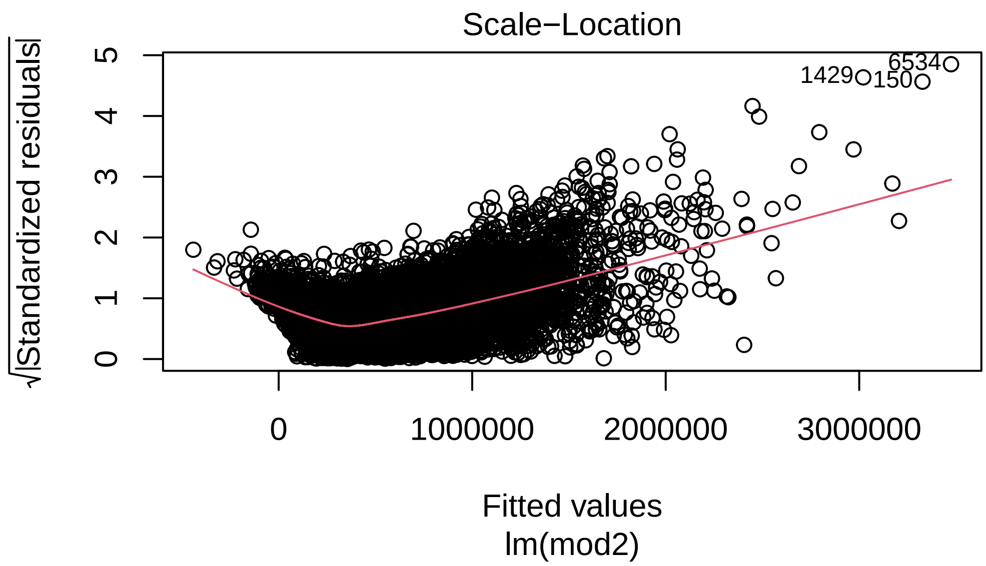

Scale−Location
√|Standardized residuals|
Fitted values
lm(mod1)
1429
150
6534
0
1
2
3
4
0
1000000
2000000
3000000

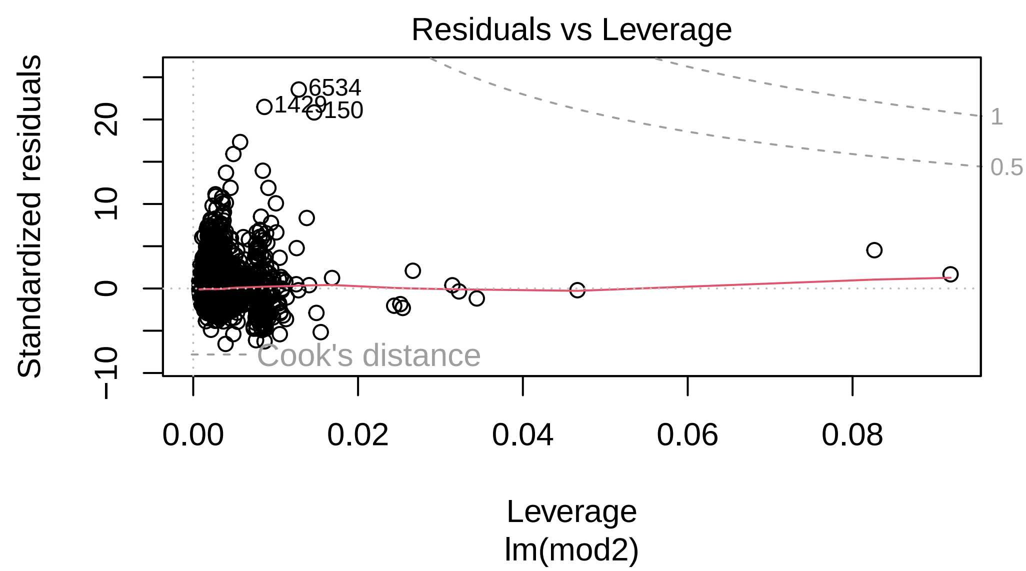

Residuals vs Leverage
Standardized residuals
Leverage
lm(mod1)
6534
150
15414
Cook's distance
1
0.5
−5
5
15
0.00
0.02
0.04
0.06
0.08

```
hedon2 %>%
  plot()
```

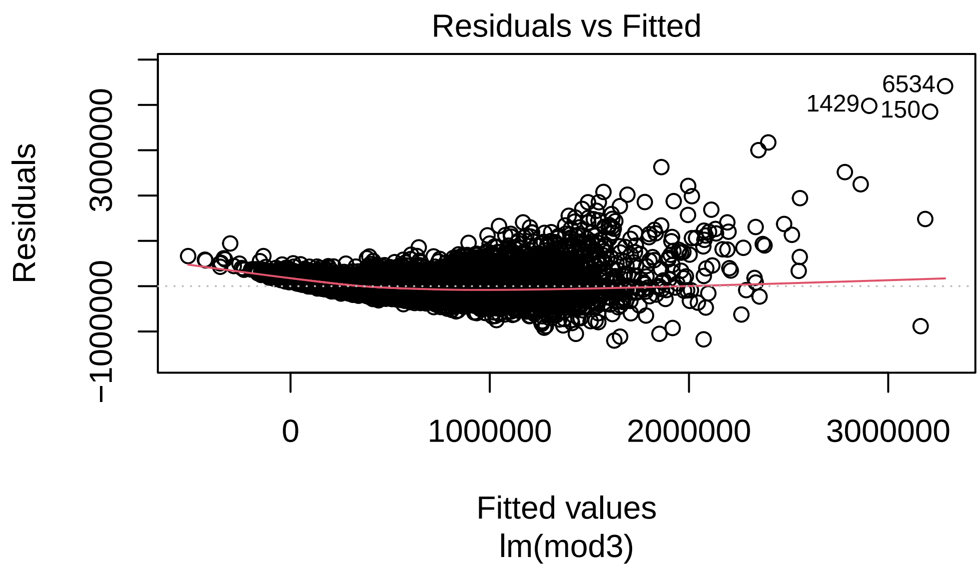

Residuals vs Fitted
Residuals
-1000000
3000000
0
1000000
2000000
3000000
Fitted values
lm(mod2)
6534
1429
150

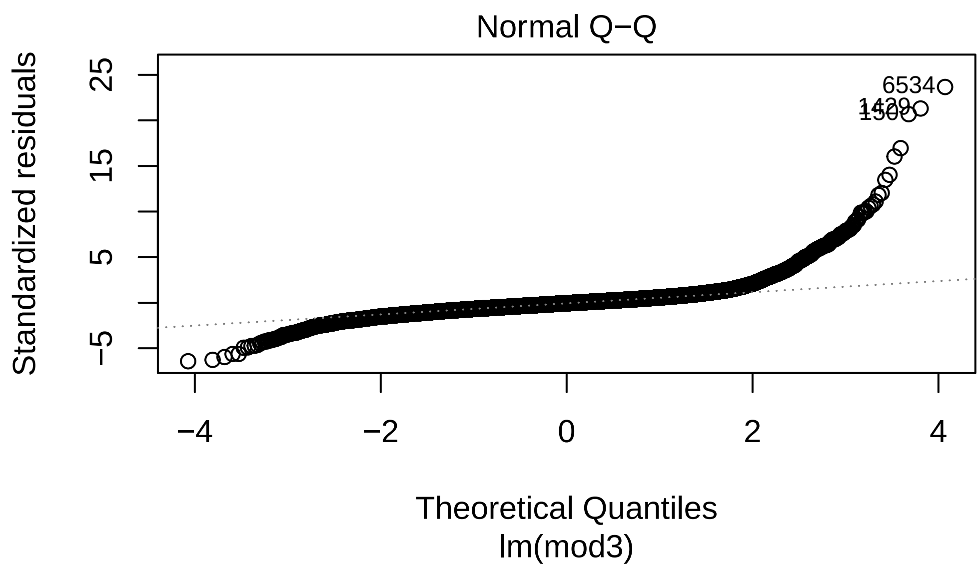

Normal Q−Q
Standardized residuals
−5
5
15
25
−4
−2
0
2
4
Theoretical Quantiles
lm(mod2)
6534
1429
150

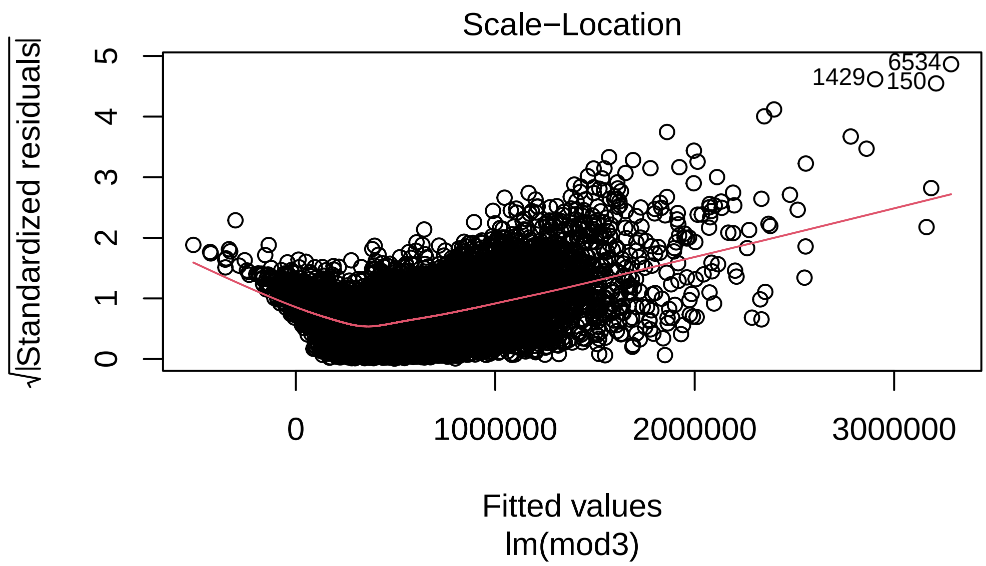

Scale−Location
√|Standardized residuals|
0
1
2
3
4
5
0
1000000
2000000
3000000
Fitted values
lm(mod2)
6534
1429
150

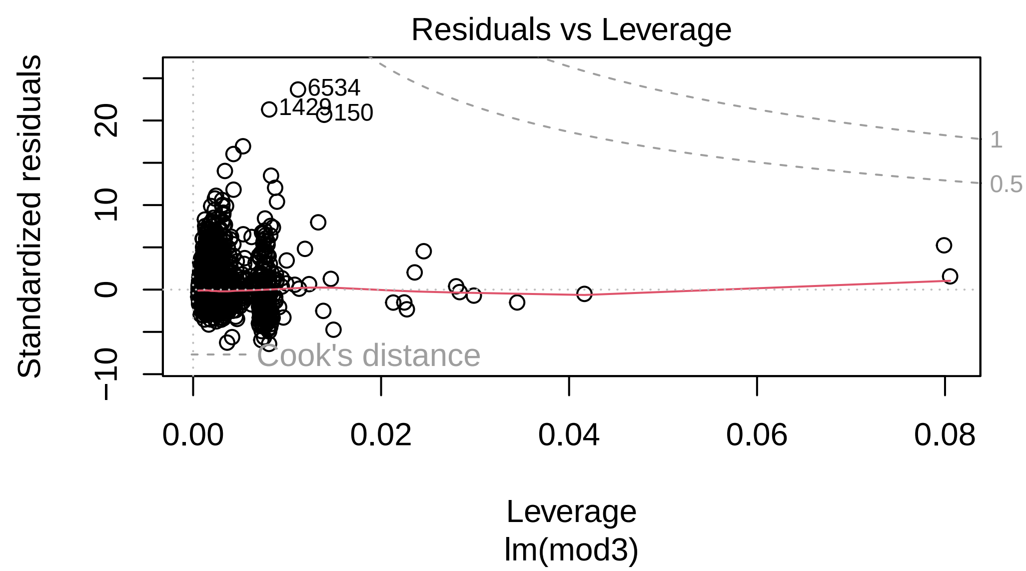

Residuals vs Leverage
Standardized residuals
−10
0
10
20
0.00
0.02
0.04
0.06
0.08
Leverage
lm(mod2)
6534
1429
150
1
0.5
Cook's distance

```r
hedon3 %>%
  plot()
```






Scale−Location
√|Standardized residuals|
Fitted values
lm(mod3)
6534
1429
150
0
1
2
3
4
5
0
1000000
2000000
3000000


Residuals vs Leverage
Standardized residuals
Leverage
lm(mod3)
6534
1429
150
Cook's distance
1
0.5
−10
0
10
20
0.00
0.02
0.04
0.06
0.08

Oppgave 7

```
hedon1 %>%
    linearHypothesis(c("year_month2014-06=0", "year_month2014-07=0",
                       "year_month2014-08=0", "year_month2014-09=0",
                       "year_month2014-10=0", "year_month2014-11=0",
                       "year_month2014-12=0", "year_month2015-01=0",
                       "year_month2015-02=0", "year_month2015-03=0",
                       "year_month2015-04=0", "year_month2015-05=0"),
                     white_adjust = hc3)
```

```
hedon2 %>%
    linearHypothesis(c("year_month2014-06=0", "year_month2014-07=0",
                       "year_month2014-08=0", "year_month2014-09=0",
                       "year_month2014-10=0", "year_month2014-11=0",
                       "year_month2014-12=0", "year_month2015-01=0",
                       "year_month2015-02=0", "year_month2015-03=0",
                       "year_month2015-04=0", "year_month2015-05=0"),
                     white_adjust = hc4)
```

```
hedon3 %>%
    linearHypothesis(c("year_month2014-06=0", "year_month2014-07=0",
                       "year_month2014-08=0", "year_month2014-09=0",
                       "year_month2014-10=0", "year_month2014-11=0",
                       "year_month2014-12=0", "year_month2015-01=0",
                       "year_month2015-02=0", "year_month2015-03=0",
                       "year_month2015-04=0", "year_month2015-05=0"),
                     white_adjust = hc1)
```

Oppgave 8

```
kc_house_data_6666 <- here("maps/kc_house_data_6666_Sindre_og_Morten.gpkg") %>%
  st_read() %>%
  st_transform(2926)
```

```
Reading layer `kc_house_data_6666_Sindre_og_Morten' from data source
  `/Users/sindreespedal/Documents/HVL /Høst 2022/MSB 204 - Bolig - R/Termpaper_msb_205_H22_S
  using driver `GPKG'
```

```
Simple feature collection with 1887 features and 51 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 1226414 ymin: 72921.15 xmax: 1495965 ymax: 286273.8
Projected CRS: NAD83(HARN) / Washington North (ftUS)
```

```
kc_house_data_6666 <- kc_house_data_6666 %>%
  mutate(
    dist_cbd = st_distance(cbd, ., by_element = TRUE),
    dist_cbd_km = set_units(dist_cbd, km),
    year_month = substr(date, start = 1, stop = 7)
  )
```

```
kc_house_data_6666 <- kc_house_data_6666 %>%
  rename(low = inc_fam_low_per,
         mid = inc_fam_med_per,
         high = inc_fam_high_per)
```

```
hedon3_seed <- lm(mod3, data = kc_house_data_6666)
```

```
huxreg("Full" = hedon3, "seed" = hedon3_seed,
       error_format = "[{statistic}]",
       note = "{stars}. T statistic in brackets.")
```

```
kc_house_data_6666_mat_nb <- knearneigh(kc_house_data_6666, k = 3)
kc_house_data_6666_nb <- knn2nb(kc_house_data_6666_mat_nb)
kc_house_data_6666_W <- nb2listw(kc_house_data_6666_nb, style = "W")
```

```
kc_house_data_6666_mat_nb10 <- knearneigh(kc_house_data_6666, k = 10)
kc_house_data_6666_nb10 <- knn2nb(kc_house_data_6666_mat_nb10)
kc_house_data_6666_W10 <- nb2listw(kc_house_data_6666_nb10, style = "W")
```

```
lm.morantest(hedon3_seed, kc_house_data_6666_W)
```

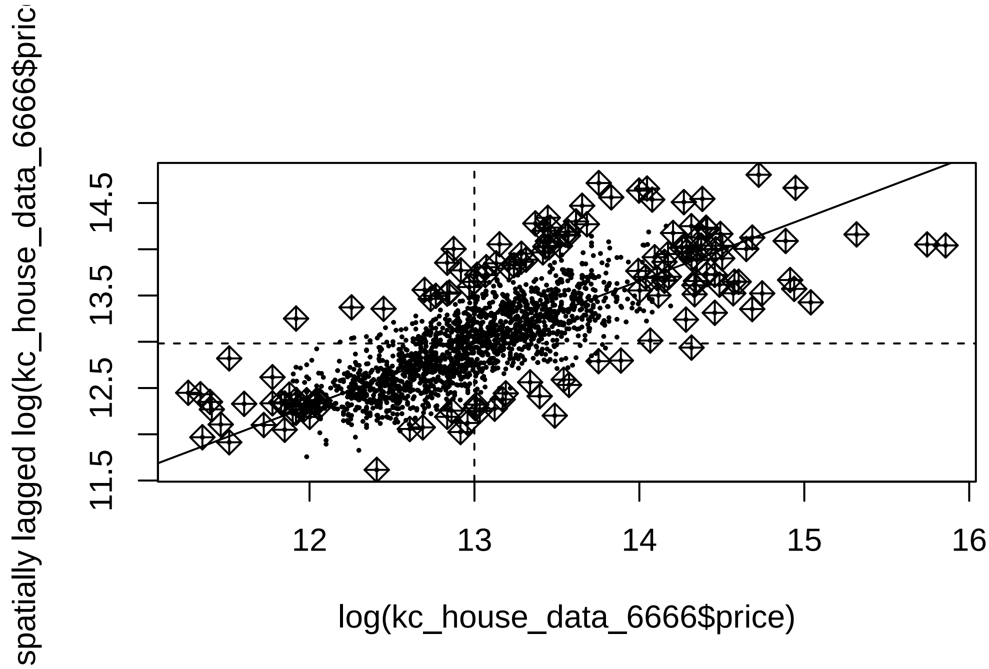
```

    Global Moran I for regression residuals

data:
model: lm(formula = mod3, data = kc_house_data_6666)
```

```
weights: kc_house_data_6666_W

Moran I statistic standard deviate = 14.429, p-value <
0.00000000000000022
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
    0.2493169179    -0.0031956991     0.0003062782
```

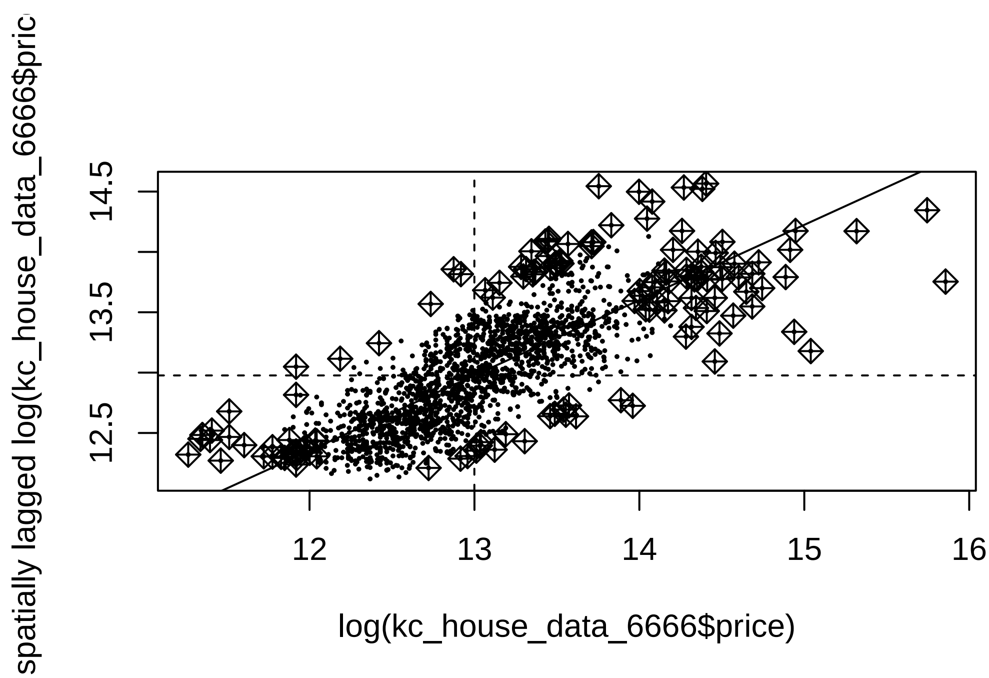
```
lm.morantest(hedon3_seed, kc_house_data_6666_W10)
```

```

    Global Moran I for regression residuals

data:
model: lm(formula = mod3, data = kc_house_data_6666)
weights: kc_house_data_6666_W10

Moran I statistic standard deviate = 23.341, p-value <
0.00000000000000022
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
   0.22243363165   -0.00257874315    0.00009293224
```

```
moran.plot(log(kc_house_data_6666$price), listw = kc_house_data_6666_W, labels = FALSE, pc
```




```
moran.plot(log(kc_house_data_6666$price), listw = kc_house_data_6666_W10, labels = FALSE,
```



```r
kc_lagrange_3 <- lm.LMtests(hedon3_seed, kc_house_data_6666_W,
                test = "all")
kc_lagrange_3
```

```
    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_data_6666)
weights: kc_house_data_6666_W

LMerr = 201.35, df = 1, p-value < 0.00000000000000022


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_data_6666)
weights: kc_house_data_6666_W

LMlag = 158.33, df = 1, p-value < 0.00000000000000022


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_data_6666)
weights: kc_house_data_6666_W

RLMerr = 58.563, df = 1, p-value = 0.00000000000001965


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_data_6666)
weights: kc_house_data_6666_W

RLMlag = 15.537, df = 1, p-value = 0.00008091


    Lagrange multiplier diagnostics for spatial dependence
```

```
data:
model: lm(formula = mod3, data = kc_house_data_6666)
weights: kc_house_data_6666_W

SARMA = 216.89, df = 2, p-value < 0.00000000000000022
```

```r
kc_lagrange_10 <- lm.LMtests(hedon3_seed, kc_house_data_6666_W10,
               test = "all")
kc_lagrange_10
```

```
    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_data_6666)
weights: kc_house_data_6666_W10

LMerr = 516.64, df = 1, p-value < 0.00000000000000022


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_data_6666)
weights: kc_house_data_6666_W10

LMlag = 384.36, df = 1, p-value < 0.00000000000000022


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_data_6666)
weights: kc_house_data_6666_W10

RLMerr = 195.48, df = 1, p-value < 0.00000000000000022


    Lagrange multiplier diagnostics for spatial dependence
```

```
data:
model: lm(formula = mod3, data = kc_house_data_6666)
weights: kc_house_data_6666_W10

RLMlag = 63.197, df = 1, p-value = 0.000000000000001887


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_data_6666)
weights: kc_house_data_6666_W10

SARMA = 579.84, df = 2, p-value < 0.00000000000000022
```

Står ovenfor et lokalt fenomen.

```r
SDEM_seed <- errorsarlm(mod3, data = kc_house_data_6666, listw = kc_house_data_6666_W, Dur
```

```
Warning in errorsarlm(mod3, data = kc_house_data_6666, listw = kc_house_data_6666_W, : invers
  reciprocal condition number = 3.66948e-22 - using numerical Hessian.
```

```r
SLX_seed <- lmSLX(mod3, data = kc_house_data_6666, listw = kc_house_data_6666_W, Durbin =
```

```r
SEM_seed <- errorsarlm(mod3, data = kc_house_data_6666,
                       listw = kc_house_data_6666_W,
                       Durbin = FALSE)
```

```
Warning in errorsarlm(mod3, data = kc_house_data_6666, listw = kc_house_data_6666_W, : invers
  reciprocal condition number = 2.98752e-22 - using numerical Hessian.
```

```r
summary(impacts(SDEM_seed), zstats = TRUE)
```

```
Impact measures (SDEM, estimable, n):
                          Direct        Indirect          Total
bedrooms           -55451.6219980  -4613.17433117 -60064.7963291
bathrooms           53626.4113799  36980.17371122  90606.5850911
sqft_living           175.7742652     30.22786172    206.0021269
```

```
sqft_lot              0.2824354     -0.08160875      0.2008266
sqft_above          152.7660773    -32.85655989    119.9095174
floors           -91335.2230838  75552.21163843 -15783.0114454
grade             15609.5928986  30804.80464857  46414.3975471
yr_built           -639.1704395  -2561.41094245  -3200.5813819
yr_renovated          5.1995105     -2.76274016      2.4367704
waterfront       622560.2731168 218044.97779100 840605.2509078
condition         30130.1753333  31557.01839360  61687.1937269
view              64083.6941345 -40006.85519396  24076.8389406
dist_cbd_km       -2569.4234501  -6284.40921448  -8853.8326646
EHD_percen          449.6163607  -1774.67442839  -1325.0580677
low                1306.5453784 241823.43325007 243129.9786285
high              69059.4247645 191089.31456117 260148.7393256
year_month2014-06  18133.0425458  16084.89596899  34217.9385148
year_month2014-07   6034.5327081 -42500.45736095 -36465.9246528
year_month2014-08   6093.5118217   3378.45043745   9471.9622592
year_month2014-09   1423.5814432  62437.09002176  63860.6714649
year_month2014-10  14499.9452150 -18351.57378083  -3851.6285658
year_month2014-11   2235.9386207 -33855.95614274 -31620.0175221
year_month2014-12 -13549.6890497  -8142.87636377 -21692.5654135
year_month2015-01    -65.0910468 -39621.06434916 -39686.1553960
year_month2015-02  10586.9531230  87108.09979248  97695.0529155
year_month2015-03  39246.5463108  66207.58639561 105454.1327064
year_month2015-04  49360.6422879   7192.13837802  56552.7806659
year_month2015-05   8095.1445820 -19177.71676235 -11082.5721803
========================================================
Standard errors:
                          Direct        Indirect          Total
bedrooms            6711.6855023  12712.1182210  15758.7284291
bathrooms          11209.2017677  21798.9143461  27380.6136712
sqft_living           15.4918048     29.7984216     37.2055417
sqft_lot               0.1000278      0.1776749      0.2047074
sqft_above            15.4315968     29.5223135     36.5351351
floors             12550.1550132  21670.2776284  25765.2918425
grade               7391.5072563  13671.4425120  16302.0183553
yr_built             262.5168786    439.0488801    501.7116318
yr_renovated          13.0421630     25.4144237     32.0131830
waterfront         69937.4264709 166283.9061562 200946.6595742
condition           7875.6460222  15294.7835801  19036.1290497
view                7147.0650340  13206.2274690  15402.7050972
dist_cbd_km         4797.1119871   4981.3569659   1005.0878539
EHD_percen           642.1485972    725.4079865    429.0027641
low               140847.4122912 178157.2625623 142993.0436437
```

```
high               98187.8613508 124693.2308738 101617.7056047
year_month2014-06  22924.7276570  46004.3468202  57849.4726113
year_month2014-07  23402.1207882  48077.0462521  60718.4863822
year_month2014-08  23069.3548625  46263.4235249  58297.5703325
year_month2014-09  23968.6053126  48683.2541736  61924.3880882
year_month2014-10  24151.5254898  48709.5540237  61352.6343275
year_month2014-11  24941.2040139  49712.5596154  62628.1163299
year_month2014-12  24671.5491069  48353.8240097  61544.8249795
year_month2015-01  28310.7779466  55838.4927300  70669.0977056
year_month2015-02  25851.1053121  51172.7437992  64496.1881445
year_month2015-03  23051.6750908  46704.0038942  58843.5108418
year_month2015-04  22718.2244616  45827.0751594  57549.2131835
year_month2015-05  32015.8953309  63790.3336579  81004.9933381
========================================================
Z-values:
                        Direct    Indirect       Total
bedrooms          -8.261951782 -0.36289580 -3.81152557
bathrooms          4.784141859  1.69642273  3.30915100
sqft_living       11.346274206  1.01441151  5.53686676
sqft_lot           2.823568526 -0.45931503  0.98104223
sqft_above         9.899563823 -1.11293987  3.28203295
floors            -7.277617128  3.48644410 -0.61256870
grade              2.111828123  2.25322270  2.84715650
yr_built          -2.434778453 -5.83399949 -6.37932465
yr_renovated       0.398669342 -0.10870757  0.07611772
waterfront         8.901675462  1.31128131  4.18322580
condition          3.825740168  2.06325367  3.24053244
view               8.966435009 -3.02939316  1.56315652
dist_cbd_km       -0.535618818 -1.26158580 -8.80901369
EHD_percen         0.700174948 -2.44645008 -3.08869354
low                0.009276318  1.35735939  1.70029235
high               0.703339739  1.53247545  2.56007295
year_month2014-06  0.790981809  0.34963861  0.59149958
year_month2014-07  0.257862643 -0.88400725 -0.60057368
year_month2014-08  0.264138805  0.07302638  0.16247611
year_month2014-09  0.059393587  1.28251677  1.03126851
year_month2014-10  0.600373886 -0.37675512 -0.06277854
year_month2014-11  0.089648383 -0.68103426 -0.50488534
year_month2014-12 -0.549203011 -0.16840191 -0.35246774
year_month2015-01 -0.002299161 -0.70956543 -0.56157722
year_month2015-02  0.409535801  1.70223626  1.51474150
year_month2015-03  1.702546394  1.41759980  1.79211150
year_month2015-04  2.172733277  0.15694081  0.98268556
```

```
year_month2015-05  0.252847671 -0.30063672 -0.13681344

p-values:
                  Direct                 Indirect        Total
bedrooms          0.00000000000000022204 0.71668272      0.00013811
bathrooms         0.00000171719379271629 0.08980585      0.00093579
sqft_living       < 0.000000000000000222 0.31038644      0.00000003079306
sqft_lot          0.00474923             0.64600795      0.32657192
sqft_above        < 0.000000000000000222 0.26573425      0.00103062
floors            0.00000000000033972825 0.00048949      0.54016156
grade             0.03470119             0.02424511      0.00441117
yr_built          0.01490091             0.0000000054114 0.00000000017787
yr_renovated      0.69013686             0.91343444      0.93932545
waterfront        < 0.000000000000000222 0.18976274      0.00002874016797
condition         0.00013038             0.03908853      0.00119307
view              < 0.000000000000000222 0.00245046      0.11801578
dist_cbd_km       0.59222202             0.20709787      < 0.000000000000000222
EHD_percen        0.48381805             0.01442708      0.00201039
low               0.99259868             0.17466705      0.08907595
high              0.48184405             0.12540515      0.01046502
year_month2014-06 0.42895461             0.72660993      0.55418574
year_month2014-07 0.79651292             0.37669230      0.54812397
year_month2014-08 0.79167296             0.94178512      0.87093094
year_month2014-09 0.95263862             0.19966143      0.30241492
year_month2014-10 0.54825709             0.70635560      0.94994286
year_month2014-11 0.92856663             0.49584981      0.61363937
year_month2014-12 0.58286614             0.86626710      0.72448751
year_month2015-01 0.99816554             0.47797366      0.57440410
year_month2015-02 0.68214650             0.08871109      0.12983788
year_month2015-03 0.08865299             0.15630764      0.07311511
year_month2015-04 0.02980040             0.87529150      0.32576222
year_month2015-05 0.80038593             0.76369153      0.89117826
```

```r
huxreg("SEM" = SEM_seed, "OLS" = hedon3_seed,
    error_format = "[{statistic}]",
    note = "{stars}. T statistic in brackets.")
```

```r
LR.Sarlm(SDEM_seed, SEM_seed)
```

```

    Likelihood ratio for spatial linear models
```

```
data:
Likelihood ratio = 113.09, df = 28, p-value = 0.000000000003465
sample estimates:
Log likelihood of SDEM_seed  Log likelihood of SEM_seed
                  -25688.38                   -25744.92
```

```r
LR.Sarlm(SDEM_seed, SLX_seed)
```

```
    Likelihood ratio for spatial linear models

data:
Likelihood ratio = 149.89, df = 1, p-value < 0.00000000000000022
sample estimates:
Log likelihood of SDEM_seed  Log likelihood of SLX_seed
                  -25688.38                   -25763.32
```

```r
LR1.Sarlm(SDEM_seed)
```

```
    Likelihood Ratio diagnostics for spatial dependence

data:
Likelihood ratio = 149.89, df = 1, p-value < 0.00000000000000022
sample estimates:
Log likelihood of spatial error model           Log likelihood of OLS fit y
                            -25688.38                             -25763.32
```

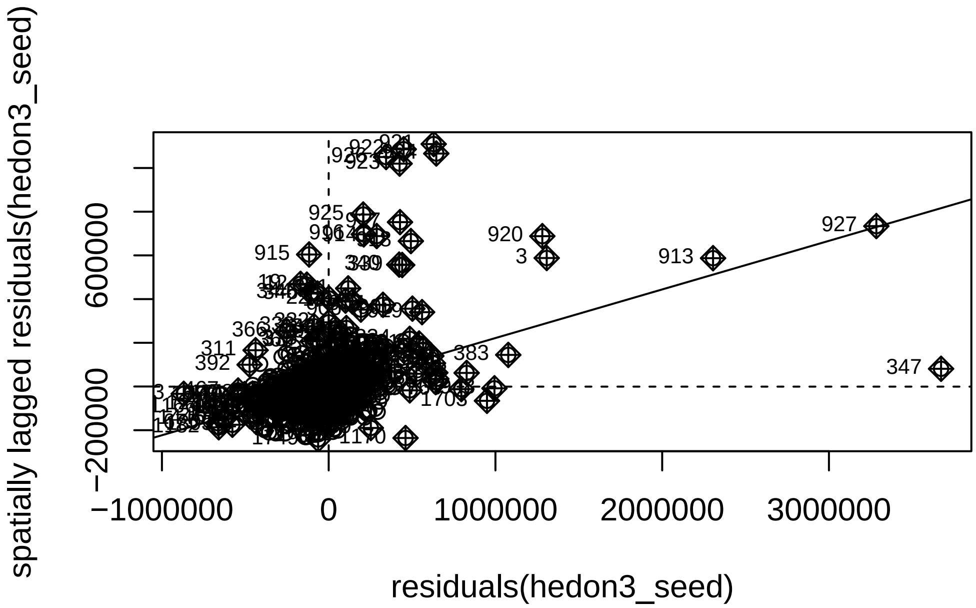
```r
Hausman.test(SEM_seed)
```

```
    Spatial Hausman test (asymptotic)

data:  NULL
Hausman test = 91.271, df = 29, p-value = 0.00000002317
```

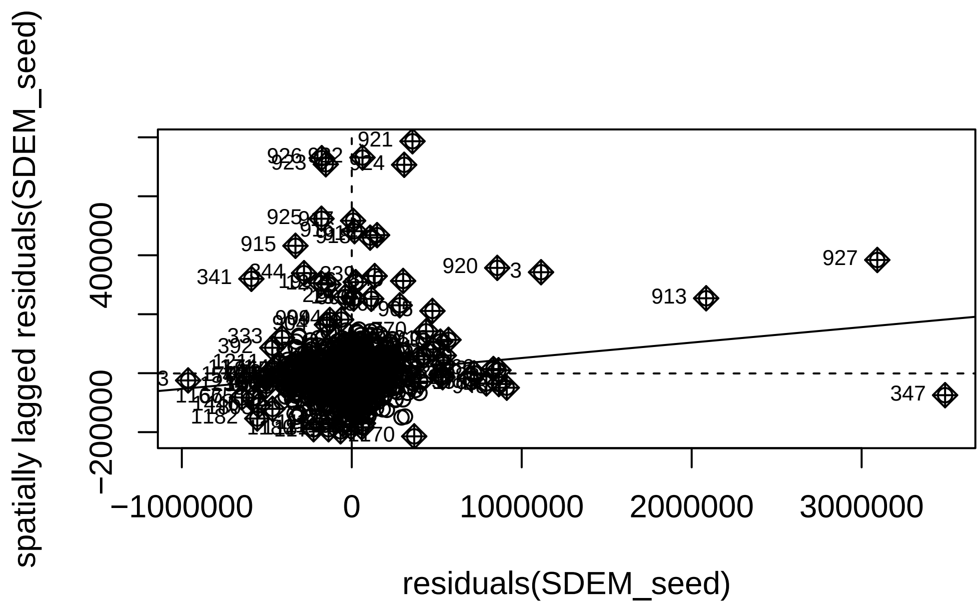
```r
bptest.Sarlm(SEM_seed, studentize = TRUE)
```

```
	studentized Breusch-Pagan test

data:
BP = 472.28, df = 28, p-value < 0.00000000000000022
```

```r
moran.plot(residuals(hedon3_seed), listw = kc_house_data_6666_W10)
```




```r
moran.plot(residuals(SDEM_seed), listw = kc_house_data_6666_W10)
```




```
moran.test(residuals(SDEM_seed), listw = kc_house_data_6666_W10)
```

```
	Moran I test under randomisation

data:  residuals(SDEM_seed)
weights: kc_house_data_6666_W10

Moran I statistic standard deviate = 5.5663, p-value = 0.00000001301
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
    0.05236473632    -0.00053022269     0.00009030298
```

Oppgave 9

```
set.seed(442)
kc_houses_env_var_omit_2000 <- kc_houses_env_var_omit[sample(1:nrow(
    kc_houses_env_var_omit), 2000, replace = FALSE), ]
```

```r
hedon3_2000 <- lm(mod3, data = kc_houses_env_var_omit_2000)
```

```r
huxreg("Full" = hedon3, "2000 Seed" = hedon3_2000, "666 Seed" = hedon3_seed,
    error_format = "[{statistic}]",
    note = "{stars}. T statistic in brackets.")
```

```r
kc_house_data_2000_mat_nb <- knearneigh(kc_houses_env_var_omit_2000, k = 3)
```

```
Warning in knearneigh(kc_houses_env_var_omit_2000, k = 3): knearneigh: identical
points found
```

```
Warning in knearneigh(kc_houses_env_var_omit_2000, k = 3): knearneigh: kd_tree
not available for identical points
```

```r
kc_house_data_2000_nb <- knn2nb(kc_house_data_2000_mat_nb)
kc_house_data_2000_W <- nb2listw(kc_house_data_2000_nb, style = "W")
kc_house_data_2000_mat_nb10 <- knearneigh(kc_houses_env_var_omit_2000, k = 10)
```

```
Warning in knearneigh(kc_houses_env_var_omit_2000, k = 10): knearneigh:
identical points found
```

```
Warning in knearneigh(kc_houses_env_var_omit_2000, k = 10): knearneigh: kd_tree
not available for identical points
```

```r
kc_house_data_2000_nb10 <- knn2nb(kc_house_data_2000_mat_nb10)
kc_house_data_2000_W10 <- nb2listw(kc_house_data_2000_nb10, style = "W")
```

```r
lm.morantest(hedon3_2000, kc_house_data_2000_W)
```

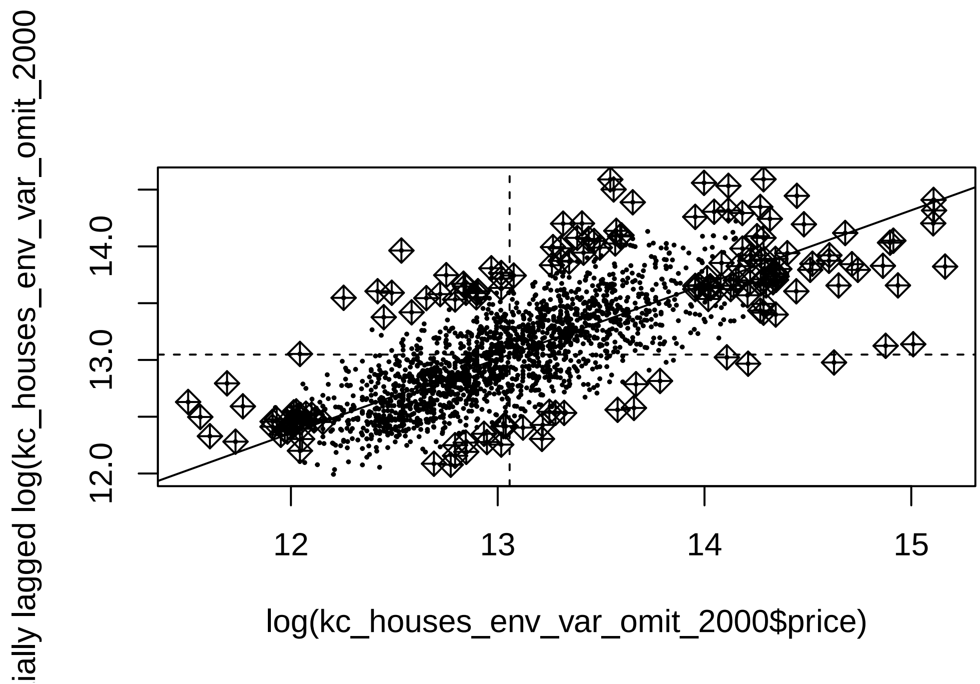
```

    Global Moran I for regression residuals

data:
model: lm(formula = mod3, data = kc_houses_env_var_omit_2000)
weights: kc_house_data_2000_W
```

```
Moran I statistic standard deviate = 19.702, p-value <
0.00000000000000022
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
    0.3293899740    -0.0029972881     0.0002846206
```

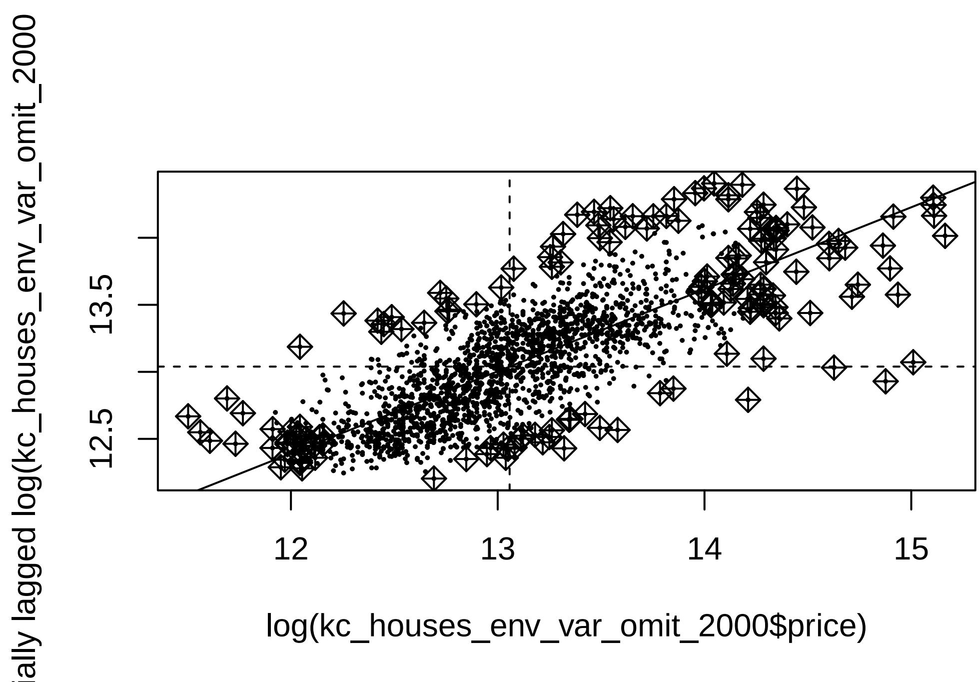
```
lm.morantest(hedon3_2000, kc_house_data_2000_W10)
```

```

    Global Moran I for regression residuals

data:
model: lm(formula = mod3, data = kc_houses_env_var_omit_2000)
weights: kc_house_data_2000_W10

Moran I statistic standard deviate = 31.769, p-value <
0.00000000000000022
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
   0.29449186906   -0.00249822173    0.00008739112
```

```
moran.plot(log(kc_houses_env_var_omit_2000$price), listw = kc_house_data_2000_W, labels =
```




```
moran.plot(log(kc_houses_env_var_omit_2000$price), listw = kc_house_data_2000_W10, labels
```



```r
kc_lagrange_3_2000 <- lm.LMtests(hedon3_2000, kc_house_data_2000_W,
               test = "all")
kc_lagrange_3_2000
```

```
    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_houses_env_var_omit_2000)
weights: kc_house_data_2000_W

LMerr = 378.11, df = 1, p-value < 0.00000000000000022


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_houses_env_var_omit_2000)
weights: kc_house_data_2000_W

LMlag = 286.6, df = 1, p-value < 0.00000000000000022


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_houses_env_var_omit_2000)
weights: kc_house_data_2000_W

RLMerr = 117.34, df = 1, p-value < 0.00000000000000022


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_houses_env_var_omit_2000)
weights: kc_house_data_2000_W

RLMlag = 25.831, df = 1, p-value = 0.0000003727


    Lagrange multiplier diagnostics for spatial dependence
```

```
data:
model: lm(formula = mod3, data = kc_houses_env_var_omit_2000)
weights: kc_house_data_2000_W

SARMA = 403.94, df = 2, p-value < 0.00000000000000022
```

```r
kc_lagrange_10_2000 <- lm.LMtests(hedon3_2000, kc_house_data_2000_W10,
               test = "all")
kc_lagrange_10_2000
```

```
    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_houses_env_var_omit_2000)
weights: kc_house_data_2000_W10

LMerr = 962.92, df = 1, p-value < 0.00000000000000022


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_houses_env_var_omit_2000)
weights: kc_house_data_2000_W10

LMlag = 637.61, df = 1, p-value < 0.00000000000000022


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_houses_env_var_omit_2000)
weights: kc_house_data_2000_W10

RLMerr = 414.65, df = 1, p-value < 0.00000000000000022


    Lagrange multiplier diagnostics for spatial dependence
```

```
data:
model: lm(formula = mod3, data = kc_houses_env_var_omit_2000)
weights: kc_house_data_2000_W10

RLMlag = 89.343, df = 1, p-value < 0.00000000000000022


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_houses_env_var_omit_2000)
weights: kc_house_data_2000_W10

SARMA = 1052.3, df = 2, p-value < 0.00000000000000022
```

```
SDEM_2000 <- errorsarlm(mod3, data = kc_houses_env_var_omit_2000, listw = kc_house_data_20
                        Durbin = TRUE)
```

```
Warning in errorsarlm(mod3, data = kc_houses_env_var_omit_2000, listw = kc_house_data_2000_W
  reciprocal condition number = 6.28505e-22 - using numerical Hessian.
```

```
SLX_2000 <- lmSLX(mod3, data = kc_houses_env_var_omit_2000, listw = kc_house_data_2000_W,
```

```
SEM_2000 <- errorsarlm(mod3, data = kc_houses_env_var_omit_2000, listw = kc_house_data_200
```

```
Warning in errorsarlm(mod3, data = kc_houses_env_var_omit_2000, listw = kc_house_data_2000_W
  reciprocal condition number = 5.33723e-22 - using numerical Hessian.
```

```
summary(impacts(SDEM_2000), zstats = TRUE)
```

```
Impact measures (SDEM, estimable, n):
                       Direct        Indirect           Total
bedrooms         -30592.94178869  -20105.0802651 -50698.0220537
bathrooms         34762.67276136     146.1957466  34908.8685079
sqft_living         125.47461649      60.0165781    185.4911946
sqft_lot              0.04180504      -0.2380269     -0.1962219
sqft_above           74.82343808     -29.4992447     45.3241933
floors           -56874.13527711   13574.7704869 -43299.3647902
```

```
grade                68566.63243022   13860.5656514  82427.1980817
yr_built              -480.79752481    -536.7049615  -1017.5024863
yr_renovated            34.12060048      46.1510549     80.2716554
waterfront          681300.02810705 -155449.6844768 525850.3436303
condition            40224.93608819   17962.6565719  58187.5926601
view                 46809.91610667   -5981.3518441  40828.5642626
dist_cbd_km          11002.49341959  -20094.8088868  -9092.3154672
EHD_percen            -817.64003942     334.9963959   -482.6436436
low                 117037.96717950  192433.4956686 309471.4628481
high                 53129.58720850  392429.0258539 445558.6130624
year_month2014-06    20375.86236089   -1555.6342206  18820.2281403
year_month2014-07    18879.30725331   41640.2303234  60519.5375767
year_month2014-08    19020.34065553   20948.8109692  39969.1516247
year_month2014-09    25168.14470943   34714.7696766  59882.9143860
year_month2014-10    34230.43602873  -24052.3807848  10178.0552439
year_month2014-11     4267.26852115      29.3847236   4296.6532448
year_month2014-12    22606.33704884   18754.5874007  41360.9244496
year_month2015-01     2972.13384669  -33048.5284444 -30076.3945977
year_month2015-02    52910.35193412   42134.1320326  95044.4839667
year_month2015-03    43584.39129506  -12639.3068686  30945.0844265
year_month2015-04    51533.76818229   19698.3516934  71232.1198756
year_month2015-05    98422.75381824   82466.8078649 180889.5616831
========================================================
Standard errors:
                          Direct        Indirect          Total
bedrooms             5556.4555790  11434.3654400  14600.5454176
bathrooms            8992.6792246  18062.9648216  23232.5842142
sqft_living            12.5016002     26.2079447     33.1120633
sqft_lot                0.1004654      0.2102977      0.2495483
sqft_above             12.2717942     24.8060831     30.9543016
floors              10060.0946881  18930.0798333  23391.0629156
grade                5949.7550606  11308.1503730  14013.2430856
yr_built              217.2640681    391.3989410    476.1497088
yr_renovated           10.4884595     22.1129056     28.0814780
waterfront          56005.2072961 110394.8163550 137782.4489490
condition            6557.3812379  13100.8285277  16590.2266099
view                 5952.6445018  11528.1713800  13923.1300046
dist_cbd_km          4914.4598926   5105.6044897    949.7498928
EHD_percen            488.6160800    581.9310282    410.1847858
low                120256.1771198 168279.2846075 158001.0194239
high                84340.1153851 110346.9325864  94442.1302367
year_month2014-06   18079.6082844  36948.3590203  47522.2569141
year_month2014-07   18692.7108899  38353.6603310  49225.6242856
```

```
year_month2014-08  19241.2830628  39193.0950351  50730.4503563
year_month2014-09  19279.9278712  39857.5343023  51580.3919217
year_month2014-10  18966.0939959  38950.5714097  49813.5090193
year_month2014-11  21167.6967106  43605.0687216  56060.1109822
year_month2014-12  19819.5980164  40719.8851218  51684.0825210
year_month2015-01  23649.1681181  49092.4462474  62674.1205507
year_month2015-02  21469.2743616  43037.0984653  55826.0681634
year_month2015-03  19132.3135819  38582.0926756  49926.9293161
year_month2015-04  18351.2726377  36972.5324272  47779.0929162
year_month2015-05  24699.2320078  51255.6242155  65833.7783096
========================================================
Z-values:
                      Direct      Indirect       Total
bedrooms          -5.5058376 -1.7583031057 -3.47233755
bathrooms          3.8656636  0.0080936739  1.50258224
sqft_living       10.0366845  2.2900146826  5.60192196
sqft_lot           0.4161138 -1.1318570080 -0.78630834
sqft_above         6.0971882 -1.1891939824  1.46422924
floors            -5.6534394  0.7171005409 -1.85110719
grade             11.5242782  1.2257146566  5.88209293
yr_built          -2.2129638 -1.3712478633 -2.13693817
yr_renovated       3.2531565  2.0870642524  2.85852673
waterfront        12.1649407 -1.4081248523  3.81652633
condition          6.1342988  1.3711084405  3.50734164
view               7.8637177 -0.5188465410  2.93242714
dist_cbd_km        2.2388001 -3.9358334410 -9.57337878
EHD_percen        -1.6733793  0.5756634028 -1.17664931
low                0.9732387  1.1435364496  1.95866751
high               0.6299444  3.5563202044  4.71779503
year_month2014-06  1.1270080 -0.0421029313  0.39602976
year_month2014-07  1.0099823  1.0856911691  1.22943159
year_month2014-08  0.9885173  0.5345025942  0.78787299
year_month2014-09  1.3054066  0.8709713304  1.16096276
year_month2014-10  1.8048227 -0.6175103449  0.20432319
year_month2014-11  0.2015934  0.0006738832  0.07664368
year_month2014-12  1.1406052  0.4605756461  0.80026427
year_month2015-01  0.1256760 -0.6731896854 -0.47988539
year_month2015-02  2.4644686  0.9790188822  1.70251080
year_month2015-03  2.2780513 -0.3275951612  0.61980748
year_month2015-04  2.8081850  0.5327834043  1.49086380
year_month2015-05  3.9848508  1.6089318807  2.74767097

p-values:
```

```
                    Direct                  Indirect    Total
bedrooms            0.0000000367417216651   0.07869595  0.00051595
bathrooms           0.00011079              0.99354225  0.13294681
sqft_living         < 0.000000000000000222  0.02202047  0.0000000211988
sqft_lot            0.67732676              0.25769456  0.43168687
sqft_above          0.0000000010795042638   0.23436334  0.14313132
floors              0.0000000157268611467   0.47331206  0.06415413
grade               < 0.000000000000000222  0.22030607  0.0000000040511
yr_built            0.02690014              0.17029770  0.03260302
yr_renovated        0.00114131              0.03688233  0.00425613
waterfront          < 0.000000000000000222  0.15909410  0.00013534
condition           0.0000000008553560082   0.17034115  0.00045261
view                0.0000000000000037748   0.60386776  0.00336324
dist_cbd_km         0.02516892              0.000082908 < 0.000000000000000222
EHD_percen          0.09425265              0.56484272  0.23933551
low                 0.33043467              0.25281593  0.05015174
high                0.52873093              0.00037609  0.0000023841451
year_month2014-06 0.25973912                0.96641664  0.69208307
year_month2014-07 0.31250377                0.27761565  0.21891003
year_month2014-08 0.32289938                0.59299386  0.43077100
year_month2014-09 0.19175444                0.38376981  0.24565704
year_month2014-10 0.07110244                0.53689816  0.83810095
year_month2014-11 0.84023458                0.99946232  0.93890701
year_month2014-12 0.25403424                0.64510309  0.42355770
year_month2015-01 0.89998837                0.50082662  0.63130889
year_month2015-02 0.01372166                0.32757065  0.08865966
year_month2015-03 0.02272352                0.74321778  0.53538454
year_month2015-04 0.00498216                0.59418352  0.13599726
year_month2015-05 0.0000675225448709682     0.10763124  0.00600202
```

```r
huxreg("SEM" = SEM_2000, "OLS" = hedon3_2000,
    error_format = "[{statistic}]",
    note = "{stars}. T statistic in brackets.")
```

```r
LR.Sarlm(SDEM_2000, SEM_2000)
```

```
    Likelihood ratio for spatial linear models

data:
Likelihood ratio = 90.376, df = 28, p-value = 0.00000001732
```

```
sample estimates:
Log likelihood of SDEM_2000  Log likelihood of SEM_2000
                  -26860.32                    -26905.51
```

```r
LR.Sarlm(SDEM_2000, SLX_2000)
```

```

    Likelihood ratio for spatial linear models

data:
Likelihood ratio = 307.64, df = 1, p-value < 0.00000000000000022
sample estimates:
Log likelihood of SDEM_2000  Log likelihood of SLX_2000
                  -26860.32                    -27014.14
```

```r
LR1.Sarlm(SDEM_2000)
```

```

    Likelihood Ratio diagnostics for spatial dependence

data:
Likelihood ratio = 307.64, df = 1, p-value < 0.00000000000000022
sample estimates:
Log likelihood of spatial error model           Log likelihood of OLS fit y
                            -26860.32                             -27014.14
```

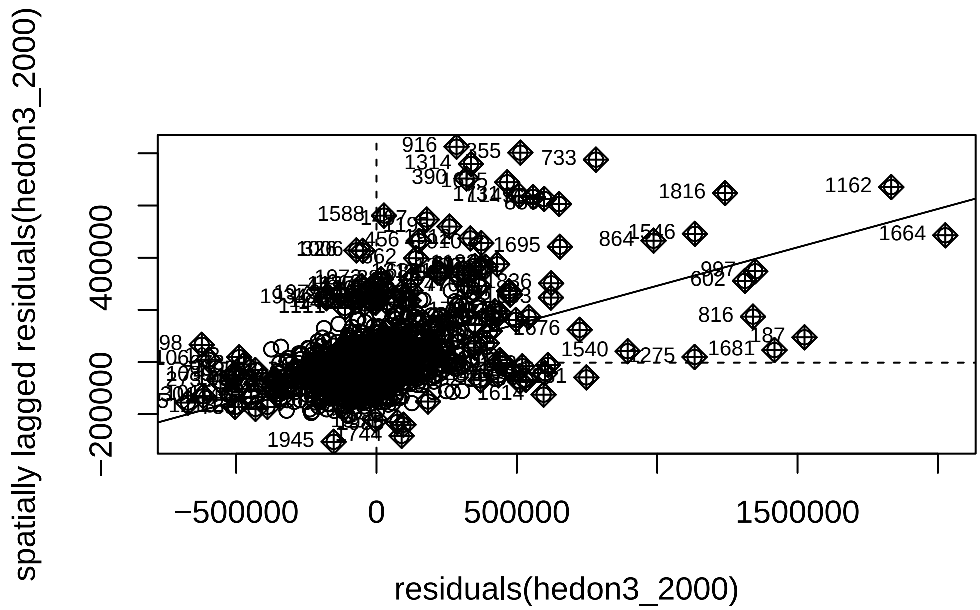
```r
Hausman.test(SEM_2000)
```

```

    Spatial Hausman test (asymptotic)

data:  NULL
Hausman test = 87.794, df = 29, p-value = 0.00000007926
```

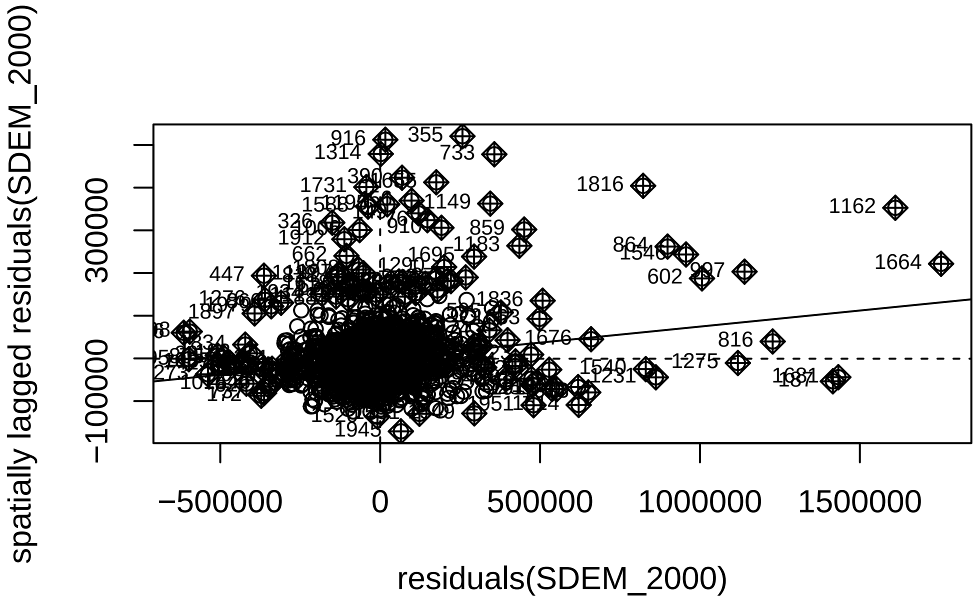
```r
bptest.Sarlm(SEM_2000, studentize = TRUE)
```

```
	studentized Breusch-Pagan test

data:
BP = 350.25, df = 28, p-value < 0.00000000000000022
```

```
moran.plot(residuals(hedon3_2000), listw = kc_house_data_2000_W10)
```




```
moran.plot(residuals(SDEM_2000), listw = kc_house_data_2000_W10)
```




```
moran.test(residuals(SDEM_2000), listw = kc_house_data_2000_W10)
```

```
	Moran I test under randomisation

data:  residuals(SDEM_2000)
weights: kc_house_data_2000_W10

Moran I statistic standard deviate = 8.052, p-value =
0.0000000000000004073
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
     0.0752019576     -0.0005002501      0.0000883917
```

References

Bishop, Kelly C., Nicolai V. Kuminoff, H. Spencer Banzhaf, Kevin J. Boyle, Kathrine von Gravenitz, Jaren C. Pope, V. Kerry Smith, og Christopher D. Timmins. 2020. «Best Practices for Using Hedonic Property Value Models to Measure Willingness to Pay for Environmental Quality». *Review of Environmental Economics and Policy* 14 (2): 260–81. https://doi.org/10.1093/reep/reaa001.

	Hedon1	Hedon2	Hedon3
(Intercept)	6210939.368 ***	753975.919 ***	2061277.768 ***
	[44.671]	[4.710]	[15.431]
bedrooms	-39049.632 ***	-25328.756 ***	-28985.854 ***
	[-19.156]	[-14.673]	[-16.344]
bathrooms	46453.883 ***	27307.508 ***	32395.209 ***
	[13.238]	[9.211]	[10.627]
sqft_living	172.124 ***	133.612 ***	136.077 ***
	[37.305]	[34.160]	[33.757]
sqft_lot	-0.260 ***	0.170 ***	0.145 ***
	[-7.084]	[5.062]	[4.415]
sqft_above	-2.100	95.399 ***	72.713 ***
	[-0.470]	[23.754]	[17.943]
floors	24564.665 ***	-67284.965 ***	-37074.484 ***
	[6.558]	[-19.390]	[-11.038]
grade	124528.853 ***	68800.113 ***	72917.129 ***
	[57.276]	[35.485]	[36.707]
yr_built	-3586.252 ***	-695.032 ***	-1277.559 ***
	[-50.384]	[-9.384]	[-18.400]
yr_renovated	9.073 *	27.281 ***	25.515 ***
	[2.310]	[8.189]	[7.470]
waterfront	574412.210 ***	609996.992 ***	605095.325 ***
	[30.786]	[38.808]	[37.367]
condition	19563.382 ***	30535.045 ***	31399.330 ***
	[7.763]	[14.203]	[14.269]
view	44765.891 ***	49887.512 ***	46864.744 ***
	[19.781]	[26.008]	[23.877]
year_month2014-06	3621.508	8905.815	7520.424
	[0.520]	[1.519]	[1.244]
year_month2014-07	-273.639	4115.231	3527.267
	[-0.039]	[0.705]	[0.586]
year_month2014-08	4935.598	10538.047	8170.200

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
2.14e+04	1.01e+15				
2.14e+04	1e+15	12	5.32e+12	9.47	1.29e-18

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
2.12e+04	6.96e+14				
2.12e+04	6.9e+14	12	5.84e+12	14.9	9.97e-32

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
2.14e+04	7.59e+14				
2.14e+04	7.53e+14	12	5.97e+12	14.1	7.69e-30

	Full	seed
(Intercept)	2061277.768 ***	2951606.497 ***
	[15.431]	[5.856]
bedrooms	-28985.854 ***	-56078.935 ***
	[-16.344]	[-7.850]
bathrooms	32395.209 ***	55620.735 ***
	[10.627]	[4.675]
sqft_living	136.077 ***	180.269 ***
	[33.757]	[10.946]
sqft_lot	0.145 ***	0.234 *
	[4.415]	[2.216]
sqft_above	72.713 ***	135.065 ***
	[17.943]	[8.278]
floors	-37074.484 ***	-62111.658 ***
	[-11.038]	[-4.828]
grade	72917.129 ***	35767.297 ***
	[36.707]	[4.625]
yr_built	-1277.559 ***	-1605.519 ***
	[-18.400]	[-6.107]
yr_renovated	25.515 ***	4.871
	[7.470]	[0.354]
waterfront	605095.325 ***	535045.039 ***
	[37.367]	[7.286]
condition	31399.330 ***	26646.594 **
	[14.269]	[3.201]
view	46864.744 ***	58143.104 ***
	[23.877]	[7.790]
dist_cbd_km	-9347.083 ***	-10371.011 ***
	[-58.299]	[-16.627]
EHD_percen	-1174.710 ***	-1306.890 ***
	[-15.393]	[-4.523]
low	165562.375 ***	172068.567

	SEM	OLS
(Intercept)	1517018.818 **	2951606.497 ***
	[2.978]	[5.856]
bedrooms	-56861.333 ***	-56078.935 ***
	[-8.620]	[-7.850]
bathrooms	47921.645 ***	55620.735 ***
	[4.423]	[4.675]
sqft_living	176.457 ***	180.269 ***
	[11.696]	[10.946]
sqft_lot	0.278 **	0.234 *
	[2.738]	[2.216]
sqft_above	147.353 ***	135.065 ***
	[9.745]	[8.278]
floors	-90036.310 ***	-62111.658 ***
	[-7.151]	[-4.828]
grade	21291.047 **	35767.297 ***
	[2.875]	[4.625]
yr_built	-774.223 **	-1605.519 ***
	[-2.919]	[-6.107]
yr_renovated	2.695	4.871
	[0.215]	[0.354]
waterfront	560430.090 ***	535045.039 ***
	[8.418]	[7.286]
condition	20057.266 **	26646.594 **
	[2.622]	[3.201]
view	69681.781 ***	58143.104 ***
	[9.622]	[7.790]
dist_cbd_km	-11551.471 ***	-10371.011 ***
	[-14.198]	[-16.627]
EHD_percen	-1250.900 ***	-1306.890 ***
	[-3.354]	[-4.523]
low	143735.222	172068.567

	Full	2000 Seed	666 Seed
(Intercept)	2061277.768 ***	1210875.723 **	2951606.497 ***
	[15.431]	[2.786]	[5.856]
bedrooms	-28985.854 ***	-32673.993 ***	-56078.935 ***
	[-16.344]	[-5.474]	[-7.850]
bathrooms	32395.209 ***	37190.457 ***	55620.735 ***
	[10.627]	[3.854]	[4.675]
sqft_living	136.077 ***	129.767 ***	180.269 ***
	[33.757]	[9.623]	[10.946]
sqft_lot	0.145 ***	0.001	0.234 *
	[4.415]	[0.005]	[2.216]
sqft_above	72.713 ***	69.394 ***	135.065 ***
	[17.943]	[5.267]	[8.278]
floors	-37074.484 ***	-50159.047 ***	-62111.658 ***
	[-11.038]	[-4.702]	[-4.828]
grade	72917.129 ***	77406.714 ***	35767.297 ***
	[36.707]	[12.162]	[4.625]
yr_built	-1277.559 ***	-917.749 ***	-1605.519 ***
	[-18.400]	[-4.033]	[-6.107]
yr_renovated	25.515 ***	32.312 **	4.871
	[7.470]	[2.866]	[0.354]
waterfront	605095.325 ***	651420.645 ***	535045.039 ***
	[37.367]	[10.743]	[7.286]
condition	31399.330 ***	41317.349 ***	26646.594 **
	[14.269]	[5.855]	[3.201]
view	46864.744 ***	47129.031 ***	58143.104 ***
	[23.877]	[7.405]	[7.790]
dist_cbd_km	-9347.083 ***	-9361.880 ***	-10371.011 ***
	[-58.299]	[-17.962]	[-16.627]
EHD_percen	-1174.710 ***	-866.591 ***	-1306.890 ***
	[-15.393]	[-3.527]	[-4.523]
low	165562.375 ***	317959.816 ***	172068.567

	SEM	OLS
(Intercept)	493503.786	1210875.723 **
	[1.191]	[2.786]
bedrooms	-27143.081 ***	-32673.993 ***
	[-5.298]	[-5.474]
bathrooms	34985.810 ***	37190.457 ***
	[4.223]	[3.854]
sqft_living	114.684 ***	129.767 ***
	[9.876]	[9.623]
sqft_lot	0.071	0.001
	[0.710]	[0.005]
sqft_above	80.237 ***	69.394 ***
	[6.876]	[5.267]
floors	-58151.130 ***	-50159.047 ***
	[-5.900]	[-4.702]
grade	68554.269 ***	77406.714 ***
	[11.793]	[12.162]
yr_built	-449.658 *	-917.749 ***
	[-2.081]	[-4.033]
yr_renovated	23.638 *	32.312 **
	[2.448]	[2.866]
waterfront	704814.899 ***	651420.645 ***
	[13.064]	[10.743]
condition	35870.875 ***	41317.349 ***
	[5.806]	[5.855]
view	50271.932 ***	47129.031 ***
	[8.552]	[7.405]
dist_cbd_km	-10019.088 ***	-9361.880 ***
	[-13.784]	[-17.962]
EHD_percen	-1250.388 ***	-866.591 ***
	[-3.767]	[-3.527]
low	264677.218 *	317959.816 ***