S&DS 625: Housing Project

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Contents

Introduction

In this study, we aim to explore how a home's proximity to food retailers, such as grocery stores and supermarkets, contributes to its value. This is a valuable question to answer from the perspective of someone trying to buy a home; for instance, an individual may be interested in moving with their family to an affordable home while being located within a convenient distance from a grocery store to shop for food. For this case study, we specifically focus on single-family homes in New Haven and consider their total assessed values.

In addition to the parcel dataset for Connecticut properties, we utilize the Connecticut Supplemental Nutrition Assistance Program (SNAP) Authorized Retailers dataset, which contains information such as store type (supermarket, convenience store, farmer's market, etc.) and latitude/longitude coordinates that we use together with the spatial format of the parcel data.

Data Preprocessing and Exploration

Subset Construction

In order to address our study's objective, we take the perspective of a potential homebuyer and restrict our analysis to single-family homes. This came with several challenges: - State use codes that were clearly labeled as single-family homes according to their descriptions were not always reliable. There exist cases where these "single-family" properties actually pointed to vacant lots or other land used for non-residential purposes. Despite this, these codes were generally effective as an initial filter. - State use codes and descriptions were inconsistent across different towns. - Data quality and completeness varied significantly across towns; for some towns, initial filtering based on state use code would be more effective and lead to less case-by-case inspections of state use descriptions.

```
# Load libraries
library(sf)
```

```
## Linking to GEOS 3.11.0, GDAL 3.5.3, PROJ 9.1.0; sf_use_s2() is TRUE
```

```
library(leaflet)
library(webshot)

# Load CT parcel data
d <- st_read("data/CT-parcel-data/4c5501b8-b68e-4888-bf6a-d92670d69c3b.gdb/")
```

```
## Reading layer 'CT_Parcels' from data source
##   '/Users/boseongyun/Desktop/sds625/Day 3, 4/data/CT-parcel-data/4c5501b8-b68e-4888-bf6a-d92670d69c3
##   using driver 'OpenFileGDB'

## Warning in CPL_read_ogr(dsn, layer, query, as.character(options), quiet, : GDAL
## Message 1: organizePolygons() received a polygon with more than 100 parts. The
## processing may be really slow.  You can skip the processing by setting
## METHOD=SKIP, or only make it analyze counter-clock wise parts by setting
## METHOD=ONLY_CCW if you can assume that the outline of holes is counter-clock
## wise defined

## replacing null geometries with empty geometries
## Simple feature collection with 1247506 features and 46 fields (with 45 geometries empty)
## Geometry type: MULTIPOLYGON
## Dimension:     XY
## Bounding box:  xmin: -8207340 ymin: 5009497 xmax: -7991341 ymax: 5168563
## Projected CRS: WGS 84 / Pseudo-Mercator
```

```
# Observe below that state use descriptions are unreliable, but also that
# multiple state use codes can correspond to single family homes
d$State_Use_Description <- toupper(d$State_Use_Description)

# Filter for codes that contain the word FAMILY and could be single-family
d_sf <- d[which(grepl("FAMILY", d$State_Use_Description) &
                !grepl("[2-9]", d$State_Use_Description) &
                !grepl("TWO", d$State_Use_Description) &
                !grepl("THREE", d$State_Use_Description) &
```

```
                !grepl("FOUR", d$State_Use_Description) &
                !grepl("FIVE", d$State_Use_Description) &
                !grepl("SIX", d$State_Use_Description) &
                !grepl("MULTI", d$State_Use_Description)), ]

# Display table of mappings between State Use Description and State Use
table(d_sf$State_Use_Description, d_sf$State_Use, useNA = "always")
```

```
##
##                                0    101   1010   1011   1013   1070    110
##   1 FAMILY                     0      0      0      0      0      0      0
##   1 FAMILY ON COM LN           0      0      0      0      0      0      0
##   1 FAMILY PLANNED COMM        0      0      0      0      0      0      0
##   1 FAMILY WF                  0      0      0      0      0      0      0
##   1-FAMILY                     0      0      0      0      0      0      0
##   HSNG AUTH 1 FAMILY           0      0      0      0      0      0      0
##   ONE FAMILY                   0  18133   2316      0      0      0      0
##   ONE FAMILY - LAKE REGION     0      0      0      0      0      0      0
##   ONE FAMILY - LAKEFRONT       0      0      0      0      0      0      0
##   ONE FAMILY + ACCESSORY UNIT  0      0      0     51      0      0      0
##   RES SINGLE FAMILY            0   5996      0      0      0      0      0
##   SINGLE  FAMILY OF            0      0      0      0      0      0      0
##   SINGLE  FAMILY RF            0      0      0      0      0      0      0
##   SINGLE  FAMILY WF            0      0      0      0      0      0      0
##   SINGLE FAMILY                0 220638  82547      1      0      0      0
##   SINGLE FAMILY - VACANT       0      0      0      0      0      0      0
##   SINGLE FAMILY GC             0      0      0      0      0      0      0
##   SINGLE FAMILY GCF            0      0      0      0      0      0      0
##   SINGLE FAMILY INLAW          0      0      0      0      0      0      0
##   SINGLE FAMILY OF             0      0      0      0      0      0      0
##   SINGLE FAMILY PUD            0      0      0      0      0      0    127
##   SINGLE FAMILY RES            0  19344      0      0      0      0      0
##   SINGLE FAMILY RF             0      0      0      0      0      0      0
##   SINGLE FAMILY UNIT           0      0      0      0      0      0      0
##   SINGLE FAMILY VAC           93      0      0      0      0      0      0
##   SINGLE FAMILY W/ IN-LAW      0      0      0      0      0     31      0
##   SINGLE FAMILY WA             0      0      0      0      0      0      0
##   SINGLE FAMILY WACC           0      0      0      0      0      0      0
##   SINGLE FAMILY WATER          0      0      0      0    316      0      0
##   SINGLE FAMILY WF             0      0      0      0      0      0      0
##   <NA>                         0      0      0      0      0      0      0
##
##                               112    114    115    201    941   <NA>
##   1 FAMILY                     0      0      0      0      0    646
##   1 FAMILY ON COM LN           0      0      0      0      0     88
##   1 FAMILY PLANNED COMM        0      0      0      0      0     95
##   1 FAMILY WF                  0      0      0      0      0     49
##   1-FAMILY                     0      0      0      0      0   2097
##   HSNG AUTH 1 FAMILY           0      0      0      0     61      0
##   ONE FAMILY                   0      0      0      0      0      0
##   ONE FAMILY - LAKE REGION     0      0      0      0      0    312
##   ONE FAMILY - LAKEFRONT       0      0      0      0      0    222
##   ONE FAMILY + ACCESSORY UNIT  0      0      0      0      0      0
```

```
##   RES SINGLE FAMILY                0      0      0      0      0      0
##   SINGLE  FAMILY OF                0      0      0      0      0     65
##   SINGLE  FAMILY RF                0      0      0      0      0    163
##   SINGLE  FAMILY WF                0      0      0      0      0     57
##   SINGLE FAMILY                    0      0      0      0      0    859
##   SINGLE FAMILY - VACANT           0      0      0      0      0     45
##   SINGLE FAMILY GC                 0      0      0      0      0     30
##   SINGLE FAMILY GCF                0      4      0      0      0      0
##   SINGLE FAMILY INLAW              0      0      0      0      0     62
##   SINGLE FAMILY OF               205      0      0      0      0    107
##   SINGLE FAMILY PUD                0      0      0      0      0      0
##   SINGLE FAMILY RES                0      0      0   2236      0      0
##   SINGLE FAMILY RF                 0      0      0      0      0    100
##   SINGLE FAMILY UNIT               0      0      6      0      0      0
##   SINGLE FAMILY VAC                0      0      0      0      0      0
##   SINGLE FAMILY W/ IN-LAW          0      0      0      0      0      0
##   SINGLE FAMILY WA                 0      0      0      0      0     63
##   SINGLE FAMILY WACC               0      0      0      0      0    172
##   SINGLE FAMILY WATER              0      0      0      0      0      0
##   SINGLE FAMILY WF                 0      0      0      0      0   1286
##   <NA>                             0      0      0      0      0      0
```

We observe that the large majority of properties in this subset are captured by state use codes "101" and "1010", with these mapping to multiple descriptions (One Family, Res. Single Family, Single Family, Single Family Res.) which all have the same meaning. As a result, we can use these codes to form a heuristic to gauge town data quality with respect to how easily we can isolate single-family homes.

```r
# View the distribution of single family homes with codes 101 and 1010 in each
# town, looking also at NAs
d$sh <- ifelse(is.na(d$State_Use), NA,
               ifelse(d$State_Use %in% c("101", "1010"), "Single", "Others"))

# Comment out for brevity
# table(d$sh, d$Town_Name, useNA = "always")
```

The distribution of NAs and how many single family homes are captured by the two codes depends a lot on the town, although it's important to note that the percentage of single family homes in different Connecticut towns also varies.

Going forward, let's zoom into a particular town/city: New Haven. Based on the table, 9168 properties have state use code "101" or "1010", 2968 are missing a state use code, and 15242 fall in the "Others" bin. Clearly, many candidate single-family homes are captured by the two state use codes, but there are also more than 18000 properties that we need to investigate further to identify other single-family homes. In addition to requiring a closer look, New Haven is also interesting with respect to our study because parts of the city are considered food deserts.

```r
# Subset the original dataset to only New Haven
dnh <- d[d$Town_Name == "NEW HAVEN", ]

# Some initial observations show the many codes and descriptions, we comment
# this out to reduce clutter in the output
# table(dnh$State_Use)
# table(dnh$State_Use_Description)
# table(dnh$State_Use, dnh$State_Use_Description, useNA = "always")
```

We repeat the same analysis above looking at the descriptions with FAMILY and observe that in New Haven, descriptions containing FAMILY that do not refer to multi-family homes are all captured by description SINGLE FAMILY and all of these codes are 1010.

```
nh_sf <- dnh[which(grepl("FAMILY", dnh$State_Use_Description) &
                   !grepl("[2-9]", dnh$State_Use_Description) &
                   !grepl("TWO", dnh$State_Use_Description) &
                   !grepl("THREE", dnh$State_Use_Description) &
                   !grepl("FOUR", dnh$State_Use_Description) &
                   !grepl("FIVE", dnh$State_Use_Description) &
                   !grepl("SIX", dnh$State_Use_Description) &
                   !grepl("MULTI", dnh$State_Use_Description)), ]
table(nh_sf$State_Use, nh_sf$State_Use_Description, useNA = "always")
```

```
##
##        SINGLE FAMILY <NA>
##   1010          9168    0
##   <NA>             0    0
```

Moreover, we also observe that 101x codes correspond to single-family homes, with the last digit indicating some type of accessory/special feature. As a result, we can create an initial filter for candidate single-family homes and focus on the remaining state use codes/descriptions.

```
# Create state use code-based filter checking if state use code starts with 101
sfh_coded <- dnh[which(startsWith(dnh$State_Use, "101")), ]
table(sfh_coded$State_Use, sfh_coded$State_Use_Description, useNA = "always")
```

```
##
##        SFR IN-LAW SFR RIVERFRONT SFR WATER SINGLE FAMILY <NA>
##   1010          0              0         0          9168    0
##   1012         26              0         0             0    0
##   1013          0              0        39             0    0
##   1015          0             13         0             0    0
##   <NA>          0              0         0             0    0
```

While we were able to confidently skip over properties with certain state use descriptions such as "APT 4-UNIT", "PARK GAR MDL-96", and "YACHT CLUB", others weren't as clear. For instance, some descriptions are prefixed by "HSNG AUTH" or "CITY", indicating ownership by a housing authority or the city of New Haven, with "HSNG AUTH MDL-01" and "CITY MDL-01" corresponding to single-family homes based on manual inspection and cross-referencing with websites like Zillow and Redfin. On the other hand, "MDL" suffixes other than "MDL-01" did not correspond to single-family homes. As a result, we can construct another loose filter for additional candidate single-family homes based on the inclusion of "MDL-01" in the state use description column.

```
# Create state use description-based filter checking for inclusion of "MDL-01"
# Exclude apartments
mdl_01 <- dnh[which(grepl("MDL-01", dnh$State_Use_Description) &
                    !grepl("APT", dnh$State_Use_Description)), ]

# Combine with state use code-based candidates
sfh <- rbind(sfh_coded, mdl_01)
dim(sfh)
```

```
## [1] 9425   48
```

It's important to note that our methods for isolating single-family homes, while motivated by meticulous exploration and cross-referencing properties, is based on heuristics. In particular, our "MDL-01" filter may have introduced some properties that shouldn't be considered single-family either due to data quality issues or the fact that it wasn't practical to spot-check every single property with state use description containing "MDL-01".

To address this, we will run a few sanity checks on several variables and investigate extreme cases.

```
# Explore extremes of assessed total
head(st_drop_geometry(sfh[order(sfh$Assessed_Total, decreasing = T),
                          c("Link", "Owner", "Location", "Assessed_Total",
                            "State_Use_Description")]), 12)
```

```
##                         Link                                    Owner
## 777573 52070-392 1188 00101                    CITY OF NEW HAVEN PARK
## 769380 52070-244 0365 00500                          YALE UNIVERSITY
## 761570 52070-125 1039 01341              HOUSING AUTHORITY OF NEW HAVEN
## 768352 52070-251 1072 00100                   CT CLINICAL  SERVICES INC
## 758051 52070-094 0999 02600                NEW HAVEN MONTHLY MEETING OF
## 767998 52070-218 0494 00100              ELLIS CHARLES D & LORIMER LINDA
## 768103 52070-219 0458 01900 BROWN INVESTMENT ADVISORY & TRUST COMPANY TR
## 768067 52070-218 1075 00100                           ALEXANDER MARTHA O
## 768367 52070-251 1073 00400                                GREWAL ELENA
## 781176 52070-033 0868 00100               198 COVE STREET LMTD PARTNER
## 768364 52070-251 1073 00100                        CARTER LOUISE B EST
## 758711 52070-102 1030 00100                    CITY OF NEW HAVEN GOLF
##                  Location Assessed_Total State_Use_Description
## 777573   358 SPRINGSIDE AV       15926750     REC FACIL  MDL-01
## 769380     43 HILLHOUSE AV        3682000      PVT UNIV  MDL-01
## 761570  1435 QUINNIPIAC AV        2400230     HSNG AUTH  MDL-01
## 768352     787 PROSPECT ST        1793960         SINGLE FAMILY
## 758051  223 EAST GRAND AV         1682030     RELIGIOUS  MDL-01
## 767998      55 HIGHLAND ST        1549940         SINGLE FAMILY
## 768103 352 SAINT RONAN ST         1548820         SINGLE FAMILY
## 768067     123 EDGEHILL RD        1520890         SINGLE FAMILY
## 768367    130 EDGEHILL RD         1502970         SINGLE FAMILY
## 781176         198 COVE ST        1437380             SFR WATER
## 768364     100 EDGEHILL RD        1422540         SINGLE FAMILY
## 758711       35 EASTERN ST        1403780     REC FACIL  MDL-01
```

```
tail(st_drop_geometry(sfh[order(sfh$Assessed_Total, decreasing = T),
                          c("Link", "Owner", "Location", "Assessed_Total",
                            "State_Use_Description")]), 12)
```

```
##                         Link                     Owner          Location
## 775605 52070-325 0516 00900    SGH PROPERTY GROUP LLC  26 CHERRY ANN ST
## 771583 52070-304 0046 03700          BETTER HAVEN LLC      90 ADELINE ST
## 766915 52070-168 0781 03200              LANE LOSER J    117 FILLMORE ST
## 766544 52070-302 0072 00800             ZARAGOZA LUIS       31 FRANK ST
## 770929 52070-275 0033 03200           CHONA ARMANDO JR       73 MORRIS ST
## 759470 52070-126 1051 01200        SSG PROPERTIES LLC      242 BARNES AV
```

```
## 764114 52070-275 0030 00600              GANT MARITZA     124 ROSETTE ST
## 764533 52070-265 0058 00100           MEANY WILLIAM H    146 CARLISLE ST
## 777012 52070-342 0152 00500 NATIONAL CONSTRUCTION LLC    6 EVERGREEN CT
## 762032 52070-152 0844 00401                TYLER LARK       6 WELTON ST
## 757827 52070-090 0998 00800               MORENO JIMMY       47 REVERE ST
## 780897 52070-035 0854 00700                 GOFF DAVID 287 LIGHTHOUSE RD
##        Assessed_Total State_Use_Description
## 775605          51240         SINGLE FAMILY
## 771583          51170         SINGLE FAMILY
## 766915          49700         SINGLE FAMILY
## 766544          48370          CITY  MDL-01
## 770929          48160         SINGLE FAMILY
## 759470          47110         SINGLE FAMILY
## 764114          44870         SINGLE FAMILY
## 764533          42210         SINGLE FAMILY
## 777012          42000         SINGLE FAMILY
## 762032          41370         SINGLE FAMILY
## 757827          40670         SINGLE FAMILY
## 780897          40250         SINGLE FAMILY
```

Examining the higher end of assessed total values, "358 SPRINGSIDE AV" stands out with an assessed total of almost $16 million. This is unrealistic and is confirmed to be a park/school area with 3 buildings; it appears that the data regarding the entire plot of land has incorrectly been attributed to the first of the three buildings, which indeed is a single-family home, based on cross-referencing the Vision Appraisal database. Similarly, "223 EAST GRAND AV" corresponds to a plot of land with a collection of 3 buildings belonging to a religious society. Therefore, these 2 properties shouldn't be considered in our subset of single-family homes.

The lower end of assessed total values, on the other hand, were confirmed through Vision Appraisal and appears to be in part due to severe depreciation based on their "effective year built" measures.

```
# Occupancy may give us a hint, expectation is 1 if all data is accurate
table(sfh$Occupancy, useNA = "always")
```

```
##
##    0    1    2    3    4    5    6    7    8    9   10   12   14   15   16   24
##    1 9275   94   24    5    5    2    2    2    2    2    2    1    1    1    1
## <NA>
##    5
```

```
# Check 0 case - outbuilding at 115 CRANSTON ST, valid
st_drop_geometry(sfh[which(sfh$Occupancy == 0), c("Owner", "Location")])
```

```
##                    Owner        Location
## 761786 SKOMRO BARBARA M  115 CRANSTON ST
```

```
# Check NA cases - all confirmed to be single-family
st_drop_geometry(sfh[is.na(sfh$Occupancy), c("Owner", "Location")])
```

```
##                     Owner             Location
## 756973    BALLARD TANYA R        124 OAKLEY ST
## 761741       BAILEY ALVAN    603 MIDDLETOWN AV
```

```
## 765422     ASSIOBO FAROUZ       136 ROSETTE ST
## 769017  BRIONES STEPHANIE        70 WOOLSEY ST
## 773391 COLUMBUS HOUSE INC 324 WEST DIVISION ST
```

```r
# Check >= 4 cases, commented out to avoid long output
# Properties with a lot of occupants are generally rooming houses
# Multiple tenants, but the home itself is a single-family model according to
# Vision Appraisal
# st_drop_geometry(sfh[which(sfh$Occupancy >= 4), ])
```

We also checked for any duplicate listings and found that there were two properties at each of "1 RESERVOIR ST" and "115 CRANSTON ST". When cross-referenced with Vision Appraisal, we found that the two properties located at "1 RESERVOIR ST" correspond to two separate single-family homes. In contrast, the two properties at "115 CRANSTON ST" refer to the same home, based on the photos provided by Vision Appraisal, with one of the entries containing incorrect information (0s for all room-related columns) which should be removed.

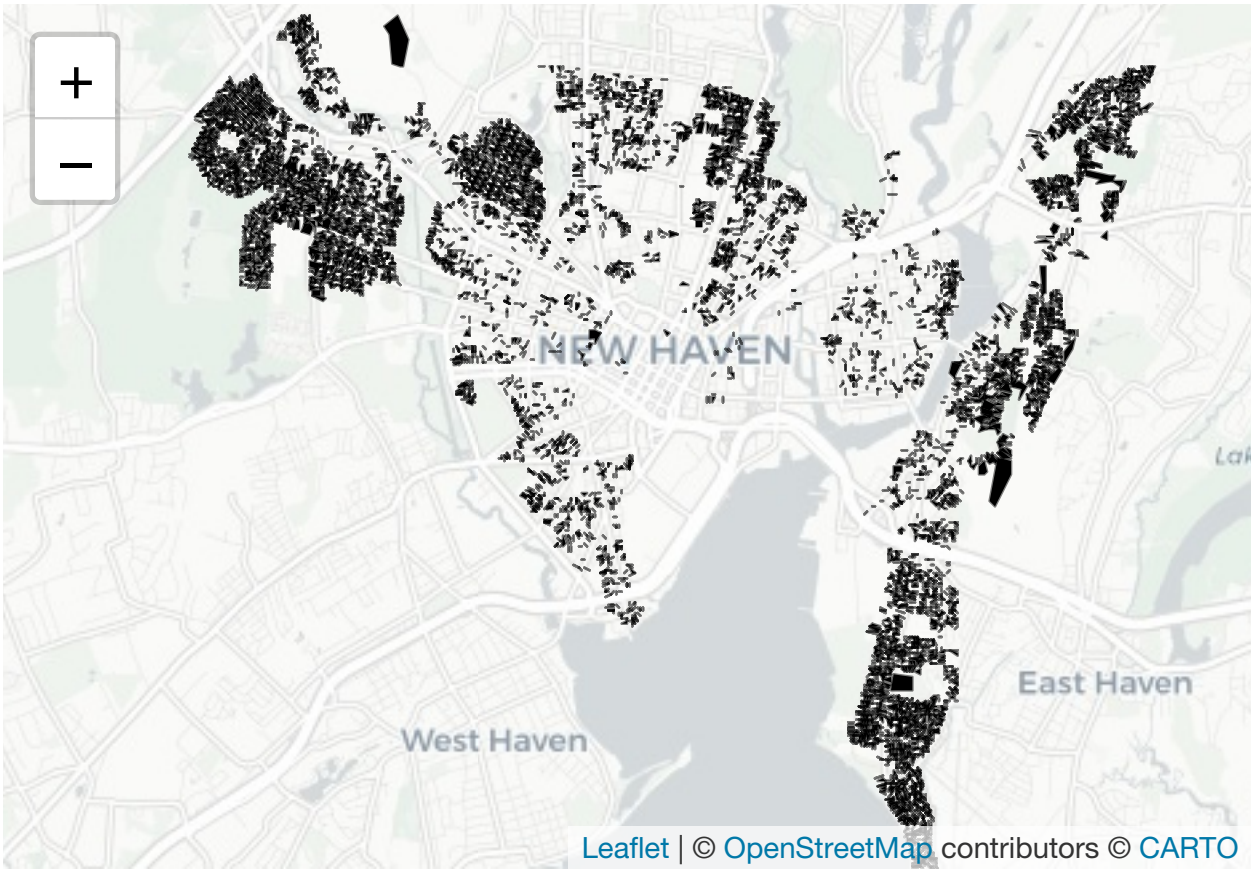
```r
# List locations with more than one property
sfh[which(duplicated(sfh$Location)), ]$Location
```

```
## [1] "1 RESERVOIR ST"  "115 CRANSTON ST"
```

```r
# Inspect corresponding properties, commented out for brevity
# sfh[which(sfh$Location %in% c("1 RESERVOIR ST", "115 CRANSTON ST")), ]
```

As a sanity check, we also plotted the properties superimposed on a map of New Haven leveraging their shapefiles. We then inspected any properties that were unusually large and checked Vision Appraisal, revealing several more areas of land with multiple buildings' assessments represented by only one of the properties.

```r
# Convert to latitude/longitude
sfh <- st_transform(sfh, crs = 4326)

# Map plot
leaflet() %>%
  addProviderTiles(providers$CartoDB.Positron) %>%

  # Center on New Haven
  setView(lng = -72.93, lat = 41.30, zoom = 12) %>%

  # Add sfh homes
  addPolygons(data = sfh,
              color = "black",
              weight = 1,
              fillColor = "black",
              popup = ~paste("Location:", Location,
                             "<br>State Use: ", State_Use_Description),
              group = "Homes")
```




```
# Remove properties that aren't single-family and incorrect duplicate
to_exclude <- c("52070-392 1188 00101", "52070-094 0999 02600",
                "52070-033 0868 00900", "52070-102 1030 00100",
                "52070-280 0249 02701", "52070-142 1060 01400",
                "52070-125 1039 01341", "52070-098 1001 00200",
                "52070-024 0920 02800")
sfh_final <- sfh[which(!(sfh$Link %in% to_exclude)), ]
```

Base Features

We consider the following variables:

1. **Effective Area** - By accounting for different parts of a property (e.g. a garage or porch) in addition to living area, effective area better captures the contributory value of these property features than living area alone. We would expect that properties with larger effective areas tend to have higher total assessed values.

2. **Number of Bedrooms** - The number of bedrooms is related to the amount of living space in a home, which in turn we expect to be associated with a home's assessed value.

3. **Total Number of Bathrooms** - Like the number of bedrooms, the number of bathrooms is also related to the amount of living space in a home. To get a single total, we define Total Bathrooms as Number_of_Baths + 0.5 * Number_of_Half_Baths.

4. **Condition** - Property condition categories (e.g., Excellent, Poor) are expected to show variation in housing prices, with "worse" conditions being associated with lower assessed values.

5. **Zone** - Different zoning regulations (e.g., residential, commercial) that affect property use, including permissions for commercial activities like restaurants, can influence assessed value.

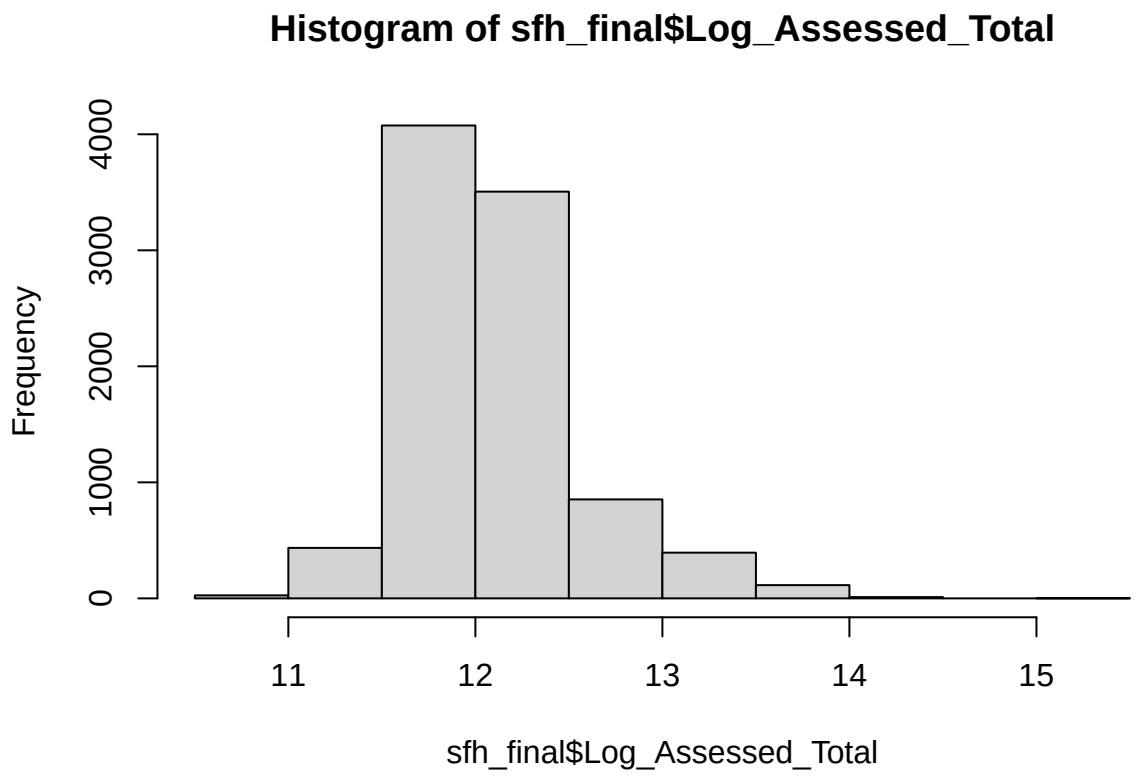
6. **Effective Age** - Effective year built (EYB), unlike actual year built (AYB), accounts for home improvements. We can create a variable for Effective Age = (2024 - EYB) which is more intuitive, where we expect an "older" home to have a lower assessed value from depreciation due to lack of renovations/modernization.

Since we're dealing with price data in our response, we will work with the logarithm of assessed total value.

```
# Check for missing values
sum(is.na(sfh_final$Assessed_Total))
```

```
## [1] 0
```

```
# Create Log_Assessed_Total variable and plot histogram as sanity check
# Histogram looks reasonable
sfh_final$Log_Assessed_Total <- log(sfh_final$Assessed_Total)
hist(sfh_final$Log_Assessed_Total)
```

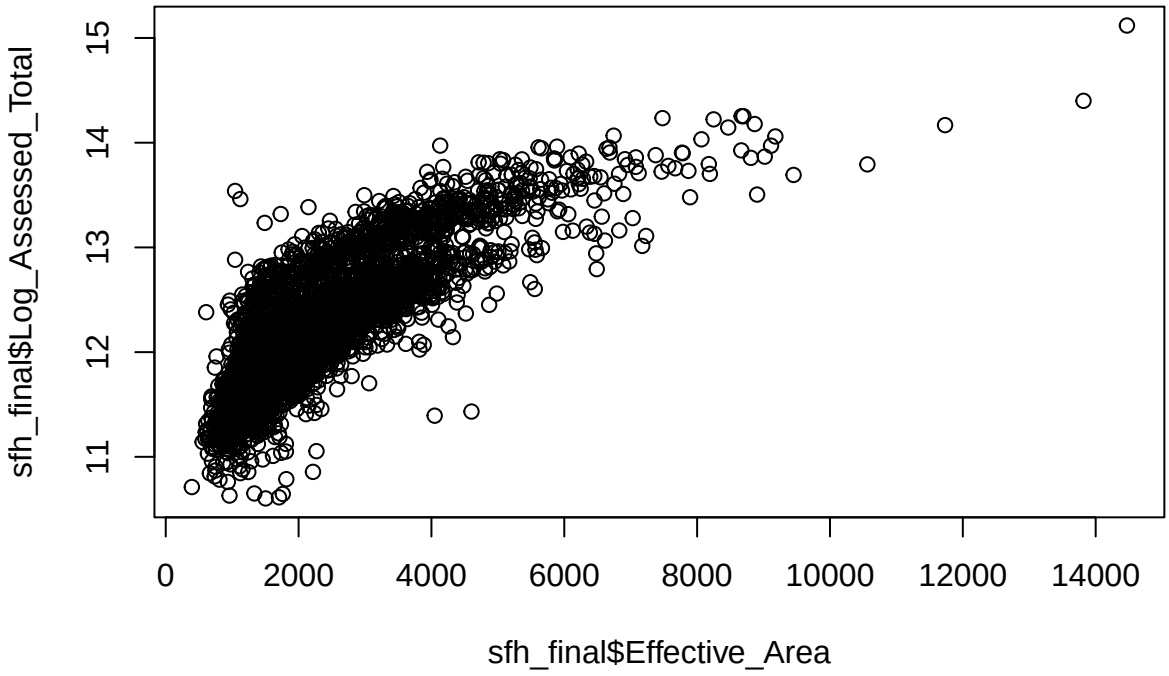


Next, we'll take a look at Effective Area. When plotting vs. log assessed total, we see that using a square root transformation results in a more linear relationship in the scatterplot while still having a natural interpretation.

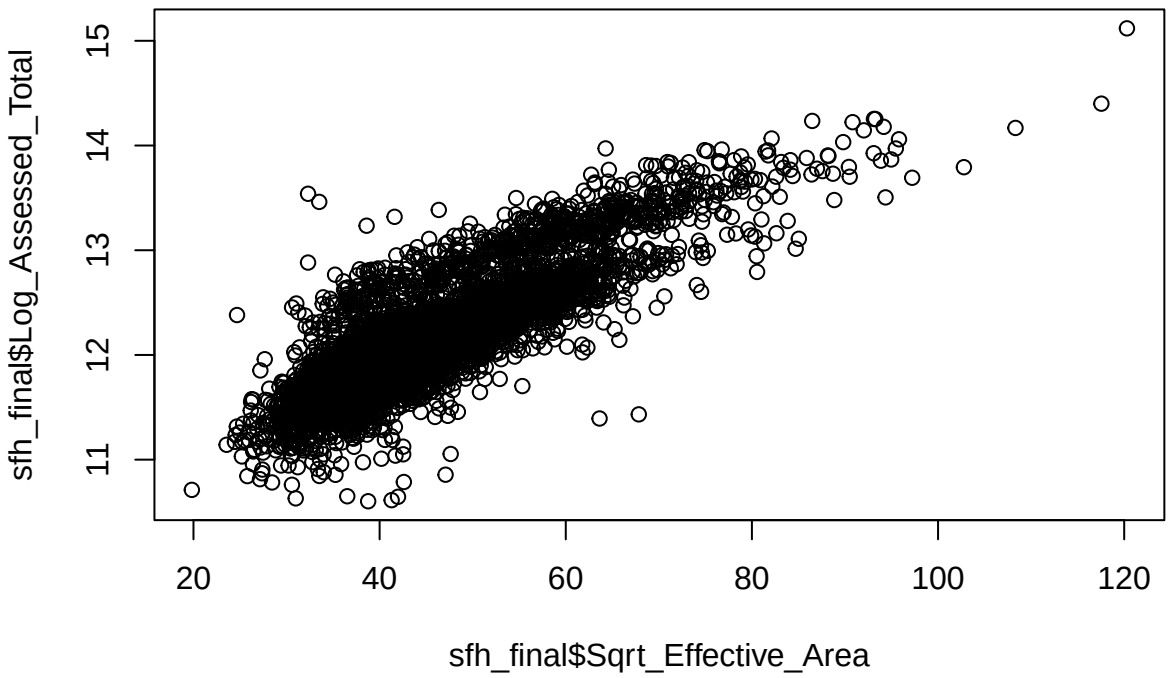
```r
# Check for missing values
sum(is.na(sfh_final$Effective_Area))
```

```
## [1] 0
```

```r
# Plot vs. Log Assessed Total, untransformed
plot(sfh_final$Effective_Area, sfh_final$Log_Assessed_Total)
```




```r
# Has some curvature, try square root transformation
# More linear relationship
sfh_final$Sqrt_Effective_Area <- sqrt(sfh_final$Effective_Area)
plot(sfh_final$Sqrt_Effective_Area, sfh_final$Log_Assessed_Total)
```



We observe that there are a number of bedrooms that are equal to 0 and has NA values. We inspect further to find out what these properties are.

Since properties with 0 number of bedrooms are small, we manually check every property. After cross-checking with Vision Appraisal, it appears that some missing values have been converted to 0. We fix the values for these properties as we expect single-family homes to have at least 1 bedroom unless they are studios such as the properties located at "34 BURTON ST" and "132 COVE ST", using sites like Zillow, Redfin, and Realtor as references.

```
# Get table of bedroom counts
table(sfh_final$Number_of_Bedroom, useNA = "always")
```

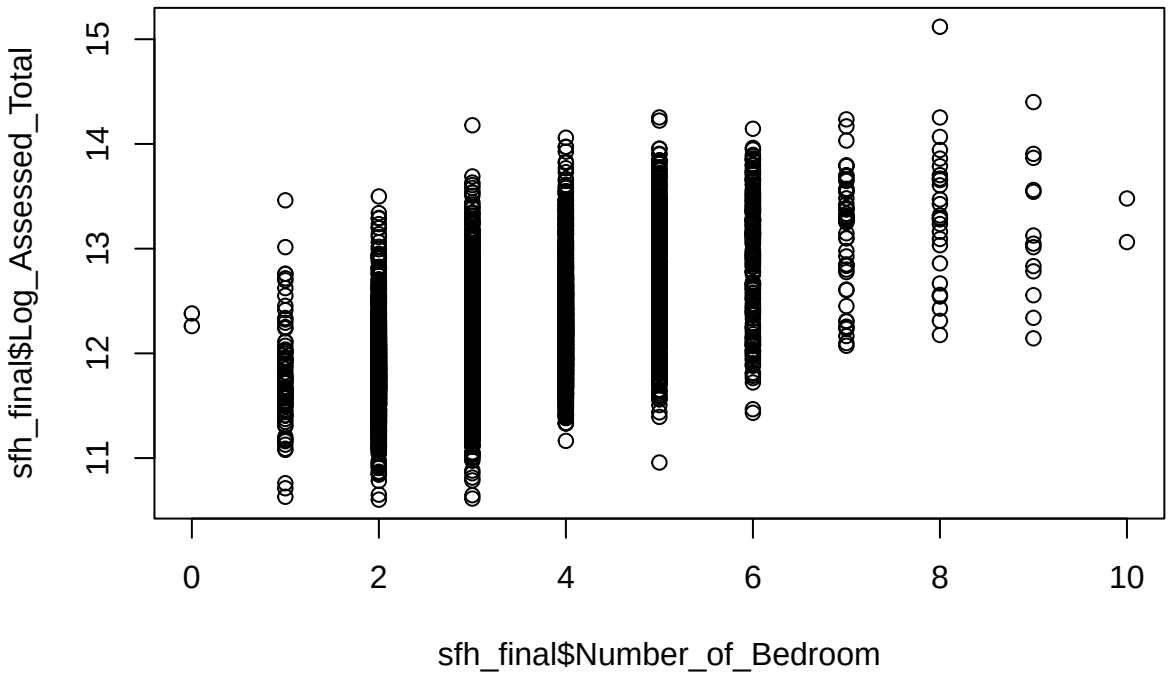
```
##
##    0    1    2    3    4    5    6    7    8    9   10 <NA>
##    5   89 1585 5224 1747  477  195   52   26   13    2    1
```

```
# Identify properties with 0 or missing number of bedrooms
st_drop_geometry(sfh_final[which(sfh_final$Number_of_Bedroom == 0 |
                                   is.na(sfh_final$Number_of_Bedroom)),
                           c("Owner", "Location", "Number_of_Bedroom",
                             "Number_of_Baths", "Number_of_Half_Baths")])
```

```
##                              Owner      Location Number_of_Bedroom
## 778843            STEVENS MARGARET J 34 BURTON ST                NA
## 780965             HELLYAR E MICHAEL   132 COVE ST                 0
## 762212              DASCANIO JOSEPH  532 CHAPEL ST                 0
```

```
## 771060           CONNECTION FUND INC    98 PARK ST                 0
## 771919 GARLAND TRUST ASSOCIATION INC   348 ELM ST                 0
## 773938    SUB-SCRIBE ASSOCIATES LLC  445 GEORGE ST                0
##        Number_of_Baths Number_of_Half_Baths
## 778843               1                    0
## 780965               0                    1
## 762212               2                    0
## 771060               0                    0
## 771919               3                    0
## 773938               0                    0
```

```
bedroom_rows <- row.names(sfh_final[which(sfh_final$Number_of_Bedroom == 0 |
                                    is.na(sfh_final$Number_of_Bedroom)), ])
corrected_bedrooms <- c(0, 0, 1, 3, 6, 4)
sfh_final[bedroom_rows, "Number_of_Bedroom"] <- corrected_bedrooms

# Plot vs. log assessed total
plot(sfh_final$Number_of_Bedroom, sfh_final$Log_Assessed_Total)
```



We repeat the same procedure for the number of bathrooms and half bathrooms. Since there are more than 4000 properties listed with 0 half bathrooms, we will focus on missing values since it would be impractical to check for true 0 half bathrooms and distinguish them from artifacts of missingness.

```
# Get table of bathroom counts
table(sfh_final$Number_of_Baths, useNA = "always")
```

```
##
##    0    1    2    3    4    5    6    7    8    9   10 <NA>
##    6 5556 2914  735  151   34   10    4    2    2    1    1
```

```
# Identify properties with 0 or missing number of bathrooms
st_drop_geometry(sfh_final[which(sfh_final$Number_of_Baths == 0 |
                                   is.na(sfh_final$Number_of_Baths)),
                           c("Owner", "Location", "Number_of_Bedroom",
                             "Number_of_Baths", "Number_of_Half_Baths")])
```

```
##                              Owner          Location Number_of_Bedroom
## 758255         SANMARTIN MEJIA NELLY 255 LEXINGTON AV                 1
## 763284 QUINNIPIAC SHELFISH FARM LLC     269 FRONT ST                 3
## 777198           S&E APARTMENTS LLC      26 DOWNES ST                4
## 780965            HELLYAR E MICHAEL       132 COVE ST                0
## 771060          CONNECTION FUND INC        98 PARK ST                3
## 773938   SUB-SCRIBE ASSOCIATES LLC      445 GEORGE ST                4
## 774921          ALBANIA DENTAL LLC     1395 CHAPEL ST                2
##        Number_of_Baths Number_of_Half_Baths
## 758255              NA                    1
## 763284               0                    1
## 777198               0                    2
## 780965               0                    1
## 771060               0                    0
## 773938               0                    0
## 774921               0                    0
```

```
bath_rows <- row.names(sfh_final[which(sfh_final$Number_of_Baths == 0 |
                                         is.na(sfh_final$Number_of_Baths)), ])

# 1395 CHAPEL ST does not have any information about number of bathrooms
# Replace 0 with NA to reflect missingness
corrected_baths <- c(2, 0, 2, 1, 2, 2, NA)
sfh_final[bath_rows, "Number_of_Baths"] <- corrected_baths

# Get table of half bathroom counts
table(sfh_final$Number_of_Half_Baths, useNA = "always")
```

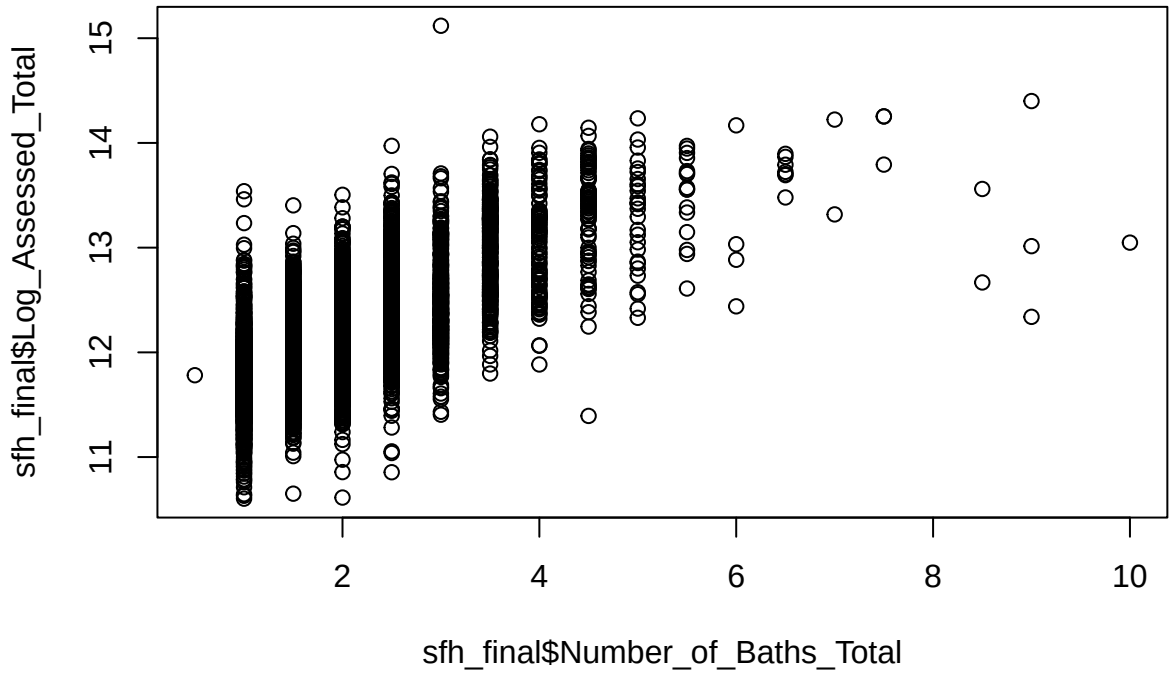
```
##
##    0    1    2    3    6 <NA>
## 4855 4345  171    8    1   36
```

```
# Identify properties with missing half bathroom counts
# Show first few rows for brevity
head(st_drop_geometry(sfh_final[which(is.na(sfh_final$Number_of_Half_Baths)),
                           c("Owner", "Location", "Number_of_Bedroom",
                             "Number_of_Baths", "Number_of_Half_Baths")]))
```

```
##                       Owner         Location Number_of_Bedroom Number_of_Baths
## 754940     UBIERA BRAYANN J     145 HALL ST                 3               2
## 755109           WALL JACOB     99 MYRON ST                 3               3
## 755307 MCNAMARA KELLY MARIE  37 SHOREHAM RD                 4               2
```

```
## 755349   TARGOVE MARGARET W      20 ALDEN ST                 3              2
## 755625   SCHEIBEL RONALD W  72 OCEAN VIEW ST                2              2
## 756335          ZUNIGA GALO 1015 TOWNSEND AV                 3              2
##        Number_of_Half_Baths
## 754940                   NA
## 755109                   NA
## 755307                   NA
## 755349                   NA
## 755625                   NA
## 756335                   NA
```

```
half_bath_rows <- row.names(sfh_final[which(is.na(
                                    sfh_final$Number_of_Half_Baths)), ])
corrected_half_baths <- c(1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1,
                          0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1,
                          1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0)
sfh_final[half_bath_rows, "Number_of_Half_Baths"] <- corrected_half_baths

# Create total bathrooms variable
sfh_final$Number_of_Baths_Total <- sfh_final$Number_of_Baths +
                                   0.5 * sfh_final$Number_of_Half_Baths

# Plot vs. log assessed total
plot(sfh_final$Number_of_Baths_Total, sfh_final$Log_Assessed_Total)
```



Next, we inspect property condition, observing there is a nice 1-to-1 correspondence between conditions and

their descriptions.

```
# Table of condition and descriptions
table(sfh_final$Condition, sfh_final$Condition_Description, useNA = "always")
```

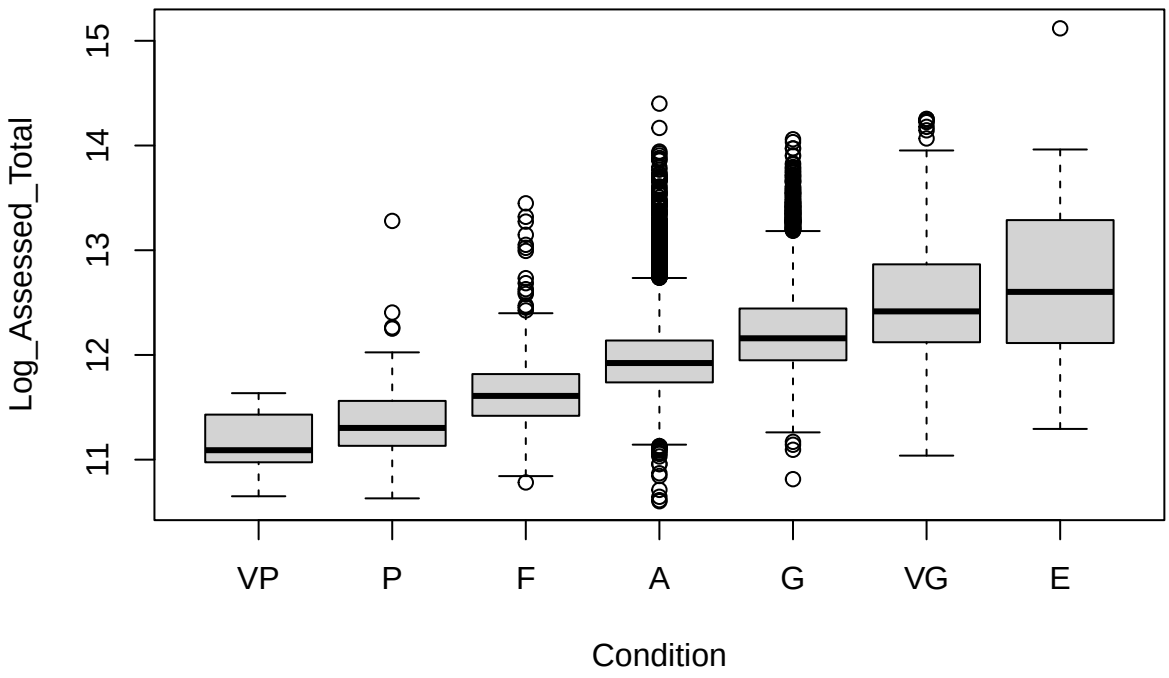
```
##
##        Average Excellent    F Good Poor    U Very Good Very Poor <NA>
##   A       5216         0    0    0    0    0         0         0    0
##   E          0        77    0    0    0    0         0         0    0
##   F          0         0  326    0    0    0         0         0    0
##   G          0         0    0 3304    0    0         0         0    0
##   P          0         0    0    0   37    0         0         0    0
##   U          0         0    0    0    0    2         0         0    0
##   VG         0         0    0    0    0    0       441         0    0
##   VP         0         0    0    0    0    0         0        13    0
##   <NA>       0         0    0    0    0    0         0         0    0
```

There are two properties with condition listed as "U". Inspecting these locations in Vision Appraisal, it's likely that "U" represents Unknown or Unspecified as the condition data field is missing on Vision Appraisal. Using Redfin, we replace these unknown conditions.

```
# Substitute with Redfin's condition data
unk_cond_rows <- row.names(sfh_final[which(sfh_final$Condition == "U"), ])
sfh_final[unk_cond_rows, "Condition"] <- c("A", "A")
sfh_final[unk_cond_rows, "Condition_Description"] <- c("Average", "Average")
```

We also see there is a condition listed as "F" with description "F". We initially thought this may correspond to "Fair", and so to justify this we made boxplots grouped by condition. We should expect the mean log assessed total to increase with "better" condition levels.

```
# Boxplot of log assessed total by condition
boxplot(Log_Assessed_Total ~ factor(Condition,
                                    levels = c("VP", "P", "F", "A", "G",
                                               "VG", "E")),
        xlab = "Condition", data = sfh_final)
```




```
# Update description to fair
sfh_final[which(sfh_final$Condition == "F"), "Condition_Description"] <- "Fair"

# We'll use condition description so that our model summaries later are easier
# to read and interpret
# Convert condition description to a factor and set "Average" as the reference
sfh_final$Condition_Description <- as.factor(sfh_final$Condition_Description)
sfh_final$Condition_Description <- relevel(sfh_final$Condition_Description,
                                           ref = "Average")
```

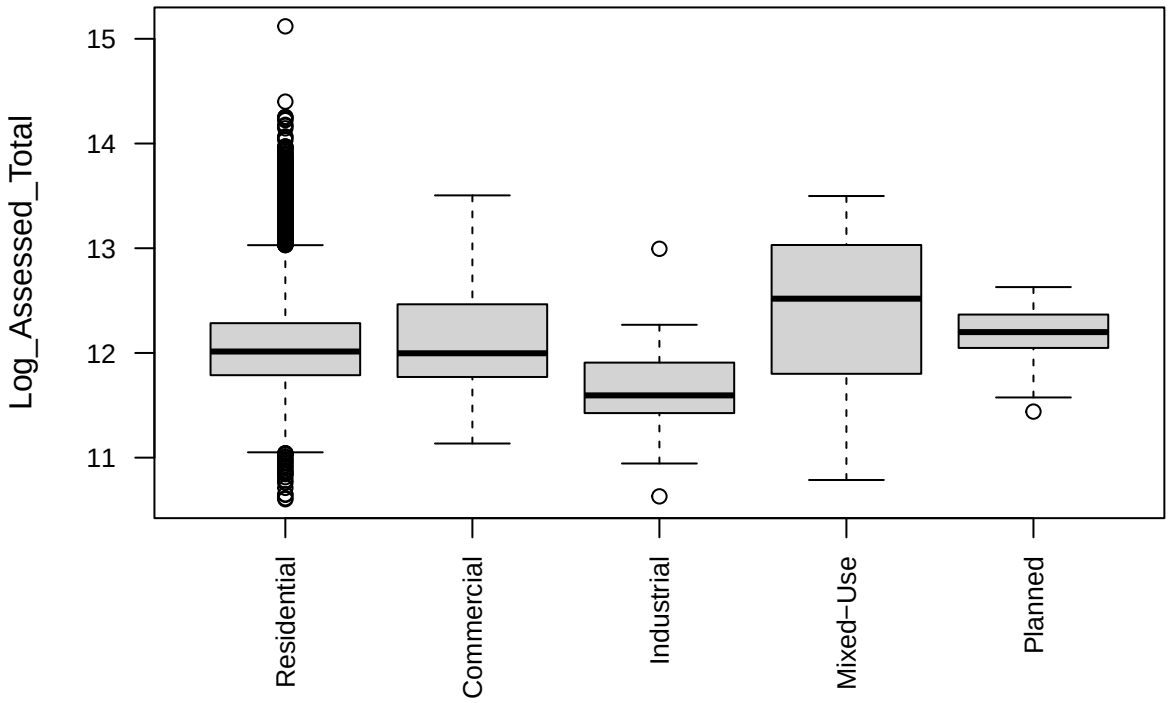
Next, we take a closer look at zoning districts. Because there are so many different zones, with many only corresponding to a handful of homes, we decided to group them based on their descriptions into five broader categories that represent their overall use: Residential, Mixed-Use, Commercial, Industrial, and Planned Development. The result is a more interpretable categorical variable. To achieve this, we referred to Article II of New Haven's Zoning Ordinances available on the Municode Library.

```
# Table of zone counts
table(sfh_final$Zone)
```

```
##
##      BA  BA/RM1  BA/RM2  BA/RS2     BA1      BB      BC      BD     BD1     CEM
##      56       3       5       1       7       3      10       6       7       3
##      IH  IH/RM2      IL PDD 119  PDD 26  PDD 39  PDD 49  PDD 52 PDU 102 PDU 106
##      24       1       7      12       2       4      13       1       4      30
## PDU 108  PDU 16  PDU 72  PDU 75     RH1     RH2     RM1     RM2 RM2/RS2      RO
```

```
##       7       1       1       2      27      21    1892    1688       5      22
##     RS1 RS1/RS2     RS2
##     374       3    5174
```

```r
# Define broader groupings based on zone descriptions
residential <- c("RS1", "RS2", "RS1/RS2", "RM1", "RM2", "RM2/RS2", "RH1", "RH2")
mixed_use <- c("RO", "BA/RM1", "BA/RM2", "BA/RS2", "CEM")
commercial <- c("BA", "BA1", "BB", "BC", "BD", "BD1")
industrial <- c("IL", "IH", "IH/RM2")
planned_development <- c("PDD 119", "PDD 26", "PDD 39", "PDD 49", "PDD 52",
                         "PDU 102", "PDU 106", "PDU 108", "PDU 16", "PDU 72",
                         "PDU 75", "PDU 95")

# Assign zone categories
sfh_final$Zone_Category <- ifelse(sfh_final$Zone %in% residential,
                                  "Residential", NA)
sfh_final$Zone_Category <- ifelse(sfh_final$Zone %in% mixed_use,
                                  "Mixed-Use", sfh_final$Zone_Category)
sfh_final$Zone_Category <- ifelse(sfh_final$Zone %in% commercial,
                                  "Commercial", sfh_final$Zone_Category)
sfh_final$Zone_Category <- ifelse(sfh_final$Zone %in% industrial,
                                  "Industrial", sfh_final$Zone_Category)
sfh_final$Zone_Category <- ifelse(sfh_final$Zone %in% planned_development,
                                  "Planned",
                                  sfh_final$Zone_Category)

# Convert to factor, set "Residential" as reference
sfh_final$Zone_Category <- as.factor(sfh_final$Zone_Category)
sfh_final$Zone_Category <- relevel(sfh_final$Zone_Category, ref = "Residential")

# Boxplot of log assessed total by zone category
boxplot(Log_Assessed_Total ~ Zone_Category, data = sfh_final, cex.axis = 0.8,
        las = 2, xlab = "")
```

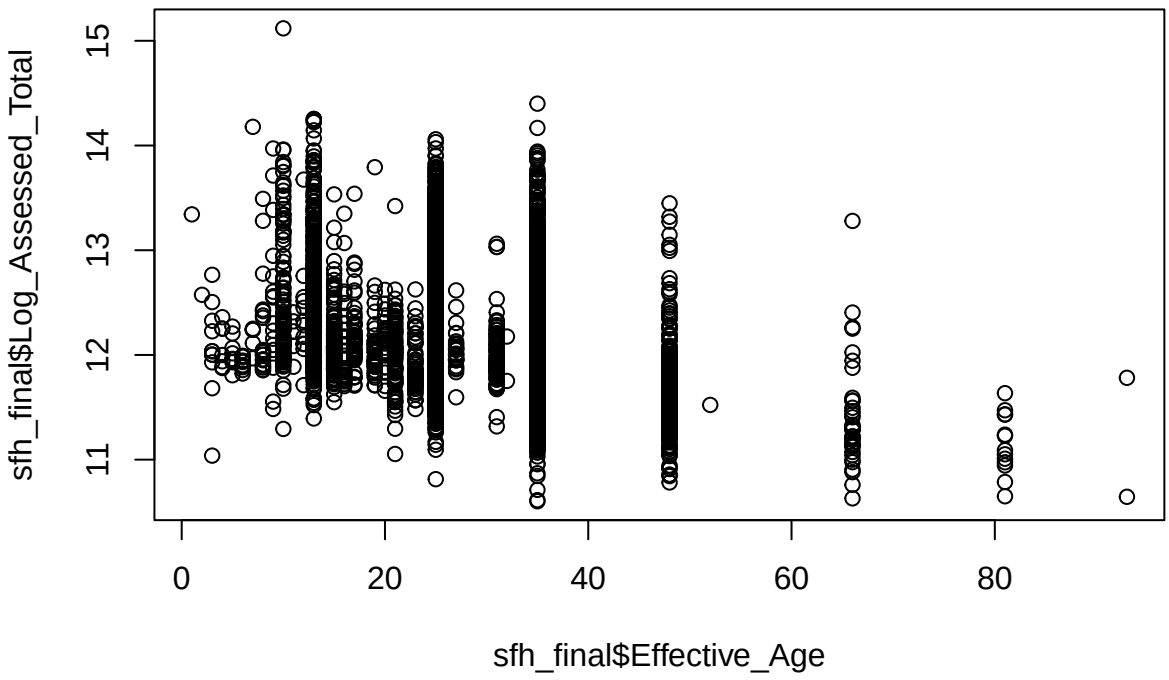


Lastly, we create the effective age variable.

```
# Check for missing effective year built
sum(is.na(sfh_final$EYB))
```

```
## [1] 0
```

```
# Create effective age variable and plot against log assessed total
sfh_final$Effective_Age <- 2024 - sfh_final$EYB
plot(sfh_final$Effective_Age, sfh_final$Log_Assessed_Total)
```

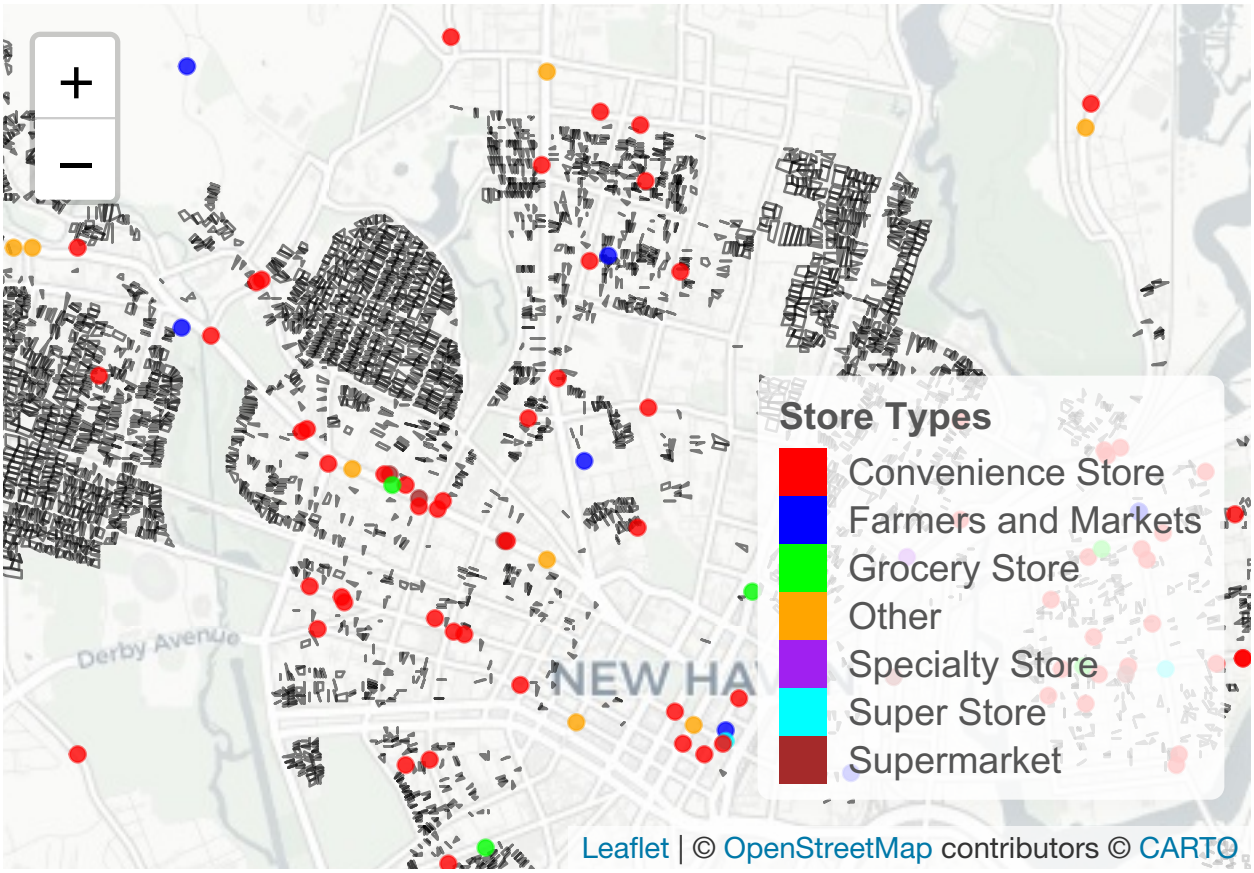

sfh_final$Log_Assessed_Total
11
12
13
14
15
0
20
40
60
80
sfh_final$Effective_Age

Food Access Features

To create meaningful and interpretable features related to proximity to food, we took two approaches to the idea of proximity:

1. Distance to nearest food retailers
2. Number of food retailers within some radius

```
# Load SNAP data
s <- read.csv("data/CT_SNAP_Authorized_Retailers_20240920.csv")

# Convert to spatial
sg <- st_as_sf(s, coords = c("Longitude", "Latitude"), crs = 4326, remove=FALSE)
sfh_final <- st_transform(sfh_final, crs = 4326)

# Visualize store locations, superimposed on New Haven map and geometries of
# single-family homes in our subset
pal <- colorFactor(
  palette = c("red", "blue", "green", "orange", "purple", "cyan", "brown"),
  domain = sg$Store.Type
)
leaflet() %>%
  addProviderTiles(providers$CartoDB.Positron) %>%

  # Center on New Haven
  setView(lng = -72.93, lat = 41.32, zoom = 13) %>%

  # Add sfh homes
  addPolygons(data = sfh_final,
              color = "black",
              weight = 1,
              fillColor = "transparent",
              popup = ~paste("Location:", Location,
                             "<br>State Use: ", State_Use_Description),
              group = "Homes") %>%

  # Add stores, colored by type
  addCircleMarkers(data = sg,
                   radius = 3,
                   color = ~pal(Store.Type),
                   stroke = TRUE,
                   weight = 1,
                   fillOpacity = 0.8,
                   popup = ~paste0("Store: ", Store.Name,
                                   "<br>Type: ", Store.Type),
                   group = "Stores") %>%
  addLegend(
    position = "bottomright",
    pal = pal,
    values = sg$Store.Type,
    title = "Store Types",
    opacity = 1
  )
```



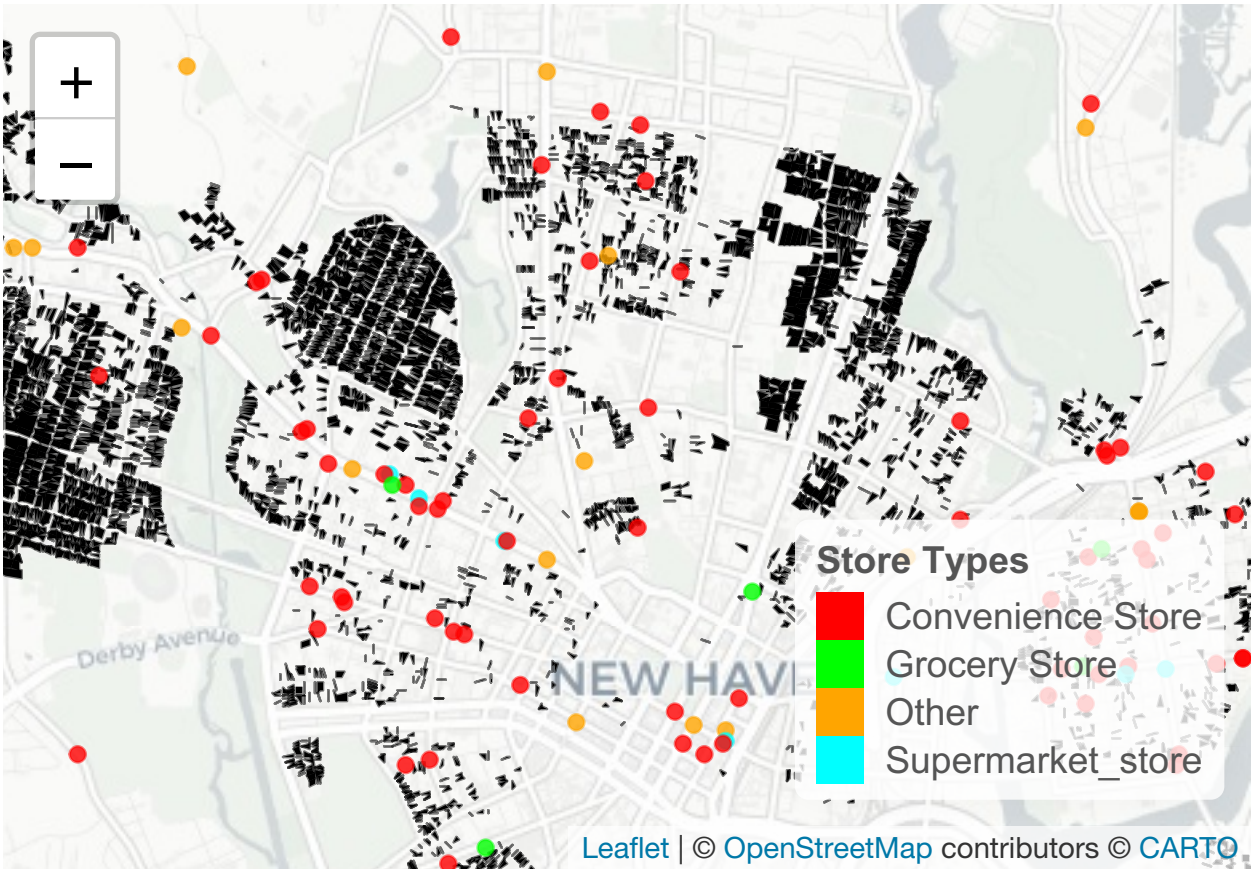
Certain store types like specialty stores are relatively infrequent. Moreover, we could technically consider super stores and supermarkets together, since we can view super stores as extensions of supermarkets that happen to include non-food items as well. As a result, we decided to group super stores and supermarkets together, leave convenience stores and grocery stores as is as separate groups, and bucket the rest into "Other."

```
# View counts by store type
table(sg$Store.Type)
```

```
##
##   Convenience Store Farmers and Markets       Grocery Store               Other
##                1108                  94                 255                 570
##     Specialty Store         Super Store          Supermarket
##                  25                 224                 194
```

```
# Create store type groups
sg$Store.Type.Grouped <- "Other"
sg$Store.Type.Grouped[sg$Store.Type == "Convenience Store"] <- "Convenience Store"
sg$Store.Type.Grouped[sg$Store.Type == "Grocery Store"] <- "Grocery Store"
sg$Store.Type.Grouped[sg$Store.Type %in%
                      c("Supermarket", "Super Store")] <- "Supermarket_store"

# Re-visualize with new groups
palGrouped <- colorFactor(
  palette = c("red", "green", "orange", "cyan"),
  domain = sg$Store.Type.Grouped
```

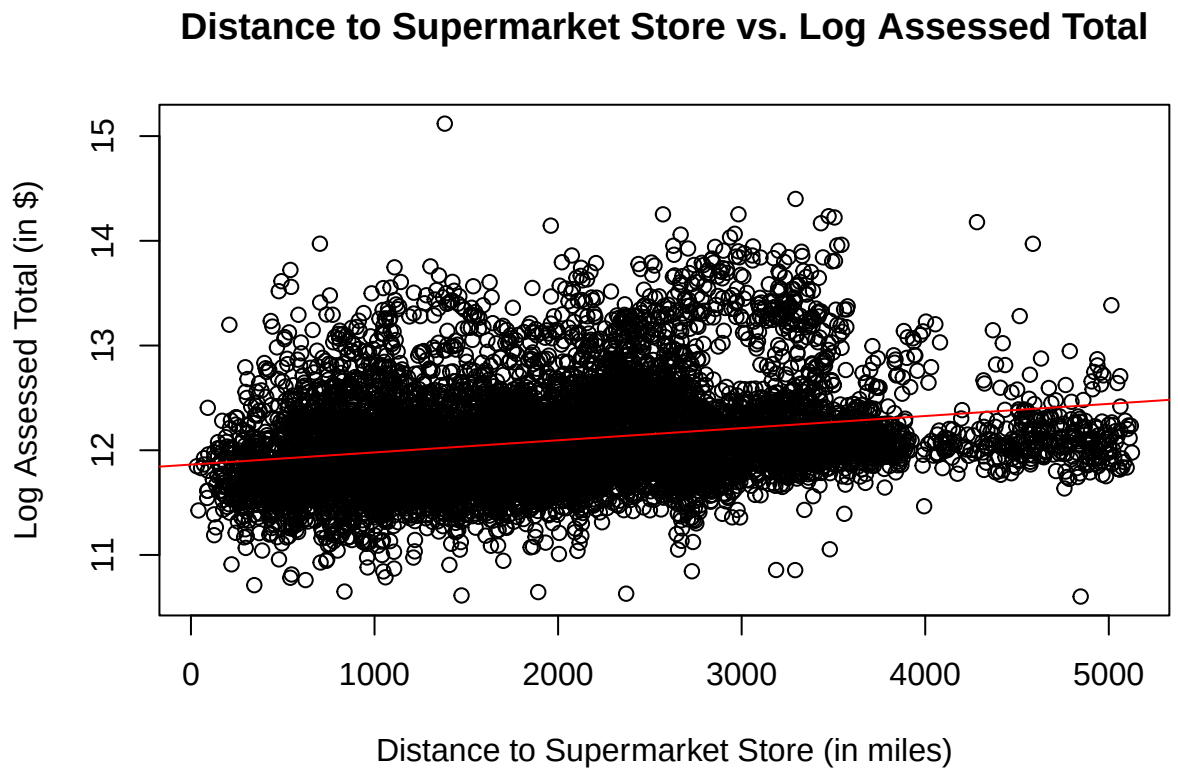
```
)
leaflet() %>%
  addProviderTiles(providers$CartoDB.Positron) %>%

  # Center on New Haven
  setView(lng = -72.93, lat = 41.32, zoom = 13) %>%

  # Add sfh homes
  addPolygons(data = sfh_final,
              color = "black",
              weight = 1,
              fillColor = "black",
              popup = ~paste("Location:", Location,
                             "<br>State Use: ", State_Use_Description),
              group = "Homes") %>%

  # Add stores, colored by type
  addCircleMarkers(data = sg,
                   radius = 3,
                   color = ~palGrouped(Store.Type.Grouped),
                   stroke = TRUE,
                   weight = 1,
                   fillOpacity = 0.8,
                   popup = ~paste0("Store: ", Store.Name,
                                   "<br>Type: ", Store.Type),
                   group = "Stores") %>%
  addLegend(
    position = "bottomright",
    pal = palGrouped,
    values = sg$Store.Type.Grouped,
    title = "Store Types",
    opacity = 1
  )
```



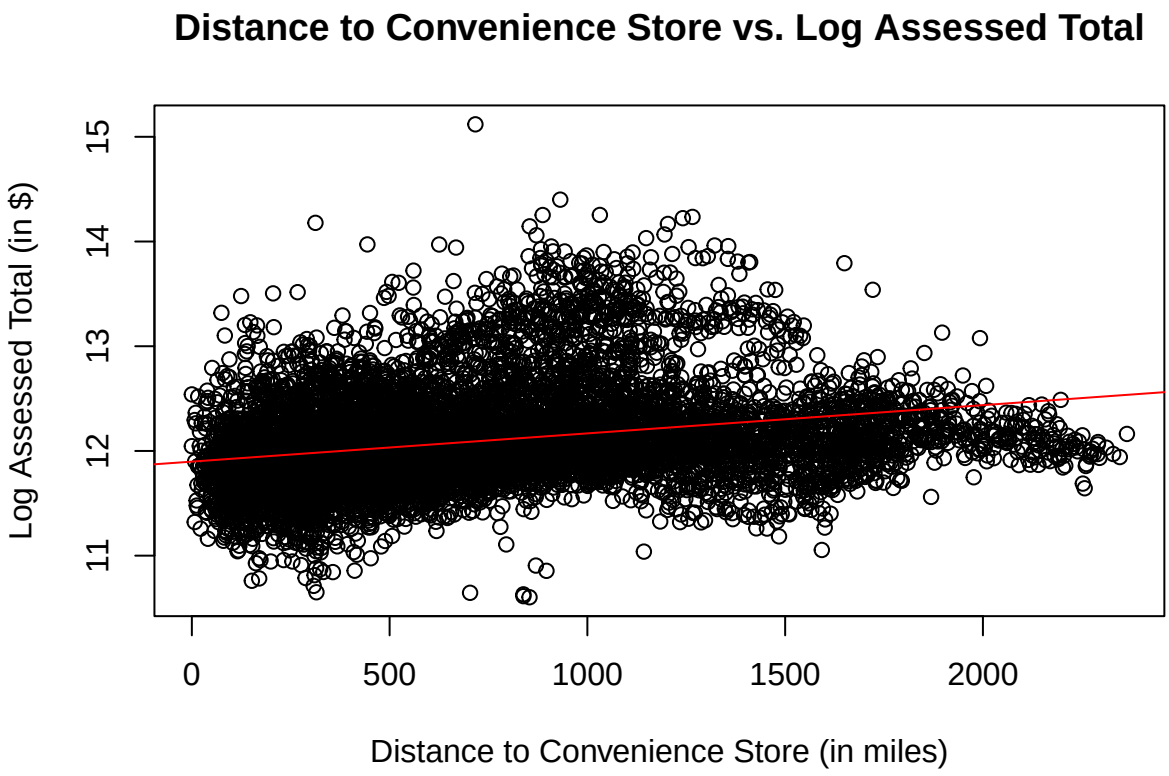
For our first approach to "proximity", we compute the distance in meters to the nearest store of each grouped store type we defined earlier.

```
# Transform back to WGS 84 Mercator so calculations are in meters
sfh_final <- st_transform(sfh_final, crs = 3857)
sg <- st_transform(sg, crs = 3857)

# Define the store types to analyze
target_store_types <- unique(sg$Store.Type.Grouped)

# Initialize distance and area columns for each target store type
for (type in target_store_types) {

  # Define column names for distance and area
  dist_col <- paste0("dist_", type)

  # Subset SNAP retailers of the current Store Type
  stores_type <- sg[sg$Store.Type.Grouped == type, ]

  # Find the nearest store of the current type for each home
  nearest_store_indices <- st_nearest_feature(sfh_final, stores_type)

  # Calculate distances to the nearest store
  distances <- st_distance(sfh_final,
                           stores_type[nearest_store_indices, ],
                           by_element = TRUE)
```

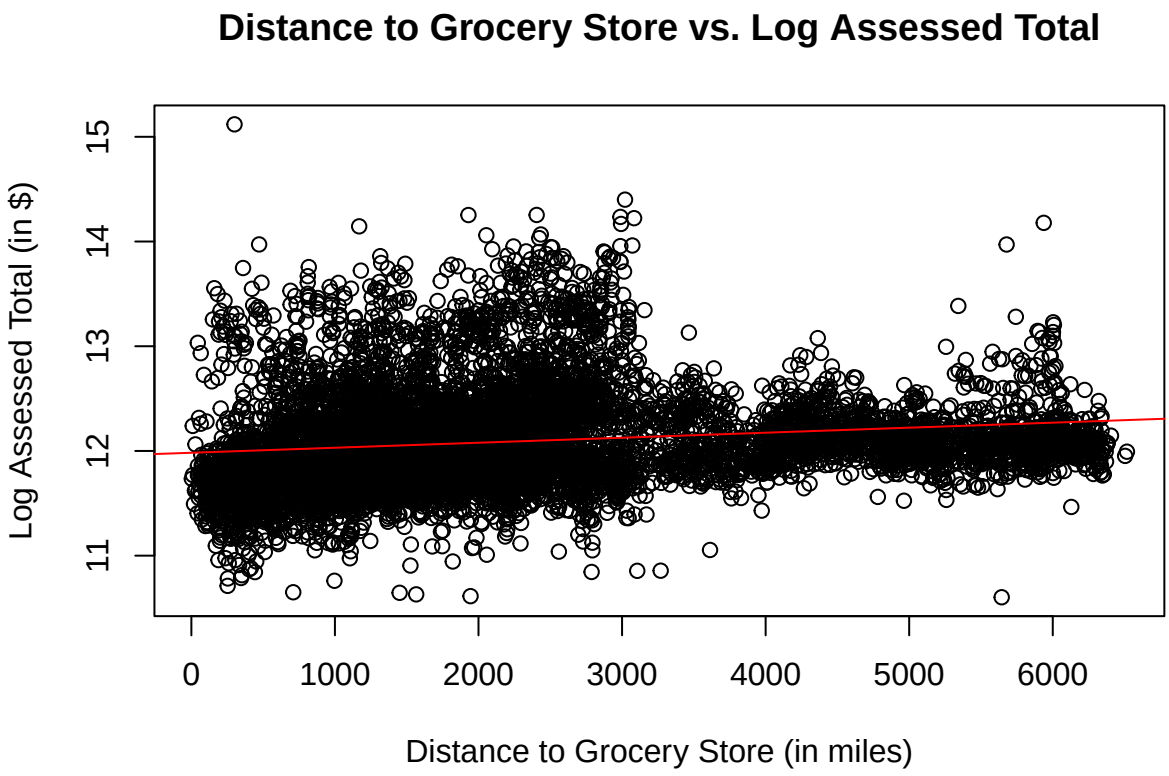
```r
  # Assign distances to the home data (convert to numeric, e.g., meters)
  sfh_final[[dist_col]] <- as.numeric(distances)
}

# Plot new distance features vs. log assessed total

# Plot distance to Supermarket Store vs. Log Assessed Total
ssdist_ls <- lm(Log_Assessed_Total ~ dist_Supermarket_store, data = sfh_final)
plot(sfh_final$dist_Supermarket_store, sfh_final$Log_Assessed_Total,
     main = "Distance to Supermarket Store vs. Log Assessed Total",
     xlab = "Distance to Supermarket Store (in miles)",
     ylab = "Log Assessed Total (in $)")
abline(ssdist_ls, col = "red")
```




```r
# Plot distance to Convenience Store vs. Log Assessed Total
csdist_ls <- lm(Log_Assessed_Total ~ `dist_Convenience Store`, data = sfh_final)
plot(sfh_final$`dist_Convenience Store`, sfh_final$Log_Assessed_Total,
     main = "Distance to Convenience Store vs. Log Assessed Total",
     xlab = "Distance to Convenience Store (in miles)",
     ylab = "Log Assessed Total (in $)")
abline(csdist_ls, col = "red")
```




```r
# Plot distance to Grocery Store vs. Log Assessed Total
gsdist_ls <- lm(Log_Assessed_Total ~ `dist_Grocery Store`, data = sfh_final)
plot(sfh_final$`dist_Grocery Store`, sfh_final$Log_Assessed_Total,
     main = "Distance to Grocery Store vs. Log Assessed Total",
     xlab = "Distance to Grocery Store (in miles)",
     ylab = "Log Assessed Total (in $)")
abline(gsdist_ls, col = "red")
```




```
# Plot distance to Other Store vs. Log Assessed Total
otdist_ls <- lm(Log_Assessed_Total ~ `dist_Other`, data = sfh_final)
plot(sfh_final$dist_Other, sfh_final$Log_Assessed_Total,
     main = "Distance to Other Store vs. Log Assessed Total",
     xlab = "Distance to Other Store (in miles)",
     ylab = "Log Assessed Total (in $)")
abline(otdist_ls, col = "red")
```

Peter Added (Comment what we observe)

Our analysis shows that there is a weak positive relationship between the distance to stores and the log of the total assessed value of properties, with the strongest positive relationship observed for supermarkets. For stores classified as "other," the relationship appears much weaker, with no clear linear pattern. These findings suggest that proximity to supermarkets might not always result in higher property values.

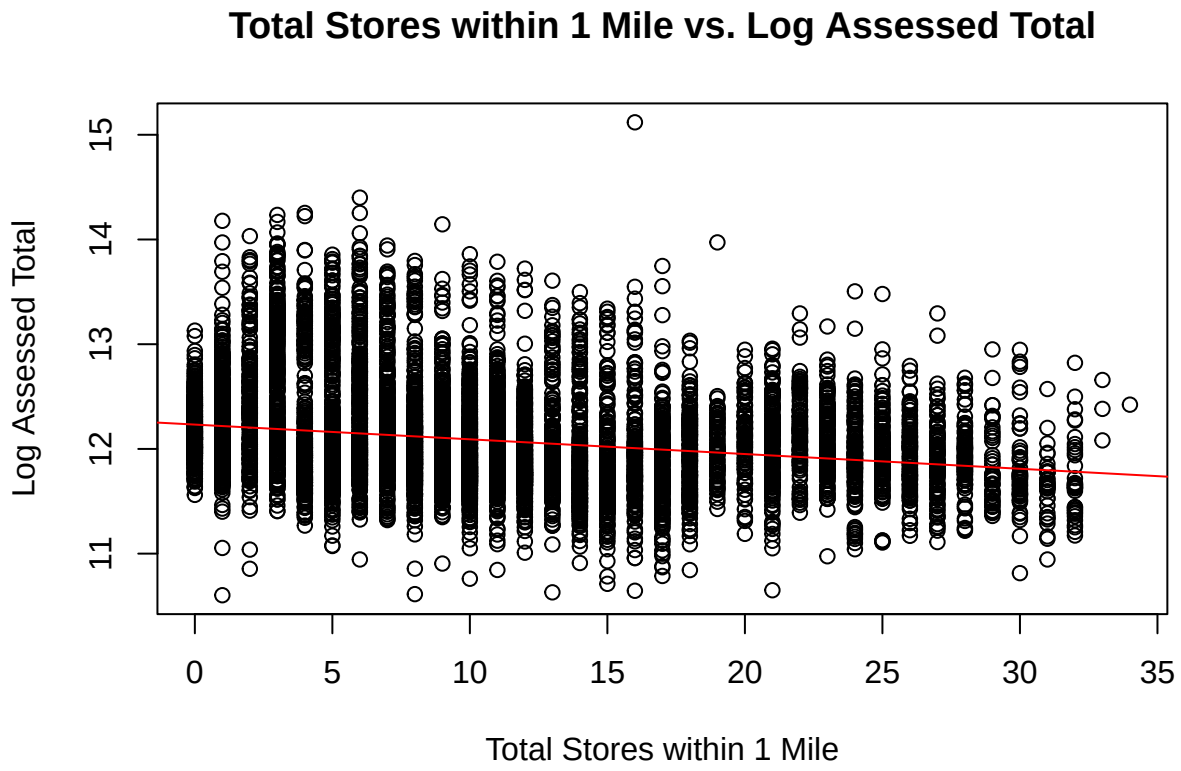
While living close to a supermarket may offer convenience, it also brings potential downsides like traffic, noise, and higher crime rates. Expensive properties are often located in more secluded areas with fewer stores nearby. Residents in these affluent neighborhoods may prefer upscale restaurants over grocery stores, which may reduce the value placed on proximity to supermarkets.

Additionally, economic factors likely play a role. Operating grocery stores in expensive areas can be financially challenging due to high operating costs, making it difficult for such businesses to survive. Even upscale stores, like Foxtrot and Erewhon, face these challenges, leading to store closures in some affluent areas.

Overall, our results suggest that the impact of store proximity on property values is complex and depends on a variety of factors, including neighborhood affluence and the type of store. This relationship requires a nuanced understanding that goes beyond simple distance measures.

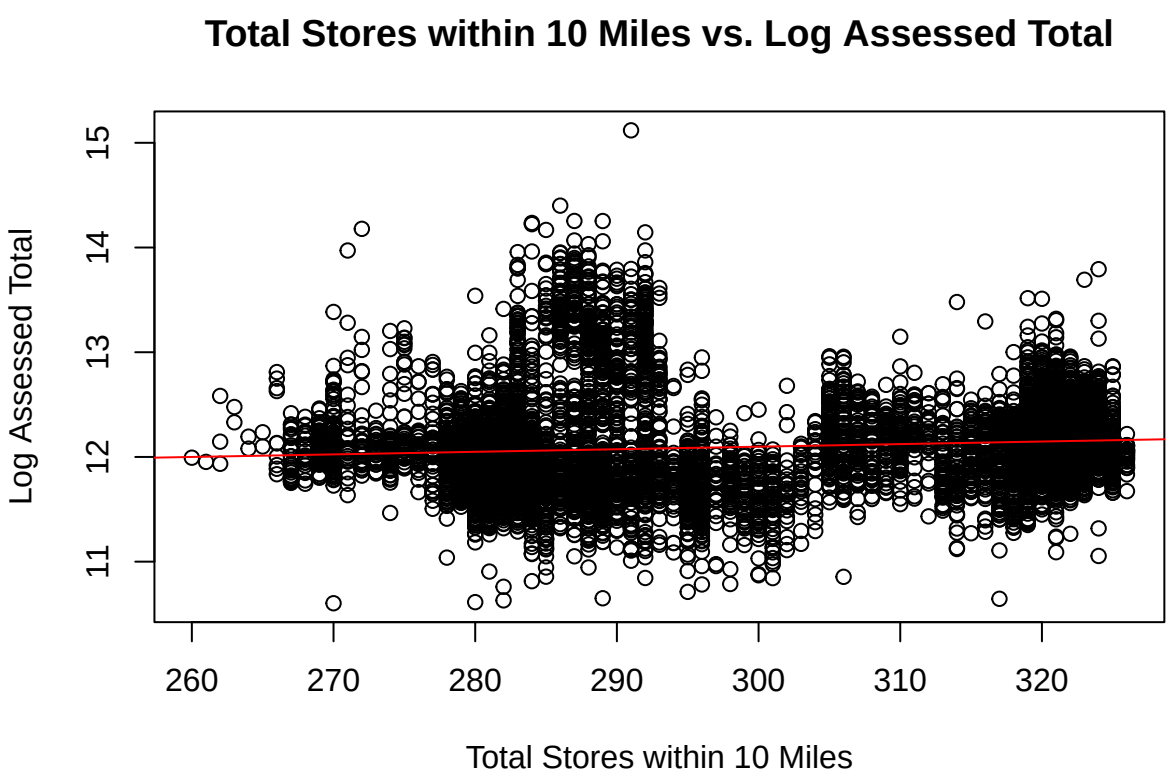
```
# Compute distance matrix
dist_matrix <- st_distance(sfh_final, sg, by_element = FALSE)

# ~1 mi = 1609 m, ~2 mi = 3218 m, and ~10 mi = 16090 m
radii_labels <- c("1_mile", "2_miles", "10_miles")
radii_meters <- c(1609, 3218, 16090)

for (i in 1:3) {
```

```
  # Count the number of stores within the distance for each home
  counts <- apply(dist_matrix, 1, function(x) sum(x <= radii_meters[i]))

  # Add the counts to the data frame with a descriptive column name
  column_name <- paste0("total_", radii_labels[i])
  sfh_final[[column_name]] <- counts
}

# Plot new count features vs. log assessed total

# Plot Total Stores within 1 Mile vs. Log Assessed Total
mile1_ls <- lm(Log_Assessed_Total ~ total_1_mile, data = sfh_final)
plot(sfh_final$total_1_mile, sfh_final$Log_Assessed_Total,
     main = "Total Stores within 1 Mile vs. Log Assessed Total",
     xlab = "Total Stores within 1 Mile", ylab = "Log Assessed Total")
abline(mile1_ls, col = "red")
```




```
# Plot Total Stores within 2 Miles vs. Log Assessed Total
mile2_ls <- lm(Log_Assessed_Total ~ total_2_miles, data = sfh_final)
plot(sfh_final$total_2_mile, sfh_final$Log_Assessed_Total,
     main = "Total Stores within 2 Miles vs. Log Assessed Total",
     xlab = "Total Stores within 2 Miles", ylab = "Log Assessed Total")
abline(mile2_ls, col = "red")
```


```r
# Plot Total Stores within 10 Miles vs. Log Assessed Total
mile10_ls <- lm(Log_Assessed_Total ~ total_10_miles, data = sfh_final)
plot(sfh_final$total_10_mile, sfh_final$Log_Assessed_Total,
     main = "Total Stores within 10 Miles vs. Log Assessed Total",
     xlab = "Total Stores within 10 Miles", ylab = "Log Assessed Total")
abline(mile10_ls, col = "red")
```



Peter Added: Comment what we observe

Our analysis of the number of stores within specified radii reveals an interesting pattern: there appears to be a zero to negative association between the total number of stores nearby and the log of the total assessed value of single-family homes. This pattern holds across 1-mile, 2-mile, and 10-mile radii.

These results are consistent with earlier findings. Areas with higher property values tend to have fewer nearby stores, reinforcing the idea that affluent neighborhoods may not support many retail businesses. The financial costs of operating stores in these areas can be prohibitively high, leading to challenges for retailers, especially those requiring high foot traffic or lower margins.

In wealthier areas, where residents have greater purchasing power, the demand may shift toward upscale restaurants and specialty stores rather than supermarkets and convenience stores. This trend is reflected in broader urban economics, where retail compositions change as neighborhood income levels rise. Affluent areas often favor boutique-style retail that caters to higher income consumers, further reducing the need for everyday stores.

Overall, the association between store density and property values is complex and context-specific, much like proximity to stores. While having stores nearby may indicate convenience, it can also signify congestion or economic unsustainability, particularly in wealthier areas. A nuanced approach is needed to fully understand this relationship.

Modeling

While these marginal plots provide valuable intuition, they do not tell the full story, as they only show relationships in isolation. To capture the joint dynamics of multiple factors that determine housing values, we now turn to a more rigorous modeling approach.

Step 1: Baseline Model

Our baseline model includes essential predictors that we believe sufficiently explain the total assessed values of properties. These predictors are:

- (a) Square Root of Effective Area,
- (b) Number of Bedrooms,
- (c) Total Number of Bathrooms,
- (d) Property Condition,
- (e) Zoning Categories, and
- (f) Effective Age of the Property.

These variables were previously found to be positively correlated with the log of total assessed values, providing a solid foundation for our model.

Step 2: Proposed Model

In the advanced model, we introduce two new sets of variables: (a) distance to stores and (b) the number of stores within specified radii. This allows us to observe how the inclusion of these features changes the model's performance.

By comparing the baseline and advanced models, we can assess the changes in coefficients, adjusted R-squared, residual standard erorr, and importantly, determine whether the added predictors provide statistically significant effects on property values. This will be formally tested using an ANOVA test, which helps us assess the overall fit and complexity of the model.

Conclusion:

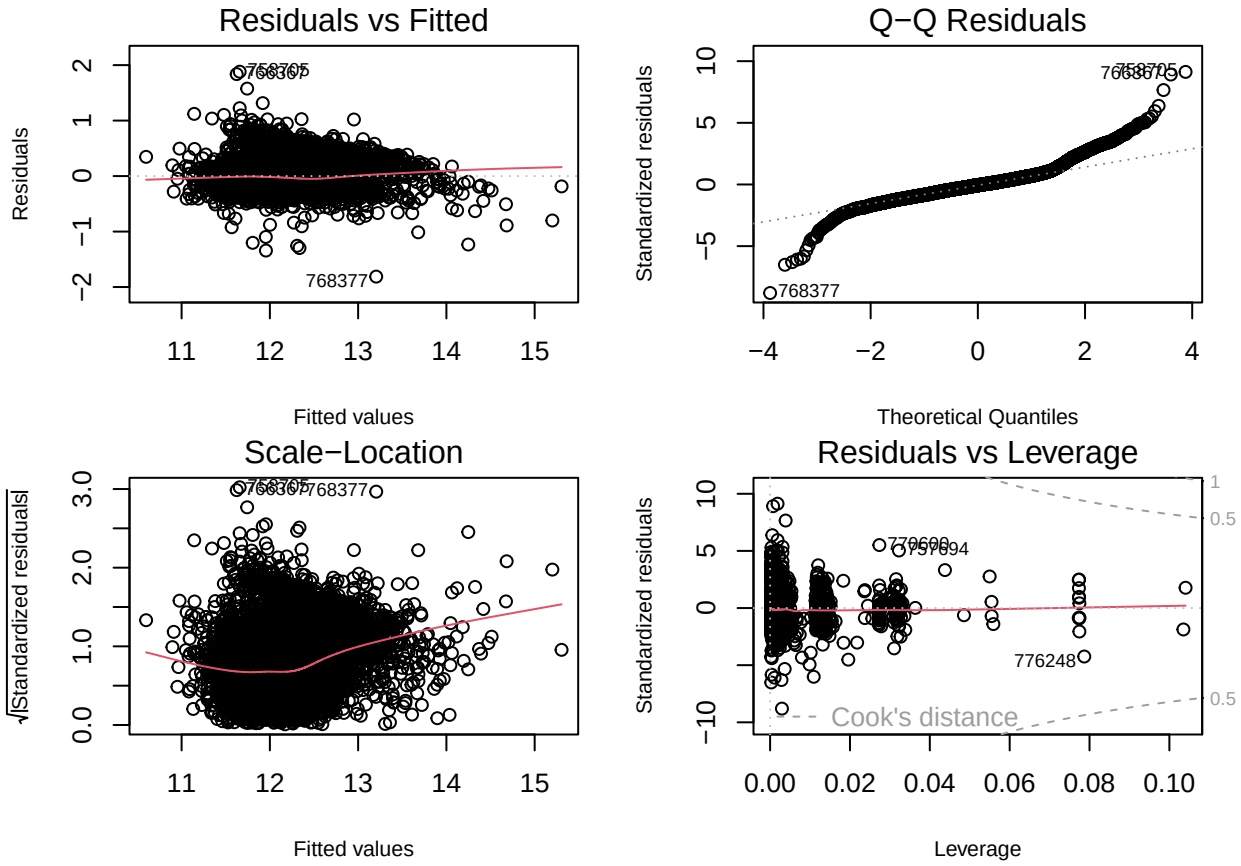
Through this two-step approach, we aim to uncover how both traditional property features and proximity to stores influence the assessed values of homes. While proximity to stores might seem like a convenience factor, its relationship with property value is more nuanced, especially in affluent areas where retail store presence might be limited. ## Baseline Model

```
# Fit baseline model
m1 <- lm(Log_Assessed_Total ~ Sqrt_Effective_Area + Number_of_Bedroom +
         Number_of_Baths_Total + Condition_Description + Zone_Category +
         Effective_Age, data = sfh_final)

# Check model summary
summary(m1)
```

```
##
## Call:
## lm(formula = Log_Assessed_Total ~ Sqrt_Effective_Area + Number_of_Bedroom +
##     Number_of_Baths_Total + Condition_Description + Zone_Category +
##     Effective_Age, data = sfh_final)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.81187 -0.11658 -0.01217  0.08936  1.88106
```

```
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    10.5278120  0.0188636 558.101  < 2e-16 ***
## Sqrt_Effective_Area             0.0372393  0.0003809  97.776  < 2e-16 ***
## Number_of_Bedroom              -0.0141046  0.0029393  -4.799 1.62e-06 ***
## Number_of_Baths_Total           0.0699904  0.0039629  17.661  < 2e-16 ***
## Condition_DescriptionExcellent  0.2594459  0.0262929   9.868  < 2e-16 ***
## Condition_DescriptionFair      -0.1542599  0.0137657 -11.206  < 2e-16 ***
## Condition_DescriptionGood       0.0606080  0.0063445   9.553  < 2e-16 ***
## Condition_DescriptionPoor      -0.2457624  0.0375466  -6.546 6.24e-11 ***
## Condition_DescriptionVery Good  0.1399730  0.0143437   9.759  < 2e-16 ***
## Condition_DescriptionVery Poor -0.4274557  0.0619092  -6.905 5.36e-12 ***
## Zone_CategoryCommercial        -0.0806801  0.0220031  -3.667 0.000247 ***
## Zone_CategoryIndustrial        -0.1893669  0.0366378  -5.169 2.41e-07 ***
## Zone_CategoryMixed-Use         -0.0819313  0.0361773  -2.265 0.023553 *
## Zone_CategoryPlanned            0.0440296  0.0247806   1.777 0.075637 .
## Effective_Age                  -0.0059266  0.0004862 -12.189  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2062 on 9400 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.8007, Adjusted R-squared:  0.8005
## F-statistic:  2698 on 14 and 9400 DF,  p-value: < 2.2e-16
```

```r
# Diagnostic plots
par(mfrow = c(2, 2))
par(mar = c(4, 4, 1.5, 1.5))
plot(m1, cex.lab = 0.8)
```

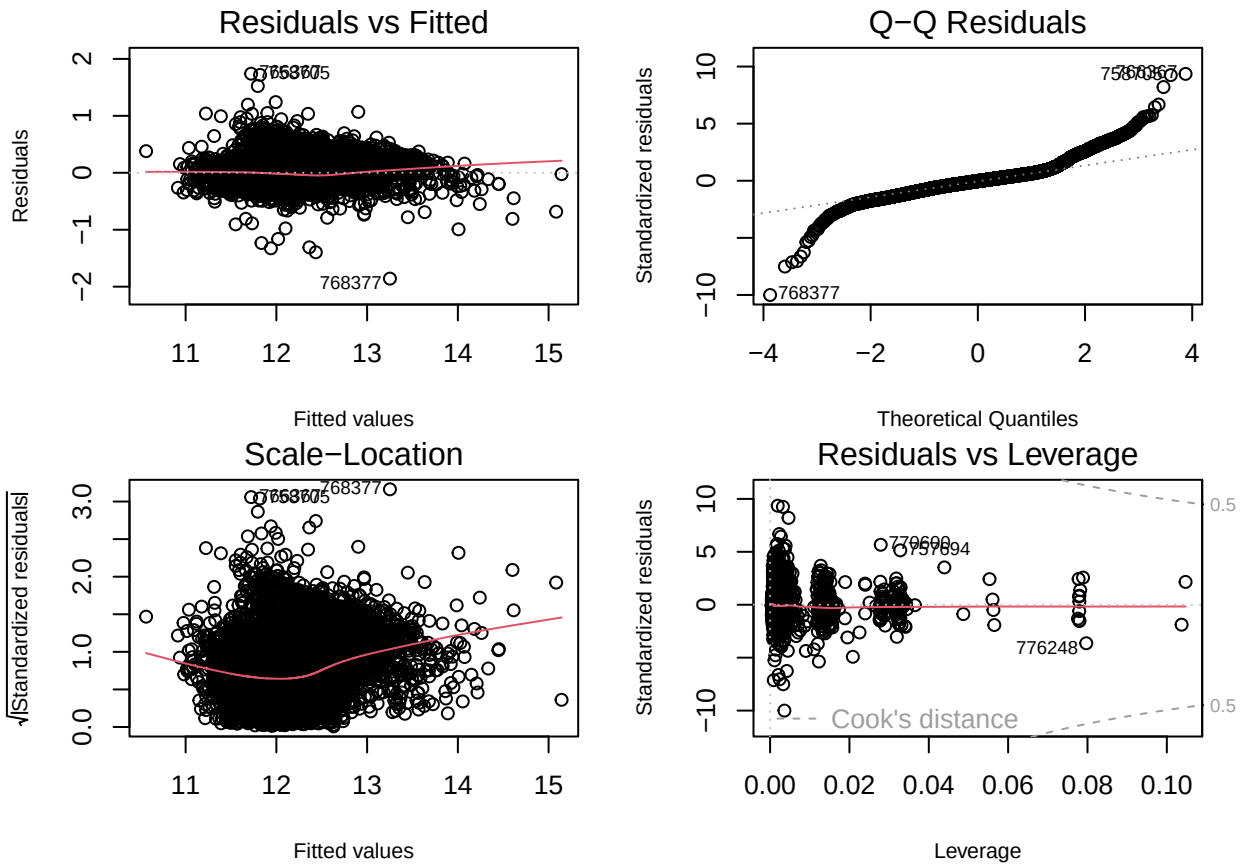



```
# Fit proposed model with food access features
m2 <- lm(Log_Assessed_Total ~ Sqrt_Effective_Area + Number_of_Bedroom +
         Number_of_Baths_Total + Condition_Description + Zone_Category +
         Effective_Age + `dist_Convenience Store` + dist_Other +
         `dist_Grocery Store` + dist_Supermarket_store + total_1_mile +
         total_2_miles + total_10_miles, data = sfh_final)


# Check model summary
summary(m2)
```

```
##
## Call:
## lm(formula = Log_Assessed_Total ~ Sqrt_Effective_Area + Number_of_Bedroom +
##     Number_of_Baths_Total + Condition_Description + Zone_Category +
##     Effective_Age + `dist_Convenience Store` + dist_Other + `dist_Grocery Store` +
##     dist_Supermarket_store + total_1_mile + total_2_miles + total_10_miles,
##     data = sfh_final)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.85860 -0.09659 -0.00503  0.07749  1.73991
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    1.071e+01  4.789e-02 223.639  < 2e-16 ***
```

```
## Sqrt_Effective_Area             3.430e-02  3.595e-04  95.416  < 2e-16 ***
## Number_of_Bedroom              -2.306e-03  2.693e-03  -0.856 0.391945
## Number_of_Baths_Total           6.144e-02  3.597e-03  17.083  < 2e-16 ***
## Condition_DescriptionExcellent  2.383e-01  2.376e-02  10.031  < 2e-16 ***
## Condition_DescriptionFair      -1.220e-01  1.251e-02  -9.750  < 2e-16 ***
## Condition_DescriptionGood       4.960e-02  5.806e-03   8.544  < 2e-16 ***
## Condition_DescriptionPoor      -1.944e-01  3.400e-02  -5.718 1.11e-08 ***
## Condition_DescriptionVery Good  1.204e-01  1.298e-02   9.276  < 2e-16 ***
## Condition_DescriptionVery Poor -4.209e-01  5.597e-02  -7.520 5.97e-14 ***
## Zone_CategoryCommercial        -3.952e-03  2.003e-02  -0.197 0.843571
## Zone_CategoryIndustrial        -1.923e-01  3.315e-02  -5.799 6.88e-09 ***
## Zone_CategoryMixed-Use         -3.747e-02  3.280e-02  -1.142 0.253309
## Zone_CategoryPlanned            3.302e-02  2.255e-02   1.464 0.143199
## Effective_Age                  -6.133e-03  4.415e-04 -13.893  < 2e-16 ***
## `dist_Convenience Store`        7.220e-05  5.536e-06  13.041  < 2e-16 ***
## dist_Other                     -6.933e-05  4.090e-06 -16.952  < 2e-16 ***
## `dist_Grocery Store`            3.406e-05  3.741e-06   9.103  < 2e-16 ***
## dist_Supermarket_store          1.268e-05  5.225e-06   2.427 0.015263 *
## total_1_mile                   -9.516e-03  4.767e-04 -19.963  < 2e-16 ***
## total_2_miles                   3.518e-03  1.984e-04  17.729  < 2e-16 ***
## total_10_miles                 -5.206e-04  1.402e-04  -3.713 0.000206 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1861 on 9393 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.8378, Adjusted R-squared:  0.8374
## F-statistic:  2310 on 21 and 9393 DF,  p-value: < 2.2e-16
```

```r
# Diagnostic plots
par(mfrow = c(2, 2))
par(mar = c(4, 4, 1.5, 1.5))
plot(m2, cex.lab = 0.8)
```




```
# Model comparison
anova(m1, m2)
```

```
## Analysis of Variance Table
##
## Model 1: Log_Assessed_Total ~ Sqrt_Effective_Area + Number_of_Bedroom +
##     Number_of_Baths_Total + Condition_Description + Zone_Category +
##     Effective_Age
## Model 2: Log_Assessed_Total ~ Sqrt_Effective_Area + Number_of_Bedroom +
##     Number_of_Baths_Total + Condition_Description + Zone_Category +
##     Effective_Age + `dist_Convenience Store` + dist_Other + `dist_Grocery Store` +
##     dist_Supermarket_store + total_1_mile + total_2_miles + total_10_miles
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1   9400 399.66
## 2   9393 325.44  7    74.219 306.03 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Model Results

The results of our baseline model show that traditional property features like square root of effective area, number of bathrooms, property condition, zoning categories, and effective age explain a significant portion of the variation in the log of total assessed value. The adjusted R-squared value of 0.8005 indicates that about 80% of the variability is explained by these features. The residual standard error of 0.2062 suggests that the unexplained variation is relatively small but leaves room for improvement.

In the proposed model, we observe that the adjusted R-squared increases to 0.8374, which reflects an improvement of over 3%. While this change may not be considered substantial, it does suggest that store-related variables add some explanatory power to the model. Additionally, the residual standard error decreases to 0.1861, indicating that the model is better at predicting property values with less unexplained variation. Although the improvement in fit is moderate, it demonstrates that incorporating proximity and store count measures refines our understanding of property value determinants.

Proximity to convenience stores, grocery stores, and supermarkets shows significant associations with property values, with convenience stores having a positive effect, indicating higher values for properties farther from these stores. Additionally, the number of stores within 1 mile shows a negative association with property values, while the number within 2 miles shows a positive relationship. This suggests that a moderate distance from stores is more desirable for homeowners.

The ANOVA comparison reveals that the inclusion of store-related variables significantly improves the model ($F = 306.03$, $p < 2.2e\text{-}16$). The reduced residuals in the proposed model, with a narrower range (-1.86 to 1.74), indicate a better fit and improved prediction accuracy.

In conclusion, the diagnostic metrics (R-squared, residuals, ANOVA) show that store proximity and count are essential factors in explaining property values, adding depth to our understanding of urban housing dynamics in New Haven.

Limitations of the Model and Analysis

One key limitation in our model diagnostics is the Q-Q plot, which shows that the residuals do not align well with the theoretical normal distribution. This deviation from normality may suggest that the model's assumptions are not fully met, potentially affecting the reliability of our inferences. Similarly, the Scale-Location plot indicates heteroscedasticity, meaning that the variance of residuals is not constant across fitted values, which can impact the accuracy of coefficient estimates and standard errors.

Multicollinearity is another concern in our model. Given the inclusion of multiple highly related predictors—such as distances to different types of stores and store counts within varying radii—there may be correlation among these variables. This can inflate the standard errors of the coefficients and make it difficult to identify the individual effect of each variable. We did not conduct a formal test for multicollinearity (such as VIF), but this should be considered in future work.

Another limitation stems from the observational nature of the dataset. Since we are working with existing property and store data, it is difficult to make causal statements about the relationship between proximity to stores and property values. Without experimental or quasi-experimental design, we cannot rule out unobserved confounders that could bias the results, such as local amenities, crime rates, or public services, which may also influence property values.

Lastly, our analysis focuses on a specific geographic area—New Haven, CT—so the generalizability of our findings may be limited. Property dynamics in other regions may differ, especially in areas with different urban layouts or economic conditions. Moreover, our store classification could be refined further, as some types of stores may impact property values in more nuanced ways than others. These limitations should be kept in mind when interpreting our results and considering future research.

Conclusion

In this study, we explored how proximity to food retailers, such as grocery stores and supermarkets, influences the total assessed value of single-family homes in New Haven, CT. By combining property parcel data with store location data from the Connecticut SNAP dataset, we aimed to understand the role that convenience plays in property valuation. Our findings suggest that while proximity to stores is important, the relationship between store proximity and property value is more nuanced than expected.

The results indicate that homes farther from convenience stores tend to have higher assessed values, which may reflect a preference for more peaceful environments away from high-traffic retail areas. In contrast, having too many stores within close proximity, particularly within a 1-mile radius, is associated with lower property values. This pattern suggests that while accessibility to stores is a factor, excessive retail presence may reduce the appeal of certain neighborhoods. Overall, the inclusion of store proximity and store count variables improved our model's performance, though the impact on property values remains context-dependent.

While proximity to food retailers is a meaningful factor, our findings suggest that other potential influences—such as neighborhood amenities, crime rates, or local services—may also play a role in determining property values. Future research could investigate these additional factors to offer a more comprehensive understanding of what drives property value in different urban settings.

Sessioninfo

```
sessionInfo()
```

```
## R version 4.4.1 (2024-06-14)
## Platform: aarch64-apple-darwin20
## Running under: macOS 15.0.1
##
## Matrix products: default
## BLAS:   /Library/Frameworks/R.framework/Versions/4.4-arm64/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/4.4-arm64/Resources/lib/libRlapack.dylib;  LAPACK v
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## time zone: America/New_York
## tzcode source: internal
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
## [1] webshot_0.5.5 leaflet_2.2.2 sf_1.0-17
##
## loaded via a namespace (and not attached):
##  [1] cli_3.6.3               knitr_1.48              rlang_1.1.4
##  [4] xfun_0.47               highr_0.11              processx_3.8.4
##  [7] DBI_1.2.3               KernSmooth_2.23-24      jsonlite_1.8.8
## [10] glue_1.7.0              colorspace_2.1-1        htmltools_0.5.8.1
## [13] e1071_1.7-14            ps_1.7.7                scales_1.3.0
## [16] rmarkdown_2.28          grid_4.4.1              munsell_0.5.1
## [19] crosstalk_1.2.1         evaluate_0.24.0         jquerylib_0.1.4
## [22] classInt_0.4-10         fastmap_1.2.0           lifecycle_1.0.4
## [25] yaml_2.3.10             compiler_4.4.1          htmlwidgets_1.6.4
## [28] Rcpp_1.0.13             rstudioapi_0.16.0       leaflet.providers_2.0.0
## [31] farver_2.1.2            digest_0.6.37           R6_2.5.1
## [34] class_7.3-22            callr_3.7.6             magrittr_2.0.3
## [37] tools_4.4.1             proxy_0.4-27            units_0.8-5
```