HW2

Group 11

2024-03-31

QUESTION 1

Regress log price onto all variables but mortgage.

What is the R2? How many coefficients are used in this model and how many are significant at 10% FDR?

Re-run regression with only the significant covariates, and compare R2 to the full model. (2 points)

From the following regression output, this regression has 41 coefficients in total, excluding the intercept. Its R^2 is 1-7186.9/13003.4 = 0.4473061, indicating that about 44.73% of the variability in the logarithm of the price is explain by the model. Out of the 43 coefficients, 36 are significant under a False Discovery Rate (FDR) of 10%.

```
## Q1

## Read in the data
homes <- read.csv("homes2004.csv")

# regress log(PRICE) on everything except AMMORT
pricey <- glm(log(LPRICE) ~ .-AMMORT, data=homes)
summary(pricey)
```

```
##
## Call:
## glm(formula = log(LPRICE) ~ . - AMMORT, data = homes)
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)    1.108e+01  5.202e-02 213.063  < 2e-16 ***
## EAPTBLY       -5.068e-02  1.954e-02  -2.594 0.009497 **
## ECOM1Y        -3.875e-02  1.603e-02  -2.418 0.015634 *
## ECOM2Y        -1.617e-01  4.002e-02  -4.041 5.35e-05 ***
## EGREENY        4.495e-02  1.167e-02   3.853 0.000117 ***
## EJUNKY        -2.107e-01  4.251e-02  -4.956 7.27e-07 ***
## ELOW1Y         5.584e-02  1.926e-02   2.900 0.003736 **
## ESFDY          7.676e-02  2.463e-02   3.117 0.001832 **
## ETRANSY       -6.172e-03  2.109e-02  -0.293 0.769743
## EABANY        -1.599e-01  2.997e-02  -5.337 9.60e-08 ***
## HOWHgood       6.894e-02  2.192e-02   3.145 0.001664 **
## HOWNgood       9.863e-02  1.827e-02   5.400 6.76e-08 ***
## ODORAY        -8.105e-02  2.758e-02  -2.938 0.003306 **
```

```
## STRNAY           -8.550e-02  1.338e-02  -6.389 1.71e-10 ***
## ZINC2             3.962e-07  4.730e-08   8.377  < 2e-16 ***
## PER               7.186e-02  5.208e-03  13.799  < 2e-16 ***
## ZADULT           -1.051e-01  9.060e-03 -11.605  < 2e-16 ***
## HHGRADBach        1.352e-01  1.912e-02   7.072 1.59e-12 ***
## HHGRADGrad        1.561e-01  2.160e-02   7.230 5.06e-13 ***
## HHGRADHS Grad    -7.271e-02  1.808e-02  -4.022 5.79e-05 ***
## HHGRADNo HS      -3.125e-01  2.651e-02 -11.788  < 2e-16 ***
## NUNITS            7.306e-04  4.333e-04   1.686 0.091767 .
## INTW             -7.311e-02  3.681e-03 -19.861  < 2e-16 ***
## METROurban       -3.385e-02  1.511e-02  -2.241 0.025044 *
## STATECO          -4.380e-03  2.460e-02  -0.178 0.858706
## STATECT           8.528e-03  2.629e-02   0.324 0.745628
## STATEGA          -1.030e-01  2.679e-02  -3.844 0.000121 ***
## STATEIL          -3.760e-01  4.868e-02  -7.724 1.20e-14 ***
## STATEIN          -1.668e-01  2.672e-02  -6.243 4.41e-10 ***
## STATELA          -2.491e-01  3.154e-02  -7.899 2.99e-15 ***
## STATEMO          -1.616e-01  2.864e-02  -5.640 1.73e-08 ***
## STATEOH          -1.016e-01  2.800e-02  -3.628 0.000287 ***
## STATEOK          -3.193e-01  2.877e-02 -11.097  < 2e-16 ***
## STATEPA          -4.375e-01  2.920e-02 -14.985  < 2e-16 ***
## STATETX          -3.139e-01  3.010e-02 -10.428  < 2e-16 ***
## STATEWA           1.277e-01  2.580e-02   4.952 7.42e-07 ***
## BATHS             2.027e-01  1.004e-02  20.195  < 2e-16 ***
## BEDRMS            2.878e-03  8.424e-03   0.342 0.732630
## MATBUYY           3.072e-01  1.139e-02  26.969  < 2e-16 ***
## DWNPAYprev home   1.302e-01  1.489e-02   8.745  < 2e-16 ***
## VALUE             1.257e-06  4.078e-08  30.810  < 2e-16 ***
## FRSTHOY          -1.288e-01  1.438e-02  -8.959  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.4629866)
##
##     Null deviance: 13003.4  on 15564  degrees of freedom
## Residual deviance:  7186.9  on 15523  degrees of freedom
## AIC: 32230
##
## Number of Fisher Scoring iterations: 2
1-7186.9/13003.4
```

```
## [1] 0.4473061
```

After removing the insignificant variables ("ETRANS", "NUNITS", "BEDRMS") and re-estimate the model, the R^2 is 1-7188.3/13003.4 = 0.4471984. There is only a very small decrease in R^2, suggesting that the removed variables contributed little to explaining the variability in log-price.

```r
# extract pvalues
pvals_pricey <- summary(pricey)$coef[-1,4]

# @ 10% FDR
source("fdr.R")
cutoff10 <- fdr_cut(pvals_pricey, q=0.1)
print(cutoff10) # 0.0379
```

2

```
## [1] 0.02504391
```

```r
print(sum(pvals_pricey<=cutoff10)) # 37
```

```
## [1] 36
```

```r
# example: those variable insignificant at cutoff10
names(pvals_pricey)[pvals_pricey > cutoff10]
```

```
## [1] "ETRANSY" "NUNITS"  "STATECO" "STATECT" "BEDRMS"
```

```r
# you can use the `-AMMORT' type syntax to drop variables
# re-estimate the model
pricey_drop <- glm(log(LPRICE) ~ . - AMMORT - ETRANS - NUNITS - BEDRMS, data=homes)
summary(pricey_drop)
```

```
##
## Call:
## glm(formula = log(LPRICE) ~ . - AMMORT - ETRANS - NUNITS - BEDRMS,
##     data = homes)
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      1.109e+01  5.055e-02 219.409  < 2e-16 ***
## EAPTBLY         -4.777e-02  1.937e-02  -2.466 0.013665 *
## ECOM1Y          -3.826e-02  1.591e-02  -2.405 0.016173 *
## ECOM2Y          -1.639e-01  3.964e-02  -4.134 3.58e-05 ***
## EGREENY          4.453e-02  1.165e-02   3.822 0.000133 ***
## EJUNKY          -2.111e-01  4.251e-02  -4.965 6.93e-07 ***
## ELOW1Y           5.449e-02  1.915e-02   2.845 0.004443 **
## ESFDY            7.585e-02  2.447e-02   3.100 0.001939 **
## EABANY          -1.610e-01  2.995e-02  -5.374 7.83e-08 ***
## HOWHgood         6.931e-02  2.190e-02   3.165 0.001555 **
## HOWNgood         9.897e-02  1.826e-02   5.421 6.00e-08 ***
## ODORAY          -8.154e-02  2.756e-02  -2.958 0.003097 **
## STRNAY          -8.565e-02  1.334e-02  -6.418 1.42e-10 ***
## ZINC2            3.966e-07  4.729e-08   8.387  < 2e-16 ***
## PER              7.209e-02  5.045e-03  14.290  < 2e-16 ***
## ZADULT          -1.052e-01  9.048e-03 -11.627  < 2e-16 ***
## HHGRADBach       1.360e-01  1.912e-02   7.116 1.16e-12 ***
## HHGRADGrad       1.569e-01  2.159e-02   7.268 3.81e-13 ***
## HHGRADHS Grad   -7.279e-02  1.807e-02  -4.027 5.66e-05 ***
## HHGRADNo HS     -3.128e-01  2.650e-02 -11.800  < 2e-16 ***
## INTW            -7.317e-02  3.680e-03 -19.882  < 2e-16 ***
## METROurban      -3.368e-02  1.510e-02  -2.231 0.025685 *
## STATECO         -3.646e-03  2.458e-02  -0.148 0.882075
## STATECT          9.387e-03  2.627e-02   0.357 0.720842
## STATEGA         -1.024e-01  2.673e-02  -3.832 0.000128 ***
## STATEIL         -3.760e-01  4.867e-02  -7.726 1.17e-14 ***
## STATEIN         -1.669e-01  2.669e-02  -6.255 4.08e-10 ***
## STATELA         -2.489e-01  3.152e-02  -7.896 3.06e-15 ***
## STATEMO         -1.612e-01  2.863e-02  -5.632 1.82e-08 ***
## STATEOH         -9.926e-02  2.784e-02  -3.565 0.000365 ***
## STATEOK         -3.192e-01  2.876e-02 -11.097  < 2e-16 ***
## STATEPA         -4.370e-01  2.915e-02 -14.993  < 2e-16 ***
## STATETX         -3.136e-01  3.008e-02 -10.426  < 2e-16 ***
```

```
## STATEWA           1.287e-01  2.579e-02   4.990 6.12e-07 ***
## BATHS             2.038e-01  9.370e-03  21.747  < 2e-16 ***
## MATBUYY           3.073e-01  1.138e-02  27.009  < 2e-16 ***
## DWNPAYprev home   1.306e-01  1.489e-02   8.772  < 2e-16 ***
## VALUE             1.257e-06  4.055e-08  31.009  < 2e-16 ***
## FRSTHOY          -1.291e-01  1.436e-02  -8.991  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.462986)
##
##     Null deviance: 13003.4  on 15564  degrees of freedom
## Residual deviance:  7188.3  on 15526  degrees of freedom
## AIC: 32227
##
## Number of Fisher Scoring iterations: 2
```

`1-7188.3/13003.4`

```
## [1] 0.4471984
```

QUESTION 2

Fit a regression for whether the buyer had more than 20 percent down (onto everything but AMMORT and LPRICE). Interpret effects for Pennsylvania state, 1st home buyers and the number of bathrooms.Add and describe an interaction between 1st home-buyers and the number of baths. (2 points)

In the logistic regression model predicting the likelihood of a buyer putting down more than 20% of the purchase price, significant predictors include the state of Pennsylvania ("STATEPA"), whether the buyer is purchasing their first home ("FRSTHOY"), and the number of bathrooms ("BATHS"). The positive coefficient for "STATEPA" (0.6011) indicates that, all else equal, buyers in Pennsylvania are about 1.824 times more likely to make a larger down payment compared to buyers in other states. This might reflect state-specific market conditions or policies that favor or require larger down payments.

Conversely, "FRSTHOY" has a negative coefficient (-0.37), suggesting first-time home buyers are less likely to make a down payment of over 20%, with the odds being about 30.3% lower than repeat buyers (odds multiplier is 0.697). This could be due to first-time buyers having less accumulated wealth or being more cautious with their initial home investment.

The negative coefficient for "BATHS" (-0.2445) implies that as the number of bathrooms increases, the likelihood of making a larger down payment decreases, with the odds being about 21.7% lower than repeat buyers (odds multiplier is 0.783), possibly reflecting higher overall property prices or buyer preferences for more modest homes when making larger down payments.

```
## Q2

# create a var for downpayment being greater than 20%
homes$gt20dwn <-
    factor(0.2<(homes$LPRICE-homes$AMMORT)/homes$LPRICE)

# regress gt20dwn on everything except AMMORT and LPRICE
gt20dwn_y <- glm(gt20dwn ~ .- AMMORT - LPRICE, data=homes, family='binomial')
summary(gt20dwn_y)

##
```

```
## Call:
## glm(formula = gt20dwn ~ . - AMMORT - LPRICE, family = "binomial",
##     data = homes)
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -1.293e+00  1.831e-01  -7.065 1.61e-12 ***
## EAPTBLY           1.505e-02  7.025e-02   0.214 0.830424
## ECOM1Y           -1.619e-01  5.809e-02  -2.787 0.005325 **
## ECOM2Y           -3.131e-01  1.600e-01  -1.957 0.050385 .
## EGREENY          -1.569e-03  3.984e-02  -0.039 0.968582
## EJUNKY           -9.697e-03  1.608e-01  -0.060 0.951913
## ELOW1Y            4.635e-02  6.627e-02   0.699 0.484292
## ESFDY            -2.670e-01  8.276e-02  -3.227 0.001252 **
## ETRANSY          -6.270e-02  7.616e-02  -0.823 0.410416
## EABANY           -8.187e-02  1.157e-01  -0.708 0.479137
## HOWHgood         -1.372e-01  7.947e-02  -1.726 0.084398 .
## HOWNgood          1.597e-01  6.730e-02   2.372 0.017669 *
## ODORAY            1.041e-01  9.811e-02   1.061 0.288528
## STRNAY           -9.644e-02  4.737e-02  -2.036 0.041783 *
## ZINC2            -1.277e-07  1.874e-07  -0.682 0.495530
## PER              -1.253e-01  1.855e-02  -6.752 1.46e-11 ***
## ZADULT            1.944e-02  3.188e-02   0.610 0.542024
## HHGRADBach        1.797e-01  6.596e-02   2.725 0.006431 **
## HHGRADGrad        2.729e-01  7.288e-02   3.745 0.000181 ***
## HHGRADHS Grad    -2.064e-02  6.376e-02  -0.324 0.746192
## HHGRADNo HS      -7.246e-02  9.845e-02  -0.736 0.461720
## NUNITS            2.377e-03  1.428e-03   1.664 0.096100 .
## INTW             -6.327e-02  1.372e-02  -4.613 3.98e-06 ***
## METROurban       -8.000e-02  5.389e-02  -1.485 0.137672
## STATECO          -2.513e-02  8.491e-02  -0.296 0.767257
## STATECT           7.870e-01  8.825e-02   8.918  < 2e-16 ***
## STATEGA          -2.223e-01  9.455e-02  -2.351 0.018716 *
## STATEIL           5.870e-01  1.635e-01   3.590 0.000330 ***
## STATEIN           2.431e-01  9.352e-02   2.599 0.009336 **
## STATELA           5.932e-01  1.077e-01   5.506 3.67e-08 ***
## STATEMO           5.309e-01  9.730e-02   5.456 4.87e-08 ***
## STATEOH           7.642e-01  9.480e-02   8.061 7.59e-16 ***
## STATEOK           1.291e-01  1.027e-01   1.257 0.208850
## STATEPA           6.011e-01  1.007e-01   5.968 2.40e-09 ***
## STATETX           2.935e-01  1.073e-01   2.736 0.006221 **
## STATEWA           1.525e-01  8.819e-02   1.730 0.083717 .
## BATHS             2.445e-01  3.419e-02   7.152 8.57e-13 ***
## BEDRMS           -2.086e-02  2.908e-02  -0.717 0.473120
## MATBUYY           2.587e-01  3.927e-02   6.588 4.45e-11 ***
## DWNPAYprev home   7.417e-01  4.857e-02  15.272  < 2e-16 ***
## VALUE             1.489e-06  1.452e-07  10.256  < 2e-16 ***
## FRSTHOY          -3.700e-01  5.170e-02  -7.156 8.29e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 18873  on 15564  degrees of freedom
```

```
## Residual deviance: 16969  on 15523  degrees of freedom
## AIC: 17053
##
## Number of Fisher Scoring iterations: 4
```

The interaction between "FRSTHO" and "BATHS" indicates that the negative impact of having more bathrooms on the likelihood of a larger down payment is further reduced for first-time buyers, with an odds multiplier of exp(-0.202)=0.817, suggesting different purchasing behaviors or financial strategies among this group.

```
# add interaction between "FRSTHO" and "BATHS"
gt20dwn_y_2 <- glm(gt20dwn ~ .- AMMORT - LPRICE + BATHS*FRSTHO, data=homes, family='binomial')
summary(gt20dwn_y_2)
```

```
##
## Call:
## glm(formula = gt20dwn ~ . - AMMORT - LPRICE + BATHS * FRSTHO,
##     family = "binomial", data = homes)
##
## Coefficients:
##                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -1.378e+00  1.851e-01  -7.444 9.76e-14 ***
## EAPTBLY         1.217e-02  7.020e-02   0.173 0.862337
## ECOM1Y         -1.608e-01  5.806e-02  -2.770 0.005612 **
## ECOM2Y         -3.181e-01  1.598e-01  -1.991 0.046511 *
## EGREENY        -2.305e-03  3.987e-02  -0.058 0.953900
## EJUNKY         -5.332e-03  1.606e-01  -0.033 0.973520
## ELOW1Y          4.950e-02  6.627e-02   0.747 0.455066
## ESFDY          -2.715e-01  8.276e-02  -3.280 0.001036 **
## ETRANSY        -6.147e-02  7.612e-02  -0.808 0.419333
## EABANY         -9.206e-02  1.155e-01  -0.797 0.425505
## HOWHgood       -1.324e-01  7.938e-02  -1.668 0.095245 .
## HOWNgood        1.630e-01  6.728e-02   2.423 0.015399 *
## ODORAY          1.022e-01  9.804e-02   1.043 0.297090
## STRNAY         -9.672e-02  4.736e-02  -2.042 0.041136 *
## ZINC2          -1.479e-07  1.897e-07  -0.780 0.435530
## PER            -1.266e-01  1.859e-02  -6.811 9.67e-12 ***
## ZADULT          2.195e-02  3.193e-02   0.687 0.491817
## HHGRADBach      1.818e-01  6.597e-02   2.755 0.005863 **
## HHGRADGrad      2.770e-01  7.294e-02   3.797 0.000146 ***
## HHGRADHS Grad  -1.967e-02  6.374e-02  -0.309 0.757647
## HHGRADNo HS    -7.767e-02  9.837e-02  -0.790 0.429774
## NUNITS          2.284e-03  1.415e-03   1.613 0.106646
## INTW           -6.421e-02  1.371e-02  -4.684 2.81e-06 ***
## METROurban     -8.407e-02  5.391e-02  -1.560 0.118848
## STATECO        -3.523e-02  8.516e-02  -0.414 0.679103
## STATECT         7.739e-01  8.837e-02   8.758  < 2e-16 ***
## STATEGA        -2.317e-01  9.489e-02  -2.441 0.014636 *
## STATEIL         5.738e-01  1.635e-01   3.509 0.000450 ***
## STATEIN         2.367e-01  9.369e-02   2.526 0.011534 *
## STATELA         5.893e-01  1.079e-01   5.464 4.66e-08 ***
## STATEMO         5.194e-01  9.749e-02   5.328 9.95e-08 ***
## STATEOH         7.505e-01  9.493e-02   7.906 2.66e-15 ***
## STATEOK         1.174e-01  1.029e-01   1.141 0.253976
## STATEPA         5.816e-01  1.009e-01   5.761 8.34e-09 ***
```

```
## STATETX           2.875e-01  1.075e-01   2.675 0.007473 **
## STATEWA           1.535e-01  8.829e-02   1.739 0.082036 .
## BATHS             2.994e-01  3.824e-02   7.829 4.92e-15 ***
## BEDRMS           -2.157e-02  2.913e-02  -0.741 0.458931
## MATBUYY           2.590e-01  3.929e-02   6.592 4.33e-11 ***
## DWNPAYprev home   7.338e-01  4.868e-02  15.073  < 2e-16 ***
## VALUE             1.448e-06  1.458e-07   9.927  < 2e-16 ***
## FRSTHOY          -2.137e-02  1.184e-01  -0.180 0.856799
## BATHS:FRSTHOY    -2.020e-01  6.207e-02  -3.255 0.001135 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 18873  on 15564  degrees of freedom
## Residual deviance: 16958  on 15522  degrees of freedom
## AIC: 17044
##
## Number of Fisher Scoring iterations: 4
```

QUESTION 3

Focus only on a subset of homes worth $> 100k$.

Train the full model from Question 1 on this subset. Predict the left-out homes using this model. What is the out-of-sample fit (i.e. R2)? Explain why you get this value. (1 point)

```r
# Take a subset of the data
subset <- which(homes$VALUE>100000)

# regress log(PRICE) on everything except AMMORT
pricey_subset <- glm(log(LPRICE) ~ .-AMMORT - gt20dwn, data=homes[subset,])
summary(pricey_subset)
```

```
##
## Call:
## glm(formula = log(LPRICE) ~ . - AMMORT - gt20dwn, data = homes[subset,
##     ])
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)    1.134e+01  5.567e-02 203.782  < 2e-16 ***
## EAPTBLY       -2.515e-02  2.119e-02  -1.187 0.235407
## ECOM1Y        -3.579e-02  1.722e-02  -2.078 0.037734 *
## ECOM2Y        -1.097e-01  4.803e-02  -2.284 0.022417 *
## EGREENY        4.153e-02  1.177e-02   3.529 0.000418 ***
## EJUNKY        -1.302e-01  5.122e-02  -2.542 0.011029 *
## ELOW1Y         9.975e-03  1.952e-02   0.511 0.609351
## ESFDY          1.288e-02  2.706e-02   0.476 0.634200
## ETRANSY       -5.148e-03  2.267e-02  -0.227 0.820354
## EABANY        -6.940e-02  3.846e-02  -1.805 0.071176 .
## HOWHgood       1.441e-02  2.465e-02   0.585 0.558767
```

```
## HOWNgood            6.651e-02  2.016e-02    3.299 0.000972 ***
## ODORAY             -8.135e-02  3.036e-02   -2.679 0.007391 **
## STRNAY             -7.165e-02  1.414e-02   -5.067 4.09e-07 ***
## ZINC2               3.307e-07  4.361e-08    7.583 3.62e-14 ***
## PER                 7.868e-02  5.293e-03   14.863  < 2e-16 ***
## ZADULT             -1.118e-01  9.326e-03  -11.985  < 2e-16 ***
## HHGRADBach          1.349e-01  1.926e-02    7.006 2.57e-12 ***
## HHGRADGrad          1.555e-01  2.141e-02    7.264 3.98e-13 ***
## HHGRADHS Grad      -3.571e-02  1.883e-02   -1.897 0.057889 .
## HHGRADNo HS        -1.821e-01  3.026e-02   -6.018 1.82e-09 ***
## NUNITS              5.284e-04  4.953e-04    1.067 0.286145
## INTW               -6.950e-02  4.392e-03  -15.825  < 2e-16 ***
## METROurban         -1.868e-02  1.628e-02   -1.147 0.251214
## STATECO             8.999e-03  2.259e-02    0.398 0.690333
## STATECT            -8.232e-03  2.449e-02   -0.336 0.736784
## STATEGA            -8.656e-02  2.515e-02   -3.441 0.000581 ***
## STATEIL            -1.098e-01  5.477e-02   -2.005 0.045025 *
## STATEIN            -1.199e-01  2.646e-02   -4.533 5.88e-06 ***
## STATELA            -1.773e-01  3.252e-02   -5.453 5.06e-08 ***
## STATEMO            -8.185e-02  2.819e-02   -2.904 0.003697 **
## STATEOH            -6.932e-02  2.733e-02   -2.536 0.011224 *
## STATEOK            -1.661e-01  3.210e-02   -5.174 2.33e-07 ***
## STATEPA            -2.805e-01  3.151e-02   -8.904  < 2e-16 ***
## STATETX            -1.277e-01  3.442e-02   -3.711 0.000207 ***
## STATEWA             1.267e-01  2.370e-02    5.346 9.13e-08 ***
## BATHS               1.805e-01  1.003e-02   17.997  < 2e-16 ***
## BEDRMS             -1.831e-02  8.588e-03   -2.132 0.033029 *
## MATBUYY             3.133e-01  1.154e-02   27.148  < 2e-16 ***
## DWNPAYprev home     1.145e-01  1.466e-02    7.812 6.11e-15 ***
## VALUE               1.125e-06  3.880e-08   28.992  < 2e-16 ***
## FRSTHOY            -1.211e-01  1.502e-02   -8.058 8.48e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.375933)
##
##     Null deviance: 7300.4  on 12143  degrees of freedom
## Residual deviance: 4549.5  on 12102  degrees of freedom
## AIC: 22626
##
## Number of Fisher Scoring iterations: 2
```

```
# get the predicted "log(LPRICE)" on the other subset of "homes"
price_pred <- predict(pricey_subset, newdata=homes[-subset,])

# Use the code ``deviance.R" to compute OOS deviance
source("deviance.R")

# call the function "deviance" to calculate the deviance of the predictions made
# on the left-out sample
D <- deviance(y=log(homes$LPRICE[-subset]), pred=price_pred, family="gaussian")

# Null model has just one mean parameter
ybar <- mean(log(homes$LPRICE[-subset]))
```

```r
D0 <- deviance(y=log(homes$LPRICE[-subset]), pred=ybar, family="gaussian")

# out-of-sample predicted R2
1-D/D0
```

```
## [1] -0.04988871
```

The model trained on homes valued over \$100k resulted in an out-of-sample (OOS) R^2 of -0.049. This negative R^2 suggests that the model performs worse on unseen data than a naive model that predicts the average log price for all observations, indicating potential over-fitting to the training data.

Negative R^2 in this context points to the model's limited generalizability. For GLMs, especially with transformed outcomes like log prices, R^2 may not be the most appropriate measure of model performance. Alternative evaluation metrics, such as AIC, BIC, or cross-validation, should be considered to better assess the model's predictive accuracy and to ensure it captures underlying trends rather than noise.