arbkrv_MSB_205

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(sjekker om jeg får pushet)

Oppgave 1)

Artikkelen tar for seg den hedoniske eiendomsverdimodellen som en av de mest direkte fremvisningen av hvordan private markeder kan avsløre forbrukerens betalingsvillighet (WTP) for miljøkvalitet. Modellen har blitt tatt i bruk på mange bruksområder siden den først ble utviklet på 19-70 tallet og har med årene akselerert i takt med fremskritt innen økonometri og økt datatilgjengelighet. Modellen tar utgangspunkt i at kjøpere velger eiendommer utfra boligegenskaper og stedspesifikke fasiliteter, og etter å ha blitt raffinert gjennom førti år har den blitt en de fremste tilnærmingene til å verdsette endringer i miljøfasiliteter innen offentlig politikk og akademisk forskning.

Det hedoniske rammeverket ble først etablert som en likevektsmodell for å forstå hvilket utslag differensierte produktpriser hadde på forbrukerens etterspørsel etter produktegenskaper/attributter. Når det brukes i boligsammenheng inkluderer den informasjon om tilbudet av boliger, husholdningers preferanser og inntekt, utviklers avgjørelser om nye boliger og videresalg av eksisterende boliger. Markedslikevekt vil oppstå når flytting ikke vil øke nytten for husholdninger. Likevekts konsept viser til et forhold mellom boligpriser og boligkarakteristikk/egenskap som avslører hver kjøpers MWTP for hver fasilitet med forutsetningen om at kjøpere er fult informert, mobile og i stand til å kjøpe kontinuerlige nivåer av hver egenskap.

Hver kjøpers MWTP for fasiliteten kan estimeres i tre trinn: 1. Estimere den hedoniske prisfunksjonen ved å bruke observerte salgsdata. 2. Delvis differensiere prisfunksjonen med hensyn til renter for å estimere implisittprisfunksjon. 3. Tolke de resulterende implisitt-prisverdiene betalt av hver kjøper som estimater av kjøperens MWTP.

Over tid kan MWTP-en til kjøpere endres, dette kan sees på som en endring i funksjonen for implisittpris for fasiliteten/egenskapen. Faktorer som kan være med på å endre kjøperes

MWTP kan være retningslinjer som øker arbeidsproduktivitet, induserer migrasjon, gir ny informasjon rundt fasilitetene eller endrer fasilitetsnivåer.

Definere markeder og innhente data.

Det første steget i bruk av den hedoniske eiendomsverdimodellen er å definere markedet slik at det tilfredsstiller «loven om én prisfunksjon». Det vil si at identiske hus vil selges for samme pris hvor som helst i markedet. De romlige og tidsmessige grensene som tilfredsstiller den betingelsen vil kunne variere på tvers av rom og tid fordi informasjon, institusjoner og flyttekostnader endres. Det er vanlig å definere markedet som et enkelt storbyområde over noen år. Det vil være lettere å opprettholde betingelsen om én prisfunksjon mellom lokasjoner i et storbyområde, mens det vil være mindre sannsynlig hvis markedet defineres til å omfatte flere storbyområder og/eller flere år. Dette fordi den hedoniske eiendomsverdimodellen ignorer arbeidsmarkedshensyn og heterogene flyttekostnader, noe som gjør det vanskelig å oversette hedoniske priser til MWTP-målinger dersom markedet omfatter flere storbyområder. Arbeidsmarkedshensyn og heterogene flyttekostnader kan komme fra flytting mellom storbyområder. Samtidig som arbeidstakere kanskje må bytte jobb, samt at det vil forekomme variasjoner i skattepolitikk og levekostnader (sett vekk fra boliger).

Dersom man slår sammen data fra en lang periode vil man også få lignende problemer med MWTP-målinger. Dette fordi boligfunksjoner kan endre seg under høykonjunkturer dersom makroøkonomiske faktorer er med på å endre beløpene boligkjøpere er villig til å betale for fasiliteter. Samtidig som policyer som feks forbedrer luftkvaliteten vil være med på å redusere kjøperes MWTP for flere luftkvalitetsforbedringer.

Neste trinn vil være å innhente data. Når det kommer til datainnsamling, er gullstanderen inn hedoniske eiendomsverdistudier et tilfeldig utvalg av boligtransaksjonspriser og egenskaper/fasiliteter for det aktuelle studieområde.

Utelatt variabel skjevhet

Miljøfasiliteter i den hedoniske eiendomsverdimodellen viser tendenser til å være romlig korrelert på grunn av naturlige trekk ved geografi, miljøtilbakemeldingseffekter og stemmegivning om lokale fellesgoder. Potensialet for romlig korrelasjon fører til utbredt bekymring for utelatt-variabel skjevhet. Dette fordi det vil være usannsynlig for forskere å inkludere alle fasiliteter som vil være betydningsfulle for kjøpere. Videre vil også uobserverte fasiliteter kunne korreleres med fasiliteter av interesse, og dermed føre til skjevhet. Et eksempel vil være dersom en velstående familie flytter til områder med bedre luftkvalitet og deretter stemmer for å øke offentlig skolefinansiering, vil MWTP estimatet for luftkvalitet være skjev dersom skolekvalitet er utelatt fra modellen. For at de resulterende estimatene skal være troverdige må forskningsdesignet isolere eksogen variasjon i fasilitetene av interesse.

Oppgave 2)

i)

Lastet ned datsett fra Kaggle, sjekket variblene og definisjonene. Ser greit ut.

ii)

```
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)

Sorterer salgene etter dato med siste salg først:

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

iv)

Velger ut siste salg fra datasettet:

```
kc_house_data <- kc_house_data %>%
  # Denne blir for enkel. Samme hus kan ha flere id-er
  # id gåt på salg. Vi må benytte koordinater for å finne
  # duplicater
  # distinct(id, .keep_all = TRUE)
  # Jeg forslår
  mutate(
    year = year(date),
```

```
    month = month(date),
    day = mday(date)
    ) %>%
  select(id, price, year, month,day, everything()) %>% # last sale first
  arrange(desc(year), desc(month), desc(day)) %>%
   # in case of duplicates, choose laste sale
  distinct(paste(long, lat, sep = ""), .keep_all = TRUE)
```

v)

```
kc_house_data_sf <- st_as_sf(kc_house_data,
                             coords = c(x = "long",
                                        y = "lat"),
                             crs = 4326)
```

vi)

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

vii)

Bruker koordinater, 47.60621, -122.33207, fra Seattles wikipediaside som CBD for Seattle:

```
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 <- st_read("../maps/WADOH_Environmental_Health_Disparities_Index_Calculated_f
  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
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
)
```

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

```
Reading layer `tracts10' from data source
  `/Users/ag/Dev/assignments/msb205/stud_22/innlevert/maps/censusSHP/tracts10.shp'
  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 <- st_read("../maps/censusSHP/tracts10_shore.shp") %>%
  st_transform(2926)
```

```
Reading layer `tracts10_shore' from data source
  `/Users/ag/Dev/assignments/msb205/stud_22/innlevert/maps/censusSHP/tracts10_shore.shp'
  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_shore_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 20832 features with 25 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 20832 features with 69 fields and geometry type Point.
```

```r
st_write(kc_tracts10_shore_env_var, "../maps/censusSHP/kc_tracts10_shore_env_var.gpkg", ap
```

```
Deleting layer `kc_tracts10_shore_env_var' using driver `GPKG'
Writing layer `kc_tracts10_shore_env_var' to data source
  `../maps/censusSHP/kc_tracts10_shore_env_var.gpkg' using driver `GPKG'
Writing 20832 features with 69 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
```

```
summary(kc_tracts10_shore_env_var)
```

```
      id                 price               year          month
 Length:20832       Min.   :  75000   Min.   :2014   Min.   : 1.000
 Class :character   1st Qu.: 323000   1st Qu.:2014   1st Qu.: 4.000
 Mode  :character   Median : 452000   Median :2014   Median : 6.000
                    Mean   : 543491   Mean   :2014   Mean   : 6.553
```

```
                     3rd Qu.: 650000   3rd Qu.:2015   3rd Qu.: 9.000  
                     Max.   :7700000   Max.   :2015   Max.   :12.000  

      day             date                              bedrooms    
 Min.   : 1.0   Min.   :2014-05-02 00:00:00.00   Min.   : 0.00  
 1st Qu.: 8.0   1st Qu.:2014-07-23 00:00:00.00   1st Qu.: 3.00  
 Median :16.0   Median :2014-10-20 00:00:00.00   Median : 3.00  
 Mean   :15.7   Mean   :2014-10-31 09:23:25.99   Mean   : 3.38  
 3rd Qu.:23.0   3rd Qu.:2015-02-19 00:00:00.00   3rd Qu.: 4.00  
 Max.   :31.0   Max.   :2015-05-27 00:00:00.00   Max.   :33.00  

   bathrooms      sqft_living       sqft_lot           floors     
 Min.   :0.000   Min.   :  290   Min.   :    520   Min.   :1.000  
 1st Qu.:1.750   1st Qu.: 1430   1st Qu.:   5105   1st Qu.:1.000  
 Median :2.250   Median : 1930   Median :   7680   Median :1.500  
 Mean   :2.118   Mean   : 2092   Mean   :  15424   Mean   :1.487  
 3rd Qu.:2.500   3rd Qu.: 2560   3rd Qu.:  10800   3rd Qu.:2.000  
 Max.   :8.000   Max.   :13540   Max.   :1651359   Max.   :3.500  

   waterfront           view          condition         grade       
 Min.   :0.00000   Min.   :0.0000   Min.   :1.000   Min.   : 1.000  
 1st Qu.:0.00000   1st Qu.:0.0000   1st Qu.:3.000   1st Qu.: 7.000  
 Median :0.00000   Median :0.0000   Median :3.000   Median : 7.000  
 Mean   :0.00768   Mean   :0.2384   Mean   :3.414   Mean   : 7.663  
 3rd Qu.:0.00000   3rd Qu.:0.0000   3rd Qu.:4.000   3rd Qu.: 8.000  
 Max.   :1.00000   Max.   :4.0000   Max.   :5.000   Max.   :13.000  

   sqft_above   sqft_basement       yr_built     yr_renovated    
 Min.   : 290   Min.   :   0.0   Min.   :1900   Min.   :   0.00  
 1st Qu.:1200   1st Qu.:   0.0   1st Qu.:1951   1st Qu.:   0.00  
 Median :1570   Median :   0.0   Median :1975   Median :   0.00  
 Mean   :1797   Mean   : 295.6   Mean   :1971   Mean   :  85.65  
 3rd Qu.:2230   3rd Qu.: 580.0   3rd Qu.:1996   3rd Qu.:   0.00  
 Max.   :9410   Max.   :4820.0   Max.   :2015   Max.   :2015.00  

    zipcode       sqft_living15    sqft_lot15     paste(long, lat, sep = "")
 Min.   :98001   Min.   : 399   Min.   :   659   Length:20832              
 1st Qu.:98033   1st Qu.:1490   1st Qu.:  5155   Class :character          
 Median :98065   Median :1850   Median :  7678   Mode  :character          
 Mean   :98078   Mean   :1995   Mean   : 13005                             
 3rd Qu.:98117   3rd Qu.:2370   3rd Qu.: 10142                             
 Max.   :98199   Max.   :6210   Max.   :871200                             
```

```
        geometry        dist_cbd        dist_cbd_km        GEO_ID_TRT
POINT         :20832   Min.   :  3228   Min.   : 0.9838   Length:20832
epsg:2926     :    0   1st Qu.: 32361   1st Qu.: 9.8635   Class :character
+proj=lcc ...:     0   Median : 54576   Median :16.6349   Mode  :character
                       Mean   : 60937   Mean   :18.5737
                       3rd Qu.: 83377   3rd Qu.:25.4134
                       Max.   :253647   Max.   :77.3117

  FEATURE_ID     TRACT_LBL          TRACT_STR           TRACT_INT
Min.   :10153   Length:20832       Length:20832       Min.   :  100
1st Qu.:36346   Class :character   Class :character   1st Qu.:10600
Median :44764   Mode  :character   Mode  :character   Median :24901
Mean   :38371                                         Mean   :21342
3rd Qu.:45279                                         3rd Qu.:31204
Max.   :45838                                         Max.   :32800
NA's   :25                                            NA's   :25
  TRACT_FLT      TRACT_DEL          TRTLABEL_F         TRTLABEL_C
Min.   :  1.0   Length:20832       Length:20832       Length:20832
1st Qu.:106.0   Class :character   Class :character   Class :character
Median :249.0   Mode  :character   Mode  :character   Mode  :character
Mean   :213.4
3rd Qu.:312.0
Max.   :328.0
NA's   :25
 TRTLABEL_T          COUNTY_STR          COUNTY_INT  STATE_STR
Length:20832       Length:20832       Min.   :33   Length:20832
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:20832       Length:20832       Length:20832
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:20832       Min.   :2.792e+06
1st Qu.:2.491e+07   1st Qu.: 23562   Class :character   1st Qu.:2.281e+07
```

```
Median :4.131e+07   Median : 32944   Mode  :character   Median :3.451e+07
Mean   :1.829e+08   Mean   : 48442                      Mean   :1.771e+08
3rd Qu.:7.308e+07   3rd Qu.: 47962                      3rd Qu.:6.688e+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.: 23226   1st Qu.:0.047091   1st Qu.:0.21668   1st Qu.:0.47602
Median : 31358   Median :0.074766   Median :0.30477   Median :0.61143
Mean   : 47090   Mean   :0.100073   Mean   :0.31157   Mean   :0.58835
3rd Qu.: 46624   3rd Qu.:0.134040   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.: 3.180   1st Qu.: 8.93   1st Qu.:21.15
Median : 41.00   Median : 7.000   Median :13.52   Median :33.26
Mean   : 43.64   Mean   : 9.027   Mean   :16.63   Mean   :35.34
3rd Qu.: 67.00   3rd Qu.:12.820   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   :213      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.: 3.250   1st Qu.:25.61   1st Qu.: 0.00
Median :20.00   Median : 4.310   Median :30.46   Median : 0.04
Mean   :19.79   Mean   : 4.778   Mean   :31.37   Mean   :11.42
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   :101      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 : 9.83   Median :50.03   Median :6.044   Median :  8730.9
Mean   :13.58   Mean   :51.19   Mean   :6.002   Mean   : 17184.5
3rd Qu.:16.34   3rd Qu.:52.32   3rd Qu.:6.583   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.   : 0.240   Min.   :0.03454   Min.   :0.0523
1st Qu.:0.03957   1st Qu.: 5.305   1st Qu.:0.06594   1st Qu.:0.1420
Median :0.05164   Median :11.950   Median :0.11278   Median :0.2680
Mean   :0.07438   Mean   :16.522   Mean   :0.21700   Mean   :0.5230
3rd Qu.:0.07891   3rd Qu.:26.270   3rd Qu.:0.23841   3rd Qu.:0.7588
```

```
 Max.   :0.63781   Max.   :54.680   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.   :  1.00   Min.   :  1.00
 1st Qu.:0.000003   1st Qu.: 25.00   1st Qu.: 21.00
 Median :0.000290   Median : 48.00   Median : 43.00
 Mean   :0.016325   Mean   : 48.16   Mean   : 44.63
 3rd Qu.:0.002900   3rd Qu.: 72.00   3rd Qu.: 67.00
 Max.   :0.640000   Max.   :100.00   Max.   :100.00
 NA's   :25         NA's   :25       NA's   :25
```

ii)

I *tracts10_shore* ligger flere observasjoner i havet, og disse settes til NA verdier. Dette kan være hus som ligger langs kysten eller har fått upresis beliggenhet i datasettet. *Tract10* kutter kartet ved sjøgrensen og dermed er ikke disse 25 NA verdiene med blant observasjonene.

QGIS viser disse observasjonene ved *tracts10*, *tracts10_shore* & *kc_houses_env_var*:

BILDENE MÅ LEGGES INN PÅ NY

observasjon utenfor WA state utenfor_WAstate.png

Observasjon utenfor kystlinjen.a utenfor_kystlinjen_1.png

Observasjon utenfor kystlinjen.b](utenfor_kystlinjen_2.png

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 20831 features with 69 fields and geometry type Point.
```

```
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 20831 features with 70 fields and geometry type Point.
```

Oppgave 5

Får ikke geoda og qis til å funke

Oppgave 6

i)

Når man ser på boligpriser i sammenheng med boligstørrelse ser man at boliger med høy pris og liten størrelse befinner seg rundt Seattle sentrum. Videre ser man boligene som er av stor størrelse til høy pris finnes øst i Seattle. Til slutt ser man at boligene av liten størrelse og til lav pris, sammen med boligene av stor størrelse til lav pris befinner seg i nær sentrum av Seattle.

Funn fra EDA

```
attach(kc_houses_env_var_omit)
```

1. Huskarakteristika

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

2. Huskarakteristika, distanse til cbd og tracts_var

```
mod2 <- "price ~ bedrooms + bathrooms + year_month + linguist_2 + poverty_pe + POC_percen
```

3. Huskarakteristika, distanse til cbd og EHD

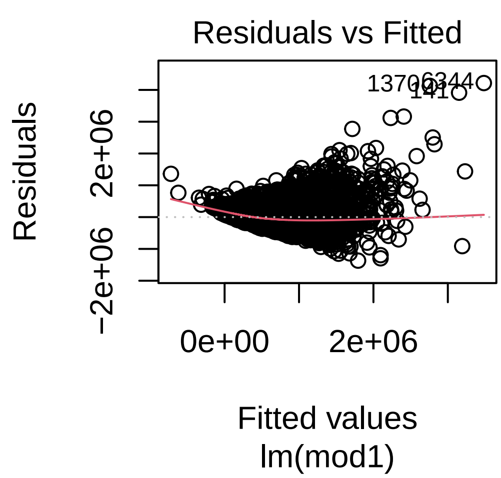
```
mod3 <- "price ~ bedrooms + bathrooms + sqft_living + sqft_lot + sqft_above + floors + gra
```

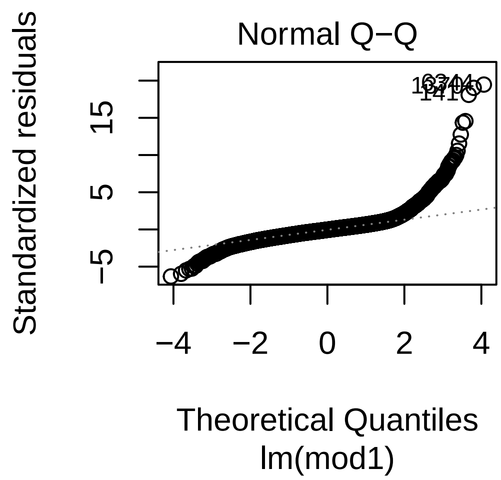
```
hedon1 <- lm(mod1, data = kc_houses_env_var_omit)
hedon2 <- lm(mod2, data = kc_houses_env_var_omit)
hedon3 <- lm(mod3, data = kc_houses_env_var_omit)
```

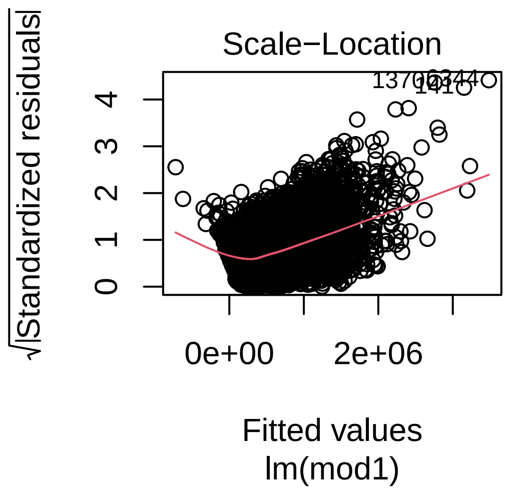
```
huxreg("Hedon1" = hedon1, "Hedon2" = hedon2, "Hedon3" = hedon3,
    error_format = "[{statistic}]",
    note = "{stars}. T statistic in brackets.")
```

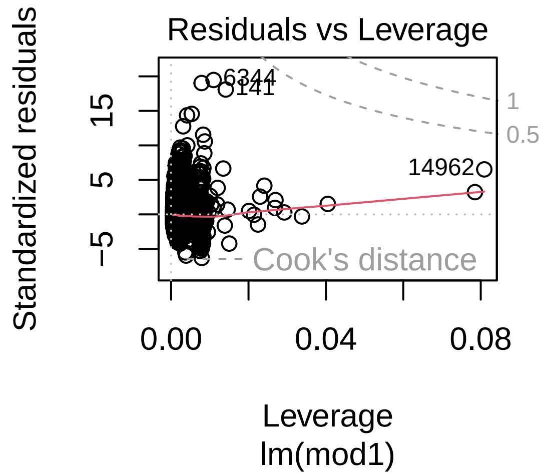
Plots

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

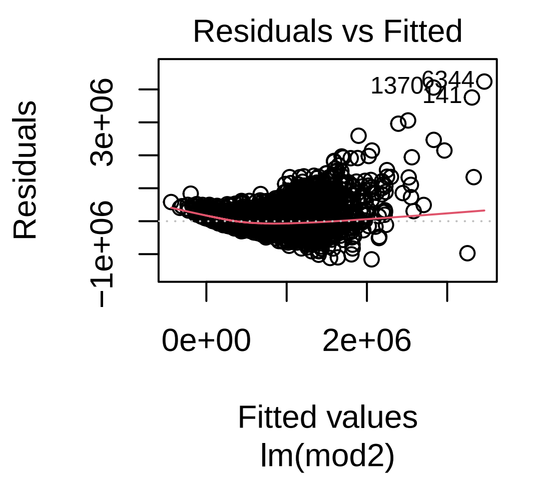


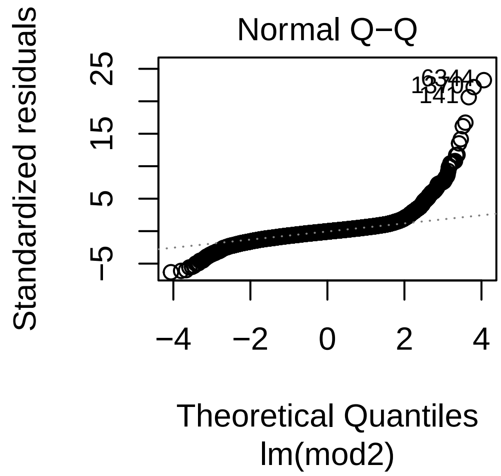

Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(mod1)
−5
5
15
−4
−2
0
2
4
141

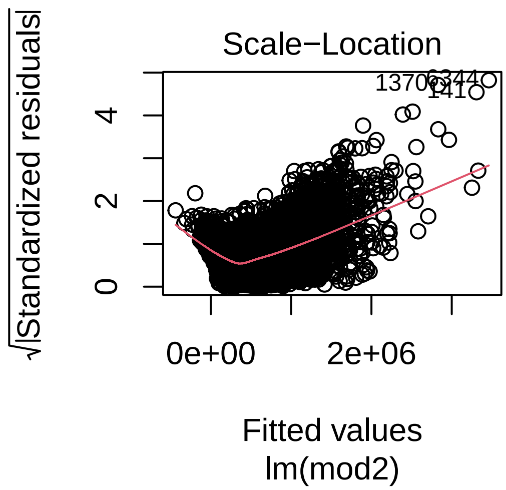

Scale−Location
√|Standardized residuals|
Fitted values
lm(mod1)
0
1
2
3
4
0e+00
2e+06
141

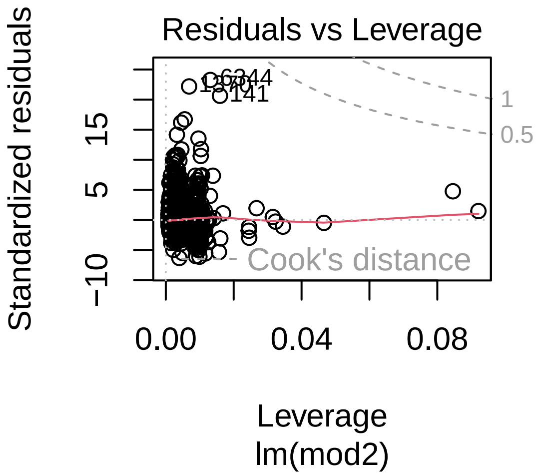

Residuals vs Leverage
Standardized residuals
−5
5
15
6344
141
14962
1
0.5
Cook's distance
0.00
0.04
0.08
Leverage
lm(mod1)

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

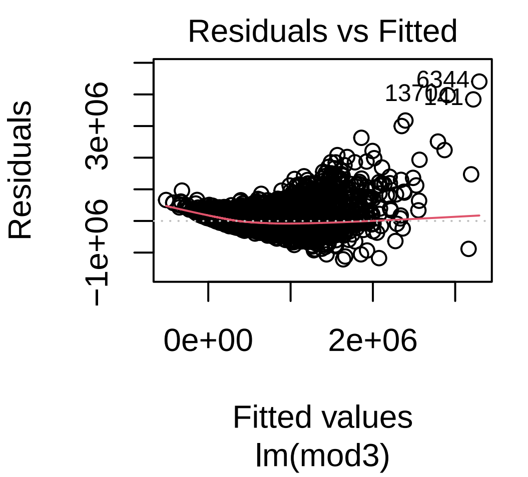

Residuals vs Fitted
Residuals
−1e+06
3e+06
13706
6344
141
0e+00
2e+06
Fitted values
lm(mod2)

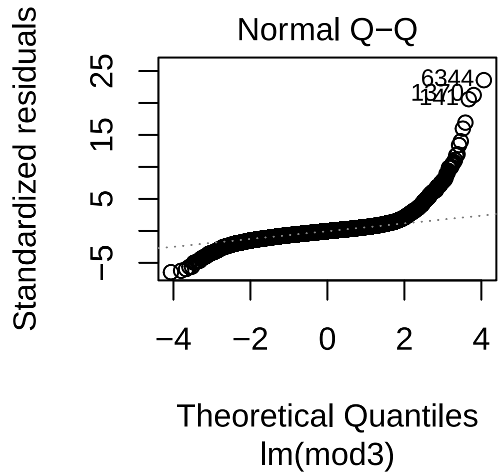

Normal Q−Q
Standardized residuals
−5
5
15
25
6344
13706
141
−4
−2
0
2
4
Theoretical Quantiles
lm(mod2)

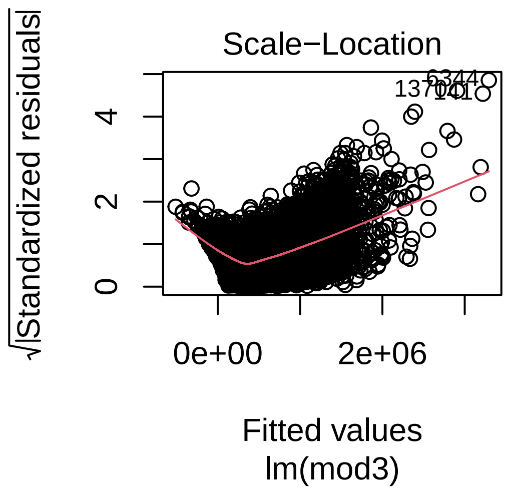

Scale−Location
√|Standardized residuals|
0
2
4
13706
6344
141
0e+00
2e+06
Fitted values
lm(mod2)

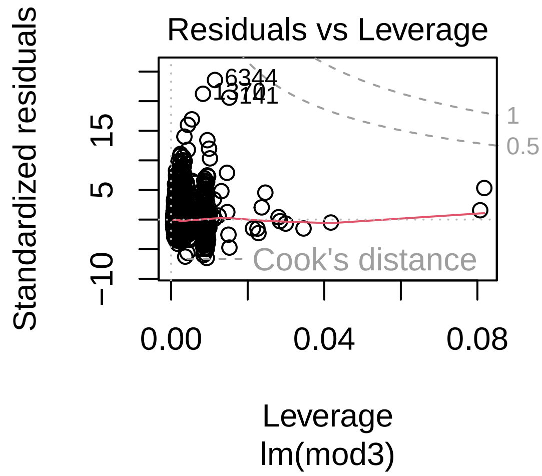

Residuals vs Leverage
Standardized residuals
−10
5
15
0.00
0.04
0.08
Leverage
lm(mod2)
6344
13701
141
1
0.5
Cook's distance

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


Residuals vs Fitted
Residuals
−1e+06
3e+06
0e+00
2e+06
Fitted values
lm(mod3)
6344
13701
141


Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(mod3)
6344
1370
141
−5
5
15
25
−4
−2
0
2
4


Scale−Location
√|Standardized residuals|
Fitted values
lm(mod3)
6344
1370
141
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 = Ikke signifikant variasjon i salgspris basert på salgstidspunkt

Velger å forkaste denne nullhypotesen siden F- og P-verdiene er signifikant, og det er dermed rimelig å anta at tids-dummiene gir en effekt i modellen til tross for at de er insignifikant på individuelt nivå. Indikasjonen her er at salgspris varierer etter salgstidspunkt.

Oppgave 8

```r
Seattle_5555 <- here("kc_house_data_5555_Vilde_og_Susann.gpkg") %>%
  st_read() %>%
  st_transform(2926)
```

```
Reading layer `kc_house_data_5555_Vilde_og_Susann' from data source
  `/Users/ag/Dev/assignments/msb205/stud_22/innlevert/AKMSB205_VNH_SBS/kc_house_data_5555_Vil
  using driver `GPKG'
Simple feature collection with 1887 features and 51 fields
Geometry type: POINT
Dimension:     XY
Bounding box:  xmin: 1234612 ymin: 72563.3 xmax: 1521844 ymax: 287204.8
Projected CRS: NAD83(HARN) / Washington North (ftUS)
```

```r
Seattle_5555 <- Seattle_5555 %>%
  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
Seattle_5555 <- Seattle_5555 %>%
  rename(low = inc_fam_low_per,
```

```r
         mid = inc_fam_med_per,
         high = inc_fam_high_per)
```

```r
hedon3_seed <- lm(mod3, data = Seattle_5555)
```

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

```r
hedon3_seed <- lm(mod3, data = Seattle_5555)
```

```r
Seattle_5555_knn3 <- knearneigh(Seattle_5555, k = 3)
Seattle_5555_nb3 <- knn2nb(Seattle_5555_knn3)
Seattle_5555_W3 <- nb2listw(Seattle_5555_nb3, style = "W")
```

```r
Seattle_5555_knn10 <- knearneigh(Seattle_5555, k = 10)
Seattle_5555_nb10 <- knn2nb(Seattle_5555_knn10)
Seattle_5555_W10 <- nb2listw(Seattle_5555_nb10, style = "W")
```

```r
lm.morantest(hedon3_seed, Seattle_5555_W3)
```

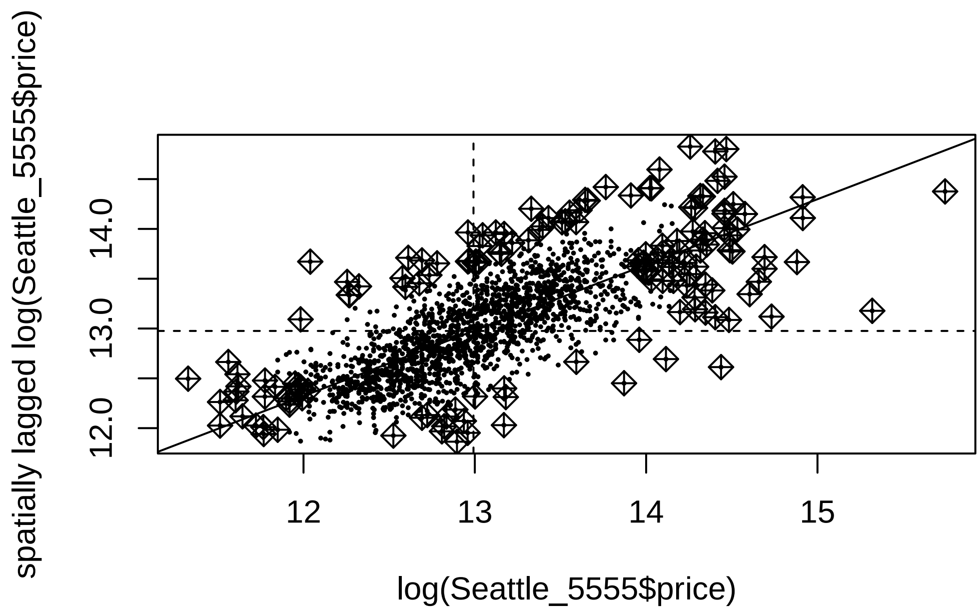
```

    Global Moran I for regression residuals

data:
model: lm(formula = mod3, data = Seattle_5555)
weights: Seattle_5555_W3

Moran I statistic standard deviate = 17.661, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
    0.3049996301    -0.0032574475     0.0003046602
```

```r
lm.morantest(hedon3_seed, Seattle_5555_W10)
```

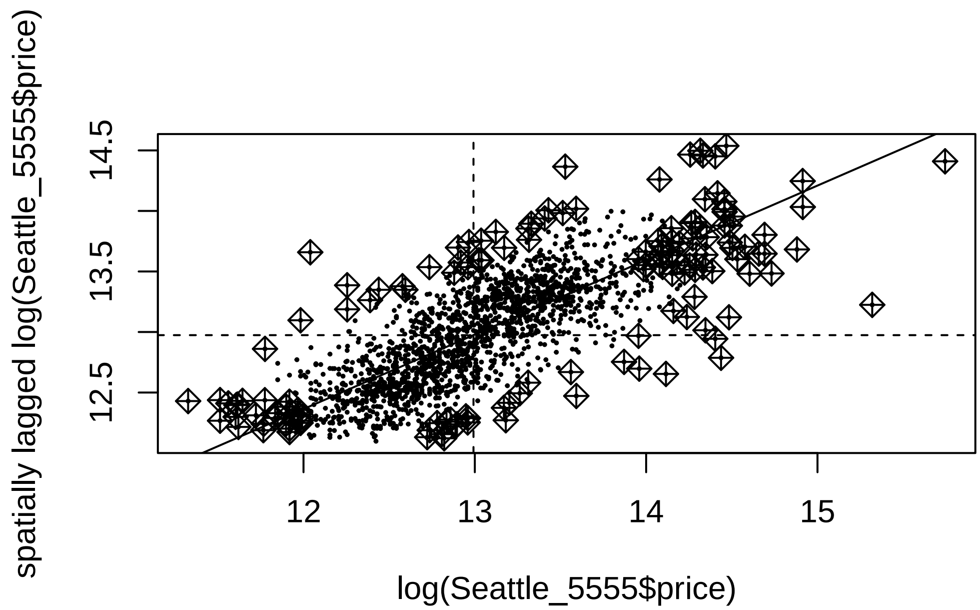
```

    Global Moran I for regression residuals
```

```
data:
model: lm(formula = mod3, data = Seattle_5555)
weights: Seattle_5555_W10

Moran I statistic standard deviate = 26.145, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
    2.493192e-01    -2.611589e-03     9.285358e-05
```

```
moran.plot(log(Seattle_5555$price), listw = Seattle_5555_W3,
           labels = FALSE, pch = 20, cex = 0.3)
```




```
moran.plot(log(Seattle_5555$price), listw = Seattle_5555_W10,
           labels = FALSE, pch = 20, cex = 0.3)
```



iv)

Gi kommentar

```
kc_lagrange_3 <- lm.LMtests(hedon3_seed, Seattle_5555_W3,
                   test = "all")
kc_lagrange_3
```

```
    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = Seattle_5555)
weights: Seattle_5555_W3

LMerr = 302.81, df = 1, p-value < 2.2e-16


    Lagrange multiplier diagnostics for spatial dependence

data:
```

```
model: lm(formula = mod3, data = Seattle_5555)
weights: Seattle_5555_W3

LMlag = 209.63, df = 1, p-value < 2.2e-16


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = Seattle_5555)
weights: Seattle_5555_W3

RLMerr = 105.01, df = 1, p-value < 2.2e-16


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = Seattle_5555)
weights: Seattle_5555_W3

RLMlag = 11.835, df = 1, p-value = 0.0005812


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = Seattle_5555)
weights: Seattle_5555_W3

SARMA = 314.64, df = 2, p-value < 2.2e-16
```

```
kc_lagrange_10 <- lm.LMtests(hedon3_seed, Seattle_5555_W10,
               test = "all")
kc_lagrange_10
```

```
    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = Seattle_5555)
```

```
weights: Seattle_5555_W10

LMerr = 649.16, df = 1, p-value < 2.2e-16


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = Seattle_5555)
weights: Seattle_5555_W10

LMlag = 437.67, df = 1, p-value < 2.2e-16


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = Seattle_5555)
weights: Seattle_5555_W10

RLMerr = 266.45, df = 1, p-value < 2.2e-16


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = Seattle_5555)
weights: Seattle_5555_W10

RLMlag = 54.951, df = 1, p-value = 1.236e-13


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = Seattle_5555)
weights: Seattle_5555_W10

SARMA = 704.11, df = 2, p-value < 2.2e-16
```

v)

```
SDEM_seed <- errorsarlm(mod3, data = Seattle_5555, listw = Seattle_5555_W3, Durbin = as.fo
```

```
Warning in errorsarlm(mod3, data = Seattle_5555, listw = Seattle_5555_W3, : inversion of asy
  reciprocal condition number = 4.96834e-22 - using numerical Hessian.
```

Ovenfor advarer de om numeriske problemer, vi ser vekk ifra det her

```
SLX_seed <- lmSLX(mod3, data = Seattle_5555, listw = Seattle_5555_W3, Durbin =  as.formula
```

```
SEM_seed <- errorsarlm(mod3, data = Seattle_5555, listw = Seattle_5555_W3, Durbin = FALSE)
```

```
Warning in errorsarlm(mod3, data = Seattle_5555, listw = Seattle_5555_W3, : inversion of asy
  reciprocal condition number = 4.50408e-22 - using numerical Hessian.
```

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

```
Impact measures (SDEM, estimable, n):
                        Direct      Indirect         Total
bedrooms         -2.986051e+04 -2.387268e+04 -5.373319e+04
bathrooms         5.076329e+04  7.882934e+03  5.864622e+04
sqft_living       1.041087e+02  3.400515e+01  1.381138e+02
sqft_lot          2.816748e-01 -2.520514e-01  2.962337e-02
sqft_above        1.220160e+02            NA  1.220160e+02
floors           -7.592111e+04  2.466124e+04 -5.125988e+04
grade             5.859546e+04 -5.398046e+02  5.805565e+04
yr_built         -8.065074e+02 -1.410067e+03 -2.216574e+03
yr_renovated     -1.592019e+01            NA -1.592019e+01
waterfront        5.152796e+05            NA  5.152796e+05
condition         2.095740e+04            NA  2.095740e+04
view              5.383952e+04            NA  5.383952e+04
dist_cbd_km      -1.058543e+04  2.152152e+03 -8.433278e+03
EHD_percen        6.869534e+02 -1.759394e+03 -1.072441e+03
low               2.745175e+05 -1.156757e+05  1.588418e+05
high              2.048633e+05  9.302486e+04  2.978882e+05
year_month2014-06 -2.115417e+03            NA -2.115417e+03
year_month2014-07  1.152788e+04            NA  1.152788e+04
```

```
year_month2014-08  2.027332e+04            NA  2.027332e+04
year_month2014-09  1.275583e+04            NA  1.275583e+04
year_month2014-10 -1.029709e+04            NA -1.029709e+04
year_month2014-11  8.060550e+03            NA  8.060550e+03
year_month2014-12 -1.066479e+04            NA -1.066479e+04
year_month2015-01 -1.997118e+03            NA -1.997118e+03
year_month2015-02  5.327941e+03            NA  5.327941e+03
year_month2015-03  4.214777e+04            NA  4.214777e+04
year_month2015-04  5.114368e+04            NA  5.114368e+04
year_month2015-05  2.641630e+04            NA  2.641630e+04
========================================================
Standard errors:
                        Direct     Indirect        Total
bedrooms          6.022639e+03 1.140368e+04 1.439002e+04
bathrooms         1.002251e+04 1.945947e+04 2.490203e+04
sqft_living       1.343249e+01 1.906847e+01 2.561423e+01
sqft_lot          1.355666e-01 2.530288e-01 2.884836e-01
sqft_above        1.351351e+01           NA 1.351351e+01
floors            1.114619e+04 1.782075e+04 2.209280e+04
grade             6.656466e+03 1.238841e+04 1.523326e+04
yr_built          2.261629e+02 3.739220e+02 4.532813e+02
yr_renovated      1.042121e+01           NA 1.042121e+01
waterfront        5.188322e+04           NA 5.188322e+04
condition         6.717333e+03           NA 6.717333e+03
view              6.721668e+03           NA 6.721668e+03
dist_cbd_km       9.753264e+03 9.777356e+03 8.543903e+02
EHD_percen        5.564463e+02 6.475081e+02 4.182455e+02
low               1.173313e+05 1.577185e+05 1.389885e+05
high              8.691298e+04 1.126854e+05 9.636860e+04
year_month2014-06 1.834326e+04           NA 1.834326e+04
year_month2014-07 1.877617e+04           NA 1.877617e+04
year_month2014-08 1.941187e+04           NA 1.941187e+04
year_month2014-09 2.004808e+04           NA 2.004808e+04
year_month2014-10 1.950932e+04           NA 1.950932e+04
year_month2014-11 2.058919e+04           NA 2.058919e+04
year_month2014-12 2.125263e+04           NA 2.125263e+04
year_month2015-01 2.357920e+04           NA 2.357920e+04
year_month2015-02 2.148421e+04           NA 2.148421e+04
year_month2015-03 1.953927e+04           NA 1.953927e+04
year_month2015-04 1.865478e+04           NA 1.865478e+04
year_month2015-05 2.684120e+04           NA 2.684120e+04
========================================================
Z-values:
```

	Direct	Indirect	Total
bedrooms	-4.95804380	-2.09341926	-3.73405882
bathrooms	5.06492645	0.40509489	2.35507788
sqft_living	7.75051411	1.78331785	5.39207548
sqft_lot	2.07776009	-0.99613725	0.10268649
sqft_above	9.02918393	NA	9.02918393
floors	-6.81139383	1.38384981	-2.32020781
grade	8.80278761	-0.04357336	3.81111244
yr_built	-3.56604714	-3.77101829	-4.89006265
yr_renovated	-1.52767155	NA	-1.52767155
waterfront	9.93152698	NA	9.93152698
condition	3.11989846	NA	3.11989846
view	8.00984549	NA	8.00984549
dist_cbd_km	-1.08532175	0.22011592	-9.87052078
EHD_percen	1.23453662	-2.71717758	-2.56414209
low	2.33967779	-0.73343166	1.14284129
high	2.35710872	0.82552688	3.09113342
year_month2014-06	-0.11532393	NA	-0.11532393
year_month2014-07	0.61396316	NA	0.61396316
year_month2014-08	1.04437763	NA	1.04437763
year_month2014-09	0.63626205	NA	0.63626205
year_month2014-10	-0.52780387	NA	-0.52780387
year_month2014-11	0.39149430	NA	0.39149430
year_month2014-12	-0.50181047	NA	-0.50181047
year_month2015-01	-0.08469829	NA	-0.08469829
year_month2015-02	0.24799340	NA	0.24799340
year_month2015-03	2.15708002	NA	2.15708002
year_month2015-04	2.74158552	NA	2.74158552
year_month2015-05	0.98416988	NA	0.98416988

p-values:

	Direct	Indirect	Total
bedrooms	7.1207e-07	0.03631174	0.00018842
bathrooms	4.0856e-07	0.68540776	0.01851882
sqft_living	9.1038e-15	0.07453458	6.9648e-08
sqft_lot	0.03773146	0.31918346	0.91821179
sqft_above	< 2.22e-16	NA	< 2.22e-16
floors	9.6658e-12	0.16640445	0.02032964
grade	< 2.22e-16	0.96524449	0.00013834
yr_built	0.00036241	0.00016258	1.0080e-06
yr_renovated	0.12659411	NA	0.12659411
waterfront	< 2.22e-16	NA	< 2.22e-16
condition	0.00180913	NA	0.00180913

```
view              1.1102e-15 NA         1.1102e-15
dist_cbd_km       0.27777918 0.82578088 < 2.22e-16
EHD_percen        0.21700301 0.00658413 0.01034312
low               0.01930038 0.46329520 0.25310449
high              0.01841785 0.40907253 0.00199394
year_month2014-06 0.90818837 NA         0.90818837
year_month2014-07 0.53923967 NA         0.53923967
year_month2014-08 0.29631071 NA         0.29631071
year_month2014-09 0.52460563 NA         0.52460563
year_month2014-10 0.59763547 NA         0.59763547
year_month2014-11 0.69543190 NA         0.69543190
year_month2014-12 0.61580084 NA         0.61580084
year_month2015-01 0.93250126 NA         0.93250126
year_month2015-02 0.80413951 NA         0.80413951
year_month2015-03 0.03099943 NA         0.03099943
year_month2015-04 0.00611434 NA         0.00611434
year_month2015-05 0.32503199 NA         0.32503199
```

```r
huxreg("SEM" = SEM_seed, "OLS" = hedon3_seed, error_format = "[{statistic}]", note = "{sta
```

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

```
    Likelihood ratio for spatial linear models

data:
Likelihood ratio = 44.58, df = 11, p-value = 5.751e-06
sample estimates:
Log likelihood of SDEM_seed  Log likelihood of SEM_seed
                  -25491.25                   -25513.54
```

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

```
    Likelihood ratio for spatial linear models

data:
Likelihood ratio = 213.65, df = 4, p-value < 2.2e-16
sample estimates:
```

```
Log likelihood of SDEM_seed  Log likelihood of SLX_seed
                  -25491.25                   -25598.07
```

Fortsetter ved å kontrollteste SDEM-modellen mot OLS-modellen

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

```

    Likelihood Ratio diagnostics for spatial dependence

data:
Likelihood ratio = 237.04, df = 1, p-value < 2.2e-16
sample estimates:
Log likelihood of spatial error model           Log likelihood of OLS fit y
                            -25491.25                             -25609.76
```

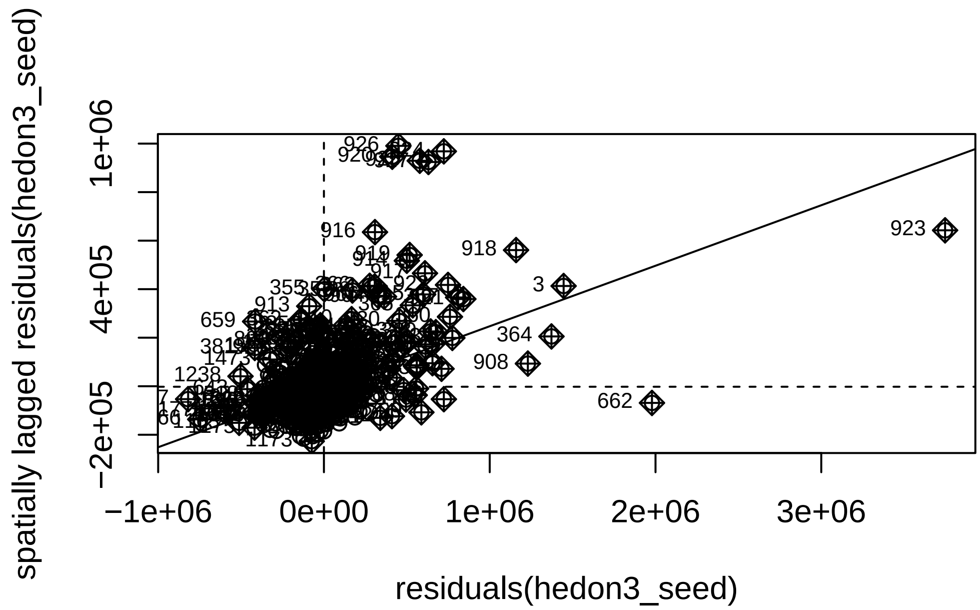
```r
Hausman.test(SEM_seed)
```

```

    Spatial Hausman test (asymptotic)

data:  NULL
Hausman test = 108.49, df = 29, p-value = 4.096e-11
```

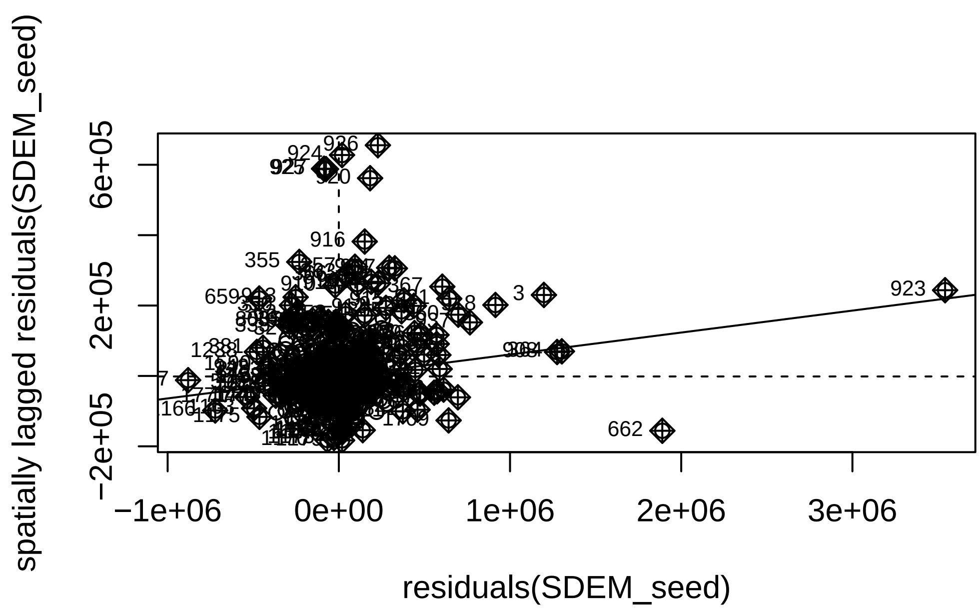
```r
bptest.Sarlm(SEM_seed,studentize = TRUE)
```

```

    studentized Breusch-Pagan test

data:
BP = 302.59, df = 28, p-value < 2.2e-16
```

```r
moran.plot(residuals(hedon3_seed), listw = Seattle_5555_W10)
```




```
moran.plot(residuals(SDEM_seed), listw = Seattle_5555_W10)
```



```r
moran.test(residuals(SDEM_seed), listw = Seattle_5555_W10)
```

```
	Moran I test under randomisation

data:  residuals(SDEM_seed)
weights: Seattle_5555_W10

Moran I statistic standard deviate = 6.6347, p-value = 1.626e-11
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
     6.239672e-02     -5.302227e-04      8.995663e-05
```

Oppgave 9)

```r
set.seed(864)
# Måtte bli kvitt noenb obs. med NA
# disse NA-ene skapte problemer helt mot slutten fordi hedon_2000
# og kc_house_data_2000_W3 hadde forskjellig dimensjon
kc_house_env_var_omit_2000 <-
  kc_houses_env_var_omit[!sf::st_is_empty(kc_houses_env_var_omit), ] |>
  na.omit() |>
  slice_sample(n = 2000)
```

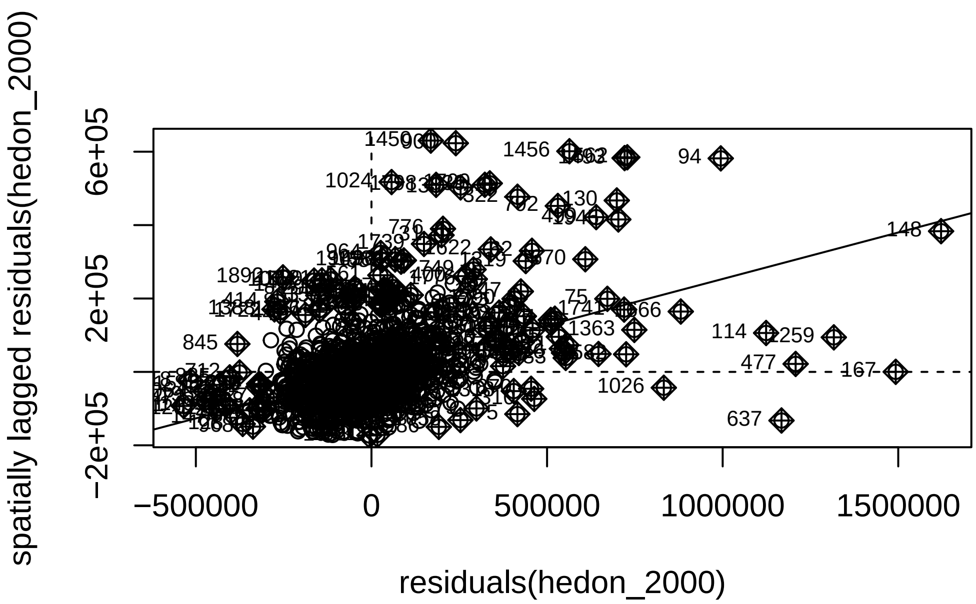
```r
#hedon_2000 <- lm(mod3, data = x)
hedon_2000 <- lm(mod3, data = kc_house_env_var_omit_2000)
```

```r
huxreg("Full" = hedon3, "2000 Seed" = hedon_2000, "1111 Seed" = hedon3_seed,
    error_format = "[{statistic}]",
    note = "{stars}. T statistic in brackets.")
```

```r
kc_house_data_2000_mat_nb3 <- knearneigh(kc_house_env_var_omit_2000, k = 3)
kc_house_data_2000_nb3 <- knn2nb(kc_house_data_2000_mat_nb3)
kc_house_data_2000_W3 <- nb2listw(kc_house_data_2000_nb3, style = "W")
```

```r
kc_house_data_2000_mat_nb10 <- knearneigh(kc_house_env_var_omit_2000, k = 10)
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
moran.plot(residuals(hedon_2000), listw = kc_house_data_2000_W10)
```



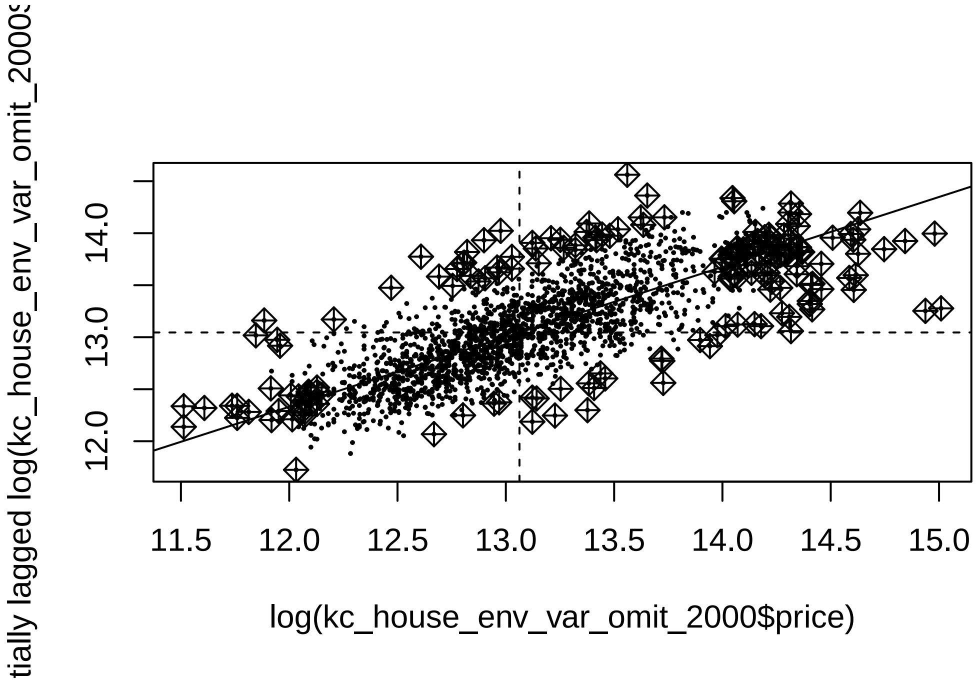

```r
lm.morantest(hedon_2000, kc_house_data_2000_W3)
```

```

	Global Moran I for regression residuals

data:  
model: lm(formula = mod3, data = kc_house_env_var_omit_2000)
weights: kc_house_data_2000_W3

Moran I statistic standard deviate = 17.345, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance 
    0.2912085475    -0.0030513138     0.0002878174 
```

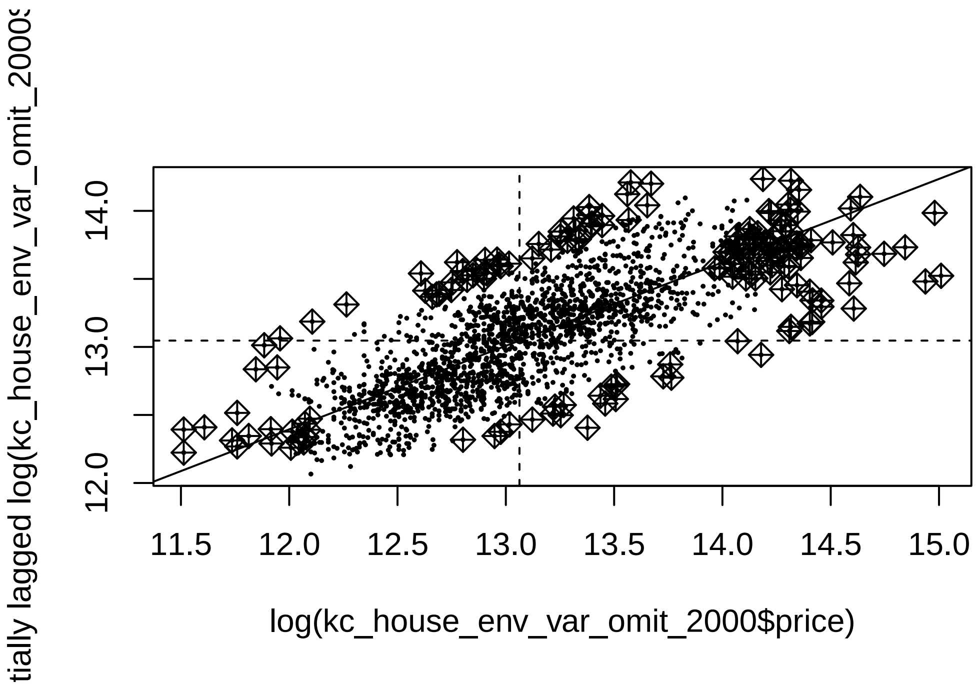
```r
lm.morantest(hedon_2000, kc_house_data_2000_W10)
```

```

	Global Moran I for regression residuals

data:  
model: lm(formula = mod3, data = kc_house_env_var_omit_2000)
weights: kc_house_data_2000_W10

Moran I statistic standard deviate = 27.438, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance 
    0.2531938374    -0.0025368696     0.0000868698 
```

```r
moran.plot(
  log(kc_house_env_var_omit_2000$price),
  listw = kc_house_data_2000_W3,
  labels = FALSE,
  pch = 20,
  cex = 0.3
  )
```




```
moran.plot(log(kc_house_env_var_omit_2000$price), listw = kc_house_data_2000_W10, labels =
```



```r
kc_lagrange_3_2000 <- lm.LMtests(hedon_2000, kc_house_data_2000_W3, test = "all")
kc_lagrange_3_2000
```

```
    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_env_var_omit_2000)
weights: kc_house_data_2000_W3

LMerr = 292.37, df = 1, p-value < 2.2e-16


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_env_var_omit_2000)
weights: kc_house_data_2000_W3

LMlag = 195.45, df = 1, p-value < 2.2e-16


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_env_var_omit_2000)
weights: kc_house_data_2000_W3

RLMerr = 108.28, df = 1, p-value < 2.2e-16


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_env_var_omit_2000)
weights: kc_house_data_2000_W3

RLMlag = 11.363, df = 1, p-value = 0.0007494


    Lagrange multiplier diagnostics for spatial dependence
```

```
data:
model: lm(formula = mod3, data = kc_house_env_var_omit_2000)
weights: kc_house_data_2000_W3

SARMA = 303.73, df = 2, p-value < 2.2e-16
```

```r
kc_lagrange_10_2000 <- lm.LMtests(
  hedon_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_house_env_var_omit_2000)
weights: kc_house_data_2000_W10

LMerr = 715.68, df = 1, p-value < 2.2e-16


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_env_var_omit_2000)
weights: kc_house_data_2000_W10

LMlag = 422.81, df = 1, p-value < 2.2e-16


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_env_var_omit_2000)
weights: kc_house_data_2000_W10

RLMerr = 341.04, df = 1, p-value < 2.2e-16
```

```
    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_env_var_omit_2000)
weights: kc_house_data_2000_W10

RLMlag = 48.171, df = 1, p-value = 3.907e-12


    Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = mod3, data = kc_house_env_var_omit_2000)
weights: kc_house_data_2000_W10

SARMA = 763.85, df = 2, p-value < 2.2e-16
```

```
SDEM_2000 <- errorsarlm(mod3, data = kc_house_env_var_omit_2000, listw = kc_house_data_200
```

```
Warning in errorsarlm(mod3, data = kc_house_env_var_omit_2000, listw = kc_house_data_2000_W3
  reciprocal condition number = 9.72445e-22 - using numerical Hessian.
```

```
SLX_2000 <- lmSLX(mod3,
                  data = kc_house_env_var_omit_2000,
                  listw = kc_house_data_2000_W3,
                  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_house_env_var_omit_2000,
  listw = kc_house_data_2000_W3,
  Durbin = FALSE
  )
```

```
Warning in errorsarlm(mod3, data = kc_house_env_var_omit_2000, listw = kc_house_data_2000_W3
  reciprocal condition number = 8.80636e-22 - using numerical Hessian.
```

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

```
Impact measures (SDEM, estimable, n):
                        Direct      Indirect         Total
bedrooms          -3.130899e+04  4.445366e+03 -2.686362e+04
bathrooms          2.213922e+04  1.676980e+04  3.890902e+04
sqft_living        1.174368e+02  1.025043e+01  1.276872e+02
sqft_lot           3.649267e-01 -8.945982e-01 -5.296715e-01
sqft_above         7.897401e+01            NA  7.897401e+01
floors            -2.314432e+04 -3.690488e+03 -2.683481e+04
grade              5.732499e+04  1.242326e+04  6.974825e+04
yr_built          -9.128642e+02 -1.506823e+03 -2.419687e+03
yr_renovated       1.523628e+01            NA  1.523628e+01
waterfront         4.742882e+05            NA  4.742882e+05
condition          3.706943e+04            NA  3.706943e+04
view               5.258746e+04            NA  5.258746e+04
dist_cbd_km       -2.295098e+04  1.559192e+04 -7.359058e+03
EHD_percen        -9.562841e+02 -4.188036e+02 -1.375088e+03
low                1.137646e+05  4.429370e+04  1.580583e+05
high               1.646368e+05  1.695889e+05  3.342257e+05
year_month2014-06  8.953495e+03            NA  8.953495e+03
year_month2014-07  8.564234e+03            NA  8.564234e+03
year_month2014-08  2.767286e+04            NA  2.767286e+04
year_month2014-09 -2.095903e+04            NA -2.095903e+04
year_month2014-10  2.707585e+03            NA  2.707585e+03
year_month2014-11  5.993841e+02            NA  5.993841e+02
year_month2014-12 -2.722234e+03            NA -2.722234e+03
year_month2015-01  3.974942e+04            NA  3.974942e+04
year_month2015-02  1.191019e+04            NA  1.191019e+04
year_month2015-03  5.250386e+04            NA  5.250386e+04
year_month2015-04  4.830341e+04            NA  4.830341e+04
year_month2015-05  3.872821e+04            NA  3.872821e+04
========================================================
Standard errors:
                       Direct     Indirect        Total
bedrooms          5.083858e+03 1.014573e+04 1.270914e+04
bathrooms         8.372151e+03 1.628167e+04 2.027677e+04
sqft_living       1.076379e+01 1.582658e+01 2.115714e+01
```

```
sqft_lot           8.563636e-02 2.352980e-01 2.522674e-01
sqft_above         1.058682e+01           NA 1.058682e+01
floors             9.501958e+03 1.518858e+04 1.887287e+04
grade              5.574441e+03 1.014357e+04 1.245945e+04
yr_built           1.948143e+02 3.119986e+02 3.801846e+02
yr_renovated       8.720093e+00           NA 8.720093e+00
waterfront         4.995163e+04           NA 4.995163e+04
condition          5.688944e+03           NA 5.688944e+03
view               5.452305e+03           NA 5.452305e+03
dist_cbd_km        9.102626e+03 9.138156e+03 7.472245e+02
EHD_percen         4.552411e+02 5.344568e+02 3.571498e+02
low                1.063752e+05 1.451509e+05 1.366304e+05
high               7.906870e+04 1.013236e+05 8.443372e+04
year_month2014-06 1.543571e+04           NA 1.543571e+04
year_month2014-07 1.517259e+04           NA 1.517259e+04
year_month2014-08 1.596380e+04           NA 1.596380e+04
year_month2014-09 1.605480e+04           NA 1.605480e+04
year_month2014-10 1.577896e+04           NA 1.577896e+04
year_month2014-11 1.695880e+04           NA 1.695880e+04
year_month2014-12 1.716770e+04           NA 1.716770e+04
year_month2015-01 1.867057e+04           NA 1.867057e+04
year_month2015-02 1.763202e+04           NA 1.763202e+04
year_month2015-03 1.587651e+04           NA 1.587651e+04
year_month2015-04 1.537367e+04           NA 1.537367e+04
year_month2015-05 2.110250e+04           NA 2.110250e+04
========================================================
Z-values:
                       Direct   Indirect        Total
bedrooms          -6.15850973  0.4381513 -2.11372389
bathrooms          2.64438873  1.0299801  1.91889666
sqft_living       10.91035229  0.6476721  6.03518142
sqft_lot           4.26135211 -3.8019797 -2.09964323
sqft_above         7.45965377         NA  7.45965377
floors            -2.43574242 -0.2429778 -1.42187195
grade             10.28354033  1.2247430  5.59802116
yr_built          -4.68581605 -4.8295813 -6.36450517
yr_renovated       1.74726089         NA  1.74726089
waterfront         9.49494850         NA  9.49494850
condition          6.51604793         NA  6.51604793
view               9.64499493         NA  9.64499493
dist_cbd_km       -2.52135812  1.7062439 -9.84852262
EHD_percen        -2.10061014 -0.7836061 -3.85017021
low                1.06946496  0.3051561  1.15683080
```

```
high               2.08219993  1.6737346  3.95843857
year_month2014-06  0.58005090         NA  0.58005090
year_month2014-07  0.56445447         NA  0.56445447
year_month2014-08  1.73347577         NA  1.73347577
year_month2014-09 -1.30546852         NA -1.30546852
year_month2014-10  0.17159464         NA  0.17159464
year_month2014-11  0.03534354         NA  0.03534354
year_month2014-12 -0.15856715         NA -0.15856715
year_month2015-01  2.12898857         NA  2.12898857
year_month2015-02  0.67548642         NA  0.67548642
year_month2015-03  3.30701450         NA  3.30701450
year_month2015-04  3.14195654         NA  3.14195654
year_month2015-05  1.83524295         NA  1.83524295

p-values:
                  Direct     Indirect   Total
bedrooms          7.3433e-10 0.66127662 0.03453886
bathrooms         0.00818386 0.30301935 0.05499741
sqft_living       < 2.22e-16 0.51719708 1.5878e-09
sqft_lot          2.0319e-05 0.00014354 0.03576024
sqft_above        8.6819e-14 NA         8.6819e-14
floors            0.01486126 0.80802258 0.15506343
grade             < 2.22e-16 0.22067208 2.1681e-08
yr_built          2.7885e-06 1.3682e-06 1.9592e-10
yr_renovated      0.08059209 NA         0.08059209
waterfront        < 2.22e-16 NA         < 2.22e-16
condition         7.2184e-11 NA         7.2184e-11
view              < 2.22e-16 NA         < 2.22e-16
dist_cbd_km       0.01169028 0.08796268 < 2.22e-16
EHD_percen        0.03567520 0.43327130 0.00011804
low               0.28486021 0.76024725 0.24734149
high              0.03732421 0.09418276 7.5441e-05
year_month2014-06 0.56188030 NA         0.56188030
year_month2014-07 0.57244488 NA         0.57244488
year_month2014-08 0.08301114 NA         0.08301114
year_month2014-09 0.19173336 NA         0.19173336
year_month2014-10 0.86375622 NA         0.86375622
year_month2014-11 0.97180580 NA         0.97180580
year_month2014-12 0.87400991 NA         0.87400991
year_month2015-01 0.03325521 NA         0.03325521
year_month2015-02 0.49936677 NA         0.49936677
year_month2015-03 0.00094296 NA         0.00094296
year_month2015-04 0.00167823 NA         0.00167823
```

```
year_month2015-05 0.06646970 NA         0.06646970
```

```r
huxreg(
  "SEM" = SEM_2000,
  "OLS" = hedon_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 = 55.307, df = 11, p-value = 6.809e-08
sample estimates:
Log likelihood of SDEM_2000  Log likelihood of SEM_2000
                  -26675.95                   -26703.60
```

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

```

    Likelihood ratio for spatial linear models

data:
Likelihood ratio = 214.48, df = 4, p-value < 2.2e-16
sample estimates:
Log likelihood of SDEM_2000  Log likelihood of SLX_2000
                  -26675.95                   -26783.19
```

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

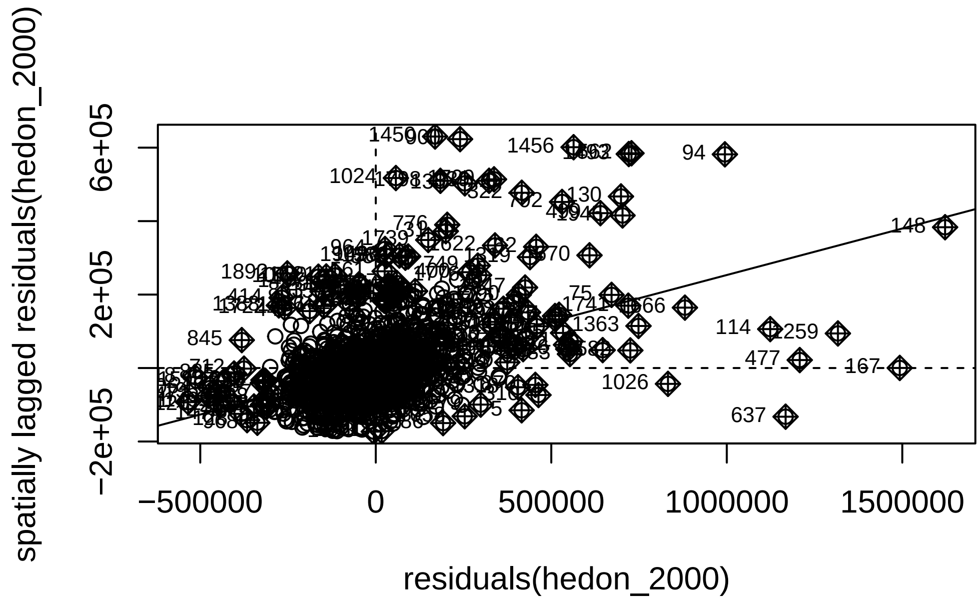
```

    Spatial Hausman test (asymptotic)

data:  NULL
Hausman test = 125.28, df = 29, p-value = 6.195e-14
```

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

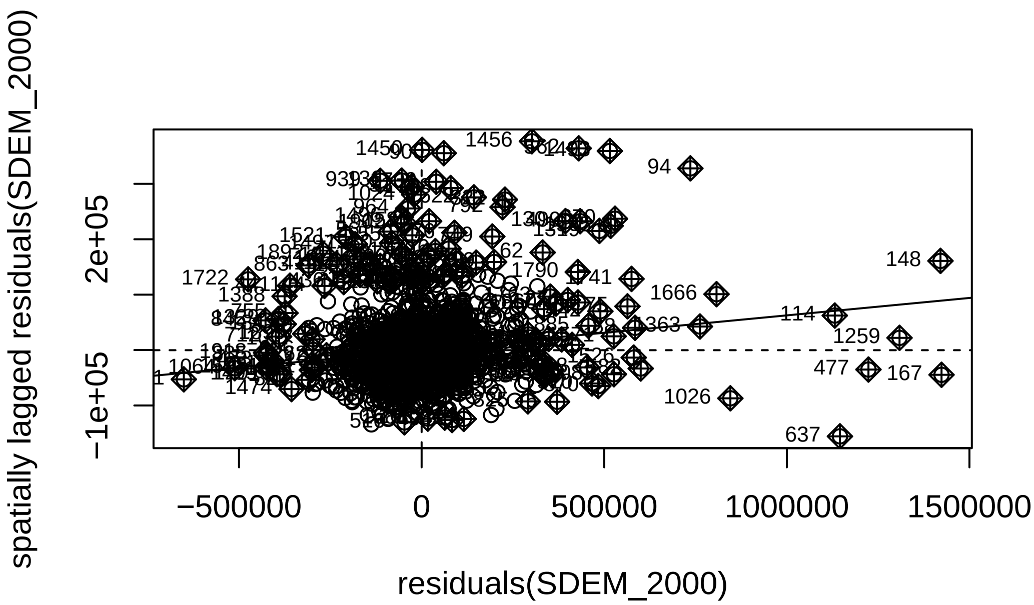
```
	studentized Breusch-Pagan test

data:
BP = 336.14, df = 28, p-value < 2.2e-16
```

….. Se på de under

```r
moran.plot(residuals(hedon_2000), listw = kc_house_data_2000_W10)
```




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




```r
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 = 6.748, p-value = 7.495e-12
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
     6.285517e-02     -5.002501e-04      8.814896e-05
```

	Hedon1	Hedon2	Hedon3
(Intercept)	6313025.450 ***	1089489.051 ***	2130287.043 ***
	[44.418]	[6.598]	[15.625]
bedrooms	-39491.626 ***	-26937.688 ***	-29538.753 ***
	[-19.029]	[-15.185]	[-16.421]
bathrooms	47763.773 ***	18161.356 ***	33397.583 ***
	[13.345]	[5.996]	[10.773]
sqft_living	171.612 ***	197.251 ***	134.765 ***
	[36.636]	[67.876]	[33.018]
sqft_lot	-0.262 ***	0.198 ***	0.142 ***
	[-7.091]	[5.794]	[4.316]
sqft_above	1.113		74.579 ***
	[0.244]		[18.120]
floors	20678.948 ***	-27298.085 ***	-38264.370 ***
	[5.317]	[-8.584]	[-11.054]
grade	124151.309 ***	79088.195 ***	72582.660 ***
	[56.102]	[40.730]	[36.030]
yr_built	-3636.960 ***	-917.414 ***	-1314.377 ***
	[-49.991]	[-12.023]	[-18.553]
yr_renovated	8.725 *	26.058 ***	26.463 ***
	[2.187]	[7.607]	[7.637]
waterfront	578809.205 ***	624776.037 ***	612425.331 ***
	[30.542]	[36.356]	[35.086]
condition	19371.200 ***	25891.324 ***	31664.903 ***
	[7.560]	[11.776]	[14.197]
view	45358.477 ***	43746.294 ***	47286.985 ***
	[19.757]	[22.494]	[23.843]
year_month2014-06	2526.287	7482.018	6048.496
	[0.351]	[1.224]	[0.973]
year_month2014-07	-1074.259	3823.542	2341.517
	[-0.150]	[0.628]	[0.378]
year_month2014-08	5526.935	10287.123	7616.074

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
2.08e+04	9.92e+14				
2.08e+04	9.86e+14	12	5.74e+12	10.1	4.18e-20

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
2.05e+04	6.97e+14				
2.05e+04	6.91e+14	12	5.65e+12	14	1.66e-29

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
2.08e+04	7.4e+14				
2.08e+04	7.34e+14	12	5.98e+12	14.1	8.81e-30

	Full	seed
(Intercept)	2130287.043 ***	2247057.508 ***
	[15.625]	[4.991]
bedrooms	-29538.753 ***	-35524.497 ***
	[-16.421]	[-5.530]
bathrooms	33397.583 ***	53315.969 ***
	[10.773]	[5.012]
sqft_living	134.765 ***	123.682 ***
	[33.018]	[8.436]
sqft_lot	0.142 ***	0.194
	[4.316]	[1.383]
sqft_above	74.579 ***	103.416 ***
	[18.120]	[7.029]
floors	-38264.370 ***	-56603.680 ***
	[-11.054]	[-4.891]
grade	72582.660 ***	64750.263 ***
	[36.030]	[9.246]
yr_built	-1314.377 ***	-1333.557 ***
	[-18.553]	[-5.679]
yr_renovated	26.463 ***	-13.547
	[7.637]	[-1.128]
waterfront	612425.331 ***	397624.998 ***
	[35.086]	[7.025]
condition	31664.903 ***	24129.450 **
	[14.197]	[3.203]
view	47286.985 ***	58911.225 ***
	[23.843]	[8.375]
dist_cbd_km	-9279.825 ***	-9027.631 ***
	[-56.915]	[-16.569]
EHD_percen	-1159.411 ***	-1256.604 ***
	[-14.939]	[-4.785]
low	178344.936 ***	211688.022 *

	SEM	OLS
(Intercept)	1101504.011 *	2247057.508 ***
	[2.538]	[4.991]
bedrooms	-26320.368 ***	-35524.497 ***
	[-4.553]	[-5.530]
bathrooms	49085.572 ***	53315.969 ***
	[5.239]	[5.012]
sqft_living	104.779 ***	123.682 ***
	[7.984]	[8.436]
sqft_lot	0.353 **	0.194
	[2.593]	[1.383]
sqft_above	115.333 ***	103.416 ***
	[8.546]	[7.029]
floors	-74846.055 ***	-56603.680 ***
	[-6.765]	[-4.891]
grade	62224.102 ***	64750.263 ***
	[9.581]	[9.246]
yr_built	-725.313 **	-1333.557 ***
	[-3.201]	[-5.679]
yr_renovated	-14.511	-13.547
	[-1.393]	[-1.128]
waterfront	530349.890 ***	397624.998 ***
	[10.172]	[7.025]
condition	20798.454 **	24129.450 **
	[3.094]	[3.203]
view	52882.242 ***	58911.225 ***
	[7.825]	[8.375]
dist_cbd_km	-10040.913 ***	-9027.631 ***
	[-13.333]	[-16.569]
EHD_percen	-1037.651 **	-1256.604 ***
	[-3.033]	[-4.785]
low	268772.504 **	211688.022 *

	Full	2000 Seed	1111 Seed
(Intercept)	2130287.043 ***	2209072.003 ***	2247057.508 ***
	[15.625]	[5.683]	[4.991]
bedrooms	-29538.753 ***	-31804.872 ***	-35524.497 ***
	[-16.421]	[-5.873]	[-5.530]
bathrooms	33397.583 ***	25816.220 **	53315.969 ***
	[10.773]	[2.884]	[5.012]
sqft_living	134.765 ***	121.691 ***	123.682 ***
	[33.018]	[10.346]	[8.436]
sqft_lot	0.142 ***	0.192 *	0.194
	[4.316]	[2.090]	[1.383]
sqft_above	74.579 ***	69.207 ***	103.416 ***
	[18.120]	[5.956]	[7.029]
floors	-38264.370 ***	-17382.461	-56603.680 ***
	[-11.054]	[-1.765]	[-4.891]
grade	72582.660 ***	67853.357 ***	64750.263 ***
	[36.030]	[11.567]	[9.246]
yr_built	-1314.377 ***	-1345.005 ***	-1333.557 ***
	[-18.553]	[-6.638]	[-5.679]
yr_renovated	26.463 ***	20.197 *	-13.547
	[7.637]	[2.072]	[-1.128]
waterfront	612425.331 ***	339543.751 ***	397624.998 ***
	[35.086]	[6.036]	[7.025]
condition	31664.903 ***	42733.946 ***	24129.450 **
	[14.197]	[6.744]	[3.203]
view	47286.985 ***	58012.448 ***	58911.225 ***
	[23.843]	[10.227]	[8.375]
dist_cbd_km	-9279.825 ***	-8544.073 ***	-9027.631 ***
	[-56.915]	[-18.429]	[-16.569]
EHD_percen	-1159.411 ***	-1463.513 ***	-1256.604 ***
	[-14.939]	[-6.584]	[-4.785]
low	178344.936 ***	187824.751 *	211688.022 *

	SEM	OLS
(Intercept)	1370727.758 ***	2209072.003 ***
	[3.631]	[5.683]
bedrooms	-32639.887 ***	-31804.872 ***
	[-6.735]	[-5.873]
bathrooms	21663.376 **	25816.220 **
	[2.676]	[2.884]
sqft_living	115.398 ***	121.691 ***
	[10.970]	[10.346]
sqft_lot	0.394 ***	0.192 *
	[4.595]	[2.090]
sqft_above	78.278 ***	69.207 ***
	[7.377]	[5.956]
floors	-20993.453 *	-17382.461
	[-2.212]	[-1.765]
grade	59599.759 ***	67853.357 ***
	[10.861]	[11.567]
yr_built	-848.301 ***	-1345.005 ***
	[-4.325]	[-6.638]
yr_renovated	13.202	20.197 *
	[1.511]	[2.072]
waterfront	465501.750 ***	339543.751 ***
	[9.266]	[6.036]
condition	35741.096 ***	42733.946 ***
	[6.239]	[6.744]
view	53845.738 ***	58012.448 ***
	[9.785]	[10.227]
dist_cbd_km	-9712.647 ***	-8544.073 ***
	[-15.296]	[-18.429]
EHD_percen	-1494.674 ***	-1463.513 ***
	[-5.079]	[-6.584]
low	176552.299	187824.751 *