Chapter 8: heteroskedasticity

We start again by loading the data and filtering it so that we restrict it to properties that host at most 6 people. Also, as in Chapter 3, we again create a variable review_scores_rating_standardized with the standardized review score.

Our point of departure for Chapter 8 is, as for Chapter 4, the richer model from Chapter 3 where we regress the log price on review_scores_rating, accommodates, and 4 neighborhood characteristics.

```
estimatesFullModel \leftarrow lm(log(price) \sim review_scores_rating_standardized + accommodates + Centrality + Quantum summary(estimatesFullModel)
```

```
##
## Call:
## lm(formula = log(price) ~ review_scores_rating_standardized +
##
      accommodates + Centrality + Quietness + Coolness + Fanciness,
##
      data = listings_clean_filtered)
##
## Residuals:
       Min
##
                 10
                     Median
                                   30
## -1.48845 -0.24997 0.01026 0.23530 0.94151
##
## Coefficients:
##
                                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                                                0.49275 6.292
                                     3.10015
                                                                   8e-10 ***
## review_scores_rating_standardized 0.05000
                                                0.01887
                                                          2.650 0.00837 **
## accommodates
                                                0.01480 14.625 < 2e-16 ***
                                     0.21641
## Centrality
                                     0.08591
                                                0.04406
                                                         1.950 0.05186 .
## Quietness
                                     0.12896
                                                0.04451
                                                          2.897 0.00397 **
## Coolness
                                                0.07834
                                                         1.226 0.22079
                                     0.09606
## Fanciness
                                    -0.14765
                                                0.05382 -2.744 0.00634 **
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.3834 on 414 degrees of freedom
## Multiple R-squared: 0.3494, Adjusted R-squared:
## F-statistic: 37.05 on 6 and 414 DF, p-value: < 2.2e-16
```

The reported point estimates are unbiased (Chapter 3)/consistent (Chapter 5) under MLR1-MLR4. The standard errors are valid when we make the additional assumption of homoskedasticity.

Next, we test the null of homoskedasticity.

```
bptest(estimatesFullModel)
##
   studentized Breusch-Pagan test
##
## data: estimatesFullModel
## BP = 19.232, df = 6, p-value = 0.00379
The null of homoskedasticity is rejected.
Next, we do weighted least squares.
# Obtain residuals
residuals_full_model <- residuals(estimatesFullModel)</pre>
# Step 2: Regress squared residuals on predictors to model heteroskedasticity
squared_residuals <- residuals_full_model^2</pre>
model_resid_squared <- lm(squared_residuals ~ review_scores_rating_standardized + accommodates + Centra
# Obtain fitted values from this regression
fitted_values <- fitted(model_resid_squared)</pre>
# Step 3: Calculate weights as inverse of the square root of fitted values
weights <- 1 / sqrt(fitted_values)</pre>
## Warning in sqrt(fitted_values): NaNs produced
# Step 4: Run the WLS regression with these weights
wls_model <- lm(log(price) ~ review_scores_rating_standardized + accommodates + Centrality + Quietness
                data = listings_clean_filtered, weights = weights)
# Summary of the WLS model
summary(wls_model)
##
## Call:
## lm(formula = log(price) ~ review_scores_rating_standardized +
       accommodates + Centrality + Quietness + Coolness + Fanciness,
##
##
       data = listings_clean_filtered, weights = weights)
##
## Weighted Residuals:
                      Median
                                     3Q
##
        Min
                  1Q
                                             Max
## -2.84538 -0.41093 0.01522 0.37911 1.47203
##
## Coefficients:
##
                                      Estimate Std. Error t value Pr(>|t|)
                                                  0.46508
                                                          7.030 8.64e-12 ***
## (Intercept)
                                       3.26967
## review_scores_rating_standardized 0.05635
                                                  0.01872
                                                           3.011 0.002766 **
                                                  0.01377 14.919 < 2e-16 ***
## accommodates
                                       0.20550
## Centrality
                                       0.10411
                                                  0.03976 2.618 0.009164 **
## Quietness
                                                  0.04266 2.959 0.003266 **
                                       0.12621
## Coolness
                                       0.07941
                                                  0.07390 1.075 0.283179
## Fanciness
                                      -0.17061
                                                  0.04430 -3.851 0.000136 ***
```

```
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6209 on 411 degrees of freedom
## (3 observations deleted due to missingness)
## Multiple R-squared: 0.3722, Adjusted R-squared: 0.363
## F-statistic: 40.61 on 6 and 411 DF, p-value: < 2.2e-16</pre>
```

Observe the error message. It appears because some fitted values are negative. This can in principle happen, as we use a linear regression. Therefore, we "lose" some observations. In practice, one would fine-tune things now to avoid this. One can do that by using a more flexible specification for the explanatory variables, with interactions, square terms, and so on.

We won't do that now, for the time being.

##

Finally, we use the stargazer package to show OLS results side-by-side OLS results with robust standard errors and weighted least squares results without and with robust standard errors. For the WLS estimates, in theory, one does not need them if one gets the weighting function right.

## ##	Dependent variable:							
##	Dependent variable:							
##		log(price)						
##		OLS	OLS (Robust SE)	WLS	WLS (Robust SE)			
##		(1)	(2)	(3)	(4)			
##			0.050		0.050			
##	${\tt review_scores_rating_standardized}$							
##		(0.019)	(0.019)	(0.019)	(0.018)			
##								
##	accommodates	0.216***	0.216***	0.206***	0.206***			
##		(0.015)	(0.015)	(0.014)	(0.015)			
##								
##	Centrality	0.086*	0.086**	0.104***	0.104***			
##		(0.044)	(0.040)	(0.040)	(0.034)			
##								
##	Quietness	0.129***	0.129***	0.126***	0.126***			
##		(0.045)	(0.048)	(0.043)	(0.045)			
##								
##	Coolness	0.096	0.096	0.079	0.079			
##		(0.078)	(0.073)	(0.074)	(0.071)			
##								
##	Fanciness	-0.148***	-0.148***	-0.171***	-0.171***			
##		(0.054)	(0.054)	(0.044)	(0.045)			
##								

## Co	nstant	3.100***	3.100***	3.270***	3.270***		
##		(0.493)	(0.476)	(0.465)	(0.449)		
##							
##							
## Ob	servations	421	421	418	418		
## R2	2	0.349	0.349	0.372	0.372		
## ==			.=======	========			
## No	ote:			*p<0.1; **p<0.05; ***p<0.01			

This shows that standard errors are almost unchanged. If anything, they get smaller. This can in principle happen, as it does here. More often, they get bigger.