Termpaper

Sindre og Morten

“Data gitt med tillatelse fra King County” ^ (**KCGISC?**).

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

```
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.

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

iv.

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

v & vi.

```
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

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

viii.

```
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

```
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
```

```
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 = FALSE)
```

```
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.   :2.466e+06   Min.   :  7060   Length:398
 Class :character   1st Qu.:1.933e+07   1st Qu.: 20586   Class :character
 Mode  :character   Median :3.362e+07   Median : 29573   Mode  :character
                    Mean   :1.616e+08   Mean   : 44019
                    3rd Qu.:5.601e+07   3rd Qu.: 43667
                    Max.   :1.526e+10   Max.   :738820

  Shape_area          Shape_len            low                 mid
 Min.   :2.466e+06   Min.   :  7060   Min.   :0.009298   Min.   :0.0000
 1st Qu.:1.933e+07   1st Qu.: 20586   1st Qu.:0.053302   1st Qu.:0.2391
 Median :3.362e+07   Median : 29573   Median :0.092424   Median :0.3339
 Mean   :1.616e+08   Mean   : 44019   Mean   :0.125013   Mean   :0.3327
 3rd Qu.:5.601e+07   3rd Qu.: 43667   3rd Qu.:0.166534   3rd Qu.:0.4261
 Max.   :1.526e+10   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.   :0.00e+00   Min.   :  1.00   Min.   :  1.00  
 1st Qu.:0.1612   1st Qu.:5.50e-06   1st Qu.: 25.00   1st Qu.: 25.00  
 Median :0.3652   Median :5.30e-04   Median : 50.00   Median : 50.00  
 Mean   :0.6046   Mean   :2.62e-02   Mean   : 50.38   Mean   : 50.38  
 3rd Qu.:0.9119   3rd Qu.:8.70e-03   3rd Qu.: 75.00   3rd Qu.: 75.00  
 Max.   :3.3682   Max.   :6.40e-01   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           Shape_area
Min.   :2.792e+06   Min.   :  8012   Length:21436       Min.   :2.792e+06
1st Qu.:2.485e+07   1st Qu.: 23500   Class :character   1st Qu.:2.281e+07
Median :4.123e+07   Median : 32920   Mode  :character   Median :3.445e+07
Mean   :1.809e+08   Mean   : 48212                      Mean   :1.750e+08
3rd Qu.:7.308e+07   3rd Qu.: 47962                      3rd Qu.:6.628e+07
Max.   :1.526e+10   Max.   :738820                      Max.   :1.526e+10
NA's   :25          NA's   :25                          NA's   :25
  Shape_len           low                 mid                high
Min.   :  8012   Min.   :0.009298   Min.   :0.06768   Min.   :0.06129
1st Qu.: 23204   1st Qu.:0.047091   1st Qu.:0.21668   1st Qu.:0.47602
Median : 31185   Median :0.074766   Median :0.30219   Median :0.61143
Mean   : 46861   Mean   :0.100082   Mean   :0.31115   Mean   :0.58877
3rd Qu.: 46624   3rd Qu.:0.133557   3rd Qu.:0.39313   3rd Qu.:0.72987
Max.   :738820   Max.   :0.501433   Max.   :0.67904   Max.   :0.88162
NA's   :25       NA's   :25         NA's   :25        NA's   :25
  EHD_percen       linguist_2       poverty_pe      POC_percen
Min.   :  1.00   Min.   : 0.450   Min.   : 1.97   Min.   : 7.54
1st Qu.: 19.00   1st Qu.: 3.120   1st Qu.: 8.93   1st Qu.:21.13
Median : 41.00   Median : 7.000   Median :13.60   Median :33.26
Mean   : 43.64   Mean   : 9.003   Mean   :16.65   Mean   :35.33
3rd Qu.: 67.00   3rd Qu.:12.730   3rd Qu.:22.95   3rd Qu.:46.34
Max.   :100.00   Max.   :40.350   Max.   :75.48   Max.   :92.70
NA's   :25       NA's   :220      NA's   :25      NA's   :25
  transporta      unemploy_2       housing_pe      traffic_pe
Min.   :12.00   Min.   : 1.000   Min.   :15.14   Min.   : 0.00
1st Qu.:18.00   1st Qu.: 3.230   1st Qu.:25.64   1st Qu.: 0.00
Median :20.00   Median : 4.310   Median :30.46   Median : 0.10
Mean   :19.77   Mean   : 4.775   Mean   :31.37   Mean   :11.52
3rd Qu.:21.00   3rd Qu.: 6.050   3rd Qu.:35.73   3rd Qu.:19.14
Max.   :26.00   Max.   :13.620   Max.   :64.87   Max.   :84.98
NA's   :25      NA's   :102      NA's   :25      NA's   :25
    diesel          ozone            PM25         toxic_rele
Min.   : 0.14   Min.   :46.73   Min.   :3.787   Min.   :   823.9
1st Qu.: 5.60   1st Qu.:49.24   1st Qu.:5.488   1st Qu.:  4143.8
Median :10.16   Median :49.97   Median :6.044   Median :  8827.6
Mean   :13.68   Mean   :51.17   Mean   :6.002   Mean   : 17251.1
3rd Qu.:16.88   3rd Qu.:52.32   3rd Qu.:6.579   3rd Qu.: 17237.2
Max.   :92.63   Max.   :62.89   Max.   :7.897   Max.   :186434.6
NA's   :25      NA's   :25      NA's   :25      NA's   :25
```

```
   hazardous_         lead_perce         superfund          facilities    
 Min.    :0.02303   Min.    : 0.24   Min.    :0.03454   Min.    :0.0523  
 1st Qu.:0.03985   1st Qu.: 5.34   1st Qu.:0.06595   1st Qu.:0.1420  
 Median :0.05160   Median :11.99   Median :0.11046   Median :0.2680  
 Mean    :0.07409   Mean    :16.60   Mean    :0.21696   Mean    :0.5248  
 3rd Qu.:0.07891   3rd Qu.:26.48   3rd Qu.:0.23841   3rd Qu.:0.7588  
 Max.    :0.63781   Max.    :54.68   Max.    :1.46778   Max.    :3.3682  
 NA's    :25        NA's    :25       NA's    :25        NA's    :25      
   wastewater          sen_pop_pe         socio_perc    
 Min.    :0.000000   Min.    :  1.0   Min.    :  1.00  
 1st Qu.:0.000003   1st Qu.: 25.0   1st Qu.: 20.00  
 Median :0.000290   Median : 48.0   Median : 43.00  
 Mean    :0.016168   Mean    : 48.1   Mean    : 44.51  
 3rd Qu.:0.002900   3rd Qu.: 71.0   3rd Qu.: 67.00  
 Max.    :0.640000   Max.    :100.0   Max.    :100.00  
 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.
```

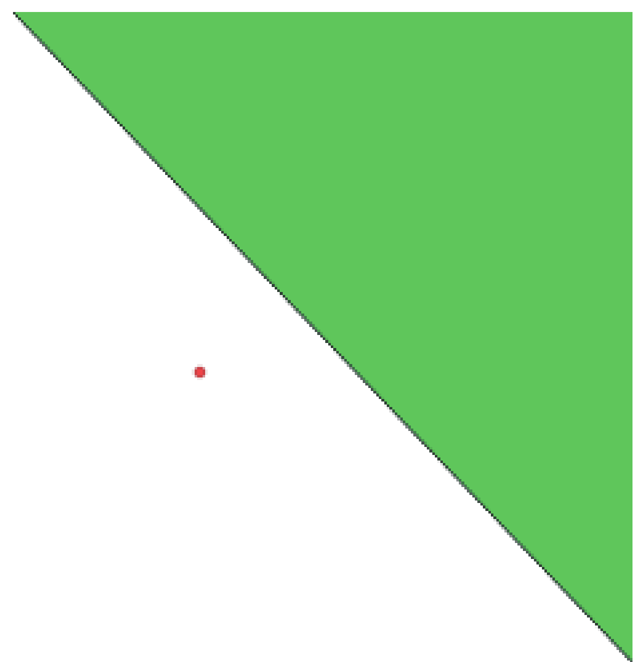


Figure 1: observasjon utenfor WA state

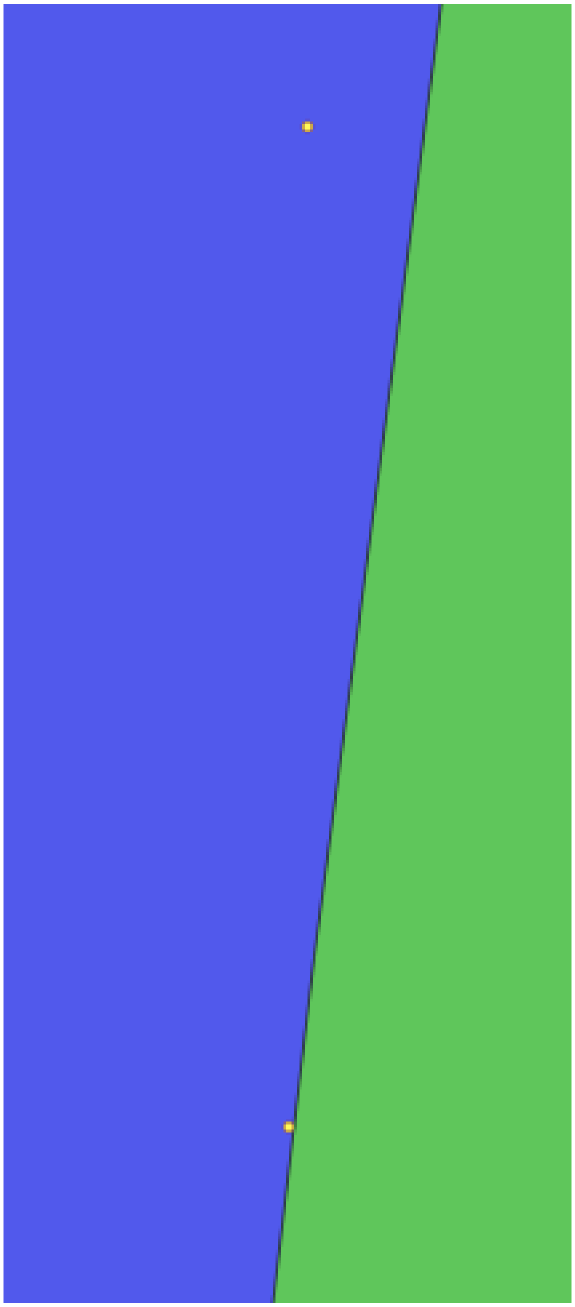


Figure 2: Observasjon utenfor kystlinjen.a

Figure 3: Observasjon utenfor kystlinjen.b

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

```
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

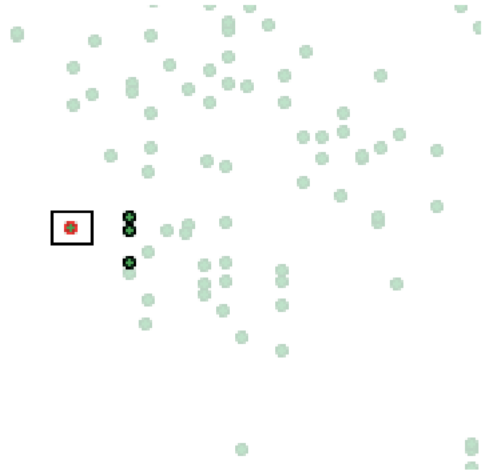


Figure 4: K-nearest 3

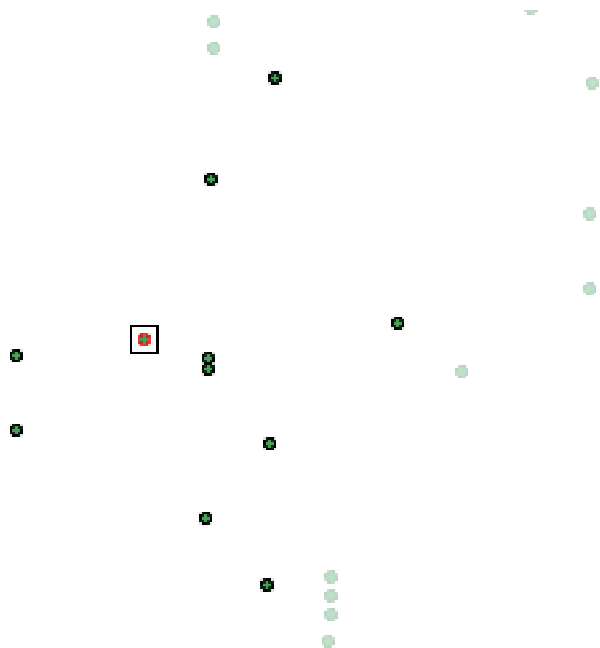


Figure 5: K-nearest 10

Oppgave 6

i)

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 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 blir det dyrere.

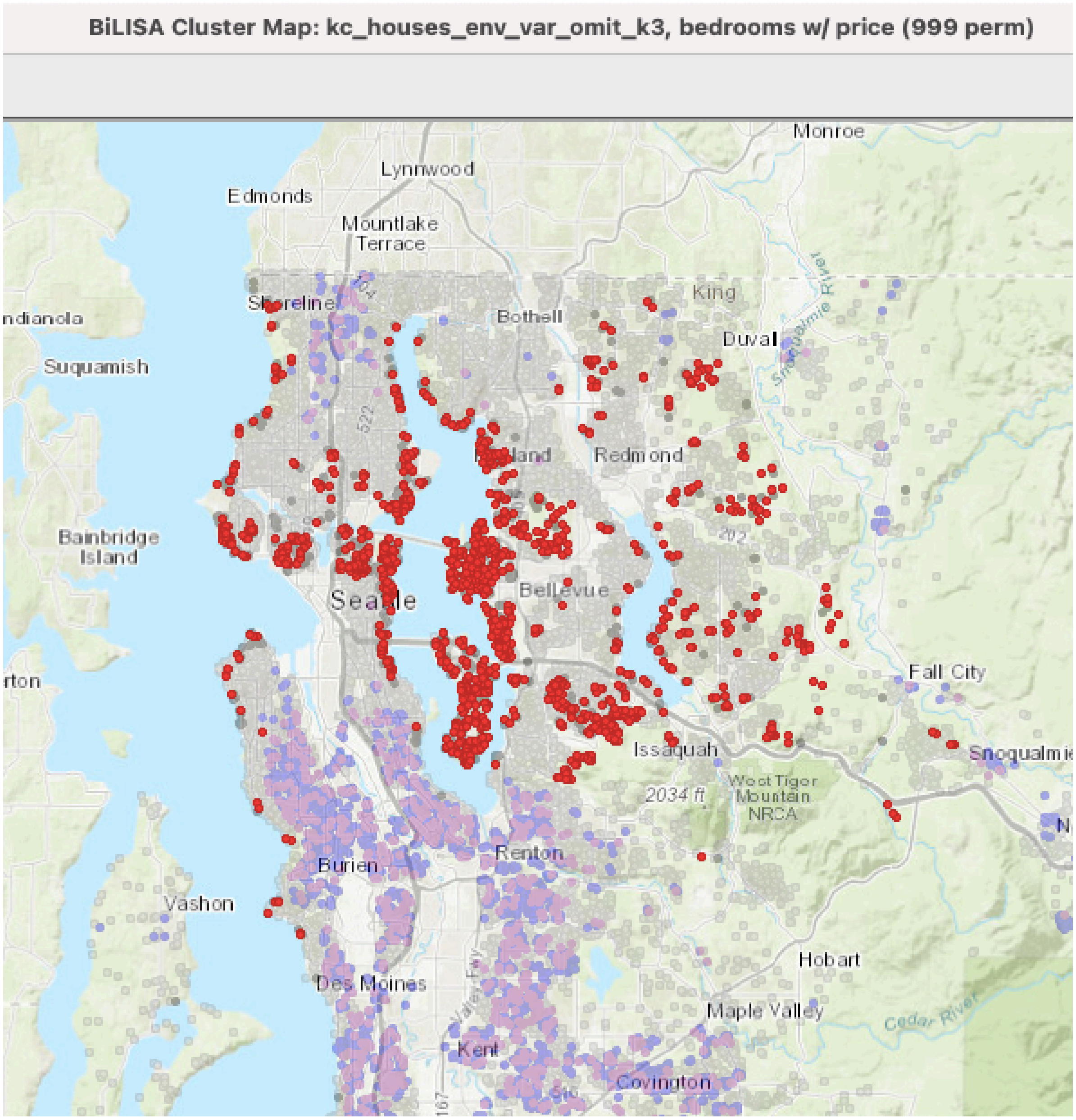


Figure 6: K3 - Store og dyre boliger

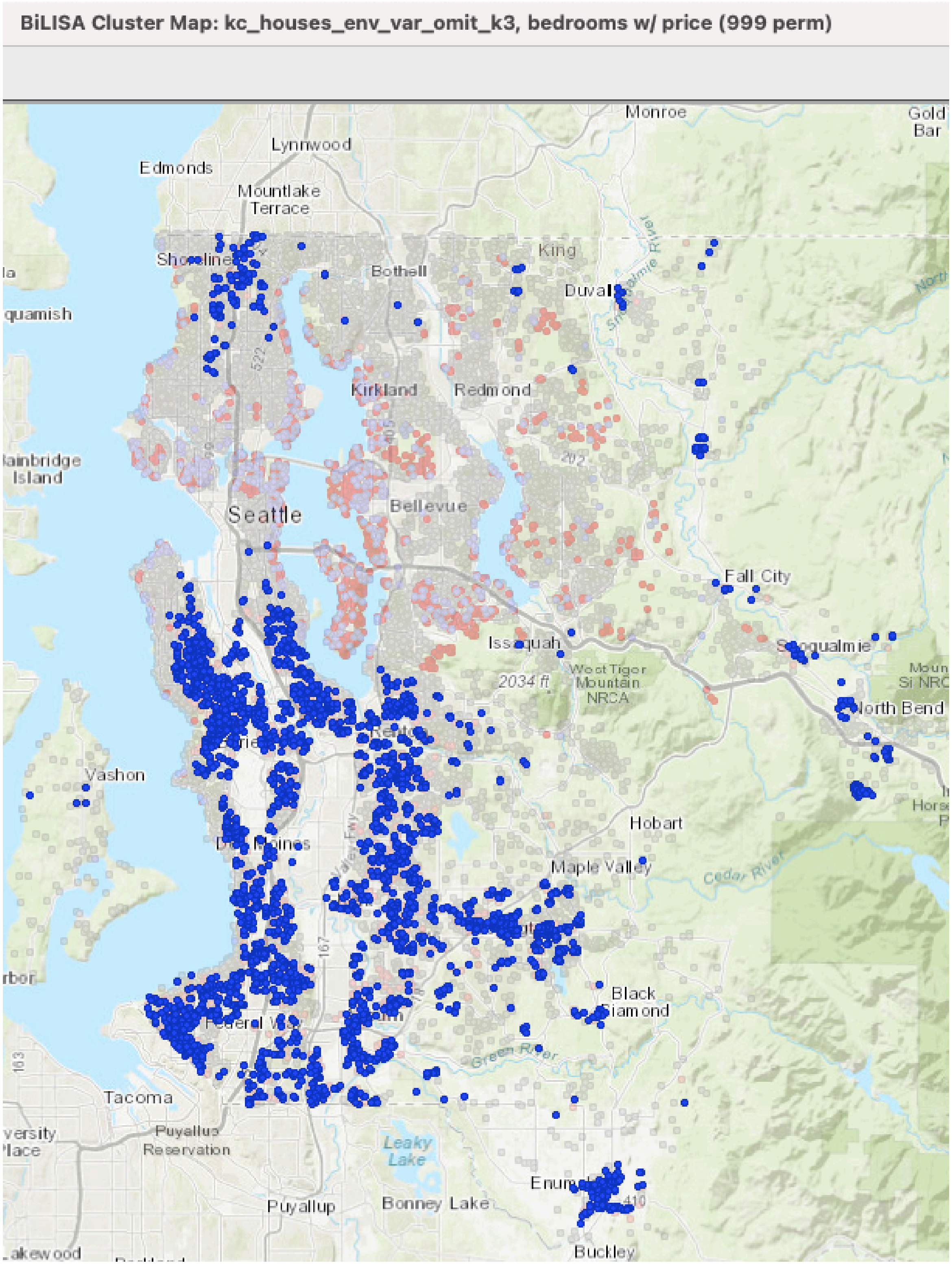


Figure 7: K3 - Små og billige boliger

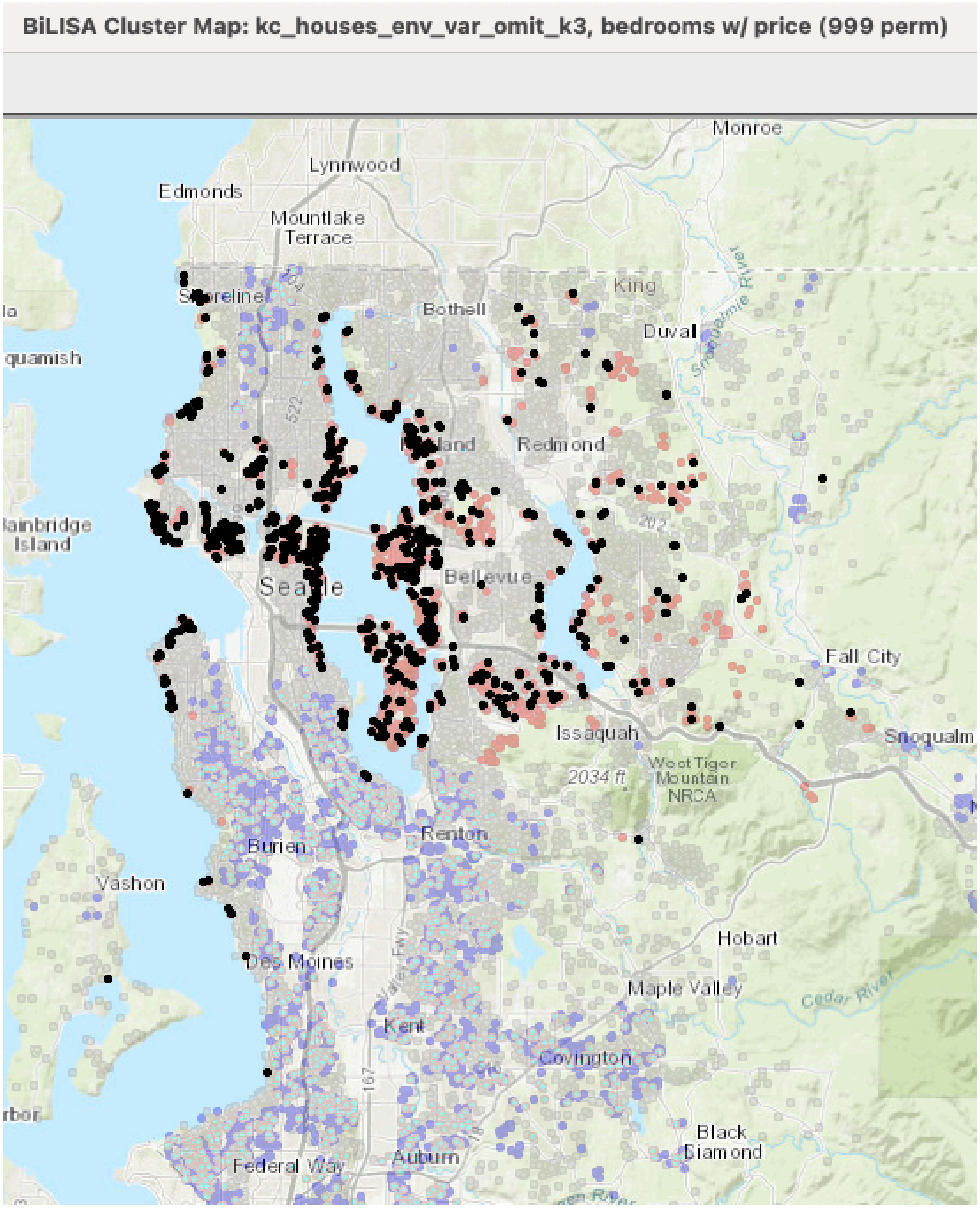


Figure 8: K3 - Små og dyre boliger

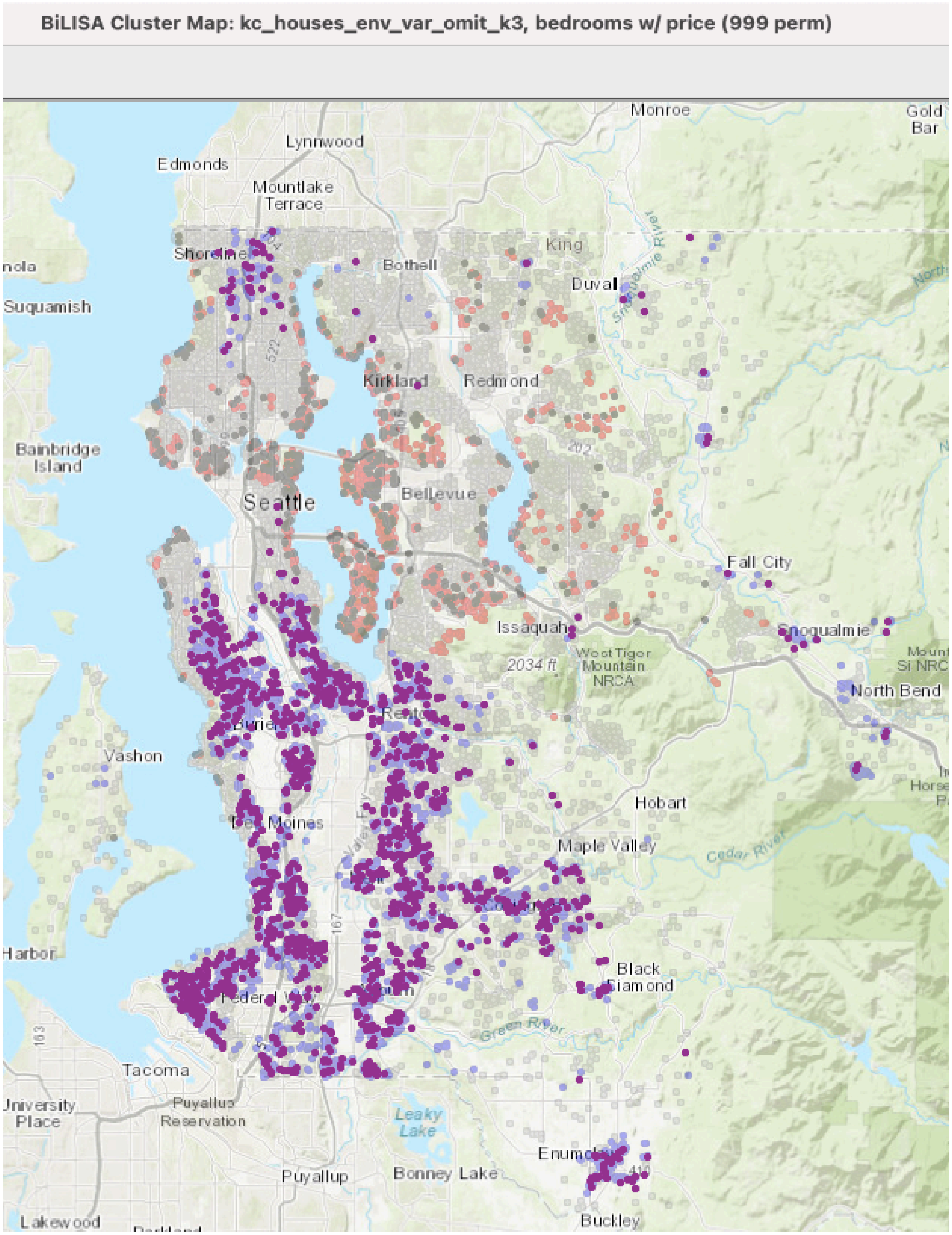


Figure 9: K3 - Store og billige boliger

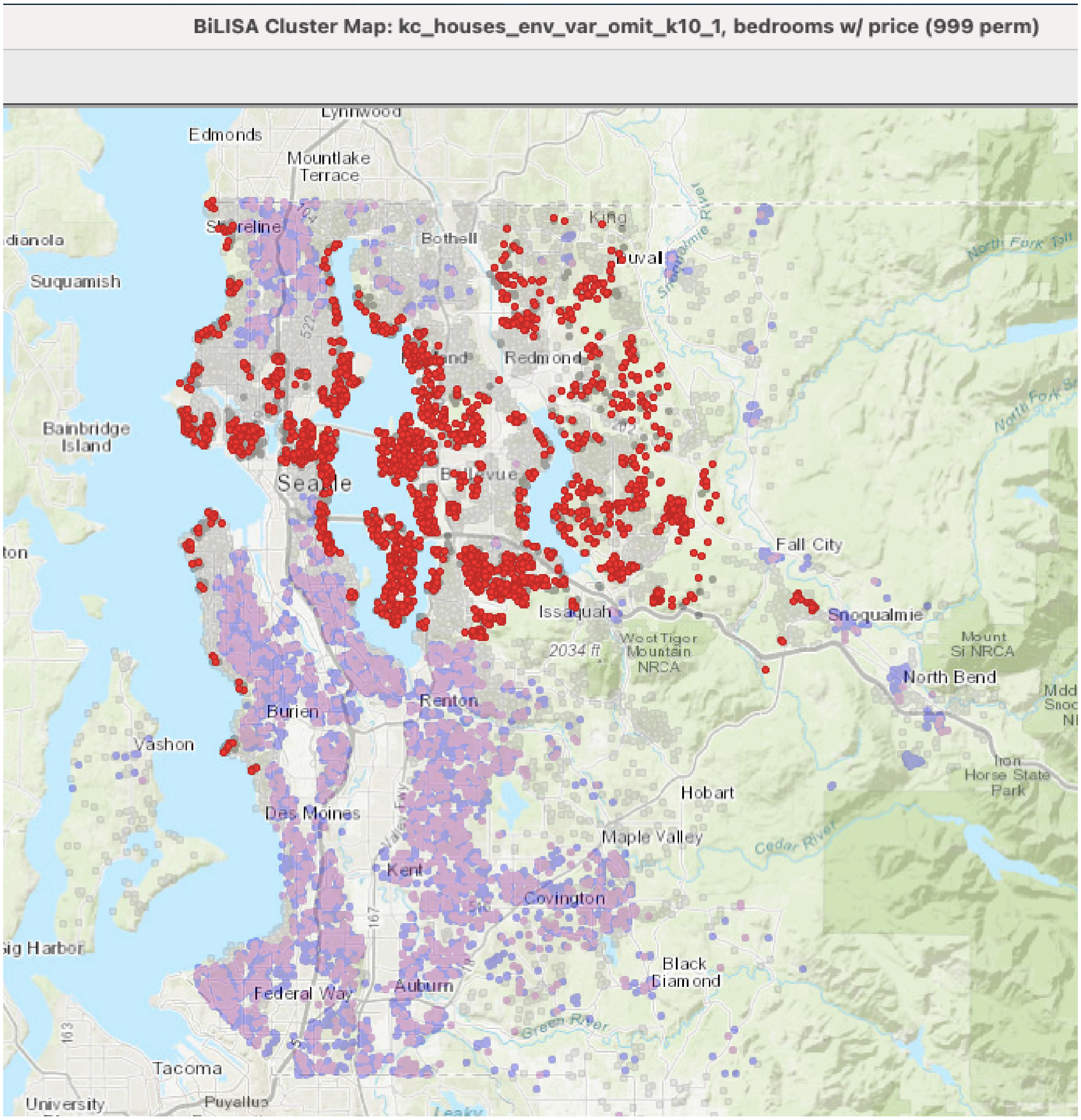


Figure 10: K10 - Store og dyre boliger

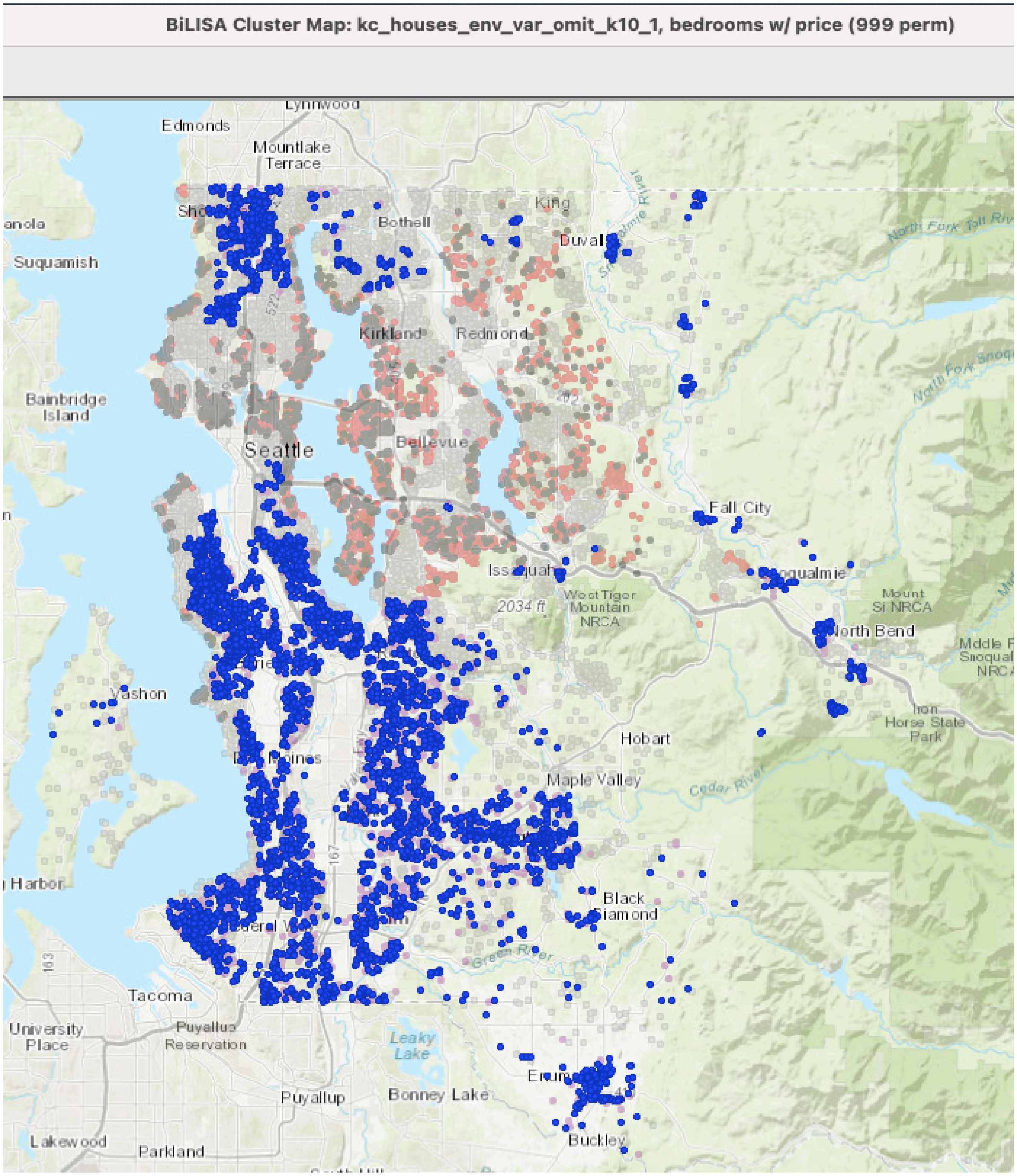


Figure 11: K10 - Små og billige boliger

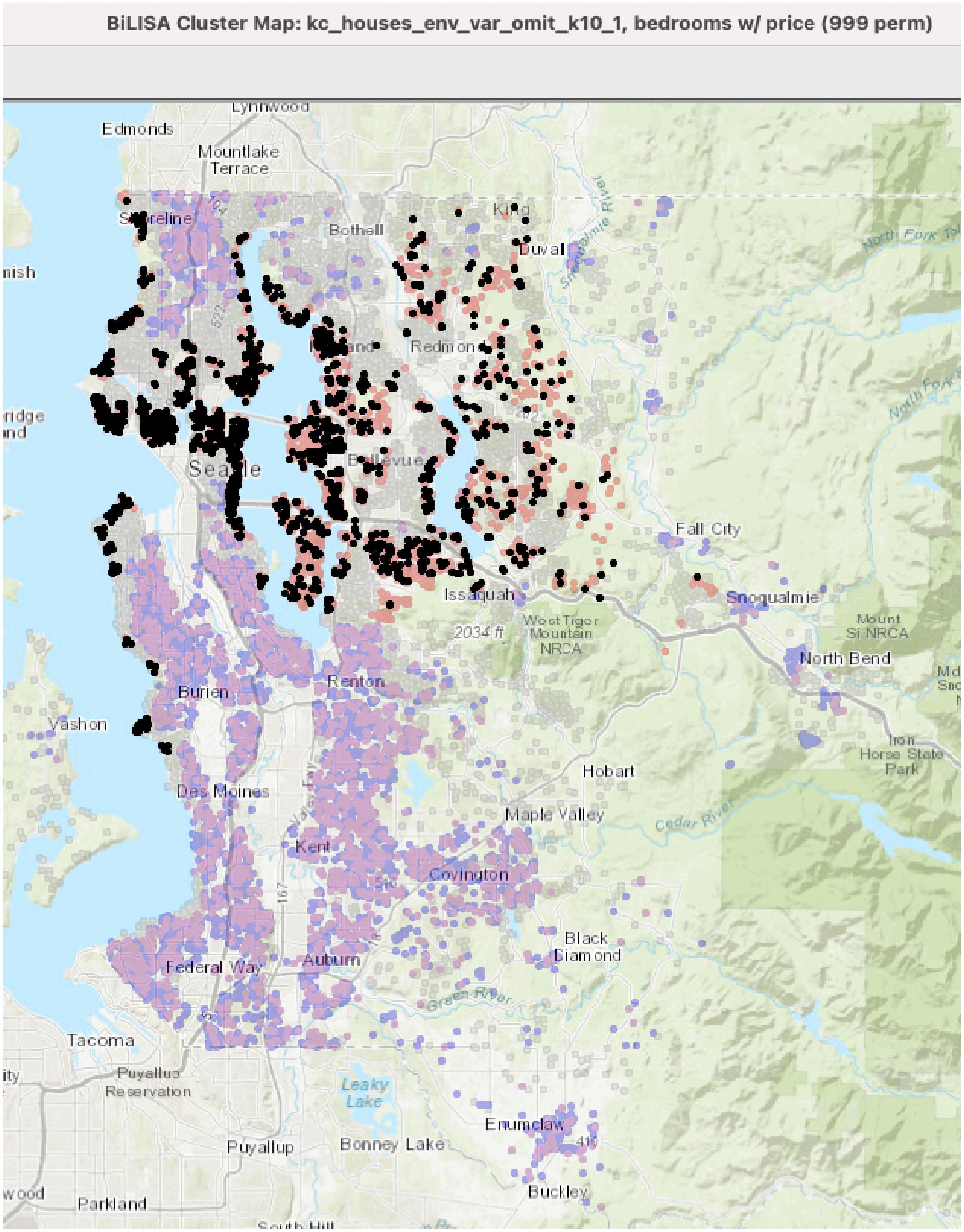


Figure 12: K10 - Små og dyre boliger

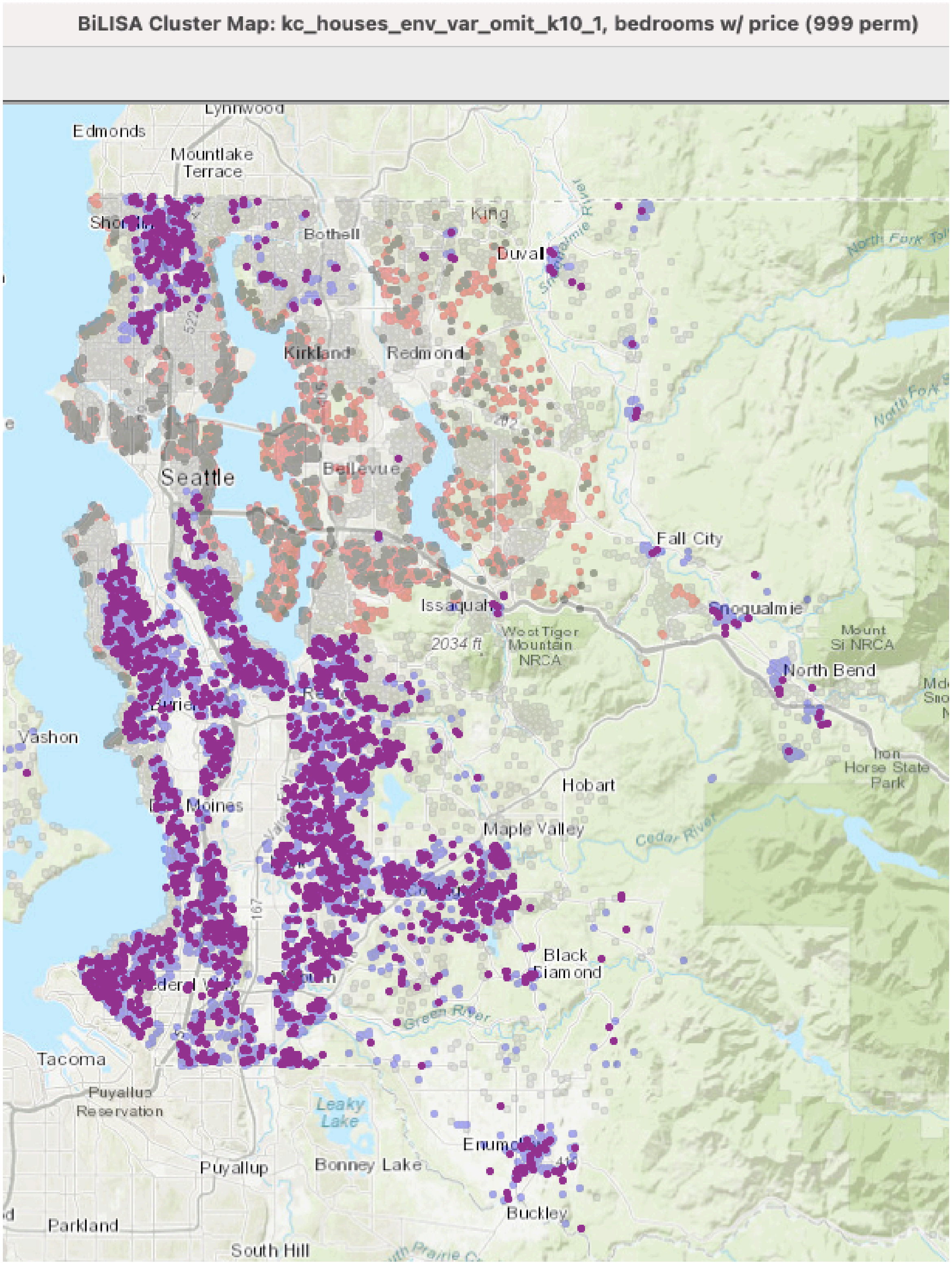


Figure 13: K10 - Store og billige boliger

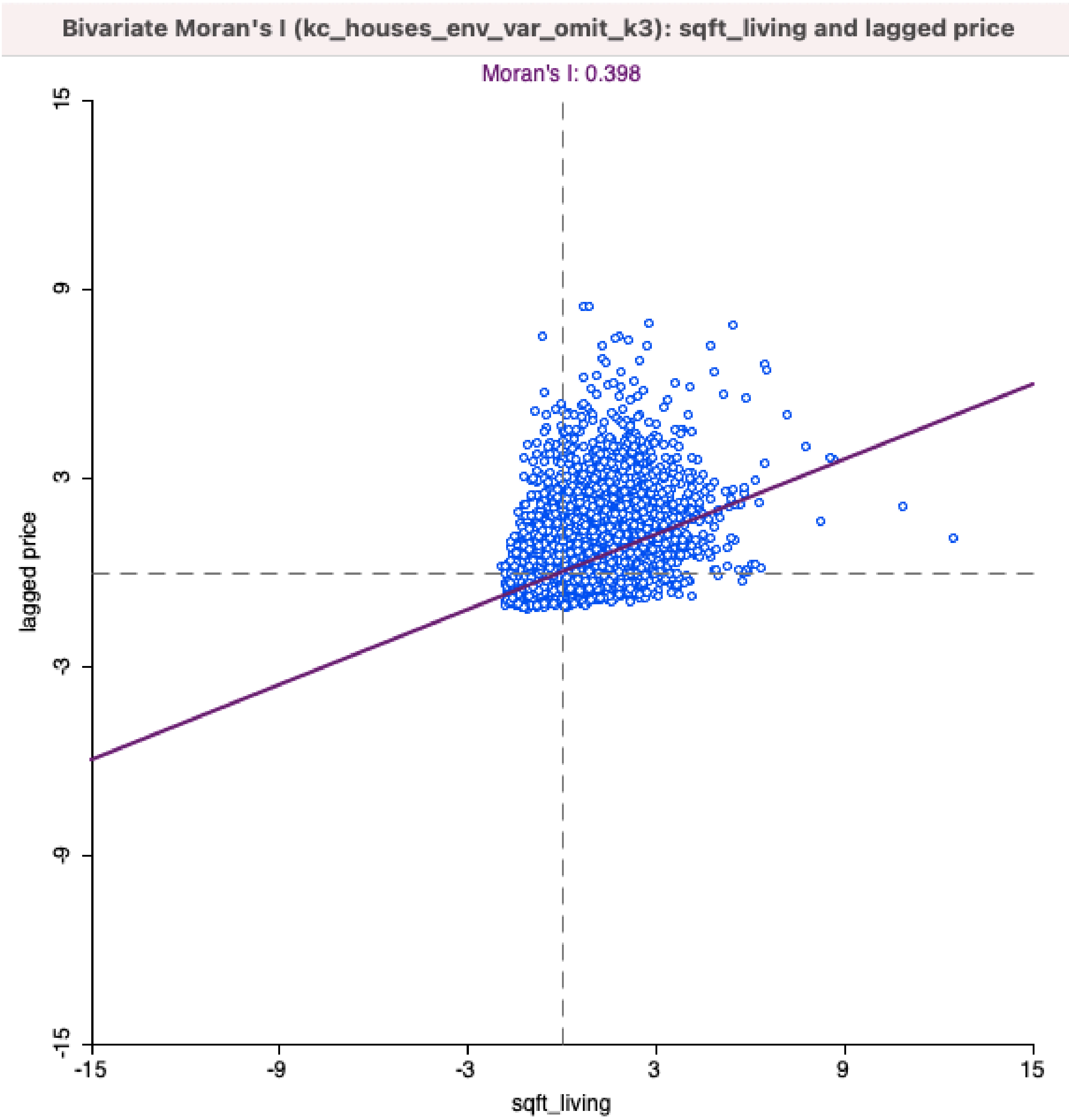


Figure 14: K3 - Bivariate Moran I

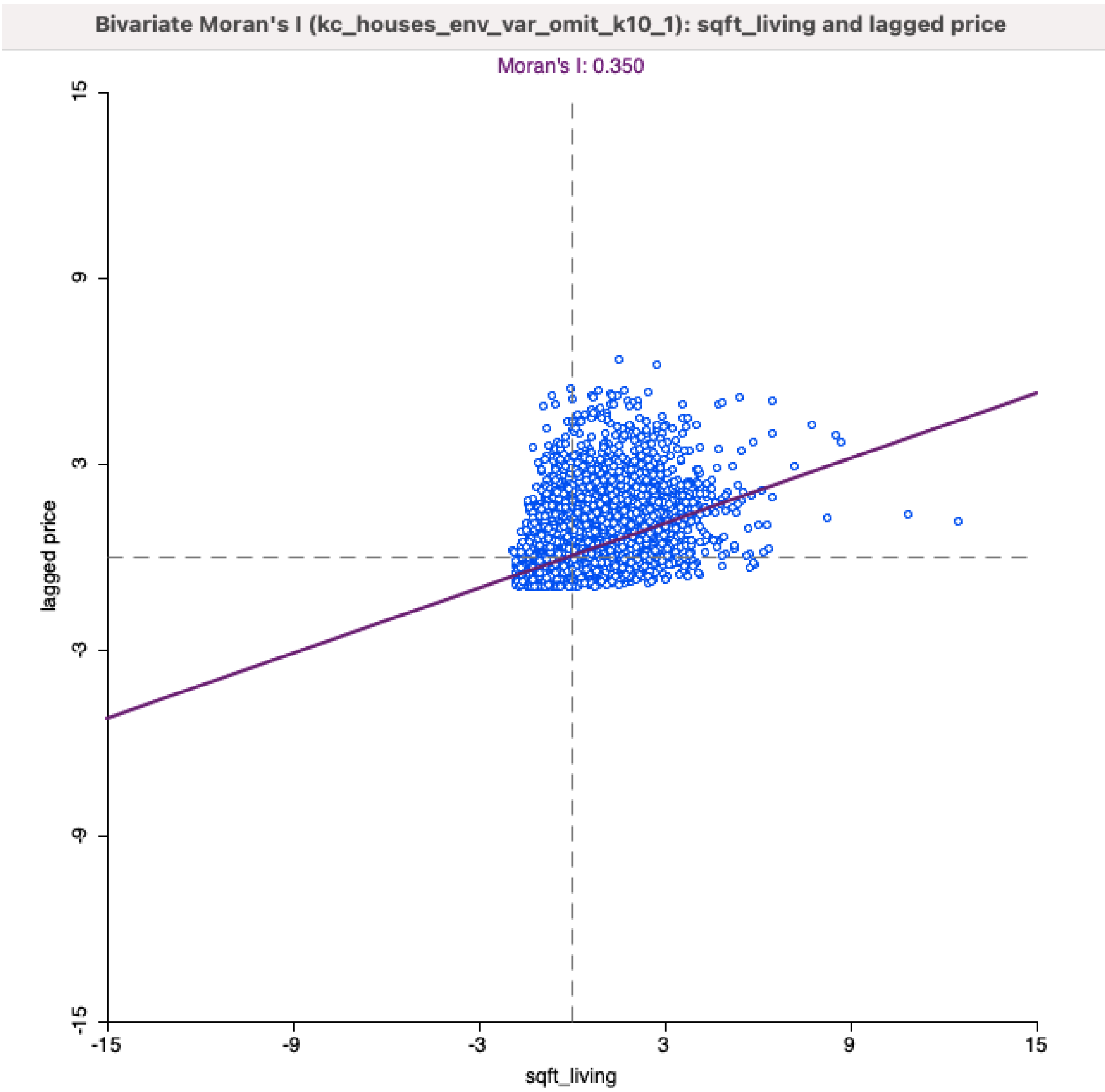


Figure 15: K10 - Bivariate Moran I

Verdier som er positive taler for klynging. 1 = perfekt klyning og 0 = perfekt tilfeldighet.

```
attach(kc_houses_env_var_omit)
```

1. Huskarakteristika

```
mod1 <- "price ~ bedrooms + bathrooms + sqft_living + sqft_lot + sqft_above +
floors + grade + yr_built + yr_renovated + waterfront +
condition + view + year_month"
```

2. Huskarakteristika + distanse til cbd + tracts_var

```
mod2 <- "price ~ bedrooms + bathrooms + sqft_living + sqft_lot + sqft_above +
floors + grade + yr_built + yr_renovated + waterfront +
condition + view + year_month + dist_cbd_km + linguist_2 +
poverty_pe + POC_percen + unemploy_2 + sen_pop_pe +
facilities + wastewater + traffic_pe + diesel + superfund +
transporta + housing_pe + ozone + PM25 +
toxic_rele + hazardous_ + lead_perce + socio_perc"
```

3. Huskarakteristika + distanse til cbd + EHD

```
mod3 <- "price ~ bedrooms + bathrooms + sqft_living + sqft_lot + sqft_above +
floors + grade + yr_built + yr_renovated + waterfront +
condition + view + dist_cbd_km + EHD_percen +
low + high + year_month"
```

```
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.")
```

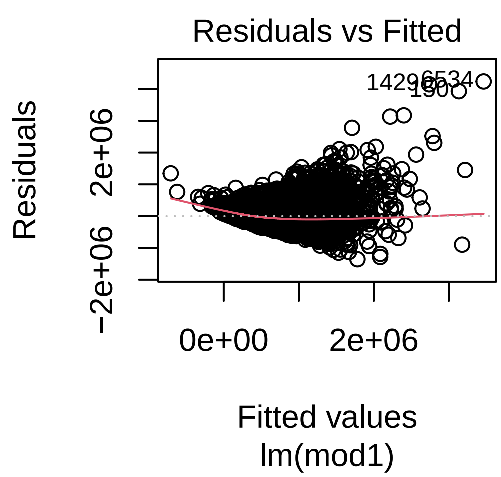
(**Kuminoff2010?**) viser til at når en prisfunksjon skiftes over tiden, vil en modell som ignorerer tilfellet få resultater som er skjeve i estimater av helningen til prisfunksjonen, og også derfor estimatene av MWTP. Dette skjer fordi en standard DID-modellen kombinerer informasjon fra to hedoniske prisfunksjoner, altså beskrivelse av markedet før og etter tilfellet forklares i et estimat av MWTP (Bishop mfl. 2020).

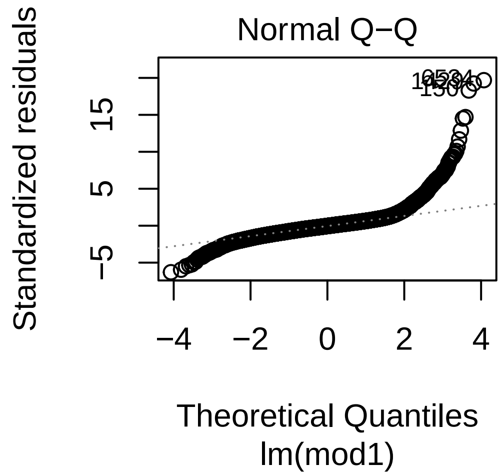
Bishop forklarer videre at man kan møte på denne utfordringen ved å generalisere DID-modell ved å samhandle prisfunksjonsparametere med tidsperiode-dummy. Dette tillater en endring over tid på prisfunksjonsformen.

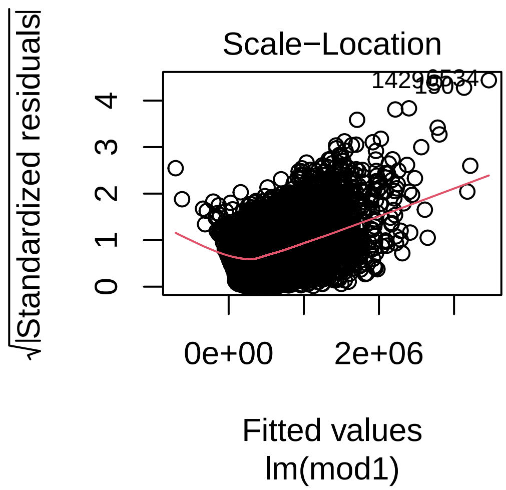
beskrivelse av huxreg Vi kan se ut fra resultatene (*tabellen kom til sist i pdf*) at forklaringskraften i mod2 er såvidt høyere enn forklaringskraften i mod3. Selvom mod2 har den sterkeste forklaringskraften så er den såpass marginal at vi velger å gå for mod3 på grunn av færre variabler og med det lettere å arbeide med. I mod3 får vi samlet alle de miljøemessige variablene i en variabel (EHD_percen).

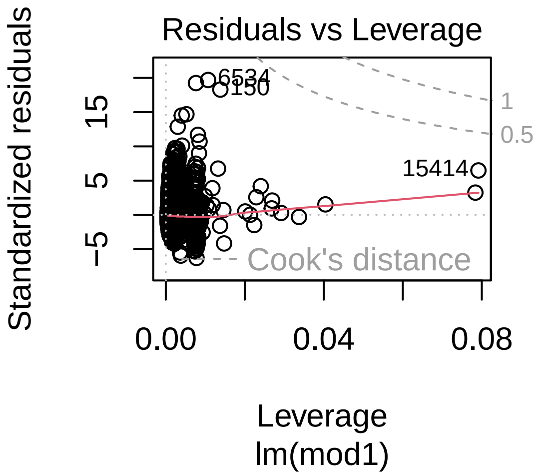
Plots

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

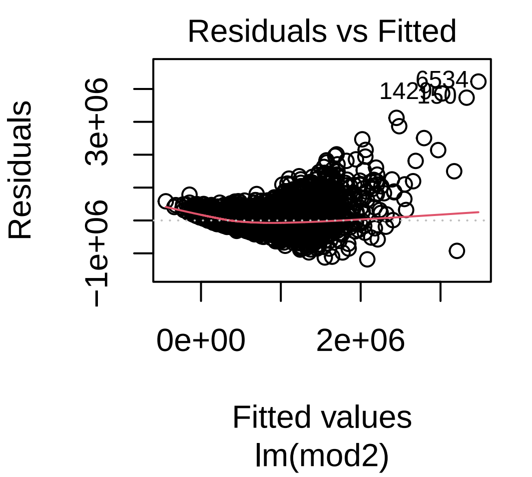


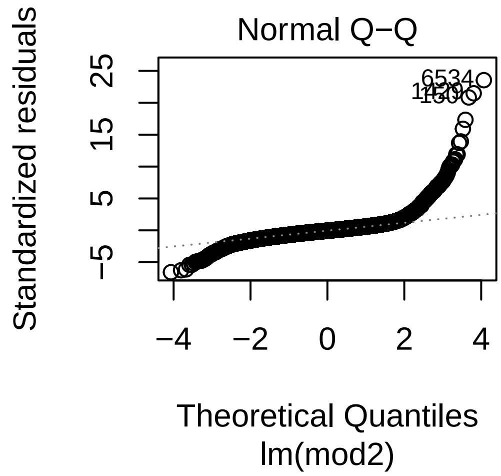

Normal Q−Q
Standardized residuals
−5
5
15
−4
−2
0
2
4
Theoretical Quantiles
lm(mod1)

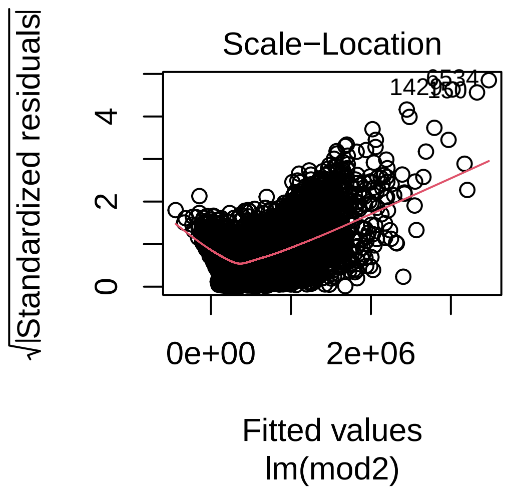

Scale−Location
√|Standardized residuals|
0
1
2
3
4
0e+00
2e+06
Fitted values
lm(mod1)

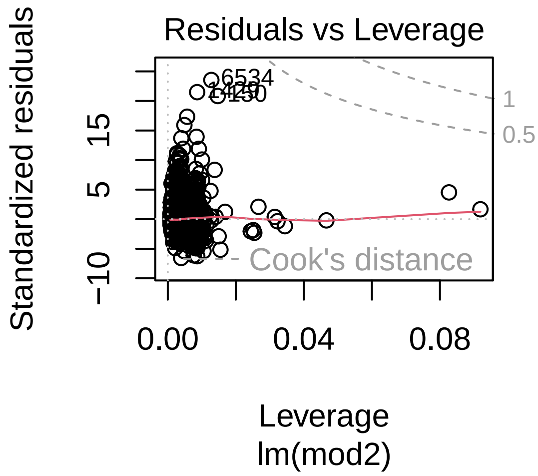



```r
hedon2 %>%
  plot()
```

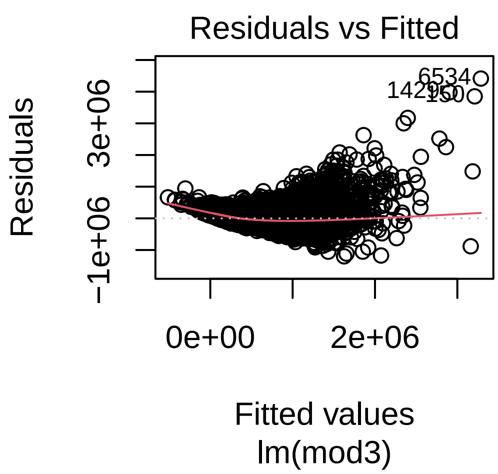


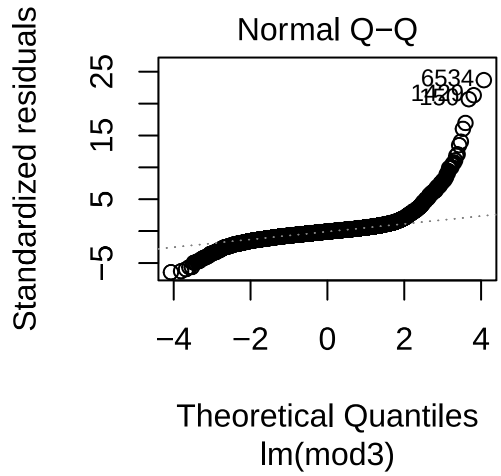

Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(mod2)
6534
1429
150
−5
5
15
25
−4
−2
0
2
4

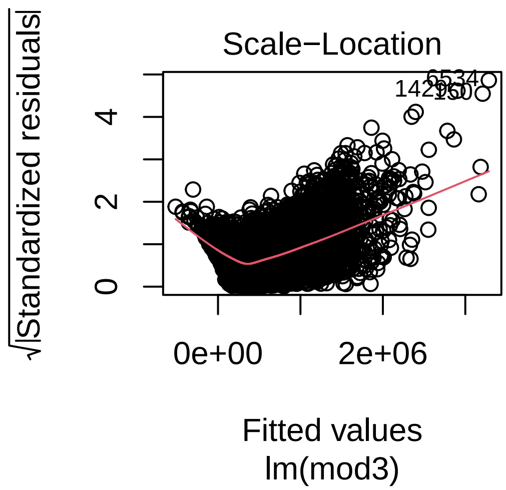

Scale−Location
√|Standardized residuals|
Fitted values
lm(mod2)
6534
1429
150
0
2
4
0e+00
2e+06

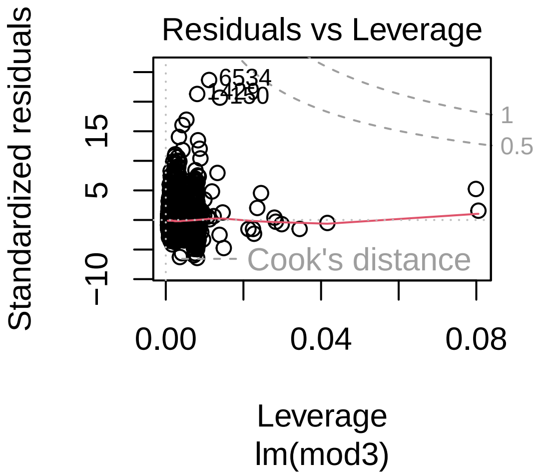



```r
hedon3 %>%
  plot()
```




Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(mod3)
6534
−5
5
15
25
−4
−2
0
2
4


Scale−Location
√|Standardized residuals|
Fitted values
lm(mod3)
6534
0
2
4
0e+00
2e+06



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)
```

```r
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)
```

H_0 = Det er ikke forskjell mellom salgspris basert på salgstidspunktet.

Denne nullhypotesen kan vi forkaste på bakgrunn av signifikante F- og P-verdiene. Dette indikerer på at tidsdummyene vi bruker har en effekt, selvom de individuellt ikke er signifikante. Dette sier oss at det er forskjellige salgspriser ved forskjellige salgstidspunktet.

Oppgave 8

i.

```r
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)
```

```r
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)
  )
```

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

ii.

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

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

```r
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")
```

```r
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")
```

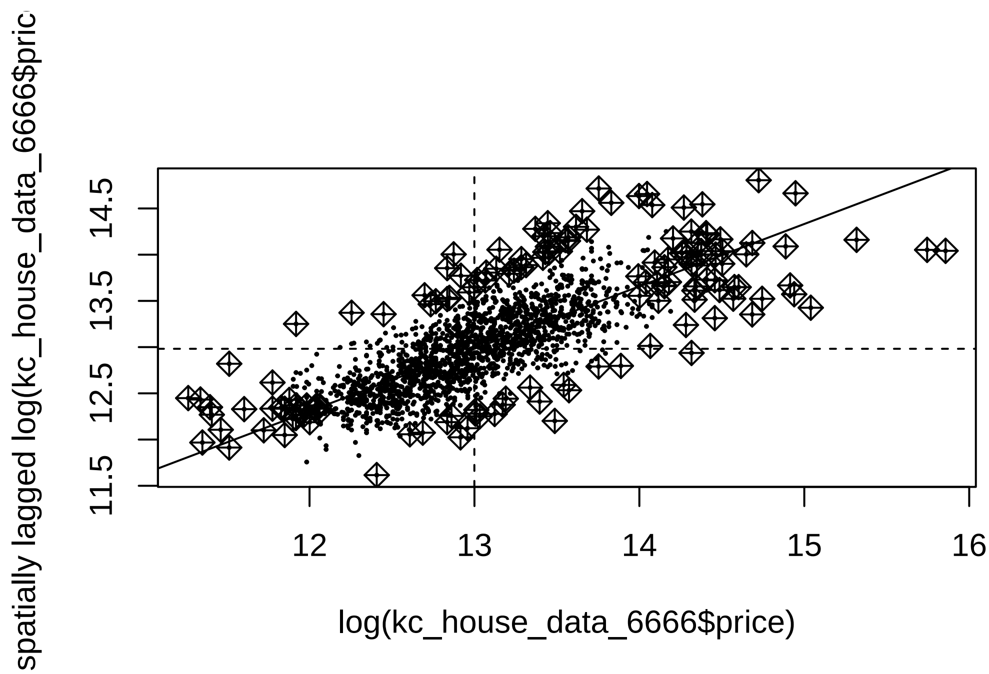
```r
lm.morantest(hedon3_seed, kc_house_data_6666_W)
```

```

    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 < 2.2e-16
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
    0.2493169179    -0.0031956991     0.0003062782
```

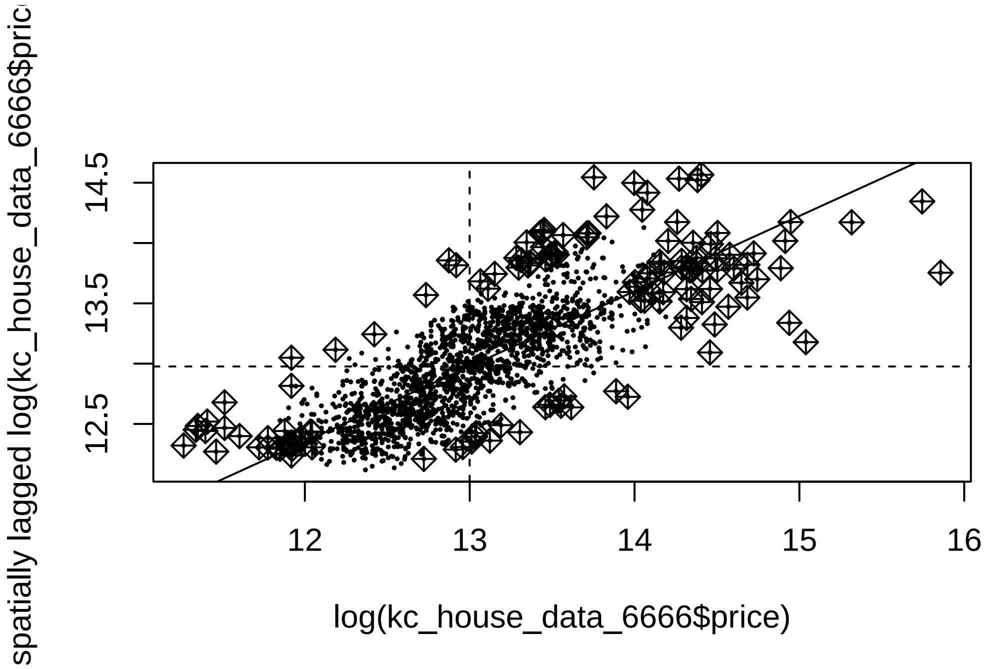
```r
lm.morantest(hedon3_seed, kc_house_data_6666_W10)
```

```
    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 < 2.2e-16
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
    2.224336e-01    -2.578743e-03     9.293224e-05
```

```
moran.plot(log(kc_house_data_6666$price), listw = kc_house_data_6666_W,
           labels = FALSE, pch = 20, cex = 0.3)
```




```
moran.plot(log(kc_house_data_6666$price), listw = kc_house_data_6666_W10,
           labels = FALSE, pch = 20, cex = 0.3)
```



Ut i fra Global Morans I og plottene kan vi se at p-verdiene er signifikante som betyr vi kan forkaste $H_0 = Ingenromligeffektiresidualene$. Som betyr at vi har uforklarte spatial effects i residualene.

Vi kan se i plottene at de indikerer det samme. Vi ser at linjen har et positivt stigningstall. Dersom det ikke hadde vært noen effekt ville denne linjen vært mer vannrett ved den stiplede linjen.

iv.

```
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 < 2.2e-16


    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 < 2.2e-16


    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 = 1.965e-14


    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 = 8.091e-05


    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 < 2.2e-16
```

```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 < 2.2e-16


	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 < 2.2e-16


	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 < 2.2e-16


	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 = 1.887e-15


	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 < 2.2e-16
```

Ved å ta en Langrangs multiplikatortest for *K10* og *K3* får vi at verdiene på LMerr og LMlag er signifikante. Når det kommer til RLMerr og RLMlag så kan vi se at disse også er signifikante. For å komme frem til hvilken vi velger av RLMerr og RLMlag så vil vi se på høyeste verdi. Vi ser at RLMerr har høyest verdi på både *K10* og *K3*, med det kan vi si at det beste valget er en robust error modell (SEM).

v.

Her står vi ovenfor et lokalt fenomen. Veldig ofte benyttes det lokale effekter når det jobbes med boligdata og boliglitteratur ettersom det gir som oftest effekter lokalt og de nærmeste rundt seg (**LeSage2014?**).

```
SDEM_seed <- errorsarlm(mod3, data = kc_house_data_6666,
                        listw = kc_house_data_6666_W,
                        Durbin = as.formula(~ bedrooms + bathrooms + sqft_living + sqft_lo
                                              sqft_above + floors + grade + yr_built + yr_
                                              condition + view + dist_cbd_km +
                                              EHD_percen + low + high))
```

```
Warning in errorsarlm(mod3, data = kc_house_data_6666, listw = kc_house_data_6666_W, : invers
  reciprocal condition number = 3.55444e-22 - using numerical Hessian.
```

```
SLX_seed <- lmSLX(mod3, data = kc_house_data_6666, listw = kc_house_data_6666_W,
                  Durbin = as.formula(~ bedrooms + bathrooms + sqft_living +
                                        sqft_lot + sqft_above + floors + grade + yr_built
                                        yr_renovated + waterfront + condition + view +
                                        dist_cbd_km + EHD_percen + low + high))
```

```
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.
```

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

```
Impact measures (SDEM, estimable, n):
                         Direct      Indirect         Total
bedrooms          -5.499710e+04 -4.901160e+03 -5.989826e+04
bathrooms          5.285257e+04  3.787409e+04  9.072666e+04
sqft_living        1.768634e+02  2.690962e+01  2.037730e+02
sqft_lot           2.596053e-01 -1.065106e-01  1.530947e-01
sqft_above         1.519736e+02 -2.785419e+01  1.241195e+02
floors            -9.031067e+04  7.605223e+04 -1.425845e+04
grade              1.495722e+04  2.822956e+04  4.318678e+04
yr_built          -6.312618e+02 -2.492492e+03 -3.123753e+03
yr_renovated       5.825219e+00 -4.537998e+00  1.287221e+00
waterfront         6.068063e+05  2.013749e+05  8.081812e+05
condition          2.929110e+04  3.150592e+04  6.079702e+04
view               6.410576e+04 -3.681377e+04  2.729200e+04
dist_cbd_km       -1.500263e+03 -7.429483e+03 -8.929746e+03
EHD_percen         3.381464e+02 -1.685720e+03 -1.347574e+03
low                3.285715e+03  2.381347e+05  2.414204e+05
high               5.472224e+04  1.967397e+05  2.514619e+05
year_month2014-06  1.398950e+04            NA  1.398950e+04
year_month2014-07  1.345523e+04            NA  1.345523e+04
year_month2014-08  6.830114e+03            NA  6.830114e+03
year_month2014-09 -9.264447e+03            NA -9.264447e+03
year_month2014-10  1.830891e+04            NA  1.830891e+04
year_month2014-11  6.708168e+03            NA  6.708168e+03
year_month2014-12 -1.113140e+04            NA -1.113140e+04
year_month2015-01  7.347229e+03            NA  7.347229e+03
year_month2015-02 -1.362163e+03            NA -1.362163e+03
year_month2015-03  2.792870e+04            NA  2.792870e+04
year_month2015-04  4.870156e+04            NA  4.870156e+04
year_month2015-05  8.821624e+03            NA  8.821624e+03
========================================================
Standard errors:
                       Direct     Indirect        Total
bedrooms          6.729454e+03 1.268870e+04 1.580682e+04
bathrooms         1.123226e+04 2.174456e+04 2.736907e+04
sqft_living       1.552549e+01 2.977009e+01 3.726593e+01
sqft_lot          9.997138e-02 1.777446e-01 2.048172e-01
sqft_above        1.547574e+01 2.951845e+01 3.661721e+01
floors            1.256966e+04 2.178506e+04 2.596963e+04
grade             7.415280e+03 1.368050e+04 1.638300e+04
yr_built          2.628897e+02 4.397516e+02 5.037085e+02
yr_renovated      1.306494e+01 2.534776e+01 3.198411e+01
waterfront        7.008149e+04 1.673386e+05 2.023185e+05
```

```
condition         7.901669e+03 1.528025e+04 1.909289e+04
view              7.159577e+03 1.321062e+04 1.544535e+04
dist_cbd_km       4.798613e+03 4.979985e+03 1.010028e+03
EHD_percen        6.419941e+02 7.246967e+02 4.280279e+02
low               1.410026e+05 1.780698e+05 1.435120e+05
high              9.820909e+04 1.248818e+05 1.022919e+05
year_month2014-06 2.161892e+04           NA 2.161892e+04
year_month2014-07 2.178440e+04           NA 2.178440e+04
year_month2014-08 2.170979e+04           NA 2.170979e+04
year_month2014-09 2.215994e+04           NA 2.215994e+04
year_month2014-10 2.270132e+04           NA 2.270132e+04
year_month2014-11 2.352435e+04           NA 2.352435e+04
year_month2014-12 2.309511e+04           NA 2.309511e+04
year_month2015-01 2.662155e+04           NA 2.662155e+04
year_month2015-02 2.438627e+04           NA 2.438627e+04
year_month2015-03 2.163065e+04           NA 2.163065e+04
year_month2015-04 2.142501e+04           NA 2.142501e+04
year_month2015-05 2.991329e+04           NA 2.991329e+04
========================================================
Z-values:
                       Direct   Indirect       Total
bedrooms          -8.17259407 -0.3862618 -3.78939394
bathrooms          4.70542667  1.7417735  3.31493425
sqft_living       11.39180803  0.9039148  5.46807790
sqft_lot           2.59679594 -0.5992336  0.74747001
sqft_above         9.82012284 -0.9436200  3.38964798
floors            -7.18481396  3.4910273 -0.54904312
grade              2.01708067  2.0634886  2.63607280
yr_built          -2.40124161 -5.6679538 -6.20151051
yr_renovated       0.44586639 -0.1790295  0.04024564
waterfront         8.65858222  1.2033977  3.99459849
condition          3.70695155  2.0618718  3.18427474
view               8.95384811 -2.7866804  1.76700385
dist_cbd_km       -0.31264524 -1.4918686 -8.84109072
EHD_percen         0.52671262 -2.3261044 -3.14833177
low                0.02330252  1.3373115  1.68223180
high               0.55720137  1.5754063  2.45827818
year_month2014-06  0.64709529         NA  0.64709529
year_month2014-07  0.61765439         NA  0.61765439
year_month2014-08  0.31460980         NA  0.31460980
year_month2014-09 -0.41807190         NA -0.41807190
year_month2014-10  0.80651331         NA  0.80651331
year_month2014-11  0.28515843         NA  0.28515843
```

```
year_month2014-12 -0.48198069         NA -0.48198069
year_month2015-01  0.27598803         NA  0.27598803
year_month2015-02 -0.05585779         NA -0.05585779
year_month2015-03  1.29116344         NA  1.29116344
year_month2015-04  2.27311699         NA  2.27311699
year_month2015-05  0.29490656         NA  0.29490656

p-values:
                  Direct     Indirect   Total
bedrooms          2.2204e-16 0.69930282 0.00015102
bathrooms         2.5334e-06 0.08154809 0.00091665
sqft_living       < 2.22e-16 0.36604057 4.5494e-08
sqft_lot          0.00940978 0.54901709 0.45477990
sqft_above        < 2.22e-16 0.34536388 0.00069982
floors            6.7302e-13 0.00048117 0.58297586
grade             0.04368710 0.03906623 0.00838717
yr_built          0.01633954 1.4451e-08 5.5924e-10
yr_renovated      0.65569376 0.85791452 0.96789729
waterfront        < 2.22e-16 0.22882247 6.4804e-05
condition         0.00020977 0.03921995 0.00145117
view              < 2.22e-16 0.00532510 0.07722758
dist_cbd_km       0.75455020 0.13573360 < 2.22e-16
EHD_percen        0.59839317 0.02001298 0.00164205
low               0.98140896 0.18112098 0.09252390
high              0.57738985 0.11516269 0.01396050
year_month2014-06 0.51757028 NA         0.51757028
year_month2014-07 0.53680318 NA         0.53680318
year_month2014-08 0.75305794 NA         0.75305794
year_month2014-09 0.67589455 NA         0.67589455
year_month2014-10 0.41994694 NA         0.41994694
year_month2014-11 0.77552277 NA         0.77552277
year_month2014-12 0.62981967 NA         0.62981967
year_month2015-01 0.78255726 NA         0.78255726
year_month2015-02 0.95545510 NA         0.95545510
year_month2015-03 0.19664701 NA         0.19664701
year_month2015-04 0.02301913 NA         0.02301913
year_month2015-05 0.76806526 NA         0.76806526
```

```
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 = 95.981, df = 16, p-value = 1.952e-13
sample estimates:
Log likelihood of SDEM_seed  Log likelihood of SEM_seed
                  -25696.93                   -25744.92
```

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

```
    Likelihood ratio for spatial linear models

data:
Likelihood ratio = 157.78, df = 1, p-value < 2.2e-16
sample estimates:
Log likelihood of SDEM_seed  Log likelihood of SLX_seed
                  -25696.93                   -25775.82
```

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

```
    Likelihood Ratio diagnostics for spatial dependence

data:
Likelihood ratio = 157.78, df = 1, p-value < 2.2e-16
sample estimates:
Log likelihood of spatial error model           Log likelihood of OLS fit y
                            -25696.93                             -25775.82
```

Ut fra resultatene i likelihood ratio test ser det ut til at SDEM er den beste modellen å anvende.

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

```
	Spatial Hausman test (asymptotic)

data:  NULL
Hausman test = 91.271, df = 29, p-value = 2.317e-08
```

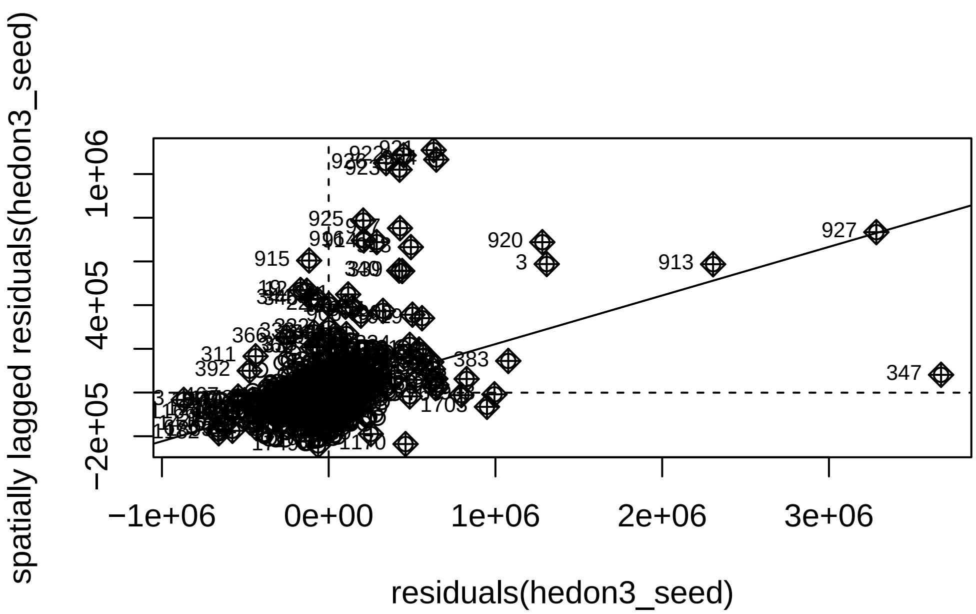
```r
bptest.Sarlm(SEM_seed, studentize = TRUE)
```

```
	studentized Breusch-Pagan test

data:
BP = 472.28, df = 28, p-value < 2.2e-16
```

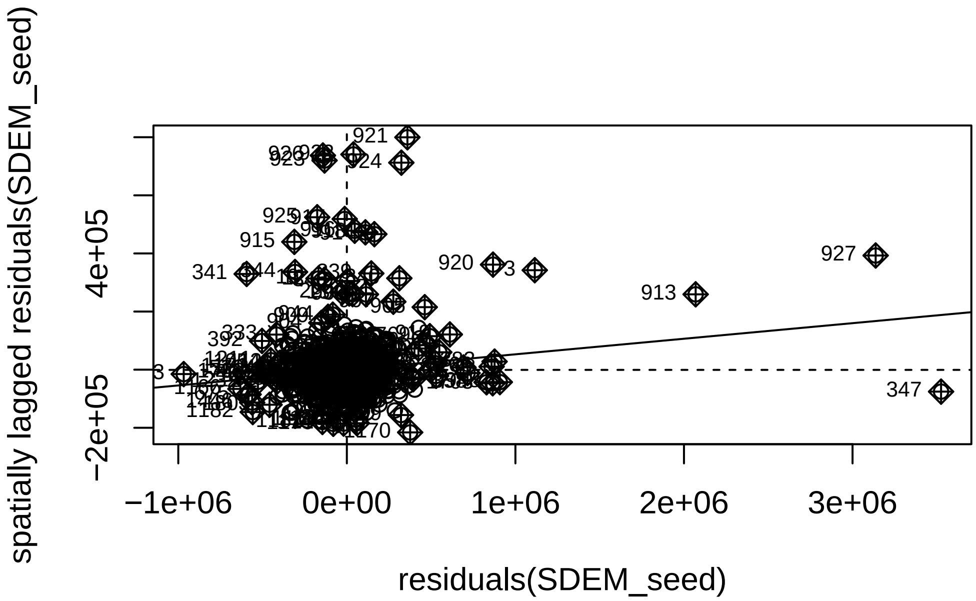
Vi kan forkaste $H_0 = ingenheteroskedastisitet$ og vi har heteroskedastisitet.

vi.

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



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




```r
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 = 5.6986, p-value = 6.04e-09
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
     5.358418e-02     -5.302227e-04      9.017628e-05
```

Vi ser at SDEM reduserer den romlige effekten i feilleddet. Likevel ser vi at Moran I ikke er signifikant.

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), ]
```

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

```
huxreg("Full" = hedon3, "2000 Seed" = hedon3_2000, "6666 Seed" = hedon3_seed,
    error_format = "[{statistic}]",
    note = "{stars}. T statistic in brackets.")
```

```
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
```

```
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
```

```
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")
```

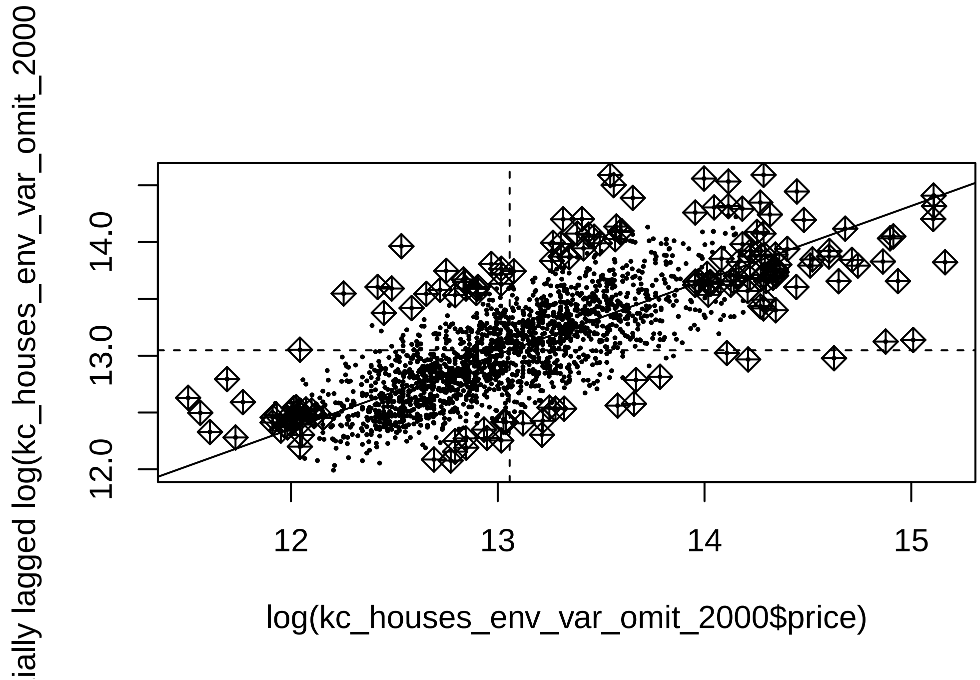
```
lm.morantest(hedon3_2000, kc_house_data_2000_W)
```

```
    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 < 2.2e-16
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
    0.3293899740    -0.0029972881     0.0002846206
```

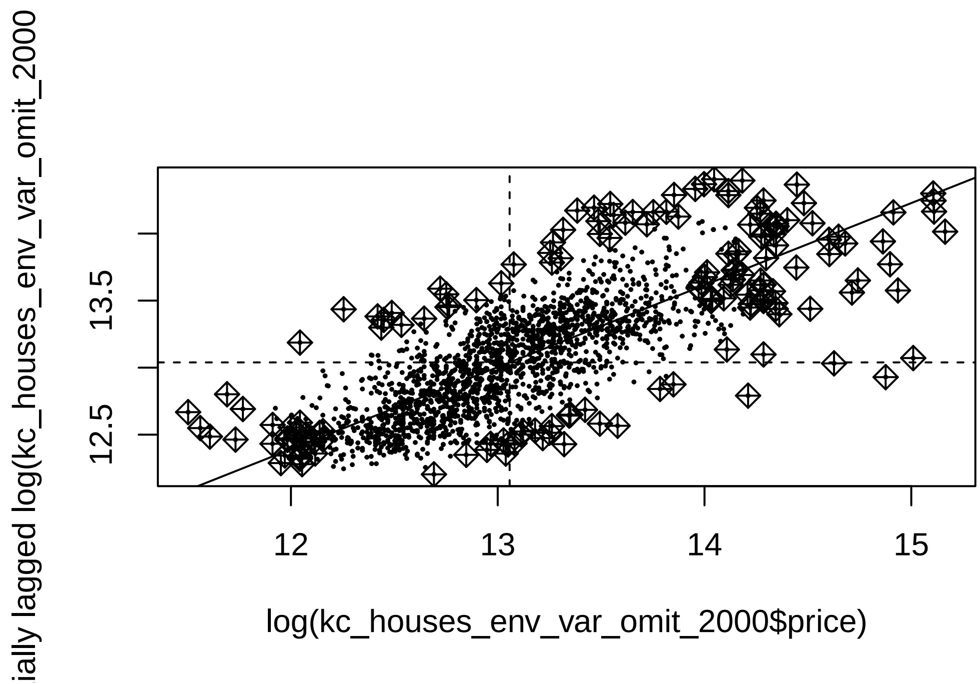
```
lm.morantest(hedon3_2000, kc_house_data_2000_W10)
```

```
    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 < 2.2e-16
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
    2.944919e-01    -2.498222e-03     8.739112e-05
```

```
moran.plot(log(kc_houses_env_var_omit_2000$price),
           listw = kc_house_data_2000_W,
           labels = FALSE, pch = 20, cex = 0.3)
```




```
moran.plot(log(kc_houses_env_var_omit_2000$price),
           listw = kc_house_data_2000_W10,
           labels = FALSE, pch = 20, cex = 0.3)
```




```
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 < 2.2e-16


    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 < 2.2e-16
```

```
    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 < 2.2e-16


    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 = 3.727e-07


    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 < 2.2e-16
```

```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 < 2.2e-16
```

```
    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 < 2.2e-16


    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 < 2.2e-16


    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 < 2.2e-16


    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 < 2.2e-16
```

```
SDEM_2000 <- errorsarlm(mod3, data = kc_houses_env_var_omit_2000,
                        listw = kc_house_data_2000_W,
                        Durbin = as.formula(~ bedrooms + bathrooms + sqft_living +
                                              sqft_lot + sqft_above + floors + grade +
                                              yr_built + yr_renovated + waterfront + condi
                                              dist_cbd_km + EHD_percen + low + high))
```

```
Warning in errorsarlm(mod3, data = kc_houses_env_var_omit_2000, listw = kc_house_data_2000_W
  reciprocal condition number = 6.1448e-22 - using numerical Hessian.
```

```
SLX_2000 <- lmSLX(mod3, data = kc_houses_env_var_omit_2000,
                  listw = kc_house_data_2000_W,
                  Durbin = as.formula(~ bedrooms + bathrooms + sqft_living +
                                        sqft_lot + sqft_above + floors + grade +
                                        yr_built + yr_renovated + waterfront + condition +
                                        view + dist_cbd_km + EHD_percen + low + high))
```

```
SEM_2000 <- errorsarlm(mod3, data = kc_houses_env_var_omit_2000,
                       listw = kc_house_data_2000_W,
                       Durbin = FALSE)
```

```
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         -3.075205e+04 -2.247129e+04 -5.322334e+04
bathrooms         3.423368e+04 -1.631010e+03  3.260267e+04
sqft_living       1.253952e+02  6.287994e+01  1.882752e+02
sqft_lot          4.806154e-02 -2.349830e-01 -1.869214e-01
sqft_above        7.523532e+01 -2.925435e+01  4.598098e+01
floors           -5.561932e+04  1.368998e+04 -4.192934e+04
grade             6.770711e+04  1.292796e+04  8.063507e+04
yr_built         -4.587992e+02 -4.960215e+02 -9.548207e+02
yr_renovated      3.521763e+01  4.774245e+01  8.296009e+01
waterfront        6.853044e+05 -1.543870e+05  5.309174e+05
condition         4.022586e+04  1.853773e+04  5.876359e+04
view              4.654533e+04 -6.562806e+03  3.998253e+04
dist_cbd_km       1.105390e+04 -2.022838e+04 -9.174482e+03
EHD_percen       -8.500003e+02  3.434215e+02 -5.065788e+02
low               1.264530e+05  2.114531e+05  3.379061e+05
high              6.278235e+04  3.924744e+05  4.552568e+05
year_month2014-06  1.931245e+04            NA  1.931245e+04
year_month2014-07  9.751026e+03            NA  9.751026e+03
```

```
year_month2014-08  1.329819e+04            NA  1.329819e+04
year_month2014-09  1.803634e+04            NA  1.803634e+04
year_month2014-10  3.838567e+04            NA  3.838567e+04
year_month2014-11  1.900585e+03            NA  1.900585e+03
year_month2014-12  1.728078e+04            NA  1.728078e+04
year_month2015-01  1.012296e+04            NA  1.012296e+04
year_month2015-02  4.369173e+04            NA  4.369173e+04
year_month2015-03  4.603373e+04            NA  4.603373e+04
year_month2015-04  4.546592e+04            NA  4.546592e+04
year_month2015-05  8.107050e+04            NA  8.107050e+04
========================================================
Standard errors:
                       Direct     Indirect        Total
bedrooms          5.563631e+03 1.144840e+04 1.463721e+04
bathrooms         9.002426e+03 1.803797e+04 2.323683e+04
sqft_living       1.251559e+01 2.619389e+01 3.313395e+01
sqft_lot          1.005473e-01 2.101829e-01 2.497489e-01
sqft_above        1.226682e+01 2.480388e+01 3.095845e+01
floors            1.005275e+04 1.895356e+04 2.342522e+04
grade             5.946730e+03 1.129971e+04 1.400539e+04
yr_built          2.172062e+02 3.918882e+02 4.771913e+02
yr_renovated      1.048488e+01 2.203532e+01 2.802190e+01
waterfront        5.603553e+04 1.105735e+05 1.381409e+05
condition         6.551837e+03 1.304760e+04 1.653907e+04
view              5.954891e+03 1.155019e+04 1.395671e+04
dist_cbd_km       4.901740e+03 5.094681e+03 9.564346e+02
EHD_percen        4.873906e+02 5.801452e+02 4.107363e+02
low               1.200056e+05 1.684072e+05 1.586236e+05
high              8.406277e+04 1.104436e+05 9.504437e+04
year_month2014-06 1.636636e+04           NA 1.636636e+04
year_month2014-07 1.696122e+04           NA 1.696122e+04
year_month2014-08 1.721259e+04           NA 1.721259e+04
year_month2014-09 1.714393e+04           NA 1.714393e+04
year_month2014-10 1.728983e+04           NA 1.728983e+04
year_month2014-11 1.907930e+04           NA 1.907930e+04
year_month2014-12 1.828553e+04           NA 1.828553e+04
year_month2015-01 2.154223e+04           NA 2.154223e+04
year_month2015-02 1.929155e+04           NA 1.929155e+04
year_month2015-03 1.725704e+04           NA 1.725704e+04
year_month2015-04 1.657911e+04           NA 1.657911e+04
year_month2015-05 2.223002e+04           NA 2.223002e+04
========================================================
Z-values:
```

	Direct	Indirect	Total
bedrooms	-5.52733454	-1.96283173	-3.63616687
bathrooms	3.80271645	-0.09042093	1.40306022
sqft_living	10.01911852	2.40055741	5.68224337
sqft_lot	0.47799948	-1.11799293	-0.74843745
sqft_above	6.13323569	-1.17942623	1.48524818
floors	-5.53274454	0.72229053	-1.78992270
grade	11.38560309	1.14409716	5.75743275
yr_built	-2.11227478	-1.26572194	-2.00091823
yr_renovated	3.35889755	2.16663297	2.96054481
waterfront	12.22981932	-1.39623873	3.84330273
condition	6.13963071	1.42077670	3.55301541
view	7.81632029	-0.56819878	2.86475341
dist_cbd_km	2.25509642	-3.97049022	-9.59237803
EHD_percen	-1.74398189	0.59195791	-1.23334303
low	1.05372542	1.25560638	2.13023878
high	0.74685078	3.55361905	4.78993898
year_month2014-06	1.18000878	NA	1.18000878
year_month2014-07	0.57490134	NA	0.57490134
year_month2014-08	0.77258518	NA	0.77258518
year_month2014-09	1.05205412	NA	1.05205412
year_month2014-10	2.22013015	NA	2.22013015
year_month2014-11	0.09961502	NA	0.09961502
year_month2014-12	0.94505241	NA	0.94505241
year_month2015-01	0.46991265	NA	0.46991265
year_month2015-02	2.26481198	NA	2.26481198
year_month2015-03	2.66753296	NA	2.66753296
year_month2015-04	2.74236225	NA	2.74236225
year_month2015-05	3.64689273	NA	3.64689273

p-values:

	Direct	Indirect	Total
bedrooms	3.2513e-08	0.04966573	0.00027673
bathrooms	0.00014312	0.92795272	0.16059888
sqft_living	< 2.22e-16	0.01637012	1.3294e-08
sqft_lot	0.63265057	0.26357001	0.45419634
sqft_above	8.6109e-10	0.23822850	0.13747809
floors	3.1526e-08	0.47011587	0.07346634
grade	< 2.22e-16	0.25258335	8.5403e-09
yr_built	0.03466289	0.20561265	0.04540120
yr_renovated	0.00078254	0.03026285	0.00307095
waterfront	< 2.22e-16	0.16264262	0.00012139
condition	8.2714e-10	0.15538169	0.00038084

```
view               5.3291e-15 0.56990000 0.00417334
dist_cbd_km        0.02412728 7.1725e-05 < 2.22e-16
EHD_percen         0.08116225 0.55387878 0.21744781
low                0.29200865 0.20925872 0.03315190
high               0.45515364 0.00037997 1.6683e-06
year_month2014-06 0.23799672 NA         0.23799672
year_month2014-07 0.56535802 NA         0.56535802
year_month2014-08 0.43976792 NA         0.43976792
year_month2014-09 0.29277472 NA         0.29277472
year_month2014-10 0.02640993 NA         0.02640993
year_month2014-11 0.92064997 NA         0.92064997
year_month2014-12 0.34463212 NA         0.34463212
year_month2015-01 0.63841743 NA         0.63841743
year_month2015-02 0.02352422 NA         0.02352422
year_month2015-03 0.00764104 NA         0.00764104
year_month2015-04 0.00609990 NA         0.00609990
year_month2015-05 0.00026543 NA         0.00026543
```

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

Vi ser (*tabellen kom til sist i pdf*) **SEM** har lavere verdi i AIC enn OLS, som indikerer på at vi må ta hensyn til romelig autokorrelasjon i feilleddet.

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

```
    Likelihood ratio for spatial linear models

data:
Likelihood ratio = 80.083, df = 16, p-value = 1.608e-10
sample estimates:
Log likelihood of SDEM_2000  Log likelihood of SEM_2000
                  -26865.47                   -26905.51
```

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

```
    Likelihood ratio for spatial linear models
```

```
data:
Likelihood ratio = 318.96, df = 1, p-value < 2.2e-16
sample estimates:
Log likelihood of SDEM_2000  Log likelihood of SLX_2000
                  -26865.47                   -27024.95
```

SDEM ser ut til å være en bedre modell enn SLX. Når vi sjekket autokorrelasjon i feilleddet så ble det enn autokorrelasjon i X-variablene.

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

```

    Likelihood Ratio diagnostics for spatial dependence

data:
Likelihood ratio = 318.96, df = 1, p-value < 2.2e-16
sample estimates:
Log likelihood of spatial error model           Log likelihood of OLS fit y
                            -26865.47                             -27024.95
```

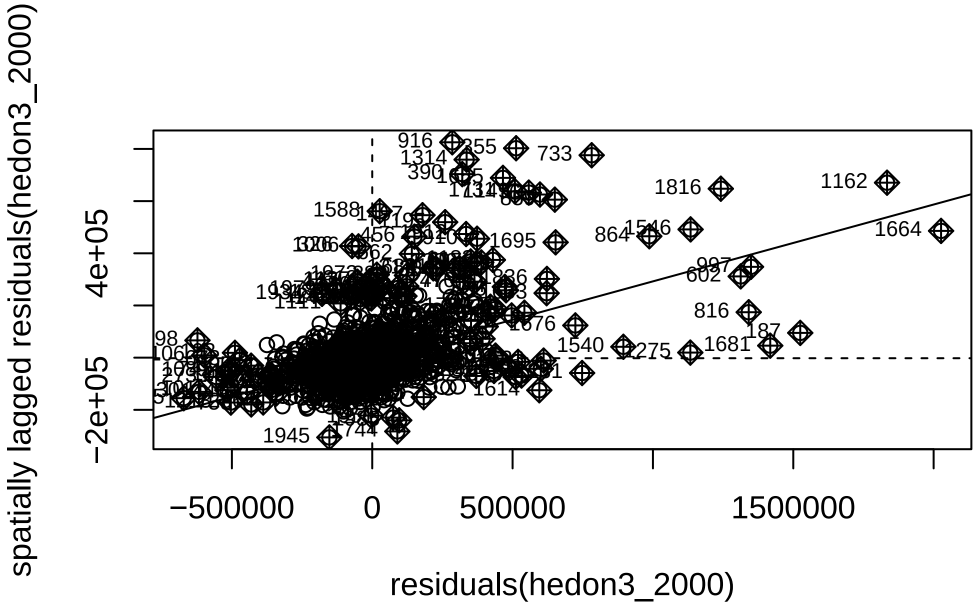
```
Hausman.test(SEM_2000)
```

```

    Spatial Hausman test (asymptotic)

data:  NULL
Hausman test = 87.794, df = 29, p-value = 7.926e-08
```

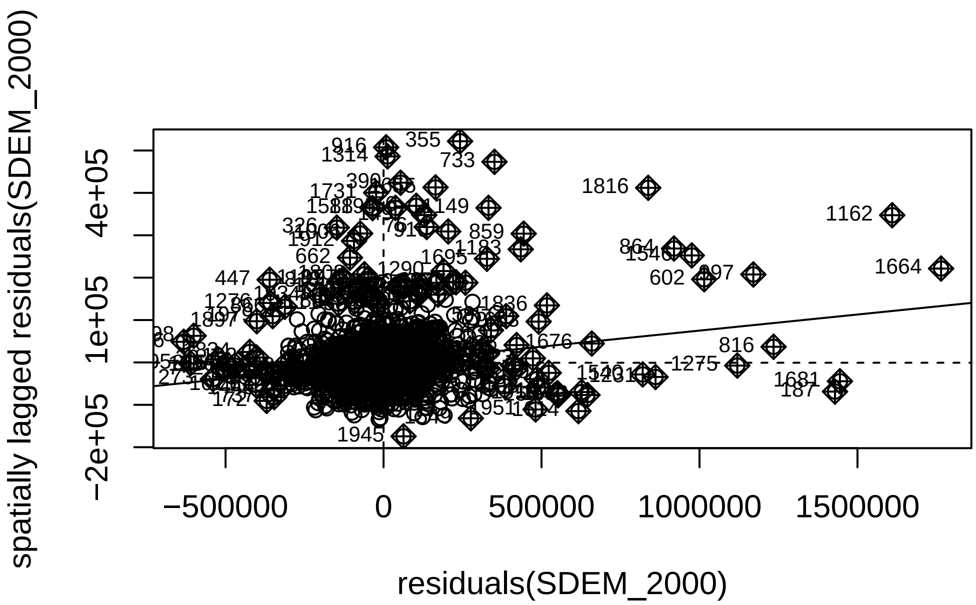
```
bptest.Sarlm(SEM_2000, studentize = TRUE)
```

```

    studentized Breusch-Pagan test

data:
BP = 350.25, df = 28, p-value < 2.2e-16
```

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




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



Vi ser at SDEM tar noe av autokorrelasjonen i feilleddet.

```
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 = 8.1227, p-value = 2.28e-16
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
     7.585639e-02     -5.002501e-04      8.836742e-05
```

oppsumering.

Vi ser at SDEM fungerer og fjerner store deler av den romlige effekten som er i OLSen. Vi ønsket i utgangspunktet å ta i bruk modell 2, men vi fikk ikke til beregningen der og gikk over til modell 3 på grunn av error som oppsto.

#Konklusjon

Vi ser ikke store forskjeller på resultatene på de forskjellige datasettene. SDEM er den beste modellen for alle tre datasettene.

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	6666 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 ***