Explaining house price with year & size

MODELING WITH DATA IN THE TIDYVERSE

Albert Y. Kim

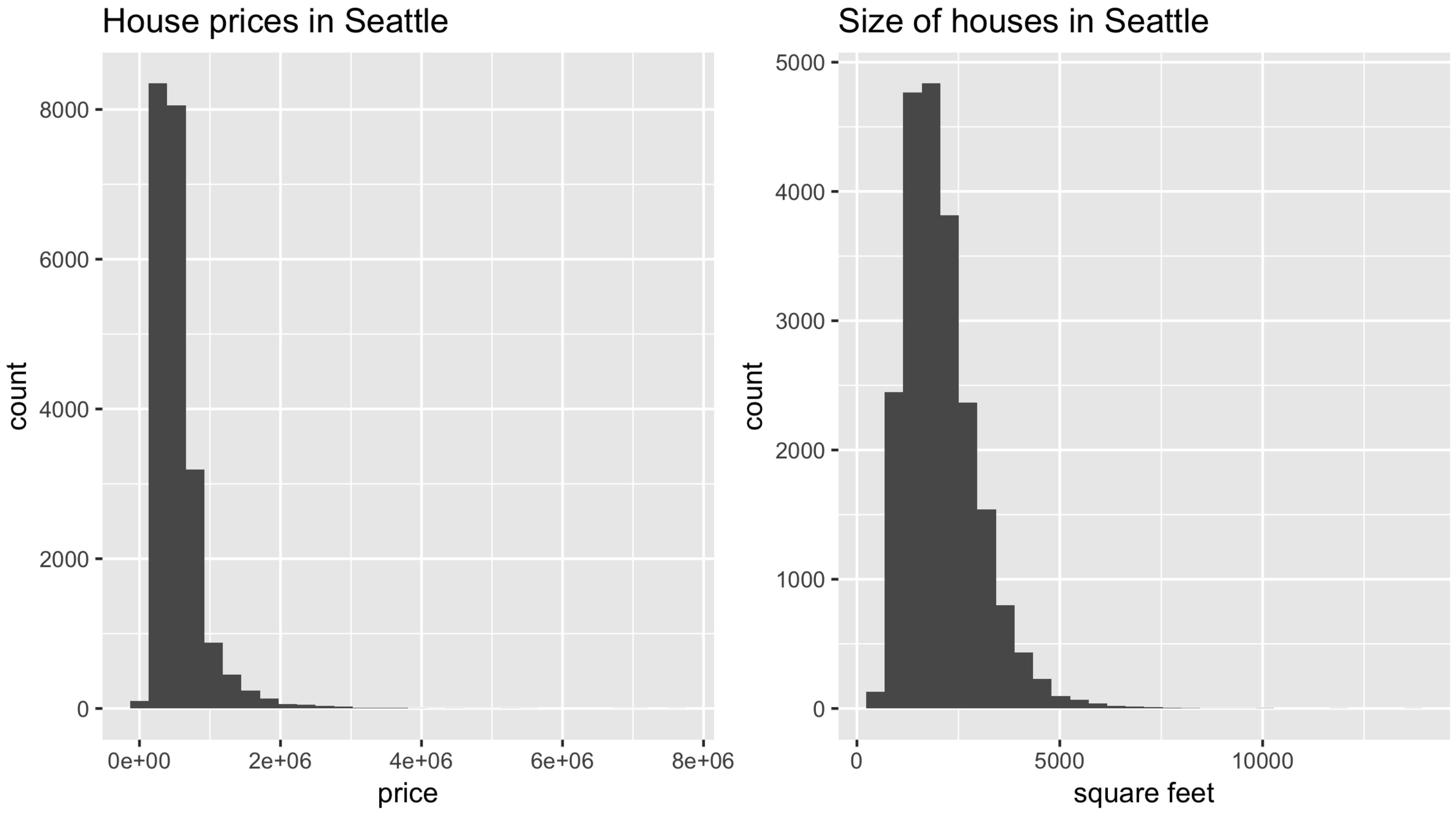
Assistant Professor of Statistical and Data Sciences

Refresher: Seattle house prices

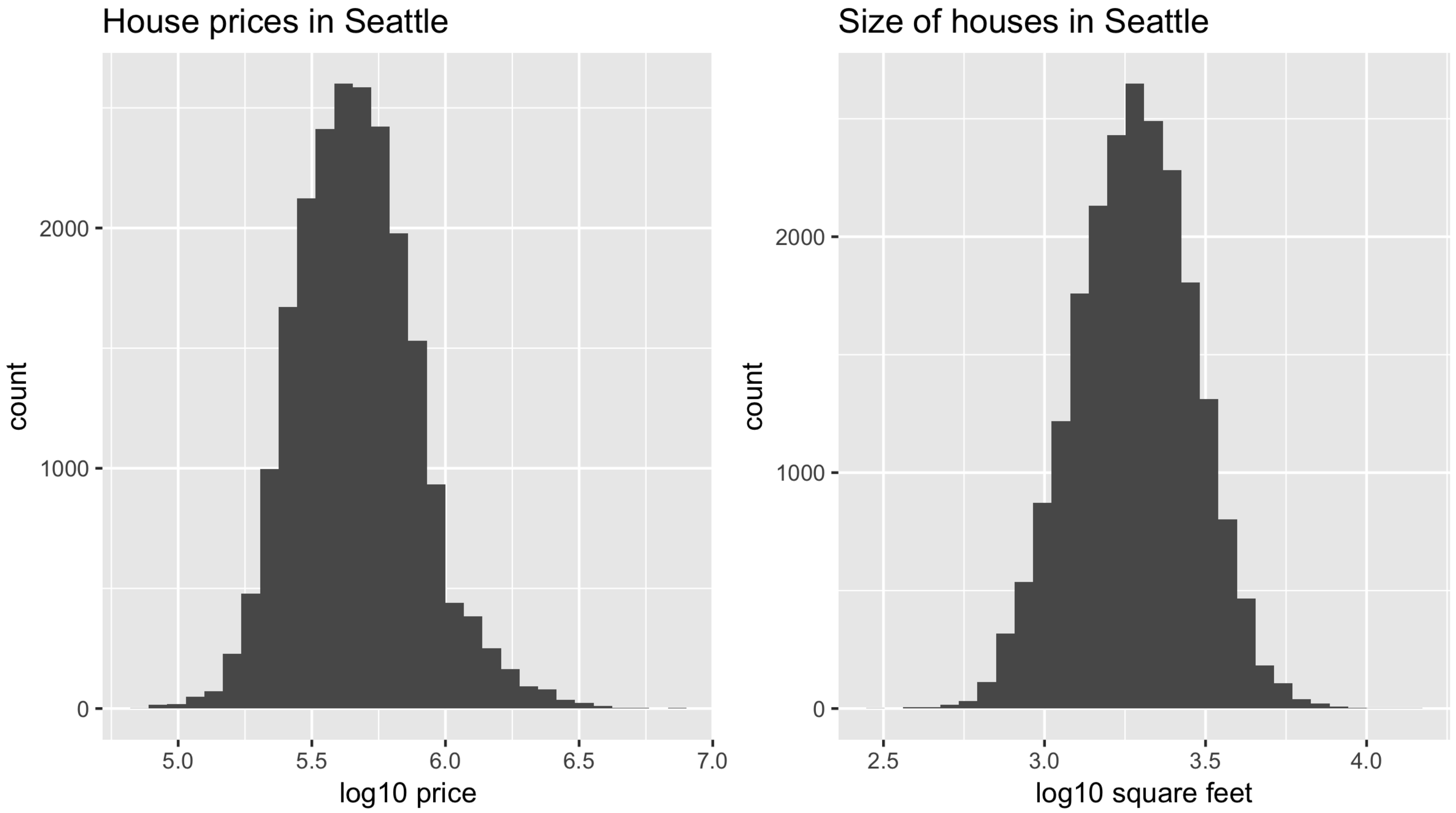
```
library(dplyr)
library(moderndive)

# Preview only certain variables:
house_prices %>%
  select(price, sqft_living, condition, waterfront) %>%
  glimpse()
```

```
Observations: 21,613
Variables: 4
$ price       <dbl> 221900, 538000, 180000, 604000...
$ sqft_living <int> 1180, 2570, 770, 1960, 1680, 5420...
$ condition   <fct> 3, 3, 3, 5, 3, 3, 3, 3, 3, 3, 3...
```

Refresher: Price and size variables



Refresher: log10 transformation



Refresher: Data transformation

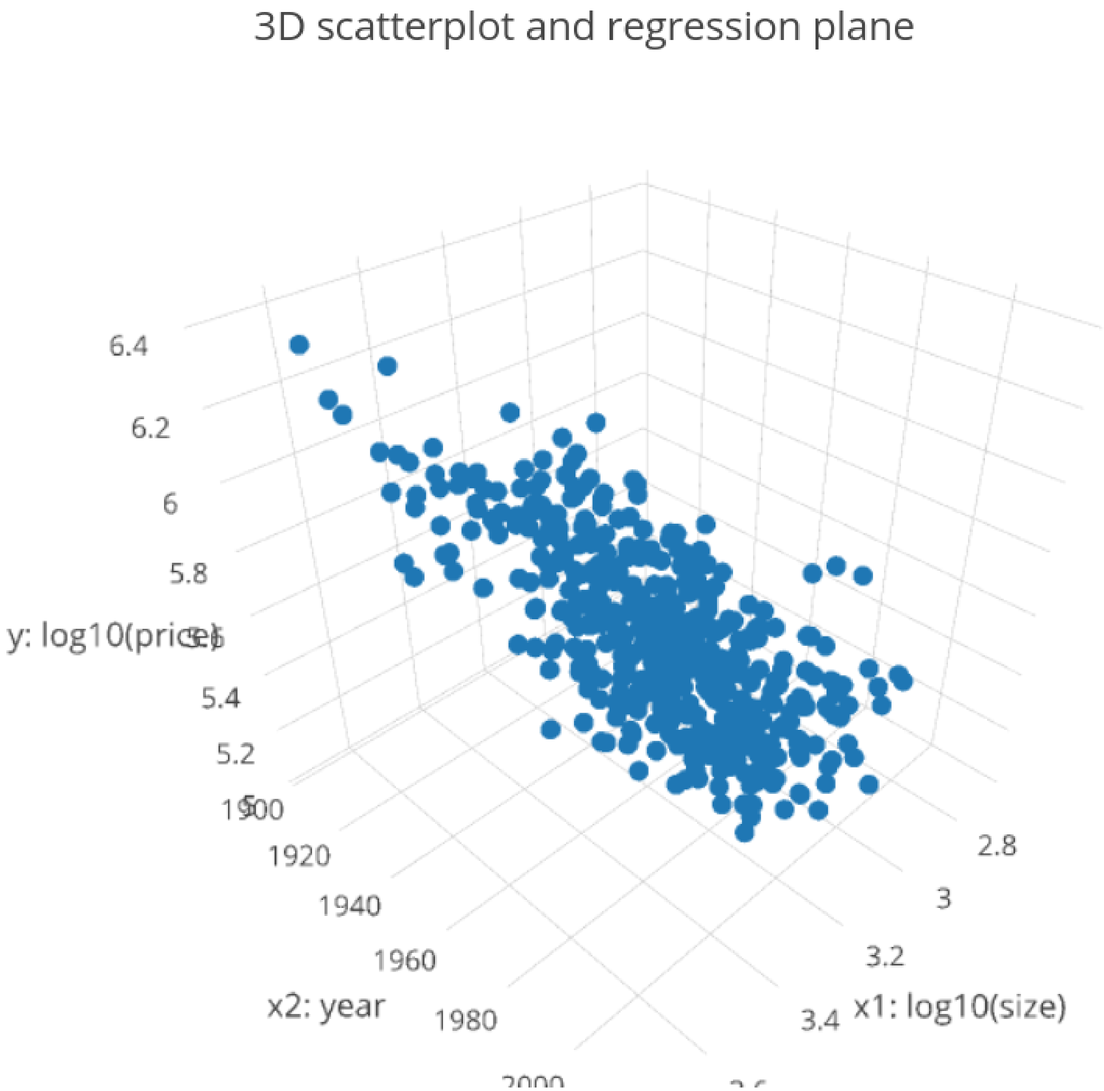
```
# log10() transform price and size
house_prices <- house_prices %>%
  mutate(
    log10_price = log10(price),
    log10_size = log10(sqft_living)
  )
```

Model for house price

- Outcome variable y - house price (USD): `price`
- Two numerical explanatory/predictor variables:
  - x_1 - house size: `log10_size`
  - x_2 - year built: `yr_built`

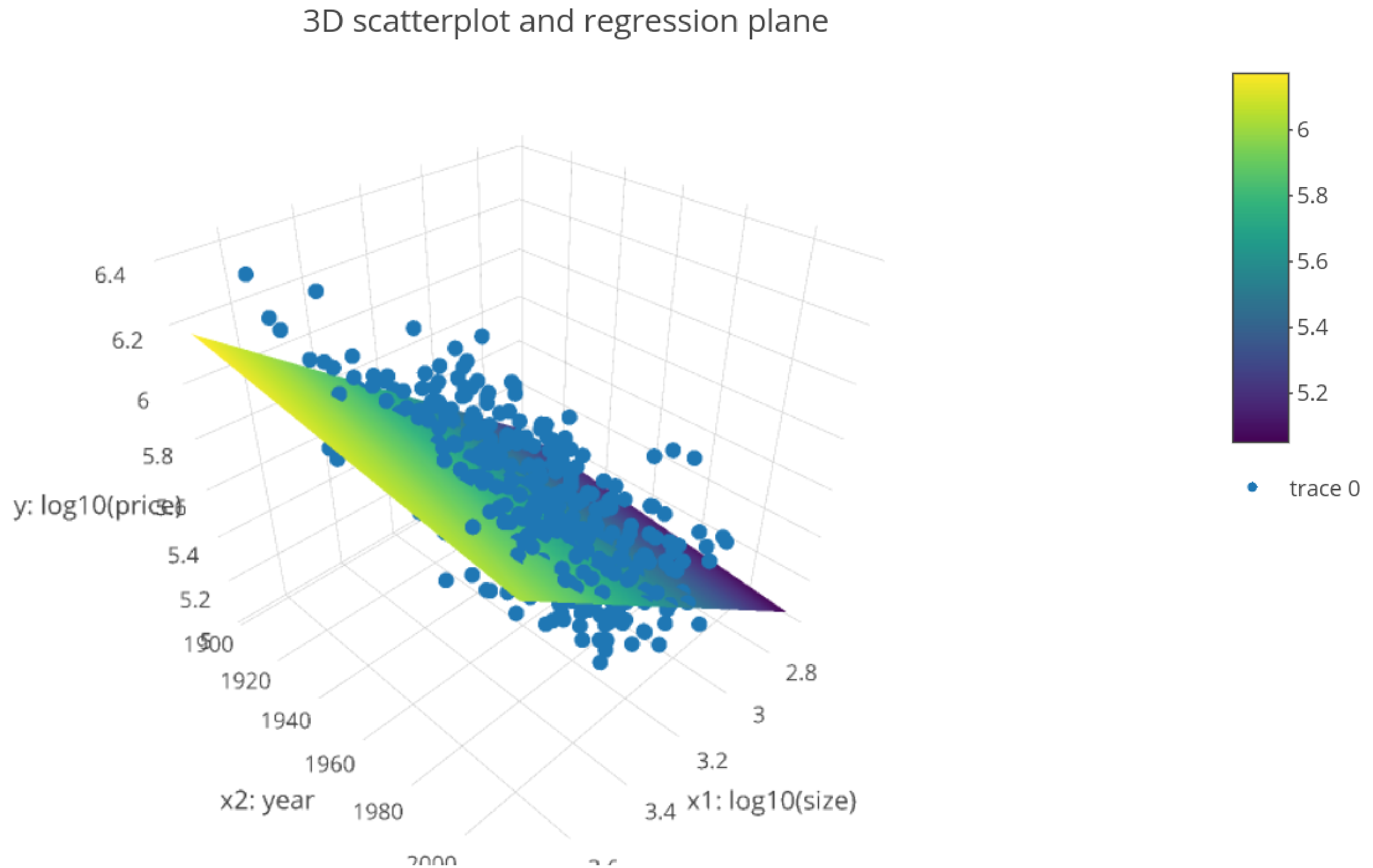
Exploratory visualizing of house price, size & year

3D scatterplot of `log10_price`, `log10_size`, and `yr_built`



Regression plane

3D scatterplot with regression plane (link to **interactive version**).



Regression table

```r
# Fit regression model using formula of form: y ~ x1 + x2
model_price_1 <- lm(log10_price ~ log10_size + yr_built,
                    data = house_prices)
# Output regression table
get_regression_table(model_price_1)
```

```
# A tibble: 3 x 7
  term       estimate std_error statistic p_value...
  <chr>         <dbl>     <dbl>     <dbl>   <dbl>...
1 intercept   5.38      0.0754      71.4        0...
2 log10_size  0.913     0.00647     141.        0...
3 yr_built   -0.00138   0.00004     -33.8       0...
```

Let's practice!

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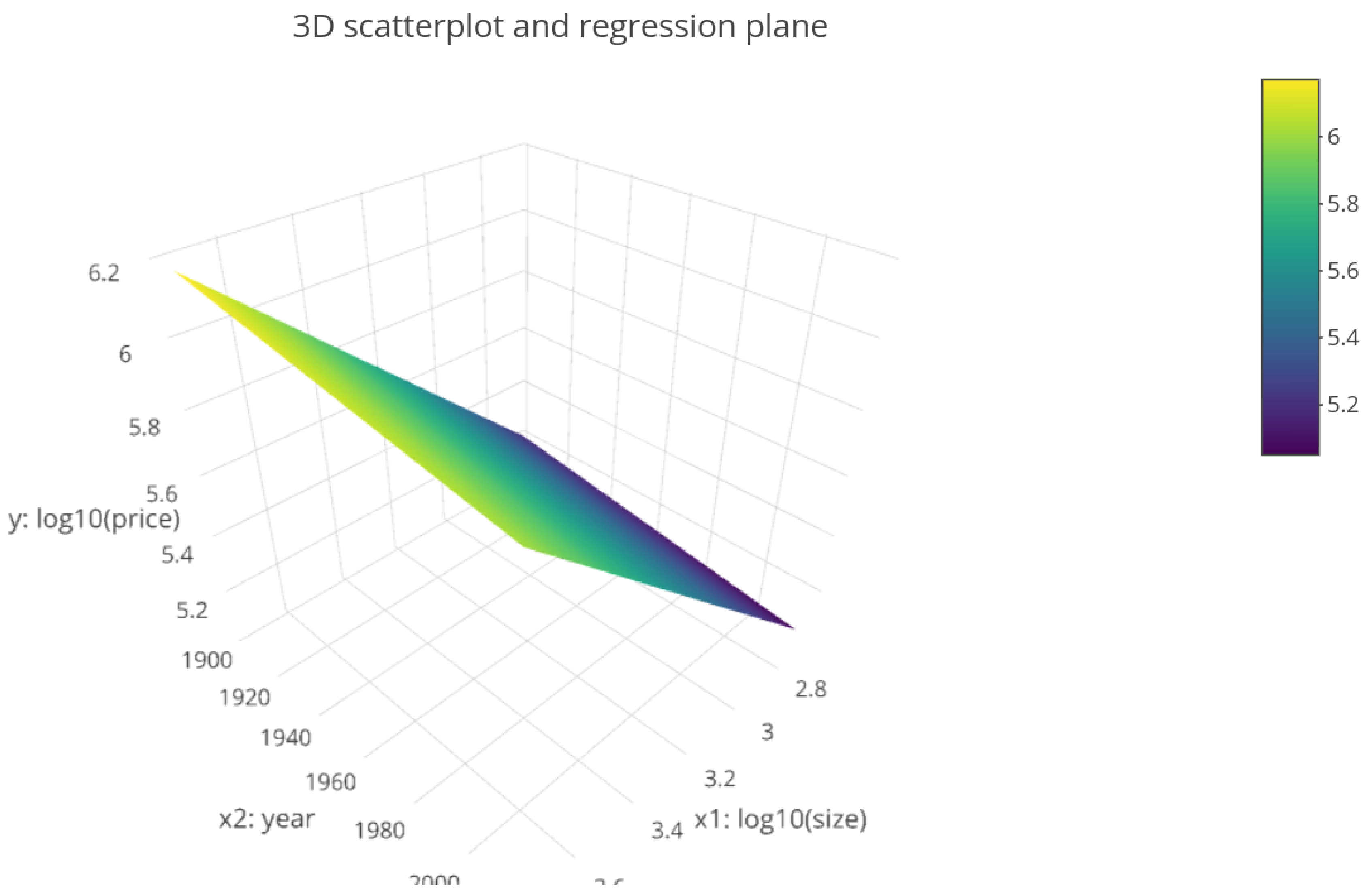
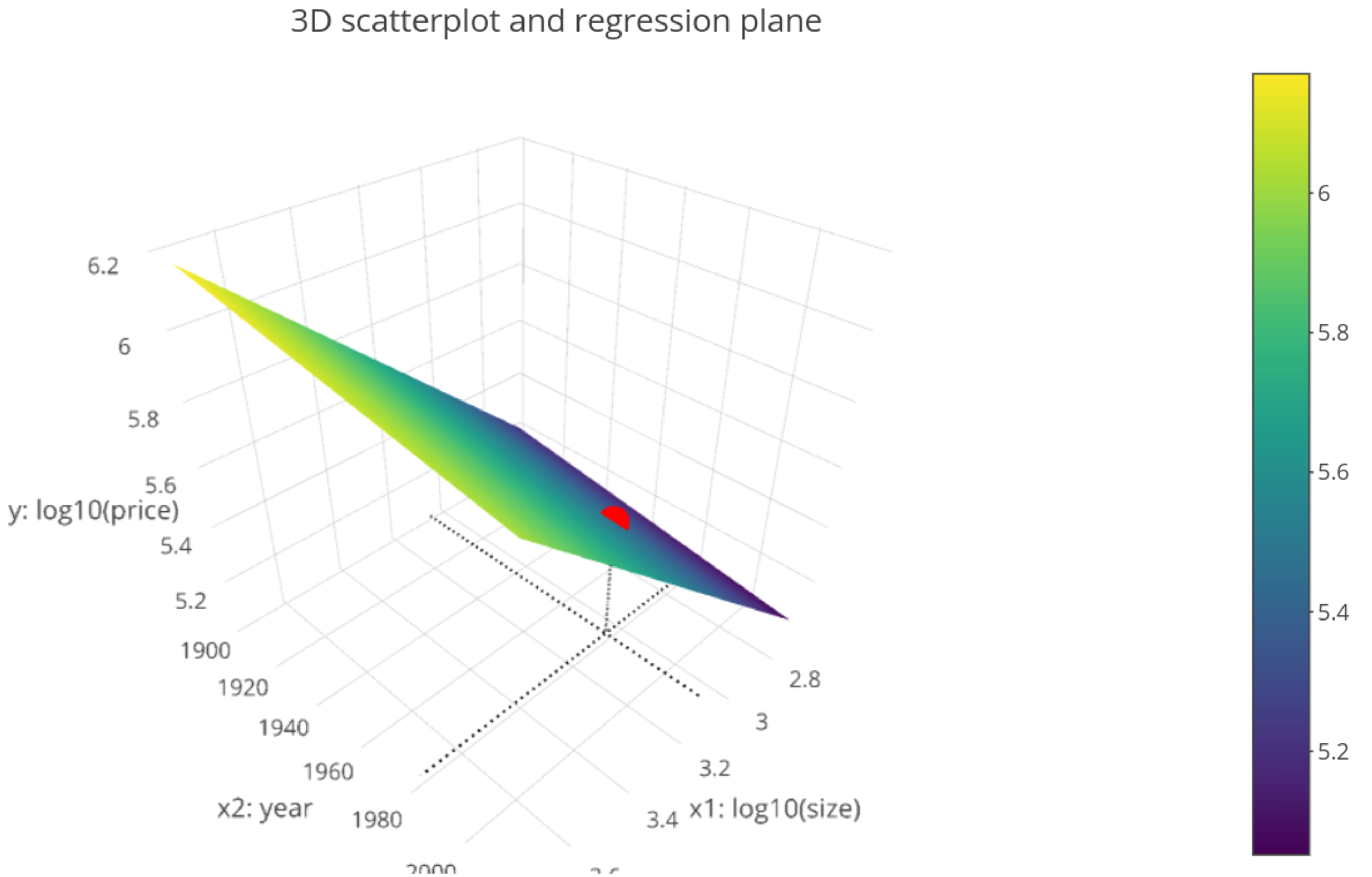
Refresher: regression plane



Regression plane for prediction



Predicted value

```
# Fit regression model using formula of form: y ~ x1 + x2
model_price_1 <- lm(log10_price ~ log10_size + yr_built,
                    data = house_prices)
# Output regression table
get_regression_table(model_price_1)
```

```
# A tibble: 3 x 7
  term       estimate std_error statistic p_value lower_ci...
  <chr>         <dbl>     <dbl>     <dbl>   <dbl>    <dbl>...
1 intercept   5.38      0.0754        71.4       0  5.24...
2 log10_size  0.913     0.00647     141.         0  0.901...
3 yr_built   -0.00138   0.00004     -33.8        0 -0.00146...
```

Predicted value

```
# Make prediction
5.38 + 0.913 * 3.07 - 0.00138 * 1980
```

```
5.45051
```

```
# Convert back to original untransformed units
10^(5.45051)
```

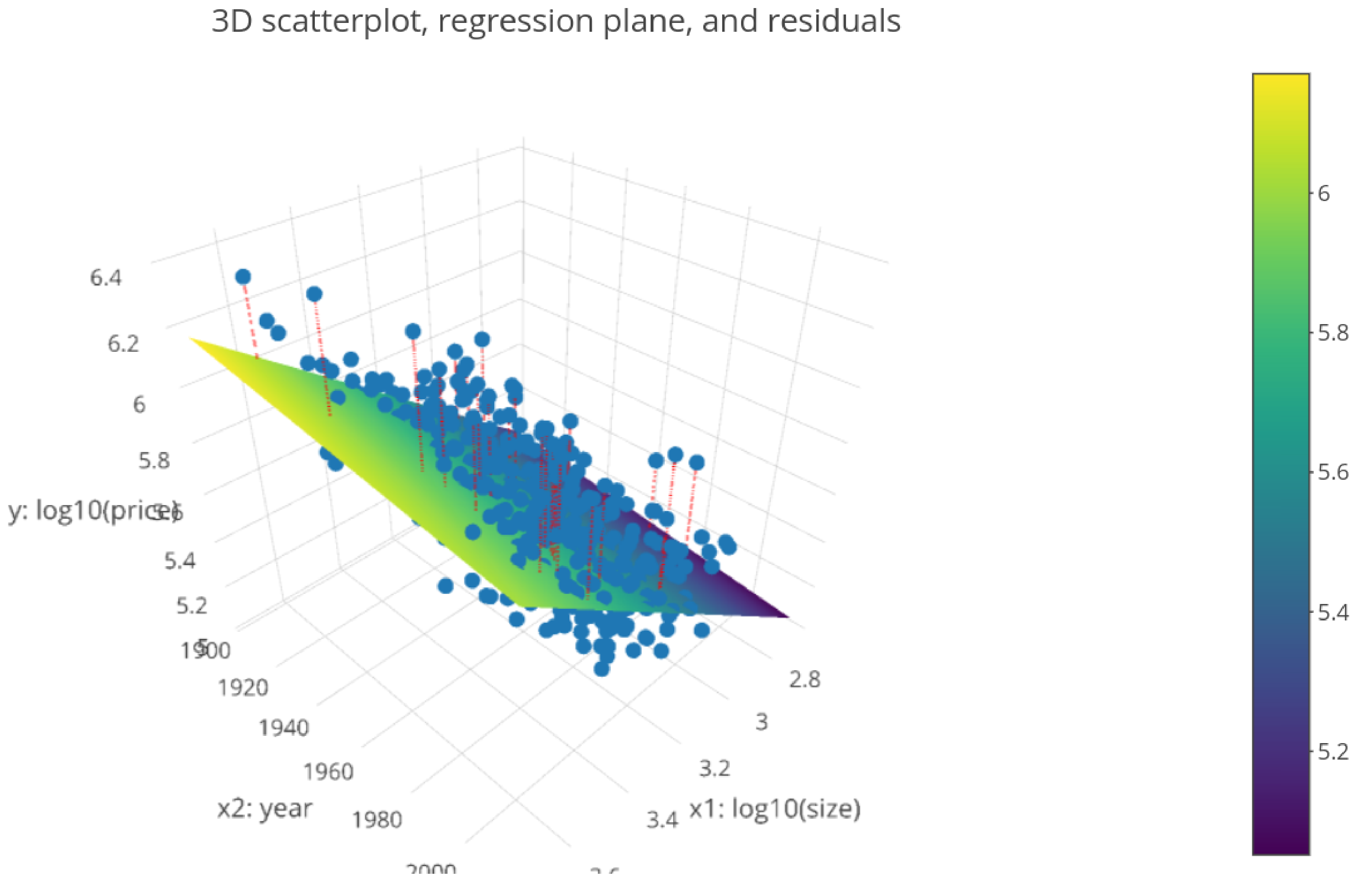
```
282169.5
```

Computing all predicted values and residuals

```r
# Output point-by-point information
get_regression_points(model_price_1)
```

```
# A tibble: 21,613 x 6
      ID log10_price log10_size yr_built log10_price_hat
   <int>       <dbl>      <dbl>    <dbl>           <dbl>
 1     1        5.35       3.07     1955            5.50
 2     2        5.73       3.41     1951            5.81
 3     3        5.26       2.89     1933            5.36
 4     4        5.78       3.29     1965            5.69
 5     5        5.71       3.22     1987            5.60
 6     6        6.09       3.73     2001            6.04
 7     7        5.41       3.23     1995            5.59
...
```

Best fit and residuals



Sum of squared residuals

```
# A tibble: 21,613 x 6
      ID log10_price log10_size yr_built log10_price_hat
   <int>       <dbl>      <dbl>    <dbl>           <dbl>
 1     1        5.35       3.07     1955            5.50
 2     2        5.73       3.41     1951            5.81
...
```

```
# Square all residuals and sum them
get_regression_points(model_price_1) %>%
  mutate(sq_residuals = residual^2) %>%
  summarize(sum_sq_residuals = sum(sq_residuals))
```

```
# A tibble: 1 x 1
  sum_sq_residuals
             <dbl>
1             585.
```

Let's practice!

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Explaining house price with size & condition

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Data Sciences

Refresher: Exploratory data analysis

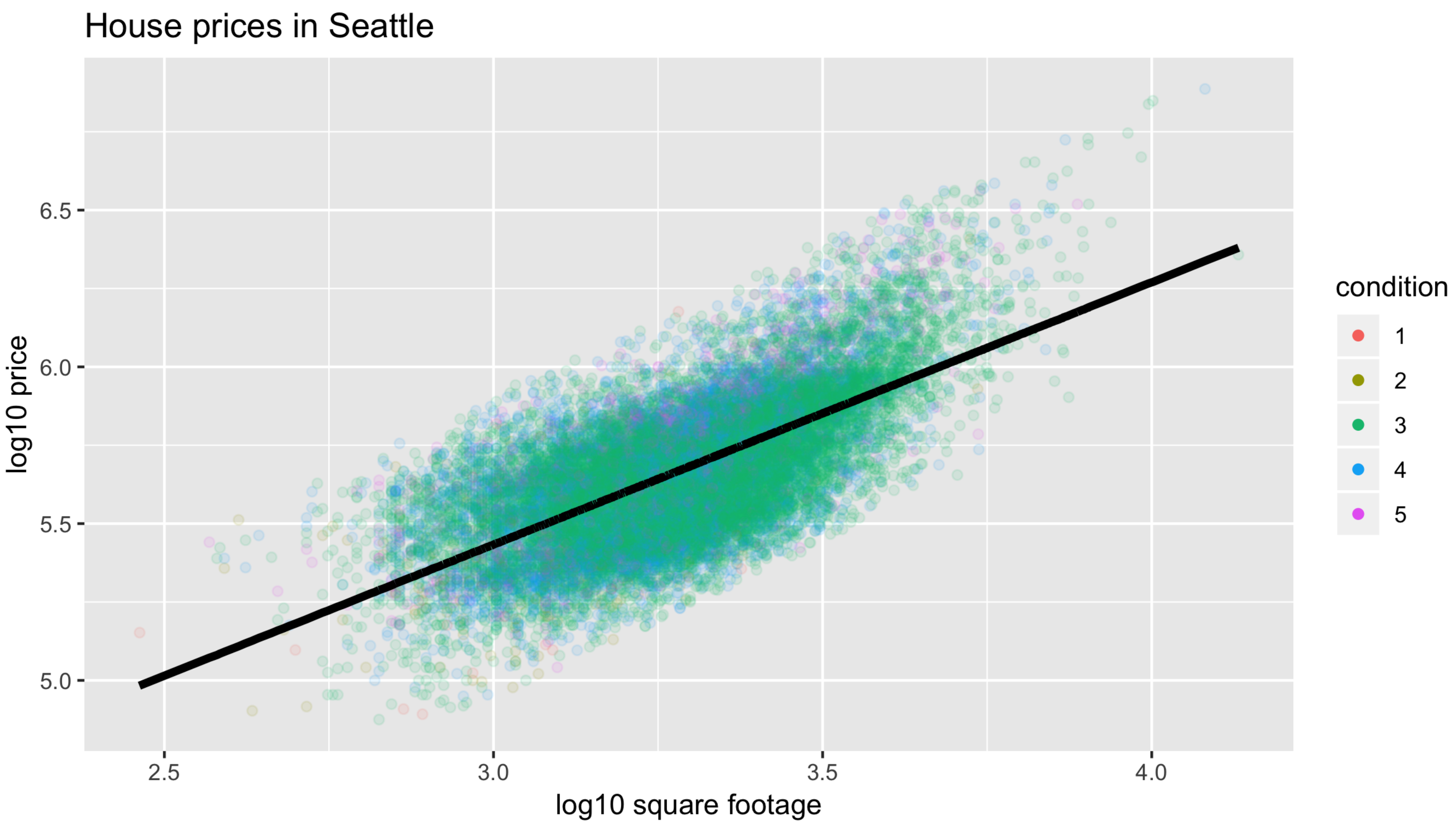
```
library(dplyr)
library(moderndive)

# log transform variables
house_prices <- house_prices %>%
  mutate(
    log10_price = log10(price),
    log10_size = log10(sqft_living)
  )
```

Refresher: Exploratory data analysis

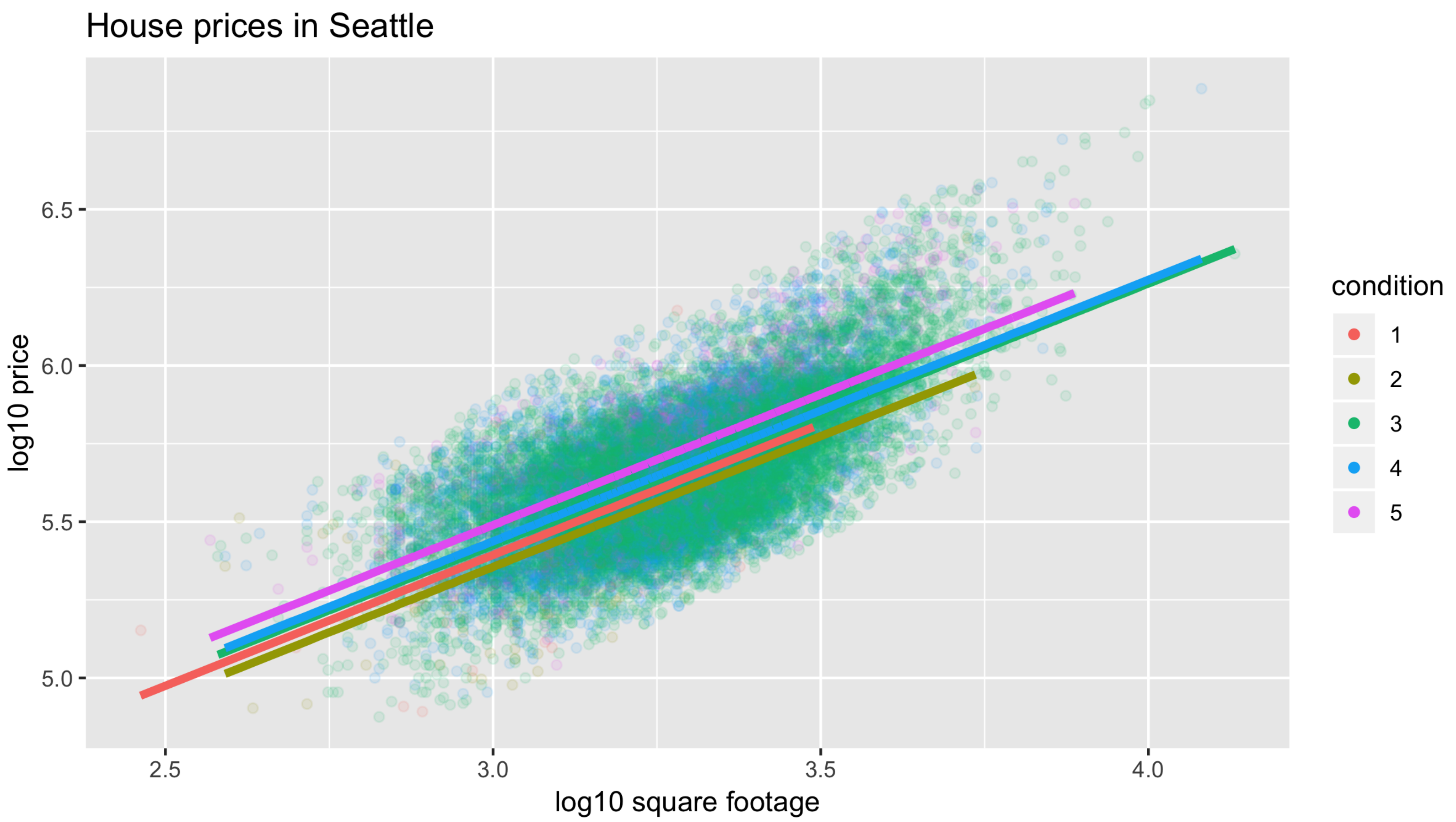
```
# Group mean & sd of log10_price and counts
house_prices %>%
  group_by(condition) %>%
  summarize(mean = mean(log10_price),
            sd = sd(log10_price), n = n())
```

```
# A tibble: 5 x 4
  condition  mean    sd     n
  <fct>     <dbl> <dbl> <int>
1 1          5.42 0.293    30
2 2          5.45 0.233   172
3 3          5.67 0.224 14031
...
```

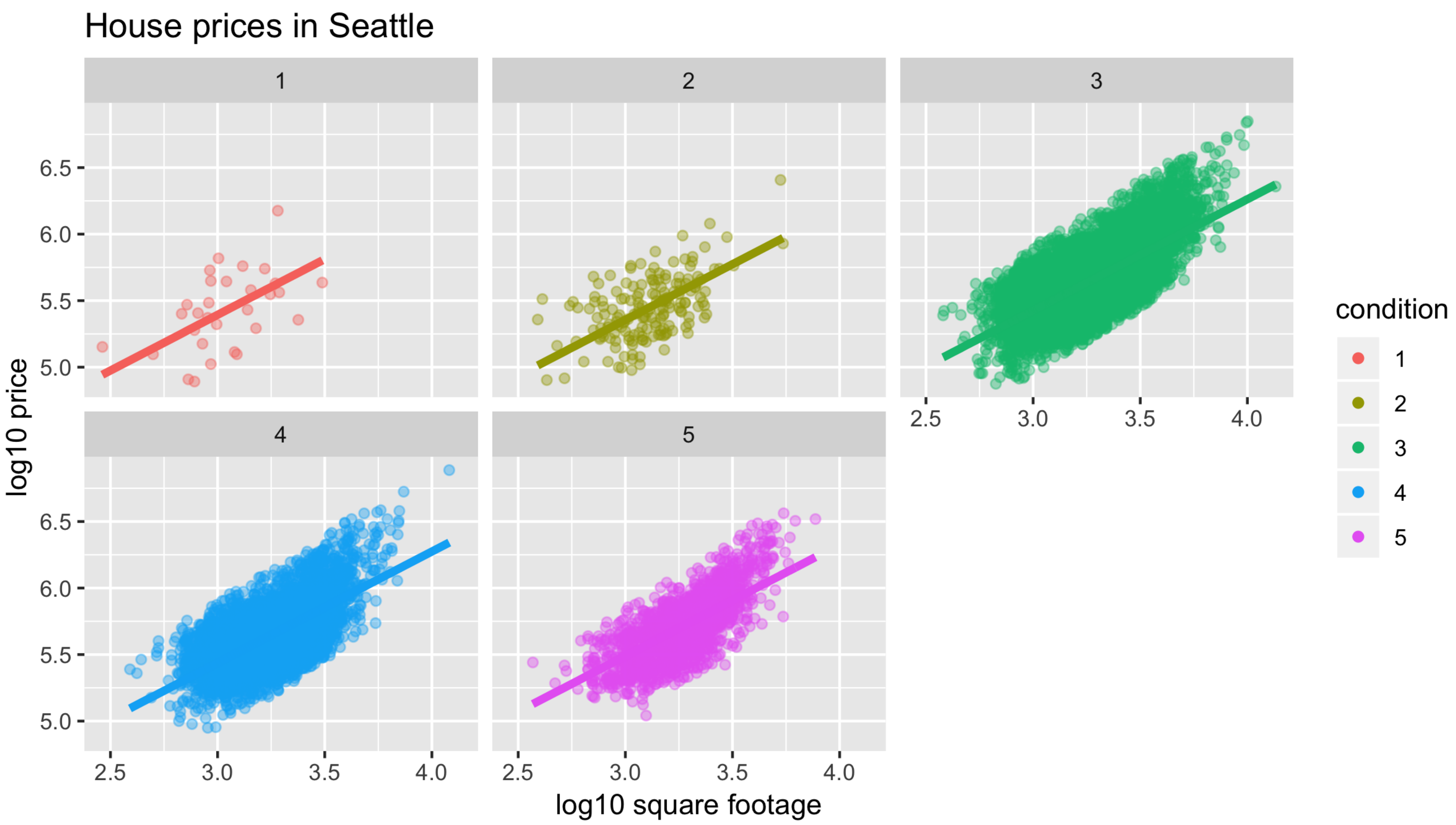
House price, size, and condition



Parallel slopes model



Parallel slopes model



House price, size, and condition relationship

```
# Fit regression model using formula of form: y ~ x1 + x2
model_price_3 <- lm(log10_price ~ log10_size + condition,
                    data = house_prices)


# Output regression table
get_regression_table(model_price_3)
```

```
# A tibble: 6 x 7
  term       estimate std_error statistic p_value lower_ci...
  <chr>         <dbl>     <dbl>     <dbl>   <dbl>    <dbl>...
1 intercept     2.88      0.036     80.0    0        2.81...
2 log10_size    0.837     0.006    134.     0        0.825...
3 condition2   -0.039     0.033     -1.16   0.246   -0.104...
4 condition3    0.032     0.031      1.04   0.3     -0.028...
...
```

Let's practice!

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Predicting house price using size & condition

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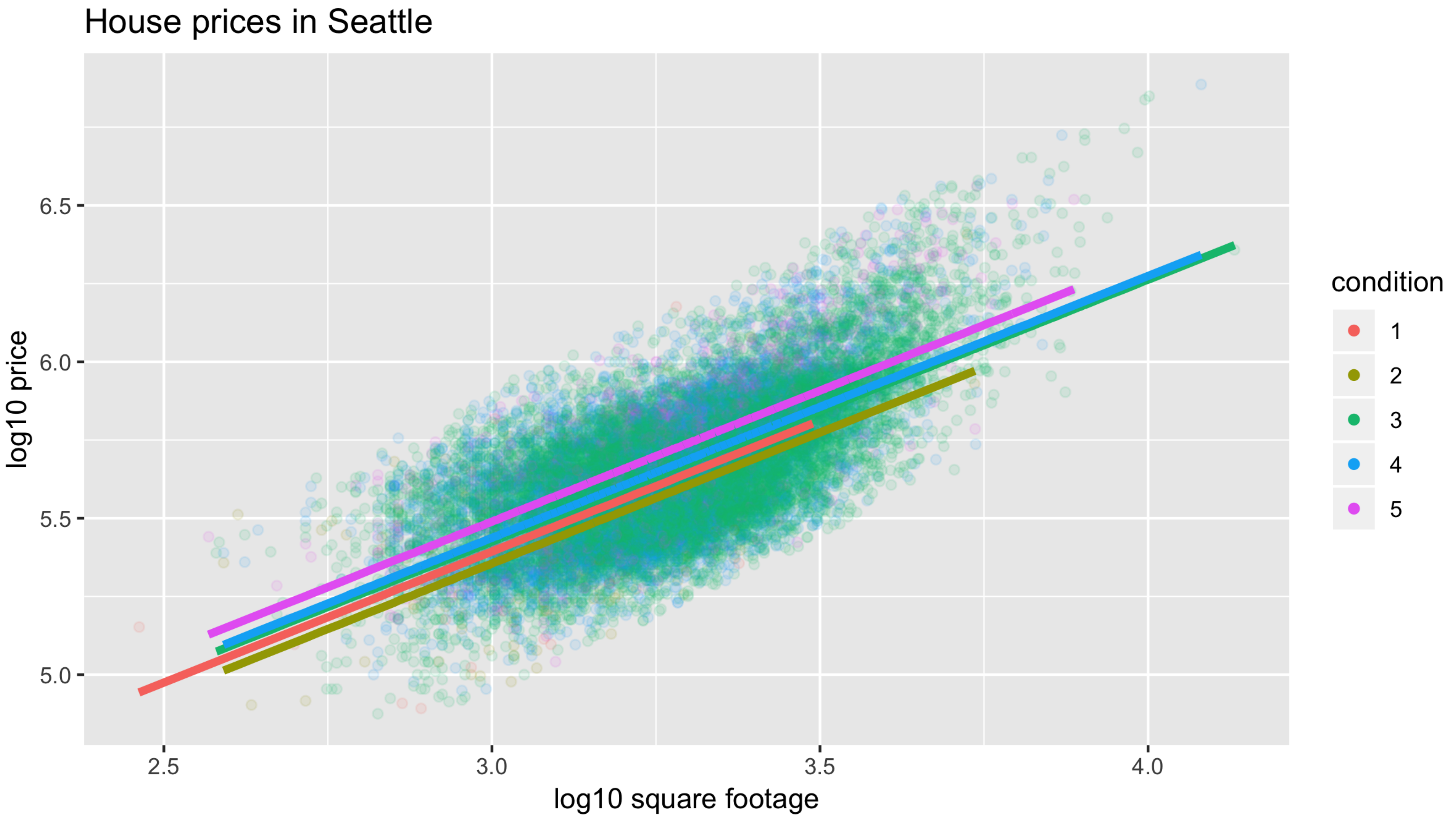
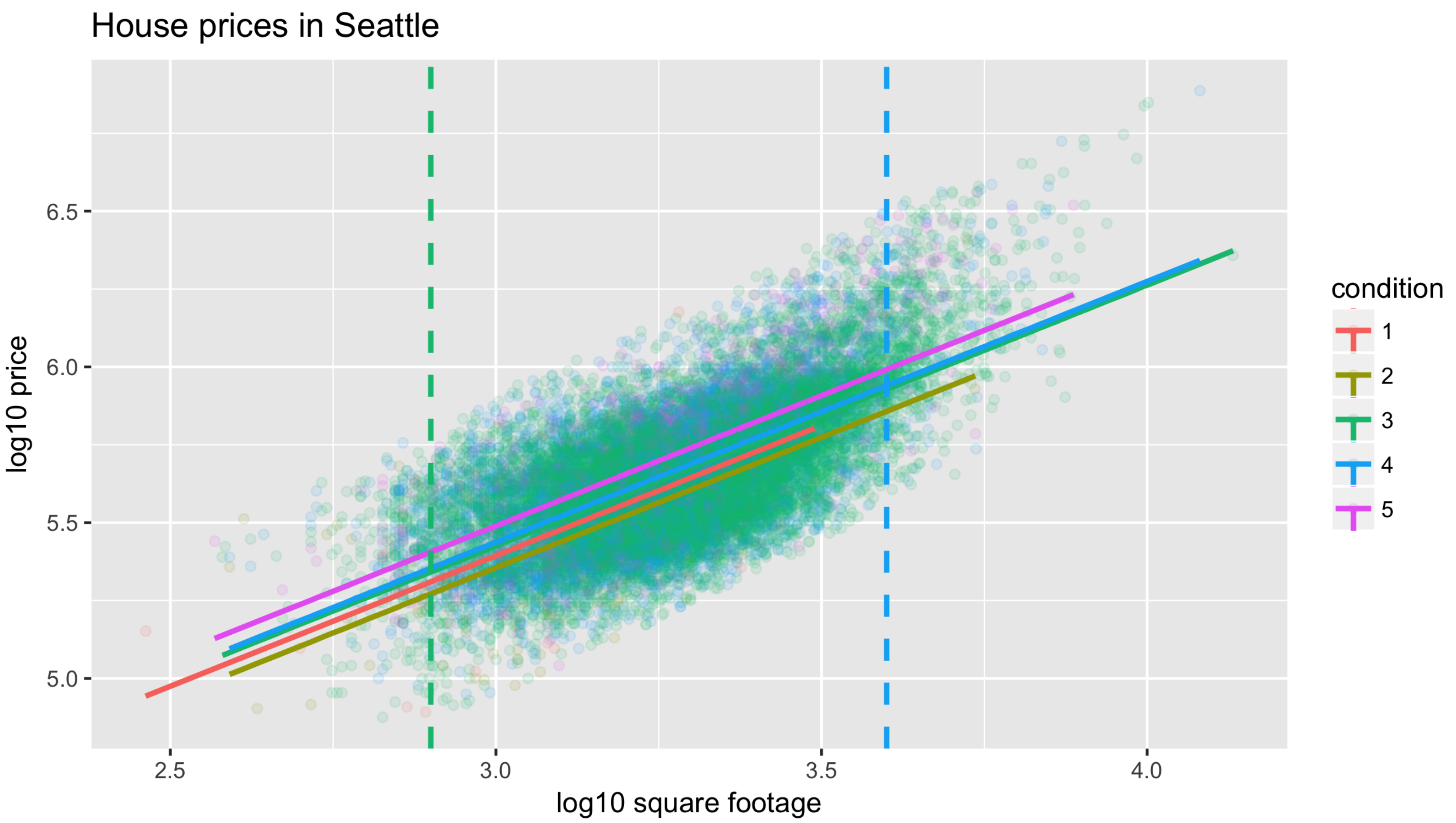
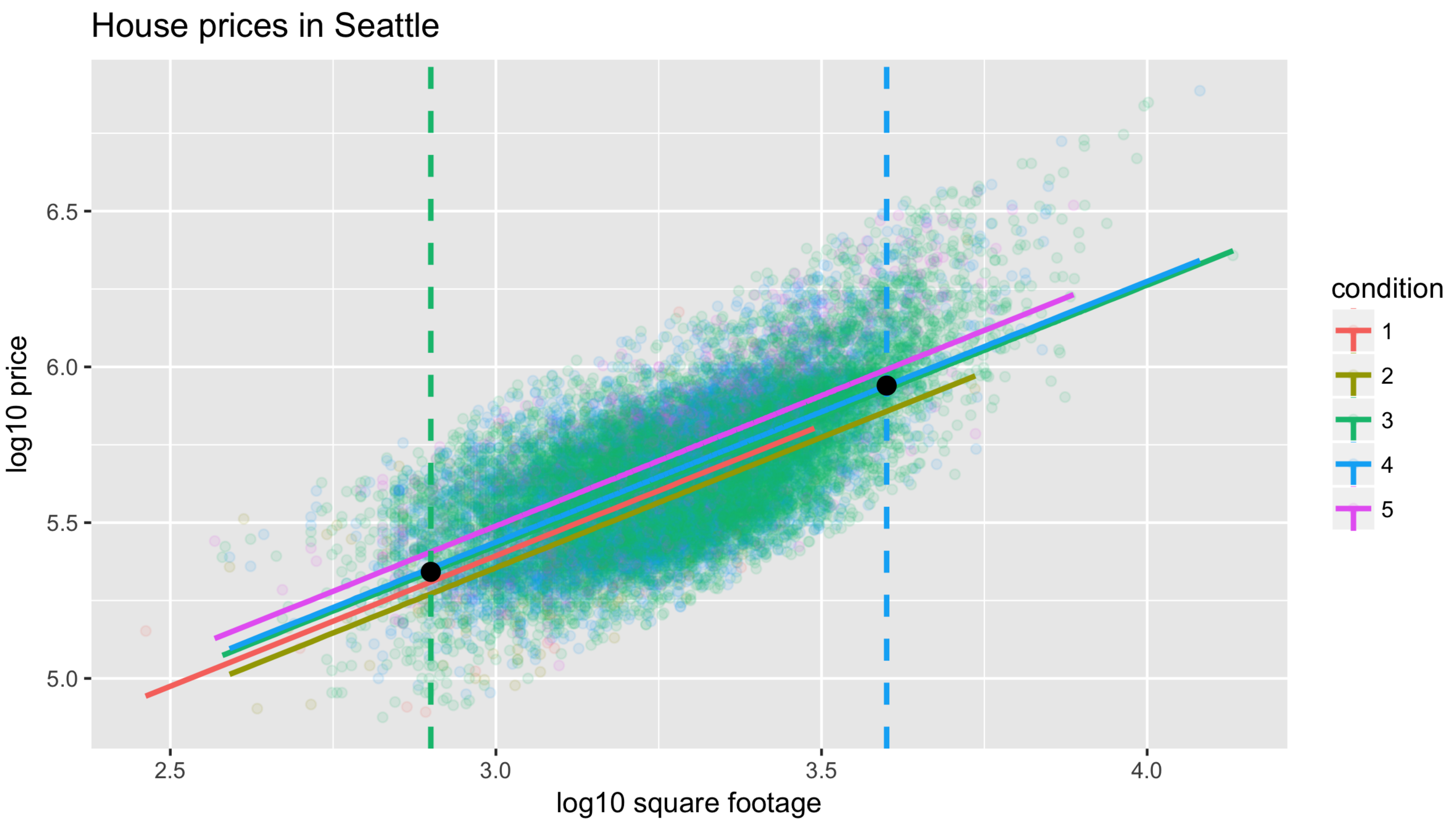
Refresher: Parallel slopes



Making a prediction



Visualizing predictions



Numerical predictions

Using values in `estimate` in regression table below:

- First house: $\hat{y} = 2.88 + 0.032 + 0.837 \cdot 2.90 = 5.34$
- Second house: $\hat{y} = 2.88 + 0.044 + 0.837 \cdot 3.60 = 5.94$

```
# Fit regression model and get regression table
model_price_3 <- lm(log10_price ~ log10_size + condition,
                    data = house_prices)
get_regression_table(model_price_3)
```

```
# A tibble: 6 x 7
  term        estimate std_error statistic p_value lower_ci...
  <chr>          <dbl>     <dbl>     <dbl>   <dbl>    <dbl>...
1 intercept      2.88      0.036      80.0   0        2.81...
2 log10_size     0.837     0.006     134.    0        0.825...
...
```

Defining "new" data

```
# Create data frame of "new" houses
new_houses <- data_frame(
  log10_size = c(2.9, 3.6),
  condition = factor(c(3, 4))
)
new_houses
```

```
# A tibble: 2 x 2
  log10_size condition
       <dbl> <fct>
1        2.9 3
2        3.6 4
```

Making predictions using new data

```
# Make predictions on new data
get_regression_points(model_price_3,
                      newdata = new_houses)
```

```
# A tibble: 2 x 4
     ID log10_size condition log10_price_hat
  <int>      <dbl> <fct>               <dbl>
1     1        2.9 3                    5.34
2     2        3.6 4                    5.94
```

Making predictions using new data

```
# Make predictions in original units by undoing log10()
get_regression_points(model_price_3,
                      newdata = new_houses) %>%
  mutate(price_hat = 10^log10_price_hat)
```

```
# A tibble: 2 x 5
     ID log10_size condition log10_price_hat price_hat
  <int>      <dbl> <fct>               <dbl>     <dbl>
1     1        2.9 3                    5.34   219786.
2     2        3.6 4                    5.94   870964.
```

Let's practice!

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